Robust Earthquake Early Warning at a Fraction of the Cost: ASTUTI Costa Rica

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Smartphone-based Earthquake Early Warning with a Fixed Network:
ASTUTI Costa Rica

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**Key Points:**

- Smartphones used in a fixed network can provide earthquake early warning performance similar to scientific-grade instrumentation
- For 6 months in Costa Rica our system detected the events that caused wide-spread felt shaking and had 0 false alarms
- 2 of the 5 events were triggered by P-waves on the phones, suggesting that smartphone-based EEW could be more effective than previously thought

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Abstract

We show that smartphones deployed in a fixed network can provide earthquake early warning (EEW) performance comparable to scientific-grade systems. The ASTUTI (Alerta Sísmica Temprana Utilizando Teléfonos Inteligentes) network comprises stations throughout Costa Rica. Using accelerometer data, we implement a non-parametric ground-motion detection and alerting strategy considering that much of the country’s population resides in the interior near the capital, San Jose, and that nearly the entire country experiences shaking during earthquakes greater than $\sim M_w 6$. Rather than waiting until earthquakes exceed a large magnitude, we issue alerts when four stations exceed acceleration thresholds. Data latency over 6 months is 0.35-0.45 secs. We simulate the 2012 M7.6 Nicoya earthquake using on-phone vibrations and find median first-alert latency of $\sim 9$-$13$ secs after origin time and alert-receipt latency of $\sim 4$ secs. During the 6 months there were 13 earthquakes that caused “did-you-feel-it” (DYFI) reports. From offline reanalysis, we detected and alerted on 5 of these, all which produced shaking in San Jose. Two events were triggered by P-waves. The system did not produce any false alerts. Undetected events did not produce wide-spread felt shaking. We assess alerting the entire population upon event detection. For events outside or inside of the network, respectively, 15-70% of the population would receive alerts in time to undertake drop-cover-hold-on (DCHO). Similar populations would receive alerts and not feel shaking. This strategy may be effective if users are tolerant of feeling no shaking when they receive alerts from correct detections.

Plain Language Summary

Networks of low-cost, fixed-location smartphones can provide Earthquake Early Warning performance on par with scientific grade instrumentation.
1 Introduction

Earthquake early warning (EEW) attempts to rapidly detect earthquakes and to alert people and systems with enough time for protective actions to be taken before damaging shaking arrives [Heaton, 1985]. EEW systems are operational in a handful of regions and they are now rapidly being developed and adopted globally [Allen and Melgar, 2019]. As with many techno-scientific advances with the potential for large societal impacts, however, the earliest projections of EEW system performance and benefits to society have been modified and scaled back as the theoretical [M A Meier, 2017; Sarah E. Minson et al., 2018; S.E. Minson et al., 2019; Trugman et al., 2019], empirical [M A Meier, 2017; Trugman et al., 2019], practical [David J. Wald, 2020a], and social [Nakayachi et al., 2019; Becker et al., 2020; S McBride et al., 2020] limitations of EEW are elucidated. In parallel with this evolution in understanding, EEW instrumentation and network design has also rapidly evolved. Although most systems, such as ShakeAlert in the U.S. [Given et al., 2018; Kohler et al., 2020] use traditional seismic instrumentation, it has recently become clear that low-cost, consumer-grade sensors in smartphones including MEMS accelerometers [E Cochran et al., 2009; J Evans et al., 2014; Kong et al., 2016] and GNSS chips [S.E. Minson et al., 2015] are sensitive enough to be effectively used in EEW systems, even in crowd-sourced modes [Lawrence et al., 2014; S.E. Minson et al., 2015; Finazzi, 2016; Kong et al., 2016; Finazzi and Fassò, 2017; Kong et al., 2018; Kong et al., 2019b; Finazzi, 2020; Kong et al., 2020].

Given this rapidly evolving context, it is important to consider that a one-size-fits-all approach to EEW may not be appropriate, in particular for resource-limited populations. Varied EEW objectives and performance requirements could likely be achieved with different combinations of instrumentation, algorithms, alerting strategy, and messaging strategy [Y. Fujinawa et al., 2011]. For instance, EEW objectives for automated industrial systems with large action-costs (such as nuclear power plants) may require highly sensitive instrumentation, high ground-motion prediction accuracy levels, low false alarm tolerance, and large annual budgetary allocations [Strauss and Allen, 2016]. Alternatively, if the EEW objective is to promote population participation in an immediate low cost-of-action response such as Drop-Cover-Hold-On (DCHO) [Porter and Jones, 2018], then sensor sensitivity may be lower, ground-motion prediction accuracy may not be as important, false alarm tolerance may be higher, and budgetary allocation may be much smaller. Our work here examines this low-budget end of the spectrum.

Specifically, we ask: can off-the-shelf smartphones deployed in a fixed network provide EEW in a reliable and effective enough manner so that significant populations receive warnings in time for DCHO protective actions to be undertaken? Instead of investing in the institutional overhead of designing, building, and maintaining our own sensing hardware and communications platform [Anthony et al., 2019], the smartphone network approach leverages the massive research and development programs of smartphone providers such that sensors, field computing, and communications platforms are provided in a single compact unit. Moreover, the constant competition in this consumer space assure frequent technological updates as instrumentation becomes obsolete. Although there are now multiple examples of smartphone-based EEW methodologies and capabilities [S.E. Minson et al., 2015; Finazzi, 2016; Kong et al., 2016; Finazzi and Fassò, 2017; Kong et al., 2018; Kong et al., 2019b; Kong et al., 2020], to the best of our knowledge, there have been no evaluations of smartphones used, over extended periods of time, to provide EEW for a specific region.
Ideally, an EEW system would issue actionable alerts prior to P-wave arrival, affording the most time possible for protective actions. Even though a felt P-wave would hopefully serve as a natural EEW system alerting people to imminent shaking [David J. Wald, 2020a], site and path effects can preclude P-waves being felt ubiquitously, so a minimum criterion for an EEW system to be effective is for it to deliver alerts prior to the arrival of strongest shaking associated with S-waves. Currently, many operational EEW systems detect earthquakes using some permutation of point-source parameter estimation from the early P-wave. For instance, ShakeAlert uses a small amount of the P-wave (>0.2 secs) from 4 stations and empirical scaling relations to estimate point-source event location and magnitude [Chung et al., 2019]. In Japan, P-wave parameter estimation is augmented with a particle filter technique to combine ground motion observations and information about where shaking has not been observed [Tamaribuchi et al., 2014]. In Mexico, an event’s body wave magnitude, $m_b$, is estimated empirically from the rate of seismic energy released between P- and S-wave arrivals at a series of free-field acceleration stations along the country’s subduction zone coast [Cuéllar et al., 2017]. Point-source-based parameter estimation, albeit fast at initial detections, exhibits degraded performance when events become large and magnitude estimates saturate [Hoshiba et al., 2010]. Moreover, theoretical studies have recently found that the conventional EEW approach of using source parameters to forecast shaking causes alerts to be too slow for higher levels of shaking [M A Meier, 2017; Sarah E. Minson et al., 2018; Trugman et al., 2019], and to mostly produce missed and false alerts due to the intrinsic factor-of-two variability of ground motion [Gregor et al., 2014; S.E. Minson et al., 2019]. Accordingly, EEW practitioners are exploring and/or incorporating alternate methodologies including line-source estimates from strong-motion data [Böse et al., 2012], surface displacements from GNSS data [S. E. Minson et al., 2014], and ground-motion based approaches that issue alerts when one or more stations observe shaking above a threshold [Kodera et al., 2018; E S Cochran et al., 2019].

