Sakib *et al.*
Health Information Science and Systems (2022) 10:28
https://doi.org/10.1007/s13755-022-00190-y

Health Information Science and Systems

RESEARCH

A GIS enhanced data analytics approach for predicting nursing home hurricane evacuation response

Nazmus Sakib[1], Kathryn Hyer[2], Debra Dobbs[2], Lindsay Peterson[2], Dylan J. Jester[3,4], Nan Kong[5] and Mingyang Li[1*]

Abstract

Nursing homes (NHs) are responsible for caring for frail, older adults, who are highly vulnerable to natural disasters, such as hurricanes. Due to the influence of highly uncertain environmental conditions and varied NH characteristics (e.g., geo-location, staffing, residents' health conditions), the NH evacuation response, namely evacuating or sheltering-in-place, is highly uncertain. Accurate prediction of NH evacuation response is important for emergency management agencies to accurately anticipate the NH evacuation demand surge with healthcare resources proactively planned. Existing hurricane evacuation research mainly focuses on the general population. For NH evacuation, existing studies mainly focus on conceptual studies and/or qualitative analysis using a single source of data, such as surveys or resident health data. There is a lack of research to develop analytics-based method by fusing rich environmental data with NH data to improve the prediction accuracy. In this paper, we propose a Geographic Information System (GIS) data enhanced predictive analytics approach for forecasting NH evacuation response by fusing multisource data related to storm conditions, geographical information, NH organizational characteristics as well as staffing and residents characteristics of each NH. In particular, multiple GIS features, such as distance to storm trajectory, projected wind speed, potential storm surge and NH elevation, are extracted from rich GIS information and incorporated to improve the prediction performance. A real-world case study of NH evacuation during Hurricane Irma in 2017 is examined to demonstrate superior prediction performance of the proposed work over a large number of predictive analytics methods without GIS information.

Keywords: Nursing home, Hurricane evacuation, Predictive analytics, GIS data, Vulnerable population

Introduction

Skilled nursing facilities, or nursing homes (NHs), are responsible for caring for frail, older adults by providing 24/7 personal and medical care, and daily living assistance. Most older adults in the NHs suffer from significant functional (e.g., physical, cognitive, social) limitations, aging-related disabilities, vision/hearing impairments and multiple chronic disease, which make them highly vulnerable to natural disasters, such as hurricanes [1–3]. Their impaired mobility, diminished sensory awareness, and chronic health conditions make them less likely to respond and adapt appropriately during hurricanes, leaving their lives clearly at risk to the aftermath of hurricanes, such as physical damage of NH infrastructures, storm surge and massive flooding, power outage, and disruption of medical supplies. Existing studies show that both the mortality and morbidity of NH residents significantly increase during hurricanes [4, 5].

Due to devastating threats and negative consequences of hurricanes on vulnerable NH residents, many NHs have to evacuate and move their frail residents away from hazard regions to safer places. However, whether to evacuate a NH is one of the most complex and difficult decisions encountered by NH administrators. The

*Correspondence: mingyangli@usf.edu
[1] Department of Industrial and Management Systems Engineering, University of South Florida, Tampa, FL 33620, USA
Full list of author information is available at the end of the article

prospects of not evacuating in response to hurricanes can be tragic. For instance, 34 residents were presumed to have drowned at St. Rita's NH in Chalmette, LA, after its facility owners refused to evacuate before landfall of Hurricane Katrina in 2005 [6]. In Hurricane Irma in 2017, 14 residents died from heat-related illness after power losses post-storm at Hollywood Hills NH in Hollywood, FL. On the other hand, evidence has shown that evacuation has an adverse effect on the health and wellbeing of many frail and impaired residents. The disruption associated with evacuation, changes of environment and care routines, and the trauma of moving itself may result in physical injuries, functional declines, and depression, which further complicates NH evacuation [7]. Successful modeling and prediction of NH evacuation response (i.e., evacuating or sheltering in place) of NH administrators is of great importance. It will enrich the understanding of the multi-factorial complexity of NH evacuation decisions by identifying and quantifying the effects of different internal and external factors with an evidence base that is informative and critical to disaster preparedness and response. It will also help local emergency authorities to better plan and manage healthcare resources to meet with the NH evacuation demand surge in a more proactive manner.

In the existing literature of both qualitative studies and quantitative studies in investigating evacuation responses, many studies mainly focused on the evacuation choices of community-dwelling households from the general population [8–11]. Baker [8] studied a number of hurricanes in the Atlantic states from Texas through Massachusetts occurring between 1961 and 1989, where sample surveys from the general population were used to identify characteristics, such as hazardousness of the region, public service, residence type, perceived risk, and general storm severity, influencing aggregate-level evacuation rates. Wolshon et al. [9] combined results from a survey on state evacuation plans performed by Louisiana State University and other published studies at the time. The work summarized evacuation policies and procedures implemented by state authorities, focusing on the transportation service utilization and response perspective for the general population. Whitehead et al. [10] examined prospective hurricane evacuation behavior of North Carolina coastal residents following occurrence of Hurricane Bonnie through telephone surveys, and concluded that storm severity, reception of evacuation order, possibility of flooding, housing structure, and socio-demographic disparity to important determinants of evacuation. Hasan et al. [11] considered post-storm damage assessment data of households affected by Hurricane Ivan and characterized various factors affecting evacuation behavior.

Many of these studies considered a single source of data in the context of non-disaster conditions by extracting aggregated individual characteristics without explicitly considering the rich information form actual storms. Unlike the above studies which focused on studying healthy individuals from the general population, we will focus on studying the evacuation response of NH populations at the organization level and each organization consisting of frail older adults with complex health conditions and functional limitations. There is a need to incorporate both internal factors that could comprehensively describe the different aspects (e.g., staffing, dwelling residents) of an organization and further integrate them with the highly heterogeneous geo-spatial characteristics of NHs in the context of actual disaster conditions. In the existing long-term care literature of NH evacuation, many focused on conceptual and qualitative studies [12–14] based on descriptive statistics or narrative summaries, and they often utilized a single source of data, such as retrospective surveys and telephone questionnaire, without taking into account the spatial heterogeneity of environmental characteristics of NHs and quantifying the influence of environmental conditions on evacuation response. Some of existing qualitative studies consider linear statistical models [15] in quantifying the influence of different input factors for prediction performance output of evacuating or sheltering-in-place. However, they only consider limited environmental characteristics at the aggregate level. Further, the linear models developed in these quantitative studies may not be appropriate in capturing the potential nonlinear relationship between various inputs and the evacuation response and the prediction performance accuracy will be greatly undermined.

To fill the aforementioned research gap, in this paper we propose a GIS-integrated predictive analytics framework for evacuation response prediction of NHs by integrating multi-source data from NH residents, NH facilities and environmental conditions in the context of a real disaster scenario. In particular, we extract multiple GIS features to comprehensively characterize the spatially heterogeneous environmental conditions (e.g., both geographical condition and storm conditions) of NHs at different spatial locations in the state of Florida. With the incorporation and integration of such rich GIS information with NH resident and staffing characteristics, we considered different linear and nonlinear machine learning methods to achieve the improved evacuation response prediction of NHs in real disaster scenarios. The influence of environmental conditions on NHs evacuation are further quantified explicitly in the presence of varied characteristics of individual NH facility.

The remaining of the paper is organized as follows. In the next section, we will introduce the proposed methodology of extracting various GIS features and NH features as well as the development of different machine learning models to integrate the extracted features. Then, we will give a concrete real-world example using the recent disaster scenario of Hurricane Irma to compare the prediction performance of different machine learning models and emphasize the prediction performance benefits of incorporating multiple GIS features extracted. The model interpretation results based on linear classification model will be also discussed. Conclusions are provided in the end.

Methodology

To develop a predictive analytics method for investigating the multifactorial nature of NH evacuation response and further predicting the evacuation response of NH facilities, the features extracted (to be explained below) are based on the following conceptual model described in Fig. 1.

Extracting environmental characteristics

Due to the devastating threats and negative consequences of hurricanes on vulnerable NH residents, such as drowning, shutdown of life-sustaining devices, and shortage of medical supplies, many NHs have to evacuate and move their frail residents away from hazard regions to safer places. The severity of actual damage on NHs in different storm-affected regions may vary significantly. Thus, the anticipated geographical conditions in the neighboring area of each NH before a storm's arrival tend to become important external factors (beyond the facility's control) that may influence NH administrators' evacuation decisions. In this section, we extracted a series of environmental features to represent various environmental characteristics (e.g., storm characteristics, geographic characteristics of each NH) that may affect NH evacuation decision. They will be incorporated as predictors while developing different predictive models. Before extracting environmental features, we first obtained the actual evacuation responses (i.e., evacuation or shelter-in-place) of all NHs in the state of Florida during Hurricane Irma from the Florida Agency for Health Care Administration (AHCA) [16]. AHCA is the statutory organization responsible for health and policy planning in Florida. The agency also reports emergency response information of long-term care providers during extreme event scenarios, such as hurricanes. Figure 2 visualizes geolocation of all NHs in operation in the state of Florida and individual evacuation status during Hurricane Irma. Such response data will further be utilized as labeled outputs in "Classification models" and "Performance evaluation" sections for predictive models training and prediction performance evaluation. Furthermore, we also extracted the geolocation of each NH to facilitate the calculation of NH-specific environmental features. The latitudes and longitudes of each NH location were extracted using ArcGIS Online World Geocoding Service [17].

