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Vulnerability Assessment of Groundwater Influenced Ecosystems in the Northeastern United States

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Abstract: Groundwater-influenced ecosystems (GIEs) are increasingly vulnerable due to groundwater extraction, land-use practices, and climate change. These ecosystems receive groundwater inflow as a portion of their baseflow or water budget, which can maintain water levels, water temperature, and chemistry necessary to sustain the biodiversity that they support. In some systems (e.g., springs, seeps, fens), this connection with groundwater is central to the system's integrity and persistence. Groundwater management decisions for human use often do not consider the ecological effects of those actions on GIEs. This disparity can be attributed, in part, to a lack of information regarding the physical relationships these systems have with the surrounding landscape and climate, which may influence the environmental conditions and associated biodiversity. We estimate the vulnerability of areas predicted to be highly suitable for the presence of GIEs based on watershed (U.S. Geological Survey Hydrologic Unit Code 12 watersheds: 24–100 km^2) and pixel (30 m $\times$ 30 m pixels) resolution in the Atlantic Highlands and Mixed Wood Plains EPA Level II Ecoregions in the northeastern United States. We represent vulnerability with variables describing adaptive capacity (topographic wetness index, hydric soil, physiographic diversity), exposure (climatic niche), and sensitivity (aquatic barriers, proportion urbanized or agriculture). Vulnerability scores indicate that ~26% of GIEs were within 30 m of areas with moderate vulnerability. Within these GIEs, climate exposure is an important contributor to vulnerability of 40% of the areas, followed by land use (19%, agriculture or urbanized). There are few areas predicted to be suitable for GIEs that are also predicted to be highly vulnerable, and of those, climate exposure is the most important contributor to their vulnerability. Persistence of GIEs in the northeastern United States may be challenged as changes in the amount and timing of precipitation and increasing air temperatures attributed to climate change affect the groundwater that sustains these systems.

Keywords: adaptive capacity; sensitivity; exposure; landscape; wetland; conservation

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1. Introduction

Practices that promote ecosystem integrity and persistence are at the forefront of natural resource management in the face of climate change and anthropogenic activity [1–3]. Ecosystem modifications or loss have contributed to the recent worldwide species decline, described as the sixth great mass extinction event [4,5]. Consequently, efforts to mitigate loss of ecosystems and the species they support have been prioritized [6,7]. Freshwater ecosystems are some of the most threatened systems in the world, owing to anthropogenic effects on water quantity and quality [8–10]. Threats to these systems are diverse and occur at various spatial scales, which make their conservation and management especially challenging [11]. Frameworks that can help identify where freshwater ecosystems are threatened, and that consider groundwater connectivity, could inform proactive management and mitigation to enhance the resilience of these systems.

Freshwater ecosystems directly influenced by groundwater contributions (hereafter termed groundwater-influenced ecosystems or GIEs) can occur in a wide variety of forms (e.g., fens, springs, rivers, lakes). The environmental conditions in these ecosystems reflect their geological setting, climate conditions, and landscape position [12,13]. GIEs can stay saturated during times of drought [14] and can act as carbon capture or carbon runoff zones [15,16]. Additionally, groundwater-influenced systems can improve water quality in surface water systems by providing summertime cold water habitats for aquatic species, cooling summer water temperatures, supporting micro-fauna that promote the breakdown of contaminants [17], and by regulating nutrient cycling and decomposition of organic matter [18].

Shallow groundwater systems are inherently vulnerable to a variety of human practices, such as land use (e.g., farming, urbanization), which can create pollution that degrades ecosystems (e.g., contaminated runoff) and can result in excessive water use (e.g., irrigation, [19]). Disruptions in groundwater flow timing, volume, temperature, and composition can affect the integrity and persistence of GIEs [20–22]. For example, concentrated groundwater extraction from private and municipal wells in Oregon threatened >18% of GIE clusters (watersheds containing two or more types of groundwater-dependent ecosystems), while 70% of GIE clusters were threatened by groundwater contamination [21]. Additionally, GIEs are vulnerable to reduced precipitation and increased evapotranspiration attributed to climate change, leading to reduced groundwater recharge and increased groundwater withdrawals [22–24]. GIEs are connected to groundwater by local and regional flow paths that determine the sources of water that discharge to a GIE [19,25,26]. Local groundwater flow paths are more sensitive to changes in climate (i.e., precipitation, air temperature, evapotranspiration) than regional groundwater flow paths [27]. Additionally, upslope groundwater recharge areas connect GIEs to the surrounding landscape and watershed processes and affect the duration and amount of groundwater received by GIEs [25].

Groundwater extraction for anthropogenic needs is expected to increase with increasing human populations in the northeastern United States (U.S.) [28]. As one of the most densely populated areas of the U.S., the region's landscapes are intensively modified with agriculture and urbanization [29], which may amplify effects of climate change by increasing surface temperatures [30,31]. These increased temperatures may affect groundwater recharge and water table depth [22], which could affect the occurrence, distribution, and condition of GIEs. Further, coastal aquifers are particularly vulnerable to groundwater extraction [28]. The northeastern U.S. includes >28,000 km of coastline where coastal aquifers and their associated GIEs may be at risk from this extraction [28]. A growing human population can further lead to increases in pollution, which can alter water chemistry, creating additional threats to a region's GIEs [32].

Vulnerability can be defined as the degree to which a system is susceptible to, and unable to cope with, the combined effects of climate change and anthropogenic modifications [33]. Magness et al. [34] calculated vulnerability by combining estimates of exposure, system sensitivity, and the adaptive capacity of the system. Exposure is estimated by quantifying factors attributable to climate change, such as changes in air temperature and precipitation [34,35]. Factors that affect a system's survival, persistence, fitness, or regeneration, such as land use, provide an aggregated estimate of sensitivity. Factors that promote adaptation responses, such as protected areas managed for conservation that can sustain ecosystem integrity, provide an aggregated estimate of adaptive capacity [34]. Within this framework, system vulnerability is estimated spatially by summing data layers representing the variables contributing to exposure, adaptive capacity, and sensitivity into a relative vulnerability score. This approach to estimating vulnerability provides a systematic and hypothesis-driven framework to examine factors influencing GIEs' potential vulnerability.

We conducted a vulnerability assessment of areas predicted in the northeastern U.S. to be highly suitable for GIEs [36], using the Magness et al. [34] framework to identify vulnerable GIEs and watersheds. We estimated vulnerability at two spatial scales: 30 m pixels and U.S. Geological Survey Hydrologic Unit Code (HUC) 12 watersheds (24–100 km^2). We identified areas predicted to be highly suitable for GIE occurrence [36] that also were predicted to be highly vulnerable, and we identified the input variables (i.e., exposure, sensitivity, adaptive capacity) with the most substantial contributions to GIE vulnerability. We further evaluated predicted vulnerability of areas in current conservation management that have predicted high suitability for GIE occurrence, as well as the vulnerability of watersheds surrounding those GIEs. By identifying the variables with the greatest contributions to the vulnerability scores, our results could inform management and conservation of groundwater-influenced ecosystems in the northeastern U.S.

2. Methods

2.1. Study Area

Our study extent spanned two EPA Level II ecoregions (Atlantic Highlands and Mixed Wood Plains; [37]; source: https://www.epa.gov/eco-research/ecoregion-download-files-region; accessed on 27 January 2021) with similar physical and biological conditions in portions of nine northeastern U.S. states (Connecticut, Massachusetts, Maine, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont) (Figure 1). We combined the ecoregions into one extent for our analysis. Suitability at a 30 m resolution for GIEs within our study area was obtained from ensembled correlative distributions models created for the two EPA ecoregions [36]. These ensembled models used known locations of GIEs and environmental variables representing topography, geology, and vegetation to predict suitability for GIEs across the ecoregions.

