HAZRUNOFF

PROJECT

"Integration of sensing and modelling technologies for early detection and follow-up of hazmat and flood hazards in transitional and coastal waters"

3.4.1 Evaluation of social media and internet systems for early alerting.

Funded by
European Union
Civil Protection
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WP 3	Evaluation of social media and internet systems for early alerting incidents
Action	Use of third party social media analytics platforms to search to assess use for incident alerting and to appraise impact of risk communications.
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authors	P Harold, A Kibble, E Huckle (Public Health England)
participants	Public Health England

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Introduction

This report details work prepared by Public Health England (PHE) in support of Work Package 3, Tools for situational awareness and emergency response.

For this Work Package, PHE has aimed to pilot the potential for use of media and social media platforms for alerting of environmental pollution incidents within specific aquatic and marine environments (rivers, estuaries, coastal waters) as well as case study areas defined within Hazrunoff

Internet news feeds and social media have the potential to aid incident response. Real-time incident monitoring has been used to help track disease outbreaks and obtain intelligence from communities affected by flooding but has not been applied to environmental pollution events[1; 2]. Such models typically follow a methodology similar to that outlined in Figure 1 opposite.

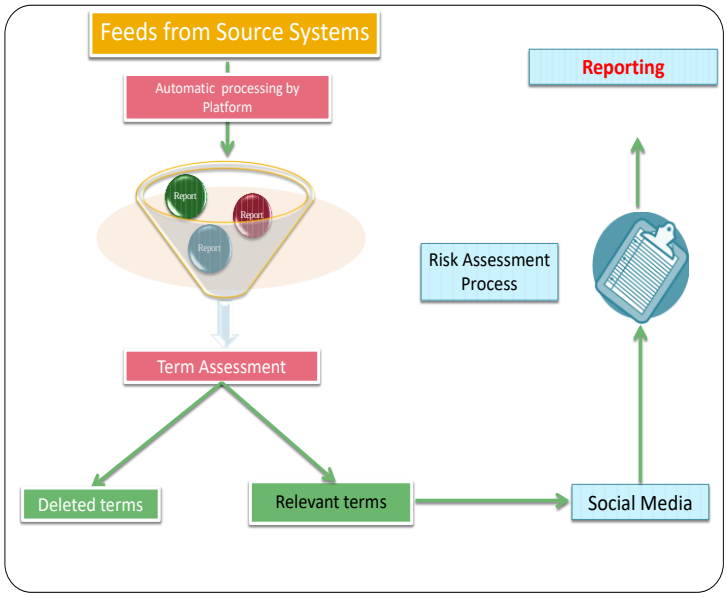


Figure 1: Methodology schematic for web trawling models.

This report describes development of an algorithm based upon the above model and application of this to analysis of social media and internet platforms for alerting of flooding and hazmat incidents. The report also describes an assessment of the impact to stakeholders from public facing warning and informing messages, issued by response agencies during and after such incidents. The work represents tasks 3.4.1 and 3.4.2 of the Hazrunoff Project.

[1] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3261963/

[2] http://staffwww.dcs.shef.ac.uk/people/N.Ireson/publications/iscram2015trids.pdf

Development of the Search Algorithm

The International Programme on Chemical Safety (IPCS) defines a chemical incident as "*an occurrence of public health concern caused by an acute release of a toxic or potentially toxic agent*". (WHO Collaborating Centre, 1999)[3].

Based upon this definition PHE developed an algorithm comprising a series of basic steps to identify search terms, apply terms to real time alerting, analyse results and iterate to refine terms (as below).

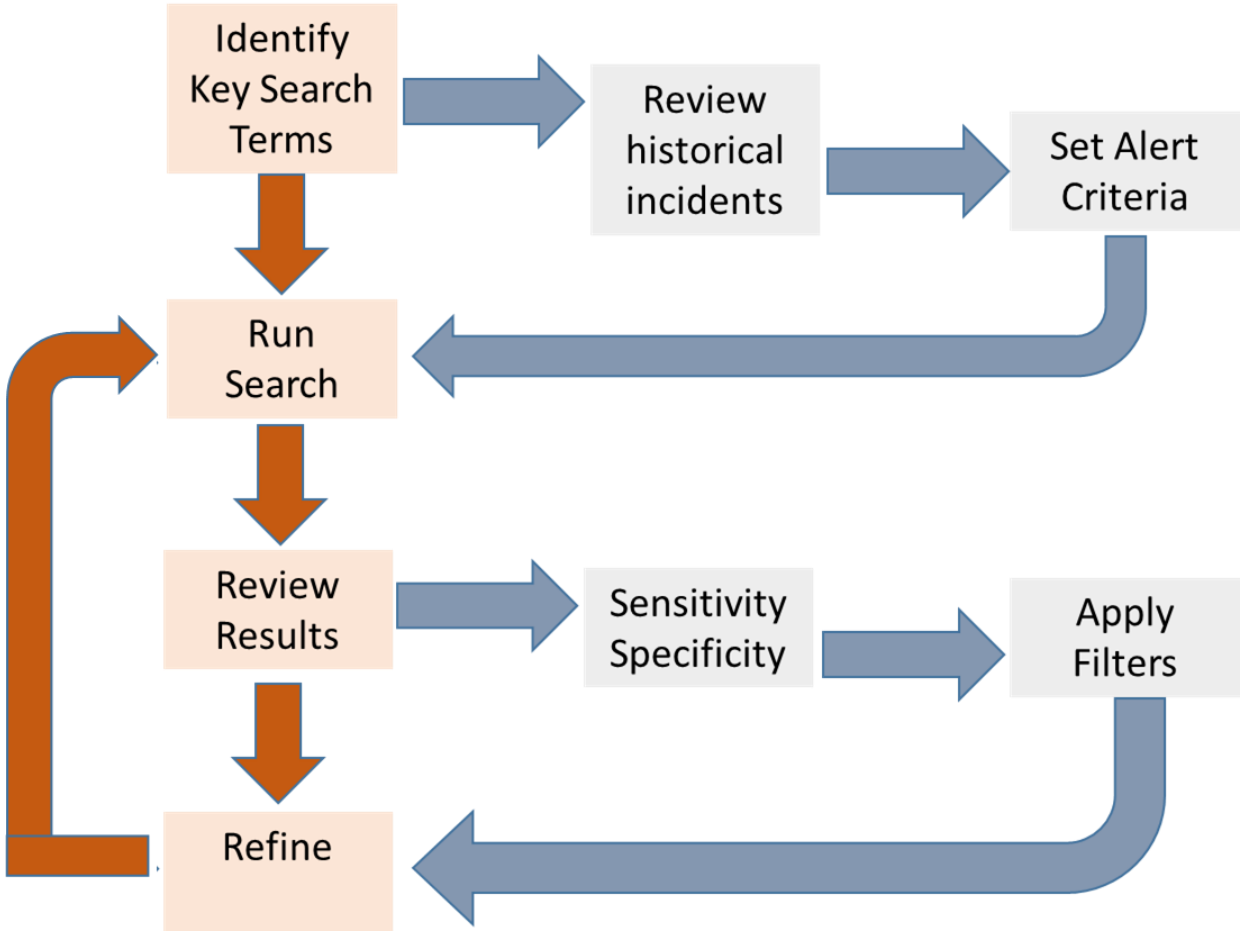


Figure 2: Proposed algorithm for incident surveillance

[3] 1999 Who Collaborating Centre for an International Clearing House for Major Chemical Incidents.

Development of Search Terms

Records of chemical incidents in the coastal and riverine environment for Wales and reported to key UK response agencies were reviewed for the period 2011-2018[4] and categorised according to incident type (see Figure 3 and Table 1).