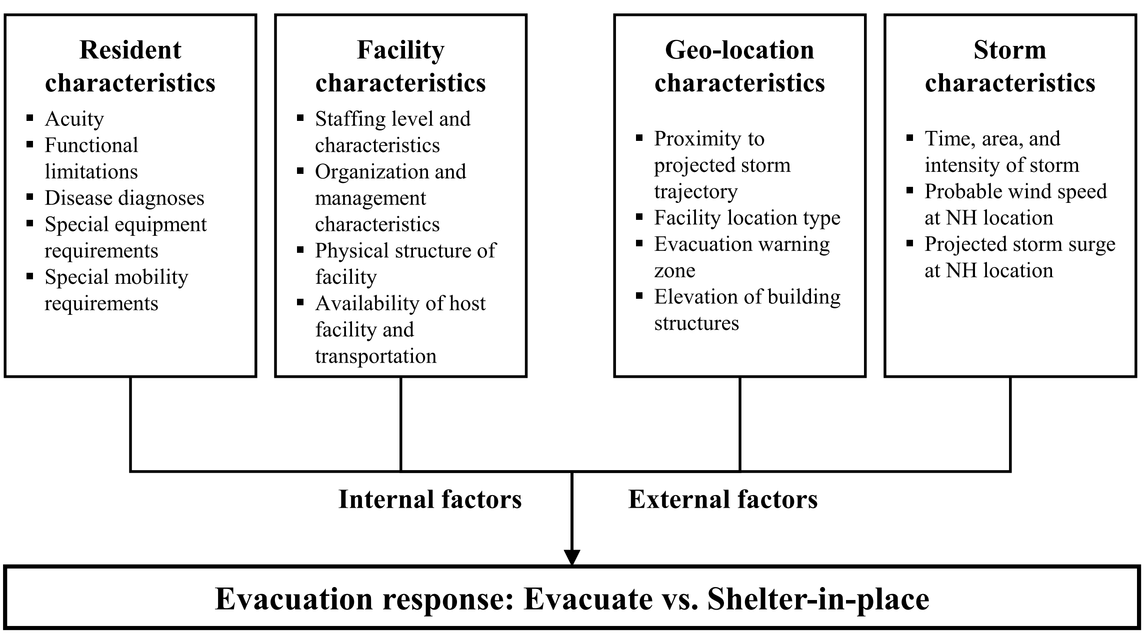

Fig. 1 A conceptual model for evacuation decision-making criteria for NHs during hurricanes

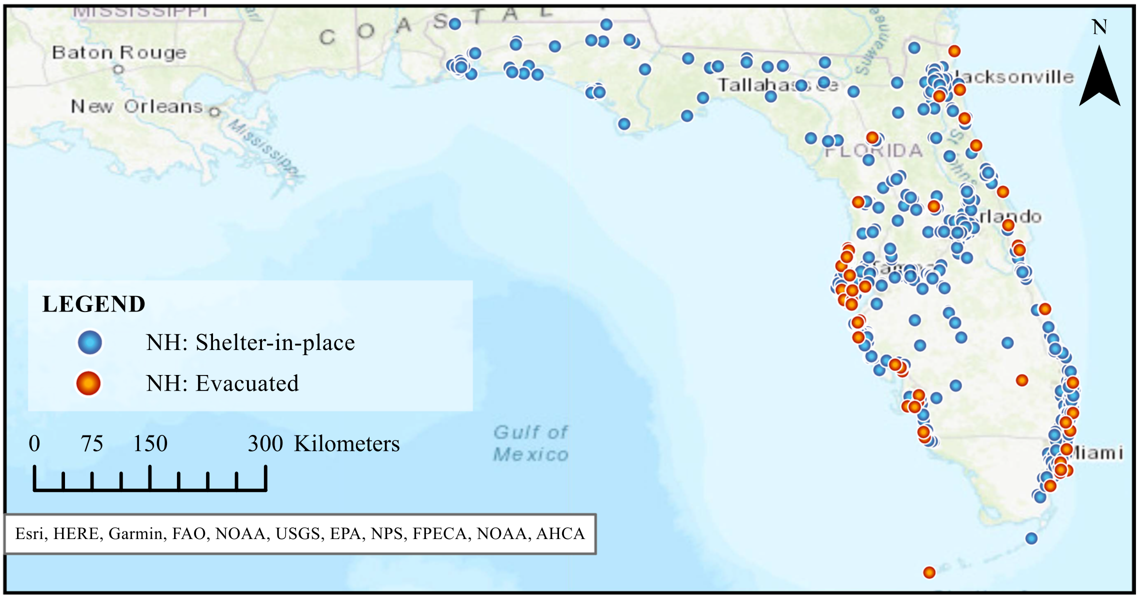

Fig. 2 Extracted geolocations and evacuation status of NHs in FL during hurricane Irma

We began with extracting the storm characteristics affecting NH evacuation decisions. The storm GIS data was extracted from the National Hurricane Center (NHC) of the National Oceanic and Atmospheric Administration (NOAA) [18]. During a hurricane event, NHC monitors and records rich spatial–temporal information of a storm every 3–6 h, including current storm location, projected trajectory, spatial probability distribution of wind speeds, and potential storm surge areas. It allows us to extract and calculate different NH-specific storm features and investigate their impacts on NH evacuation. As a storm approaches, the closeness between the projected storm path and the location of a NH may reflect the level of storm threat and can be potentially relevant to evacuation decision of a NH. We extracted the projected storm path, which represented the forecast trajectory of the center locations of a storm. To quantify the proximity of a NH to the projected storm path, we calculated the shortest Euclidean distance from each NH geolocation point to the projected storm path, as shown in Fig. 3.

The building damage and power outage resulting from high and sustained wind speeds may greatly affect the NH administrators' evacuation decisions. To investigate the impact of the projected wind speed on the NH evacuation decision, we extracted the spatial probability distribution map of wind speeds over a regularly spaced (5 km) grid of points, as shown in Fig. 4. The projected wind speed probability at a specific 5km-by-5km grid area represented the cumulative probability of sustained (1-minute) surface (10-meter altitude) wind speeds equal to or exceeding 50-knot (i.e., 57.5 mph) within a 120-h time period. According to the Beaufort Wind Scale [19], 50-knot winds are classified officially as storm-force winds which can cause significant structural damage. As shown in Fig. 4, NHs located closer to the projected storm path tend to have a higher probability of experiencing higher winds, and vice versa.

As the adage "hide from the wind, run from the water" suggests, another important aspect which may considerably affect the vulnerability and safety of a NH location during hurricane is the projected flood risk. We considered the potential storm surge and elevation at each NH location as external and inherent features respectively to characterize the potential flood risk. Figure 5 shows the spatial map of potential storm surge associated with the storm, which describes the risk of potential coastal flooding due to a storm. Both the predicted areas (where inundation from storm surge could occur) and the predicted heights (that water could reach in those areas) were numerically determined by the Sea, Lake, and Overland Surges from Hurricanes (SLOSH) model developed by National Weather Service [20]. The tidal mask region refers to the area usually submerged during daily or seasonal high tides. As shown in Fig. 5, several NHs located in coastal regions at high potential storm surge evacuated before hurricane landfall. Apart from examining the food risk resulting from potential storm surge, we further considered the inherent geographic characteristics of each NH facility, namely, the elevation. Inland NHs in low-lying regions may also potentially experience flooding

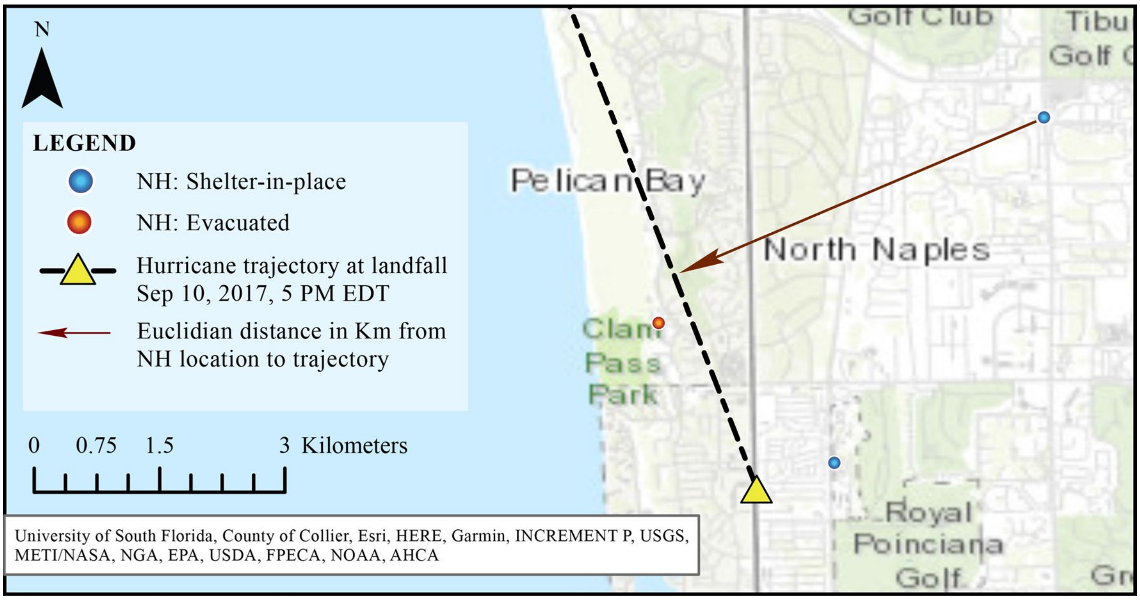

Fig. 3 NH-specific proximity distance to the projected storm path

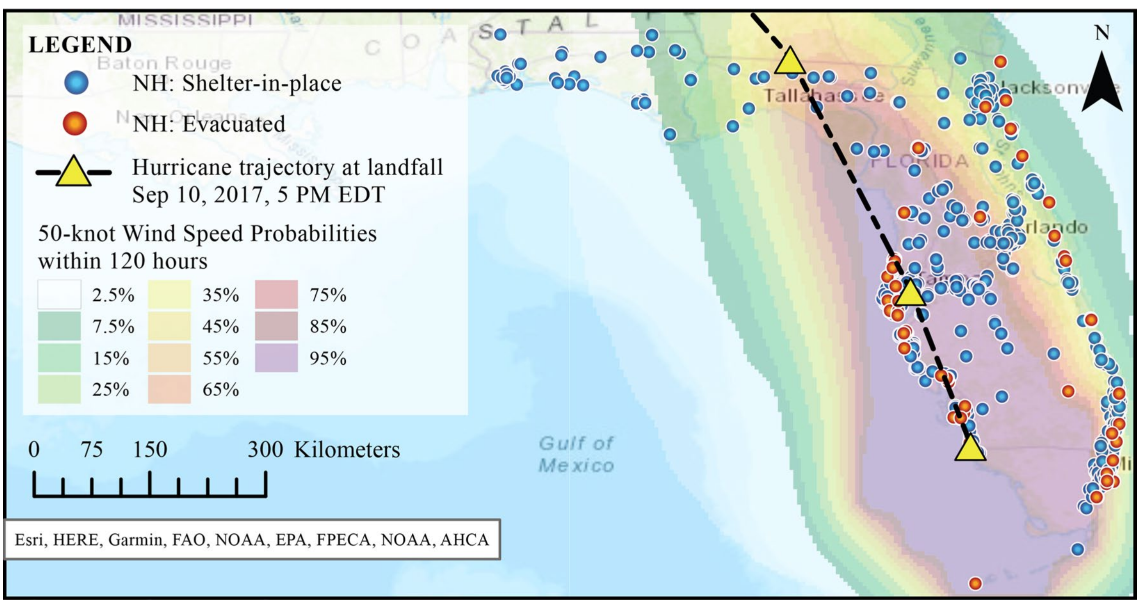

Fig. 4 50-knots cumulative wind speed probability map

due to the rain water deposition and/or the rise of water levels in nearby ponds, lakes, rivers, or other water reservoirs. To extract the elevation of each NH, we considered the Florida Digital Elevation Model (DEM) [21] developed by the University of Florida GeoPlan Center. Figure 6 shows the spatial map of elevation values recorded on a 5m-by-5m statewide grid. The elevation value from a grid area which is the closest to a NH's geolocation point has been selected as the approximate elevation value for that NH.

