Article

Healthcare Access in the Aftermath: A Longitudinal Analysis of Disaster Impact on US Communities

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Abstract: Research on climate-related disasters and healthcare infrastructure has largely focused on short-term, localized impacts. This study examined the long-term association between climate-related disasters and healthcare facilities across 3108 contiguous United States counties from 2000 to 2014. Utilizing databases like the National Establishment Time Series and the Spatial Hazards and Events Losses Database, we classified county-level infrastructure changes ("never had", "lost", "gained", and "always had") and disaster severity (minor, moderate, severe), respectively. Autoregressive linear models were used to estimate the total number of moderate and severe disasters (2000–2013) associated with the change in the number of healthcare establishments in 2014, after adjusting for healthcare establishments, total population, and poverty in 2000. Results demonstrate that an increase in one moderate disaster was significantly associated with increased hospital infrastructure (Count, 0.14; 95% CI, 0.03–0.25), while severe disasters were significantly associated with a decrease (Count, -0.31; 95% CI, -0.47–-0.14). Similar but stronger associations were observed for ambulatory care (Moderate: Count, 2.52; 95% CI 0.91–4.12 and Severe: Count, -5.99; 95% CI, -8.53–-3.64, respectively). No significant associations were found among pharmacies. These findings highlight the varying impacts of climate-related disasters on healthcare accessibility. Future initiatives should prioritize strengthening existing infrastructure and enhance disaster recovery strategies.

Keywords: environmental health; disasters; healthcare accessibility; longitudinal studies; United States; health infrastructure

1. Introduction

Climate change threatens our world's ecosystem with more intense, frequent, and fatal weather-related disasters. In the United States (US) alone, fifteen or more billion-dollar weather-related events have occurred each year from 2015 to 2020 [1]. Approximately 24% of global deaths are due to modifiable environmental factors [2]. Climate-related disasters, such as extensive flooding or wind damage, can destroy crucial healthcare infrastructures in our communities, including pharmacies, hospitals, and ambulatory care centers [3]. As a result, healthcare may be disrupted, turning away patients and interrupting access to medication or routine appointments [4]. For example, Superstorm Sandy and the aftermath of Hurricane Katrina led to short-term health system closures, destruction of medical records, and a spike in medication demand, resulting in missed medical appointments and

Int. J. Environ. Res. Public Health **2025**, 22, 733

2 of 13

increased rates of uncontrolled hypertension [4]. Additionally, disasters obstruct continuity of care, worsening chronic health issues [5,6].

Post-disaster recovery efforts, which include the repairing or rebuilding of damaged infrastructure, require significant resources and collaboration between local and federal governments. However, communities that are of low socioeconomic status (SES) (e.g., low income) may experience greater challenges in their recovery. For example, communities have less insurance, savings, and personal resources to devote to their recovery [7]. Disaster-related losses in these communities have also been associated with worsening physical and mental health among those already at risk for poor health outcomes [7,8]. Worsening health-related conditions in low SES communities demonstrate the necessity for healthcare services that are both accessible and available post-disaster. However, an analysis examining the differences between Hurricane Katrina and Hurricane Sandy on healthcare provider availability demonstrated that access to care post-disaster remains inequitable [9]. After Katrina, researchers noted a county-level decline in primary care physicians, medical specialists, and surgeons—an effect not seen in affected counties after Sandy [9]. The median household income in counties at the time affected by Katrina ($45,800) was below the national average ($50,233), whereas the median income for counties affected by Sandy ($65,000) was well above ($56,516) [9]. These disparities underscore how county-level socioeconomic differences ultimately shape both acute disaster response and long-term recovery.

Research to date on post-disaster healthcare accessibility and availability has largely focused on single disasters and the short-term impacts of disrupted healthcare services on communities [10–12]. Additionally, past work has concentrated on the immediate effects of disasters on operations within specific healthcare facilities such as the staffing or availability of services in hospital centers [10–12]. Investigation of the long-term impact of climate-related disasters on diverse types of healthcare facilities at a larger, national scale has largely been unexplored [13]. Disasters significantly alter local healthcare infrastructure that can have lasting effects on human health. Shifting the focus beyond the immediate disaster response to the broader recovery period may reveal several crucial factors that influence health outcomes.

In our study, we address this gap by assessing the relationship between healthcare accessibility and disasters longitudinally throughout the US. To address this relationship, we focus on US counties, utilizing data from three primary datasets: healthcare infrastructure; disaster losses; and geographical polarization. We examine disaster losses over an extended period of time (2000 to 2014) and include data across various hazard types and levels of impact. In our study, we evaluate three large categories of healthcare infrastructure: (1) pharmacies; (2) hospital-based inpatient care; and (3) ambulatory care. Our research examines how disasters impact the way these healthcare institutions are distributed across the continental US over a 15-year time span, while controlling for confounding by race/ethnicity and SES.

2. Materials and Methods

2.1. Study Sample

This longitudinal cohort study linked data from three primary data sources to create an annual panel dataset of counties in the contiguous US from 2000 to 2014 totaling 46,620 county-years, including longitudinal data on disaster losses and healthcare infrastructure. The study had a total of 3108 continental nonwater US counties. To establish consistency over time, the 2000 US Census geographies were utilized for the demographic and socioeconomic measurements.

Int. J. Environ. Res. Public Health **2025**, 22, 733

3 of 13

2.2. Measures

2.2.1. Exposure Variables

<u>Health and Healthcare Institutions.</u> The presence of healthcare facilities was measured using 2000 to 2014 business data from the National Establishment Time Series (NETS) database, licensed from Walls & Associates (Denver, CO, USA) in January 2017 [14]. From the NETS, records were categorized as ambulatory care or as pharmacies using 8-digit Standard Industrial Classification (SIC) codes (Table S1) according to methods published elsewhere [15]. Healthcare facilities were geocoded and aggregated to county for each year in which a business was open, focusing on 2000 and 2014. Using this information, we assessed counts of healthcare facilities per county and change over time. Categories of change in healthcare facilities were divided as follows: (1) Never (counties having no facilities at both time points (2000–2014)), (2) Lose (counties going from having at least one facility in 2000 to having none in 2014), (2) Gain (counties going from having no facilities in 2000 to having at least one in 2014), and (4) Always present (counties having at least one at both time points (2000–2014)). Due to the distribution of the NETS resource, ambulatory care values were measured using a threshold value of 10 facilities per county per year, rather than the initial threshold of one facility.

