Early-warning systems in geophysics

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Introduction

"*If an early-warning system had been in place when the tsunami of 26 December 2004 struck the Indian Ocean region, many thousands of lives could have been saved. That catastrophe was a wake-up call for governments and many others about the role early warning can play in avoiding and reducing the human and physical impacts of natural hazards.*"

By this statement Kofi Anan, former UN Secretary General, set the stage after the devastating Indian Ocean tsunami 2004. Natural hazards threaten people and values worldwide. Since 2007 more than 50 % of the global population have been living in urban environments and we see an increasing accumulation of economic values in high-risk areas, e.g., in coastal regions. Thus, the vulnerability of societies to natural hazards is actually increasing.

Since 2005 two global UN conferences on *Disaster Risk Reduction* have resulted in the *Hyogo Framework of Action* (ISDR, 2005) and the *Sendai Framework* (UNDRR, 2015). Both frameworks identify early-warning systems for hazards as key components for disaster management and disaster risk-reduction strategies. Early-warning systems are understood in both frameworks as end-to-end systems. To be effective, early-warning systems must be people-centred and must integrate four elements: (i) knowledge of the risks faced; (ii) technical monitoring and warning service; (iii) dissemination of meaningful warnings to those at risk; and (iv) public awareness and preparedness to act. Failure in any one of these elements can mean failure of the whole early-warning system. Roughly, one may differentiate among meteorological, hydrological, geological and anthropogenic hazards; all of these have individual characteristics like warning lead times or impact area. A single hazard or combinations or cascades of them can lead to direct devastating impact for people, the environment and/or technical infrastructures.

In this short overview we will focus on early-warning systems for a set of geological and geophysical hazards, demonstrating a subjective selection of early-warning technologies, developments and realisations. Hence, this review does not claim completeness; nevertheless, by focusing on a few geohazards, the general and internationally agreed strategy of the implementation of early-warning systems for natural hazards should become clear. A more comprehensive overview is given by Merz et al. (2020).

Earthquake early warning (EEW)

During an earthquake, different types of seismic waves are radiated from the earthquake's hypocentre. First, weaker but faster-moving P-waves can be detected at a regional sensor network from which, in turn, signals are transmitted to data processing centres. In a second step, algorithms quickly (in the order of one second) estimate the earthquake's location and magnitude. Based on empirically derived ground-motion prediction equations (GMPEs), the system can then predict which level of ground motion is to be expected at the target site. If a certain threshold is exceeded, the system will send an (automatic) alert before slower but more destructive S-waves and surface waves arrive at the target site. Examples of this source-estimation-based approach are EPIC (Allen, 2007) and FINDER (Böse et al., 2015), where the latter even takes into account the fact of source finiteness, i.e., it considers the rupture plane location.

As an alternative to the source-estimation approach, it is possible to use the observations of shaking within an expanding wavefront to predict shaking at more distant sites, with the PLUM method being a recent example (Kodera et al., 2018). Such a propagation-based approach requires a relatively dense instrument network to be effective but can then result in more accurate predictions, albeit at the price of shorter warning times.

In this way, the regional EEW system may be thought of as three interlinked components: (1) a real-time (strong-motion) seismic monitoring network, (2) one or more software platforms receiving and processing the real-time signals from the monitoring network and issuing an alarm, and (3) a technological infrastructure and a set of operational protocols to broadcast the alarm and implement specific damage reduction strategies.

Given the processing chain, this means that people near the epicentre (in the order of kilometres to a few tens of kilometres away) will have little, if any, advance warning, while those farther away may have critical seconds to brace for shaking. Paired with automated responses that can slow trains or shut off gas lines, early-warning systems may help prevent some of the fatalities and injuries as well as damage typically associated with major quakes.

In some cases, small-scale EEW systems may be based on one or just a few monitoring sensors, installed in proximity of the target to be protected by the incoming ground motion. This is usually referred to as a de-centralised (or on-site) early-warning system and relies solely on the lag between the P- and S-wave. Applications of this early-warning scheme are growing, especially in industrial installations, which can react promptly (and automatically) to the early detection of the earthquake. For example, such a system is currently implemented and tested in Germany in the *Industriepark Knapsack* near Cologne.

EEW systems now provide public alerts in Mexico, Japan, South Korea and Taiwan, and alerts to selected user groups in India, Turkey, Romania and the United States. They are also being tested for use in Italy, Switzerland, Chile, Israel, Nicaragua, Spain, New Zealand, Iceland, as well as in Costa Rica and El Salvador. Examples are discussed in Clinton et al. (2016) and Parolai et al. (2017).

It should be noted that the lead time of early warning depends strongly on the tectonic regime and resulting seismicity pattern. For example, in Mexico or Japan the subduction zone, in particular the plate boundary (megathrust), is easily identified as the dominant source of moment release. The large distance between the possible seismic sources and the vulnerable areas and cities (up to hundreds of kilometres) represents here a highly suitable case for the application of a standard regional EEW, and lead times (i.e., the time available for action between the first detection and the arrival of the strong shaking) of several tens of seconds can be achieved. On the contrary, the seismic hazard in Europe is related to a multitude of potential seismic sources, often very close to inhabited areas. This reduces the lead time in many cases to a few seconds, therefore allowing only automated, very rapid emergency actions to be undertaken, and mostly excluding the possibility of alerting the general public.

