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RESEARCH ARTICLE

Understanding Spatiotemporal Patterns and Drivers of Urban Flooding Using Municipal Reports

Stacie DeSousa[1] | Aditi S. Bhaskar[1] | Christa Kelleher[2] | Ben Livneh[1,3]

[1]Department of Civil, Environmental, and Architectural Engineering, University of Colorado-Boulder, Boulder, Colorado, USA | [2]Department of Civil and Environmental Engineering, Lafayette College, Easton, Pennsylvania, USA | [3]Cooperative Institute for Research in Environmental Sciences, University of Colorado-Boulder, Boulder, Colorado, USA

Correspondence: Aditi S. Bhaskar (aditi.bhaskar@colorado.edu)

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ABSTRACT

Urban flooding is an increasing threat to cities and resident well-being. The Federal Emergency Management Agency (FEMA) typically reports losses attributed to flooding which result from a stream overtopping its banks, discounting impacts of higher frequency, lower impact flooding that occurs when precipitation intensity exceeds the capacity of a drainage system. Despite its importance, the drivers of street flooding can often be difficult to identify, given street flooding data scarcity and the multitude of storm, built environment, and social factors involved. To address this knowledge gap, this study uses 922 street flooding reports to the city in Denver, Colorado, USA from 2000 to 2019 in coordination with rain gauge network data and Census tract information to improve understanding of spatiotemporal drivers of urban flooding. An initial threshold analysis using rainfall intensity to predict street flooding had performance close to random chance, which led us to investigate other drivers. A logistic regression describing the probability of a storm leading to a flood report showed the strongest predictors of urban flooding were, in descending order, maximum 5-min rainfall intensity, population density, storm depth, storm duration, median tract income, and stormwater pipe density. The logistic regression also showed that rainfall intensity and population density are nearly as important in determining the likelihood of a flood report incidence. In addition, topographic wetness index values at locations of flooding reports were higher than randomly selected points. A linear regression predicting the number of reports per area identified percent impervious as the single most important predictor. Our methodologies can be used to better inform urban flood awareness, response, and mitigation and are applicable to any city with flood reports and spatial precipitation data.

1 | Introduction

Urban flooding is an increasing concern around the globe (Kundzewicz and Pińskwar 2022; Lei et al. 2023; Mei et al. 2024; Mobini et al. 2022; National Academies of Sciences, Engineering, and Medicine 2019; Rainey et al. 2021). Currently, the effective functioning of stormwater infrastructure is faced with many challenges, including increased stormwater due to increased development (Lei et al. 2023; Yosua, Kusuma, and Nugroho 2024; Zhu et al. 2023), aging infrastructure (Šiljeg, Milošević, and Mamut 2024; Yosua, Kusuma, and Nugroho 2024) and intensified storm events attributed to climate change (Fofana et al. 2022; Moftakhari et al. 2018; National Academies of Sciences, Engineering, and Medicine 2019; Rainey et al. 2021).

Outside of coastal areas, flooding is typically classified as either fluvial or pluvial. While fluvial flooding occurs when a stream overflows its bank, pluvial flooding occurs when natural or engineered drainage systems fail to effectively manage precipitation, leading to ponding or overland flow (Moftakhari et al. 2018; Rosenzweig et al. 2018). Whereas high-magnitude and low-frequency events often characterise fluvial flooding, a range of event sizes can lead to pluvial flooding (Rosenzweig et al. 2018). Pluvial flooding, sometimes called urban flooding when it occurs in urban areas, can result from storms that surpass design specifications or from inadequate maintenance of drainage systems (Rosenzweig et al. 2018). Despite its growing occurrence, pluvial flooding events receive less attention than fluvial flooding events. Historically, researchers have documented most flooding incidents by examining peak stream discharge or reviewing insurance claims within National Flood Insurance Program (NFIP)-insured areas, which typically coincide with the 100-year floodplain. These conventional records often overlook events outside of a floodplain, or flooding that cannot be connected to monetary damage (Galloway et al. 2018; Moftakhari et al. 2018; National Academies of Sciences, Engineering, and Medicine 2019; Rosenzweig et al. 2018). Regardless, pluvial flooding events can still have significant consequences. Urban flooding has been known to lead to traffic disruptions, emotional distress, and property damage (Galloway et al. 2018; Knight et al. 2021; Moftakhari et al. 2018; National Academies of Sciences, Engineering, and Medicine 2019) with impacts of each of these problems compounding due to high-frequency occurrence. Work from Moftakhari et al. (2018) showed that the aggregated cost of all high-frequency flooding events can exceed those of low-frequency, high magnitude events for which cities are more commonly prepared.

Current methods used to understand urban flooding predominantly rely on modelling analyses using programs such as CUHP, SWMM and HEC-RAS (Qi et al. 2021; Teng et al. 2017). However, because there is no widespread monitoring of street flooding as there is for streamflow, the accuracy of these models is hard to evaluate without observations with which to compare. These approaches can require substantial time and monetary costs, data requirements and implementation challenges. Additionally, these types of analyses are often based on design-storms and a simplified portrayal of the built environment.

To circumvent these challenges, previous researchers have used crowd-sourced reports of urban flooding in the form of municipal service reports in conjunction with rainfall data (Bouwens et al. 2018; Michelson and Chang 2019; Sadler et al. 2018; Smith and Rodriguez 2017; Tian et al. 2019) and topographic studies (Gaitan, ten Veldhuis, and van de Giesen 2015; Kelleher and McPhillips 2020) to understand patterns in urban flooding, but previous work has often examined storm variables separately from topographic and other built environment variables. Building upon this body of work, this study aims to understand how spatial and temporal drivers comparatively influence the likelihood of urban flooding. Methodologies of this paper can easily be applied to any city with municipal flood reports and spatial precipitation data (from either radar or a rain gauge network).

In this analysis, we conceptualise pluvial flooding as the result of compounding factors of rainfall characteristics, built infrastructure, and social variables (Figure 1). Not only are the storm characteristics that lead to pluvial flooding important but also the characteristics of the land where the rain falls and information about the people affected during the flooding, given many studies have shown that flood exposure can be high for vulnerable populations (Qiang 2019; Tate et al. 2021). Focusing on just one or two of these variables would leave significant parts of the story untold.