<u>Disaster Impact.</u> Disaster impact losses were measured using 2000 to 2014 data from the Spatial Hazards and Events Losses Database for the United States (SHELDUS™), licensed from the Center for Emergency Management and Homeland Security at Arizona State University (Phoenix, AZ, USA), a national database of eighteen different hazard types at county level resolution for all 50 states [16]. SHELDUS™ consolidates multiple disaster databases, including data from the National Climatic Data Center, US Geological Survey, and others. For every event with any measured loss, SHELDUS™ provides: location (county), time (begin and end date), inflation-adjusted direct losses (property and crop damage, fatalities, injuries), and type of hazard (peril). SHELDUS™ is a leading dataset relating to disasters and is used across dozens of studies [17–19]. We created a three-level typology: severe, moderate, and minor impact. For each county during 2000–2014, a severe disaster month was classified as greater than $50 property damage per capita and/or three or more fatalities, a moderate disaster month as between $10 and $50 of property damage per capita and/or two fatalities, and a minor disaster month occurs as fewer than $10 property damage per capita and/or has one fatality from disasters [20]. The disaster impact variable was created by totaling up the number of months in a year for each category for each county.

<u>Geographical Polarization Data.</u> Geographical polarization data was reported as a single metric value named the Index of Concentration at the Extremes (ICE). The ICE value represents the extent to which a county's population are organized into the extremes of deprivation and privilege utilizing 2018 household income. The ICE value is a commonly used measure to assess disparities utilizing a geographical perspective [21]. Values range from −1 to +1, with a value of −1 indicating the most deprived county and a value of +1 indicating the most privileged county. For this project, we compared non-Hispanic white high-income groups versus person-of-color low-income groups. High-income counties were defined as populations that were part of the top quintile of household income and low-income counties were defined as populations that were part of the bottom quintile of household income [21].

2.2.2. Covariates

Covariate data were assessed using data from the Longitudinal Tract Database provided by Brown University, including decennial census data from 2000 and 2010 and data from the National Historical Geographic Information Systems [22]. Longitudinal

Int. J. Environ. Res. Public Health **2025**, 22, 733

4 of 13

Tract Database data were produced at the census tract-level and were aggregated to the county-level. Using these data for each county, the annual community-level social and demographic characteristics were obtained: (1) the proportion of white residents, (2) poverty rate, measured as the percentage of individuals living below the federal poverty line, (3) owner-occupied homes, measured as the proportion of owner-occupied housing units (compared to renters), (4) proportion of college educated, measured as the proportion of residents aged 25 or older who have completed a bachelor's degree, and (5) total county population. To avoid over-controlling, we identified a priori the most important confounding variables for inclusion in the analysis. Total population was included to adjust our estimates of change in the number of medical establishments relative to the baseline size of the county. For socioeconomic status, we selected poverty rate, based on prior disaster research and empirical evidence [7,8,23]. Since racial/ethnic composition of counties may reflect structural inequities in counties that relate to both vulnerability to climate-related disasters and the availability of healthcare resources, we also included the proportion of white residents [24]. By adjusting for total population, poverty rate, and non-Hispanic white residents, we aim to minimize residual confounding and better isolate the specific effects of disaster exposure on healthcare infrastructure over time and across geographic areas.

2.3. Statistical Analysis

We calculated descriptive statistics of healthcare infrastructure, demographic, socioeconomic, and geographical polarization characteristics for 2000, 2014 (healthcare infrastructure only), and 2018 (geographical polarization data only). Total counts of healthcare infrastructure were calculated for each county during the time period as well as the average proportion of such counties living below poverty, unemployed, college educated, or residing in owner-occupied housing units (Table 1). In addition, average ICE values of each county were calculated (Table 1). Because minor disasters encompassed a broad range of event hazards and were overrepresented in our dataset, they introduced considerable variability, making systematic analysis more challenging (Table 2). Given the study's focus on more intense disasters with significant public health consequences, we limited our analyses to moderate and severe events to enhance clarity.

Table 1. Demographic and socioeconomic characteristics (2000) and climate-related disasters (2000) across categories of change (2000–2014) in healthcare facilities for 3108 continental nonwater US counties.

	No. (%)								
		Pharmacies				Hospitals			
2000 Characteristic [a]	**All Counties (n = 3108)**	**Never** [e] **(n = 116)**	**Lose (n = 66)**	**Gain (n = 28)**	**Always (n = 2898)**	**Never (n = 307)**	**Lose (n = 86)**	**Gain (n = 150)**	**Always (n = 2565)**
Race/ethnicity [b]									
Predominantly NH white	2671 (85.9)	96 (82.8)	51 (77.3)	24 (85.7)	2500 (86.3)	267 (87.0)	63 (73.3)	129 (86.0)	2212 (86.2)
Predominantly NH black	45 (1.4)	2 (1.7)	2 (3.0)	0	41 (1.4)	5 (1.6)	5 (5.8)	3 (2.0)	32 (1.2)
Predominantly Hispanic/Latino	33 (1.1)	4 (3.4)	2 (3.0)	0	27 (0.9)	4 (1.3)	2 (2.3)	5 (2.7)	23 (0.9)
Other or Racially/ethnically mixed	359 (11.6)	14 (12.1)	11 (16.7)	4 (14.3)	330 (11.4)	37 (10.1)	16 (18.6)	14 (9.3)	298 (11.6)
Living below poverty, mean (SD), %	14.2 (6.5)	16.6 (8.9)	17.4 (8.5)	15.3 (8.8)	14.0 (6.3)	16.1 (7.4)	17.6 (7.5)	15.0 (7.6)	13.8 (6.2)
Unemployed, mean (SD), %	6.2 (3.4)	6.0 (6.6)	5.9 (4.2)	6.2 (4.2)	6.2 (3.1)	5.7 (3.8)	6.9 (3.4)	6.2 (3.2)	6.2 (3.3)
College Educated, mean (SD), %	16.5 (7.8)	16.4 (6.0)	15.6 (6.3)	15.6 (7.8)	16.5 (7.9)	14.0 (5.6)	12.3 (3.9)	13.8 (7.7)	17.1 (8.1)
Ownership-Occupied Housing Units, mean (SD), %	74.1 (7.6)	73.2 (10.4)	74.8 (5.8)	76.2 (6.0)	74.1 (7.5)	77.0 (6.8)	76.0 (8.4)	77.9 (6.1)	73.5 (7.5)
Total Population, mean (SD)	89,956.1 (293,542.8)	3058.1 (2892.6)	6659.0 (4560.4)	8853.4 (7253.6)	96,115.0 (303,068.1)	7433.3 (6428.5)	10,635.9 (6740.9)	17,713.2 (12,661.53)	106,717.2 (320,604.4)

