`www.SewageMap.co.uk` and `POOPy`: Open-source tools for understanding and communicating the environmental impacts of combined sewer overflows in real-time

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Abstract

Combined Sewer Overflow (CSO) discharges occur when combined sewer systems exceed capacity leading to the discharge of untreated sewage and storm-water into rivers and seas. These events introduce pollutants such as microplastics, pharmaceuticals, and faecal matter into the environment, negatively impacting water-quality & ecosystems, as well as posing a risk to public health. In England, UK, rising public concern about CSOs has driven large infrastructure efforts and led to legislation requiring water companies to enhance monitoring through what is called Event Duration Monitoring (EDM). EDM tracks whether a CSO is discharging and for how long. Since 2020, EDM summary statistics have been published and widely discussed in the public domain. More recently, real-time EDM data has been provided by water and sewerage companies and visualised on maps by these companies and some non-governmental organizations. However, challenges remain: inconsistencies in EDM data sources create barriers for analysing these new public datasets. Moreover, current visualisations don't clearly link CSOs to their environmental impacts. These challenges are compounded by low overall public-trust in water companies. To address this, we developed the open-source `python` toolkit `POOPy` (**P**ollution Discharge Monitoring in **O**bject **O**riented **Py**thon) and the data-visualisation website `www.SewageMap.co.uk`. `POOPy` provides a standardised interface to EDM datasets from diverse sources and provides functionalities to link CSO spills to impacted rivers. We use `POOPy` as part of the data processing pipeline which feeds into `www.SewageMap.co.uk`. This website shows the current status of thousands of EDMs across the country as well as identifying river stretches that are downstream of recently active CSOs. This website receives thousands of views per month and is regularly used by citizen-scientists, recreational water users and academic scientists. Around 80% of users access the application via mobile or tablet devices, emphasizing the need to prioritize mobile users when designing interfaces for environmental datasets. We argue that our workflow offers a scalable and transparent model for interpreting, processing and communicating live environmental data-streams to the public.

Synopsis

SewageMap.co.uk and POOPy: open-source tools for processing combined sewer overflow spill data and visualizing their environmental impact on rivers

Introduction

Combined sewer networks transport domestic, commercial and industrial waste alongside storm-water from snow-melt and rainfall to waste-water treatment facilities. When the capacity of these sewers is breached, for instance during heavy rainfall events, the excess is discharged into rivers or other waterbodies to prevent sewage backflow. Such Combined Sewer Overflow (CSO) events discharge a mix of treated & untreated wastewater and stormwater into the natural environment and are a source of diverse pollutants including microplastics,[1] pharmaceuticals[2,3] and faecal matter.[4] CSO events (also termed CSO 'spills') adversely impact water quality,[5] the functioning of natural ecosystems[6] and can pose a risk to human health.[7,8]

In the United Kingdom, pollution of rivers and coastal seas by CSOs is currently a topic of major public concern. The environmental impacts of CSOs onto waterways have prompted major infrastructure projects such as the *Thames Tideway Tunnel* to reduce spill frequency at 57 CSOs in London, UK.[9] Public outrage over the quantities of sewage pollution, both legal and illegal,[10] has also contributed to the passing of legislation[11] which places obligations onto Water and Sewerage Companies (WASCs) to reduce the frequency and durations of CSO spills, as well as monitor their impact on water-quality using high-frequency sensors.[12]

Part of this increased public attention is a consequence of the recent expansion in real-time monitoring to nearly all known CSOs in England in response to legislation. Event Duration Monitoring (EDM) determines if a CSO is in operation (i.e., discharging) or not and if so, for how long the discharge was ocurring. An EDM sensor works by measuring the water-level in a tank or sewer and triggering an alert if the level exceeds some threshold, for instance the level of the weir between a storm-tank and the environment. As a consequence, EDM sensors do not record any information on the volume of discharge or the concentration of any potential contaminant. Since 2020, annual summary statistics of CSO spill frequency and duration from EDM have been published by the UK Government,[13] and are widely reported in the media[14].[15] In addition to raising the public profile of CSOs as an environmental stressor, EDM data has also been used by academics to diagnose flaws in existing water infrastructure[16] and model likely micropollutant loads to the environment.[17] A recent study also identified that prior to the widespread deployment of EDM, the frequency of CSO spills was underestimated in widely used hydraulic models.[18] In addition to historical datasets, as of 2025, WASCs now provide live EDM data (i.e., that indicates whether a given CSO is spilling or not) to 3rd parties via application programming interfaces (APIs). These live datasets are also shared via maps generated by WASCs that visualise spatially which CSOs are currently active (e.g., `www.thameswater.co.uk/edm-map`). Despite these successes we have identified three challenges currently facing the widespread usage and interpretation of EDM data in England. Whilst we focus on England we argue our results have implications for the usage of EDM in other areas of the globe.

First, differing structures between EDM data sources provided by each WASC makes it challenging for potential end-users (e.g., academics, citizen-scientists, NGOs) to easily process data from multiple companies at once. This creates a barrier to entry limiting the usage of EDM data in the wider environmental science ecosystem, making it more challenging for the full environmental impact of CSOs, and their ultimate drivers, to be determined.

Second, most visualisations of EDM data fail to adequately communicate how a CSO spill may be impacting the environment, in particular rivers and seas. A topic of significant concern to the public is the risk to public health from entering rivers polluted by raw sewage. However, most existing EDM visualisation platforms simply identify the location of spilling CSOs as a point, and do not attempt to locate which water-bodies may be being impacted.

