FloodNet: low-cost ultrasonic sensors for real-time measurement of hyperlocal, street-level floods in New York City

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Key Points:

• Low-cost, ultrasonic sensors were designed and built to monitor the profiles of hyperlocal, street-level floods
• Sensor hardware, network architecture, and data ingestion, processing, and visualization tools were designed to maximize data usability
• The FloodNet project is installing flood sensors across New York City to collect data for community, city agency, and research stakeholders

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Abstract
Flooding is one of the most dangerous and costly natural hazards, and has a large impact on infrastructure, mobility, public health, and safety. Despite the disruptive impacts of flooding and predictions of increased flooding due to climate change, municipalities have little quantitative data available on the occurrence, frequency, or extent of urban floods. To address this, we have been designing, building, and deploying low-cost, ultrasonic sensors to systematically collect data on the presence, depth, and duration of street-level floods in New York City (NYC), through a project called FloodNet. FloodNet is a partnership between academic researchers and NYC municipal agencies, working in consultation with residents and community organizations. FloodNet sensors are designed to be compact, rugged, low-cost, and deployed in a manner that is independent of existing power and network infrastructure. These requirements were implemented to allow deployment of a hyperlocal, city-wide sensor network, given that urban floods often occur in a distributed manner due to local variations in land development, population density, sewer design, and topology. Thus far, 81 FloodNet sensors have been installed across the five boroughs of NYC. These sensors have recorded flood events caused by high tides, stormwater runoff, storm surge, and extreme precipitation events, illustrating the feasibility of collecting data that can be used by multiple stakeholders for flood resiliency planning and emergency response.

1 Introduction
Of the many hazards that are expected to increase with climate change, flooding is one of the most dangerous and costly (National Academies of Sciences, Engineering, and Medicine, 2019), and can have a large influence on public health, infrastructure, and mobility in urban areas (Galloway et al., 2018). For example, climate change is projected to increase the frequency and magnitude of precipitation events (Lenderink & Van Meijgaard, 2010; Sillmann et al., 2013), which can overwhelm urban rivers, streams, and drainage systems, resulting in pluvial or fluvial flooding (National Academies of Sciences, Engineering, and Medicine, 2019). Additionally, sea level rise associated with climate change has been observed to increase coastal flooding during high tides. In New York City (NYC), for example, there is an increasing trend in the number of days with cumulative rainfall over 1.75 inches since 1950 (Depietri & McPhearson, 2018), and in community-reported evidence of increased coastal flooding due to high tides (Science and Resiliency Institute, Jamaica Bay, NYC, 2023). While flooding from extreme events - such as hurricanes, typhoons, and cyclones - can cause catastrophic damage, it has been estimated that floods from smaller, yet more frequent, storms have a large cumulative impact as well (Moftakhari et al., 2017; National Academies of Sciences, Engineering, and Medicine, 2019).

Urban flooding is affected by a number of local factors including upstream land use and development; the size of vegetated and impervious areas; population density and human contributions to the sewer system; drainage and sewer design; and physical characteristics, including elevation and watershed topography. The combination of these factors make flood events highly specific to a city block, street corner, or other subsection of a neighborhood (New York City Stormwater Resiliency Plan, 2021). The highly-localized and ephemeral nature of urban flooding make it challenging to measure, as monitoring needs to happen at a hyperlocal resolution and in real-time. As such, very little data exist on the frequency and extent of urban surface flooding (Galloway et al., 2018), and there is an unmet need for hyperlocal information on the presence, depth, and duration of street-level floods.

There is a range of stakeholders that require real-time, accurate, and reliable data on flood events, including flood frequency, depth, and profile in flood-prone locations (Silverman et al., 2022). In discussions with city agencies, community members, and researchers, we have identified needs that include: data for the development and validation of hydro-
logical models that predict flooding (city agencies and researchers) (New York City Stormwater Resiliency Plan, 2021); flood data for resilience and transportation planning, emergency response, issuing flash flood warnings, and tracking flood frequency over time (city agencies); data that can be used for day-to-day decision making and longer-term advocacy when faced with living with flood water (community members); and data that can signal when to collect samples when evaluating flood water quality (researchers) (Silverman et al., 2022). While some data sources exist, such as crowd-sourced flood data and US Geological Survey (USGS) stream gauges, each has limitations that prevent them from meeting all these needs (Helmrich et al., 2021).

Crowd-sourced data, including social media posts and reports from community members or citizen scientists (such as the Community Flood Watch Project in NYC (Science and Resiliency Institute, Jamaica Bay, NYC, 2023), and flood reports made to NYC’s 311 service request line (NYC 311, 2023)), are limited in that they require that someone observes the event and that the observer creates a report (Helmrich et al., 2021). Additional challenges with crowd-sourced data are that the data are not always correctly or precisely geotagged, reports rarely include flood depth readings over the duration of an event, and observers are discouraged from collecting data during hazardous conditions that might be present during high tides or extreme rain events. Existing water level sensors, such as USGS stream gauges, overcome some of the challenges above by collecting continuous, real-time data on water depths in the locations in which they are deployed. However, many of these sensors are deployed to monitor water bodies (as opposed to flooding at the street-level) and are too expensive and bulky for large scale deployment in urban areas, which precludes their ability to be deployed in a network to capture hyper-local flooding across a city scale.

Therefore, our aim was to develop real-time flood sensors that overcome the limitations described above. In particular, the goals of this work were to design a sensor that is low-cost (allowing deployment of a large sensor network and increasing accessibility for community science), accurate (enabling detection of flood depths as low as 10 mm), flexible for multiple use cases and installation scenarios (not requiring power or connectivity infrastructure), robust to withstand long-term deployment in the urban environment, and easy to construct with a simple open-source design. Community engagement and collaboration with NYC municipal agencies are also core components of the FloodNet project that have been instrumental in assisting project implementation, including selection of sensor installation locations, development of tools for meaningful data access and visualization, and collation of growing knowledge about the experience and impacts of flooding within communities most at risk.

In this paper, we describe technical aspects of our project, FloodNet, including the design of FloodNet’s ultrasonic-based sensor hardware, network architecture, data ingestion and analysis pipeline, and data visualization tools.

2 Prior Research on Flood Sensing

Previous research has been conducted to design water level sensors using various sensing modalities, each of which has opportunities and limitations for measuring flood depths. Moreover, most previous flood monitoring efforts have focused on water bodies, and have not been deployed in an urban street-level setting where the street is dry most of the time. Here we discuss the strengths and weaknesses of prior flood monitoring strategies, which have provided motivation and justification for the FloodNet sensor design and hardware choices.

Generally, water level sensors can be divided into contact and non-contact designs (Kang et al., 2021). Contact sensors include bubble or float gauges (Kang et al., 2021), pressure sensors (Garcia et al., 2015), and capacitive or conductivity-based sensors (Chetpattananondh...
et al., 2014). Pressure sensors placed within drainage infrastructure, for example, have been used to detect street-level flooding through monitoring the surcharging of sewers (Gold et al., 2023). Contact sensors, however, have a number of limitations that make them ill-suited for wide-spread and long-term sensing of street-level floods. For one, contact sensor readings are potentially influenced by the composition, temperature, and turbidity of the water being monitored (Chetpattananondh et al., 2014). Moreover, given that these sensors must contact floodwaters that often have poor water quality, they are subject to fouling and require frequent maintenance, which are challenges for long-term installation. Additionally, the logistics of deploying contact sensors on the sidewalk or street in the urban environment in a manner that allows water contact are challenging and can make them susceptible to damage or vandalism.