Int. J. Environ. Res. Public Health **2025**, 22, 733

5 of 13

Table 1. *Cont.*

| | No. (%) | | | | | | | |
| | Pharmacies | | | | Hospitals | | | |
2000 Characteristic [a]	**All Counties (n = 3108)**	**Never [e] (n = 116)**	**Lose (n = 66)**	**Gain (n = 28)**	**Always (n = 2898)**	**Never (n = 307)**	**Lose (n = 86)**	**Gain (n = 150)**	**Always (n = 2565)**
Index of Concentration at the Extremes (ICE)									
ICEwnhinc [c], mean (SD)	0.10 (0.13)	0.09 (0.18)	0.07 (0.09)	0.11 (0.19)	0.11 (0.13)	0.10 (0.07)	0.02 (0.11)	0.09 (0.11)	0.11 (0.10)
Climate-related Disaster (total number) [d]									
Minor Disaster	5355	42	55	19	5239	267	72	203	4813
Moderate Disaster	603	36	14	5	548	66	15	19	503
Severe Disaster	305	18	11	4	272	39	6	11	249

| | No. (%) | | | |
| | Ambulatory Care [e] | | | |
2000 Characteristic	**Never (n = 495)**	**Lost (n = 21)**	**Gain (n = 201)**	**Always (n = 2391)**
Race/ethnicity				
Predominantly NH white	403 (81.4)	15 (71.4)	172 (85.6)	2081 (87.0)
Predominantly NH black	14 (2.8)	2 (9.5)	6 (3.0)	23 (1.0)
Predominantly Hispanic/Latino	12 (2.4)	1 (4.8)	1 (0.5)	19 (0.8)
Other or Racially/ethnically mixed	66 (13.3)	3 (14.3)	22 (10.9)	268 (11.2)
Living below poverty, mean (SD), %	17.3 (7.7)	17.2 (8.7)	15.7 (7.1)	13.4 (6.0)
Unemployed, mean (SD), %	5.9 (4.4)	7.8 (4.5)	6.3 (3.6)	6.2 (3.1)
College Educated, mean (SD), %	13.3 (4.7)	13.0 (3.4)	13.0 (4.6)	17.5 (8.3)
Ownership-Occupied Housing Units, mean (SD), %	76.2 (7.0)	77.5 (5.3)	78.0 (4.8)	73.3 (7.5)
Total Population, mean (SD)	5585.2 (3751.8)	9285.9 (3415.9)	10,466.9 (4657.25)	114,813.9 (330,653.4)
Index of Concentration at the Extremes (ICE)				
ICEwnhinc, mean (SD)	0.07 (0.09)	0.04 (0.08)	0.08 (0.13)	0.12 (0.09)
Climate-related Disaster (total number)				
Minor Disasters	354	30	246	4725
Moderate Disasters	110	4	50	439
Severe Disasters	66	6	22	211

[a] Data are from the 2000 US Census report unless otherwise indicated. [b] Racial/ethnic composition was assessed by predominant (>60%) racial/ethnic group. Places with no predominant group were classified as racially/ethnically mixed areas. [c] Index of Concentration at the Extremes (ICE) for non-Hispanic white high-income vs. person of color low-income 2018 value. High-income is defined as counties that were part of the top quintile of household income and low-income is defined as counties that were part of bottom quintile of household income. The ICE variable ranges from −1 (least privileged) to +1 (most privileged). [d] Data are from the SHELDUS[TM] national database unless otherwise indicated. [e] Due to the distribution of the NETS resource, ambulatory care values were defined as: (1) Never (counties having less than 10 facilities at both time points (2000–2014)), (2) Lost (counties that had at least 10 facilities in 2000 to less than 10 in 2014), (3) Gain (counties that had less than 10 facilities in 2000 to at least 10 in 2014), and (4) Always (counties always having at least 10 facilities at both time points (2000–2014)).

We fit multivariable linear models to estimate our primary outcome of interest: the change in the number of medical establishments in 2014 associated with a 1-unit increase in the number of years exposed to each type of moderate and severe disaster from 2000 to 2013 (Table 3). While the analysis does not follow a traditional longitudinal panel, this approach is characterized as a single-period change model with temporal ordering. This method, therefore, allows us to examine changes within a defined temporal framework. As mentioned above, poverty, total population, and non-Hispanic white residents were included in our adjusted models based on an a priori justification. Other variables such as race/ethnicity, homeownership, and education levels, were excluded to avoid overadjustment and multicollinearity. Additionally, to assess the robustness of our results, we conducted sensitivity analyses using change scores (the difference between the baseline (2000) and outcome (2014) values) as the dependent variable (Table S2).

Int. J. Environ. Res. Public Health **2025**, 22, 733

6 of 13

Table 2. Change in climate-related disaster occurrences (2000–2014) across categories of change in healthcare facilities (2000–2014) for 3108 continental nonwater US counties.