This study analyzes crowd-sourced reports of urban flooding from the City and County of Denver. We employed multiple

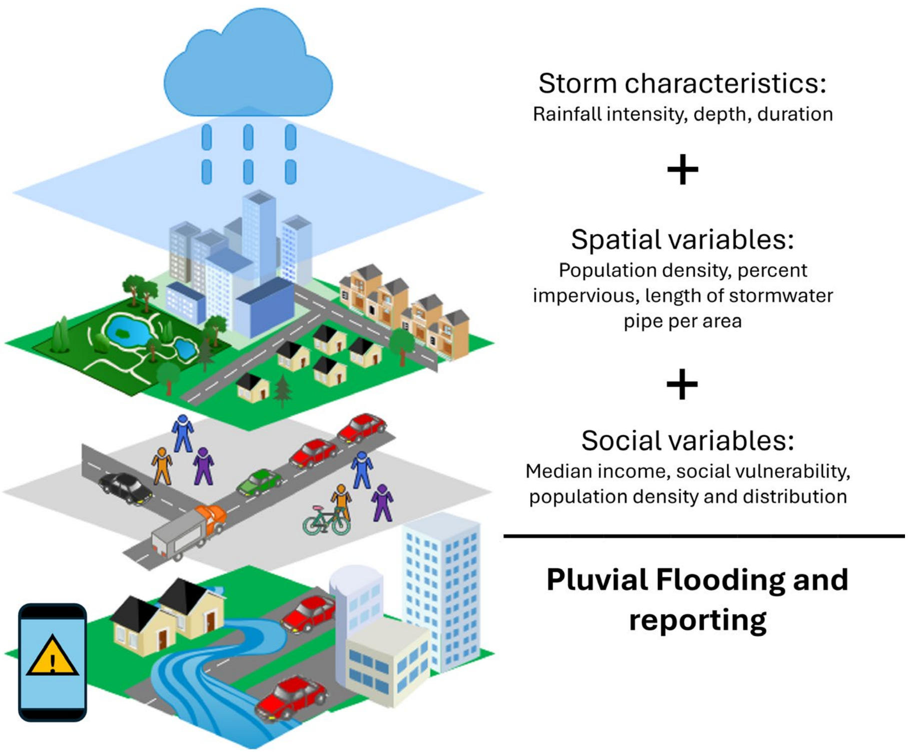

FIGURE 1 | A conceptual illustration of the factors leading to pluvial flooding analysed in this study and its consequences.

methodologies, including rainfall threshold analysis, exploration of spatial characteristics as drivers, topographic wetness index (TWI), and logistic regression analysis, to gain a better understanding of drivers of urban flooding in Denver, CO. Using these methods, this research seeks to address the following questions:

1. Which storm characteristics best predict flood report incidence?
2. Which built and social variables explain the most variance in urban flood reports?
3. How do storm characteristics, built variables and social variables together influence the likelihood of urban flooding reports?

The overall goal of this work is to examine the spatiotemporal patterns of urban flooding, and which variables are most effective at predicting urban flooding. We specifically seek to compare the predictive power of variables which are often examined separately: storm characteristics, built variables and social variables.

2 | Methods

2.1 | Study Area

This analysis focused on the City of Denver, Colorado, USA. Denver, located 19 km east of the Rocky Mountain foothills, is a major metropolitan area in Colorado with a population of about 3 million people. From 2010 to 2020, the city's population grew by 17% with 178 census tracts (U.S. Census Bureau QuickFacts n.d.). Denver has a semi-arid climate with seasonal variability. The area receives an average annual precipitation of 391 mm, with most falling between April and September. Denver has an average annual temperature of 10.1°C. The monthly average minimum temperature is −1.3°C and the maximum is 23.1°C (US Department of Commerce n.d.). Denver lies within the South Platte River Basin, which originates in the Rocky Mountains. Denver's downtown is east of the confluence of Cherry Creek and the South Platte River.

Helpful to this study, Denver has the Mile High Flood District (MHFD). The MHFD is a multi-jurisdiction, government-funded entity responsible for stormwater and watershed management in the metropolitan Denver area. The MHFD has stream and rain gauge networks as a part of their larger, MHFD flood monitoring system.

2.2 | Flood Reports

We received a database of flood reports from the City and County of Denver Department of Transportation and Infrastructure Wastewater Management Division. Each flood report was from a person who sought to report an issue related to local drainage. These flood reports included a date, location and information about the reason for the flood report. Complaints came from multiple sources and people, beginning in 1966 until 2019. In this study, we focused solely on flood reports from 2000 to 2019

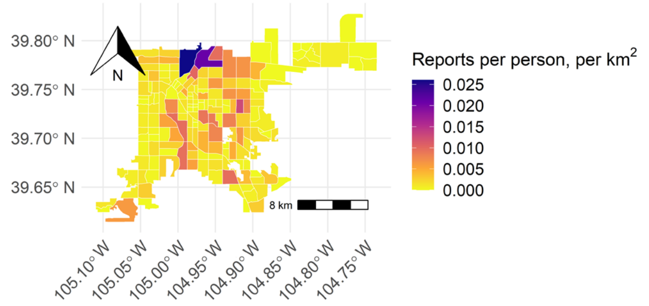

FIGURE 2 | A map of the City and County of Denver, indicating flood-reporting hotspots by census tract. We normalised the total amount of reports in a census tract by area and population in each tract.

to ensure that we would have corresponding rain gauge data. Additionally, we were only interested in flood reports pertaining to flooding during rain events, so we excluded reports that were associated with categories of icing, unknown, other, constant discharge, erosion, siphon, private and maintenance. We also filtered flood reports to only those which occurred between April and October to capture reports from the rain season in Denver, Colorado, as opposed to winter storms. This process gave us 922 reports of street flooding (Figure 2). We will use flood report to refer to these specific flood reports. We did not have knowledge of the process to create official flood reports during the historical timeframe of this study.

2.3 | Storm Data

In addition to flood reports, we acquired storm data from the MHFD rain gauge network. Rain gauges that had no data were removed from analysis. Within Denver, CO, we used 30 rain gauges (Figure 3). These gauges are 1 mm tipping bucket gauges reporting every tip. We considered any incremental accumulation (tip) in rainfall depth exceeding 5 mm invalid. Rain gauges record at least a value of 0 every 12 h (if there is no rain) to indicate they are functioning (Wilson et al. 2022).

