Investigating the Use of Citizen-Science Data as a Proxy for Flood Risk Assessment in New York City

Riccardo Negri
PhD Candidate, Center for Urban Science and Progress, New York University, New York, USA

Megan (Meg) Fernandez
Undergraduate Student, Tandon School of Engineering, New York University, New York, USA

Yi-Jen (Jennifer) Tsai
Undergraduate Student, New York University Abu Dhabi, Abu Dhabi, UAE

Bing Yan Tan
Masters Graduate Student, Center for Urban Science and Progress, New York University, New York, USA

Luis Ceferino
Assistant Professor, Civil and Urban Engineering Department & Center for Urban Science and Progress, New York University, New York, USA

ABSTRACT:

New York City (NYC) has an extensive waterfront and numerous low-lying neighborhoods that make it highly exposed to the impacts of extreme weather events. With global warming increasing the frequency and intensity of these events, the NYC government has created *Stormwater Flood Maps* to assess flood hazards and manage risks, informing residents and government agencies on potential flood disruptions. However, these maps rely on complex Hydrological and Hydraulic (H&H) models, which require expensive computational resources and may not always accurately reflect the built environment, e.g., urban surface, the stormwater system. This study investigates the potential of citizen science data, specifically 311 service requests, as a tool for understanding and quantifying flood hazards and risks and complementing H&H models. 311 service requests provide novel and unique information for urban flood risk characterization as they are community-generated, updated daily, and geo-referenced, allowing for near-real-time insights into the changing flood risk landscape across the city. By analyzing data from Hurricane Ida in 2021, we found a moderate correlation (Pearson coefficient $\rho = 0.56$) between the number of 311 requests related to flooding and the level of risk, estimated using the Stormwater Flood Map. Further, we characterized performance variations of 311 data as a proxy for risk across the city, revealing that some high-risk census tracts had only a limited number of 311 service requests, while other low-risk areas recorded a high volume of requests. This result highlights potential inconsistencies between the traditional H&H models and actual flood conditions, and underscores the value of citizen-generated data in characterizing flood risk. However, H&H models are conditional on design event characteristics which may differ from the specific events recorded by 311 requests (e.g., Hurricane Ida), making direct comparisons more nuanced. Additionally, 311 data may be subject to reporting bias influenced by factors such as socio-economic status, location, and time of day. To address these limitations, we outline future studies to improve the accuracy of this methodology.

1 BACKGROUND AND MOTIVATION

New York City (NYC) is a coastal city, situated on a complex network of rivers, estuaries, islands, and waterways. While the coast has provided many resources that gave rise to diverse communities along the waterfront, it also makes NYC exposed to various forms of flooding, including coastal, tidal, inland (flash), and riverine flooding (Van Lenten et al., 2014). Multiple natural and human factors influence the risk of flooding, including the likelihood of flood events, the geography of the shoreline (elevation, slope, and shoreline conditions), and the city's infrastructure networks and land use. Global climate models already predict an increase in storm intensity due to higher ocean water evaporation, resulting in more concentrated rainfall (Colbert, 2022). In addition, while most models do not show a significant increase in storm frequency, they predict an increase in the proportion of tropical storms that reach intense levels (category 4 or 5) (Knutson, 2022). This phenomenon is exacerbated by increasing urbanization and the extension of impervious surfaces. With the impact of global warming causing increased precipitation, and urbanization exacerbating the issue, the risk of flash flooding in NYC is rapidly rising, particularly due to its coastal location and heightened exposure to meteorological events from the ocean. In 2021, Hurricane Ida struck NYC, causing inland flash flooding in several parts of the city and taking the life of 13 people (Newman et al., 2021). Hurricane Ida set a new record for hourly precipitation, with 3.15 inches of rainfall released between 8:00 and 9:00 PM, surpassing any historical record (Plumer, 2021).

