Summary of Data Readiness for Disasters: Gap Analysis Workshop

(March 29-30, 2022)

Introduction

CENAPRED, together with CrisisReady, and GFDRR, explored the potential of human mobility data and earth observation services to identify gaps and support effective implementation of the Disaster Risk Reduction framework. It is relevant to mention that disasters are not natural, and hazards should not evolve into disasters. Therefore, data plays a crucial role in the decision-making process throughout the disaster management cycle. GFDRR/ World Bank's work focuses on increasing cities' resilience, considering the Sendai framework, the SDGs, and Paris Agreement, on boosting economic growth and social development. CrisisReady's work focuses on the use of large-scale private datasets to improve resilience and response to public health emergencies (Balsari et al., 2022).

The workshop was designed around data readiness for disasters:

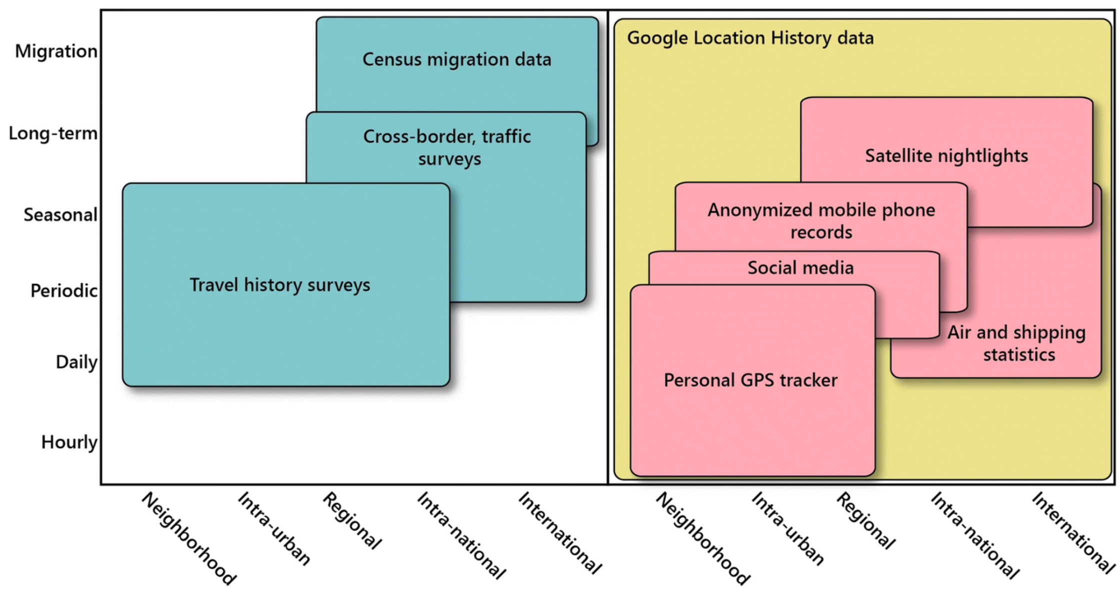
1. Data readiness (Access to the data)
    a. Data use: Legal data agreements with private companies need to be formed
    b. Ethical, legal, and data responsibility questions emerge
    c. How do we get data, and how should it be transferred (security)?
2. Method readiness (Processing the data)
    a. When working with large datasets in time-sensitive disasters, we shouldn't be inventing methods.
    b. What kind of methodologies produce practical results to guide resource allocation, effective evacuation, and public safety, among others.
3. Translational dynamics: How are the insights from the analysis communicated to the policymakers, and how do we engage in local networks to support data publications to improve policy interventions.
    a. Collaboration with people from different backgrounds (data science, research, government)
    b. The need for a common language

The workshop's main objective was to identify the gaps and provide valuable recommendations on integrating novel data sources (mobility data and earth observation) for disaster risk management frameworks. The workshop was held on March 22-23, 2022, at the CENAPRED offices. It consisted of eight panels and two landscape exercises.

Mobility Data: Concepts & State of the Art

In the past, mobility data has been collected through census migration data, cross-border & traffic surveys, and travel history surveys. Nowadays, technology gives us various data that improve spatial and temporal resolution, such as satellite nightlights, social media, personal GPS tracking, air & shipping statistics, and anonymized mobile phone records. This workshop centers on data obtained by the GPS of mobile phones, captured by different apps, and Call Detail Record (Ruktanonchai et al., 2018) (CDR), which comes from the towers of mobile phone providers. The following image shows the datasets available depending on the spatial and temporal resolution.

