Ride, Sink, or Swim:
Mapping Extreme Floods and the Burdens of Buses in Queens, NYC

by

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Contents

1 Introduction

Street and coastal flooding are some of today's most pressing climate risks in New York City, and are common occurrences during heavy rainfall events (Solecki, 2012; C. Rosenzweig et al., 2011) due to reasons varying from the overwhelming of drainage systems (Agonafir et al., 2021) to impermeable depressions on streets (Safaei-Moghadam et al., 2023). Street flooding has become a dangerous threat to the residents of New York City due to intensifying storms that have overwhelmed drainage systems, basement dwellings, subways, and roads (Agonafir et al., 2021; Solecki, 2012). The flooding and failure of drainage systems on September 1, 2021, resulting from the 3.47 inch-per-hour rainfall rate left by remnants of Hurricane Ida (Mossel et al., 2024), highlighted the dangerous and uneven vulnerabilities of the city's geography (Blackmore, 2024), gaps in its infrastructural sustainability, and need for more effective flood-mitigation infrastructure.

The New York City Department of Transportation's Street Design Manual, Third Edition (2020) states that increasing permeable space on NYC's roads "wherever safe and feasible" is a major priority for improving the current state of drainage and flood resilience across the city (NYC Department of Transportation, 2020, p. 250). Flooded roads can be devastating to surface transportation, including private vehicles and public transit. Particularly, floods threaten the mobility of residents who depend on buses to travel to work, recreation, and essential services like healthcare (Abenayake et al., 2022; Chang et al., 2011; Chen et al., 2015; Suarez et al., 2005). Buses are essential to many of the 2.3 million residents of Queens (U.S. Census Bureau, 2024), who boarded the borough's bus routes 151,535,451 times in 2023 (Metropolitan Transportation Authority, 2024a). The bus is an indispensable mobility tool for many residents, even amid a flood and other extreme weather events.

Recently, the growth of bike-sharing in NYC (branded primarily as Citi Bike) has created the opportunity for more bus riders to supplement the the "last mile" of their bus trips with a bike ride (Shaheen et al., 2010, p. 159), which may expand the variety of practical destinations to travel to by bus (Campbell & Brakewood, 2017). However, despite their utility and new use cases, Queens buses have suffered ridership decline in recent years due to low reliability, slowing speeds, and the loss of commuters to other modes of transportation (Metropolitan Transportation Authority, 2023b). Combined with the nearly 46% drop in ridership during the COVID-19 pandemic, which the MTA claims has "slowly continued to recover" (Metropolitan Transportation Authority, 2023b, p. 10), measures to repair bus service in Queens have become increasingly essential to its survival as an effective mode of transportation.

The borough of Queens in New York City experienced an exceptional 2,092.03 mm. (about 82.32 in.) of rainfall over the course of 2023 (NYS Mesonet, 2024). Simultaneously, the borough amassed 1,152 citizen reports of street and highway flooding throughout 2023 (NYC311, 2024). Many studies have focused on hypothetical or future flooding scenarios through hydraulic modeling (Chang et al., 2011; G. Liu et al., 2023; Safaei-Moghadam et al., 2023; Suarez et al., 2005). Yet, the exceptional flooding of 2023 gives cause to researching the effects of a past flood on surface public transportation networks. This study contributes to the body of literature by illustrating a potential association between flooding and transportation, and using citizen-reported data to account for the nuances of genuine flooding conditions (Negri et al., 2023; B. R. Rosenzweig et al., 2018). This study also addresses the United Nations' Sustainable Development Goal 11, *Sustainable Cities and Communities*, by investigating the short-term robustness of urban infrastructure to past floods and suggesting solutions to improve infrastructure sustainability against long-term climate change.

This research aims to understand the effects of flooding on the Queens bus system and its riders in flood-vulnerable areas. Scripting with R[1] and GIS mapping with Esri ArcGIS Pro allows us to approach this topic using statistical and spatial analyses. Using precipitation records, NYC311 street flooding reports, and bus performance metrics from 2023, this project was able to:

1. Use citizen-reported 311 data to identify areas experiencing the most reported floods in Queens during an abnormal flooding season, and;
2. Measure the extent to which a seasonal change in total flooding locations and their spatial distribution impacted bus delays in Queens, in 2023.

[1] Multiple R scripts used in this study require the packages `dplyr`, `RSocrata` and `writexl` to run properly. Please install these packages before attempting to recreate any processes in R mentioned here.

2 Literature Review

2.1 The state of weather and seasons in Queens, NYC

As shown in Figure 1, the 1991-2020 climate normals for New York City (NYC) describe a high seasonality in temperature and low seasonality in precipitation (NOAA, 2024b). Maximum temperatures peak in the summers and bottom out in the winters, while spring and fall are in close proximity near the low-middle of this range. The same pattern holds true for minimum and average temperatures. Simultaneously, precipitation remains consistent throughout the climate normals, with a difference of less then 3 inches of snow between any two seasons. Snow is highly specific to winters in NYC, with an average of 21.3 inches that no other season nears statistically. The stark differences between summers and winters, versus the relative similarities of spring and fall, helped me achieve a fairer comparison of seasonal bus and flood data.

Season	MAX TEMP (°F)	MIN TEMP (°F)	AVG TEMP (°F)	PRECIP (IN)	SNOW (IN)
Annual	61.6	47.0	54.3	43.29	25.9
Winter	41.9	28.5	35.2	9.95	20.6
Spring	58.6	43.0	50.8	11.15	4.9
Summer	81.2	66.3	73.8	11.82	0.0
Autumn	64.7	50.2	57.5	10.37	0.4

Figure 1. Climate Normals from JFK International Airport weather station, 1991-2020.

(NOAA, 2024b)

However, climate normals do not depict the potential of severe weather throughout the seasons. A primary concern of this study is recognizing which seasons in 2023 had experienced severe weather events (such as flooding) that could have impacted the bus network in Queens. To start seeking any possible association, I reviewed weather events that occurred in NYC over the course of 2023.

According to the National Oceanic and Atmospheric Administration (NOAA), New York State

(NYS) experienced 7 “Billion-Dollar Disasters,” which are weather events that create damages or costs of $1 billion or more (NOAA, 2024a). Of these 7 disasters, 2 were specifically flooding events, 4 were severe storms, and 1 was a winter storm. Of these, I could identify both flooding events and 1 severe storm as events specifically impacting NYC, by observing whether the event increased rainfall (as a percent of the average precipitation amount) over the city. From July 9 to July 11, NYS experienced a severe flooding event (NOAA, 2024a) that, according to the National Weather Service (NWS), leading to roughly 48 hours of severe flooding conditions in parts of southeastern New York. (NWS, 2024a). Flooding also occurred from August 5 to August 8 as part of a series of severe weather events over the Northeastern states, contributing to an increase over average precipitation over NYC that month (NOAA, 2024a). Finally, in winter 2023, a flooding event caused by powerful storms from December 16 to December 18 caused precipitation over NYC to exceed average levels by 200-300% (NOAA, 2024a).

Although not cited by NOAA, the city experienced an air quality alert and a dense smoke advisory on June 7, 2023. This was brought on by northerly winds pushing wildfire smoke from Quebec, Canada. (NWS, 2024b). The Air Quality Index was lowered to “Unhealthy” for the area (NWS, 2024b) as PM2.5 levels peaked (Thurston et al., 2023), while visibility near JFK Airport dropped to less than 2 miles (NWS, 2024b). This dangerous air quality was linked by Thurston et al., (2023) to creating a greater number of hospital emergency room visits for residents with asthma. The combination of dangerous conditions for traveling outdoors, an increased number of vehicles traveling to emergency rooms, and lower surface visibility for ground vehicles (including buses) could have made June 7 (and surrounding days) a precarious time for the bus, potentially delaying trips and discouraging passengers.

NOAA does not explicitly cite any notable “Billion Dollar” weather events within the spring or fall that affected precipitation in NYC. However, the largest flood of 2023 by total precipitation amount happened on September 29, when roughly 8.16 inches of inundation fell over Queens (NYS Mesonet, 2024) causing extensively-documented destruction and detrimental effects to New Yorkers’ lives (Blackmore, 2024; Offenhartz et al., 2023). NOAA recorded 3 “Billion Dollar” weather events in spring 2023. However, none of these caused above-average precipitation levels in the city, and therefore they are not credited for any severe flooding events there (NOAA, 2024a).

2.2 Using 311 data for flood impact applications

To accomplish this study, one of my earliest considerations was to use 311 reports as a proxy representation of street inundation during flood events. This would ideally allow areas highly impacted areas by flooding, down to street-level locations (and thus, individual bus routes too), to be identified.

One database of location-precise street flooding reports in NYC is aggregated by NYC311. NYC311 is an official service that allows residents to report various issues and concerns (mostly regarding city government-provided services) to the departments responsible for managing and mitigating them. The methodology adopted in this study pulls from Agonafir et al. (2022), which set out to identify whether NYC311 complaints and precipitation data could be used in tandem to accurately predict the spatial concentration of flooding in NYC (Agonafir et al., 2021). Agonafir et al. (2022) states that urban areas in the U.S. are disproportionately damaged by storm activity, in large part due to the percent of surface area that is impermeable in cities. However, this impact can vary on a per-street basis, which previous studies have encountered difficulty establishing. Often it is elevation, slope, the hyperlocal condition of drainage systems (Agonafir et al., 2021), or the design of surrounding buildings and infrastructure (Bulti & Abebe, 2020) which create these nuances. The NYC government claims its sewer system "typically has the capacity to handle 1.75 inches of rain per hour," (NYC Recovery, 2024) which storms like those of September 1, 2021 and September 29, 2023 have exceeded by their hourly rainfall rate.

However, Agonafir et al. presents the advantage of using NYC311 to pinpoint flooding, as 311 data is inherently local (Agonafir et al., 2021). Due to the broad accessibility of smartphones, computers, and social media, all of which NYC311 accepts reports through, citizen-reported data can now inform a comprehensive, borough-wide flood reporting study (Agonafir et al., 2021). The study collected precipitation data and 311 reports of street flooding, sewer backups, clogged catch basins, and manhole overflows from 2010-2019. Then, the data was summarized by week, and a correlation analysis was run for each NYC ZIP code. This process found that precipitation was "the primary driver of street flooding," being the most significant explanatory variable to flooding in 93% of Queens zip codes (Agonafir et al., 2021, p. 8). The findings state that "in the majority of NYC ZIP codes, the SF [street flooding] reports are consistent with and heavily affected by rain events," and that street flooding reports were more closely associated with precipitation than any of the other 311 report types studied (Agonafir et al., 2021, p. 6).

NYC311 data has been used in other studies about urban flooding (Dixon et al., 2021; B. Smith & Rodriguez, 2017; Negri et al., 2023). Like Agonafir et al. (2021), Negri et al. (2023) successfully established that NYC311 flooding reports reflect street flooding risk with a Pearson coefficient p of 0.56, reflecting moderate correlation. Other 311 studies have encouraged precautions to avoid the bias stemming from uneven reporting rates across the city. Homeownership rates, property values, race, and median income per capita have been suggested to skew these rates towards specific neighborhoods (Agostini et al., 2024; He, 2023; Kontokosta & Hong, 2021; Z. Liu et al., 2024; Minkoff, 2016). As these statistics differ broadly across Queens, it was crucial that this study incorporated a methodology to reduce reporting bias as much as possible.

Informed by Chen (2015), Rosenzweig (2011), and Solecki (2012)'s emphasis on increased flooding risks in coastal areas, I hypothesized that while NYC311 flood report data would show increased street flooding across all of Queens, flood locations will be primarily concentrated within communities in the borough's low-lying coastal neighborhoods due to the risk of inundation brought by extreme rainfall events. This would particularly include areas along the East River, the Long Island Sound, and Jamaica Bay. For example, the Rockaways (CD 14) are a low-lying sandy peninsula along Jamaica Bay that would be prone to a greater flood risk than Rego Park (CD 6), an inland neighborhood.

2.3 The state of buses in Queens, NYC

In 2023, 151,535,451 boardings were recorded on bus routes primarily serving Queens (Metropolitan Transportation Authority, 2024a). According to the Metropolitan Transportation Authority (MTA), which is responsible for public bus operations in NYC, 52% of residents in the borough ride public transportation everyday (Metropolitan Transportation Authority, 2023b). Split evenly among these residents, this averages to about 123 boardings taken per person for the year. Especially in the southern and eastern parts of the borough, where subway lines and stops are scarce (Metropolitan Transportation Authority, 2024e), local commutes that go beyond walking distance are served either a car (which not all residents have the desire, ability, or finances to own or hire), a bike/scooter/other personal mobility device (also limited by ability and finances), or riding the bus. The Long Island Rail Road supplements the lack of subway access by providing transportation from parts of southern and eastern Queens to limited destinations west (towards Manhattan) or east (towards Long Island). However, for most people, the bus is likely more cost-effective per ride than an LIRR fare (which is $4.25 at its lowest for traveling within "Zone 3," or destinations between Jamaica and the eastern border of Queens) or committing to the purchase and maintenance of a car or other mobility device. MTA buses are more optimized than the LIRR for local stops, and only cost $2.90 for one ride, which can be decreased with subsidized fares, passes, and fare capping (Metropolitan Transportation Authority, 2024c).

According to the MTA, which plans and operates the bus network, Queens is served by 110 bus routes which have had statistics about their passenger totals, delays, and other metrics uploaded to NYS's Open Data portal (Metropolitan Transportation Authority, 2023a). This data is split up into two time-based fare periods: the "Peak" period (which includes data recorded between 7:00 AM to 9:00 AM and 4:00 PM to 7:00 PM) and the "Off-Peak" period (which is all other data recorded outside of the Peak period) (Metropolitan Transportation Authority, 2023a). The MTA uses Peak and Off-Peak labels in their data collection, scheduling, and fare pricing for some modes of transportation (Metropolitan Transportation Authority, 2024c) because the agency associates specific time frames with "weekday rush hours" in NYC (Metropolitan Transportation Authority, 2024d).

