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RESEARCH ARTICLE

Automated detection of illicit discharges in storm drains using a distributed network of low-cost IoT sensors

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ABSTRACT
A novel, sensor-driven approach that automates the detection of transient illicit discharges in storm drains was piloted across ten storm drain outfalls in southern California. The sensor network continuously monitors key hydrologic and water quality variables. An automated algorithm utilizing a differential exponentially weighted moving average model was deployed to identify trends that indicate a potential illicit discharge. When a potential discharge is detected, an email alarm notifies stormwater managers in near-real-time. The manager may view the data immediately via a custom visualization dashboard and/or follow up in-person at the offending site. Rapid responses enabled by automated detection greatly improve the likelihood that intermittent illicit discharges will be detected, traced and eliminated. Results from the pilot program show that the open-source, 3D printed, internet-of-things (IoT)-enabled sensors utilized herein offer a financially viable product, facilitating widespread network coverage for automated illicit discharge detection in resource-limited programs.

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Introduction

Unpermitted, non-stormwater discharges into the municipal separate storm sewer system (MS4) degrading receiving water quality, compromising network flood control capacity and threatening public health are known as illicit discharges (Brown, Caraco, and Pitt 2004). Illicit discharges are a major drawback of separate wastewater and stormwater sewers; discharged pollutants can enter the receiving water body untreated (Cook 1992; Zhang et al. 2023). Illicit discharge detection and elimination (IDDE) program requirements pervade stormwater infrastructure permits in the USA and Australia (CA Water Boards 2024; Victorian Stormwater Committee 1999), yet general guidance on how to conduct surveillance or take follow-up remedial action remains slim. IDDE programs commonly rely on periodic sampling at system outfalls, which can be successfully deployed to source track continuous discharges (Hachad et al. 2022). Periodic sampling may miss intermittent discharges due to limited spatial-temporal resolution (Brown, Caraco, and Pitt 2004; Irvine et al. 2011; Shi et al. 2022). A different approach is necessary for monitoring programs to detect intermittent discharges, such as those from industrial/commercial dumping, accidental spills, and improper cross-connections (Schiff, Beck, and Fassman-Beck 2021).

Inspecting storm drains for illicit discharges is a concern for municipalities all over the world with separate wastewater and stormwater sewer systems (Schilperoort et al. 2023). The USA's Clean Water Act (1972) established a permit system and requirements for jurisdictions discharging runoff into waters of the United States (United States Code 2021), including owners and operators of MS4s. Permit requirements, called minimum control measures (MCMs), contain exigencies for public education, construction site runoff control, etc., as well as preventing periodic and persistent illicit discharges through approved IDDE programs (CA Water Boards 2024; Cook 1992). Elsewhere, Australia's Litter Act 1987 provides similar provisions protecting the storm drain and receiving waters from harmful discharges (Victorian Stormwater Committee 1999).

Illicit discharges can enter the MS4 in myriad deleterious ways. Brown, Caraco, and Pitt (2004)

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depicts common examples of illicit discharges, including leaking sanitary sewers, illegal cross-connections, accidental spills, industrial or commercial dumping, and polluted runoff from outdoor washing and irrigation activities. These illicit discharges have widely varying pollutant loads, from essentially raw sewage to potable water runoff, as well as variable discharge regimes. Spills may be random, but dumping activities and cross-connections may present an identifiable pattern (up to and including continuous discharge). Evidence remains limited and context-dependent regarding the relative harm to receiving waters from intermittent illicit discharge sources, likely because these events have not been successfully documented by current IDDE programs.

Despite the ubiquity of IDDE requirements, general guidance for municipalities is extremely limited on the critical first step of *detecting* the illicit discharges (Brown, Caraco, and Pitt 2004; Irvine et al. 2011). A typical IDDE program across the USA relies on periodic pollutant sampling (often for *E. coli*) augmented by a community hot line to identify likely illicit discharges (Anne Arundel County 2024; City of Ithaca, 2024; Irvine et al. 2011; Linn County 2024; Minnesota Pollution Control Agency 2024; Schiff, Beck, and Fassman-Beck 2021; Watertown 2011). Permit conditions or compliance monitoring plans may dictate the scope and frequency of monitoring, as well as how monitoring is accomplished. Stormwater discharge permit requirements in the USA are distinguished by the size of the community served by the MS4, yet there is little distinction in the guidance for IDDE (CA Water Boards 2024). Periodic sampling programs are effective at identifying *continuous* illicit discharges (Brown, Caraco, and Pitt 2004; Hachad et al. 2022; Schiff, Beck, and Fassman-Beck 2021; Zhang et al. 2023). However, intermittent and transient illicit discharges, such as those produced by industrial dumping and outdoor washing, are generally recognized to require a higher temporal resolution of monitoring to be reliably captured (Schiff, Beck, and Fassman-Beck 2021; Shi et al. 2022). These discharges will only be captured if the sampling team is on-site while the discharge event is still occurring (Tuomari and Thompson 2004).

Increasing the frequency of manual sampling programs has obvious logistical and cost implications; more sampling means more person-hours means more cost. The most direct solution for IDDE programs hoping to prevent intermittent and transient flows is to use remote sensing equipment and automated detection algorithms (PG Environmental 2018). The barriers to entry for IDDE programs in this regard are largely trade-offs between cost, equipment security, and technological maturity. Multi-parameter sensing equipment from reputable vendors often cost tens of thousands of dollars (In-Situ 2024; YSI 2024), while in-situ instruments have a tendency to be vandalized if not properly secured (Office of Construction Safety 2021). Additionally, tethered sensors (i.e. unable to wirelessly transmit data) require frequent visits to retrieve instrument data for discharge analysis. Cheaper instrumentation, as well as advances to internet-of-things (IoT) connectivity, are prerequisites for any attempt at automated detection of illicit discharges (PG Environmental 2018).

Recently, researchers have developed sensors for use in the storm sewer with IoT connectivity that potentially enable network-wide continuous monitoring BoSL wiki, 2024). Shi et al. (2022) showed that depth, electrical conductivity (EC), and temperature were effective indicator variables for identifying illicit discharges during dry-weather in storm drains. The pilot work described herein included those parameters as well as an in-line sensor for turbidity (Wang et al. 2024), an out-of-water radar-based sensor that measures depth and velocity (Catsamas et al. 2023), and a low-power camera. Turbidity may be an important variable to differentiate harmful discharges from relatively harmless ones (i.e. turbidity correlates with highly polluted water, [Wang et al. 2024]). Non-contact radar sensors allow for data to be collected while avoiding the stress to the instrument, such as fouling or blocking debris, of being within the water flow (Catsamas et al. 2022). Intermittent photography of the conduits is an effective quality check on the sensor data. Open-source design and 3D printed components contribute to the approachable cost of the IoT sensors (Shi et al. 2021). During the pilot program described in this manuscript, approximately ten locations were instrumented with IoT sensors obtained from the BoSL research laboratory (https://www.bosl.com.au/wiki/Main_Page.) to capture and telemetrically report the five hydrologic and water quality variables (depth, EC, temperature, turbidity, velocity) at a comparable cost to a single multi-parameter sensing instrument from reputable vendors (In-Situ 2024; YSI 2024).