Using the rain gauge network, we created Thiessen polygons (Figure 3) with the voronoi function from the dismo R package (v 1.3-14; Hijmans et al. 2023). All analyses were performed using R Statistical Software (R version 4.3.0 n.d.). Each polygon represents the 'area of influence' for a specific rain gauge. We linked flood report occurring within a polygon with that polygon's rain gauge data. By linking each flood reports to a polygon, we estimated the storm characteristics that led to a flood report. If the nearest rain gauge associated with a flood report lacked data for the specific time of the service report (due to damage or malfunction), we removed that rain gauge from the polygon network. We then created a new set of polygons and linked the flood reports to the next closest rain gauge. At the end of this process, all but five flood reports were linked to a rain gauge. These five flood reports, which lacked rain gauge data, were removed from the analysis. The distances between linked rain gauges and flood reports ranged from under 1 to 4 km (Figure 4).

After extracting all rain gauge data from the MHFD, we used the USGS Rainmaker R package (v1.0.2; Corsi and Carvin 2023) to distinguish storm events and quantify rainfall intensities

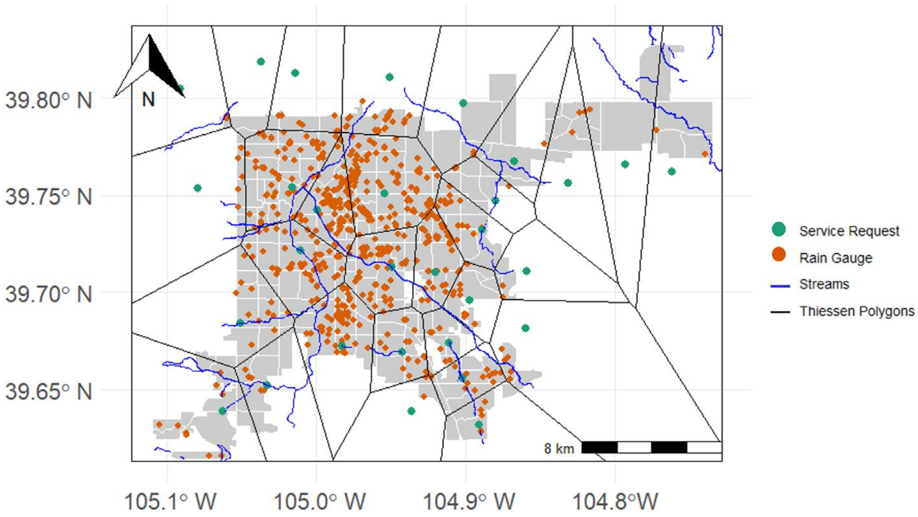

FIGURE 3 | A map of the City and County of Denver including locations of flood reports, rain gauges, Thiessen polygons and local streams.

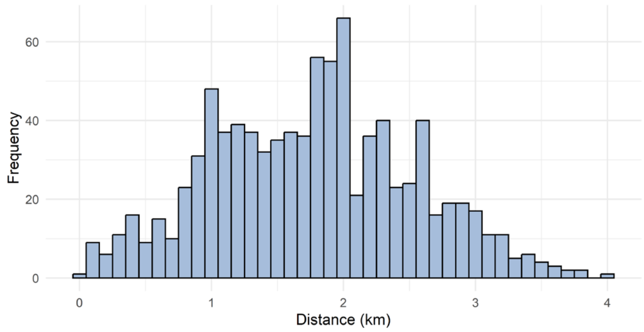

FIGURE 4 | Distances of flood reports to rain gauges.

from rain gauge data. The USGS Rainmaker package calculates the following storm characteristics: duration, total depth, overall intensity and maximum rainfall intensity for 5-, 10-, 15-, 30-, 60-, 120-, and 240-min durations of each storm event from tipping bucket rain gauge data. Within the Rainmaker package, we set each rain gauge tip to equal 1 mm, matching the tipping rate of the rain gauges in our dataset (Wilson et al. 2022). We also set the interevent period to 24 h, meaning that if any tips occurred within 24 h of each other, we considered this as one storm. We chose 24 h because flood reports had dates of flooding, but not times.

This process allowed us to link flood reports to storm events. We linked storm events to flood reports based on dates and rain gauge polygons. We linked a storm with a flood report if the storm was recorded by a rain gauge within the same polygon and occurred within a day before the flood report was made. Occasionally, storm events spanned multiple days. A flood report could be matched at any day during a multi-day storm. Additionally, we did not use flood reports if there was not matched storm event. We also acknowledge that there is some uncertainty regarding the timing of storms and the dates of flood reports, which could have impacts on this analysis, but did our best to minimise or account for this uncertainty.

Of 922 flood reports, 603 were linked to storms and only these 603 were used for this study. There are a few potential reasons that not all flood reports had linked storms. One is due to rain gauge errors. Either the rain gauge linked with the flood reports was transmitting, but not tipping, or the linked rain gauge was far away from the flood report. Additionally, flood reports caused by drinking water or wastewater line breaks, would not correspond to a storm. It was not always clearly written in a flood report whether there were water line breaks. Lastly, there could be inaccuracies with flood report reporting due to human error such as transcribing incorrect values for date, time, or location or using the reporting system incorrectly.

2.4 | Climate Analysis

First, we looked at rainfall variation across Denver to see if localised differences in long-term average rainfall explained spatial variation in flood reports. To perform this analysis, we mapped flood reports on top of Parameter-elevation Regressions on Independent Slopes Model (PRISM) data to see if high densities of flood reports corresponded to areas of high rainfall. PRISM data are long-term climate data that comes from the PRISM Climate Group at Oregon State University, which is derived from multiple climate monitoring sites across the continental United States. We used average monthly and annual rainfall from the last 30 years with a spatial resolution of 800 m across Denver. This analysis is referenced in Figure S1.

2.5 | Predictive Threshold

Before moving to more complex analyses, our first goal was to determine whether specific thresholds for rainstorm characteristics could predict the occurrence of street flooding. Previous work has used threshold analysis to predict flooding or stream flow response with rainfall thresholds (Bouwens et al. 2018; Kampf et al. 2018; Tian et al. 2019; Wilson et al. 2022). The threshold analysis determined a value for a certain characteristic that when exceeded, predicts flooding. Studies that have evaluated such a threshold in rainfall intensity have interpreted these threshold values as representing situations where infiltration excess overland flow was expected to occur.

In our study, we aimed to identify threshold values for storm duration, total depth, overall intensity and maximum rainfall intensity that, when exceeded, could distinguish between storms that led to flood reports and those that did not. We tested threshold values for each of these storm characteristics over periods of 5, 10, 15, 30, 60, 120, and 240 min. For each characteristic, we tested a range of values from the minimum to the maximum, in increments of 1/1000 of the respective value's range.