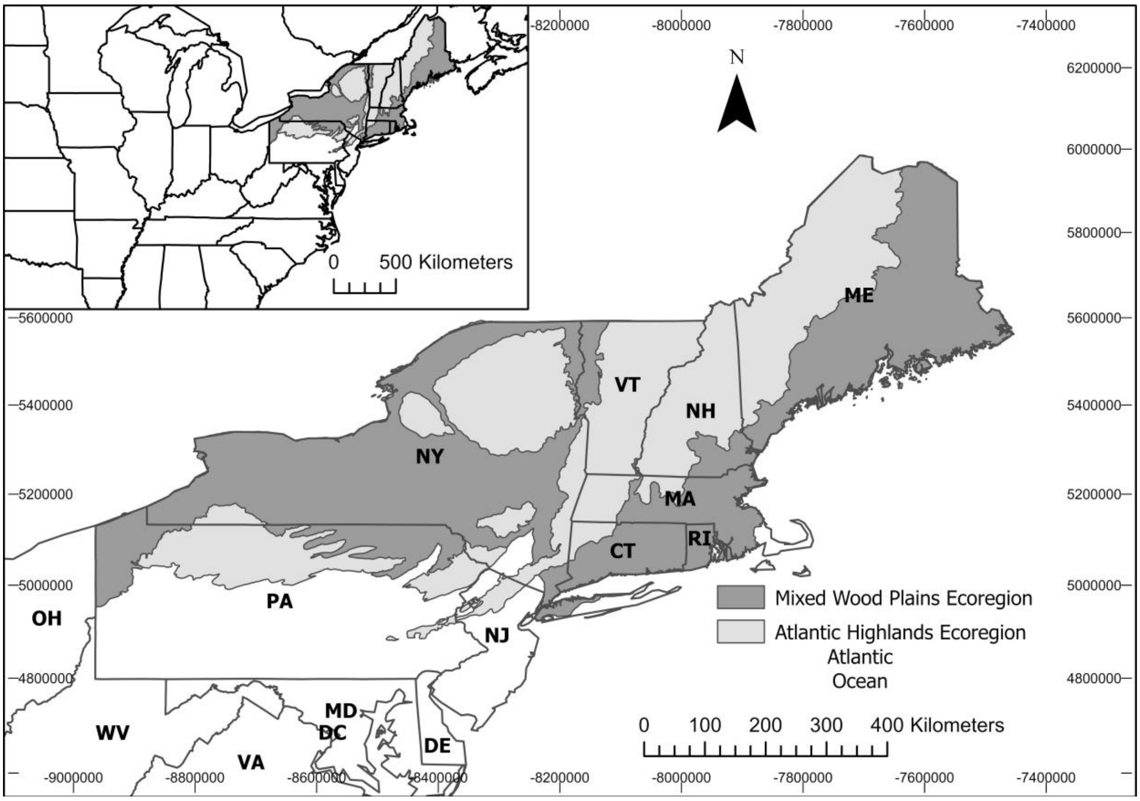

Figure 1. Environmental Protection Agency (EPA) Level II Ecoregions [37] (Atlantic Highlands, Mixed Woods) in the northeastern United States (source: https://www.epa.gov/eco-research/ecoregions-north-america; accessed on 27 January 2022). State abbreviations: Connecticut (CT), Delaware (DE), Maine (ME), Maryland (MD), Massachusetts (MA), New Hampshire (NH), New Jersey (NJ), New York (NY), Ohio (OH), Pennsylvania (PA), Rhode Island (RI), Vermont (VT), Virginia (VA), West Virginia (WV), District of Columbia (DC).

2.2. Vulnerability Framework

We used the conceptual framework of Magness et al. [34] to estimate vulnerability of pixels in the study extent by calculating *sensitivity* (i.e., degree to which ecosystem survival, persistence, fitness, or regeneration may be affected by stressors), *adaptive capacity* (i.e., capacity of an ecosystem to cope with stressors, including adaptation responses), and *exposure* (i.e., effect of climate change experienced by the locale). Vulnerability was summed as (1) *adaptive capacity* − *sensitivity* = *resilience* and (2) *exposure* − *resilience* = *vulnerability* (Figure 2). We calculated vulnerability at the pixel (30 m × 30 m) and watershed extents [mean vulnerability score of pixels within HUC12 watersheds (24–100 km^2; 4185 HUC12 watersheds in study area)].

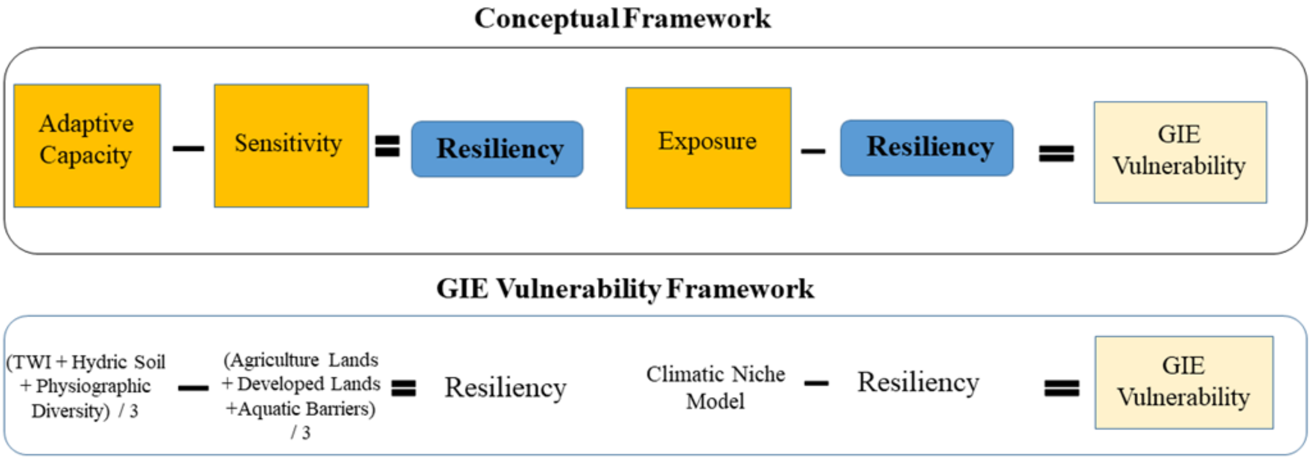

Figure 2. Vulnerability conceptual framework [34] and the framework used to estimate groundwater-influenced ecosystem (GIE) vulnerability across our study area. Orange boxes in the conceptual framework represent the core components of estimating vulnerability (tan boxes). Source data for the variables are listed in Table 1. Abbreviations: Topographic Wetness Index (TWI).

Table 1. Data used to estimate exposure, adaptive capacity, and sensitivity categories for GIEs under current climate and anthropogenic conditions. Variable abbreviations: minimum temperature (tmin), maximum temperature (tmax), precipitation (prcp), mean annual temperature (bio1), isothermality (bio3), mean temperature of driest quarter (bio9), mean temperature of warmest quarter (bio10), annual precipitation (bio12), precipitation of driest month (bio14), precipitation of warmest quarter (bio18), annual evapotranspiration (ET), potential evapotranspiration (PET), evapotranspiration in the growing season (ET-GS; May 15–September 15).

Category	Data	Variables	Source
Exposure	tmin, tmax, prcp	Bio1, 3, 9, 10, 12, 14, 18	https://daymet.ornl.gov/
	Evapotranspiration	ET, PET, ET-GS	https://lpdaac.usgs.gov/products/mod16a2gfv006/
Adaptive capacity	Topographic Wetness Index (TWI)	TWI	https://umassdsl.org/data/ecological-settings/
	Physiographic Diversity	Physiographic diversity	https://developers.google.com/earth-engine/datasets/catalog/CSP_ERGo_1_0_US_physioDiversity
	Hydric Soil	Percent hydric soil	https://www.nrcs.usda.gov/resources/data-and-reports/gridded-soil-survey-geographic-gssurgo-database
Sensitivity	Agriculture Land Cover	Percent agriculture land	https://www.mrlc.gov/data/nlcd-2019-land-cover-conus
	Developed Land Cover	Percent developed land	https://www.mrlc.gov/data/nlcd-2019-land-cover-conus
	Aquatic Barriers	Aquatic barriers	https://umassdsl.org/data/ecological-settings/

2.3. Sensitivity

We calculated sensitivity with three variables (Table 1): developed land use, agricultural land use, and aquatic barriers. Agriculture can affect water quality by contributing nutrients (e.g., nitrogen and phosphorus) and pesticides to groundwater ecosystems [21,22]. Urbanization and agriculture can lead to increased groundwater extraction for public water supplies and irrigation [21,22]. We extracted 30 m pixels from urbanized and agricultural land uses by selecting land cover classes (developed, pasture/hay, and cultivated crops) within the National Land Cover Database (NLCD; source: https://www.mrlc.gov/data; 2019; accessed on 10 November 2022) that represented these land-use types. Pixels extracted from these land-use types were given a value between 0.5 and 1, corresponding with the weights assigned by McGarigal et al. [38] (developed-high intensity = 1, developed-medium intensity = 0.8, developed low-intensity = 0.5, pasture/hay = 0.5, cultivated crops = 0.5) and all other pixels within the study area were given a value of 0. Aquatic barriers represent the relative degree to which road–stream crossings and dams potentially impede upstream and downstream movement of water. Aquatic barriers (e.g., roads, dams) can alter the flow and temperature of surface water, which can reduce downstream recharge and decrease the thermal influence of groundwater [20,22]. We represented the effect of aquatic barriers by using an aquatic barriers dataset created for the Northeast [39] with values ranging from 0 (no aquatic barrier effect) to 1 (high aquatic barrier effect). We clipped the data layers to the extent of the study area, resampled the clipped layers to 30 m pixels, and summed the resampled data layers with Geographic Information Systems (GIS) software (ArcGis Pro v. 2.8.0; ESRI; Redland, CA, USA) to estimate sensitivity (Figure 2).

2.4. Adaptive Capacity

We calculated adaptive capacity with three variables: topographic wetness index, physiographic diversity, and hydric soils (Table 1). Topographic wetness index is the relative amount of moisture at any point in the landscape [38] contributed by up-gradient topography, which has been shown to be positively associated with GIEs in the northeastern U.S. [40]. Physiographic diversity is an estimated index of physiographic types [41]. Hydric soil affects landscape suitability for groundwater-influenced systems [36] and is represented as percentage of hydric soil in the gridded soil survey geographic database for the conterminous United States [42]. We clipped the data layers to the study area extent, resampled the clipped data to 30 m pixels, and summed the resampled data to estimate adaptive capacity (ArcGIS Pro v. 2.8, Redland, CA, USA) (Figure 2).

2.5. Exposure

We calculated climate exposure with climatic niche models (CNMs). These models use current geographic distribution data for ecosystems or species to infer climatic environmental requirements [43]. This modeling technique has been used to predict species or ecosystem range shifts under current and projected climate scenarios [44–46]. We used CNMs to model the current climatic niche of GIEs to calculate climate exposure of these ecosystems.