Much recent development of water level sensor technologies has focused on non-contact sensing modalities such as camera (Lo et al., 2015; Filonenko et al., 2015; Hiroi & Kawaguchi, 2016), ultrasonic (Mousa et al., 2016; Loftis et al., 2018), and LiDAR-based sensors (Loftis et al., 2018; Paul et al., 2020), given their relative low cost, ease of installation, compatibility with wireless connectivity, and lower maintenance requirements when compared with sensors that contact flood waters.

Visual sensing techniques that utilize camera-based technologies (such as preexisting video surveillance cameras (CCTVs) or traffic cameras) paired with image analysis algorithms and computer vision (CV) have been used to generate real-time flood data and predictive flood alerts (Lo et al., 2015; Filonenko et al., 2015; Hiroi & Kawaguchi, 2016; Sabbatini et al., 2021; Moy de Vitry et al., 2019; Jan et al., 2022; Jafari et al., 2021; Arshad et al., 2019). Camera-based sensors can be mounted to existing infrastructure and provide quantitative complexity unmatched by one-dimensional data capture, but they come with a host of challenges. For one, image analysis and CV approaches can struggle with low-quality images, and cameras affected by heavy rain, fog, or glare may not be able to provide useful data. These sensing systems also have limited success in processing imagery in low light, limiting their nighttime effectiveness (Lo et al., 2015). Data from camera-based sensors may not include flood depth measurements, and existing cameras are not always positioned in locations that are most at risk for flooding (Helmar et al., 2021). Moreover, these technologies use a large amount of power and are highly reliant on availability of existing power and communication infrastructure, and therefore less independent and flexible than low-powered counterparts described below (Lo et al., 2015). This also renders them vulnerable to extreme weather events, when they may be needed the most. Finally, the use of cameras raises ethical concerns relating to privacy, surveillance and consent. Collected images would need to be anonymized, risks associated with unintended uses of imagery would need careful consideration, and stringent data security protocols would be required.

Another camera-based approach to flood monitoring is the use of satellite imagery to track flood water inundation. The unparalleled field of view and global coverage offered makes this particularly suitable for large-geographical-scale flood event tracking (Li et al., 2018). However, its shortcomings (Olthof & Svacina, 2020) make it impractical for urban flood monitoring, including the high cost of long term image acquisition, low temporal and spatial resolution, difficulty in gathering water depth data, and, importantly for pluvial flood events, its inability to obtain imagery through cloud cover.

The increasing affordability of ultrasonic and LiDAR time-of-flight sensors has yielded other novel flood monitoring approaches. Each of these sensor modalities detects water levels by emitting a pulsed sound or light wave and measuring the round trip travel time of the pulse after it reflects from a surface and returns to the sensor; this travel time can be converted to distance based on the speed of the ultrasonic or LiDAR pulse.

LiDAR has become a popular tool to measure the physical world and is used for oceanography, archaeology, topographical modeling, and urban planning. Paul et al. re-

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cently used a LiDAR-based flood sensor to measure water levels with relative error around 0.1\% and at angles as small as 40 degrees to the planar surface (Paul et al., 2020). However, while LiDAR is becoming more affordable, it is still too expensive to deploy a large number of sensors for spatial coverage at the city-scale, and it can be affected by both the relative calmness and opacity of the water being measured (Paul et al., 2020). Additionally, LiDAR is best used to measure complex surfaces and is difficult to scale in a wireless environment, given the amount of raw data it produces.

Alternatively, several flood monitoring projects have had success in using ultrasonic distance sensors given their low cost, low power consumption, and opportunities for flexible deployment due to their ability to use solar power and transmit data over low-power wide area networks (Mousa et al., 2016; Loftis et al., 2018; Kang et al., 2021; Bartos et al., 2018). Examples of flood monitoring projects that utilize ultrasonic sensors include StormSense, an IoT water-level monitoring system in Hampton Roads, Virginia that employs wireless ultrasonic sensors that are deployed over water bodies and connected to a Long Range Wide Area Network (LoRaWAN) (Loftis et al., 2018), Open Storm with installations in Ann Arbor, Michigan and Dallas-Fort Worth, Texas (Bartos et al., 2018), and an ultrasonic sensor project carried out by a research team from King Abdullah University of Science and Technology in Saudi Arabia that utilized ultrasonic sensors installed over street traffic, to monitor and model flood events and traffic flow (Mousa et al., 2016).

Due to the opportunities presented by ultrasonic-based sensors, we employed ultrasonic range finders as the basis for the FloodNet sensor design described below. While prior studies have used ultrasonic sensor networks for riverine (Bartos et al., 2018) and urban flood monitoring (Loftis et al., 2018; Kang et al., 2021; Lo et al., 2015; Hiroi & Kawaguchi, 2016; Mousa et al., 2016), there are limited examples of such systems being deployed at street-level on a city-wide scale, let alone in a metropolitan area as dense and granularly complex as New York City. FloodNet, as a result, offers a novel approach to developing a scalable, reliable, informative, flood-sensing network to aid in urban resilience efforts.

3 FloodNet Sensor Network

The FloodNet project is a collaboration between academic researchers at New York University and the City University of New York with NYC municipal agencies (NYC Mayor’s Office of Climate & Environmental Justice, Office of Technology and Innovation, and Department of Environmental Protection). FloodNet has been focused on (1) the design, construction, and deployment of sensors to record street-level floods in NYC; (2) the development of data analysis tools for accurately processing flood data; and (3) community engagement and the sharing and communication of flood data to various stakeholders in meaningful ways. The FloodNet sensors (Figure 1) are novel in that they were designed to be compact, rugged, low-cost, and independent of existing urban power and network infrastructure, allowing the project to go beyond the limitations of some previously developed ultrasonic flood sensing systems. These specifications make the deployment of a hyperlocal, city-wide sensor network possible.

More specifically, the FloodNet sensor network was designed to meet the following criteria:

1. Sense water depth with an accuracy of $\leq 25$ mm
2. Transmit data to a central server every $\approx 1$ min
3. Operate autonomously in the environment for long periods of time
4. Operate independent of existing power and networking infrastructure
5. Comprise low-cost components for sensor network scalability
Local Flood Sensor
Sensor de Inundación de Barrio

This sensor monitors flooding at this location. The information is used to better understand the problem and to inform the community.

This is not a camera and no identifying information is being collected.

Figure 1. (A) Closeup of the FloodNet sensor, showing the (i) ultrasonic sensor cone, (ii) sensor housing, (iii) solar panel for battery charging, and (iv) antenna for data transmission. (B) Signage that is installed with each sensor. (C) FloodNet engineers installing a sensor in the field. (D) FloodNet sensor and sign installed on a U-channel pole in the Bronx, NY

In addition to sensor hardware, the FloodNet system includes a data ingestion and analysis pipeline, user facing dashboards that display sensor readings in real-time, and a tool that can send automated flood alerts to subscribing government agencies, community members, or other stakeholders when a flood is detected. All information on the sensor design, including build instructions, quality control practices, and data analysis pipelines, is open-source and provided in a GitHub repository (FloodNet, 2022b). While FloodNet is currently focused on NYC, FloodNet sensor designs could be utilized in other locations.

