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Data predictive approach to estimate nuisance flooding impacts on roadway networks: a Norfolk, Virginia case study

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Abstract

Climate change and sea level rise have increased the frequency and severity of nuisance flooding events, leading to cascading impacts on roadway networks. While these flooding events are typically low impact and span only a few hours, they consistently cause disturbances in traveller's daily routines. This paper uses the City of Norfolk, Virginia, as a case study area to quantify the impacts of nuisance flooding on the transportation network using empirical data. Using a combination of traditional and crowdsourced data, a data-predictive approach is proposed to expand the spatial coverage and temporal resolution of traffic volume data. The random forest decision tree model specification utilizes roadway features, traffic flow characteristics, and hydrological data to estimate personal vehicle volumes on 7736 segments in the study area. Model outputs suggest that the presence of flooding events consistently reduces network-wide vehicle-hours of travel, with an average reduction in travel of 21%. These estimates are line with the spatially limited ground truth count station volume data, which show an average reduction in traffic volumes by 12% and an average reduction in travel speed by 6%. Results suggest that the impact of nuisance flooding on travellers comes in the form of abandoned trips (decreased travel demand) and increased travel times (due to decreased speeds). The data-predictive framework proposed here can be used to expand the spatial coverage and temporal resolution of other types of transportation data, whether for the purpose of examining impacts of other types of disruptions or routine traffic management strategies.

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Keywords: nuisance flooding; roadway network impact; data predictive model; crowdsourced data

1. Introduction

Rising sea levels and subsequent coastal flooding are increasingly affecting coastal communities across the US. Almost 30 coastal cities have witnessed more than double the number of annual flood days in the 2010s as compared to the 1950s, with more than 10 major cities on the US east coast experiencing a fourfold or greater increase in the

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frequency of flooding (US EPA, 2016). With continued relative sea level rise, nuisance flooding (which can occur in high tide without the presence of a major storm) is expected to occur more frequently, and propagate to more inland locations (NOAA, 2016). There is a growing need to understand the subsequent impacts to people and civil infrastructure (traveller response, frequency and duration of roadway closures, reduction of infrastructure life and stormwater drainage capacity, etc.). The existing literature on transportation disruptions due to flooding are mostly focused on major storms, with much of the research oriented towards evacuation and rehabilitation efforts, and not the recovery of daily transportation activities. Coastal nuisance flooding is considered a minor disruption compared to consequences of catastrophic storms. However, inundated areas in coastal cities greatly deteriorate the mobility of road users, by increasing travel delay and by disrupting the ability to complete trips. A report by NOAA (2014) shows that there is a significant increase in the occurrence of nuisance flooding in the US north-east coast, with most notable changes in sea level rise observed in the tidal gauges in the Chesapeake Bay. This study aims to quantify the transportation impacts associated with nuisance flooding borne by roadway users via a case study of Norfolk, Virginia, using a combination of state agency collected data and crowdsourced data.

2. Background and literature review

Historically, nuisance flooding has been a low-frequency, low spatial- and temporal- scale disruption on the transportation system, considered to have minor impacts. However, nuisance flooding frequencies have changed significantly in the last decade or so, with the Atlantic Coast experiencing the biggest increase in frequency from 2000 to 2015 (75% along the Northeast Atlantic and 125% along the Southeast Atlantic) (US EPA, 2016). The studies examining the impacts of sea level rise on transportation are relatively recent and often include significant data limitations (in temporal or spatial resolution and coverage). Furthermore, the studies rely heavily on projected data, rather than characterizing empirical evidence of impacts. For example, a study conducted by Jacobs et al. (2018) identifies the most vulnerable roads in the Eastern US to the risk of nuisance flooding using Federal Highway Administration's Highway Performance Monitoring System (HPMS) data, combined with flood frequency maps, and future projections of annual minor tidal flood frequencies and durations. The study estimates that the current total vehicle hours of delay due to nuisance flooding at over 100 million hours annually, and projects this delay to increase to 160 million vehicle-hours by 2020 and 1.2 billion vehicle-hours by 2060. As the study notes, HPMS data report annual average daily traffic (AADT), which is not uniformly distributed throughout the day. Further, the study only includes impacts on highways in the HPMS, and ignores urban streets. On a city-wide scale, Suarez et al. (2005) estimates the indirect costs of increased flooding in Boston by examining the effects of coastal flooding due to sea level rise and riverine flooding due to heavy rainfall events. The study simulates these effects in an urban transportation model and projects an increase in delay and lost trips of around 80% in 2100 compared to 2000, with an assumed sea rise level of 0.3 cm per year and an increase in magnitude of heavy rainfall events of 0.31% per year. As a part of a larger study in Portland, Oregon (Chang et al., 2010), an analysis of traffic impacts due to coastal flooding disruptions is conducted. The study uses predicted flooding frequency and locations based on hydrological models to determine impacts of flooding on the roadway network in 2035, using the four-step regional travel demand model (TDM). There was a non-linear relationship found between precipitation and travel disruption impacts. The study predicted a negligible change in vehicle miles travelled (VMT), however, vehicle-hours of delay increased by 10% in one of the sub-areas analyzed. More broadly, Koetse, et al. (2009) presents a literature review of studies on the impact of climate change and weather on transport, and describe several studies which utilize digital elevation models to estimate the inundation risk of transportation networks under various sea level rise scenarios (see, e.g. Wright and Hogan (2008), Kafalenos and Leonard (2008)).