In particular, the Propagation of Local Undamped Motion (PLUM) algorithm is a ground-motion-based approach that was developed as an alternative to source-parameter EEW methodologies [Kodera et al., 2018; E S Cochran et al., 2019; M A Meier et al., 2020]. PLUM arose in response to the 2011 M9.0 Tohoku-oki earthquake, whose productive aftershock sequence led to many missed events and false alarms from the point-source algorithm when simultaneous small earthquakes were combined into a single larger event (Hoshiba et al., 2011; Kodera et al., 2018). Unlike most EEW methods that attempt to characterize source parameters and forecast expected shaking, PLUM uses shaking to directly forecast shaking. By using strong ground motion that accrues sometime between P- and S-wave arrivals to directly forecast ground motion, alerts can be issued for strong shaking as soon as it is observed without having to wait for the rupture (and earthquake magnitude) to grow in size. PLUM handles inter-event variability well, reducing false and missed alerts due to inaccuracies in the ground motion forecast [Kodera et al., 2018; E S Cochran et al., 2019].

In addition to detection methodology, alerting criteria are also quite variable. ShakeAlert issues alerts for ground motions predicted to be greater than Modified Mercalli Intensity (MMI) III [Thakoor et al., 2019]. In Japan, warnings are issued by the JMA (Japan Meteorological Agency) to seismic hazard blocks [Yukio Fujinawa and Noda, 2013], roughly four per prefecture, when any evaluation point inside a block is predicted to experience shaking greater than JMA IR (intensity reading) 4.0 (MMI VI), but only after an IR of 5L (MMI 7) is forecast in at least one
area [Kamigaichi et al., 2009; Kodera et al., 2018]. In Mexico, if rapidly estimated magnitude is greater than \( m_s \), 6, public warnings are issued in Mexico City and other inland locales. Alerting criteria are further complicated by the simple physical fact that earthquake magnitude is not static; rather, it increases as an earthquake rupture evolves. The promise of EEW systems has been amplified by the idea that differences between the ways large and small earthquakes start could potentially be used to predict the final size of a growing earthquake, rather than relying on rapidly updating contemporaneous estimates of source parameters and ground motion [Olson and Allen, 2005; Melgar and Hayes, 2019]. However, a growing number of studies have shown that the early P-wave holds little to no predictive power [M-A Meier et al., 2017; Goldberg et al., 2019; Trugman et al., 2019]. Furthermore, Minson et al. (2018) recently showed that given the velocities at which earthquake ruptures grow and seismic waves propagate, together with the exponential decay of ground-motion with distance from a propagating rupture, users’ warning time for the strongest shaking will often be brief if EEW systems wait to issue alerts until earthquakes grow large enough that their forecast shaking is strong. Accordingly, it is becoming clear that EEW offers the most potential for successful mitigating actions to be taken if alert thresholds are set at lower ground-motion levels than those expected to cause damage [Sarah E. Minson et al., 2018; Saunders et al., 2020].

It is important to consider that while an EEW system with low alert thresholds would likely produce alerts without subsequent shaking, the number of missed alerts would be minimized and the system would have the best chance of being effective when it mattered most during medium to larger events. For such a strategy to be successful, users must be more tolerant of receiving unnecessary alerts (the ‘Boy Who Cried Wolf’ phenomena) than is often assumed. Although there are essentially no studies explicitly addressing the ‘Boy Who Cried Wolf’ phenomenon for EEW, other scientific communities with more established alerting relationships with users caution against the implicit assumption that user false alarm tolerance is low [Roulston and Smith, 2004]. In fact, the small amount of evidence that exists suggests that EEW users may be surprisingly false-alarm tolerant. Nakayachi et al. (2019), found from surveys associated with alerts from two Japanese events that, indeed, the user population was surprisingly tolerant of false alerts. Anecdotal surveys in Mexico found similar attitudes [Allen et al., 2018].

In this contribution, we implement the ASTUTI (Alerta Sismica Temprana Utilizando Teléfonos Inteligentes; Earthquake Early Warning Utilizing Smartphones) network and we evaluate the coupling of a fixed smartphone network and ground-motion based detection methodology with a low-threshold alert strategy. Smartphone MEMs accelerometers are well-suited for ground-motion based EEW methodologies, having been shown to have noise levels sufficiently low to permit detection of small (M4-5) earthquakes [Kong et al., 2016; Finazzi and Fassò, 2017; Kong et al., 2018; Kong et al., 2019a; Kong et al., 2019b; Finazzi, 2020; Kong et al., 2020]. Although we introduced the concept of smartphone crowd-sourced EEW [S.E. Minson et al., 2015], we maintain that it is prudent to question crowd-sourcing’s operational reliability and overall practicality. Even though efforts such as The Earthquake Network Project [Finazzi, 2016] and MyShake [Kong et al., 2016] report high initial enrollment rates, and even though Google has recently announced that the Android operating system will have native ability to use accelerometer data for EEW detection purposes [Press, 2020], there is no guarantee that users will continue to permit their phones to be utilized for extra-personal purposes, especially as internet privacy advocacy becomes a more penetrative societal issue [Ketelaar and Van Balen,
Additionally, depending on citizen subscribers, with their changing preferences and resources, likely poses a substantial risk in operating a warning system that requires continuous data from the near-source-regions of the most damaging expected earthquakes. Finally, as commercial entities with proprietary algorithm and data policies are poised to increase by orders of magnitude the number of EEW-capable sensors and to issue public-safety alerts themselves [Stogaitis et al., 2020], we assert that it becomes ever more important that the scientific community have access to transparently collected and freely available smartphone data.