2.6. Geographic Distribution Data

We trained our CNM models by compiling location data for 3168 GIEs that were field-verified during 1981–2020 by state Natural Heritage Programs (see [36] for geographic distribution data sources). We reduced spatial autocorrelation in the dataset by removing occurrences within 2 km of other recorded locations, which removed 296 locations from the dataset. We reduced the effect of spatial sorting bias (SSB) with point-wise distance sampling that produced a subsample with SSB = 1. We used the final SSB-reduced dataset (1690 locations) for training the CNMs.

2.7. Climate Variables

We selected climate variables to include in our CNMs by reviewing literature describing effects of climate change on GIEs [19,22,28,47,48] (Table 1). We included ten climate variables in the CNMs that measured or estimated temperature, precipitation, and annual evapotranspiration (Table 1). We estimated seven bioclimatic variables (Table 1) with monthly Daymet V4 Daily Surface Weather and Climatological summaries (1 km resolution; [49]). Maximum temperature (tmax), minimum temperature (tmin), and precipitation (prcp) during 1980–2019 were used to calculate the seven bioclimatic variables using the 'biovars' function within the 'dismo' R (v1.4.1106) package [50]. We estimated evapotranspiration (ET), potential evapotranspiration (PET), and evapotranspiration in the growing season (ET-GS) from MOD16A2 V.6 Terra Net Evapotranspiration 8-day Global dataset (https://lpdaac.usgs.gov/products/mod16a2gfv006/; accessed on 25 January 2023) within a web-available mapping system (Google Earth Engine, GEE; https://earthengine.google.com/; [51]) to obtain average annual rates during 2001–2019. All climate data layers were clipped to the extent of our study area and resampled to 1 km pixels if the source data were not 1 km resolution. We compared all variables with a Pearson correlation test and determined that none of the climatic variables were highly correlated ($R^2 < 0.60$).

2.8. CNM Development and Evaluation

We selected two climatic niche modeling methods, maximum entropy (Maxent) and generalized additive models (GAM), which have been used frequently and have outperformed other climatic niche modeling methods [43,52–54]. No single modeling approach will perform best in every scenario [55], thus we developed two statistically contrasting models and integrated the predictions by calculating the mean suitability score for each pixel. Maxent is a machine learning modeling method that estimates suitability by finding the distribution that achieves maximum entropy given the environmental conditions at occurrence locations [56]. Generalized additive models smooth data to fit non-linear functions with non-parametric distributions. We developed our CNMs within the 'dismo' (Maxent; [50]) and 'mgcv' (GAM; [57]) packages in R (version 1.4.1106). We generated 20,000 pseudo-absence locations by randomly sampling across the study area extent. We partitioned occurrence (1690) and pseudo-absence data (20,000) into training (1352 presences and 16,902 background points) and testing (338 presences and 4225 background points) datasets with a K-fold cross validation with five folds. We evaluated CNM prediction accuracy with five metrics: area under the curve (AUC) estimates, Cohens Kappa statistic, sensitivity rates, specificity rates, and the true skill statistic (TSS). We evaluated CNM performance with each metric with thresholds to determine if the CNM was informative: AUC $\geq$ 0.70 [58], Cohens Kappa $\geq$ 0.50 [59], sensitivity and specificity rates $\geq$ 0.70, and TSS $\geq$ 0.50 [60].

2.9. Pixel-Scale Vulnerability Calculation

We scaled (0 to 1) 30 m data representing adaptive capacity and sensitivity and averaged the scaled pixel values separately for both. We subtracted the sensitivity pixel values from the adaptive capacity pixel values and scaled (0 to 1) the resulting pixel values to estimate resiliency in each 30 m pixel in the study extent (Figure 2). We used the CNM models, which produced climatic niche suitability scores from 0 (least suitable) to 1 (most suitable), to calculate exposure. We scaled the exposure estimate as 1 − suitability score, assigning the greatest exposure score to the smallest climate niche suitability. We resampled the 1 km exposure raster data to 30 m pixels, and we calculated the vulnerability raster as exposure − resilience, scaling the resultant pixels from 0 (least vulnerable) to 1 (most vulnerable). We classified the scaled vulnerability values into four vulnerability categories: least [$0 \leq$ value ≤ 0.25], low [$0.25 <$ value ≤ 0.50], moderate [$0.50 <$ value ≤ 0.75], and high [$0.75 <$ value ≤ 1.0].

2.10. Land Ownership

We identified lands in conservation ownership within the study extent with the Protected Areas Database for the United States (PAD-US; https://www.usgs.gov/core-science-systems/science-analytics-and-synthesis/gap/science/protected-areas; accessed on 5 October 2022). The PAD-US database designates 10 land ownership types; we calculated the average vulnerability scores in areas in the Federal, Joint, Non-Governmental Organization, Private, and State ownership types. The PAD-US also assigns the type of conservation practices that occur within each protected area into four categories: (1) managed for biodiversity, where natural disturbance events proceed or are mimicked; (2) managed for biodiversity, where natural disturbance events are suppressed; (3) managed for multiple uses, including extractive (e.g., mining or logging) or off-highway motor vehicles (OHV) use; and (4) no known mandate for biodiversity protection. We calculated the average vulnerability scores in each protected area and then identified the number and total area of protected areas that had moderate [0.50 < value ≤ 0.75] or high vulnerability [0.75 < value ≤ 1.0] for each conservation practice type.

2.11. Landscape Suitability Model Comparison

We created a polygon layer from the ensembled model raster predicting areas that are suitable (80th percentile) for GIEs [36], and we used this polygon layer to extract (mask) pixels from the pixel-scale vulnerability raster to identify GIEs with vulnerability score > 0.50 (indicating vulnerable). We identified areas predicted to be suitable for GIEs that also contained vulnerable pixels (>0.50) that are within the United States Department of Agriculture's (USDA) recommended 30 m wide conservation buffer around shallow groundwater (source: https://www.fs.usda.gov/nac/buffers/guidelines/1_water_quality/15.html; accessed on 10 March 2023). We calculated the average vulnerability score of pixels occurring within 30 m of each GIE-suitable polygon by overlaying the buffered (30 m) GIE polygons as a mask on the landscape vulnerability raster and then identified GIEs that are highly (value > 0.75) or moderately (0.50 < value ≤ 0.75) vulnerable.

We extracted patches of contiguous pixels (≥10 ha area) with high vulnerability (>0.75), converted the pixels to polygons, and calculated the distance between the edge of each GIE polygon and the nearest high-vulnerability polygon (mean = 54 ha, Standard Deviation = 301.4 ha). This allowed us to determine the number and total area of areas predicted to be suitable for GIEs that are within close proximity (<200 m) to highly vulnerable polygons. We calculated the proportion of GIE areas and highly vulnerable areas (>0.75 vulnerability) within each HUC12 watershed to identify watersheds with the greatest proportion of areas that are both suitable for GIEs and also vulnerable.

3. Results

3.1. GIE and Watershed Vulnerability

Approximately 34% of the study area (334,150 km^2) is estimated to be at least moderately vulnerable (Table 2), and 54% of watersheds (representing 53% of the study area) are at least moderately vulnerable (Figure 3). Scaled estimates of adaptive capacity, exposure, and sensitivity are presented in Figure 4. Approximately two thirds of HUC12 watersheds are predicted to contain highly suitable conditions for GIEs, and areas predicted to be suitable for GIEs are relatively small (range: 0.2–1992 ha, mean = 2.4 ha, Standard Deviation = 11.4; [36]). Highly vulnerable areas are also small and vary in size (range: 0.12–31,969 ha, mean = 3.6 ha, Standard Deviation = 68.9). Of the HUC 12 watersheds predicted to contain highly suitable conditions for GIEs, 199 (representing 5% of total watershed area) contain GIEs with moderate vulnerability. Only 0.6% of GIEs (0.6% of total GIE area) are predicted to be highly vulnerable (Table 3) within 30 m of GIE edges. Approximately 26% of pixels with high suitability for GIEs (representing 28% of total GIE area) are within 30 m of land predicted to be at least moderately vulnerable. Areas predicted to be suitable for GIEs and within 30 m of highly vulnerable pixels vary in size (range: 0.8–394 ha, mean = 2.4 ha, Standard Deviation = 10.3) and generally are smaller than the highly vulnerable areas around them (range: 0.1–1217 ha, mean = 52.3 ha, Standard Deviation = 150.9). Of the 195,225 ha of area predicted to be suitable for GIEs that are within 30 m of moderately or highly vulnerable pixels, climate exposure and land-use practices (Table 4) are important drivers of vulnerability. Most (98.5%) areas suitable for GIEs are >200 m from large (≥10 ha) highly vulnerable areas of the landscape (Table 5).

Table 2. Total area (km^2) and percentage of area of Hydrologic Unit Code 12 (HUC12) watersheds (24–100 km^2) in the study area (Figure 1) and their partitioning by vulnerability score. Groundwater-influenced ecosystems (GIE).

Vulnerability Categories	Square Kilometers	Percent of Ecoregion	GIE Area (km^2)	Percent of Total GIE Area
0 ≤ value < 0.25	4836	1.5	1212	19.6
0.25 ≤ value < 0.50	203,236	63.2	4308	69.5
0.50 ≤ value ≤ 0.75	105,787	32.9	669	10.8
0.75 < value ≤ 1	7728	2.4	11	0.2
	Number of HUC12 Watersheds	**Percent of Watersheds**	**GIE Area (km^2)**	**Percent of Total GIE Area**
0 ≤ value < 0.25	0.25	0.6	34.92	0.5
0.25 ≤ value < 0.50	19	44.5	5633	80.5
0.50 ≤ value ≤ 0.75	23	54.6	1329	19.0
0.75 < value ≤ 1	0.14	0.3	0	0.0

Table 3. Vulnerability scores within 30 m of areas predicted by [36] to be suitable for groundwater-influenced ecosystem (GIE) occurrence in the northeastern United States study area (Figure 1). Vulnerability score range estimates are cumulative (e.g., ≥0.50 indicates 0.50–1 totals). The conceptual framework for estimating vulnerability [34] is provided in Figure 2.

