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Can we monitor the natural environment analyzing online social network posts? A literature review

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A B S T R A C T

A number of works have addressed the question of assessing the status and the $\frac{2}{4}$ quality of the environment through the lens of Online Social Networks (OSNs). These contributions fall in the area of human-centric sensing, area specialized in using what people spontaneously say on social media to detect the occurrence of given events. Research in this area has exhibited interesting results, regardless of the accuracy of sensing operations. In fact, in some cases it is possible to corroborate the information extracted from OSN posts with the ground truth obtained from specialized hardware sensors. In others, the information extracted from OSNs does not reveal true environmental conditions. Nevertheless, OSNs may help shed light on the sensitivity of human beings to a wide variety of environmental phenomena. We here review the work that has been published to this date. In particular, we provide a survey that may benefit both environmental and computer scientists, as this work aims to show where we stand in the understanding of the complex relationship between human beings and the natural environment, when this is mediated by OSNs.

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1. Introduction

Understanding the dynamics and the state of health of the natural environment has always been one of the main interests of people, in all historical times. Almost 2000 years ago, Pliny the Younger wrote a description of the eruption of the Vesuvius which is still nowadays studied by millions of students from all around the world [1]. The interest for the study and analysis of environmental dynamics is as live as ever, as new awareness for its state of health is strong, being an important component of human wellbeing [2].

Nevertheless, such type of interest roots in the one normally exhibited by people for weather forecasts, as well as in the fear which instead natural disasters or pollution hazards trigger. In fact, regardless of the specific phenomenon and where and when people discuss it, assessing the status and predicting the dynamics of the natural world, in any of its aspects, is an age-old problem of statistical inference. Even simply knowing whether it will rain or not on a short notice may attract much attention: harvesting, warfare, trips and outdoor sporting events often depend on it [3]. Before the Grand Prix, one of Formula One pilots' most-discussed arguments is the weather, as reliable forecasts are key to winning a race. Such type of interest is exacerbated when considering natural hazards and pollution spillovers whose effects can harm properties and human lives [4]. For this reason we have seen in the past decades a proliferation of different sensors aiming at quantifying specific physical phenomena [5–7]: temperature, wind speed, humidity, ozone layer thickness, chemicals' concentrations, etc. Many of such quantities are then reported by the news or specific websites, providing the population with a representation of environmental conditions and of how they may be evolving.

The reporting and discussion of any of the aforementioned phenomena has however changed since the introduction of Web 2.0 paradigms, in particular with the widespread use of Online Social Networks (OSNs) [8]. OSNs have fostered, since their birth, new lifestyles, habits and ways of communicating. Personal communications now follow a one-to-all information flow, allowing posts and comments to be read, answered and reposted by a multitude of users. In addition, posts can in principle touch upon any topics, as users can spontaneously write anything with no censorship, often acting as a human-based sensor [9,10]. All this has been exploited by many works that have appeared in the scientific literature on human-centric computing to assess the following

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idea: the big data of spontaneously shared posts, that typically exposes what a person thinks and how s/he feels and behaves, could be an interesting source of environmental related information. In essence, a person, when posting on an OSN, may reveal some information pertaining the surrounding environment, thus acting in a way that resembles how a sensor works.

We should not be mistaken thinking of OSNs as a new sensing technology, which may seamlessly be integrated with legacy ones. In fact, whenever people post information pertaining the natural environment, they throw a representation of what they perceive, rather than a measurement quantifying the magnitude of a physical phenomenon. Different people may perceive the same physical phenomenon in different ways, for a number of different reasons. A thoroughly studied example is the one related to temperature: women are more sensitive to temperature (mainly cool) and less to humidity than men [11–13]. In many cases, hence, the many existing different ways of perceiving the world may represent a source of uncertainty which is difficult to factor out.

On the other hand, it may be possible to find natural events whose perception is still strongly subjective, but also affected by how much a person feels threatened, i.e., close to given critical ecological thresholds [14]. Non-cognitive environmental aesthetics, for example, a branch of aesthetic philosophical studies, explains human reaction to these events in terms of primordial, perceptive and emotional states. In [15] the authors argue: *those…who have at heart the welfare of humans or nonhumans react to environmental degradation with dismay*, stating the existence of a shared attitude towards given classes of events. Contrasting conclusions arrive from other areas of research, however. Recent research on mass media, for instance, has observed that the media may mistakenly represent the severity or frequency of natural hazards, thus altering the way in which those events are perceived and understood [16]. In [17], the authors analyze the psychological dimensions of air pollution, revealing how its perception may be independently influenced by the 'social class' of a person and by the fact that people are reluctant to acknowledge the existence of potential risks in the neighborhoods where they live.

Nevertheless, an observation of what people spontaneously say regarding a given phenomenon, regardless of its correspondence to the ground truth measured by a sensor, can provide the research community with important insights concerning human wellbeing [2]. For this reason, unlike other surveys which take different or broader perspectives on the study of the existing body of work concerning OSN-based sensing [18–27], we here concentrate on those works that seek to assess the status or the quality of the environment. Additionally, we only look at those works that have based their findings on the analysis of spontaneous posts, as opposed to those participatory or citizen sensing initiatives which require some degree of user involvement [28,29]. Compared to the corpus of works that, instead, study the use of OSNs to enhance emergency situation awareness, we take a different perspective, as such works only focus on critical events, which may be of any kind, ranging for example from nuclear incidents, to war events, to natural disasters, in order to aid authorities during search and rescue operations [30–36]. In essence, we here provide an updated critical map and overview of what is available to this date, as well as suggestions of what may still be missing, for the benefit of data engineers and scientists, as well as for environmental scientists, psychologists, philosophers and for all those interested to understand how human beings perceive and report their perception of the environment on OSNs.