The following sections explain how FloodNet sensors meet the design criteria listed above, with technical details on the sensor design, operation, deployment scenarios, and networking infrastructure.

3.1 Sensor Core Components

FloodNet sensors (Figure 1) use the Maxbotix MB7389 ultrasonic range-finder (Maxbotix, 2021) to measure distance to the horizontal surface below the sensor, with a detection range between 30-500 cm, and 1 mm resolution. The sensor transmits 42 kHz ultrasound pulses, which it detects on return to the sensor after reflection from any large surface directly below. Sensor accuracy is a key design criterion for FloodNet, and the MB7389 sensor’s datasheet specifies the accuracy as being 1% of the measured distance, which equates to 30 mm (i.e., ±15 mm) with a typical mounting height of 3 m, satisfying design criteria 1; data illustrating this accuracy are described in Section 5.1.

The microcontroller unit (MCU) platform at the core of the sensor is the Heltec HTCC-AB02 (Heltec, 2022a) development board that uses the Heltec HTCC-AM02 (Heltec,
Table 1. Bill of materials (BOM) for prototype sensor unit including cost in USD (at time of writing)

<table>
<thead>
<tr>
<th>Item</th>
<th>Cost (USD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ultrasonic sensor</td>
<td>$99.95</td>
</tr>
<tr>
<td>Mounting hardware</td>
<td>$22.96</td>
</tr>
<tr>
<td>Heltec AB02 dev. board</td>
<td>$14.40</td>
</tr>
<tr>
<td>Antenna</td>
<td>$12.85</td>
</tr>
<tr>
<td>Breakout components</td>
<td>$11.44</td>
</tr>
<tr>
<td>Solar panel 0.6W</td>
<td>$9.00</td>
</tr>
<tr>
<td>LiPo battery - 400 mAh</td>
<td>$6.95</td>
</tr>
<tr>
<td>Solar mount</td>
<td>$6.00</td>
</tr>
<tr>
<td>Custom breakout board</td>
<td>$0.50</td>
</tr>
<tr>
<td>Cable glands</td>
<td>$0.45</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>$184.50</strong></td>
</tr>
</tbody>
</table>

The bill of materials, excluding mounting hardware costs, for the sensor is listed in Table 1. At the time of writing (September 2023), the total cost of the sensor parts was <$200 USD, allowing the sensors to meet design criterion 5. The build process for the sensor is included on the project’s public Github page (FloodNet, 2022a).
3.2 Sensor Deployment

The FloodNet sensor network is designed to monitor and collect data from various urban flood scenarios, and is indifferent to the cause of the flooding or water level change. For example, the sensors can measure the profiles of floods caused by stormwater runoff, high tides, storm surge, water infrastructure failures, or compound events, and are able to measure water depths over ground-level or water bodies, as long as the sensor is placed above and at a 90° angle to the surface to be monitored. Nonetheless, sensor deployments have a few key requirements: (1) mounting infrastructure (e.g., sign post, pole, wall, overhang, etc.) located directly above the surface to be monitored; (2) a LoRaWAN gateway within range for ingestion of the transmitted data; and (3) sunlight exposure to recharge the sensor’s battery. This section describes how these requirements inform the sensor installation process.

U-channel posts, used to mount street signs, are some of the most abundant pieces of street hardware in NYC (Figure 1). The NYC Department of Transportation (DOT) granted FloodNet permission to mount sensors on these sign posts. The posts are typically >3 m tall, providing a mounting height out of reach of passersby, and include 5 cm spaced mounting holes running vertically up the U-channel. FloodNet sensors must be mounted such that the ultrasonic beam is transmitted perpendicular to the ground surface. This configuration is important because ultrasonic pulses transmitted at an angle greater than 5° from vertical may not be returned to the sensor following reflection.

While plentiful, U-channel sign posts present some sensor installation limitations. First, sign posts are typically located on the sidewalk (i.e., not the roadway), and therefore may not be located directly above the lowest point in an area of interest (i.e., the location most likely to flood first). As such, in many locations, sensors are unable to measure flooding before water depth exceeds the street curb height (usually ≈15 cm in NYC). U-channel posts with vegetation beneath pose another challenge, as the shifting vegetation can produce variance in sensor measurements during non-flooded conditions. U-channel posts can also be susceptible to damage (i.e., being pushed off-vertical) or removal; these changes can be detected in real-time sensor readings and must be monitored as part of ongoing operation and maintenance. Despite the limitations of U-channel sign posts, their plenitude in NYC make them great candidates for sensor mounting. In situations where U-channel posts are unusable or unavailable, sensors can also be mounted on other types of roadway infrastructure, such as street lights or utility poles, using modified mounting hardware.

All installed sensors are accompanied by the installation of signage that provides information about the FloodNet project, the type of data collected by the sensor and where to access it, and an explanation that no identifying information is collected by the sensor (Figure 1).

3.3 Data Collection

For each data point collected by the sensor, seven distance measurements are recorded at 150 ms intervals, based on the recorded time between sending and receiving the ultrasound pulse. A median of these seven measurements is taken as a means of internal filtering, to exclude any erroneously small or large range measurements that could be reflections from smaller surfaces, such as the base of a light pole, and ensure that ranging is to the largest surface below the sensor, such as the street, sidewalk, or floodwater.

The sensor also includes an internal temperature sensor that it uses to correct distance measurements for the temperature-dependent speed of the ultrasound pulse through air (i.e., speed of sound increases with an increase of air temperature). Of note is that this temperature compensation can over-correct if, for example, the sensor is exposed
to direct sunlight, causing it to absorb heat and measure warmer temperatures than ambient air. In this case, the sensor assumes that the ultrasonic pulse travels faster and for a longer distance than it actually does, and will record an exaggerated distance to the ground (this phenomenon is further described in Section 5.4).

After determining the median distance value, it is transmitted to a nearby internet connected gateway using LoRaWAN networking technology, described in the next section.

3.4 Networking and Data Transmission

Every sensor must be within range of an internet-enabled gateway for data transmission and ingestion. FloodNet team members install LoRaWAN gateways in flood prone areas to receive sensor data payloads; gateways can receive data from sensors deployed within a ≈2 km radius. The internet-connected gateways forward these small (∼28 byte) data payloads to our LoRaWAN network provider, The Things Network (The Things Network, 2022), which packages the data and delivers them via the MQ Telemetry Transport (MQTT) lightweight publish/subscribe messaging protocol (MQTT, 2022) to project servers. The gateways themselves can be mounted inside or outside, but their 1 m antennas are mounted as high as possible outside for optimum coverage. Typically, gateways are mounted on the roofs of buildings on mounting points such as railings or existing vertical poles to ensure that the gateway and antenna are securely fastened.