New technologies represent new opportunities for EEW, such that most EEW systems in the next years and decades will likely include one or more of the following innovations, for which mostly some prototypes are already operational. Where the earthquake hazard is offshore as in subduction zones, systems are expected to be amphibious and cross shorelines; *S-Net* in Japan is an example of this approach. More diverse geophysical observations will be considered, including not just seismic sensors but also high-rate GNSS, fibre optic sensing devices (distributed acoustic sensing) and sensors on the seafloor. Observatory-grade sensors will form a backbone network supported by a large number of cheap MEMS accelerometers and by millions of mobile phones everywhere in urban environments; the feasibility of this approach has been demonstrated with the *MyShake* platform in California (Allen et al., 2020), and the *ShakeAlert* approach is now covering the entire western coast of the United States.

Machine-learning algorithms have been sporadically used for early-warning algorithms for a considerable time (e.g., Böse et al., 2008) but the rapid developments of ever more sophisticated algorithms and faster GPUs (Graphics Processing Unit) have led to an explosion of seismological applications of deep-learning (DL) methods in the last two to three years.

DL models need to be tuned by training with a large number of samples from past earthquakes. There are several modes in which DL is employed. Firstly, DL models can be used in supporting the source-estimation task; pilot studies demonstrated the possibility to directly extract information on magnitude and location based on just a few seconds of waveforms (Münchmeyer et al., 2021a). Secondly, in end-to-end estimation, the target variable, e.g., peak ground acceleration (PGA) or intensity, is predicted directly from a few seconds of waveforms recorded at stations of a network (Münchmeyer et al., 2021b), allowing the creation of predicted shake maps in real time (Fig. 1). This approach implicitly combines the benefits of source-estimation- and propagation-based approaches. Finally, DL can be used to predict key parameters such as distance and magnitude from single station recordings and thus theoretically improve decentralised warning strategies.

Machine-learning algorithms can also be trained to produce probabilistic warnings, i.e., estimate the likelihoods of certain levels of shaking to be exceeded rather than making a deterministic prediction. This offers the possibility of allowing different users to set not only different trigger thresholds but also different probabilities depending on the costs of false and missed alarms, a possibility of particular interest to automated systems.

DL approaches still have some shortcomings. The largest events or most intense shaking is often predicted rather poorly by DL algorithms because due to the Gutenberg-Richter frequency-magnitude distribution only few large events are available for training; DL algorithms are notoriously bad at extrapolation (another reason for the difficulty with large events is that the rupture of large events often takes more time to develop than is available to make a decision on whether to warn, but this affects DL and classical methods alike). Transfer learning from other regions has shown good promise to mitigate this issue but cannot fully solve it (Münchmeyer et al., 2021a; Jozinović et al., 2021); another approach being explored is to train algorithms with synthetic data or using magnitude balancing approaches (Datta et al., 2022). In evaluating the performance of early-warning algorithms it is thus of utmost importance to pay special attention to the largest events. Finally, the results of ML algorithms are often inscrutable, making it impossible to understand