Vulnerability Score	GIEs Counts	Percent of GIEs	GIE Area (km^2)	Percent of Total GIE Area
<0.25	13,847	4.8	361	5
<0.50	196,795	67.9	5045	68.1
≥0.50	77,344	26.7	1952	26.4
≥0.75	1878	0.6	45	0.6

Table 4. Number and proportion of areas predicted to be suitable for groundwater-influenced ecosystems (GIEs) [36] that are within ≤30 m of areas predicted to be vulnerable owing to sensitivity (land use) and exposure (climate) in the study area (Figure 1). Vulnerability score range estimates are cumulative (e.g., ≥0.50 indicates 0.50–1 totals). Variables combined to estimate sensitivity and exposure components of vulnerability are indicated in Table 1. The conceptual framework for vulnerability [34] is provided in Figure 2.

		Number of GIEs			
		Exposure ≥0.50	**Exposure ≥0.75**	**Sensitivity ≥0.50**	**Sensitivity ≥0.75**
Exposure	≥0.50	31,563	-	5837	177
Exposure	≥0.75	-	774	185	3
Sensitivity	≥0.50	5837	185	14,419	-
Sensitivity	≥0.75	177	3	-	460
		Percent of Vulnerable GIE area			
		Exposure ≥0.50	**Exposure ≥0.75**	**Sensitivity ≥0.50**	**Sensitivity ≥0.75**
Exposure	≥0.50	40.8	-	7.5	0.2
Exposure	≥0.75	-	1.0	0.2	<0.01
Sensitivity	≥0.50	7.5	0.2	18.6	-
Sensitivity	≥0.75	0.2	<0.01	-	0.6

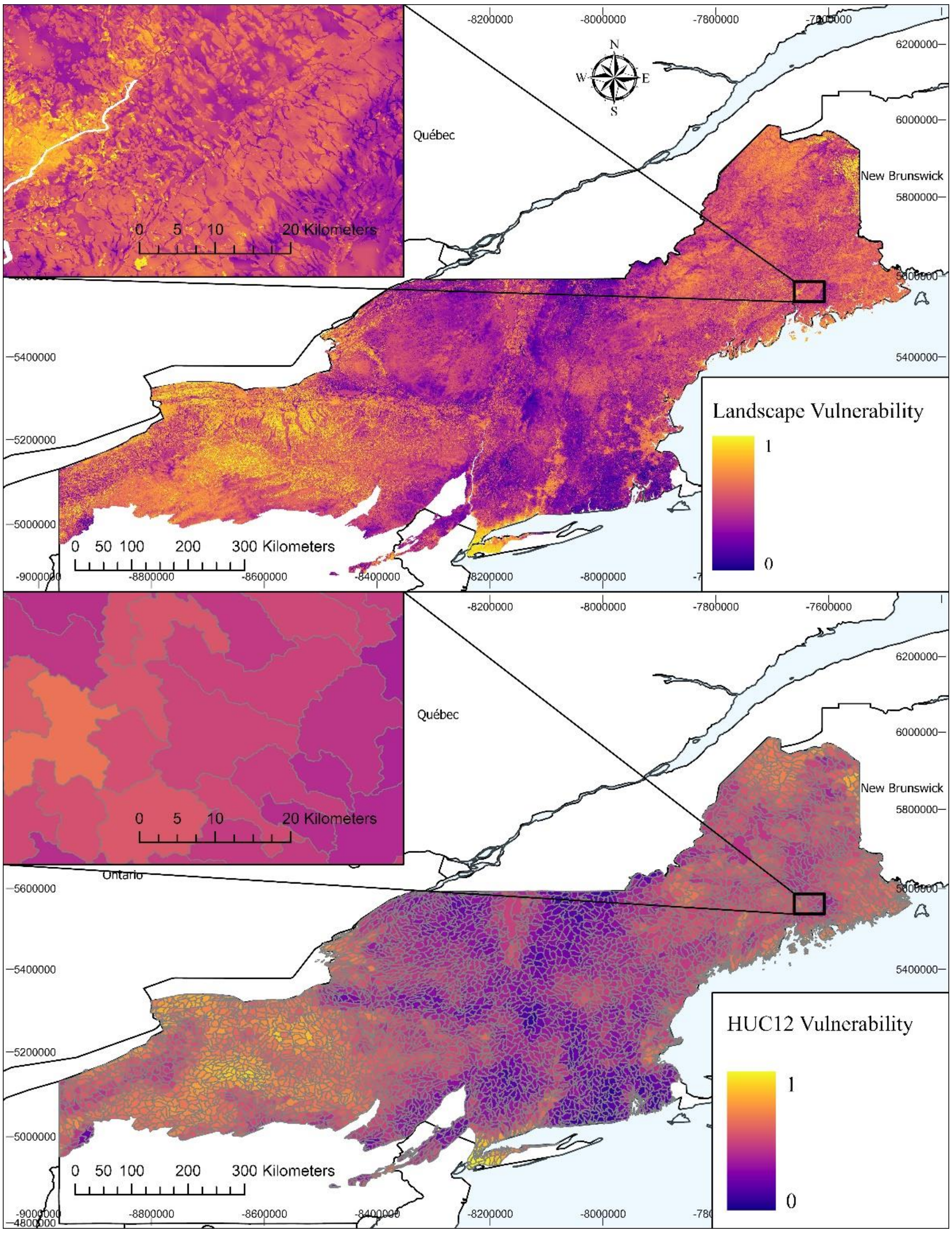

Figure 3. Estimated 30 m pixel and Hydrologic Unit Code (HUC) 12 watershed vulnerability across the northeastern United States study area (Figure 1). Grey lines in the lower frame indicate HUC12 watershed boundaries.

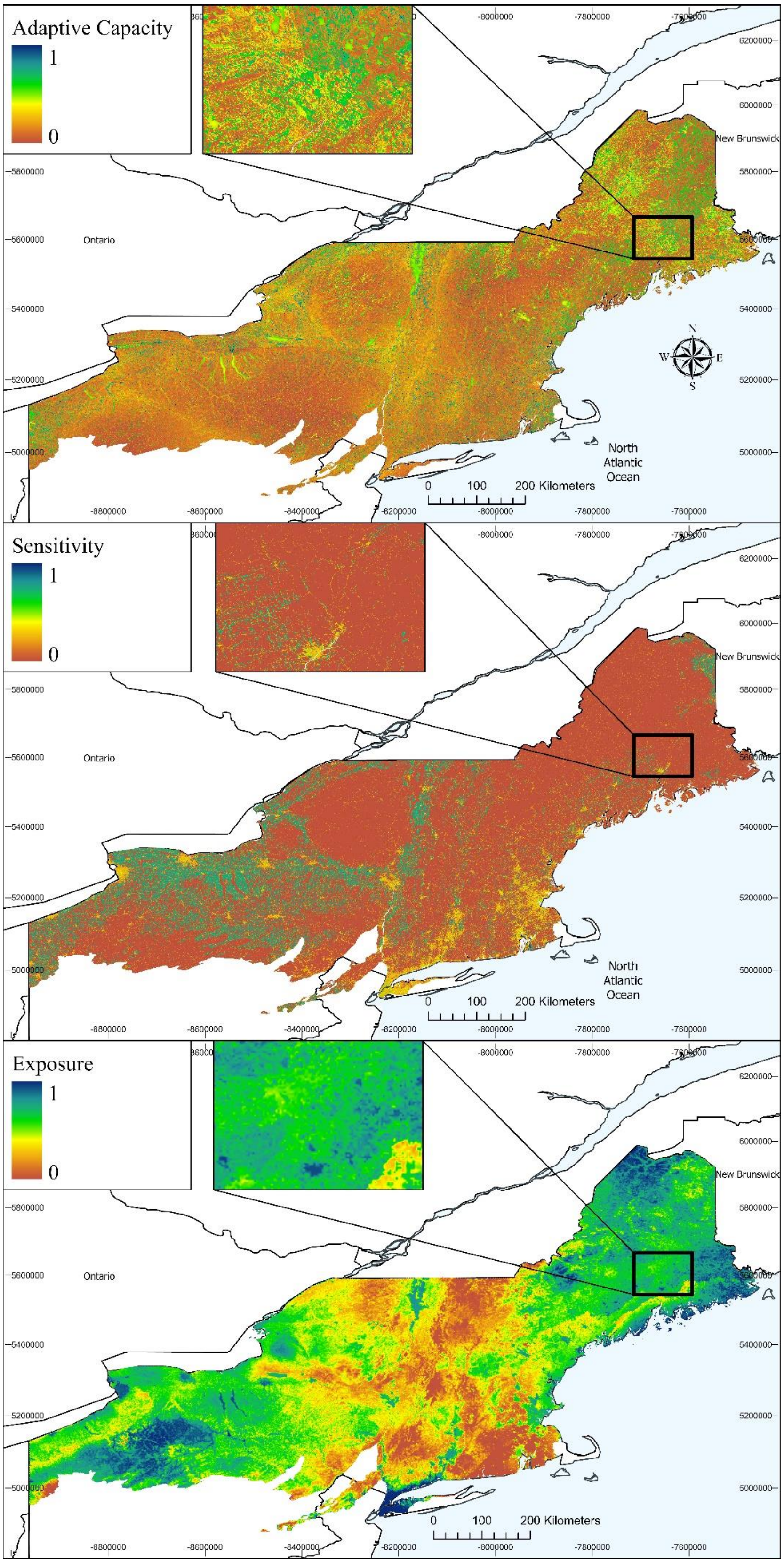

Figure 4. Scaled estimates of landscape adaptive capacity, sensitivity, and exposure calculated to estimate groundwater-influenced ecosystem (GIE) vulnerability in the study area (Figure 1). The conceptual framework for estimating vulnerability [34] is provided in Figure 2.

