CHAPTER 4

Technological innovations for smart resilience

Even the poorest countries and most excluded communities can be empowered by smart digital technologies that are interconnected and autonomous, and can communicate, analyse and use data to drive intelligent action for disaster resilience. Innovation for smart resilience is therefore a key pathway to empowering and including.

Across developed and developing countries, Governments are increasingly using technology innovations that can promote inclusion and empowerment. These are the technologies that have emerged in the fourth industrial revolution, commonly known as industry 4.0. Industry 4.0 includes innovations in robotics, analytics, artificial intelligence (AI) and cognitive technologies, nanotechnology, quantum computing, wearables, the internet of things (IoT), big data, additive manufacturing, and advanced materials.

Opportunities from big data

Big data refers to the computer analysis of very large data sets to reveal patterns, trends, and associations. Big data has three elements: data crumbs; the capacity to analyse and use these data; and the community of people who produce, analyse and use the data.[164]

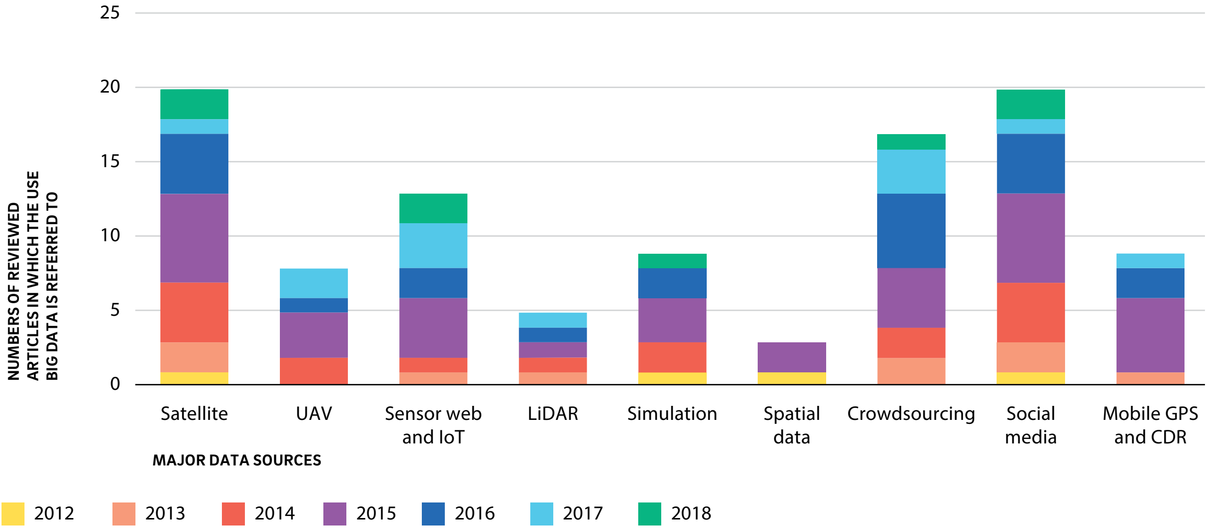
For disaster resilience the data crumbs can come from a wide variety of sources. These include satellite imagery, aerial imagery, videos from unmanned aerial vehicles (UAVs), the internet of things and sensor webs, airborne and terrestrial light detection and ranging, simulations, crowdsourcing, social media, mobile global positioning system (GPS) and call data records (CDR).[165]

The increasing use of these sources is illustrated in Figure 4-1, which shows the number of reviewed articles on these subjects over recent years. On this basis, the fastest-growing sources are satellite imagery, crowdsourcing, and social media.

Big data has opened up promising approaches for smart resilience that empowers the poor. Mobile phone data, for example, can provide an incredibly detailed view of population behaviour and movement in areas previously observed only infrequently and indirectly. Social networks like Twitter, Facebook and others, are already improving the ability of humanitarian and other organizations to monitor and respond to disasters. Further, these opportunities are clearly increasing as mobile phone penetration and internet access move, albeit slowly in the poorest countries, towards universality. Nevertheless, using big data is not easy. Typically, big data is high-volume, high-velocity, and/or high-variety, integrating many diverse data sources and requiring dense infrastructure networks. It is also unstructured and imprecise with a lot of 'big noise' that needs to be filtered out, requiring new forms of computer processing and analytics to enhance decision-making, the discovery of insights and process optimization.

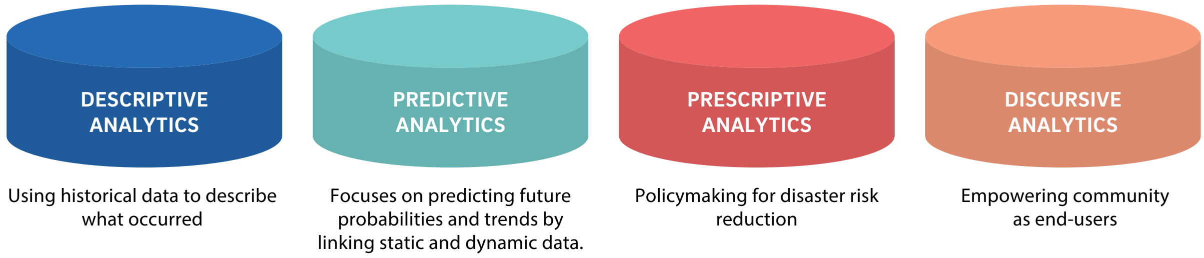
Big data can help in all phases of disaster management; filling in gaps in information flows in pre-response and post-disaster situations, using four types of analytics: descriptive, predictive, prescriptive and discursive (Figure 4-2).

FIGURE 4-1 Use of big data sources for disaster management, 2012–2018



Source: Manzhu Yu and others, 2018.
Note: Based on distribution of reviewed article by major data sources and year of publications.

FIGURE 4-2 Big data: four types of analytics for smart resilience



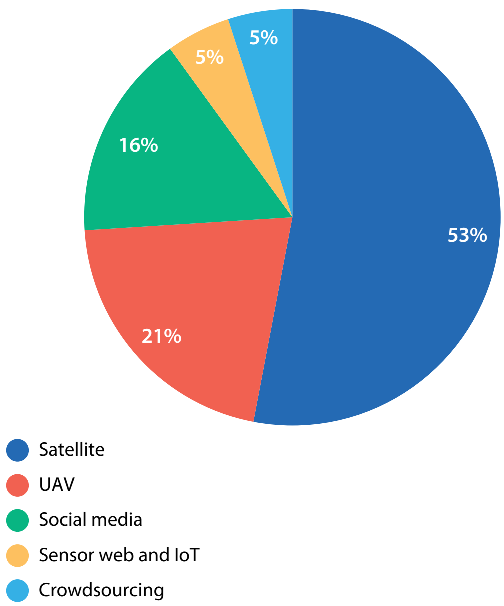
Source: ESCAP based on Data Pop Alliance Synthesis Report, 2015.

Descriptive analytics

Descriptive analytics can be used to highlight risk and to produce situation analyses particularly for damage assessment and people affected. As indicated in Figure 4-3, the most important data sources for this purpose are images from satellites and UAVs/drones. Remote sensing provides a quick initial assessment when in-situ observation is not yet available and can guide responders to the priority areas to be inspected (Box 4-1 and Box 4-2).[166]

All recent major disasters have been covered by multiple satellites and drones. These smaller devices are more flexible than manned aircrafts and can cover disaster-impacted areas close-up to produce higher resolution images. Drones can also provide 3 dimensional (3D) data that provides more meaningful information on the situation facing survivors of a disaster such as the extent of damage to buildings, indicating collapsed roofs, rubble piles, and inclined facades.

FIGURE 4-3 Data sources used for damage assessment, in percentage



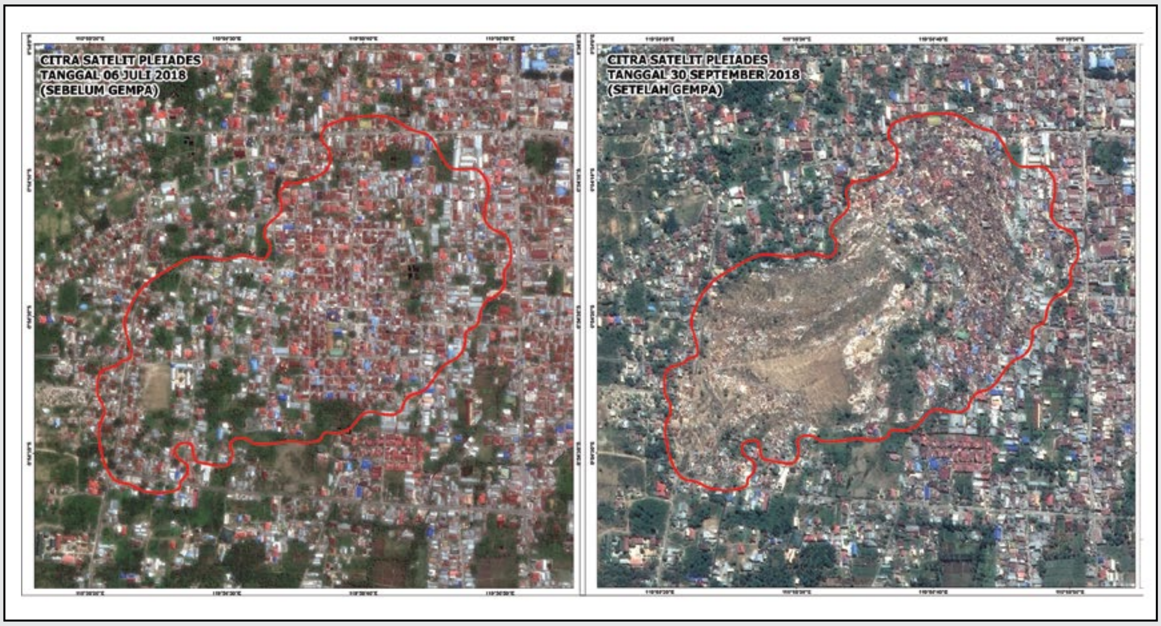
Source: Manzhu Yu and others, 2018.

