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# Alerting people prioritising territories over technologies. A design framework for local decision makers in France

Esteban Bopp<sup>a</sup>, Johnny Douvinet<sup>b</sup>

<sup>a</sup>UMR 6049 ThéMA, Université de Franche-Comté, France

<sup>b</sup>UMR 7300 ESPACE, Avignon Université, France

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## Highlights

- Facing disasters, characteristics of territories influence the alerting tools required.
- A spatial decision support system is applied to see how 13 alerting tools fit in 40 French municipalities.
- The greater the number of inhabitants, the more diverse the alerting tools needed.
- National LBAS (Location-Based Alerting Systems) are poorly adapted to municipal scale.
- Few tools are suitable for municipalities with a low population and poor access to telecommunication networks.

**Keywords:** alert; alerting tools; municipality; risk; spatial decision support system

## Abstract

Public alerting is a major challenge in a world where risks and communication modes are constantly evolving. Since a few years, new massive alerting tools geolocating the population in real time (Cell Broadcast or Location-Based SMS) have been deployed at national level in several countries. However, this evolution does not always reach with local needs. Decision-makers can use a wide multiplicity of tools and this can induce vulnerability differences from one territory to another. To help decision makers in their choice of equipment, this study proposes a Spatial Decision Support System and applied it in 40 various French municipalities in order to observe how 13 alerting tools are adapted (or not) to the characteristics of the municipalities. Early findings highlighted a great diversity of adapted tools between municipalities and within municipalities, in different alert zones. Alerting tool equipment must be considered at an infra-municipal scale to fully consider the diversity of alert zones. The greater the number of inhabitants, the more diverse the alerting tools needed. Also, few tools are suitable for municipalities with a low population and poor access to telecommunication networks. Finally, as tools geolocating individuals are suitable for highly populated municipalities, such national equipment shall not be used on small alert zones involving few individuals.

## 1. Introduction

### 1.1. Definitions

In the face of a disaster, alerting tools are a central component of warning systems which connect: 1) a hazard detection centre (meteorologists, geologists, industrialists, etc.); 2) a decision-making centre (the authority that takes, or not, the decision to alert); 3) a target population that must be informed of the situation. Alert tools link authorities who decide to alert, to people who receive it. They enable people to be alerted of an imminent danger so that they can implement safety measures, reducing as possible human and economic losses caused by a disaster (DGSCGC, 2013). Alerting tools capture the individual's attention with a signal (a light, a sound) or a message (audible or readable) in order to interrupt the daily activities (Douvinet, 2018). Broadcast messages contain behavioural instructions

(Wood et al., 2018). Should the distinction between “alert” and “warning” be unclear (Bean, 2019), the term “alerting tool” seems more appropriate than “warning tool” because an alert is conveyed by any tool that can make a signal to reveal the danger (sound, visual, voice, but also textual). On the other hand, a warning is a descriptive message of instructions and recommendations, which excludes tools that cannot perform this function (siren, alert box).

### **1.2. Constant technical progress in alert diffusion**

During the last two decades, alerting tools have evolved considerably. The rise of digital technologies has led to the development of new communication methods that crisis managers have seized upon to develop a new generation of alerting tools: cell phones, social networks, and smartphone applications (Palen et al., 2009). These new tools can contribute additional services, such as the exchange of more interactive content or the real-time geolocation of users (Bopp et al., 2019). Two alerting tools, considered as Location-Based Alerting Systems (LBAS), are being deployed in many countries: Cell Broadcast (CB) and Location-Based SMS (LB-SMS). CB allows the broadcast of an alert message on the scale of one or more telecommunications cells where the telephones within range receive a message (Aloudat and Michael, 2011; Axelsson and Novak, 2007). The message is displayed on the main screen with the emission of a sound whether the telephone is switched off or not (ETSI, 2010). LB-SMS sends SMS messages to cell phones linked to one or more target cells, allowing the authorities to know the number of people who have received the message (Azid et al., 2015; Leo et al., 2015). The USA, Canada, Lithuania, Greece, and Italy, for example, use CB while Belgium, Australia, Iceland, and Tunisia use LB-SMS. In 2018, a European decree obliged all member states to deploy a LBAS on a national scale before June 2022.

These new alerting tools have not been developed everywhere (Bopp, 2021). More traditional tools (siren, door-to-door, loudspeaker, radio/TV, etc.) are still widely used in most countries, including those that already have an LBAS. For example, Belgium and the USA link LBAS and complementary alerting tools (sirens, social networks, radio, road panels) using the Common Alerting Protocol (CAP), a computer program that facilitates the interconnection between different alerting tools (Botterell, 2006). However, very disparate situations emerge at finer scales where local authorities must decide on the alerting tools to be developed and activated in times of crisis within their territory (Lee, 2019). This diversity among the tools used has led to a great heterogeneity in the way the alert is disseminated from one territory to another. These local variations can be explained by differences in political decisions among territories (Lassa et al., 2019), but the economic situation of the territories is also an important feature: not all of them have the means to buy efficient but often expensive alert solutions from private companies, like smartphone applications, automatic call machines, or connected sirens (Bopp, 2021). Therefore, some territories are more vulnerable because they are less well equipped in quantity and quality.

### **1.3. A gap in spatial approaches in alerting tool effectiveness studies**

Spatial and territorial components have often lacking in alert studies. Most research dealing with local alerts focuses on the concept of an Early Warning System (EWS). EWSs are implemented in the face of a well-identified hazard with rapid kinetics and highly destructive potential (Piciullo et al., 2018). EWS are able to quickly detect the hazard, generally using automated sensors, and to automatically inform the decision makers (Basher, 2006). Yet EWS studies are hazard-focused, and do not sufficiently address the question of how the alert should be disseminated to the population in an efficient way.

Other works have focused on the in-depth study of an alerting tool in a given territory. In particular, the siren has been studied, notably its effectiveness with regard to its acoustic characteristics (Mathews et al., 2017; Zunkel, 2015), the advantages and limitations in making it a national alert tool

(Douvinet et al., 2021), and the differences that exist between territories that are equipped and those that are not (Bopp, 2021). Chatterjee et al. (2002) studied how drivers reacted to an alerting message broadcast on variable message signs, finding that only one fifth turned away from the danger zone. Pries et al. (2006) observed potentially long delivery times in SMS alerting systems depending on the targeted dissemination area. LBAS (Cell Broadcast and LB-SMS) have also been well studied. They are efficient (Bean et al., 2015; Vivier et al., 2019), have a homogeneous efficiency on a large scale (Bopp and Douvinet, 2020), including in rural areas (Samarajiva and Waidyanatha, 2009).

At the individual level, other research works have studied how the alert is received and interpreted by the population. The content of the messages should be adapted to the hazard, the social profile of the target populations, and their location (Grant and Smith, 2019), but issuer identification, the nature of the danger, and the instructions to follow are essential points (Wood et al., 2015). Spatial information is also essential in alert messages and helps to improve the perception of danger (Cain et al., 2021). Using crisis exercises, Cavaliere et al. (in press) studied how the signal (sound, visual) and the message conveyed were perceived by individuals located in a public place. They found that the sender of the alert must be different depending on the nature of the danger. Perreault et al. (2014) did not observe any behavioural differences depending on the type of alerting message broadcast and its tone (scary or regular).

Despite these advances, we have identified several gaps both in the scientific literature. First, no study holistically observes the effectiveness and complementarity of different combinations of alerting tools in a given territory, while several studies underline the importance of a multi-channel alert (Bean et al., 2015; Bopp and Douvinet, 2020; Douvinet et al., 2020). Second, the adaptation of alerting tools to the municipality scale has not been studied, although this is the most effective level for disaster risk reduction actions (Russell et al., 2021). We do not know if municipal characteristics can play a role in the quality of the alert and the quantity of suitable tools. Thus, the capacity of the tools to adapt to one type of territory rather than another (urban, peri-urban, rural, coastal, mountainous, etc.) or to a certain scale (infra-municipal, municipal, departmental, regional, national) is also unknown. Third, we did not find institutional doctrines adapted to local scales even though some guidelines exist on an international scale about how to build an efficient warning system (5G Americas, 2018; BEREC, 2020; ETSI, 2010). As a result, local decision makers do not have any help when it comes to choosing the appropriate alerting tools to use. Fourth, territories that are insufficiently equipped – or equipped with tools that are not very effective – have not been identified, and therefore not been helped, by national authorities. Thus, studying the ways in which the alerting tools are adapted to different municipalities would make it possible to improve the knowledge of local alerts and perhaps to identify a typology of municipalities according to suitable tools.

#### **1.4. Objectives and research questions**

This article had six main objectives:

- 1) Create a method to identify the spatial, morphological, and environmental criteria that make an alerting tool suitable or not for a municipality;
- 2) Propose, using these criteria, a Spatial Decision Support System (SDSS) to help local decision makers to choose the tools that are best suitable on their territory;
- 3) Appreciate the adaptation of tools through scales (groups of municipalities, municipalities, sub-municipal alert zone);
- 4) Identify which tools can be easily adapted and those that are more difficult to adapt;
- 5) Try to classify the municipalities depending on the number and the nature of suitable tools, so as to be able to predict appropriate equipment for a larger sample of municipalities;