Only a few studies have characterized the impacts of flooding events on transportation systems using empirical data, and these studies focus on large-scale disruptions. For example, New York City taxi and subway ridership datasets were made publicly available for 2010 through 2013, during which hurricanes Irene and Sandy significantly disrupted the transportation and power networks in the area. Zhu et al. (2016) and Donovan and Work (2017) used these datasets to propose new methodologies to quantify city-scale transportation system resilience to extreme events. These studies serve as post-disruption analysis. Zhu et al. presented resilience curves, which showed that Hurricane Sandy had a slower transportation recovery rate than Hurricane Irene. Resilience of the roadway network was found to be better in both disruptions than the subway network. In the post disruption period of Hurricane Sandy, Donovan and Work found an increase in delay of over two minutes per mile about two days after the hurricane had struck, although a faster traffic flow was observed during most of the post-disruption period. A day-to-day traffic evolution process after an unexpected network disruption was modelled in a study conducted by He and Liu (2012). The study proposes a prediction-correction process, where traffic flow and the travel link cost are a weighted average of the expected and experienced traffic conditions after a disruption. Data for this study was obtained from driver behaviour surveys and loop detector data. The process was validated with data from the I-95 bridge collapse in Minneapolis. Authors suggest this traffic assignment method can be utilized effectively for prioritization of traffic flow restoration strategies.

Furthermore, when it comes to cost of flooding on transportation systems, the existing literature focuses on infrastructure damages in major storms like hurricanes Katrina and Rita (see, e.g. Grenzeback and Lukmann (2007), Jacob et al. (2007)). While these damages are significant in major storms, they are not as evident during nuisance flooding. In Norfolk, annual frequencies of nuisance flooding events are accelerating at a quadratic rate, with the number of high tide flood days in 2016 almost double that in 2000 (Sweet et al., 2018). The entire city has an elevation of less than 5 meters from the sea level, making it particularly susceptible to climate change and sea level rise (Kleinosky et al., 2006). It is necessary to estimate the impacts of such flood events from a different perspective. In this study, we utilize 9 months of empirical flooding and traffic data in 2017 to assess the travel impacts for personal vehicles due to nuisance flooding in Norfolk.

3. Methodology and data

The impacts of flooding borne by travellers on a roadway network for this study are accounted for by comparing the vehicle-hours of travel (VHT) on a day with recorded flood event versus days without a flood event. To assess the total vehicle-hours of travel on any day, we estimate the link volumes in the entire roadway network of the study area, and multiply it with the average travel time for that link in the specified time period. Flooded day traffic volumes and vehicle hours of travel are compared with those of non-flooded days, to estimate the network-wide impacts of nuisance flooding. For each flooded day (FD), four non-flooded days (NFDs) are selected to obtain an average NFD link volume. These NFDs are selected from three weeks around the week containing the FD, but not within the same week as the FD, to avoid the pre- and post-disruption effects of a FD on the NFD average link volume. This is somewhat similar to the approach taken by Zhu et al (2016), where the data is compared to the same day in the prior year, to observe differences in traffic flow but account for seasonal traffic variation. Since we only have 9 months of data, we use comparable days within the three week window minimize effects of seasonal traffic variation. The flooding in the study area may occur due to two environmental conditions: high tides or rainfall, or both. The NFDs for a high-tide (but no rainfall) FD are picked as the same type of day (workday or non-workday) with no rainfall within the three week window. For FDs with rainfall, the NFDs are chosen from the same type days that experienced rainfall, but recorded no flooding. Traffic delays occurring due to flooding are evaluated using the equation 2:

$$VHT_{i,j} = (v_{i,j} * tt_{i,j}) \tag{1}$$

$$\Delta\, Travel = \sum_{i,j} [(VHT_{i,j})_{FD} - (VHT_{i,j})_{\,NFD}] \tag{2}$$

Where i= roadway segment
j= time-of-day (TOD)
$\Delta\, Travel$ is the network-wide difference in veh-hrs of travel on a FD compared to NFD
$tt_{i,j}$ = travel time on segment *i* during TOD *j*
$v_{i,j}$= traffic volume on segment *i* during TOD *j*
$(VHT_{i,j})_{FD}$= VHT on segment *i* during TOD *j* on a FD
$(VHT_{i,j})_{NFD}$= VHT on segment *i* during TOD *j* on a NFD

Virginia Department of Transportation (VDOT) collects traffic data at 12 continuous count stations (CCS) on freeways and arterials within the city of Norfolk (locations shown in Figure 1). This data is collected at 15-minute intervals throughout the year. However, due to the limited spatial representation of these 12 count stations, the network-wide effects of flooding events cannot be deciphered. Streetlight Data (founded in 2011) is a commercial platform that provides various types of transportation data such as road segment volume data, origin-destination (OD)