Herein, the historical challenges of automating IDDE were newly explored by deploying state-of-the-art remote sensing equipment to an MS4 in southern California. The objectives of this pilot program were to: *i)* investigate the feasibility of distributed, continuous monitoring in an urban separate storm sewer, *ii)* explore the use of an automated algorithm to detect illicit discharges, and *iii)* confirm automated system performance by following up on discharge alarm notifications. The hypothesis is that continuous network monitoring enabled by IoT sensors combined with automated alarms is an effective strategy to identify transient discharges that would otherwise be missed by a traditional grab sample based dry-weather monitoring program.

Methods

Distributed, continuous monitoring in an urban storm sewer

Site descriptions

Orange County (OC) is an ultra-urbanized corridor located between the counties of Los Angeles and San Diego in California, USA. Home to more than three million people, nearly all of OC's 2500 km^2 land area is post-development, with more than 39% devoted to impervious land uses (Dewitz and U.S. Geological Survey 2021; USAFacts 2024). The climate zone is western Mediterranean (Beck et al. 2018), with a well-defined dry-season (typically without any measurable precipitation) between May and September, and an average annual precipitation between 25 and 30 cm (NOAA (2017); County of Orange et al. 2018). IDDE response programs occur year-round, with targeted reconnaissance monitoring efforts to detect illicit discharges occurring during the dry season, per the approved permit compliance monitoring plan (Santa Ana Region 2009). The northern portion of the county is contained within the Santa Ana watershed, and the MS4 discharge within this region is regulated by the Phase I MS4 permit administered by the Santa Ana Regional Water Quality Control Board (CA Water Boards 2024). The area for the current study is the North OC MS4 operated by various North OC cities, the County of Orange and the Orange County Flood Control District (Permittees).

Despite a 5-month dry season with no expected rainfall, it is common for MS4 outfalls to continuously discharge some flow (Schiff, Beck, and Fassman-Beck 2021). This could be contribution from nearby irrigation, rising groundwater intrusions or infiltration, emergency fire fighting flows, non-commercial vehicle washing, dechlorinated swimming pools and other permissible discharges, or heretofore unrecognized sources of illicit discharge. The current IDDE program(s) within OC use a variety of means to locate and eliminate illegal discharges, including interagency communication, community hotlines and web reporting of incidents. This is a countywide emergency water pollution response program that operates on a 24/7/365 basis. The dry season IDDE monitoring program is informed by a rotating outfall sampling schedule that establishes a baseline condition for reasonable discharge through an outfall (Santa Ana Region 2009; Schiff, Beck, and Fassman-Beck 2021). The current targeted reconnaissance monitoring program component approved by the permit deploys a manual sampling team to 30 MS4 outfalls during the dry season, with three sites typically sampled per day. Each outfall is sampled five times per dry season. The monitoring includes field rapid tests and subsequent laboratory analyses for a variety of constituents, which are compared to statistically based tolerance intervals generated for this program. If a detection of potential transient illicit discharge is identified, such as through observations or field tests, the monitoring staff contact the tributary permittee jurisdiction(s) for follow-up investigation. Detecting active transient illegal discharges is highly limited to being in the right place at the right time for the field teams. For samples processed later at a laboratory, the results are tallied monthly and distributed to the permittees for follow-up. The delay between sample collection and laboratory results (often days to weeks) challenges efficient identification and elimination of transient illicit discharges. The cost for sampling and laboratory analysis was approximately US$244,000 in 2024.

Ten candidate outfalls were identified for the automated detection of illicit discharge pilot program in the spring of 2024. Outfalls were selected based on their relative ease/safety of access and location within the network. Major outfalls were preferred to increase the likelihood of seeing an illicit discharge, and the potential for a water quality impact if/when a discharge occurs in close proximity to the receiving water. Sensor placement was primarily practically oriented for the pilot study, as opposed to using a complex algorithm such as those developed to protect drinking water networks from contamination (Adedoja et al. 2018). MS4 site locations are shown in Figure 1; site IDs, geometric descriptions, and installation/maintenance dates for each conduit are given in Table 1. Site IDs were anonymized to preserve confidentiality and avoid attributing potential illicit discharge signals to specific responsible parties in the applicable permittee jurisdictions.

Each site was instrumented with four BoSL sensors collectively covering five key hydrologic and water quality variables. One in-line sensor captured depth, temperature, and EC (heretofore the DTEC sensor); one in-line sensor captured turbidity (TURB sensor); one radar sensor captured depth and velocity (RAD sensor); and one color camera (CAM) captured photographs as a first-line qualitative check. The specific sensors deployed were selected based on availability, and all sensors were deployed at all locations in the absence of precedence identifying reliable indicators of potential illicit discharges. Figure 2 shows a typical installation within the MS4 that shows the CAM and RAD sensors installed along the conduit crown, while the in-line sensors, DTEC and TURB, are installed along the conduit invert. Low dams were constructed to

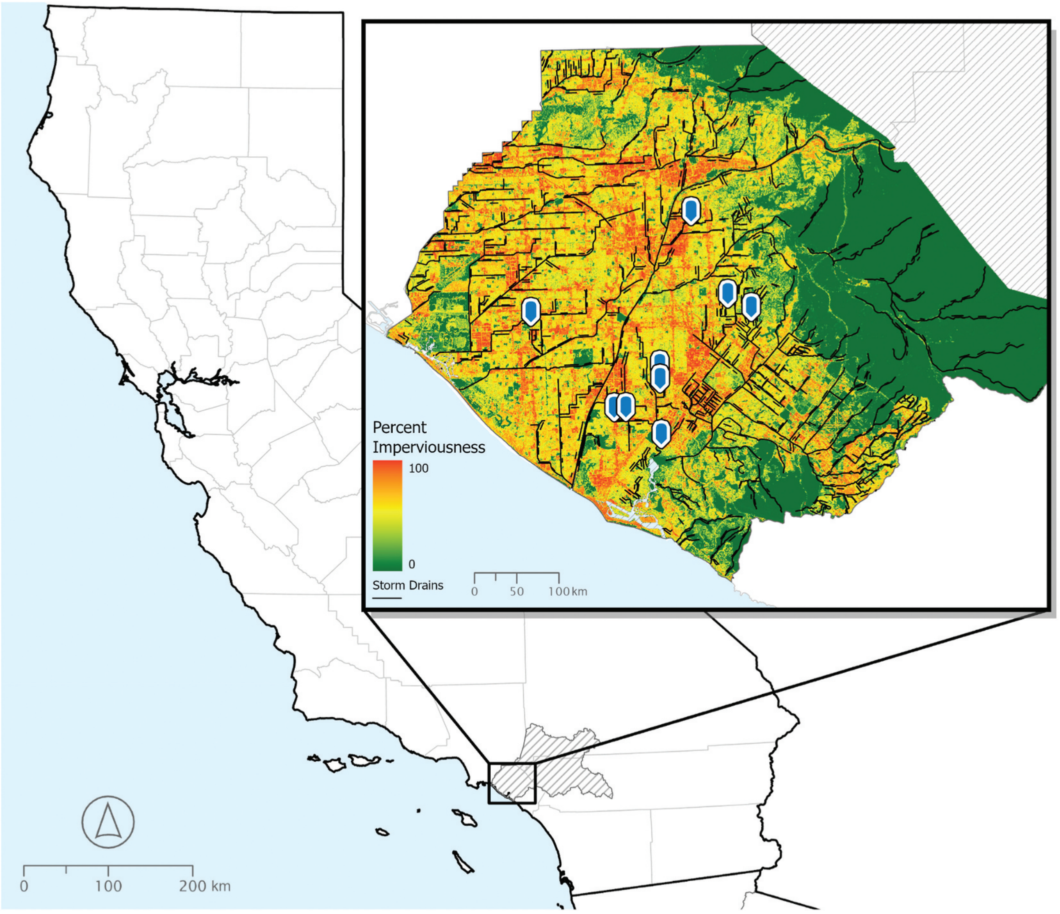


Figure 1. GIS map of monitoring sites in north OC. Hatched region is the Santa Ana Watershed. Color scale of the inlay is percent imperviousness from the national land cover dataset (2021). Black lines on the inlay are the MS4s. Blue icons are monitoring locations instrumented for the current research. Note: two sites in very close physical proximity appear as a single icon in the figure.

ensure that the in-line sensors stay continually submerged. Overall, 40 BoSL sensors were installed across 10 MS4 locations. The Supplemental Information and the BoSL Wiki page (https://www.bosl.com.au/wiki/Main_Page) provide additional details about the BoSL sensors deployed herein.