Implications for spatial and temporal resolution of mobility data



Ruktanonchai et al (2018)

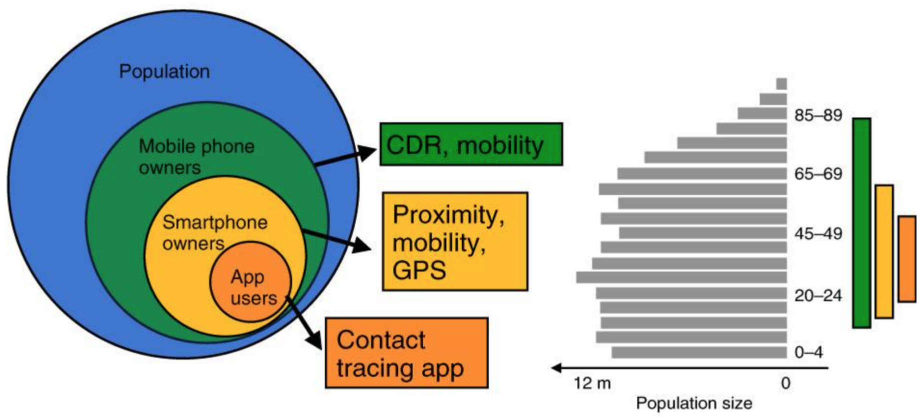
It is essential to mention that every type of data has its challenges and limitations, mainly in three critical areas:

1. Representativeness: What is your data coverage, and what demographic does it represent (Kishore et al., 2022).
2. Privacy: Aggregation/anonymization protocols, regulatory requirements, and data agreements (Greenwood, et al, 2017) (Nissenbaum, H, 2004) (Wood, et al, 2020) (Greenwood et al., 2020).
3. Data reliability: appropriate baselines, transparency about analytic protocols, frequency of access, and pipeline sustainability (Pérez-Arnal et al., 2021).

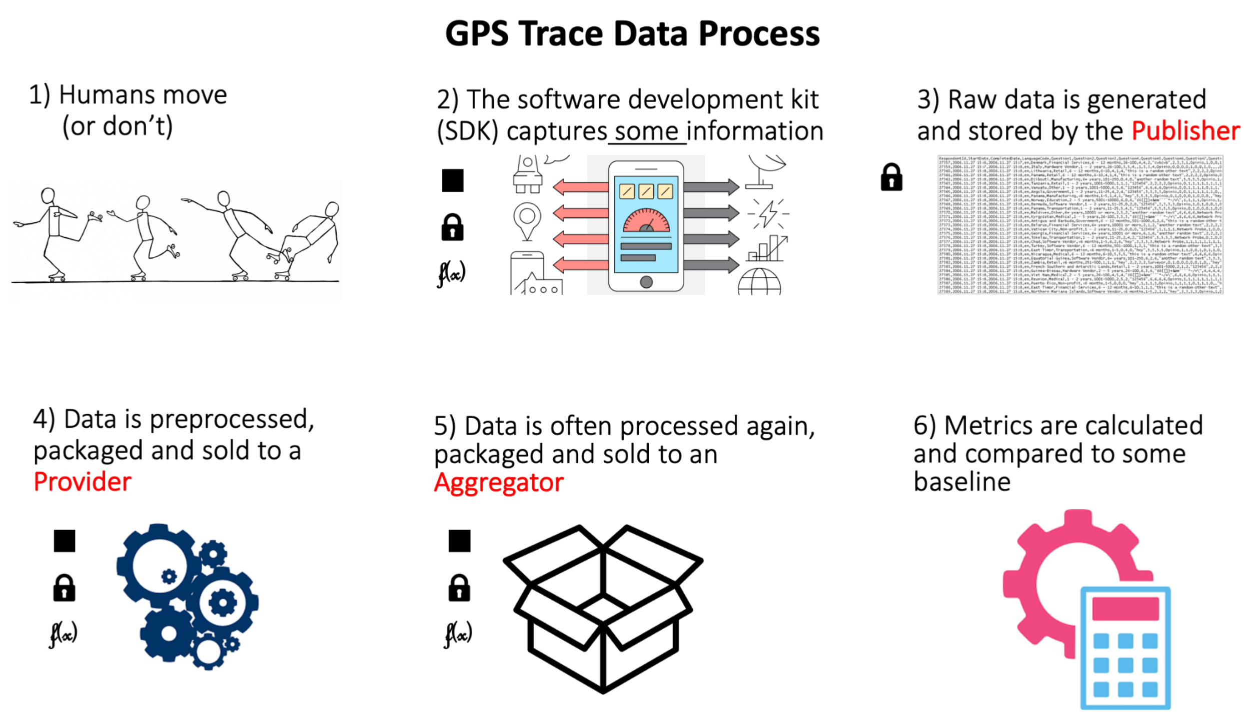
CDR data comes directly from mobile phone operators. It has good representativeness, has variable spatial/ temporal resolution, and is regulated at a national level. Since it is regulated, it is hard to access without partnerships in place during time-sensitive situations.