Extracting NH characteristics

The NH administrator's decision of evacuating or sheltering-in-place may not only be affected by external

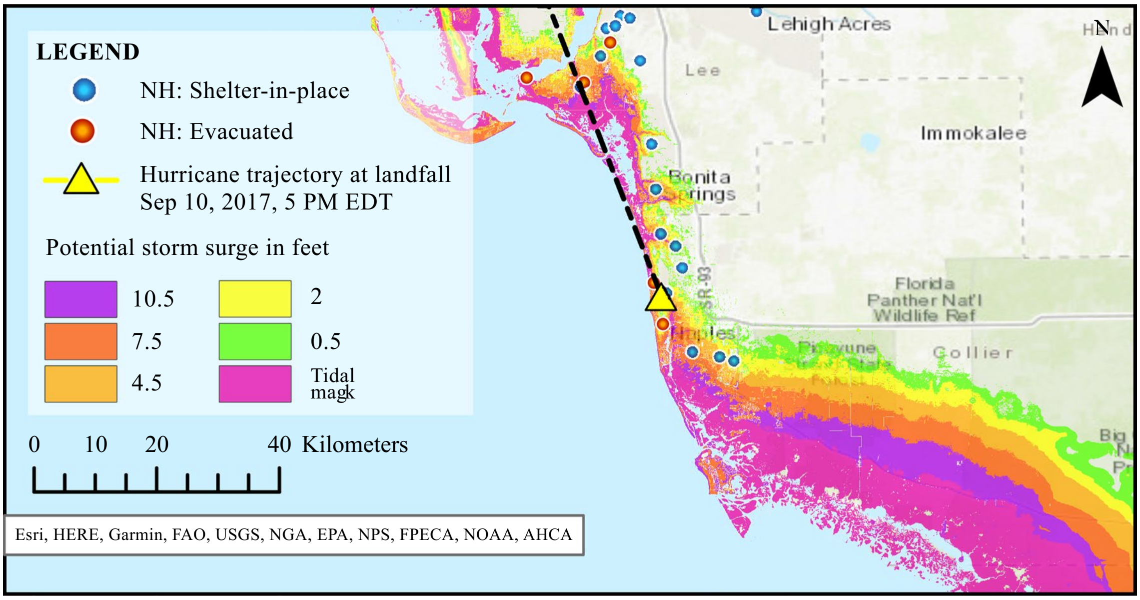

Fig. 5 Potential storm surge heights near coastal region

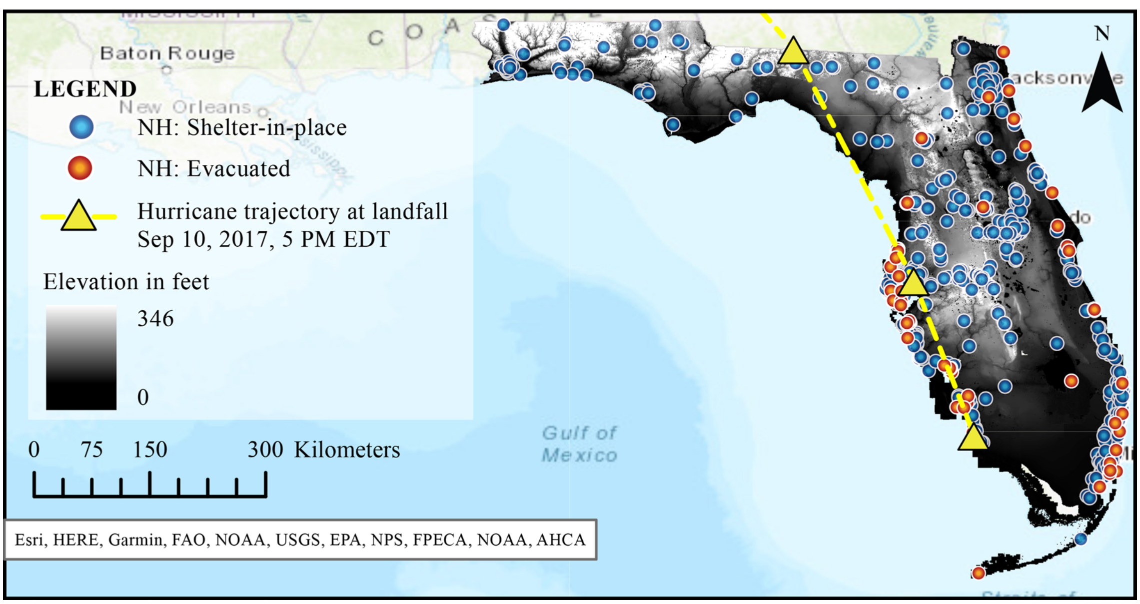

Fig. 6 Elevation of NH location as mapped by FL DEM

factors of environmental characteristics as described above. It may also be affected by various internal factors related to each NH facility. In this section, we will further investigate various internal factors' influence by comprehensively extracting various aspects of NH characteristics, such as organizational characteristics, staffing characteristics and resident characteristics of each NH. To comprehensively evaluate the NH characteristics from different aspects, we consider the most updated Certification and Survey Provider Enhanced Reports (CASPER) data of each NH closest to the storm season. CASPER data, originally known as Online Survey Certification And Reporting (OSCAR) data, is the annual regulatory inspection data collected by state survey agencies and maintained by the Centers for Medicare and Medicaid Services (CMS) [22]. It contains rich facility-level NH data related to the overall organization, such as size and ownership, as well as the aggregate characteristics of caregivers and residents within each NH. Based on the domain knowledge of expertise as well as national guidelines for NH evacuation [23] we extract the NH characteristics based on the CAPSER data from three aspects, namely, (i) organizational properties, (ii) aggregated staffing characteristics, and (iii) aggregated resident characteristics, which will be elaborated with details as follows.

From the organizational perspective, existing studies indicate that the structural characteristics of an organization, such as ownership type, may have major implications in the extent of challenges the NH administrators would face in making decisions during the storm. For instance, government-owned facilities may have greater access to financial and/or transportation resources/support from government agencies than for-profit facilities, which would lower for-profit facilities' logistics capabilities and increase financial concerns in initializing evacuation [24, 25]. Further, NHs of different sizes may have different likelihoods of exhausting their own organizational resources and may decide to evacuate due to their self-insufficiency. For a NH within a larger NH chain, it may be easier to identify and prepare the hosting facility within the chain to receive the evacuees, making the evacuation more convenient. To comprehensively quantify various organizational characteristics of each NH, we extract and calculate various organization level features based on CASPER data of each NH, such as the type of ownership, the overall size and the average occupancy rate. To quantify detailed organizational structure, we also introduce the binary indicators, "Any special care unit", to indicate whether the facility contains a special care unit (e.g., special units for caring residents with Alzheimer's Disease and Related Disorders) and various binary indicators under "Medical team structure", to indicate whether the medical team contains senior leadership and advanced medical personnel in the facility. The set of organizational features extracted are summarized in Table 1.

NH staffing also plays an important role in disaster preparedness and response (e.g., evacuating or sheltering-in-place) against hurricane from the following two aspects. First, adequate staffing is required in order to ensure the care continuity and the success of disaster preparedness to weather out the storm or evacuate safely. Second, NH caregivers, such as nurses and aides, must be trained or have the right skills mix to tackle unique challenges during extreme hazard scenarios, such as hurricanes [12]. If the facility is sheltering-in-place, adequate staff is crucial in avoiding increased morbidity and mortality of residents, as the staff would provide formal care, emotional support to residents, and also complete preparatory tasks such as strengthening building structures and storing supplies. For evacuation, the staff needs to coordinate transfer efforts, carry residents onto vehicles and transport them, and help them relocate into new hosting facility. Many NHs may face the challenges of staffing shortage and caregiver absenteeism during a hurricane because many staff members may evacuate by themselves or have concerns for their own family members. The NH may have less self-sufficiency accordingly to shelter-in-place successfully with adequate staffing. To comprehensively investigate the influence of staffing characteristics affecting evacuation response, staffing levels of 3 different types of direct caregivers, such as registered nurses, licensed practical nurses, certified nursing assistants, and 6 types of non-direct caregivers, such as administrative nurse, occupational therapy services, physical therapy services, activities staff, social services, and housekeeping staff, are extracted and calculated based on CASPER data. Hours per resident per day (HPRD) [26] is considered as the aggregate measure to characterize the staffing level of each type of caregiver. Specifically, for NH i, the HPRD of the kth type of caregiver can be calculated as

$$HPRD_{ik} = \frac{\text{Total FTE of caregiver type } k \times 70 \text{ hours bi-weekly}}{14 \text{ days} \times \text{Number of residents in NH } i} \tag{1}$$

For each type of caregiver, part-time and temporary employees are converted into full-time equivalent (FTE) to facilitate the calculation of total FTE. For physical therapists, both the therapists and therapist assistants are taken into account. The extracted staffing characteristics features of each NH are summarized in Table 1.

In addition to the organizational and staffing characteristics, characteristics of the vulnerable residents in a NH are also important aspects that NH administrators need to take into account and thus may potentially influence the NH evacuation decision. Many NH residents are non-ambulatory and bed-ridden, and evacuating them safely is more challenging because it requires more efforts from nursing staff as well as special transportation means, such as wheelchair conversion vans. For those residents with morbid obesity, specific equipment, such as lift and transfer equipment, need to be prepared. Many of NH residents may have complex medical conditions, such as