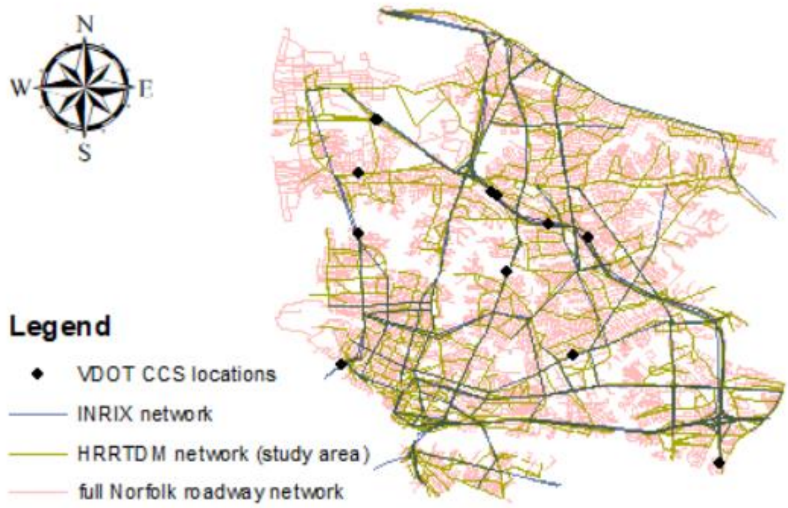

Fig. 1. Roadway network coverage by various data sources.

analysis data, zonal activity data, etc. In this platform, Streetlight (StL) trip indices (estimated link volumes) and travel speeds are projected from signals or pings (called StL trip counts), generated from applications using location-based services (LBS) on mobile phones, tablets, connected cars, and other electronic devices. LBS-data enabled devices are reported to have an approximately 23% penetration rate among all traffic (Streetlight, ND [1]). Thus, with sufficient samples of StL trip counts across the Norfolk roadway network, Streetlight Data is able to provide significantly greater spatial coverage of traffic volume estimates (StL trip indices) compared to the VDOT CCS data. The network links coded in green in Figure 1 show the extent of spatial coverage of Streetlight Data used in this case study. The calibration process of the StL trip indices on these links and in zonal analyses is internal to Streetlight Data as a part of their data cleaning and imputation process, but is disclosed by Streetlight Data to be based on AADT metrics from VDOT roadways in Bristol, VA (Streetlight, ND [2]). Thus, direct application of the StL trip indices may not serve as accurate link volume estimates for Virginia. In fact, on examining the ratio of VDOT CCS volumes to StL trip indices for 35 randomly sampled days in 2017, we found that these ratios were typically closer to 1 during peak periods of travel, but ranged from 0.2 to 26 at other time periods in the day (median value of 1.57). Streetlight Data obtains the speed information on individual links from commercial partner INRIX. To confirm, StL link speed estimates were compared with INRIX data provided by RITIS (a relatively more established commercially available data source which estimates travel speeds and travel times based on location information emitted by GPS-based mobile devices) for two weekdays in March 2017, across all CCS locations for all time-of-day (TOD) periods. There was no statistically significant differences observed when comparing both speed datasets. Thus, this study utilizes a data-predictive approach to transform the raw StL trip counts to estimated traffic volumes, rather than directly using the StL trip indices as traffic volumes. StL link speeds, on the other hand, was directly used as one of the model inputs.

Three different types of input variables are used in developing the predictive model to transform StL trip counts to link volumes for the spatial extent of the study network: roadway, traffic, and hydrological variables. Roadway characteristics consist of geometric features like number of lanes, speed limit, and per lane capacity, which are obtained from the Hampton Roads Regional Travel Demand Model (HRRTDM). Thus, the roadway network analyzed in this study is limited to the links in the HRRTDM data set (shown in green in Figure 1), which includes interstates, other freeways and arterials in Norfolk. Minor streets (minor arterials, collectors and local streets, shown in orange in Figure 1) are excluded. This spatial coverage is significantly greater than the VDOT CCS station coverage, but not as extensive as the StL network coverage. Traffic characteristics include the crowdsourced StL trip counts and speeds, type of day (work day [Monday through Friday] versus non-work day [weekends and holidays]), and TOD (segmented into five periods per day, matching the Streetlight default, and include early AM [12 to 6 am], peak AM [6 to 10 am], mid-day [10 am to 3 pm], peak PM [3 to 7 pm], and late PM [7 pm to 12 am]). Hydrological characteristics include flood, rain gauge, and tidal gauge data. Flood data from the Hampton Road Sanitation District (HRSD) is crowdsourced, and is collected when City of Norfolk employees report the flooded locations on a specific day in a mobile phone application (Sadler et al., 2018). Due to the lack of a timestamp associated with the flood report (only date data), flood data is coded in as a binary variable, with any day with one or more flood reports (number of flood locations in the city) considered a FD and any day without flood reports considered a NFD. Spatial distribution of flood locations is not considered in this model, due to lack of city-wide spatial representation of the small sample of reports for each FD. The rainfall data, collected at 15-minute intervals, comes from HRSD, which has seven stations in the city. Tide level data is available at the sole tidal gauge in the city at Sewell's Point, and data collected every six minutes is archived and obtained by NOAA Tides and Currents. These two datasets are aggregated to match the TODs specified in the traffic data description. Finally, VDOT CCS data are considered as ground truth volumes, and serve as the calibration and validation dataset for the models here. The framework for the overall data-predictive volume estimation is shown in Figure 2.

