Social Distance Integrated Gravity Model for Evacuation Destination Choice

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Abstract

Evacuation is an effective and commonly taken strategy to minimize death and injuries from an incoming hurricane. For decades, interdisciplinary research has contributed to a better understanding of evacuation behavior. Evacuation destination choice modeling is an essential step for hurricane evacuation transportation planning. Multiple factors are identified associated with evacuation destination choices, in which long-term social factors have been found essential, yet neglected, in most studies due to difficulty in data collection. This study utilized long-term human movement records retrieved from Twitter to (1) reinforce the importance of social factors in evacuation destination choices, (2) quantify individual-level familiarity measurement and its relationship with an individual's destination choice, (3) develop a big data approach for aggregated county-level social distance measurement, and (4) demonstrate how gravity models can be improved by including both social distance and physical distance for evacuation destination choice modeling.

Keywords: big data, disaster management, evacuation, social media, social distance

1. Introduction

Hurricanes are one of the most common yet costliest natural hazards in the United States. In 2016, hurricanes and associated heavy rainfall, storm surges, and strong winds caused death, injuries, and economic losses to coastal areas in the United States (NOAA, n.d.). One of the primary mechanisms for protecting people from impending hurricanes and their hazards is evacuating the potentially affected area. Many disciplines, including geography, sociology, engineering, and political science, have contributed to a better understanding of evacuation behavior. Generally speaking, there are two different perspectives or foci for the research (Trainor et al., 2013). Transportation engineering studies focus on routing and destinations employing three-step models for evacuation: trip generation, trip distribution, and route assignment. The trip generation step models the evacuating population size and their response time (Herrera et al., 2019; Zhu et al., 2018). The second step, trip distribution, models where trips end based on opportunities provided by each potential destination using origin-destination metrics (et al., Bian et al., 2019; Cheng G. 2011). Then, in the last step, trips are assigned to different routes to optimize infrastructure usage (Bayram & Yaman, 2018; Ukkusuri et al., 2017).

Social scientists, however, focused more on individual- and household-level decision-making, aiming to gain a better understanding of how different factors affect evacuation decisions and behaviors. For example, studies have identified factors that affect evacuation decisions, including vehicle ownership, age, income, housing type, and other factors (Dow & Cutter, 1998; 2002; Huang et al., 2016). Also, multiple social factors have been found essential to understanding evacuation time estimate (Lindell & Perry, 1992; Lindell & Prater, 2007), departure time distribution (Huang et al., 2012; 2017), transportation mode (Lindell & Perry, 1992; Lindell & Prater, 2007), evacuation route choices (Dow & Cutter, 2002; Prater et al., 2000), and other evacuation logistics, including travel time, destinations, and accommodation (Bian et al., 2019; Lindell et al., 2011; Wu et al., 2012). Findings of social factors in evacuation models have been reviewed by Lindell et al. (2019), Lindell et al. (2020), and Sorensen et al. (2020).

One challenge here is that some potentially useful social factors have not been examined in previous evacuation research. This is especially true for long-term related social factors. For example, how many counties has an individual visited in the last three years, and how much time he/she has visited each county? One potential solution is to collect social media data to retrieve digital footprints left by social media users. Social media data have been widely used in natural hazard-related research to understand evacuation behavior (Kumar & Ukkusuri, 2018; Martin et al., 2017; Sadri et al., 2017). Besides the ability to provide rapid and easily accessible data, another advantage of social media is that long-term records can be retrieved. However, only limited studies have utilized the long-term records from social media for evacuation behavior studies (Jiang et al., 2019b).

This study aims to extend the functionality of social media data in evacuation behavior studies by utilizing users' long-term traveling records from Twitter. Specifically, this study asks the following questions:

1) Are social media users more likely to evacuate to places they are familiar with?

2) How can social distance derived from social media data help to improve evacuation modeling?

To address these two questions, this study first reinforces findings from existing studies that social factors do play important roles in evacuation destination choices by quantifying the individual-level familiarity of each evacuated Twitter user, and then introduces a big data approach to measure county-to-county social distance based on geotagged tweets. Lastly, this study demonstrates how social distance can be integrated into gravity models to improve evacuation transportation planning.

2. Literature Review

2.1 Human Mobility Measured by Distance

Power law is one of the most commonly used distributions to model displacement distance in human movements. For example, the trip occurrence probability decreases as travel distance increases (Eq. 1), with the power law written as

$$p(d) \sim \alpha d^{-\beta} \qquad \text{Eq. 1}$$

where $p(d)$ is the trip occurrence probability, d is the trip distance, α is a constant, and β is the scaling parameter (Brockmann et al., 2006; Mandelbrot, 1983). Researchers further confirmed that the scaling parameter β should be larger than 1 and smaller than 3. When $\beta > 1$, the trip occurrence probability forms an inverse proportional relationship with trip distance. When $\beta > 3$, this movement is Brownian, where the length of trip exhibits a Gaussian distribution (Jiang et al., 2009).

Benefitting from the prevalence of Global Positioning System (GPS) and location-enabled social media platforms, the availability of geotagged social media posts provides researchers with opportunities to advance understanding of human mobility. Noulas et al. (2011) collected 12 million user check-in data on Foursquare generated by more than 679,000 users in 111 days. This study provided an exploratory analysis of spatiotemporal distribution of users' check-in locations for multiple categories of places. Similarly, Cheng Z. et al. (2011) collected about 22 million check-in data from nine social media platforms and modeled individuals' travel distance with power-law distribution. Their power-law model agrees with previous human mobility studies using non-social media data sources (Brockmann et al., 2006; Gonzalez et al., 2008). In a cross-city study conducted by Noulas et al. (2012), more than 35 million trips were retrieved from Foursquare check-in data in 31 cities from different countries. This study shows that power law governs human mobility patterns in all the cities, though β varies with city size and population density.

