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Geographical Information Systems-Based Assessment of Evacuation Accessibility to Special Needs Shelters Comparing Storm Surge Impacts of Hurricane Irma (2017) and Ian (2022)

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Abstract: Research on hurricane impacts in Florida's coastal regions has been extensive, yet there remains a gap in comparing the effects and potential damage of different hurricanes within the same geographical area. Additionally, there is a need for reliable discussions on how variations in storm surges during these events influence evacuation accessibility to hurricane shelters. This is especially significant for rural areas with a vast number of aging populations, whose evacuation may require extra attention due to their special needs (i.e., access and functional needs). Therefore, this study aims to address this gap by conducting a comparative assessment of storm surge impacts on the evacuation accessibility of southwest Florida communities (e.g., Lee and Collier Counties) affected by two significant hurricanes: Irma in 2017 and Ian in 2022. Utilizing the floating catchment area method and examining Replica's OD Matrix data with Geographical Information Systems (GISs)-based technical tools, this research seeks to provide insights into the effectiveness of evacuation plans and identify areas that need enhancements for special needs sheltering. By highlighting the differential impacts of storm surges on evacuation accessibility between these two hurricanes, this assessment contributes to refining disaster risk reduction strategies and has the potential to inform decision-making processes for mitigating the impacts of future coastal hazards.

Keywords: hurricane evacuation; transportation accessibility; coastal inundation; special needs shelters; replica data

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1. Introduction

Between 2000 and 2019, hurricanes and tropical storms, many times followed by events like coastal flooding, occurred substantially in the United States compared to other types of hazards such as landslides and earthquakes [1]. Unfortunately, the increasing intensity and frequency of natural disasters exacerbated by climate change are likely to increase, and vulnerabilities will rise dramatically [2,3]. This will result in greater physical damage to infrastructure, significant economic losses, and heightened risks to human life and safety.

As a state surrounded by coastlines on three sides, as shown in Figure 1, Florida faces an average of three or more destructive and potentially devastating hurricanes each hurricane season [4]. With climate change causing global warming and rising sea levels, an increasing number of tropical storms have the potential to intensify into major hurricanes [5,6]. Given the high likelihood of hurricane occurrences and the increasing frequency of such events, it is unsurprising that multiple hurricanes impact similar regions of Florida within a relatively short time frame. For example, Hurricanes Irma and Ian struck Lee and Collier Counties in southwest Florida five years apart.

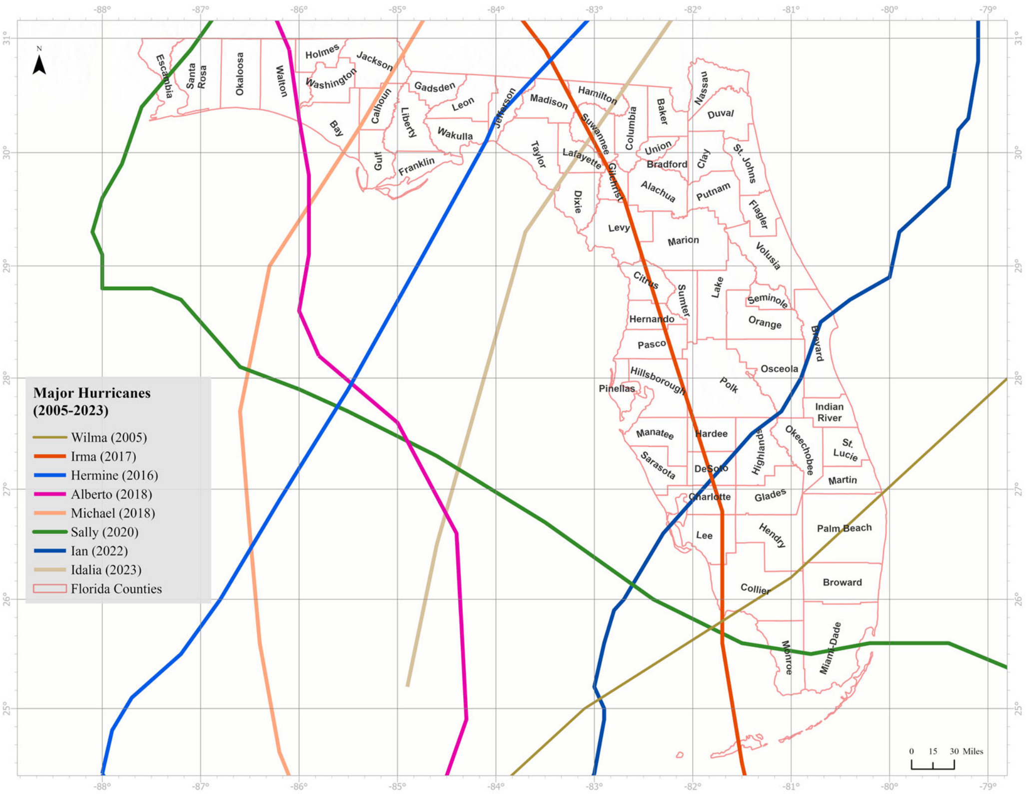


Figure 1. Historical major hurricane paths in Florida [7,8].