Whilst some attempts have been made for coastal waters (e.g., by Southern Water's *'Rivers and Seas Watch'* service[19]) there is currently no way for the public to easily identify links between a given river and CSO spills.

Finally, a lack of public trust in WASCs[20] means that there is significant demand for transparent, independent sources of EDM data analysis and visualization. For instance, Southern Water's EDM visualisation tool *'BeachBuoy'* (now replaced by *'Rivers and Seas Watch'* referred to above) used an algorithm to determine if a detected CSO event was 'genuine' or 'impacted' water quality, and the visualisation of the spill was adjusted accordingly. However, an independent expert review of this tool found that (emphasis added): '*the main issue identified was that in spite of demonstrable good practice* ***there was no joined up clarity and documentation of the end-to-end spill data flow*** *from overflow sensor detection through verification to the Environment Agency and Beachbuoy reporting. This, in the opinion of the reviewer, prevents Southern Water regaining the previously lost trust by members of the public.*'. Clearly, a more transparent data processing chain would have improved public trust in this situation.

Here, we describe how we created an open-source, transparent EDM processing toolkit ('**P**ollution Discharge Monitoring in **O**bject **O**riented **Py**thon – `POOPy`) and an online data visualisation site (`www.SewageMap.co.uk`) that resolves these challenges. `POOPy` encapsulates key concepts of EDM (e.g., monitors, discharges, water companies) into distinct `python` classes. Crucially, the data derived from each WASC is an instance of the same underlying class allowing each EDM data source to be treated and processed by the user in the same way, significantly lowering the barrier to entry. Having encapsulated key concepts of EDM in `POOPy`, we have added capabilities to process that data to determine which rivers are downstream of a spilling CSO and therefore are potentially polluted. This framework can easily be extended to implement other, more complex, ways of identifying environmental impacts from CSOs. Next, to visualise and communicate EDM data, and its impact on rivers, we generated an automatic data-processing and visualisation pipeline that identifies polluted rivers in real-time, displaying them on the website `www.SewageMap.co.uk`. This visualization receives thousands of views per month from the public. The website is used by academic researchers to communicate the connectivity of chemical pollution in river networks, citizen scientists who use it to identify reaches of rivers to sample, and members of the public who use it in their risk assessments for whether they, or a pet, ought to enter a waterway.

In this manuscript we describe in detail how these tools are constructed. Our explicit goal is to provide a blueprint for others, in industry, the academy or neither to build on. We seek to demonstrate that building open-source, transparent, software using publicly available data is a viable way to create complex and sophisticated visualizations of environmental datasets. Finally, we will discuss how our approach for identifying 'impacted' rivers compares to more sophisticated models of water-quality in rivers.

POOPy

`POOPy` is a `Python`[21] package for processing live and historical EDM data-streams. The source-code is freely available at `github.com/AlexLipp/POOPy` and is licensed under a GPL3.0 license. The code is unit-tested, fully documented and installation instructions are provided alongside examples of usage. The package depends on standard scientific `Python` packages (e.g., `pandas`, `numpy`[22,23]) and the `GDAL/OGR` geospatial programming library[24]

Structure

`POOPy` represents EDM data from different sources in a consistent format following the object oriented programming paradigm with three main classes: `Event`, `Monitor` and `WaterCompany`. The overall structure and relationship between classes is indicated in Figure 1 and detailed, briefly, below.

An `Event` represents a period of time in which a given event duration monitor has the same status. There are currently three concrete implementations of the `Event` abstract class:

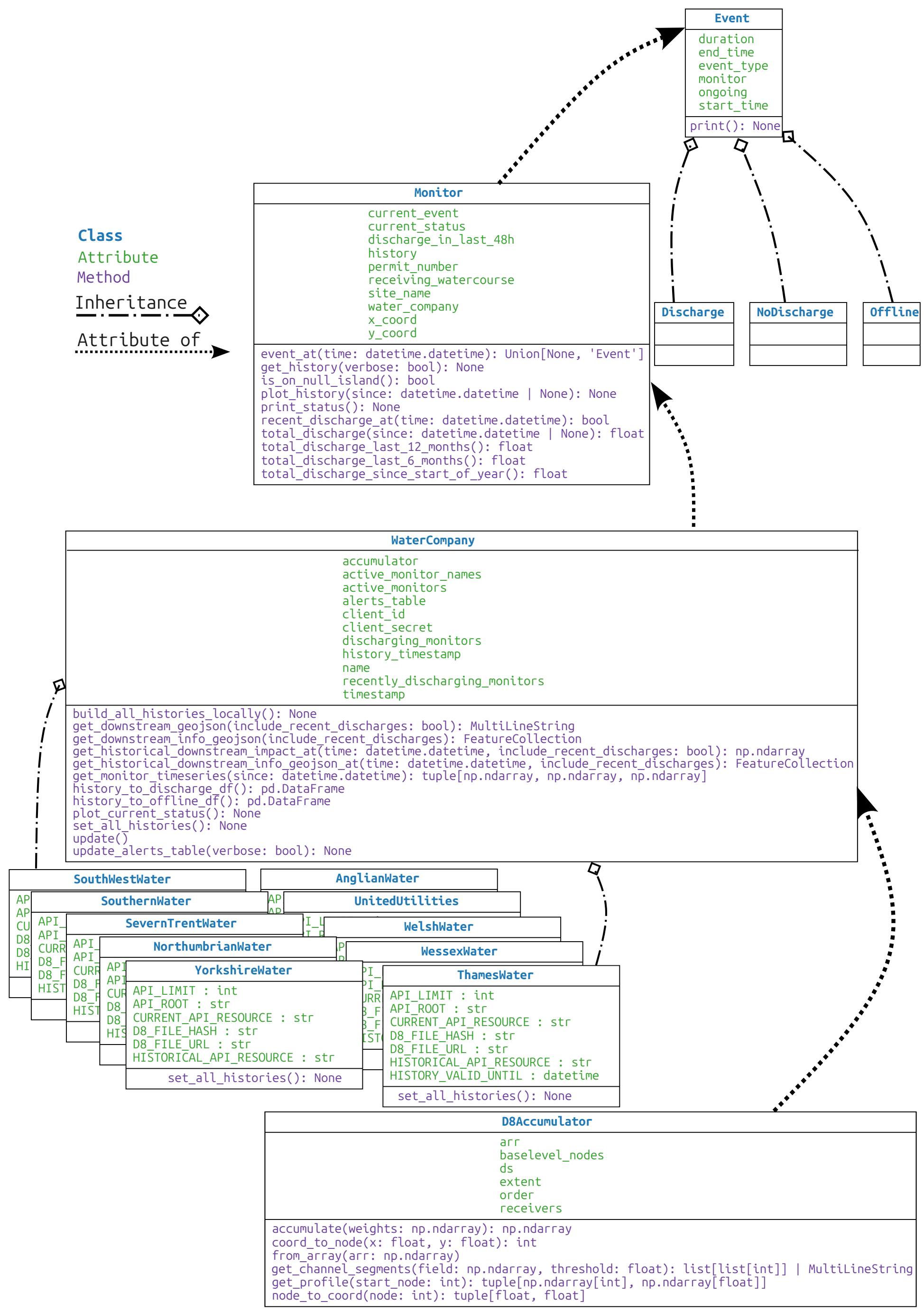

Figure 1: Simplified structure of the POOPy package indicating how different classes relate to eachother, and summarising their public attributes and methods.

Discharge, NoDischarge and Offline which correspond to the monitor recording a CSO spill, a period of no spill activity, or when it is offline (e.g., under maintenance) respectively. An Event stores key characteristics as attributes in the class such as start-time and end-time, from which it can calculate the duration. If an event is ongoing, the duration updates automatically in real-time. Each Event stores as an attribute the Monitor to which it is associated.

A Monitor, in turn, has as an Event attribute corresponding to the current status of the Monitor. It is in this Monitor class that metadata such as location, permit number, and the name of the receiving watercourse are stored as attributes. The WaterCompany attribute of a Monitor links that monitor to the WASC which maintains and operates the monitor. Where the past status of an EDM monitor is provided, the history of all statuses at a Monitor is stored in the history attribute which is a List of Event instances.

A WaterCompany class instance corresponds to a network of multiple EDM monitors maintained by an individual WASC. A WASC is represented by a concrete implementation of the base WaterCompany class (e.g., ThamesWater) that inherits generic attributes and methods from WaterCompany. The motivation behind creating subclasses for each WASC is that although different WASCs share EDM data using different conventions, the underlying concepts are the same. As a result, we can declare the shared concepts (i.e., multiple Monitor instances, which can have a status of either Discharge, NoDischarge or Offline) in the WaterCompany base class but have unique implementations in each WASC subclass.

Processing historical data

POOPy also allows the past status of a CSO to be queried and explored, where appropriate data is available. At the time of writing, only Thames Water provide an API to historical records of EDM data[25] and so currently only the ThamesWater class implements these features. Nonetheless, due to the generic and extensible nature of POOPy it can easily be extended to all other classes should future APIs be made available. As discussed previously, historical CSO statuses are stored in the `Monitor` instances of a `WaterCompany` as a list of `Event` instances. This history must be built from a list of alerts returned by the event duration monitor. Each EDM returns an alert when it changes status. For instance, when the level sensor exceeds the threshold, it will produce a 'Start' alert. When the level sensor drops below the threshold it returns a 'Stop' alert. The raw data from a given event duration monitor is therefore a sequence of 'Stop' and 'Start' alerts associated with timestamps. Equivalent alerts are also returned for when a monitor goes offline ('Offline Stop', 'Offline Start'). A typical alert stream for an event duration monitor is shown in Table 1.

Table 1: A schematic example of an alert stream for an event duration monitor. This stream would be stored in `POOPy` as a list of `Event` objects as follows: `[(N)oDischarge, (D)ischarge, N, Offline, N, D, N, D, N]`, with the start and endtime of the events determined from the Timestamps.