Human mobility patterns were also studied during previous natural hazards using social media data. Based on geotagged tweets, for example, Wang and Taylor (2014) examined New York City residents' daily travel patterns under the impact of Hurricane Sandy. This study found that although an individual's activity center was shifted, their daily travel distances still follow power-law distribution. The shift of the activity center was caused by evacuation from flood-prone areas to safer areas. However, the shift of activity center was not the focus of their study and thus was not further examined. In another study by Wang and Taylor (2016), they further confirmed their findings by testing whether human travel distance follows power-law distribution under multiple natural hazards. They collected Twitter users' movement data during four typhoons (two in Japan and two in the Philippines), three earthquakes (in the Philippines, Chile, and the U.S.), three winter storms (in Britain, Germany, and the U.S.), three extreme rainstorms in the U.S., and two wildfires in Australia.

These studies provided two important contributions. First, although natural hazards caused perturbation for human movements, an individual's travel distance distribution was still governed by the power-law distribution. Second, a shift of an individual's activity space center can be observed, but the relationship between traveling center shift distance and an individual's daily activity space was unrelated. These studies demonstrated the feasibility of using Twitter data to study human mobility patterns during natural hazards and the fitness of power-law distribution of travel distance during natural hazards. Also, the two studies by Wang and Taylor (2014, 2016) revealed the shift in activity centers caused by hazard-related evacuations, but patterns of such shifts were not further examined. This latter point raised the question about whether evacuation distances of individuals still fit power-law distribution, which was examined in this paper.

2.2 Evacuation Destination Choices

Existing studies have developed multiple origin-destination models for evacuation transportation management at the aggregated geographical level. Evacuation destination choice is an important factor in determining evacuation transportation distribution (Murray-Tuite & Wolshon, 2013). Evacuation destination choice decisions vary among evacuees and are affected by multiple factors. Among those factors, accommodation is an important one that may decide evacuation destination. Common accommodation choices include, but are not limited to, friends' relatives' places, hotels/motels, and public shelters. Post-hurricane survey data showed that most evacuees chose to stay at a friend's or relative's home, as illustrated from evacuation behavior studies for Hurricane Floyd (Cheng et al., 2008) and Hurricane Ivan (Mesa-Arango et al., 2013). To examine factors that affect evacuees' destination choices, Cheng et al. (2008) developed multinomial logit models for evacuees who went to friend's/relative's places and to hotels/motels. Their study found influential variables, including evacuation distance, whether the destination is affected by hurricane, population composition of destination, whether the destination is in a metropolitan statistical area, transportation convenience, and the probability of finding a place to stay at the destination. With evacuation-specified Traffic Analysis Zones

(TAZs), Wilmot et al. (2006) developed three models for zonal aggregated evacuation destination choice. Comparing their gravity model, intervening opportunity model, and an extended intervening opportunity model that considered evacuation direction and hurricane path, only small differences were found (Wilmot et al., 2006). They further tested the transferability of the gravity model. The gravity model calibrated using data from Hurricane Floyd in South Carolina also worked with Hurricane Andrew in Louisiana (Wilmot et al., 2006). With the same survey data from Hurricane Floyd in South Carolina, Cheng et al. (2011) further extended the gravity model with dynamic features considering the storm path, road situation, and destination accommodation availability. However, the transferability of this dynamic model has not been tested (Cheng et al., 2011).

Current gravity-derived trip distribution models calculate opportunities to each destination based on several factors, including pushing factors at origin, pulling at destination, and travel distance between origin and destination. Social factors included in existing models focus heavily on the pushing force at origins, such as information hurricane characteristics and evacuees' vehicle ownership, risk perceptions of local residents (Dow & Cutter, 2002; Lindell et al., 2005), and pulling force at destinations, such as lodging options and cost (Lindell et al., 2011).

Since most evacuation studies rely on survey data, very limited long-term travel information can be collected. One of the advantages of using social media data is the availability of long-term data. For example, Jiang et al. (2019b) revealed that evacuated social media users have significantly larger long-term activity space than non-evacuated social media users.

3. Data and Study Area

3.1 Hurricane Matthew and Its Affected Area

Hurricane Matthew was formed on September 28, 2016, and rapidly developed into a Category 5 storm, becoming the first Category 5 hurricane since 2007 in Atlantic basin (Stewart, 2017). It caused 585 direct deaths, with 34 in the United States. Based on the predicted track and the intensity of Hurricane Matthew, coastal residents from Georgia, South Carolina, and North Carolina were ordered to evacuate.

This study focuses on evacuation behavior of Twitter users living in these ten coastal counties before Hurricane Matthew: Chatham, GA; Brunswick, NC; Beaufort, Berkeley, Charleston, Colleton, Dorchester, Georgetown, Horry, and Jasper in SC (Figure 1).