GPS traces have low representativeness, high spatial/ temporal resolution, and sometimes lack regulation. There is no clear framework for using this data, and it is vital to have partnerships between data providers and governments to agree on how this data should be used and shared (Grantz et al., 2020).

This data is generated only when the apps are on, so the software detail kit (SDK) does not capture every movement from every person. When mobile phone data is collected, it is aggregated, processed, and transformed in different ways. Depending on the provider, publisher, or aggregator, methods and metadata are different, therefore the importance of sharing protocols and standardized methodologies. (Kishore, et al, 2020)



Grantz, K.H., Meredith, H.R., Cummings, D.A.T. *et al. Nat Commun* **11,** 4961 (2020).



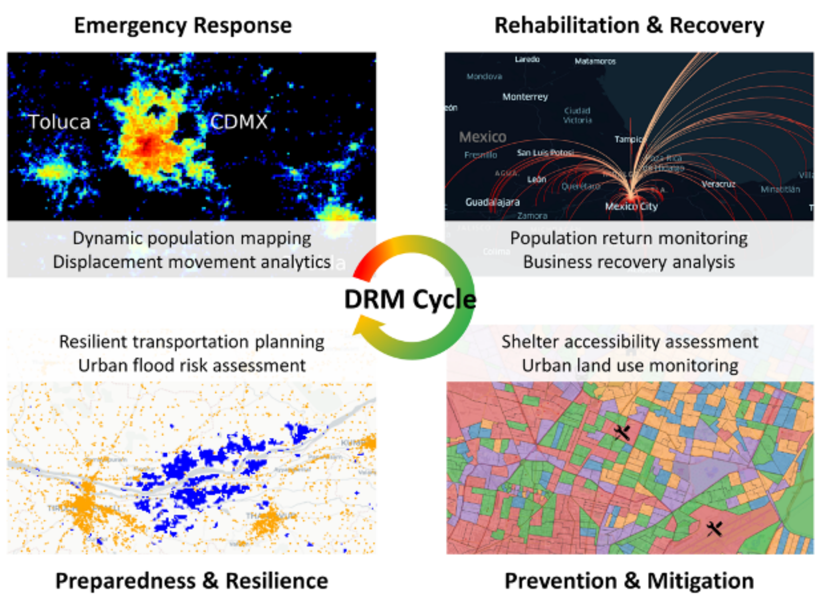
Kishore et al, 2020

Essential steps: (i) check quality of data; (ii) filter out irrelevant users; (iii) test representativeness; (iv) analysis.

The level of aggregation is significant for interpretation. One of the main failures is to take a top-down approach without considering the local context. Instead, information should be tailored for the decision-making process and assured a skim pipeline that includes data readiness, methods readiness, and translational readiness. The following table extracted from Yabe et al 2022 summarizes the types of mobile phone location data.

Data type	Description	Pros and Cons	Providers (e.g.)
Mobile phone call detail records (CDR)	Location information of cell phone towers when users make calls or text messages	(+) substantial coverage of the population (-) Low spatial and temporal resolution compared to GPS datasets	NCell, Orange, Vodafone, Turkcell
Smartphone GPS location data (Location Intelligence firms)	GPS data collected and aggregated from several third party smartphone applications	(+) precise location information of users (-) No transparency in data generation process; covers a small sample of population compared to CDR; available for fewer countries	Cuebiq, Veraset, Safegraph, Unacast
Smartphone GPS location data (Major Tech firms)	GPS data collected and aggregated from their own platforms	(+) Available in standardized formats across multiple countries and across time (-) Outputs restricted to selected metrics produced by the tech firms	Google, Facebook, Apple, Yahoo Japan

Use Cases



GFDRR is developing tools & use cases to inform urban and disaster risk management using mobility data from GPS datasets, taking advantage of the new data sources. It can be used through the four stages of the DRM cycle (Yabe, T. et al, 2021,).