Maintenance activities

Affordability is an enticing attribute of open-source hardware and software sensors, but users must develop their own experience to document sensor operation and maintenance requirements. The current pilot investigation allowed for monthly visits to each site to check sensor physical condition and conduct maintenance if/when needed (Table 1). The maintenance activities during each site visit include site safety checks, in-line sensor cleaning, battery replacement, and sensor calibration. Briefly, the DTEC calibration check involved submerging the sensor to three known depths and fitting a linear regression to the measured data versus known values. The specific procedures are detailed in the Sensor Operating Manuals created for this project, and made publicly available through the Open Science Framework: https://osf.io/cx54j. Calibration was conducted during each visit to check for sensor drift; total maintenance time for each visit was also recorded.

In addition to hydrologic and water quality variables, the BoSL sensors also report key parameters related to the sensor's operational condition (battery level, cellular connectivity quality, etc). An automated program called the Sensor Health Report was created to provide daily updates that greatly simplify the management of a distributed sensing network by answering questions like: are the sensors still reporting? What is the current battery life? Is the transmission signal strong enough at this site? The Python source code for the Sensor Health Report is available on Github (https://github.com/SCCWRP/IDEE-sensor-health-report), while an example report is provided in the Supplemental Information.

Table 1. Anonymized Site IDs, and outfall geometries. Box Culvert (BC) dimensions are given as cross-sectional (width × height); Round Pipe (RP) dimension is given as cross-sectional diameter.

Site ID	Outfall Shape	Geometry (m)	Installation Date	Maintenance Dates
Site A	Box Culvert	3.1 × 2.1	5/29/2024	6/24/2024 7/02/2024 8/06/2024 9/13/2024
Site B	Round Pipe	1.0	5/29/2024	6/24/2024 7/02/2024 8/06/2024 9/13/2024
Site C	Box Culvert	2.1 × 2.0	5/29/2024	6/25/2024[1]
Site D	Box Culvert	8 × 5	5/29/2024	6/24/2024 8/06/2024 9/17/2024
Site E	Box Culvert	3.7 × 2.4	5/28/2024	6/25/2024 7/02/2024 8/05/2024 9/16/2024
Site F	Box Culvert	2.1 × 2.0	5/29/2024	6/25/2024 7/02/2024 8/05/2024 9/16/2024
Site G	Round Pipe	1.2	5/28/2024	6/25/2024 7/02/2024 8/05/2024 9/16/2024 9/17/2024
Site H	Round Pipe	0.9	5/28/2024	6/25/2024 8/05/2024 9/16/2024 9/17/2024
Site I	Round Pipe	1.7	5/29/2024	–[2]
Site J	Round Pipe	1.8	5/29/2024	–[2]

(1) Only one maintenance activity occurred because of human habitation nearby. (2) Sites I and J were vandalized and subsequently excluded from monitoring.

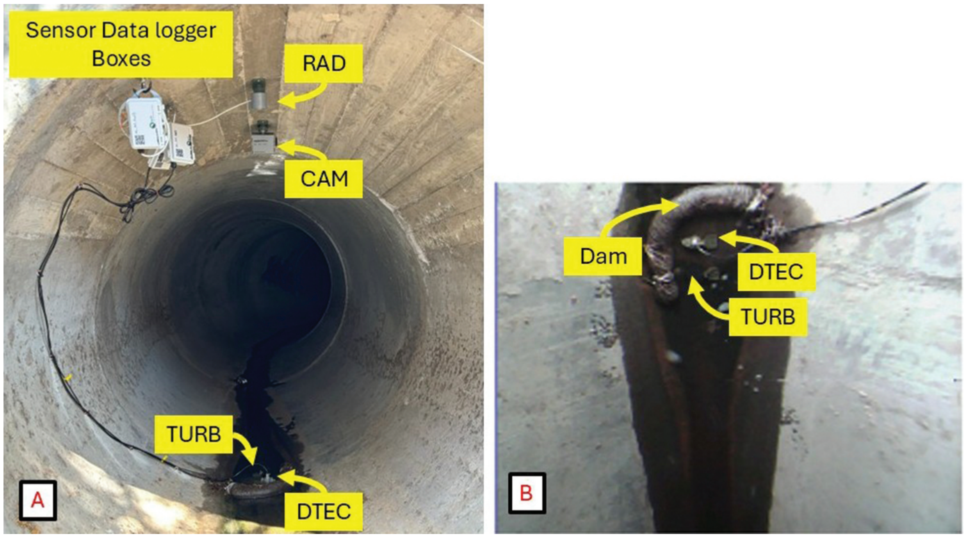


Figure 2. Typical sensor installation in a round pipe. A) view of installation from outfall. RAD, and CAM sensors were installed near the conduit crown; TURB and DTEC sensors were installed along the conduit invert. B) view of conduit invert from CAM. A low dam was constructed to promote continual submersion of TURB and DTEC sensors.

Automated algorithm to detect illicit discharges

Transient illicit discharges in the MS4 are hypothesized to be identifiable as sudden deviations from an established baseline. Some flow is almost always present in the north OC MS4 despite the extended dry season; however, the flow magnitude is inconsistent (Schiff, Beck, and Fassman-Beck 2021). To account for the inconsistent flow, 'deviation from a baseline' is determined by the difference of two exponentially weighted moving average (EWMA) models, as described in this section. The EWMA data analysis is automatically implemented thanks to web dashboard centralization of the distributed time series.

EWMA difference model

The EWMA model is a time-series analysis technique used to detect anomalies or deviations from baseline behavior in monitoring systems (Hunter 1986). It builds on the exponentially weighted moving average, which is a statistical method that applies exponentially decreasing weights to historical data, giving more importance to recent observations while still considering past data. The EWMA is commonly expressed as,

$$EWMA(t) = a * X(t) + (1 - a) * EWMA(t - 1) \quad (1)$$

where $X(t)$ is the time series variable at the current time step, $EWMA(t-1)$ is the model value at the previous time step, and α is the exponential weight applied to each time series value. The EWMA difference model extends this concept by comparing two EWMA series: a short-term EWMA and a long-term EWMA. The short-term EWMA captures recent trends and rapid changes in the data while the long-term EWMA represents the baseline or normal operating conditions over an extended period. Per Equation 1, the short-term EWMA has a larger α-value, as more of the current model value is related to the current (and recent) time series values.