Alert	Timestamp
Stop	2023-12-04T15:15:00
Start	2023-12-04T10:30:00
Offline stop	2023-12-04T09:00:00
Offline start	2023-11-25T03:00:00
Stop	2023-11-20T20:45:00
Start	2023-11-20T18:45:00
Stop	2023-11-20T14:30:00
Start	2023-11-20T07:30:00

To build histories for a given `Monitor`, `POOPy` iterates through the list of alerts from the present day back in-time creating `Event` instances and appending them to the history list. For instance if a 'Stop' alert is found at time 'XXXX' followed by a 'Start' alert at time 'YYYY' a `Discharge` instance is created with these timestamps. If the 'Start' alert is followed by another 'Stop' alert at time 'ZZZZ' a `NoDischarge` is created and appended to the history array after the `Discharge`. At this point, certain quality control procedures take-place. We assume, for instance, that 'Start' alerts can only be followed chronologically by 'Stop' alerts. Currently if a series of alerts violates this rule they are skipped until valid sub-sequences are found, although more complicated procedures for dealing with these exceptions (for instance, creating an `Unknown` subclass of `Event`) could be considered.

Examples of use

Whilst full examples of usage are provided on the GitHub repository (`github.com/AlexLipp/POOPy`) as Jupyter Notebooks, a demonstration of capabilities is given below.

Exploring the current status of an EDM network

Let us consider an example where we want to explore the data for some water company, for instance, Southern Water.

```
from poopy.companies import SouthernWater
sw = SouthernWater()
```

This command queries the Southern Water EDM API[26] which details the current status of every EDM monitor in its network, and stores it in the object `sw`. We can now easily access and query this data, for instance, to determine how many current monitors there are in the sensor network:

```
WASC_name = sw.name
num_edm_monitors = len(sw.active_monitors)
print(f"Number of active EDM monitors mainted by {WASC_name}: {num_edm_monitors}")
```

which returns: `Number of active EDM monitors mainted by SouthernWater: 1014`. We can also easily access monitors that are currently recording a CSO discharge:

```
num_current_CSO_discharges = len(sw.discharging_monitors)
print(f"Number of current CSO discharges: {num_current_CSO_discharges}")
```

which returns (on 10/4/2025): `Number of current CSO discharges: 2`. Let us now inspect an individual monitor that is discharging:

```
discharging_cso = sw.discharging_monitors[0]
```

This is an instance of `Monitor` which as a command to print to terminal a summary of its attributes and current status:

```
discharging_cso.print_status()
```

returning:

```
--------------------------------------
Event Type: Discharging
Site Name: SRN0458
Permit Number: Unknown
OSGB Coordinates: (433728.51788530155, 128744.04611448379)
Receiving Watercourse: UN-NAMED TRIBUTARY OF THE RIVER TEST
Start Time: 2025-01-15 12:41:17
End Time: Ongoing
Duration: 122506.87 minutes
```

or these can be accessed directly, for instance:

```
x, y = discharging_cso.x_coord, discharging_cso.y_coord
print(f"Coordinates of {discharging_cso.site_name}: {x}, {y}")
```

giving:

```
Coordinates of SRN0458: 433728.51788530155, 128744.04611448379.
```

Each `Monitor` stores its current status as one of the three sub-classes of `Event`. In this case, as a CSO is active, the type of the current event is `Discharge`. We can now access useful data for this event directly, such as when the current `Event` started and its `Duration`. In this particular example, as the event is ongoing, the end-time attribute is `None`, and so the duration uses the current time-stamp to determine the event duration:

```
current = discharging_cso.current_event
print(f"Event start time: {current.start_time}")
print(f"Event end time: {current.end_time}")
print(f"Event duration: {current.duration:.0f} minutes")
```

returns:

```
Event start time: 2025-01-15 12:41:17
Event end time: None
Event duration: 122516 minutes.
```

Exploring the historical status of an EDM network

As only Thames Water currently provide an API to historical EDM data we will demonstrate the historical CSO capabilities of `POOPy` using the `ThamesWater` class. This class is instantiated in a similar way to the `SouthernWater` class above with the exception that the Thames Water API requires credentials to be provided to access historical data. These can be passed to the API during instantiation as follows:

```
from poopy.companies import ThamesWater
tw_client_id = "[client_id]"
tw_client_secret = "[client_secret]"
tw = ThamesWater(tw_client_id, tw_client_secret)
```

We now access and build the history of one particular monitor at 'Bourton-On-The-Water':

```
monitor = tw.active_monitors["Bourton-On-The-Water"]
monitor.get_history()
```

which populates the `history` attribute. Once the history attribute has been populated, helpful summary statistics indicating for how long a given CSO has been discharging over different timeframes can be calculated. In addition, a simple plotting function has been created to quickly summarise the history of records at a monitor:

```
last_12_months = monitor.total_discharge_last_12_months()
print(f"Total discharge in the last 12 months: {last_12_months:.2f} minutes")
since_2022 = monitor.total_discharge(since = datetime.datetime(2022, 1, 1))
```

```
print(f"Total discharge since 2022: {since_2022:.2f} minutes")
monitor.plot_history()
```

which returns:

```
Total discharge in the last 12 months: 82370.75 hrs
Total discharge since 2022: 264795.00 hrs
```

and the plot shown in Figure 2.