BOX 4-1 Use of big data for damage assessment in the 2018 Sulawesi earthquake

The World Bank response to the Sulawesi earthquake and tsunami, started with a rapid assessment of the damage-affected areas using the Global Rapid Post-disaster Damage Estimation methodology. This was the first disaster response report to produce sector-based preliminary economic loss estimates, based on scientific, economic and engineering data and analysis.

Based on an open loss modelling approach, it included satellite and remote sensing imagery from a variety of sources. Other inputs were information from early assessments, as well as social media data for results calibration. Spatial characteristics developed for tsunami events included inundation extent and ground deformation analysis.

BOX 4-1 **Pre- and post-tsunami satellite images**



Source: International Disaster Charter, 2018.
Disclaimer: The boundaries and names shown and the designations used on this map do not imply official endorsement or acceptance by the United Nations.

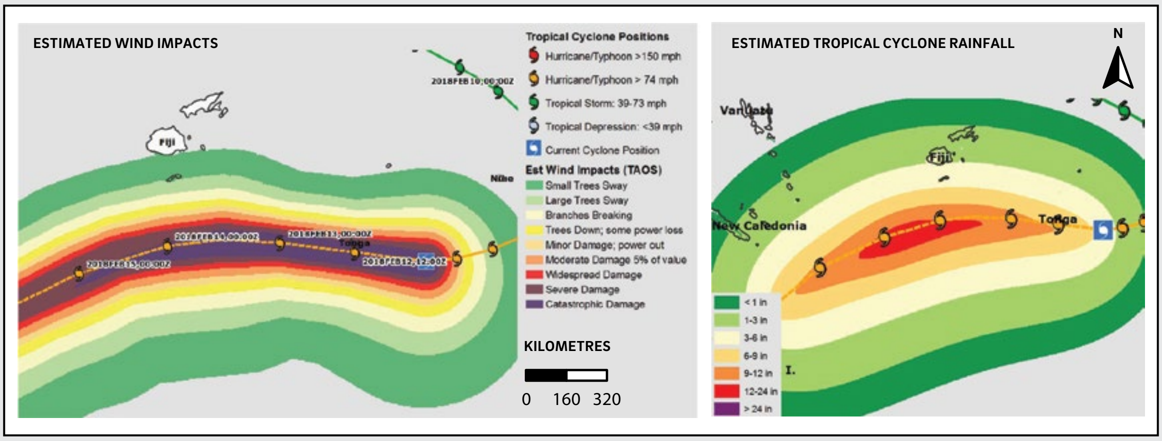
The main benefit was speed. Within 10–14 days of an event, stakeholders could access loss estimates and the spatial distribution of damage. Total economic damages were estimated at $500 million; $180 million for the housing sector; $185 million for commercial/industrial buildings; and $165 million for infrastructure.[a] The World Bank used this to programme its support for recovery and reconstruction with funding of up to $1 billion for the disaster-affected areas of Lombok and Sulawesi.

a Deepti Samant Raja (2016).

BOX 4-2 Impact-based forecasting and damage assessment for cyclone Gita

Between 10 to 13 February 2018, tropical cyclone Gita hit several countries in the Pacific, first Samoa, followed by Niue, Tonga, and Fiji.[a] The cyclone was predicted well in advance, so Governments could prepare for the impacts and plan countermeasures.[b] This involved the use of big data to estimate cyclone tracks and wind and rain impacts.

Tonga's post disaster needs assessment was carried out using drones. These had the advantage over satellites of producing higher-resolution imagery which was important for small-area damage estimation.[c] Drone images also captured damaged buildings and infrastructure and land cover and enabled rapid mapping which accelerated the process of reconstruction and recovery.



Source: Pacific Disaster Center, 2018.
Disclaimer: The boundaries and names shown and the designations used on this map do not imply official endorsement or acceptance by the United Nations.

a ReliefWeb (2018).
b Marit Virma (2018).
c Ibid.

Disaster risk reduction can now take advantage of descriptive analytics and big data. Intensive use of descriptive analytics was a key feature of the rescue of the Thai junior football team trapped in a flooded cave underneath a mountain (Box 4-3).

Google Earth Engine, a cloud platform is also available to support location-specific damage and risk assessment-related analysis and decision-making. This uses datasets gathered from satellites, and GIS vectors datasets, as well as social, demographic, weather, digital elevation models and climate data.[167] Another example is the Open Data Cube, an open-source solution for accessing, managing and analysing large quantities of GIS data, with an analytical framework of data structures and tools to analyse gridded data sets including post-disaster impact assessments.[168] The Australian Geoscience Data Cube is the Government's open source analysis platform which uses the Open Data Cube initiative to support the descriptive analytics application.

Predictive analytics

Predictive analytics uses big data ecosystems as a basis for predicting both sudden and slow-onset disasters.

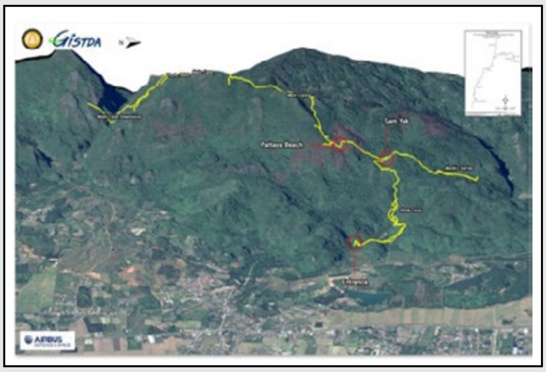
Earthquakes

A sensor web is a wireless sensor network architecture that uses the World Wide Web, enabling access to sensor networks and archived sensor data that can be discovered and accessed using standard protocols and application programming interfaces.[169] These sensors can be embedded in a wide variety of objects from buildings to mobile phones along with the many other smart objects that form part of the rapidly expanding internet of things (IoT). Data from these sensor webs can be combined with satellite data and other sources including user-generated data that reach various

BOX 4-3 The use of technology in Thailand cave rescue: Life-saving operation in a challenging terrain

In June/July 2018, 12 boys went on a field trip, in Thailand's Chiang Rai province, with their football coach and became trapped deep inside a cave underneath a mountain. The prevailing stormy weather conditions meant that flooding was imminent. The rescue was supported by 3D high-resolution satellite images, which provided better visualization and understanding of the risk scenarios, evaluation differences, and topographic features of the area. For instance, in the search for alternative access, the availability of real-time images helped to find openings to drop off survival boxes and seek any sinkholes for managing the water flowing into the cave system in order to maintain the water level. The rescue was supported by a variety of image data products in conjunction with contextual collateral information from multiple platforms.

BOX 4-3 3D-Satellite Image Map of Tham Luang, Khun Nam Nang Non-Forest Park, Chiang Rai, Thailand



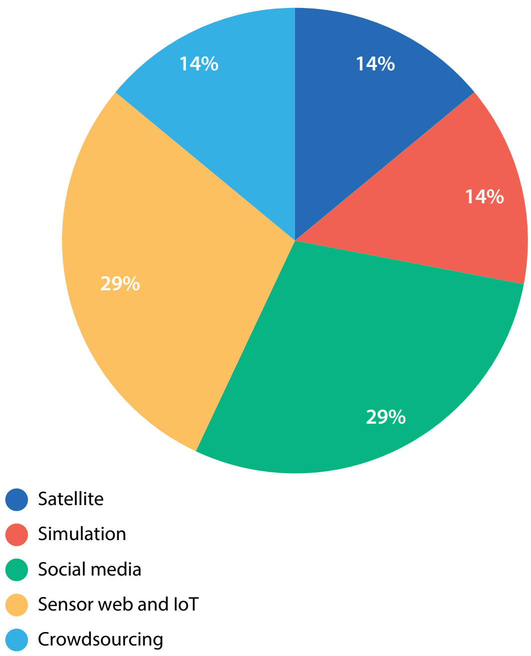
Source: Geo-Informatics and Technology Development Agency (GISTDA), 2019.
Disclaimer: The boundaries and names shown and the designations used on this map do not imply official endorsement or acceptance by the United Nations.

platforms in real time through social media such as Twitter. These data can help predict extreme events such as earthquakes and tsunamis (Figure 4-4).[170]

Sensor costs have significantly decreased over the last decade making dense seismological networks and earthquake early-warning systems more affordable. In high-seismic-risk areas, these networks can give a better understanding of the location, timing, causes, and impacts of earthquakes and tsunamis. Even so, the warning time is short. Seismic waves travel at around two miles per second; therefore, someone who lives 30 miles from the epicentre could only receive 15 seconds of warning.