	No. (%)				
		Pharmacies			
Change in Characteristic (2000–2014)	**All Counties (n = 3108)**	**Never (n = 116)**	**Lose (n = 66)**	**Gain (n = 28)**	**Always (n = 2898)**
Climate-related Disaster, mean (SD),%:					
Minor Disaster	7.5 (221.1)	−13.8 (105.4)	19.7 (129.2)	−21.4 (87.6)	−7.7 (227.0)
Moderate Disaster	−5.8 (7.5)	18.1 (61.3)	10.6 (43.4)	17.9 (39.0)	5.1 (58.7)
Severe Disaster	−2.1 (42.5)	1.7 (47.5)	3.0 (58.1)	−3.6 (57.6)	2.1 (41.7)
		Hospitals			
Change in Characteristic (2000–2014)		**Never (n = 307)**	**Lose (n = 86)**	**Gain (n = 150)**	**Always (n = 2565)**
Climate-related Disaster, mean (SD),%:					
Minor Disaster		9.4 (146.0)	33.7 (192.0)	2.5 (208.8)	5.3 (230.0)
Moderate Disaster		−7.5 (60.3)	4.6 (59.2)	−0.7 (53.7)	−6.2 (58.4)
Severe Disaster		−2.3 (49.5)	3.5 (38.9)	−1.3 (30.6)	−2.3 (42.3)
		Ambulatory Care			
Change in Characteristic (2000–2014)		**Never (n = 495)**	**Lose (n = 21)**	**Gain (n = 201)**	**Always (n = 2391)**
Climate-related Disaster, mean (SD),%:					
Minor Disaster		13.1 (138.0)	−47.6 (143.6	−0.50 (165.4)	7.4 (239.0)
Moderate Disaster		−5.9 (62.6)	4.6 (63.2)	−6.0 (75.3)	−5.8 (55.8)
Severe Disaster		−1.2 (49.7)	3.5 (53.9)	0 (40.0)	−2.2 (41.0)

Table 3. Adjusted autoregressive models measuring change in total number of healthcare establishments in 2014 with total number of moderate and severe climate-related disasters for 3108 nonwater US counties.

	Pharmacies			**Hospitals**			**Ambulatory Care**		
	Count (β)	**SE**	**95% CI**	**Count (β)**	**SE**	**95% CI**	**Count (β)**	**SE**	**95% CI**
Climate-related Disasters									
Moderate Disaster	0.09	0.08	(−0.06, 0.24)	0.14 *	0.06	(0.03, 0.25)	2.52 **	0.82	(0.91, 4.12)
Severe Disaster	0.10	0.11	(−0.12, 0.32)	−0.31 ***	0.08	(−0.47, −0.14)	−5.99 ***	1.20	(−8.35, −3.64)
Model Fit	$R^2 = 0.97$			$R^2 = 0.97$			$R^2 = 0.99$		
N=	3108								

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Counts were adjusted for poverty rates in 2000, the total number of healthcare establishments in 2000, total population in 2014, and non-Hispanic white residents.

3. Results

3.1. Differences in Counties by Changes in Healthcare Facilities (2000–2014)

Counties that went from having at least one type of healthcare facility from 2000 to having none in 2014 had a higher proportion of residents living below poverty. Counties that experienced a loss of healthcare facilities, as well as those that never had such facilities at either time point, experienced consistently high levels of poverty. In contrast, counties that gained or always had a healthcare facility in their counties tended to have lower poverty rates. For example, counties that never had or lost pharmacies had poverty rates of 16.6% and 17.4%, respectively, while counties that gained or maintained facilities had rates of 15.3% and 14.0%, respectively (Table 1). A similar pattern was observed for both

Int. J. Environ. Res. Public Health **2025**, *22*, 733

7 of 13

hospitals (16.1% and 17.6% vs. 15.0% and 13.8%) and ambulatory care (17.3% and 17.2% vs. 15.7% and 13.4%) (Table 1). These differences, while suggestive, are descriptive and not intended to imply causal associations. These differences may reflect broader socioeconomic differences between counties.

Counties that *lost* healthcare facilities had higher levels of segregation (lower ICE scores) compared to counties that consistently had healthcare facilities at both time points, across all categories of healthcare facilities (Table 1).

3.2. Changes in Disasters (2000–2014) by Changes in Healthcare Facilities (2000–2014)

Counties that lost their pharmacies (n = 66), hospitals (n = 86), and ambulatory care (n = 21), from 2000 to 2014, experienced more severe disasters. However, only counties that lost hospitals and ambulatory care facilities experienced more moderate disasters. These unadjusted differences are descriptive in nature and are not adjusted for confounding; they are not intended to suggest causality.

3.3. Change in Total Number of Healthcare Establishments in 2014 with Total Number of Moderate and Severe Disasters

While an increase in one moderate disaster was associated with a statistically significant increase in hospital infrastructure over the time period (Count, 0.14; 95% CI, 0.03–0.25), we observed a significant decrease in hospital infrastructure (Count, -0.31; 95% CI, $-0.47–-0.14$) associated with severe disaster. We observed a similar pattern of association for ambulatory care (Moderate: Count, 2.52; 95% CI, 0.91–4.12 and Severe: Count, -5.799; 95% CI, $-8.35–-3.64$, respectively). We observed no significant association between moderate or severe disasters in relation to pharmacies (Table 3).

The sensitivity analyses using change scores confirmed the strength, direction, and significance of the associations observed with our primary model, reinforcing the robustness of our findings. These results are presented in Table S2.

4. Discussion

This study describes changes in healthcare availability associated with climate-related disasters across the contiguous US between 2000 and 2014. Few prior studies have evaluated post-disaster changes in different types of healthcare facilities at the national level.

Our research found that over the 15-year period, counties that always lacked access to healthcare services or lost their facilities were more likely to have high poverty levels (Table 1). Additionally, counties that lost their healthcare facilities experienced higher racial segregation, indicated by lower ICE values (Table 1). Especially in rural areas, the closure of healthcare facilities often worsens economic instability [25–27]. As care is delayed, chronic conditions like cardiovascular disease and cognitive decline become more difficult to manage [5,28–30]. On the other hand, counties that always had or gained healthcare services over the 15-year period were more likely to experience lower poverty levels (Table 1). Counties that always had their healthcare facilities exhibited less racial segregation, indicated by higher ICE values (Table 1). These communities often have economic and political influence that enable them to secure resources/policies that maintain their healthcare infrastructure [26,31–33].

Nevertheless, when disaster recovery strategies are effectively coordinated between the federal and local level, they yield significant benefits. After Hurricane Irma in 2017, the state of Florida and the Federal Emergency Management Agency (FEMA) instituted the Coordinated Place-Based Recovery Support (CPBRS) initiative to support local leadership in the most affected counties with tailored state and federal recovery resources. The CPBRS model demonstrates a locally executed, state-managed, and federally supported framework for disaster response. The success of this effort demonstrated the possibility

Int. J. Environ. Res. Public Health **2025**, 22, 733

8 of 13

of establishing cross-agency disaster recovery protocols that are efficient and equitable, particularly assisting historically underserved communities. For example, its goals closely aligned with local needs and priorities such as infrastructure improvements or water system upgrades in the most impacted counties [34].