This study tests the use of citizen-science data as a proxy to estimate flood risk in NYC. More specifically, we use flood-related 311 service requests issued and recorded by the NYC Government during Hurricane Ida, and compare their predictions of flood risk with estimates obtained using Hydrologic & Hydraulic (H&H) models. H&H models, which are key to estimating flood hazards and risk, rely on several factors such as soil properties, land use and cover, and sewage system features. These parameters can be difficult to determine and vary over time. The NYC Department of Environmental Protection (DEP) has developed H&H models to simulate the flow of rainwater over the ground surface and within the sewer pipes. The NYC DEP's entire H&H model, composed of 13 sub-models, takes several days of processing time to calculate pluvial flooding and sewer system overflows across NYC (NYC Department of Environmental Protection Bureau of Wastewater Treatment, 2012). On the other hand, the use of citizen science data is growing among various communities, including scientists, city government agencies, and engineers. The information collected through citizen science efforts has proven to have tremendous potential to support research and inform decision making across various fields, as demonstrated in an effort to map the most relevant Citizen Science projects voted to disaster risk reduction (Hicks et al., 2019). Citizen science not only provides valuable data sets, but also increases public engagement and awareness in science and research by involving the public in data collection (de Sherbinin et al., 2021). Thus, this paper assesses whether 311 service requests, which are user-generated, updated daily, and geo-referenced, could serve as a useful complementary tool to estimate flood risk in cities due to their accessibility and ease of use.

2 DATA

2.1 *Stormwater flood maps*

New York City's Stormwater flood maps were developed to help the NYC government understand the effects of rainfall-induced flooding in the current and future climates. Two flood scenarios are provided for inland flash flooding: moderate and extreme. The moderate scenario assumes a rain pour of 2 inches in an hour (10% probability of occurrence in NYC). In comparison, the extreme one assumes 3.5 inches of rain in an hour (1% probability of occurrence in NYC) (NYC Mayor's Office of Resiliency, 2021). The flood maps consider both current and future sea levels. Predictions about future sea levels, based on the outcomes of the New York Panel on Climate Change, include the moderate scenario in the future year 2050 (2.5 feet of sea level rise, 90th percentile estimate for the 2050s) and the extreme scenario in the future year 2080 (4.8 feet of sea level rise, 90th percentile estimate for the 2080s). Flooding in future scenarios results from the compounded effects of rainfall, potential blocked storm drains, and outfalls from sea level rise. In total, there are three distinct maps: moderate rain event with current sea level, moderate rain event with 2050 expected sea level rise, and extreme rain event with 2080 expected sea level rise. Each map distinguishes between areas subjected to deep flooding (1 ft and more) and those subjected to nuisance flooding (from 4 inches to 1 ft). For this study, we used the Stormwater flood map corresponding to an extreme rain event and the 2080 expected sea level rise, including only the deep areas. We take these maps as a reference because Hurricane Ida's rainfall in NYC had a return period of approximately 100 years, according to JBA Risk Management. The maximum hourly rainfall during the storm was close to the value used to model the extreme storm scenario, which was 3.15 inches compared to the modeled value of 3.5 inches.

2.2 *Citizen Science Data: 311 service requests*

The 311 database is a collection of service requests recorded by NYC residents, which is accessible through NYC OpenData. 311 is a non-emergency number that alerts municipal services to address infrastructural issues ranging from noise complaints to parking violations. Each service request, or complaint, contains data on the date the complaint was filed, the type of complaint, a brief description, and the complaint's location (City of New York, 2023) .

2.3 Census Tracts Demographics

The United States Census Bureau provides datasets that contain information about the population and boundaries of Census Tracts (CTs). These datasets are created through the decennial census and the American Community Survey and provide detailed demographic information about the residents of a specific geographic area.

2.4 Map PLUTO

MapPLUTO is a dataset created by the NYC Department of City Planning that provides comprehensive land use and zoning information for all properties in NYC. The dataset includes information such as tax lot boundaries, address ranges, and zoning designation for each property, as well as a variety of other attributes such as community district, borough, and CT information. We combined this dataset with the CTs Demographics to estimate the number of tax lots potentially impacted by a flood.