The team has done studies for Mexico, Chennai (India), Costa Rica, and Kathmandu (Nepal), (Yabe, et al, 2020). For example, the case study for Mexico(2017

Earthquake) measured population displacement and return patterns (+ Income inequality), predictors of population displacement, and disruptions and recovery of local businesses (Yabe, et al, 2021).

GFDRR with MindEarth created a python library called Mobilkit to help with standard mobility analysis to facilitate mobility data analytics.

Another application field of mobility data is epidemics (Iyer, et al, 2020). Many public health decisions come down to denominator problems and resource allocation issues. These are exacerbated during disasters and among highly mobile groups. There are three main parameters of transmission, the probability of infection given contact (contagiousness), duration of infectiousness, and contact per unit time.
The first two components are related to biology and epidemiology; for the third, mobility data can be helpful. Different spatial spread occurs depending on transmission parameters. Mobility data can predict outbreaks, monitor non-pharmaceutical interventions, and help decision-makers get more targeted risk maps than traditional data.

Key takeaway: how do we structure translational networks in peacetime so we can activate them quickly in a disaster.

Data Providers

For this panel, we had participation from two mobile phone companies (AT&T, Telefonica), one aggregator (Spectus), and one publisher (Meta). All of them mentioned how important privacy is for their business (Wood, A., et al, 2020). Most of them use differential privacy to create insights into different business areas; there is a difference between location and mobility data. Location data has a commercial use to improve the user experience and has a retail value.

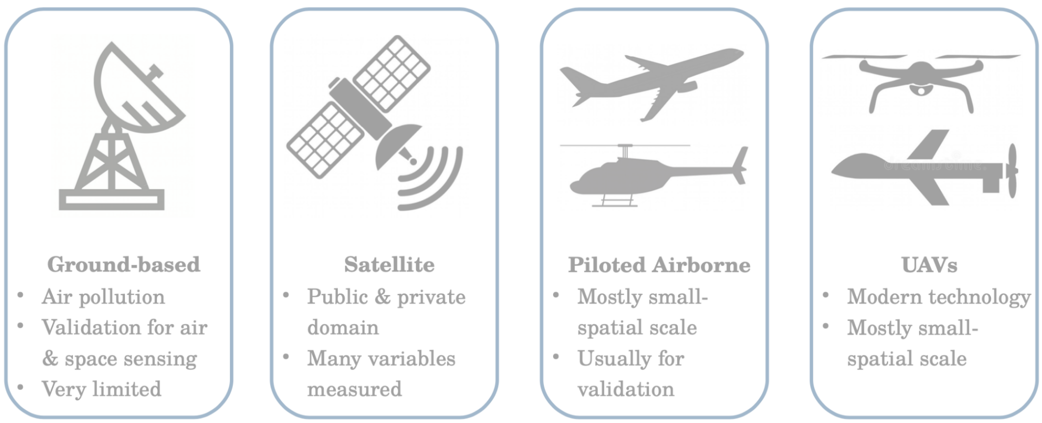
Meanwhile, mobility data doesn't have a retail value, and it is mainly used for the "data for good" programs (Maas et al. 2019). The main challenges from the data provider side are balancing data privacy vs. utility and how to monetize the insights of the data they generate. It would be helpful to correct bias when the data is processed, be transparent on how the information is used (participatory design), and use caution with data of minorities. One gap that could be addressed is for policymakers to be aware of these novel data sources and to have established partnerships/agreements in place to access these data whenever disaster strikes.

Each panelist presented case studies on how the data has been used by society or governments. For example, Telefonica participated in a case study to analyze the economic impact of the 2017 earthquake in Mexico. AT&T worked with CONAGUA to inform the population about hazards in their areas (till now, 60 hurricane alerts). In addition, Meta has many case studies (wildfires, floods, hurricanes, etc.), and they have the Data for Good platform where researchers can find datasets, case studies, and training courses.

The panel's conclusion was the need to develop an ecosystem of data sharing from different sources and create valuable insights for policymakers. For example, there is a lack of regulation regarding privacy and methodology standards, the spatial resolution for aggregation, what makes it compatible with data providers, and what will happen with federated analytics.

Earth Observation Data (Remote Sensing for DRM): Concepts & State of the Art

There are four areas fundamental for remote sensing: ground-based, satellite, piloted airborne, and UAVs.



This workshop focused on satellite imagery; it has four types of resolution, spatial, temporal, spectral, and radiometric. It can be used for many things regarding DRM; the most common one is comparing before and after images of an area affected by a hazard. It can also be used for ground displacement, storm & weather, fire detection & atmospheric gases, and climatological & agricultural.