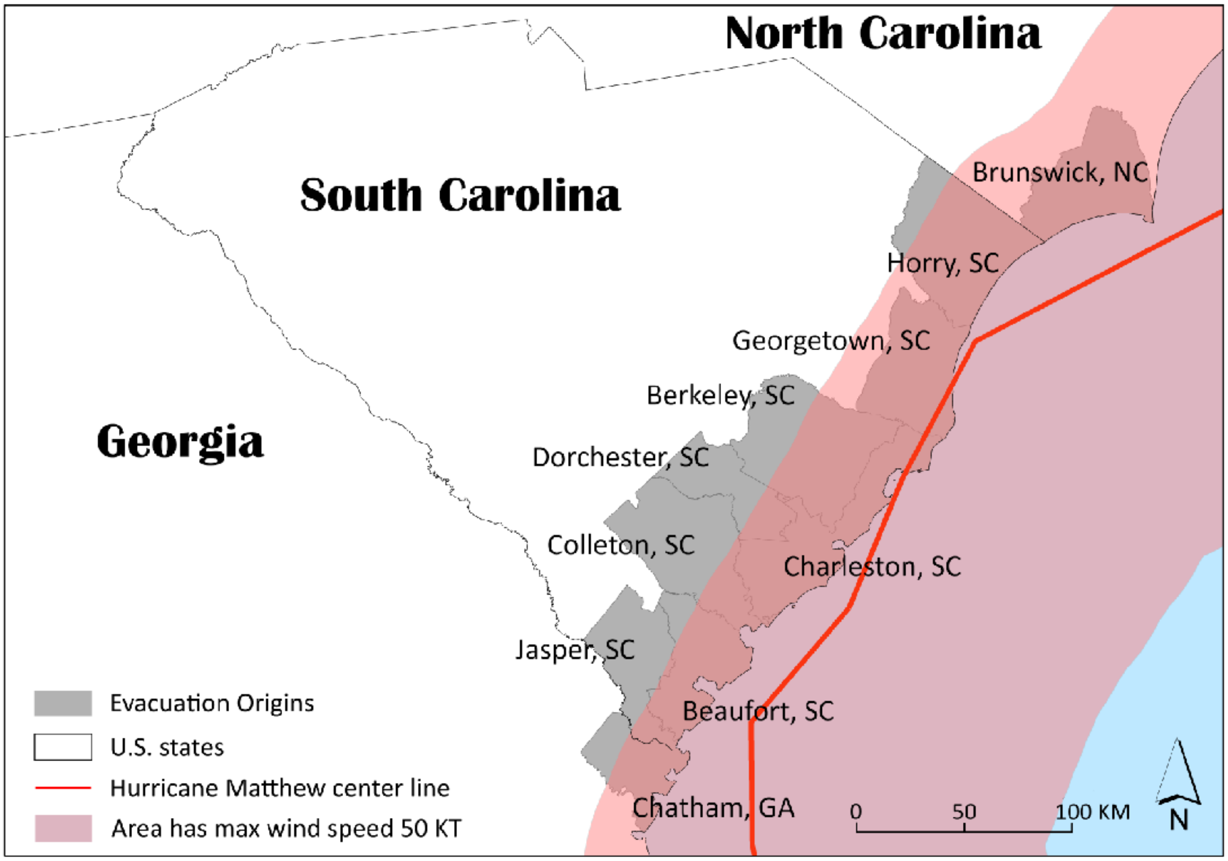

Figure 1. Hurricane Matthew Path and the 10 Selected Counties

3.2 Data Collection and Preprocessing

Geotagged tweets were collected with the Twitter Stream Application Programming Interface (API) between July 2016 and December 2016. Streamed tweets were stored in a Hadoop environment and queried with Apache Impala in this study. We defined the resident county of a Twitter user as the county from which the user has posted the largest number of tweets (Martin et al., 2017; McNeill et al., 2017; Martin et al., 2020a; Jiang et al., 2019b). From the massive Twitter dataset we collected, we identified local users whose resident county was one of these 10 counties.

The Twitter selection process followed Martin et al. (2017) and Jiang et al. (2019b). Based on the predicted path of Hurricane Matthew, the governor of South Carolina issued a mandatory evacuation order on October 4th, 2016 (hereinafter "10/4"), followed by the governor of North Carolina and the governor of Georgia, who issued evacuation orders on October 6th. Given these evacuation orders, we considered the pre-evacuation time span as October 2nd, 2016 (hereinafter "10/2") to 10/4, as evacuation was assumed to start after the evacuation order (10/4). The selected counties were under the impact of Hurricane Matthew between October 7th (hereinafter "10/7") and October 9th (hereinafter "10/9"). We assumed the evacuation process had finished before the arrival of Hurricane Matthew (10/7) and that evacuees would not return before Hurricane Matthew had left (10/9). Therefore, we considered the post-evacuation time span as 10/7 to 10/9.

If a local user identified from the previous step posted during both pre-evacuation and post-evacuation periods, this user was collected for further analysis. Then, we compared each user's posting location during the pre-evacuation and post-evacuation periods. If this user posted from within the 10 counties during pre-evacuation time and posted from outside the 10 counties during post-evacuation time, this user was considered an evacuated user. Also, each user's pre-evacuation and post-evacuation locations must be at county level or finer to be considered a valid location. Users with state-level locations were eliminated as they could not be located in a specific county.

All the users we collected so far were manually checked to insure they were real, personally owned accounts. We used Twitter API to retrieve the most recent 3,200 tweets those users had posted (3,200 was the maximum number of historical tweets allowed to be queried by Twitter). Those who denied permission or deleted their accounts were eliminated from our dataset. Eventually, we collected 1,286 evacuated users with accessible historical tweets for further analysis.

4. Power-Law Distribution

Existing studies agree that power-law distribution governs individuals' daily travel distance distribution during multiple natural hazards (Wang & Taylor, 2014; 2016), but not many tested whether evacuation distance follows power-law distribution (Martin et al., 2017). As evacuation distance is one of the most important factors for evacuation transportation planning, understanding the distribution of evacuation distance is an essential step.

The *poweRlaw* package (Gillespie, 2015) in R was used for this test. This package applies the bootstrap method to search for the best parameter using maximum likelihood estimation (MLE). The null hypothesis in this test was that evacuation distance distribution follows power-law distribution. The bootstrap process converged at about 3,500 iterations and remained stable through 5,000 iterations. The estimated value was $\beta = 2.1776$ with a 95% confidence interval between 2.176 and 2.178. The scaling variable $\alpha = 115.03$. The final estimation generated a power-law distribution function as:

$$f(d) = 115.03 \times d^{-2.1776} \qquad \text{Eq. 2}$$

The p-value for the power-law fitness test was 0.526. As a result, we could not reject the null hypothesis that evacuation distance distribution follows power-law distribution. Also, the resulted $\beta = 2.1776$ agreed with previous human mobility studies that $1 < \beta < 3$ (Cheng et al., 2011; Jurdak et al., 2015).