3 METHODOLOGY

3.1 Literature review

User-generated data, such as messages posted on social media, incident reports from satellite navigation apps, and non-emergency service requests, have been used extensively during the past decade to study different phenomena. Earlier research has utilized this dataset to train models that anticipate flood-related 311 service requests, incorporating both topological and demographic variables as predictors. (Agonafir et al., 2022). Other works have analyzed flood-related 311 calls issued during a severe weather event, studying their geographical distribution and the demographics of the issuers (Rainey et al., 2021; Oliva & Olcina, 2022). Flood-related calls have also been compared with rain measurements, finding significant spatial correlations between the number of calls and the precipitation intensity (Smith & Rodriguez, 2017). All these studies conclude that 311 service requests are good indicators of flooding, and can sometimes provide better information than H&H models. In our analysis, we estimated pluvial flood risk in two different ways: with 311 service requests and with the Stormwater flood maps. By comparing the outcomes of the two alternative analyses, we study if 311 service requests are a reasonable proxy to estimate risk and analyze the underlying factors that determine their accuracy.

3.2 Method

3.2.1 Defining Risk

In our analysis, we start measuring the flood risk of each CT using three different metrics. First, we select the tax lots in Map Pluto that spatially overlap (even partially) with the Stormwater flood map. Then, for each selected tax lot, we determine the number of associated buildings and residents. Finally, we aggregate these three quantities (number of residents, number of buildings and number tax lots overlapped with the Stormwater flood map) at CT level, obtaining three different metrics of risk. Figure 1 shows the outcome of the selection process in QGIS.

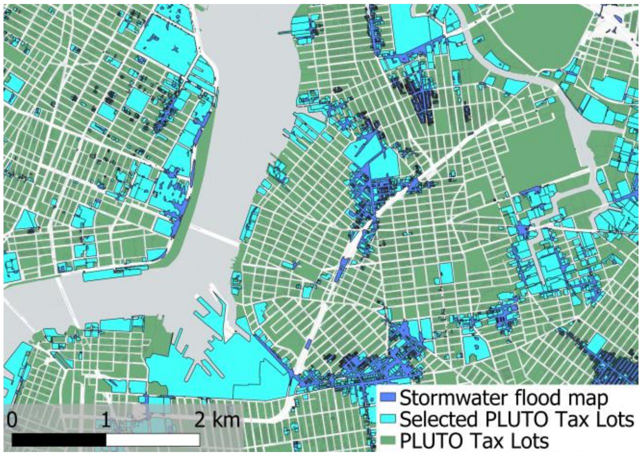

Figure 1: Map Pluto full dataset (green) and Map PLUTO selected features (light-blue) overlapping with the Stormwater flood map (dark-blue).

3.2.2 Count of flood-related 311 service requests

To determine the correlation between flood risk and the number of flood-related 311 service requests, we examine requests made during Hurricane Ida from September 1st to September 3rd, 2021 (Figure 2). By filtering the data for entries containing keywords such as 'Sewer,' 'Water System,' 'Storm,' and 'Standing Water,' we count the number of flood-related requests in each Census Tract. Figure 3 shows a flowchart that outlines the process of selecting relevant 311 service requests from the entire dataset. It is important to note that while Hurricane Ida had a maximum rainfall intensity comparable to that used in the stormwater flood map, other event characteristics may differ, which can limit the direct comparison between the map and the 311 reports for a single event.

For example, the H&H model that generated the stormwater flood map assumed a uniform rainfall intensity, while in reality, intensity varies spatially and temporally. Also, the tide level is another key input of the H&H model. High tide levels reduce the outflow of the stormwater system, affecting its ability to drain stormwater. The tide level during Hurricane Ida may be different from that assumed in the model, which can further impact the accuracy of the comparison. These must be taken into account when interpreting the results of the analysis. In the limitations section, we suggest some measures that future studies can adopt to overcome these issues.