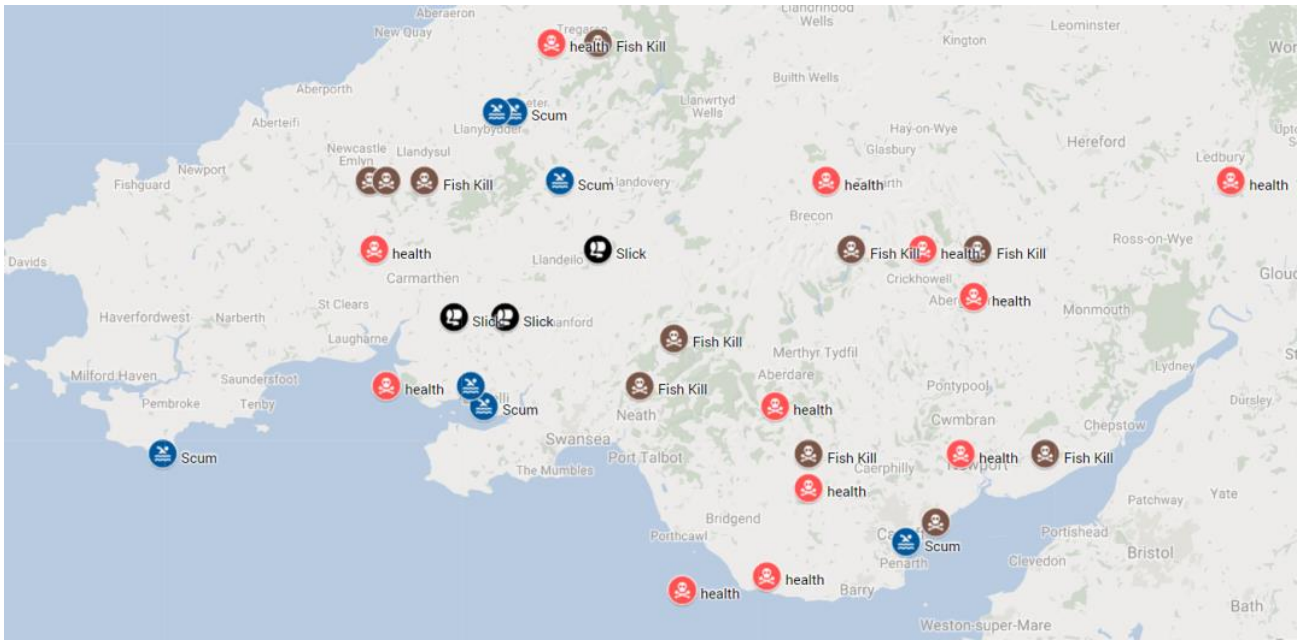


Figure 3: Illustration of incidents across the Bristol Channel / Severn Catchment area

Incident Type	Key Words
Slurry	Fish Kill / Agricultural Pollution / Odour / Silt / River / Lake / beach
Oil Spill	Sheen / Odour / Slick / Staining / river / lake / canal / beach
Chemical	Discoloration / Gas cloud / Odour / Haze / Fish Kill / River / Lake / Health
Blue Green Algae	Algal Bloom / Scum / Lake / Dock / Canal / Health / Swimming
Fire	Smoke / Plume / Odour / Ship / Dock / Health
Vegetable Oil	Fats / Grease / wax / Odour / Beaches / Dogs / Pets
Flooding	Pollution / Health / Damage / Disease

Table 1: Summary of Main Incident Types and key words

[4] Data were not available from all sources for the whole period covered.

From the results of the review a Boolean search string was defined and piloted for one month using European Media Monitoring (EMM) software[5].

combination						*proximity 15**
	river	*rivers*	*sea*	*ocean*	*oceans*	
and						
	oil	*fish*	*birds*	*flood*	*sewage*	*slurry*
and						
	pollution	*chemical*	*toxic*	*incident*	*incidents*	*accident* *accidents*
not						
	plastic					

Table 2: Boolean search string used for EMM

**proximity 15 means combinations of terms must be within 15 words of each other to attempt to ensure the terms are linked*

During the pilot period, approximately 140,000 articles were reviewed by EMM[6,7]. From these a total of 290 media articles matched the search criteria but only 18 of these related to actual incidents.

As such results from the pilot suggested that the search terms were useful for discounting large numbers of articles and avoiding large numbers of false reports (specificity) but was less effective at identifying genuine incidents (sensitivity). These terms are discussed further in later sections. However, several major incidents were detected during the pilot, confirming the potential applicability of the search terms/search string for surveillance and alerting purposes

As this tool looked solely at global news media sources it was always likely to only return positive results for major incidents. In order to look at surveillance on a more localised level a more sensitive search tool was required. Thus, the study subsequently involved review, selection and use of a tool capable of searching social media as well as main-stream media.

[5] http://emm.newsbrief.eu/overview.html

[6] Big Data and the Global Public Health Intelligence Network (GPHIN) M Dion P AbdelMalik and A Mawudeku Can Commun Dis Rep. 2015 Sep 3;41(9):209-214. eCollection 2015 Sep 3

[7] Emerg Infect Dis. 2009 May; 15(5): 689–695. Use of Unstructured Event-Based Reports for Global Infectious Disease Surveillance. Mikaela Keller,corresponding author Michael Blench, Herman Tolentino, Clark C. Freifeld, Kenneth D. Mandl, Abla Mawudeku, Gunther Eysenbach, and John S. Brownstein

Review of Social Media Platforms

A variety of social media analysis tools are available, varying in sophistication and cost. The following represents a review of those considered within the Hazrunoff Project.

TweetDeck

TweetDeck is free a social media dashboard application for management of Twitter accounts. It is owned by Twitter and available to anyone with a Twitter account. It displays multiple timelines in a single interface (Figure 4) and allows users to set up searches in real time or to retrospectively search Tweets. Users can define a search area and timelines. It and allows basic sentiment filtering of searches to collect positive or negative Tweets.