Figure 2 shows a histogram of evacuation distance distribution among the evacuees. There were a few evacuees who traveled less than 50 miles. They stopped immediately after they left the evacuation zone. Most of the evacuees evacuated to places about 150 miles away from coastal areas. That is about the distance from Charleston to Columbia in South Carolina. As one of the state evacuation strategies was to reverse lanes of Interstate Highway 26 (I-26) so that all the lanes of I-26 were directed from Charleston to Columbia to accelerate the evacuation process, 29.2% of evacuees from Charleston ended in the Columbia metropolitan area.

Unlike ideal power-law distribution (the green line in Figure 2), the peak evacuation distance appears at the range between 100 and 150 miles, rather than at the beginning. Also, a bump can be found in Figure 2, about 600 miles at the distance. The power-law distribution of evacuation distances implicitly assumes that hotels, shelters, and other accommodations are uniformly distributed on a featureless space. However, in reality, accommodation opportunities are nonuniformly distributed. This explains why the evacuation distance distribution pattern differs from the power-law distribution.

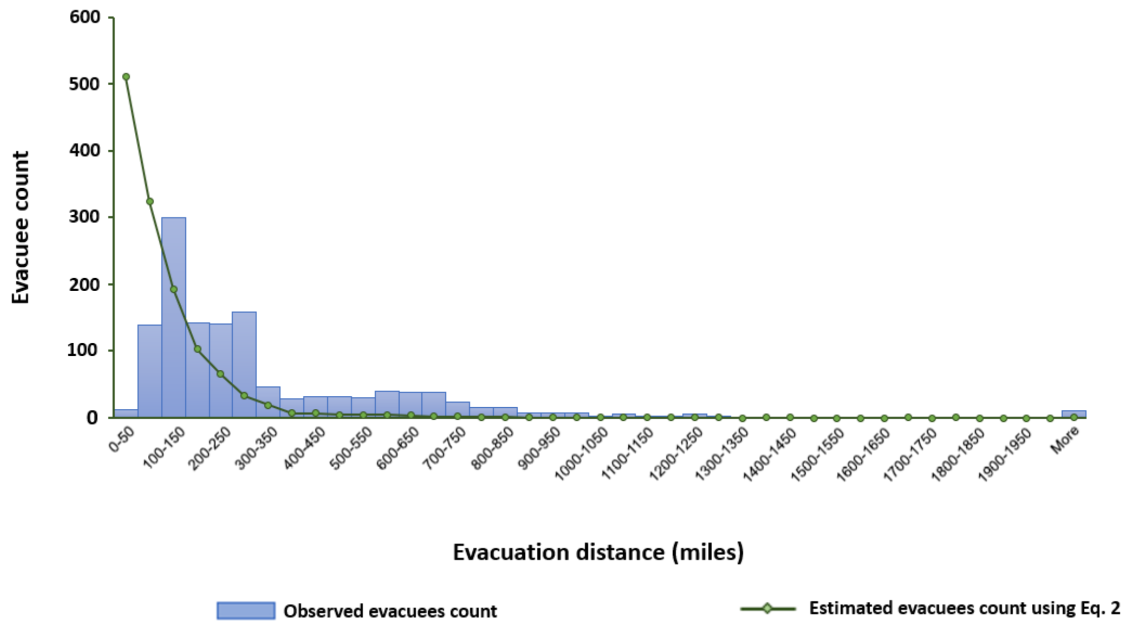

Figure 2. Evacuation Distance Distribution

5. Familiarity Measurement Using Twitter Data for Destination Choice

Survey data collected from multiple hurricane evacuations reported that over half of evacuees chose friends' or relatives' places as evacuation destinations (Mesa-Arango et al., 2013; Bian et al., 2019; Lindell et al., 2019; Smith & McCarty, 2009). Mesa-Arango et al. (2013) developed a household-level nested logit model to analyze demographic and socioeconomic characteristics that affect evacuation destination choices based on survey data. Variables used in the model were directly from survey, such as race, income, previous experience with hurricanes, and whether need to work during evacuation (Mesa-Arango et al., 2013). Long-term travel behaviors were undiscussed since they were directly unavailable from survey data. Bian et al. (2019) tackled this problem using community-level data from the American Community Survey

(ACS) as a surrogate measurement for social factors. For example, length of living in the current community was used to measure the social network size in that study.

This section examines the relationship between evacuation destination choices and long-term social factors retrieved from social media. We used social media data to quantify the familiarity of destination for evacuees, using the assumption that people who evacuated to friends' or relatives' have a high degree of familiarity with that destination. Specifically, we focused on all the places an individual had visited before, and the likelihood that this individual would choose a place where he/she spent more time than a place he/she spent less time.

For all the evacuated users, we retrieved each user's most recent 3,200 historical tweets; the maximum number of historical tweets allowed to access using Twitter API. An independent dataset was built to store each user's historical tweets for further individual-level analysis. Then, we applied three steps to test these two hypotheses. First, for each evacuated Twitter user, we searched all the counties from which this user tweeted. Second, we retrieved all the available tweets for users identified from the previous step. As all the users' historical tweets can be traced back to 2014, we identified how many days a user tweeted from each county since 2014 as tweeting frequency. Third, we ranked familiarity for all the counties from which this user had tweeted based on tweeting frequency identified in the previous step. For example, if an individual user tweeted from County A 200 days and County B 100 days, for this specific user, County A was ranked as the highest familiarity. If this user evacuated to County A, we counted this user chose the first in rank.

