**INTRODUCTION**

**M**ACHINE learning has become a dominant data processing paradigm for the extraction of information from remote sensing data. The underlying strategy is to establish a model from limited but properly encoded prior knowledge (i.e., training samples) to assign a thematic label (e.g., a damage state in the application context of this article) to an instance under analysis (e.g., a building). Such methods are especially useful if explicit modeling based on, e.g., mechanical models, is too complex. At the same time, such approaches require both a sufficient amount of prior knowledge and viable descriptors to characterize the instances under analysis in order to achieve high predictive accuracy. However, many applications suffer from the unavailability of a sufficient number of training samples. In numerous cases, gathering training samples can become immensely expensive and time consuming. Under these circumstances, various approaches have been proposed for alleviating the scarceness of training samples. For instance, multi objective-based sparse representation classifiers [1], generation of virtual samples [2], an active learning methods [3]–[5] have been adopted in previous studies. Other approaches aim at compiling a training set in a fully automated manner from specified input data. The use of top-of-atmosphere reflectance to identify samples of forest areas [6] and fusion of multisource geo data [7] are such examples.

In the explicit application context of this work, studies that aim to ext act natural hazard-induced damage levels of the built environment have extensively deployed machine learning algorithms in recent years. Supervised machine learning classifiers have shown high performance in terms of accuracy in disaster events, such as the 2010 Haiti earthquake [8]–[10], the 2011 Tohoku-Oki earthquake–tsunami [11]–[14], the 2016 Kumamoto earthquake [15], and the 2018 Sulawesi, Indonesia earthquake–tsunami [16], [17]. However, a careful reader may realize that the training data were provided after more than a month for the 2010 event [18], after four months for the 2011 event [19], after two months for the 2016 event [20], and after one week for the 2018 event [21]. Note that the last event’s training data were sooner than others because it was based on visual interpretation of high-resolution optical imagery. However, it was later confirmed it contained several misclassifications [17], [22].

The necessary logistics for conducting a field survey directly after a major natural disaster and the subsequent digitization of the data are expensive and time-consuming. Furthermore in most cases, avoidance of human exposure to hazardous areas is recommended. In the context of disaster mitigation, damage mapping is a race against the clock. The faster a satisfactory estimate is provided, the faster the first aid can be sent and the higher the chances that people who are trapped in collapsed buildings will survive [23]. As described earlier, a critical issue of the application of machine learning for damage mapping using remote sensing data is the lack of training data. Among the potential solutions is the development of a global network by building upon crowd sourcing for rapid damage assessment [24]. Another potential solution is to transfer training data that have been collected from one disaster event to another disaster event. To realize this objective, the database must be sufficiently large to consider various sensors, seasonal variations, various building types and infrastructural typologies, and heterogeneous types of disasters. Furthermore, not all disasters are recorded by remote sensing data, and training data are available for even fewer events. There are, however, recent studies for a specific type of disaster [25], [26].

There is another alternative for exploiting the experience that has been gathered from previous disasters. For decades, researchers have been collecting data to correlate the amount of damage with a metric of the disaster intensity, namely, the demand parameter at a specified location [27]–[32]. Intensity denotes the level of severity produced by a disaster in a particular location. The demand parameter refers to a quantitative measure of the intensity to which an asset is subjected. For the case of earthquakes, the peak ground acceleration (PGA), the peak ground velocity (PGV), the Modified Mercalli Intensity, and the spectral response are often used as demand parameters [28], [33], [34]. For tsunamis or floods, the inundation depth has commonly been used as a demand parameter because it can be measured from postdisaster field surveys [22], [31], [32], [35]. However, other demand parameters have been proposed [30], [36]. A fragility function, often idealized by a sigmoid function, is defined as the relationship between the probability that an asset reaches or exceeds a damage state and the demand it experiences [28], [30], [36], [37]. Fragility functions, together with instrumentation and numerical simulations of the demand parameter, is often used to approximate, in real time, the number of assets that have been damaged within a specified area [38]–[42]. Recently, whether this aggregated damage information can replace training samples for the establishment of a damage map with a higher spatial resolution (building units instead of uniform spatial grids) from remote sensing data was investigated. A simple experiment from the 2011 Tohoku-Oki earthquake–tsunami is reported in [43], from which a linear discriminant function is calibrated over a bi dimensional feature space via exhaustive search. The calibration implied to find a linear discriminant function that yields a damage scenario that is consistent with the aggregates that are computed from the demand parameter and the fragility function. The accuracy of the results was on the same level as those of previous studies in which standard supervised machine learning was applied. Following the referenced study, a modification of the supervised logistic regression method was proposed in [44]. Here, the training data are replaced with probabilistic information that is computed from demand parameters and fragility functions. This enabled the use of an n dimensional feature space and optimization methods to calibrate the discriminant function.

There is, however, a substantial pitfall in relying on fragility functions: fragility functions are available only for limited types of disasters, such as earthquakes and tsunamis. There is also a controversy regarding the transferability of fragility functions that have been constructed from empirical data, for instance, whether fragility functions for wooden buildings that were constructed in Japan can be used in other countries. To establish a solution that is independent of the availability of fragility functions, we uniquely deploy the estimated demand parameter directly after a hazardous event for automatic rule-based training sample selection. The spatial distribution of the affected buildings is expected to be consistent with the spatial distribution of the demand parameter. Namely, areas that are assigned a low demand parameter should contain mainly non damaged buildings. In contrast, areas with a medium and large demand parameter likely include buildings with different damage levels. Using these assumptions, our objective is to learn a model that can solve a dichotomous classification problem and distinguish between two thematic classes: “severely damaged buildings” and “non severely damaged buildings.” The most common approach, termed change detection, aims to identify changes between a pair of images recorded before and after a disaster, from which changed samples are associated with severely damaged buildings and non changed samples are associated with non severely damaged buildings. It is assumed that, given that the images’ recording time is close, the changes between the images are associated with the effects of the disaster. We provide two novel methods for calibrating a support-vector-machine-based discriminant function. As feature space, we use hand-engineered features computed from remote sensing data. The demand parameter is used to collect the training data automatically. Using automatic sample selection for change detection is not a new idea. Previous studies have first used unsupervised classification to collect reliable samples of changed and non changed samples and then improve the classifier using supervised/semi supervised classification algorithms [45], [46]. Unfortunately, such approaches to collect training samples do not provide a complete representation of the classes in the feature space. Furthermore, to the best of our knowledge, unsupervised techniques perform poorly when the disaster-affected area is much smaller than the area covered by the remote sensing data. Our contributions can be highlighted as follows.

1) The demand parameter allows reducing the search for changes to solely areas with medium/large demand parameters.

2) We use a threshold on the demand parameter to collect non changed samples. The demand parameter has a clear physical meaning, and thus, the selection of the demand threshold is very intuitive and does not require preliminary processing, such as unsupervised classification algorithms.

3) Because the demand parameter information is independent of remote sensing data, the collected non changed samples provide a better representation of the class non changed in the feature space.

4) We integrate information from in-place sensors (i.e., ground motion sensor, tidal gauges), numerical simulation of a natural phenomenon, and remote sensing.

The remainder of this article is organized as follows. Section II introduces the proposed approaches to calibrate a classifier model. Empirical evaluations are conducted in Section III. Additional comments regarding the proposed methods and the studied cases are provided in Section IV. Finally, the conclusions are drawn in Section V.