We evaluated each tested value with a performance metric to see how well it predicted when flood reports occurred. Pearson correlation evaluates linear relationships, whereas our type of threshold testing required a performance metric for a binary response variable. Others have used kappa to evaluate binary classification of relatively common events (Kampf et al. 2018) and the equitable threat score to assess the performance of categorical forecasts (Brill and Mesinger 2009; Hogan et al. 2010). We used Matthews Correlation Coefficient (MCC) as a performance metric for each tested threshold. MCC has been determined to be a good choice of a performance metric, particularly in situations where datasets are imbalanced (Chicco and Jurman 2020). An imbalanced dataset is one where rare events are being examined and therefore the sample size for each binary response category (e.g., storms that led to street flooding and those that did not) is very different. Our dataset was imbalanced, with 404 unique storms that led to a street flooding report and 20 827 storms that did not.

MCC values will range from −1 to 1. A score of +1 denotes perfect prediction, 0 indicates performance no better than random guessing, and −1 signifies complete disagreement between prediction and observation. MCC takes into consideration the true positive (TP), true negative (TN), false positive (FP) and false negative (FN) predictions made by a classifier. In our case, the classifier is the predictive threshold value. We calculated MCC by the following:

$$\mathrm{MCC} = (\mathrm{TP} \times \mathrm{TN} - \mathrm{FP} \times \mathrm{FN}) \,/\, \sqrt{((\mathrm{TP} + \mathrm{FP}) \times (\mathrm{TP} + \mathrm{FN}) \times (\mathrm{TN} + \mathrm{FP}) \times (\mathrm{TN} + \mathrm{FN}))} \tag{1}$$

In our case, we classified a storm as a TP when the threshold predicts it will lead to street flooding, and it is recorded as having led to street flooding. We classified it as a TN when the threshold predicts it will not lead to street flooding, and it is not recorded as having led to street flooding. We labelled a storm as a FP when the threshold predicted it would lead to street flooding, but no flooding was recorded. Conversely, we labelled it as a FN when the threshold predicted it would not lead to street flooding, but flooding was recorded. We consider the tested value with the highest magnitude MCC score to be the strongest predictor of the occurrence of a flood report.

2.6 | Geographic Variables

We additionally considered the influence of geographic variables, including social and built variables, on street flood reporting. We chose to examine these variables at the census tract-level scale as opposed to a watershed scale as the census tract scale is consistent with government agency data collection while also being fine enough to analyse at a neighbourhood scale. The variables we analysed were percent imperviousness, length of stormwater mains, population density, median income, social vulnerability index (SVI) and TWI. We selected these variables as they span key variables describing patterns and drivers of urban flooding (Figure 1).

We imported the population of each census tract in Denver to R from the 2020 US Census using the tidycensus package (v1.4.4; Walker and Herman 2023). We imported tract boundaries using the tigris package (v2.0.3; Walker 2023). We determined the population density for each tract by dividing the population of that tract by its corresponding calculated area (in square kilometres). We also examined median income per tract which we extracted from the 2020 census, using the tidycensus R package.

We calculated the percent impervious area for each census tract by importing a shapefile of impervious surfaces in Denver (Denver Open Data Catalogue), then used the st_area function in the R sf package (v1.0.13; Pebesma 2018) to calculate the area of impervious surfaces. The spatial resolution of this layer is 0.5 ft, with each pixel in the aerial imagery representing a 0.5-ft by 0.5-ft area on the ground.

We calculated the stormwater pipe density of tracts by importing a shapefile of Denver's stormwater sewer network (Denver Open Data Catalogue), calculating the length of stormwater in a tract (in meters) with the st_length function in the sf package, and then dividing by the area of the tract (in meters squared). We used sf tools in R to calculate lengths and areas.

We also considered the SVI of each tract, to investigate whether descriptors of the local population may be related to urban flooding. Existing work emphasises that there are many places across the US and around the globe where flood exposure and social vulnerability are high, due to the complex interactions between environmental factors and social, political and economic factors within these areas (Rolfe et al. 2020; Tate et al. 2021). The Centers for Disease Control and Prevention (CDC) and Agency for Toxic Substances and Disease Registry (ATSDR) have created an SVI for census tracts to help identify which communities will require aid in the event of a hazardous event (Flanagan et al. 2011). Note that social vulnerability of a community is not inherent in individuals but is created by societal forces that remove capacity and power from communities (Jones et al. 2024). The four main categories of variables used in SVI include socioeconomic status, household characteristics (age, disability status, single-parent and English-language proficiency), racial and ethnic minority status and housing and transportation type. We used the overall state-wide ranking percentile values associated with each census tract. SVI uses a percentile ranking which indicates the percentage of tracts that are as vulnerable as or less vulnerable than a given tract. For example, an SVI value of 0.95 indicates that the tract of interest is more vulnerable than 95% of all tracts in the state.

TWI quantifies the propensity of a location to accumulate water based on its topographic characteristics. To calculate TWI, we acquired a bare earth one-meter resolution digital elevation model (DEM) from the USGS National Map (U.S. Geological Survey 2022). For each DEM, we used the terrain function in the raster R package (v3.6.20; Hijmans 2023) to calculate flow accumulation and local slope for each cell in the map. We calculated TWI as follows:

$$\mathrm{TWI} = \ln(a / \tan(\beta)) \tag{2}$$

where a represents the total upslope contributing area, or flow accumulation, of a cell, and $\tan(\beta)$ represents the slope of each point. We replaced any cells with zero slope with 0.001 to be compatible with the equation.

We were interested in TWI variation between locations of flood reports and the rest of Denver, so we extracted values from the 922 locations of flood reports. While we realise that the point from a flood report used to calculate TWI may not represent the exact location of the flood occurrence, this approach made the most sense in the absence of additional information. For comparison, we also extracted 922 random TWI values from all impervious surfaces in Denver. We limited the random points to impervious surfaces to constrain analysis to areas where a flood report is possible. Although flooding is possible on a pervious surface like a compacted sports field or park, we left this out of the analysis because these areas may not be reportable. For all variables, we performed a Wilcoxon signed-rank test to see if the medians of values in areas of flooding and without flooding were significantly different.

2.7 | Regression Analysis

2.7.1 | Logistic Regression

To understand the power of influence that each variable has on the likelihood of a flood report, we constructed a logistic regression for the probability of a flood report occurring across storms and census tracts. To do this, we constructed a singular data frame to organise data by storm. Each storm has temporal data from its rain gauge. Then, if we were able to link a storm to a flood report, its geographic data came from the tract which contained the flood report. If a storm did not lead to a flood report, its geographic data came from the tract which contained the corresponding rain gauge. We omitted storms recorded by rain gauges outside of Denver from analysis because we only had flood reports within Denver. We removed one tract from regression analysis because it had no population and thus no census data.