Hurricane Irma made landfall on Cudjoe Key in Monroe County, Florida, as a Category 4 hurricane on 10 September 2017. After its landfall, it weakened to a Category 3 hurricane as it moved north through Collier and Lee Counties [9]. In 2022, five years after Hurricane Irma hit southwest Florida, Hurricane Ian, which moved northwest and continued to rapidly intensify over warm waters, struck the region of Collier and Lee Counties again with the destructive force of a Category 4 storm. Importantly, it intensified faster than any other hurricane in the 2022–2023 Atlantic hurricane season. On the morning of September 28, Hurricane Ian strengthened to a Category 4 hurricane over the Gulf of Mexico, with maximum sustained winds of 155 mph, just shy of a Category 5 storm [10]. At 3:05 p.m., Ian made landfall near Cayo Costa, Florida, delivering a devastating blow to multiple coastal cities in southwest Florida, including Cape Coral. It tied the record for the fifth-strongest hurricane to hit the United States and became the strongest hurricane to strike Florida since Hurricane Michael (2018). The storm surge was the deadliest aspect, causing 41 deaths, 36 of which occurred in Lee County, Florida. Freshwater flooding in central and eastern Florida resulted in 12 direct deaths, with 8 related to the sea, 4 wind-related, and 1 surge wave-related [11,12].

In the literature, researchers have mostly focused on emergency planning and response efforts for Hurricane Irma (2017) [13–15] and Hurricane Michael (2018) [16–19], respectively, and there are not many research studies focusing on understanding the impact of the "young" Hurricane Ian (2022) on infrastructure resilience. In addition, there is a lack of studies looking into comprehensive assessments of evacuation accessibility of vulnerable populations in the same area or group of counties impacted by different hurricanes. Current research has also not been conducted such as comparative analyses focusing on how storms expose the vulnerabilities of key infrastructure systems (e.g., transportation networks and utility services). Without such analyses, it would be difficult for decision-makers to develop more robust infrastructure design and retrofit strategies to cope with the unique challenges posed by future hurricanes of similar magnitudes and trajectories.

Although agencies' evacuation orders have been given 2 to 5 days in advance generally, the experience of Hurricane Irma in 2017 taught us many painful lessons. A significant portion of this population resides in rural areas, which often face challenges such as difficulties related to evacuation procedures, staffing of emergency operations centers, debris cleanup after the hurricane passed [20], and a lack of nearby hurricane shelters equipped to accommodate individuals with disabilities or medical needs. Also, as of 2021, Florida has the third-highest percentage of elderly residents in the United States, with individuals aged 65 and older making up 21.3% of the population [21]. The mentioned limitations can result in increased fatalities in the week following a hurricane, particularly in vulnerable communities (e.g., senior communities and low-income areas), and communities with poor access to public healthcare during emergencies [22]. More importantly, as a state with a high density of elderly residents and extensive rural areas, the allocation of special needs facilities and supplies for evacuation, such as special needs shelters (SpNS) [17,23,24], is critical for the efficiency and reliability of evacuations in affected areas. In response to these concerns, this study chooses the elderly population (those that are 65 and over) in Collier and Lee Counties to represent the scenario demand to evaluate evacuation accessibility to special needs shelters.

Hence, this research aims to bridge the knowledge gap regarding the differing impacts of storm surges that occurred due to hurricanes Irma and Ian on evacuation accessibility in Collier and Lee Counties, focusing on rural communities with elderly populations that often require special needs sheltering [17,25]. With the help of GIS-based tools, an appropriate floating catchment area method, and Replica's OD Matrix data, this study will perform a comparative analysis of the evacuation challenges brought by these hurricanes. The ultimate goal is to provide practical insights into the effectiveness of current evacuation plans and support the improvement of disaster risk reduction strategies, ensuring better preparedness for future hurricanes that may hit the same region with similar and higher intensities.

2. Study Area

To begin with, a key component to generate scenarios of this analysis is mapping the tracks of both Hurricane Irma and Ian to identify possible overlaps and variations in their impacted zones. Based on the tracks and landfall details shown in Figure 2, Hurricane Irma primarily caused storm surge flooding in the southern region, submerging the road networks in densely populated cities in southwest Florida, such as Cape Coral and Naples. Hurricane Ian approached from the southwest, intersecting perpendicularly with the coastline, resulting in more severe and prominent flooding along the southwest coast. It gains one part of the value of comparative analysis by examining how differences in storm paths—Irma's southward surge versus Ian's perpendicular coastal intersection—amplified flooding in distinct areas. The major similarity is that both hurricanes led to mandatory evacuations in Lee and Collier Counties in southwest Florida [26].