Gateways require a continuous power source, such as an AC power outlet. The gateway typically used (i.e., MikroTech LtAP (Mikrotik, 2022)) measures 17 x 17 x 4 cm, weighs ≈500 g, and consumes around 5 W of power (similar to a small phone charger). The gateway also requires an internet connection to upload sensor payloads. A wired ethernet connection is preferred, but a gateway that incorporates a cellular modem and SIM card with low data rate plan can be used where ethernet connectivity is difficult to obtain. The data throughput of the device is minimal, at around 5 MB/day, which would not exceed a data plan bandwidth of 64 kbps. So far, FloodNet has mounted gateways on the rooftops of local businesses, community organizations, academic institutions, public schools, and apartment buildings.

Each sensor transmits its distance measurement payload (i.e., the median of seven independent distance measurements, as described in Section 3.1) via LoRaWAN to the nearest gateway. The gateway forwards this payload to our LoRaWAN network provider (The Things Network (The Things Stack, 2022)), which routes it to our project servers. To allow for an extensible platform for sensor data ingestion, storage, analysis, visualization, and sharing, FloodNet uses a server setup hosted at New York University, running a set of open source tools. More specifically, the FloodNet data pipeline is composed of a combination of Docker containers (Docker, 2022) including: (1) a load-balanced HTTP reverse proxy for the efficient routing of secure web traffic from a set of subdomains to each service running on the server; e.g: dataviz.floodnet.nyc (Traefik (Traefik, 2022)); (2) a data routing/processing layer for data ingestion and processing (NodeRed (Node-RED, 2022)); (3) a time-series database for data storage (InfluxDB (InfluxData, 2022)); (4) a dashboard platform for data visualization (Grafana (GrafanaLabs, 2022)); and (5) a public facing dashboard built on the FieldKit platform (Fieldkit, 2023) at dataviz.floodnet.nyc. The data pipeline is illustrated in Figure 2.

3.5 Sensor Power Consumption

Figure 3 shows the sensor’s current consumption during all possible states of the sensor operating in LoRaWAN Class A, the default LoRaWAN class in which the end device (i.e., the sensor) always initiates the communication. The sensor’s data collection and transmission periodicity is ≈1 min; the total duration of each cycle varies by a few
Figure 2. FloodNet data pipeline including deployed sensors, gateway, backend services, and data dashboards.

milliseconds due to the varying receive windows after a transmission, allowing the opportunity for bi-directional communication. In Figure 3, (a), (b), (d), and (f) are wake periods, and (c), (e), and (g) are sleep periods. The current consumption spike at the beginning of period (a) is when the sensor awakens from a deep sleep state. During every sensing period, seven measurements are taken from the ultrasonic ranging sensor, with seven corresponding current consumption peaks observed during period (a) in Figure 3. After the measurements are collected, a median is applied to these seven measurements and the result is transmitted in period (b). A short receive window (Rx1; period (d)), follows the transmission period (Tx) and a sleep period (c). Next, a second receive window Rx2, period (f), is typically opened one second after Rx1. The sensor enters a low power state between the receive windows to save power, period (e). The sleep period (g) lasts until the next sensing state (a) occurs.

Table 2 details the average current consumption of different sensor states during a single cycle illustrated in Figure 3. For one such sleep-wake cycle, the wake-time (i.e., the sum of periods (a), (b), (d), and (f)) was ≈2.7 s and sleep-time (i.e., the sum of periods (c), (e), and (g)) was ≈60.5 s (i.e., the duty cycle was approximately 4.5%). The average consumption of one sleep-wake cycle is ≈708 µA. This average varies from cycle to cycle but is within the range of 700-750 µA. Based on these observations, with a fully charged 400 mAh battery with no additional power or means of charging, the estimated lifetime of the sensor can be up to 22 days and 17 hours. This headroom in power consumption can accommodate periods of reduced sunlight, prolonged cover on the solar panel (e.g., snow), or a panel failure.

Battery operation and solar charging of the deployed sensors have been successful thus far. The sensors utilize a 0.6 W solar panel, mounted at an angle of 45°. Figure 3 illustrates the battery levels of three sensors deployed in locations with different cloud coverage, shade, and mounting conditions, which contribute to the differences in their battery trends. The three sensors also displayed differences in average voltage levels due to expected variations in lithium polymer battery condition. The sensor deployed at 5th Avenue and Hoyt Street had the best power harvesting of the three sensors illustrated in Figure 3 due to less shade from buildings and trees. However, this sensor had a rapid discharge cycle from January 1 to 3, 2021, due to minimal battery charging caused by consistent heavy cloud cover. Nonetheless, the sensor battery was able to fully charge on the following day as the cloud cover reduced. In conditions of full sun exposure, a single day of sun is sufficient to charge the 400 mAh battery completely. Conversely, the sensor deployed at 6th Avenue and Waverly place had less favorable power harvesting
Figure 3. (A) Sensor current consumption in milliamperes (mA) during different operational states. The total cycle is approximately 60 s; only the first 13 s is presented, the remainder of the time the sensor is in sleep mode. (B) Battery charge-drain cycles for select sensors, over the month of January 2021.

conditions, as observed by the slower upward charging trend after the heavy cloud cover period. However, given the headroom provided through the battery size and low power consumption design, the sensors were able to operate through adverse weather conditions and maintain a healthy battery voltage level.

4 Data Processing, Visualization, and Use in Community Engagement

4.1 Flood Sensor Data Ingestion and Calibration

There are a number of data processing stages implemented to convert distance measurements collected by the sensors to clean profiles of flood depth; the data pipeline is illustrated in Figure 4. First, any data point where the ultrasonic pulse did not return to the sensor (which the sensor records as the maximum range value = 5000 mm) is labeled as ‘undefined’, which is the designation for a missing data point. The remaining
Table 2. Typical duration and average current consumption of different sensor operational states detailed in Figure 3. These values vary from cycle to cycle but on average are below 1 mA.

<table>
<thead>
<tr>
<th>Period</th>
<th>Sensor State</th>
<th>Duration (ms)</th>
<th>Avg. current consumption</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a)</td>
<td>Sensing</td>
<td>2500</td>
<td>14.1 mA</td>
</tr>
<tr>
<td>(b)</td>
<td>Up-link transmission (TX)</td>
<td>67</td>
<td>115 mA</td>
</tr>
<tr>
<td>(c)</td>
<td>Sleep after TX until RX1</td>
<td>5000</td>
<td>22.4 µA</td>
</tr>
<tr>
<td>(d)</td>
<td>Receive window 1 (RX1)</td>
<td>52</td>
<td>18.3 mA</td>
</tr>
<tr>
<td>(e)</td>
<td>Sleep between RX1 and RX2</td>
<td>1000</td>
<td>18.5 µA</td>
</tr>
<tr>
<td>(f)</td>
<td>Receive window 2 (RX2)</td>
<td>59</td>
<td>19.3 mA</td>
</tr>
<tr>
<td>(g)</td>
<td>Sleep until next sensing cycle</td>
<td>54500</td>
<td>21.3 µA</td>
</tr>
</tbody>
</table>

Distance measurements collected at time $t$ ($z_t$) are then converted to flood depth ($D_t$); this calculation occurs in NodeRed. To calculate $D_t$, the measured distance between the sensor and the ground below must be known under stable and non-flooded conditions. This value is determined through a dynamic calibration procedure that occurs at 5 AM daily, in which $z_t$ collected over the previous three nights (between 10 PM and 5 AM; $n \approx 1260$) are analyzed to determine the median value ($z_{night\text{-}median}$). Daytime measurements are excluded from the calculation because of their temperature related variance, as discussed in Section 3.1. If the standard deviation of $z$ exceeds 5 mm (signifying either a flood or large variance related to noisy or unstable conditions), the previous day’s $z_{night\text{-}median}$ calculation is used. To calculate $D_t$, the sensor’s distance measurement at that time ($z_t$) is subtracted from $z_{night\text{-}median}$ (Equation 1).

$$D_t = z_{night\text{-}median} - z_t$$  \hspace{1cm} (1)

This dynamic calibration approach allows the project to adapt to changes in sensor height, caused, for example, by a shift in U-channel post position or seasonal variation in baseline $z_{night\text{-}median}$ readings.

