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Review Article

Integrating strong-motion recordings and twitter data for a rapid shakemap of macroseismic intensity

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ABSTRACT

Rapid estimation of the intensity of seismic ground motions is crucial for an effective rapid response when an earthquake occurs. To this end, maps of updated grond-motion fields (or *shakemaps*) are produced by using observations or measurements in near real-time to better constrain initial estimates. In this work, two types of observations are integrated to generate shakemaps right after an earthquake: the common type of data recorded by physical sensors (seismic stations) and the data extracted from social sensors (Twitter), or the combination of both. We investigate an approach to extract an approximation of the macroseismic intensity from social sensors 10 min after the earthquake; the approach relies on Twitter feeds to define the "felt area" where the earthquake was felt by the population, and the "unfelt locations" where the earthquake was not reported. Two recent earthquakes in France of moderate magnitude are studied and the results are compared to the official macroseismic intensity maps for validation. For the two studied cases, we note that Peak Ground Acceleration recordings far from the epicenter tend to underestimate the entire macroseismic field, and that the tweets from "felt areas" are complementary for a better estimation of the intensity shakemap. We highlight the importance and the limits of each type of observations when generating the seismic shakemaps.

1. Introduction

Earthquakes may affect very large areas within seconds, and can be felt over tens of thousands of square kilometers. Being unpredictable, they put crisis managers in difficulty, since it is very difficult to quickly establish the intensity of a seismic event: depending on its earthquake rupture, the soil conditions, the building topologies and the presence of any unstable condition, an earthquake can indeed be felt very widely without causing significant damage, or on the contrary, be felt only at a moderate distance, but with significant damage in the epicenter area. Thus, depending on the intensity of the earthquake, it generally takes authorities between 24 h and several days to have a clear view of human balance tolls [1]. In this context, rapid estimation of the intensity of ground motions is an important issue, which is the first essential step to rapid loss assessment. These maps, referred to as a *shakemaps* [2], can be produced different seismic intensity measures (IMs). Besides the intrumental IMs such as peak ground acceleration and velocity (PGA & PGV) and spectral accelerations (SA), macroseismic intensity (MI) is also widely used. Indeed, quantifying the severity of the earthquakes on the basis of observations of human perception (felt), and of the effects on the buildings (damages) and the environment, macroseismic intensity scales (e.g. EMS-98 european scale: [3]; Modified Mercalli intensity scale - MMI [4]): have the strong advantage to be understandable by a large audience, thus allowing to share shakemaps with crisis managers and the general public.

Ground Motion Prediction Equations (GMPEs) are used to roughly estimate the amplitude of seismic ground motion and are thus useful to generate the shakemap. They relate a ground motion parameter to a set of explanatory variables describing the earthquake: the seismic source (magnitude and faulting mechanism), the geometric spreading (distance attenuation), and the local site characteristics [5]. When deriving shakemaps, IMs predicted by these GMPEs are then conditioned by the values of collected field observations, taking into account the spatial correlation between the IMs at different locations (e.g. Ref. [6], with the aim of estimating ground-motion fields with enhanced accuracy).

These field observations can either come from *physical instrumental*

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sensors or from *social sensors*. In the first case, these are measurements recorded from seismic stations (e.g., broadband seismometers, accelerometers) and expressed in terms of PGA/PGV/SA/etc. Available within seconds after an earthquake. These punctual observations provide exact measurements of an instrumental IM at specific points of interest, and they can be used as proxies to derive MI values using Ground Motion to Intensity Conversion Equations (GMICEs). In the second case, these are observations of the effects of the earthquake, allowing a direct estimate of the MI at the scale of a district or a municipality. Ideally, MI is estimated using field observations to assess the level of damage to the buildings by type of vulnerability, supplemented by macroseismic questionnaires filled out by authorities having a vision of the average effects on their territories (e.g. mayors of affected municipalities). As this process is very time consuming, online testimonial procedures by the general public have been in place for about twenty years, such as the Did You Feel It (known as "*DYFI*") questionnaire from the US Geological Survey or the one from the European Mediterranean Seismological Center (EMSC). In France, the French Central Seismological Office (BCSF) offers its own questionnaire. These online questionnaires allow the rapid collection of numerous testimonies, and the estimation of the level of intensity in less than 1 h. In the spirit of the "*DYFI*" reports, EMSC has developed a testimony system based on "thumbnails" within its LastQuake application [7]; it visually represents the effects linked to different levels of MI [8], hence it facilitates rapid collection of testimonies via mobile devices. Today, the community of LastQuake users in some countries is considerably large that the spatio-temporal analysis of application launches allows automatic detection of earthquakes as well as a first characterization of the macroseismic field [9]. If these initiatives based on the voluntary collection of individual testimonies allow a relatively rapid estimation of the lowest intensity levels of the order of 3–4, the assesment of higher intensities linked to damages (i.e. greater than 6) remains difficult [10]. This is due to *(1)* the level of information required for the estimation of these intensities (statistical estimate of damages to buildings together with a qualification of its vulnerability), and to *(2)* the effect on populations exposed to such levels of ground motions, who are generally frightened, and take much longer time before testifying (cf. "Doughnut Effect" suggested by Ref. [9]).

In addition, thanks to social sensors based on the principle of "crowd-sourcing" (i.e., proactive involvement of citizens), it is also possible to set up "passive" contributions based on social media monitoring. Hence, after observing that the collection rate of tweets during the first hour after the occurrence of an earthquake was much faster than that of *DYFI*, Crooks et al. [11] demonstrated that the Twitter platform could be used as a valuable "Distributed Sensor System". Therefore, social media can be valuable for rapidly assessing damage during large-scale disasters, and thus can be part of social sensors reporting an earthquake [12]. In particular, messages posted publicly on Twitter, known as 'tweets', published by the users and related to earthquake events can be rapidly collected and analyzed. However, social media data raises important challenges regarding information extraction, requiring researchers to design sophisticated methods for extracting useful knowledge from the noisy data: social media feeds do not explicitly and purposefully contribute to disaster detection and analysis (e.g. Ref. [13]). Hence, we refer to the exploitation of such social media as crowd-harvesting. Previous studies have shown positive links between Twitter data collected within 10 min after the earthquake and earthquake detection and intensity estimation [14–17].

In this paper, we highlight the need and the importance of the different types of observations to assess the shakemap at different stages following an earthquake. Considering the need to quickly collect reliable observations when an earthquake occurs, instrumentally recorded IMs like PGA, when available, are the quickest observations that we can collect within less than 1 min. Later, social sensors provide complementary information about the shaking's spatial distribution and intensity. Twitter, for example, can provide us with the MI (or minimum intensity at "felt areas") through the analysis of published data, within 10 min. Then, *DYFI*-like reports provide more detailed information about MI thanks to crowd-sourcing at a later stage. However, these data arrive gradually several hours after the earthquake, and provide better but still uncertain values of MI. In the following, the MI map generated from the processing of all of the available macroseismic information – several months after the earthquake – is considered as the reference intensity to compare and validate our computation of shakemaps.

In this work, we aim to generate shakemaps right after an earthquake while including social media data, in the hope that such social sensors may complement the information obtained from instrumental sensors. The social sensors, which provide only a sparse and uneven spatial coverage, are not accurate measurements, but rather an approximation of the MI. Practically, our approach relies on Twitter feeds to define the "felt area" where the earthquake was felt by the population, and the "unfelt locations" where the earthquake was not reported by the tweets, and then considered as unfelt. Both these positive and negative proofs of the feeling of earthquakes are defined by analyzing the tweets posted within 10 min after an earthquake, as described in Section 2. Then, in Section 3, data from the various sources (seismic stations and Twitter) are combined using Bayesian Networks to update prior estimates of ground shaking, as well as providing an assessment of the related uncertainties. Two earthquake events of magnitude 5.2 that occurred recently in France are studied in Section 4: we investigate how the detection of felt and unfelt areas and the combination with ground-motion recordings can enhance the prediction of the distirubtion of macroseismic intensity.

2. Twitter as a real-time social seismic sensor

2.1. A global social network to monitor earthquakes around the world

Social media possess and broadcast data of millions of connected social sensors that share events online on a daily basis [18]. When a natural disaster occurs, social media platforms allow sharing testimonies spontaneously and quickly, mainly coming from those citizens being affected by the event [16]: these 'local citizens' tend to exchange information related to their own perception of ground-motions or of visible impacts [19], while people not present in the affected area tend to relay this information or to express their empathy [20]. However, when the risk becomes very high, the amount of information coming from the 'local citizens' affected by the event decreases sharply because of an opportune self-protection behavior [8,16].

Twitter has over 321 million active users in 2020 (TIZ, 2020), with practical features such as short messages publication in real time, free streaming Application Programming Interface (API) making it possible to automate monitoring tasks, ability to attach pictures and to share GPS geolocation, etc. Researchers have observed a strong and immediate spread of tweets when a significant earthquake happens [16,21]. For example, the Amatrice earthquake of Mw 6.2 (Italy, August 2016) has caused more than 150,000 tweets in the first 48 h [22]. Twitter is now considered as a social sensor for natural hazards, by allowing shared access to live data streams.

Nonetheless, continuous monitoring of Twitter addresses important challenges. First, we need to set up and maintain a robust IT infrastructure connected to the Twitter's servers through the free public API. Second, we need to retrieve the tweets satisfying specific search criteria, usually via keywords, taking into account the constraints associated with free language. Targeted queries should be defined to be generic enough to capture a maximum of tweets dealing with the subject, while remaining specific enough in order not to "pollute" the data with off-topic messages [23]. Yet, Twitter does not give free access to the totality of messages exchanged at a given time via its streaming API. In addition, Twitter delivers only a portion of the total messages with "black-boxing" sampling rules and thresholds. This is not critical since we are not seeking to get the entire flow, however it can have a significant impact when aiming at quantitatively describing the dataset. Then, after being retrieved, the tweets must undergo a first post-processing step to eliminate duplicates or messages sent by "robots" which contain no information. Although potentially cumbersome, the implementation and maintenance of this type of architecture has become relatively common, and it does not present any major difficulties. Finally, the main challenge resides in the fine-grained extraction of relevant information from each tweet and its metadata, so that we can have the necessary information on which to conduct analysis.

The most crucial information needed to map the intensity distribution from the earthquake is the geolocation of the tweets. However, since the development of Twitter in 2006, the number of tweets that are natively geotagged (i.e. sharing the user's location via their GPS geographic coordinates by the users or twitter) consists less than 1% of the tweets [24,25]. Twitter also recently announced plans to further remove this functionality (Twitter, 2019). Alternatively, a common way to find the location of the tweets is to use the Named Entity Recognition (NER) techniques to identify mentions of places in the text of the tweets, and to retrieve the corresponding geographic coordinates via specialized web-services (e.g. OpenStreetMap). Additionally, another data processing step is needed to remove disambiguation of geolocation of the events: for example, if an earthquake occurs in California, it is more likely that a tweet from a witness mentioning the city of "Dublin" evokes the Californian locality rather than the capital of Ireland; these techniques allow a significant and relatively robust enrichment at the municipal scale [17,23]. More complex approaches have recently been proposed, consisting of grouping tweets mentioning the same toponyms to improve their location [26], or jointly predicting location and other thematic attributes via semi-supervised approaches [27]. In addition to the geolocation of the event, tweets contain information that helps better identifying the spread of the earthquake shaking, such as the identification of witnesses [28,29], the detection of damage [30], the description of the level of intensity of the shaking [31], the reporting of victims [16], etc., that are worth extracting using Natural Language Processing (NLP) and other topic modeling approaches.