We excluded evacuation origin county from the familiarity rank, so this rank represents each user's familiarity rank to evacuation destination county. In other words, the more days a user tweeted from the county, the more likely this user would evacuate to the county. All the counties an individual had been to were ranked. This process was applied to all evacuated users, and their destination choice rank was summarized. Since evacuation origin county, the residential county of each user, was excluded from the familiarity ranking, all the counties included in the rank can be viewed as a potential evacuation destination for the specific user.

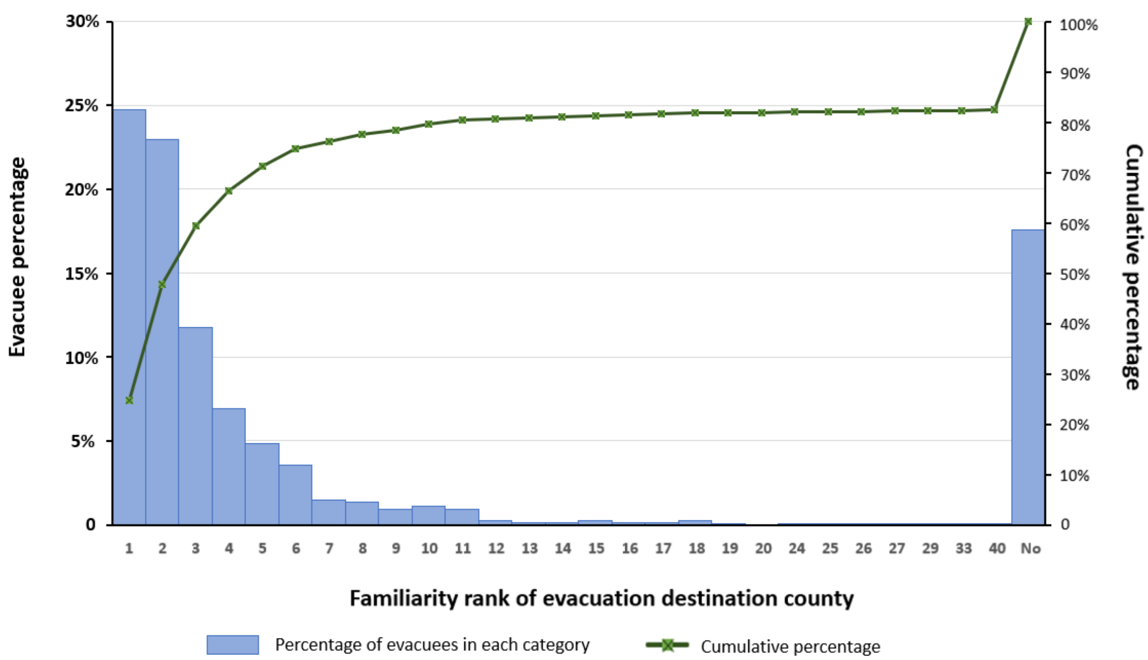

Figure 3. Evacuation Destination Popularity vs. Familiarity Rank

Figure 3 shows evacuees' destination choices. The x-axis is the familiarity rank, and each bar represents the percentage of evacuees who chose to evacuate to a county with a corresponding familiarity rank. Among 1,286 evacuees, 82.4% (1,060 evacuees) chose to evacuate to a county he/she had visited before. Specifically, 24.7% (318 evacuees) chose the county with the highest familiarity rank as evacuation destination. Also, 22.9% (295 evacuees) chose to evacuate to the county with the second highest familiarity rank. This result was further tested with Spearman's rank order correlation test (Spearman, 1904). This test resulted in $p <$

0.001, indicating that the evacuee number and familiarity rank are significantly negatively correlated, whereby the former decreases with the latter's increase.

This analysis illustrated that familiarity with places is associated with evacuation destination decisions. Most evacuees chose their evacuation destination to be a county with a high familiarity rank. The higher familiarity rank a county has, the more likely an evacuation trip will occur.

6. Improved Gravity Model

The gravity model is commonly used to model economic activities, trades, and human travel between a pair of places (Kepaptsoglou et al., 2010; Lewer & Van den Berg, 2008; Santana-Gallego et al., 2016). It can be written as Eq. 3:

$$N_{ij} = G\,\frac{O_i^{\beta_1} D_j^{\beta_2}}{d_{ij}^{\alpha}} \quad . \qquad \text{Eq. 3}$$

When used for evacuation, N_{ij} represents the evacuation population from the origin i to the destination j. O_i and D_j are the total population sizes of the origin i and the destination j respectively. The denominator part is a fringe function, interpreted as the cost from traveling between the origin i and the destination j. In the traditional gravity model, the fringe function is based on physical distance (d_{ij}) between the origin i and the destination j. As power-law distribution indicates, when the distance between two places increases, the probability of travel occurrence decreases. G is the gravitational constant, functioning as a scaling parameter. β_1, β_2 and α are heuristic parameters for the origin population (O_i), the destination population (D_j), and the physical distance (d_{ij}).

Previous studies have examined the fitness of the gravity model and the intervening opportunity model. The relationship between the gravity model and the intervening opportunity model, and their extended forms, are reviewed by Chen (2005). Existing evacuation models only consider the physical distance (d_{ij}^{α}) as the difficulty of making the trip between each pair of origin and destination. As indicated in Eq. 3, an increase in the physical distance decreases the trip occurrence when other parameters are unchanged. We argued that social distance between a pair of places also functions in such gravity-based evacuation models. An increase in the social distance decreases trip occurrence when other parameters are unchanged. Section 6.2 provides a test of how social distance improves the accuracy of traditional gravity model. In this study, social distance was represented as the inverse of the familiarity measurement aggregated at county level, which was calculated as a social connection measurement.