This survey is organized as follows. In Section 2 we explain how we have chosen the works that are here discussed, in addition to how we here analyze their contributions. Section 3 provides a high level overview of the analyzed body of literature, for the benefit of both technical and non-technical audiences. Technical details are analyzed in Section 4. Finally, a critical discussion is provided in Section 5, where also possible future directions of work are delineated.

2. Methods

We here describe the criteria applied to select the scientific contributions of interest and then move on to explain how such works have been grouped and compared. We also technically discuss the data science approaches employed in these works, exhibiting which have been the paths taken to detect environmental events or to measure its variables.

2.1. Literature selection

The scientific literature that has been selected and analyzed in this work fits three different requirements.

The first is the interest for some quantity related to the natural environment: either concentrating on the natural phenomena and metrics that characterize its state (e.g., storm, aurora, temperature, humidity, etc.) or on those events and variables that denote its health status (e.g., air/water/land pollution). In particular, we considered geological (e.g., earthquakes, volcanic activities, landslides, etc.), oceanographic (e.g., breaking waves, tsunamis, etc.) and meteorological (e.g., storm, aurora, etc.) events [37], as well as the quantitive variables measured within the United States Department of Agriculture Water Erosion Prediction Project [38]: solar radiation, temperature, wind speed, average dew point temperature and precipitation. In addition to the aforementioned variables, we also selected pollution-related ones.

The second is that of basing the proposed study on posts that have been spontaneously written on OSNs.

Finally, we only consider those works which compare the results obtained from OSNs to the ground truth, defined in terms of objective physical measurements (e.g., temperature value, pollution concentration value, etc., obtained from legacy sensors).

2.2. Taxonomies for the analysis of environmental phenomena

To simplify the discussion of their contributions, we apply two different taxonomies to the body of work selected in Section 2.1, adopting two different perspectives.

With the first one, which resorts to a top-down approach, we acknowledge the role that emotional reactions have in OSN-based environmental sensing. Scientific contributions have been hence classified based on the rarity and severity of the event. Natural (e.g., earthquakes) and human-generated (e.g., radioactive material spillover) hazards clearly fall in one group. Everyday ones, such as a rainy day, in another. This distinction will be adopted when discussing papers in Section 3.

With the second one, instead, we concentrate on the data categories that have been analyzed by the scientific community and on how these have influenced their results. Adopting this method in Section 4, we group scientific contributions according to the mathematical nature of the observed variable. In particular, we distinguished those works that assessed categorical variables, such as the detection of an event (e.g., thunderstorm), opposed to those which measured quantitative ones (e.g., temperature and pollution concentration values).

2.3. Data science techniques

The analysis proceeds with an overview of the initial set of data and the analysis of the algorithmic components considered in each work. To this aim, we break down our analysis in terms of the:

1. Environmental phenomenon of interest;

2. OSN data source that has been selected to observe the given phenomenon;
3. Post selection technique that has been utilized to separate pertinent posts from the whole corpus of OSN data;
4. De-noising techniques that have been implemented to eliminate any automatically generated posts, such as advertisements;
5. Post classification strategy used to remove any posts that do not meet the requirement of being spontaneous;
6. Variable detection or measurement criteria, i.e., what post dependent function is used to detect or measure the phenomenon of interest;
7. Comparison to the ground truth and performance, i.e., have specialized sensors been used to verify the authenticity of what has been detected or measured.

Per each of these seven points, we will compare the techniques that have been utilized across the different groups described in Section 2.2, highlighting and discussing any relevant differences that may emerge.

3. Literature review

Before proceeding, let us remind our review concentrates on those works which utilize the appearance of spontaneous posts on popular OSNs to reveal, detect or measure either the status or the quality of the natural environment. We deliberately ignore, hence, those works that are based on the use of specific communication channels, devoted to support participatory sensing campaigns (e.g., in [39], a WeChat-based application was developed to allow volunteers submit reports of surface water quality problem in China). Following such guideline, in Section 3.1 we focus our attention to those works that aim at the detection of natural disasters. We then move on reviewing the works that have instead concentrated on measuring weather (Section 3.2) and pollution-related (Section 3.3) variables.

3.1. Natural disasters

OSN spontaneous user posts concerning natural disasters have been exploited to detect the occurrence and location of disasters. The studies that have been carried out to this date have principally exploited Twitter to detect earthquakes, typhoons, flooding, tornadoes and landslides.

In particular, Power et al. [40] built a notification system to detect bushfires [41]. To this aim, the proposed system tracked the tweets mentioning the keyword *fire*. When the tweet count exceeded a historical baseline by a preset threshold, a potential alert event was triggered. Due to the many possible meanings of the keyword, the system resorted to a Support Vector Machine (SVM) classifier to determine the percentage of tweets that were actually associated with a fire disaster. If more than the 10% of tweets were classified as positive, a notification email was sent to subscribed crisis coordinators. In addition to time and fire locations, estimated from tweet geo-tags, the notification email also included the topics obtained from the posts to assist during the process of assessing the reliability of the information related to the fire event. The authors evaluated the system in the period June to September in 2013, and found the accuracy to be 78.6%.