In the automated EWMA difference model, an alarm is triggered if short-term (α) EWMA exceeds the long-term (β) EWMA by a predefined threshold (e.g. a percentage difference):

$$\text{Alarm Condition} : \text{EWMA\_}\alpha(\text{t}) > \text{EWMA\_}\beta(\text{t}) * (1 + \text{threshold}) \quad (2)$$

For the pilot investigation herein, the values for the automated EWMA difference model are included in Table 2. With data collected at 6-min intervals, model parameterization means 95% of a value's influence is gone by approximately 6-hr for the long-term EWMA (the 'baseline'), and around 1.5-hr for the short-term EWMA (the potential deviation).

Table 2. EWMA difference model parameterization.

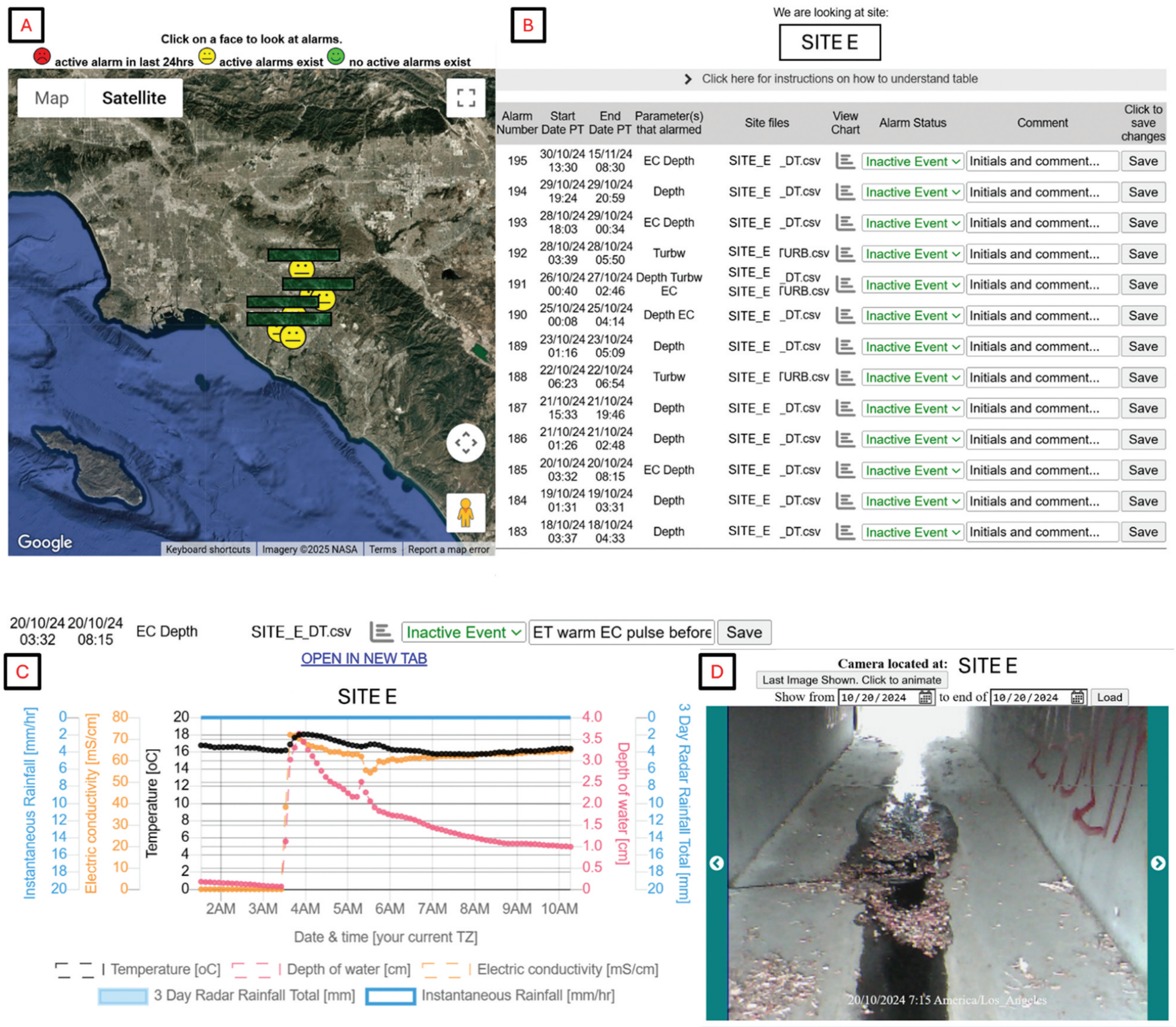
Short-term EWMA Coef (α)	Long-term EWMA Coef (β)	Difference Threshold (%)
0.2	0.05	50

The EWMA difference model was chosen for this project due to its numerous advantages, making it particularly well suited for illicit discharge detection in stormwater systems. One key strength is the model's use of a short-term EWMA, which ensures high sensitivity to recent changes in sensor data, enabling the detection of abrupt illicit discharges or anomalies (Roberts 1959). At the same time, the long-term EWMA establishes a robust baseline that accounts for normal variation in the system, such as seasonal or diurnal patterns, thereby reducing the likelihood of false alarm caused by natural fluctuations (Hunter 1986). Another advantage is the EWMA difference model's adaptability; its moving average factors and threshold values can be tuned to accommodate specific site conditions and sensor characteristics, offering flexibility across diverse monitoring scenarios (Lucas and Saccucci 1990). Furthermore, the exponential smoothing inherent in the EWMA process reduces the impact of noise and outliers in the sensor data, enhancing the reliability of the detection algorithm (Box, Jenkins, and Reinsel 2015).

Confirm system performance with discharge alarm follow ups

The primary monitoring period for this study was June 1–October 1, 2024, corresponding with the dry-season in southern California, and the otherwise regularly scheduled illicit discharge detection manual sampling program outlined in the MS4 permit. During this period, the automated alarm system was active, and each potential discharge alarm was reviewed remotely using a visualization dashboard (shown in Figure 3). Although no field follow-ups occurred during this project phase, the dashboard enables the user to examine each alarm for possible benign explanations, such as re-wetting of a previously dry sensor, that might indicate a 'false' alarm. The dashboard also organizes photo evidence and sensor activity trends that enable easy assessment as to whether the alarm could be reasonably disregarded.

Subsequent to the primary monitoring period, an 'All-Hands Week' was conducted during the week of October 9–16, 2024, where field investigation teams conducted in-person follow-up investigations on active discharge alarms. Permittees within various North OC cities and the County were engaged to follow up on discharge



We are looking at site:

SITE E

Click here for instructions on how to understand table

Alarm Number	Start Date PT	End Date PT	Parameter(s) that alarmed	Site files	View Chart	Alarm Status	Comment	Click to save changes
195	30/10/24 13:30	15/11/24 08:30	EC Depth	SITE_E _DT.csv		Inactive Event	Initials and comment...	Save
194	29/10/24 19:24	29/10/24 20:59	Depth	SITE_E _DT.csv		Inactive Event	Initials and comment...	Save
193	28/10/24 18:03	29/10/24 00:34	EC Depth	SITE_E _DT.csv		Inactive Event	Initials and comment...	Save
192	28/10/24 03:39	28/10/24 05:50	Turbw	SITE_E TURB.csv		Inactive Event	Initials and comment...	Save
191	26/10/24 00:40	27/10/24 02:46	Depth Turbw EC	SITE_E _DT.csv SITE_E TURB.csv		Inactive Event	Initials and comment...	Save
190	25/10/24 00:08	25/10/24 04:14	Depth EC	SITE_E _DT.csv		Inactive Event	Initials and comment...	Save
189	23/10/24 01:16	23/10/24 05:09	Depth	SITE_E _DT.csv		Inactive Event	Initials and comment...	Save
188	22/10/24 06:23	22/10/24 06:54	Turbw	SITE_E TURB.csv		Inactive Event	Initials and comment...	Save
187	21/10/24 15:33	21/10/24 19:46	Depth	SITE_E _DT.csv		Inactive Event	Initials and comment...	Save
186	21/10/24 01:26	21/10/24 02:48	Depth	SITE_E _DT.csv		Inactive Event	Initials and comment...	Save
185	20/10/24 03:32	20/10/24 08:15	EC Depth	SITE_E _DT.csv		Inactive Event	Initials and comment...	Save
184	19/10/24 01:31	19/10/24 03:31	Depth	SITE_E _DT.csv		Inactive Event	Initials and comment...	Save
183	18/10/24 03:37	18/10/24 04:33	Depth	SITE_E _DT.csv		Inactive Event	Initials and comment...	Save