Explanatory variables used as input to the regression included storm depth, storm duration, maximum 5-, 10-, 15-, 30-, 60-, 120-, and 240-min intensities, percent impervious, population density, stormwater pipe density, median income and SVI. We normalised each variable from 0 to 1 using the minimum and maximum value for each variable so that final coefficients are comparable.

We began with all explanatory variables, some of which were collinear. To address this, we removed the variable with the highest variance inflation factor (VIF) one at a time, until all variables had a VIF equal to or below five (Helsel et al. 2020). For final variable selection, we selected the resulting variables by AIC in a stepwise algorithm using the step function in the *stats* package in R (v 4.3.0; R Core Team (2023)).

We validated our assumption of linear relationships between the explanatory and predicted variables by plotting the logit values versus mean values at quantiles for each predictor variable and visually inspecting for linearity. We also confirmed that there were no outliers influencing the model by plotting the model residuals versus leverage and visually inspecting for any outliers beyond Cook's distance.

2.7.2 | Linear Regression

We additionally analysed a linear regression which focused on how spatial variables of a tract led to incidences of flood reports per area in that tract. We then used the lm and step functions in the *stats* package of R (v 4.3.0; R Core Team (2023)) to create a linear model which related number of flood reports per area of a tract to the spatial variables, population density, percent impervious, length of stormwater per area, median income and SVI. Each variable was normalized from zero to one so that final coefficients would be the same scale for comparison.

To perform this linear regression, we assumed that our explanatory variables were independent, linearly related to our predictor, homoscedastic, and no outliers exerted significant leverage. To ensure the independence of explanatory variables, we conducted multicollinearity diagnostics, examining VIFs and correlation matrices. We also visually examined scatter plots of each explanatory variable against the response variable to confirm the linearity assumption. We assessed homoscedasticity by plotting the residuals against the fitted values from our regression model, visually inspecting for a consistent spread of residuals across all fitted values on the plot. Lastly, we used Cook's distance and standardised residuals to visually inspect for any outliers of significance influence.

3 | Results

3.1 | Climate and Rainfall Intensity Thresholds

We found that spatial rainfall patterns did not explain areas of high flooding (Figure S1). Areas of higher 30-year normal annual rainfall did not correlate to areas of higher flooding. We then investigated spatial and temporal variables to better explain the pattern of street flooding.

We generated a series of values for predictive rainfall thresholds and associated values of MCC for each characteristic, shown in Table 1. As previously mentioned, the value of MCC will be in between −1 and 1, with a value of 0 being the same as random chance. Most of our MCC metrics were close to 0, meaning that a single variable, rainfall characteristic is not the best predictor of a flooding report occurrence (Table 1).

Storms that led to a flood report had a higher maximum 5-min intensity compared with those that did not (Figure 5, Table 2). As an example of threshold analysis, Figure 5a shows the best-performing threshold for a 5-min intensity (the threshold was determined by selecting the threshold with the maximum MCC value which was 0.12), indicating that storms with a maximum 5-min intensity below 82.7 mm/h should not lead

TABLE 1 | Estimated threshold values for various storm variables potentially predictive of flood report occurrence.

Variable	Max MCC	Threshold
Overall intensity (mm/h)	0.04	0.8
Maximum 5-min intensity (mm/h)	0.12	82.7
Maximum 10-min intensity (mm/h)	0.13	65.8
Maximum 15-min intensity (mm/h)	0.14	52.2
Maximum 30-min intensity (mm/h)	0.14	25.9
Maximum 60-min intensity (mm/h)	0.14	17.1
Maximum 120-min intensity (mm/h)	0.15	9.5
Maximum 240-min intensity (mm/h)	0.14	5.6
Duration (h)	0.05	395.5
Depth (mm)	0.10	23.6

Note: The performance metric, MCC (Matthews Correlation Coefficient) evaluates the threshold.

to flood reports, while those above this threshold should. This threshold was not helpful in distinguishing between flooding report response, as 97% of all storms, regardless of whether a flood was reported, fell below this threshold. This indicates that the threshold does not effectively differentiate between storms that led to flood reports and those that do not. Additionally, this threshold for maximum 5-min rainfall intensity corresponds to about an 85% probability that storms will lead to flood reports (Figure 5b). The threshold failed to predict about 15% of flood reports, further highlighting its limitations in accurately identifying flood-inducing storms.

3.2 | Comparing Variables for Flood-Reported Versus Non-Flood-Reported Storms

In analysing storm characteristics, we observed higher values for depth, duration and intensity in storms leading to flood reports compared with those that did not, aligning with expectations (Figure 6a,b,f, Table 2). We saw a similar pattern when looking at spatial variables. Percent imperviousness was higher for storms associated with flood reports as compared with those without (Figure 6e, Table 2). We expected this because more impervious surfaces prevent water infiltration, increasing the likelihood of flooding.

Population density also resulted in a higher value in storms triggering flood reports (Figure 6c, Table 2). This observation could indicate a greater number of affected individuals reporting floods and increased land development without adequate stormwater drainage leading to more flooding.

When examining stormwater pipe density (Figure 6f, Table 2), we found a slightly lower median for storms linked to flood reports compared with those that were not. This difference was statistically significant. This could indicate that denser stormwater pipes in an area more effectively drain streets of stormwater and reduce the likelihood of street flooding. While this analysis lacks the depth of a modelling-based approach, it highlights the potential relationship between stormwater infrastructure, development density and flood events.

The median SVI values for storms leading to flood reports versus those that did not were nearly identical (Table 2, Figure S2). We saw a higher mean for SVI in cases when storms produced flood reports (Figure S2). A higher SVI indicates that a more vulnerable population sees more flood reports. SVI encompasses various indicators such as education levels, English proficiency, and access to resources, any of which could influence an individual's ability to report a flood event. There was a lower median for median income for storms that did lead to flood reports, indicating flood reports occur more often in tracts with lower incomes (Figure 6d, Table 2).

When looking at TWI, we saw the mean and median values are higher at points where street flooding was recorded when compared with points randomly selected from Denver (Figure 6g). These differences were statistically significant. This suggests that areas predisposed to higher water accumulation are prone to flooding. Despite this potential explanatory power, we were unable to include TWI in regression analyses because storms that did not lead to flood reports are not associated with a particular location and census tract data, like flood reports are.