Sakaki et al. built a system to monitor Japanese tweets to detect earthquakes and track typhoon paths in Japan [42]. They treated geo-tagged tweets related to earthquakes as sensor readings revealing where an earthquake was occurring. This was performed aggregating sensor readings and utilizing a probabilistic spatio-temporal model. The authors also presented the results of the evaluation of their algorithm, showing it was capable of successfully estimating the time of occurrence and the location of earthquake centers of twenty-five earthquakes during the August to October 2009 timespan. In their work the authors underlined an inherent limitation of social sensors: when earthquake centers falled in remote areas, i.e., areas where only few people live, such systems failed to provide accurate location estimates. In addition to earthquakes, they applied their methodology to estimate the trajectory of typhoons, concluding the algorithm could produce satisfactory results.

An OSN-based earthquake detector for Australia and New Zealand has been presented by Robinson et al. in [43]. Their system detected an earthquake event by examining the sudden surge of earthquake-related tweets that were published in its proximity. Differently from Sakaki et al., they determined the location of tweets mainly resorting to user profiles. While such approach helped increase the count of the tweet samples that were processed by their earthquake detector, such an approach resulted in a coarser estimation of the earthquake center location. Nevertheless, in their work the authors showed how their detector was able to achieve a precision of 0.85 and a recall of 0.77 for twenty-one earthquake events.

Middleton et al. described a real-time crisis mapping system based on Twitter tweets [44]. In particular, they compared the tweet counts related to given critical situations (i.e., flooding or tornadoes), originating from specific areas, to the the tweet counts registered in a baseline situation (no critical event is occurring). An evaluation was performed using two natural disasters: the flood caused by hurricane Sandy in 2012 and the Oklahoma tornado in 2013. The generated crisis map was contrasted with the one generated by governmental agencies. The authors showed how their method, based on the analysis of spontaneous tweets, supported the identification of highly impacted geographical areas with a fine resolution, e.g. streets and buildings.

Avvenuti et al. [45] also created crisis maps from Twitter posts, adopting a different approach. Their system first searched Twitter posts using keywords related to the natural disasters of interest, namely the 2012 Emilia earthquake and 2013 Sardegna flood in Italy. The collected posts were then processed by a SVM classifier to decide whether the posts were reporting damages caused by the cited disasters. After filtering damage reporting posts, the system applied semantic annotation to find the phrases that referred to a location. Areas with one or more filtered posts were then highlighted on a map utilizing different shade intensities to denote the severity of the damage, as reflected by the filtered post count. The authors evaluated the crisis map comparing it to the official data concerning economic loss. They found that despite a low recall for areas of low damage, their approach exhibited a satisfactory performance with precision of 0.867 and recall of 0.813 in the Emilia earthquake.

Avvenuti et al. described a real time earthquake detection system of Italy based on live feeds obtained through the Twitter Streaming Application Programming Interface (API) [46]. The authors used the live feeds recorded over a time interval of two months to fine tune the set of keywords utilized to search for posts that report earthquake events, and ended up with *terremoto* (earthquake) and *scossa* (tremor). These words were found to be the most frequently used ones by OSN users during the first-hand reporting of earthquakes. After further noise removal, they developed a C4.5 classifier to determine whether a tweet were related to an earthquake in progress. They reported their classifier achieved a high accuracy (over 90%). Next, they fed the filtered posts to a burst detection algorithm. The algorithm was capable of detecting earthquakes of a magnitude $>$ 3.5, with a precision of 0.75 and a recall of 0.82.

Several researchers in the field of geophysics have used Twitter posts to improve the estimation of ground shaking intensity after earthquakes. Shaking intensity, measured with the Modified Mercalli Intensity scale (MMI), measures the observed effect of an earthquake on a scale of 1 to 12. The shaking intensity in a site of interest depends on earthquake-based features, for example, the moment magnitude, its distance from the epicentre, and other geological factors. Using geo-tagged earthquake-related Twitter posts published 10min after 86 significant earthquakes that happened in Japan in 2011 and 2012, Burks et al. [47] applied a regression model to estimate shaking intensity. They showed that, by combining text features of Twitter posts with earthquake-based features in regression models, it was possible to decrease the Mean Square Error (MSE) of the estimated shaking intensity from 1.88 to 0.99.

Kropivnitskaya et al. also found similar improvement of MMI estimation using social sensor data. In [48], they considered the post frequency (tweet / min) of the tweets that mentioned the keyword *earthquake* in various human languages, collected 10 min after several earthquakes in the South Napa earthquake in Californa, US, in 2014. When compared to MMI estimation based on only seismic sensor data, they showed that the addition of OSN data could reduce the Root Mean Square (RMS) error from 2.9 to 0.58 MMI units. They further corroborated their approach in [49] using data relative to8 more earthquakes which occurred in the United States, Japan and Chile in 2014.

Musaev et al. described a global landslide detection system which integrated physical sensor readings of seismic activity with rainfall and social sensor readings from Twitter, Instagram and YouTube [50]. Social media posts were first crawled by searching for the keywords *landslide* and *mudslide*. After removing noise, the posts were geo-tagged matching location names with titles of geo-tagged Wikipedia articles. The system was then used to estimate the probability of landslides in small square cells of 2.5 minutes, using a confidence weight to combine various sensor readings. The confidence weights were calculated based on the reliability exhibited by each type of sensor in detecting landslide events in the training set. Their system achieved a precision and a recall of approximately 0.8, and was able to correctly detect forty-two landslides occurring in different parts of the World in October 2013.