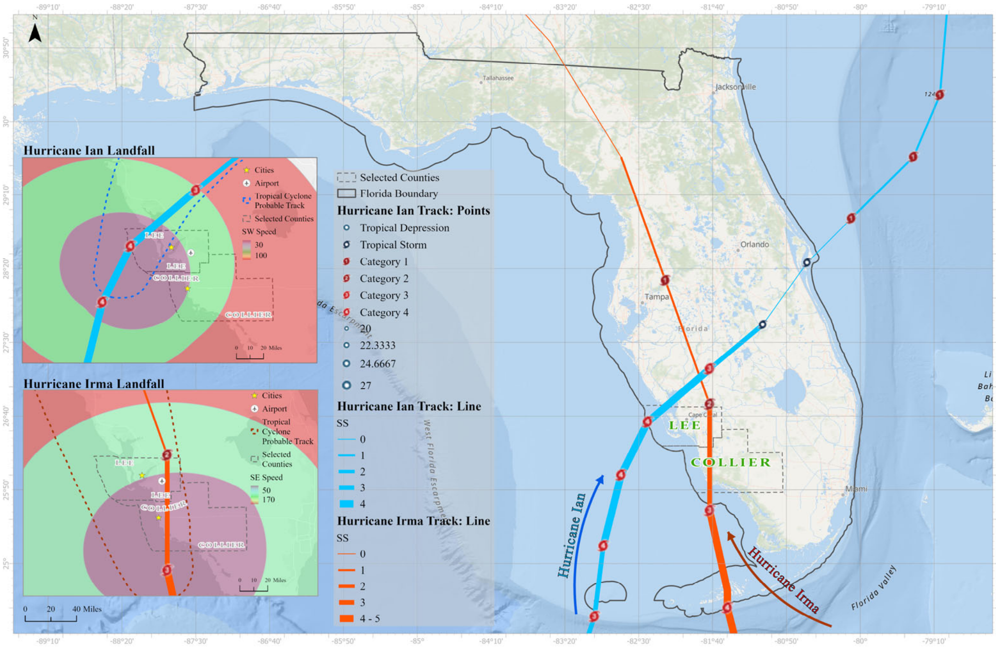
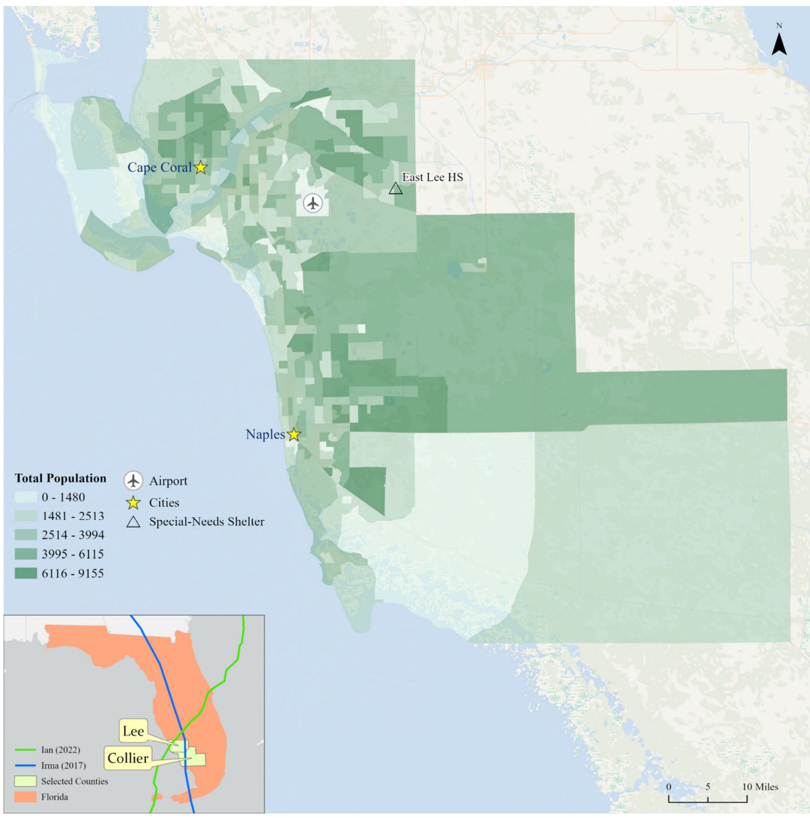


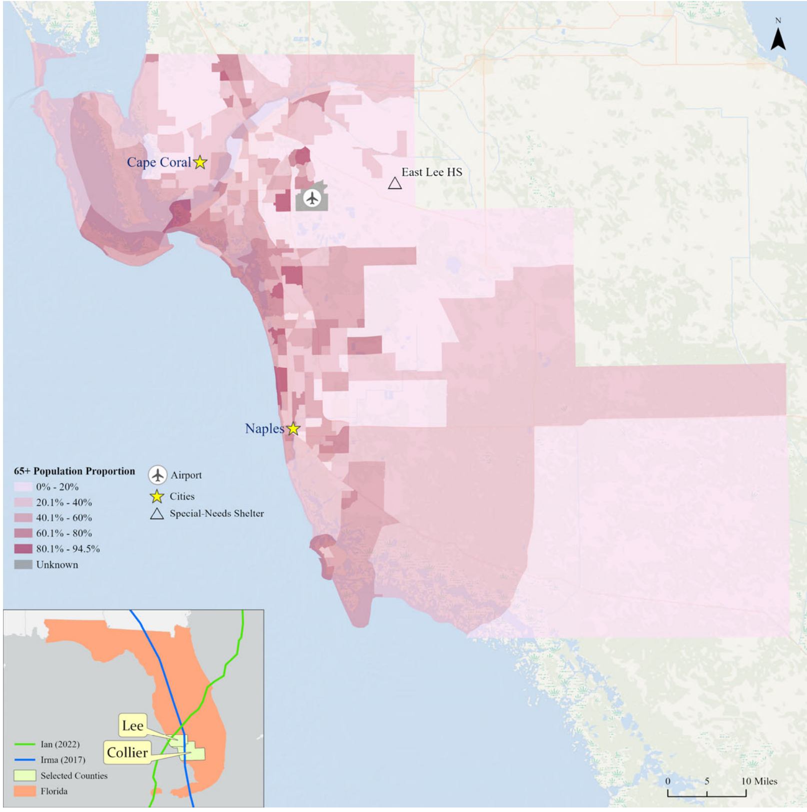
Figure 2. The tracks and wind fields of two hurricanes in this research [7].

These two counties share the following characteristics of 2020 Census Tracts in Florida according to the U.S. Census Bureau's data [27] (as shown in Figure 3a,b): (1) Excluding areas designated as nature reserves and non-residential land, both counties have high total populations, with significant residential populations in both coastal cities and inland rural areas. (2) The elderly population is concentrated near the coastline, at a considerable distance from the only SpNS located in the northeastern part of the region [28].