2 Materials and Methods

2.1 System Design

Costa Rica's seismic hazard is due primarily, though not exclusively, to earthquakes generated by oblique subduction of the Cocos plate below the Caribbean plate at rates up to ~ 8.5 cm/yr along the Middle America Trench (MAT) [DeMets et al., 2010; Protti et al., 2014](Figure 1). In contrast to other subduction zones, the portion of the plate interface where MAT earthquakes tend to nucleate is overlain by land rather than the seafloor [Protti et al., 2014]. Since 1853, 8 earthquakes greater than Mw 7.0 have occurred either on the northern Nicoya (1853, 1900, 1950, 2012) or southern Osa (1856, 1904, 1941, 1983) peninsulas [Kobayashi et al., 2014; Protti et al., 2014] The majority of Costa Rica’s ~5M population resides in the greater San Jose region, ~60-200 km from the Pacific coast and principal seismogenic zone (Figure 1). For greater San Jose as well as Costa Rica’s coastal regions, 10% expected peak ground acceleration (PGA) exceedance over the next 50 years is 0.55-0.90g, in the upper ranges of global seismic hazard [Pagani et al., 2020]. Recently, the Mw 7.6 2012 Nicoya peninsula earthquake caused shaking throughout the entire country, with PGA values as high as 0.5-1.4g and MMI V-VII reported in San Jose (Figure 1b), and it is generally accepted that M > 6 events are felt country-wide.

Given Costa Rica’s seismotectonic framework and population distribution we designed the ASTUTI with these principles: (1) Our EEW efforts are focused on warning people, not automated systems, and our targeted user response is DCHO. Because the cost of taking action for DCHO is so low, this implies that detection and alerting thresholds can be low. (2) We prioritize detecting and alerting for MAT earthquakes, the events that have the highest probability of affecting the largest percentage of the population, especially San Jose. Although San Jose’s central location exposes it to earthquake sources from the entire country, most non-MAT sources would be too close to San Jose to permit warnings. (3) If we wait to issue an alert until an event has grown large enough to cause shaking damage, then it will most likely be too late to issue actionable warnings [Sarah E. Minson et al., 2018; Trugman et al., 2019]. Accordingly we attempt to issue warnings at the earliest detection of events of potential concern. (4) Because of local ground-motion variability [S.E. Minson et al., 2019] and because it is unlikely that earthquake ruptures are deterministic [M-A Meier et al., 2017; Goldberg et al., 2019; Trugman et al., 2019] our detection and alerting is entirely non-parametric. In addition to making no attempt to estimate source information (such as location and magnitude), the alert does not include information about predicted ground-motion levels. (5) Based on the previous design principles, Costa Rica’s generally small areal extent, and the country-wide shaking from MAT events such as the 2012 Nicoya event, we do not attempt to designate intra-country warning precincts; rather we evaluate the scenario where every alert will be issued for the entire country. (6) Because of the previous design priorities, there will likely be a number of alerts
issued for smaller events when users will feel no shaking although an event was correctly detected. This will require rapid post-event messaging and constant user interaction and education to remind users that the system performed correctly even if they did not feel shaking [S McBride et al., 2020]. We stress, however, that, as of January 2021, we are not issuing public alerts, aside from those sent to our small group of beta testers. We leave thorough investigation of this topic to a future paper.

2.2 Hardware, Network, and Data Architecture

From September to December 2019 we constructed the ASTUTI network (Figure 1a). For the duration of the testing period, the network comprised 82 stations. Closest to the MAT and most of the strongest expected sources, station spacing is ~30 km and it increases to 30-50 km away from the MAT. Higher station density closer to the subduction zone is similar to the SASMEX configuration in Mexico [Espinosa-Aranda et al., 2009; Cuéllar et al., 2017; 2018; Suárez et al., 2015]. Phones are installed on the ground floors of buildings in protective boxes and affixed to floors or walls (Figure 2). Previously, in addition to accelerometer data from smartphones, we have discussed and used GNSS, which typically requires outdoor installation [S.E. Minson et al., 2016]. We found that many devices overheated, however, so for the initial phase of ASTUTI we made the operational decision to only employ phones installed on interior walls. Accordingly, the only data we use for ASTUTI are from on-board accelerometers. To date, our approach utilizes smartphones with the Android Operating System (Android OS). Criteria for phone choice included in-country availability and cost (Supp. Mat).

Onboard the phones, our control and sensing software is called QED (for ‘Quick Event Detection’; Figure 3; Supp. Mat). QED controls sensor sampling and logging, detects events, and prepares data (via formatting, filtering, or on-board data reduction) for use in various downstream processing algorithms, and sends data in short, labeled messages. QED harnesses as much on-board computation from the smartphone’s CPU as possible, thereby eliminating some computational load (and potential latency increases) when large numbers of stations are active in the network. QED supports either continuous or triggered streaming at sampling rates up to 100 Hz for accelerometer data. From December 2019 to late August 2020, phones streamed at 10 Hz; subsequently we increased streaming rate for the entire network to its current rate of 100 Hz. At 100 Hz, data rate for each site is ~70-100 Mb/day.

Data from the phones are streamed using the UDP (User Datagram Protocol) protocol to a cloud-based data receiver (Supp. Mat). We prefer UDP to TCP/IP (Transmission Control Protocol/Internet Protocol) because it eliminates latency caused by two-way communications regarding packet completeness and, similar to others [J R Evans et al., 2005], we have found UDP packet loss to be negligible. The UDP receiver passes data to a MQTT (Message Queuing Telemetry Transport) broker that distributes it to processing and archiving subscribers (Figure 3, see Acknowledgments, Samples, and Data section below for information on accessing the archived data). As of January 2021 we have collected more than 0.5 Tb of data. The phones actively maintain NTP (Network Time Protocol) clock corrections to ensure timing accuracy (Supp. Mat) and they periodically check in to a settings server comprising a MySQL (My Structured Query Language) database that provides configurable control parameters.
Additionally, a management console provides a map- and table-based general monitoring and control interface for the network.