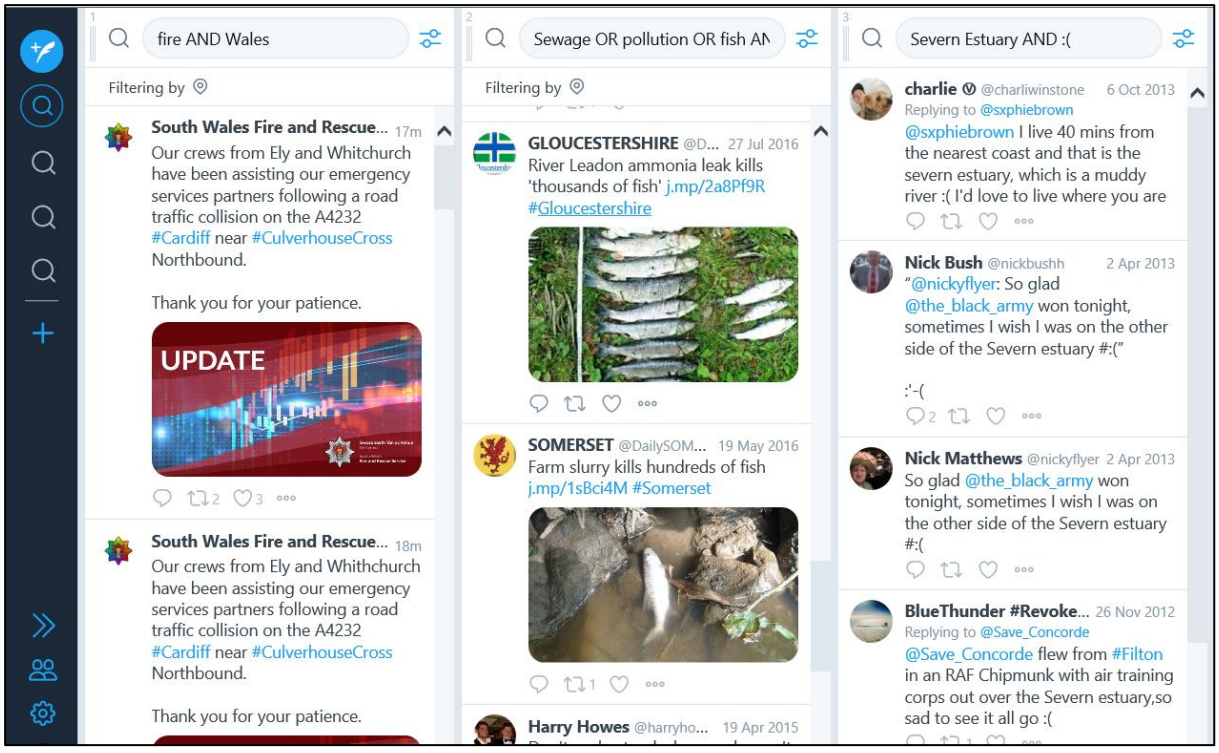


Figure 4: Illustration of TweetDeck

Its main limitation is that it will only track Twitter activity and requires a high degree of manual review. As it only allows analytics for accounts set up by the user it cannot track trends related to third party tweets.

As such it is of limited application for automated monitoring and more sophisticated tools are needed for this, as described below.

COSMOS

A variety of free tools are available for social media analytics. For Hazrunoff, Public Health England reviewed COSMOS developed by Cardiff University Social Data Science Lab. The tool runs on a PC (preferably Mac) and allows searches of Twitter for key terms. Other similar tools are available including CHORUS, developed by Brunel University.

Unlike TweetDeck the tool does not display Tweets but downloads them at defined intervals as comma separated value (.csv) files, which can then be analysed for a variety of parameters including frequency / volume, key words, gender, sentiment and location (Figure 5). Tweet interlinkage networks can also be displayed.

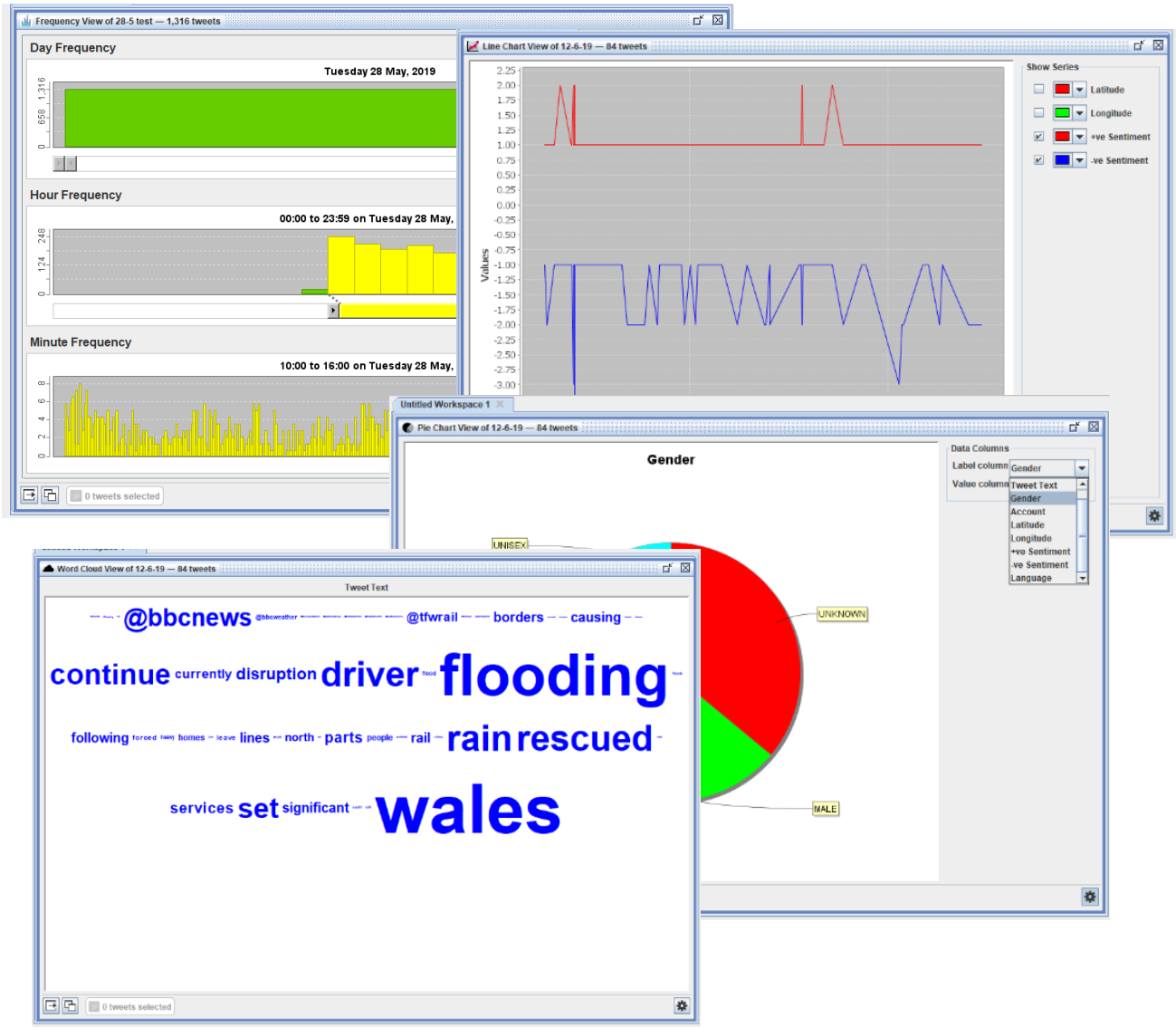


Figure 5: Images from COSMOS Twitter Analysis

Trials with COSMOS identified that while running in real-time, the data can only be displayed and analysed after collection. Data can be collected and downloaded every 15 minutes or so but then needs to be manually imported into the analytical window to view the various parameters. So, whilst very useful for *a posteriori* analysis of data, the tool again has limitations for real-time alerting. Again, COSMOS is limited to Twitter and is only freely available for research purposes.

Brandwatch

Beyond the types of free tools mentioned above there are many highly sophisticated, commercial social media analysis platforms available, enabling subscribers to undertake bespoke searches and display results in real-time via web-based dashboards[8].

Principally designed for marketing many can be applied to crisis management. For Hazrunoff, Public Health England used a product called Brandwatch Analytics (Figure 6).

Based upon user defined Boolean queries the system scans multiple social media and internet platforms, displaying results in real-time as user defined statistics such as volume, trends, word clouds, demographics

Results can also be filtered for specific media platforms, specific authors, geographical locations to county level, emotion and sentiment etc.

Multiple searches can be undertaken simultaneously and displayed to multiple users. Real-time alerts can be set to notify users of increases in activity, trends etc.

Key benefits of systems such as Brandwatch are their ability to search a wide range of key social media and internet sites, provide and display data in real-time, operate multiple searches simultaneously, issue real-time alerts, and enable sophisticated analysis and data refinement.

The key disadvantage of such sites is that subscriptions can be expensive.