3.3 | Power of Influence of Different Variables on a Flood Report

The logistic regression analysis aimed to understand the contribution of spatial and temporal variables to flood report incidence and the influence of significant variables on the likelihood of flood reporting after a storm. Looking at explanatory variables and coefficients for temporal variables, we observed that both storm depth and 5-min maximum rainfall intensity had a positive coefficient and relationship to the log-odds of a flood report happening (Table 3). We also see that the 5-min maximum intensity had the strongest influence on a flood report occurring after a storm. Depth of a storm was the third highest influencing variable on whether a storm report occurs. Differently, we saw that duration had a negative coefficient, indicating that the shorter the storm duration, the increased likelihood of a flood report happening. When analysed alone, longer storms saw more flooding (Figure 6b, Table 2). However, when we analysed duration and storm depth together, the biggest effect was from storms with a larger depth.

Considering spatial variables, population density had the second highest coefficient, and second most influence overall (Table 3). The positive coefficient indicates an increase in population density will increase the likelihood of a flood report incident.

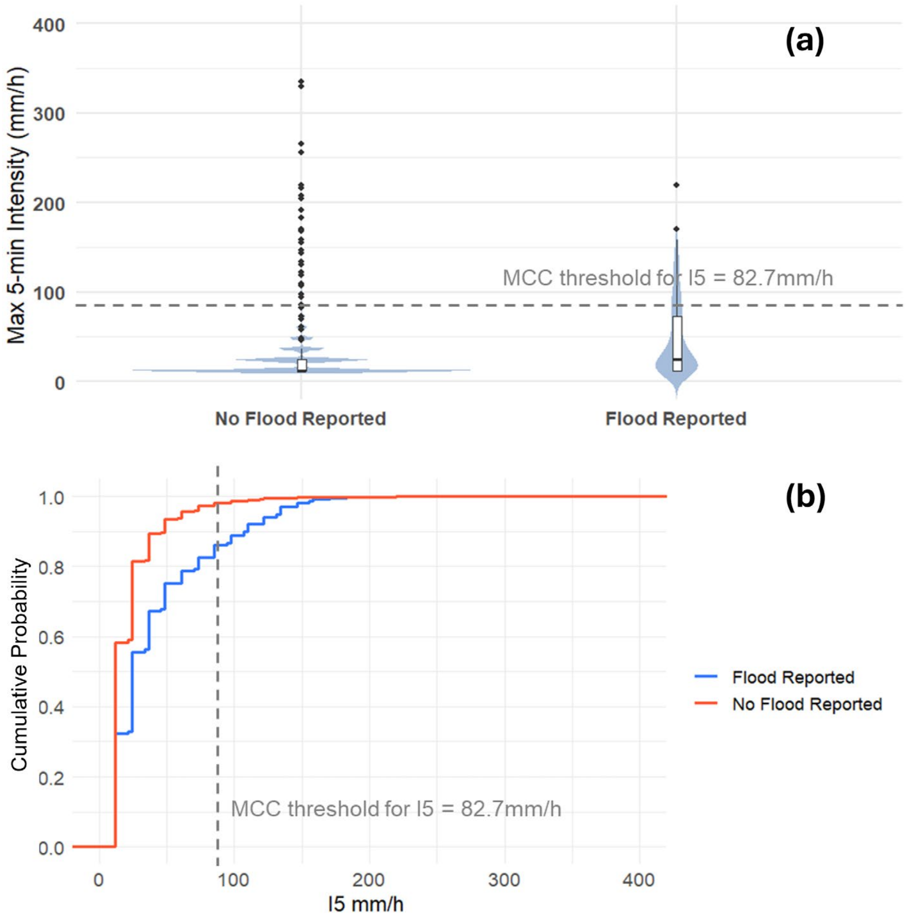

FIGURE 5 | (a) Violin plot and (b) CDF showing the distribution of all maximum 5-min intensities, differentiating between flooding and non-flooding events, with the predictive threshold overlaid; MCC = 82.7 mm/h for max 5-min intensity.

TABLE 2 | Comparison of median values for variables among storms with and without flood reports, along with corresponding p values from the Wilcoxon signed-rank test.

Variable	Median for flood report not occurring	Median for flood report occurring	p
Depth (mm)	4.06	**10.2**	<0.001
Duration (h)	2.63	**7.77**	<0.001
I5 (mm/h)	12.19	**24.38**	<0.001
I10 (mm/h)	6.10	**18.29**	<0.001
I15 (mm/h)	8.13	**16.256**	<0.001
I30 (mm/h)	4.06	**8.13**	<0.001
I60 (mm/h)	2.03	**5.08**	<0.001
I120 (mm/h)	1.52	**3.43**	<0.001
I240 (mm/h)	0.762	**1.78**	<0.001
Percent impervious	46.2	**53.1**	<0.001
Population density (per km^2)	2081	**2733**	<0.001
Median tract income	**84 456**	77 442	<0.001
SVI	0.481	0.481	0.01286
Stormwater pipe density (m/m^2)	**0.008**	0.007	0.0462

Note: Bold values denote a significant increase in distribution shift.