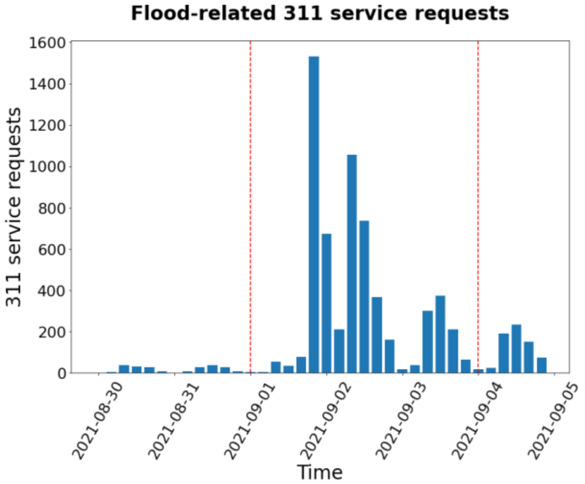

Figure 2: Flood-related 311 service requests issued at the turn of Hurricane Ida. The red dashed lines indicate the time window of our analysis (Sep. 1st - Sep. 3rd).

3.2.3 Correlation between flood risk and number of 311 service requests

To visualize the relationship between flood risk and the number of 311 service requests, we create a scatter plot, with each point representing a census tract. The horizontal axis displays the number of flood-related 311 service requests made, while the vertical axis represents the level of risk, which was defined by the number of residents, the number of buildings, and the number of tax lots that intersect with the Stormwater Flood Map. We then calculate the correlation coefficient ρ between the two variables.

3.2.4 Analysis of census tracts distant from the regression line

In this analysis, we focus on CTs that deviate from the regression curve obtained from plotting the number of flood-related 311 service requests against the number of tax lots. We consider a shaded area of ± 0.75 standard deviations around the curve and examine the CTs that fall outside this range. We use 0.75 (total width of 1.50 standard deviations) so that the CTs outside it make up 25% of the sample. We visualize the points outside the shaded area using QGIS to examine the characteristics of the corresponding CTs and the H&H model predictions.

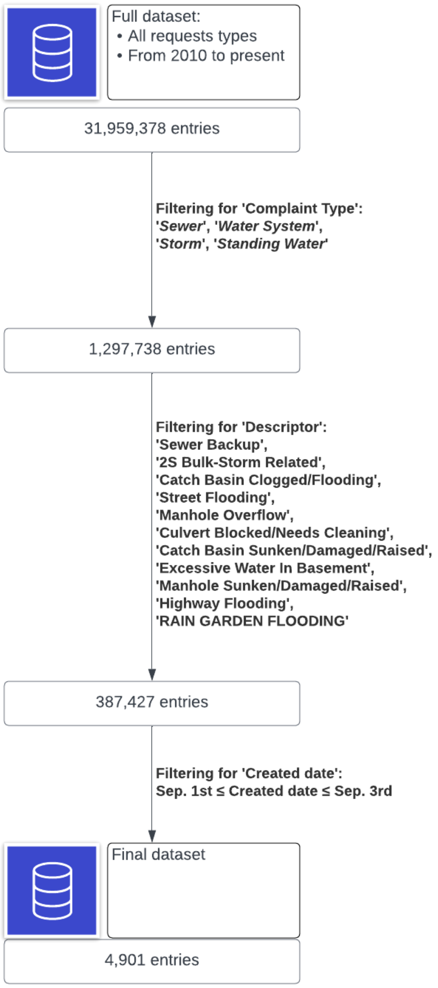

Figure 3: Flowchart illustrating the filtering process of the 311 dataset.

4 RESULTS AND DISCUSSION

Our findings indicate a moderate correlation ($\rho = 0.560$) between the number of flood-related 311 service requests and the number of tax lots at risk of flooding, as defined by the Stormwater flood map (Figure 6). The correlation is slightly weaker when we define risk by the number of buildings ($\rho = 0.471$) (Figure 5). We also found that there is no correlation ($\rho = 0.075$) when defining risk by the number of residents (Figure 4). The moderate correlation (Pearson coefficient $\rho = 0.560$) between the number of tax lots included in the Stormwater flood map and the number of 311 service requests issued during the passage of Hurricane Ida indicates that flood-related 311 service requests can be used as a proxy to estimate flood risk at Census Tract Level.