4.2 Flood Depth Data Processing

After converting distance measurements to depths, the sensor data are processed through a series of filter stages to filter anomalous data related to: (1) low-level measurement noise within our acceptable range of error, (2) the impact of direct sunlight on temperature compensation, and (3) objects located below the sensor, which is a type of noise more likely to be experienced by water level sensors monitoring flooding on streets and sidewalks than those installed over water bodies, making data filtering critically important for the FloodNet project. In the following, a measured ‘event’ is defined as a series of one or more depth readings greater than 10 mm.

The first filter stage is designed to target the first two anomalies listed above. To correct for low-level measurement noise, all reported depths less than 10 mm are assigned a value of zero. This filter stage also works to filter measurements impacted by solar irradiance incident on the sensor housing, causing the ultrasonic sensor’s internal temperature sensor to read greater than ambient temperatures. When this occurs, the ultra-
Data Collection
For each data point, seven distance ($z_t$) measurements are recorded at 150 ms intervals; the median is selected and transmitted.

STAGE 0
a) Distance ($z_t$) measurements >5000mm set to ‘undefined’
b) Distance ($z_t$) measurements converted to depth ($D_t$) (Eq 1)

STAGE 1
Depth ($D_t$) measurements <10mm assigned value of zero

STAGE 2
Measurements with a gradient between two consecutive data points >254 mm/min set to ‘undefined’

STAGE 3
Detected blips and boxes set to ‘undefined’ using, sequentially (Eqs 2 and 3):
a) Blip filter 
b) Box filter 
c) Blip filter

Figure 4. Sequential stages used to collect and filter flood sensor data. Data processing during data collection occurs on the sensor, whereas filter stages 0 to 3 occur on the FloodNet servers in NodeRed.

sonic sensor’s calculation of distance is slightly increased as the speed of sound in air is considered greater. As such, measured $z_t > z_{night−median}$, resulting in negative calculated depth values (i.e., measurements that dip below ground level). This phenomenon has also been observed by others utilizing ultrasonic sensors for water level monitoring (Mousa et al., 2016). Assigning all depths less than 10 mm a value of zero corrects for this anomaly. Regardless, the resulting measurement error caused by this effect is typically within the range of our target accuracy (i.e., ±25 mm).

The second filter stage applies a gradient-based filter to target non-flood depth measurements caused by objects located under the sensor. When people, animals, or large objects—such as trash, bicycles, vehicles, etc.—pass beneath or are placed under a sensor, there is an immediate increase in depth measured from ground surface to the height of the object. These non-flood measurements can be distinguished from floods by their profile as floods have a gradual onset (Figure 5), which allows the use of a filter that assesses the change in depth values between two time-adjacent depth measurements ($\Delta depth/\Delta time$) on a rolling basis. The upper threshold for allowable change in depth over time was set at 254 mm per minute, which is a rate six times greater than the fastest rate of flood onset we have measured thus far in NYC (i.e., during Hurricane Ida). Any data point that exceeds the allowable $\Delta depth/\Delta time$ threshold is labeled as ‘undefined’ and is not included in the data visualization or alerting platforms. Of note, however, is that this filter stage can miss non-flood events when a sensor is experiencing weak network connectivity and there are longer periods of time between adjacent depth measurements, reducing the chance that the gradient threshold is exceeded.
Figure 5. Examples of flood and non-flood event data recorded by FloodNet sensors. An ‘event’ is defined as a series of one or more depth readings greater than 10 mm.

To address non-flood data points that are not captured by the gradient filter, we characterized three primary types of noise events that appear in the sensor data - (1) blips, (2) boxes, and (3) pulse chains (each is described below) - and designed a series of real-time filters to target them. This third filter stage applies three filters in the following order: a blip filter, followed by a box filter, followed by another blip filter to clean up non-flood data points that the box filter can leave behind. Each filter is described below.

Blips occur when sensor readings increase for a single measurement and return to the original (or a similar) value at the next time point. These single, anomalous measurements are likely caused by a person, vehicle, or object temporarily located beneath the sensor in the moment a measurement is collected. For sensors that are consistently uploading data (i.e., collecting and transmitting data every 1 min), these readings can be confidently filtered from the dataset because they are clearly transient. Blip events are characterized by three consecutive readings with values of $D_1 = D$, $D_2 = D + \Delta D$, and $D_3 = D \pm 0.1\Delta D$, where $D$ is any depth measurement $\geq 0$, and $\Delta D$ is a change in depth greater than 2 mm (i.e., $D_2 - D_1 > 2$ mm).

To recognize this condition, a blip metric for depth measurement $D_2$ is calculated following Equation 2. To apply the filter in real-time, any depth measurement that is at least 2 mm greater than the previous measurement is held in memory and not released to the database or visualization platform until the next measurement ($D_3$) arrives, to assess whether the depth measurement is a blip. If the blip metric is less than 0.1, point $D_2$ is characterized as a blip and is set to ‘undefined’, otherwise, the measurement remains unmodified.

Under certain conditions, a low frequency of available data points caused by poor network connectivity could cause a flood event to only be measured in a single data point, mimicking the characteristics of a blip. To reduce the risk of filtering out low sample count flood events, if blips are detected in instances where $D_1$ and $D_3$ span more than 6 minutes, the filter will query our weather database for reports of precipitation from any rain gauge located in NYC, and will only filter if there has been no reported precipitation in the past hour. Incorporation of tide data to check the possibility of coastal floods is still under development.

\[
BlipMetric(D_2) = \left| \frac{D_3 - D_1}{D_2 - D_1} \right|
\]  

Boxes occur when sensor readings increase immediately and then remain at a constant (or near constant) value for a sustained period of time. This can happen when a static object (e.g., parked vehicle, garbage, etc.) is placed beneath the sensor. The box filter was designed to detect a sharp increase in depth measurement, followed by one or
more measurements that remain within 10% of the initial increase in depth. Concretely, given a sequence of depth values of length $N$, box events are characterized as measurements where $D_1 = 0$, $D_2 = \Delta D$, and $D_n = D_2 \pm 0.1 \Delta D$ for each sequential measurement $n$ in $[3, N]$, until some measurement $D_N$ deviates from the original increase in height ($\Delta D$) by more than 10%. To recognize this condition, a box metric for measurement $D_n$ is calculated following Equation 3, with values less than 0.1 indicating that $D_n$ is part of a box. In real-time application, if the conditions of $D_1$ and $D_2$ are met, then $D_2$ is held in memory until the following point $D_3$ is received. If $D_3$ and subsequent depth measurements (until $D_N$) meet the stated condition of a box, then $D_2$ through $D_N$ will be set to ‘undefined’. To prevent false positives, such as mistakenly filtering out the top of a flood, given that standing water may have the appearance of a plateau in the flood profile, we restrict the box filter to only filtering non-flood events that start at zero (i.e., $D_1 = 0$). In cases when poor network connectivity causes sparse data points, the box filter will follow the logic of the blip filter and will only continue to filter points if there was no rain within the past hour of a measured data point.

$$
BoxMetric(D_n) = \left| \frac{D_n - D_2}{D_2} \right| 
$$

Pulse chains are characterized as a noisy series of blips and boxes (and blips on top of boxes) that cannot be easily categorized into the other two categories. These anomalous measurements are a more challenging case and are not addressed by the filters explicitly, but can be captured partially by a combination of both the blip and box filters. Thus, some pulse chains may remain after the application of the three filter stages. Ongoing research is being conducted to optimize data analysis strategies to recognize and filter out this measurement noise.