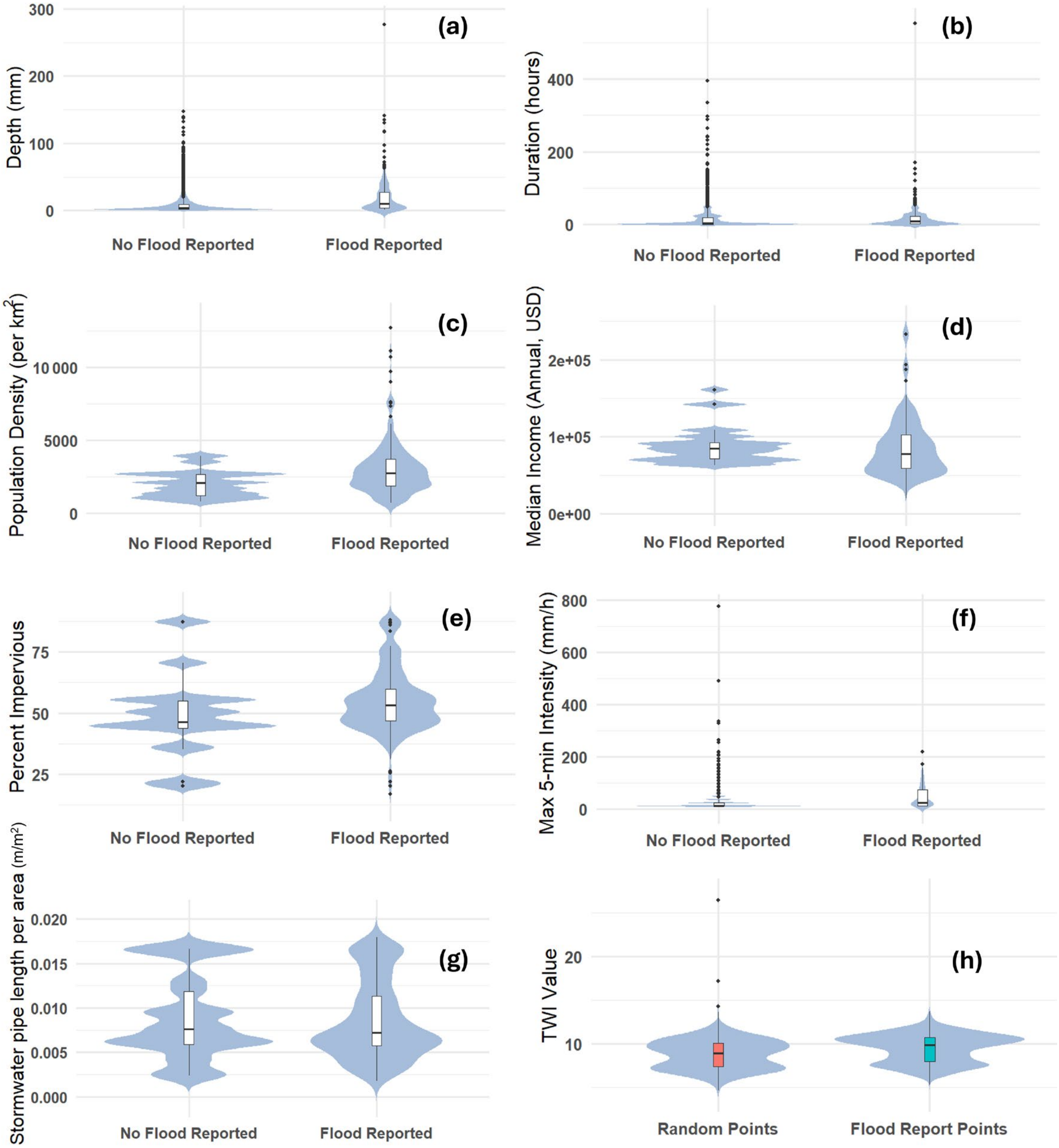

FIGURE 6 | Comparing storm and spatial characteristics of flood-inducing and non-flood events with violin plots: (a) depth, (b) duration, (c) population density, (d) median income, (e) percent impervious, (f) maximum 5-min intensity, (g) stormwater pipe density, (h) TWI. TWI boxplots are shown in a different colour as they compare random points versus flood report points, whereas all other boxplots show storms in which no flood was reported versus storms in which there was a flood reported.

Looking at median income, we see that there is also a positive coefficient, meaning a storm occurring in an area with a higher median income can expect a higher likelihood of flood reports. While median tract income alone has a negative relationship with the probability of flooding (Figure 6d, Table 2), median tract income is also negatively correlated to population density. After we included the population density, which has the strongest spatial effect on increasing the probability of flooding, and the median tract income in the model, we see that the effect of median tract income is positive. This indicates that there is a greater probability of flooding reports in storms and tracts in dense, wealthy areas (given that dense areas have lower income overall) than in less dense, lower income areas. Last, stormwater pipe density had a negative coefficient, indicating a decrease in stormwater pipe density being associated with an increase in the likelihood of a flood report.

Notably, all variables were significantly different in the single variable analysis, but not all variables showed up in the regression, likely due to correlation to other variables. For example, SVI did not show up in the regression and is correlated with the other spatial variables, especially median income. Percent impervious also did not show up in the regression and was related to stormwater pipe density and population density, where population density also indicates increased population to report flooding. This model has a chi-squared value of 1047.8 with 8 degrees of freedom (8 predictor variables) and gives a p value of 0.359. Our intention of creating a model was not prediction, but

TABLE 3 | Logistic regression values and performance for representing spatial and temporal variables of a storm leading to a flood report or no flood report. All coefficients are normalised.

	Coefficient	Std. error	z	Pr (>z)
Intercept	−5.62	0.18	−30.54	<0.001
Depth	8.39	1.25	6.65	<0.001
Duration	−3.68	1.43	−2.57	0.01
Maximum 5-min intensity	12.37	1.13	10.86	<0.001
Population density (per km^2)	12.02	0.55	21.64	<0.001
Median income	2.30	0.39	5.84	<0.001
Stormwater pipe density	−1.39	0.15	−9.14	<0.001

TABLE 4 | Linear regression values and performance for representing spatial variable influence on amount of flood reports per area.

	Coefficient	Std. error	t	Pr (>t)
Intercept	−4.10	1.18	−3.47	0.00064
Percent impervious	17.27	2.19	7.86	3.84×10^{-13}

rather to understand the impact each variable has on the probability of a flood report.

3.4 | Predicting the Density of Flood Reports

We also performed a linear regression to examine how spatial variables interact and influence the density of flood reports in a tract. Notably, only percent impervious showed up as a significant variable in this regression (Table 4; $R^2 = 0.262$). Percent impervious had a positive coefficient and relationship with the amount of flood reports that happen per area. We expected this relationship because impervious surfaces lead to runoff and more water flowing into stormwater systems. It was interesting, however, that the algorithm selected percent impervious as the only important spatial predictor for flood reports per area. This may have happened because we only had 176 tracts, or data points, to describe spatial variability of close to 400 km^2. The 176 tracts may not be enough to distinguish variability in other inputs to the model. Additionally, other variables may not have shown up in the regression because they were correlated with each other.

4 | Discussion

4.1 | Drivers of Urban Flooding

In this study, we performed several analyses to explore the predictive ability of single and multiple variables to explain flooding in Denver, CO, USA. We found the maximum 5-min intensity and population density to be the strongest drivers of flood reports. Differently, Smith and Rodriguez (2017) found that in New York City, New York, USA, maximum hour and daily rainfall drove most flooding, whereas areas with combined sewer systems experienced less flooding. Additionally, Michelson and Chang (2019) found that in Portland, Oregon, USA, flooding increased as depth of 3-day storms increased up to 10 cm. These differences are driven in part by differences in climate as well as infrastructure. Denver does not have combined sewers, or the dense impervious cover found in New York City and does not experience the longer storms driven by atmospheric rivers, as seen in Portland.