For the sake of completeness, we here briefly review a body of works that did not aim at detecting natural disasters resorting to OSNs, but rather concentrated on understanding the awareness and behavior of OSN users during such events. Ripberger et al., for example, measured public attention to severe weather conditions in response to the release of weather information by comparing the daily Twitter posts that contained the keyword *tornado* with the number of tornado watches and warnings released by public authorities [51]. The authors found a strong positive association between the post count and the issuance of the weather information. Lin et al. studied the repost behavior of Twitter and Weibo during extreme weather events, finding that the percentage of reposts was doubled during the events they considered [52]. De-Longueville et al. studied Twitter posts during a forest fire event in South of France in July 2009. They collected the posts by searching for the keyword *incendie* [53]. They observed that more posts were published when the fire approached densely populated areas and when the fire was commented in headline news. On the other hand, only a few posts appeared during night time. Vieweg et al. and Verma et al. examined the posts that appeared on Twitter during the Oklahoma grassfires in 2009, the Red River Floods in 2009 and 2010, and the 2010 Haiti earthquake, finding that more geolocation information was shared in relation to such events, while aiming at extracting tactical information from such tweets [54,55]. When analyzing the behavior exhibited during grassfire events, the authors speculated that people may be more concerned about their location because such hazard may hit populated areas in unforeseen manners, depending on the wind direction. On the other hand, the regions that may be affected by floods may be more easily inferred from previous floods. Wang et al. focused on the temporal and spatial evolution of Twitter posts during an interval of time where nine wildfires developed [56]. They collected tweets containing the keywords *fire* and *wildfire*, and noticed that the peak of daily post count appeared on the day of the outbreak of six wildfires. They also found that the greatest number of posts related to a given wildfire would appear the day after its outbreak. They justified such time lag observing that it took time for the distribution of information through the OSN. Finally, Murakami et al. performed a topic analysis via text mining of Twitter posts for an earthquake and tsunami which occurred near Japan in 2011. With their work, they were able to identify shortage of supplies and the occurrence of frauds as a consequence of the disasters [57].

3.2. Weather

Weather information, e.g. temperature, wind speed and rainfall are generally easily available in highly-populated areas. Although there may be no particular incentive to develop OSN-based systems to detect weather conditions in such locations, such idea has been widely explored by the scientific community, which has been capable of exhibiting the existence of high correlations between OSN posts and weather conditions.

Lampos et al. proposed a methodology to estimate the occurrence and magnitude of an event [58]. As a benchmark, they investigated the effectiveness of their system for determining the levels of rainfall from Twitter tweets for five UK cities for one year. Their system unveiled the correlation between text features in tweets and the daily rainfall amount using a statistical learning framework. When compared to the rainfall levels sensed by traditional weather stations, their system achieved a RMS error of 2.602 mm.

Li et al. analyzed peoples mood, as reflected by tweets, against weather conditions, suggesting mood may be a interesting indicator as it is in general affected by weather conditions [59]. In their work the authors showed how, according to the tweets that their system processed, people were likely to feel happier for a mild drop in temperature, but uncomfortable for a sharp drop. They also showed the possibility, utilizing OSNs, of detecting the negative effect that rainfall and snowfall have on peoples moods.

Lee et al. studied the problem of detecting actual allergy incidents from tweets, and examined the number of incidents against weather conditions from authoritative sources [60]. Analyzing tweets, they could observe the increase of allergy incidents in correspondence of high temperatures, resorting to allergy-related tweet counts.

3.3. Pollution

While pollution may hit any of the elements that constitute the Earth, the works that exhibit the characteristics sought in this review all concentrate on air pollution. Works that consider other Earth environments exist (e.g., [39]), but we found they resorted to custom applications specifically developed for the given task, rather than to OSN sites containing spontaneous and generic posts.

3.3.1. Air pollution: $PM_{2.5}$ and PM_{10}

Several works have put their focus on sensing major pollutants in air pollution. Their work showed that human reactions in social media exhibit a high correlation with the concentrations of respirable suspended particles PM_{10} and fine suspended particles $PM_{2.5}$. Typically, the works first determined a suitable dictionary for selecting pollution-related OSN posts, and then examined the correlation of the count of pollution-related posts with ground-truth values from weather stations.

Wang et al. studied the correlation between Sina Weibo posts and daily $PM_{2.5}$ values in 74 cities in China [61]. They first discovered two common topics in the OSN posts, namely *air quality* and *pollution* by running a topic clustering algorithm on the posts that contained the bootstrap terms *pollution, air, breathe* and *cough*. Next, the top twenty-five terms in the two topics were added to a dictionary. They then counted the number of Weibo posts that contains words in the dictionary per day. The daily post frequency was then verified to have a high correlation with the average $PM_{2.5}$ values in the selected cities, where Pearson correlation values were recorded as high as 0.718.

Another line of works applied different approach to build the dictionary and examined the correlation between OSN posts and $PM_{2.5}$ values on a finer temporal and spatial granularity.

Tse et al. studied approximately 1,500,000 Weibo posts uploaded during a period of one year in 2012 in five Chinese cities, Hong Kong, Guangzhou, Beijing, Chengdu and Shanghai [62]. They found that a manually constructed dictionary could exhibit a higher performance to classify pollution-related posts, compared to machine learning algorithms (namely Naive Bayesian classifier and Support Vector Machine). Running a fine grained correlation analysis (city district, period two hours), they observed a strong tie between the pollution levels ($PM_{2.5}$) provided by pollution measurement stations and the post count recorded within two hours and a distance of five from the sensors.

Such work has been further extended by Sammarco et al. in [63]. In particular, the authors examined Twitter posts published in Paris, France and Sao Paulo, Brazil during the March-April 2016 timespan and Weibo posts collected from October 2012 to April 2014, for a group of Chinese cities. With their work they were able to confirm the existence of a direct relationship between the count of OSN posts and $PM_{2.5}$ and PM_{10} concentration values, as provided by specialized sensors. In addition, this work pointed out the necessity of building keyword dictionaries which reflected existing cultural differences and pollution perceptions across different nations.