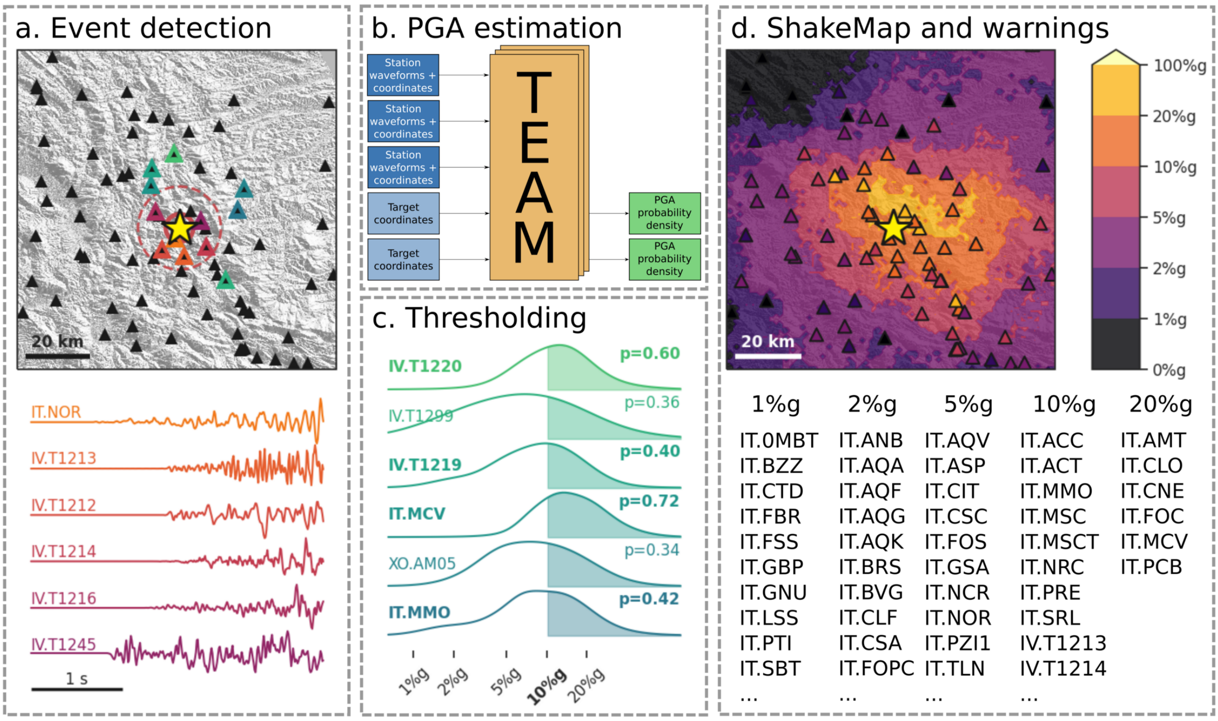


Figure 1: *Schematic view of a DL early-warning workflow for the October 2016 Norcia event (Mw=6.5) 2.5 s after the first P-wave pick (3.5 s after origin time). a) An event is detected through triggering at multiple seismic stations. The waveform colours correspond to the stations highlighted with orange to magenta outlines. The circles indicate the approximate current position of P (dashed) and S (solid) wavefronts. b) The input to the DL model (TEAM) are raw waveforms and station coordinates; it estimates probability densities for PGA at a target set. The exceedance probabilities for a fixed set of PGA thresholds are calculated based on the estimated PGA probability distribution. c) If the probability exceeds a threshold, a warning is issued, here* 10 % *PGA with a probability threshold of* 40 % *resulting in warnings for the stations highlighted. The colours correspond to the stations with green outlines in (a). d) The real-time shake map shows the highest PGA levels for which a warning is issued. Stations are coloured according to their current warning level (from Münchmeyer et al., 2021b).*

when or why the algorithm might have gone wrong if it does, and understanding the limits of applicability except by experimentation. Current developments in *Explainable AI* might provide a pathway here, but at the moment they cannot keep up with physical intuition, making the workings of classical algorithms relatively easy to follow.

Volcano early warning (VEW)

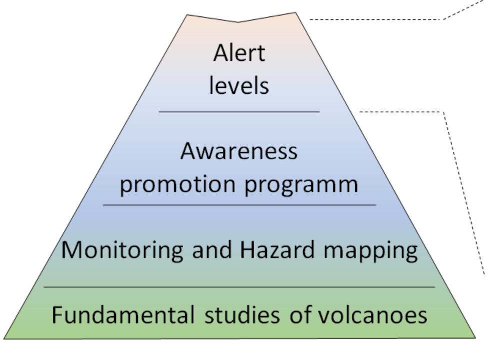
Economic losses due to volcano eruptions have increased in recent decades, as vividly demonstrated by the billion-Euro losses during the Icelandic Eyjafjallajökull eruption in 2010 sending ash clouds over continental Europe, or the 2021 La Palma eruption, sending extensive lava flows, ash and lapilli over populated, touristic and industrially used grounds.

There are around 1500 volcanoes considered active. *Active* means that the volcano has produced at least one eruption during the past 10 ka, suggesting that further eruptions from this volcano are highly likely. The 10 ka limit and therefore the number of 1500 volcanoes is somewhat arbitrary and does not reflect the true vast number of potential volcanic sites, which is expected to be much higher. About 800 million people live in a 100 km radius of one of the active volcanoes listed by the *Smithsonian Global Volcanism Program* (GVP), which is why operative monitoring and an early-warning system implementation are important for the population, industry and relevant infrastructures.

Forecasting the behaviour of volcanoes in the long-term is challenging, maybe elusive for some volcanoes. The preparation processes effective beneath a volcano prior to an eruption, however, may well allow for the detection of unrest several days, weeks or even months prior to an eruption. Once buoyant magma is rising through the crust, degassing and pressurising, the effects can be monitored by geophysical, geochemical and geodetic techniques, and critical thresholds of the four parameters, seismicity, deformation, gas concentration and temperature increase, can be communicated towards alert levels and volcano early-warning systems (VEWS) as summarised in Figure 2.

Surprising eruptions do still occur, however, even at those sites well studied and monitored, and where a VEWS is implemented. The 2018 flank collapse and tsunami at Anak Krakatau was anticipated by scientists, but unexpected by authorities, killing 430 peo-

(a) Elements of a VEWS



(b) Volcano alert level chart

Code	Narrative	Levels
Red	Eruption in progress	Levels 1 (Minor eruption) to 4 (Massive explosive eruption)
Orange	Warning	Accelerating intense unrest: eruption likely within hours to days
Yellow	Watch	Intense Unrest
Green	No immediate risk	Levels from Quiescent to Strong Unrest

Figure 2: *(a) Common elements of a volcano early-warning system (VEWS), highlighting the broad basis of fundamental sciences, monitoring and hazard mapping needed to be effective. At the top, alert levels are considered by the civil authorities and decision makers (not shown here explicitly). Modified after Tilling (1989). (b) Summary of a colour-coded volcano alert level chart, effective at most active and monitored volcanoes worldwide.*

ple (Palmer, 2020). Similarly, the 2019 Stromboli violent eruption occurred surprisingly, as did the Whakaari/White Island in that same year, with 1 and 21 fatalities, respectively. The problems of developing and improving a VEWS are multifold. Some unexpected eruptions are near-surface steam-driven explosions, meaning that the monitoring design is not able to identify such processes. Other unexpected eruptions occurred, while heightened unrest was reported but ignored for years. Probably most of the unexpected eruptions occur due to a lack of sufficient monitoring, though. The reason is that the high price tag of setting up local monitoring makes it nearly impossible to instrumentally monitor all 1500 active volcanoes worldwide. Besides the high costs of precision instruments (some cost tens of thousands of Euros for a single sensor and logger system), the more sophisticated analysis methods enabled by modern instrumentation require more highly trained observatory staff now than in the past, providing another challenge for the modernisation of volcano observatories. Therefore, an editorial published in *Nature Communications* ("Overcoming financial limitations in global volcano monitoring" 2021) emphasised the need for equitable international partnerships in the volcano science community, with two principal aims: firstly, to better understand a volcano's past, present and future behaviour, and secondly, to develop data timelines allowing to forecast (or early warn of) imminent eruptions.