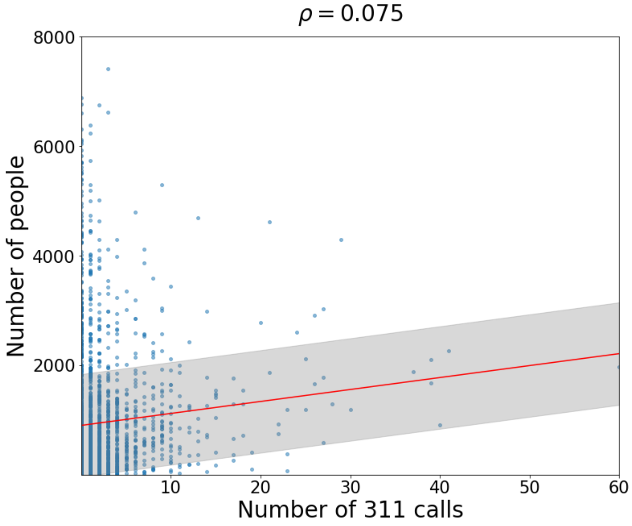

Figure 4: Correlation between 311 Calls and Number of Residents within the Stormwater flood map (each blue dot represents a CT; the red line ithe linear regression).

A possible explanation for the insignificant correlation between the number of flood-related 311 service requests and the number of residents in a given area during Hurricane Ida is that only ground-floor dwellings are directly impacted by flooding. As a result, an increase in population density due to a greater number of floors does not necessarily translate into a corresponding increase in the number of 311 service requests, especially in NYC, where many people reside in high-rise and medium-rise residential buildings.

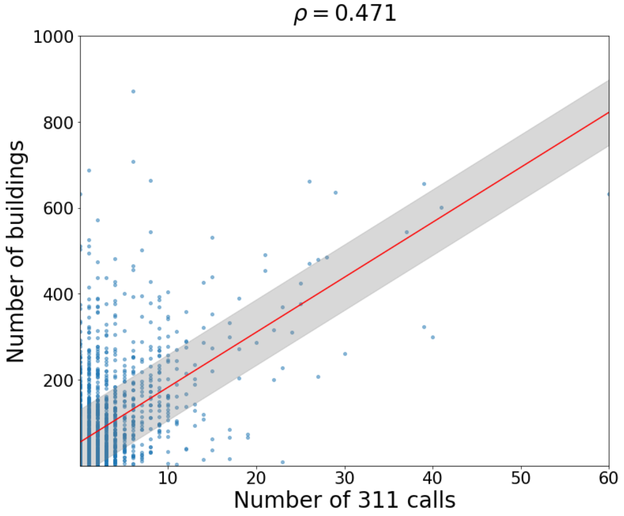

Figure 5: Correlation between 311 Calls and Number of Buildings within the Stormwater flood map (each blue dot represents a CT; the red line is the linear regression).

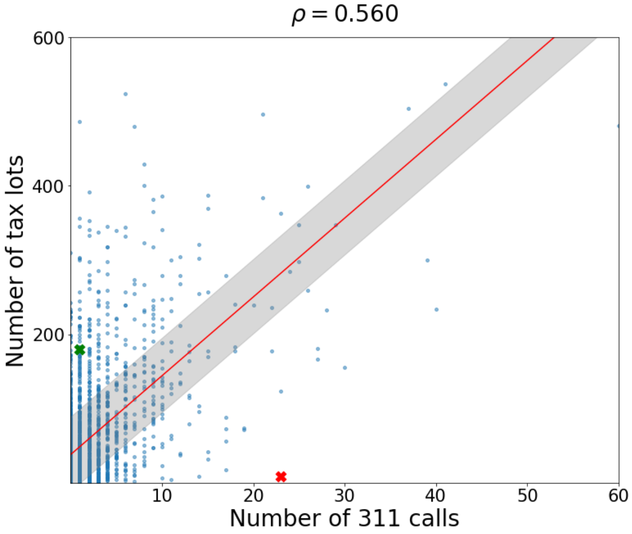

Figure 6: Correlation between 311 Calls and Number of Tax Lots within the Stormwater flood map (each blue dot represents a CT; the red line is the linear regression).