20/10/24 03:32	20/10/24 08:15	EC Depth	SITE_E_DT.csv		Inactive Event	ET warm EC pulse before	Save

Figure 3. Screenshots of visualization dashboard. A) Google earth map of project locations (site names redacted) with current alarm status; B) itemized list of alarms by date, duration, parameter. Alarm status and comments allow managers to track follow up investigations. Data from the alarm are quickly viewable in 'view Chart'; C) result of clicking the plot icon in the 'view chart' column, data fields from the alarming sensor are shown; D) slideshow of photos from CAM during this event.

alarms, and in several instances they created intentional discharges of their own (e.g. ~10–15 L of saline water was introduced upstream of the sensor to provoke EC).

The purposes of the on-site follow up investigations during the All-Hands Week were twofold: 1) provide compelling evidence that the automated alarm system is effective in providing notifications to investigate potential illicit discharges in real-time, and 2) test automated system reliability through intentional discharges.

Results

The success of the automated transient discharge detection system pilot tested herein is contingent upon: *i)* the ability of the sensors to survive the monitoring period, *ii)* ability of the sensors to detect evidence of illicit discharges, and *iii)* the speed at which a positive detection can be translated into an alarm notification for onsite follow-up investigations to validate occurrence and/or track the source.

Feasibility of distributed continuous monitoring

Sensor maintenance requirements are key decision-making criteria for an automated program. The incentive to disrupt the status quo and exert the effort needed to change the illicit discharge monitoring to meet permit conditions is not viable if it takes as much or more effort to maintain sensors and communications as it does to operate a manual monitoring program, regardless of the success rate.

Site safety

In May 2024, ten MS4 sites in north OC were each instrumented with four BoSL sensors, per Table 1. Sites I & J were vandalized within a day of installation and abandoned for the duration of the pilot test. Several other sites also had varying degrees of instrument interference. At Site B, several of the sensors were destroyed on 4 June 2024, but replacements were unharmed. At Site E, the CAM lens was spray-painted on 9 October 2024. In some instances (e.g. Site F), cages were deployed to protect the RAD and CAM sensors (shown in Figure 4).

Sensor security was not the only concern; field crew safety was paramount. Sites that showed active signs of human habitation (e.g. tents, personal belongings, etc.) were excluded from maintenance activities during that visit. In these cases, maintenance was either rescheduled or skipped to avoid direct encounters.

Maintenance burden

The feasibility of using remote sensors for automated detection of illicit discharges is closely related to the sensor maintenance burden. In-line sensors that are continually submerged require more physical maintenance to ensure data quality. Sensor fouling occurs from algal growth and debris accumulation; the most common issues were observed in sunny locations, where algal growth was severe (Figure 5(A)). The in-line sensors were cleaned during each monthly maintenance visit (Figure 5(B)). The frequency of sensor calibration checks deployed in this study was adopted to determine if sensor drift, fouling, or other site conditions induced cause for concern. Conversely, the non-contact (out-of-water placement) of the RAD avoided these maintenance requirements.

Each monthly maintenance visit during the pilot program also included depth calibration to assess drift from the DTEC sensor. Table 3 contains information about the magnitude of depth sensor drift at each site for the 2024 dry-weather monitoring season, inferred from regression outcomes. The slope of the regression varied only 0.95–1.14; all sensors maintained their out-of-the-box calibration (on 5/23/2024 prior to installation) to within 14% and a goodness-of-fit (R^2) in excess of 0.98. Sensor drift was therefore determined not to be a critical issue for the intended application of alarm notifications. Sites C, I & J were not calibrated due to human habitation disrupting maintenance activities.

Discharges detected

The automated alarm system was fully online for the dry season pilot program between June 1 and October 1, 2024. Based on the previous experience of the dry season manual monitoring program, no transient discharges were expected (Schiff, Beck, and Fassman-Beck 2021). Contrary to this expectation, multiple alarms were received from each site. Figure 6 shows an example alarm from the TURB sensor at Site E, coupled with visual evidence of discharge from the CAM.

The turbidity data shows a spike, causing the short- and long-term EWMA models to divorce, triggering an alarm. The continuous discharge trickle is seen in the CAM photos to increase in width before returning to the

Figure 4. Cages were deployed at some sites to deter vandalism/theft of RAD and CAM sensors.

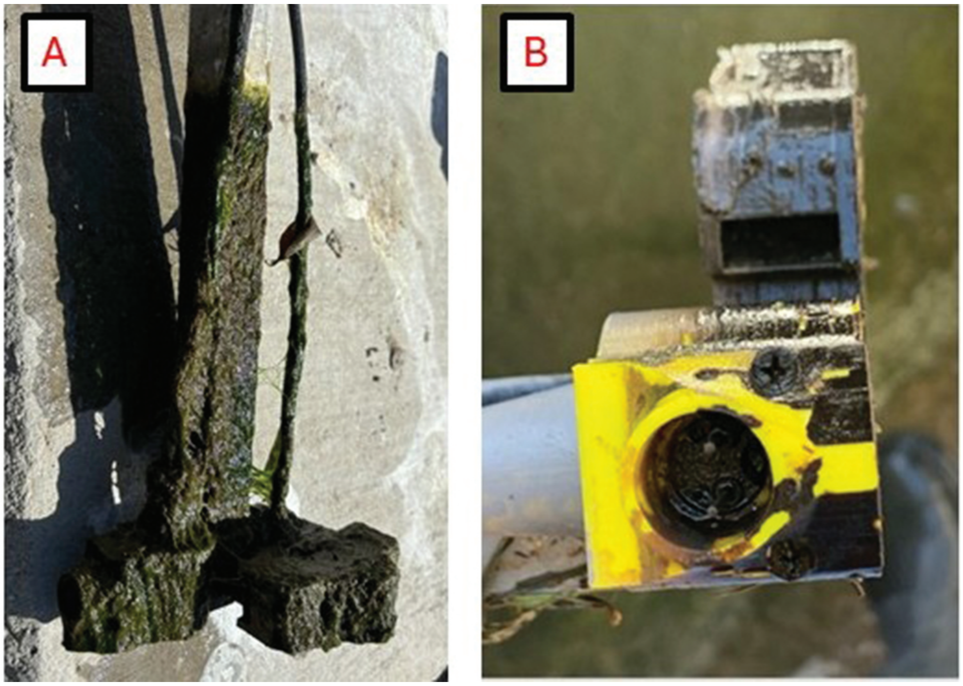


Figure 5. In-water sensor fouling A) before, and B) after regular maintenance.

Table 3. Calibration results from DTEC sensor drift exercise on maintenance days.