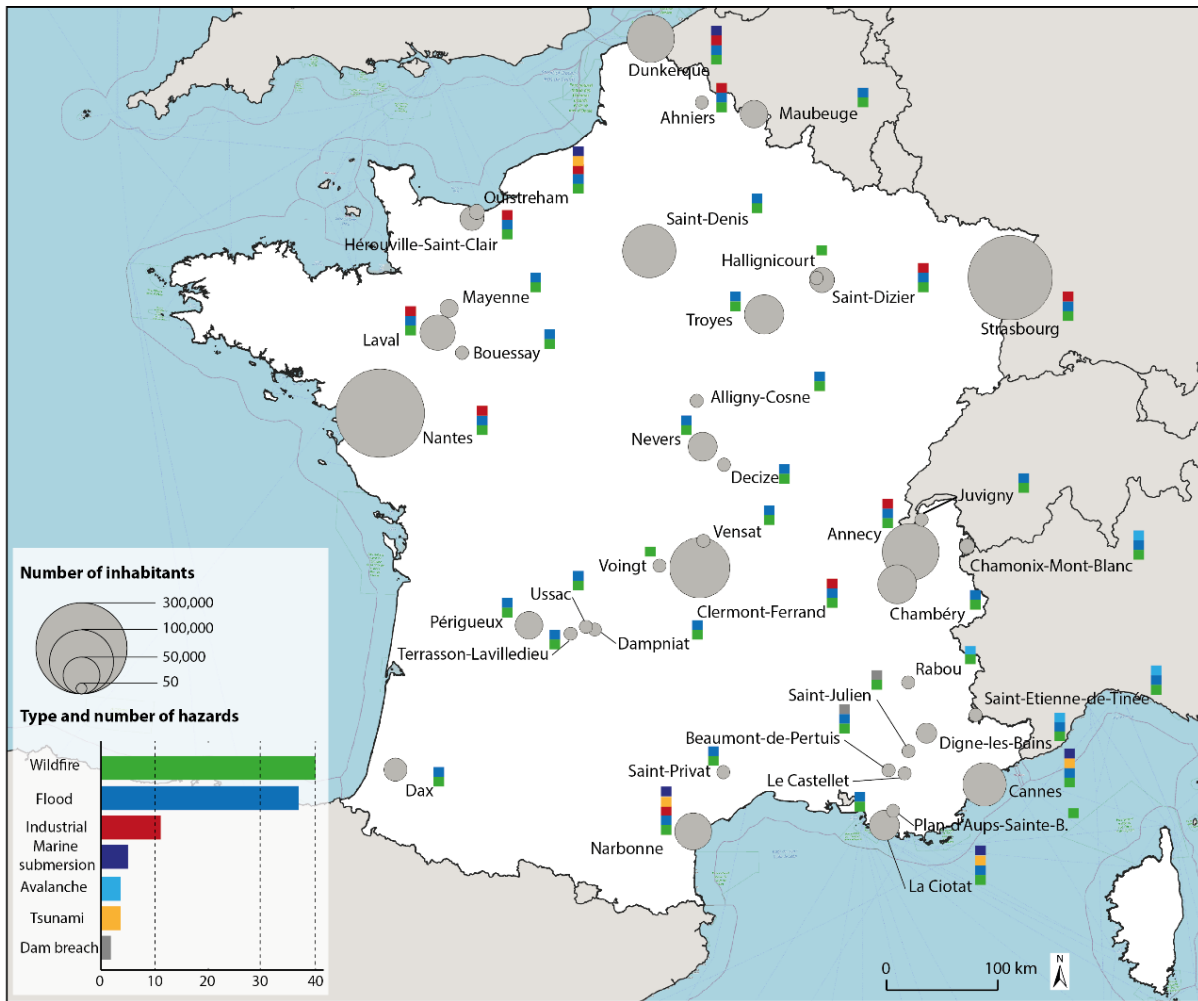
- 6) Identify municipalities with poor alert capabilities and characterise them in order to propose planning solutions to reduce their vulnerability.

Results should then improve knowledge on how to optimise the alert dissemination at local levels. We focused here on the smallest territorial level of alert in France (the municipalities), and we assume that the diffusion of the alert is not spatially uniform at municipal scale and that an efficient diffusion system requires different tools from one municipality to another. The article is structured as follows: Part 2 presents the method and data used, and Part 3 presents the results, subsequently discussed in Part 4.

## **2. Study sites and metric identification**

### **2.1. A sample of 40 heterogeneous municipalities**

The method is applied on a sample of 40 French municipalities. France present a very fine-meshed territorial network at local scale (34,968 municipalities for 630,000 km<sup>2</sup>), and a high level of exposure to multiple risks (André, 2012): floods, forest fires, tsunamis, landslides, storms, earthquakes, etc. Even if the human vulnerability remains limited compared to other countries (Behlert et al., 2020), more than 25,000 people have died in France over the last 50 years as a result of natural disasters, according to the EmDat database. The 40 studied municipalities present heterogeneous number of inhabitants (**Table 6; Figure 1**): fewer than 1,000 inhabitants (n=10); between 1,000 and 9,999 inhabitants (n=10); between 10,000 and 49,999 inhabitants (n=10); more than 50,000 inhabitants (n=10). These are also located in different geographical contexts (coastal, mountains, urban, rural, isolated rural) and the sampling covered a wide range of potential natural and manmade disasters (flood, forest fire, tsunami, avalanche, industrial accident, and dam breach).



**Figure 1.** The locations of the 40 sample municipalities

## 2.2. Alerting tool panel

We have considered 13 alerting tools (**Figure 2**). We distinguish between traditional tools (sirens, door-to-door, mobile loudspeakers, etc.) to other tools that use numerical vectors (smartphone app, social media, etc.). France use the siren as the main alerting tool for 60 years (Douvinet et al., 2021) but Cell Broadcast (CB) is deployed at the national scale since June 2022 and Location-Based SMS (LB-SMS) will be expected in 2023. Not all countries with LBAS allow local decision makers to use CB and/or LB-SMS. This possibility has not yet been acted in France but these tools are included in the panel because one of the objectives of this study was also to examine whether LBAS are appropriate at the municipal level. We also distinguished between primary and complementary tools (**Figure 2**). Primary tools are disseminators without which the alert could not be effective while complementary tools must not be activated alone, while complementary tools remain important because they reinforce the alert locally, targeting certain categories of population (e.g. variable message signs, which warn motorists).

Alerting tools and climate change

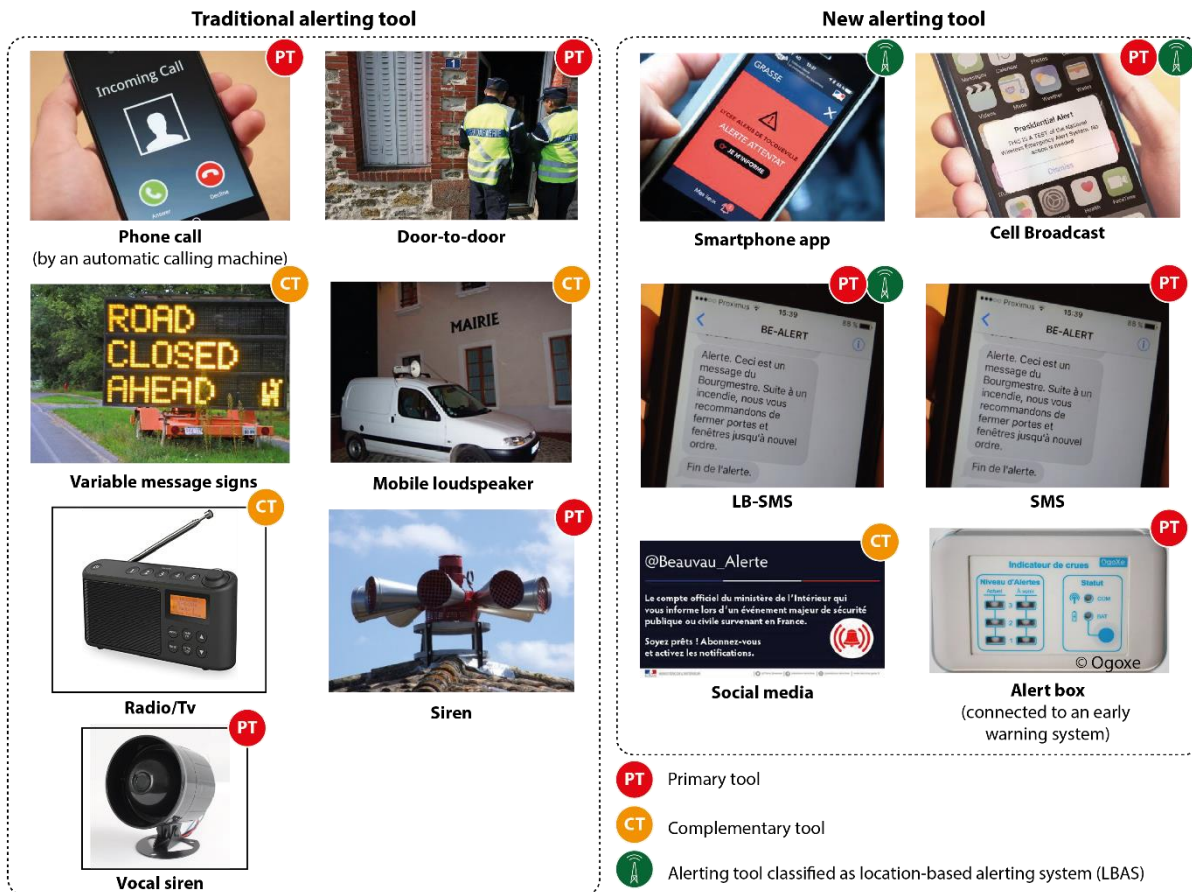


Figure 2. Nature and categorisation of the 13 alerting tools that are, or will soon be, usable at the municipal level in France

### 2.3. Metric identification

Several metrics that could impact the effectiveness of alert were identified: (1) the kinetics of hazards; (2) the number and position of individuals in space, (3) the spatial distribution of buildings and the area of the risk zone; (4) the municipality equipment. **Table 1** lists all the metrics identified.

#### 2.3.1. Hazard kinetics

The kinetics of hazards gives an idea of how long it takes local decision makers to issue the alert. The alert delay corresponds to the time between the hazard (H) detection and the alert diffusion to the population (Daupras et al., 2015). Some alerting tools take time to be activated (Radio/TV, door-to-door, mobile loudspeaker) and cannot be used when the hazard is too imminent. Other tools are particularly appropriate for a short delay (alert box). We identified 3 thresholds: sudden hazards (the hazard H can occur in less than 15 minutes); very rapid hazards ( $H < 1$  hour); rapid hazards ( $H < 5$ h). Hazards expected in more than 5 hours have not been considered in this study. The methods used to apply minimum kinetics to each hazard zone are explained below (see 2.4.1).

#### 2.3.2. Number and location of individuals

Sirens are not a spatially accurate tool and cannot be used in areas with a low population size (Douvinet et al., 2021). We consider that below 50 individuals, individual tools (door-to-door, alert box), should be preferred to sirens. The number of households is studied nor the number of individuals for door-to-door and alert box. Door-to-door for mass alerts is to be avoided: during the 2018 rapid floods in Trèbes in the Aude, the firefighters could not visit all the homes and 6 individuals who were not alerted died. We consider that above 100 households, door-to-door is not appropriate. Alert box is appropriate

when integrated into an early warning system. These are costly solutions, and mass media should also be preferred over alert boxes when the number of households is above 1,000.

The number of individuals equipped with a phone must be counted for tools using mobile telephony. The estimating method is explained below (see 2.4.1). Network congestion problems may affect mobile telephony solutions in times of crisis (Leo et al., 2015). The congestion depends on the number of people in each telecommunication cell, the alert delay, and the tool. Phone calls are more subject to congestion than smartphone app and (LB)SMS, while CB is not subject to network congestion (Sanders, 2011). The congestion thresholds (**Table 2**) are taken from the experience of countries using these solutions (Aloudat and Michael, 2011; Bonaretti and Fischer-Preßler, 2021; ETSI, 2010). Also, CB and LB-SMS may encounter significant edge effects when the alert area is not identical to the telecommunications cell area (Bopp, 2021). Individuals located outside the danger zone but in a cell that intersects the danger zone will receive an inappropriate alert. This issue is particularly important in territories where the danger zones are small but the telecommunications cells are large. We consider that when the number of unaffected individuals receiving the alert is twice the number of individuals affected by the hazard, CB and LB-SMS are no longer appropriate.