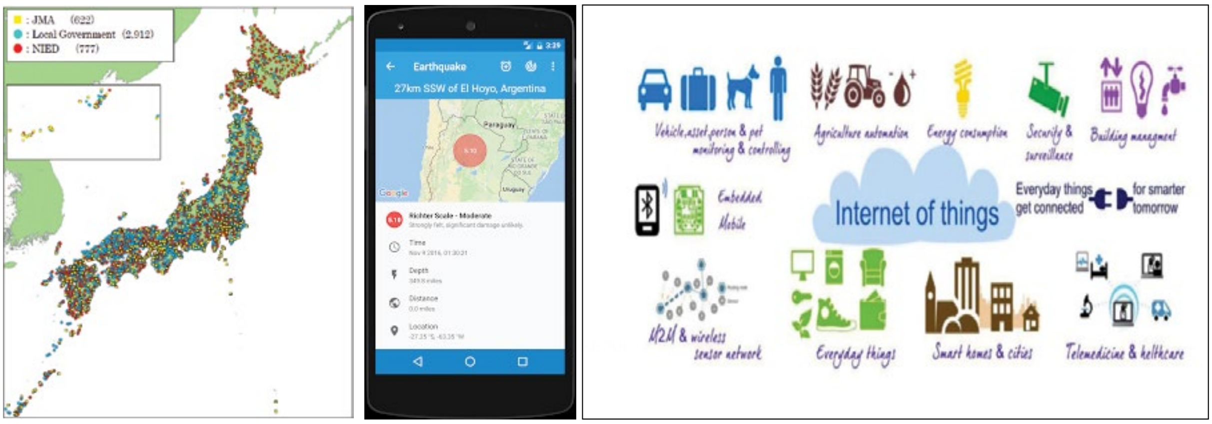
Sensor webs and the IoT have enabled efficient earthquake early warning systems in Japan (Figure 4-5). Zizmos, for example, uses smartphone apps to detect motion and serve as seismic sensors in high-risk areas.[171, 172] This network can provide up to 90 seconds of warning.

FIGURE 4-4 Data sources used for predictive analytics, in percentage



Source: Manzhu Yu and others, 2018.

FIGURE 4-5 IoT provides affordable earthquake early warning to communities in Japan



Sources: Japan Meteorological Agency, 2012; Android weather apps, 2016; Slideshare.net, 2015.
Disclaimer: The boundaries and names shown and the designations used on this map do not imply official endorsement or acceptance by the United Nations.

Tsunamis

Tsunamis in the ocean can be detected by the deep-ocean assessment and reporting of tsunamis (DART) system which comprises a series of surface buoys linked with recording devices on the sea floor that detect pressure changes caused by tsunamis. The surface buoy receives information from the recorder via an acoustic link, and then transmits data to a satellite, for onward dissemination (Figure 4-6). The system detects earthquakes and abnormal changes in sea level and helps scientists decide whether an earthquake has triggered a tsunami.

A tsunami wave in the open ocean can travel at more than 800 kilometres an hour, crossing the Pacific Ocean in less than one day. But if it is locally generated, a 'near field' tsunami, it can hit the coast within minutes, and up to a few hours at most. Buoys can be installed in the deep ocean, but this requires using a large number, which is quite difficult. A second option is to install the buoys along the shoreline, but they would provide very little warning. Recent innovations suggest a third option that use the faster acoustic waves radiating from the earthquake that triggered a tsunami.[173, 174]

Other options are also possible. For example, taking advantage of the installation of many new trans-oceanic and regional telecommunication cable systems, a Joint ITU/UNESCO/WMO Task Force has been working on establishing a global network of smart cables equipped with sensors that provides real-time data for ocean climate monitoring and disaster mitigation, particularly for tsunamis. Such system can mitigate the very costly problem of intentional vandalism or unintentional damage that sea-surface buoys are prone to.

FIGURE 4-6 Tsunami warning system in Indonesia

NETWORK OF BUOYS

MECHANISM

To record an earthquake, determine its location and strength.
↓
Depending on earthquake severity, a potential tsunami warning will be issued by national meteorology, climatology and geophysics agency.
↓
Issuance of tsunami warning: text messages and sirens.

NETWORK OF BUOYS

MECHANISM

To record changes in the sea level in deep water, by using buoy network.
↓
The buoys send a signal to a data center.
This alerts the national meteorological agency.
↓
This agency informs local authorities.

TIDAL GAUGES

MECHANISM

To measure changes in sea level every 15 minutes
↓
These send the data to the national meteorological agency.

Source: Singhvi and others, 2018.

Additionally, container ships and other commercial vessels can act as passive markers for vertical sea-surface motions, and precise Global Navigation Satellite Systems (GNSS) positions from these ships can be used to detect tsunamis. High accuracy GPS and satellite communications can serve to create a dense, low-cost tsunami sensing network that, when connected to big data ecosystems and the IoT, would improve detection and predictions of tsunamis, especially for near-field tsunamis, where communities are at a heightened risk due to the shorter evacuation lead time available.

Tropical cyclones

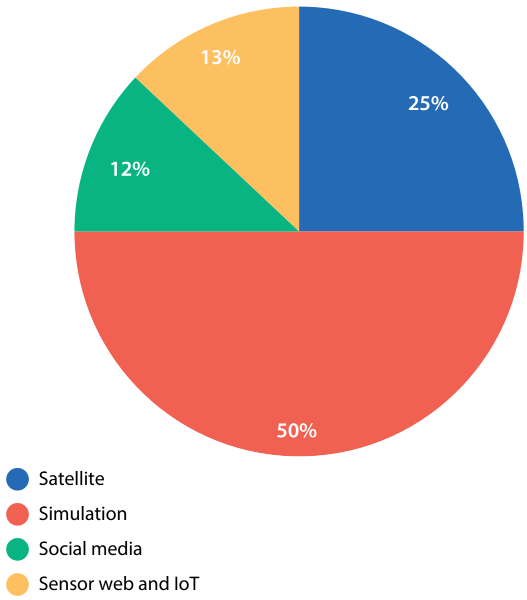
Flood and cyclone forecasting uses computer simulations. Increasingly this involves nested modelling that couples hydrologic and climate/weather models, which offer improved lead times and better locational accuracy (Figure 4-7). Tropical cyclone simulation can be based on sea surface temperature, ocean state, atmospheric parameters and retrospective seasonal prediction. These data can be combined with Earth observation satellite data on hydrologic, land cover, atmospheric and other ocean related data. Social media can then send early warning messages to communities at risk.

The China Meteorological Administration (CMA), for example, uses big data for gridded, smart and impact-based typhoon forecasting.[175] Impact-based typhoon forecasts and warnings help to pinpoint, with far more location and timing accuracy, the community at risk. This has improved evacuation exercises — number of people and timing of evacuation. Evacuations that occur just before a typhoon makes landfall helps increase compliance, as it minimizes livelihood disruption. Exposed economic assets can be protected through impact-based forecasting that enables risk-informed, spatial land use planning. As a result, there has been a significant decrease in casualties, even for super-typhoons (Box 4-4), and a reduction in disaster losses, as a proportion of GDP, as shown in the case of China in (Figure 4-8).[176]

Floods

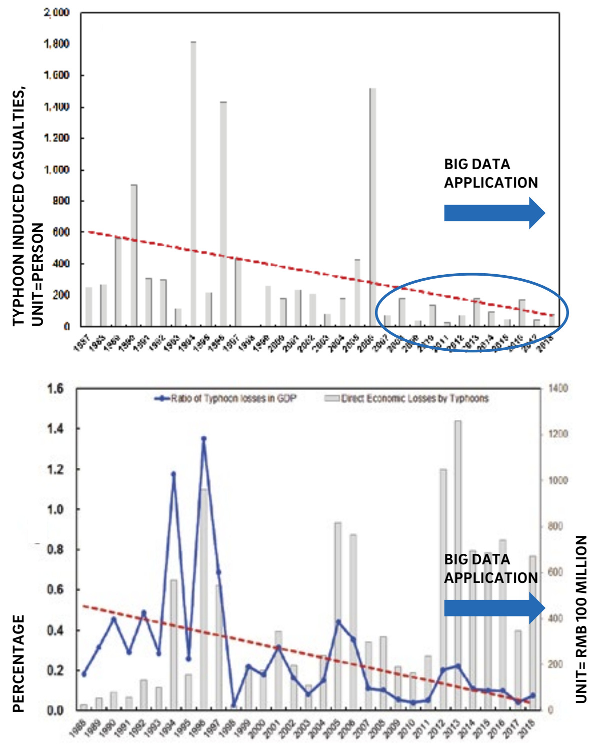
There has not been comparable advances in flood forecasting. Floods, especially recurring ones, therefore continue to be a driver of immiseration and disempowerment. Floods are complex because of their multiple cascading impacts, particularly in the case of flash floods. Forecasting can, however,

FIGURE 4-7 Data sources used for predictive analysis that is effective in cyclone and flood forecasting, in percentage



Source: Manzhu Yu and others, 2018.

FIGURE 4-8 Typhoon casualties and losses in China, 1987–2018

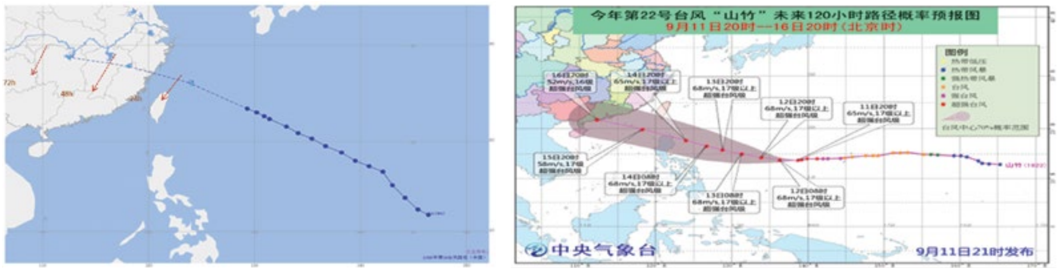


Source: CMA, 2018.