The time-based fare period “has its roots in congestion pricing on urban freeways,” as “during the peak [of traffic], when highways are congested, every additional user creates a demand for additional space.” (M. Smith, 2009, p. 26). The relevance of time-based fare periods to NYC buses is demonstrated by the MTA’s pursuit of new congestion pricing policies in Manhattan’s Central Business District (CBD), also known as the “Congestion Relief Zone” from 60th Street south (Metropolitan Transportation Authority, 2024b). Roughly 700,000 vehicles enter the CBD across weekday mornings and evenings, creating exceptional congestion in this timeframe (Metropolitan Transportation Authority, 2024b). When it takes effect in January 2025, congestion pricing will charge passenger vehicle drivers entering the CBD from 5:00 AM to 9:00 PM on weekdays, and 9:00 AM to 9:00 PM on weekends (Metropolitan Transportation Authority, 2024g). Since this time range includes the previously-defined Peak period for MTA buses, we can assume that Peak period buses entering or leaving the CBD will be affected by congestion pricing’s impact on traffic.

The Queens bus network is currently in the planning phase of a major redesign conducted by the MTA (Metropolitan Transportation Authority, 2023b). The redesign was initiated in 2019 to address four key priority areas that the current bus network must improve in: “Reliable Service,” “Faster Travel,” “Better Connections,” and “Simplified Service” (Metropolitan Transportation Authority, 2023b). These are crucial priorities considering some of the most pressing issues of the bus network. The average speed of a Queens bus in 2019 was 8.7 miles per hour, which had decreased from 4 years prior (at 9.0 MPH) (Metropolitan Transportation Authority, 2023b). Ridership had declined by 5.3% from 2014 to 2019, while on-time performance decreased by 12% overall from 2014 to 2018 (Metropolitan Transportation Authority, 2023b). To improve upon these metrics, the MTA claims in its redesign report that it seeks to “make it easier to travel by bus,” “expand accessibility,” and “improve transit equity” in Queens-Brooklyn corridors (Metropolitan Transportation Authority, 2023b, p. 22-23).

2.4 Evaluating bus transportation against the landscape of floods

Regarding the MTA's bus redesign plans, I noticed while reading it that there is a complete lack of mention of flooding or climate change in the redesign document's outline of problems and solutions. In the document, there are no mentions of the terms "rain," "flood," "flooding," "climate," and "climate change," while "congestion" is mentioned 7 times and "traffic" is mentioned 20 times (Metropolitan Transportation Authority, 2023b p. 6-73). The lack of emphasis on flooding and severe weather events contrasts research showing that severe weather events can cause transportation delays and trip loss (Suarez et al., 2005), operational costs to public transit agencies (Chang et al., 2011), transit accessibility (Chen et al., 2015), transit demand (Singhal et al., 2014), and even system-wide transportation system failure (Abenayake et al., 2022).

The above studies raise several reasons for concern that 2023 flooding in NYC may have been significantly detrimental to the bus network and bus passengers. Chang et al. (2011) established that of all climate impacts, urban flooding had produced the highest negative impact on transportation by total cost -linking back to flooding events in NYC from as early as 2004 and 2007 (Chang et al., 2011). Abenayake et al. (2022) highlights how global climate change has propelled increases in the frequency and intensity of urban flooding, making road network resilience "a local and global imperative in recent years" yet "an under-explored branch of urban resilience." (Abenayake et al., 2022) A city's surface transportation network is inherently affected by the condition of its overall road network (Abenayake et al., 2022) due to factors like rising water tables (Chang et al., 2011), which are particularly detrimental to low-lying and coastal areas (Chen et al., 2015). Considering these sources, a disruption to bus services in Queens could make trips to essential destinations (including but not limited to home, work, childcare, eldercare, grocery stores, and healthcare facilities) significantly more difficult without accessible alternatives for riders.

While many studies focus on future risk or computer models of hypothetical flooding (Chang et al., 2011; G. Liu et al., 2023; Safaei-Moghadam et al., 2023; Suarez et al., 2005), other studies argue that these models do not always account for the nuances of genuine flooding conditions (Negri et al., 2023; B. R. Rosenzweig et al., 2018). Negri et al. (2023) highlights how one stormwater flood model for NYC "assumed a uniform rainfall intensity, while in reality, intensity varies spatially and temporally," (p. 4) while Rosenzweig et al. (2018) mentions that well-accepted models like the NWS's Flash Flood Guidance are not as accurate to highly urbanized places as they are to rural areas.

There are several benefits to analyzing the real-world data and effects of past flooding events. First, this will provide more accurate flooding data than a simulation. Second, the impact of street flooding on city infrastructure and services in 2023 is well-documented, including halted traffic (Offenhartz et al., 2023). Third, we have extensive rainfall data, citizen reports, and bus performance metrics that will make a comprehensive study possible and worthwhile.

Based on these findings, I chose to seek a seasonal association between flooding and one transportation metric that tends to significantly affect the average passenger's daily experience on the bus. From the MTA's open data catalog, I selected Customer Journey Time Performance (CJTP; also referred to here as bus on-time performance, bus delays, or bus timeliness) for this purpose. CJTP is defined as the percent of bus rides that are completed within 5 minutes of a customer's scheduled arrival time at their destination (Metropolitan Transportation Authority, 2023a), which is a statistical identifier of whether bus service is meeting the priorities of the MTA: Reliable Service (as reliability depends on moving passengers from their origins to their destinations on-time), Faster Travel (a trip arriving on-time signifies that the trip was not delayed), and Better Connections (passengers on a delayed bus are more likely to miss any connecting buses they might need to board). I hypothesized that the number of unique flooding locations and the median CJTP will be negatively associated, so that as flooding increases (in one CD or overall), median CJTP will decrease.

2.5 Dividing the neighborhood: Using Community Districts to summarize and compare statistics

NYC's Community Districts (CDs) are well-defined, consistent political boundaries that aggregate several neighborhoods into districts that are used for legislative and planning purposes (NYC Department of City Planning, 2024b). They are drawn along roadway boundaries making them practical for analyzing surface transportation. All CD boundaries and demographic data can be viewed at https://communityprofiles.planning.nyc.gov.

Initially because of these factors, I approached CDs as analysis zones for summarizing flooding and bus data. Then, upon comparing CDs with neighborhood boundaries, Census tracts, and Transportation Analysis Zones (TAZs), I found more benefits to using CDs for this study than any other tool for analyzing multiple communities.

Table 1

Queens Community Districts and sample neighborhoods.

Community District (CD)	Sample Neighborhoods
1	Astoria, Queensbridge, Long Island City
2	Hunters Point, Long Island City, Woodside
3	East Elmhurst, Jackson Heights, North Corona
4	Corona, Corona Heights, Lefrak City
5	Glendale, Maspeth, Middle Village
6	Forest Hills, Rego Park
7	Bay Terrace, College Point, Flushing
8	Fresh Meadows, Holliswood, Jamaica
9	Kew Gardens, Ozone Park, Richmond Hill
10	Howard Beach, Lindenwood, Ozone Park
11	Auburndale, Bayside, Douglaston
12	Hollis, Jamaica, North Springfield Gardens
13	Bellaire, Bellerose, Queens Village, Rosedale
14	The Rockaways

(NYC Department of City Planning, 2024b)

While many neighborhoods in NYC are named and well-known, their boundaries are often subjective—residents often have different perceptions of their neighborhood's boundaries (Coulton et al., 2001). This would make an objective statistical comparison between neighborhoods difficult or impossible. Considering the findings of Agostini et. al. (2024), Kontokosta & Hong (2021), and others who researched bias in NYC311 reporting, basing this study's findings on data within neighborhood boundaries would also risk skewing results towards neighborhoods with higher rates of 311 reporting. The use of CDs as analysis zones remedies this by having discrete number labels and boundaries, while aggregating multiple neighborhoods that may have different reporting rates into one statistical set.

A common practice among transportation studies is the use of Transportation Analysis Zones (TAZs) to divide an urban area into "mutually exclusive and exhaustive zones" (Suarez et al., 2005, p. 235) in which metrics with relevance to transportation are aggregated (Chang et al., 2011). Instead of TAZs, several 311 studies use Census tracts to aggregate their data (Agonafir et al., 2021; Agostini et al., 2024; Kontokosta & Hong, 2021; Z. Liu et al., 2024; Minkoff, 2016.)

Figure 2. Transportation Analysis Zones for NYC, 2012-2040, as proposed by the New York Metropolitan Transportation Council.

(New York Metropolitan Transportation Council, 2012)

Figure 3. Census tracts across Queens and Brooklyn.

(NYC Department of City Planning, 2024d)

These tools are valid methods of aggregating data on a large-scale in NYC, but not the most representative of Queens communities. First, the polygon boundaries of TAZs appear idiosyncratic, as TAZs are not widely recognized by community members, as opposed to CDs which see greater recognition. Second, TAZs and Census tracts in NYC are notably smaller than CDs by area and population; for example, tracts are designed to include 2,500 to 8,000 residents within their borders (Lamacchia, 1994), but the median resident population of a CD in Queens is 169,790.[2] (NYC Department of City Planning, 2024d). The relatively small population that data within a single tract or TAZ applies to causes me to question their usefulness in drawing conclusions from data, when CD data applies to many more residents. Third, small-area analysis zones by area may also result in zones with no 311 or bus data, which would complicate my analysis. The large area of CDs increases the likelihood that each CD will include a sufficient amount of 311 and bus data to analyze.

[2]Based on the 2020 U.S. Census, which is the latest demographic data aggregated by Community District on the NYC Population FactFinder website.

3 Methodology

3.1 Precipitation analysis and selecting a study time frame

To address the research questions of this study, it was essential to establish a control season with relatively typical conditions for NYC's climate and an experimental season with abnormal flooding conditions. In the literature review, I examined some case studies of extreme weather events in 2023 and which seasons they occurred in. Here, I describe the statistical analysis involved in choosing an experimental and control season.

It is important to note the statistically low seasonality of precipitation in New York City, which generally makes precipitation levels consistent throughout the year (NOAA, 2024b). fall 2023 represents an exception to this trend and illustrates how rainfall can be consistent while extreme weather is not. However, through examining precipitation and case studies I identified reasons to avoid comparing two opposing climate extremes with each other—for example, comparing fall 2023 (the wettest season of the year by total precipitation, at 675.2 mm.) (NYS Mesonet, 2024) and the driest season of the year, based on total precipitation alone. If extremes were to be compared by this metric, winter was the driest season of 2023 (at 468.5 mm.) (NYS Mesonet, 2024) and thus would be the ideal candidate to compare against fall. However, the flooding in mid-December 2023 (NOAA, 2024a) was an abnormal weather event that could skew data for the control season, so winter was excluded from the comparison. I also ruled out summer 2023, the third driest season of the year (at 478.8 mm.) (NYS Mesonet, 2024). Despite its relative closeness in total rainfall to winter (with only 10.3 mm. more precipitation), the period of poor air quality in June 2023 due to a wildfire event (NWS, 2024b; Thurston et al., 2023) and two events experienced by southern New York that July and August (NOAA, 2024a; NWS, 2024a) outlined could also create extraneous influence on that season's bus ridership and bus data.

After this preliminary research into seasonality, I opted to analyze how the highest rainfall days of 2023 were distributed between the four seasons. For my approach, I wrote an R script to identify the amount of rainfall recorded for each day in 2023 and then calculate the 90th percentile of rainfall totals. I used the 90th percentile as a landmark for storm size based on the NYC Department of Environmental Protection Stormwater Manual's use of this as the designation of a "small storm event" for the city's drainage system. (NYC Department of Environmental Protection, 2024b, p. 2-13)

```
rainfallDaily <- rainfall_YMDSort %>%
  group_by(Y,M,D) %>%
  filter(Y==23) %>%
  summarise(sum_mm = sum(precip_1hr_max..mm.))


rainfallDailyAmts <- rainfallDaily$sum_mm
rainfallDailyPercntl <- quantile(rainfallDailyAmts, probs = c(0.9), na.rm=TRUE)
print(rainfallDailyPercntl)
```

Printing *rainfallDailyPercntl* output a 90th percentile rainfall total of 17.382 mm. There were 36 days in 2023 within the 90th percentile. I categorized each of these days by meteorological season to understand which seasons experienced the highest and lowest number of statistically substantial rainfall days. This process placed fall 2023 at the highest end with 13 substantial rainfall days (36.11% of all substantial rainfall days) and spring 2023 at the lowest end with only 6 days (16.67%). This provides empirical evidence for considering fall 2023 as the abnormal flooding season in this study, and spring 2023 as the drier control season.

Following the logic outlined above, I chose spring 2023 as the control season. Spring saw 469.7 mm. of precipitation, which was 69.6% of equivalent precipitation in the fall, and no major flooding events in NYC.

Table 2

Comparing 2023 meteorological seasons by precipitation sums and notable extreme weather events.