Important for understanding and monitoring a volcano is a reduction of personnel, instrumental, and data costs. Instrumental costs are already falling, as demonstrated by the low cost (MEMS-type) seismometers (e.g., https://quakesaver.net/), the easy and cost-effective access by unmanned aerial vehicles (UAVs or drones), the gravimeters developed in a European project (http://www.newton-g.eu), or modern computer vision approaches such as applied to webcams (Walter, 2011), combined with modern data science approaches (Korolev et al., 2021). Also, personnel costs are reducing, as data science and remote sensing approaches are studied in international and interdisciplinary partnerships.

Despite these advances, field instrumental and scientific capabilities are still demanding in a sense that volcanoes have to be revisited regularly, sensors are multi-parametric, and data communication has to be guaranteed in the long run. Out of the 1500 listed active volcanoes, this is done with sufficient quality at only a few dozens of them. Worldwide around 100 volcano observatories exist, many of them are so badly equipped that surprising eruptions are bound to occur again and again. Disparities in the standard of monitoring should be reduced and free data access should be pushed to enable decentralised volcano monitoring and support early-warning systems. For submarine events, such as the 2022 Hunga Tonga eruption, few or no near-field measurements are available. For such events, remote sensing and global network data are thus one of the only information sources to be expanded.

Free and decentralised availability of satellite data acquired by the *European Space Agency* (ESA) has already become an important element in VEWS worldwide. The sharp increase of the amount of data, awareness of intellectual property rights and data publications, and improved data science approaches are highly promising (as highlighted by Witze, 2019). Volcano deformation and change detection, for example, is monitored by automatic satellite radar interferometry (InSAR) and spectral data analysis (Valade et al., 2019; Ghosh et al., 2021). Therefore, continuation and possibly expansion of geophysical remote sensing techniques is needed, such as provided by the planned *TanDEM-L* mission. By this, (i) monitoring the thousands of otherwise unmonitored volcanoes on the globe is in reach, and (ii) modern volcano observatories can indeed realise important partnerships, including local instrumental networks as well as international remote sensing and data science expertise.

Tsunami early warning (TEW)

Tsunamis are relatively rare but potentially high-impact natural phenomena which may affect large portions of a coastline taking thousands of people‘s lives and devastating settlements and infrastructure. Tsunamis – gravitational waves in the ocean – can be triggered by various physical phenomena capable of bringing the sea level out of equilibrium, including earthquakes, subaerial or submarine landslides, volcano eruptions, meteo-conditions or asteroid impacts (Grezio et al., 2017). Most of the devastating tsunamis are, however, caused by shallow submarine earthquakes as a result of a static residual deformation of the seafloor. Whereas it is not feasible to predict the exact location and magnitude of a future triggering earthquake, it is nevertheless possible to evaluate source parameters within a few minutes after an event started and to use this information to assess a pending tsunami hazard and issue corresponding warnings before the wave strikes the coast.

Tsunami early-warning efforts started 1949 in the United States when in response to the M8.6 Aleutian Islands earthquake and tsunami that devastated the city of Hilo, Hawaii, the *Pacific Tsunami Warning Center* (PTWC) was established in Honolulu. Tsunami early warning remained restricted to the Pacific Basin where, in addition to the US PTWC and later WCATWC (*West Coast and Alaska Tsunami Warning Center*), also Japan and the Soviet Union operated their national early-warning centres. The situation changed drastically after the giant Sumatran 2004 boxing-day earthquake and tsunami that killed more than 250 000 people across the whole Indian Ocean. Many countries and international organisations coordinated by the UNESCO *Intergovernmental Oceanographic Commission* (IOC) started developing tsunami early-warning capacities at transocean and national levels (e.g. Lauterjung et al., 2010). In particular, a German consortium of research institutions, led by GFZ Potsdam, together with Indonesian institutions has built the *Indonesian Tsunami Early-Warning System* (InaTEWS) in the GITEWS project (Rudloff et al., 2009), see Figure 3. All initiatives were then additionally fostered by the two very large tsunamigenic earthquakes in 2010 (Maule, Chile) and 2011 (Tohoku-oki, Japan). Presently, we count around 20 tsunami early-warning systems (TEWS) worldwide (Joseph, 2011). They aim to forecast the tsunami arrival time as well as the degree of the hazard impact, usually expressed by warning levels ranging from ’no tsunami’ to ’major warning’. It is worthwhile to note that there is no common alert-level classification among different warning centres.

A TEWS for earthquake-triggered tsunamis encompasses the following steps: (i) detect an earthquake; (ii) estimate source parameters; (iii) evaluate the tsunamigenic impact potential for local and distant coasts; (iv) disseminate corresponding warning information. Newly collected observations from various kinds of land- and ocean-based sensors are used to update the forecast with time. Depending on the expected tsunami source proximity, TEWS can be classified as operating with near- or far-field tsunamis. Near-field or local TEWS (e.g., Japan, Indonesia, Chile, Mediterranean) have to deal with hazard lead times as short as 15–20 minutes. This leaves no more than 5-15 minutes to issue an alert. In contrast, far-field TEWS (e.g., PTWC, India, Australia) operate with source zones at much greater distances, often transoceanic. Correspondingly, such TEWS are in a much more comfortable position to retrieve detailed source parameters and to provide more accurate forecasts.