By constantly monitoring tweets, earthquakes can be detected automatically and quickly [32–34]. Earthquakes are not predictable and can happen in anytime in few seconds: this kinetic behavior is translated to the tweets' activity. When an earthquake strikes, Twitter activity is marked by a very rapid rise of the number of related tweets, which peaks within few minutes, and then decreases gradually within a period that depends on the size of the earthquake [16,22]. Boccia Artieri et al. [14] explained that this observation of rapid increase of twitter activity followed by a gradual decrease are caused by the "witnessing" activity of the users to the event, followed by other activities related to information research, to expression of empathy and to commentary in the upcoming minutes to hours. Thus, the main peak of activity is generated almost exclusively by people who have personally felt the earthquake. Several studies have been carried out in recent years to analyze the tweets exchanged during the first minutes after an earthquake so as to be able to deduce information related to the intensity of the earthquakes, and thus contribute to the rapid calculation of shakemaps. These studies are based on two main approaches to extract the intensity information from the tweets.

The first approach consists of generating empirical equations relating the number of tweets relative to the population density in a community to the MI [17,35]. This approach is easy to implement and independent from the language used for the tweets, and it generally shows satisfying performances. Nevertheless, the main limitation of this work is that it strongly depends on the number of Twitter users at the moment of developing the empirical equations. However, the users' number is different from one country (or region) to another, and it also changes with time: while the number of Twitter users grows in some countries, it stagnates in others. Consequently, these relationships might not be adapted for different regions, or no longer be valid few months after their publication.

The second approach consists in developing predictive models via machine learning approaches to evaluate the maximum intensity of the earthquake [36] or to map the local intensity [12,15,37], or via the development of lexicons to different degrees of MI [31]. This approach relies on a tweet-by-tweet analysis taking into account the content of each message individually, and it is therefore more durable and robust. However, these methods are more complex to set up and they necessitate a periodic validation and adaptation for the changes made by Twitter itself, like the maximum characters in a tweet that was increased in 2017 from 140 to 280 characters, as well as the continuous evolution of the behavior of the Twitter users, like the tendency to use less hashtags [23]. Furthermore, many of these approaches require large datasets to calibrate the models, which are not always available due to the nature of the seismic phenomenon with significant return periods. Indeed, many regions of the world with moderate seismicity have not experienced significant earthquake since the appearance of Twitter in 2006, and therefore have very partial datasets for calibration.

Alternatively, Resch et al. [30] proposed to combine machine-learning topic models with spatiotemporal clustering to deduce the extent of the area presenting damage. Accordingly, MI greater than or equal to 6 or 7 in the EMS-98 intensity scales and MMI can be assigned to the area of damage detected, depending on the mean level of vulnerability of the building in the study area.

2.2. Extraction and analysis of twitter feeds in France

In 2019, 58% of the French population has an active use of social media (WeAreSocial, 2019), among which Twitter ranks sixth behind Facebook, YouTube, Instagram, WhatsApp and Snapchat. Based on the geotagged tweets (i.e. with GPS coordinates in their metadata) as an approximation to the location of Twitter users, Auclair et al. [23] showed that the most active users on Twitter correspond to the most densely populated areas, with the highest concentration in Paris. Consequently, Twitter is more likely to provide us data to calibrate MI inside urban areas rather than in rural ones. It should be noted that the characteristics of the buildings in these urban areas may present specificities to be taken into account in the attribution of MI values based on the tweets (e.g. ground-motions generally better felt in high-rise buildings).

Since April 2017, the SURICATE-Nat platform [23] allows monitoring and continuous analysis of original tweets (e.g. excluding retweets) written in French following the occurrence of natural disasters (earthquakes and floods), via the interrogation of Twitter's free streaming API. After an automatic detection of earthquakes on the basis of an algorithm similar to that proposed by Earle et al. [34]; tweets associated to an event undergo some processing to extract the thematic information (supervised classification) and the geolocation (NER of administrative toponyms). For this work, we use tweets posted for Barcelonnette earthquake which occurred on April 7, 2014 (and therefore before SURICATE-Nat was developed) and for Le Teil earthquake which occurred on November 11, 2019 (see in-depth description of case studies in Section 4), illustrated in Fig. 1.a.

For the Barcelonnette earthquake, 8996 tweets were collected by VisiBrain company with the same search criteria as those used by SURICATE-Nat (see Table 1) and 3003 were geolocated by SURICATE-

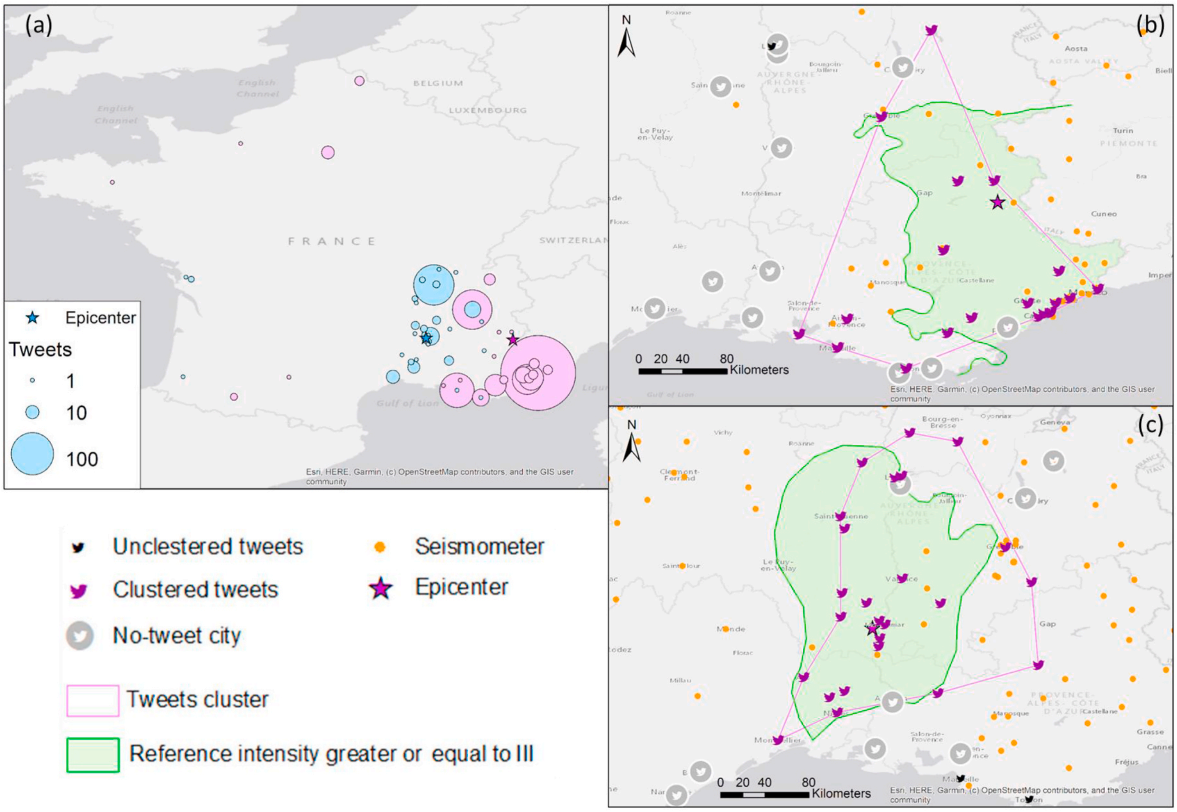

Fig. 1. Upper left (a): Epicenters (from RéNaSS) and geolocated tweets via the analysis of messages posted within 10 min after the earthquakes: Barcelonnette – purple; Le Teil – blue. Right: Comparison of the clustering of geolocated tweets sent 10 min after an earthquake, with the area of intensity greater than or equal to 3 for (b) Barcelonnette earthquake of April 7, 2014, and (c) the Le Teil earthquake of November 11, 2019. Isoseismal areas of intensity equal or greater than 3 come from BCSF for the Barcelonnette earthquake, and has been manually derived by the authors from BCSF DYFI-like reports for Le Teil earthquake. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 1
Keywords used (in French) for the collection of tweets related to the theme of earthquakes.

Event	Extraction mode	Searched keywords	Excluded keywords	Nb. tweets (of which are geolocated)		
				Full dataset	First 10 min after the EQ	Activity peak (tweet/min)
Barcelonnette April 07, 2014	Twitter full firehose through VisiBrain (paying service/full data)	"seisme"/"seismes"/"séisme"/"séismes"/"tremblement de terre"/"tremblements de terre"/"magnitude"/"terre tremble"	"politique"/ "politiques"	8996 (3003)	3853 (687)	269 at T0+2' (86 at T0+3')
Le Teil November 11, 2019	Twitter streaming API (free/ sample data)			6427 (3112)	498 (187)	67 at T0+4' (36 at T0+4')

Nat algorithms. For the Teil earthquake, 6427 tweets were collected by SURICATE-Nat platform, among which 3112 have been geolocated. For both earthquakes, we observe a sharp peak of tweets mentioning keywords from the French lexical field related to earthquakes (see Table 1), which reaches its maximum between two and 4 min after the occurrence of the earthquakes (Table 1 and Fig. 2). The number of tweets received in the two cases are very different (3853 tweets collected in 10 min for the Barcelonnette earthquake, and 498 for the Teil event). These differences can be explained by two main factors: first, the dataset of the Barcelonnette earthquake is complete; this was not anymore the case during the Le Teil earthquake due to the sampling procedure done by the public API of Twitter. Second, the Barcelonnette earthquake was felt along the French Riviera, a very densely populated area which gave rise to the publication of numerous tweets (see Fig. 1a). In both cases, we can see that most of the geotagged tweets within 10 min of the earthquake's occurrence are concentrated in the region near the epicenter, with however a few points located far from the epicentral zone. These few points can be explained either by the publication of messages using keywords related to the theme of "earthquake" but not linked to earthquakes that have just occurred, or by the publication of messages originating from witnesses but poorly geolocated (bad recognition of geographic toponyms) or referring to distant localities for various reasons.