Season	Precipitation (mm.)	Notable weather events	90th percentile days
Winter 2023	468.5	1 flood (Dec 16-18)	7 days
Spring 2023	469.7	No NOAA-recognized events	6 days
Summer 2023	478.7	1 flood, 1 severe storm, 1 extreme air quality event	10 days
Fall 2023	675.2	Heavy rainfall (Sept 29)	13 days

(NYS Mesonet, 2024; NOAA, 2024a; NWS, 2024b)

Precipitation data was provided courtesy of New York State Mesonet, which provides "high-quality weather data at high spatial and temporal scales," including precipitation data, from multiple weather stations around NYS (Brotzge et al., 2020, p. 1827). Mesonet's dataset provided hourly amounts of precipitation from January 1 to December 31, 2023, as recorded by the Queens weather station (located in the neighborhood of Pomonok, roughly between JFK International Airport and LaGuardia Airport) (NYS Mesonet, 2024). This data was ingested into the R data frame *rainfall*. Then, using the R script below, I made the records sortable by year and month independently, then filtered total seasonal precipitation from this dataset for spring (see Table 2).

```
# Adding year/month/day labels to hourly data for filtering purposes
rainfall_YMDSort <- rainfall %>%
  mutate(Y = substring(rainfall$time_end,3,4),
         M = substring(rainfall$time_end,6,7),
         D = substring(rainfall$time_end,9,10))
# Filtering hourly data to only entries for March (03), April (04), and May (05)
rainfall_0323 <- rainfall_YMDSort %>%
  filter(Y==23) %>%
  filter(M=="03")
```

```
rainfall_0423 <- rainfall_YMDSort %>%
  filter(Y==23) %>%
  filter(M=="04")
rainfall_0523 <- rainfall_YMDSort %>%
  filter(Y==23) %>%
  filter(M=="05")
# Binding months into one spring 2023 data frame
  rainfall_Spring23 <- rbind(rainfall_0323, rainfall_0423, rainfall_0523)
# Calculating precipitation sum for spring
  rainfall_Spr_SUM <- rainfall_Spring23 %>%
    summarise(sum_mm = sum(precip_1hr_max..mm., na.rm=TRUE))
```

Table 3

Output for rainfall_Spr_SUM from R script.

$\text{sum}_m m$
469.66

I also ran this code on the months of September, October, and November for fall, then bound and summarized into a *rainfall_Fall23* data frame (see result in Table 3). The modifier *na.rm=TRUE* was added to the *summarise* command in order to remove null values: hours where no value for rainfall was recorded. Note that records with a precipitation amount of zero were kept in the database; this only applies to true null values. This command removed 4 hourly records from spring (all on April 17), and 4 hourly records from fall (all on November 14).

Table 4

Output for rainfall_Fall_SUM from R script.

$\text{sum}_m m$
675.22

3.2 Importing CDs and the Queens bus network

With the study time frame selection and rainfall analysis completed, I then acquired, aggregated, and imported the relevant spatial data into GIS software (ArcGIS Pro).

I created a new map in ArcGIS Pro using the Long Island State Plane projection, and added a vector layer of all New York City CDs (NYC Department of City Planning, 2024c) above the basemap. To only show CDs within the boundaries of Queens while excluding bodies of water, I added New York City's Neighborhood Tabulation Areas (NTAs) (NYC Department of City Planning, 2024a) on a new layer, which only features NYC's land area. I selected only Queens NTAs (where the *boro_name* field equaled Queens) and clipped those NTAs into a separate layer via the *Layer from Selection* tool. I then clipped the CDs layer to the newly created Queens-only NTAs layer, and converted the output to the North American Datum of 1983.

NYC DCP's Community Districts data also includes Joint Interest Areas (JIAs), which are generally large parks or airports (LaGuardia or JFK International). Since JIAs are not residential areas, their in-depth analysis is not directly relevant to this research. Thus, the maps depicting CDs in this project do not label or show statistics for the JIAs, although they are still included with a white cross-stitched pattern. All 14 Queens CDs were labeled with their official number, which remained on during my analysis to observe changes in flooding and bus data between specific CDs.

Next, I added bus routes and stops to the project using 3 MTA-provided General Transit Feed Specification (GTFS) for Queens, Brooklyn, and MTA Bus Company routes (Metropolitan Transportation Authority, 2024f). I converted bus routes in the 3 "shapes.txt" files to polylines using the ArcGIS *GTFS Shapes to Features* geoprocessing tool, then merged all into one layer. The stops in all 3 "stops.txt" files, accordingly, were converted to points using the *GTFS Stops to Features* tool and merged into the "QRoutes" layer.

Unaltered routes from the GTFS data are split into several segments and not recognized by ArcGIS Pro as unified lines. To amend this, I used the *Create Routes* tool to join the polyline segments, which simplified later analysis.

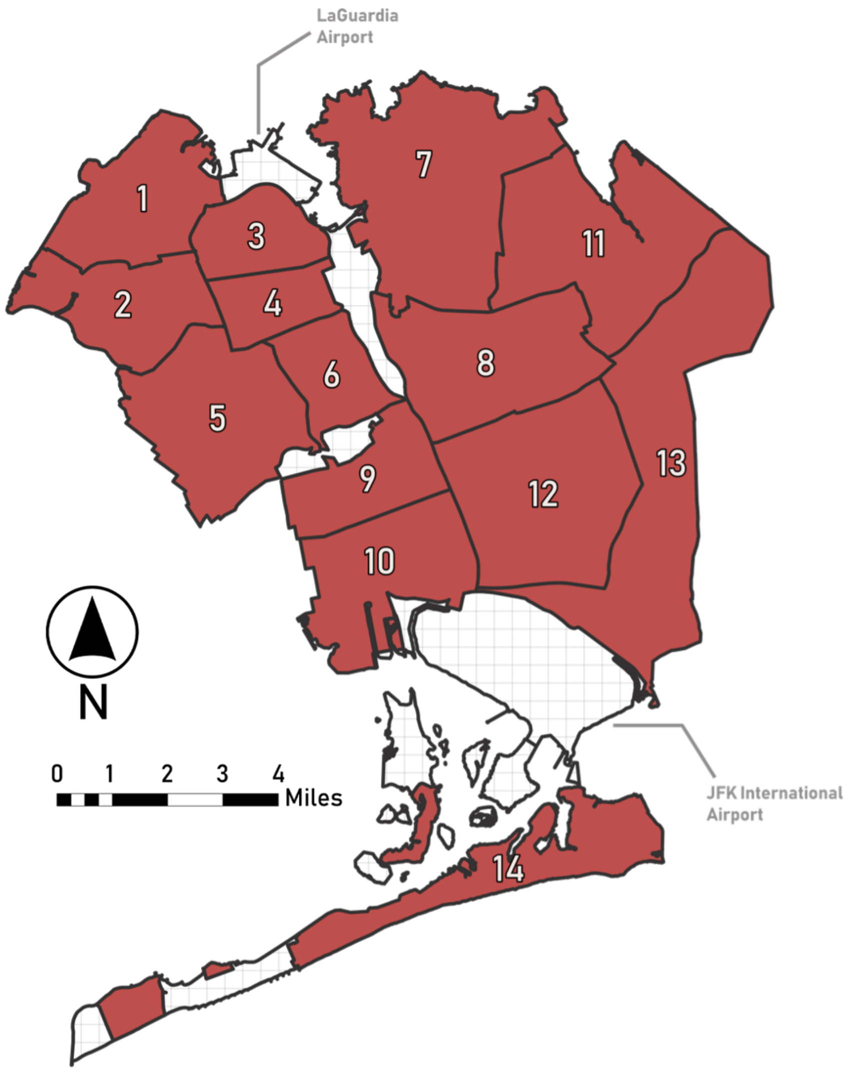

Figure 4. Queens Community Districts with labels. JIAs are cross-hatched and airports in Queens are labeled.

3.3 Aggregating and mapping 311 data

On April 17, 2024, I downloaded 776,871 NYC311 records from the NYC Open Data portal, filtering for reports that originated in Queens and had a *Created Date* between January 1, 2023 at 12:00:00 AM and December 31, 2023 at 11:59:59 PM. These filters were set using NYC Open Data's online querying tool to improve processing time and shrink overall file size.

Each NYC311 record includes a *Descriptor* field that briefly describes the reported issue. NYC311 offers four labels in its dataset that describe street flooding: "Highway Flooding (SH)," and "Flooding on Highway," which apply to floods reported on major public roads such as expressways and freeways, and "Street Flooding (SJ)" and "Flooding on Street," which apply to all other types of roads. (NYC311, 2024). [3]

These reports are filed under the responsibility of the NYC Department of Environmental Protection (DEP). Considering these facts, I wrote an R script to filter this dataset only by instances of reports filed to the DEP with the above descriptors:

```
reports311 <- read.csv("/[Directory]/311_20240417.csv")


rep_floods <- reports311 %>%
filter(Agency.Name=="Department of Transportation" |
Agency.Name=="Department of Environmental Protection") %>%
filter(Descriptor=="Highway Flooding (SH)" |
Descriptor=="Street Flooding (SJ)" |
Descriptor=="Flooding on Highway" |
Descriptor=="Flooding on Street") %>%
      rep_floods <- rep_floods %>%
      mutate(Y = substring(rep_floods$Created.Date,9,10),
             M = substring(rep_floods$Created.Date,1,2),
             D = substring(rep_floods$Created.Date,4,5))


write_xlsx(rep_floods, "/[Directory]/FloodReports.xlsx")
```

I then used the filtering tools in Microsoft Excel to separate data in the spring and fall time frames into separate seasonal databases, and calculated the sum of flooding reports in each season (see

[3] From here on, I refer to the former two labels as "street flooding" and the latter two labels as "highway flooding". Notably, reports labeled as "Flooding on Street" or "Flooding on Highway" are only present in the fall dataset (NYC311, 2024).

Table 5).

Potential bias in 311 reporting can create a disproportionate raw number of reports, including repeat reports, in different locations across a city (Agostini et al., 2024; He, 2023; Kontokosta & Hong, 2021; Z. Liu et al., 2024; Minkoff, 2016). To reduce the skew that the raw number of reports could have on distribution (for instance, one instance of flooding in one location being reported multiple times), I took the approach of analyzing and mapping only unique locations of 311 flooding reports through spring and fall. This approach was also followed by Agonafir et al. (2021). The result of this processing is a reduction of 45 reports in the spring (16.24% of that season's total reports) and 277 reports in the fall (45.41% of the seasonal total), but all locations where floods were reported in either season were kept intact. While the reason that duplicate-location reports made up a significant share of fall 2023 reports is somewhat unknown, I assume it is because flooding was far more severe during that fall, causing an excess of reporting from affected citizens.

While this method does not entirely rule out location-based bias and an effect on my analysis (for example, a coastal neighborhood that experiences frequent floods having lower reporting rates overall than neighborhoods that flood less often), it helps to prevent the statistical severity of floods from being skewed by abnormally high or low reporting rates.

Table 5

Total reports of street and highway flooding by season, before removing duplicate and null locations.

Season	Total Flooding Reports
Spring	277
Fall	610

Table 6

Unique locations of street and highway flooding reports by season and month.

Season	Total Unique Locations of Flooding Reports
Spring	232
Fall	333

Within both seasons' datasets, I removed duplicate locations with the *Remove Duplicates* feature in Excel.[4] This tool allows rows in a spreadsheet to be deleted when two or more duplicate values are detected in one or more columns. I used this tool to detect and automatically remove reports that duplicated the latitude and longitude of another report (while keeping one report with the same coordinates in tact). I then repeated this process using the *Incident.Address* field. Since not all reports had their latitude and longitude or address logged, these steps caught a significant number of duplicates but not all. To remove the remaining few, I used conditional formatting rules to highlight duplicate values in the *X.Coordinate..State.Plane.* and *Y.Coordinate..State.Plane.* fields, and deleted any duplicates found. Among deleted 311 reports, 1 duplicate point in the spring was manually removed from the neighborhood of Sunnyside despite not being detected by the *Remove Duplicates* feature. Additionally, 1 duplicate point in the fall was manually removed from the neighborhood of Whitestone for the same reason.

The spreadsheets with unique flooding locations were then plotted in ArcGIS using their X- and Y-coordinate (State Plane) fields as two separate point data layers: one for locations in the spring and one for locations in the fall. The final plotted 311 dataset includes a marginal number of locations counted within one of Queens' handful of JIAs, rather than CDs. This amounts to 3 locations in the fall and 1 location in the spring. Excluding these points, the 311 location totals are 232 for the spring and 333 for the fall. Since some flood locations lie on the boundary between a JIA and a CD, or are in a JIA but include a residential address in their metadata, I opted not to exclude them from total location counts for the sake of data integrity.

Next, I utilized the *Summarize Within* geoprocessing tool to calculate the sum of unique flooding locations per season within each of Queens' CDs. This was a prerequisite for the process of associating the bus CJTP metric with flooding locations later on. The tool's output created a CD layer that could be symbolized by the sum of 311 locations per CD (see Figure 6).

[4] Note that some of the same flooding locations exist across spring and fall. This is to ensure an accurate distribution of flood locations within each season.