2.3.3. Spatial aggregation of buildings and risk zone size

The building aggregation (BA) level is important for acoustic tools (sirens, vocal sirens) or targeted tools (door-to-door) (Zunkel, 2015). We used the nearest neighbour mean to estimate this aggregation. The thresholds retained attempt to match the boundaries between dense urban areas (BA < 15 m), suburban areas (15 m < BA < 30 m), and spread-out rural areas (BA > 30 m). We believe that the siren is not appropriate in spread-out rural areas, where the exposed individuals are spatially disaggregated and distant from each other. Since the vocal siren has a much smaller acoustic area than the siren, we believe that this tool is only appropriate in dense urban areas (BA < 15 m). The size of the risk zone must be relatively small for door-to-door and mobile loudspeaker solutions (Nishino et al., 2021). They are mobile tools and too large an area would require major means (many vehicles, many agents) with a lengthy diffusion delay, whereas mass means are efficient. We consider that above 100 hectares, door-to-door must be avoided, and that for 500 hectares, mobile loudspeakers are not suitable.

2.3.4. Municipal equipment

Two types of municipality equipment were examined: main road and telecommunications coverage. A main road (with high traffic) going through the hazard zone justifies the use of variable message signs. Tools using mobile telephony are dependent on telecommunications coverage quality. The Telecommunications Coverage Rate (TCR) gives the number of individuals covered by the telecommunications networks compared to the target population. We believe that below 75% of individuals covered, these tools are not effective enough. As was the case for a previous study on the evaluation of LBAS performance in France (Bopp and Douvinet, 2020), 2G, 3G and 4G shapefile data were used for SMS, LB-SMS and phone calls. Only 4G data were used for Cell Broadcast social media on smartphone and smartphone apps, since these will only be deployed on 4G networks in France and they require a sufficient level of connection to work.

**Table 1.** List and abbreviations of selected metrics

Metrics	Abbreviation
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Hazard kinetics	HK
Number of Targeted Households	TH
Number of Targeted Individuals	TI
Number of Non-Targeted Individuals Reached	NTIR
Number of Equipped Individuals	EI
Building aggregation	BA
Risk Zone Size	RZS
Main road location	MR
Telecommunications Coverage Rate	TCR

**Table 2.** Details of the characteristics of the 13 alerting tools that have a consequence on their suitability at the municipal level, and thresholds retained for each of the metrics referring to these features

Alerting tools	Features	Metric selected thresholds
Alert box	Used in relation with an early warning system in rapid kinetics hazard zone	HK < 15 min
	Costly solution in proportion to the number of dwellers to be alerted	TH < 1000
Cell Broadcast	Edge effect related to the cellular network	TI/NTIR > 0.5
	Telecommunications network must be efficient	TCR(4G) > 75%
Door-to-door	Used for targeted alerts involving few people	TH < 100
	Not effective in large area	RZS < 100 hectares
Location-Based SMS	Edge effect related to the cellular network	TI / NTIR > 0.5
	Risk of network congestion	EI < 30,000 when HK < 1h EI < 10,000 when HK < 15 min
	Telecommunications network must be efficient	TCR(2G-3G-4G) > 75%
Mobile loudspeaker	Used for targeted alerts involving few people	TH < 1000
	Not effective in large area	RZS < 500 hectares
Phone call	Telecommunications network must be efficient	TCR(2G-3G-4G) > 75%
	Risk of network congestion	EI < 20,000 when H < 1h EI < 1000 when HK < 15 min
Radio/TV	Tool that can be long to activate	HK > 1h
Smartphone app	Telecommunications network must be efficient	TCR(2G-3G-4G) > 75%
	Risk of network congestion	EI < 30,000 when HK < 1h EI < 10,000 when HK < 15 min
SMS	Telecommunications network must be efficient	RIC > 75%
	Risk of network congestion	EI < 30,000 when HK < 1h EI < 10,000 when HK < 15 min
Social media on smartphone	Effective only for small target network of individuals	EI < 200
	Telecommunications network must be efficient	TCR(4G) > 75%
Siren	Tool that cannot be used for targeted alerts involving very few people	TI > 50
	Not very effective in areas where buildings are widely dispersed	BA < 30 m (average of nearest neighbours)
Variable message signs	Effective when a main road (MR) goes through a danger zone	MR crosses H
Vocal siren	Small audibility zone: not very effective in areas where buildings are dispersed	BA < 15 m (average of nearest neighbours)

### 3. Overview of the Spatial Decision Support System

According to Crossland (2008), a Spatial Decision Support System (SDSS) must: (1) provide mechanisms for imputing spatial data, (2) enable the representation of spatial relationships and structures, (3)

include spatial data analysis techniques, and (4) provide results on a variety of spatial forms, including maps. **Figure 4** summarises all the steps in SDSS construction.

### **3.1. Input spatial data**

Population and hazard location are the two main spatial data required for SDSS implementation. To consider the daily mobility of individuals, we located people at their place of residence and at their workplace, at the building scale. Residents found in the INSEE data (2019) were located in each residential building of the BD-TOPO data (2020), in proportion to the number of dwellings. Working people were localised using both “Workplace” INSEE database (2016) and BD-TOPO data (2020). The “Workplace” database gives the number of jobs offered by each municipality, and the detailed socio-professional categories. We located jobs depending on the nature of the buildings in the BD-TOPO as follows: farmers in farm buildings, workers in industrial buildings, and executives, employees, craftspeople, company managers, and intermediate professions in commercial and service buildings. In addition, retired, unemployed, and inactive individuals were located in residential buildings, in proportion to the number of dwellings. This way, a very fine-meshed spatial location of individuals was obtained for two different periods: night (resident people) and day (working people).

Hazard spatial data came from different sources (**Table 2**). The hazards involved were flood, marine submersion, snow avalanche, tsunami, wildfire, industrial accident, and dam breach. Hazards that are not predictable (earthquake), without an exhaustive database at the national level (landslide), complex to spatialize at the municipal scale (storm, tornado, intense precipitation, cold or heat wave, etc.) and with too slow a kinetic (drought) were not retained. All spatial data concerning hazards were open-source State data (see **Table 8** in the appendix). In some cases, additional processing was necessary (see **Table 7** in the appendix). For industrial risks, a threshold of 1 km around the high-risk sites (Seveso, Upper-tier), and 500 m around the lower-risk sites (Seveso, lower-tier) were chosen with regard to the precautionary zones mentioned in Technological Risk Prevention Plans (Laurent et al., 2021). Tsunami data was created, due to a lack of availability. The exposed areas were extracted from a Digital Terrain Model. They correspond to the sets of pixels of altitude lower than the maximum expected run-up and having a direct contact with the coastline (5 m). The forest fire hazard data was derived from the vegetation zones of the BD-TOPO database. Only closed forests (e.g. areas with at least 40% tree cover) and shrublands were kept. A 50m buffer was applied to each forest patch of more than 10 hectares so that the dwellings bordering the forest patches were included in the danger zone. Forest patches smaller than 10 hectares were not retained, to avoid the multiplication of tiny and incoherent risk zones.

Telecommunications antennas (for LBAS) were also included in the SDSS, using ARCEP data. Voronoï polygons were created to model the telecommunications cells and to measure the edge effect. Individuals from municipalities neighbouring the sampled municipalities were also located to consider this edge effect. Finally, main roads from the BD-TOPO database were added in the SDSS. The existence of a main road going through a danger zone justified the use of variable message signs. We chose to use the numbered or named roads from the BD-TOPO database, i.e. the main infrastructure roads in France (highways, national roads, departmental roads).

### **3.2. Alert zone identification**

An alert zone is an area exposed to a hazard and in which people are located (at home or at work). Alert zones are heterometric and may overlap within municipalities. We identified three levels of alert zones: level 1 (L1), level 2 (L2), and level 3 (L3). The first (L1) alert zone corresponds to the entire municipal territory. No particular risk is associated with this zone but it enables the identification of tools suitable for the diffusion of an alert to all the citizens of the municipality. The identification of L1

zones guarantees a certain flexibility of the SDSS since it allows the identification of tools adapted to areas not exposed to known hazards (L2), offering a possible anticipation of the occurrence of a hazard that is difficult to map and forecast (earthquake, hail, tornado, etc.). There are 40 L1 zones in the sample, i.e. as many as there are municipalities.

The second (L2) corresponds to the scale of each continuous risk zone (a flood zone, an avalanche zone, a forest plot) in which people live or work. Within a municipality, there may be several L2 zones for the same hazard: 1) if there are multiple areas involved (e.g. several non-contiguous forest patches for forest fire risk); 2) if there is only one area (contiguous) but the hazard source is multiple (e.g. two rivers that meet give rise to two distinct L2 flood zones). In total, 455 L2 zones were identified in the municipalities studied (average of 11.38 per municipality).

The third (L3) exists when there are several groups of buildings (in which people live or work) within the same L2 alert zone. We considered that it should be possible to distinguish the alerting tools within the same L2 alert zone, especially when territorial configurations require it. Thus, when a group of 5 or more buildings (containing residents or workers) is more than 200 m away from another group of buildings, we consider that L3 zones are necessary (as many zones as there are groups of 5 or more buildings separated by at least 200 m; **Figure 3**). When this is the case, the L2 is still calculated and appears in the municipality results in order to give the decision maker the choice between "global" L2 equipment or "precise" L3 equipment. We identified 231 L3 zones (average of 5.78 per municipality).