2.3 PGAN Detection Algorithm and Alerting Strategy

Any EEW processing algorithm that operates on acceleration data can subscribe to the MQTT broker. Here, we report on a new algorithm, PGAN (for ‘Peak Ground Acceleration with N vertices’) that is an adaption of the PLUM method for a network of smartphones. PGAN is similar to PLUM in that it is a non-parametric ground-motion based algorithm which does not attempt to estimate anything about a detected earthquake’s source, such as magnitude or epicentral location. When PLUM is run as a component of JMA’s operational EEW system, however, it not only utilizes high quality seismometers, but data feeds are also monitored by JMA personnel to ensure quality control and flag noisy data. To compensate for the noisier nature of smartphone MEMS accelerometers installed in buildings susceptible to anthropogenic noise, as well as for the lack of human monitoring, PGAN requires multiple neighboring stations to experience anomalous accelerations in order to trigger an alert. The network is divided into a polygonal mesh with a configurable number of vertices greater than or equal to three. Here, we report on a quadrilateral (PGAN-4) configuration because we found an unacceptably large number of false alerts for triangular configurations.

In detail, PGAN-4 station locations are organized into a set of unique polygons whose sides are all less than a configurable length (currently 40 km). We permit polygons to overlap. Once per second PGA values are measured at each station and the values are compared with a primary threshold (currently 0.6%g). If any station’s PGA is above the threshold, the polygon it belongs to is marked as potentially triggered. The PGA values at each of the remaining stations in that polygon are compared with a secondary threshold (currently 0.55%g). If PGA values at all stations in a potentially triggered polygon are above the thresholds, an alert is issued. If not, the incoming PGA values continue to be monitored for up to 15 seconds (configurable), and the polygon will trigger if the remaining station PGA values rise above the secondary PGA threshold. Otherwise, the polygon times out, and no alert is triggered. Once a polygon is triggered, an alert is sent out using the Amazon Web Services Simple Notification System (AWS SNS). As of January 2021, alerts are only being sent to a small number of beta-subscribers in our research team.

3 Data Quality and System Latency

Below, we characterize the system’s data quality and latency during a six month evaluation period from December 2019 to June 2020. Generally, during this time, daily system up-time (defined as the percentage of each day the entire network was transmitting data) was reliably greater than 95%. After June 2020, as Covid-19 pandemic restrictions significantly limited travel in Costa Rica, we were not able to visit stations for routine or time-dependent site visits. Accordingly, station up-time and network coverage decreased during this period. In the Supporting Information section we provide more details about system operation.

3.1 Data Quality

As with any seismic sensor, coupling to the ground and site-specific noise conditions control an individual phone’s sensitivity. MEMS accelerometers in smart-phones have been shown to have
the sensitivity to discriminate ground motions caused by earthquakes from background noise [J Evans et al., 2014] even in crowd-sourcing scenarios where they rest on tables [Finazzi, 2016; Kong et al., 2016; Finazzi and Fassò, 2017; Kong et al., 2019b]. In our fixed-network approach, phones do not rest on tables nor are they placed in seismically quiet underground vaults, rather they are affixed to floors, baseboards, and walls in built structures, typically homes, schools, fire departments, hospitals, or municipal buildings (Figure 2). As such, they record accelerations through the filter of a built structure emplaced in locally varying soil and/or rock substrate. This type of installation means that individual stations will record earthquakes (Figure 4a) as well as ambient non-seismic accelerations from myriad sources such as road traffic, domestic motion, or thunder [Finazzi, 2020]. In addition to site-specific noise, we have found that some phones experience sporadic, unexplained, transient noise spikes, either on individual or multiple accelerometer components simultaneously (Figure 4b).

To construct the most appropriate data for the PGAN algorithm we combine the raw acceleration data from the three orthogonal MEMS accelerometers into a PGA data type sampled and sent at 1 Hz (the ‘P’, for ‘PGA’, message). The P message value is the vector norm of the individually de-meaned 100 Hz acceleration values and has units of m/s², also expressed as a percent of gravitational acceleration, %g. To mitigate the transient noise spikes while permitting real seismic accelerations to pass, final formation of the P message implements a simple filter that takes the 30th percent highest value in a 1 second window (3rd highest if accelerometer sampling is 10 Hz, 30th highest if accelerometer sampling is 100 Hz; Figure 4b) [Kamigaichi et al., 2009].

Because the PGAN algorithm only requires exceedance of ground acceleration above a threshold, we characterize site and network data quality by examining histograms of PGA data. Generally, the entire network exhibits mean-P-values of 0.25%g. Over periods of time varying from minutes to days, individual stations may experience elevated deviations from this background behavior (Figure 5). The causes of these transient periods of elevated background noise are varied and likely related to temporally changing site-specific noise such as local construction projects, changing traffic patterns, or persistent regional storms.

### 3.2 Latency Budget

Understanding and documenting the latency budget, along with assessing alert validity, is a critical aspect of EEW system operation. We define ASTUTI system latency, δt latency, as the sum of three components \( δt_{\text{data}} + δt_{\text{detect}} + δt_{\text{alert}} \) where \( δt_{\text{data}} \) is the time it takes for data to be transmitted from the phones and received by the hub, \( δt_{\text{detect}} \) is the time it takes for a given processing algorithm to detect an event, and \( δt_{\text{alert}} \) is the time it takes for a message to be received by a user after it has been sent by the processing algorithm. Of these, \( δt_{\text{data}} \) and \( δt_{\text{alert}} \) are only dependent on telecommunications factors and they are independent of the specifics of a given earthquake event. For different earthquakes, \( δt_{\text{detect}} \) depends on multiple factors including magnitude, rise-time, hypocentral location, near-source network geometry, and local site acceleration response. These factors will control the time it takes for seismic waves to travel from an earthquake to be sensed by a phone, the time it takes for a site to exceed detection thresholds, and the time it takes a particular algorithm to issue a detection.

From six months of continuously-streamed data, we find that \( δt_{\text{data}} \) varies from 0.35 to 0.45 seconds depending on time of day; peak internet usage (early evening when people arrive home
from work) also correlates with higher \( \delta_{\text{data}} \) (Figure 6a). For comparison, published \( \delta_{\text{data}} \) for the Italian [Satriano et al., 2011], the Chinese [Zhang et al., 2016], and ShakeAlert [E S Cochran et al., 2018] EEW networks are 0.9, 2, and 1-3 secs, respectively.