Table 5. Number and proportion of areas predicted to be suitable for groundwater-influenced ecosystems (GIEs) [36] and occurrences within cumulative distance (m) bands around the GIEs extending out of areas predicted to be highly vulnerable (score ≥ 0.75) to large patches (>10 ha) in the study area (Figure 1). The conceptual framework for the vulnerability [34] score is provided in Figure 2.

Distance Band (m)	Number of GIEs in Distance Band	Percent of Total GIEs	GIE Area (km^2) in Distance Band	Percent of GIE Area
<50	1628	0.6	56	0.8
<100	2581	0.9	78	1.1
<200	4049	1.5	109	1.6
<300	5243	1.9	127	1.8
<400	6277	2.3	139	2.0
<800	9599	3.5	177	2.5

3.2. State Scale

New York, Pennsylvania, and Maine contain the greatest total land area that is moderately vulnerable (Figure 5; Table 6). Maine (64.7%), New York (46.2%), and New Hampshire (28%) contain the largest proportions of moderate landscape vulnerability by state (Figure 5; Table 6). The largest total area of watersheds that are at least moderately vulnerable are in New York (911; 51% of state), Maine (831; 76%), and Pennsylvania (517; 32%). Watersheds that are highly vulnerable (>0.75) occur in New York (14; 0.5% of state) and New Jersey (2; 0.1% of state) (Figure 5; Table 7). Climate exposure is the greatest contributor to high vulnerability of lands in Connecticut, and climate exposure and land-use practices are both contributors to moderate and high vulnerability in Maine, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, and Vermont. (Figure 6; Table 8).

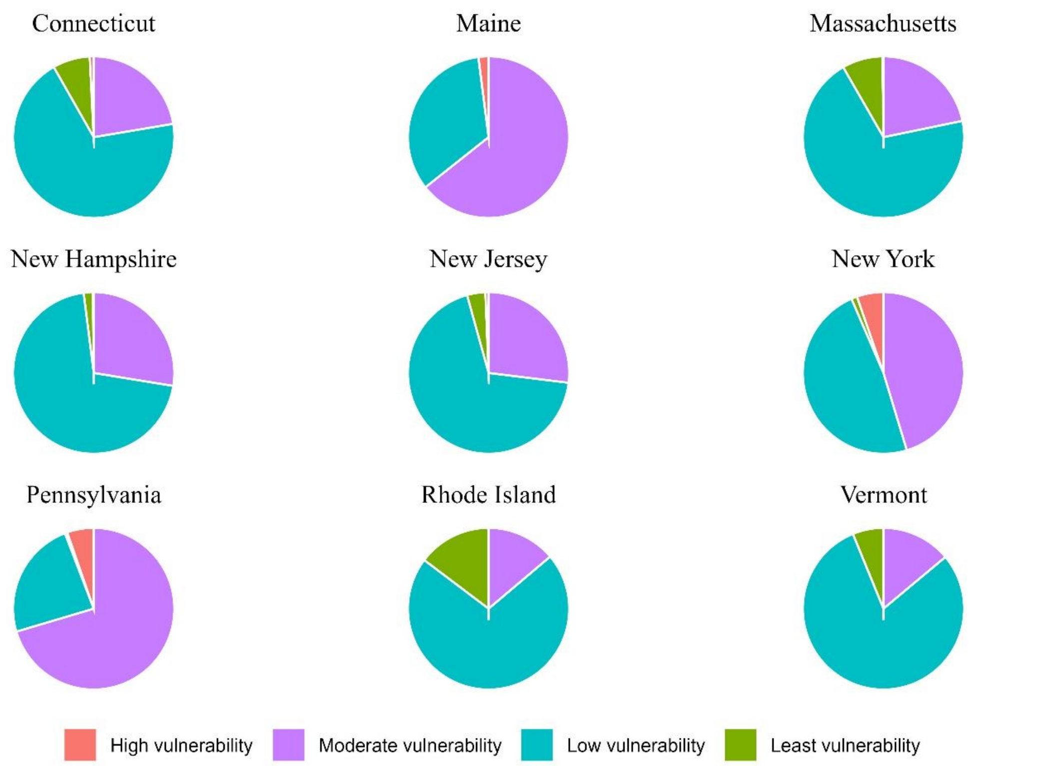

Figure 5. Proportion of land area vulnerability predicted in 30 m pixels summarized by states in the study area's Environmental Protection Agency (EPA) Level II Ecoregions (Atlantic Highlands, Mixed Woods) in the northeastern United States. EPA A Level III ecoregions in the study area are indicated in Figure 1. Values used to create pie charts can be found in Table 6.

Table 6. Area (km^2) of land in vulnerability score ranges within the study region by state (Figure 1). Vulnerability score range estimates are cumulative (e.g., ≥0.50 indicates 0.50–1 totals). The conceptual framework for vulnerability [34] is provided in Figure 2.

Vulnerability Score	<0.25	<0.25	<0.50	<0.50	≥0.50	≥0.50	≥0.75	≥0.75
State	**Area (km^2)**	**Percent of State**	**Area (km^2)**	**Percent of State**	**Area (km^2)**	**Percent of State**	**Area (km^2)**	**Percent of State**
Connecticut	1374	8.0	12,743	74.1	4104	23.9	143	0.8
Maine	46	0.0	39,941	33.8	76,437	64.7	2383	2.0
Massachusetts [1]	2248	7.9	19,259	67.5	5995	21.0	46	0.2
New Hampshire	623	1.9	23,685	71.6	9271	28.0	49	0.2
New Jersey [1]	107	0.4	2003	7.9	785	3.1	18	0.1
New York [1]	2057	1.2	84,188	49.1	79,204	46.2	9316	5.4
Pennsylvania [1]	291	0.2	14,427	9.3	42,737	27.6	3238	2.1
Rhode Island	586	16.2	2845	78.7	551	15.3	0.20	0.0
Vermont	2251	6.5	29,225	84.7	5101	14.8	15	0.0

Note(s): [1] Estimates are based on the area of the state within the study area.

Table 7. Area (km^2) of HUC12 watersheds by vulnerability score range within the study region of each state (Figure 1). Vulnerability score range estimates are cumulative (e.g., ≥0.50 indicates 0.50–1 totals). The conceptual framework for vulnerability [34] is provided in Figure 2.

Vulnerability Score	<0.25	<0.25	<0.25	<0.50	<0.50	<0.50	≥0.50	≥0.50	≥0.50	≥0.75	≥0.75	≥0.75
State	**Number of Watersheds**	**Area (km^2)**	**Percent of State**	**Number of Watersheds**	**Area (km^2)**	**Percent of State**	**Number of Watersheds**	**Area (km^2)**	**Percent of State**	**Number of Watersheds**	**Area (km^2)**	**Percent of State**
Connecticut	0	0	0	154	14,049	81.7	30	2937	17.1	0	0	0
Maine	0	0	0	230	27,412	23.2	831	8998	76.1	0	0	0
Massachusetts [1]	0	0	0	215	22,341	78.3	38	3176	11.1	0	0	0
New Hampshire	0	0	0	299	29,221	88.4	44	3790	11.5	0	0	0
New Jersey [1]	0	0	0	39	2161	8.5	17	749	2.9	2	24	0.1
New York [1]	0	0	0	721	76,597	44.7	911	87,526	51.1	14	798	0.5
Pennsylvania [1]	0	0	0	111	8049	5.2	517	49,456	31.9	0	0	0
Rhode Island	0	0	0	56	3319	91.8	2	187	5.2	0	0	0
Vermont	1	287	0.008	253	31,794	92.1	15	2711	7.9	0	0	0

Note(s): [1] Estimates are based on entire state area but the entirety of these states do not occur in the study area.