BOX 4-4 Big data makes a difference: a tale of two typhoons

In August 2006, super typhoon Saomeo hit Zhejiang province killing 483 people, displacing 1.8 million and causing losses of $2.5 billion. In contrast, in September 2018 super typhoon Mangkhut hit Guangdong Province killing just 16 people, displacing 1.5 million and causing direct losses of $2.1 billion.[a, b] The substantial reductions in mortalities and economic losses were attributed to big data applications that, by 2018, had enabled impact-based forecasting and risk-informed early warning.

Between 2006 and 2018 there had been substantial improvements in observational capacities of orbiting earth observation satellites, which resulted in more accurate and higher resolution data.[c] Typhoon Mangkhut was tracked and monitored more frequently by eight dedicated satellites as opposed to the three for Saomeo in 2006. Further, Mangkhut's track was forecast using cone areas indicating possible dynamic risk zones, providing a more precise location of possible impacted areas.[d]



Source: China Meteorological Administration, 2019.
Disclaimer: The boundaries and names shown and the designations used on this map do not imply official endorsement or acceptance by the United Nations.

a China Meteorological Administration (2019).
b Organisation for Economic Co-operation and Development (OECD) (2019).
c Ibid.
d Ibid.

also benefit from big data, by overlapping real-time data onto maps of flood hazards, exposure and vulnerability. In this case, data from multiple platforms can be used as the basis for a precipitation estimate for a couple of hours in conjunction with a forecast for the few days (Box 4-5). A web-geographic information system (GIS) platform, for example, can aggregate data in space and time and build scenarios of risk and damage.[177]

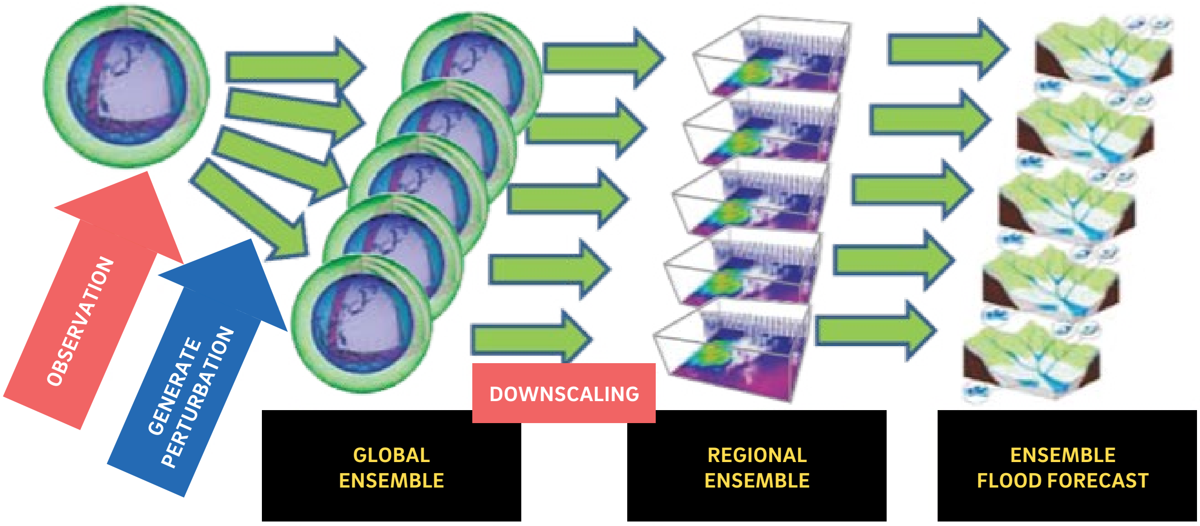
A recent innovation in climate modelling is the use of an ensemble prediction system (EPS). Instead of offering a single forecast, an EPS offers a group or ensemble of forecasts indicating a range of possible outcomes (Figure 4-9). EPS is particularly useful in transboundary river-basins where it is difficult to get hydrologic data. It is also possible to incorporate rainfall predictions from multiple weather centres, as well as rainfall and river observations from many platforms and institutions. Some stations offer forecasts for up to 16 days in advance.[178]

The experience of EPS for 2018 flood forecasting for Sri Lanka was a mixed bag of success. While it captured the intensity of torrential rain two days in advance,the forecast was not precise in its exact location (Figure 4-10).[179] The location accuracy can be improved not only with quality of downscaling ensembles but with densification of data network and putting in place an appropriate big data ecosystem.

Prescriptive analytics

Prescriptive analytics goes beyond description and inferences to incorporate pro-poor policy action. For example, policymakers can create a series of policy scenarios and run predictive analyses on the likely outcomes. In doing this, they must take into account complex interactions between climate, social and ecological systems to develop scenarios and trajectories that combine actions for pro-poor adaptation and mitigation. They can indicate pathways at four levels; risky (taking no action), passive (not backed by vulnerability responsive policy actions and budget), active (backed by vulnerability responsive policy actions and budget), and full (institutionalized responses supported by both short- and long-term policy actions).

FIGURE 4-9 **Ensemble prediction system: nested modelling for flood forecasting with longer lead-time**

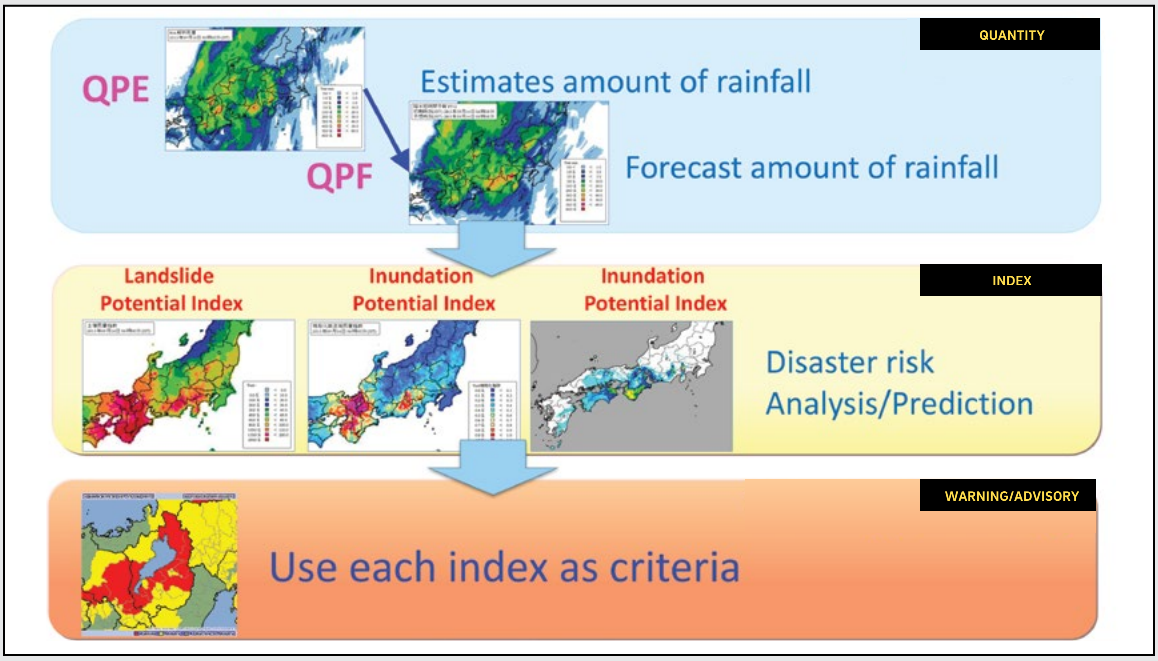


Source: Tomoki Ushiyama, ICHARM, 2019.

BOX 4-5 Big data used for flood forecasting in Japan

The Japan Meteorological Agency (JMA) uses a quantitative precipitation estimation (QPE) and a quantitative precipitation forecast (QPF) as warning criteria to identify risk levels of flood inundations and landslides in certain locations.[a]

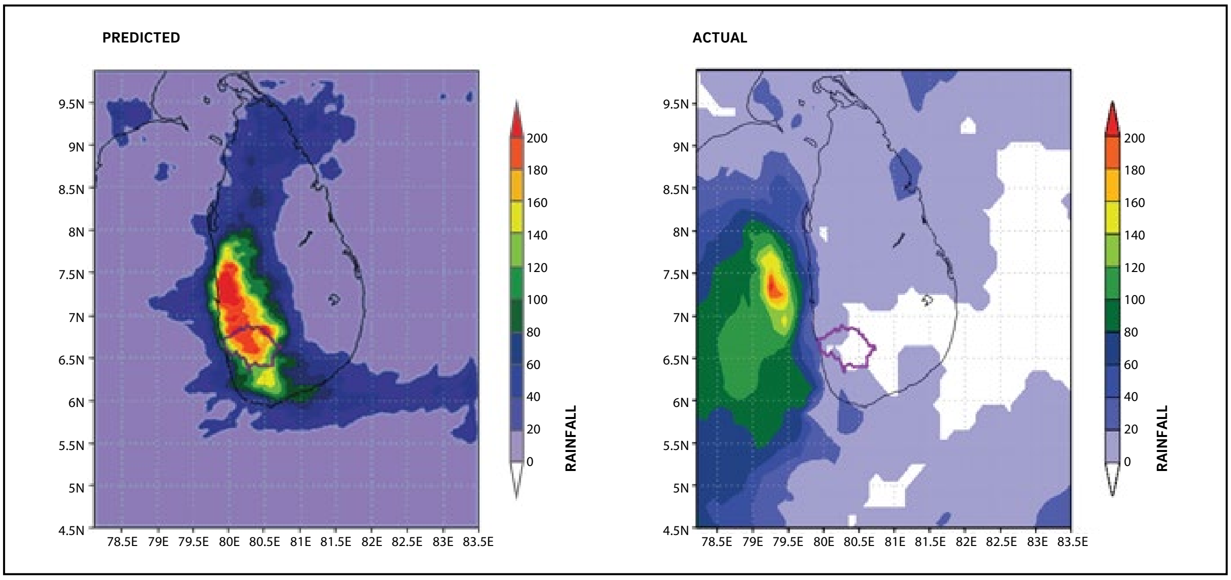
Based on QPE and QPF, potential risk indices have been developed for landslides and flood inundations. These indices serve as warning criteria for heavy rain, inundation and landslides. The model helps the Public Weather Service issue severe weather warnings. The JMA has built a solid disaster database to determine proper warning criteria.