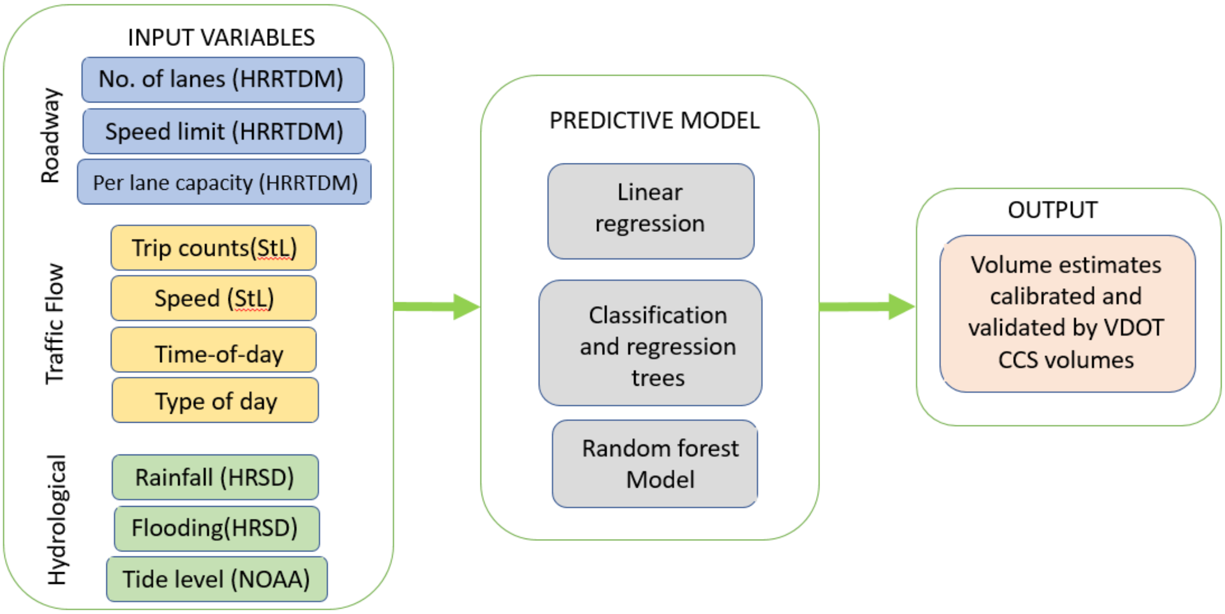

Fig. 2. Data predictive model framework for volume estimation

As seen in Figure 2, several types of predictive models are utilized in this study to predict the link volumes, to check for best prediction accuracy without overfitting the data. We start with the linear regression model to see if there is a linear relation between the variables and the volumes on the roadway. Classification & regression trees (CRT) and Random forest (RF) models, which group data points with similar dependent variable values together based on their independent variables, are also used here. In CRT models, a parent node in the CRT is divided based on any independent variable into two child nodes, such that each child node is more homogenous (or less impure) than the parent node. Homogeneity is measured by the least squared deviation measure of impurity (within-node variance). The process continues until constraints such as minimum number of cases per node, maximum tree depth, node homogeneity, minimum change in improvement are satisfied. In our study, 70% of the observations was reserved for training the dataset, and 30% reserved for validation. Through trial and error, a 50-20 split of data in parent node and child node was used (minimum 50 observations from the dataset in the parent node, and minimum 20 observations in the child node), which was pruned to avoid overfitting. Pruning reduces the size of decision trees, trying to keep the nodes from being very specific, thereby keeping the model more generalized. Random forest models are a step further in decision tree modelling from CRT models. In random forests, similar to the CRT models, a 70-30 split of observations is used for training and testing the dataset, respectively. Random sampling of subsets of data is performed on the training dataset, to fit these samples into a model prediction, while reducing the total error in the model. The response variables are divided into groups until the resulting predictions reach a minimum amount of node impurity (sum of squared deviations between predicted and actual value, a certain type of error). Random forest is a preferred method because it introduces randomness into the model, as opposed to CRT, which greedily searches for the best predictors to create subsets. CRT models are also prone to overfitting of the data, and random forest addresses the issue by creating various random groups of randomly selected regression trees while running the model. Once the model is developed, errors are calculated for training and testing data, which is used as a criterion for selection of the appropriate model. Errors calculated for these models are Root mean squared error (RMSE) and normalized root mean squared error (NRMSE), given by equations 3 and 4.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(v_{obs,i}-v_{model,i})^2}{n}} \quad (3)$$

$$NRMSE = \frac{RMSE}{v_{obs,max} - v_{obs,min}} \quad (4)$$

Where i= observations in the dataset
n= maximum number of observations in the dataset
$v_{obs,i}$=observed VDOT CCS volumes
$v_{model,i}$=predictive model's estimated volumes

4. Results and discussion

4.1. Continuous Count Station (CCS) trend analysis

To understand the baseline roadway network impacts due to flooding, the variation of traffic across all VDOT CCS locations with available data were compared. The CCS are strategically placed on major arterials and freeways where there are no historic congestion/bottlenecking issues, to ensure accurate volume estimates. Due to the specific location selection criteria and sparse spatial representation of CCS across Norfolk, an accurate estimation of the flooding impacts throughout the network cannot be made, but general trends can be observed. The CCS volumes and speeds on FDs are compared with their respective NFD counterparts, per the methodology described. The data is compared at 15-minute intervals for the 24-hour day, then aggregated over eight FDs in the 9 month study period. A two-sample one-tailed paired Student's t-test was conducted to observe the patterns, and the p-values for volume and speed comparisons are summarized in Table 1.