3.4 Aggregating and mapping Bus On-Time Performance data

On March 27, 2024, I downloaded the latest version of the *MTA Bus Customer Journey-Focused Metrics: Beginning 2020* dataset from the State of New York open data portal. With an R script, I filtered down the records to only those from spring and fall 2023 with a *borough* value of "Queens":

```
buses <- read.csv("/[Directory]/CJTP_20240327.csv")


buses_YMDSort <- buses %>%
  mutate(Y = substring(buses$month,3,4),
         M = substring(buses$month,6,7))


buses_Q <- buses_YMDSort %>%
  filter(borough=="Queens") %>%
  filter(Y==23)


# Spring:
  # Filter to spring
cjtp_0323 <- buses_Q %>%
  filter(M=="03")
cjtp_0423 <- buses_Q %>%
  filter(M=="04")
cjtp_0523 <- buses_Q %>%
  filter(M=="05")


# Fall:
# Filter to fall
cjtp_0923 <- buses_Q %>%
  filter(M=="09")
```

```
cjtp_1023 <- buses_Q %>%
  filter(M=="10")
cjtp_1123 <- buses_Q %>%
  filter(M=="11")
```

Since Customer Journey-Focused Metrics are divided into Peak and Off-Peak periods, I was then able to use a filter to separate data for each month into these respective periods, and start adding statistics to include in the resulting data frame. An example is shown below, using Peak data (pk_09) and Off-Peak data (op_09) from September, but the same process was repeated for all spring and fall months.

```
# September 2023 Peak
  pk_09 <- cjtp_0923 %>%
    filter(period=="Peak") %>%
    summarize(mean_CJTP = mean(customer_journey_time_performance),
              median_CJTP = median(customer_journey_time_performance),
              min_CJTP = min(customer_journey_time_performance),
              max_CJTP = max(customer_journey_time_performance),
              mean_cust = mean(number_of_customers),
              median_cust = median(number_of_customers) %>%
    mutate(Month = "09",
           Period = "P")
# September 2023 Off-Peak
  op_09 <- cjtp_0923 %>%
    filter(period=="Off-Peak") %>%
    summarize(mean_CJTP = mean(customer_journey_time_performance),
              median_CJTP = median(customer_journey_time_performance),
              min_CJTP = min(customer_journey_time_performance),
              max_CJTP = max(customer_journey_time_performance),
```

```
            mean_cust = mean(number_of_customers),
            median_cust = median(number_of_customers) %>%
  mutate(Month = "09",
         Period = "OP")
```

After repeating this process for each study month (as well as February 2023 and August 2023 for contextual purposes), I bound all the resulting data frames into one data frame, "MonthsOnly":

```
MonthsOnly <- rbind(pk_08, op_08, pk_09, pk_10, pk_11, pk_03, pk_04, pk_05,
op_09, op_10, op_11, pk_02, op_02, op_03, op_04, op_05)
```

I again used the *rbind* and *filter* functions to bind data from March, April, and May into a spring CJTP dataset, and September, October, and November into a fall CJTP dataset. Here, the *group_by* function is also used to calculate the statistics for one route over the course of three months, creating mean, median, minimum, and maximum data across an entire season instead of separate months. The example below depicts this process applied to fall data, Peak and Off-Peak:

```
CJTP_Fall <- rbind(cjtp_0923, cjtp_1023, cjtp_1123)
# Filter to peak
CJTP_Fall_P <- CJTP_Fall %>%
  filter(period=="Peak")
# Merge months --> 1 season
CJTP_Fall_P_Merged <- CJTP_Fall_P %>%
  group_by(route_id) %>%
  summarize(mean_CJTP = mean(customer_journey_time_performance),
            median_CJTP = median(customer_journey_time_performance),
            min_CJTP = min(customer_journey_time_performance),
            max_CJTP = max(customer_journey_time_performance))
# Filter to Off-Peak, keep months separate
```

```
CJTP_Fall_OP <- CJTP_Fall %>%
  filter(period=="Off-Peak")
# Merge months --> 1 season
CJTP_Fall_OP_Merged <- CJTP_Fall_OP %>%
  group_by(route_id) %>%
  summarize(mean_CJTP = mean(customer_journey_time_performance),
            median_CJTP = median(customer_journey_time_performance),
            min_CJTP = min(customer_journey_time_performance),
            max_CJTP = max(customer_journey_time_performance))
```

Table 7

Custom datasets exported for analysis using writexl.

Dataset Name	Description
CJTP_Spr_P_Merged	CJTP aggregates per route for spring (Peak period)
CJTP_Spr_OP_Merged	CJTP aggregates per route for spring (Off-Peak period)
CJTP_Fall_P_Merged	CJTP aggregates per route for fall (Peak period)
CJTP_Fall_OP_Merged	CJTP aggregates per route for fall (Off-Peak period)
MonthsOnly	Separated Customer Metrics for study months, February, and August

The median CJTP of fall and spring combined, by fare period, was then captured using this script:

```
CJTP_P_Stats <- rbind(CJTP_Fall_P,CJTP_Spr_P)
CJTP_P_Stats <- CJTP_P_Stats %>%
  summarize(median_CJTP = median(customer_journey_time_performance))


CJTP_OP_Stats <- rbind(CJTP_Fall_OP,CJTP_Spr_OP)
CJTP_OP_Stats <- CJTP_OP_Stats %>%
  summarize(median_CJTP = median(customer_journey_time_performance))
```

Table 8

Output for Peak and Off-Peak dataset medians, from CJTP_P_Stats and CJTP_OP_Stats.

Median Peak CJTP	Median Off-Peak CJTP
0.6527189	0.6861122

After exporting the bus metric datasets to Microsoft Excel format, I added them to the contents of the ArcGIS project, and created a table join between each of the CJTP "Merged" datasets and the QRoutes layer. This primarily allowed for the bus data to be symbolized on the map, but also (by unchecking the *Keep all input records* option in the tool) excluded all routes that were not in the CJTP datasets from the resulting polyline layers. This was a convenient way to remove all routes except the Queens routes I am studying, which resulted in 110 total routes plotted on the map.[5]

3.4.1 Summarizing by CD

Although the bus route layer is spatial data, CJTP data lacks spatial awareness along the routes it applies to. This means that one route stretching from hypothetical point *A* to point *B* has one static CJTP value at any given point in time, which does not change along the route.

This created the need for a method of assigning CJTP values to CDs without having location-specific CJTP data. The compromise I developed accounts for all routes that intersect a CD, then calculates the median CJTP percentage between these routes, and assigns the resulting value to that CD.

I performed a *Pairwise Intersect* between the QRoutes and the clipped CDs layer. A key feature of *Pairwise Intersect* is how "features or portions of features that overlap between the input feature layers or feature classes will be written to the output feature class" (Esri, 2024) . The tool split each unified bus route into one new segment within each CD the route intersects.

I wrote another R script to filter metrics for each CD individually, based only on buses within the list of routes that intersect. Values for spring and fall, as well as Peak and Off-Peak fare periods,

[5] *I altered the route_id values for SBS routes and buses Q6 through Q9 in the CJTP "Merged" datasets because their default labels (ex. "Q06" instead of Q6) had to be changed to match with the routes labels in the MTA-provided routes.txt file. Following this fix, the Add Join feature was successful with all 110 records each time it ran.*

were retained and kept separate. Below is an example of the process for CD 3, using spring Peak data:

```
cd3_unique_lines <- Centroid_Spr_P %>%
  filter(official_cd_num=="3")
unique(cd3_unique_lines$route_id)
rm(cd3_unique_lines)
#Spr_P
cd3_Spr_P <- CJTP_Spr_P %>%
  filter(route_id=="Q48" | route_id=="Q66" | route_id=="QM20") %>%
  # Values from unique(cd3_unique_lines$route_id)-Shortened for example
  # Above is all unique values discovered from cd1_unique_lines
  summarize(mean_CJTP = mean(customer_journey_time_performance),
            median_CJTP = median(customer_journey_time_performance),
            min_CJTP = min(customer_journey_time_performance),
            max_CJTP = max(customer_journey_time_performance),
            mean_cust = mean(number_of_customers),
            median_cust = median(number_of_customers) %>%
  mutate(Season = "Spring",
         Period = "P",
         CD = "3")
```

I bound 4 new data frames for each season/fare period combination into one data frame for each CD, then I bound all CD data frames into one "CDMetrics" data frame. This data frame was split into 4 separate data frames for the different season/fare period combinations:

```
cd3 <- rbind(cd3_Spr_P, cd3_Spr_OP, cd3_Fall_P, cd3_Fall_OP)


# Bind all CD data to 1 metrics sheet
```

```
CDMetrics <- rbind(cd1, cd2, cd3, cd4, cd5, cd6, cd7, cd8, cd9, cd10,
cd11, cd12, cd13, cd14)

#Sort into standard seasons + periods sheets for export to Excel:
CD_Spring_P <- CDMetrics %>%
  filter(Season=="Spring" & Period=="P")
CD_Spring_OP <- CDMetrics %>%
  filter(Season=="Spring" & Period=="OP")
CD_Fall_P <- CDMetrics %>%
  filter(Season=="Fall" & Period=="P")
CD_Fall_OP <- CDMetrics %>%
  filter(Season=="Fall" & Period=="OP")
```

I exported these data frames using *writexl*, added the tables into the ArcGIS project, then joined each with the CDs layer to symbolize CJTP percentage per CD (see Figures 7 and 8).

4 Analysis

4.1 Illustrating the seasonal and spatial distribution of flooding in Queens

To review what was outlined in the Methodology section, I selected spring and fall as the control and experimental study months respectively because the latter represents an abnormal month with recorded major flooding, while the former featured far less severe weather while being a comparable season. This is reflected by the 2023 precipitation data from Queens (NYS Mesonet, 2024), seen in Figure 5. In the fall, a major spike in total precipitation appears over September (438.1mm precipitation) that overshadows the smaller spikes present in January (165.08mm), April (277.04mm), and December (247.43mm).

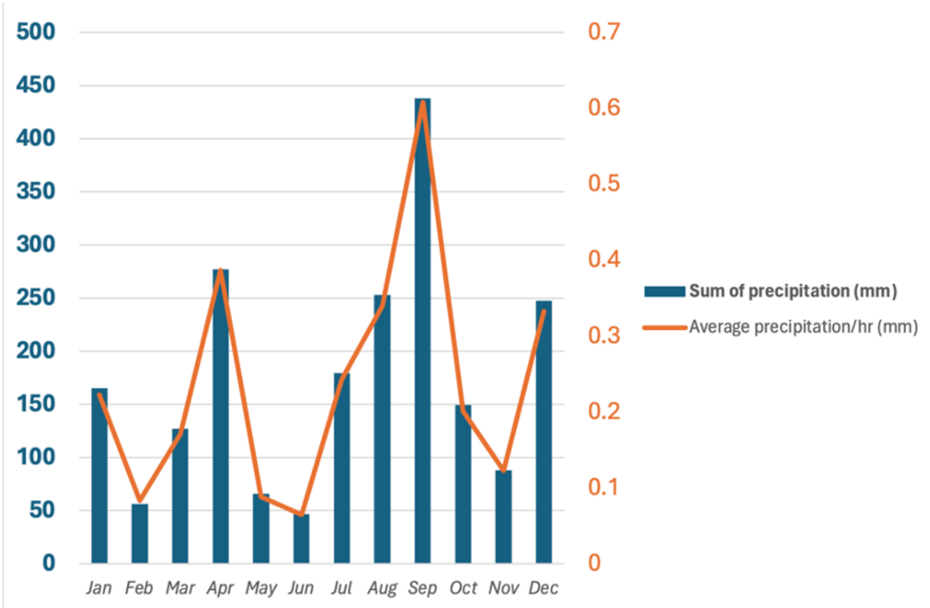

Figure 5. Sum and average precipitation per month in 2023.

For 311 flooding locations to be an accurate identifier of flooding conditions in 2023 overall, they would have to follow the trends of rainfall throughout the year. This is the case within these datasets: for each month that observed an increase in precipitation, that month saw a corresponding increase in flooding locations.

Table 9

Total precipitation vs. unique flooding locations (February and August included for context).

Month	Total Precipitation (mm.)	Flooding Locations
February	55.99	33
March	127.01	51
April	277.04	101
May	65.61	81
August	252.84	113
September	438.1	232
October	149.3	76
November	87.82	28

Table 10

Total precipitation vs. unique flooding locations, % Change

Month	Total Precipitation (% Change)	Flooding Locations (% Change)
March	126.84	52.94
April	118.12	107.69
May	-76.32	-25.00
September	73.27	111.50
October	-65.92	-64.85
November	-41.18	-64.29

Three of the six studied months (March, April, and September) saw increases in flood locations coinciding with increases in precipitation. April is of particular note because the % Change in both statistics for that month are so similar to each other, with precipitation increasing by 118.12% over March and flooding locations increasing by 107.69%. September saw a disproportionately high increase in flooding locations (+111.50%) compared to its increase in rainfall (+73.29%). March saw a disproportionately low increase in flooding locations (+52.94%) compared to its increase in rainfall (126.84%). The other three months (May, October, and November) saw decreases in both statistics. October saw near-parity in the % Change between precipitation (-65.92%) and flooding locations (-64.85%) that month. May and November did not record the same degree of parity, but nonetheless recorded decreases in both statistics.

Relative change is important because it helps to identify the association between precipitation and flooding locations, but also which months were outliers relative to other months of the year. For context, September alone had a 111.50% increase in flooding locations (239 total) than August (113), the next most flooded month by total locations, which highlights its nature as a flooding outlier. April was also an outlier by this logic, seeing a 107.69% increase in flooding locations (101 total). By total unique flooding locations, September, April, and October (76 total) experienced the most severe flooding within the study time frame. In contrast, May (81), March (51), and November (28) recorded the fewest flooding locations.