The association between disasters and changes in availability of healthcare facilities also varies by the intensity of disaster and the category of healthcare facility. Counties that experienced a loss of healthcare facilities across all types from 2000 to 2014 also experienced a greater increase in severe climate-related disasters (Table 2). Even after adjusting for potential confounders, a significant decrease in healthcare facilities—particularly hospitals and ambulatory care—was observed in these counties following each severe climate-related disaster. As the severity of Hurricane Katrina demonstrated, many facilities were either not rebuilt or their services reduced, leading to disruptions to necessary medical care [35].

Rebuilding facilities after severe climate-related disasters is further complicated by financial constraints and coordination among governmental agencies [36]. In low-income communities and communities of color, recovery efforts are often systematically excluded from access to rebuilding resources [37]. Thus, among communities that are already afflicted with pre-existing healthcare accessibility challenges, the destructive impact of disasters may widen existing disparities [38–40]. A study among Hurricane Ike survivors found that those with a lower annual income and a high school degree or equivalent were more likely to experience depression post-climate-related disaster compared to wealthier, more educated survivors [7,8]. In another case, the aftermath of Hurricane Katrina led to disruptions to access to care for those with chronic diseases. Medical records were lost due to water damage, and one of the most frequently cited challenges was medication procurement, specifically its availability, due to the spike in demand post-disaster [41].

In contrast to our findings regarding severe disasters, moderate disasters were associated with a significant increase in hospitals and ambulatory care throughout the time period. This idea fits the notion that disasters can, in some cases, lead to (possibly unequal) redevelopment [42–44]. Moderate disasters may provide governing agencies with an opportunity to learn and develop policies that prioritize investment in and the construction of resilient infrastructure, proactively addressing the risks of future, more severe climate-related events. For instance, traditional "build-back-better" efforts and disaster response protocols often leave communities vulnerable to future hazards due to the tendency to rebuild to prior, inadequate engineering standards [45–47]. Novel initiatives, like Alternative Project Delivery Methods, a process involving earlier collaboration between designers and contractors, can leverage stakeholders in the community to develop more robust and resilient infrastructure reconstruction [48].

Finally, we observed the absence of an association between the presence of pharmacies and moderate or severe disasters over time. We presume that the absence is largely due to the already existing low number of pharmacies within parts of the US, termed "pharmacy deserts" [49,50]. Especially as online pharmacies become more prevalent, communities become increasingly reliant on delivery infrastructure rather than the physical presence of pharmacies. The frequent closures over the past decade driven by the growing role of pharmacy benefit managers (PBMs), have also reduced access, leading to poorer health outcomes and increased costs from hospitalizations and emergency room visits [51,52]. Therefore, the shifting dynamics of pharmacy accessibility demonstrate nuances in how healthcare systems are impacted by disasters, influencing health outcomes and community recovery.

Strengths and Limitations

This study utilized a longitudinal dataset to analyze healthcare infrastructure in association with climate-related disasters. Linking four national datasets consisting of

Int. J. Environ. Res. Public Health **2025**, 22, 733

9 of 13

demographic, social stratification, healthcare infrastructure, and climate-related disaster events between 2000 and 2014, the findings provide relevant information to inform the development of resilient communities with robust healthcare infrastructure.

There are some limitations within this study. First, data licensing agreements limited the healthcare infrastructure data available after 2014. However, the relations we examined between disaster and access to healthcare infrastructure may be conservative given the increasing intensifying effect of climate-related disasters [53–55]. Second, our operationalization of demographic, healthcare infrastructure, or climate-related disaster variables may have resulted in misclassification. However, we used datasets and variables that have been validated in previous research [21,56–59]. Third, there may be unmeasured confounders that we did not account for with our autoregressive model such as the effects of systemic racism along with preexisting geographic vulnerability. For example, historical redlining is associated with communities having poor health outcomes lacking access to healthcare facilities from practices like the systemic closures of hospitals or the inaccessibility of pharmacies [60–62]. Such communities are often located in areas prone to flooding or other environmental hazards [63,64]. As a result, delayed or even absent recovery efforts can further discourage trust in the medical system and potentially delay necessary medical care [65,66]. Controlling for or exploring these effects may involve incorporating redlining maps and additional geospatial data and is a focus for future research. Our modeling approach assumes that change in healthcare infrastructure began after the baseline year. However, if counties were already on a declining or growing trajectory before 2000, and those trends continued, adjusting for baseline levels may introduce horse-racing bias—a spurious association between disaster exposure and change due to prior, unmeasured trends [67]. Our sensitivity analysis produced similar results, reducing concern related to this bias. We acknowledge this potential limitation and interpret findings with caution. Fourth, the racial composition may introduce a limitation, as a wide majority of counties (85.9%) are predominantly white, as shown in Table 1. However, the distribution reflects the overall demographic composition of the U.S., with findings that are broadly representative of national trends. While regional differences in disaster recovery may exist, future research could explore such nuances in more diverse populations. A more detailed analysis, however, is beyond the scope of this study.

5. Conclusions and Further Research

Building on the limitations noted above, we have identified several promising directions for future studies. While our study sought to test associations between climate-related disasters and healthcare infrastructure, future research should focus on testing the potential underlying mechanisms driving the trends we observed. Factors such as policy response, funding availability, and community resilience measures are promising areas of future study. Additionally, based on prior research, our study examined three key types of healthcare infrastructures: pharmacies, hospitals, and ambulatory care. However, future work could expand our analysis to other facilities, including community health centers, urgent care facilities, or long-term care institutions. Finally, additional socioeconomic and demographic variables, such as healthcare workforce availability or rural–urban disparities, could be evaluated as modifiers of the association between disasters and healthcare infrastructure.

The study examines the temporal change in the availability of various healthcare institutions across the contiguous U.S. counties associated with climate-related disasters. Combining national data from 2000 to 2014, our findings describe the differential impact of climate-related disasters on disruptions to healthcare facilities. Hospital and ambulatory care are less accessible in counties that experienced a greater number of severe climate related disasters. Given the US's diversity in geography, population, and policy, it is

Int. J. Environ. Res. Public Health **2025**, *22*, 733

10 of 13

important to examine the factors that influence how communities respond and recover from disaster. Developing innovative strategies, such as an effective coordination between local, state, and federal resources, to enhance resilience within healthcare infrastructure can protect public health and reduce healthcare disparities during increasingly severe disasters.