### 4.3 Data Storage, Visualisation and Alerting

Raw data and filtered flood depth measurements are stored in a database (InfluxData, 2022), which is optimized for large-scale, time-series data ingestion and retrieval. Currently, the FloodNet project utilizes two real-time data visualization platforms: a Grafana-based platform that the FloodNet team uses internally (GrafanaLabs, 2022), and a public-facing dashboard openly available on the web (dataviz.floodnet.nyc). The design of the public-facing dashboard incorporated feedback collected from city agency personnel and community residents to ensure data visualization is useful and meaningful to both stakeholder groups.

Following feedback from stakeholders, the data visualization platforms enable users to view sensor data alongside other sources of information that contextualize how flood data were collected and provide important touchpoints for understanding the impacts of flooding. For example, users can learn about the infrastructure on which a sensor is mounted, when it was installed, and whether it collects measurements over a sidewalk, road, or waterway. Additionally, tide gauge and precipitation data are provided to contextualize how environmental factors impact street-level flooding. We are conducting ongoing research to learn how to best incorporate qualitative documentation of flood events (such as photos, videos, and written accounts) into our visualization platforms.

Flood sensor data present several opportunities for real-world application. One key application for the data is a real-time flood alerting system, triggered when measured flood depths reach a specified depth threshold. This alerting system has been identified as a critical feature by some of our stakeholders, including both community members and municipal employees involved in emergency management and response. During pilot testing of the alerting system during summer 2021, flood alerts were sent via email or messaging app to registered users when measured flood depths reached 7.6 cm. During Hurricane Ida (1 Sept 2021), the FloodNet system alerted NYC Emergency Management
of flooding recorded by the sensors installed in the Gowanus neighborhood in Brooklyn
50 minutes before they received other notifications of the event.

FloodNet’s ongoing outreach and collaboration at the local community level has
found that flood sensor data can support community residents’ decision making when
faced with chronic floods, in addition to increasing their understanding of how flooding
impacts their neighborhoods. For example, community members who participated in a
focus group on FloodNet data and public engagement noted that sharing summary flood
data with their neighbors would be a good way to communicate whether they live in a
flood zone, in what time of year floods are most likely to occur, and what resources are
available to prepare for flood events. Through presentations, community meetings, edu-
cational workshops, community walkthroughs, and community-collected feedback on
flood sensor placement, we have heard a desire among community members to use flood
sensor data to validate community experiences of flooding in the eyes of elected officials
and other people in power. This can serve to support action plans and advocacy that
connect flooding to other relevant community issues in flood-prone areas.

5 Results and Discussion

FloodNet sensor installation and data collection are ongoing. To date, a total of
81 FloodNet sensors have been installed in flood-prone areas across the five boroughs
of NYC (Figure 6). Sensor installations have been staggered, with some sensors installed
for years and others installed more recently. We plan to expand the network to across
NYC in the coming years. Analysis of sensor data from flood events and static baseline
measurements provides insight about the functionality of ultrasonic sensors and the par-
ticularities of flood monitoring in general.

5.1 Validation of Sensor Measurements

Sensor measurements were validated in three ways: (1) in-laboratory testing be-
fore deployment; (2) comparison with data from tide gauges operated by the National
Oceanographic and Atmospheric Administration (NOAA); and (3) comparison with man-
ually collected flood depth measurements during a street-level, tidal flood event.

The flood sensor assembly process follows a detailed quality assurance (QA) pro-
cedure (FloodNet, 2022a). After the assembly, and before deployment, sensors undergo
a data validation test to ensure accurate measurements. During this in-laboratory qual-
ity control (QC) testing, each sensor is tested for accuracy at known mounting heights
that are similar to actual deployment scenarios. These heights are measured with a stan-
dard scale, and the mounts are aligned at a perpendicular angle to the ground surface
using a spirit level. The duration of this test is one hour, and a median of seven mea-
surements are collected every minute. The observed sensor measurements at all mount-
ing heights must be within \(h_i \pm n_{\text{allowed}}\) to pass the QC test, where \(h_i\) is the known mount-
ing height and \(n_{\text{allowed}}\) is the acceptable noise floor, which is 1% of the measured dis-
tance (Maxbotix, 2021). All of the FloodNet sensors constructed thus far have met this
QC criteria.

To test the ability of FloodNet sensors to detect water level changes under real-
world conditions, sensors were mounted over tidally-influenced water bodies (Gowanus
Canal in Brooklyn and the Jamaica Bay estuary in Queens). Changes in water level due
to the daily tidal cycle measured by the FloodNet sensors were compared with measure-
ments collected by nearby tide gauges operated by NOAA, and found to be similar with
similar periodicity (Figure 7).

Finally, the FloodNet sensors demonstrated accuracy in measuring water depths
during an actual street-level flood event. A validation experiment was conducted dur-
Figure 6. FloodNet’s public facing data dashboard. The map view of the dashboard, shown here, includes the locations of the 81 sensors installed across the five boroughs of NYC as of October 2023. Each circle indicates a sensor location and is color coded corresponding to the real-time measured flood depth; the depth value in inches is indicated by the number located in the center of each symbol.

5.2 Network and Data Acquisition Performance

FloodNet sensors collect distance data every minute and transmit these data payloads to our servers via LoRaWAN. One factor affecting data transmission (i.e., sensor uptime), however, is the signal strength between the sensor transmitting the data and the gateway receiving it. Low signal strength caused, for example, by a gateway being
Figure 7. (A) Comparison of water level data collected by a FloodNet sensor installed above the Gowanus Canal in Brooklyn (black line), which is tidally influenced, with the tide level measured by a NOAA tide gauge located at the Battery, NY (NOAA station ID: 8518750; dashed blue line). The FloodNet sensor measurements are very similar to those from the NOAA tide gauge with a slight temporal delay due to being installed in different locations in New York Harbor. (B) FloodNet sensor measurements (black line) collected during a high tide flood in Hamilton Beach, Queens on July 23, 2021, compared with measurements collected intermittently by manually reading the depth value off of a standard ruler (blue data points and line).