Table 8. Areas (km^2) predicted to be highly vulnerable (≥0.75) owing to adaptive capacity, sensitivity (land use) and exposure (climate) within the study region (Figure 1). Variables combined to estimate adaptive capacity, sensitivity, and exposure are indicated in Table 1. The conceptual framework for the vulnerability [34] score is provided in Figure 2. State abbreviations: Connecticut (CT), Maine (ME), Massachusetts (MA), New Hampshire (NH), New Jersey (NJ), New York (NY), Pennsylvania (PA), Rhode Island (RI), Vermont (VT).

		km^2								
		CT	**ME**	**MA**	**NH**	**NJ**	**NY**	**PA**	**RI**	**VT**
Exposure	High	105	237	1	4	8	2025	454	0	0.02
	Moderate	27	2096	41	42	10	7195	2738	0.2	15
Adaptive Capacity	High	0.02	1	0.02	0.01	0.003	2	1	0	0
	Moderate	1	28	0.4	1	0.1	86	30	0	0.3
Sensitivity	High	6	10	7	2	0.5	32	7	0.1	1
	Moderate	19	2146	31	38	10	7931	2976	0.01	13
		Percent								
Exposure	High	73.3	10.0	2.0	7.4	42.5	21.7	14.0	0	0.1
	Moderate	19.1	87.9	87.3	84.0	54.0	77.2	84.5	80.9	95.6
Adaptive Capacity	High	0.01	0.02	0.03	0.02	0	0.02	0.03	0	0
	Moderate	0.5	1.2	0.9	1.0	0.5	0.9	0.9	0.3	2.2
Sensitivity	High	4.0	0.4	14.2	4.3	2.5	0.3	0.2	69.6	4.7
	Moderate	13.4	90.0	66.4	75.1	56.6	85.1	91.9	6.4	86.0

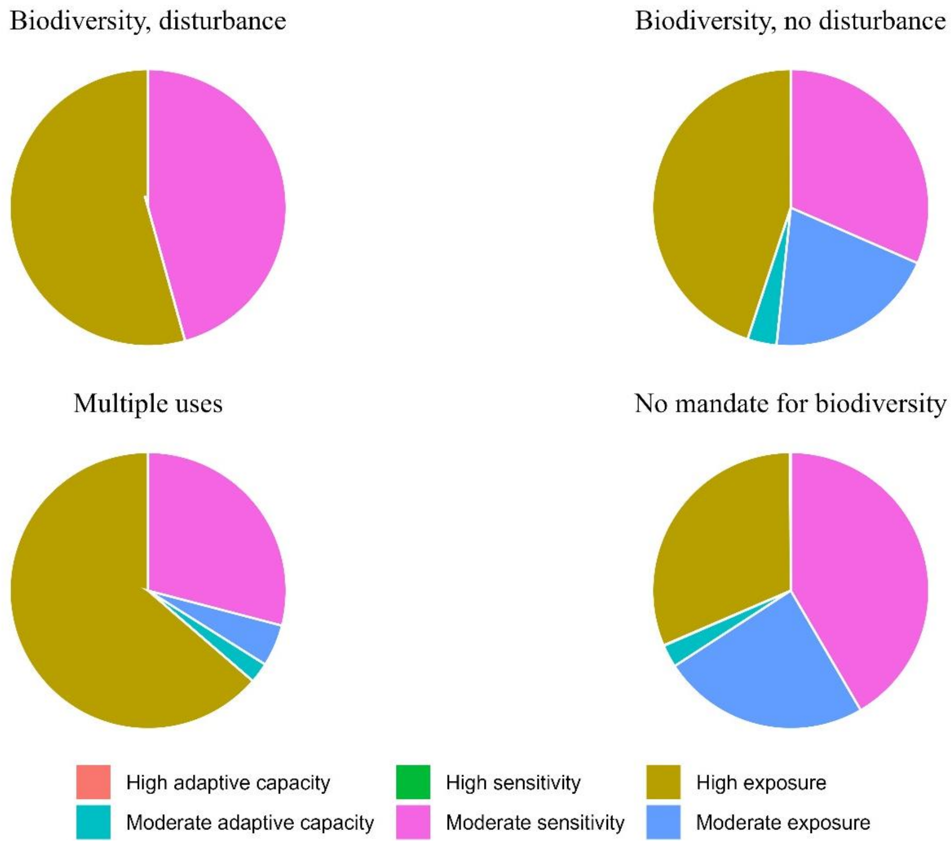

Figure 6. Proportion of the study area predicted to be highly vulnerable (≥0.75) owing to adaptive capacity, sensitivity (indicated by land use), and exposure (indicated by climate) within the Protected Areas Database for the United States (PAD-US), summarized by management type. High adaptive capacity does not appear on any pie charts because estimates are low or are 0 for those categories Management types: (1) managed for biodiversity—disturbance events proceed or are mimicked, (2) managed for biodiversity—disturbance events suppressed, (3) managed for multiple uses—subject to extractive (e.g., mining or logging) or OHV use, and (4) no known mandate for biodiversity protection (PAD-US Source: https://www.sciencebase.gov/catalog/item/602ffe50d34eb1203115c7ab). Values used to create pie charts can be found in Table 12. Variables combined to estimate sensitivity and exposure are indicated in Table 1.

3.3. Vulnerability of Protected Areas

State-owned lands account for the most land area with moderate or high vulnerability (Table 9). The majority (69%) of protected areas that are highly vulnerable have no mandate for biodiversity conservation (category 4), and 25% are managed for multiple uses (category 3; Table 10). Approximately 18% of the area predicted to be suitable for GIEs occurs in lands mapped in the PAD-US database, with the most (6.8%) occurring in the "managed for biodiversity with natural disturbance events suppressed" (category 2) and "managed for multiple uses" (7.7%) conservation types (Table 11). Climate exposure and land-use practices both contribute to high vulnerability in management categories 2, 3, and 4 (Figure 7; Table 12). For all land ownership types, vulnerability can be attributed to effects of both land use and climate exposure (Figure 8; Table 13). The majority of GIE area that has moderate or high vulnerability occurs within PAD-US protected areas in management categories 3 and 4 (Table 11).

Table 9. Distribution of landscape vulnerability scores calculated in 30 m pixels summarized by land ownership type in the study area (Figure 1). Vulnerability score range estimates are cumulative (e.g., ≥0.50 indicates 0.50–1 totals). The conceptual framework for the vulnerability [34] score is provided in Figure 2. Ownership types are described in the Protected Areas Database for the United States (PAD-US; https://www.usgs.gov/core-science-systems/science-analytics-and-synthesis/gap/science/protected-areas; accessed on 5 October 2022).

Vulnerability Score	<0.25	<0.25	<0.50	<0.50	≥0.50	≥0.50	≥0.75	≥0.75
Ownership Type	**Area (km^2)**	**Percent of Ownership Type**	**Area (km^2)**	**Percent of Ownership Type**	**Area (km^2)**	**Percent of Ownership Type**	**Area (km^2)**	**Percent of Ownership Type**
Federal	266	2.3	6835	59.3	4640	40.3	33	0.3
Joint	0.73	0.0	1001	25.7	2862	73.5	23	0.6
Non-Governmental Organization	244	4.0	3469	57.1	2510	42.3	10	0.2
Private	376	2.0	9280	49.7	9188	49.2	65	0.4
State	1027	2.1	30,236	60.7	19,269	38.7	86	0.2

Table 10. Distribution of landscape vulnerability scores calculated in 30 m pixels and summarized by land management type in our study area (Figure 1). Vulnerability score ranges estimates are cumulative (e.g., ≥0.50 indicates 0.50–1 totals). The conceptual framework for the vulnerability [34] score is provided in Figure 2. Management types are described in the Protected Areas Database for the United States (PAD-US; https://www.usgs.gov/core-science-systems/science-analytics-and-synthesis/gap/science/protected-areas; accessed on 5 October 2022) and include (1) managed for biodiversity—disturbance events proceed or are mimicked, (2) managed for biodiversity—disturbance events suppressed, (3) managed for multiple uses—subject to extractive (e.g., mining or logging) or OHV use, and (4) no known mandate for biodiversity protection.

		Mean Vulnerability Score < 0.25	**Mean Vulnerability Score < 0.50**	**Mean Vulnerability Score ≥ 0.50**	**Mean Vulnerability Score ≥ 0.75**
Management Type	**Number of Protected Areas**	**Number of Protected Areas**	**Number of Protected Areas**	**Number of Protected Areas**	**Number of Protected Areas**
Biodiversity, disturbance (1)	1527	52	1152	303	1
Biodiversity, no disturbance (2)	9602	506	6906	2239	18
Multiple uses (3)	25,205	1432	18,874	5106	75
No mandate for biodiversity (4)	31,780	977	17,003	12,579	206
Total	68,114	2967	43,935	20,227	300
	Proportion	Proportion	Proportion	Proportion	Proportion
Biodiversity, disturbance (1)	0.02	0.02	0.03	0.01	0.003
Biodiversity, no disturbance (2)	0.14	0.17	0.16	0.11	0.06
Multiple uses (3)	0.37	0.48	0.43	0.25	0.25
No mandate for biodiversity (4)	0.47	0.33	0.39	0.62	0.69

Table 11. Groundwater-influenced ecosystem (GIE) area within the moderate and high landscape vulnerability lands within the Protected Areas Database for the United States (PAD-US), summarized by management type. Management types: (1) managed for biodiversity—natural disturbance events proceed or are mimicked, (2) managed for biodiversity—disturbance events are suppressed, (3) managed for multiple uses—subject to extractive (e.g., mining or logging) or off-highway vehicle use, and (4) no known mandate for biodiversity protection (Source: https://www.sciencebase.gov/catalog/item/602ffe50d34eb1203115c7ab).