2.3. Agnostic extraction of the raw felt area from tweets

Resch et al. [30] proposed the topic-modeling procedure to identify "hot-spots" of geolocated tweets classified as "earthquake-related": the clusters thus identified have relatively strong ground-motions and they correspond to what the authors call the "earthquake footprint". Alternatively, Mendoza et al. [12] proposed identifying an "area of interest" grouping together the "municipalities affected by the earthquake" via a

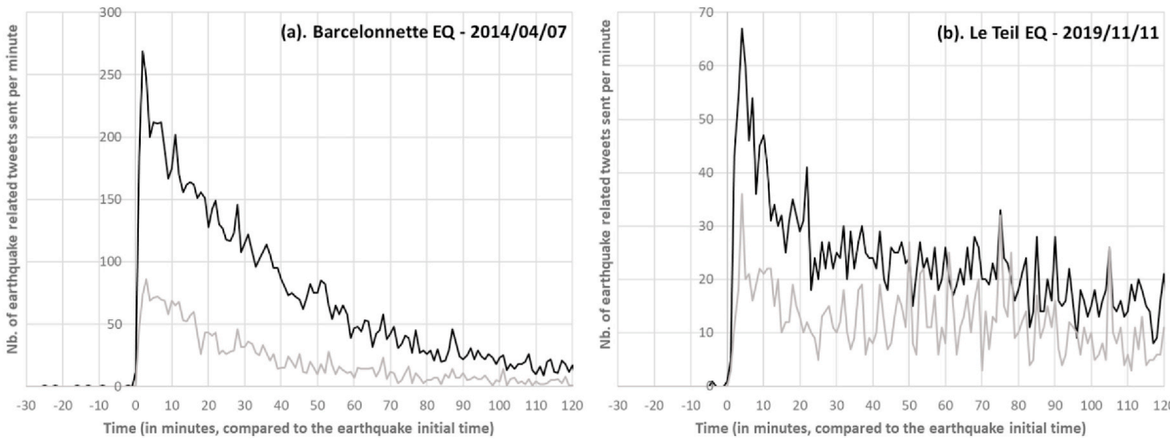

Fig. 2. Evolution of the number of tweets collected every minute before and after the occurrence of the two earthquakes: (a). Barcelonnette event; (b). Le Teil event. Black curves represent the number of all the tweets and grey curves represent the number of tweets with known (native or inferred) geolocation.

supervised binary classification of tweets aggregated at the municipal level.

Here, we propose another clustering approach for the geolocated tweets that does not require calibration of any predictive algorithm based on the analysis of the textual content, nor the knowledge of the characteristics of the earthquake, and is easy to implement at any study area. The spatio-temporal clustering approach is based on ST-DBSCAN algorithm [38] that is Density-Based Spatial Clustering of Applications with Noise (DB-SCAN [39]); extended to the time domain. This approach was successfully applied to identify, in the areas impacted, which evolve with time, by other fast kinetic phenomena such as forest fires [40]. Contrary to other clustering approaches, DB-SCAN algorithms have the ability in discovering clusters with arbitrary shape; they can easily process large amounts of data [41]; they also integrate relevant authoritative demographic and environmental information, such as population density [40]; and finally, DB-SCAN algorithms do not require the predetermination of the number of clusters.

Practically, Twitter users posting earthquake-related tweets (i.e. using lexical field of earthquakes), within a short time period, by mentioning places geographically close, implies the occurrence of a new event and the detection of clusters. Our DB-SCAN algorithm requires the determination of two parameters within a specific period: (1) the “size” parameter describing the minimum number of neighboring tweets to declare a cluster, and (2) the “proximity” parameters in space and time describing the minimum distance and duration between the tweets to be assigned to the same cluster.

Our study limits the analysis to the direct tweets posted during the first 10 min after the earthquake, excluding the “retweets”: the peak of the activity of users on Twitter generally occurs during the first 10 min after the earthquake, and those users are mainly the direct witnesses of the earthquake [14–17]. Limiting the collection of tweets to 10 min makes it possible to produce a first shakemap very quickly to respond to the first questions from the civil protection services and to execute possible rapid response systems such as PAGER [42].

We consider that there is a “temporal proximity” between tweets when they have been sent less than 10 min apart. Since we only consider tweets sent within 10 min after the earthquake’s occurrence, this temporal proximity between tweets is in our case always verified. his temporal dimension can be modified for other usage. This temporal dimension parameter is however interesting to keep, in particular in a perspective of continuous monitoring of Twitter, and can for example make it possible to detect clusters corresponding to aftershocks occurring shortly after the main shock. Regarding the "spatial proximity", we introduce a site-specific parameter instead of a fixed value, defined by the radius in which the residential population is greater than or equal to 2,500,000 inhabitants. We compute this parameter on the fly from the grid of the French population delivered by the French Institute of Statistics (INSEE) with a 200 m mesh-grid. Therefore, spatial proximity parameter is larger in the countryside than in large cities.

The parameter describing the minimum number of points (e.g. georeferenced tweets) necessary to declare a cluster may however differ depending on the regional density of Twitter users and must therefore be tuned specifically according to the study area. For France, the sensitivity analysis presented Appendix 1 shows, however, that this parameter has only a limited impact on our approach, the area (and geometry) of the main cluster remaining unchanged up to important values of this parameter. The main effect of changing this parameter is to significantly modify the number of clusters detected by the algorithm, which has no impact on our method since we only consider the main cluster. For this study, we fix a minimum number of points of 5 as a criterion to define a cluster.

Fig. 1 (b and c) shows the first approximation of the extent of the felt area of the earthquakes based on the cluster approach considering tweets during the first 10 min (Fig. 1a). It is however interesting to note that, when this analysis is extended to longer durations, new clusters may appear. Most of them are located within the already identified felt area, due to the tweets posted by "late witnesses", or people commenting on the earthquake, citing the most affected places. A few clusters that are spatially de-correlated from the impacted area are due to tweets mentioning the event as a pretext to talk about the seismic risk in other territories, or users who regret not having felt the ground-motions far from the epicenter. Spatio-temporal clustering within 10 min therefore acts as a natural “agnostic” filter allowing first-order identification of the felt area without any knowledge of the earthquake or any analysis of the content of tweets other than the detection of mentions of places. Furthermore, the absence of tweets from certain large municipalities with more than 50,000 inhabitants seems to indicate that the intensity of the ground-motions was very low, insufficient to arouse the "testimony" reflex from Twitter users (Fig. 1). These localities are subsequently referred to as “unfelt locations”.

Another important observation that emerges from Fig. 1.b is the “truncated” form of felt-areas extracted from clusters, in areas where no tweets are available: along borders (no tweets collected in Italy due to the fact that we collect messages in French language only), in the sea and in the uninhabited areas (e.g. mountainous areas to the east of the epicenter of the Barcelonnette earthquake). This well known bias in macroseismicity related to missing data must be taken into account when assigning the MI level.

3. Generation of twitter-enhanced shakemaps

The principle of shakemaps relies on the combination of *a priori* GMPE estimates with field observations, in order to constrain uncertainties on the ground-motion field generated by an earthquake event. This section details the algorithm used for the generation of shakemaps; then, a method to integrate tweets as observations is proposed.

3.1. Shakemap algorithm

Recently, several shakemap approaches have been developed in order to condition the ground-motion field upon the observations: among them, the method based on multivariate normal distribution [43] constitutes the technical basis for the USGS ShakeMap v4 service [44]; in parallel, an approach based on a Bayesian Network (BN) framework has been proposed by Gehl et al. [45]. Both methods consider that the ground-motion parameters (more specifically their logarithms) are normally distributed and spatially correlated, and that the conditioning data (i.e., the observations) can have non-zero uncertainty; the latter point is especially important for the inclusion of macroseismic data, which are only imperfect proxies for ground-motion parameters such as PGA (and reciprocally). In the following sections, we use the BN approach to generate the shakemap.

The proposed BN method [45] is based on the Bayesian updating of correlated Gaussian fields: the prior distribution of the ground-motion field, consisting of a simple predictive scenario of the earthquake event with a GMPE, is updated with the observations in order to generate a posterior distribution of the ground motion at each grid point. To this end, a Gaussian BN models the distribution of a given ground-motion parameter Y at each grid point i (see Fig. 3). Thanks to the lognormal assumption used in most GMPEs, a lognormal-normal conversion is able to express the conditional probability of Yi as a normal distribution, with the mean expressed as:

$$\mu_{(Y_i|U,W)} = X_i + \sigma_\zeta \cdot \sum_{j=i}^{n} t_{ij} \cdot U_j + \sigma_\eta \cdot W \tag{1}$$

where Xi is the mean estimate of the ground-motion parameter from the GMPE, $\sigma\zeta$ is the standard-deviation of the intra-event term, and $\sigma\eta$ is the standard-deviation of the inter-event term. The matrix of elements tij results from the Cholesky decomposition of the correlation matrix between the intra-event terms: spatial correlation models such as the one from Jayaram & Baker [6] may be used to compute this correlation, based on the distances between all grid points and observations. The variables U_j and W follow a standard normal distribution and they are essential to model the statistical dependence between the Y_i, and consequently the updating process. In case of a recording from a seismic station, a virtual grid point is added to the BN as an evidence, and the BN is solved accordingly.

In the case the observation results from macroseismic data, the uncertain link between the MI and the reference ground-motion parameter Y_i (e.g., log PGA) is taken into account by adding an extra node Z_i in the BN, as shown in Fig. 3. The variable Z_i is assumed to follow a normal distribution conditioned on Y_i, quantified as follows:

$$\begin{cases} \mu_{(Z_i|Y_i)} = f(Y_i) \\ \sigma_{(Z_i|Y_i)} = \sigma_{GMICE,Y_i} \end{cases} \tag{2}$$

where *f(.)* is a function referring to a ground-motion-intensity conversion equation (GMICE), such as the model proposed by Caprio et al., [46]; and $\sigma_{GMICE,Yi}$ is the standard deviation related to the GMICE function.

This framework is implemented in a Matlab code, where the Gaussian BN is modelled thanks to the Bayes Net toolbox [47]. It may be used to generate shakemaps of usual ground-motion parameters, such as PGA or SA at various periods. However, we also require shakemaps expressed in MI: such maps are useful to communicate on the effects of the earthquake, since there is a direct link between the felt MI and the effects on the built areas and the population. Moreover, some vulnerability models, such as the semi-empirical method by Lagomarsino & Giovinazzi [48], use the MI as an input in order to predict damage distributions over built areas. Therefore, the shakemaps that are presented in the subsequent sections of the paper are expressed in terms of MI: such maps are obtained by converting PGA shakemaps with a GMICE. As one may argue that the shakemap algorithm could be adapted to directly update MI variables, we currently lack robust intensity prediction equations (IPE) and spatial correlation that are applicable to macroseismic fields.

3.2. Integration of twitter data into shakemaps

The limit between intensity domains 2 and 3 always remains tricky to distinguish on the sole basis of individual data, which makes it difficult to assess the actual proportion of the population of a given locality having felt the tremors. However, although a few tweets may come from areas of intensity 2 quickly after an earthquake - especially in large cities where populations are concentrated - we make the hypothesis that, if people mention the earthquake right after its occurrence in localities close to each other (i.e. clusters), there are high chances that they have felt it with an intensity greater than or equal to 3, corresponding to weakly felt shakings according to the EMS-98 macroseismic scale [3].