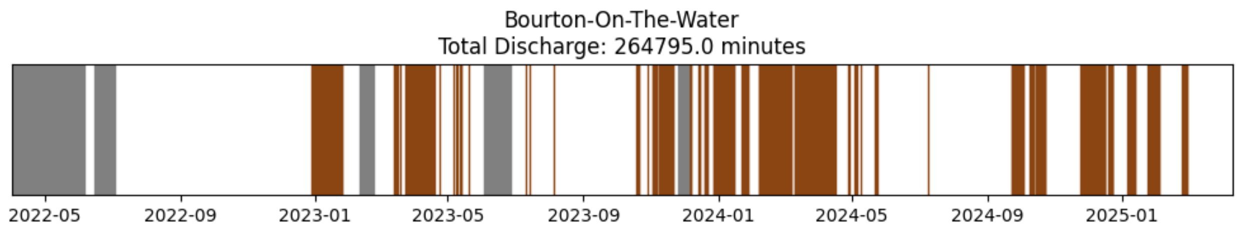

Figure 2: A 'barcode' plot of the historical EDM data from the 'Bourton-On-The-Water' monitor maintained by Thames Water. Brown bars indicate CSO discharges, grey bars indicate periods where the monitor is offline and white bars are periods where the CSO is not discharging. Figures like these can easily be generated in `POOPy` using the `plot_history()` method of the `Monitor` class.

It is possible to access directly the individual historical events using standard `python` indexing. Each entry in the `history` attribute is an `Event` object:

```
fifth_event =  monitor.history[4]
fifth_event.print()
```

which returns:

```
Event Type: Not Discharging
Site Name: Bourton-On-The-Water
Permit Number: CTCR.2036
OSGB Coordinates: (417620, 219070)
Receiving Watercourse: Groundwater
Start Time: 2025-02-26 23:30:00
```

```
End Time: 2025-02-27 19:15:00
Duration: 1185.0 minutes
```

Identifying rivers downstream of CSO spills using EDM data

Abstracting EDM data into `POOPy` objects provides a simple interface to, for instance, feed information on CSO spills, live, into environmental models. As a very simple demonstration of this we describe how we have implemented a simple method into `POOPy` for identifying which rivers are downstream of active CSO spills.

Our method relies on the `D8` flow-routing algorithm[27] to direct flows of water (and contaminants) through a drainage network. The `D8` algorithm assumes, for a raster representation of an area, that each pixel 'donates' flow (of water, sediment, etc.) to up-to one of the eight neighbouring pixels, or itself (where it is a 'sink'). Each pixel in the raster is therefore assigned one of nine values to indicate which (if any) of the neighbouring pixels 'receives' its flow. Typically, these flow-directions are calculated from digital elevation models by determining which neighbouring pixel (if any) is topographically lowest, and it is assumed that water flows into that lowest pixel. This approach is accurate on areas of converging flow but its simple nature results in inaccuracies in areas of flat topography (i.e., lakes, floodplains) or divergent flow (i.e., braided river channels, human modified rivers). Nonetheless the simplicity of the approach means it is computationally efficient for even large raster images. Specifically, for any given location within the raster domain it is possible to 'trace' the area downstream by simply iteratively following the `D8` flow-directions until a sink pixel is reached.

In this particular case, we use `D8` rasters calculated from the SRTM1s digital elevation model using the `RichDEM` software.[28,29] We calculate `D8` rasters for the area covered by each WASC. As part of `POOPy` we define a `D8Accumulator` class which processes the `D8` raster allowing flow to be accumulated efficiently across the area. As this involves processing large images with many pixels, we perform these flow-accumulation calculations in `Cython`, which is computationally faster than `Python`. Each `WaterCompany` stores a `D8Accumulator` in the `accumulator` attribute, and raster file is then automatically loaded into memory during `WaterCompany` instantiation.

For the end-user however, `POOPy` simply wraps all these calculations into the `get_downstream_geojson()` method of the `WaterCompany` class, which returns, in a geoJSON Multilinestring format,[30] all river segments that are currently downstream of a discharging CSO. Optionally, this can return all river segments downstream of all CSOs that have discharged in the last 48 hours. For instance, in the case of the Thames Water object instantiated previously:

```
geojson = tw.get_downstream_geojson(include_recent_discharges = True).
```

This geoJSON object can be manipulated in `python` using standard geospatial libraries or outputted for use by Geospatial Information Systems. Alternatively, `POOPy` implements a plotting function that provides a visual, spatial summary of the state of all CSOs operated by a WASC and the downstream affected rivers:

```
tw.plot_current_status()
```

which will produce a plot similar to Figure 3.

Combining this geospatial processing with historical data (where available) allows for historical environmental impacts to be calculated. For instance, we can calculate which rivers were downstream of CSOs at a given point in time as follows:

```
time = datetime.datetime(2024, 7, 16) # 16th July 2024
geojson = tw.get_historical_downstream_impact_at(time=time)
```

This output could, for instance, be compared against historical water-quality observations to evaluate the extent to which CSOs adversely impact on water quality. Whilst we have focussed on one, very simple, method for identifying rivers impacted by CSO pollution here, we emphasise that `POOPy` could easily be extended to consider more complex, or alternative