3.3.2. Air Quality Index (AQI)

Governments often use the Air Quality Index (AQI) to inform the citizen the level of air pollution [64]. Although its definition may vary from country to country, it usually accounts for how air pollutants may induce adverse health effects. High AQI values indicate that the population may be at risk.

Mei et al. applied text mining techniques to examine the Weibo posts that were written during one month at the end of 2013 [65]. In their work, the authors resorted to a bag-of-words (BOW) vector approach to account for the number of posts published within a given city. They then applied a linear regression model to assess the degree of correlation of the obtained feature vectors with the daily AQI values provided by the Ministry of Environmental Protection of China. They showed how with such an approach they were capable of obtaining a satisfactory performance, with an overall AQI error below sixty. In particular, the regression model never confused a highly-polluted day as a day with good air quality. The authors also pointed out an additional important result that was obtained. With their regression model, words like *haze* or *pollution* were associated to positive weights, whereas words like *sunny* and *cold* to negative ones: in essence, such approach was capable of detecting positive and negative signals from Weibo posts.

Jiang et al. inspected the pollution-related Weibo posts which appeared in 2012 and 2013 and found a high correlation between the number of posts that mentioned the keyterm *air pollution* and the AQI of Beijing [66]. In particular, after removing posts about indoor air pollution, advertisements and retweets they obtained Weibo posts from individual users expressing their observation or feeling concerning air pollution. The number of daily individual messages was found to be strongly correlated to daily AQI values. In addition, pollution-related posts, where a positive feeling emerged, were found being negatively correlated to AQI values. Accordingly, when a negative sentiment could instead be recorded, high AQI would be in general observed, exhibiting a correlation computed over one year with a Pearson coefficient of 0.62.

In [67], the authors developed a smog disaster forecasting system termed B-Smog. The system utilized both OSN data and physical sensor data to forecast smog disasters. The OSN data used by B-Smog amounted to the *smog opinion* that could be recorded from posts, amounting to the percentage of Weibo posts that mentioned good weather and the percentage that instead used the term smog. As ground truth, the work treated an increase of AQI above 150 as the appearance of a smog disaster. The system exhibited an acceptable performance when tested for 12 hours in Beijing, China, exhibiting a precision and recall above 0.8.

Tse et al. [69] applied a non-negative matrix factorization technique to reveal the relationship between the discussion of weather, outdoor activities and traffic congestion on Weibo. This has been performed applying a Granger causality test, applied to the time series of the daily frequency of posts containing keywords related to the aforementioned topics.

Finally, Tao et al. inspected the terms that were most commonly used to describe air quality in four megacities in China. The regression performed on bigrams in Weibo posts and daily $PM_{2.5}$ values revealed that the terms with strongest correlation were different among the cities [70]. For example, *misty foggy* had the largest positive correlation in Beijing, while *dust-haze* in Guangzhou.

4. Technical review

In this Section we will consider the same works that have been presented in Section 3, from a more technical angle. In particular, we will compare the aforementioned works, highlighting their commonalities, as well as their differing points, summarizing the findings of such discussion in Tables 1 and 2.

4.1. Natural disasters

Existing works in natural disasters detection typically treat a sudden increase in OSN post frequency within a short-term temporal window as a trigger for alert. However, irrelevant posts and social interaction posts often skew the increase of post frequency and affect the accuracy of the detection systems. Therefore, researchers often apply several phases to gradually filter the collected OSN posts to spontaneous posts reporting that some target event is in progress. In addition, to determine the location of the target event, detection systems usually need to either restrict the post collection to a certain region, or use post metadata or textual content to group the posts collected in smaller regions. We discuss such workflow resorting to the organization shown in Fig. 1 and explained, point per point, in the following:

1. *Select event related posts*
   Detection systems typically first collect posts related to target events using a public API of the given OSN, e.g. Twitter search API. Such public APIs usually allow their users to specify search keywords and location restrictions. Existing works take advantage of this API interface and restrict the search scope with a few bootstrap keywords, e.g. *earthquake* and *flooding*. The location of the target events can then be further limited by setting a circular scope around a geolocation, specifying a local, or selecting bootstrap keywords in certain languages.

Table 1
Comparison between works on disaster detection.

Phenomenon (location) [ref]	Location source	Geolocation output	Real time	Ground truth comparison
Bushfire (Australia and New Zealand) [40]	Post geotag	City, urban area	Yes	Yes
Earthquake, typhoon (Japan) [42]	Post geotag	Earthquake center, typhoon trajectory	No	Yes
Earthquake (Australia, New Zealand) [43]	User profile	City or larger region	No	Yes
Earthquake (Italy) [46]	User profile	–	Yes	Yes
Earthquake and flood (Italy) [45]	Post content	City, municipality	No	Yes
Earthquake (Japan) [47]	Post geotag	Latitude, longitude	No	Yes
Earthquake (US, Japan, Chile) [48] [49]	Post geotag, link to city, post content	City	No	Yes
Flood (US) [44]	Post content	Street / building	Yes	Yes
Landslide (global) [50]	Post content	Latitude, longitude	No	Yes

Table 2
Comparison between works on weather and air pollution.