For tax lots, the risk metric that shows the strongest correlation with 311 service requests, we study the CTs that deviate from the regression line in more than 0.75 standard deviations, i.e., outside the shaded area in Figure 6. Out of a total of 2079 CTs, 517 lie outside the shaded area (25% of the total). Our examination of these CTs aims to uncover any potential discrepancies between the H&H model and real flood conditions. We found 197 CTs (10%) below the shaded area, i.e., with a high number of 311 service requests and low risk areas according to the Stormwater Flood Map. We present one of these CTs (highlighted in red in Figure 6), located in Brooklyn near the Gowanus channel, to illustrate discrepancies between H&H models and 311 calls (Figure 7). From September 1st to 2nd, 21 flood-related 311 service requests were issued from this CT. They are all concentrated within one block of houses, indicating that the block experienced flooding. Despite this high volume of requests, the extent of the Stormwater flood map coverage in this area is limited, with only 9 out of 506 tax lots (less than 2%) being identified as at risk. The lots included in the Stormwater map are not the ones that issued the service requests. The ratio between the number of tax lots and 311 service requests in this CT is 0.43, while the average ratio for points within the shaded area is 12.80. The discrepancy between the results obtained from the analysis of 311 service requests and the H&H models is noteworthy as the precipitation intensity experienced during Hurricane Ida was similar to the level used in the Extreme Scenario of the Stormwater model (3.15 inches compared to 3.5 inches per hour). On the other hand, we found that 320 CTs are above the shaded area (15% of the sample), i.e., with high risk of flooding according to the Stormwater Flood Map but with only a limited number of 311 service requests. Figure 8 shows one of these CTs in Southern Brooklyn, near Coney Island. We observe that 180 of its 416 tax lots (43%) are within the Stormwater flood map. However, during the storm, only two 311 service requests related to flooding were issued from that location. This discrepancy suggests that Ida's flooding covered less area than the Stormwater Map in this CT. While Ida reached slightly lower precipitation than the one considered in the Stormwater Map (3.15 inches maximum hourly rainfall during Ida v.s. 3.5 inches for the H&H model), the large discrepancy (46% lots predicted to flood vs. 2 requests) may indicate that the H&H model is overestimating flood hazards in the CT.

The findings from this study can have important implications in the use of citizen science for the NYC Department of Environmental Protection, the owner of the H&H model. The results point to the areas where collecting better built environment data could improve the accuracy of the H&H model in reflecting actual flood patterns, e.g.,in CTs that deviate largely from the 311 requests. In response, the NYC Department of Environmental Protection may also choose to install flood-monitoring sensors in these areas to assess the accuracy of their flood predictions and gather more data to inform future decision-making in these regions. For example, the NYC FloodNet project is already enhancing the understanding of local flood patterns through the deployment of real-time flood depth sensors at ultra-local geographic scales (Silverman et al., 2022). The framework outlined in this paper can provide guidance on where to strategically place these sensors with the goal of improving the predictions of the H&H model.

Figure 7: CT where the H&H model might be underestimating the flooding risk (also indicated in red in Figure 6).

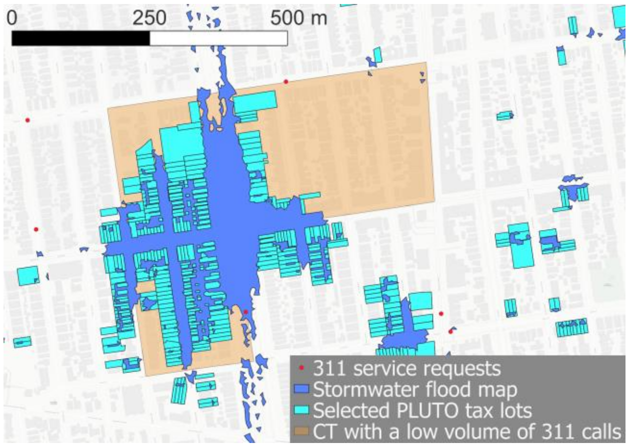

Figure 8: CT where the H&H model might be overestimating the flooding risk (also indicated in green in Figure 6).