Table 1 Descriptive statistics summary of the integrated NH evacuation data

Statistic/Feature	All facilities* N = 653	Evacuated facilities N = 59 (9.04%)	Sheltered facilities N = 594 (90.96%)
Organizational structure (Y/N)			
For profit facility	72%	53%	74%
Not for-profit facility	25%	44%	24%
Government facility	2%	3%	2%
Chain-facility	61%	58%	61%
Part of a CCRC	9%	20%	8%
Size (# beds)	123.3 (48.6)	118.8 (48.47)	123.74 (48.63)
Resident count	107.47 (44.33)	99.54 (44.53)	108.26 (44.27)
Occupancy rate	87.09% (11.36)	83.96% (15.84)	87.4% (10.79)
ADRD special care unit	13%	14%	13%
Non-ADRD special care unit	5%	3%	5%
Any special care unit	17%	17%	17%
Has organized resident group	98%	97%	98%
Has organized family members group (feet) (%)	42%	37%	42%
Payer mix (% residents)			
Medicare	54.98% (22.2)	48.71% (26.39)	55.6% (21.66)
Medicaid	20.28% (14.37)	19.46% (13.83)	20.36% (14.43)
Private pay and other	24.75% (17.98)	31.83% (24.55)	24.04% (17.05)
Environmental GIS features			
Distance from projected trajectory 24 h prior decision (Km)	112.56 (78.04)	66.11 (55.48)	117.17 (78.48)
50 knots wind speed probability 24 h prior (%)	61.14 (28.37)	55.17 (15.37)	61.74 (29.29)
Potential storm surge 24 h prior (feet) (%)	0.24 (1.21)	0.3 (1.17)	0.23 (1.21)
Elevation of facility (feet)	45.1 (47.71)	12.36 (13.05)	48.35 (48.67)
Staffing characteristics (HPRD)			
Registered nurses	0.49 (0.58)	0.54 (0.84)	0.49 (0.55)
Licensed practical nurses	0.95 (0.37)	1.02 (0.71)	0.95 (0.32)
Certified nursing assistants	2.82 (0.77)	2.99 (1.19)	2.81 (0.72)
Direct care nurse staffing**	4.27 (1.37)	4.56 (2.63)	4.24 (1.17)
Administrative Nurse	0.28 (0.22)	0.31 (0.39)	0.27 (0.19)
Occupational therapy services	0.26 (0.16)	0.24 (0.12)	0.27 (0.16)
Physical therapy services	0.31 (0.2)	0.28 (0.19)	0.31 (0.21)
Activities staff	0.21 (0.16)	0.26 (0.37)	0.21 (0.13)
Social services	0.11 (0.13)	0.15 (0.36)	0.11 (0.08)
Housekeeping staff	0.58 (0.57)	0.79 (1.64)	0.56 (0.3)
Medical team structure (Y/N)			
Medical director only	18%	19%	18%
Physician extender only	0.5%	0%	1%
Full medical team	45%	39%	45%
No medical team	4%	5%	4%
Resident characteristics (% residents)			
Acuindex (patient acuity)	10.94 (1.2)	11.01 (1.34)	10.93 (1.18)
Behavioral healthcare needs	18.13% (17.31)	18.69% (15.1)	18.07% (17.53)
Dementia or Alzheimer's	42.98% (17.26)	43.91% (17.17)	42.88% (17.28)
Depression	33.73% (21.1)	31.77% (21.31)	33.93% (21.08)
Intellectual disability	1.19% (3.6)	1.03% (1.56)	1.21% (3.74)
Physical restraint use	0.63% (1.74)	0.23% (0.62)	0.67% (1.81)
Serious mental Illness	29.6% (17.46)	27.96% (14.31)	29.77% (17.75)
Medication utilization (% residents)			
Antipsychotics	18.11% (11.31)	16.93% (9.59)	18.23% (11.46)
Antianxiety	25.31% (10.71)	24.64% (9.69)	25.37% (10.81)
Antidepressants	48.53% (13.05)	47.48% (12.8)	48.63% (13.08)
Sedative/hypnotics	7.36% (5.96)	7.05% (5.07)	7.39% (6.04)

* Mean (SD)

**Sum of RN, LPN, CNA

renal and respiratory diseases, and they may either need special care, such as dialysis, or be highly oxygen dependent. If the NH is sheltering-in-place, power outages and inadequate medical supplies (due to road disruption) may be devastating to their residents. Existing studies also show that for those residents with mental conditions, such as, dementia or anxiety, NH evacuation and relocation availability may have detrimental effects on their health outcomes and induce post-traumatic stress [13]. To comprehensively investigate the influence of resident characteristics from different aspects, several aggregate features in a NH facility, such as the percentage of residents having aforementioned conditions, the percentage of residents receiving different types of medications (e.g., antipsychotics, antianxiety, antidepressants, sedative/hypnotics), the percentage of residents who require physical restraints and the percentage of residents covered under Medicare, Medicaid, or paying by themselves, are extracted and calculated from CASPER data. To further quantify the highly varied health conditions and acuities of NH residents, a composite index feature called "Acuindex" is employed to summarize the overall resident acuity in the facility [27, 28]. Acuindex is a numeric measure calculated by first combining the percentage of residents requiring nursing staff assistance with different activities of daily living, such as eating, toileting, bed transferring, and the percentage of residents requiring special treatments, such as respiratory treatment, suctioning, intravenous therapy, tube feeding, etc., and then further dividing by the total number of residents in the facility. A higher Acuindex value indicates that facility has a frailer population of residents with more extensive care needs and vice versa. The extracted resident characteristics related features are summarized in Table 1.

Classification models

After extracting various features that may potentially affect the NH evacuation decision (as described above), in this section, we will develop data-driven predictive models to predict the binary decision of "evacuating" or "sheltering-in-place" by comprehensively investigating different classification algorithms. For NH facility i, the binary response variable y_i is labelled as "1" if the facility has evacuated, and "0" if the facility has sheltered-in-place. Different features that represent different aspects of the ith NH, such as environmental characteristics, NH facility characteristics and NH dwelling-residents' characteristics, will serve as input variables $\boldsymbol{x}_i$ for the developed predictive models. Since the sheltered-in-place NHs account for about 90% of the total number of NHs in the dataset, there is considerable classification imbalance issue, which will significantly affect the modeling accuracy [29]. To address such class imbalance issue, up-sampling technique is performed for the minority class to create an equally balanced dataset for model development as follows [30]. First, the dataset is divided into training dataset and testing dataset randomly into large and small portions (e.g., 80% data randomly selected for training set and rest 20% for testing set) by keeping the same ratio of observations of minority class, i.e., evacuated NHs, to majority class, i.e., shelter-in-place NHs, in both data sets. Then, individual observations from the minority class in the training dataset are randomly sampled until the sizes of majority and minority class observations in the dataset become equal. The prepared training dataset and testing dataset are used for model training and model assessment, respectively.

We first investigate the linear classification model of logistic regression (LR) and its regularized variants. These models aim to find the optimal model parameters $\boldsymbol{\theta}_{LR}$ by minimizing the loss function

$$\begin{aligned} l(\boldsymbol{\theta}_{LR}) = \sum_{i=1}^{n}\{-y_i\boldsymbol{\theta}_{LR}^T\boldsymbol{x}_i + \log[1+\exp\boldsymbol{\theta}_{LR}^T\boldsymbol{x}_i]\} \\ + \lambda_1\|\boldsymbol{\theta}_{LR}\|_2^2 + \lambda_2\|\boldsymbol{\theta}_{LR}\|_1 \end{aligned} \tag{2}$$

where the first term is the negative log-likelihood function of LR, and the last two terms contain L2-norm and L1-norm penalties, respectively. The former terms represent the goodness-of-fit and a smaller negative log-likelihood function value indicates a better goodness-of-fit. The latter terms control the complexity by shrinking the irrelevant model parameters towards zero (in L2-norm) and exactly equal to zero (in L1-norm), respectively. When both $\lambda_1 = 0$ and $\lambda_2 = 0$, the model is conventional LR; when $\lambda_1 > 0$ and $\lambda_2 = 0$, it becomes the LR model with Ridge penalty, and when $\lambda_1 = 0$ and $\lambda_2 > 0$, it becomes the LR model with LASSO penalty. Regularization-based LR models are considered to address the potential overfitting issues of conventional LR for prediction performance improvement. The tuning parameter λ in both ridge and LASSO penalties are determined based on the cross-validation (CV).

After investigating the linear classification model, we further investigate different tree-based nonlinear classification modeling approaches, namely classification and regression tree (CART) and tree-based assembling methods. For CART, the impurity measure of GINI index is considered for tree plotting and a tree model will stop growing once all its leaf nodes only contain a single class of either "evacuation" or "sheltering-in-place". To mitigate the overfitting issue of CART, pruning is further considered based on CV to merge some of the branches to form a smaller tree. Due to the high variance of CART, we further considered the tree-based ensemble methods, namely, random forest and gradient-boosted tree, to further strengthen the prediction accuracy. The former ensemble learning methods generate a large number of deep trees in the parallel structure while the latter generates a large number of simple trees in sequential manner. The tuning parameters, such as size of trees in random forests or the depth of tree in gradient-boosted tree, are also determined based on the CV.

Although tree-based classification methods give nonlinear decision boundaries, they are established based on the rectangular-shaped partitions of the feature space. We further investigate other nonlinear classification models, such as memory-based method of nearest-neighbor classification, optimization-based method of support vector machines (SVM) and network-based method of artificial neural network (ANN), which constructs nonlinear decision boundaries based on varied assumptions and criteria. K-Nearest Neighbor (KNN) directly performs the prediction based on the major vote of its K-neighbor data points, i.e., $\hat{y} = \text{argmax}_{k\in\{0,1\}} \frac{1}{K}\sum_{N_x} \mathrm{I}(\mathrm{y_i} = \mathrm{k})$, where N_x is an index set of K-nearest neighboring observations for input variables $\boldsymbol{x}$ and $\mathrm{I}(\cdot)$ is an indicator function. In KNN, to make prediction of evacuation response of a NH with input features $\boldsymbol{x}_0$, its k nearest NHs with observed evacuation response in the feature space are first identified and the corresponding closeness is evaluated based on the Euclidean distance, $distance_{(i)} = \|\boldsymbol{x}_{(i)} - \boldsymbol{x}_0\|$, where $x_((i))$ is input features of the ith neighboring NH with observed evacuation response [31]. Based on the majority vote of the observed evacuation response among k nearest NHs, the predicted evacuation response of NH will be obtained. SVM and ANN are more computationally demanding nonlinear classification methods which either formulate the classification problem as an optimization model, or capture the nonlinear mapping among inputs and outputs with a multi-layer network structure, respectively. The tuning parameters and settings of each method, such as choice of K in KNN, kernel type and cost settings in SVM, and number of neurons in layer in ANN, are also determined based on CV [31, 32].

Performance evaluation

During the model development stage, 10-fold CV is employed to: (i) obtain the expected estimate of the test accuracy, (ii) tune model parameter values such that overfitting can be avoided. CV is achieved by partitioning the training dataset into several approximately equal-sized folds and building a model on the dataset by progressively holding one fold out for validation. CV-accuracy is calculated as the average accuracy obtained over all the validation set predictions, i.e., $Acc_{CV} = \frac{1}{10\times n_m}\sum_{m=1}^{10}\sum_{i=1}^{n_m} \mathrm{I}(\mathrm{y_{i,m}} = \hat{\mathrm{y}}_{\mathrm{i,m}})$, where $y_{i,m}$ and $\hat{y}_{i,m}$ are observed and predicted values in the mth validation set with sample size n_m , respectively. $\mathrm{I}(\cdot)$ is an indicator function, and 10 is the number of folds in the dataset. Limiting exposure to the full training dataset allows selection of model parameters that do not perfectly fit the training data but are generalized adequately resulting in optimal performance over unseen test data, hence reducing overfitting.