Source: Japan Meteorological Agency, 2019.
Disclaimer: The boundaries and names shown and the designations used on this map do not imply official endorsement or acceptance by the United Nations.

a Japan Meteorological Agency (2019).

FIGURE 4-10 Predicted and actual rainfall in Sri Lanka, 24 May 2019



Source: Tomoki Ushiyama, ICHARM, 2019.
Disclaimer: The boundaries and names shown and the designations used on this map do not imply official endorsement or acceptance by the United Nations.

These scenarios can be seen as iterative, continually evolving processes for managing change within complex climate-sensitive systems. In Kazakhstan, for example, climate, geo-spatial and socioeconomic data have been used to create a flood vulnerability index that indicates the outcomes of different levels of policy action.[180]

Running policy scenarios can be considered a top-down approach. Another prescriptive application which is more bottom-up and empowering is behaviour 'nudging'. This might involve, for example, collecting from individuals their data on energy consumption, or their exposure to health risks, as a basis for providing them with personalized reports that might nudge them in a positive direction.

Another prescriptive use of big data is for index-based flood insurance (IBFI). In South Asia, IBFI systems use satellite data and computer-based flood models to assess the location, depth and duration of flooding and indicate when and where flooding reaches the threshold at which damage is severe enough to warrant compensation.[181] This simplifies decision-making and speeds up the delivery of insurance payouts which has helped alleviate the asymmetric impacts on poor farmers (Figure 4-11). IBFI has successfully been piloted in 2017/18 in Bihar, India.[182]

Discursive analytics

Discursive analytics involves using data to empower communities at risk. Data sources include satellite and aerial imagery combined with user-generated data. During major disasters, a useful way of following people is to use the call records of mobile phones which are regularly collected by phone companies for monthly billing. The United Nations Global Pulse initiative has shown several cases where mobile phone location data have been used to understand people's response during major disasters.[183]

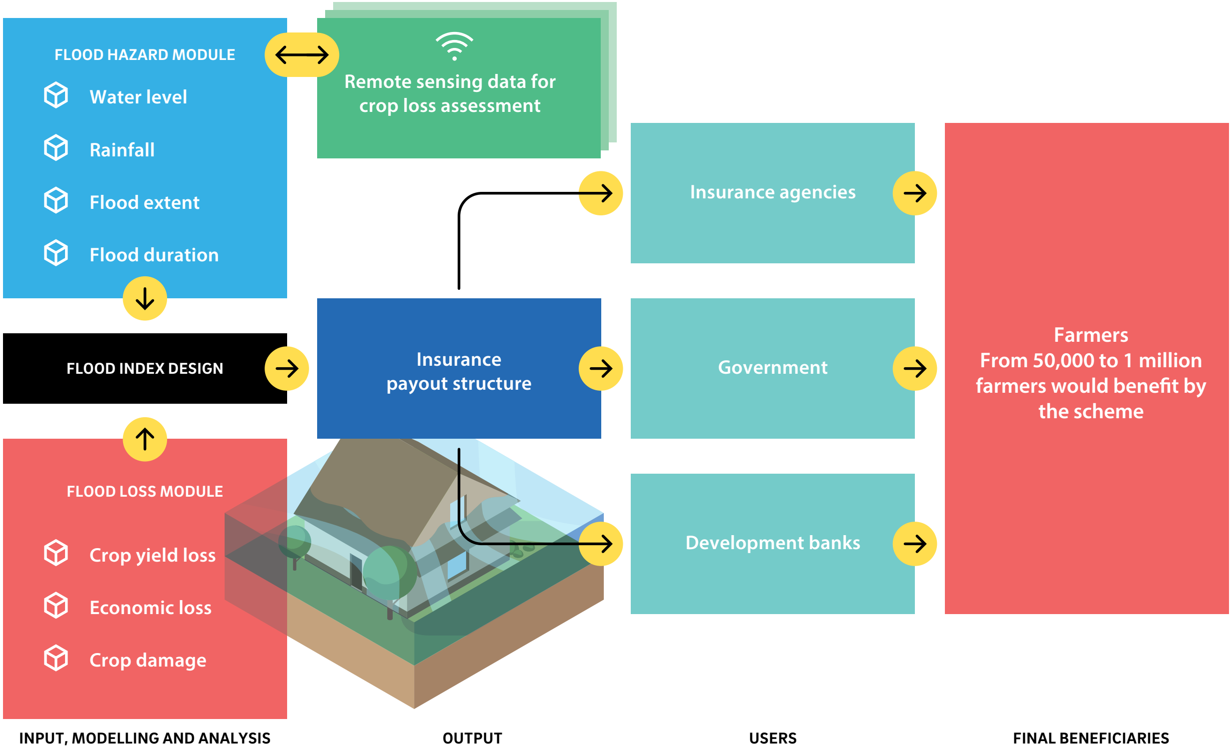
Discursive analytics can also make use of mobile phones to receive messages and alerts (Box 4-6). These activities are more efficient however when embedded alongside productive and prescriptive analytics into an overall systems approach.

Counting the excluded

Building disaster resilience for the most vulnerable communities requires good baseline data disaggregated by gender, age, and disabilities. Such data are often scarce or completely missing, since official data collection systems often exclude the most vulnerable people who are hardest to reach.

International household surveys can omit these people either by accident or by design. The Demographic and Health Surveys (DHS) and the Multiple Indicator Cluster Surveys, for example, do

FIGURE 4-11 Index-based flood insurance



Source: Amarnath, 2017.

not cover people who are homeless, or who sleep in shops or workplaces not enumerated as dwellings. Nor do they cover mobile, nomadic or pastoralist populations or people in refugee camps. Moreover, household surveys will typically under-represent those in fragile, disjointed or multiple occupancy households, those in slums who are difficult to identify and interview, those living illegally or stigmatized within households (due to mental health problems or other disabilities), or those living in their place of work such as domestic workers or security guards.[184] As a result, any mapping of the population for purposes of protecting the poorest is likely to omit important groups.

Figure 4-12 shows the standard sampling methodology based on census records with corresponding enumerated areas (EAs) and primary sampling units (PSUs). The second row of boxes shows the risks of exclusion at different stages, and the third row indicates some potential solutions.

Census enumeration areas are often arbitrary and delineated for administrative convenience rather than corresponding to population distribution. An alternative is to start again with satellite images which indicate populated areas. These geographical areas can then be divided into a grid of one kilometre squares. These 'primary grid cells' are then analysed to identify those with the highest residential populations, using characteristics such as building patterns, community size, and proximity to other land uses. These higher-population cells are then sub-divided into secondary grid cells of perhaps 15 square metres. From this set, some are chosen at random and screened for residences, either manually or by computer. In the chosen secondary cell, enumerators then carry out a micro-census contacting every household. This is termed one-stage sampling, as opposed to two-stage sampling which involves selecting households randomly. These new approaches have been used in urban slums of Hanoi, Kathmandu and Dhaka and indicate that gridded population sampling and one-stage sampling do address the problem of undercounting.[185]

Gridded population data can also be combined with other data to estimate the size and locations of populations at risk. This is illustrated in Figure 4-13 for populations in areas at risk of land degradation in Central Asia.