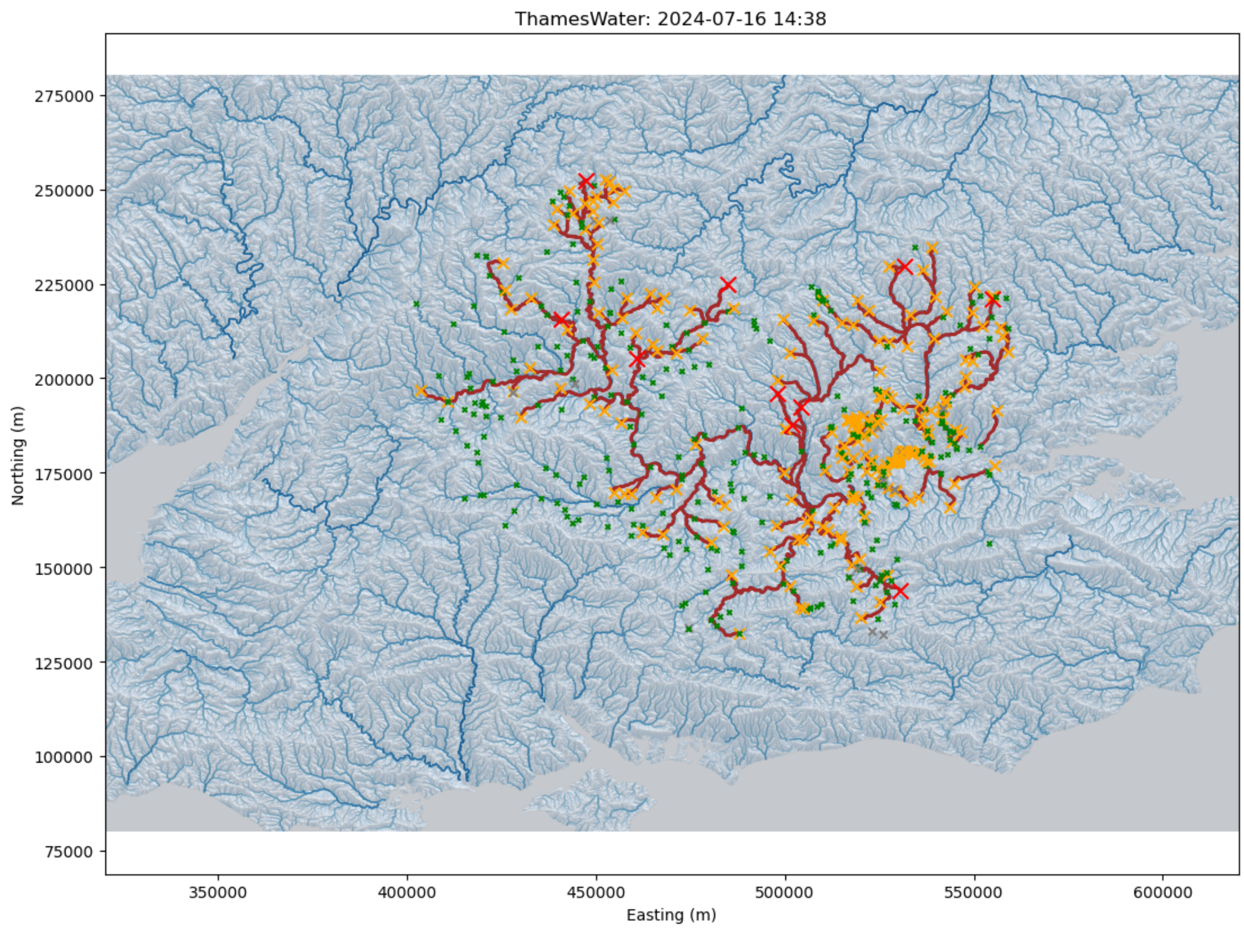

Figure 3: An example of the output of the `plot_current_status` method of the `WaterCompany` class generated for the Thames Water EDM network on the 16th of July 2024. Red crosses are CSO discharges, orange crosses are CSOs that have discharged in the last 48 hours and green crosses are CSOs that are not discharging. Brown lines indicate river reaches downstream of active or recent CSO discharges. Blue lines correspond to the underlying river-network where the strength of colouration indicates the modelled upstream area (logarithmic scale).

methods for calculating the generic 'environmental impact' by adding additional methods to the `WaterCompany` class. We describe our motivation for focussing, initially, on this simple downstream tracing method in the Discussion.

A real-time national visualisation of CSO status and downstream rivers

Here we describe how we used `POOPy` as part of a real-time, national, interactive map (`www.SewageMap.co.uk`) of CSO status and also of rivers downstream of recent CSO spills. Screenshots from `www.SewageMap.co.uk` highlighting its key features are shown in Figure 4. The overall data pipe-line behind this visualisation is shown in Figure 5. The source-code and user interface design files for the website is freely available in at `github.com/JonnyDawe/UK-Sewage-Map`.

The underlying data for this visualisation are APIs provided by WASCs. For most English WASCs, we use the APIs that are compiled at the *Storm Overflow Hub* operated by *Stream*.[31] The exception to this is Thames Water who provide an additional API which includes historical EDM data. The capability to include data from Welsh Water is currently under development. A `python` script executes at regular intervals that runs a series of `POOPy` command that ingests these datastreams and generates 1) geoJSON files for rivers downstream of recent (within the last 48 hours) CSO spills; and 2) JSON files which contain a tabulated history of past CSO spills (currently limited to monitors operated by Thames Water). At present, this script runs on hardware hosted at the Department of Earth Sciences, University College London. The generated files are uploaded to a cloud data storage service (Amazon Simple Storage Service). Using a content delivery network (CloudFront) these data files are made securely accessible for external read-access (available at `github.com/AlexLipp/sewage-map`)

`www.SewageMap.co.uk` reads these data files and displays them graphically, combining them with information on CSO status read directly from the original WASC geospatial APIs. This client-side application, developed using TypeScript[32] and React,[33] runs entirely in the user's web browser without requiring server-side processing. The application is statically hosted and employs a full map layout to highlight its primary focus on spatial data.[34] Users can easily view regional information through icons on the map and visualize downstream flows. For more detailed insights, users can click on features to access pop-ups, allowing them to access more specific information, such as historical data and previous overflow events. This hierarchical approach enables users to obtain both a UK-wide overview and detailed regional or single-location insights within a single, user-friendly interface. The design process adopted a mobile-first approach, incorporating responsive layouts to ensure optimal viewing and interaction across a range of devices. This decision was validated by the observation that 78% of users accessed the application via mobile or tablet devices between April 2024 and 2025. This highlights the essential need to cater to mobile users when sharing environmental analytical data, ensuring that the information remains accessible and user-friendly for everyone.