This study underscores the significance of considering multiple variables within the context of urban flooding analysis. We found that single-variable threshold analyses failed to capture the complexities of urban flooding and proved inadequate as predictors. Pluvial flooding is caused by rainfall, but also the geographic terrain where that rainfall occurs, including both social and physical factors of the urban landscape. This is true for any city, including Denver.

While other studies have focused on correlations of individual variables (Kelleher and McPhillips 2020; Michelson and Chang 2019; Smith and Rodriguez 2017) to flooding, this study is the first to consider a combined view of temporal and spatial variables. Temporal and spatial factors both play crucial roles in urban flooding analysis; neglecting either can lead to incomplete results. Furthermore, examining them together provides a more comprehensive understanding.

We examined the distinct contributions of various variables to the overall likelihood of a flood report. Our logistic regression showed the spatial variable, population density, and a temporal variable, maximum 5-min intensity, can be nearly equal predictors for a flood report (Table 3). While other researchers have also found the importance of rainfall intensity and percent imperviousness (Bouwens et al. 2018; Candela and Aronica 2016; Smith and Rodriguez 2017), our finding allows us to consider simultaneous influence of temporal and spatial variables.

Most correlations between variables and urban flooding were expected, such as more intense storms, locations with higher TWI, increased population densities and higher percent imperviousness all leading to a higher likelihood or amounts of flooding (Figure 6). Socioeconomic variables presented more nuance and could benefit from further analysis. We saw significantly lower median incomes and higher SVI values when comparing storms that lead to flood reports and those that do not (Figure 6). These values could reflect populations affected by floods but may be skewed by populations with capacity for flood reporting. Community resilience to urban flooding can be measured using indicators such as public facilities, spatial structure of land use, flood management organisations, rescue capability, weather forecast accuracy, vulnerable population and individual capability (Laurien et al. 2020; Xu et al. 2020; Zhong et al. 2020).

4.2 | City-Wide Analysis Supports Improved Water Management and Hazard Mitigation

The MHFD has a flood warning system that is used by emergency response organisations in the Denver metropolitan area. The current notification system warns of urban flooding when 12.7 mm (0.5 in) of rain has fallen within 10 min. This is equivalent to a 10-min rainfall intensity of 76.2 mm/h. Our 10-min MCC suggested threshold was 66 mm/h (Table 1), so the MHFD threshold is higher than our derived threshold. Additionally, our threshold had an MCC grade of 0.130 on a scale from −1 to 1, deeming it a poor performing threshold (Chicco and Jurman 2020). Our findings suggest using a 5-min intensity is somewhat better performing, with the best performing 5-min intensity threshold at 82.7 mm per hour. This value falls between the 2- and 5-year NOAA Atlas 14 recurrence interval for Denver (NOAA ATLAS 14). An approach that uses spatial as well as temporal variables may be more effective in predicting street flooding. Other cities which use rainfall observations to inform flood warning systems could utilise our methods to evaluate or determine rainfall threshold values. We completed our analysis in Denver, and the MHFD operates in communities outside of Denver, where spatial characteristics could result in a different threshold. Our analysis suggests that areas with higher population densities may require a different rainfall intensity threshold for urban flooding.

The biggest limitation in our study was our reliance on public reports of flooding incidents. Relying on such data is a double-edged sword: it is a useful way to detect the presence of flooding, but flood report occurrence may be biased to certain areas within a city or at certain times (Kontokosta and Hong 2021; Liu, Bhandaram, and Garg 2024; Minkoff 2016). For example, more reports happened during weekdays and after typical work hours. To minimise this uncertainty, we carefully linked flood reports to storms, and found that a majority corresponded to storms.

Previous work on municipal flood reports shows that low-income and minority neighbourhoods are less likely to make calls for nuisance issues (Kontokosta and Hong 2021). Without knowing the motivations of those making flood reports, the study is missing insight into what causes urban flooding or affected populations. Building a predictive model based on potentially biased reports has the potential to underestimate flooding in areas with marginalised populations. For example, while we observe more flood reports in tracts with lower median incomes and higher social vulnerability indices, it is likely that these populations under-report flooding, suggesting the actual discrepancy is even larger than observed. Suggested follow-up work would be to improve understanding of the motivations to make flood reports. There may also be the opportunity to use other tools, in addition to reporting mechanisms, to account for this potential unequal flood reporting. An alternative to using these reports would be equal surveying or sensing of flooding in cities to better understand incidences of urban flooding (Sullivan et al. 2024; Hino and Nance 2021).

While flood reports are a useful approach to study flooding, they also limit our ability to understand the severity of floods in terms of damage or hazard. Our methods leave us unable to analyse water velocity, depth or quality, characteristics used to determine a flood's hazard (Gaitan, ten Veldhuis, and van de Giesen 2015; Middelmann-Fernandes 2010). While such information is generally challenging to come by, researchers are using alternative methods to acquire data to understand more (Hong and Shi 2023; Lo et al. 2015).

5 | Conclusions

We used a variety of methods to understand the drivers of urban flooding. Our initial threshold analysis of storm characteristics was insufficient in determining likelihood of flooding. In our novel analysis combining spatial and temporal variables in a logistic regression, we saw that rainfall intensity and population density are nearly as important in determining the likelihood of a flood report. In addition, TWI values at locations of flooding reports were higher than randomly selected points and a linear regression predicting the number of reports per area identified percent impervious as the single most important predictor.

Overall, these findings provide valuable insights into urban flooding that could be used to examine pluvial flooding prediction systems or prioritise allocation of flood response resources. A similar approach as ours can be applied to any city that also has records of pluvial flooding and spatial rainfall data, from radar or a rain gauge network. Complex relationships between variables suggest the need for a spatiotemporal perspective with urban flooding. Not only are rainfall characteristics important to consider, but so is the environment which the rain falls on; this includes topography, the built environment, and population characteristics. Since we consider areas with higher population density and higher percent imperviousness at higher risk of urban flooding, these areas should become target areas for increased flood awareness, response, mitigation, and recovery. Further investigation should be on areas with lower median incomes or more vulnerable populations for potential disparities in flooding and mitigation of flooding.

There is still unknown information about motivations behind creating flood reports and our work indicates certain populations are at a higher risk of urban flooding. Any solutions or next steps should keep this in mind, as correcting for a specific group of people who write flood reports may inadvertently perpetuate further inequities (Galloway et al. 2018; Hino and Nance 2021; National Academies of Sciences, Engineering, and Medicine 2019).

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Data Availability Statement

The data and codes that support the findings of this study are available from: DeSousa and Bhaskar (2024).

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.