Following model development and tuning, each optimized model is utilized to generate prediction on previously unseen test dataset and prediction accuracy is evaluated. Several metrics are employed to assess model effectiveness from different aspects, namely, test accuracy, test sensitivity, test specificity, and test balanced accuracy. Test accuracy is simply the proportion of correctly predicted class labels against the total number of observations in the test data, i.e., $Acc_{test} = \frac{1}{n_t}\sum_{j=1}^{n_t} \mathrm{I}(\mathrm{y_j} = \hat{\mathrm{y}}_\mathrm{j})$, where y_j $\hat{y}_j$ are observed and predicted values, respectively, and n_t is the total number of test observations. Test accuracy is an overall metric and may not fully explain individual class-specific prediction performance. Test sensitivity is used to measure prediction performance of the model for the minority class (evacuated) as a proportion of the number of correctly predicted evacuated NHs against the total number of observed evacuated NHs, i.e., $Acc_{sens} = \frac{1}{n_{evac}}\sum_{j=1}^{n_{evac}} \mathrm{I}(\mathrm{y_{j,evac}} = \hat{\mathrm{y}}_{\mathrm{j,evac}})$, where $y_{j,evac}$ and $\hat{y}_{j,evac}$ are observed and predicted values for evacuation, respectively, and n_{evac} is the total number of evacuated NHs in test dataset. Similarly, test specificity measures prediction performance of the model for the majority class (shelter-in-place) as a proportion of the number of correctly predicted shelter-in-place NHs against the total number of observed shelter-in-place NHs, i.e., $Acc_{spec} = \frac{1}{n_{shelter}}\sum_{j=1}^{n_{shelter}} \mathrm{I}(\mathrm{y_{j,shelter}} = \hat{\mathrm{y}}_{\mathrm{j,shelter}})$, where $y_{j,shelter}$ and $\hat{y}_{j,shelter}$ are observed and predicted values for shelter-in-place, respectively, and $n_{shelter}$ is the total number of shelter-in-place NHs in test dataset. Here, the minority (evacuated NHs) is defined as the positive class, and the majority (shelter-in-place NHs) is defined as negative class in the context of sensitivity and specificity, respectively. Assessing sensitivity and specificity of the predictions produced by each model enhances the ability to compare models in terms of their flexibility in detecting rare classes and differentiating data from the majority class, and also allows determining the effect of up-sampling in performance improvement. Since test accuracy may indicate greater model performance even if the model predicts all majority class in the test data correctly and misses all minority class, an improved measure is desirable. Test balanced accuracy is the average of test sensitivity and test specificity, i.e.,

$Acc_{bal} = \frac{Acc_{sens}+Acc_{spec}}{2}$, and provides a better representation of the prediction performance [31].

Real case study

Data description and preprocessing

Hurricane Irma was one of the major hurricanes in history over the open Atlantic Ocean. The storm made initial landfall in Florida near Cudjoe Key as a Category 4 (130 mph) hurricane on September 10, 2017 9 AM and afterwards made final landfall at Marco Island as Category 3 (115 mph) on September 10, 2017 3:35 PM, moving up the state and dissipating over the next day. An estimated 6.5 million people were ordered to evacuate causing scarcity of supplies and fuel, and heavy traffic along evacuation routes. One direct and 33 indirect deaths were reported in South Florida. The storm caused significant destruction by uprooting trees, damaging building roofs and structures, excessive inland flooding and coastal surge, and heavy rainfall. More than 75% clients in the state lost power for almost a week, and half of all crops in Miami-Dade county was ruined [33]. The estimated cost of damages in flood loss to homes in all storm-affected state was between 25-38 billion USD [34], with state property damages costing hundreds of millions USD in different counties. As with any extreme event, long-term care service residents and staff were at greater risk. 684 NHs were in operation during the hurricane, among which a total of 85 facilities decided to evacuate pre- or post-landfall.

To maintain consistency with the scope of the study, several inclusion/exclusion criteria were applied to the list of operating NHs. NHs which evacuated after landfall were not considered since the decision was based on post-storm damages and aftereffects, rather than evaluation of pre-storm anticipated risks. NHs which evacuated many days in advance (on or before 96 h of landfall) were excluded since the storm was considerable distance away from FL and related environmental data was not yet available. NHs with facility characteristics data missing entirely or with data recorded on inappropriate survey dates (i.e., survey significantly predating the storm), categorized as hospital-based facilities, and/or with incorrectly reported nursing staff levels (i.e. greater than 24, or 0 HPRD) were removed. The resulting dataset contained a total of 653 NHs, of which 59 (9.04%) evacuated and the rest 594 (90.96%) sheltered-in-place. The evacuation status was encoded as binary numbers, where 1 indicated evacuated and 0 shelter-in-place, such that it can be used as a numerical response during modeling. Table 1 presents descriptive statistics of the selected NHs with various characteristics stratified by evacuation status.

Following extraction of NH-specific environmental features as described in "Extracting environmental characteristics" section and facility structural, staffing and resident characteristics data as described in "Extracting NH characteristics" section, a joint dataset was created including all extracted features of each NH. To prepare for predictive modeling, the dataset is treated with several preprocessing measures. The data was randomly split into 80-20 train-test subsets. The training set is intended to be utilized in model estimation, while the test set remained as unseen data for later predictions. Based on the training set, redundant facility characteristics features were removed by evaluating correlation coefficients between all possible pairs of features and setting a cutoff of 0.6 and guided by domain knowledge. For instance, Social services HPRD feature was removed as it was highly correlated with Registered nurses HPRD. Existence of multicollinearity among undetected feature combinations was determined with calculation of Variance Inflation Factor (VIF) with cutoff set at 5. According to disaster management timelines, NHs need to take decision on whether to evacuate or shelter-in-place at least 24 to 36 h prior storm occurrence to allow sufficient time for clearing the area or completing preparations, respectively [35, 36]. The environmental features recorded between 24-h and 36-h prior decision were highly correlated and repetitive as the storm's projected trajectory changed little. Hence, the environmental features extracted from geographic observations were recorded 24-h prior evacuation decision of each NH, assuming it is the last time NHs can make decision. The final set of features included 4 environmental features and 32 facility characteristics features in the joint dataset. Since NHs sheltering in place substantially outnumbered evacuated facilities, up-sampling was applied to training dataset to balance proportion of each class and ease estimation of predictive models.

Prediction performance comparison

To investigate how different environmental features impact predictive performance individually and altogether, 1 baseline and 5 different proposed modeling strategies were adopted as detailed in Table 2. As the conventional approaches consider only facility characteristics influencing evacuation decision in literature, D1-BASE strategy was set up for model estimation using only the facility characteristics dataset and no GIS features. Hence D1-BASE was the baseline for comparison against proposed strategies. The proposed D2-DIST, D3-WSP, D4-SURG, D5-ELEV strategies were set up where each dataset contained only one GIS-feature in addition to facility characteristics – distance between facility and storm trajectory, 50-knot wind speed probabilities at facility location, potential storm surge at facility location, and elevation of facility location, respectively.

Table 2 Different predictive modeling strategies

Short name	Modeling strategy description	Strategy type
D1-BASE	NH facility characteristics without any GIS features	Conventional
D2-DIST	NH facility characteristics with 1 GIS feature only: distance between facility and storm trajectory	Proposed
D3-WSP	NH facility characteristics with 1 GIS feature only: probable wind speed at facility location	Proposed
D4-SURG	NH facility characteristics with 1 GIS feature only: potential storm surge at facility location	Proposed
D5-ELEV	NH facility characteristics with 1 GIS feature only: elevation at facility location	Proposed
D6-FULL	NH facility characteristics with all 4 GIS features	Proposed

Table 3 Different machine learning methods considered

Model name	Model description	Model type
L1-Log	Logistic Regression (LR)	Linear
L2-Lasso	LASSO LR	Linear
L3-Ridge	Ridge LR	Linear
NL1-RF	Random Forest	Non-linear
NL2-DT	Decision Tree	Non-linear
NL3-GBT	Gradient Boosted Trees	Non-linear
NL4-SVM	Support Vector Machines	Non-linear
NL5-KNN	K-Nearest Neighbor	Non-linear
NL6-ANN	Artificial Neural Network	Non-linear

This allowed evaluation of marginal change in prediction performance of the models compared to baseline and determination of the best individual GIS-feature. D6-FULL contained all 4 GIS-features together in addition to NH facility characteristics to include all available information in modeling.

For each of the modeling strategies, 9 different linear and non-linear predictive classification models were employed, as listed in Table 3, to establish functional relationship between evacuation response and heterogeneous facility characteristics and GIS-features. Each predictive model differs in mathematical formulation and estimation process. Some involve pre-setting hyperparameters of the model configuration to maximize prediction accuracy suitable for respective data. Unknown values of hyperparameters which maximize prediction accuracy are found by searching through the numerical space by trial-and-error. In this case, optimal hyperparameters of each model were determined with 10-fold CV, as described in "Performance evaluation" section, on training dataset to maximize prediction performance, i.e., CV-accuracy. For instance, regularization parameter was optimized for LASSO and Ridge logistic regression, number of trees and number of features randomly chosen at each split was tuned for Random Forest, number of trees for Gradient Boosted Trees, cost and kernel parameters for Support Vector Machines, number of nearest neighbors in K-nearest Neighbor, number of units in hidden layer for Artificial Neural Network, etc. Features of test dataset was fed to each tuned model to predict evacuation response and compared with observed responses to evaluate test classification accuracy. Furthermore, test sensitivity, test specificity and test balanced accuracy are evaluated to assess prediction performance of each category of evacuation response. Comparison of prediction performance obtained over each modeling strategy and predictive model are visualized in Figs. 7, 8, 9, 10, and 11, and numerically reported in Table 4.

Several insights were obtained from the results through perspectives of each performance metrics. From CV-accuracy and test accuracy in Figs. 7 and 8, it is evident that incorporation of one or more GIS-features improved performance significantly for most models compared to baseline strategy. Incorporating all 4 GIS-features improved performance for all models the most. Among individual features, elevation of facility (D5-ELEV strategy) and distance of facility to storm trajectory (D2-DIST) interchangeably provided the strongest improvement in prediction accuracy. Non-linear models in general provided increased CV- and test-accuracies for all strategies since they are more capable of capturing non-linear relationship between the features and evacuation responses, and their greater model complexity allows optimal generalization over the data. In contrast, linear models were largely dependent on available information in the training dataset and higher margins of accuracy improvements were obtained with inclusion of GIS-features compared with non-linear models. Sensitivity and Specificity in Figs. 9 and 10 show prediction accuracies achieved for minority and majority classes respectively. Incorporation of GIS-features greatly improved predictive capacity of minority class, since more information was available in informing class separation. Balanced accuracy provided a better criterion in discerning model efficacy for individual class prediction. Especially for a few models, such as Random Forest and SVM, incorporating GIS-features was the only way to obtain any correct prediction for minority class.