Much effort is made in installing sensors and gateways in locations that ensure good signal strength. Nonetheless, FloodNet sensors deployed thus far have had transmission efficiencies of less than 100% (Figure 8), which is typical for LoRaWAN networks. For example, in analyzing the transmission efficiencies of 21 sensors that were installed and operating during the full six month period of October 2022 to April 2023, eight had transmission efficiencies that were greater than 75%, seven were between 50 and 75%, and the remaining six were between 35 and 46%. Given that the sensors collect and transmit data every minute, a transmission efficiency of greater than 50% is relatively good, and means...
Figure 8. Data transmission efficiencies of a subset of FloodNet sensors, showing percent of payload uploads per day, where 100% equals 60 successful uploads/hour over 24 hours. The percentage provided on the left hand side of the figure is the average daily transmission efficiency across all days in the period between October 2022 to April 2023. The 21 sensors included here are a subset of the total number of sensors installed thus far, and were selected because they were installed and operated during the full duration of the six month period from October 2022 to April 2023.

that, on average, data packets sent by a sensor were received at a frequency of at least every other minute.

Poor sensor uptime can be caused by a variety of factors. First, if a sensor is observed to have consistently low upload rates, it is often caused by poor or inconsistent gateway coverage. This can be a function of pure distance between the sensor and the gateway - as seen for sensor 19 (Figure 8), which was located 1.8 km from the nearest gateway - or can be due to seasonal or environmental effects that could impede the signal, such as increased tree foliage in summer, or nearby high voltage electrical or heavy metal infrastructure. Sensor 18, for example, was mounted next to the underpass of a steel railway bridge that impeded signal transmission.

Second, downtime can manifest in an otherwise well-performing sensor as a sudden and complete loss of connectivity for a period of time, which can be caused by the temporary malfunction of a gateway or sensor. A gateway malfunction can cause an outage across multiple sensors that rely on that gateway for connectivity. For example, in February 2023, two apparent gateway outages occurred, the first affecting sensors 8, 11, 12, and 14, and the second affecting sensors 9, 13, 16, and 18. During the first gateway outage, sensor 8 initially had a total outage, but was able to regain connectivity, albeit weaker in signal strength, with another gateway shortly after, and sensor 11 saw a drop in connectivity, but never completely lost connectivity due to proximity to another, further gateway. Improved gateway connectivity was gained through deployment of two new gateways in March 2023, first reconnecting sensors 8 and 12, and later reconnecting sensors 9, 11, 13, 14, 16, and 18. Additionally, vertical bands can be observed across all sensors in January and February 2023 related to short term system-wide outages caused by server infrastructure maintenance, when downtime was less than a day.

To reduce the loss of data during transmission, different antenna types and/or the use of a cellular network for data transmission instead of LoRaWAN are being consid-
ered for the next iteration of the sensor design to increase the packet success rate. We also plan to implement onboard flash memory to store data on the sensor. In the event of a network disruption, the sensor will re-transmit stored data once the disruption is resolved, minimizing the loss of data packets.

5.3 Data Filter Performance

Between October 2020 and May 2023, a total of 6,641 events were recorded by the sensors (Table 3); each event is defined as a series of one or more depth readings greater than 10 mm (the predetermined noise threshold). Of these, 360 were manually identified as flood events, 7 as snow events (i.e., snow accumulation during winter storms), and the rest (6,274) as non-flood events. The non-flood events (described in Section 4.2) result from the nature of the sensors being located over active streets and sidewalks in NYC, and included blips, boxes, pulse chains, and complex noise (the latter is a catch-all category for events that did not fit into the other three). Most (74%) of the non-flood events were identified as blips.

As described in Section 4.2, we developed and implemented a series of automated data processing stages to filter non-flood events from the depth data, thereby removing false positive events from the data visualization and alerting platforms. As shown in Table 3, the use of all three filter stages described above resulted in an overall reduction of reported non-flood events by 76%, whereas only 19% of the non-flood events were captured after the gradient filter stage alone. Blip events were the most common and easiest to filter, with 92% of blips correctly classified. Boxes and pulse-chains occurred less frequently, but were more challenging to capture, as shown by the correct identification of 65% boxes and 32% of pulse chains. All flood and snow events remained unfiltered, indicating that the filters did not result in false negative results.

There are some challenges to automatically distinguishing flood events from non-flood events, including having sparse data points at times for some sensors. More specifically, when data are not received from the sensor regularly (e.g., every minute), it is difficult to distinguish a possible flood event from a non-flood. For example, with frequent data points, large gradients of flood depth per time can be readily identified as unlikely coming from a flood event. However if the data points are separated by long or irregular time intervals, a large increase in depth that is physically unlikely at a 1 minute resolution could be possible at a 5 or 10 minute resolution because the large instantaneous gradient is now spread over a longer period of time. In an extreme case, if only one measurement is received over the duration of a flood, it could appear as just a blip, which is why blip and box filters are both limited by the length of the time window they’re allowed to operate on; this challenge will be alleviated with engineering improvements to increase data transmission.

Additionally, there are events that do not match the aforementioned non-flood or flood event patterns. For example, some non-flood events have two points that meet neither the characteristics of a box nor a blip, some boxes don’t start at zero and are not identified because the box filter requires the first point to have a depth of zero, and sometimes the tops of boxes have a large variance or have boxes or noise on top of boxes, both of which would bypass the box filter.

Our goal is to release data to stakeholders as close to real-time as possible, ideally within 5-10 minutes of the start of an event. Therefore, frequent data collection (≈ 1 minute interval) is needed for the filters to be able to rapidly recognize flood events. Additionally, we are conducting ongoing research to improve the data filters’ ability to distinguish floods from non-flood events. One avenue being explored is training machine learning models to identify the patterns of flood event data, with a goal of reducing the number of false positive floods reported for non-flood events, which is important for a reliable
Table 3. Counts of flood, snow, and non-flood events that were recorded by FloodNet sensors between October 2020 and May 2023, in which an event is defined as a series of one or more depth readings greater than 10 mm. Total event numbers presented for the unfiltered data were manually counted. The numbers of non-flood events identified after the gradient filter stage and after application of all three filter stages are presented; the percentages provided are calculated as the number of events identified by the filters divided by the number of events identified in the unfiltered data.

<table>
<thead>
<tr>
<th>Event Type</th>
<th>Unfiltered Data</th>
<th>After Gradient Filter (Stage 2)</th>
<th>After All Filter Stages (Stage 3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number Events Identified Manually</td>
<td>Number Non-flood Events Identified</td>
<td>Percent of Total from Unfiltered Data</td>
</tr>
<tr>
<td>Flood</td>
<td>360</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td>Snow</td>
<td>7</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td>Blip</td>
<td>4641</td>
<td>990</td>
<td>21%</td>
</tr>
<tr>
<td>Box</td>
<td>812</td>
<td>235</td>
<td>29%</td>
</tr>
<tr>
<td>Pulse Chain</td>
<td>597</td>
<td>58</td>
<td>10%</td>
</tr>
<tr>
<td>Complex Noise</td>
<td>224</td>
<td>4</td>
<td>2%</td>
</tr>
<tr>
<td>Total Non-Flood Events</td>
<td>6634</td>
<td>1287</td>
<td>19%</td>
</tr>
</tbody>
</table>

public flood alert system. Additionally this will help in post-hoc flood labeling and boundary regression allowing computation of flood event statistics.