Table 1. CCS volume and speed trends.

# Count Station	Facility type	FD average volume (veh)	NFD average volume (veh)	% change volume	Volume p-value	FD average speed (mpg)	NFD average speed (mph)	% change speed	Speed p-value
1	Principal Arterial	188.35	210.80	-11%	<0.0001	37.64	38.77	-3%	<0.0001
2	Freeway	709.50	789.70	-10%	<0.0001	59.94	62.10	-3%	<0.0001
3	Freeway	594.59	655.47	-9%	<0.0001	60.00	62.44	-4%	<0.0001
4	Freeway	553.78	627.52	-12%	0.0001	71.91	77.76	-8%	<0.0001
5	Principal Arterial	79.76	96.60	-17%	<0.0001	34.85	40.04	-13%	<0.0001
6	Principal Arterial	91.77	111.75	-18%	<0.0001	35.52	38.63	-8%	<0.0001
7	Principal Arterial	174.11	188.87	-8%	<0.0001	36.84	39.01	-6%	<0.0001
8	Principal Arterial	144.77	160.87	-10%	<0.0001	36.19	37.14	-3%	<0.0001
9	Principal Arterial	98.32	109.86	-11%	<0.0001	43.84	48.55	-10%	<0.0001

Results from Table 1 show that links volumes and speeds on the freeways and principal arterials at CCS locations are statistically significantly lower on FDs than on NFDs (all p values <0.05). On average, traffic volumes decreased by 12% and speeds decreased 6% on a FD compared to NFDs. This result suggests that traffic demand is lower on FDs. At the same time traffic volumes are decreasing, those who are traveling on FDs also experience increased travel times.

4.2. Traffic volume model training and validation

While general trends of traffic impacts of nuisance flooding can be observed with the CCS data, a network wide impact assessment requires more spatial coverage. Here, the proposed data predictive model (using agency provided roadway characteristics and weather data along with crowdsourced traffic flow and flood data) estimates volumes across all freeways and arterials in Norfolk. The dataset used for model calibration (training) and validation (testing) consists of all the input variables and traffic count data from all CCS for 35 randomly selected days (approximately 13% of total days during study period), with different environmental conditions as shown in Figure 3. The days with flooding but no rainfall is an indicator of flooding due solely to high tide levels.

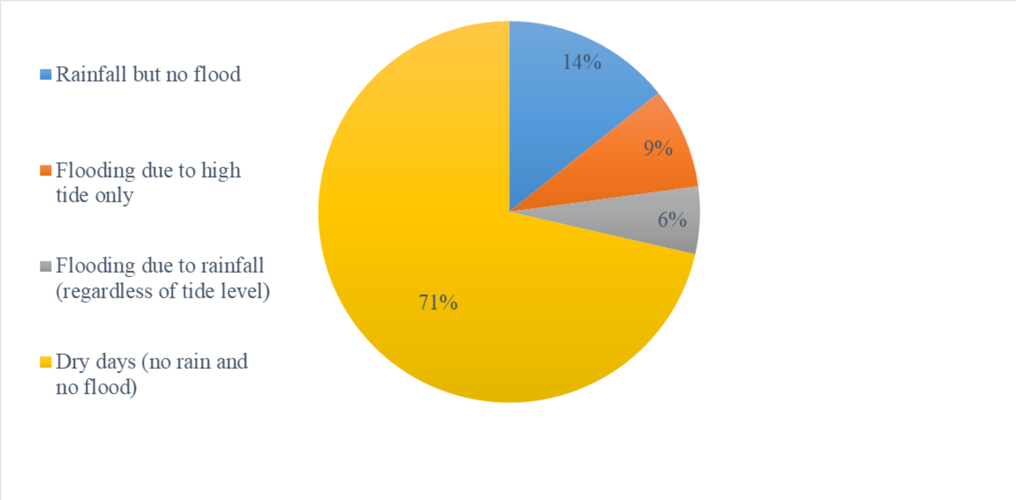

Fig. 3. Distribution of type of days within calibration dataset.

Linear regression and CRT models were calibrated with all the variables previously mentioned in the three categories: hydrological, roadway, and traffic flow characteristics. The model fit results (RMSE and NRMSE values), along with statistically significant variables, are shown in Table 2 for comparison across models. StL trip indices were also compared against the ground truth CCS data. As seen in the model fit results, the two random forest model specifications outperformed linear regression and CRT. For random forest models, the first model (RF1) uses only the roadway and traffic flow characteristics as input variables. In this model, the StL dynamic crowdsourced trip counts had less importance than some other static variables like number of lanes and type of day, which is counterintuitive. When the hydrological variables are introduced into the random forest mode specification (RF2), tide level and rainfall were found to be the least important variables, but the StL trip count became the highest significance variable, which is intuitive. The final model specification's (RF2) relative variable importance is shown in Figure 4. Other relatively high importance variables describe patterns associated with traffic flow in specific environments, such as TOD, per lane capacity, posted speed limit, and link speed. This model specification also proved to be the best performing (lowest RMSE and NRMSE), as seen in Table 2.