Site Name	Site A		Site B		Site D		Site E		Site F		Site G		Site H	
Maintenance Dates	Slope	R^2	Slope	R^2	Slope	R^2	Slope	R^2	Slope	R^2	Slope	R^2	Slope	R^2
5/23/2024	–	–	1.03	1.00	–	–	1.04	1.00	1.03	1.00	–	–	–	–
7/2/2024	1.11	1.00	1.10	1.00	0.97	0.99	1.01	1.00	1.12	0.99	1.14	1.00	1.05	0.98
8/5/2024	1.05	0.99	1.05	0.99	1.06	0.99	1.05	0.99	1.04	0.99	1.10	0.99	1.05	0.99
9/13/2024	0.95	0.99	1.16	0.99	1.11	1.00	1.06	0.99	1.07	0.99	1.07	0.99	1.11	1.00

trickling flow condition a few hours later. The turbidity alarm was triggered at 13:20 on 27 August 2024. Notably, this event raised neither a depth nor velocity alarm, despite clear increases in flow.

Table 4 contains a summary of the automated alarms during the primary monitoring period broken out by site and the monitored water quality variable. The take-away from Table 4 is that there were many more alarms during the primary monitoring period than were anticipated; 846 alarms were activated during the four months of monitoring between June 1 and October 1, 2024. The total number of alarms per site may be less than the sum of the individual water quality alarms because the automated system combines coincident alarms (e.g. a single 'alarm' may exist for Depth and Turbidity at the same time). False alarms were not considered part of the alarm total for each site.

To improve our confidence in the reliability of the automated alarms, each alarm was retrospectively analyzed to determine if there were conditions that erroneously produced a 'false' alarm, such as the sensor being out-of-water, undergoing maintenance, and signal connectivity issues. Photos from the CAM sensors were heavily referenced in the retrospective analysis. Per Table 4, Site C was the most reliable site (i.e. had the fewest alarms where some disqualifying factor was identified) at only 3% false alarms, while Site H had the highest rating of false alarms at 37%. Overall, 78% of automated alarms indicated a 'true alarm', i.e. evidence of a discharge event.

There were five primary causes of false alarms across all study sites:

- Faulty velocity readings
- In-water sensors are not submerged
- Excessive noise
- Sensor connectivity issues
- Sensor maintenance activities

The relative rates of each false alarm cause are shown in Figure 7; examples of each false alarm cause can be found in the Supplemental Information (Figures S3–S7). The leading cause, accounting for 46% of all false alarms, was alarms triggered by faulty velocity readings

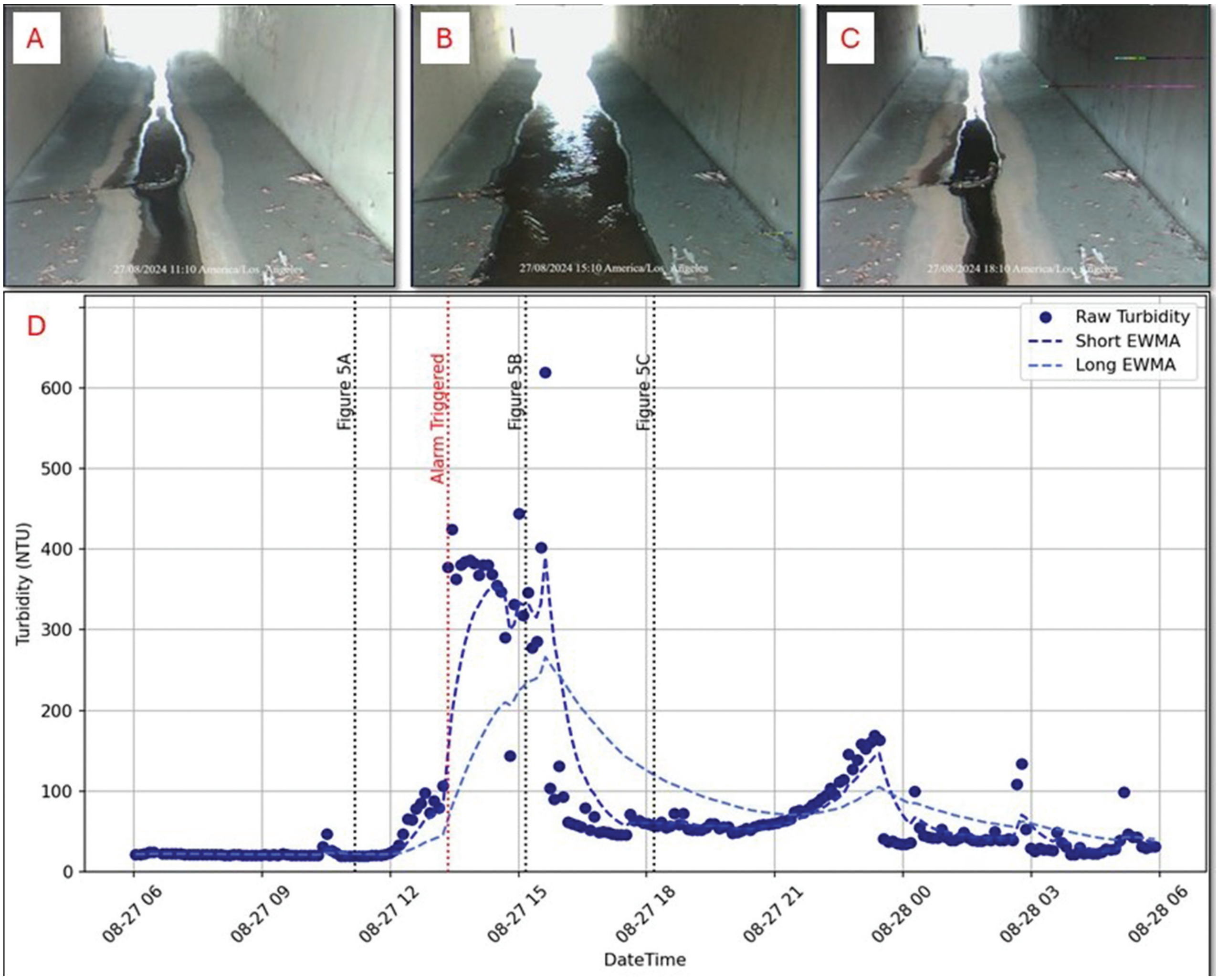


Figure 6. Detected discharge event at Site E in August 2024. A) CAM photo taken at 11:10 prior to main discharge pulse; B) CAM photo taken at 15:10 during the discharge; C) CAM photo taken at 18:10 after discharge has subsided; D) TURB data showing short- and long-term EWMA models with timing of CAM photos annotated.

Table 4. Summary of alarms by site, variable. Date range: June 1–Oct 1, 2024.

Site Name	Depth (DTEC)	DEPTH (RAD)	Temp (DTEC)	EC (DTEC)	Turbidity (TURB)	Velocity (RAD)	Total Alarms per Site*	False Alarms per Site (% of Total)
Site A	75	27	16	8	0	0	73	25 (34%)
Site B	6	0	1	61	0	0	41	2 (5%)
Site C	25	0	0	1	10	0	31	1 (3%)
Site D	6	1	1	2	0	5	12	4 (33%)
Site E	152	2	0	59	51	10	160	8 (5%)
Site F	34	0	0	25	41	46	112	22 (20%)
Site G	44	0	0	33	15	73	96	29 (30%)
Site H	76	0	0	70	71	89	155	58 (37%)

*The total number of alarms per site may be less than the sum of the individual water quality alarms because the automated system combines coincident alarms (e.g. a single "alarm" may exist for Depth and Turbidity at the same time).

from RAD sensors, which detected sudden changes in velocity without corresponding fluctuations in water level. This was followed by 30% of alarms triggered when the sensor was not actually submerged, indicated by significant changes in temperature or turbidity while EC remained at 0 and water level stayed constant.