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References

1. NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters. 2024. Available online: https://www.ncei.noaa.gov/access/billions/ (accessed on 23 April 2025).
2. Prüss-Üstün, A.; Wolf, J.; Corvalán, C.; Bos, R.; Neira, M. *Preventing Disease Through Healthy Environments: A Global Assessment of the Burden of Disease from Environmental Risks*; World Health Organization: Geneva, Switzerland, 2016.
3. Centers for Disease Control and Prevention. Guidance for Reopening Healthcare Facilities After Water and Wind Damage. Updated 24 October 2024. Available online: https://www.cdc.gov/infection-control/hcp/reopen-health-facilities/water-wind-damage.html (accessed on 22 July 2022).
4. Baum, A.; Barnett, M.L.; Wisnivesky, J.; Schwartz, M.D. Association Between a Temporary Reduction in Access to Health Care and Long-term Changes in Hypertension Control Among Veterans After a Natural Disaster. *JAMA Netw. Open* **2019**, *2*, e1915111. [CrossRef] [PubMed]
5. Mokdad, A.H.; Mensah, G.A.; Posner, S.F.; Reed, E.; Simoes, E.J.; Engelgau, M.M. When chronic conditions become acute: Prevention and control of chronic diseases and adverse health outcomes during natural disasters. *Prev. Chronic Dis.* **2005**, *2*, A04. [PubMed]
6. Hikichi, H.; Tsuboya, T.; Aida, J.; Matsuyama, Y.; Kondo, K.; Subramanian, S.V.; Kawachi, I. Social capital and cognitive decline in the aftermath of a natural disaster: A natural experiment from the 2011 Great East Japan Earthquake and Tsunami. *Lancet Planet. Health* **2017**, *1*, e105–e113. [CrossRef] [PubMed]
7. Fothergill, A.; Peek, L.A. Poverty and Disasters in the United States: A Review of Recent Sociological Findings. *Nat. Hazards* **2004**, *32*, 89–110. [CrossRef]
8. Tracy, M.; Norris, F.H.; Galea, S. Differences in the determinants of posttraumatic stress disorder and depression after a mass traumatic event. *Depress Anxiety* **2011**, *28*, 666–675. [CrossRef]
9. Bell, S.A.; Klasa, K.; Iwashyna, T.J.; Norton, E.C.; Davis, M.A. Long-term healthcare provider availability following large-scale hurricanes: A difference-in-differences study. *PLoS ONE* **2020**, *15*, e0242823. [CrossRef]
10. Chambers, K.A.; Husain, I.; Chathampally, Y.; Vierling, A.; Cardenas-Turanzas, M.; Cardenas, F.; Sharma, K.; Prater, S.; Rogg, J. Impact of Hurricane Harvey on Healthcare Utilization and Emergency Department Operations. *West. J. Emerg. Med.* **2020**, *21*, 586–594. [CrossRef]
11. Davidow, A.L.; Thomas, P.; Kim, S.; Passannante, M.; Tsai, S.; Tan, C. Access to Care in the Wake of Hurricane Sandy, New Jersey, 2012. *Disaster Med. Public Health Prep.* **2016**, *10*, 485–491. [CrossRef]

Int. J. Environ. Res. Public Health **2025**, *22*, 733

11 of 13

12. Stehling-Ariza, T.; Park, Y.S.; Sury, J.J.; Abramson, D. Measuring the impact of Hurricane Katrina on access to a personal healthcare provider: The use of the National Survey of Children's Health for an external comparison group. *Matern. Child Health J.* **2012**, *16* (Suppl. S1), S170–S177. [CrossRef]

13. Davis, J.R.; Wilson, S.; Brock-Martin, A.; Glover, S.; Svendsen, E.R. The Impact of Disasters on Populations with Health and Health Care Disparities. *Disaster Med. Public Health Prep.* **2010**, *4*, 30–38. [CrossRef]

14. Walls & Associates. *National Establishment Time-Series (NETS) Database*; Walls & Associates: Oakland, CA, USA, 2015.

15. Hirsch, J.A.; Moore, K.A.; Cahill, J.; Quinn, J.; Zhao, Y.; Bayer, F.J.; Rundle, A.; Lovasi, G.S. Business Data Categorization and Refinement for Application in Longitudinal Neighborhood Health Research: A Methodology. *J. Urban Health* **2021**, *98*, 271–284. [CrossRef]

16. ASU Center for Emergency Management and Homeland Security. The Spatial Hazard Events and Losses Database for the United States, Version 23.0 [Online Database]. Arizona State University: Phoenix, AZ, USA, 2025. Available online: https://sheldus.org (accessed on 23 April 2025).

17. Schultz, J.; Elliott, J.R. Natural disasters and local demographic change in the United States. *Popul. Environ.* **2013**, *34*, 293–312. [CrossRef]

18. Borden, K.A.; Cutter, S.L. Spatial patterns of natural hazards mortality in the United States. *Int. J. Health Geogr.* **2008**, *7*, 64. [CrossRef]

19. Gall, M.; Borden, K.A.; Emrich, C.T.; Cutter, S.L. The Unsustainable Trend of Natural Hazard Losses in the United States. *Sustainability* **2011**, *3*, 2157–2181. [CrossRef]

20. Michael, Y.L.; Smiley, K.T.; Clay, L.; Hirsch, J.A.; Lovasi, G.S. Uneven Growth in Social Capital Organizations After Disasters by Pre-Disaster Conditions in the United States 2000–2014. *Disaster Med. Public Health Prep.* **2023**, *17*, 1–8. [CrossRef]

21. Krieger, N.W.P.; Chen, J.T.; Rehkopf, D.H.; Subramanian, S.V. *Geocoding and Monitoring US Socioeconomic Inequalities in Health: An Introduction to Using Area-Based Socioeconomic Measures—The Public Health Disparities Geocoding Project Monograph*; Harvard School of Public Health: Boston, MA, USA, 2022. Available online: http://www.hsph.harvard.edu/thegeocodingproject (accessed on 6 December 2023).