5.4 Impact of Seasonal Temperature Changes on Distance Readings

As previously mentioned, there is a known effect of ambient weather conditions on ultrasonic distance measurements (Mousa et al., 2016). To evaluate this effect on FloodNet sensor readings, daily mean distances to the ground were calculated for data collected by a FloodNet sensor (located at the intersection of Hoyt Street and 5th Street in Brooklyn) between 10 PM and 5 AM each day, over the course of a year. Night time values were evaluated alone to assess seasonal-dependence of sensor readings due to ambient temperature, without the confounding impact of direct sunlight on the sensor during the day. To understand baseline (i.e., non-flood) conditions, known flood and snow events were excluded from the dataset, as were absolute values greater than two standard deviations from the mean.

Despite no change in the physical height of the sensor as installed, there was a statistically significant shift in the baseline distance measurements made by the sensor over the course of a year (Figure 9), with greatest distances measured in January and smallest measured in August. Colder ambient temperatures in the winter decrease the velocity of ultrasonic pulses, resulting in longer times of return and exaggerated distance measurement if the temperature is not fully accounted for in the distance calculation. Conversely, warmer temperatures in summer would lead to calculation of shorter distances due to faster velocity and shorter time of return of the ultrasonic pulse. As such, it is possible that the internal temperature sensor housed within the casing of the ultrasonic sensor erroneously detected lower than ambient temperatures during the winter and higher than ambient during the summer. Nonetheless, the magnitude of difference between greatest and smallest distance measurement was only 12 mm, which is within the allowable noise floor of the sensor. Additionally, the dynamic calibration procedure described in Section 4.1 accounts and corrects for this temperature-dependent phenomena.

5.5 Flood Sensor Data Examples: Hurricane Ida and Tidal Flooding

Even with ongoing upgrades to the sensor design, network performance, and data analysis pipeline, the FloodNet sensors deployed thus far have been able to collect a rich
Figure 9. Difference in daily nighttime mean distance measurements (under non-flooded conditions from 10 PM to 5 AM) from the annual mean for a flood sensor located at Hoyt Street and 5th Avenue (Brooklyn) over 12 months from 2020 to 2021. Temperature data represent ambient conditions and were sourced from a nearby New York State Mesonet managed weather station at the Brooklyn Navy Yard (ID: bknyrd), which is located ≈ 3 km away from the sensor.

dataset, capturing the profiles of pluvial and tidal floods in NYC neighborhoods. The arrival of the remnants of Hurricane Ida in NYC on September 1, 2021 was a landmark event, with record rainfall (up to 79 mm/h recorded in Central Park) resulting in unprecedented flooding across NYC. All three FloodNet sensors deployed at the time in the Gowanus neighborhood in Brooklyn measured flood profiles during the storm, with the most extreme flooding occurring at the intersection of Carroll Street and 4th Avenue (Figure 10). A peak flood depth of 890 mm above the sidewalk was recorded (water depths in the roadway were deeper), as well as a rapid rate of onset (up to 91 mm/min for the first 5 minutes of the flood). See Silverman et al. (Silverman et al., 2022) for a description of flood data collected by these same sensors during Tropical Storm Henri (August 21, 2021).

Data from the sensors indicate that flood events have been more frequent in locations susceptible to regular tidal flooding. The northernmost block of Beach 84th Street on the Rockaway peninsula in Queens, for example, is a coastal area that experiences regular tidal flooding (Figure 10). In the 17 months between December 2021, when the sensor was installed, and April 2023, the sensor located on this block measured 121 distinct flood events, between 29 and 560 mm in depth, during relatively high, high-tide events, which occur on a semi-monthly basis, typically coinciding with the full moon or new moon. For example, in September 2022, the FloodNet sensor recorded 13 distinct flood events on 7 consecutive days, following the approximately 12 hour period of the tidal cycle. Other sensors located in coastal areas have measured a similar degree of flooding.

6 Conclusions and Future Work

The design of the FloodNet sensor allows accurate measurement of street-level floods as shallow as 10 mm, at a frequency of one measurement per minute under optimal conditions. The associated sensor network transmits measured data to our servers and through
the FloodNet data analysis pipeline, which enables flood data visualization and provision of alerts to users in near real-time.

Given the success of FloodNet sensors in monitoring floods thus far, and the potential utility of flood sensor data (Silverman et al., 2022), we plan to expand the sensor network across NYC’s five boroughs. To accomplish the expansion, ongoing research is being conducted to iterate the sensor design to make it more manufacturable for scale-up, to improve connectivity for data transmission, and to update the data analysis pipeline to improve the detection and logging of flood events. All sensor design files are located on the FloodNet Github page (FloodNet, 2022b), which is updated as new designs are implemented. A variety of stakeholders, including NYC residents, are being consulted as we iterate the design of the FloodNet web-based data dashboard and data sharing tools, and offline materials to improve the meaningful sharing and communication of collected flood data. Additionally, given the thousands of locations that are at risk of flooding in NYC (New York City Stormwater Resiliency Plan, 2021), it is unlikely that a flood sensor network will be distributed enough to monitor every one. As such, and given the relevance of the data to municipalities for uses such as emergency management, urban planning, decision making for capital improvement projects and other resource allocation, an additional line of ongoing research is to create a risk and equity based framework to help prioritize flood sensor deployment locations in a systematic and equitable way.

In conclusion, FloodNet sensors were designed specifically to overcome challenges related to measuring floods in a distributed manner across a complex urban environment, and have demonstrated ability to collect street-level flood data, regardless of the flood typology (e.g., pluvial, fluvial, tidal, storm surge, infrastructure-related). While the FloodNet project is based in NYC, the sensor design is flexible for other locations and contexts, with an open-source design available for others who would like to build and deploy flood sensors in their own communities.

7 Open Research

All sensor hardware designs and associated software are available on our publicly accessible Github organization (FloodNet, 2023b). Data used in the analysis can be found in this Zenodo dataset (FloodNet, 2023a). Time series visualizations of all of our flood sensor data can be found on our public facing data dashboard (FloodNet, 2023c).

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Figure 10. Examples of flood data collected by FloodNet sensors: (A) Data collected by the sensor located at the intersection of Carroll Street and 4th Avenue in Brooklyn during Hurricane Ida (September 1, 2021). The black line represents the flood depth data (secondary y-axis); blue bars represent rainfall intensity (primary y-axis; precipitation data was sourced from a rain gauge at the New York State Mesonet managed weather station at the Brooklyn Navy Yard (ID: bknyrd) located $\approx$ 2.7 km from the sensor). The flood sensor is located over a sidewalk, therefore flood depths were greater in the adjacent roadway. (B) Data collected by the sensor located on Beach 84th Street in Rockaway, Queens over the course of 18 months (December 2021- May 2023). The Black line represents the flood depth data (secondary y-axis); the blue line (primary y-axis) represents the tide height above the mean higher high water (MHHW) level. Tide data are from NOAA for the North Channel, NY tide station (NOAA station ID: 8517201). (C) Same data as in Panel B, but zoomed in to a week period from September 5 to September 14, 2022, when high tide flooding caused by the full moon on September 10 caused 13 consecutive flood events, with floods, occurring every 12 to 24 hours.