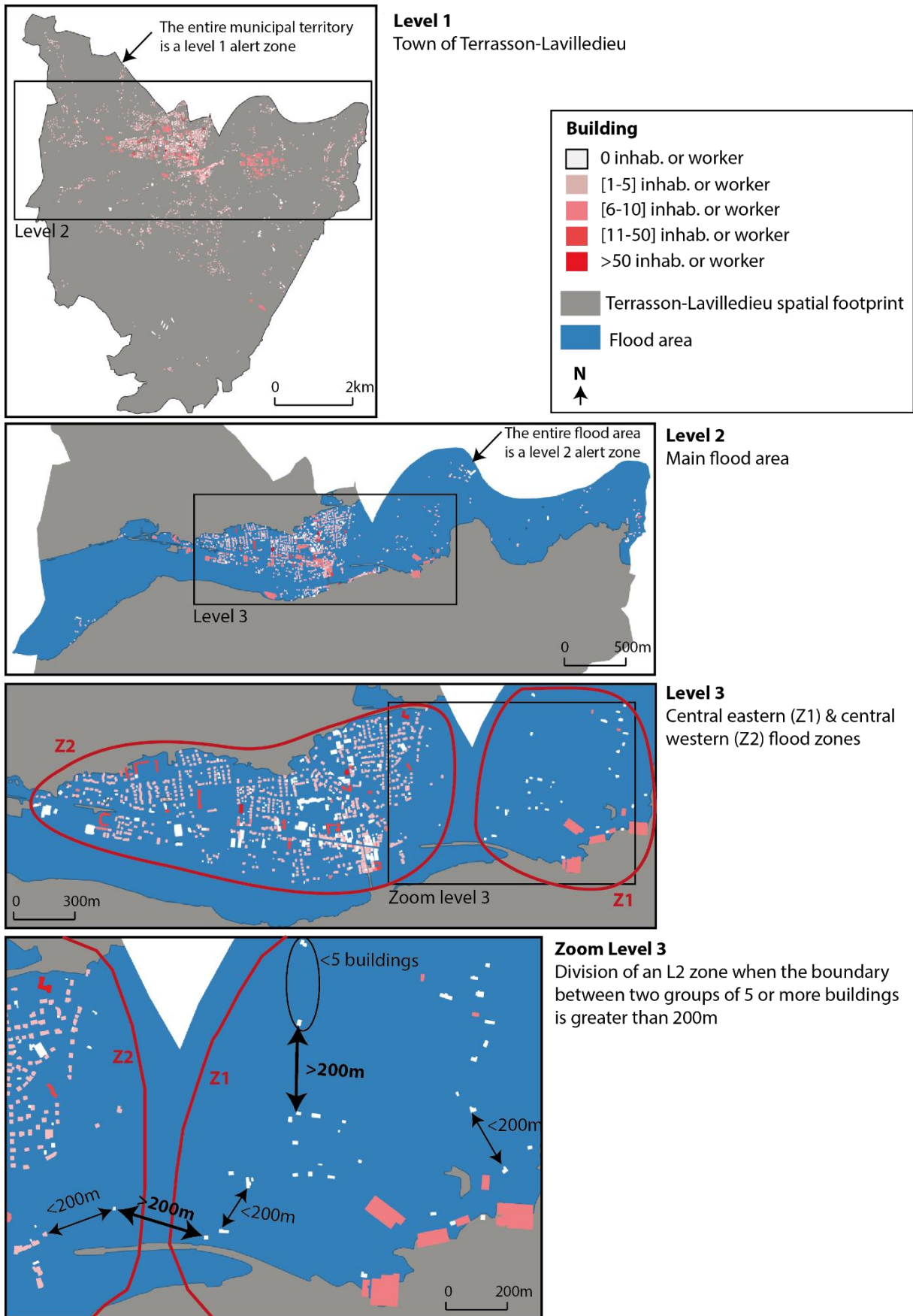


Figure 3. Method for identifying three alert zone scales within municipalities

### 3.3. Metric processing

Metrics were calculated for each alert zone in a GIS. The households, residents, and workers were counted for each hazard zone. Building aggregation was calculated using the average distance to the nearest neighbour. The numbers of equipped individuals were estimated by inferring data from a governmental study, representative of the French population (Arcep, 2020). As age is related to the probability of having a cell phone, we took this parameter into account to estimate the number of equipped individuals within each alert zone. The Telecommunications Coverage Rate was obtained by calculating the number of individuals located in the areas covered by the type of telecommunications (2G-3G-4G for phone calls, LB-SMS and SMS; 4G for Cell Broadcast, social media on smartphone and smartphone app) and dividing this number by the total number of target individuals. The telecommunications network vector data is public data from ARCEP (see **Table 8** in the appendix).

The hazard kinetics measurements depend on the geographical context, the hazard nature and known scenarios. We have retained the minimum possible kinetics for each alert zone in order to avoid the risk of having tools whose diffusion temporality would be higher than the arrival of the phenomenon. We classified the minimum expected kinetics in three classes: sudden (less than 15 minutes), very fast (between 15 minutes and 1 hour), and fast (more than 1 hour). On the Mediterranean coast, a tsunami is likely to arrive in 15 minutes (Sahal et al., 2013). We also considered that the warning time for a technology risk is likely to be less than 15 minutes. For the forest fire hazard, the warning time necessary depended on the size of the burnable area (Kaur and Sood, 2020). We considered that below 100 ha, the warning time would be less than 1h. The marine submersion and the avalanche risks (considering for the latter that the alert warns of a high risk and not of an effective triggering) have kinetics considered as higher than 1 hour because their predictability depends on a predictable meteorological state. In this case, we are rather on the pre-alert (the setting in vigilance of the populations) and not a phase of alert vis-à-vis an effective hazard. For flood risk, we used Passini's formula to estimate the concentration time of the watersheds and thus the warning time (sudden, very fast, or fast) for each river (Salimi et al., 2017). The related formula is as follows:

$$CT = 60 * 1.08 * \frac{((S * L)^{\frac{1}{3}})}{i^{1/3}}$$

With *CT*: the concentration time from the watershed to the municipality; *S*: the surface of the watershed to the municipality; *L*: the length of the watercourse to the municipality; *i*: the average slope of the watercourse to the municipality.

### 3.4. Outputs

Results are given in the form of a contingency table where the suitability of the 13 alert tools for each area of the municipality is a Boolean variable (0 or 1). A cartographic output is also possible (**Figure 5**) to support the decision-making process.

### 3.5. Result analysis

Four indicators were created to achieve the objectives of the study. Two indexes give information on the alertability of municipalities (easily or hardly to alert). The first index is the Tool Availability Index (TAI), which corresponds to the municipality's ability to have a large number of suitable tools, considering the importance of having primary tools. The latter were weighted by two compared to the complementary tools in this index:

$$TAI = \frac{2 * (\sum PTa) + (\sum CTA)}{(2 * PTmax + CTmax) * NZ}$$

With *TAI*: the Tool Availability Index; *PTa*: Primary Tool adapted to at least one zone of the municipality; *CTa*: Complementary Tool adapted to at least one zone of the municipality; *PTmax*: maximum number of Primary Tools that could be suitable in one zone (this variable is invariant and is equivalent to 7); *CTmax*: maximum number of Complementary Tools that could be adapted to one zone (this variable is also invariant and is equivalent to 4); *NZ*: number of zones in the municipality.

The second index is the Minimum Equipment Effort Index (MEEI), which corresponds to the minimum number of alerting tools of different natures required to have at least one primary alerting tool suitable for each of the municipality zones. It indicates the minimum investment required to have equipment covering all the alert zones with at least one primary tool.

The third index is the Tool Variability Index (TVI). It quantifies the variability of the tools between the zones of the same municipality. It reveals the diversity of situations within the same municipality, and between municipalities when compared on a larger scale. The higher the index is, the more heterogeneous are the ways to deliver the alert within the municipality. If the variability of alerting tools within a zone is a good thing (multi-channel alerting is more efficient), the variability of the tools between different zones can induce differences and spatial inequalities in the functioning and quality of alerts. Remember that for each zone, a tool has a value of 1 when it is suitable and 0 when it is not. The variability index is expressed as follows:

$$TVI = \frac{\bar{X}\sigma(AT)}{\bar{X}\sigma(AT)max}$$

With *TVI* the Tool Variability Index;  $\bar{X}\sigma(AT)$  the average of the variance of the alerting tools suitable for the different zones;  $\bar{X}\sigma(AT)max$  the maximum average of the variance of the alerting tools suitable for the different zones.

The fourth index is the Adaptability Index (AI). It is tool-focused, calculated for each tool at the municipality level but also at the level of the whole study area, in order to appreciate the suitability of each tool. The index corresponds to the percentage of zones where the tool is suitable. The value is then normalised between 0 and 1. In order to identify a possible classification of the tools, a Principal Component Analysis and a Hierarchical Cluster Analysis were performed on the adaptability index of the 13 tools for the 40 municipalities.