22. Logan, J.R.X.Z.; Stults, B. Interpolating US decennial census tract data from as early as 1970 to 2010: A longitudinal tract database. *Prof. Geogr.* **2012**, *66*, 412–420. [CrossRef] [PubMed]

23. Yabe, T.; Tsubouchi, K.; Fujiwara, N.; Sekimoto, Y.; Ukkusuri, S.V. Understanding post-disaster population recovery patterns. *J. R. Soc. Interface* **2020**, *17*, 20190532. [CrossRef]

24. Bailey, Z.D.; Krieger, N.; Agenor, M.; Graves, J.; Linos, N.; Bassett, M.T. Structural racism and health inequities in the USA: Evidence and interventions. *Lancet* **2017**, *389*, 1453–1463. [CrossRef]

25. U.S. Government Accountability Office. Rural Hospital Closures: Affected Residents Had Reduced Access to Health Care Services. GAO-21-93. Published 22 December 2024. Available online: https://www.gao.gov/assets/gao-21-93.pdf (accessed on 6 January 2025).

26. Kaufman, B.G.; Thomas, S.R.; Randolph, R.K.; Perry, J.R.; Thompson, K.W.; Holmes, G.M.; Pink, G.H. The Rising Rate of Rural Hospital Closures. *J. Rural. Health* **2016**, *32*, 35–43. [CrossRef]

27. McCarthy, S.; Moore, D.; Smedley, W.A.; Crowley, B.M.; Stephens, S.W.; Griffin, R.L.; Tanner, L.C.; Jansen, J.O. Impact of Rural Hospital Closures on Health-Care Access. *J. Surg. Res.* **2021**, *258*, 170–178. [CrossRef]

28. Wald, A. Emergency department visits and costs for heat-related illness due to extreme heat or heat waves in the United States: An integrated review. *Nurs. Econ.* **2019**, *37*, 35–48.

29. U.S. Environmental Protection Agency. Climate Change and the Health of Socially Vulnerable People. Published April 11, 2023. Available online: https://www.epa.gov/climateimpacts/climate-change-and-health-socially-vulnerable-people (accessed on 8 November 2024).

30. Arrieta, M.I.; Foreman, R.D.; Crook, E.D.; Icenogle, M.L. *A Network Approach to Facilitating Continuity of Care for Patients with Chronic Diseases in the Aftermath of a Natural Disaster*; Center for Healthy Communities Research Office, University of South Alabama: Mobile, AL, USA, 2007.

31. Guo, J.; Dickson, S.; Berenbrok, L.A.; Tang, S.; Essien, U.R.; Hernandez, I. Racial disparities in access to health care infrastructure across US counties: A geographic information systems analysis. *Front. Public Health* **2023**, *11*, 897007. [CrossRef] [PubMed]

32. Caldwell, J.T.; Ford, C.L.; Wallace, S.P.; Wang, M.C.; Takahashi, L.M. Racial and ethnic residential segregation and access to health care in rural areas. *Health Place* **2017**, *43*, 104–112. [CrossRef] [PubMed]

33. Muñoz, C.; Tate, E. Unequal Recovery? Federal Resource Distribution after a Midwest Flood Disaster. *Int. J. Environ. Res. Public Health* **2016**, *13*, 507. [CrossRef] [PubMed]

34. Federal Emergency Management Agency. Locally Executed State Managed, Federally Supported Recovery. Published 12 March 2021. Secondary. Available online: https://www.fema.gov/sites/default/files/2020-11/fema_florida-hurricane-irma-recovery_case-study.pdf (accessed on 31 March 2025).

Int. J. Environ. Res. Public Health **2025**, *22*, 733

12 of 13

35. Griffies, W.S. Health Care Infrastructure Post-Katrina: Disaster Planning to Return Health Care Workers to Their Home Communities. *Psychiatr. Serv.* **2010**, *61*, 70–73. [CrossRef]

36. Vigdor, J. The Economic Aftermath of Hurricane Katrina. *J. Econ. Perspect.* **2008**, *22*, 135–154. [CrossRef]

37. Ferreira, R.; Davidson, T.; Buttell, F.; Contillo, C.M.; Leddie, C.; Leahy, C.; Nuñez-Dune, C.; Lentz, B.; Simkins, M.; Jerolleman, A.; et al. Barriers to equitable disaster recovery: A scoping literature review. *Int. J. Disaster Risk Reduct.* **2024**, *110*, 104628. [CrossRef]

38. Stough, L.M.; Sharp, A.N.; Resch, J.A.; Decker, C.; Wilker, N. Barriers to the long-term recovery of individuals with disabilities following a disaster. *Disasters* **2016**, *40*, 387–410. [CrossRef]

39. Committee on Post-Disaster Recovery of a Community's Public Health, Medical, and Social Services; Board on Health Sciences Policy; Institute of Medicine. *Healthy, Resilient, and Sustainable Communities After Disasters: Strategies, Opportunities, and Planning for Recovery*; National Academies Press: Washington, DC, USA, 2015. Available online: https://www.ncbi.nlm.nih.gov/books/NBK316532/ (accessed on 23 April 2025).

40. Straker, H.; Finister, S. Not business as usual. *J. Health Care Poor Underserved* **2007**, *18*, 241–245. [CrossRef]

41. Arrieta, M.I.; Foreman, R.D.; Crook, E.D.; Icenogle, M.L. Providing continuity of care for chronic diseases in the aftermath of Katrina: From field experience to policy recommendations. *Disaster Med. Public Health Prep.* **2009**, *3*, 174–182. [CrossRef]

42. Elliott, J.R.; Clement, M.T. Natural Hazards and Local Development: The Successive Nature of Landscape Transformation in the United States. *Soc. Forces* **2017**, *96*, 851–876. [CrossRef]

43. Fox Gotham, K.; Greenberg, M. *Crisis Cities: Disaster and Redevelopment in New York and New Orleans*; Oxford University Press: Oxford, UK, 2014.