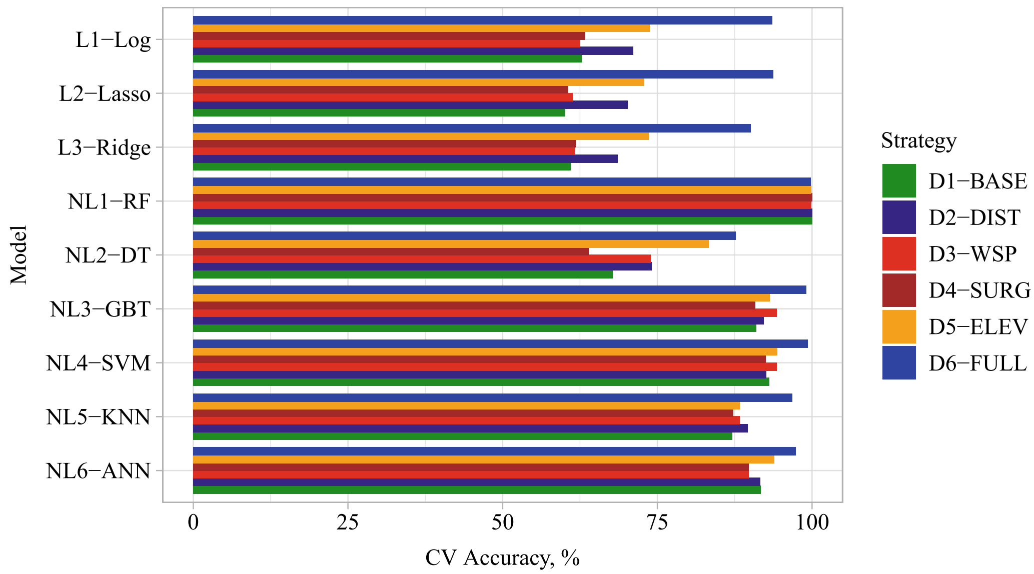

Fig. 7 Prediction performance comparison among different models based on CV accuracy

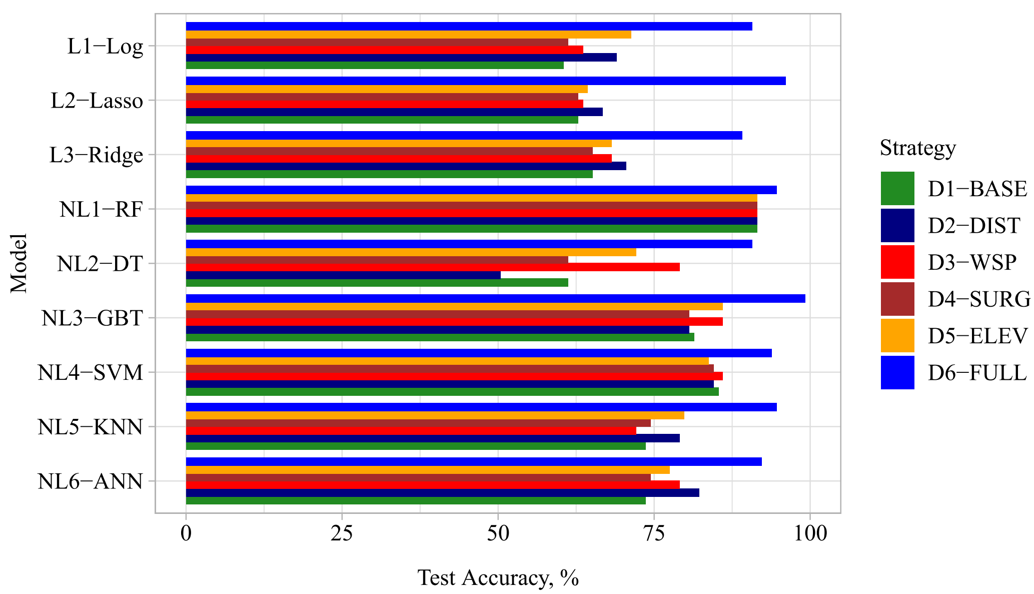

Fig. 8 Prediction performance comparison among different models based on Test accuracy

Comparing all metrics across models and strategies, Gradient Boosted Tree (NL3-GBT) with incorporation of all 4 GIS-features (D6-FULL) was the best model for the dataset in predicting NH evacuation decision response. With high CV-accuracy (0.877), it gave the highest performance on unseen data with test accuracy of 0.992. It could detect both minor and major classes with high accuracy (test sensitivity of 1 and test specificity of 0.992), showing the best performance at test balanced accuracy of 0.966. A close contender was LASSO Logistic model (L2-Lasso), which was also the best among all linear models. Contrary to expectations from a complex model and despite achieving high CV- and test accuracies, Random Forest failed at predicting minority class (e.g., Fig. 9) and was overly biased towards majority class (e.g., Fig 10) [37]. Decision Tree

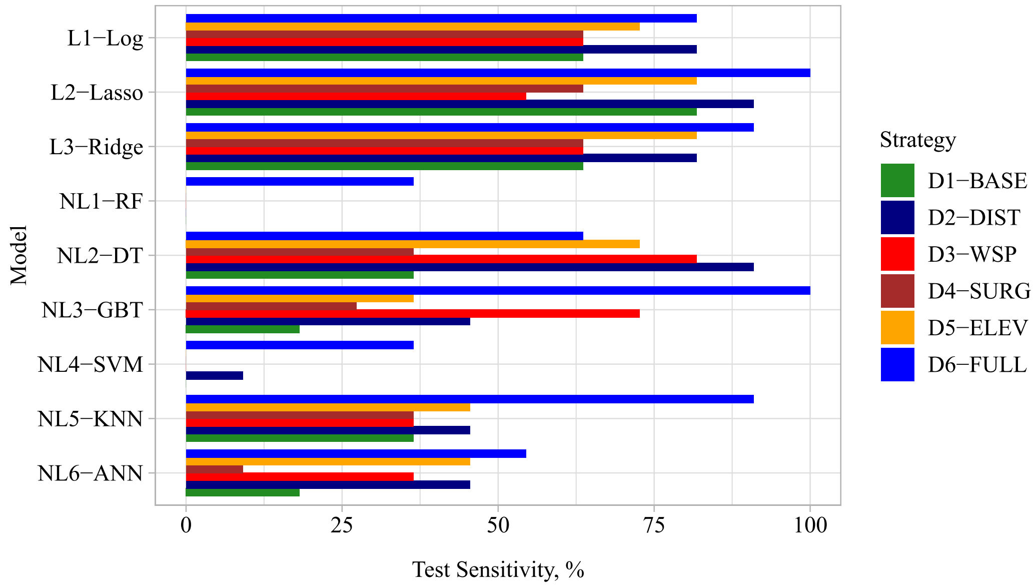

Fig. 9 Prediction performance comparison among different models based on Test sensitivity

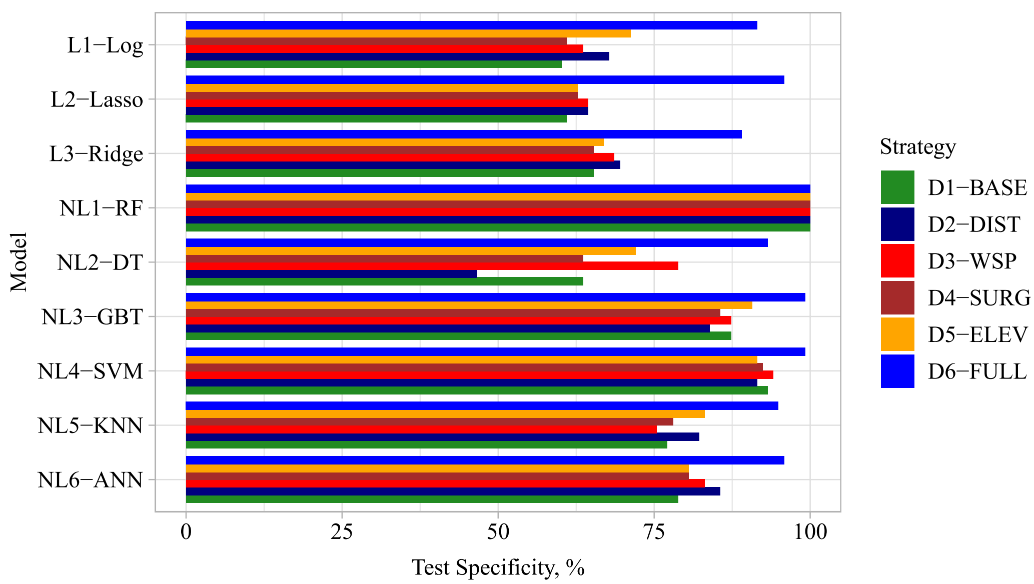

Fig. 10 Prediction performance comparison among different models based on Test specificity

(NL2-DT) performance was often unstable across different strategies since the modeling method of training single trees leads to high variance in predictions.

Up-sampling played an important role in improving prediction accuracy, and it is illustrated by a further case study as follows. The previously best performing model NL3-GBT was applied to the dataset with all GIS-features (D6-FULL) before and after up-sampling. As observed in Fig. 12 and Table 5, the imbalanced dataset results in poor accuracies and balancing the classes enhanced performance across all metrics. Particularly as seen in test sensitivity, up-sampling drastically improved the model's ability to detect minority class. The model became more nuanced towards class distinctions in the feature space resulting in higher prediction accuracy.

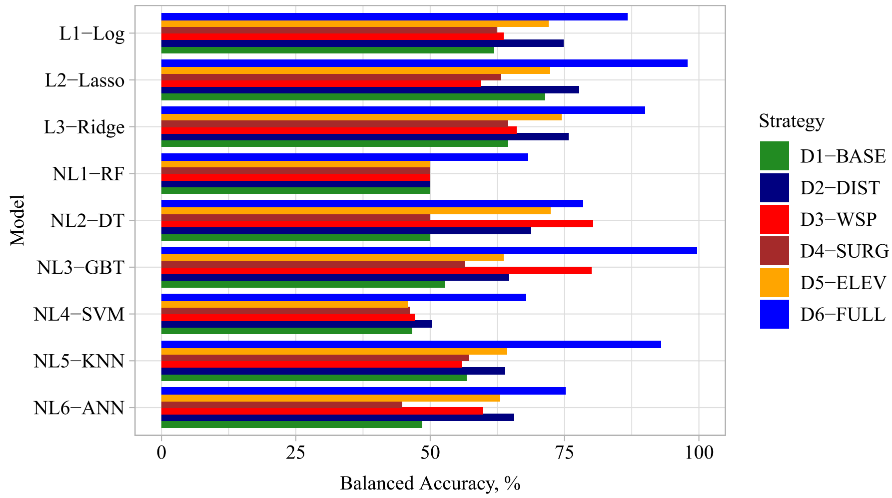

Fig. 11 Prediction performance comparison among different models based on Test balanced accuracy

Investigating the impact of different influencing factors on evacuation response

As described in the previous section, in general, nonlinear predictive model exhibits superior prediction performance than linear predictive model due to the nonlinear nature between evacuation response output and different input variables. However, this does not imply that linear model, such as LR, has no usefulness. As compared to nonlinear predictive model, linear predictive model has more meaningful model interpretation, which will help enrich the understanding and evidence base of evacuation process for healthcare professionals. Further, LR is considered because its model interpretation (e.g., odds ratio) and data uncertainty quantification (e.g., standard errors, p values) are more easily accepted concepts and terminologies by the public health experts. Table 6 summarizes the model estimation results of LR by including all GIS-features. For significant features, both the signs and magnitude of their estimated coefficients, e.g., $\hat{\beta}$, have meaningful interpretations. Positive (or negative) sign of a feature indicates that the increased value of that feature will increase (or decrease) the probability of a NH to be evacuated. Further, the actual influence of a feature can be quantified by the adjusted odds ratio value, which is a ratio of the evacuation probability over the shelter-in-place probability of a NH by holding other features constant.