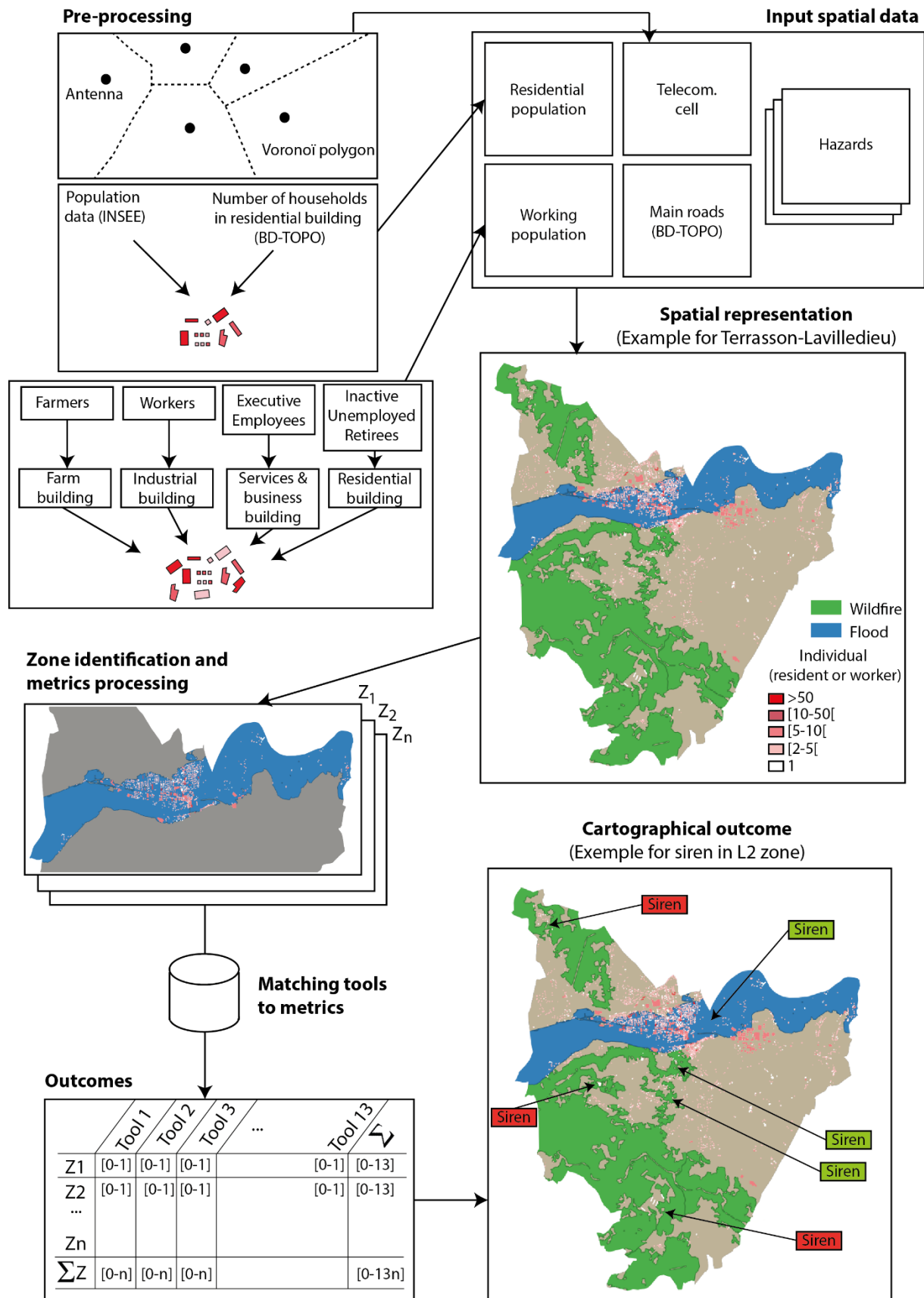
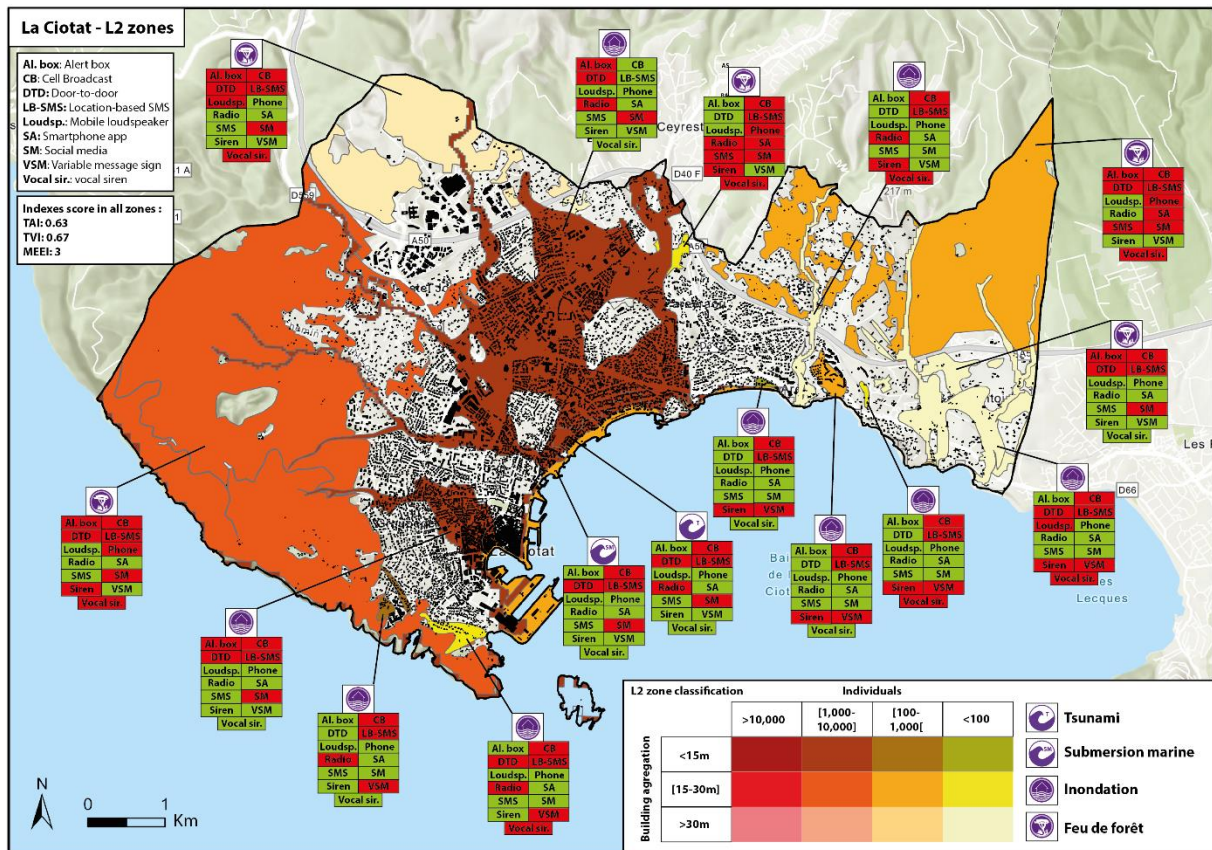


Figure 4. Overall SDSS structure (example for Terrasson-Lavilledieu)



**Figure 5.** Examples of cartographical output for L2 zones in the municipality of La Ciotat (35,366 inhabitants). The colours of the zones correspond to a classification depending on the number of inhabitants and the aggregation of buildings. Some zones of the same class may have different suitable tools.

## 4. Results

### 4.1. Different alertability levels

The average Tool Availability Index (TAI) is 0.51 ( $SD \pm 0.15$ ). The municipality with the highest TAI is Ahniers (0.68), and Rabou has the lowest (0.19). The TAI is not significantly correlated with the number of inhabitants ( $r=0.19$ ,  $p=0.229$ ), the number of workers ( $r=0.19$ ,  $p=0.241$ ) or the number of alert zones ( $r=0.08$ ,  $p=0.617$ ). We classified municipalities into 5 classes depending on their number of inhabitants, but did not observe any significant difference in TAI within these groups (Kruskal-Wallis test (non-parametric data);  $\chi^2=9.36$ ;  $p=0.052$ ; **Table 3**). However, the TAI is positively correlated with the municipal share of individuals residing in an area covered by 4G networks ( $r=0.61$ ,  $p<0.0005^{***}$ ), and to a lesser extent with the share of areas subject to a hazard with sudden kinetics ( $r=0.32$ ,  $p=0.041^*$ ). The TAI is also negatively correlated with the level of aggregation of the buildings ( $r=-0.47$ ,  $p=0.002^{**}$ ) which means that the more dispersed the municipality habitat, the lower the number of suitable alerting tools. The Gini index for the TAI is 0.15, so the number of adapted tools is not very heterogeneous among the municipalities.

The average Tool Variability Index (TVI) presents similar values in comparison with the TAI (0.51,  $SD \pm 0.15$ ). The municipality with the highest TVI is Troyes (0.74), and Rabou is again the lowest (0.14). The TVI is significantly correlated with the number of inhabitants ( $r=0.70$ ,  $p<0.0005^{***}$ ), the number of workers ( $r=0.68$ ,  $p<0.0005^{***}$ ), the share of areas subject to a hazard with sudden kinetics ( $r=0.42$ ,  $p=0.0076^{**}$ ), the municipal share of individuals residing in an area covered by 4G networks ( $r=0.44$ ,  $p=0.0048^{**}$ ), and to a lesser extent with the number of alert zones ( $r=0.34$ ,  $p=0.032^*$ ). The TVI is significantly higher for cities with between 50,000 and 100,000 inhabitants than for cities with fewer



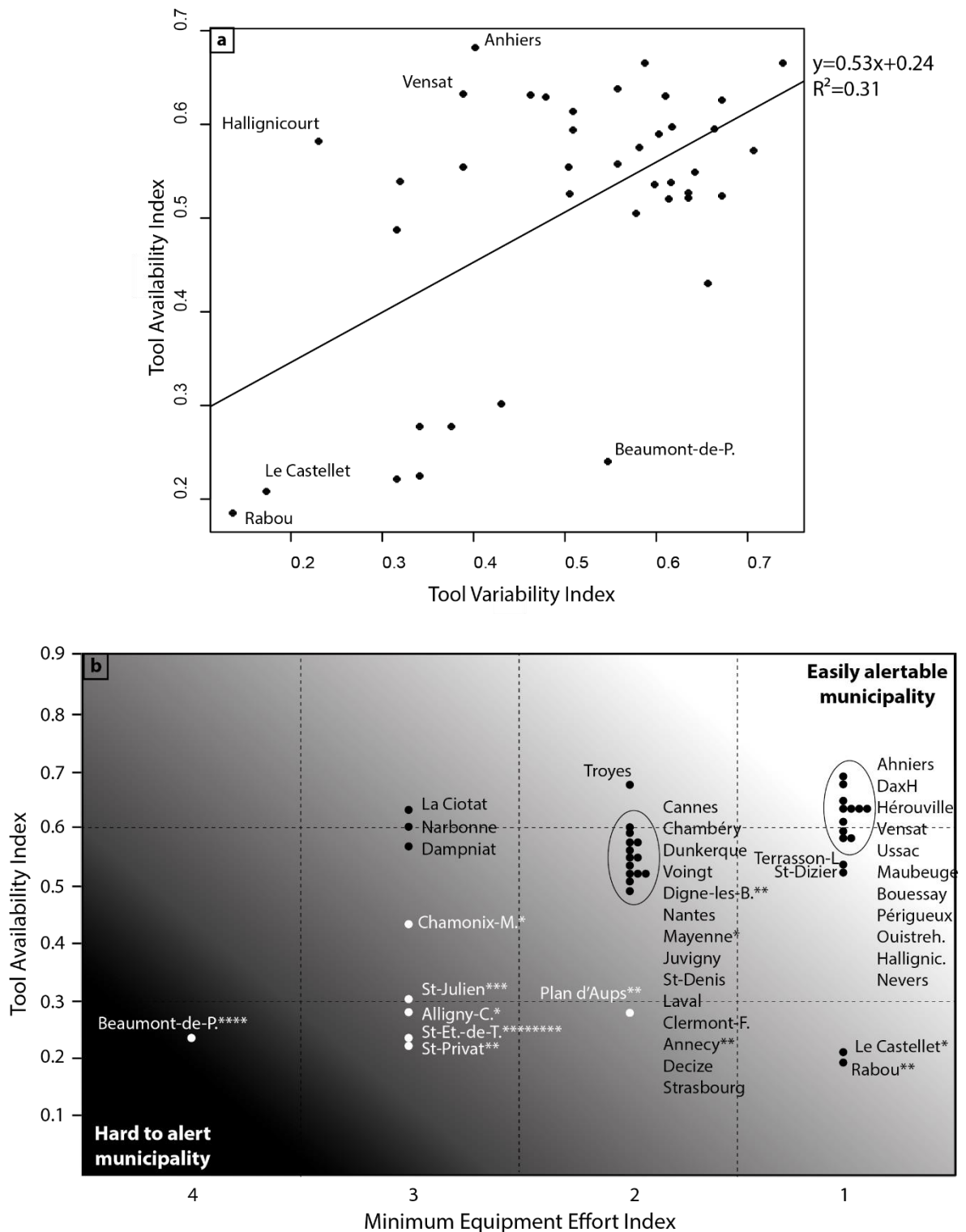
than 50,000 inhabitants (**Table 3**). It is significantly lower for cities with fewer than 1,000 inhabitants than for cities with more than 10,000 inhabitants (**Table 3**). The Gini index for the TAI is 0.16, which indicates that there is not a wide diversity of tools among the municipalities.