(**a**)

Figure 3. *Cont.*



(**b**)

Figure 3. (**a**) Total population distribution map; (**b**) aging population (age 65 and up) percentage over total population [7,26].

Special needs populations primarily consist of the elderly, disabled, other vulnerable individuals, and certain young groups [17]. These vulnerable communities, especially the elderly population who make up a significant portion of individuals with special needs, face added challenges due to limited transportation options and a lack of accessible, safe service destinations. The time required to reach safety before the hurricane hits is further complicated by health issues and specific access and functional needs that these individuals may have. The scenario of each county has large elderly populations concentrated near the coastline and situated far from the only SpNS, presenting unique challenges of evacuation. Analyzing these factors can help improve and prepare effective future evacuation plans, including the maintenance and proper allocation of transportation, medical services, and shelter facilities, to maximize safety and efficiency.

3. Methodology

In this study, we used the regional OD Matrix data provided by Kimley–Horn Associates and Replica, which was incorporated into the geodatabase and interpolated with socioeconomic information from U.S. Census data using the Geographic Information System (GIS). Replica is a data platform that assists public and private sector organizations in making informed decisions about transportation, infrastructure, and urban planning. By integrating data from diverse sources, such as GPS, mobile devices, and public records, their models offer valuable insights into travel patterns, destinations, and the factors influencing mobility. The platform's capability to produce high-fidelity, granular data makes it an indispensable tool for optimizing transportation networks, enhancing land use planning, and improving public service delivery.

With the output obtained from Replica, the next step of research involved applying population data, congested travel times, and SpNS capacity to calculate accessibility indices using the enhanced two-step floating catchment area (E2SFCA) method. Utilizing ArcGIS Pro to process the aging population of each grid, the congested travel time of each travel unit, and barriers selected and generated based on inundation, we graphed the results in combination with potential storm surge inundation data from the National Hurricane Center (NHC) [29,30] for an evacuation accessibility assessment. This assessment aims to contribute to the field by addressing accessibility challenges that special needs populations might have faced during two hurricane evacuations.

As shown in Figure 4, the research workflow began with screening census tract information to calculate population density for each tract using the population and acreage values from the U.S. Census Bureau dataset [27]. This step was validated by comparing it with more detailed block-level population distribution data. Next, we exported the OD Matrix, which included trips on specified dates stored on the Replica platform. These data featured various departure times at a 0.5-mile resolution [31] and used GIS tools to interpolate population information for each origin. After filtering the OD Matrix based on departure times, destination endpoints, and route connectivity, we retained trips concentrated in the selected counties for further analysis. The statewide shelter plan mentioned earlier provided the locations and capacities of SpNS, which were used in the E2SFCA method to calculate the demand–supply ratio. Additionally, with GIS visualization, the hurricane storm surge flooding (inundation mapping) was filtered to show waves that would have the largest possibility to be as high as 9 feet above the ground when each hurricane was approaching to hit the coastline.

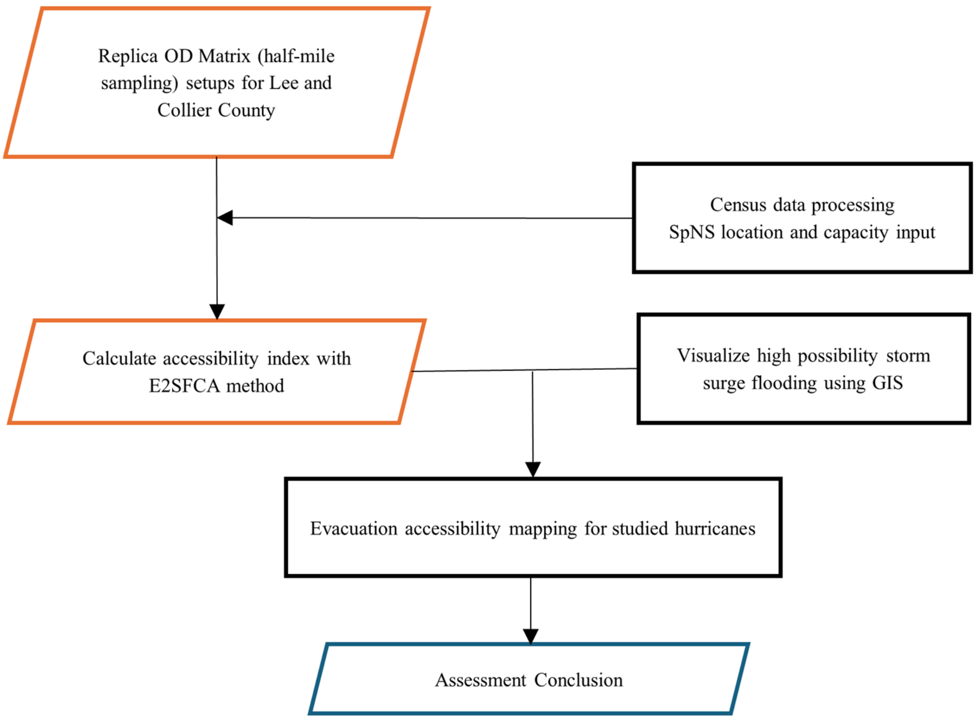


Figure 4. Research flowchart.