In order to robustly and simultaneously measure the real-time distribution of \( \delta_{\text{detect}} \) and \( \delta_{\text{alert}} \), as well as to test the full operation of the ASTUTI EEW system, we used smartphones’ programmable vibration feature to cause the phones to shake at expected relative arrival times for a scenario earthquake. We use the M7.6 2012 Nicoya earthquake as a scenario event and program S-wave arrival time for each site calculating hypocentral distance (see methods) using a fixed move-out value for \( V_s \) of 3.2 \( \text{km/s} \) (Figure 6b-d). Each phone vibrated for \( \sim 10 \) seconds.

Although they certainly do not reproduce the frequency nor amplitude content of real seismic waves interacting with built structures, smartphone vibrations are decent proxies for local earthquake accelerations in that they exceed the threshold values we use for earthquake detection at specified times consistent with the earthquake rupture evolution and seismic wave propagation (Figure 6c). Of course, the model of seismic wave propagation for the event could be more sophisticated but the constant \( V_s \) value is sufficient for the purpose of estimating average values of \( \delta_{\text{detect}} \) and \( \delta_{\text{alert}} \). Note here we use S-wave arrival times to be conservative, but it is possible that trigger thresholds could be exceeded in the P-wave (see System Performance below).

Over a period of 3 days, we repeated the test, vibrating the phones on the Nicoya peninsula three times an hour at the M7.6 scenario relative times, resulting in a total of 216 simulations (Figure 6d). For this scenario, we find \( \delta_{\text{detect}} \) for the PGAN-4 method has a mean value of \( \sim 12-13 \) seconds. We measured \( \delta_{\text{alert}} \) by sending text message alerts to a set of 15 people with cell phones in and around the greater San Jose region. We find mean value for \( \delta_{\text{alert}} \) is \( \sim 4 \) seconds (Figure 6d). Because this is from a small number of phones that were relatively close together, it is not clear how representative this metric is of latencies that would occur when sending many thousands of alerts across a wider geographic region. For comparison we note, that in a recent test of ShakeAlert in San Diego county using the U.S. federal Wireless Emergency Alert (WEA) system [Sarah E. Minson et al., 2020], median \( \delta_{\text{alert}} \) was \( \sim 13 \) seconds. To the best of our knowledge no other smartphone EEW projects have reported alerting latency data [Finazzi, 2016; Kong et al., 2016; Finazzi and Fassò, 2017; Kong et al., 2018; Kong et al., 2019a; Kong et al., 2019b; Finazzi, 2020; Kong et al., 2020].

4 System Performance

4.1 Event Accuracy and Timeliness

We evaluate ASTUTI’s performance in both detecting earthquakes and delivering alerts to people who will potentially experience shaking for a given earthquake, based on off-line playback from Dec 2019 to June 2020. Because of Covid-19 related travel restrictions limiting field work and equipment maintenance, and because of algorithm tuning and development of our alert messaging algorithm, the entire system was not operational until August 2020.

We use Did You Feel It (DYFI) data to provide both a self-consistent metric and the most natural ground-truth for whether people in a given region experienced shaking [Atkinson and Wald, 2007]. If, alternatively, our objective were to evaluate performance for non-human ‘users’ such
as critical facilities, lifeline, and/or structures, then DYFI reports would be less appropriate than instrumental strong-motion measurements such as ShakeMaps [David J Wald, 2000].

During the period of assessment, ASTUTI using the PGAN-4 algorithm detected 5 of the 13 events ($M_w$ 4.5-5.3) that were accompanied by DYFI reports of shaking somewhere in Costa Rica (Figure 7, Figure S1, Table S1). The majority of these events (9 of 13) occurred outside of the network, either offshore in the MAT or within neighboring Panama’s international borders (Figure S1). Four of the detected events had thrust mechanisms and one had a strike-slip mechanism and they ranged in magnitude from from $M_w$ 4.8 to $M_w$ 5.3. Only one of the detected events (2020-03-07, $M_w$ 5.2) had an epicenter entirely within the network (Figure 7d, 8d).

Generally, the ASTUTI-detected events were accompanied by stronger shaking that was felt by much larger percentages of the population as defined by interpolated DYFI reports. The detected events had a median MMI of 4.3 and a max MMI of 6 with ~17% to 73% (41% median) of the population experiencing felt shaking of at least MMI 2-3. In contrast, the non-detected events had median MMI of 2.9 and max MMI of 3.8 with 0 to 19% (0.002% median) of the population experiencing felt shaking of at least MMI 2-3.

For each detected event, in addition to the associated DYFI data we plot the estimated position of the S-wave front (assumed to be the front of peak shaking) at the time that the alert was issued (solid magenta circles in Figure 7). Detection times, $\delta_{\text{detect}}$, for PGAN-4 ranged from 11-30 secs (median 22 secs, Table 1, Figure 7). (In the Supplemental Material section we present results using the PGAN-3 configuration exhibiting median $\delta_{\text{detect}}$ of 16.8 seconds). The 11-30 second range of detection times compares well with other scientific grade systems constructed and operated in similar seismic hazard settings, such as Cascadia and Mexico. For Cascadia, in 2019-2020 Shake Alert issued 4 alerts with $\delta_{\text{detect}}$ timing ranging from 8.3-13.9 seconds [ShakeAlertEventPage, 2020]. Published examples from the SASMEX system in Mexico show $\delta_{\text{detect}}$ values for 3 events ranging from 12-18 seconds [Cuéllar et al., 2018] and, although not explicitly presented, we estimate from data presented in the recent SASMEX performance summary [Cuéllar et al., 2017] that minimum $\delta_{\text{detect}}$ is ~ 8 seconds.