[8] https://www.brandwatch.com/blog/social-media-analytics-tools/

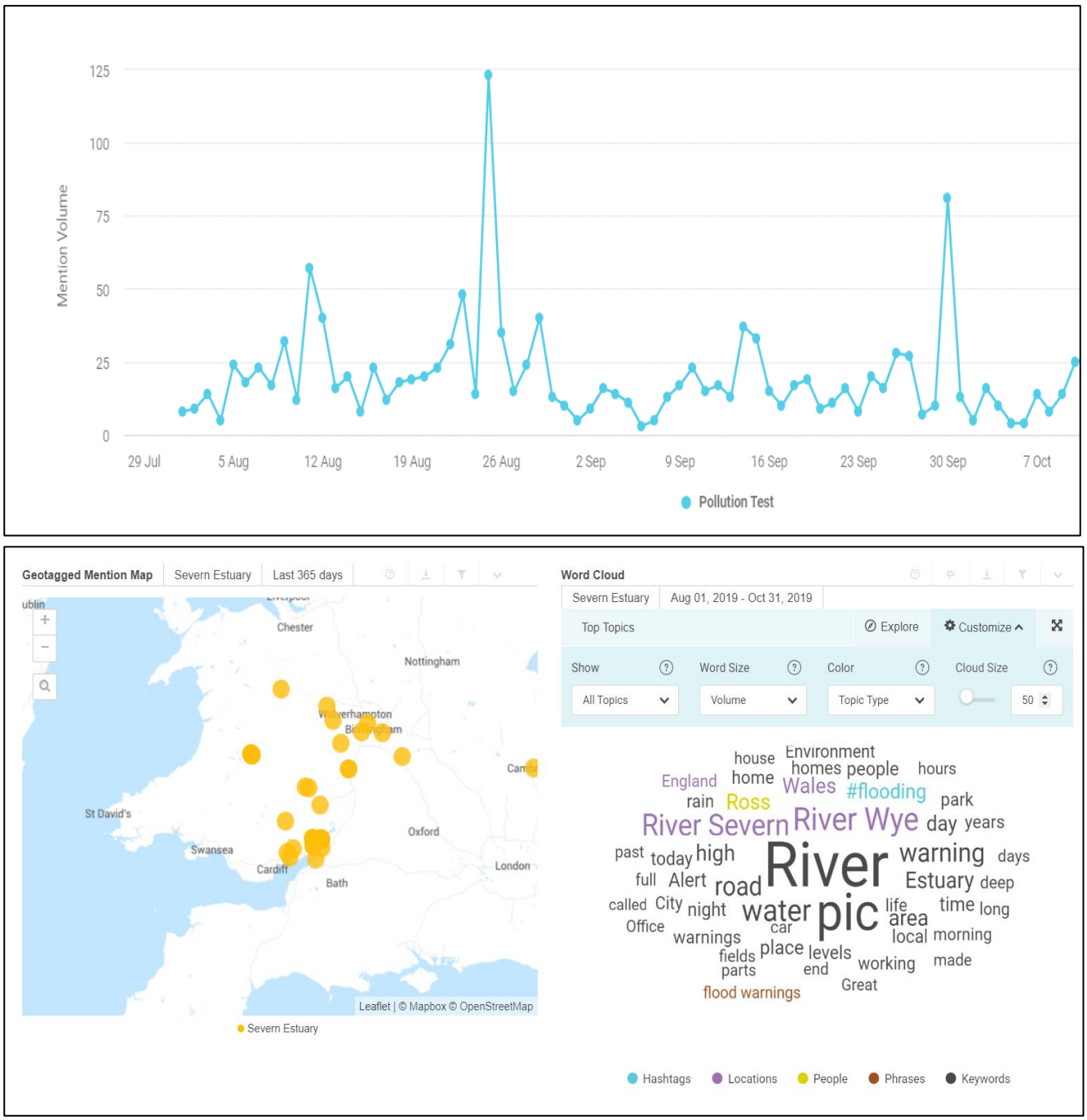


Figure 6: Illustration of Brandwatch Dashboard

The table below summarises the systems reviewed as part of the Hazrunoff study

Name & Website	**Search Type**	**Platforms**	**Collection / Display**	**Analysis**	**Alerts**	**Cost**
Tweet-Deck https://tweetdeck.twitter.com/	Multiple Boolean – Key words and operators	Twitter	Collects and displays matching Twitter posts in real time	No.	No	Free
COSMOS http://socialdatalab.net/	Multiple Boolean – Key words and operators	Twitter	Collects matching Twitter posts and downloads at time intervals	Yes –downloaded or imported posts	No	Free for research
Brandwatch https://www.brandwatch.com/products/analytics/	Multiple Boolean – Key words and operators. Filters to refine data	Multiple social media and internet platforms	Collects matching posts - and displays analysis in real time	Yes. Real-time dashboards	Yes – real-time alerts to users	Yes – annual subscription fee

Table 3: Comparison of Social Media Search Tools used during Project

Social Media Pilot Study for Alerting

Surveillance using Brandwatch was undertaken over a 3 month period from 01/08/19 – 31/10/19, using the search terms defined from initial web site monitoring studies:

"((river OR beach* OR estuary* OR canal* OR ocean* OR lake* OR dock* OR sea OR marina* OR harbour* OR shore* OR ship* OR boat*) AND (chemical* OR Sewage* OR slurry* OR algae NOT plastic*) AND (pollution* OR incident* OR accident* OR spill* OR fish-kill*))".*

The search term was further refined to only search for articles and posts from the UK (by including "country:uk" to the term) and looking only for posts in English. The inclusion of the * after key words enabled variants such as plurals of the words to be picked up by the search.

A dashboard was set up to display real-time search results as total posts over time, daily key words, most active internet and social media sites and geographical location of posts (Figure 6).

A series of additional searches were also run simultaneously using the same structure as defined above. These pollutant specific searches namely; chemical incidents, algae and sewage, were completed to see any differences in sensitivity compared to searches for all incident types in a single search term. A search for floods in Wales was also set up as:

"(flood AND warning* AND (river* OR sea) state:wa94)"*

Searches were also set up for the case study areas, comprising the general search query for all incidents but also specifically requiring mention of named rivers and areas associated with and including each study area as illustrated for Severn Estuary below:

((river* OR estuary* OR beach* OR shore* OR (bristol AND channel) OR dock* OR marina* OR ship*) AND (Taff OR Severn OR Wye OR Usk) AND (chemical* OR oil OR Sewage* OR slurry* OR algae*) AND (incident* OR accident* OR pollut* OR spill* OR flood* OR fire* OR hazard*) (NOT plastic) country:uk)

Dashboards were set up for each search and reviewed daily and / or when alerts were received. Data did not need to be exported as they are retained within the platform. Reviews involved manual inspection of posts to establish if they related to actual acute incidents. Any positive returns were reviewed against Public Health and Environment Agency databases to establish if incidents had been notified to relevant agencies.

Assessment of Public Messages

In addition to the review described above, incidents were also investigated to establish if any warning and informing messages had been issued by response agencies. Where this was the case any responses were assessed for sentiment and emotion using the software provided by the tool. To complete this aspect of the work it was also necessary to look at historical incidents retrospectively. Brandwatch has access to historical data but requires additional paid subscription for access.

For this aspect of the study 2 incidents were reviewed. One current incident detected during the pilot study and relating to illness from exposure to sea water around Essex on 25th August 2019 and one historical incident relating to a long running wood chip fire at Newport docks in the Severn Estuary during December 2015.

Dashboards were set up for each incident to display graphs of sentiment or emotion categories for posts, from all sources or from only social media sites (Twitter, Facebook and Instagram) over the relevant time periods (Figure 7).