The Minimum Equipment Effort Index (MEEI) is a quantitative discrete variable. The average MEEI is 1.88 (SD±0.82). The highest MEEI is 4 (Beaumont-de-Pertuis) which means that 4 different primary tools are needed to equip all the alert zones of this municipality. On the other hand, 15 municipalities have a MEEI of 1, which means that these municipalities could be equipped with a single primary tool.

The regression line between TAI and TVI ( $y=0.53x+0.4$ ) is able to explain 31% of the point distributions (**Figure 6.a**). The majority of municipalities are characterised by a high TAI and TVI, while some are characterised by a low TAI and TVI (Le Castellet, Rabou). Also, some municipalities deviate from the linear model by having a high TAI but a rather low TVI (Anhiers, Vensat, Hallignicourt) or the opposite (Beaumont-de-Pertuis). All these municipalities are sparsely populated. **Figure 6.b** shows the TAI of municipalities depending on their MEEI. It allows us to distinguish between "difficult to alert" and "easily alertable" municipalities. The first are characterised by a low number of suitable tools and a consequent minimal equipment effort. Six municipalities have a MEEI higher than or equal to 3 (i.e. it takes at least 3 primary tools to equip all the alert zones) and a TAI lower than 0.5. Moreover, some municipalities have one or more alert zones where no primary tools are suitable (12 municipalities on 40), the worst situation being for Saint-Etienne-de-Tinée where there are 8 alert zones without suitable primary tools! Easily alertable municipalities are characterised by a high number of suitable tools and a low minimum equipment investment needed: 13 municipalities have a TAI higher than 0.5 and a MEEI of 1 (i.e. one primary tool is sufficient to equip all the alert zones).

**Table 3.** Analysis of the variance of TAI and TVI depending on a classification of the municipalities by the number of inhabitants (two values in the same row with a different letter are significantly different according to the Tuckey post-hoc test).

	Statistical test	>100k. inhab. n=5	[100k-50k] inhab. n=5	]50k-10k] inhab. n=10	]10k-1k] n=10	<1,000 inhab. n=10
TAI Kruskal-Wallis	X <sup>2</sup> =9.36 Df=4 p=0.052	a 0.52	a 0.60	a 0.59	a 0.44	a 0.44
TVI ANOVA	X <sup>2</sup> =0.427 Df=4 p<0.0005***	abc 0.57	a 0.67	b 0.58	cd 0.46	d 0.36

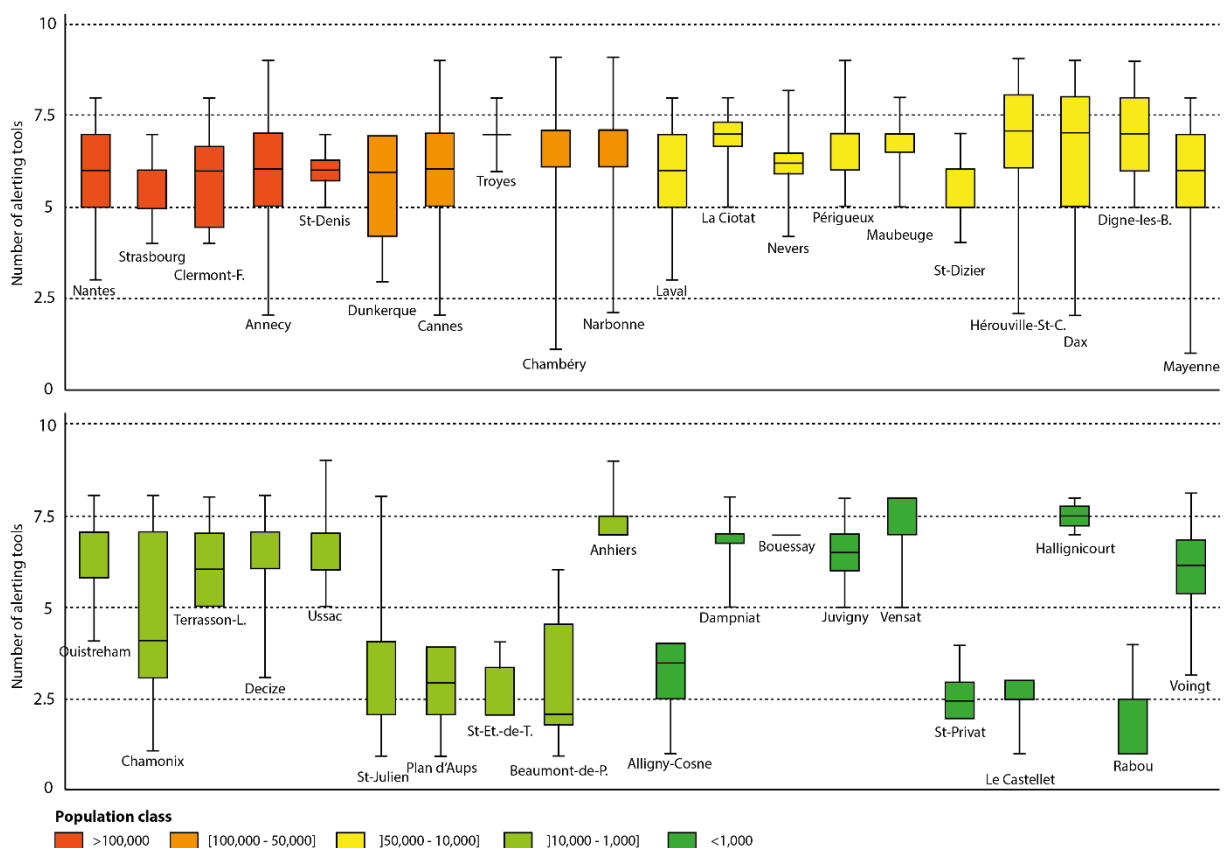


**Figure 6.** a: linear regression between TAI and TVI; b: graphical view of a gradient of alertability depending on the TAI and MEEI scores of the municipalities. The number of asterisks corresponds to the number of alert zones where no primary tools are adapted. Thus, there is significant variability in adapted alert tools at the sub-municipal scale (between alert zones) and between different municipalities.

Eight municipalities have a low number of alerting tools adapted to their zones compared to the rest of municipalities (**Figure 7**): they all have fewer than 2,500 inhabitants, but they also have poor access to telecommunications networks (on average, only 2.3% of their residents are covered by 4G). Previous work has shown that in France, municipalities with poor access to telecommunications networks are

all sparsely populated (Bopp & Douvinet, 2020). Sufficient access to a telecommunications network is a parameter that influences the suitability of 6 tools, including 4 primary tools. However, when those 6 telecommunications tools are removed from the analysis, the recalculated TAI is still significantly lower for the 8 municipalities than for the 32 others (t-test,  $t=2.96$ ,  $p=0.014^*$ ).

Therefore, parameters other than the absence of telecommunications networks play a role in the poor alertability of these municipalities. The number of inhabitants is not significantly correlated with the recalculated TAI ( $r=-0.10$ ,  $p=0.919$ ), nor is the number of alert zones ( $r=0.18$ ,  $p=0.857$ ). However, the level of building aggregation in the municipalities ( $r=-0.46$ ,  $p=0.002^{**}$ ) or the rate of alert zones subject to sudden kinetics ( $r=0.36$ ,  $p=0.023^*$ ) are significantly correlated with the revised TAI. The 8 communes in question are indeed characterised by a low building aggregation and/or a high rate of zones subject to sudden risk.

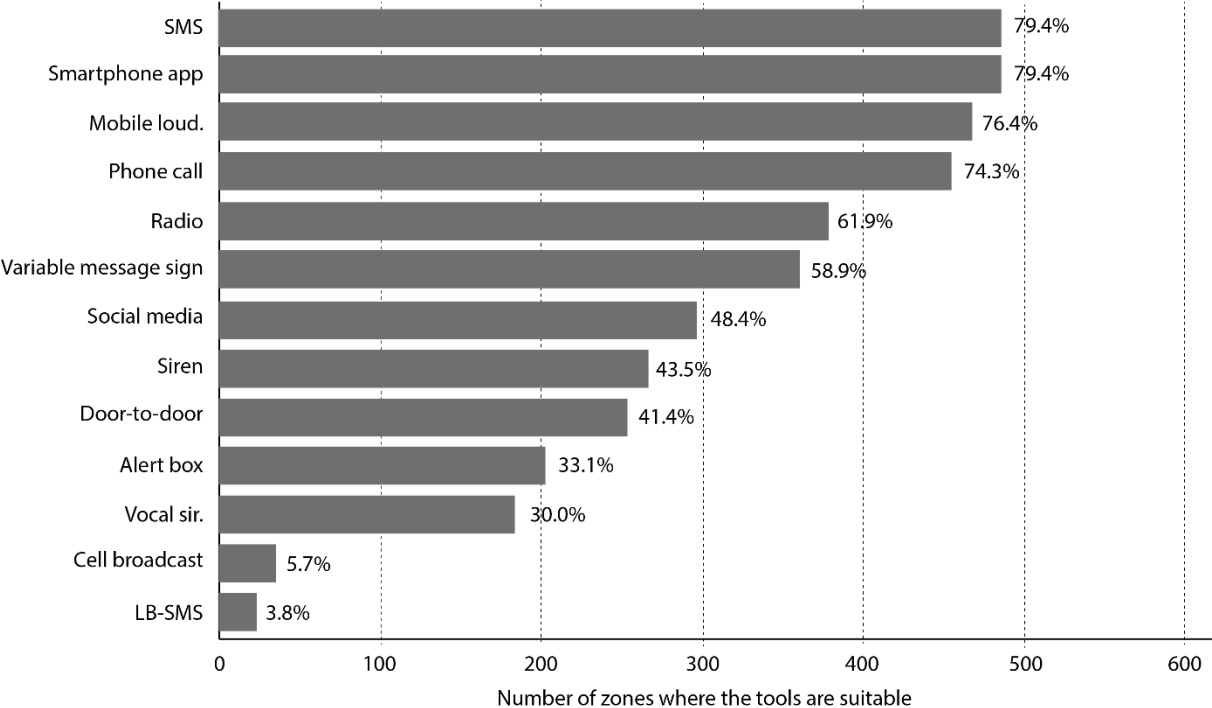


**Figure 7.** Boxplots of the number of alerting tools adapted to the zones of the 40 municipalities. The municipalities are coloured depending on their number of inhabitants and are ranked in descending order.