Discussion

Communicating water quality risk using EDM data

The approach we take to identify rivers that are 'impacted' by CSO pollution is deliberately extremely simplistic. Our approach is non-physical and does not take into account many processes that control the water-quality of rivers (i.e., advection, dispersion, biological uptake, dilution).[35] Due to this simplicity we explicitly state on the landing-page for `www.SewageMap.co.uk` that: *'on its own, this map should not be used to assess pollution or health risks at a specific location, for example, for bathing water quality'*. The reason for opting for this simplisitic approach is that the information contained within EDM data is itself extremely basic. An event duration monitor indicates only *if* a CSO is discharging, and

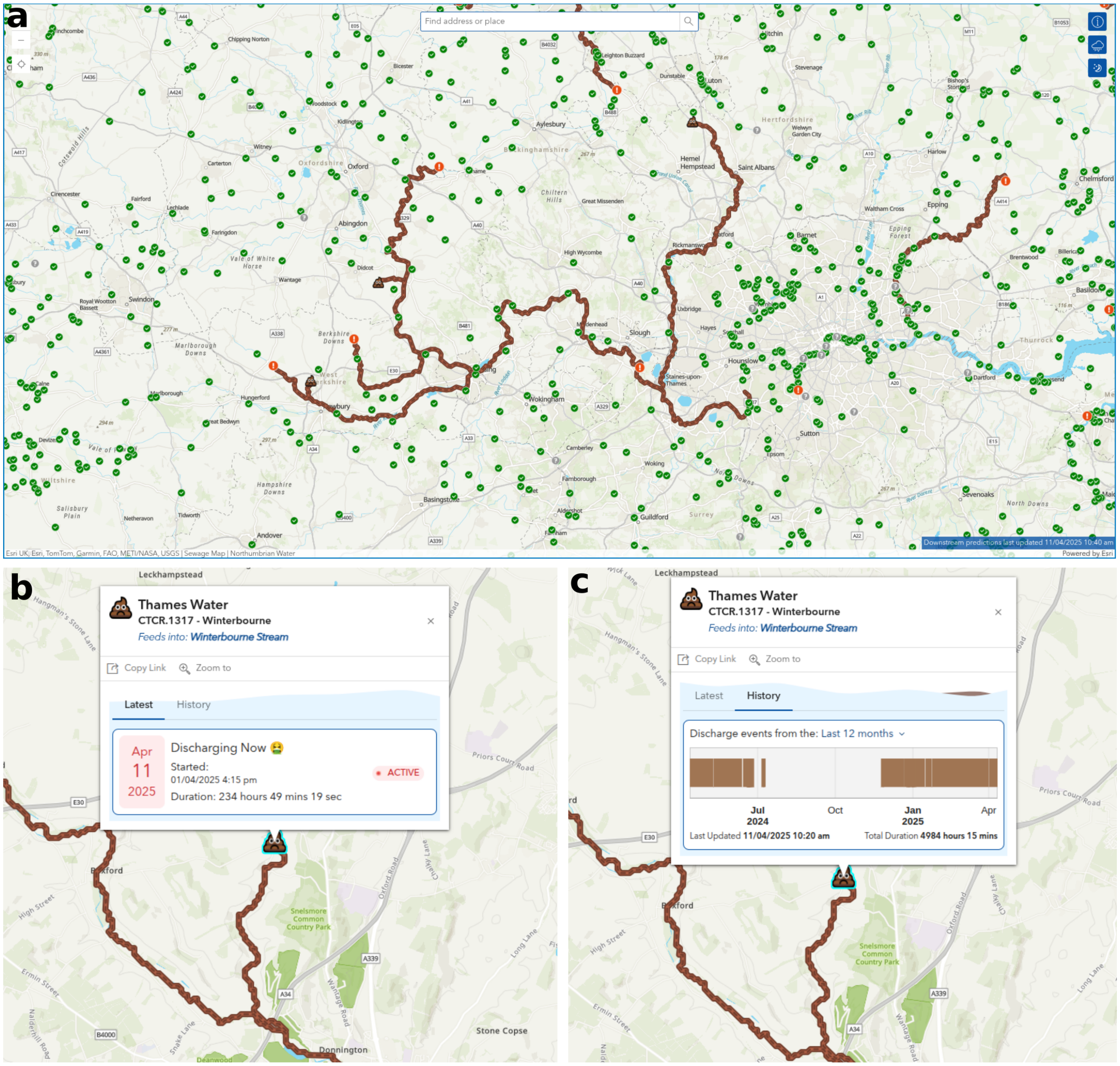

Figure 4: Screenshots from `www.SewageMap.co.uk` taken on 11/4/2025. a) The full screen representation with the status of CSOs as icons superimposed upon a basemap. Green ticks indicate CSOs that are not discharging, brown ‘poop’ emoticons are CSOs that are currently discharging and red exclamation points correspond to CSOs that have discharged in the last 48 hours. The brown lines indicate modelled (non-tidal) river stretches downstream of an active or recent CSO; b) The pop-up icon displaying summary information for a given CSO monitor and its current status; c) The ‘History’ tab showing (where live data is available) the historical record of spills for a given CSO.