Automated system performance to undisclosed discharges

During the All-Hands Week of October 9–16, 2024, permittees within the North OC region sent investigation teams to follow up on selected discharge alarms.

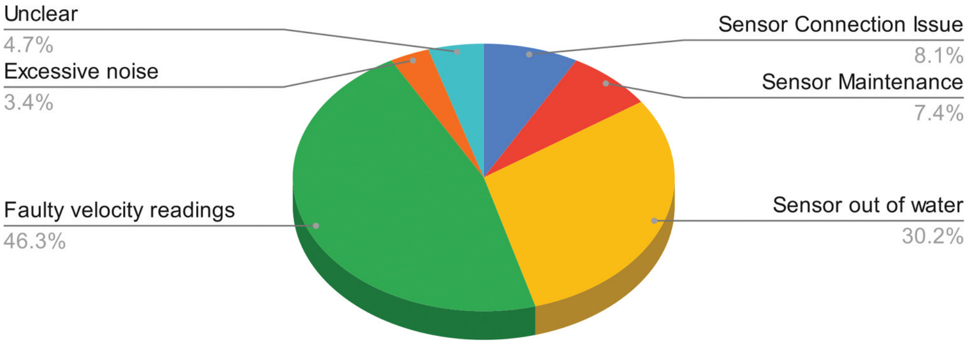


Figure 7. Breakdown of issue type that caused ‘false alarm’ designation.

Table 5. Summary of alarm investigations with manual follow-up during the all-Hands Week. For the status column, ‘C’ indicates a confirmed discharge alarm, ‘U’ indicates an unconfirmed alarm, and ‘F’ indicates a false alarm.

Site ID (Alarm ID)	DateTime (US Pacific)	Parameter Triggering Alarm	Status	Response Time	Notes
Site F	10/15/24 13:47	EC	C	30 min	Manual reading by investigation team of EC = 3600 mS/cm in discharge is considered very high.Discharge source not identified.
Site C	10/16/24 5:02	TURB	C	~3 hours	Discharge source found upstream (photo evidence in Figure 7). Also saw prolonged increased depth, but not deep enough to trigger depth alarm.
Site A	10/16/24 12:55	DEPTH	C	~8 hours	Discharge source identified.Landscaper working on broken irrigation heads.
Site G	10/16/24 13:14	TURB	U	45 min	Investigation team did not find evidence of discharge.
Site C	10/11/24 10:10	TURB	U	30 min	Investigation team did not find evidence of discharge.
Site B	10/10/24 12:31	EC	C	60 min	Intentional “spill” - approx. 15 L of saline water [unspecified concentration]
Site C	10/09/24 14:23	DEPTH	F	N/A	False alarm caused by sensor maintenance activity.
Site G	10/09/24 8:07	EC	C	30 min	Intentional “spill” – approx. 10 L of 53,840 uS/cm solution
Site F	10/09/24 10:09	EC	C	N/A*	Intentional “spill” – approx. 10 L of 54,040 uS/cm solution

*The occurrence was confirmed by camera images rather than an on-site visit.

The objectives for this phase of the project were to ensure that the automated alarm system practically enabled the investigation team to arrive on site and investigate the discharge (potentially locating a source) in a timely manner. Several instances occurred where an alarm was intentionally triggered by a bolus of saline water, without the knowledge of those responsible for checking the dashboard, to ensure that the automated alarms did not miss known discharges.

Table 5 summarizes the results of nine alarms that were followed up during the All-Hands Week. Six alarms were confirmed with visual inspections by the investigation team, two alarms were unconfirmed, and one was deemed to be a false alarm. The false alarm was caused by a maintenance visit, reinforcing the need for active communication amongst all participants. The Response Time is an estimate of the duration between when the alarm email is sent and the investigation team arrives on site, and was mostly a function of the time of day of the alarm. Figure 8 shows photo evidence (obtained by the investigation team) of the discharge at Site C.

Discussion

The objective of this study was to develop an automated system for detecting transient illicit discharges in an urban MS4 network characterized by an extended dry season. The results from this pilot program deployment demonstrate that low-cost, IoT-enabled sensors, combined with the EWMA difference detection algorithm, can identify discharge events that traditional dry-weather manual monitoring programs would likely miss. The purpose of pilot program was to explore whether greater discharge awareness and tracking

Figure 8. Evidence of a discharge during the all-Hands Week follow-up visit at Site C for alarm on October 16, 2024. The elevated discharge at the monitoring station (left) was traced to an outfall upstream (right). Photos used with permission from Craig Foster, City of Santa Ana.

could be achieved with contemporary sensing and communication technologies.

Assessment of continuous, distributed monitoring feasibility

BoSL sensors were deployed continuously to the MS4s in North OC during the dry season from June – October 2024, with monthly maintenance visits to inspect, clean, change batteries, and calibrate the sensor equipment. During this time, most sensors remained operational and submerged, with drift from factory calibration (within ±14%) deemed acceptable for the intended application of anomaly detection. Future calibration checks may be reduced to bi-monthly assessments, unless data anomalies are detected from the dashboard. Cleaning of in-water sensors with significant sunlight exposure does likely require monthly visits to remove algal growth.

Vandalism and interference did occur – two sites had to be abandoned due to equipment destruction, and others experienced CAM sensor tampering or in-line sensor debris accumulation. Notwithstanding these challenges, the sensors were able to remain in place and reliably report data across the four-month period.

The automated daily Sensor Health Report enabled the team to remotely monitor operational conditions, limiting periods of missed data and facilitating maintenance planning. The successful endurance of the majority of the network under real-MS4 conditions is a strong indicator that such a system is logistically feasible for dry-season IDDE monitoring.

Assessment of automated alarm performance

The automated system generated nearly 850 alarms across the monitored sites during the 2024 dry season, which far exceeded the number of transient discharges historically identified through the existing dry-weather monitoring program. Over three-quarters (78%) of these alarms were ultimately classified as likely indicative of a real transient discharge event. This finding suggests that intermittent/transient illicit discharges may be more common than previously recognized. Importantly, these alarms were not concentrated to a single site or water quality variable, but occurred at every site in the monitored network. This underscores how continuous, distributed monitoring for illicit discharge detection can be more informative than manual monitoring.

Variation in the number of alarms per site was expected. For example, the higher frequency of alarms at Site E may be due to its proximity to commercial and light industrial properties, but this hypothesis was not investigated within the scope of the current investigation. Furthermore, the monitoring sites are anonymized to avoid assigning additional burden to the individual Permittees within the shared MS4 system that participated in the study.

The five water quality variables tracked (depth, velocity, EC, turbidity, and temperature) also exhibited variability from which we can learn important lessons for the next monitoring campaign. Notably, temperature was a poor indicator of discharge, probably due to the limited sun exposure and thermal buffering of concrete channels. However, EC and turbidity were consistent indicators of transient discharge, unless the sensors were out-of-water. Curiously, the depth alarms were not consistent between the DTEC and RAD sensors. The expected reason is that the in-line DTEC sensor was much more sensitive to small changes in depth, so the constant EWMA parameters for this investigation were more likely to see a DTEC change as indicative of an alarm.