With the advances in geo-statistical interpolation techniques, it is also possible to integrate the disaggregated geospatial data into traditional sampling frames.[186] For Nepal, for example, statistical

BOX 4-6 The Tamil Nadu system for multi-hazard potential impact assessment and emergency response tracking (TNSMART) engages communities

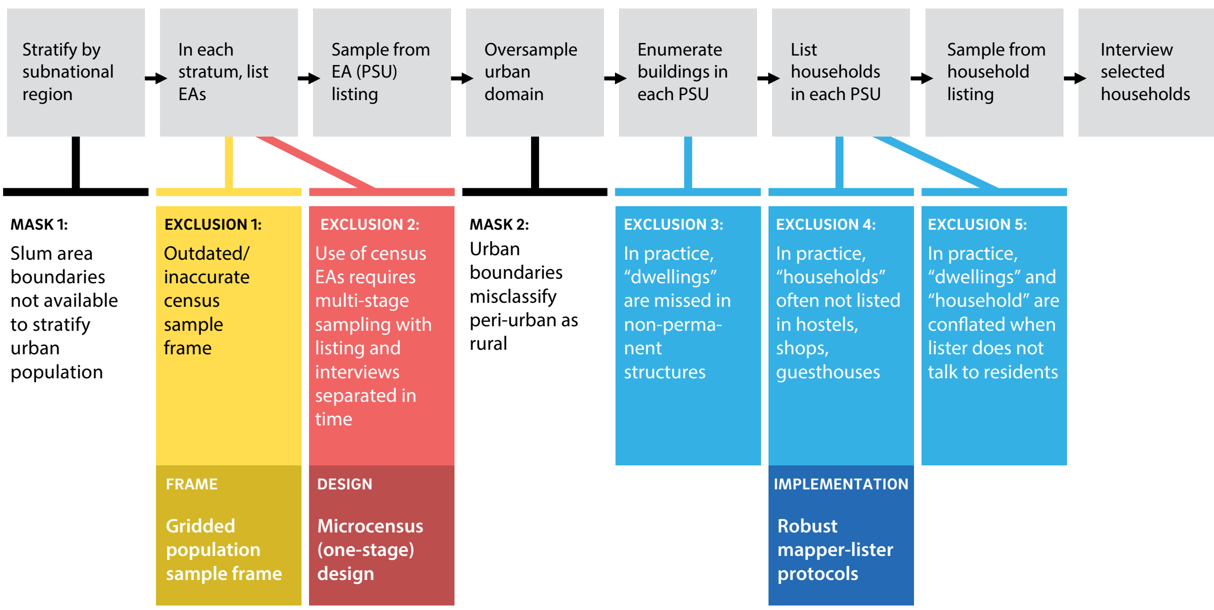
In India, the Tamil Nadu State Disaster Management Authority uses TNSMART, a web-GIS-based decision support system for operations and for communicating to communities.[a] The data sources include geospatial systems, remote sensing, satellite imageries, UAV, Light Detection and Ranging (LIDAR), and telemetry.[b]

The TNSMART web application classifies areas in terms of risk: very high, high, medium and low. The system prepares customized advisories for at-risk communities along with do's and don'ts. The TNSMART mobile application can then send alerts and information about mitigation measures while also receiving messages from users. TNSMART also provides forecast-based impact information especially for agriculture sector.

TNSMART was used, for example, during 2018 Northeast monsoon, particularly for cyclone Gaja. During the preparedness phase, TNSMART helped its 13,000 registered users understand the risk and also communicated this to field-level functionaries.[c, d] Distress messages were received from the general public in the State Control Center through the TNSMART app and forwarded to concerned officers/departments for action. TNSMART helped disaster managers provide location-based services while responding to communities at risk. This saved numerous lives due to timely evacuation.

a Tamil Nadu State Disaster Management Authority and RIMES (2019).
b Ibid.
c Ibid.
d Ibid.

FIGURE 4-12 Unintended exclusion of the poorest in a typical household survey



Source: Based on Dana Thomson and R. Bhattarai, 2018.
Note: EA = enumeration area PSU = primary sampling units (s).

geo-spatial data have been combined with DHS data to map a wealth index.[187] This wealth map is then combined with multi-hazard spatial data on floods, landslides and earthquakes to estimate the population exposed to disaster risks.

Identifying the excluded and digital empowerment

Around 2.4 billion people around the world, typically the poorest and most vulnerable lack formal identification records such as identity document (ID) cards or birth certificates.[188] They may then find it more difficult to access vital services and entitlements which can transmit exclusion over generations. To address these issues, Governments can take advantage of digital identity systems which offer greater choice and convenience. Digital identity systems strengthen the capacities of public and private sectors to deliver services and create a foundation on which to build new systems, services and markets (Figure 4-14).[189, 190]

In Bangladesh, for example, the Government is partnering with the World Bank on the Identification System for Enhancing Access to Services project. This system includes a unique identifying number and biometrics-based smart national ID cards for citizens, including those in high-risk areas, and the socially vulnerable and marginalized. Compared with laminated paper ID cards, the smart cards are more secure.[191]

Direct benefit transfer

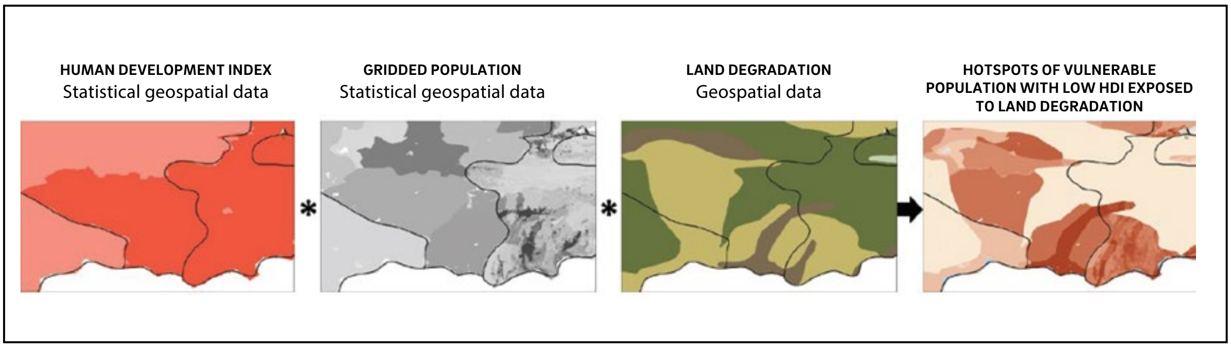
National ID cards can be used for delivering a variety of services to people at risk, including social welfare programmes. India, for example, has one of the world's largest public workfare programmes; the Mahatma Gandhi National Rural Employee Guarantee Act (MNREGA).[192] Since 2005, MNREGA has provided millions of jobs and has been a vital source of income for the rural poor who are at high risk of drought and floods. However, in the past, the programme suffered from many leakages and delays in wage payment. During droughts, some distressed poor people even found it uneconomical to work for the workfare programme so there was a fall in the number of beneficiaries.

This issue has been addressed through direct payments. In 2015–2016, the Government of India introduced a biometric-enabled national identity numbers, named Aadhar, for identifying MNREGA beneficiaries, with numbers which were linked to their bank accounts.[193] Aadhar-linked payments, reduced leakages, ensured speedy payment and helped to make the programme truly counter-cyclical (Figure 4-15). Moreover, beneficiaries now have more faith in the system, while the Government has timely and reliable data, and can transfer benefits directly to beneficiary bank accounts, which has also improved monitoring and implementation. In India, as a whole, the use of Aadhar-linked digital identity bank accounts for variety of subsidy and social protection schemes saves an estimated $11 billion per year.[194]

Risk-informed social protection

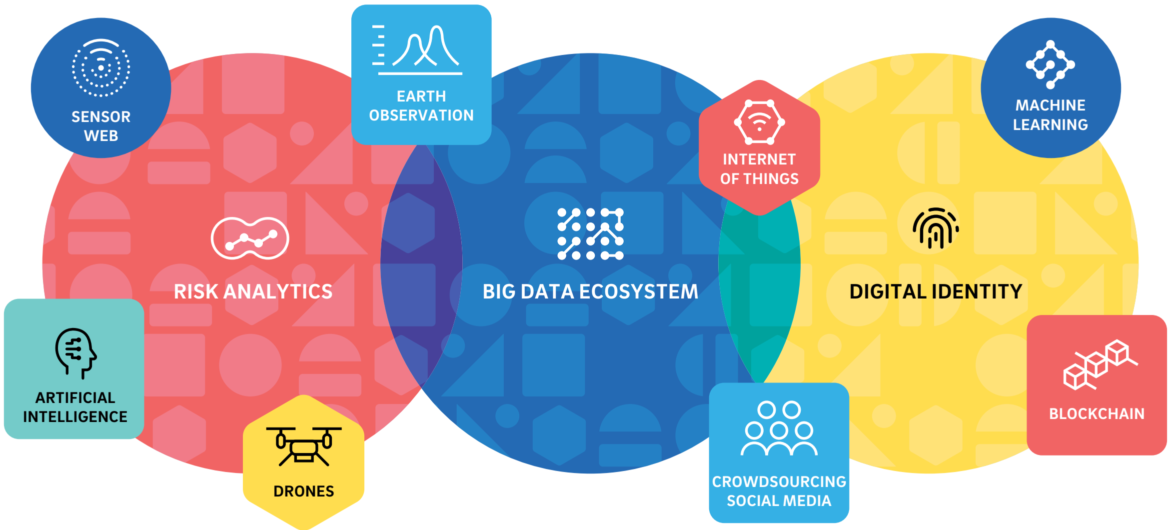
Social protection systems, as shown in Chapter 3, have the most impact on reducing extreme poverty and inequality. They help the poor and vulnerable cope with disaster risk, find jobs, and invest in the health and education of their children, while also protecting older people. Properly designed and implemented,

FIGURE 4-13 Overlaying four data sources to determine poor populations exposed to land degradation in Central Asia



Source: ESCAP, based on Global Data Lab, World Pop, FAO.
Disclaimer: The boundaries and names shown and the designations used on this map to not imply official endorsement or acceptance by the United Nations.

FIGURE 4-14 New technologies for resilience, inclusion and empowerment



social protection systems can efficiently protect the most vulnerable, both in normal times and in the event of a disaster.

Such programmes are, however, difficult to implement well. Governments often lack disaggregated data, or the mechanisms to identify and target people at risk, either for short-term emergency responses or long-term policy interventions. Another issue is fragmentation since many systems offer a range of benefits and services that are delivered in a piecemeal way. There are also challenges of horizontal and vertical coordination, including among multiple layers of government.