3.1. Literature Review of Floating Catchment Area Methods

The complexity of "spatial accessibility (SA)" to service facilities is influenced by numerous factors. Key factors include the capacity of supply points, such as the number of available sheltering spaces, and the size of the demand, represented by the population [32]. Therefore, SA varies significantly across different regions, particularly between urban and rural areas. Rural areas often face challenges due to service facilities being located miles away in denser urban centers. This scarcity of services and opportunities in rural areas can be perceived as a severe provider shortage [33]. For instance, in Northwest Florida, hurricane shelters are predominantly located in counties with larger cities [34]. In contrast, counties characterized by rural areas and lower population densities typically have few shelters, often ranging from none to at most two [3,14,19,35]. Therefore, it is crucial to investigate the challenges that rural areas face regarding transportation accessibility to shelters, particularly SpNS. Rural areas often experience longer travel times and distances, fewer sheltering facilities, and limited service availability, making it imperative to address these issues to improve evacuation efficiency and support for vulnerable populations.

The floating catchment area (FCA) method [36], derived from a gravity-based approach, has been utilized to evaluate the service areas of medical physicians. This method not only considers a predefined travel time threshold but also factors in the availability of physicians relative to the surrounding population's demand [37]. It provided simplification of the distance impedance factor β in gravity models [38]. Various FCA methods have been developed to improve SA analysis by incorporating more comprehensive constraints and assessments, such as the two-step floating catchment area (2SFCA), the enhanced two-step floating catchment area (E2SFCA), the three-step floating catchment area (3SFCA), and other advanced ratio calculation techniques [39].

3.2. Why Chose E2SFCA?

Most of the basic FCA methods can be implemented using ArcGIS Pro 2.9. However, they have limitations, such as assuming equal access for all population locations within the catchment area without considering distance impedance. Additionally, basic FCA methods unrealistically assign zero spatial accessibility to locations outside the catchment [37]. To overcome these drawbacks, the proposed enhancement to the enhanced two-step floating catchment area (E2SFCA) method involves incorporating distance decay by applying weights during both the first and second steps of the 2SFCA analysis. This approach distinguishes travel time zones by dividing them into sub-time zones according to research scales, travel mode, and network function, with weights assigned according to the Gaussian function [32].

While researchers are continuing to develop 2SFCA, the E2SFCA method is widely utilized and highly effective in healthcare accessibility analysis. Numerous research studies have employed E2SFCA or compared it with other FCAs to evaluate healthcare accessibility [3,40–42], and it is also particularly popular in many developing countries. Its application in these regions has proven valuable for identifying disparities and improving the distribution of healthcare services [43]. E2SFCA is well suited for analyzing both urban and rural areas due to its ability to incorporate reliable distance-based weighting, which accounts for variations in accessibility across different geographic contexts. Additionally, according to the literature, the E2SFCA method has consistently demonstrated effectiveness in evaluating accessibility at smaller scales, making it an appropriate choice for this study's focus on community-level evacuation accessibility. Its flexibility and proven reliability ensure robust results in diverse spatial scenarios.

However, E2SFCA is not always the best solution for every scenario, and researchers utilized more advanced FCA methods for more complex accessibility analysis, such as Hierarchical 2SFCA (H2SFCA) [44,45], integrating a Variable Distance Decay Function with FCA [38], and Multi-Modal 2SFCA [46,47]. Nevertheless, many of these bring complexities such as longer computational time, increased data requirements, or overfitting contexts for certain study areas or small rural scenarios. Compared to other variations of the FCAs, the E2SFCA model offers simplicity and greater applicability for analyzing transportation networks and demographic data in our research: specified demand (i.e., aging population), limited destinations (i.e., SpNS outside of inundation), and only two counties under distance consideration. This suitability makes it an ideal choice for studying the selected region.

3.3. Accessibility Index Calculation

A high accessibility index (AI) for the critical facility typically signifies that a large portion of the region's population can easily access the supply. This suggests that most residents can reach shelters quickly with minimal transportation barriers during hurricane evacuations. Conversely, a low AI indicates that a significant portion of the population may struggle to access shelters. Contributing factors may include the location of shelters, inadequate transportation options, or physical obstacles such as storm surges and flooding.

In this assessment, E2SFCA [32] was applied as the key role in the SpNS accessibility analysis part. This method is well suited for evaluating "global" AI compared to other floating catchment area methods within our research scope, providing a broad assessment of accessibility that typically overlooks variations in demand and supply competition in which rural areas and an aging population present a unique challenge. It is especially effective for assessing emergency accessibility during hurricanes and evacuations because it comprehensively measures both spatial and temporal factors affecting access. In our case, it captures the interactions between distance, congested travel time from Replica, population density from U.S. Census Bureau, and shelter capacity from Florida Division of Emergency Management (FDEM) [35], reflecting how these variables influence accessibility.

To begin with, the model for this study is built on the following assumptions:

- Using the 2020 census data for accessibility calculations related to 2017 and 2022 assumes that demographic changes over this period are minimal and unlikely to significantly impact overall accessibility outcomes. Since our scenarios aggregate situational travel data rather than focusing on individual year-to-year variations; additionally, the population migration of rural counties declined more with the COVID-19 pandemic [48], and the use of 2020 data provides a stable and representative basis for analysis during this timeframe.
- The SpNS established in 2005 (Table 1) at East Lee High School has not undergone significant renovations or expansions in nearly twenty years, so changes in capacity are considered negligible.
- The OD Matrix analysis used in this study does not account for critical variables such as wind speed and infrastructure damage, but the scenario closes shelters under inundation when processing AI. In addition, this study focuses on only two counties, Collier and Lee, which have extensive rural areas near their eastern boundaries. Evacuation challenges are more shaped by geographic remoteness and limited transportation infrastructure rather than storm-specific variables. As a result, the OD Matrix analysis is well suited to this study's context and objectives.
- The final results of the accessibility index would be based on available trips after data processing.