Based on the typical choice of the significance level of 0.05, significant features are available from different aspects, such as NH organizational structure, environmental conditions, caregivers working in a NH and dwelling NH residents. It confirms the need of fusing multi-source data to investigate and identify the multi-factorial determinants for NH evacuation. From organizational structure perspective, the type of ownership is a significant factor and a not-for-profit NH is more likely to evacuate (e.g., AOR = 7.76) than a for-profit NH by holding other features the same. It could be explained due to several following reasons. First, compared to not-for-profit NHs, for-profit NHs may have a less well-prepared evacuation plan, making evacuation on their own challenging. Existing studies indicated that for-profit NHs tend to have a less effective and adequate evacuation plan with higher chance of being cited for evacuation plan deficiencies [38]. NH evacuation is a complex process involving moving frail residents to the designated receiving facilities with adequate medical equipment, food, water, medication, medical record and caregivers. A thoughtful and adequate evacuation plan includes detailed evacuation procedures, transportation logistics and evacuation provisions, and will be an essential basis for ensuring successful NH evacuation. Further, for-profit NHs may also have other barriers [7, 24], such as limited logistics and financial support from public agencies and/or a lack of economic incentives for moving due to costly transportation.

From an environmental condition perspective, three GIS features, namely, distance from a NH to the projected storm path, the neighboring wind speed of a NH and NH elevation, play significant roles in influencing evacuation decisions. Specifically, the farther distance a NH to the projected storm trajectory, the less likelihood the NH will be evacuated due to a lower chance of experiencing a hurricane threat. In particular, an unit increase (in Km) of distance from a NH's location to the projected storm trajectory will decrease odds ratio between

Table 4 Numerical summary of prediction performance comparison results

Metric\Strategy	Model								
	L1-Log	L2-Lasso	L3-Ridge	NL1-RF	NL2-DT	NL3-GBT	NL4-SVM	NL5-KNN	NL6-ANN
CV accuracy									
D1-BASE	0.628	0.601	0.61	1	0.678	0.91	0.931	0.871	0.917
D2-DIST	0.711	0.702	0.686	1	0.741	0.922	0.926	0.896	0.916
D3-WSP	0.625	0.613	0.617	0.999	0.739	0.943	0.943	0.883	0.898
D4-SURG	0.633	0.606	0.618	1	0.639	0.908	0.925	0.873	0.898
D5-ELEV	0.738	0.729	0.736	0.999	0.833	0.932	0.944	0.883	0.939
D6-FULL	0.936	0.937	0.901	0.998	0.877	0.991	0.993	0.968	0.974
Test accuracy									
D1-BASE	0.605	0.628	0.651	0.915	0.612	0.814	0.853	0.736	0.736
D2-DIST	0.69	0.667	0.705	0.915	0.504	0.806	0.845	0.791	0.822
D3-WSP	0.636	0.636	0.682	0.915	0.791	0.86	0.86	0.721	0.791
D4-SURG	0.612	0.628	0.651	0.915	0.612	0.806	0.845	0.744	0.744
D5-ELEV	0.713	0.643	0.682	0.915	0.721	0.86	0.837	0.798	0.775
D6-FULL	0.907	0.961	0.891	0.946	0.907	0.992	0.938	0.946	0.922
Test sensitivity									
D1-BASE	0.636	0.818	0.636	0	0.364	0.182	0	0.364	0.182
D2-DIST	0.818	0.909	0.818	0	0.909	0.455	0.091	0.455	0.455
D3-WSP	0.636	0.545	0.636	0	0.818	0.727	0	0.364	0.364
D4-SURG	0.636	0.636	0.636	0	0.364	0.273	0	0.364	0.091
D5-ELEV	0.727	0.818	0.818	0	0.727	0.364	0	0.455	0.455
D6-FULL	0.818	1	0.909	0.364	0.636	1	0.364	0.909	0.545
Test specificity									
D1-BASE	0.602	0.61	0.653	1	0.636	0.873	0.932	0.771	0.788
D2-DIST	0.678	0.644	0.695	1	0.466	0.839	0.915	0.822	0.856
D3-WSP	0.636	0.644	0.686	1	0.788	0.873	0.941	0.754	0.831
D4-SURG	0.61	0.627	0.653	1	0.636	0.856	0.924	0.78	0.805
D5-ELEV	0.712	0.627	0.669	1	0.72	0.907	0.915	0.831	0.805
D6-FULL	0.915	0.958	0.89	1	0.932	0.992	0.992	0.949	0.958
Balanced accuracy									
D1-BASE	0.619	0.714	0.645	0.5	0.5	0.528	0.466	0.568	0.485
D2-DIST	0.748	0.777	0.757	0.5	0.688	0.647	0.503	0.639	0.656
D3-WSP	0.636	0.595	0.661	0.5	0.803	0.8	0.471	0.559	0.598
D4-SURG	0.623	0.632	0.645	0.5	0.5	0.565	0.462	0.572	0.448
D5-ELEV	0.72	0.723	0.744	0.5	0.724	0.636	0.458	0.643	0.63
D6-FULL	0.867	0.979	0.9	0.682	0.784	0.996	0.678	0.929	0.752

evacuation and shelter-in-place by a factor of 0.868 by holding other features fixed. Similarly, the greater probability of anticipated wind speed exceeding 50 knots within a 120-h time period at a NH location, the less likely that NH will evacuate with an AOR of 0.687. The severe weather conditions may present significant disruption in transfer efforts and evacuation safety since 50 knots winds and gusts or above may break branches, uproot trees, or tip or veer high profile vehicles off course [19, 39]. In addition, a NH situated on higher ground will be less likely to evacuate. For an unit elevation increase (in feet), the odds ratio between evacuation and shelter-in-place will be decreased by a factor of 0.868. This is also intuitive and self-explanatory since NH at higher elevation will be less likely experiencing potential flooding from coastal surge or inland inundation.

From NH staffing and residents' characteristics perspective, two features, namely the staffing level of licensed practical nurses and the percentage of NH residents who received antianxiety medication, play significant roles in whether a NH will be evacuated. Specifically, a NH with a higher staffing level of LPNs (quantified in

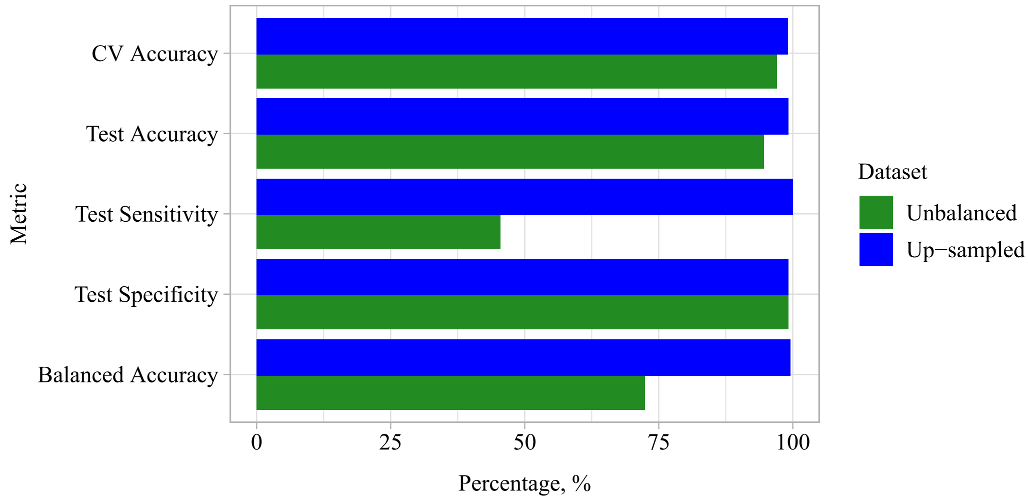

Fig. 12 The influence of up-sampling on prediction

Table 5 Numerical summary of the influence of up-sampling on prediction performance of model NL3-GBT under D6-FULL strategy

Type	Metric				
	CV accuracy	Test accuracy	Test sensitivity	Test specificity	Balanced accuracy
Imbalanced	0.97	0.946	0.455	0.992	0.724
Up-sampled	0.991	0.992	1	0.992	0.996

HPRD) indicates a low likelihood of evacuation, which can be explained from two aspects. First, LPNs are nursing staff who provide basic routine medical care, such as monitoring and recording vital signs (e.g., blood pressure, heart rate, respiration, etc.) of patients, giving injections, changing bandages and administering medications. Adequate LPNs implies that the NH has adequate workforce to self-sufficiently take care of NH residents during hurricane and sheltering-in-place requires such self-sufficiency [23]. Second, many for-profit NHs tend to consider LPN as a substitute of RN for performing advanced nursing activities since LPN is less costly. Thus, the larger number of LPNs is often positively correlated with the for-profit status of a NH, which tends to shelter in place due to the economic incentive of avoiding high evacuation costs. In addition, a NH with a higher percentage of residents who receive antianxiety medication is less likely to evacuate. It is because that NH residents with pre-existing mental disorders, as indicated by the medication provided, are more vulnerable to evacuation. The changing environment in the new hosting facility, the discontinuity of care and moving itself due to evacuation will exacerbate their mental health conditions, such as anxiety, depression and post-traumatic stress disorders [14]. Besides, easing stress, providing reassurance and persuasion to manage mental disorder symptoms of these residents during an evacuation is also challenging for caregivers with limited time but overwhelming workload [40, 41].

Conclusion

In this paper, a GIS-integrated predictive analytics framework is proposed for predicting evacuation response of NHs in hurricane disaster scenario. Data from multiple sources, such as environmental conditions, resident census in the facility, and facility staffing and organizational characteristics during the time of disaster are considered and integrated for improving the prediction performance. Specifically, several important spatial and temporal heterogeneous environmental GIS features are extracted for NHs at different spatial locations, e.g., distance to storm trajectory, projected wind speed, potential storm surge, and elevation of the facility. A number of linear and nonlinear machine learning models are applied and optimized for predicting the evacuation response and compared based on different prediction