For each detected event we plot record sections for each station’s recorded P message and the expected range of P- and S-wave velocities of 6 to 3 km/s, respectively (Figure 8). We find that 2 of the 5 events (2019-12-08 and 2020-03-07, Figure 8a,b and Figure 8g,h) triggered on the P wave, which can be seen by the magenta vertical line occurring on the left side of the record section plots. For each of these events, all four of the triggering PGAN stations exceeded the threshold (0.6 g for the first and 0.55 %g for subsequent stations; shown in dashed green lines on the right panel in each figure). The three remaining events triggered with the S-wave. For all of the events aside from that on 2020-03-07, ~ 10 seconds elapsed between the first and fourth station surpassing the threshold. For the 2020-03-07 event, only 2 seconds elapsed, because the 2020-03-07 event was entirely within the network and so spreading seismic waves from the sub-surface event arrived much more synchronously at the sensors than for events with offshore hypocenters.
4.2 Shaking

In addition to reporting the detection times we also assess the likely warning outcomes for population percentages for the case where the warning precinct for a detected event is the entire Costa Rican population (Figure 7). We use the WorldPop 1 km gridded database [Tatem, 2017] for our population data. We interpolate the spatial distribution of DYFI reports to define an area of felt shaking, reasoning that it is likely ground-shaking occurred between sites of reported shaking [Kodera et al., 2018; E S Cochran et al., 2019]. Although DYFI data contains uncertainty from humans’ perceptual subjectivity [Goltz et al., 2020], we minimize this by applying a binary “shaking” or “no-shaking” classification to DYFI reports. We contend this is a conservative approach in that, for a given earthquake, the area of felt shaking represented by DYFI data is an under- rather than over-estimation: it seems more likely that people who felt shaking would not report it rather than that people would report felt shaking when none was felt.

We categorize outcomes as True Positive-Shaking (TP-S): the system correctly detects an event and a user receives an alert prior to felt shaking; True Positive-No Shaking (TP-NS): the system correctly detects an event, a user receives an alert but does not feel shaking; No Alert (NA): the system correctly detects an event, but a user does not receive an alert prior to shaking; False Alert (FA): the system incorrectly detects an event and sends an alert, no shaking occurs anywhere; and Missed Alert (MA): a felt event occurs but the system does not issue an alert. For each of these scenarios, to permit evaluation of when users could expect to receive warning messages, in the plots we add to $\delta_{\text{detect}}$ 5 seconds, ~1 second more than the median value of $\delta_{\text{alert}}$ from the vibration tests (see section 3.2).

For PGAN-4, 15.5-71.0% (median 38.5%) of the population would have received TP-S outcomes, 27.1-83% (median 52.8 %) would have TP-NS outcomes, and 4.9-8.8% (median 2.5%) would have NA outcomes (Table 1, in Table S2 we display metrics for PGAN-3 configuration). Outcomes can be grouped further according to onshore (in-network) and offshore (out-of-network) source categories. For the onshore events (12/8/19, 3/7/20, and 3/13/20) more time after warning is received is generally available because $\delta_{\text{detect}}$ is, on average, 10 seconds faster than the two offshore events (1/21/20a,b) and because the events on either the Nicoya or Osa peninsulas are far enough away from population concentrations (Figure 7a,d,e).

Interestingly, however, the two off-shore events yield the largest TP-S outcomes because Costa Rica’s population is concentrated in and around the capital city, San Jose, near the center of the country and more than 100 km from these events (Table 1).

4.3 Missed & False Alerts

In order to analyze a self-consistent dataset of felt shaking, we further classify MAs to be events for which the system did not produce an alert but that produced enough shaking for people to file DYFI reports. This is a minimum number as there may be other, smaller events that were felt but for which no DYFI reports were filed. During the period of evaluation there were 8 such MAs with a range of $M_w$ 4-5 (Table S1, Figure S1). Six of these MAs were located well outside of the network (Figure S1). Of the remaining two, only one (12-31-2020, $M_w$ 4) was located entirely within the network, the other (4-17-2020, $M_w$ 4) was located on the Pacific coast at the edge of the network. For these events, less than 0.5% of the population reported shaking and the reported shaking never exceeded MMI III (Figure S1).
False alerts (FAs) can occur because of system glitches or non-seismic local or regional accelerations. From our time period of analysis we identified two types of system glitch sources that affected three or more neighboring stations nearly simultaneously. The first is unexpected phone vibration because of user error when programming the vibration tests. The second is regional power-grid instability causing AC electricity fluctuations that, in turn, cause multiple phones to unexpectedly vibrate simultaneously when they re-start as the regional AC power cycles off and on. Once they are identified, these are relatively straightforward FA sources to mitigate in real-time by better accounting of programmed vibrations and by identifying and excluding sites experiencing regional power cycling. Real, non-earthquake accelerations from sources such as vehicles passing on the street, thunder shaking a structure, or people moving furniture near the phone installation are more difficult to mitigate. As the number of vertices in the PGAN triggering criteria is increased, the probability of regionally simultaneous non-seismic accelerations decreases. In our early tests we found that it was necessary to include more than three stations in the PGAN detection algorithm to mitigate the effect of these types of unwanted accelerations on alert generation.

In our analysis of six months of ASTUTI data using PGAN-4, once system glitches were identified and noisy stations removed, we eliminated all FAs yielding a FA rate of 0%. This is similar to the result from offline runs of the PLUM algorithm on West Coast data that had a 0% FA rate (Cochran, et al. 2019). For further comparison, published FA rates for science-grade EEW networks range from 2.5% in Taiwan [Xu et al., 2017] to 8% for Shake Alert [Kohler et al., 2020]. The Japanese system reported many FAs after the 2011 M 9 Tohoku earthquake but to the best our knowledge has not published a FA rate [Hoshiba, 2014]. For smartphone EEW, the Earthquake Network Project sets detection thresholds so that they do not exceed 1 FA per year, per country [Finazzi, 2020]. This approach is a way to balance the often competing objectives of minimizing both MAs and FAs. The MyShake project has not reported FA rate, stating that “the false positive events are not so well quantified, because we do not have a large number of false positive samples from the system” [Kong et al., 2020].

5 Discussion

Capital costs for the entire ASTUTI network were ~USD 22,000 and annual operating and maintenance costs are ~USD 20,000. For comparison, ShakeAlert capital costs are close to USD 100 million and annual operating costs are ~ USD 39 million [Given et al., 2018]. When normalized by population for Costa Rica (~5 M) and combined populations of California, Oregon, and Washington (~52 M), ASTUTI’s capital costs are 450 times less and annual operating costs are 192 times less than Shake Alert’s. When normalized by area for the same regions (~51,100 km² and ~863,000 km², respectively), ASTUTI’s capital costs are 279 times less and annual operating costs are 119 times less than Shake Alert’s. Despite this roughly two order of magnitude difference in capital and annual costs, we find, generally, that performance metrics for our fixed-network smartphone EEW approach compare favorably with science-grade EEW, at least during our six months of evaluation. Data latency, δdata, for the ASTUTI network is lower than some science grade networks. Alerting latency, δalert, is the same regardless of the type of sensing network. Detection latency, δdetect, is similar, albeit slightly higher. If we could increase the station density by ~30% such that four stations would cover the area that three stations currently cover (at a cost of less than ~USD 10,000), detection times
could be decreased by 3-5 seconds without sacrificing FA mitigation (Supplemental Information, Table S2). Furthermore, the spatial distribution of earthquakes that occurred during the first six months of ASTUTI network operation appears to be representative of the spatial distribution of the earthquakes expected to do the most damage in Costa Rica (with the exception of the southern Caribbean region) and so it is likely that similar ASTUTI performance could be expected over longer time intervals.