4.1 Advantages

The use of 311 service requests as a means of evaluating flood risk has several strengths. Firstly, as the requests are generated by the public, they provide a wealth of valuable information without incurring any cost for the government. Secondly, the daily updates of the requests allow for real-time monitoring of flooding across different rain events, enabling a determination of which regions are more susceptible to inundation under varying levels of rainfall. Finally, the use of 311 service requests can provide early detection of changes in the landscape that may impact flooding, such as new development, updates to drainage infrastructure, and more. These advantages make 311 service requests a valuable tool for understanding and addressing the risk of flash flooding in urban areas. Additionally, the analysis of 311 service requests can serve as an effective validation tool for H&H models. By combining the real-world data provided by the service requests with the predictions of the H&H models, it's possible to gain a more complete and nuanced understanding of the risk of flash flooding in a given area. This integration of data can help to refine and improve the models, leading to better preparedness and protection against the dangers of flash flooding.

4.2 Limitations

It's important to note that while the analysis of 311 service requests can provide valuable insights into the risk of flash flooding, there are limitations to consider. First, it is worth noting that while the maximum rainfall intensity during Hurricane Ida was comparable to that used in the stormwater flood map, other event characteristics such as the spatial distribution of rainfall and tide level at the drainage discharge may differ. As a result, the comparison between the map and the 311 data generated during a single event may be limited. To overcome this issue in future studies, we suggest two possible approaches. The first approach would be to incorporate 311 data from multiple events to obtain a wider range of rainfall spatial distribution and tide levels. The second approach would be to select the characteristics of a single event, such as Hurricane Ida, and run the H&H model to match them. By doing so, we can obtain a more accurate representation of the flood extents associated with the selected event, and use this information to calibrate the H&H model for improved accuracy in future studies. Another limitation is the inherent bias in the 311 data. Some communities may be more proactive than others in reporting floods. These differences can impact the accuracy and reliability of the data and must be taken into account when interpreting the results of the analysis. (Kontokosta et al., 2017). To overcome this issue, we suggest future studies adjust the count of 311 service requests related to flooding, taking into account any variations in the reporting rate. This could be achieved by determining spatially-varying reporting rates for other types of 311 requests, and then dividing the number of flood-related service requests across different areas by those rates to normalize, thereby accounting for differences in how communities respond to emergencies. This approach has been successfully used in previous studies on correlation between flood-related calls and rain measurements (Smith et al., 2017), and has been shown to provide more robust and accurate results.

5 CONCLUSIONS

We showed that the analysis of citizen science data, like 311 service requests, can be a useful tool for characterizing the risk of flash flooding in urban settings. The user-generated nature of the data provides detailed and updated information, making it a valuable resource for monitoring and understanding flooding patterns. Additionally, when coupled with H&H models, the analysis of 311 service requests can serve as an effective validation tool. However, there are limitations to consider: the rainfall event from 311 calls may differ from the one in the H&H simulation. To address this, future studies can evaluate 311 data from multiple events or match the characteristics of a single event with the input parameters of the H&H model. Another limitation to consider is the inherent bias in 311 data that can impact the accuracy and reliability of the results. To address this limitation, future studies can evaluate recalibrating flood-related 311 service requests to control for differences in community behavior, overcoming the inherent bias in 311 data. Once these limitations are overcome, the analysis of 311 service requests can be used to fine-tune H&H model parameters, such as soil and drainage infrastructure characteristics, leading to more accurate flood predictions. In conclusion, our analysis shows that, when combined with H&H models, the analysis of 311 service requests can provide a more comprehensive understanding of flood patterns in the study area.

6 ACKNOWLEDGMENTS

We acknowledge the financial support from the NYU Tandon School of Engineering Fellowship and the NYU Connected Cities with Smart Transportation (C2SMART) Center.

7 REFERENCES

Agonafir, C. et al. (2022) “A machine learning approach to evaluate the spatial variability of New York City's 311 street flooding complaints,” Computers, Environment and Urban Systems, 97, p. 101854.