The minimum parameter set for tsunami forecasts includes earthquake location and magnitude, and can be available within a few minutes. The corresponding simplest and fastest forecast is based on a decision matrix: a table which directly assigns a warning level to earthquake magnitude, depth, and source-to-coast distance. Such a matrix is used, for instance, in the Mediterranean (NEAMTWS) and as initial warning by the US National TWS. Decision matrices are based on historical experiences. However, due to the rareness of significant tsunamis and the fact that it is not possible to establish a common attenuation relation by source-to-target distance (tsunami waves can propagate across large distances without significant loss of energy), forecast based on the decision matrix is rather uncertain. To increase forecast accuracy, modern TEWS employ physics-based simulations of the tsunami generation and propagation coupled to observation data fusion. Numerical models typically (i) predict initial conditions for tsunami propagation based on source information inverted from seismic and geodetic observations and then (ii) solve shallow-water equations to predict tsunami propagation. As tsunami simulations are in principle multi-scale – propagation distances may encompass thousands of kilometres while coastal inundation has a characteristic length of tens to hundreds of meters – different techniques are used to quantitatively assess coastal impact. These range from propagation simulations on a coarse deep-water grid coupled with offshore-to-onshore projections with simple Green‘s law (Kamigaichi, 2011) or more sophisticated local amplification factors (Gailler et al., 2018) to advanced simulation scenarios on mixed-resolution (Harig et al., 2020) or nested grids.

Numerical forecasts are constantly updated while new observations arrive, better constraining the source model. These include land-based GNSS (whose implementation into operational TEWS is ongoing; Hoechner et al., 2013) and sea-based observations like tide gauges and deep ocean-bottom pressure units (Titov et al., 2005). In the classical approach, thousands of propagation models were precomputed for all representative sources and stored in scenario databases. A hybrid approach linearly combines precomputed propagations from unit sources according to their weights

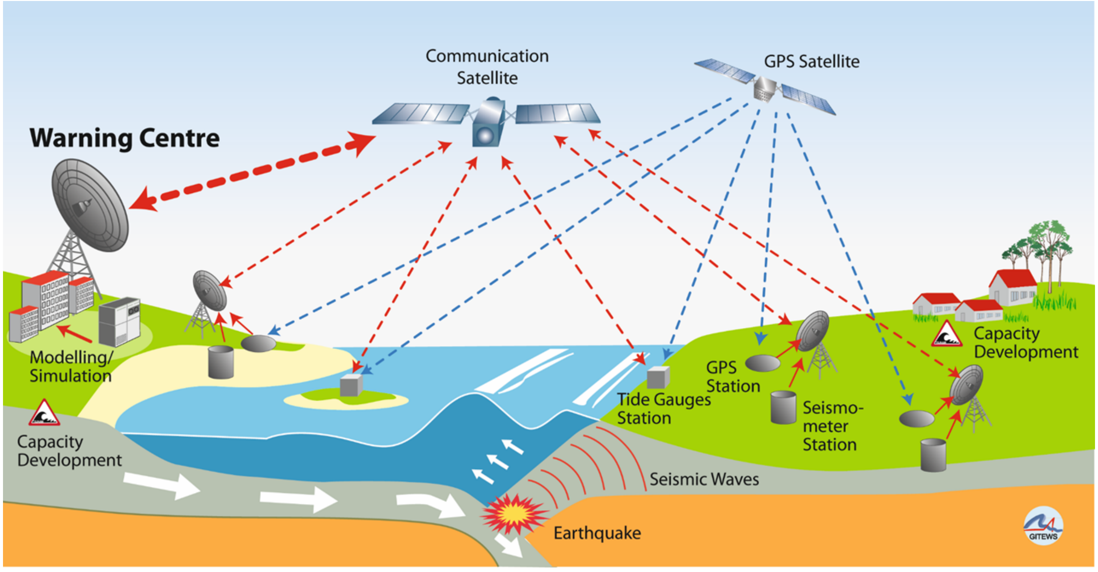


Figure 3: *Schematic layout of the German Indonesian Tsunami Warning system (InaTEWS) illustrating the complete warning chain from the upstream part (monitoring/modelling) to the downstream part (capacity development).*

assessed in real time by seismic and deep ocean observations. In the last decade, the rapid progress in HPC technologies has allowed on-the-fly simulations for arbitrary sources. Next-generation TEWS will enable realistic inundation simulations in faster than real-time mode (meaning faster than arrival of the tsunami, even for near-field situations). Thus, it was possible to compute a tsunami inundation scenario at a 5 m grid resolution in less than 1.5 minutes for the Sendai region replicating the Tohoku 2011 event (75 times faster than real time, Oishi et al., 2015). In Europe, the ChEESE project has established a new *Center of Excellence* (CoE) in the domain of Solid Earth (SE) targeting the preparation of ten community flagship European codes for the upcoming pre-Exascale (2020) and Exascale (2022) supercomputers. Two of the ten flagship codes are GPU-parallelised tsunami simulation codes of the *HySea* family (Macías et al., 2017) aimed for faster-than-real-time simulations.