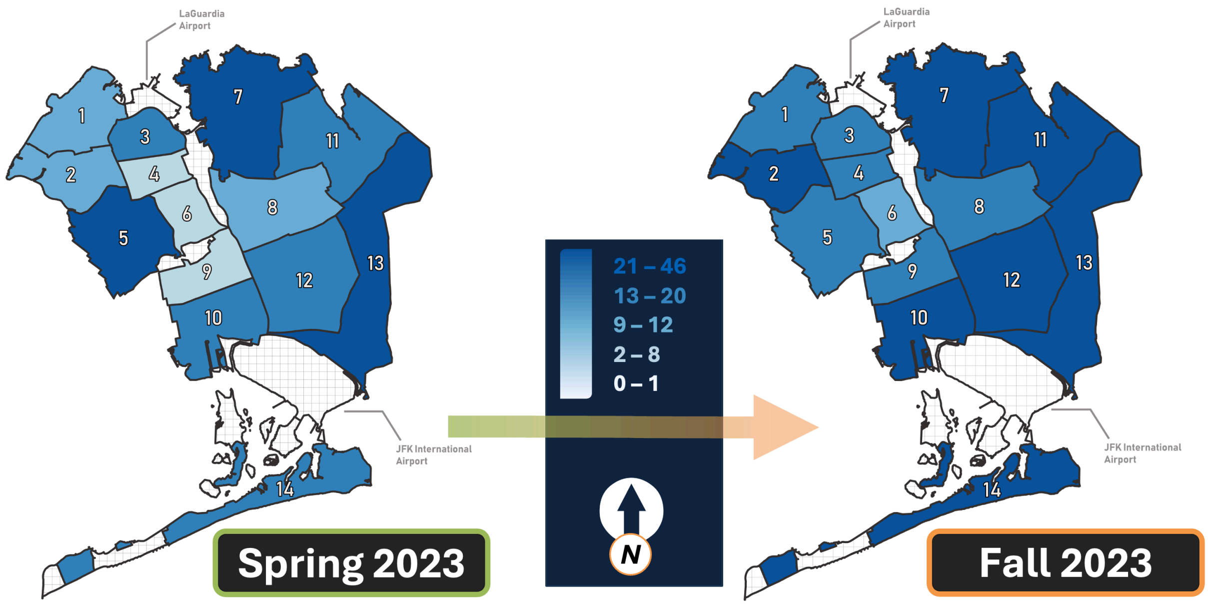

Figure 6. Unique locations of flooding reported to NYC311, by Community District. Each CD is labeled with their official numbers (e.g. "14" represents CD 14, or the Rockaways).

Table 11

Flooding Locations by CD, spring 2023 and fall 2023. Bold indicates CD 5, the only CD where flooding locations decreased between seasons.

Community Distrct (CD)	Flooding Locations	
	Spring 2023	Fall 2023
1	11	17
2	11	22
3	16	18
4	6	13
5	**26**	**13**
6	6	11
7	26	29
8	10	14
9	8	14
10	17	33
11	20	21
12	19	36
13	37	46
14	19	46

Portraying flooding locations on a map allowed me to identify CDs where flooding changed between seasons. The scale uses a custom Natural Jenks-based classification adjusted to include the minimum of both seasons combined in the lowest class, and the maximum of both seasons in the highest class.

A near-overall increase in unique flooding locations is clear. From spring to fall, 10 CDs recorded increases in flooding locations. 3 CDs recorded little change in flooding locations (CDs 3, 7, and 13 were in the same classification in both seasons), while only CD 5 experienced a decrease in flooding locations. The CDs with increased flooding locations are not all along shorelines; only 5 CDs that changed to a higher classification in the fall (these being CDs 1, 2, 10, 11, and 14) directly touch the East River, Jamaica Bay, or Long Island Sound. Many of the CDs that recorded an increase in locations are inland (CDs 4, 6, 8, 9, and 12). This may signify that flooding from overwhelmed drainage systems during storms are contributing more to flooding in inland CDs than short-term rising river tables.

4.2 Identifying the impact of flooding on Queens buses

For bus performance to reflect reported flooding locations in Queens, we would need to observe an overall decline in bus performance between spring and fall 2023 or performance declines in CDs that observed increased flooding locations over the same time frame. Establishing an association by month between flooding locations and bus performance would also serve as evidence for their connection. During the Peak fare period, median performance ranged from as high as 71.5% on time (in April) to as low as 61.0% on time (in September) over the study period. In the Off-Peak, median performance ranged from 74.1% (April) to 62.6% (September). September, October, and November fell below the overall Peak and Off-Peak period medians of 65.3% on-time and 68.6% on-time, respectively. Simultaneously, the months with the best performance were all in the spring; March, April, and May all experienced above-median bus performance.

Table 12

Median % CJTP by month, Peak and Off-Peak (February and August included for context).

Month	% Peak	% Off-Peak
February	72.0	75.8
March	69.2	72.1
April	71.5	74.1
May	66.0	69.0
August	74.9	73.6
September	61.0	62.6
October	61.4	65.5
November	62.9	65.0
Overall Median	65.3	68.6

Table 13

Change in median % CJTP, month to month.

Month	Change (Percentage Points), Peak	Change (Percentage Points), Off-Peak
March	-2.80	-3.70
April	2.30	2.00
May	-5.50	-5.10
September	-13.90	-11.00
October	0.40	2.90
November	1.50	-0.50

When comparing bus performance data to flooding data for overall months, some months show overall associations but a concrete association across the study is unclear. Studying the % change of CJTP against that of total precipitation and flooding locations per month, March and September saw both declines in Peak/Off-Peak period CJTP and increases in precipitation and flooding locations. Additionally, October and November (in Peak hours) saw minor improvements in CJTP as precipitation and flood locations lessened (November Off-Peak saw a marginal -0.5% decrease from October Off-Peak). This makes 4 months that mostly follow the negative association I hypothesized between bus performance and flood locations.

The 2 months that do not fit my hypothesis, April and May, contrastingly depict a positive trend between rainfall, 311 flooding locations, and bus on-time performance. As precipitation increased by 118.12% in April and flooding locations increased by 107.69%, CJTP rose by 2.3 percentage points in Peak hours and 2 percentage points in Off-Peak hours. Inversely, May observed a 76.32% decrease in precipitation and 25% decrease in flooding locations, but a corresponding 5.5 point decline in Peak CJTP and a 5.1 point decline in Off-Peak.

Noting the change in CJTP between Peak and Off-Peak fare periods, each month displays better performance in the Off-Peak. This is a change between +1.60 and +4.10 percentage points, with a median improvement in the Off-Peak of +2.75. I interpreted these results as a suggestion of how increased traffic congestion during Peak hours may affect the data as an extraneous variable. The maximum improvement of +4.10 suggests that the reduction of traffic in Off-Peak hours does not significantly impact bus performance data, as this small of a difference only marginally improves bus timeliness.

Table 14

Change in % CJTP between Peak period and Off-Peak period.

Month	Change (Percentage Points), Peak to Off-Peak
March	2.90
April	2.60
May	3.00
September	1.60
October	4.10
November	2.10
Median Change	2.75

Mapping bus performance by CD enabled a spatial and visual analysis of where CJTP changed between spring and fall, and how that spatially relates to changes in flooding. With the exception of CD 14, spanning the Rockaways, every CD in Queens saw drops in bus performance during the Peak period in the fall. This includes CD 5, which was the only CD to observe a decrease in its flood location total between seasons. In the fall, CDs 2, 4, 5, 6, and 10 observed the worst bus delays out of all CDs—none recorded more than 44.1% of their buses being on-time, with the lowest being CD 5 at only 38.4%. CDs 14 and 13 recorded the highest Peak % CJTP at 70.6% and 70.6% respectively.

Of the coastal CDs that recorded some of the worst bus performance metrics in the fall, some were mentioned previously as CDs that border the East River or Jamaica Bay. Out of these, CDs 2 and 10 show under 45% timeliness (Peak), while buses in CD 1 were only 57% on-time. Meanwhile, CDs 11 and 14, which touch the Long Island Sound, still experienced bus performance decline, but to a lesser degree.

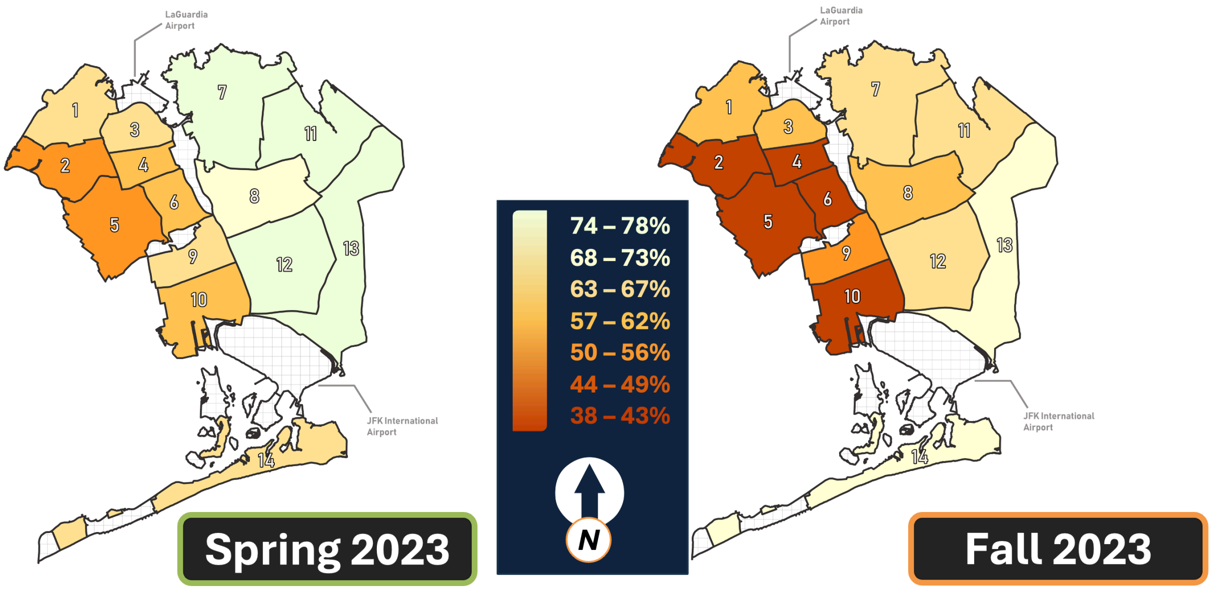

Figure 7. Bus On-Time Performance (CJTP) in the Peak fare period, by Community District. Darker shades of orange represent lower bus on-time performance.

When comparing these maps to the flooding location maps, I noticed the concentration of locations I observed in inland CDs does not appear to be reflected in the inland bus delays, which were concentrated on CDs 4 and 6 even though location increases were concentrated in CDs 4, 8, and 9. Instead, the Peak CJTP map appears to show a steep gradient where bus performance improves moving from western CDs (1-6, 9, 10) to eastern CDs (7-8, 11-13).

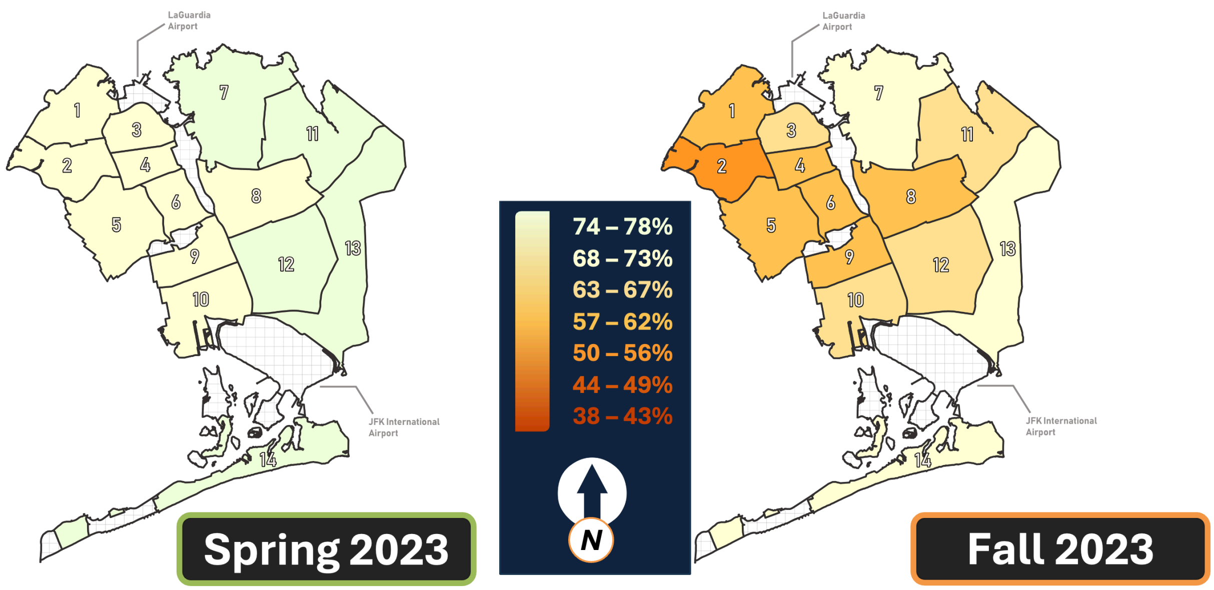

Figure 8. Bus On-Time Performance (CJTP) in the Off-Peak fare period, by Community District. Darker shades of orange represent lower bus on-time performance.

However, in the Off-Peak period, every CD in Queens saw poorer bus performance regardless of local changes in the number of flood locations. This decline appears more evenly distributed across the borough than what Peak hours showed, shifting the impact on buses to be less concentrated on the western CDs. Notably, inland CDs such as 4, 6, and 8 stand out again with bus performance of 60.5% and lower in the fall.

Considering the complete change in CJTP gradient between the Peak and Off-Peak maps, I questioned if this was due to traffic congestion being a more prominent influence upon the Peak data than the Off-Peak data. I also noticed that when the Peak period CJTP values for each CD are sorted low-to-high, the bottom 6 CDs remain the same between spring and fall (CDs 5, 2, 6, 4, 10 and 9, in order from lowest to highest CJTP). In the fall, these are also the lowest ranking during Off-Peak hours.

This could be interpreted as a sign of a consistent baseline of bus performance between those CDs, regardless of season, traffic, or other influential variables. However, because their CJTP values are significantly lower in the fall, it provides evidence that a variable affecting bus performance—

perhaps flooding—changed in the fall and is causing bus performance declines.