Improved social protection should be risk informed and sufficiently flexible and adaptable to reach specific groups that are most at risk of being excluded, and to be scaled up at times of disaster. During disasters, Governments have responded in various ways:[195]

- *Vertical expansion* — Increasing the benefit value or duration for existing beneficiaries

- *Horizontal expansion* — Adding new beneficiaries to an existing programme

- *Piggybacking* — Using social protection administrative mechanisms to deliver assistance for a separate shock-response programme

- *Parallel operation* — An additional aligned humanitarian programme

- *Refocusing* — Adjusting a social protection programme on the groups that are most vulnerable and excluded

These approaches require the main social protection programme to be sufficiently flexible and have a comprehensive mechanism for delivering benefits and services.[196] Governments also need the capacity and information to identify the vulnerable populations, determine the right responses, and prepare to scale-up.

Ideally the population at risk should already be registered, with digital IDs linked to bank accounts in which they can receive cash transfers. In Ethiopia, for example, the Productive Safety Net Programme expands at times of shock by increasing the period of time over which beneficiaries receive cash payments.[197]

Similarly, in Pakistan, following the floods of 2010 and 2011, the Government used its National Database and Registration Authority to implement a digital cash transfer scheme for 1.5 million people affected.[198] In Nepal, following the 2015 earthquake, DanChurchAid used technology from the Hello Paisa international money transfer service to make cash transfers to more than 10,000 people.[199] Governments and development agencies often prefer these systems as being more flexible and secure. Citizens too may prefer cash transfers, seeing them as a right associated with their citizen registration rather than as aid to them as 'victims'.[200]

Blockchains for empowering smallholder farmers

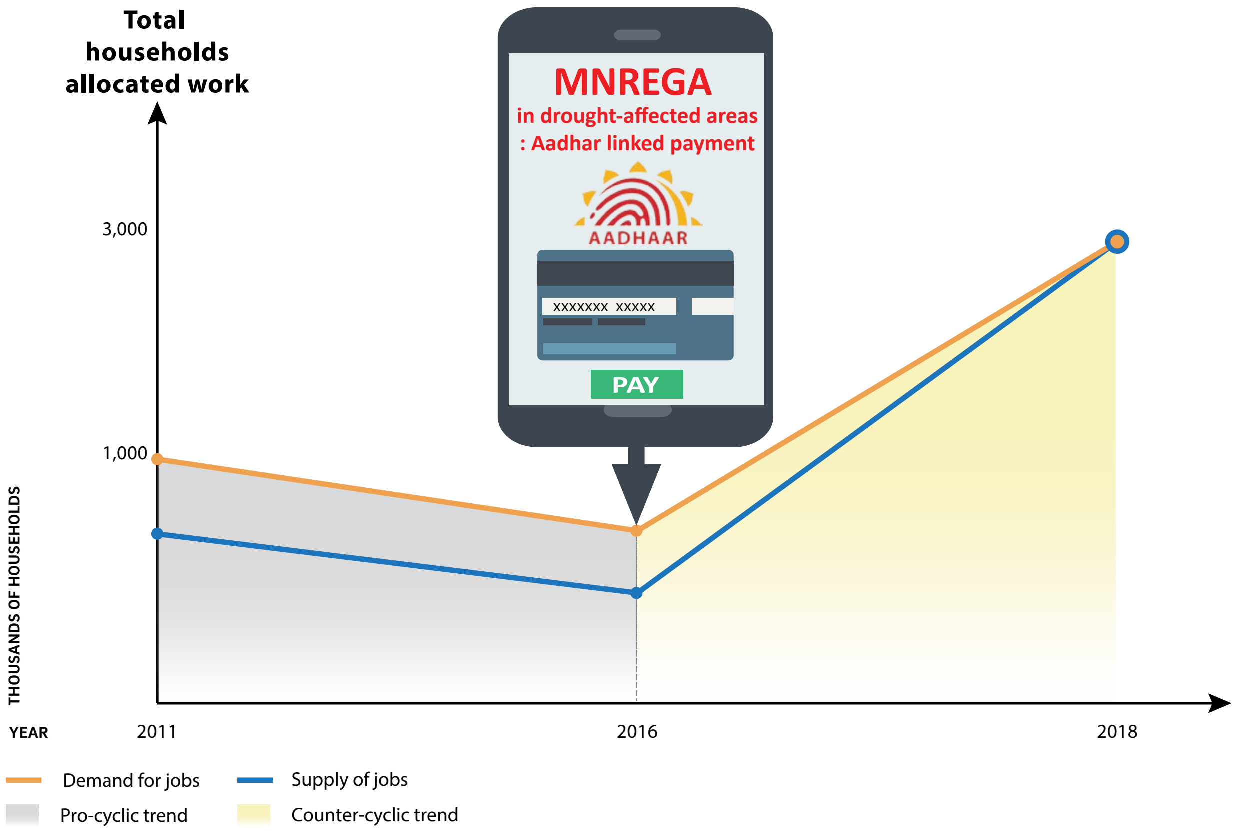
In principle, farmers affected by floods or droughts should benefit from low-cost agricultural insurance schemes. As yet, relatively few do so partly because of time-consuming mechanisms for validating claims and making payouts.[201] A better alternative is index insurance based on smart contracts which can automate and simplify the process so as to give instant payouts. Such contracts rely on automatic data feeds that provide hyperlocal weather data that eliminate the need for on-site claim assessment.[202] The contracts can use 'blockchain' technology, in which the data are held in a decentralized public digital ledger distributed across many computers. Allianz Risk Transfer and Nephila have successfully piloted such systems demonstrating that transactional processing and settlement between insurers and investors can be significantly accelerated and simplified by blockchain-based contracts.[203]

Machine learning for smart resilience

Disasters present very complex environments with very diverse types of data. Even experts can struggle to develop models that show the impacts on the built environment and society. Their work can, however, now be supplemented by machine learning in which an algorithm learns from previous data to add new information and insights. This will often require 'data mining' which involves discovering patterns in large data sets as well as 'image mining' for extracting patterns from large collections of images. Though the two terms are often used interchangeably, machine learning is a subset of artificial intelligence (AI) (Figure 4-16). The seamless linkage of machine learning with big data ecosystems — from the image, sound, and voice recognition features of smartphones, for example, enables disaster managers to identify where people are at risk.

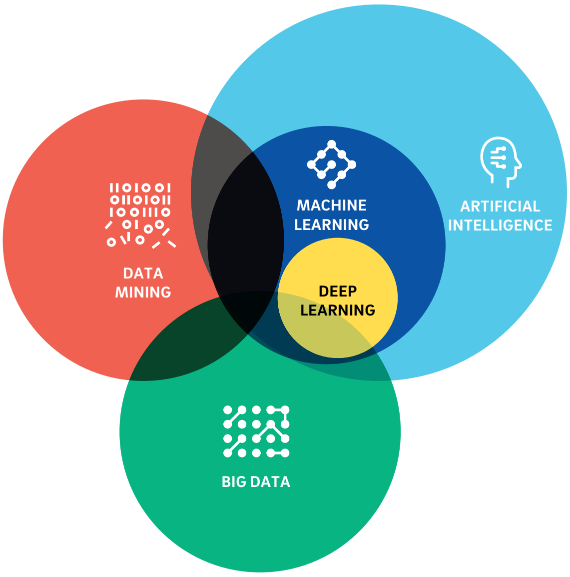
Machine learning is becoming one of the most effective methods of processing and analysing data on major heterogeneous disasters and speeding up

FIGURE 4-15 Job demand and supply in selected drought-affected areas in India, 2011–2017



Sources: ESCAP based on data from Prasad, Parijat Shradhey, and others, 2018.

FIGURE 4-16 **Machine learning a subset of artificial intelligence**



all the necessary analytics to identify the optimal responses. In the near future, we can expect more complex socioeconomic risk profiles, disaggregated by income, age, gender and a host of other vulnerabilities to become available, thus opening up vast possibilities for building smart resilience that is inclusive and empowering.

Earthquake prediction

Because large and devastating earthquakes, such as the magnitude 9.0 Tohoku earthquake that hit Japan in 2011, are currently considered unpredictable, they can be considered as the most disempowering of disasters. Scientists do not have sufficient seismic data to generate statistical insights and develop predictions. An alternative is to apply machine learning to data that are continuously generated in subduction zones; the boundaries where tectonic plates collide. These data reflect the slow deformation accumulating in the plates. This approach has been tested using computer models and could, in the future, predict the timing and size of natural subduction earthquakes.[204] However, this methodology needs much more research before it can become operational.