6.1 Social Connection Measurement

Social connection measurements have been developed and used by multiple urban studies to measure the strength of connectivity between two places (Browning & Cagney, 2002; Zhong et al., 2014). Among the different variables used in the social connection model, human movements always play important roles, although different types of human movement data are deployed in different measurements.

The social connection measurement developed in this study was based on travels retrieved from Twitter users' records. It represented the likelihood of a trip occurring between the given two counties in the long term. It was based on the assumption that the more the travels between two counties, the stronger the social connection between two counties, the shorter the social distance, and therefore, the more likely an evacuation trip occurred. Specifically, the measurement was calculated as the percentage of Twitter users traveled between the given two counties based on geotagged tweets collected in a six-month period (July 2016 to December 2016) following Eq. 4.

$$Social\ Connection = \frac{N_{OD}}{N_O} \times 100\%, \qquad \text{Eq. 4}$$

where N_{OD} is the number of Twitter users found in both the origin county O and the destination county D, and N_O is the total number of Twitter users in the origin county O.

The calculation process involved four main steps. First, we identified users who sent tweets from the 10 coastal counties in the six-month period. Second, for each individual user, we found all the counties he/she had tweeted as a user's active counties. If a user was active in more than one county, this user built a connection between each pair of active counties. For example, if a user posted geotagged tweets from County A, County B, and County C, connections were strengthened between Counties A and B, between Counties B and C, and between Counties C and A. In the third step, we aggregated to the county level. Since our focus was the social connection between the 10 counties to other counties, connections between a pair of counties within the 10 counties or a pair of counties not in the 10 counties were not calculated. Finally, the results from the previous step were divided by the total Twitter user of the origin county to standardize this measurement. For example, between July 1st and December 31st, 2016, we found that 667 Twitter users had tweeted from both Brunswick County, NC, and Mecklenburg County, NC, and that the total number of Twitter users found in Brunswick County was 25,150. In this case, $N_{OD} = 667$ and $N_O = 25{,}150$. The social connection between Brunswick County (Wilmington in Figure 4a) and Mecklenburg County (Charlotte in Figure 4a) was 2.65%, based on Eq. 4.