Development lines in tsunami early warning and forecasting are the integration of additional sensors, i.e., land and sea-bottom geodesy, smart cables (Howe et al., 2019), DAS technology or ionospheric observations using GNSS (Occhipinti et al., 2013). Other developments comprise the quantification and communication of the forecast uncertaintiy (Selva et al., 2021), the extension of TEWS to incorporate non-seismic sources: landslides (2018 Palu earthquake with massive landslides, Schambach et al., 2021; 2018 Krakatau flank collapse and tsunami, Walter et al., 2019) and volcanic explosions (the latest January 15, 2022, Tonga eruption is also distinguished by the fact that the far-field tsunami seems to not have been triggered by the displacement of the water-column near the source but was driven by a globe-encircling atmospheric pressure wave).

Space-weather early warning

Space weather is a collective term describing various hazardous effects related to space. Driven by the electrical currents in space, the variations of the induced magnetic field on the ground can create currents in the power grid lines, produce tripping of power grid systems, and burning of the power-grid transmitters (Fig. 4). Enhancements of the radiation in space may cause various anomalies on satellites or even failures of satellites. While now there are only a few thousand operating satellites, the number of spacecraft is projected to increase to 57 000 by the end of this decade. More than ever before our society now depends on technology in space, and it is therefore most important and timely to understand the vulnerabilities of our infrastructure. Moreover, routine space-weather predictions are needed for the safe operation of power grids, launch and maintenance of satellites.

The source of most of the space-weather-related phenomena is the Sun. The matured understanding of the space physics phenomena allows for the development of new tools with nowcasting or predictive capabilities. The focused research on the processes responsible for acceleration and loss of particles in the inner magnetosphere allowed us to understand the physics that governs the dynamics of the energetic particle populations trapped by the Earth's magnetic field. These advances in science allowed us to develop numerical models capable of modelling the fluxes of hazardous particle radiation. A number of such models are already operating at different research centres around the world. Advances in global magneto-hydro-dynamical (MHD) models allow us to simulate how the disturbances from the Sun propagate towards the Earth. Such models will provide longer-horizon space-weather forecasts that will enable stakeholders to respond to the predic-

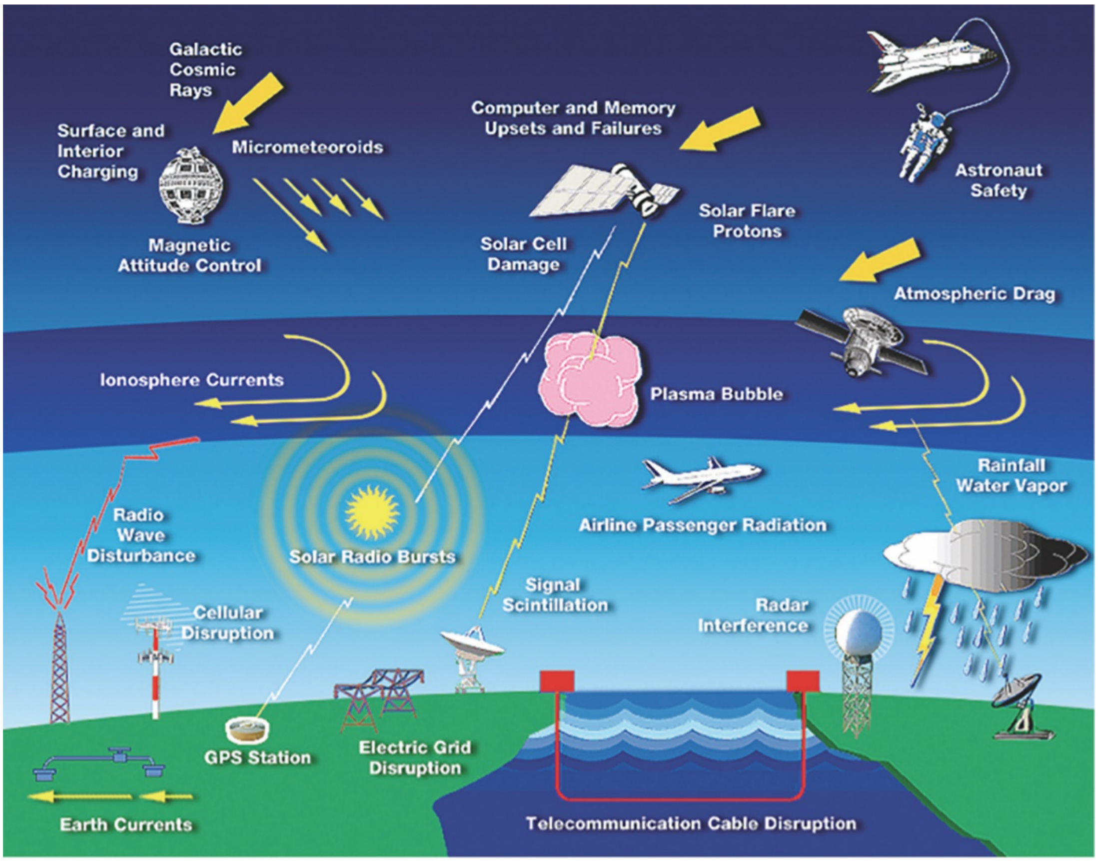


Figure 4: *Effects of space weather on various infrastructures (Baker & Lanzerotti, 2016).*

tions. There is ongoing work that focuses on coupling the global heliophysics codes with the inner magnetospheric codes and also ongoing work on developing ensemble simulations that can provide probabilistic forecasts.