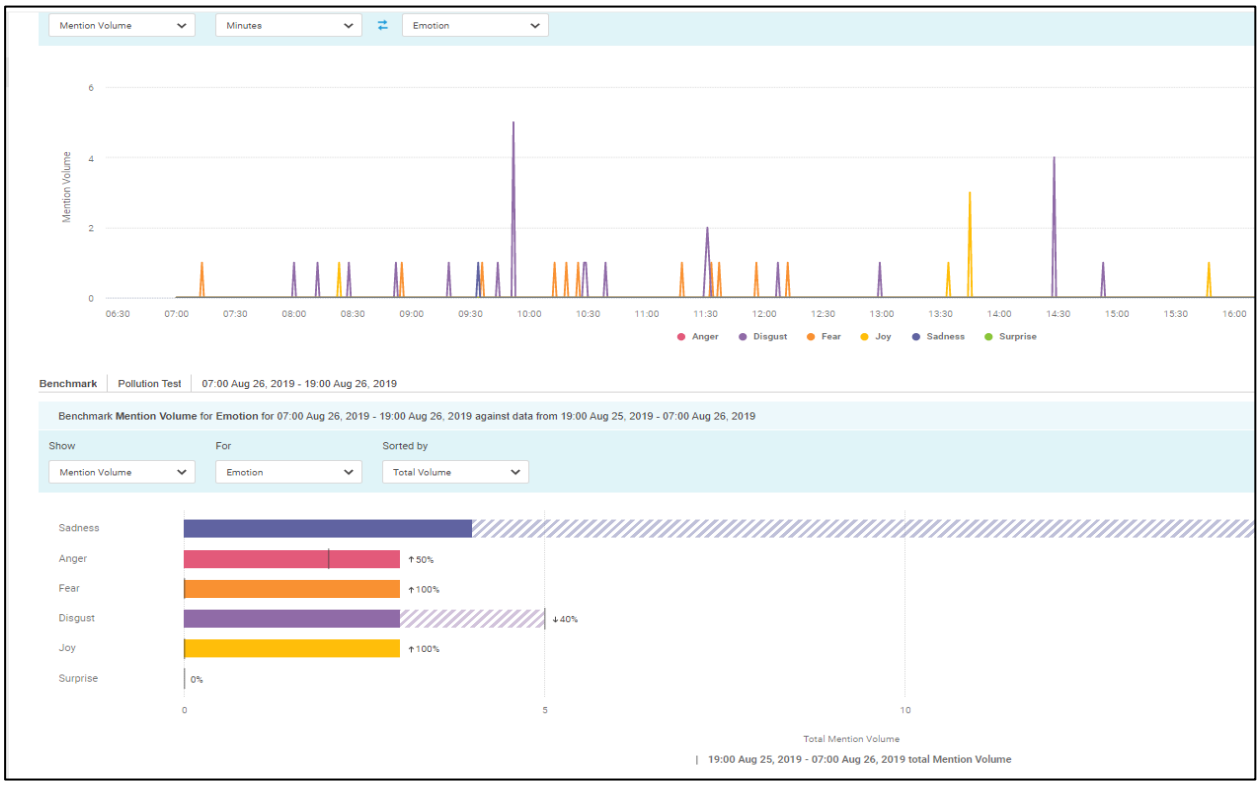


Figure 7: Illustration of sentiment and emotion analysis during an incident

Results were then used to identify the impact of warning and informing messages during the incident and immediately post incident.

Results of Pilot Study

A total of 1637 media and social media articles were collected by the search query during the trial period. When adjusting to remove repeat postings and retweets the total number of posts meeting search criteria was 200.

Of this 200 a total of 25 posts were confirmed as actual incidents within the UK with several large incidents involving multiagency response resulting in peaks of media traffic and automated alerts being issued (see Table 4 and Figure 8). Details of each incident are listed in Appendix 1.

Source	Social Media	News Media	News and Social Media
Incident Numbers	11	7	7

Table 4: Summary of incident sources

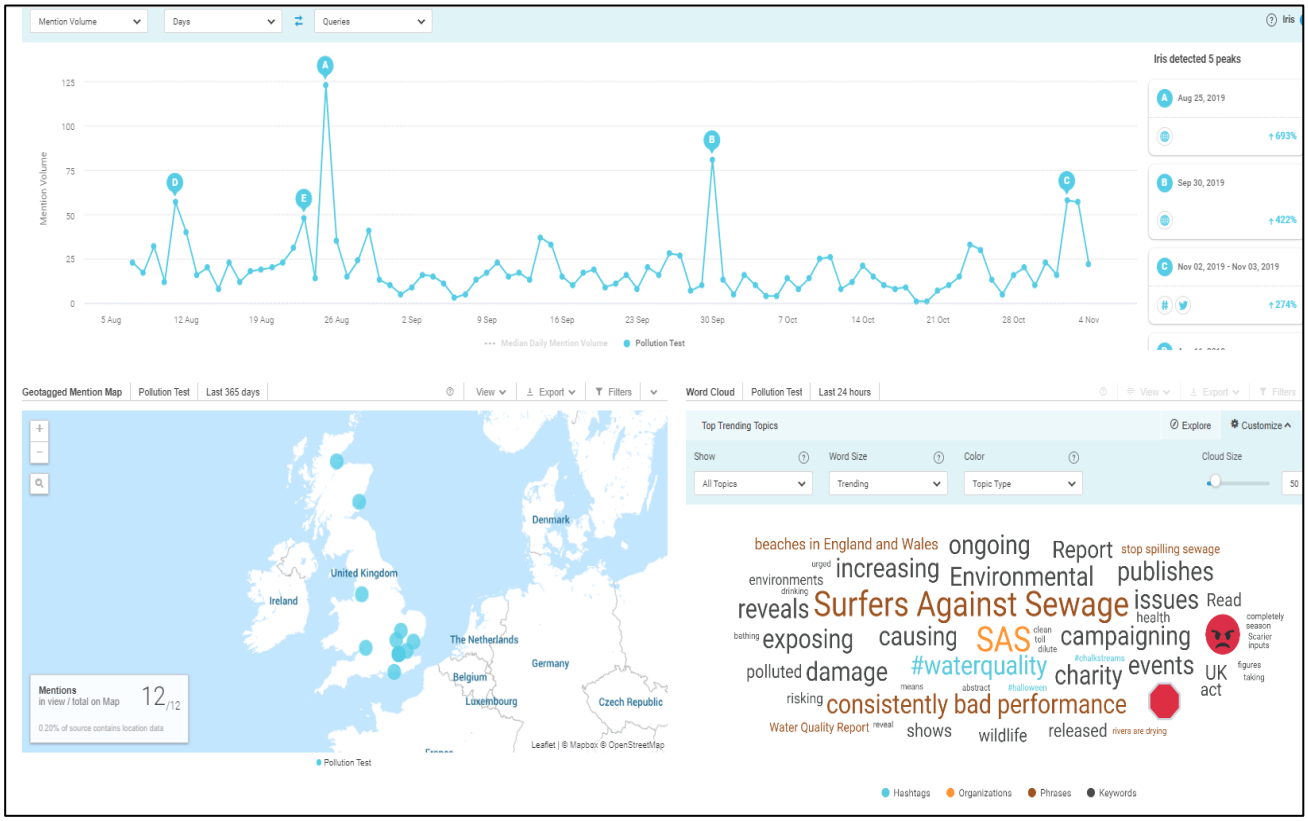


Figure 8: Dashboard display from Pilot Study

Data analysis

Results were reviewed in terms of **sensitivity** and **specificity** using a 2 x 2 table approach as displayed below (Table 5)

	Search Term met	Search Term not met	
Incident Identified	True positive A	False positive B	A+B
No Incident Identified	False negative C	True negative D	C+D
	A+C	B+D	

Table 5: Validity measurement table

Sensitivity [A/(A+C)]
Specificity [D/(B+D)]
PPV [A/(A+B)]

In the context of this evaluation, sensitivity indicates the proportion of incidents in posts that were correctly identified using the search terms (true positive) while specificity is the proportion of posts reviewed and correctly identified as not meeting search criteria (true negative). False positive results represented reports identified by the search but not relating to incidents, while false negatives related to actual incidents that were not identified by the search.