Table 2. Model fit summary.

Model Type	RMSE	NRMSE	Significant/ high importance variables	Insignificant/low importance variables
Streetlight Data	5067.53	0.253		

model				
Linear Regression	2384.43	0.085	Rainfall Tide level Flooding Number of lanes Posted speed limit TOD StL trip count	Per lane capacity Segment speed Type of day
CRT	2512.22	0.157	StL trip count Posted speed limit TOD	Rainfall Tide level Flooding Number of lanes Per lane capacity Segment speed Type of day
RF1 with roadway and traffic characteristics	Train: 679.80 Test: 1419.09	Train: 0.026 Test: 0.058	TOD Per lane capacity StL trip count	Number of lanes Type of day
RF2 with roadway, traffic, and hydrologic variables	Train: 683.20 Test: 1315.40	Train: 0.026 Test: 0.054	StL trip count TOD Per lane capacity Posted speed limit	Type of day Tide level Rainfall

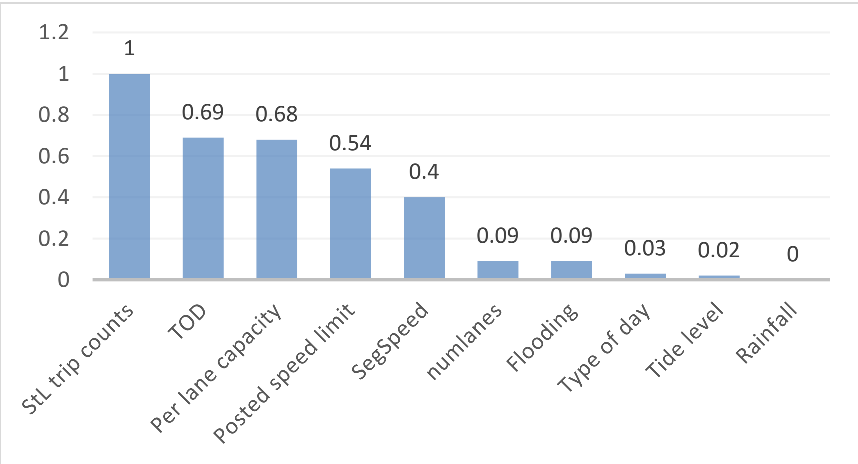

Fig. 4. Relative variable importance in RF2 model specification.

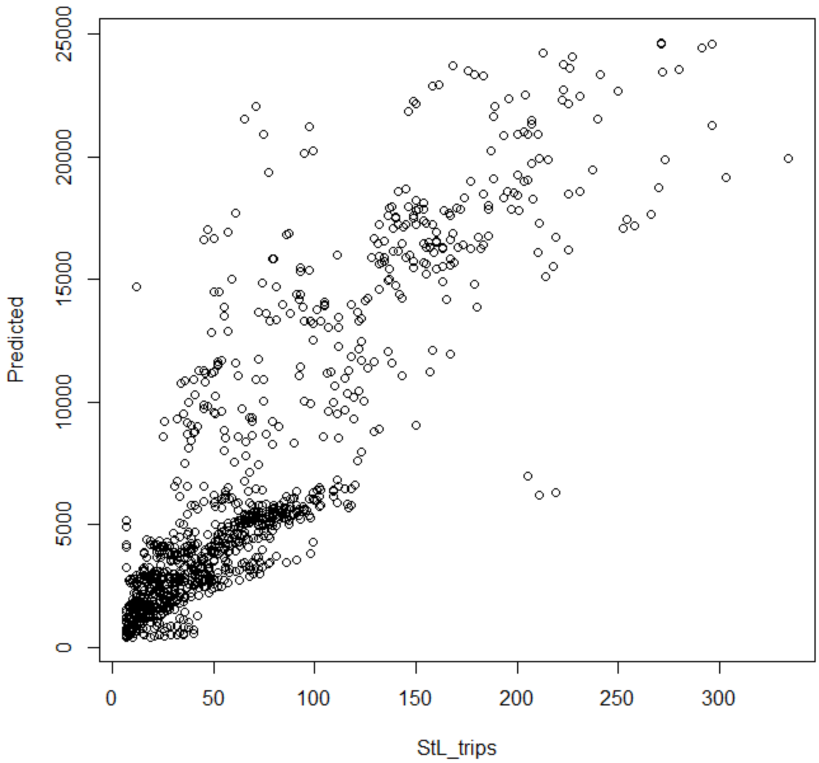

Fig. 5. Relationship of StL trip counts with predicted volumes.

Figure 5 demonstrates the high correlation between StL trip counts and predicted segment volumes in the RF2 model specification. In fact, a linear regression of the two variables reveals a R^2 of 0.75.