Reference	OSN	Inferred measure (granularity, location)	Finding
[58]	Twitter	rainfall (daily, UK cities)	Estimated rainfall with RMSE $<$ 3 mm
[61]	Weibo	$PM_{2.5}$ (daily, China cities)	High correlation, Pearson coefficient 0.718
[62]	Weibo	$PM_{2.5}$ (2 h, districts in Hong Kong and Guangzhou)	Small increment in post count implies raise of minimum $PM_{2.5}$ and PM_{10}
[63]	Twitter	$PM_{2.5}$, PM_{10} (2 h, Paris and Sao Paulo)	
	Weibo	$PM_{2.5}$, PM_{10} (2 h, China cities)	
[65]	Weibo	AQI (daily, China cities)	AQI error $<$ 60
[66]	Weibo	AQI (daily, China cities)	High correlation, Pearson coefficient 0.62
[68]	Weibo	AQI (2 to 6 h, Beijing)	Acceptable forecasting of smog (AQI $>$ 150) over 12 h

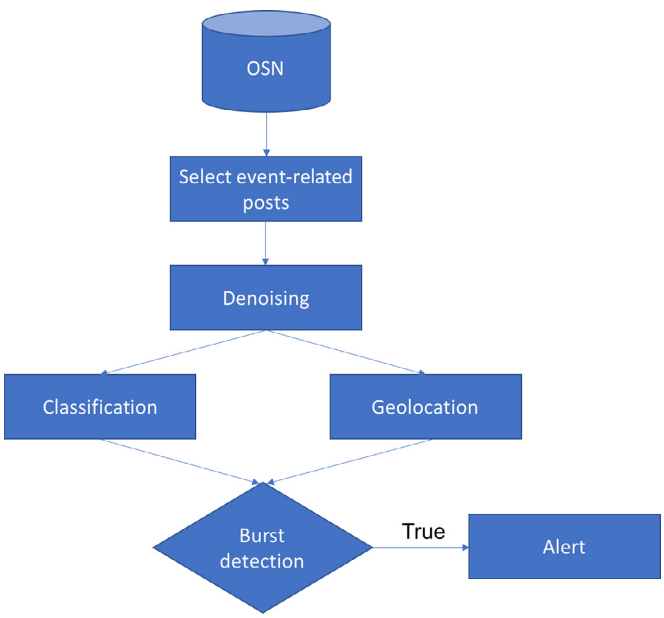

Fig. 1. Workflow of disaster detection systems.

2. *Denoising*
Post forwarding actions, links to publications in traditional media, and other types of posts collected from OSNs may skew the frequencies of event-related posts. To overcome such type of problem, researchers usually apply noise reduction actions specific to the OSN etiquette and user culture. Social interaction posts (e.g., retweets) and app generated posts can be simply removed resorting to substring matching. Forwarding posts of articles from traditional media can be removed by matching URL patterns. In some systems, stop-words or stop-phrases are also used to disambiguate different meanings of bootstrap keywords.
3. *Classification*
Depending on how much noise has been removed in the previous step, the filtered posts may include several kinds of posts that will affect the detection of disaster events. These include second-hand reports of an on-going event, any comments on newspaper articles made by users that are distant from the event of interest, discussions regarding a past event and even posts that are totally unrelated to the disaster, caused by the multiple different meanings of the bootstrap keywords. To improve the accuracy of the burst detection step, some researchers apply supervised learning techniques based on text features to identify event reporting posts. They usually examine posts in a training set and classify whether the posts are first-hand reports of a target event in progress. Typical text features include the length of posts, their originating position and the context of the keywords, the punctuation and the presence of any slang/offensive words. Some researchers use a training set of damage reports in a high impact disaster (e.g. [40]), while other researchers observe that emotion expression is common in disaster witnesses and therefore include sentiment analysis features in the classification model (e.g. [45]).
4. *Geolocation*
Only a small percentage of OSN posts include accurate geo-location information obtained from the GPS sensors of a mobile device. To estimate the location of the users who observe and/or report a disastrous event, a few works use the location information published in the user profile of OSN. Some other works perform reverse geocoding of location names in post content, utilizing geocoder services available from online maps (e.g. [44]), name matching with volunteered geographic information systems (e.g. [44]) and semantic annotation (e.g. [46]). Geolocations are then used to either further filter the OSN posts, or group the posts into different bins, before running burst detection.
5. *Burst detection*
Burst detection algorithms are used to determine the time of occurrence of a disastrous event. With this step a system triggers an alert if it detects a sudden surge in post count within a short-term temporal window, possibly after performing a comparison with the post frequencies stored in historical records.

4.2. Weather and Air Pollution

In general, all the works that have been here reviewed attempt to establish a correlation between OSN posts and a numerical

Table 3
Technical approaches taken in works regarding the estimation of weather and pollution-related quantities.

Reference	OSN	Inferred measure	Resolution & location	Technical approach
[58]	Twitter	Rainfall	Daily, UK cities	Regression with text features
[61]	Weibo	$PM_{2.5}$	Daily, China cities	Regression with filtered post frequency
[62]	Weibo	$PM_{2.5}$	Two hours, city district in HK and GZ	Regression with filtered post frequency
[63]	Twitter	$PM_{2.5}$, PM_{10}	Two hours, Paris and Sao Paulo	
	Weibo	$PM_{2.5}$, PM_{10}	Two hours, Chinese cities	
[65]	Weibo	AQI	Daily	Regression with text features
[66]	Weibo	AQI	Daily	Regression with filtered post frequency
[67]	Weibo	AQI	NA	Sentiment analysis

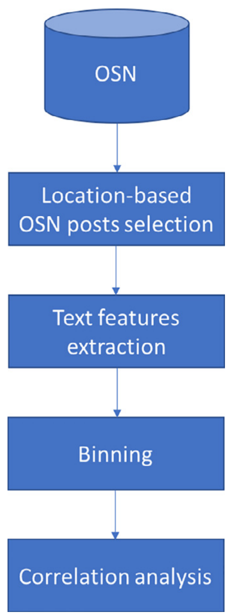

Fig. 2. Workflow of weather and pollution measurement systems: Text features regression approach.

measure of the atmospheric conditions, including rainfall, $PM_{2.5}$ or PM_{10} concentration, and AQI. Compared to the approaches that have so far been seen for the detection of natural disasters, obtaining an estimate of the intensity of some environmental measure requires more information. Therefore, the works that are here reviewed attempt to extract more features from OSN posts.