Other useful measures of validity include the positive predictive value (PPV) which is the proportion of all incidents identified that were true positives and indicates the ability to accurately predict incidents (i.e. the potential as an alerting system).

For the pilot study the total number of articles reviewed (A+B+C+D) was estimated to be greater than 5 million per day, a very conservative estimate from live internet statistics, which

estimates 500 million Twitter posts per day worldwide[9], and assuming 1% of these represent original posts from the UK.

Potential false negatives were estimated by reviewing incident databases and reports held by Public Health England, Public Health Wales, and UK environmental agencies for the trial period.

This review found that 25 incidents had been reported to / recorded by the above agencies, of which 10 matched incidents identified by the social media search, while 15 had not been identified. In contrast, 15 of the incidents identified from social media had not been reported to / recorded on agency databases.

Applying these results, calculations were made, including 95% Confidence Intervals (CI), using software available on line[10] as below:

Sensitivity = **63%** (95% CI=46% to 77%),
Specificity =**100%** (95% CI=100% to 100%).
Positive Predictive Value (PPV) = **12%** (95% CI = 9.7% to 15.9%).

	Search Term met	Search Term not met	
Incident Identified	25 True Positive	175 False Positive	200
No Incident Identified	15 False Negative	4.5×10^8 True Negative	4.5×10^8
	40	4.5×10^8	4.5×10^8

Table 6: Results of the Pilot Study

[9] https://www.internetlivestats.com/twitter-statistics/

[10] https://www.medcalc.org/calc/diagnostic_test.php

Results for the UK case study area (Bristol Channel / Severn Estuary) and included in the statistics above, did not identify any pollution incidents during the pilot period, a result which appeared to be corroborated by response agencies. It did however identify the 2 national flooding events (figure 9). These events impacted areas associated with the Severn catchment slightly after other parts of the country had been affected and media traffic for the case study area similarly reflected this delay compared to the national picture.

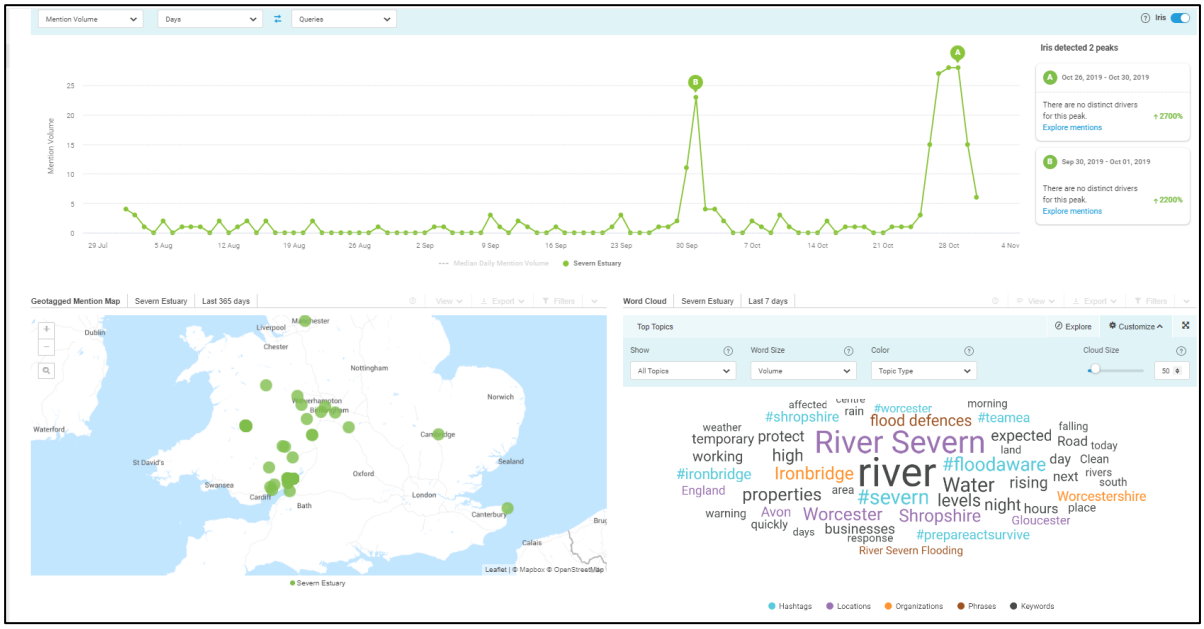


Figure 9: Dashboard for Severn Estuary pilot study search

An interesting aspect of the results from these 2 events was the number of photographs posted by members of the public showing conditions "on the ground" as well as giving the time of posting (as illustrated by figure 10 below).

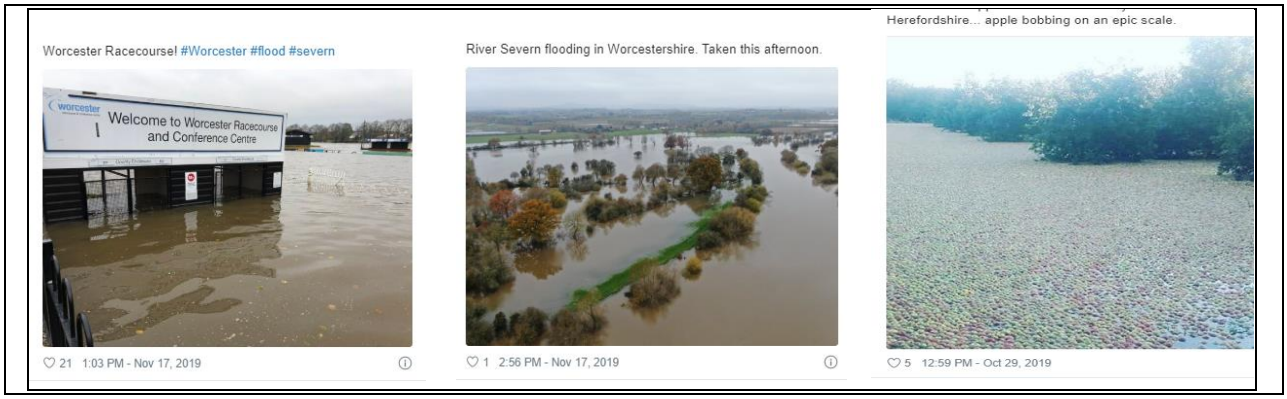
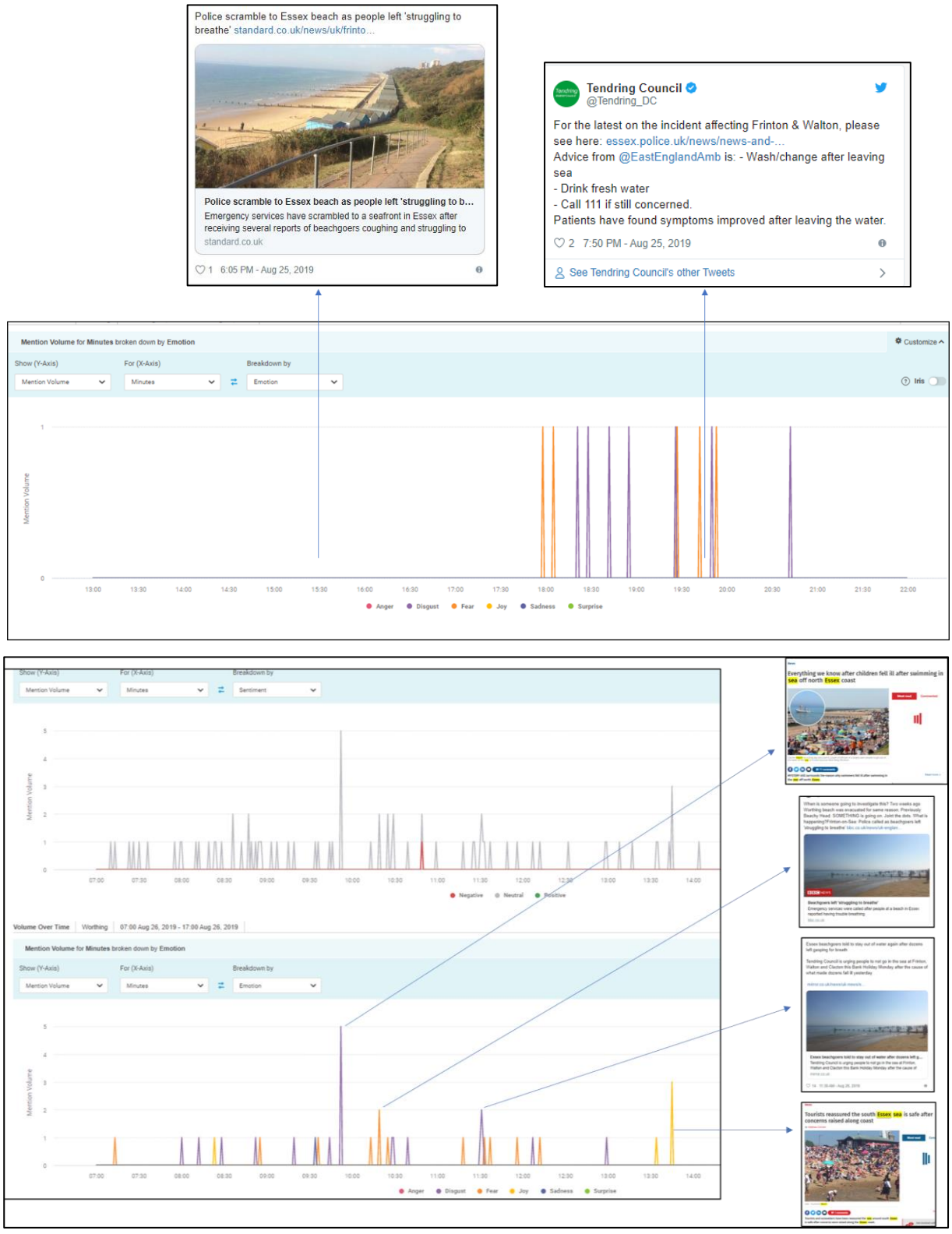