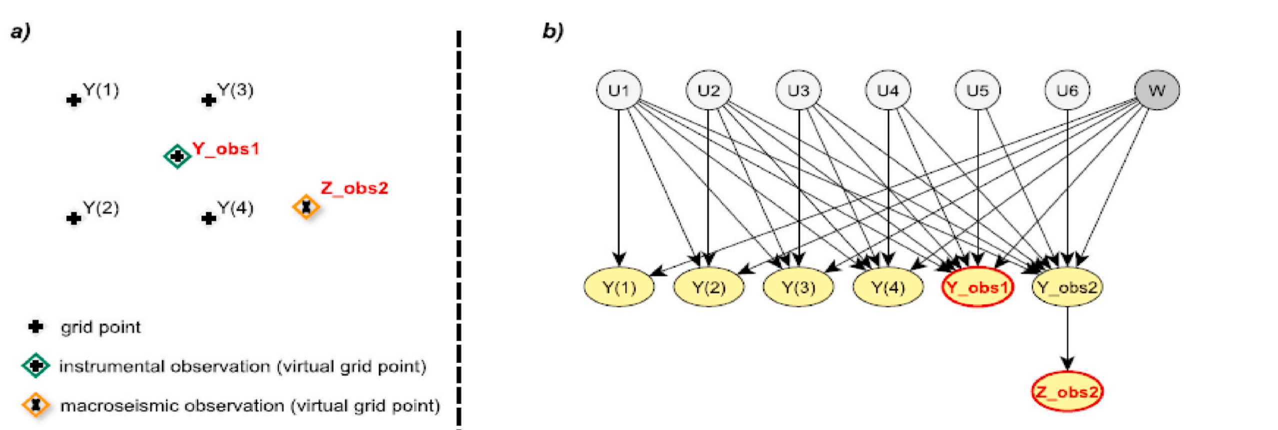

Fig. 3. (a) Example of a 4-point grid with one instrumental observation (Y_obs1) and one macroseismic observation (Z_obs2); (b) Corresponding BN, where the evidenced nodes are displayed in red. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Therefore, we consider that the "felt area" deduced from Twitter data in Section 2.3 may be translated into macroseismic observations points, assigning an intensity value equal to 3 or above (i.e. MI $\in$ [3; 12]) to each grid point with the cluster. This assumption represents the minimum information than can be extracted from tweets about intensity level, while respecting the problem of missing data identified previously.

In the same way, the "unfelt locations" are translated into macroseismic observations points, assigning intensity values ranging from 1 (unfelt shakings) to 2 (rarely noticeable shakings) - (i.e.M I $\in$ [1; 2]). It follows the hypothesis that, if people do not mention the earthquake in a given densely population location, there are high chances that they have not felt it.

Such information about the minimum intensity corresponds to a soft evidence (or observation), while our current BN only accepts hard evidence or fixed values (i.e., no option of inequality or larger than). A possible way to integrate such data is to decompose the posterior shakemap distribution over all possible values of macroseismic intensities, given the "tweet observation". Let us define $P(Yi\ |T)$ as the conditional distribution at a grid point, given Twitter evidence at a given point. It may then be expressed as:

$$P(Y_i|T) = \int_{-\infty}^{+\infty} P(Y_i|Z_{obs}) \cdot P(Z_{obs}|T) \cdot dZ_{obs} \tag{3}$$

where Z_{obs} is the MI at the location of the Twitter evidence. $P(Z_{obs}\ |T)$ represents the conditional probability of observing the value Z_{obs} given the tweet: it is proposed to estimate this probability by using the *a priori* distribution of the MI (i.e., the expected value of the intensity, given the earthquake parameters), and by truncating the distribution according the aforementioned assumptions: $P(Z_{obs} < 3\ |T) = 0$ and $P(Z_{obs} > 2\ |T) =$ 0 respectively for the unfelt and felt locations. Moreover, the bounded nature of the EMS-98 macroseismic scale is taken into account by assigning a zero probability to intensities less than 1 and greater than 12: $P(Z_{obs} < 1\ |T) = 0$ & $P(Z_{obs} > 12\ |T) = 0$. Therefore, Eq. (3) is transformed as follows:

$$P\left(Y_i|T\right) = \int_{3}^{12} P(Y_i|Z_{obs}) \cdot P_{trunc,prior}(Z_{obs}) \cdot dZ_{obs} \tag{4}$$

where *Ptrunc, prior*(Z_{obs}) is the truncated prior distribution of Z_{obs}, as illustrated in Fig. 4, in the case where the observation is within a "felt area". A similar expression is assembled for the "unfelt locations", with the integration bounds ranging from 1 to 2. In the end, it can be seen that the addition of Twitter data provides a very loose type of information (i.e., lower and upper bounds on the MI).

The main issue with the framework presented in Eq. (4) is the computation cost, since many instances of shakemaps would have to be computed (for each possible value of Z_{obs}) in order to integrate the evidence. Moreover, the problem becomes increasingly more complex when more "tweet observations" are added (i.e., generation of multiple integrals). Therefore, a first-order approximation is adopted here: instead of integrating over the possible range of Z_{obs}, the expected value estimated over the truncated distribution is directly used as an input to the shakemap (see Fig. 4).

Hereafter we detail the steps to define the value of the soft evidence at each point within the "felt area" and at the "unfelt locations". The whole process is illustrated by the flowchart in Fig. 5.

At each grid point inside the contour defined by the Twitter felt area, we estimate the mean value and the corresponding standard deviation of the MI using a GMPE and a GMICE without any observation, as an *a priori* estimate (see example illustrated in Fig. 4, left).

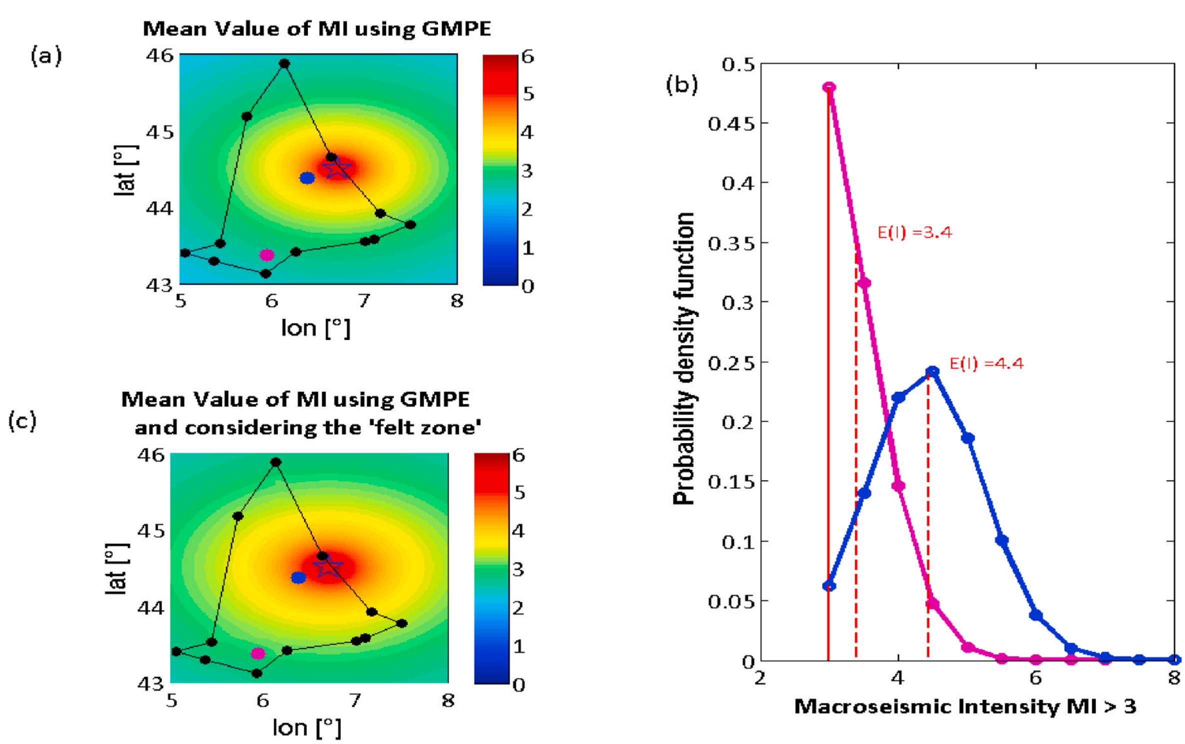

Fig. 4. (a) A priori estimation of the MI and the contour lines defining the "felt area" from Twitter data. An example of a location inside the felt area; (b) Truncated normal distribution of the macroseismic intensities at two locations shown in (a) in black and blue dots, after considering the information from the felt area, and the expected values to be entered as evidence observations (red dotted vertical lines) and implemented to generate map (c). (c) A posteriori estimation of the MI when considering the "felt area" from Twitter data. Coordinate of epicenter in (a) and (b) are from RéNaSS. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

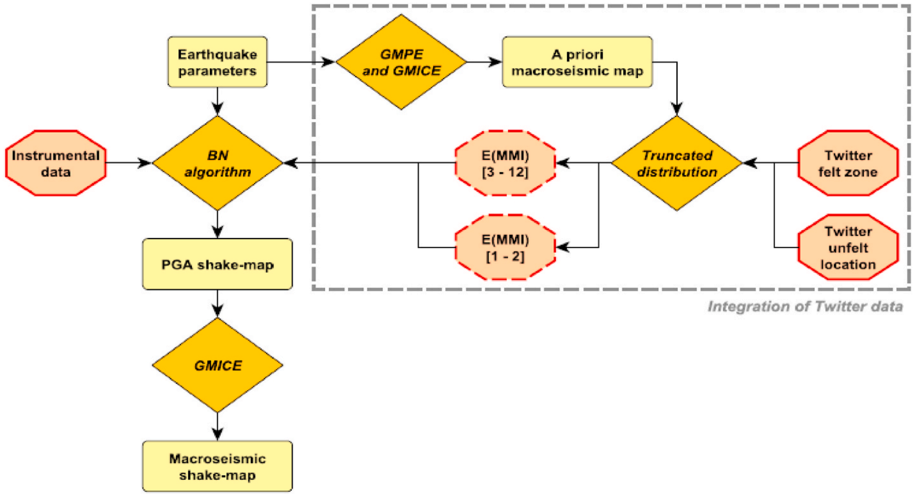

Fig. 5. Successive steps and datasets involved in the generation of shakemaps that include Twitter data. GMPE stands for Ground-Motion Prediction Equation, GMICE for Ground-Motion Intensity Conversion Equation, BN for Bayesian Network, E(MMI) for the expected value of macroseismic intensity.

Then, at each of these grid points, we generate a truncated normal distribution of MI values (using the mean and standard-deviation computed in the previous step), within the range of [3−12] or [1–2] (see example illustrated in Fig. 4).

Still at each point, we compute the expected value of the intensity under the probability distribution defined above, by summing the values of the intensity on the range [3−12] (or [1–2]) weighted by the corresponding probability. The soft evidence is then assumed to be equal to the expected value of the intensity.

Finally, these approximate observations are entered to the BN as additional evidence, in complement of the instrumental observations.

4. Application to two recent earthquakes in France

We use Twitter data to study the gain of information from the tweets extracted 10 min after an earthquake using the approach detailed in Section 2 and Section 3, to better estimate the intensity shakemaps for two recent moderate earthquakes that occurred in the south-east of France: the first event is the Barcelonette earthquake, which occurred on April 7, 2014; the second is the Le Teil earthquake, which occurred on November 11, 2019, both having the same magnitude (Ml 5.2 accroding to the French National Network for Earthquake Monitoring – RéNaSS; Mw 4.9 according to EMSC). It is interesting to generate shakemaps using Twitter data for these two events, because they are the strongest earthquakes that happened in France since Twitter was created in 2006. Nonetheless, it is challenging to reproduce the shakemaps for both events because of their specificities: directivity effect observed for Barcelonnette earthquake [49], and the rupture occurring at a very shallow depth for the Le Teil earthquake.