Table 6 LR model interpretation

Feature	$\hat{\beta}$	Odds ratio	SE ($\hat{\beta}$)	*p* value
Organizational structure				
Not for-profit facility (Y/N)	2.049	7.76	0.949	0.031*
Government facility (Y/N)	1.908	6.74	2.507	0.447
Chain-facility (Y/N)	0.481	1.618	0.781	0.538
Part of a CCRC (Y/N)	0.391	1.478	1.057	0.712
Occupancy rate (% beds)	− 0.008	0.992	0.038	0.821
ADRD special care unit (Y/N)	2.142	8.516	1.252	0.087
Non-ADRD special care unit (Y/N)	− 2.015	0.133	1.857	0.278
Has organized resident group (Y/N)	− 2.597	0.074	1.745	0.137
Has organized family members group (Y/N)	− 0.904	0.405	0.707	0.201
Medicare (% residents)	− 0.01	0.99	0.013	0.419
Medicaid (% residents)	0.062	1.064	0.038	0.109
Environmental GIS characteristics				
Distance from projected trajectory 24 h prior decision (km)	− 0.142	0.868	0.027	1.17E−07***
50 knots wind speed probability 24 h prior (%)	− 0.375	0.687	0.07	6.94E−08***
Potential storm surge 24 h prior (feet)	− 0.492	0.611	0.35	0.16
Elevation of facility (feet)	− 0.142	0.868	0.032	8.65E−06***
Staffing characteristics				
Nurse with admin duties (HPRD)	0.838	2.312	2.424	0.729
Registered nurses (HPRD)	− 2.58	0.076	1.811	0.154
Licensed practical nurses (HPRD)	− 3.358	0.035	1.504	0.026*
Certified nursing assistants (HPRD)	1.119	3.062	0.964	0.246
Occupational therapy services (HPRD)	− 0.197	0.821	3.782	0.958
Activities staff (HPRD)	2.501	12.2	2.903	0.389
Housekeeping staff (HPRD)	0.592	1.808	1.376	0.667
Medical director only (Y/N)	− 0.363	0.696	1.097	0.741
Full medical team (Y/N)	− 0.299	0.742	0.867	0.73
No medical team (Y/N)	2.49	12.06	2.018	0.217
Resident characteristics (% residents)				
Acuindex (patient acuity)	0.579	1.784	0.34	0.088
Behavioral healthcare needs	0.02	1.02	0.025	0.431
Dementia or Alzheimer's	− 0.041	0.96	0.027	0.135
Depression	− 0.004	0.996	0.018	0.835
Intellectual disability	0.064	1.066	0.123	0.605
Physical restraint use	0.131	1.14	0.358	0.715
Serious mental illness	0.016	1.016	0.032	0.615
Antipsychotics medication	− 0.033	0.968	0.046	0.478
Antianxiety medication	− 0.106	0.899	0.051	0.039*
Antidepressants medication	0.034	1.035	0.031	0.277
Sedative/hypnotics medication	0.118	1.125	0.075	0.118

* $p<0.05$; ** $p<0.01$; *** $p<0.001$

95% confidence Intervals for each parameter estimate are calculated by $\hat{\beta}_j \pm 1.96 \times SE(\hat{\beta})$, where is the respective estimated covariate coefficient and SE is the Std. Error

performance measures identify the final best predictive model. A case study on Hurricane Irma impacting NHs in FL is considered to demonstrate effectiveness of the framework, comparing prediction performance among models with and without incorporating GIS features. Furthermore, the influence of the GIS-features are quantified, together with several resident and facility characteristics identified as influential factors for evacuation response. The proposed framework will allow NH administrators to understand the multifactorial complex nature of evacuation response and the predictive capability with improved accuracy will assist emergency management agencies in planning proactive resource management strategies for evacuation demand surge during disasters, such as hurricanes. Since the major focus in this paper is to demonstrate the potentials of integrating GIS data and applying machine learning to improve NH evacuation prediction, LR is considered for model interpretation. As future work, we will consider more in-depth and state-of-the-art interpretive machine learning methods.

Funding
This study was supoorted by National Institute on Aging (Grant No. R01AG060581) and Division of Civil, Mechanical and Manufacturing Innovation (Grant Nos. 1825761 and 1825725).

Author details
[1]Department of Industrial and Management Systems Engineering, University of South Florida, Tampa, FL 33620, USA. [2]School of Aging Studies, University of South Florida, Tampa, FL 33620, USA. [3]Department of Psychiatry, University of California San Diego, La Jolla, CA 92093, USA. [4]Sam and Rose Stein Institute for Research on Aging, University of California San Diego, La Jolla, CA 92093, USA. [5]Weldon School of Biomedical Engineering, Purdue University, West Lafayette, IN 47907, USA.

Received: 28 February 2022 Accepted: 30 July 2022
Published online: 14 September 2022

References

1. Morrow BH. Identifying and mapping community vulnerability. Disasters 1999;23(1):1–18.
2. Fernandez LS, Byard D, Lin CC, Benson S, Barbera JA. Frail elderly as disaster victims: emergency management strategies. Prehosp Disaster Med. 2002;17(2):67–74.
3. Shaughnessy PW, Kramer AM. The increased needs of patients in nursing homes and patients receiving home health care. N Engl J Med. 1990;322(1):21–7.
4. Dosa D, Feng Z, Hyer K, Brown LM, Thomas K, Mor V. Effects of Hurricane Katrina on nursing facility resident mortality, hospitalization, and functional decline. Disaster Med Public Health Preparedness 2010;4(01):S28.
5. Dosa D, Hyer K, Thomas K, Swaminathan S, Feng Z, Brown L, Mor V. To evacuate or shelter in place: implications of universal hurricane evacuation policies on nursing home residents. J Am Med Directors Assoc. 2012;13(2):190-e1.
6. Harris G. In NH, a fight lost to rising waters. New York Times. 2005;7:A1.
7. Thomas KS, Dosa D, Hyer K, Brown LM, Swaminathan S, Feng Z, Mor V. Effect of forced transitions on the most functionally impaired nursing home residents. J Am Geriatr Soc. 2012;60(10):1895–900.
8. Baker EJ. Hurricane evacuation behavior. Int J Mass Emerg Disasters 1991;9(2):287–310.
9. Wolshon B, Urbina E, Wilmot C, Levitan M. Review of policies and practices for hurricane evacuation. I: Transportation planning, preparedness, and response. Nat Hazards Rev. 2005;6(3):129–42.
10. Whitehead JC, Edwards B, Van Willigen M, Maiolo JR, Wilson K, Smith KT. Heading for higher ground: factors affecting real and hypothetical hurricane evacuation behavior. Glob Environ Change Part B Environ Hazards. 2000;2(4):133–42.
11. Hasan S, Ukkusuri S, Gladwin H, Murray-Tuite P. Behavioral model to understand household-level hurricane evacuation decision making. J Transp Eng. 2011;137(5):341–8.
12. Dosa DM, Grossman N, Wetle T, Mor V. To evacuate or not to evacuate: lessons learned from Louisiana nursing home administrators following Hurricanes Katrina and Rita. J Am Med Directors Assoc. 2007;8(3):142–9.
13. Dosa DM, Hyer K, Brown LM, Artenstein AW, Polivka-West L, Mor V. The controversy inherent in managing frail nursing home residents during complex hurricane emergencies. J Am Med Directors Assoc. 2008;9(8):599–604.
14. Blanchard G, Dosa D. A comparison of the nursing home evacuation experience between Hurricanes Katrina (2005) and Gustav (2008). J Am Med Directors Assoc. 2009;10(9):639–43.
15. Brown LM, Dosa DM, Thomas K, Hyer K, Feng Z, Mor V. The effects of evacuation on nursing home residents with dementia. Am J Alzheimer's Dis Other Dementias ®. 2012;27(6):406–12.
16. Florida Agency for Healthcare Administration. 2021. Accessed https://ahca.myflorida.com/
17. Environmental Systems Research Institute (ESRI). ArcGIS Desktop. Redlands: Environmental Systems Research Institute; 2021.
18. National Oceanic and Atmospheric Administration (NOAA). NHC Data in GIS Formats; 2021. Accessed https://www.nhc.noaa.gov/gis/
19. Barua DK. Beaufort wind scale. In: Encyclopedia of coastal science. Encyclopedia of earth science series. Dordrecht: Springer; 2005. Accessed https://doi.org/10.1007/1-4020-3880-1_45
20. Jelesnianski CP. SLOSH: Sea, lake, and overland surges from hurricanes (Vol. 48). US Department of Commerce, National Oceanic and Atmospheric Administration, National Weather Service; 1992.
21. University of Florida GeoPlan Center. Florida Digital Elevation Model (DEM) Mosaic; 2012. Accessed https://www.fgdl.org/metadata/fgdl_html/flidar_mosaic_m.htm
22. Centers for Medicare and Medicaid Services (CMS). Certification and Survey Provider Enhanced Reports (CASPER); 2017. Accessed https://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/NursingHomeQualityInits/Skilled-Nursing-Facility-Quality-Reporting-Program/SNF-Quality-Reporting-Program-Public-Reporting
23. Florida Health Care Association. National criteria for evacuation decision-making in nursing homes. Tallahassee: Florida Health Care Association; 2008.
24. Brown LM, Hyer K, Polivka-West L. A comparative study of laws, rules, codes and other influences on nursing homes' disaster preparedness in the Gulf Coast states. Behav Sci Law. 2007;25(5):655–75.
25. Jester DJ, Thomas KS, Peterson LJ, Dosa DM, Andel R, Hyer K. Effect of Hurricane Irma on daily direct-care nurse staffing in nursing homes. J Am Geriatr Soc. 2021;69(8):2298–305.
26. Konetzka RT, Stearns SC, Park J. The staffing-outcomes relationship in nursing homes. Health Serv Res. 2008;43(3):1025–42.
27. Cowles CM. Nursing home statistical yearbook, 2002. Montgomery Village: Cowles Research Group; 2002.
28. Hyer K, Thomas KS, Branch LG, Harman JS, Johnson CE, Weech-Maldonado R. The influence of nurse staffing levels on quality of care in nursing homes. Gerontologist. 2011;51(5):610–6.
29. Chawla NV, Japkowicz N, Kotcz A. Special issue on learning from imbalanced data sets. ACM SIGKDD Explor Newslett. 2004;6(1):1–6.
30. Chawla NV, Bowyer KW, Hall LO, Kegelmeyer WP. SMOTE: synthetic minority over-sampling technique. J Artif Intell Res. 2002;16:321–57.
31. Hastie T, Tibshirani R, Friedman J. The elements of statistical learning: data mining, inference, and prediction. New York: Springer; 2009.
32. Bishop CM. Pattern recognition and machine learning. New York: Springer; 2006.
33. National Weather Service (NWS). Hurricane Irma Local Report/Summary; 2017. Accessed https://www.weather.gov/mfl/hurricaneirma
34. LaVito A. Irma may have caused 42.5 billion to 65 billion in property damage, report says. CNBC; 2017. Accessed https://www.cnbc.com/2017/09/19/irma-may-have-caused-42-point-5-billion-to-65-billion-in-property-damage-report.html
35. Natarajan N. Coastal storm planning, the Healthcare Facility Evacuation Center (HEC), and Patient Tracking. New York State; 2013.
36. Chen X, Meaker JW, Zhan FB. Agent-based modeling and analysis of hurricane evacuation procedures for the Florida Keys. Nat Hazards. 2006;38(3):321.
37. Breiman L, Cutler A. Random forest-manual; 2004. Accessed https://www.stat.berkeley.edu/~breiman/RandomForests/cc_manual.htm
38. Castle NG. Nursing home evacuation plans. Am J Public Health. 2008;98(7):1235–40.

39. Lindell MK, Prater CS, Peacock WG. Organizational communication and decision making for hurricane emergencies. Nat Hazards Rev. 2007;8(3):50–60.
40. Laditka SB, Laditka JN, Xirasagar S, Cornman CB, Davis CB, Richter JV. Providing shelter to nursing home evacuees in disasters: lessons from Hurricane Katrina. Am J Public Health. 2008;98(7):1288–93.
41. Claver M, Dobalian A, Fickel JJ, Ricci KA, Mallers MH. Comprehensive care for vulnerable elderly veterans during disasters. Arch Gerontol Geriatr. 2013;56(1):205–13.