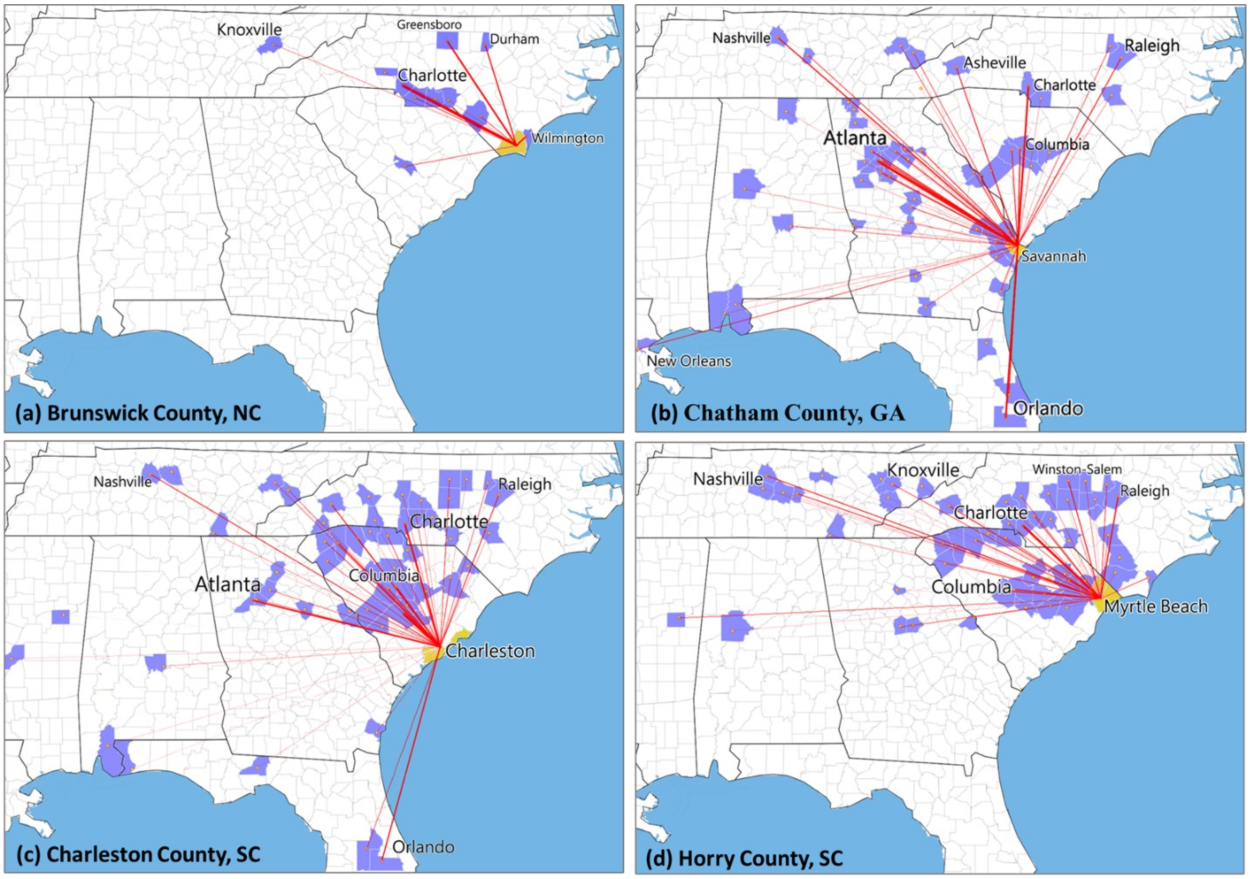

Figure 4. *The Social Connection of the Four Selected Counties*

Figure 4 shows the social connections of (a) Brunswick County, NC, (b) Chatham County, GA, (c) Charleston County, SC, and (d) Horry County, SC. For better visual illustration, connections to some counties that are too weak to be visible or counties that are too far to be included in this map scale level were eliminated in this figure. The width of the red line represents the strength of social connection between two counties. In Figure 4a, Brunswick County has the strongest connection with Mecklenburg County, stronger than connection with other counties having shorter physical distances. Chatham County (Figure 4b) has the strongest social connection with Fulton County, GA. Although some other counties have shorter physical distance from Chatham County, social connection is actually weaker than the connection between Fulton County and Chatham County. In Figure 4c, Charleston County has strong connections with counties near Columbia, SC. It also has a relatively strong connection with Fulton County, GA, and Orange County, FL. Both counties have larger physical distance than counties in South Carolina, but social connections with Charleston County are stronger. Figure 4d shows the strongest connection Horry County, SC, has with Mecklenburg County, NC. Also, it has relatively strong connections with counties near Nashville, TN. Figure 4 shows that social connections are not proportional to physical driving distance. Therefore, when modeling evacuation destination choice, the social connection should also be considered for inclusion in the fringe function to better model human mobility.

6.2 Social Distance Integrated Gravity Model

Social connection was integrated into the fringe function of the gravity model as an additional measurement of distance (considered as social distance) besides physical driving distance (Eq. 5). $f_{ij}^{\alpha 2}$ represents the county-to-county social connection between the origin i and destination j. α_2 is the heuristic parameter and l is the scaling factor.

$$N_{ij} = G \frac{O_i^{\beta_1} D_j^{\beta_2}}{d_{ij}^{\alpha_1} + l \cdot f_{ij}^{\alpha_2}}. \qquad \text{Eq. 5}$$

Since the driving distance was used in this model as the physical distance, driving was the only transportation mode we considered in this study. Therefore, counties exceeding 1000 miles away from the 10 origin counties were eliminated. Also, counties without observed traveling with any of the 10 counties were also eliminated. Specifically, if a county did not receive any evacuees during Hurricane Matthew and no common users were found with any of the 10 counties in the 6-month period, this county was also eliminated even if it was within 1000 miles. This step eliminated 38 counties from the observed 326 destination counties and left 288 counties for model calibration. The social connection was calculated using the method described in Section 6.1. A nonlinear optimization function was used in R to optimize scaling parameters (G and l) and heuristic parameters (β_1, β_2, α_1, and α_2).

For comparison, we first optimized the traditional gravity model (Eq. 3). The optimization was run in R with nonlinear model optimization. The optimized traditional model is as follows:

$$N_{ij} = 8.477 \times 10^{-5} \frac{O_i^{0.61} D_j^{0.74}}{d_{ij}^{0.92}} \qquad \text{Eq. 6}$$

We conducted an exhaustive cross-validation of this model. This cross-validation process included two rounds of leave-one-out cross-validation (Molinaro et al., 2005). This process re-sampled all the data into training and testing datasets to avoid overfitting problems. We organized the dataset into the following table (Figure 5), where each column is an evacuation origin and each row is an evacuation destination.