	Moderate Vulnerability	**Moderate Vulnerability**	**High Vulnerability**	**High Vulnerability**		
Management Type	**GIE Area**	**Percent of Total GIE Area**	**GIE Area**	**Percent of Total GIE Area**	**Total GIE Area**	**Percent of Total GIE Area**
Biodiversity, disturbance (1)	761	0.11	0	0	4611	0.7
Biodiversity, no disturbance (2)	1566	0.22	0	0	47,652	6.8
Multiple uses (3)	2305	0.33	1	<0.0001	53,536	7.7
No mandate for biodiversity (4)	1720	0.25	1	<0.0001	17,562	2.5

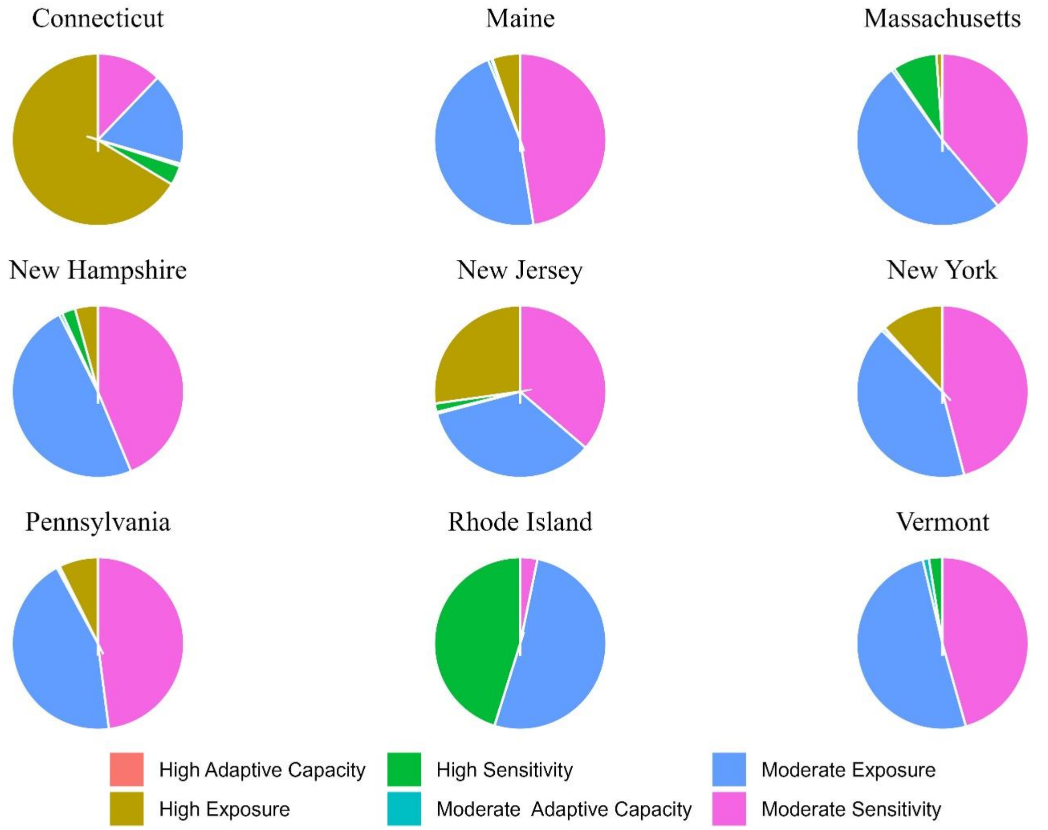

Figure 7. Proportion of land area predicted to be highly vulnerable (≥0.75) owing to adaptive capacity, sensitivity (indicated by land use), and exposure (indicated by climate) within states in Environmental Protection Agency (EPA) Level II Ecoregions (Atlantic Highlands, Mixed Woods) in the northeastern United States. High adaptive capacity and High sensitivity do not appear on any pie charts because estimates are low or are 0 for those categories. EPA Level III ecoregions in the study area are indicated in Figure 1. Values used to create pie charts can be found in Table 8. Variables combined to estimate sensitivity and exposure are indicated in Table 1.

Table 12. Variables contributing to highly vulnerable areas within the Protected Areas Database for the United States (PAD-US), summarized by management type. Management types: (1) managed for biodiversity—natural disturbance events proceed or are mimicked, (2) managed for biodiversity—disturbance events are suppressed, (3) managed for multiple uses—subject to extractive (e.g., mining or logging) or off-highway vehicle use, and (4) no known mandate for biodiversity protection (Source: https://www.sciencebase.gov/catalog/item/602ffe50d34eb1203115c7ab).

	Percent of Total	Percent of Total	Percent of Total	Percent of Total	Hectares	Hectares	Hectares	Hectares
Management Type	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
High adaptive capacity	0	0.02	0	0.2	0	0.02	0	3
Moderate adaptive capacity	0	5.5	3.6	6.0	0	7	1	83
High sensitivity	0	0	0	0.13	0	0	0	2
Moderate sensitivity	76.7	50.6	44.2	94.4	8	64	11	1298
High exposure	91.2	72.1	96.7	71.3	9	91	23	980
Moderate exposure	0	32.2	7.4	55.1	0	40	2	757

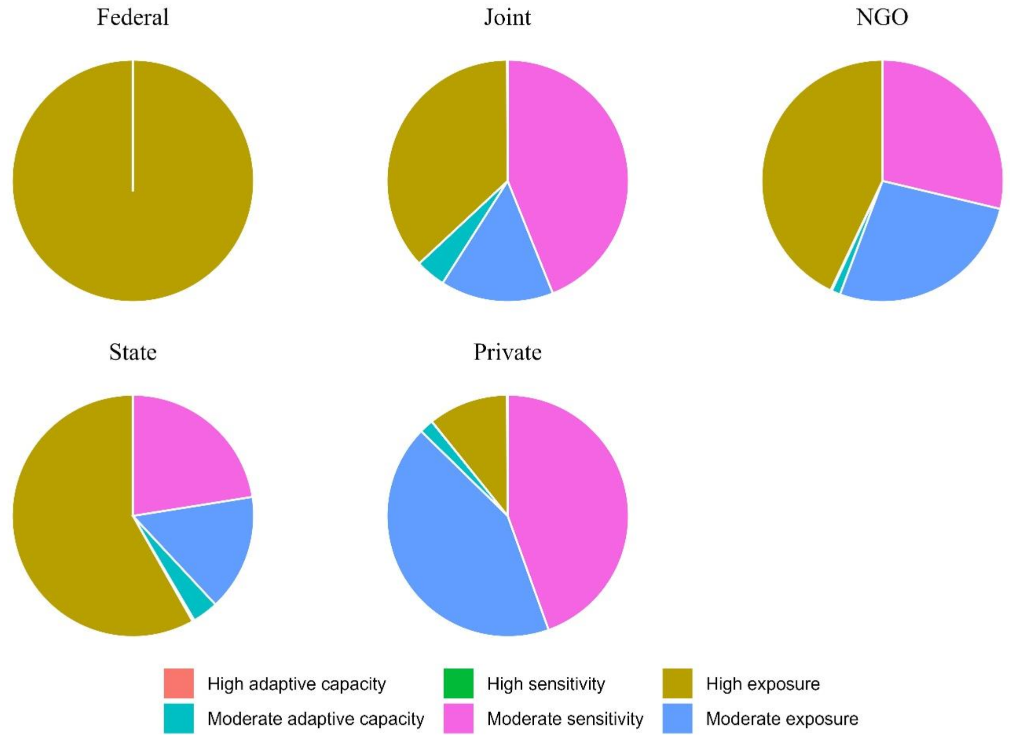

Figure 8. Proportion of the study area predicted to be highly vulnerable (≥0.75) owing to adaptive capacity, sensitivity (indicated by land use), and exposure (indicated by climate) within the Protected Areas Database for the United States (PAD-US), summarized by land ownership type. High adaptive capacity and High sensitivity do not appear on any pie charts because estimates are low or are 0 for those categories. Ownership types are described in the Protected Areas Database for the United States (PAD-US; https://www.usgs.gov/core-science-systems/science-analytics-and-synthesis/gap/science/protected-areas). Non-Governmental Organization (NGO). Values used to create pie charts can be found in Table 13. Variables combined to estimate sensitivity and exposure are indicated in Table 1.

Table 13. Variables contributing to highly vulnerable areas by land ownership types in the study area (Figure 1). The conceptual framework for the vulnerability [34] score is provided in Figure 2. Ownership types are described in the Protected Areas Database for the United States (PAD-US; https://www.usgs.gov/core-science-systems/science-analytics-and-synthesis/gap/science/protected-areas). Non-Governmental organization (NGO).

	Hectares				
Variables	**Federal**	**Joint**	**NGO**	**Private**	**State**
High adaptive capacity	0	1	0	2	0
Moderate adaptive capacity	0	41	2	33	14
High sensitivity	0	0	0.3	0.4	1
Moderate sensitivity	0	453	53	784	90
High exposure	0.4	380	80	188	232
Moderate exposure	0	156	50	754	62
	Percent of area				
High adaptive capacity	0	0.2	0	0.2	0
Moderate adaptive capacity	0	8.2	2.3	4.1	5.5
High sensitivity	0	0.0	0.3	0.1	0.4
Moderate sensitivity	0	90.0	56.6	97.5	35.4
High exposure	21.9	75.5	84.6	23.4	91.7
Moderate exposure	0	30.9	53.2	93.8	24.5

3.4. Climatic Niche Models

The Maxent and GAM CNMs, which represent exposure in the vulnerability equation, have large evaluation metrics for AUC, TSS, sensitivity, and specificity, but have small Kappa statistics (Table 14). The Maxent CNM outperformed the GAM CNM (Table 14). Precipitation in the warmest quarter, annual precipitation, precipitation in the driest month, and mean temperature in the driest quarter are the most influential climatic variables in the Maxent CNM (Table 15). Precipitation in the driest month, precipitation in the warmest quarter, annual mean temperature, and mean temperature in the warmest quarter are the most influential climatic variables in the GAM CNM (Table 15).

Table 14. Evaluation metrics for generalized additive model (GAM) and Maxent climatic niche models. Abbreviations: area under the curve (AUC), true skill statistic (TSS), Cohen's Kappa statistic (Kappa).

Model	AUC	TSS	Kappa	Sensitivity	Specificity
Maxent	0.77	0.39	0.18	0.69	0.77
GAM	0.76	0.4	0.17	0.68	0.76

Table 15. Pearson correlation and area under the curve (AUC) estimated relative variable importance (percent) of climatic variables used to estimate generalized additive model (GAM) and Maxent climatic niche models. Source data for the variables are provided in Table 1.