4.1. Data and assumptions

We use the earthquake parameters (magnitude, hypocenter location and depth) summarised in Table 2 that are estimated and published on RéNaSS to reproduce shakemaps using the same data-source that are usually available minutes after earthquakes occurring in France. To simulate spatially-correlated ground-motion fields, we use the GMPE developed by Akkar and Bommer [50] to estimate a PGA map within a rectangular area of 3° in latitude and 3° in longitude and with a resolution of 0.01° grid spacing. We refer to Jayaram and Baker [6] to model the spatial correlation function between PGA values on the map. We use the global GMICE from Caprio et al. [46]; without any regional correction factor, for the conversion between the different IMs (PGA to MI, and conversely):

$$\begin{cases} MI = 2.270 + 1.647\log_{10} PGA \quad if \ \log_{10} PGA \leq 1.6 \\ MI = -1.361 + 3.822\log_{10} PGA \ if \ \log_{10} PGA > 1.6 \end{cases} \tag{5}$$

with PGA in cm/s^2.

The first type of data used here is the instrumental data collected from the seismic stations in terms of PGA, from the French Accelerometric Network [51] and from the ORFEUS *Rapid Raw Strong Motion* (RRSM) platform (Appendix 2 and Appendix 3). In this study, we select data from seismic stations within an epicentral distance of 200 km. The distribution of the selected stations are shown in Appendix 4. The second type of data is the MIs deduced from the Twitter feeds (see Section 2 and Fig. 1).

We also use the EC8 soil classification map of France that was obtained from Monfort and Roullé [52], Negulescu et al. [53] and Tellez-Arenas et al. [54] to take into account site effects and also to correct soil amplification factors from the recordings of the stations (see Appendix 4). For the stations located in Italy, we apply a constant soil amplification factor equals to 1.35, corresponding to EC8 class B. But in

Table 2
Main characteristics of the largest two earthquakes occurred in mainland France since 2006.

Event	Date	Time UTC	Latitude (ref. RéNaSS)	Longitude (ref. RéNaSS)	Depth (km)	Ml (ref. RéNaSS)	Max. Intensity (ref. BCSF)	Last accessed
Barcelonnette	April 07, 2014	19:26:59	44.51	6.71	8	5.2	6	April 24, 2020
LeTeil	November 11, 2019	10:52:45	44.53	4.64	2		7–8	April 24, 2020

the following, we compute the ground motion on the French territory only.

Finally, we use intensity data produced by the French Central Seismological Office (BCSF) as validation data allowing us to assess the quality of our intensity shakemaps. Unlike the intensities deduced from internet questionnaires, such as *DYFI* reports, which are immediately available but are marked by high uncertainty, the BCSF final intensity maps (defined at the municipality scale) can indeed be considered valid as they are obtained by compiling a very large number of macroseismic observations (field observations in the epicentral zone, questionnaires sent by the local authorities, and finally internet questionnaires). The so-called *reference* macroseismic intensities of the Barcelonnette and Le Teil earthquakes are documented in Sira et al. [55] and Sira et al. [56] respectively. Sira et al. [55] proposed the layout of isoseismal areas, which represents the areas within which the MI is relatively homogeneous (cf. Fig. 7). This type of representation is very useful and it makes it easier to extract the macroseismic field by overcoming on one hand very localized effects and, on the other hand, border effects of the municipal administrative limits. However, these isoseismal areas were not described by Sira et al. [56]; therefore we manually derived the approximate extension of the zone of intensity greater than or equal to 3 that is reported on Fig. 1.

4.2. Case study 1: Barcelonette earthquake

The earthquake of April 7, 2014 occurred at 21:27 local time (19:27 GMT) in the French region of Alpes-de-Haute-Provence, not far from the city of Barcelonnette. With a local magnitude of 5.2 and a focal depth of 8 km, this moderate earthquake fortunately caused only small damages in a mountainous and relatively sparsely populated epicentral area. However, its ground motions have been widely felt throughout south-east of France. BCSF indicates an epicentral macroseismic intensity of 6, and intensities greater than or equal to 3 up to ≈150 km away in the direction N-160°, and up to 80 km in the direction N-70°, showing a very clear directivity effect [49]. As indicated in Section 2.2, this earthquake resulted in the publication of many tweets, especially along the French Riviera.

We generate the shakemap for the Barcelonnette earthquake, considering different sets of observations to constrain the ground motion field, and we compare the results to the BCSF reference intensities deduced from isoeismal areas. First, considering the PGA values recorded at the seismic stations only, the resulting shakemap is illustrated in Fig. 6.a. Then, considering the macroseismic "soft evidence" deduced from Twitter, the resulting shakemap is shown in Fig. 6.b. Finally, considering the whole set of observation coming from both physical (seismic stations) and social (tweets) sensors, the shakemap is shown in Fig. 6.c. Note that there is no information from Twitter outside of France, since we only collect tweets written in French. The results show very different macroseismic fields depending on the observations used, which highlights the uncertainty associated with the rapid estimate of MI from proxies. The use of PGA instrumental data only (Fig. 6a) leads to intensities between 4.5 and 5 at the epicenter and around 2 at 150 km away from the epicenter, while the use of Twitter data only (Fig. 6b) leads to higher intensities ranging from 6 at the epicenter, down to 3 at 150 km away from the epicenter. The combination of the two types of observations (Fig. 6c) results in an intermediate estimate.

The residuals computed between predicted and observed intensity values (Fig. 7a) show that the intensities are overestimated when considering Twitter data only, and on the contrary, the intensities are underestimated when considering PGA records only. The coupling of data from Twitter and PGA shows an overall reduction in residuals. Fig. 7 (b,c,d) shows, however, that the residuals do not distribute homogeneously according to the intensity levels, with a tendency to overestimate the low intensities (that occupies the largest area on the map in terms of pixels), and to underestimate the high intensities. This trend is linked to the characteristics of the GMPE used, namely its geometric attenuation. However, Fig. 7 (b,c,d) also shows that outliners may lead to different local intensities, mainly for intensity 3.

Our results show that taking into account the Twitter data in addition to the PGA seems useful for the best rapid calibration of shakemaps, however this complementarity of different types of data needs to be considered more in details. On one hand, Twitter makes it possible to identify with relative confidence the peaks of activities linked to intensities greater than or equal to 3 (see Section 2.3) that can occur up to a great distance from the epicenter. But it is difficult to extract precise indications about the level of high intensities from the tweets posted immediately after an earthquake, for the simple reason that the observations necessary for the definition of these levels are not accessible for rapid observation from a single individual. On the other hand, PGA, considered as a proxy of the MI, presents great variability for these low intensity levels, as shown by the scattering of the datasets used for the calibration of GMICEs [46]. Therefore, it seems reasonable not to consider the PGA values recorded at large distances when calculating the shakemaps, because this will result in the prediction of very uncertain intensity values.

Next, we study the shakemaps computed using both instrumental and social data, considering different cut-off distances for PGA measurements to be included as observations. Fig. 8 represents the results obtained by considering the PGA recorded within a radius of 30, 50, 100 and 200 km (with respectively 1, 4, 20 and 45 PGA measurements available). The residuals computed as the difference between the predicted intensity and the reference intensity are presented in Fig. 9. It

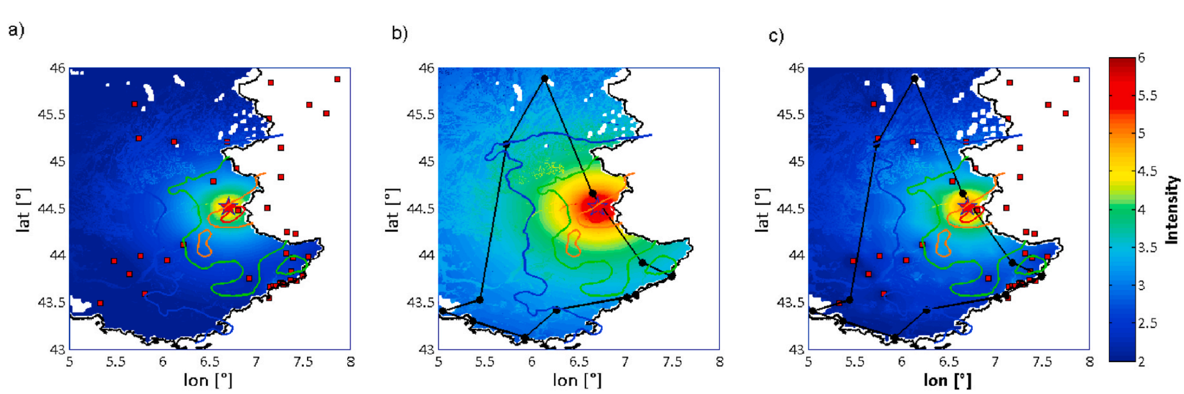

Fig. 6. Shakemaps for the Barcelonnette earthquake, taking into account the information from: (a) the seismic stations recording PGA (shown in red squares), (b) the Twitter data (the felt zone is shown in black lines), and (c) both seismic stations and Twitter data. The contour lines represent the reference isoseismal areas defined by BCSF. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

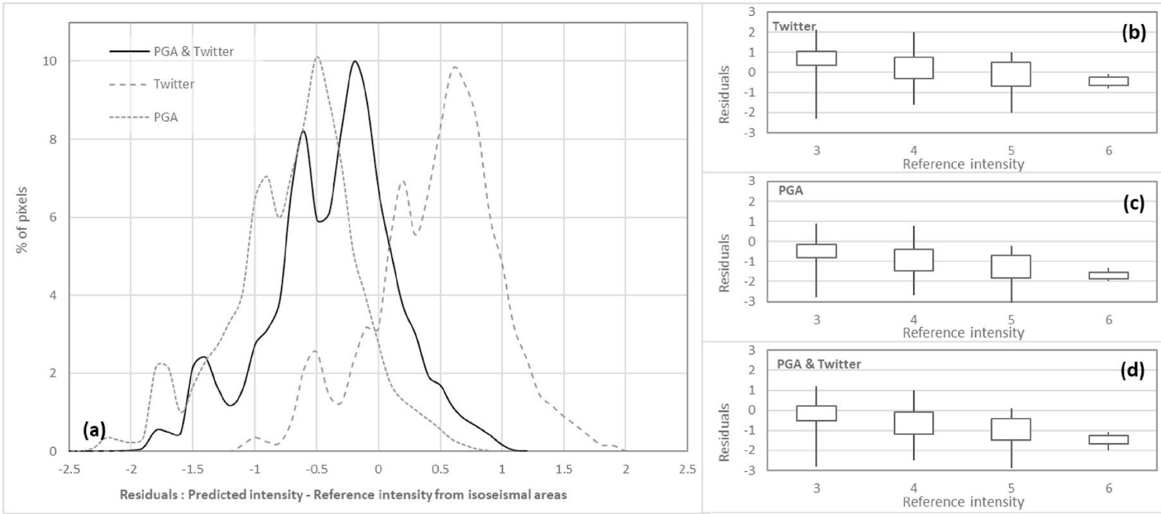

Fig. 7. Distribution of residuals (predicted intensity minus reference intensity from isoseismal areas) depending on the set of data considered to generate the shakemap: social data (Twitter) only, instrumental data (PGA) only, and social plus instrumental data. Left (a): distribution of residuals as a percentage of pixels. Right: the 4 boxplots of residuals according to the reference intensity using the different data sets (b, c & d) where the ends of the box are the mean value plus and minus 1 standard deviation, and the whiskers (the two lines outside the box) extends to the highest and lowest values.