Faster detection times for EEW systems using higher-grade sensors such as ShakeAlert and SASMEX is due primarily to P-wave based detection [Cuéllar et al., 2018; Chung et al., 2019]. We identify P-waves in the acceleration records of individual stations for all 5 detected events (Figure 8) and, notably, two of the five events were detected as the result of triggers in the P-waves. Accordingly, although ground-motion-based algorithms may be more likely to trigger on S-waves for moderate-sized events, there is no a priori requirement of this. Faster warnings could occur for larger events, such as the $M_w$ 5.2 2020-03-07 event where P arrivals triggered the event and are seen in the records of many stations (Figure 8d). Additionally, as future generation MEMs accelerometers become more sensitive, detection on the P wave could become more likely, although trigger thresholds have to be carefully considered given the noise levels at station locations. A better understanding of the relationship between expected P wave amplitudes and their spatial coherence for a variety of events would allow for improved predictions of the performance of accelerometer-based EEW.

The ASTUTI strategy of warning the entire country upon detection of any event would permit warnings to reach large percentages of the population (15-70% TP outcome) for the earthquakes that “mattered”, that is, earthquakes that caused enough shaking for people to submit DYFI reports. The detected events had median and maximum MMI levels of 4.3 and 6 with ~17% to 73% (41% median) of the population experiencing felt shaking. In contrast, the non-detected events had median and max MMI levels of 2.9 and 3.8 with 0 to 19% (0.002% median) of the population experiencing felt shaking. For smaller and sufficiently out-of-network events that did not trigger alerts, less than 0.5% of the population reported shaking and the reported shaking never exceeded MMI III. These population outcomes are a function of the spatial distribution of event locations, station density, and population spatial distribution. For example, for events that nucleate on the Nicoya or Osa peninsulas, the detecting stations are far enough away from population concentrations to afford more people time to receive warnings and undertake mitigating actions. Consistent with the results of the vibration test for the 2012 M7.6 Nicoya earthquake scenario, this suggests that the approach could work well for the case of subduction zone events of significant size (>M7). For events in the central Pacific coastal embayment between the Nicoya and Osa peninsulas, however, the events (2020-01-21a,b) occur farther away from the coastal sensors, and closer to higher population centers, leading to shorter detection and warning times. This is an unavoidable consequence of Costa Rica’s geography and is common to any EEW system reliant on land-based sensors.

For outcomes where an alert is received and no shaking experienced, we believe it is important to differentiate between event-based FA and shaking-based TP-NS outcomes. For the PGAN-4 algorithm, the 0% FA rate is lower than all other EEW systems’ reported FA rates aside from retrospective testing of PLUM with West Coast U.S. data. Our examination was only over six months, however, and so more operational time is required for a longer-term FA rate. As
expected, a low detection threshold criterion combined with a country-wide alerting region also leads to significant population percentages (20-80%) with TP-NS outcomes. TP-NS percentage could be reduced by modifying our alerting philosophy to include shaking estimation from source-parameter characterization; however, we suggest that the benefit of attempting a more refined warning may be outweighed by the added uncertainty associated with EEW parameter estimation and ground-motion prediction [Sarah E. Minson et al., 2018; S.E. Minson et al., 2019]. It is not clear what penalty there may be in terms of user engagement if an EEW system provides alerts without felt shaking, especially if users were to receive a rapid follow-on message stating that an event had been correctly detected although they did not feel shaking. In fact, the general population may appreciate receiving an alert whenever an earthquake occurred, even if no one felt it [Nakayachi et al., 2019]. Indeed, we are at the very early stages of studying the nuanced relationships between EEW system performance and human sentiment. Given this evolving understanding, a clear high-priority must be EEW pre- and post-event education and messaging [S McBride et al., 2020].

Given the concentration of Costa Rica’s population in San Jose (> 90%), it is useful to further consider outcomes for its greater metro region. S-wave arrival in San Jose for the three onshore or near-shore events (2019-12-08, 2020-03-07, 2020-03-13) was between ~30 and 50 seconds after median receipt of alert time (\(\delta_{\text{detect}} + 5 \text{ seconds}\)) (Figure 7a,d,e) . For the offshore events (2020-01-21a, 2020-01-21b) the S-wave arrival was much sooner, a few seconds after median receipt of alert time (Figure 7b,c). Thus, for three of the five detected events, our results suggest that DCHO for a large percentage of San Jose residents is an achievable objective. For the two offshore events DCHO may not be a widely achieveable objective. Because there is a paucity of studies that have directly evaluated DCHO, however, there is some uncertainty in assessing EEW users’ likely response. For instance, for the HayWired exercise [Porter and Jones, 2018], DCHO took 5-15 seconds and for a New Zealand ShakeOut exercise DCHO timing varied from 10-30 seconds (64% of participants took less than 10 seconds and 34% took 11-30 secs) [S K McBride et al., 2019]. For two actual shaking events, however, Nakayashi et al (2019) report that taking no action was the most common outcome for people who received EEW alerts. This uncertainty highlights the often counter-intuitive nature of humans’ interaction with automated warning systems and stresses the importance of further mitigation education and social science studies targeting DCHO activities.

Our investigation began by questioning whether off-the-shelf smartphones deployed in a fixed network could provide EEW in a reliable and effective enough manner so that significant populations could receive warnings in time for DCHO protective actions to be undertaken. The answer is unequivocally affirmative. As pointed out by others [David J Wald, 2020b], however, updating construction codes and practices as well as promoting more widespread and thorough acceptance of simple mitigation actions such DCHO deserve to be considered as top priorities for earthquake-related resource allocation. The fixed network approach we describe here is so inexpensive, however, that it need not interfere with other budgetary priorities for resource-limited countries that do not have the resources to maintain advanced seismic networks but that could benefit from some form of EEW. Myriad implementation scenarios can be envisioned ranging from stand-alone smartphone networks to augmentations of preexisting scientific-grade instrumentation. Basic stand-up for a network such as ASTUTI requires purchasing and installation of phones and SIM cards and spinning up instances of the processing algorithms on a
cloud-based server. Similarly, the approach is so inexpensive that the benefits of a fixed-network smartphone approach (station coverage for expected earthquake source regions and network reliability) outweigh the even lower costs associated with crowd-sourcing. Moreover, as digital home assistants become more ubiquitous, crowd-sourcing efforts (users permitting access to their personal devices) will move to fixed network modes. Especially for resource-limited populations, however, the day is still years away when user-contributed data will be spatially complete enough and temporally reliable enough to provide robust EEW capability for a larger population. Finally, with smartphone-based EEW in a nascent phase of rapid growth, we stress the need for continued scientific investigation and validation of these methodologies by the global community. Especially given the need for transparency when issues of public safety are concerned, we encourage open-access data policies for smartphone-based EEW systems.