4.3. Roadway network impacts

The RF2 model is then propagated to the HRRTDM roadway network in Norfolk, to predict the volumes on each roadway segment all TODs. The HRRTDM roadway network consists of 7736 segments, which were input into Streetlight Data to retrieve the associated StL trip counts, segment speed, and travel time on each segment. StL trip counts and segment speed, along with other roadway and hydrological variables, were used as input into the random forest model and run in R to obtain volume estimates on FDs and NFDs. Total vehicle-hours of travel on FDs and NFDs are calculated per Equation 2. There were 9 flooded days recorded by City of Norfolk (3.4% of total days in the dataset). Table 3 shows the total vehicle-hours of travel on each FD compared to the corresponding NFDs. One of the FDs was discarded due to insufficient comparable NFDs within the three weeks window. Number of flood reports refer to the number of geographic locations that were reported by City of Norfolk employees on the respective day.

Table 3. Roadway network impact summary (RF2 volume estimations).

Date	# Flood Reports	Rainfall (in)	Tide Level (ft)	VHT- FD (veh-hrs)	VHT- NFD (veh-hrs)	Δ Travel (veh-hrs)	% change VHT
1/2/2017	3	3.01	1.32	1,084,946.20	895,399.45	189,546.75	21.17%

1/8/2017	1	0.00	1.18	1,070,563.50	1,172,391.75	-101,828.25	-8.69%
3/31/2017	4	0.00	1.91	968,877.00	1,183,950.28	-215,073.28	-18.17%
7/18/2017	9	0.00	1.68	915,124.80	1,167,259.25	-252,134.45	-21.60%
8/7/2017	2	0.01	1.62	780,751.70	1,055,261.68	-274,509.98	-26.01%
8/29/2017	40	5.84	3.84	937,688.10	1,164,132.88	-226,444.78	-19.45%
9/8/2017	1	0.00	1.71	797,361.40	1,114,960.98	-317,599.58	-28.49%
9/26/2017	1	0.15	3.12	933,571.12	1,232,670.68	-299,099.56	-24.26%

Table 3 shows that based on the predicted vehicle volumes and StL travel speeds, the network wide vehicle-hours of travel were consistently reduced on a FD compared to NFDs, with the exception of the first FD. The first FD in the dataset is the day after New Year's Day, which, despite technically not being a holiday, may have different travel patterns compared to a typical work day. On an average FD, total network-wide VHT was reduced by 21%, compared to NFDs (excluding the first FD). This is likely due to an overall reduction in travel demand on FDs, as seen in the CCS data. In contrast, Table 4 presents the impact of flooding when StL trip indices are used.

Table 4. Roadway network impact summary (StL trip indices).

Date	# Flood Reports	Total Rainfall (in)	Average Tide Level (ft)	VHT- FD (veh-hrs)	VHT – NFD (veh-hrs)	ΔTravel (veh-hrs)	% change VHT
1/2/2017	3	3.01	1.32	103,634.45	189,225.87	-85,591.42	45.23%
1/8/2017	1	0	1.18	182,267.87	274,980.21	-92,712.34	-33.72%
3/31/2017	4	0	1.91	228,454.04	229,804.91	-1,350.87	-0.59%
7/18/2017	9	0	1.68	191,282.75	156,912.89	34,369.86	21.90%
8/7/2017	2	0.01	1.62	186,418.79	155,979.69	30,439.10	19.51%
8/29/2017	40	5.84	3.84	128,914.17	170,345.77	-41,431.59	-24.32%
9/8/2017	1	0	1.71	122,055.25	174,379.68	-52,324.43	-30.01%
9/26/2017	1	0.15	3.12	180,104.44	172,718.66	7,385.78	4.28%

Contrasting Table 3 with Table 4, we can see that that StL trip indices range between 10% to 25% of RF2 volume estimates, as link travel times used to calculate VHT in both tables are from the same dataset. Unlike Table 3, Table 4 shows inconsistent impact of flooding on network-wide VHT. On average, StL trip indices indicate that there is a 6.32% decrease in VHT on a FD compared to NFDs, but the range varies from a reduction of 33% to an increase of 21%. Considering the consistent reduction in traffic volumes and travel speeds at the CCS locations on FDs, the consistent pattern of VHT decrease in the RF2-based estimates seem more reasonable than the StL trip indices-based estimates. Decreased VHT on the roadway network may imply higher rates of abandoned trips, which would signify an economic impact of nuisance flooding (decreased business transactions, work productivity, etc.). Since the sample of flooded days is small (N=8), Figure 6 is shown to demonstrate the relationships between hydrological variables and estimated reductions in network-wide VHT. In Figure 6, normalized values for rainfall, tidal level and number of flood reports (locations) are shown with reduction in VHT (on a FD compared to NFDs), as estimated by the RF2 model. Figure 6 suggests that generally speaking, an increase in either tide level or rainfall level increases the reduction in VHT on a FD. This may suggest more trips are abandoned with an increase in tide or rain level. The flooding day on August 29 shows an anomaly, where despite high rain and tide levels, the reduction in VHT was not as high as other FDs. The dip in the percentage reduction of VHT in the figure can be explained by examining the day from Table 3, where it is evident that the NFDs around August 29 exhibited low VHT compared to the other NFDs throughout the study period.