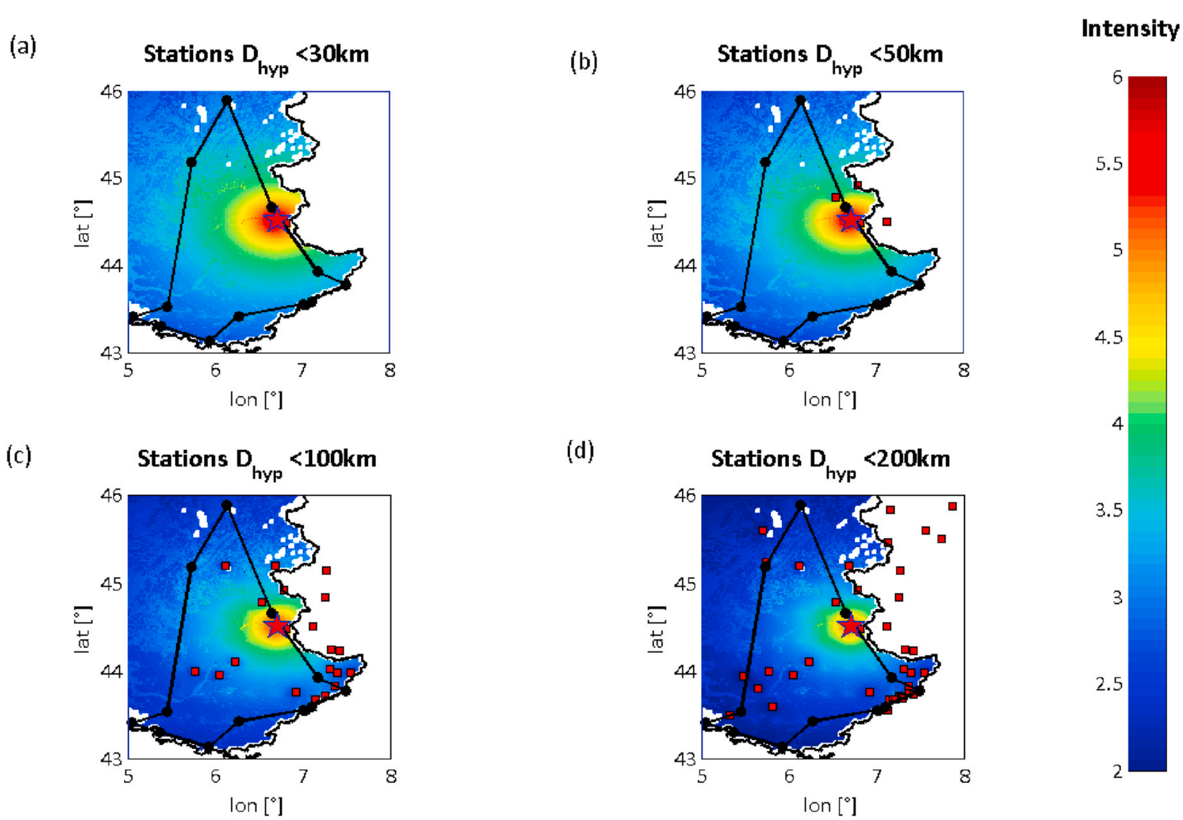

Fig. 8. Shakemaps for Barcelonette earthquake taking into account Twitter data (the black lines define the felt area using the tweets) and the ground acceleration recordings from the seismic stations (red squares) situated within (a) 30 km, (b) 50 km, (c) 100 km and (d) 200 km from the epicenter. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

indicates that accounting for PGA recorded up to 100 km contributes to the improvement of the quality of the shakemap. On the contrary, accounting for PGA recorded up to 200 km tends to degrade it. Appendix 5 illustrates this effect very clearly, with long distance PGA measurements leading in this case to the evaluation of very low intensity values, which leads in turn - due to the shakemap algorithm used - to a downward translation of the entire macroseismic field (i.e. updating of the inter-event error term, which is common to all grid points).

4.3. Case study 2: Le Teil earthquake

The earthquake of November 11, 2019 occurred at 11:52 local time

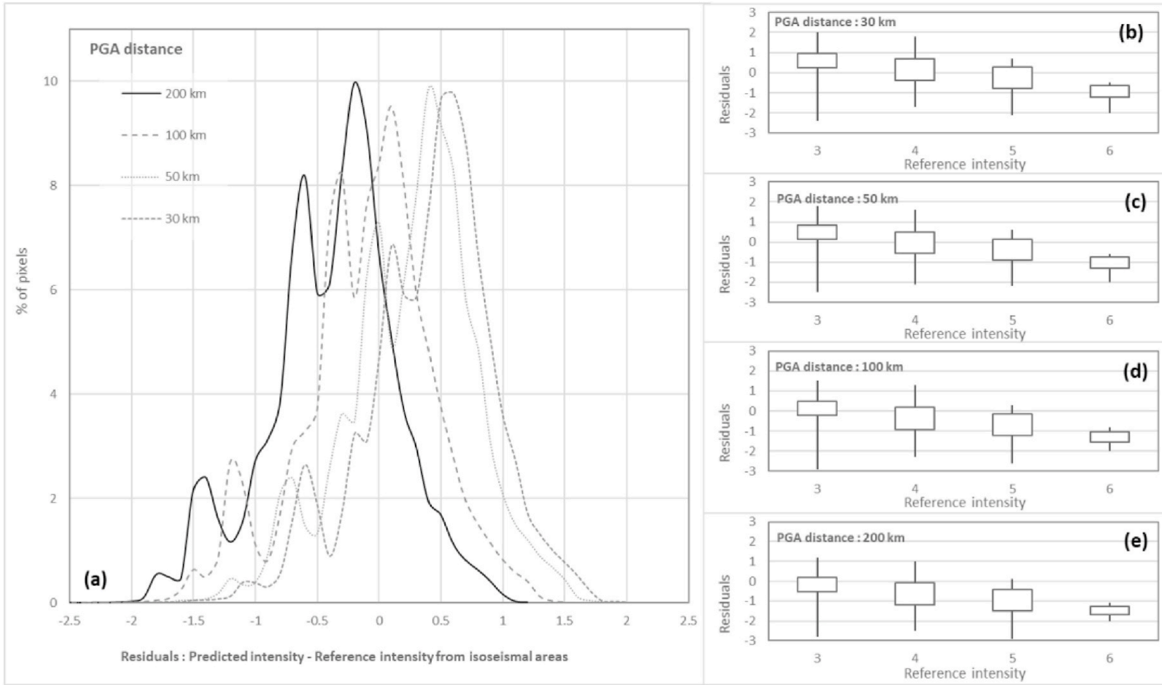

Fig. 9. Distribution of residuals (predicted intensity minus reference intensity from isoseimal areas). The estimated intensity for the Barcelonette earthquake is computed using Twitter data and PGA data. Left (a): The plot shows the residuals considering PGA data recorded within 30km, 50km, 100km and 200 km. Right: the 4 boxplots show the residuals by intensity, considering the 4 different sets of data (b, c, d & e), where the ends of the box are the mean value plus and minus 1 standard deviation, and the whiskers (the two lines outside the box) extends to the highest and lowest values.

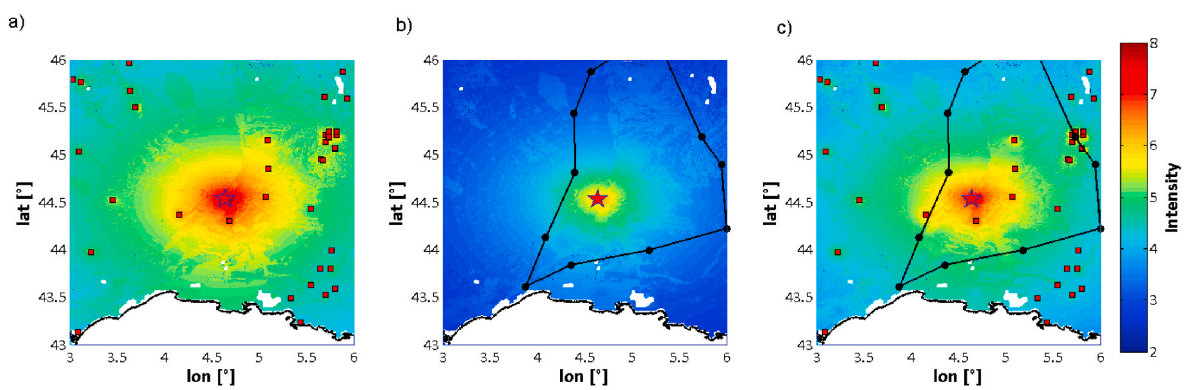

Fig. 10. Same as Fig. 6, for the Le Teil earthquake.

(10:52 GMT) along the coastal border between the French regions of Ardèche and Drôme, close to the city of Le Teil. Due to the shallow depth of its epicenter (focal depth of 2 km) and to the propagation of the rupture to the surface, as well as to the high local vulnerability of the buildings, this moderate earthquake of local magnitude 5.2 caused extensive damages within the epicentral area, with significant damages to hundreds of buildings, and the partial collapse of a few homes. Conversely, the shallow depth of the epicenter resulted in a remarkable attenuation of the intensity of the ground-motions with distance.

Although intensity values of 3 are reported by the BCSF up to 140 km from the epicenter (see Appendix 7), it is however difficult to establish the contours of the maximum extension of the area of intensity greater than or equal to 3. Indeed, the long-distance intensity values are fairly dispersed; many municipalities witnessed a felt intensity, however not precise enough for BCSF to be able to assign an intensity value [56]. It is therefore not possible to draw the outline of isoseismal areas on the basis of which to assess the precision of our shakemaps as we did in Section 4.2.

We therefore proceeded in a different way, by comparing the intensity values predicted by the shakemaps with the intensity values defined by the BCSF at the municipal level, by limiting the analysis to pixels intersecting a municipality with an observation with an intensity greater than or equal to 3. As for the Barcelonnette Earthquake, we generate different shakemaps considering three configurations of observation input data: instrumental data only (Fig. 10.a), social data only (Fig. 10.b) and both instrumental and social data together (Fig. 10. c). Taking into account PGA measurements only leads to a significant overestimation of the MI, particularly for low intensity values (Fig. 11c). Despite this reverse trend from that observed for the Barcelonnette earthquake, the results obtained confirm the fact that taking Twitter data into account as "soft evidence" improves the prediction of MI (Fig. 11d). The study of the sensitivity of the shakemap to the distance within which to consider PGA measurements also confirms the lessons gained from the Barcelonnette earthquake, according to which the long-

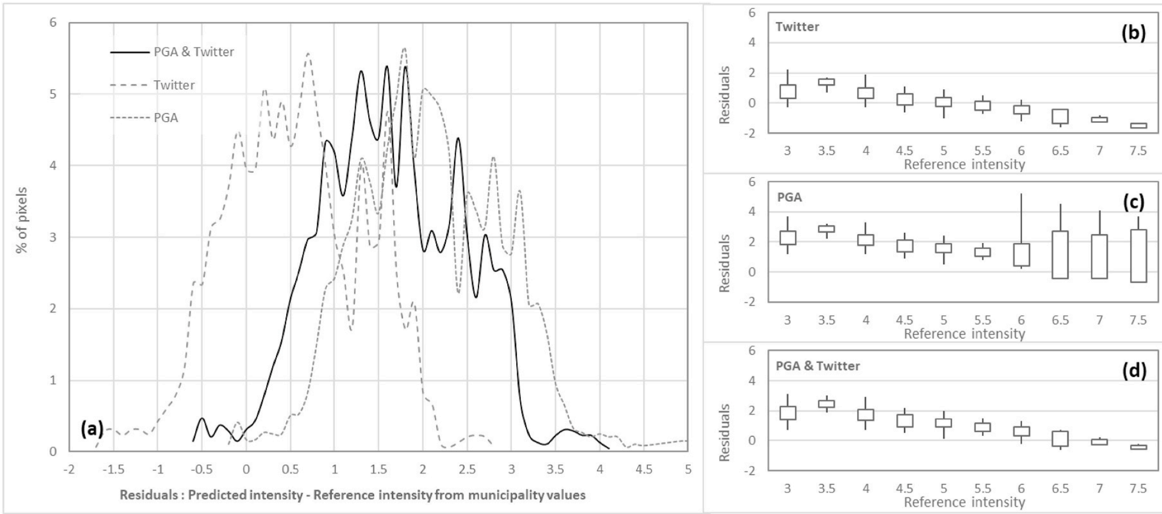

Fig. 11. Same as Fig. 7, for the Le Teil earthquake.