6 Conclusions

We have demonstrated that a fixed-network of smartphones using a ground-motion-based detection algorithm can provide operational EEW at a cost that is generally 1-2 orders of magnitude less than scientific-grade networks. The ASTUTI combination of detection capability with a country-wide alerting strategy demonstrates an effective EEW strategy for the common earthquake hazard setting where large population centers are close enough to be affected by large earthquakes but far enough away from them so that alerts may arrive in time to permit simple protective actions such as DCHO. More social science research is needed to ascertain whether populations will be tolerant of a system that correctly detects events and that sends alerts to users who do not necessarily feel shaking.

Acknowledgments, Samples, and Data

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1.
Figure 1. Costa Rica seismotectonic framework, population distribution, ASTUTI network, and the M7.6 2012 Nicoya peninsula earthquake. Basemap, WorldMap 1 km gridded population (copper colormap) and shaded topography and bathymetry (blue and gray colormaps). (a) Colored circles, earthquakes in the NEIC catalog from August 15, 2000 to June 3, 2020, colored by magnitude. White triangles, ASTUTI smartphone locations. MAT, Middle America Trench. SJ, San Jose city. (b) Beachball, focal mechanism of the 2012 Nicoya earthquake. Colored grid cells, Did You Feel It (DYFI) Modified Mercalli Intensity (MMI) values from the 2012 Nicoya earthquake.

Figure 2. A typical ASTUTI station. (a) Photo showing the smartphone enclosure affixed to a wall. (b) Photo inside the enclosure of the smartphone screen showing the QED software application display.

Figure 3. Schematic diagram of the ASTUTI approach. The general flow of alerting data and information is clockwise starts in the Device Networks box and end in the Alert System box. NTP, network time protocol. UDP, user datagram protocol. MQTT, message queuing telemetry transport. API, application programming interface. MySQL, My structure queried language.

Figure 4. Examples of raw accelerometer and PGA data types from one station. Black, raw accelerometer data. V, vertical axis; H1, horizontal axis; H2, horizontal axis. Blue, P, processed PGA data message. (a) Example of how the PGA data type preserves the signal of 3 small earthquakes at 0, ~75 and ~210 seconds. (b) Example of how the PGA data type suppresses noise spikes at ~ 0 seconds.

Figure 5. Histogram of PGA values for one station for one day (gray) and one hour (red). The current triggering threshold is 0.6%g.

Figure 6. ASTUTI system latency and M7.6 Nicoya scenario vibration test. (a) Hourly distribution of data latency, \( \delta t_{\text{data}} \), for the 6 month observation period. Each column represents the median \( \delta t_{\text{data}} \) probability distribution function for an hour of the day. (b) Location map (as in Figure 1a) showing the M7.6 Nicoya scenario vibration test. Red star, epicenter. Magenta circle, S-wave position at the time, \( \delta t_{\text{detect}} \), the time the event was detected. Green triangles, the stations that triggered the alert. (c) P-message record section from the vibration test. Stations are ordered with distance from the epicenter. Hypocentral distance shown in blue text. (d) Histograms of
time to detection, $\delta t_{\text{detect}}$ (top) and time to receipt of alert, $\delta t_{\text{alert}}$, (bottom) for all 216 vibration tests.

**Figure 7.** ASTUTI results from the 5 detected earthquakes for the PGAN-4 algorithm. Each plot has the same symbology and nomenclature. Title with white box, origin time and magnitude of the event from OVSICORI. Magenta-box title, $\delta t_{\text{detect}}$. Magenta solid circle, estimated position of S-wave (3.2 km/s) at time $\delta t_{\text{detect}}$. Magenta dashed circle, estimated position of S-wave 20 seconds after time $\delta t_{\text{detect}}$. 20 seconds represents ~5 seconds for alerting time, $\delta t_{\text{alert}}$ (see Figure 5d) and 15 seconds for protective action such as Drop-Cover-Hold-On (DCHO). Green filled triangles, four stations that triggered the alert. White solid triangles, active stations at time of event. White empty triangles, inactive stations at time of event. Colored grid squares, DYFI cells. Hot population colormap, population % True-positive (TP) outcomes. Gray population colormap, % No-alert (NA). Copper population colormap, % True-positive no-shaking (TP-NS). (a) 12 December 2019 $M_w$ 4.8. (b) 21 January 2020a $M_w$ 5.3. (c) 21 January 2020b $M_w$ 5.2. (d) 7 March 2020 $M_w$ 5.2. (e) 13 March 2020 $M_w$ 5.0.

**Figure 8.** P-message record section for the 5 detected earthquakes for the PGAN-4 algorithm. Each plot has the same symbology, nomenclature, and scale. The left column shows all stations for a particular event, the right column shows a zoomed image of only the triggering stations. Stations are ordered with distance from the epicenter. Hypocentral distance shown in blue along the vertical axis. Triggering stations, thick black. Other stations, black. Triggering time, magenta line. Pink shading, ranges of 6 and 3 km/s for P- and S-wave arrival times, respectively. (a,b) 12 December 2019 $M_w$ 4.8. (c,d) 21 January 2020a $M_w$ 5.3. (e,f) 21 January 2020b $M_w$ 5.2. (g,h) 7 March 2020 $M_w$ 5.2. (i,j) 13 March 2020 $M_w$ 5.0.

**Table 1.** Alerting outcomes for each detected event for PGAN-4 algorithms. See also Figures 7 and 8. Time to detection, $\delta t_{\text{detect}}$. TP%, percent of population with True-positive outcomes. TP-NS%, percent of population with True-positive no-shaking outcomes. NA%, percent of population with No-Alert outcomes.
Figure 3
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Table 1