Table 1. SpNS information details.

County	Shelter Type	Year Built	Site Name	Latitude	Longitude	Risk Capacity (Spaces)	Risk Capacity (Sq Ft)	Planned Usage (Spaces)
Lee	SpNS	2005	East Lee HS	26.5582528	81.601995	1305	118,297	150

Accordingly, the steps of E2SFCA are listed as follows [32,40,43,45,47,49,50]:
Step 1: Calculate the supply to demand ratio with Equation (1):

$$R_j = \frac{S_j}{\sum_{i \in \{t_{ij} \le t_0\}} P_i \cdot W_i}, \tag{1}$$

where S_j is the capacity of SpNS j, which was a buffer center with the travel time threshold radius t_0, and then t_{ij} is the travel cost (time) from population centroid i to the shelter j. W_i is the Gaussian weight function for distance decay that indicates evacuation demand change based on travel cost (Equation (2)):

$$W_i = W(t_{ij}, t_0) = \frac{e^{-\frac{1}{2} \times \left(\frac{t_{ij}}{t_0}\right)^2} - e^{-\frac{1}{2}}}{1 - e^{-\frac{1}{2}}}, \tag{2}$$

Step 2: Calculate the accessibility index with Equation (3):

$$A_i = \sum_{j \in \{t_{ij} \le t_0\}} R_j W_i \tag{3}$$

It is worth noting that since the two counties in this assessment have only one registered SpNS, the travel time threshold for data filtering was set to the maximum value of all one-way OD trips to ensure that every origin with a population count greater than zero was considered within the evacuation range. It is also important to note that this maximum value does not necessarily represent a direct trip from an origin to the SpNS destination. Some coastal origins require transferring at an intermediate destination before reaching the SpNS. This study does not account for the potential reduction in waiting time between linked trips.

3.4. Storm Surge Flooding

According to NHC, extensive hurricane forecasting and recorded information. For this study, a new product, the Potential Storm Surge Flooding Map, was utilized. This map demonstrates the coastal flooding risks associated with hurricane-induced storm surges. The projected water heights in these areas are based on the Sea, Lake, and Overland Surges from Hurricanes (SLOSHs) model [51], which takes into account the temporal and spatial uncertainties of tropical cyclones. The map is generated from simulations of the Probabilistic Hurricane Storm Surge (P-Surge 2.5) model and considers historical errors in the NHC's official track and intensity forecasts. Potential storm surge flooding is depicted by processing the 10% exceedance level values from P-Surge 2.5, indicating areas where there is a one in ten chance of storm surge exceeding the predicted levels.

This study leverages the Potential Storm Surge Flooding Map to provide a detailed risk assessment of coastal flooding during hurricanes. Both Hurricane Irma and Hurricane Ian appeared to have the highest and largest inundation no more than 3 h before the actual landing time, which was compatible with Replica's congested travel time data since most of the filtered trips had related results. By incorporating probabilistic modeling and historical forecast data, it offers a comprehensive understanding of the potential impact of storm surges, enhancing the accuracy and reliability of evacuation planning and disaster preparedness strategies.

4. Results and Discussions

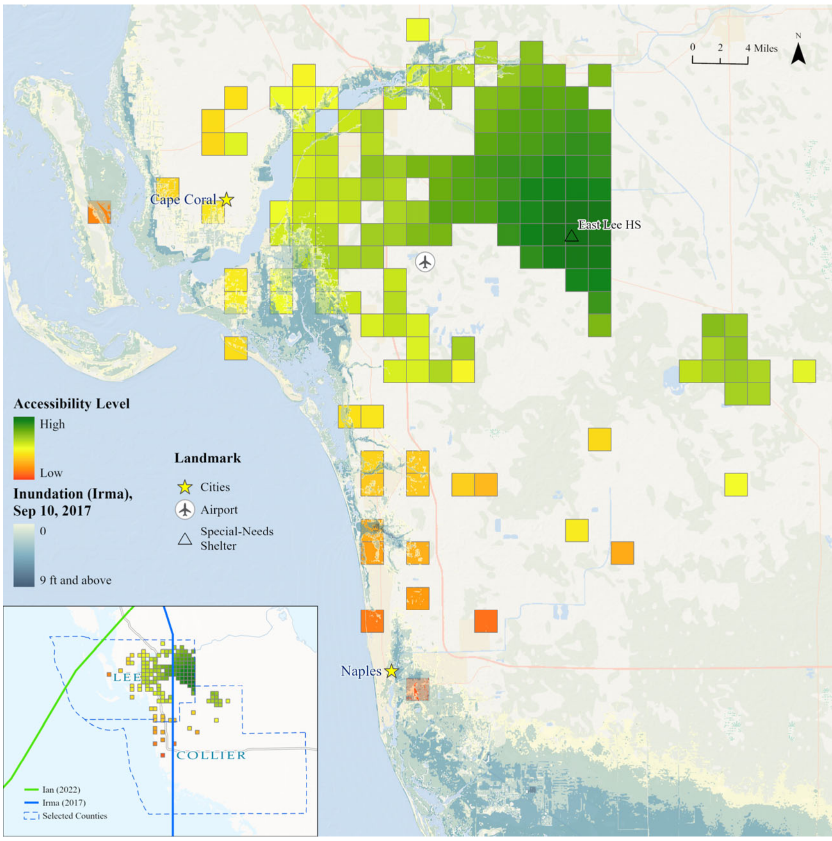
As hurricanes move inland, their speed and wind strength decrease due to land friction. This reduction in intensity means that areas closer to the actual landfall location are more likely to experience the strongest storm surges and the most severe impacts. The friction with the land surface slows down the hurricane and weakens its winds, but the immediate coastal areas still bear the brunt of the storm's initial force before this weakening occurs.