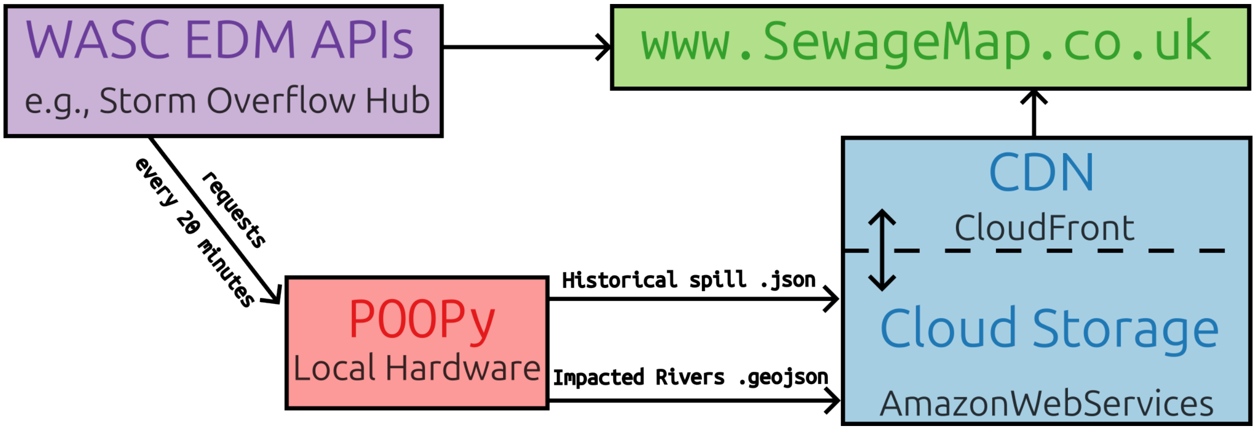

Figure 5: A schematic of the data-flow and processing that underlies `www.SewageMap.co.uk`

provides no information on the volume of the discharge or the concentration of any potential contaminant contained therein. Consequently, lacking these constraints on absolute mass loads of contaminants, including those which pose a risk to human health, it is impossible to accurately parameterize a water-quality model without making significant assumptions. Consequently we opt for an 'obviously simple' approach rather than risk making predictions that are 'precisely wrong'.

In cases where repeated observations of risk relevant parameters (e.g., counts of *Escherichia coli* or other Fecal Indicator Organisms; FIOs) are made in rivers it is possible to build statistical, predictive models of bathing water quality taking into account environmental data such as upstream rainfall, river discharge, and potentially, occurrence of CSO spills upstream.[36] This broad framework underlies the *Environment Agency's* Pollution Risk Forecasting (PRF) system which displays advisory warnings to the public on physical signs at forecast locations and online at 'Swimfo'.[37] However, in England, repeat sampling of FIOs only takes place at designated 'bathing waters' of which less than twenty are rivers. As a result, away from the very limited number of designated bathing sites where sampling takes place, it is not possible to provide real-time forecasts of water-quality in rivers. By contrast, SewageMap is able to provide, limited, information about CSO impacted rivers continuously across all inland rivers in England.

Should more accurate live data on both the quality and volume of CSO discharges, or of bathing water quality, it would be possible to extend our approach to incorporate more sophisticated models. For instance, in the coming years, WASCs in England must deploy continuous water quality sensors (for parameters including ammonium, dissolved oxygen, pH etc.) in rivers upstream and downstream of nearly all CSOs[38] and make this data openly available. However, until the widespread availability of this data, we argue that our approach represents a simple and balanced approach to provide qualitative information of areas of CSO pollution to the public. Anecdotally, discussions with users indicate that due to the clearly simplified nature of our visualization (i.e., a simple downstream trace) the limitations are well communicated and understood. Nonetheless, we argue that further studies for how members of the public interpret EDM data in the context of environmental and personal risk would be fruitful.

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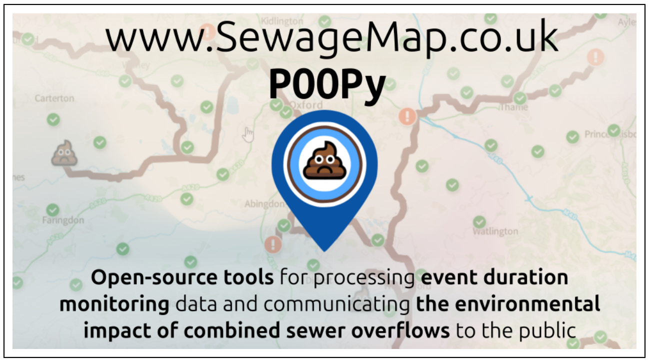
TOC Graphic


www.SewageMap.co.uk
POOPy
Open-source tools for processing event duration monitoring data and communicating the environmental impact of combined sewer overflows to the public