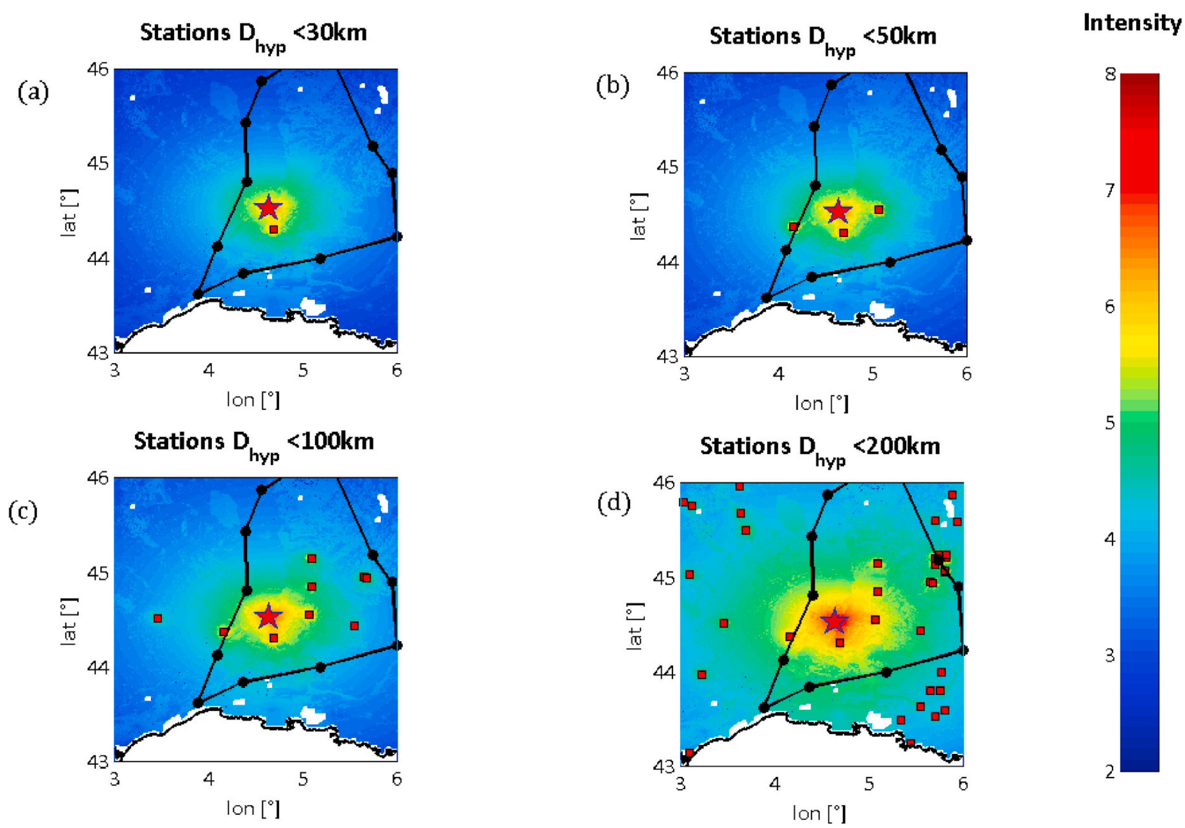

Fig. 12. Same as Fig. 8, for the Le Teil earthquake.

distance measurements tend to reduce intensity values very far from those actually observed (Fig. 12). In the case of the Le Teil earthquake, these long distance measurements lead, by chance, to the improvement of the prediction of near-field intensity, but this is only due to the analytical form of the GMPE of Akkar and Bommer [50] used in this study.

5. Conclusions and perspectives

In this work, we use two types of observations available immediately after the occurrence of an earthquake, which are the instrumental measurements of PGA on one hand, and the messages posted on Twitter on the other hand, for the rapid calculation of robust macroseismic intensity maps (i.e. shakemaps) using a BN framework. The innovation of our work is that we propose a simple method to rapidly extract intensity information from Twitter, where we translate the tweets into 'felt' or unfelt' observations with MI ≥ 3 and MI < 3 respectively. In doing so, we answer the need to inform authorities about the potential impact of the earthquake within 10 min of the occurrence of the event, via direct communication of shakemaps in terms of macroseismic intensity (MI) or via rapid loss assessment based on these shakemaps. Over time, these shakemaps can be updated as "*DYFI*"-like macroseismic reports are collected, following the methodology developed by the USGS [44].

The application of our approach to two study areas in France showed that instrumental measurements of PGA only are not able to reproduce the final shakemaps generated by official authorities, and that PGA measurements recorded far from the epicenter (beyond a hundred kilometers for earthquakes of moderate magnitude) tend to underestimate the entire macroseismic field because of very low PGA values. It is important to note that the shakemaps are initially and mostly controlled by the GMPE chosen. The observations modify the shakemap locally (through the updating of the intra-event error trem) and globally (through the updating of the inter-event error term), but they do not modify the geometrical decay of the ground motion imposed by the GMPE. Thus, future work should investigate the updating of the spatial decay of the shakemap, through the GMPE coefficient related to the source-to-site distance term, for instance.

The availability of tweets as well as their spatial distribution directly influences the intensity map, as it is the case for instrumental data. An important limitation associated to the use of Twitter comes from the absence of precise information about the location of tweets. In this work, we use Named Entity Recognition techniques for identifiying geographical features and DB-SCAN spatiotemporal clustering to extract the location of thweets with less "background noise". Future work should be undertaken to improve this geolocation inference.

It is worth reproducing this study for areas with more destructive earthquakes, with an adapted algorithm to treat Twitter data in different languages. In severely damaged zones, researchers have noticed a lack of reported intensity on platforms specific for earthquakes; people would be preoccupied with their security rather than informing and reporting [9]. However, people located a bit further from the epicenter, if not injured, tend to share on social media to inform their relatives. Using Twitter can help them share instantaneously to a mass of their contacts, and by that, help us define the 'damage zone' and fill the tweet gap of the observations in 'severely damage zones' once combined with the GMPEs. The algorithm of this work could be optimized in time, along with other types of information that could be collected earlier (eg. from early warning mobile applications) in order to generate the shakemap as early as possible.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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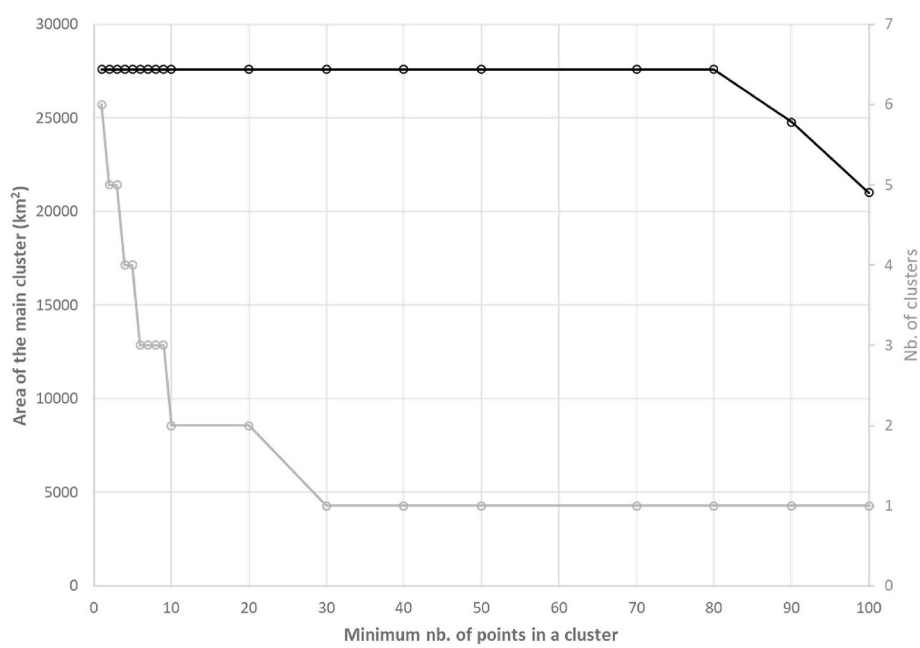
Appendix 1. Sensitivity analysis of the clustering procedure to the parameter defining the minimum number of points necessary to declare a cluster, carried out for the data from the Barcelonnette event, and expressed in terms of impact on the area of the main cluster used in this study, and on the number of clusters determined by the algorithm



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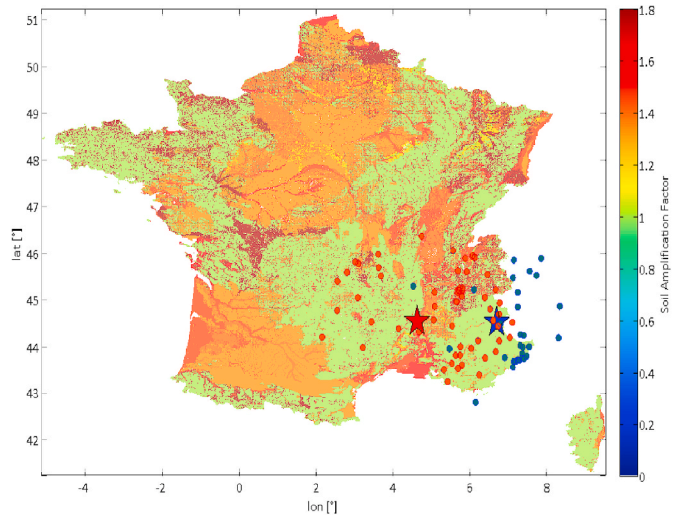
Appendix 2. PGA recordings from the Barcelonette earthquake