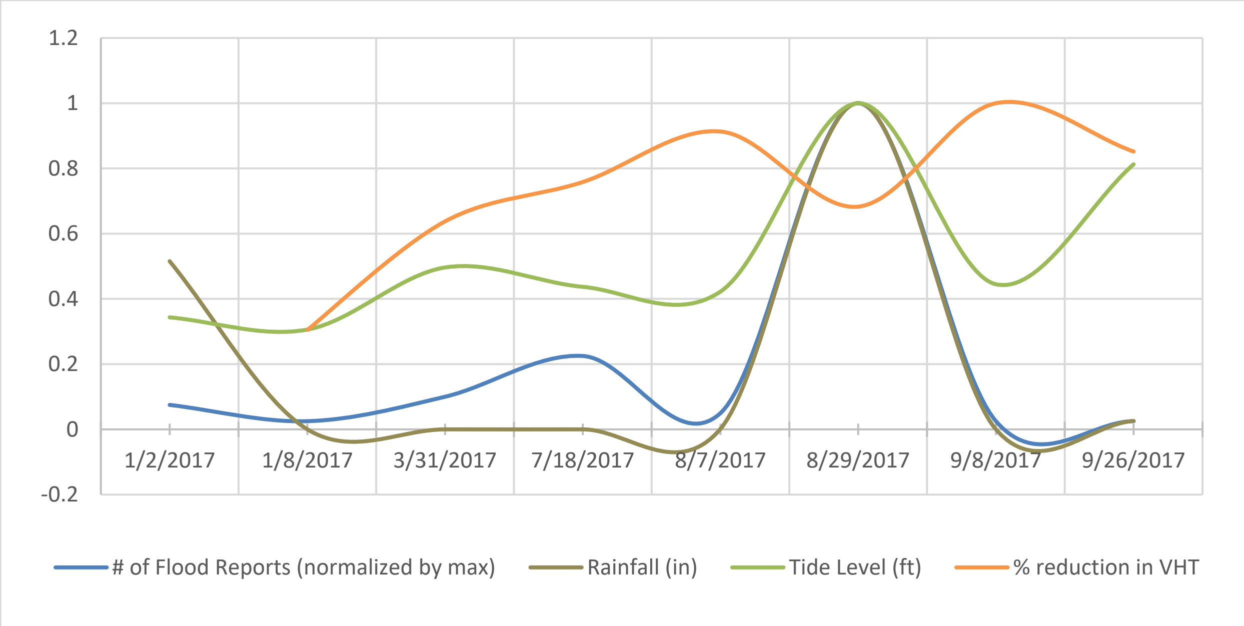

Fig. 6. Normalized comparison of roadway network impacts by date.

5. Conclusions and Limitations

Nuisance flooding is becoming increasingly frequent in coastal cities, especially in eastern coast of the US. In this study, we quantify the impacts of nuisance flooding on the transportation network in coastal Norfolk, Virginia using a data predictive approach. Limited studies have used empirical data to quantify transportation impacts of flooding due to spatial and temporal limitations of traditional transportation data sources. In this study, we supplement the spatially sparse traffic volume data (obtained at VDOT CCS locations) with predicted link volumes derived from a random forest model using crowdsourced data from LBS devices (StL trip counts), in combination with roadway characteristics and hydrological data. This allows us to expand the spatial extent of the 9 CCS locations to 7736 roadway segments throughout Norfolk. Model results estimate a consistent decrease in network-wide VHT on FDs as compared to NDFs in the same time period, with an average decrease of 21%. A decrease in VHT can imply a decrease in traffic demand, speed, or both. On examining traffic volume and speed patterns on FDs and NFDs only at the CCS locations, traffic volumes decreased on average 12% while travel speeds decreased on average 6%. These results imply that the impact of nuisance flooding on travelers in Norfolk is two-fold. First, it is likely that a travel demand is significantly reduced on a FD as compared to a NFD, implying that travelers are abandoning trips in the face of flooding (with subsequent economic opportunity costs due to productivity loss, reduction in business transactions, etc.) Secondly, for travelers choosing to travel on a FD, speeds are likely reduced, causing longer travel times (and again productivity loss).

This study is a first foray into examining the transportation impacts of nuisance flooding using empirical data. The methodology proposed here can provide the basis for estimating transportation impacts of all types of disruptions, such as accidents, construction-related lane closures, etc. While the data-predictive approach enhances the limited traditional transportation data sets, it comes with many limitations. First, the flood variable in the random forest model specification is binary, due to lack of temporal and spatial intensity information in the HRSD flood data set. Second, this HRSD flood dataset does not include all nuisance flooding disruptions, as it is biased towards the larger of the nuisance flooding events. This may bias our results, as road users prefer to not travel when there is heavy rainfall or high tide events, given historic vulnerability of roads to such events in the city. In future work, use of emerging crowdsourced datasets such as Waze data, which can identify disruptions by cause (e.g., accident versus flooding) and provide duration information for the disruption, would be able to better capture the impacts of nuisance flooding. Further, our dataset consists of personal vehicles only, ignoring impacts on freight movement. Freight transportation tends on schedule, and diversion from their regular schedule incurs significant economic cost due to greater value of travel time, which has not been quantified in this study. Lastly, since our study focuses on network-wide impacts of these flooding events, it is assumed that hydrological variables (flooding, tide level, and rainfall level) was uniform throughout the city, due to lack of availability of spatially heterogeneous data.

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