The rapidly increasing number of observations presents a challenge to researchers. The increased volume of measurements from various sources requires the development of new tools that will allow the utilisation of all of these measurements. The most promising among such tools are data assimilation and machine learning. Data assimilation allows for correcting the models by blending models and observations in an optimal way according to the underlying errors.

One of the most effective approaches to understanding and modelling the space-weather phenomena that has emerged in recent years is machine learning (ML) (e.g., Camporeale, 2019). Over the last decade, ML methods have been employed to model a variety of space-weather problems. For example, geomagnetic indices such as the planetary index Kp, provided by GFZ Potsdam, has been modelled using neural networks to forecast geomagnetic conditions from the solar wind observations (e.g., Shprits et al., 2019; Zhelavskaya et al., 2019). Furthermore, neural networks have been shown to be able to extract useful signals from relatively noisy and irregular data sets, frequently outperforming the standard techniques and streamlining the process. For instance, Zhelavskaya et al. (2016) used electric field spectrograms from the *Van Allen Probes* mission to infer special features from the spectrograms that allow inferring total plasma density by applying multi-layer perceptrons. The obtained electron densities have been used to create global models of the Earth's plasmasphere, which is a region of cold plasma in space, corotating with the Earth (e.g., Zhelavskaya et al., 2017, 2019).

Machine-learning methods have also been used for creating nowcasting models of higher-energy plasma populations in the Earth's magnetosphere. For instance, Smirnov et al. (2020) employed the gradient-boosting decision-trees ensembles to model the flux of electrons at energies of hundreds of keV in the outer radiation belt. These electrons are known to be very dynamic and governed by complex plasma physics and transport processes. One of the open questions actively explored by the space-weather community is whether the processes and dynamics of the Earth's magnetosphere can be predicted from simply using the solar images, without employing satellite measurements at all. Recent research has shown that the solar wind velocity can be well predicted through attention-based neural networks (Brown et al., 2022), which paves the way for further exploration of machine-learning capabilities in predicting the space-weather phenomena from images of the Sun. Machine-learning tools have demonstrated to capture the global dynamics from sparse observations and are remarkably good at reproducing the non-linear dynamics of complex space-physics systems but, similarly to the situation in earthquake early warning, may be most prone to error during extreme events when correct predictions are most critical. The combination of physics-based modelling with data assimilation and machine learning will be most important for achieving future predictive capabilities.

The early-warning downstream part: warning chain, communication and uncertainties

Early-warning processes are usually divided in two essential consecutive parts: the upstream and the downstream part. The upstream part comprises all monitoring activities, data evaluation, modelling activities, construction of a situation picture and formulation of a warning message. The downstream process is built around a warning chain to assure that warnings are disseminated to the communities at risk in a timely manner and preparedness plans for proper reaction are in place. The downstream process usually comprises many stakeholders like disaster risk management institutions, local administration and decision makers, broadcasting media and last but not least the people (communities) at risk, which require early-warning information to be able to react on time in order to save lives and properties (e.g., Spahn et al., 2014).

When designing early-warning systems, the information requirements and reaction capacities of communities at risk need to be taken as a principal guiding reference. Timelines, standard operation procedures (SOPs) and decision-making processes between institutions in the warning chain must be clarified and agreed upon to assure that warnings can reach their recipients. Evacuation decisions in particular play an important role. These often have to be made under time pressure and can have far-reaching consequences and are therefore a critical element in the warning process.

If the downstream processes are not properly coordinated with the upstream processes and fully functional, the warning process is likely to fail. The experiences during the devastating flooding event in the western part of Germany in the Eifel region with more than 180 casualties have clearly demonstrated this. While forecasting and early warning worked well in the upstream part of the warning process with sufficient lead time and adequate information on the level of risk, the downstream part, especially at decision-making levels, largely failed.

A sound knowledge of hazards and risks is the basic prerequisite for authorities and the population to be able to understand the possible consequences of an extreme situation, prepare accordingly and respond well in an emergency (e.g., Rafliana et al., 2022). Building on this, a good mix of risk-aware strategies at the community level, combined with greater awareness and self-protection by individuals, can contribute significantly to minimising negative consequences. Especially in quick-onset events with lead times from seconds (earthquake) to minutes or hours (floods, tsunamis, volcanoes), the population should be able to take protective measures (e.g., duck-cover-hold for earthquakes) or self-evacuate instead of waiting for orders. It will be the challenge for transdisciplinary research into the downstream part to strengthen such capacities and to give clear science-based recommendations based on risk knowledge to different types of stakeholders how to handle such situations. An exemplary activity is the so-called *Tsunami Ready* program (see, for instance, https://www.weather.gov/tsunamiready/guidelines), where practical guidelines on the community level for the mitigation of the tsunami threat have been developed (Fig. 5). This may also involve automated warning processes to protect technical infrastructure and minimise secondary effects (e.g., fires) in some cases, such as earthquake early warning or space-weather forecasting.