Lon	Lat	PGA (cm/s2)
6.810	44.480	11.331
7.116	44.507	9.669
6.538	44.786	2.365
6.791	44.921	1.981
7.263	44.835	1.482
7.326	44.246	3.633
6.225	44.108	1.061
7.420	44.227	8.582
7.319	44.016	2.220
6.683	45.208	1.281
7.392	43.975	1.489
6.045	43.951	0.745
7.265	45.148	1.102
6.922	43.753	0.690
7.553	43.986	0.718
6.117	45.206	0.506
7.374	43.831	2.243
5.767	43.988	0.815
7.263	43.709	4.643
7.146	43.667	2.850
7.258	43.699	8.942
7.367	43.740	1.942
7.185	43.671	2.231
7.212	43.675	3.920
7.285	43.699	1.934
7.489	43.784	2.170
7.295	43.690	0.490
7.425	43.730	0.670
7.134	45.460	0.461
5.744	45.241	1.626
7.131	43.548	2.675
5.643	43.801	0.301
5.484	43.941	0.168
5.807	43.588	0.373
8.325	44.178	0.406
8.353	44.849	1.144
7.747	45.513	0.358
7.568	45.602	0.214
5.697	45.609	0.176
7.157	45.838	0.158
5.332	43.492	0.244
7.869	45.875	0.043
4.542	45.279	0.142
5.570	46.040	0.230
6.164	42.795	4.533

Appendix 3. PGA recordings from the Le Teil earthquake

Lon	Lat	PGA (cm/s2)
4.689	44.307	599.882
5.069	44.557	417.023
4.156	44.369	465.877
5.097	44.850	101.730
5.550	44.429	37.278
5.089	45.154	184.330
5.653	44.956	77.990
5.675	44.942	194.140
3.450	44.519	97.217
5.699	45.137	106.242
5.768	43.988	16.677
5.801	45.065	58.958
5.807	45.063	155.292
5.806	45.070	30.313
5.699	45.204	170.694
5.737	45.182	221.314
5.736	45.186	90.644
5.736	45.187	94.863
5.727	45.195	100.553
5.740	45.193	246.231
5.643	43.801	15.794
5.744	45.241	209.444
5.821	45.209	181.485
5.759	43.803	34.924
5.822	45.242	44.439
5.543	43.627	19.914
5.333	43.492	25.114
3.221	43.970	99.081
6.045	43.951	11.968
3.694	45.500	113.894
3.097	45.034	63.373
6.225	44.109	34.629
5.807	43.588	18.443
5.702	43.523	26.978
5.697	45.609	42.085
3.636	45.676	71.123
6.402	45.037	21.288
6.540	44.788	0.098
5.933	45.589	43.164
6.622	44.550	15.107
5.438	43.237	12.361
6.407	43.747	13.145
2.554	44.761	70.240
6.749	44.429	10.104
6.772	44.676	7.554
6.791	44.921	8.731
6.778	44.110	12.066
6.683	45.209	8.829
3.623	45.965	40.025
6.689	43.881	2.060
5.889	45.881	27.566
6.255	43.383	13.538
6.473	45.533	17.952
3.111	45.763	86.917
5.572	46.045	27.370
2.810	45.575	88.781
2.563	45.385	22.857
3.028	45.798	21.092
6.064	45.923	62.588
6.136	45.892	37.278
6.133	45.904	136.359
6.091	45.938	74.752
7.050	44.184	6.671
7.116	44.507	21.190
3.090	43.135	15.696

Appendix 4. Map showing the amplification factor due to soil conditions in France. The two earthquakes epicenters are shown as stars in blue and in red for Barcelonnette and Le Teil respectively, with the corresponding seismic stations within 200 km



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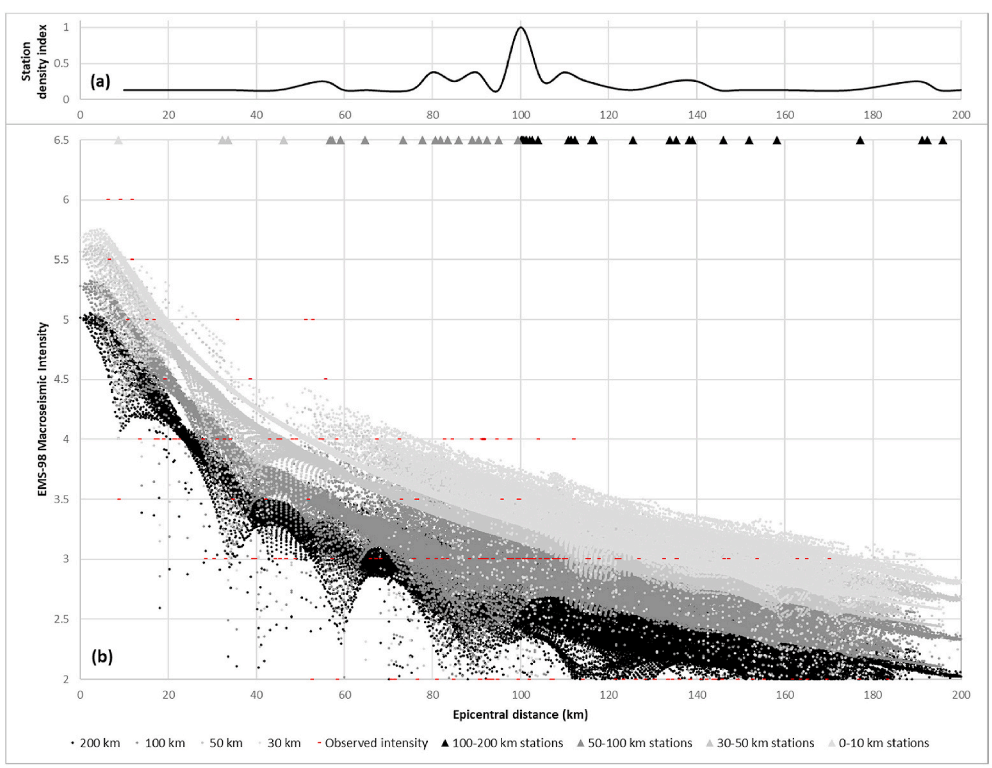
Appendix 5. (a): Normalized station density as a function of epicentral distance. (b): Distribution of predicted intensity (grey/black dots). The estimated intensity is computed using Twitter data and PGA data, considering instrumental data recorded within 30km, 50km, 100km and 200 km. The reference intensity (red lines) as a function of epicentral distance is extracted from municipality-level BCSF data



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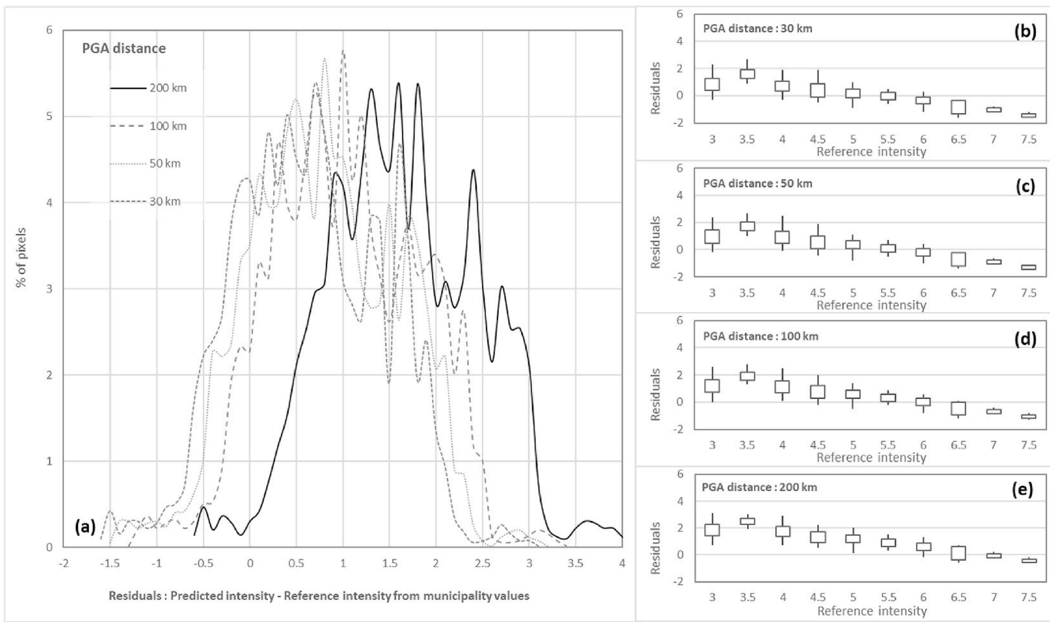
Appendix 6. Distribution of residuals (predicted intensity minus reference intensity at municipal level). The estimated intensity is computed using Twitter data and PGA data. Left (a): The plot shows the residuals considering PGA data recorded within 30km, 50km, 100km and 200 km. Right: the 4 boxplots show the residuals by intensity, considering the 4 different sets of data (b, c, d & e), where the ends of the box are the mean value plus and minus 1 standard deviation, and the whiskers (the two lines outside the box) extends to the highest and lowest values



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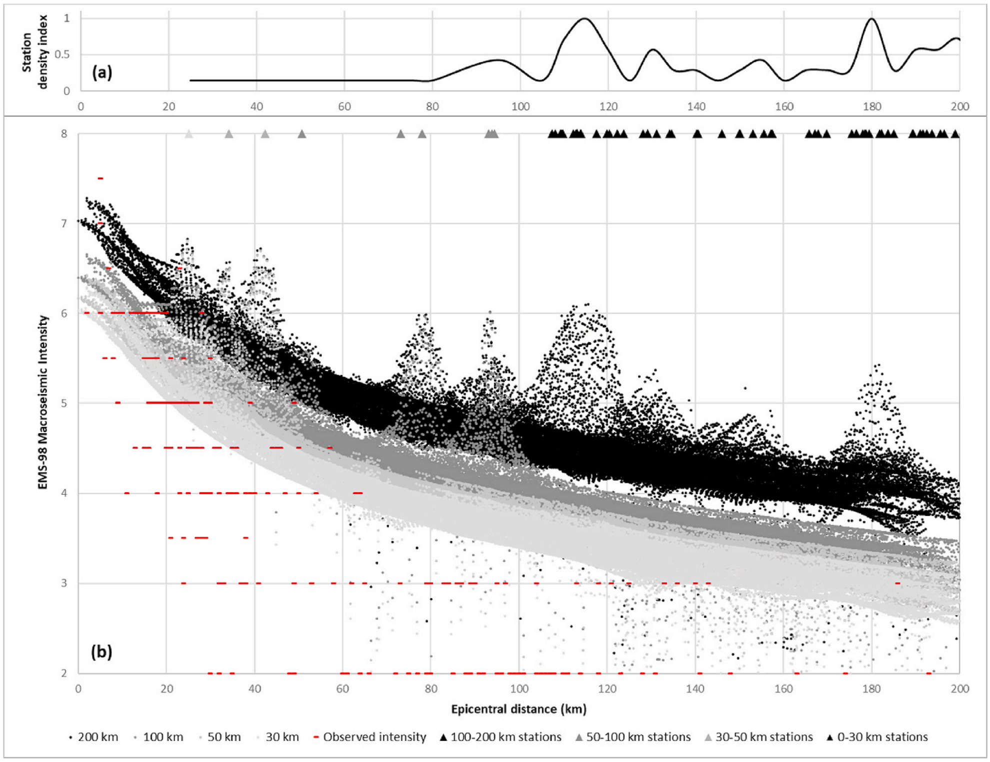
Appendix 7. (a): Normalized station density as a function of epicentral distance. (b): Distribution of predicted intensity (grey/black dots). The estimated intensity is computed using Twitter data and PGA data, considering instrumental data recorded within 30km, 50km, 100km and 200 km. The reference intensity (red lines) as a function of epicentral distance is extracted from municipality-level BCSF data



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