City of New York. (2023). 311 Service Requests [Data set]. NYC Open Data. https://data.cityofnewyork.us/City-Government/311-Service-Requests/erm2-nwe9

Colbert, A. (2022) “A Force of Nature: Hurricanes in a Changing Climate,” NASA’s Jet Propulsion Laboratory.

de Sherbinin, A. et al. (2021) “The critical importance of Citizen Science Data,” Frontiers in Climate, 3.

Department of Environmental Protection (DEP). (2022) “NYC Stormwater Flood Map.” NYC OpenData. Available at: https://experience.arcgis.com/experience/6f4cc60710dc433585790cd2b4b5dd0e

Hicks, A. et al. (2019) “Global mapping of citizen science projects for disaster risk reduction,” Frontiers in Earth Science, 7.

JBA Risk Management, (2021) “Hurricane Ida: a storm of two acts. Available at: https://www.jbarisk.com/products-services/event-response/hurricane-ida-a-storm-of-two-acts/#:~:text=Based%20on%20an%20extreme%20value,Henri%20just%20one%20week%20earlier.

Knutson, T.. (2022). “Global Warming and Hurricanes An Overview of Current Research Results.” Geophysical Fluid Dynamics Laboratory. Available at: https://www.gfdl.noaa.gov/global-warming-and-hurricanes/

Kontokosta, C., Hong, B., & Korsberg, K. (2017, October 6). Equity in 311 Reporting: Understanding Socio-Spatial Differentials in the Propensity to Complain. Bloomberg Data for Good Exchange Conference, September 24, 2017, Chicago, IL, USA.

NYC Department of Environmental Protection Bureau of Wastewater Treatment, “INFOWORKS Citywide Recalibration Report Updates to and Recalibration of October 2007 NYC Landside Model (2012). Available at https://www1.nyc.gov/assets/dep/downloads/pdf/water/nyc-waterways/citywide-ltcp/infoworks-citywide-recalibration-report.pdf

Newman, A., Ferré-Sadurní, L., Tully, T., Bromwich, J. E., & Shapiro, E. (2021, September 3). As Ida Deaths Rise, N.Y. Leaders Look Toward Future Storms. The New York Times. [Online]. Available: https://www.nytimes.com/live/2021/09/03/nyregion/nyc-flooding-ida#:~:text=Even%20so%2C%20state%20leaders%20said,Gov

NYC Mayor’s Office of Resiliency, “New York City Stormwater Resiliency Plan,” Tech. rep. (2021). Available at https://www1.nyc.gov/assets/orr/pdf/publications/stormwater-resiliency-plan.pdf

Oliva, A. and Olcina, J. (2022) “Floods and emergency management: Elaboration of Integral Flood maps based on emergency calls (112)—episode of September 2019 (Vega Baja del Segura, Alicante, Spain),” Water, 15(1), p. 2.

Plumer, B. (2021, September 2). New Yorkers Got Record Rain, and a Warning: Storms Are Packing More Punch. The New York Times. [Online]. Available: https://www.nytimes.com/2021/09/02/climate/new-york-rain-climate-change.html

Rainey, J.L. et al. (2021) Using 311-call data to measure flood risk and impacts: The case of Harris county TX during Hurricane Harvey, Institute for a Disaster Resilient Texas. Texas A&M University at Galveston.

Silverman, A.I. et al. (2022) “Making waves: Uses of real-time, hyperlocal Flood Sensor Data for Emergency Management, resiliency planning, and flood impact mitigation,” Water Research, 220, p. 118648.

Smith, B. and Rodriguez, S. (2017) “Spatial analysis of high-resolution radar rainfall and citizen-reported flash flood data in Ultra-Urban New York City,” Water, 9(10), p. 736.

Van Lenten, C.. (2014) NYC’s Risk Landscape: A Guide to Hazard Mitigation, *Government Publications Portal*. Available at: https://www1.nyc.gov/assets/em/downloads/pdf/hazard_mitigation/nycs_risk_landscape_a_guide_to_hazard_mitigation_final.pdf.