44. Pais, J.F.; Elliott, J.R. Places as Recovery Machines: Vulnerability and Neighborhood Change After Major Hurricanes. *Soc. Forces* **2008**, *86*, 1415–1453. [CrossRef]

45. Hayes, S.; Desha, C.; Burke, M.; Gibbs, M.; Chester, M. Leveraging socio-ecological resilience theory to build climate resilience in transport infrastructure. *Transp. Rev.* **2019**, *39*, 677–699. [CrossRef]

46. Ingram, J.C.; Franco, G.; Rumbaitis-del Rio, C.; Khazai, B. Post-disaster recovery dilemmas: Challenges in balancing short-term and long-term needs for vulnerability reduction. *Environ. Sci. Policy* **2006**, *9*, 607–613. [CrossRef]

47. Comfort, L.K. Risk, security, and disaster management. *Annu. Rev. Polit. Sci.* **2005**, *8*, 335–356. [CrossRef]

48. Chester, M.; El Asmar, M.; Hayes, S.; Desha, C. Post-Disaster Infrastructure Delivery for Resilience. *Sustainability* **2021**, *13*, 3458. [CrossRef]

49. Guadamuz, J.S.; Alexander, G.C.; Zenk, S.N.; Kanter, G.P.; Wilder, J.R.; Qato, D.M. Access to pharmacies and pharmacy services in New York City, Los Angeles, Chicago, and Houston, 2015-2020. *J. Am. Pharm. Assoc.* **2021**, *61*, e32–e41. [CrossRef]

50. Guadamuz, J.S.; Wilder, J.R.; Mouslim, M.C.; Zenk, S.N.; Alexander, G.C.; Qato, D.M. Fewer Pharmacies in Black and Hispanic/Latino Neighborhoods Compared With White Or Diverse Neighborhoods, 2007–2015. *Health Aff.* **2021**, *40*, 802–811. [CrossRef]

51. University of California BSoPHNirphcsBPHPS, 2022. Secondary. Available online: https://publichealth.berkeley.edu/news-media/research-highlights/nearly-1-in-3-retail-pharmacies-have-closed-since-2010 (accessed on 7 January 2025).

52. Qato, D.M.; Alexander, G.C.; Chakraborty, A.; Guadamuz, J.S.; Jackson, J.W. Association Between Pharmacy Closures and Adherence to Cardiovascular Medications Among Older US Adults. *JAMA Netw Open* **2019**, *2*, e192606. [CrossRef]

53. Smith, A.B. 2023: A Historic Year of U.S. Billion-Dollar Weather and Climate Disasters. NOAA Climate.gov. 8 January 2024. Available online: https://www.climate.gov/news-features/blogs/beyond-data/2023-historic-year-us-billion-dollar-weather-and-climate-disasters (accessed on 20 November 2024).

54. Bhatia, K.T.; Vecchi, G.A.; Knutson, T.R.; Murakami, H.; Kossin, J.; Dixon, K.W.; Whitlock, C.E. Recent increases in tropical cyclone intensification rates. *Nat. Commun.* **2019**, *10*, 635. [CrossRef]

55. Alfieri, L.; Bisselink, B.; Dottori, F.; Naumann, G.; de Roo, A.; Salamon, P.; Wyser, K.; Feyen, L. Global projections of river flood risk in a warmer world. *Earth's Future* **2017**, *5*, 171–182. [CrossRef]

56. Smiley, K.T.; Howell, J.; Elliott, J.R. Disasters, local organizations, and poverty in the USA, 1998 to 2015. *Popul. Environ.* **2018**, *40*, 115–135. [CrossRef]

57. Tsui, J.; Hirsch, J.A.; Bayer, F.J.; Quinn, J.W.; Cahill, J.; Siscovick, D.; Lovasi, G.S. Patterns in Geographic Access to Health Care Facilities Across Neighborhoods in the United States Based on Data from the National Establishment Time-Series Between 2000 and 2014. *JAMA Netw Open* **2020**, *3*, e205105. [CrossRef]

58. Howell, J.; Elliott, J.R. Damages done: The longitudinal impacts of natural hazards on wealth inequality in the United States. *Soc. Probl.* **2019**, *66*, 448–467. [CrossRef]

59. Krieger, N.; Waterman, P.D.; Spasojevic, J.; Li, W.; Maduro, G.; Van Wye, G. Public Health Monitoring of Privilege and Deprivation with the Index of Concentration at the Extremes. *Am. J. Public Health* **2016**, *106*, 256–263. [CrossRef]

60. Appolon, G.; Tang, S.; Gabriel, N.; Morales, J.; Berenbrok, L.A.; Guo, J.; Hernandez, I. Association Between Redlining and Spatial Access to Pharmacies. *JAMA Netw. Open* **2023**, *6*, e2327315. [CrossRef] [PubMed]

Int. J. Environ. Res. Public Health **2025**, 22, 733

13 of 13

61. Nardone, A.; Chiang, J.; Corburn, J. Historic Redlining and Urban Health Today in U.S. Cities. *Environ. Justice* **2020**, *13*, 109–119. [CrossRef]

62. King, C.J.; Buckley, B.O.; Maheshwari, R.; Griffith, D.M. Race, Place, And Structural Racism: A Review of Health and History in Washington, D.C. *Health Aff.* **2022**, *41*, 273–280. [CrossRef] [PubMed]

63. Berberian, A.G.; Gonzalez, D.J.X.; Cushing, L.J. Racial Disparities in Climate Change-Related Health Effects in the United States. *Curr. Environ. Health Rep.* **2022**, *9*, 451–464. [CrossRef]

64. Gutierrez, K.S.; LePrevost, C.E. Climate justice in rural southeastern United States: A review of climate change impacts and effects on human health. *Int. J. Environ. Res. Public Health* **2016**, *13*, 189. [CrossRef]

65. LaVeist, T.A.; Isaac, L.A.; Williams, K.P. Mistrust of health care organizations is associated with underutilization of health services. *Health Serv. Res.* **2009**, *44*, 2093–2105. [CrossRef] [PubMed]

66. Raker, E.J.; Arcaya, M.C.; Lowe, S.R.; Zacher, M.; Rhodes, J.; Waters, M.C. Mitigating Health Disparities After Natural Disasters: Lessons from the RISK Project. *Health Aff.* **2020**, *39*, 2128–2135. [CrossRef] [PubMed]

67. Glymour, M.M.; Weuve, J.; Berkman, L.F.; Kawachi, I.; Robins, J.M. When is baseline adjustment useful in analyses of change? An example with education and cognitive change. *Am. J. Epidemiol.* **2005**, *162*, 267–278. [CrossRef] [PubMed]