The value of combining data streams from different sensors was apparent during several events; multiple lines of evidence improve confidence in the 'truth' of the alarm. For example, after the high frequency of velocity false alarms was observed, the alarm code was adjusted to only produce a velocity alarm notification if velocity *plus one other variable* reached the alarm condition. Additionally, our custom visualization dashboard (including real-time data and photos from the CAM sensors) proved invaluable for assessing the reliability and interpreting alarms; managers could review alarm data quickly without needing to visit the site (Figure 3). An initial investigation to automate image analysis to augment alarm detection and evaluation has yielded promising results (Catsamas et al. 2025).

To further improve the reliability of the automated alarm system and reduce the occurrence of false positives, two key refinements can be implemented in future work. First, limiting velocity-based alarms to instances where abnormal velocity readings coincide with irregular depth measurements can effectively filter faulty alarms caused by RAD sensor anomalies. This approach ensures that velocity changes are only flagged when supported by corresponding hydraulic evidence. Second, to address false alarms from water quality sensors – particularly temperature and turbidity – alarms should only be triggered when both EC and depth readings confirm the sensor is fully submerged. These modifications offer a straightforward yet powerful strategy to correct 30% of the faulty alarms identified in this study.

Assessment of system performance to undisclosed discharges

Results from the All-Hands Week provide strong support for the practical utility of the automated discharge detection system. Four out of the six discharge alarms were visually confirmed in the field by an investigative team that was able to arrive on-site before the discharge event concluded. One of these events (an intentional salt-water discharge), designed to test the responsiveness of the alarm system, was successfully detected. The remaining confirmed events included discharges due to irrigation runoff or construction activity – which may or may not constitute illicit discharges under the current NPDES permit. However, these results suggest that the automated alarm system is capable of providing actionable information to stormwater managers within a reasonable timeframe that allows for manual investigation and source tracing.

Limitations/Challenges

Automating detection of transient illicit discharges in the current investigation benefits from an established dry season. That is, there is little likelihood of confounding wet-weather conditions during the 5-month period, thus somewhat simplifying the data analysis. Wet weather monitoring for transient illicit discharges is not specifically required in the existing MS4 permit for North Orange County. A complementary study by Shi et al. (2022) using the same sensor suite used rain gauge data and real-time rainfall radar images to split the dataset into dry and wet weather periods. Similarly to the current study, only dry weather illicit discharge alarms were investigated.

Vandalism and theft of expensive capital equipment present significant challenges to urban monitoring studies (Office of Construction Safety 2021). Southern California's well-documented housing issues exacerbate this concern; individuals seeking refuge in the MS4 commonly take umbrage with cameras and questions (Sahagún 2015). Municipal agencies face limitations on funding, and monitoring equipment/instruments are investments expected to last decades. These instruments are used across several monitoring programs to comply with regulatory requirements. A key innovation of the BoSL sensors used herein is the reduced cost compared to similarly enabled instruments (i.e. multi-parameter, IoT, battery-powered) from commercial vendors. If the sensors are cheap, the agency may have a greater tolerance for vandalized and/or stolen equipment, greatly increasing the number of viable monitoring sites in the MS4 network. However, even with greater tolerance for replacing removed/destroyed equipment, field reconnaissance to assess the safety of MS4 outfalls is critical at the outset of any IDDE program.

Ensuring that the in-line sensors remained submerged throughout the deployment is a relevant practical challenge. Small dams were used to create little reservoirs for the in-line sensors (seen in Figure 2(B)); however, the in-line sensors drying out did create a handful of false alarms (Figure 7). Dams were created out of simple materials including sandbags or angle brackets; hydrograph analysis is not required in the current application.

A key limitation to the potential response time from the alarms is the fact that they can occur at any time of day, while the investigative teams typically keep business hours. Additionally, municipal agencies have limited resources to follow up on alarms. Alarm sensitivity and follow-up plans should be adjusted on a site-by-site basis to ensure that egregious events that are more easily sourced are prioritized. For example, the duration of a condition that deviates from the baseline may serve as a useful secondary condition for warranting manual source investigation.

The current iteration of the BoSL sensors run on a 4 V battery that lasts approximately 4–6 weeks, depending on the cellular connectivity at the site. The technology around IoT sensors is rapidly evolving. The collaboration herein between the local researchers and the BoSL team resulted in timely updates to the software and hardware to address the specific needs of this project. Ultimately, what constitutes ‘good enough’ sensors needs to be decided upon for continuous deployment.

There is potential to prioritize alarms for manual follow-up or to minimize false alarms by cross-corroboration amongst multiple parameters. A future study is warranted to investigate optimizing the number and type of hydrologic and water quality variables that should be concurrently monitored. Such an outcome might also reduce potential program costs by reducing the number of sensors operated at each monitoring location.

After identifying the likely existence of an illicit discharge, the remaining challenge of the IDDE program is to trace the discharge to its source and prevent the illicit discharge from recurring (Brown, Caraco, and Pitt 2004; Victorian Stormwater Committee 1999). Several techniques have been developed for source-tracing discharges, such as tracer tests (Pitt et al. 2000) and temperature sensing with infrared cameras (Lepot, Makris, and Clemens 2017). While following up on illicit discharges is critical to the end success of IDDE programs, this aspect of the regulatory process (illicit discharge elimination) is outside the scope of the current study. The monitored variables (e.g. turbidity) are mere indicators of real contaminants of concern. Rather, the focus of this investigative phase was timely detections of transient illicit discharges; the detection system cannot, at this time, identify the illicit discharge source or water quality pollutant of concern. The endpoint of the detection system is an automated notification to the investigation team, enabling manual follow-up in a timely manner.

Conclusions

The investigation herein successfully demonstrates that automated detection of transient illicit discharges is not only feasible but operationally practical in real-world conditions. While traditional, manual dry-weather monitoring programs are necessary for compliance under many current MS4 permits, this study shows that complementary automated approaches can dramatically enhance detection resolution and responsiveness. By enabling near real-time alerts and reducing reliance on periodic manual sampling, this system offers municipalities a scalable and cost-effective path toward improving water quality protections. Key elements of the program include the use of low-cost, IoT sensors, reliable data transmission, a simple algorithm for near-real-time, continuous data analysis, and an interactive dashboard. The Sensor Health Report daily email enabled crews to track sensor maintenance condition remotely, limiting potential for missing data. Minimal maintenance of sensors was required for anomaly detection, with the exception of in-line sensors in direct sunlight which suffered from algal growth. The results underscore the value of distributed sensing infrastructure as a foundation for modernized stormwater monitoring programs, and they point toward a future in which smarter networks support more proactive, informed, and adaptive stormwater management.

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CRediT: **Edward Tiernan:** Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing; **Jerod Gray:** Data curation, Investigation, Methodology, Validation, Visualization; **Duy Nguyen:** Data curation, Methodology, Software, Validation; **Baiqian Shi:** Formal analysis, Methodology, Visualization, Writing – original draft; **Miao Wang:** Formal analysis, Methodology; **Kevin Dunn:** Investigation, Project administration, Writing – review & editing; **Jian Peng:** Conceptualization, Funding acquisition, Project administration, Resources, Writing – review & editing; **David McCarthy:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Software, Supervision, Validation, Writing – review & editing; **Elizabeth Fassman-Beck:** Conceptualization, Funding acquisition, Methodology, Project administration, Resources, Writing – original draft.

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Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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