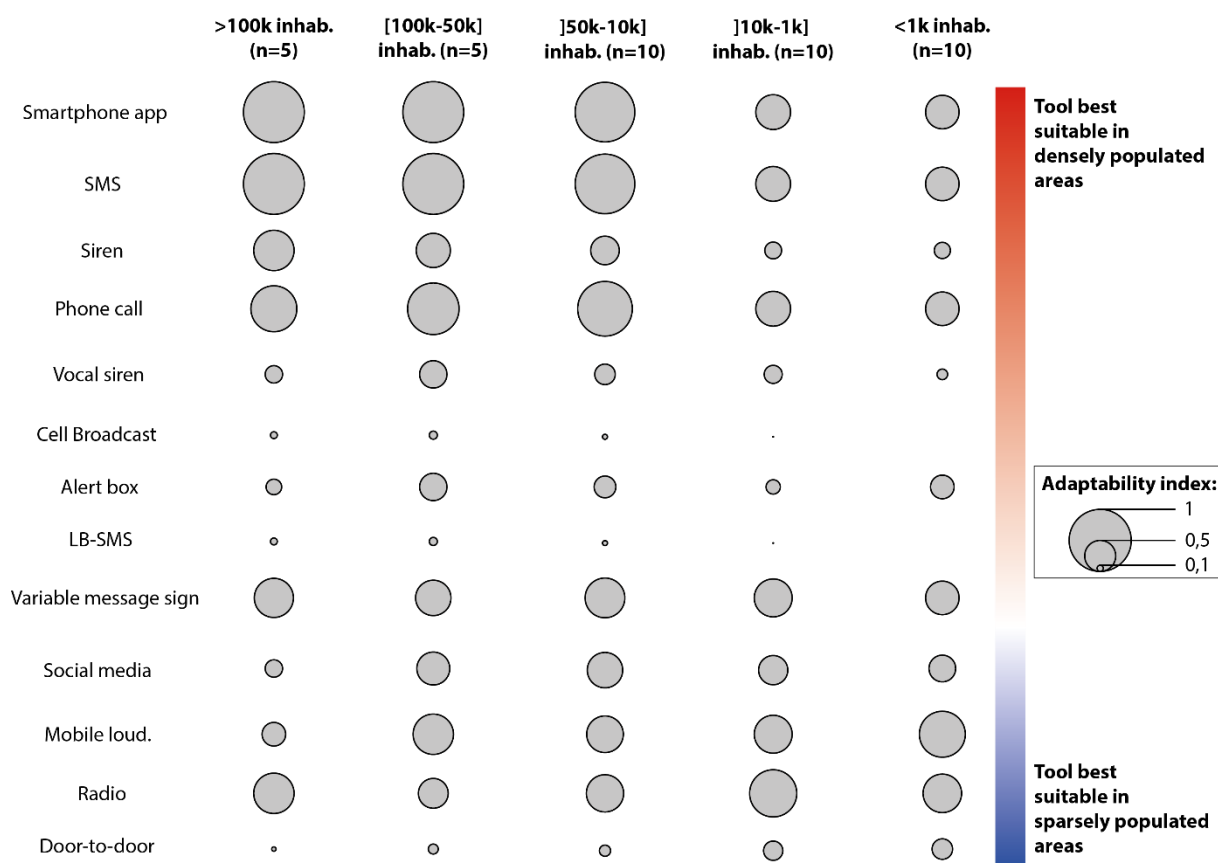
#### 4.2. Heterogeneous tool adaptability

The Adaptability Index (AI) of the tools to the 611 zones is very heterogeneous (Figure 8). SMS and smartphone applications are the best tools at the municipal scale (in nearly 80% of the zones). The mobile loudspeaker and the telephone call system are also tools that are well adapted to the municipal scale. On the other hand, LBAS (CB and LB-SMS) are the least suitable of the 13 tools studied, largely due to a lack of precision at municipal scale. This is a major issue in view of the increasing spatial and temporal uncertainty of risks. CB is a particularly suitable tool in sudden and unforeseen situations. It is the only one that can alert a large number of people quickly, in any type of territory, while at the same time issuing instructions.

Also, the adaptability of the tools varies depending on the number of inhabitants within the municipalities (**Figure 9**). Some tools are more suitable in highly populated municipalities (smartphone app, SMS, siren) while others are better in less populated municipalities (door-to-door, radio, mobile loudspeaker).



**Figure 8.** Overall adaptability of the 13 alerting tools studied for the 611 alert zones



**Figure 9.** Adaptability Index (AI) of tools for alert zones based on a classification of municipalities depending on their number of inhabitants. The tools are ranked according to an urban (red) – rural (blue) adaptability gradient. This gradient was obtained by taking the difference between the AI for municipalities with more than 50,000 inhabitants and the AI for municipalities with fewer than 10,000 inhabitants.

### 4.3. A complex categorisation

We used hierarchical clustering and principal component analysis to identify homogeneous groups of municipalities in order to explore the possibility of categorising municipalities according to the nature of the tools adapted to them (**Figure 10**). Alert box, radio and door-to-door contribute the most to dimension 1 (31.2% of the variance). Mobile loudspeakers, sirens, vocal sirens, and telecommunications tools (all telecommunications tools are grouped together, as strongly correlated) best explains dimension 2 (19.7% of the variance). The K-means method identifies 5 clusters of municipalities (**Figure 10**; **Table 4**).

The results reveal a clear trend: mass alert tools are suitable for densely populated municipalities, but not for sparsely populated areas. Conversely, targeted alerting tools are more suitable in smaller municipalities. For medium-sized municipalities (between 10,000 and 50,000 inhabitants), it is more difficult to identify clear trends (see group 3 in **Figure 10** and **Table 4**). Primary tools are not well adapted to sparsely populated municipalities, and not covered by telecommunications networks. The SD value for the TAI and TVI of each cluster taken independently are extremely close to the average SD of the TAI and TVI for the whole sample (**Table 5**). Thus, the categorisation of municipalities is complex, as even between municipalities with similarities in the nature of suitable tools, the TAI and TVI indicators may diverge.

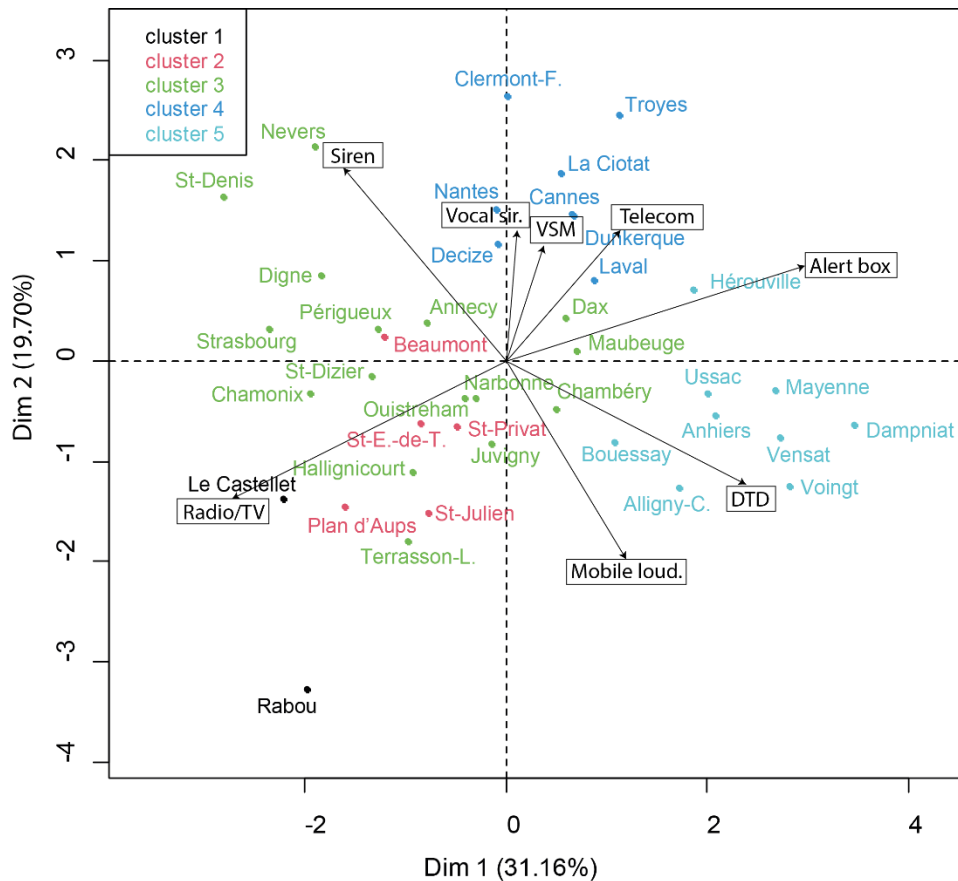
*Table 4. Summary of PCA and AHC results*

Cluster	Population (avg)	Alert zones (avg)	Trends in alerting tools adaptability
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1 (n=2)	183	3.5	High (++): radio/TV Low (--): telecommunication tools, siren
2 (n=5)	1,520	13.6	High (+): radio/TV, mobile loud. Low (-): telecommunication tools, siren
3 (n=16)	50,600	16.6	Globally heterogeneous High (+): radio/tv Low (-): alert box
4 (n=8)	95,000	21	High (++): telecommunication tools, VSM, vocal siren, siren Low (--): mobile loud., radio/tv
5 (n=9)	4,800	11.3	High (++): DTD, mobile loud., alert box Low (--): siren, radio/tv

**Table 5.** Standard deviations of the TAI and TVI indicators for each cluster of municipalities depending on the PCA results

Cluster	TAI		TVI	
	Standard deviation (SD)	Deviation from the average SD	Standard deviation (SD)	Deviation from the average SD
1 (n=2)	0.17	0.03	0.23	0.08
2 (n=5)	0.18	0.04	0.17	0.02
3 (n=16)	0.13	-0.01	0.15	0
4 (n=8)	0.06	-0.08	0.12	-0.04
5 (n=9)	0.17	0.02	0.16	0.01
Average	0.15	0	0.15	0



**Figure 10.** Hierarchical clustering and principal component analysis of the nature of the suitable tools for each of the 40 French municipalities studied

## 5. Discussion

### 5.1. Lessons learned from past disasters and suitability of the SDSS framework

The SDSS tool proposed in this article offers managers the opportunity to equip their territory with relevant alerting tools. Recent disasters have shown the importance of using the right tools according to the context. During the night of 15 October 2018, the municipality of Trèbes (Aude, south of France) was stricken by a rapid flooding of the Aude River: 200 buildings were flooded and 6 people died. The alert was conveyed by the emergency services in the form of door-to-door communication, which was clearly not the most appropriate way given the spatial configuration of the buildings (dense and numerous) and the sudden timing of the flood. Many survivors were either alerted by a neighbour or by the sudden entry of water into their house. After applying the SDSS to the flooded area in 2018, we identified that the phone call, cell broadcast, siren and voice siren were more suitable in this situation.