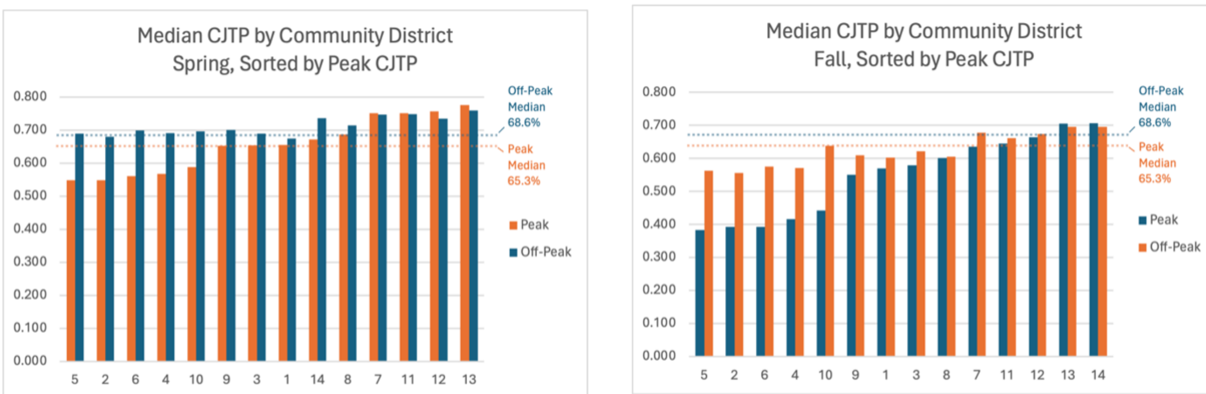

Figure 9. CDs by Peak hours median % CJTP, spring and fall, sorted lowest to highest by Peak CJTP.

CD	Fall OP	Fall P	Spring OP	Spring P
1	0.602	0.570	0.675	0.656
2	0.555	0.393	0.680	0.549
3	0.622	0.579	0.690	0.654
4	0.570	0.416	0.691	0.567
5	0.563	0.384	0.690	0.549
6	0.575	0.393	0.700	0.562
7	0.678	0.635	0.747	0.752
8	0.605	0.601	0.715	0.687
9	0.609	0.550	0.701	0.653
10	0.638	0.441	0.697	0.589
11	0.662	0.645	0.749	0.752
12	0.674	0.664	0.735	0.757
13	0.696	0.706	0.759	0.776
14	0.696	0.707	0.736	0.672

Figure 10. All median % CJTP Values by CD, season and fare period.

Additionally, the spatial gradient of bus on-time performance for Peak hours (see Figure 7) shows more drastic performance degradation in the CDs of Queens that are west of Grand Central Parkway and the Van Wyck Expressway, which bisect Queens approximately at its geographic center (CDs 1, 2, 3, 4, 5, 6, 9, 10). during spring and fall. It happens that the 6 lowest performing CDs in both seasons (CDs 5, 2, 6, 4, 10 and 9) are west of this divider as well (referred to from here as “western Queens”). This piqued my interest, as we do not have a certain reason for this contrast with “eastern Queens” (CDs 7, 8, 11, 12, 13) and the Rockaways (CD 14), which fare far better in bus on-time performance throughout all scenarios.

4.3 Understanding variation through R-Squared values

Finally, I performed multiple R-Squared analyses to understand variation between the rainfall, 311, and bus datasets. Calculating the variation between the monthly sums of rainfall (independent variable) and monthly sums of flooding locations (dependent variable), along with variation between monthly average rainfall and monthly flooding locations, yielded the results shown in Figure 11.

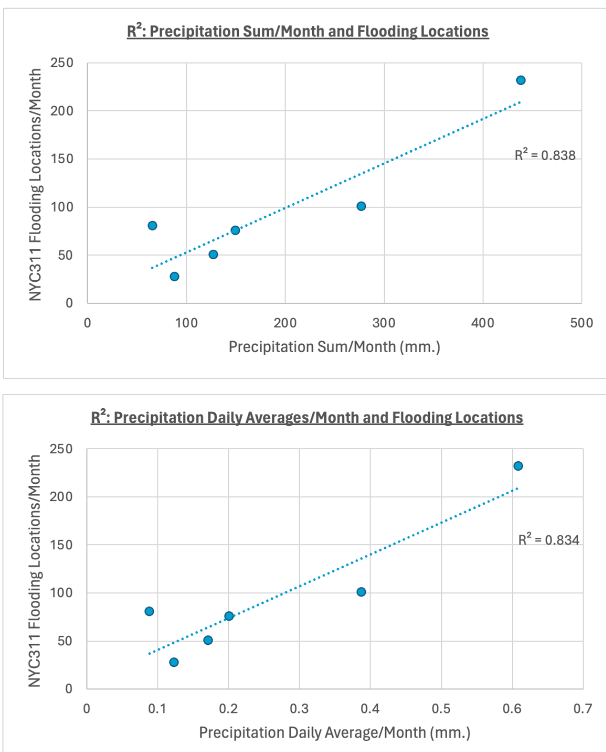

Figure 11. R-Squared comparisons between Precipitation (Sum/Daily Average) and Flooding Locations.

After establishing the overall temporal variation, I aimed to understand how flooding may explain the variation of bus performance at a CD level. I approached this question by solving for

R-Squared between the sum of flooding locations (independent variable) and recorded bus on-time performance within each CD (dependent variable), at both seasons and fare periods (see Figure 12). R-Squared values based on the association of 311 locations and bus on-time performance at a Community District level depict statistically significant and moderate relationships in fall 2023, depending on fare period. I established how this correlation was stronger in fall (0.701 Off-Peak, 0.413 Peak) than spring (0.160 Off-Peak, 0.238 Peak). Statistical significance in the CD-level data implies that there is a strong seasonal and localized correlation between flooding and bus performance, and far more explanatory of conditions in the fall.

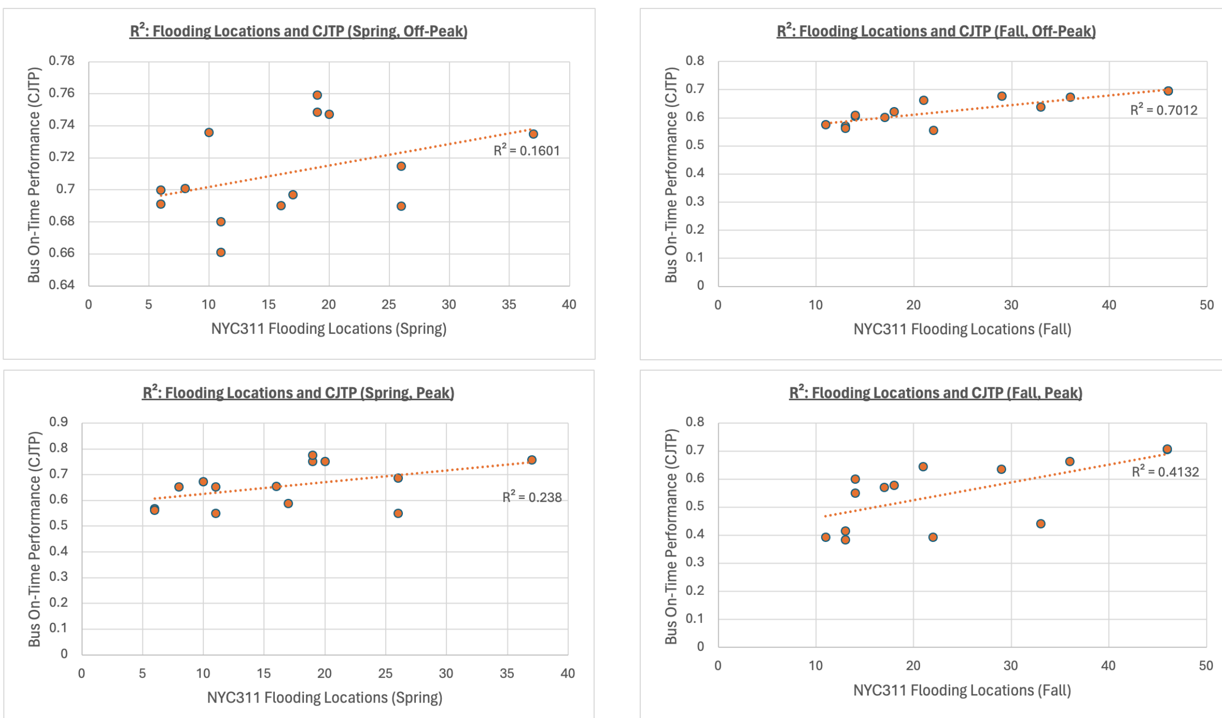

Figure 12. R-Squared comparisons between Spring and fall 2023, Peak vs. Off-Peak.

The spatial and total concentration of delays illustrate a more even spread of flood locations across Queens in the Off-Peak fare period, with no CDs that appear to show outliers in bus on-time performance. Data from Peak hours depicts even more extreme deficits in performance, particularly in western Queens. In hopes of understanding the apparent notable difference between bus on-time performance western and eastern Queens, I also opted to calculate R-Squared between flooding locations and bus-on-time performance per CD separated into sample groups of western Queens and eastern Queens (see Figure 13). I identified very high statistical significance in eastern Queens across both fare periods that was not identified in western CDs. The association in eastern Queens CDs yielded an R-Squared value of 0.918 (fall, Peak) and 0.8 (fall, Off-Peak), both far more significant than any correlation in western Queens or the spring reflected.

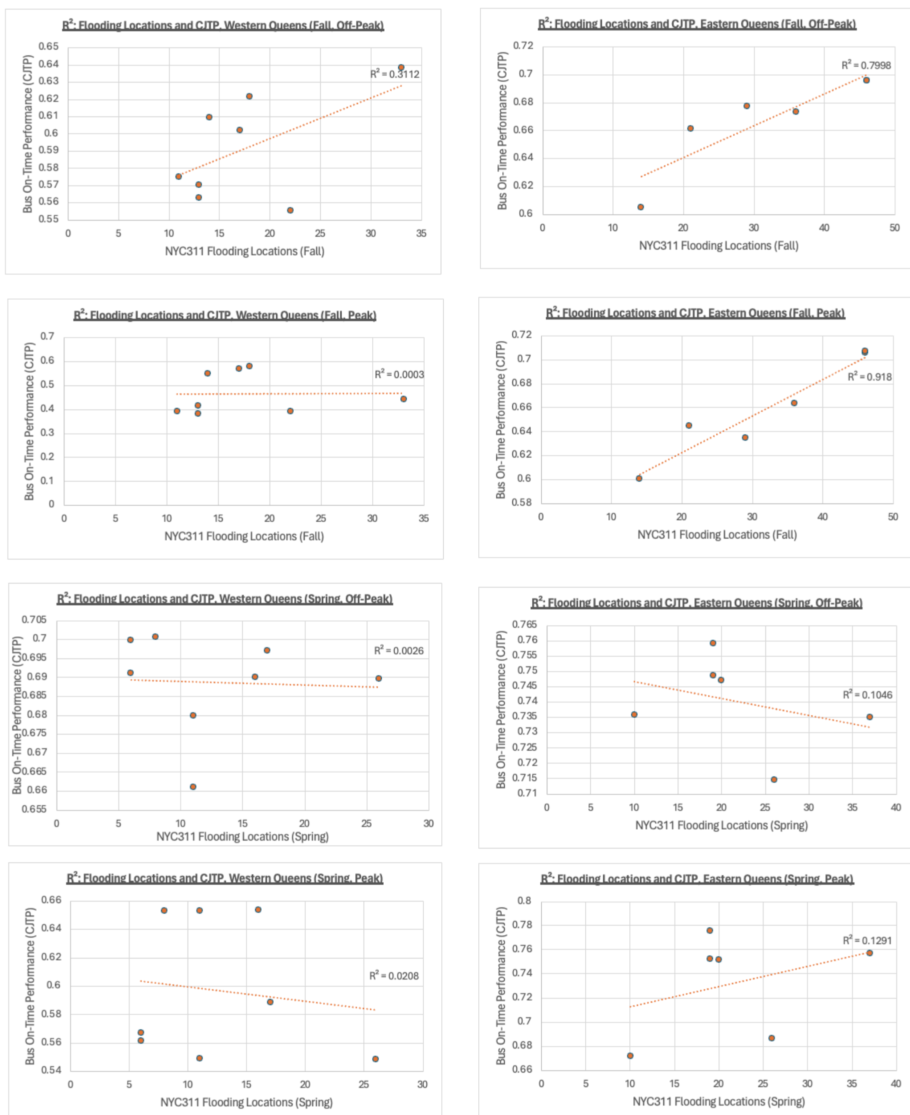

Figure 13. R-Squared comparisons between Western and Eastern Queens.

5 Takeaways

5.1 Implications

All 6 months in this study reflect a positive association between precipitation and NYC311 flooding locations. By month, September recorded the highest amount of rainfall and the largest prevalence of flooding locations. By season, fall 2023 observed greater rainfall and flooding than the spring. While my hypothesis stated that areas along the coastline would experience the brunt of flooding's effects, the reported locations of street floods seem to indicate a more nuanced result that depicted flooding increases in most coastal and inland communities during the fall of 2023. Based on the distribution of flooding locations reported to NYC311, this study established that between spring and fall, the areas in Queens at risk of flooding changed. In the fall, there was a substantial increase in flooding locations across all CDs except CD 5. Most of the locations were concentrated in northeastern Queens (CDs 7 and 11) and southeastern Queens (10, 12, and 13).