	Maxent	Maxent	GAM	GAM
Variables	**Pearson Correlation**	**AUC**	**Pearson Correlation**	**AUC**
Annual ET [1]	12.5	5.2	10.9	4.6
Growing Season ET [1]	2.2	0.8	5.6	2.7
Annual PET [2]	24.3	8.6	21.8	10.5
Snow–water equivalency	24.6	11.3	12.4	5.8
Annual mean temperature	15.8	9.3	76.3	34.9
Isothermality	12.2	5.1	6.8	3.3
Mean temperature of driest quarter	30.2	16.4	49.0	18.6
Mean temperature of warmest quarter	7.9	3.9	53.5	27.3
Annual precipitation	52.7	25.3	64.3	30.0
Precipitation of driest month	49.8	22.6	81.7	38.2
Precipitation of warmest quarter	74.7	35.4	81.0	38.8

Note(s): [1] ET (evapotranspiration). [2] PET (potential evapotranspiration).

3.5. Discussion

Landscape vulnerability estimates revealed that nearly a third of the study area was predicted to have at least moderate vulnerability, and nearly 11% of the area predicted to be suitable for GIEs in the study area was predicted to be at least moderately vulnerable. GIEs receive water from direct precipitation, as well as overland and subsurface flows, and the quantity, timing, and quality of these flows can be affected by conditions in the landscape surrounding the GIE [19,25]. Conservation measures, such as riparian buffers to protect stream water quality, may be an effective approach for protecting resources that are important for GIEs, particularly if the size of the buffer reflects the conditions in the landscape surrounding a GIE [61,62]. However, the length of the groundwater flow path from the GIE to upslope areas can vary, and conservation buffers that do not account for that variation may not meet ecological requirements for all GIEs. Varying buffer sizes to reflect landscape conditions around focal ecosystems has precedence in best management practices to protect water quality for wetland and riparian conservation [61,62].

The contrast between pixel vulnerability and vulnerability summarized at the HUC12 watershed scale illuminates how scale can influence our understanding about how aquatic resources may be affected by environmental conditions in the surrounding landscape [63–66].

Approximately 770,000 ha of land area (2.4%) in the study region was predicted to be highly vulnerable at the pixel scale. However, when scaled to the watershed, only 0.3% of the watersheds were predicted to be highly vulnerable. Additionally, 26% of GIEs had moderately vulnerable pixels within 30 m, but 19% of GIEs occurred in watersheds that were moderately vulnerable. Less than 1% of the study area's moderately or highly vulnerable HUC12 watersheds contained GIEs, and only 1.6% of GIEs occurred near (<200 m) large patches of highly vulnerable areas.

The northeast is warming faster than any other region in the continental United States [67] and continued increases in average annual air temperature and shifts in precipitation patterns could contribute to increased vulnerability of the region's GIEs to climate exposure. Predicted changes in precipitation amount and frequency that affect water cycling, coupled with longer and warmer growing seasons, could alter the contribution of groundwater discharge to the region's GIEs. Exposure, represented by climate, was the most important variable in Maine's highly vulnerable watersheds. Since 1900, Maine's average annual air temperature has increased 1.9 °C, and the length of growing seasons also has increased by 14 days [68], which may contribute to the estimated greater climate exposure. Nearly half (40%) of the moderately vulnerable GIEs were located within 30 m of areas predicted to be vulnerable to climate exposure. The northeastern United States is projected to have shorter, warmer winters [69]; increases in extreme precipitation and timing between rain events [70]; and longer, warmer growing seasons [70,71]. These projected changes in climate could alter the magnitude and timing of the spring freshet, increase evapotranspiration, increase runoff, and reduce infiltration. Our climatic niche model, which represented exposure, indicated that precipitation in the warmest quarter, annual precipitation, and precipitation in the driest month were the most influential climatic variables affecting suitability of areas in the landscape for GIE occurrence. Precipitation patterns that decrease warm-season (i.e., growing season) precipitation and increase cool-season (fall or winter) precipitation have been observed to increase groundwater temperatures [72]. Predicted increases in precipitation intensity can also lead to more surface run-off and, thus, alter the location and amount of groundwater recharge [73]. Changes in precipitation timing and frequency could play a large role in increasing climate exposure of GIEs in the Northeast.

Land-use-induced sensitivity contributed to highly vulnerable areas in nearly 1% of GIEs. Highly vulnerable areas in more than half of the states in the region were sensitive owing to land-use practices. Land-use practices can affect GIEs by lowering groundwater levels through groundwater extraction in watersheds [19,21]. The high vulnerability of watersheds in New York (5%) can be attributed primarily to sensitivity variables associated with land use. Urban development and agricultural land uses have been observed to reduce groundwater recharge, which has led to altered hydrological dynamics in the region [74]. Conversion to developed or agricultural land-use types could alter the amount and location of groundwater recharge, which may affect GIEs in the region. Additionally, land use may restrict the adaptive capacity of the region's GIEs to respond to effects of the changing climate on groundwater.

Effects of climate and land use can be both additive and synergistic [75]. For example, agriculture is a leading cause of aquatic ecosystem impairment in the United States due to excessive nutrients in surface water runoff [76]. Additionally, prolonged periods of drought can lead to increased groundwater extraction for agriculture [22]. A combination of moderate climate exposure and moderate sensitivity to land-use practices contributed to high vulnerability scores of watersheds in our study area, where 14% of the land area is agriculture and 23% is developed lands. Land use and climate change have been observed to act synergistically to inhibit water retention [77], reduce water yield in river basins [78], and alter water cycles across landscapes [79], which could pose threats to GIEs and their persistence.

Land in the protected areas database that was highly vulnerable was at risk primarily owing to climate exposure, similar to the observations of [34], where climate exposure was the main contributing factor to vulnerability in approximately half of the National

Wildlife Refuges across the United States. Private and jointly owned lands that contained highly vulnerable areas were primarily attributable to high sensitivity caused by land-use practices. The majority of these lands in our study area also had a no mandate for biodiversity conservation practice designation. In addition, the majority (62%) of the study area's protected lands in the PADUS database classified as being moderately or highly vulnerable had no protection conservation designation (level 4), which may indicate that groundwater ecosystems in these areas (2.5% of total GIEs) may not be managed for conservation.

Landscape management of GIEs may be challenging, owing to the unique potential threats from watershed activities and ecological requirements of individual GIEs [14]. An adaptive management framework to conserve GIEs could address these challenges. As new information is acquired, an adaptive management approach provides an iterative process that allows uncertainties in cause and effect and ecological responses to be considered and addressed [14,80]. This iterative approach could provide opportunities to incorporate new spatial data in the vulnerability analysis to revise or update results. Land management of vulnerable landscapes and GIE conservation practices have largely been conducted in state-owned or federally owned landscapes where practitioners develop and apply land management actions [81]. Increasing demand for public drinking water and irrigation has led to widespread groundwater over-extraction and contamination [21,23], affecting human health and ecological services [82,83]. Few management practices can directly moderate variables contributing to exposure, such as increases in average annual temperatures and the seasonality of precipitation. However, reducing groundwater extraction by modifying agriculture irrigation practices and creating more sustainable municipal water-use practices can directly benefit GIEs [22]. Examples of potential management practices that could help maintain or improve GIE persistence and integrity in the landscape include: reducing the use of pesticides in agricultural lands to improve water quality [21], prioritizing the acquisition of lands with high geodiversity [84] and adaptive capacity [1] to enhance resilience, mitigate disturbances to natural recharge areas to maintain water quantities, and restoration management practices that directly restore degraded GIEs and watersheds.

Our approach to modeling GIE vulnerability is a hypothesis- and data-driven framework that explores the contributions of climate exposure, sensitivity caused by land use, and the adaptive capacity of the landscape on GIEs. The methods used are replicable and easily interpreted and can be applied in a wide range of geographic regions and for various ecosystem types. Despite these strengths, our approach is not encompassing of all the potential threats to GIEs in the Northeast. With the high human population density of the northeastern United States, spatial data on groundwater extraction rates could be an important contributing parameter to GIE vulnerability. Likewise, groundwater contamination is also a global problem that has a significant impact on human health and ecological services not included explicitly here [82,83] and that could have negative impacts on GIE vulnerability. Our results provide insight into vulnerable watersheds and sites, however we did not quantify the potential impacts of highly vulnerable upstream areas or watersheds on downstream locations, which may underestimate the vulnerability of those locations. To date, no such spatial data exist for the Northeast that describe the full extent of groundwater extraction and contamination. The vulnerability of GIEs in the northeastern U.S. to groundwater extraction and contamination due to increasing population demands and irrigation for agriculture is an area for future research. Temporal scales could also be included in assessing the vulnerability of GIEs in the Northeast, as climate factors have been observed to have significant seasonal characteristics [85] that could drive climate exposure.

Understanding the effects of climate change and anthropogenic disturbances on ecosystems has accelerated the development of methods to assess the ability of a system to cope with change [34,86–88]. Our analysis of landscape, watershed, and GIE vulnerability in the northeastern U.S. reveals contributing factors to vulnerability for individual sites, which could inform the conservation and prioritization of these systems. Our analysis indicates that the majority of GIEs in the region do not occur in currently vulnerable areas. However, those that are highly vulnerable are mainly vulnerable to climate exposure. This presents a challenge to maintaining the integrity and persistence of these GIEs in the northeastern United States, as climate change effects are projected to increase in the region and in landscapes across the world [67].

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Conflicts of Interest: We have no competing interests to disclose.

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