To this aim, three prominent approaches may be individuated, all which take advantage of text features of OSN posts to estimate numerical measures of the natural environment, while striving to mitigate the inherent high amount of noise from social media (Table 3). We discuss these three different approaches in the following Subsections:

4.2.1. Text features regression approach

With this approach, little o no filtering steps are generally performed on the collection of OSN posts. Instead, machine learning methods are used to include more features from the posts, including ones with positive and negative effect on the inferred measures. It is hence possible to individuate the following steps (Fig. 2):

1. *Location-based OSN posts selection*
   Researchers typically collect OSN posts by searching posts published in a certain region. The locations where posts are published are determined either from geotags or from the location declared in the user profile. Usually no keywords are used to limit search results, allowing to consider more content in later steps.
2. *Text features extraction*
   Words and phrases in posts are then used to infer the intensity of the observed phenomenon. For example, *heavy rain, drizzle* and *sunshine* represents a spectrum of rainfall. Methods in text feature extraction are language-specific. In [58], 1-grams (e.g. *rain*) and 2-grams (e.g. *light rain*) of words from weather-related Web resources are used. After removing rare 1-grams and 2-grams in the collected Twitter posts, the authors found 2,159 1-grams and 7,757 2-grams. In [65], Chinese segmentation was applied to split Weibo posts into words, each consisting of one or more Chinese characters. These words deliver a more precise meaning than an individual character.
3. *Binning*
   The posts are then aggregated into a virtual document according to the granularity of the inferred measures. For example, [65] combined the daily posts published within 10-km distance from a city center into a virtual document to infer the daily AQI of the city. Such virtual document takes a bag-of-words representation, as the context of Chinese characters or English words have been partially handled in the previous step.
4. *Correlation analysis*
   The last step correlates the virtual document, obtained during the *Binning* step, with the target measure one wants to infer, using regression algorithms. For example, the authors of [58] used an ordinary least squares (OLS) regression and were able to estimate rainfall with a low error (RMSE $<$ 3 mm). In the cited work, the regression algorithm could also learn the intensity of rainfall from phrases which were there used as weights, e.g. *pour rain* resulted having a weight of 2.708, *umbrella* a weight of 0.229, whereas *rainbow* a weight of −0.294 in the utilized Twitter corpus. Similarly, a regression approach adopted in [65] generated the largest weight for the Chinese translation of *haze* for estimating AQI, while *sunshine* returned the smallest (negative) weight.

4.2.2. Filtered post frequency regression approach

Another approach utilized to estimate a numerical measure of a given environmental variable amounts to correlate such measure with the OSN post count. The intuition is simple and may be explained with the following example. As the air quality deteriorates, more people are expected to talk about the air quality situation and hence mention pollution-related terms on OSNs. Therefore, a key step of such approach is to select OSN posts that are in some way related to the target environmental status. Hence, after a first step which, just as in Section 4.2.1, aims at collecting posts close to the monitored location, the steps that follow are (Fig. 3):

1. *Collect environment-related posts*
   Various attempts from existing works fall into two broad categories:
   (a) *Build dictionary*
   Existing works first identify the vocabulary used by the OSN users to discuss a phenomenon, and then collect

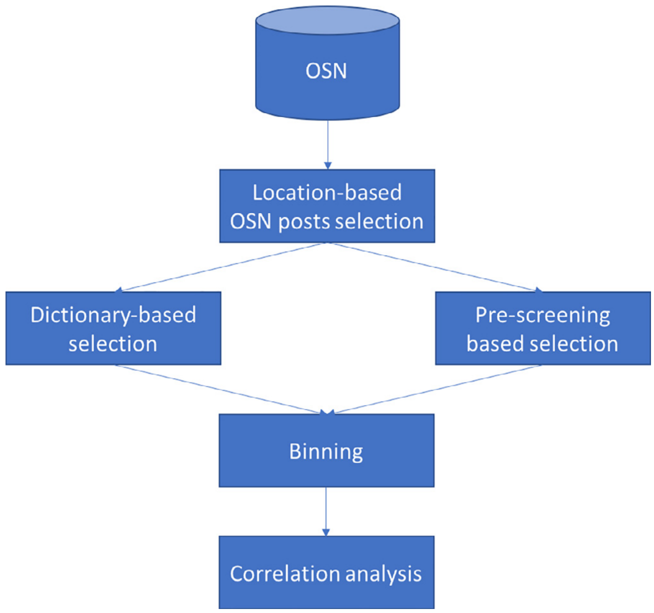

Fig. 3. Workflow of weather and pollution measurement systems: Filtered post frequency regression approach.

OSN posts by searching for its keywords. Wang et al. used Latent Dirichlet Allocation (LDA) to create topic models from messages containing bootstrap terms *pollution, air, breathe* and *cough* from Weibo [61]. They identified two common topics, namely *air quality* and *pollution*, and subsequently added the top twenty-five terms from the two topics into the dictionary. Tse et al. found that a carefully curated dictionary which included most common terms about pollution, traffic, weather and health could outperform a dictionary generated by machine learning methods [62,63]. They also pointed out the importance of preparing dedicated dictionaries per geographical area from their experiments performed for cities across three continents.