In the case of Hurricane Ian, its landfall point was closer to the remaining OD Matrix grid after filtering, as indicated in Figure 5. Despite both hurricanes being Category 4 at landfall and having similar wind speeds and rainfall, Ian's storm surge impact was more direct and widespread across the study area. This proximity to the landfall point meant that Ian's storm surge had a more immediate and severe effect on the coastal communities, leading to extensive flooding and damage. This comparison highlights the importance of considering the hurricane's approach and landfall location when assessing potential storm surge impacts and planning for disaster response and mitigation.

Table 2 lists the statistics of AI comparison after the E2SFCA calculation. While both scenarios share the same maximum AI (0.015), Irma shows a higher mean AI and standard deviation (0.0030) compared to Ian. We also compared the skewness of each AI's values. Ian's AI distribution is more skewed (4.7) than Irma's (3.2), indicating a greater concentration of low-accessibility areas during Ian. Though it indicates that on average, communities had better overall accessibility under Irma compared to Ian, and it was majorly caused by the difference in hurricane track directions.

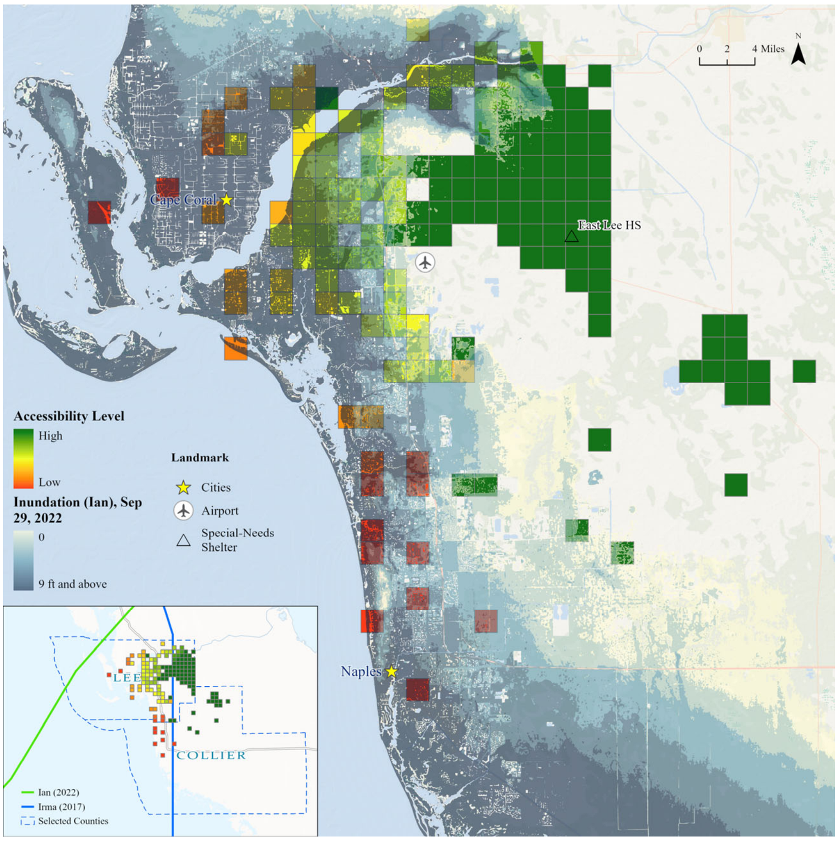
Table 2. Accessibility index statistics.

Scenario	**AI**			
Hurricane Names	**Standard Deviation**	**Maximum AI**	**Mean AI**	**Skewness**
Irma	0.0030	0.015	9×10^{-4}	3.2
Ian	0.0025	0.015	5.5×10^{-4}	4.7



(**a**)

Figure 5. *Cont.*



(**b**)

Figure 5. (**a**) Accessibility level in Hurricane Irma; (**b**) accessibility level in Hurricane Ian [7].

4.1. Hurricane Tracks and Their Impacts

As previously mentioned, both hurricanes struck the southwest coast of Florida, but they did so in markedly different ways, leading to varied impacts on the region. Hurricane Irma approached from due south at an angle to the coastline. This trajectory meant that the southern part of the study area was particularly vulnerable to significant storm surges, as the angle of approach allowed the storm to push water into these regions more effectively. The interaction between the hurricane's path and the coastal geography intensified the surge, leading to considerable flooding and damage. In contrast, Hurricane Ian made landfall with a perpendicular approach to the coastline. This straight-on trajectory resulted in a more even distribution of storm surges along the coast. The perpendicular impact meant that the force of the storm surge was spread out more uniformly across the coastal areas, rather than being concentrated in a specific section as with Irma. This difference in approach likely led to distinct patterns of flooding and damage, affecting a broader swath of the coastline.

Hurricane Ian's severe flooding had a devastating impact on the road networks in Lee County and the northwest side of Collier County. As illustrated in Figure 5b, the entire Cape Coral area, including all of Pine Island, was within high-risk flooding zones. Critical western bridges and roads in this region were also at risk, severely disrupting transportation. Additionally, sections of the I-75, which connect Lee County and Collier County along the coastline, faced significant flooding risks, highlighting the widespread impact on major evacuation routes. Consequently, from a storm surge perspective, Ian created more substantial transportation obstacles in this region compared to Irma, significantly reducing the accessibility to SpNS and hindering evacuation efforts.