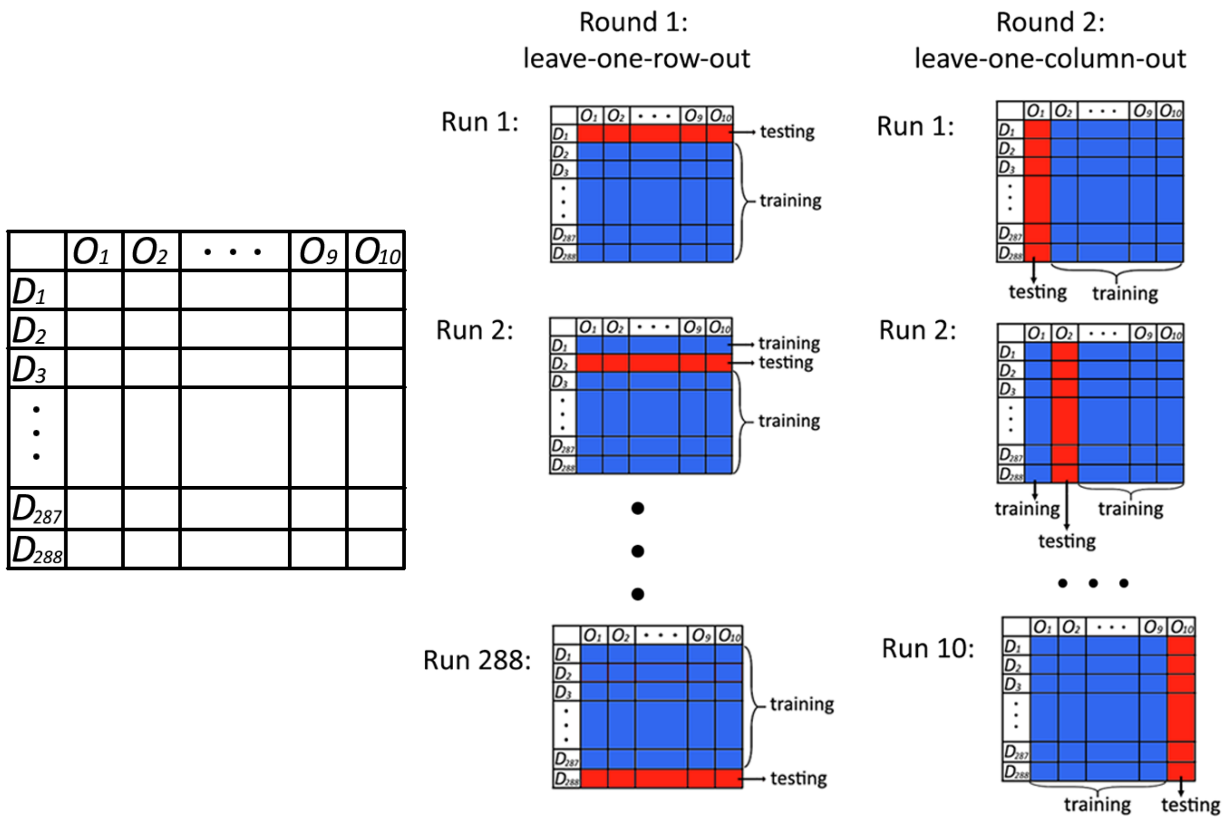

Figure 5. Cross-validation Process

The first round is leave-one-row-out cross-validation. This includes multiple runs. In each run, one row is left out as the test dataset. The remaining 287 rows are used to train the model (Eq. 3). After the model was finished training in each run, the one being left out was used to test model performance in this run. A root-mean-squared-error (RMSE) is calculated by comparing the difference between the observed value and the output from the trained model. Since we have 288 evacuation destinations, the first round of cross-validation includes 288 runs and generates 288 RMSE values. The second round of cross validation is leave-one-column-out. In this round, we leave one column out as the test dataset and use the remaining nine columns to train the model (Eq. 6). Like the previous cross-validation round, an RMSE value is calculated in each round. The second round includes 10 runs, as we have 10 evacuation origins. Therefore, 10 RMSE values were generated in the second round of cross-validation. After two rounds of leave-one-out cross-validation, a total of 298 RMSE values were generated. The overall average of RMSE for all the validation runs is 1.24, and the standard deviation is 1.68.

With the social distance integrated into the model, the improved gravity model is shown in Eq. 5. Like the previous model optimization process, the nonlinear model optimization procedure was run in R for the improved gravity model. The result is shown in Eq. 7.

$$N_{ij} = 2.66 \times 10^{-5} \frac{O_i^{0.60} D_j^{0.70}}{d_{ij}^{0.90} - 0.950 f_{ij}^{-0.83}} \quad \text{Eq. 7}$$

Like the traditional gravity model, two rounds of leave-one-out cross-validation were conducted to avoid the overfitting problem. After two rounds of cross validation, a total of 298 RMSE values were generated. The overall average RMSE was 0.80 and the standard deviation was 1.88.

Comparing these two models, the improved gravity model reduced the overall average RMSE from 1.24 to 0.80, which was a 35% error reduction. In other words, the social distance integrated gravity model shows an improvement of 35% accuracy in predicting evacuation destinations comparing to the gravity model that only considered physical distance. This demonstrates the utility of social distance in evacuation destination prediction models and can be applied to practical applications, such as evacuation transportation planning.

7. Limitations and Future Research

Although the proposed model significantly reduced RMSE, we realized some limitations to this research. The first is the Twitter representativeness issue (Jiang et al., 2019a; Malik et al., 2015). Using Twitter data introduces population biases toward a certain group and may not represent all populations with various demographic and socioeconomic characteristics. Although the representativeness issue of social media data is recognized and recent studies have advanced understanding of the demographic and socioeconomic characteristics of social media users using a different method, no unanimous solution has been reached. One potential solution is to develop a better sampling method that integrates both survey and social media data. For example, Martin et al. (2020b) compared age, gender, and race between users collected from surveys and social media in evacuation studies. Integrating multiple data sources and developing a better sampling method are required for a better understanding of evacuation destination choices of different population groups.

The second limitation is variable choices. To demonstrate the functionality of social distance, the models in this study were only modified regarding the distance (d_{ij}^{α}) in the gravity model (Eq. 5). Undoubtably, distance draws the most attention in evacuation transportation planning, but it is not the only factor. Various other social factors identified in existing studies also play important roles in evacuation destination choices, such as family size, hotel/motel availability, financial budget, and more. These variables could be used to calibrate $O_i^{\beta_1}$ and $D_j^{\beta_2}$ in Eq. 5. The proposed model can potentially be further improved by integrating more variables in the optimization function.

The third limitation concerns the evacuation transportation mode. This study eliminated evacuees who traveled more than 1000 miles, a reasonable estimate of the maximum distance that households would travel by car. However, people with long distance travel during evacuation times were observed. Evacuees were observed to travel to the west coast, including Los Angeles and Seattle. How to integrate the multiple transportation modes into the evacuation model optimization process requires further investigation.

8. Conclusion

This study responded to the calls for interdisciplinary models for evacuation behavior studies by improving current evacuation destination choice models through integrating social distance with traditional gravity models. It offered a potential solution to the challenge of lacking long-term data for essential social factors for evacuation behavior studies using a traditional data collection method (e.g., survey). The main contributions of this study came from the following three perspectives. First, this study reinforced and extended the important roles of social factors in evacuation modeling by confirming that familiarity with a previously visited place was associated with evacuation destination choice decisions. Second, it developed an approach to quantitatively measure county-to-county social distance using geotagged tweets. Third, it demonstrated how long-term social factors improved the evacuation destination choice model by integrating social distance into the gravity model.

Evacuation mobility patterns are complicated. Hardly could one generic mathematic model accurately represent such patterns. This study sheds light on how long-term traveling information retrieved from social media can quantitatively improve current transportation modeling for evacuation destination choice. With the increasing usage of social media during time-critical situations, methodological development in related research areas should be pushed further. Given the improvement observed in this study, we expected to see more studies using hazard-related social media data for evacuation model improvement.

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