Given that the number of flooding locations increased across nearly all of Queens CDs in fall 2023, and that there is a positive association between rainfall and flooding location amounts, my findings confirm those of Agonafir et al. (2021) and Negri et al. (2023): that there is quantitative evidence for NYC311 flooding locations being associated with total precipitation amounts, and vice-versa. This is also supported by the strong explanatory relationship I derived between rainfall and 311 flooding locations per month, shown by the R-Squared values of 0.838 (when using monthly rainfall sums) and 0.834 (when using monthly rainfall averages).

The association I identified between flooding and bus performance in fall 2023 largely reflected my original hypothesis of a negative association. All three months in the fall (September, October, and November) and only one month in the spring (March) recorded a negative association between bus performance and flooding locations. It is important to note that September was consistently the worst month for bus performance in both fare periods, considering the severity of flooding on September 29 which exceeded all other weather events in 2023. While my analysis of fall showed mixed associations between flooding and bus performance, the spring months of April and May showed a positive association between the variables while March reflected the negative association. Notably, April recorded the best bus performance, even though it was not the driest month in this study. Spring 2023 also contrasted fall 2023 by reflecting relatively low R-Squared values between flood prevalence and bus performance. From one point of view, this contrast could be caused by how ground-truth rainfall (and thus, potential flooding) was more severe in fall 2023 over spring 2023, which is supported by September's anomalous rainfall total (NYS Mesonet, 2024) as well as journalistic and citizen reports of September 2023 flooding (Blackmore, 2024; Offenhartz et al., 2023). From another perspective, lower precipitation amounts in one month (such as May, which only recorded 65.61 mm. of precipitation) may cease to impact bus performance once rain decreases below a certain amount, implying that in spring there were factors other than rainfall which became the primary drivers of on-time performance metrics.

My findings imply the existence of at least one underlying variable that increased the number of street flooding locations reported to NYC311, and at least one underlying variable that decreased bus on-time performance throughout fall 2023. Although other unstudied variables could be culpable (which I address in the **Limitations** below), there are 3 particularly compelling reasons for flooding to be the driving cause of fall's bus delays:

1. The existing body of literature (particularly Suarez et al., 2005, Chang et al., 2011, Chen et al., 2015, Singhal et al., 2014, and Abenayake et al., 2022), which has established how flooding hinders surface transportation, in past floods and computer-simulated floods;

2. My analysis of seasonal and localized Community District data in this study, which established a moderate correlation between flood prevalence and bus performance in the fall Off-Peak period, and a statistically significant correlation in both fare periods across eastern Queens versus Community Districts west of the Van Wyck Expressway;

3. My comparison of Peak and Off-Peak and spatial data in fall 2023 which identified decreases in bus performance across fare periods with only marginal differences in % Change between these fare periods—signifying that impacts to bus performance in the fall are not explainable

by traffic congestion alone.

This study provides evidence of a correlation between flooding and bus performance, with statistical significance in eastern Queens, that can be used by future studies to establish a concrete causal relationship between these variables using ground-truth data.

5.2 Limitations

I conceived some possible limitations to this study while authoring it, and concluded that its biggest limitations are the lack of accessible and reliable ground-truth data. This particularly includes the lack of certainty to how extraneous variables may affect this 311 and bus congestion data.

For example, spatial bias and under-reporting in 311 reporting was previously stated as a concern that this study was designed to mitigate, by mapping unique locations of 311 reports. While this eliminated duplicates from the dataset, there is no way to eliminate reporting bias entirely without a thorough comparison against ground-truth data that, currently, is not available for flooding in NYC.

Another extraneous variable that is missing reliable ground-truth data is traffic, and the amount of congestion that may be impacting the data presented here. Obtaining access to hourly traffic volumes for individual streets in Queens could allow for the impact of traffic congestion on individual bus routes to be analyzed. Simultaneously, comprehensive traffic data could help us understand whether traffic congestion is the main driver behind western Queens' long Peak period bus delays, since the flooding-bus performance relationship was deemed low in that region by my R-Squared analysis. Previously, traffic volume data for 90 streets in Queens from the NYC DOT (recorded by Automated Traffic Recorders) was publicly accessible through the NYC Open Data portal (NYC Department of Transportation, 2022). This dataset provided counts of vehicles crossing key roads in Queens, aiming to record traffic volume changes every 15 minutes throughout each year.

I most recently used this data for a separate project in 2023, comparing localized traffic congestion with bus individual bus route performance in Queens. However, in mid-2024 the version of this dataset available online was shrunk from the 27,190,511 rows that were in the 2022 version (spanning years 2000 to 2023) to 1,673,725 rows (spanning years 2000 to 2024) (NYC Department of Transportation, 2022). In correspondence with a representative from the NYC DOT in mid-2024, I was told that some of these rows were "removed in the most recent update was due to errors in the data," while other rows were removed due to "inflated rows because the data was uploaded multiple times to rectify previous errors" (*Email Correspondance with Representative from the NYC Department of Transportation*, 2024). Due to these changes, the number of streets in Queens that had traffic volume counts decreased from 90 to just 10 total. I deemed that 10 streets would not be enough to extrapolate traffic counts, and thus congestion, across our entire study area. I opted not to use the source, despite being ground-truth data, due to these pitfalls. As of November 7, 2024, the dataset has only 1,712,605 rows and has not restored all 90 Queens streets that were previously included.

5.3 Future Steps and Solution Components

In the future, researchers studying the intersection between flooding and public transportation should consider studying larger time frames than this study was able to accomplish. Approaching the issue with a larger study time frame would allow us to identify if an association between floods and delays exists outside of 2023, is limited to specific months and seasons, or has become stronger over time with the progression of anthropogenic climate change. Additionally, analyzing a greater pool of data could create the basis for more accurate predictive modeling and help public officials plan their climate change resilience efforts more strategically.

The road to more thorough studies in this field will benefit greatly from better ground-truth data. For example, NYC DOT restoring the accuracy of the Automated Traffic Volume Counts dataset, and all 90 Queens streets that were previously logged (NYC Department of Transportation, 2022), would allow future researchers to apply ground-truth traffic data to transportation studies of NYC, and increase our overall understanding of how traffic impacts public transportation.

One promising step towards a ground-truth abundance for flood and transit researchers is the project FloodNet NYC, a joint research and open data project between NYC, New York University, and the City University of New York that installs ultrasonic flood monitoring range-finders in several NYC communities. (FloodNet NYC, 2024). One of these range-finders records the distance between itself and the road surface continuously after being installed above a street or sidewalk; if said street or sidewalk floods, the distance-to-surface recorded by the range-finder's will decrease, and the FloodNet NYC servers process the estimated depth of flooding directly from that distance data (FloodNet NYC, 2024). This data is publically accessible for free at their website, https://floodnet.nyc. While by the end of 2023, there were 25 streets equipped with FloodNet range-finders in Queens, as of November 2024 that number has risen to 82. FloodNet NYC data shows potential for being used in a similar study to this one, as the larger their roster of streets with range-finders grows, the more thorough ground-truth data will be available to researchers.

This study focused on analyzing how flooding influenced bus transportation in 2023. Future studies should look towards answering the "why": identifying the variables that explain why Queens buses appear to be so much more delayed in time periods and areas with more reported flooding locations. I hypothesize that the topography of Queens, combined with drainage systems that are under-equipped for recent flooding events and intensities, might make certain areas more vulnerable to becoming rainwater catches that others, leading to floods and associated bus delays. I also encourage future studies to take into account the effectiveness of dedicated bus infrastructure in NYC as flood-resilient infrastructure.

Flooding is not an entirely natural hazard. A flood may begin with excessive rainfall, but its ability to overload drainage systems, pool on impermeable surfaces, and interfere with urban settlements is a symptom of human-made infrastructure ill-equipped to handle floods of this magnitude. The findings of this study support the idea that protective measures against flooding to improve bus delays are worthwhile to improving public transit and urban residents' mobility overall.

I noted earlier in this paper that the MTA's redesign plan for the Queens bus network does not include any mentions of flooding, weather, climate change's effects, or what can be done to protect public transit against severe weather. By doing this study, I determined that 3 of the 4 main priorities set by the MTA in its redesign proposal could be addressed in significant ways with greater investments in flood infrastructure (Metropolitan Transportation Authority, 2023b):

1. *Reliable Service* can be addressed by building bus infrastructure that is more resistant to floods, thereby reducing the risk of bus unreliability caused by flooding.

2. *Faster Travel* can be a positive externality of improving bus delays, as reducing the number of buses stuck in flood conditions could decrease bus bunching and move passengers around the city faster.

3. *Better Connections* can be created when passengers don't have to wait on a flooded street or sidewalk, while fewer delays would mean shorter wait times to board a connecting bus.

6 Supplement: Exploratory Field Studies

6.1 Using Field Studies to Illustrate Queens Road Infrastructure

I believed that exploring Queens based on the map of the 311 dataset would yield an insightful list of street conditions that may or may not contribute to flooding and the associated delays. This could provide a starting point for future studies aiming to identify the physical causes of flooding-triggered ground transportation delays, whether in Queens or other places.

As a supplemental effort to understand the ground conditions of streets in Queens, I conducted field studies with Prof. Campos and Prof. Cousins at multiple sites on October 8, 2024. This was an exploratory effort, and not conducted to draw conclusions on the causal effects behind street flooding or bus delays. However, I modeled my methodology off the good practice guidelines for fieldwork presented by Bosco & Moreno (2009) by making my observation process as systematic as possible, and exercising reflexivity with my position as an individual who does not live or commute directly in the communities I draw conclusions on (Bosco & Moreno, 2009).

Taking inspiration from Bosco & Moreno (2009)'s descriptions of fieldwork, I aimed to conduct an "open-ended, interpretive" observation of systematic elements within the urban landscape (p. 119). Based on these principles, I developed an original methodology for choosing Locations of

Interest (LOIs) to conduct field observations. First, I limited the LOIs only to sites that are identified as flood locations in the spring or fall within our dataset. I narrowed down the selection further to only identify locations that are also intersected by at least one Queens bus route (with at least one bus stop on the same block). Although no conclusions were to be drawn, I felt that limiting LOIs to areas with reported flooding and bus route(s) was important to keep locations relevant to this study's overarching topic.

I further narrowed down the criteria by running the *Kernel Density* tool on both the spring and fall 311 location datasets plotted in ArcGIS Pro. This allowed me to only select LOIs located within *Kernel Density* clusters. Since *Kernel Density* calculates the density of points in a given dataset, I used it to illustrate which LOIs were located within or near clusters of other reported flooding locations—the logic being that denser clusters of flood locations were assumedly more vulnerable to flooding, and thus the road conditions observed at these LOIs may reveal larger trends about local ground conditions.[6] Attention was also given to whether a notable body of water was located near each LOI and protections against their overflow onto the roadway in the case of inundation.

Following this process, I identified 4 LOIs that reflected all of my limiting criteria, as shown in Table 15. The resulting list of LOIs reflect a well-spread distribution across Queens, which provided a broad scope for my observations and a variety of ground conditions to analyze. 2 locations (the Jackson Heights and College Point) are closer to the northern coast (the former being near Flushing Bay, and the latter bordering Herman A. MacNeil Park, which is on the East River). 1 location is southern (Rosedale), intersecting Brookville Park, and the final location (Jamaica Hills) is roughly central in the borough and landlocked.

[6] I ran the *Kernel Density* tool for spring and fall with an environmental output cell size (about 280.36), the Planar method, and densities as output cell values.

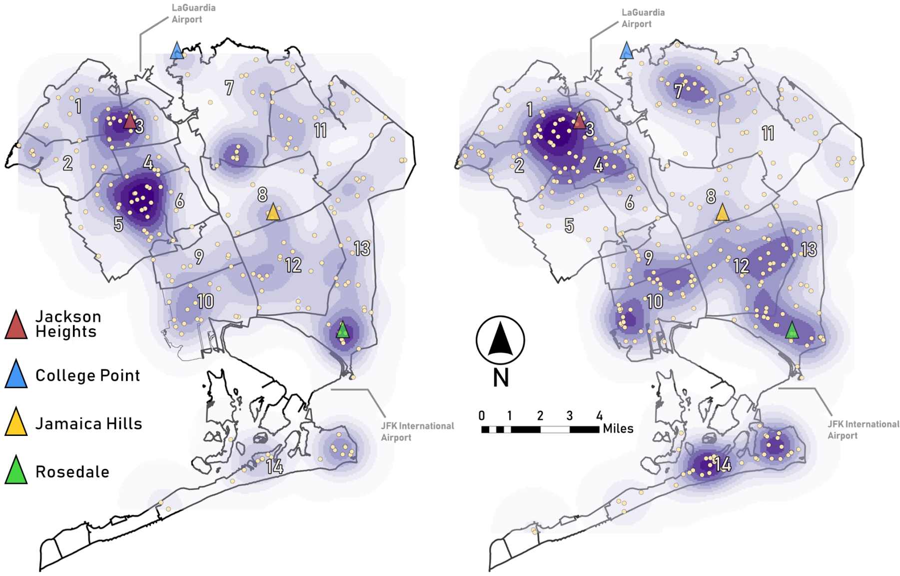

Figure 14. Kernel Density maps for 311 flooding locations (spring 2023 on left, fall 2023 on right). Circular points depict unique flooding locations, and triangles depict the LOIs listed in Figure 15.

Table 15

Locations of Interest (LOIs) and their notable properties.