The population distribution depicted in Figure 3 further underscores the challenges posed by Ian. The coastal areas, where the elderly population is particularly concentrated, faced greater evacuation difficulties. The storm surge's destruction of housing and roadways made immediate evacuation impossible, emphasizing the need for earlier evacuation efforts. Ian's storm surge was more uniformly distributed along the coast, intensifying the evacuation challenges for residents, especially those with limited mobility and special needs.

The storm surge's impact extended beyond immediate transportation and housing issues. The inundation of critical infrastructure, including emergency services and healthcare facilities, exacerbated the challenges for vulnerable populations. This widespread flooding disrupted not only evacuation routes but also the accessibility of essential services, compounding the difficulties faced by residents. As mentioned earlier, the highest and most extensive flooding from both hurricanes occurred three hours before full landfall. This timing offers critical insights for future planning that the government needs to consider helping and prompting the early evacuation is essential to ensure the safety of residents and to prevent last-minute bottlenecks on critical evacuation routes. Additionally, improving the resilience of infrastructure, such as reinforcing bridges and elevating roadways, could mitigate the impact of future storm surges.

4.2. Limitations

In Figure 5b, we again saw a slight increase in local accessibility, which is a reasonable phenomenon that the FCA calculation results will appear when applied to inundation or road closure scenarios. Other studies have also noted that when coastal populations cannot evacuate to critical facilities like shelters, the demand for these facilities by distant populations decreases [3]. This results in the capacity initially allocated for coastal areas becoming available for populations closer to the facilities. Therefore, although the overall average accessibility and minimum values decline, the origins near the SpNS show an increase in accessibility.

This phenomenon highlights a critical issue: regions already lacking evacuation accessibility will quickly lose their evacuation options when a disaster strikes. Conversely, areas with good supply and accessibility are less likely to be affected by the disaster in terms of evacuation capability. For the studied region, coastal areas far from the SpNS, including the aging population and large rural populations, already have poor evacuation accessibility. When a hurricane makes landfall, these populations are the first to lose their evacuation options. Vulnerable groups become even more at risk, a situation we must strive to avoid. This situation emphasizes the need for targeted strategies to improve evacuation options for these vulnerable populations. Strengthening infrastructure, increasing the capacity and number of SpNS, and ensuring efficient and early evacuation procedures are essential to mitigate the heightened risks faced by these communities during hurricanes and other natural disasters.

5. Conclusions

This study underscores the varied impacts of Hurricanes Irma and Ian on the southwest coast of Florida, highlighting the critical need to consider a hurricane's approach and landfall location when evaluating storm surge effects and planning for disaster response. Hurricane Irma approached from the south at an angle, resulting in significant storm surges, particularly in the southern portion of the study area. This angled path allowed for an intense surge due to the interaction between the hurricane's trajectory and the coastal geography, causing extensive flooding and damage. On the other hand, Hurricane Ian made landfall perpendicularly to the coastline, leading to a more evenly distributed storm surge across the coastal areas. This direct impact caused widespread flooding and damage across a larger area. As such, the key contributions of this paper are as follows:

1. It enhances the understanding of Hurricane Ian's impact by analyzing the evacuation accessibility of the elderly population to special needs shelters, addressing a critical gap in emergency planning for vulnerable groups in the existing research.
2. It conducts a comparative analysis of storm surge impacts from two major hurricanes, Irma and Ian, on the same region that was hit by them within a short time interval. Despite not incorporating more wind field changes, by relying on storm surge predictions at that time from NOAA, this study clearly demonstrates the significant influence of hurricane tracks on regional evacuation accessibility. This finding underscores the heightened uncertainty in evacuation planning as future hurricanes become more unpredictable in both track and intensity, providing a crucial warning for improving disaster preparedness strategies.

Findings also indicate that Hurricane Ian's severe flooding severely disrupted road networks in Lee County and the northwest part of Collier County. Critical evacuation routes, including the entire Cape Coral area and portions of the I-75, faced significant flooding risks, impeding evacuation efforts and limiting access to SpNS. The population distribution analysis showed that coastal areas, particularly those with a high concentration of elderly residents, experienced greater challenges in evacuating due to the destruction of homes and roads by storm surges. This emphasizes the necessity for earlier evacuation initiatives and improving evacuation/sheltering plans.

The research also highlights that areas already lacking in evacuation accessibility will quickly lose their evacuation options during a disaster, whereas regions with better supply and accessibility are less likely to be affected. Coastal areas distant from the SpNS, including those with aging populations and extensive rural populations, are at a heightened risk of losing their evacuation opportunities when a hurricane hits. This situation underscores the urgency for targeted strategies to enhance evacuation options for these vulnerable populations.

Future research should address several key limitations identified in this study. The use of a half-mile sample size for the OD Matrix may have limited the granularity of trip analysis, highlighting the need for finer spatial resolutions to better link trips to SpNS. Incorporating additional factors, such as wind fields and their impacts on transportation and infrastructure, is critical for developing a more comprehensive or larger-scale assessment. As discussed in the introduction, climate change is expected to increase the intensity of hurricanes. Future studies should account for related effects, such as sea level rise, on storm surge patterns, and evacuation accessibility. Furthermore, investigating the timing and effectiveness of evacuation procedures, assessing the resilience of infrastructure, and examining socioeconomic factors will provide valuable insights for refining evacuation strategies and enhancing disaster preparedness.

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