(b) *Screening*
Jiang et al. applied a different approach to collect environment related posts [66]. The authors first search Weibo posts with the bootstrap keyword *pollution*, utilized by users in Beijing. They then remove posts about indoor air pollution, reposts, advertisements and app generated posts.

2. *Binning*
OSN posts are then grouped by their location and time to match the granularity of the sought measure, e.g. daily AQI of cities. Researchers in [61] and [66] analyzed the AQI of cities, selecting posts from the location declared in user profiles. Researchers in [62] and [63], on the other hand, correlate the number of pollution-related OSN posts published in a given area with the pollution levels of that area, as obtained by local weather stations. To do this, they select those posts which contain geotags falling within a certain distance from the selected weather station.
3. *Correlation analysis*
Wang et al. compared daily post counts with AQI values, finding Pearson correlation indices up to 0.718 [61]. Jiang et al., instead, applied Gradient Tree Boosting to the daily frequency of posts with positive and negative sentiment to estimate AQI in Beijing [66]. They were able to infer AQI with an error < 30. In [63], the authors evaluated an ARMA model to predict the $PM_{2.5}$ values with a good precision from the frequency of OSN posts related to pollution.

4.2.3. Regression with sentiment

Another approach that has potential to improve the collection of environment-related posts is sentiment analysis. In their work to estimate AQI, the authors of [66] discovered that counting only posts with negative sentiment can further improve the correlation between post count and AQI. They commented that when the air quality is good, OSN posts may include cheerful comments for *no air pollution*. In [67], the authors integrated both social sensor and physical sensor data to predict smog appearance. One of the social sensors that are used is people's positive and negative feelings towards air quality.

5. Discussion

The works analyzed in this paper provide an overview of the state of the research on the detection and measurement of natural environment variables through the lens of OSNs spontaneous posts. Through such overview, it is possible to make a few considerations which may lead future research efforts and discussions.

From the point of view of the environmental phenomena that have been observed, it is possible to individuate the following trends. Most of the works, published to this date, related to the detection of natural disasters with OSNs have concentrated on earthquakes. Very little has instead been found related to the reporting of normal weather conditions, whereas much work has instead been carried out on the analysis of air pollution. The analyzed works, in addition, all point how earthquakes and polluted air conditions trigger distinct behaviors, with respect to OSN posting. When an earthquake occurs, in fact, this typically leads to the writing of very specific messages, that normally do not deviate from the use of two or three words related to the event, regardless from the specific region, and hence cultural characteristics of the person that writes the post. With severe pollution conditions, instead, terms that are indirectly related to pollution have been recorded, rather than to directly mentioning the word pollution. In fact, different works have independently, for example, concluded the existence of a strong relationship between the use of the term *haze* and the presence of high levels of $PM_{2.5}$.

In addition to showing how people react in correspondence of events of different nature, it has also been possible to observe how different OSN posting behaviors lead to different detection strategies. The works that have considered the detection of earthquakes have exploited the general behavior, focusing on the appearance of the few terms that appear when such event occurs. The measurement of air particulate matter levels has, instead, led to different approaches, ranging from the use of dictionaries to the use of learning algorithms to detect any relevant posts. Such an approach directly derives from the different, and more diverse, response that has been recorded in terms of people's reaction to high pollutant concentration values.

This literature review also shows how, so far, research efforts have mainly individuated two OSNs as viable sources of data for environmental data: Twitter and Weibo. Such microblogging sites, in fact, respond to the basic requirement of containing posts that are publicly available and hence analyzable by the research community. However, these do not clearly represent the only possible sources of data that might be interesting to reach relevant results. Other sources of relevant textual posts may be, in fact, available. In addition, the works that have been considered only concentrate on the analysis of text, ignoring any visual one. Images could, in fact, represent a source of valuable data for the assessment of the environment's status and quality. Images and videos could also represent a way to extend the number of monitored variables, especially considering pollution ones (e.g., include also water and soil pollution).

Finally, the overview that is here provided obviously suffers from the intrinsic bias due to the sole use of OSNs as the only source of environmental information. Such information is, hence, necessarily concentrated around more densely populated areas, places where people use such platforms in a pervasive way. In addition, the works that are considered are limited in terms of language variety, as only English, Chinese, Italian, Portuguese, Japanese and French are used, indicating that a wider and more deeply cross-cultural analysis is required in order to better understand the potential of such research.

6. Conclusion

This work filled the void, to the best of the authors' knowledge, of surveys reviewing the state of the art of research investigating OSNs as human-centered observation points of the natural environment. In fact, we analyzed those works which focus on how people communicate their perception of the natural environment on OSNs, including both extraordinary (e.g., earthquake) and common natural events (e.g., rainy day). In addition, we examined the growing body of works which aim, instead, at returning a picture of the quality of the environment, as depicted by OSN posts.

This survey may benefit different applications and fields of study, including emergency response, human wellbeing and environmental monitoring studies, just to mention a few examples. Concluding, we believe this review also serves the purpose of providing a first portrayal of a trend that cannot but evolve in time. In fact, from a methodological point of view, while this line of research started focusing on the task of event detection, it is now including, more and more frequently, an estimation of the consequences of such events. In addition, living in times, where more and more people understand the need of managing the planet's resources, OSNs are giving an ubiquitous voice to an awareness that has picked up momentum in the past decade. We hence expect a growing body of complex data related to the environment will be available through OSNs, data that will be useful as long as researchers will be providing means of collecting and interpreting it.

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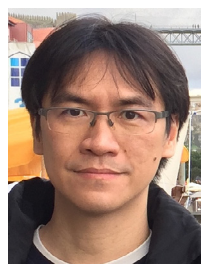

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