Figure 10: Illustration of photographs posted on Twitter during Severn area flooding event (October 2019)

Regarding the impact of warning and informing messages it was possible to use the surveillance tool to assess sentiment and analysis of posts and link these to the incident timeline and their relationship to times when messages were issued by response agencies (Figures 11, 12 and 13).



Figures 11 and 12: Emotion analysis during suspected chemical incident on Essex beaches

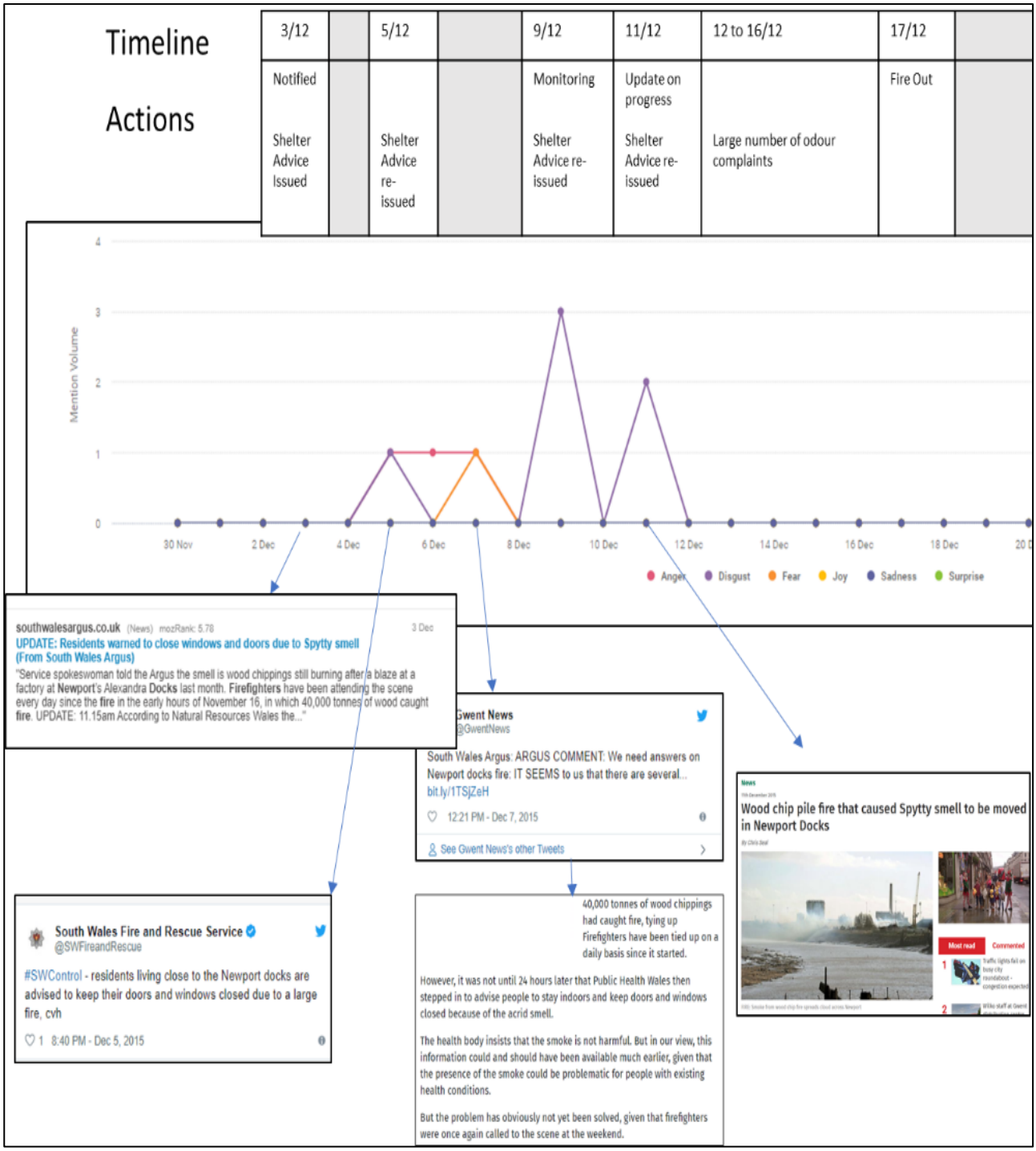


Figure 13: Emotion analysis during a long running fire at Newport Docks 2018

Discussion of Results

The study has demonstrated that the system was able to identify incidents occurring within UK coastal and riverine waters during the trial period. Similar results have been found in studies in the United States which reviewed social media traffic during major natural disasters concluding that Twitter provided a useful sensor for such incidents[11].

Performance analysis suggests that the search terms were useful at discounting false reports (100% specificity) but performed less well at identifying true incidents (63% Sensitivity and 12% PPV respectively).

Comparisons with UK response agency records showed that the system identified roughly 40% of the coastal / river/ water incidents reported by these agencies during the same period and correctly captured all of the larger and most significant incidents. This is not surprising since larger incidents will tend to be picked up by the media and social media and thus should be identified by surveillance.

The system failed to identify 15 smaller, localised incidents recorded by UK agencies, although these may not have been sufficiently significant warrant public facing messages or social media posts from the public and thus not be detected by surveillance.