Cross-street (and neighborhood)	Date of 311 Report(s)	Bus Line(s)	CD	Highest % CJTP	Lowest % CJTP
Astoria Blvd, between 86th and 87th St (Jackson Heights)	9/29/2023	Q19	3	69.0 (Spring, Off-Peak)	57.9 (Fall, Peak)
Poppenhusen Ave & College Place (College Point)	4/30/2023	Q25	7	75.2 (Spring, Peak)	63.5 (Fall, Peak)
147th Ave, intersecting Brookville Park (Rosedale)	9/18/2023, 9/30/2023	Q111	13	77.6 (Spring, Peak)	69.6 (Fall, Off-Peak)
Gothic Dr & Homelawn St (Jamaica Hills)	10/15/2023	Q30, Q31	8	71.5 (Spring, Off-Peak)	60.1 (Fall, Peak)

Citing examples of stormwater management conveyed in the NYC Mayor's Office's Stormwater Resiliency Plan (NYC Mayor's Office of Resiliency, 2021) and the NYC DEP's City Stormwater Manual (NYC Department of Environmental Protection, 2024b), I sought the following examples of design that would affect flood management:

1. Drainage (or lack thereof): including manholes and catch basins connected to the Separate Storm Sewer System (NYC Mayor's Office of Resiliency, 2021),

2. Permeable surfaces (or lack thereof): including but not limited to curb strips (grade-separated planters along the side of a street/sidewalk), dedicated bioretention planters, and porous pavement (NYC Department of Environmental Protection, 2024b),

3. Engineered protection from inundation in the case of high tide and river table rise (NYC Mayor's Office of Resiliency, 2021).

To practice reflexivity and minimize my personal bias, my observations were categorized strictly on these categories. Although I pulled outside sources to draw hypotheses and extra detail into my analysis, I had not reviewed these sources prior to conducting the field studies.

6.2 Drainage

In our field studies, we observed multiple ways drainage is arranged on Queens streets. All of these implementations were catch basins embedded into sidewalk curbs, but their differences evoked questions around their strategic placement.

At the Jackson Heights LOI, one catch basin was embedded into the curb directly on the eastbound side of Astoria Blvd, at the corner of 87th St. Another catch basin was observed on 86th St, directly after the turn off eastbound Astoria Blvd. Both of these basins were placed on slight downward grades, causing them to be lower than the relatively-flat surrounding road grade.

NYC's Street Design Manual states the criticality of street grade in resolving "ponding or flooding issues." (NYC Department of Transportation, 2020, p. 61) I hypothesize that this downward-sloped grade helps direct runoff from Astoria Blvd and 86th St into the catch basin more effectively.

Figure 15. Catch basin on Astoria Blvd, adjacent to 87th St.

Figure 16. Catch basin on 86th St off Astoria Blvd.

This may be especially relevant on Astoria Blvd, a 6 lane road (8 lanes including street parking) that appears to have a very flat grade. If the relatively flat grade of this road caused water to pond when flooding reportedly occurred, a method for directing water into the catch basin would be even more necessary.

We observed 5 total catch basins at the College Point LOI, all of which were placed at the intersection of Poppenhusen Ave and College Place. Two basins are placed directly across from each other on Poppenhusen Ave, following a left turn from College Place, while two others were arranged similarly following a right turn. Additionally, 9 sewer manholes were placed at the intersection, with 8 embedded within the road and 1 within the sidewalk.

Even though these total to 14 drainage utilities installed within a 50 foot radius of the Poppenhusen Ave/College Place intersection, it was understandable that flooding had still been reported considering how rainfall amounts exceeded the 90th percentile so frequently in 2023.

Figure 17. 2 of 5 catch basins on Poppenhusen Ave, at intersection with College Place.

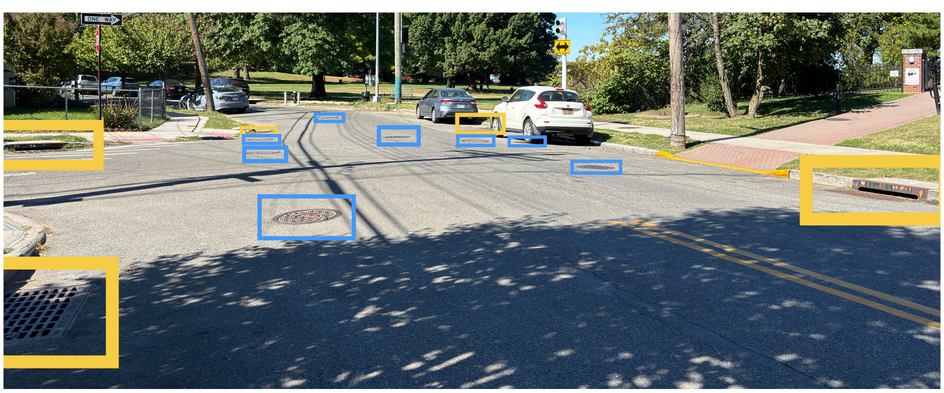

Figure 18. All 5 catch basins and 8 street manholes at the intersection of Poppenhusen Ave and College Place. Manholes are scattered throughout the intersection.

The Jamaica Hills LOI featured 3 water and sewage manholes, all at the pedestrian crossing across Gothic Dr. However, we observed no catch basins for drainage in the intersection or immediate area. If this constitutes insufficient drainage, that may have contributed to the reported flooding that occurred here in October 2023.

Figure 19. Homelawn St from its intersection with Gothic Dr, facing northeast. One sewer manhole and one ConEd manhole are visible in the far-left; otherwise, no catch basins were observed.

Finally, the stretch of 147th Ave by Brookville Park at the Rosedale LOI similarly depicted catch basins being outnumbered by manholes. While there were 4 manholes along the road between Brookville Blvd and 232nd St, we only observed 1 catch basin on the westbound side, just next to a roughly 3-foot tall brick barrier that separates the park's Conselyea's Pond from the roadway. This effectiveness of this basin at allowing water to flow in was questionable, however, considering the debris scattered on its surface (see Figure 20). A debris-clogged catch basin can tamper with water infiltration or block it entirely, which could contribute to localized street flooding issues if other drainage systems cannot compensate for the clogged catch basin. This is a known issue in Queens, as NYC311 also records complaints of clogged catch basins (Agonafir et al., 2021).

Figure 20. The catch basin on 147th Ave by Brookville Park.

Figure 21. 2 manholes on 147th Ave by Brookville Park.

6.3 Permeability, Impermeability, and Curbs

In Queens, October 8, 2024 was a sunny day with an average temperature of 62°F and no recorded precipitation. These conditions followed a stretch of 8 days without precipitation, so we did not expect to find even minor ponding on the roads. [7] However, we identified many examples of impermeable surfaces and curb design that could propagate runoff ponding on the roadway.

For example, at the College Point LOI, we found evidence of ponding at the curb where College Place terminates at the three-way intersection. The liquid appears to have spread along the curbside, although its origin point is unknown.

Figure 22. Ponding in College Point on Poppenhusen Ave, by Hermon A. MacNeil Park. A curb strip is raised just above the area with ponding.

[7] Meteorological Fall 2024 was much drier than fall 2023. Queens experienced a complete absence of rainfall above 0.01 inches from September 30 to November 20. (NWS, 2024c)

I noted that the curb strip is not able to absorb this liquid because it is raised from the street. While these curb strips can retain rainfall (NYC Department of Environmental Protection, 2024b), the curb blocks any flow of runoff from the street into the strip (except for circumstances where the volume of runoff exceeds the height of the curb). While this design may helps to protect the plants in the curb strip from harmful or polluted runoff, it may be worth investigating whether curb strips that are flush with the roadway could absorb and treat a greater volume of runoff in a street flooding event. This would reflect the NYC Street Design Manual's suggestion to keep "planted areas and stormwater source controls," including curb strips, within their surrounding roadway instead of being separated (NYC Department of Transportation, 2020, p. 61). The soil of an effectively permeable curb strip also must not be so compacted that it "behave[s] like impermeable surfaces," which is a recorded issue with urban soils due to urban construction activity (Qin, 2020, p. 1).

Figure 23. The seawall at Hermon A. MacNeil Park from the perspective of the East River. The ramped entrance bisecting the wall is at the far-left of the image.

Flood mitigation at College Point appears particularly important because of the neighborhood's proximity to the East River, which Hermon A. MacNeil Park provides direct access to merely 125 feet from Poppenhusen Ave (at their closest distance). At MacNeil, a seawall was installed that faces the East River and divides the grassy area of the park from its sandy cove.

Figure 24. The seawall at Hermon A. MacNeil Park, overlooking the East River (5’5” researcher for scale).

The two sides of the park connect via a ramp and stairs bisecting the seawall, as the park and street level were elevated from the river stage on the day of our visit. Being elevated from the East River may better protect its residents in case of a heightened river stage.

Our LOIs at College Point and Rosedale both illustrate permeable space through their proximity to parks; specifically MacNeil Park at College Point, and Brookville Park at Rosedale. MacNeil is a nearly 29-acre park bordering the East River that consists of mostly green space (with the exception of a playground and a baseball field), and 338 recorded trees (NYC Parks, 2024b). Since trees provide water retention and absorption through their leaves and roots (Qin, 2020), they add to MacNeil Park’s ability to mitigate runoff within the surrounding area.

Brookville Park borders 147th Ave, which is a two-lane asphalt road with public parking space on the Brookville Park grounds. While this description of the road emphasizes its impermeability, the park shows much more potential for runoff mitigation. Brookville is a nearly 90-acre park which features the large Conselyea's Pond, over 1,100 mapped trees, and 25.2 acres of NYC Parks-designated "Forever Wild" natural areas (NYC Parks, 2024a). This park likely provides the same types of water retention benefits of MacNeil Park but at a larger scale, as Brookville is a larger park with a greater tree population. Across 147th Ave, a series of tree planters are embedded in the sidewalk, providing greater water retention. However, future researchers should consider whether Conselyea's Pond is particularly vulnerable to flooding from extreme rainfall events, and whether this negates the retention benefits provided by Brookville Park to the surrounding community.

Figure 25. Trees and plants on the Astoria Blvd median.

Medians were determined by the NYC Street Design Manual as an effective tool for building permeable space on roadways (NYC Department of Transportation, 2020). On Astoria Blvd in Jackson Heights, the road is divided by a median lined with several trees in planting beds. These beds are surrounded by tile that may allow water to infiltrate the ground below. Along with curb strips embedded in the sidewalk, this median provides some permeable space in between the highly-impermeable 6 lanes of asphalt road. The Jamaica Hills LOI showed even lower permeability, with minimal curb strips to aid drainage.

6.4 Reflecting on Our Observations, Flooding, and Buses

Studying the road infrastructure of our 4 LOIs in Queens revealed many noteworthy points about the state of the borough's ability to flood mitigation and support reliable bus transportation. Impermeable surfaces are major contributors to the issue of urban flooding (Qin, 2020). This is why flooding is especially prevalent on city roads, which are often made of impermeable materials, lined by impermeable sidewalks, and surrounded by impermeable driveways or side roads (NYC Department of Transportation, 2020). Adding sufficient drainage and utilizing permeable space in an urban setting are two key components of flood mitigation strategy, as demonstrated by the planning being done in NYC (NYC Department of Environmental Protection, 2024b; NYC Mayor's Office of Resiliency, 2021; NYC Department of Transportation, 2020). Preparations for extreme weather may only become more essential as climate change intensifies weather patterns and sea level rise.

The association this study identified between greater flood prevalence and worse bus on-time performance, and particularly the strong R-Squared association found in eastern Queens (which includes our LOIs in College Point, Jamaica Hills, and Rosedale), suggest that flood infrastructure is vital to bus performance and reliability in this region of NYC. Future research on how these bus metrics can be improved strategically should explore the direct impact of drainage conditions and street permeability levels on this form of transportation.

Figure 26. A bus stop for the Q19 route on Astoria Blvd at Jackson Heights, near the catch basins we observed.

Figure 27. A bus stop for the Q25 route on Poppenhusen Ave at College Point.

As shown in my analysis of the MTA's redesign plan, overlap between the planning of bus infrastructure (e.g. bus lanes, transit signal priority) and flood infrastructure is not covered in the plan's overview. However, I argue that a more holistic solution would be to construct new bus infrastructure with integrated flood protections, such as drainage with tolerance for greater rainfall amounts than 1.75 inches, or increased planters along bus lanes.

Additionally, porous pavement is being implemented in select NYC areas, including at one location in College Point (NYC Department of Environmental Protection, 2024c), and has proved to be promising for use in flood mitigation strategies. By replacing traditional concrete on urban roadways, porous pavement allows water to infiltrate the ground from any point along the road, adding to the flood resilience potential provided by catch basins, permeable planting beds, and other methods of capturing rainwater (NYC Department of Environmental Protection, 2024c). Porous pavement could improve the permeability of urban roads in general, while having potential for integration in new bus infrastructure, allowing those projects to double as flood mitigation solutions without widening a thoroughfare with drainage or planters.

The NYC government reaffirmed the link between quality drainage and efficient transportation earlier this year, when it announced an investment of $51.8 million into Rosedale's flood infrastructure to help "make transportation improvements in the area." (NYC Department of Environmental Protection, 2024a) Some of the existing infrastructure in this area was installed prior to 1940, making it unable to withstand present-day rainfall levels. The new investment will include the construction of 92 catch bases, 13 storm chambers, over 2 miles of upgraded pipes for the water mains, new roads/curbs/sidewalks, and other improvements that will help relieve infrastructure in southeastern Queens. (NYC Department of Environmental Protection, 2024a)

A holistic approach to improving flood protection and transportation has the potential to protect local residents from severe floods while improving conditions for traffic and buses. Therefore, further researchers should consider studying the intersectionality between flooding infrastructure and bus performance in southeast Queens and other regions.

Figure 28. Workers installing porous pavement at a parking lot in College Point, Queens.

(NYC Department of Environmental Protection, 2024c)

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