What is inherent and characteristic for research in the downstream part is the necessarily highly transdisciplinary approach and strategy that has to be followed. Important in this field is the communication and the understanding of uncertainties of the whole warning process. It is essential to work out between science and stakeholders (especially communities at risk) the strengths and weaknesses of early-warning processes, the role of uncertainties in the decision process and the proper classification and valuation of false alarms. These transdisciplinary approaches are particularly important to take into account new types of hazards and hazard cascades like outbursts of glacial lakes and landslide dammed lakes (e.g., Cook et al., 2021), which will likely increase as a result of climate change.

Improving early-warning systems also implies better interfaces between upstream and downstream, a common vision of all actors (scientists, politicians, population) of the possible impacts of extreme events and the confidence of the population in the scientific and technical messages delivered. Such a risk culture and common trust requires preparatory work: transparency and openness of data and models used in the upstream part, solid work to ensure that technical documents are understandable by the various actors belonging to the entire risk chain, development of citizen science actions and the creation of scenarios that are made available and understood by the population and decision makers so that the possible effects can be easily communicated and visualised. It has also been shown (e.g., Kreibich et al., 2021) that individual preparations long before the actual occurrence of extreme events (storage of drinking water in homes, fitting out or reinforcement of houses to reduce damage) contribute to this risk culture and to a better reaction to warning messages.

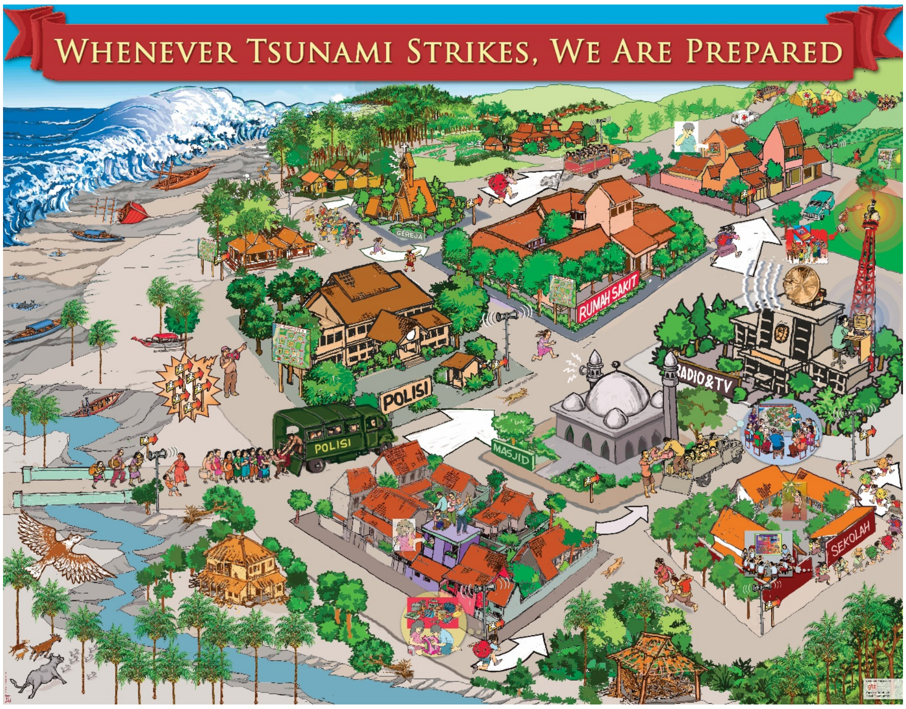


Figure 5: *Tsunami awareness and evacuation poster used in Indonesia.*

Concluding remarks and outlook

Early-warning capacities and capabilities substantially increased during the past decades. This is due to a number of technological developments:

- Increasing global and regional availability of more and more observational and monitoring data from land-based, marine-based and space-based instrumentation,
- ever increasing connectivity and communication bandwidth, and
- rapidly increasing IT capacities for faster-than-real-time data-driven simulation forecasting.

New technologies will contribute to the improvement of early warning: AI and ML techniques to process very large and multi-instrumental real-time data streams, application of HPC facilities to simulate realistic hazard situations in near and faster than real time with high spatial resolution, low-cost sensors for a number of physical parameters to build dense monitoring networks, new applications of space technologies including denser satellite networks in the direction of real-time global observational coverage of the Earth. Including the private sector with its massive sensor networks (smartphones, smart buildings) in early-warning processes can result in a paradigm shift. We will see in the coming decades a substantial improvement of forecasting capabilities for numerous hazards including multi-hazard situations with cascading effects towards improved early warning for communities and infrastructures in densely populated regions.

It will remain a huge and challenging task to reduce the vulnerability of human societies and to increase the response capabilities of communities at risk. Early-warning systems that are designed and implemented with an end-to-end approach can make an important contribution to this. This includes the implementation of automatic procedures (when lead time is short) integrated in the development of smart cities/buildings, an improved outreach to communities using the more dense and broad communication networks, a more sophisticated knowledge transfer to a broad group of stakeholders to improve their response capabilities, the definition and implementation of clear responsibilities and defined roles in disaster risk reduction (DRR) as well as easily understandable standard operation procedures (SOP), especially against the background that a number of hazards (meteorological, hydrological, hazard cascades) may occur more frequently in the future.

Instruments for achieving such goals are strengthening the interdisciplinary and transdisciplinary cooperation, the joint interdisciplinary usage of monitoring infrastructure and the break-up of scientific silos but also the softening of borders between institutions and agencies. We believe that geophysics has successfully taken on the socio-cultural responsibility to contribute to the development of a resilient society and should continue to pursue development of technologies to reduce vulnerabilities and make our world safer.

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