In contrast 15 incidents not recorded by UK agencies, were captured by the surveillance tool. These again were relatively small, short-lived incidents reported almost exclusively by the public or community groups via social media and had a low likelihood of significant response by emergency services, or pollution control / public health follow-up.

The results demonstrate the importance of the sensitivity and specificity of search terms and the balance between being too generic resulting in lots of unnecessary posts and being too specific potentially omitting genuine incidents. This also underlines the need to refine terms as more data are collated identifying trends and patterns and key social media users /groups.

Regards the timing of alerts (see Appendix 1) it was noted that several incidents were identified by the tool before appearing on agency records, although records were not from "first

[11] https://www.sciencedirect.com/science/article/pii/S2212420919301256?via%3Dihub

responders" (fire, ambulance, police) who are likely to have been alerted sooner. This does however demonstrate that in many cases reports were contemporaneous and as such did provide "real-time" reporting of incidents and developments.

This was particularly well illustrated for the case study area search, where large numbers of photographs were posted by the public during flooding events, showing conditions "on the ground" at defined locations and times, demonstrating how such tools can assist response, using citizen data.

Such information can be of great benefit to responders informing dynamic risk assessments and subsequent management actions, helping to identify affected areas, the magnitude of effects, and any unforeseen impacts linked to an event (as illustrated by figure 10 where large numbers of apples were photographed having been washed into the river from flooding. This could equally apply to other types of pollutants giving useful information.) It is important however to ensure that such posts are reliable, accurate and contempraneous to the incident being responded to.

Regarding warning and informing messages, results generally indicated negative emotions (fear and disgust) and neutral sentiment, suggesting low positive impact from such messages. It should be noted however, that there is uncertainty on how accurate the analysis of sentiment and emotion is, with many factual messages being categorised as anger or fear, suggesting a possible need for further work in this area, including capturing views of stakeholders directly.

Again, studies around natural disasters in the US assessed sentiment and emotion of posts finding generally negative emotions where people had been directly affected, and differences in emotions depending upon proximity to the disaster and vulnerability of those posting on social media.

With smaller incidents such as those identified during the Hazrunoff study such differences in emotion would likely be less obvious due to the more localised impacts compared to a natural disaster, thus resulting more localised posts and posts mainly from those directly affected.

Again, however the tool demonstrated how social media can assist in judging public feeling during and post incident, with the potential to identify concerns and help future engagement with those affected.

Conclusions and Recommendations

The pilot has demonstrated the potential usefulness of media and social media surveillance as an alerting tool, whilst identifying several limitations.

Results from the trial suggest that the search terms were very useful at discounting large numbers of articles and avoiding large numbers of false reports but performed less well at correctly identifying incidents. Findings generally reflected the low prevalence of pollution incidents, particularly major ones.

Limitations of the system included the relatively low numbers of posts that are geotagged (<1 to 10%) limiting the ability to follow the geographical development of incidents, whilst most posts tended to be after an event has occurred, limiting the alerting potential. Posts can however give a useful information of ongoing events, as illustrated by photographs and posts during Severn area floods, as well as assessing the general view of stakeholders towards official advice and messages during incident phases.

Ongoing refinement of search terms and use of filters would be likely to improve performance. This can also be very useful where an incident has been identified, allowing the user to set up a new search specific to the incident identified to run in parallel with ongoing general searches.

Assessment of sentiment and emotion analysis of public messages suggested generally low positive impact on stakeholders. It was however noted that there may be limitations regarding the analytical software, suggesting a need for further work in this area, possibly involving stakeholder surveys and interviews to improve the accuracy of the software.

From the study it is concluded that such surveillance can provide a useful addition to existing conventional processes, particularly for smaller incidents, offering responders opportunities to further investigate potential events. It is considered however that surveillance is not a replacement for existing conventional alerting techniques. The work has also illustrated how messages can be assessed in terms of their public impact and has identified potential areas for future work around this aspect.

Based upon these findings it is recommended that further trials be considered, in conjunction with media surveillance companies, both to refine search terms and improve performance, and further develop sentiment and emotion analysis software.

Appendix – Detail of incidents identified During Pilot

UK Incidents Identified During Pilot Study

Date	Incident	Number of Posts	Source	Time
3/8/19	Sewage on Beaches Brighton East Sussex	4	Twitter 4	Post Event
5 and 6/8/19	Pollution in River Sheppey Devon	13	News 5, Twitter 8	Post event
6/8/19	Pollution in River Windrush Oxfordshire	2	Twitter 2	Post Event
11/8/19	Incident on Worthing Beach East Sussex	57	News 54, Twitter 3	12:00
11/8/19	Pollution in River Frome Somerset	7	News 6. Twitter 1	12:00
17 – 20/8 / 19	Sewage warnings for UK beaches (cornwall, devon, wales, essex)	14	News 10, Twitter 4	Multiple
25/8/19	Incident on Frinton / Clacton beaches. Essex	100	News 99, Twitter 1	15:00
28/8/19	Incident at Pontins Burnham on sea. Somerset	5	News 5, Twitter 0	Post Event
3/9/19	Sewage and oil on beach Brighton	1	Twitter 1	
15/9/19	Sewage Leak on beach Worthing	1	Twitter 1	09:00
22/9/19	Sewage in River Ilkley Yorkshire	4	Twitter 3 news 1	14:39

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Date	Incident	Number of Posts	Source	Time
23/9/19	Dead Whale washed ashore Northumberland	77	News 77	
24/9/19	Sewage Spill Cornwall beach	1	Twitter 1	18:39
26 - 27/9/19	Chemical Release Minehead Sewage works Somerset	13	News 7 & 6	15:24
26 - 27/9/19	Sewage in River Hogsmill Yorkshire	4	News 4	Post Event
27/9/19	River Bourne Pollution Wiltshire	1	Twitter 1	19:06
30/9/19	Sewage warning for beaches Cornwall and Devon	3	News 3	09:18
23 - 24/10/19	Red Tide - skin rashes (Algae)Cornwall	8	News 8	Post Event
26-10-19	Slurry Pollution River Teifi Wales	2	News 2	Post Event
30-10-19	Blue Green Algae in lake Wales	2	Twitter 2	17:00
27/9/19	Flood Alerts Wales	10	10 Twitter	02:03
28/9/19	Flood Alerts Wales	44	44 Twitter	00:18
29/9/19	Flood Alerts Wales	90	90 Twitter	00:40
25 - 27/10/19	Flood Alerts Wales	335	335 Twitter	13:00

UK Incidents not Identified from Media Searches but Reported on Response Agency Databases

Incident	Notification / Time
Chlorine gas, leisure centre, Soho, London - Level 3 HAZMAT	01/08/2019 08:23
Cockle Die-off River Dee Wales	02/08/2019 16:00
Sewage in River Yorkshire	07/08/2019 12:00
Sewage on beach – Pembrokeshire Wales	09/08/2019 16:00
Cyanide detected at water treatment works - Northumbrian Water	14/08/2019 16:20
Slurry Pollution in River Llancarfan South Wales	15/08/2019 16:00
Swimming pool HAZMAT incident, Mollington	27/08/2019 16:32
Sewage on beaches Cornwall and Devon	27/08/2019 12:00
Red Algae on beaches Northumberland	27/08/2019 12:00
Slurry pollution and fish-kill River Cefni South Wales	29/08/2019 16:00
Sewage on beaches East Anglia	10/09/2019 12:00
Potential Hydrocarbon contamination of public water supply, Slough	12/09/2019 10:21
Chlorine leak at sports centre, London	23/09/2019 15:15
Minewater release River Afan Mid Wales	30/09/2019 16:00
Blue Green Algae Talybont Reservoir Brecon Wales	15/10/2019 16:00

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