Flood prediction

As discussed earlier, advances in flood forecasting have lagged. Machine learning can be used to create better forecasting models for floods. This was pilot tested in the city of Patna, in the Bihar state in India, during the September 2018 floods using Google Public Alerts (Box 4-7). The models incorporated a variety of elements, from historical events, to river-level readings, to the terrain and elevation of a specific area, to accurately predict the location and severity of floods.[205]

Exposure and vulnerability

The Keio University in Japan has developed the 5D-World Map System that provides a multi-dimensional global knowledge platform to collect and analyse ‘real time’ data on SDG-related indicators.[206] The system integrates the analytical visualization of sensor data into a knowledge sharing platform with multimedia. This can be used for community-based data sharing, awareness building and evidence-based decision making.[207] The system uses machine learning to indicate the exposure of critical infrastructure and vulnerable populations in multi-hazard risk environments (Figure 4-17 and 4-18).[208]

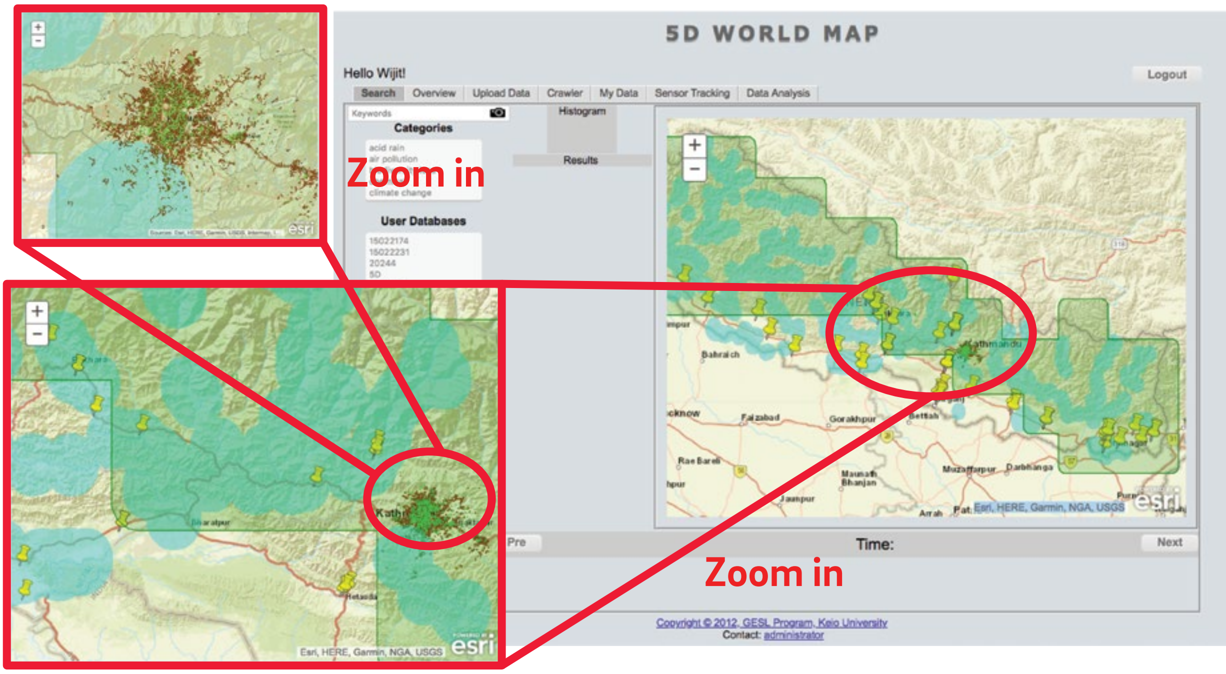
The big data ecosystem

This chapter has shown how such technological advances can be integrated into a big data ecosystem. Under this approach, asset-level data are gathered from various public and proprietary sources, such as satellites and censuses in a scalable process, along with impact data from previous disasters. These are then inserted in data-driven machine learning models that require no user inputs and can produce impact outputs at high spatial resolutions within minutes.

Real-time disaster data can generate accurate localized impacts that are updated continually as more information becomes available. These include data on ground shaking, water levels, temperature, and wind patterns from satellites and weather data. This interdisciplinary approach takes into account multiple-hazard models and dynamic data. It trains models on true observations of damage and, by seeking solutions that allow for unprecedented situational awareness, informs better decisions. Big data and machine learning thus create new grounds for risk-informed early warning, and dramatically shrink the innovation cycle by taking advantage of changing technology.

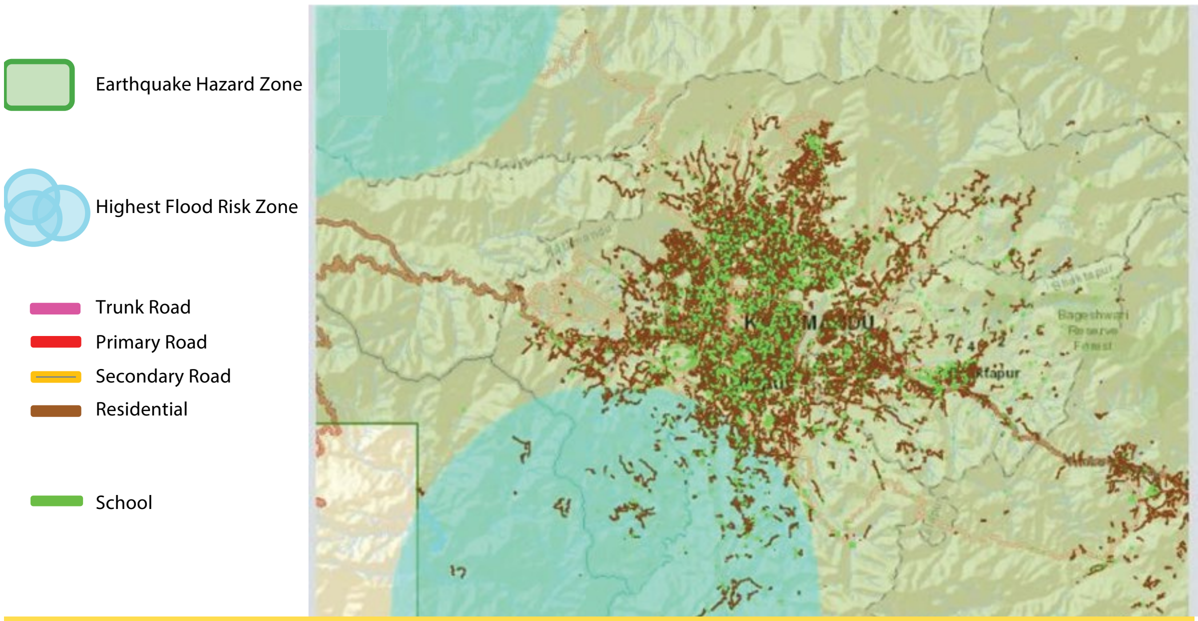
These technologies have spread rapidly in much of the world, boosting growth, opportunities, and service delivery. Yet, their aggregate impact has fallen short of what is possible and is also unevenly

FIGURE 4-17 Residential roads and educational facilities in earthquake and flood high-risk areas in Nepal



Source: Sasaki and Kiyoki, 2018.
Disclaimer: The boundaries and names shown and the designations used on this map do not imply official endorsement or acceptance by the United Nations.

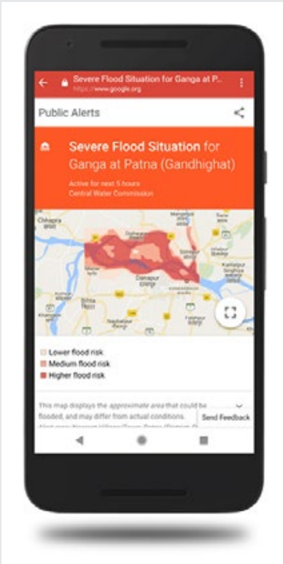
FIGURE 4-18 Image mining and machine learning enabled multi-hazard exposure mapping of Kathmandu, Nepal



THE ENTIRE REGION OF KATHMANDU IS COVERED BY EARTHQUAKE HAZARD ZONE, AND THE SOUTHERN PART OF KATHMANDU IS INCLUDED IN BOTH EARTHQUAKE AND HIGHEST FLOOD RISK ZONE.

Source: Sasaki and Kiyoki, 2018.
Disclaimer: The boundaries and names shown and the designations used on this map do not imply official endorsement or acceptance by the United Nations.

BOX 4-7 **Google Public Alerts**



Source: TechEngage, 2018.
Disclaimer: The boundaries and names shown and the designations used on this map do not imply official endorsement or acceptance by the United Nations.

When there is an important emergency alert Android phones will show a public alerts card. Google Public Alerts is a private sector platform for disseminating emergency messages such as evacuation notices for hurricanes and earthquakes and everyday alerts, such as storm warnings. Currently, it publishes content from Australia, Brazil, Canada, Taiwan Province of China, Colombia, India, Indonesia, Japan, Mexico, New Zealand, the Philippines and the United States. Google has sent out tens of thousands of public alerts which have been viewed more than 1.5 billion times. It has also activated SOS Alerts, which indicate a higher threat level of more than 200 times. Google Public Alerts has issues flood warnings which are delivered through Google Search, Google Maps, and Google Now.

distributed. There are also inherent risks, including algorithmic bias. The widespread sharing of data also raises issues of privacy and cybersecurity and potentially erodes individuals' trust in Governments and institutions.[209]

To be tools for smart resilience that empowers and includes those most at risk of being left behind, big data systems now need to address these issues. This is not easy. It means gathering sufficient data that can be translated into usable information along with coordination among multiple layers of government with integrated information systems. It is also important to build public awareness and consent, ensuring security and privacy and if necessary engaging communities in data collection, building their capacity to identify risks and vulnerabilities. Companies and Governments holding data should be open and accountable.

Above all, industry 4.0 technologies need to build disaster resilience of the poorest and most excluded. For this purpose, it is vital to close the remaining digital divide by ensuring universal and affordable high-velocity internet access and adapting people's skills to new demands. Advances in computational capabilities and communications seem likely to increase our ability to model and assess risk. But this does not automatically assure smart resilience for all. Results need to be communicated in ways that promote effective action and allow people to benefit from this rich new source of information and knowledge.

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