The Lubrizol factory fire near Rouen (2018) is another example that could justify the use of SDSS. The fire started during the night and the prefect communicated very quickly giving instructions on social networks. Fearing massive panic reactions, the prefect waited until 7.45a.m. to trigger the two sirens closest to the site. In this case, the use of the SDSS would have made it possible to better foresee the alert zoning, which was not adapted because the effects of the fire (visibility of the plume, unpleasant smell) were felt several kilometers away. Many people, not following the authorities' social network accounts and not being located near the two sirens, did not receive any information or instructions except through a few radios and/or social medias. Given the characteristics of the territory, tools such as mobile phone broadcasting, SMS, LB-SMS and radio/TV were best suited.

### 5.2. A framework replicable for other European countries

Given the harmonisation of warning at the European level and the similarity of urbanisation patterns, natural hazards and activities, these results are likely to be applicable in other European cities. In this respect, the framework provided in this study can be used outside of France. Similar results are the heterogeneity of alerting tools at different scales could be expected. But results on the performance of LBAS could vary according to geographical contexts (importance of urban areas as in Belgium, or importance of rural areas as in Finland) and political choices (technology chosen, network infrastructure developed, etc.). Two prerequisites are required before replicating this study in other countries: 1) input data (population, building, hazards, infrastructure) must be available; 2) dealing with the issue of administrative differences between European countries, which raises the question of the scale of analysis.

### **5.3. Future enhancements to the SDSS**

The SDSS is based on the adequacy or inadequacy of tools in different alert zones. This method raises two issues. Firstly, the binary vision (adapted/unadapted) could be made more flexible by proposing a gradient of the adaptability of each tool to each alert zone. However, it would be necessary to calibrate these gradients in a similar way for all tools. The extremely diverse nature of the tools means that some of them will never be 100% perfectly adapted to a zone. Meanwhile other tools are either totally suitable, or not at all (the binary logic works well for variable message signs or alert boxes, for example). It now seems necessary for the scientific and/or technical literature to take up the analysis of warning systems and tools through post-disaster feedback. Too often, the warning system is evaluated in its capacity to detect the phenomenon and not to warn individuals. A better understanding of the strengths and limitations of warning tools during a disaster would improve the calibration of the thresholds used in this study to justify the adaptability of alerting tools to territories.

The second issue concerns the thresholds below which the tools are not considered to be suitable. These thresholds can not only be debated, but also adapted depending on whether very well-adapted tools are sought, or whether the authorities accept the use of less well-adapted tools. Combinations of tools can also lead to a very effective level of alertability (complementarity between different tools deserves to be studied). This point also refers to the discussion on the acceptable rate of alertable individuals which seems complicated to define. Feedback analysis is a way to study the complementarity between tools and the accuracy of the adaptability thresholds used in this article.

Social parameters could have been considered in this study. The use of sirens for a population with a low-risk culture should be prohibited, as a siren does not broadcast any message or behavioural instructions. At the individual level, the identification and consideration of individuals who are not equipped with mobile phones, the deaf or blind, for example, could improve the effectiveness of the alert. Here again, the multimodality and complementarity of tools must be studied. Parameters regarding the governance of the municipality, or its human and financial means, could also be integrated to improve the model's accuracy. The tourist population could also be considered. Some of the municipalities studied in this article have a considerable increase in population during the tourist seasons (Chamonix-Montblanc, La Ciotat, Cannes, etc.). Nevertheless, it is necessary to identify a method to accurately locate tourist populations in space.

With climate change, the spatial and temporal uncertainty of risks increases and raises the question of new approaches to defining alert zones. In this paper, they have been defined according to the hazard zones. In future studies, it might be interesting to base alert zones on the stakes, assuming that at any time a hazard with rapid kinetics and highly destructive potential could occur. With this approach, it is possible to anticipate the unforeseeable (Reghezza-Zitt, 2019). We could also input new features of future hazards (using the R2.8 or 3.5 scenarios of the IPCC, 2017, for example), that could change the



initial characteristics of danger zones, but not all the SDDS process. Finally, it would be interesting to discuss the creation of an index of adaptability of means to risks that are difficult to predict (earthquake, tornado, etc.).

#### 5.4. Perspectives

This article has illustrated the relevance of a multi-scale approach in the study of public alerting. The level of the alert operationalisation (within which crisis management is structured) should not be confused with the scales of dissemination, which vary depending on the nature of the hazard. Some hazards require broad-based alerts, such as the multi-state COVID19 alerts in the US (Bean et al., 2021), while others require more targeted alerts (flash flood, avalanche, small forest fire, etc.). What's more, the administrative level and its size could influence the choice of alerting tools. The differences in the effectiveness of alerting tools at different scales must be assessed, using quantitative geography tools and multidimensional statistical methods.

#### 6. Conclusion

By creating and applying a SDSS method, this article has illustrated the need to adapt alerting technologies to territorial characteristics. The results show a great diversity of suitable tools: 1) between municipalities, even those with similar features, 2) within the sub-municipal scale, between different alert zones subject to a clearly identified hazard, and 3) within the sub-zonal scale, as different groups of habitats require different alerting tools within the same hazard zone. Furthermore, Cell Broadcast and Location-Based SMS appear to be unsuitable tools at the municipal level: these tools should be reserved in dense cities or for a national use, but not in rural towns or small villages, due to edge effect or insufficient telecommunication networks. In France, rural towns or small villages have benefited too little from the national policy of upgrading the warning siren network (Bopp, 2021), and a specific attention must be paid for these areas. The issue of alert inequity in space should be addressed by: 1) identifying poorly alertable municipalities, and 2) implementing aid support for such municipalities by deploying alternative tools, adapted to the rural context of these territories.

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## Appendix

*Table 6. Main characteristics of the selected municipalities*

<b>Cities</b>	<b>Inhabitants</b>	<b>Areas (km<sup>2</sup>)</b>	<b>Number of alert zones identified</b>
Nantes	306,694	65.2	31
Strasbourg	279,284	78.3	28
Clermont-Ferrand	142,686	42.7	15
Annecy	126,419	66.9	21
Saint-Denis	111,354	12.3	4
Dunkerque	88,108	43.9	26
Cannes	74,152	19.6	44
Troyes	60,460	13.2	5
Chambéry	59,183	21.0	16
Narbonne	53,954	173.0	30
Laval	49,492	34.2	9
La Ciotat	35,366	31.5	29
Nevers	33,235	17.3	8
Périgueux	29,912	9.8	15
Maubeuge	29,679	18.9	11
Saint-Dizier	24,932	43.2	17
Hérouville-Saint-Clair	22,701	10.6	8
Dax	20,891	19,7	12
Digne-les-Bains	16,186	117.1	30
Mayenne	12,893	19.9	13
Ouistreham	9,117	10.0	20
Chamonix-Montblanc	8,759	116.5	24
Terrasson-Lavilledieu	6,148	39.3	22
Decize	5,519	48.2	9
Ussac	4,169	24.6	21
Saint-Julien	2,413	75.9	20
Plan-d'Aups-Sainte-Beaume	2,113	24.9	10
Saint-Etienne-de-Tinée	1,551	173.8	20
Beaumont-de-Pertuis	1,139	56.1	12
Anhiers	916	1.7	7
Alligny-Cosne	879	34.4	8
Dampniat	743	15.4	21
Bouessay	742	9.3	3
Juvigny	645	2.7	6
Vensat	500	16.1	15
Saint-Privat	403	26.9	6
Le Castellet	289	18.9	4
Hallignicourt	284	11.9	2
Rabou	76	26.6	3
Voingt	33	6.5	6

**Table 7.** Spatial data used for hazards and additional processing performed

Hazard	Public data sources used	Additional processing
Avalanche	Map of the location of avalanche phenomena (CLPA, <i>Carte de localisation des phénomènes avalancheux</i> )	
Dam breach	Flood wave, CRIGE PACA	
Flood	EAIP ( <i>Enveloppe approchée des inondations potentielles</i> )	Data only available for territories exposed to a significant flood risk as identified by the French State. Selection of the average flood scenario corresponding to a 100 years flood.
	Flooding Zone Atlas (AZI, <i>Atlas des Zones Inondables</i> )	Data used for municipalities with low flood risk. The flood scenario also corresponding to a 100 years flood
Industrial	ICPE ( <i>Industries Classée pour la Protection de l'Environnement</i> )	High level: 1km buffer Low level: 500m buffer
Marine submersion	EAIP ( <i>Enveloppe approchée des inondations potentielles</i> )	
Tsunami	None	Selection in a DTM of areas contiguous to the coastline with an altitude lower than the maximum expected run-up and.
Wildfire	BD-TOPO, vegetation	Selection of closed forest areas (where at least 40% of the space is occupied by forest) and scrubland. More than 10 ha to avoid too much fragmentation of risk areas. Buffer of 50m at each forest to take into account the edge effect.

**Table 8.** Public data source used for spatial data

Public data source used	URL
CLPA ( <i>Carte de Localisation des Phénomènes Avalanches</i> )	<a href="https://map.avalanches.fr/">https://map.avalanches.fr/</a>
BD-TOPO	<a href="https://geoservices.ign.fr/telechargement">https://geoservices.ign.fr/telechargement</a>
ICPE ( <i>Installations Classées pour la Préservation de l'Environnement</i> )	<a href="https://www.georisques.gouv.fr/donnees/bases-de-donnees/installations-industrielles">https://www.georisques.gouv.fr/donnees/bases-de-donnees/installations-industrielles</a>
AZI ( <i>Atlas des Zones Inondables</i> )	<a href="https://www.georisques.gouv.fr/ressources-sur-les-risques-naturels">https://www.georisques.gouv.fr/ressources-sur-les-risques-naturels</a>
EAIP ( <i>Enveloppe Approchée des Inondations Potentielles</i> )	<a href="https://inspire.datasud.fr/geonetwork/srv/api/records/fr-120066022-jdd-fb022239-2083-4d31-9fc0-369117139336">https://inspire.datasud.fr/geonetwork/srv/api/records/fr-120066022-jdd-fb022239-2083-4d31-9fc0-369117139336</a>
INSEE ( <i>Institut National de la Statistique et des Etudes Economiques</i> )	<a href="https://www.insee.fr/fr/accueil">https://www.insee.fr/fr/accueil</a>
Catchment hydrology research group, INRAE	<a href="https://webgr.inrae.fr/activites/base-de-donnees/">https://webgr.inrae.fr/activites/base-de-donnees/</a>