**CONCLUSIONS**

This manuscript introduces the use of the demand parameter, which quantifies the disaster intensity, to systematically extract samples from remote sensing imagery and use them to calibrate a change detection classifier. The demand parameter of each sample is estimated via instrumentation and/or numerical simulation, which can be computed in real or near real time. We propose the use of a demand parameter map to group the samples into two subsets, where one subset is composed of samples for which the geo locations experienced low demand and the other subset is composed of samples with medium and/or large demand. We assumed that the first subset was mainly composed of non changed samples and that the second subset was composed of both changed and non changed samples. Under these constraints, two methods are reported for calibrating a discriminant function. The first method is composed of two main steps. First, the subset with low demand is used to calibrate the discriminant function using the one-class support vector machine (SVM). Second, the discriminant function is improved using the other subset. The second method uses a soft margin SVM with two regularization parameters. In contrast to the standard SVM, which employs one regularization parameter, the SVM with two regularization terms can have different levels of tolerance for the subsets, namely, the discriminant function will accept few outliers from the subset that is composed of samples with low demand while being highly flexible and accepting many outliers from the subset that is composed of samples with large demand.

The proposed methods were evaluated on three disasters: the 2011 Tohoku earthquake tsunami, the 2016 Kumamoto earthquake, and the 2018 western Japan floods. In addition, the feature space of each case study was constructed from different types of remote sensing data. Backscattering intensities from microwave imagery were used for the first case study, Lidar-based DSMs were employed in the second case study, and backscattering complex values from microwave imagery were used for the third case study. The results were of approximately the same level of accuracy as the results that were reported in previous studies in which traditional machine learning methods were employed. However, in contrast to the other studies, our methods can be used in near real time

In the aftermath of a large-scale disaster, the traditional procedure for extracting training samples represents the bottleneck in the creation of a machine-learning-based damage map. The automatic extraction of training samples is an open problem in the use of machine learning for early disaster response. Therefore, the relevance of our study is that it contributes to solutions to events from which the disaster intensity can be estimated.