Important components of satellite imagery use include the frequency in which satellites cover the earth, satellite constellations, and different satellites may take the same paths, allowing for more frequent coverage of an area. The downside of satellite constellations is the cost (\$2-\$24 per km^2). NASA has provided a nice satellite ecosystem.

With mobility data, partnerships should be set before a crisis to access the data. For example, the Copernicus Emergency Management Service supports all actors involved in managing natural or man-made disasters by providing geospatial information to inform decision-making in Europe. They would like to expand their data center to Latin America and the Caribbean. Governments can bypass the bureaucracy during a crisis and get quick access to the Copernicus data by making the requirement through the RedCross.

Use Cases

For this panel, we had three representative agencies, National Coordination of Civil Protection (CNCP), GISAT, and The International Charter.

The CNCP presented how Mexico uses satellite imagery for preventing and responding to disasters, among other topics. Several Federal institutions work with this kind of data, such as CONAFOR (Forestry management ministry), CONABIO (Biodiversity Ministry to detect deforestation), CNPC (Civil Protection), CONAGUA (Water management Ministry), and CENAPRED. Regarding prevention, satellite imagery is used to detect areas with a high probability of wildfires and increased vulnerability to landslides, among other hazards. Furthermore, CNPC uses satellite imagery to plan the response roadmap for every major disaster event. For example, during the Tabasco floods in 2020, satellite imagery was used in identifying damaged communities, supply delivery planning, and shelter logistics.

The International Charter Space & Major Disasters is a collaboration between the European Space Agency, the Center National d' Etudes Spatiales, and the Canadian Space Agency. Its objective is to help coordinate space agencies voluntarily, linking the needs of disaster and relief organizations with space technology solutions to help mitigate the effects of disasters on human life, property, and the environment. By combining the Earth observation assets of different space agencies, the Charter helps coordinate resources and expertise for rapid response to major disaster situations, supporting civil protection agencies and the international humanitarian community.

GISAT also provided examples on Earth Observation (EO) for DRM (Supporting resilient infrastructure investment in SE Asia). They have been using satellite infometry (InSAR) to detect land subsidence, landslide risk & slope instability. EO/InSAR provides an objective operational workflow and offers proven solutions; it can be tailored to the purpose and requirements of the projects. Copernicus Sentinel-1 mission offers reliable, flexible, and cost-effective solutions to retrospective mapping (archive since 2014), continuity and frequent monitoring (6 days to revisit), observations from multiple directions, and consistent coverage of large areas.

EO Data Providers

In this panel, we had the participation of the Mexican Institute for Geographic and Statistical Information (INEGI), Meta, ESRI, AWS, and Google. Each of them presented examples of using EO data for DRM. For example, INEGI has three decades of satellite images (90 Terabytes) and the computational infrastructure to process them. The capabilities of the Mexico Geospatial Data Cube are limitless. Their first prototype is ICASE Landsat, a tool to visualize mosaics of water coverage; it has a ground resolution of 30 meters per pixel. It has three layers: in addition to the value of the proportion of water identified by the classifier, complementary information is included, such as the number of valid observations in the time series (denominator) and the number of times in which said observations were classified as water (numerator). Users can visualize the layers of water coverage and explore the time series. This tool can be helpful for resilient urban planning and measures to adapt to climate change.

Another useful tool is the High-Resolution Settlement Layer (HRSL) from Meta. To increase the accuracy of the population estimations they combine settlements and census data to create the HRSL (Tobias G. et al., 2017). Researchers can access Meta´s data through their Data For Good portal or the Humanitarian Data Exchange (HDX) from OCHA.

AWS helps with training and data processing in the cloud to accelerate computing time through their Disaster Preparedness and Response program. The examples cover flooding maps to help in call centers.

For Google, it is important to inform its clients of the most accurate data on ongoing events such as fires. The SOS Alert mission is to organize information and make it accessible and useful for users before, during and after a disaster. Where they can look for shelter, how the ongoing event is evolving, and similar questions. They are aware of the tradeoff between spatial and temporal resolution to answer these questions.

ESRI uses deep learning to process Satellite imagery given its accuracy, speed, and scale. They have an end-to-end geospatial life cycle, which helps prepare data, train models, implement them, and make inferences. While processing this data, they can define the user group and the user need. For example, are the insights for the general public or emergency managers? They can also account for the time and space constraints of the data.

What unifies all the data providers is the coding experience; most of them use python. There is a need to link with universities and have continuous education to have skilled people able to process the data.

Privacy & Responsible Data Practices

Data can provide helpful information from vulnerable groups but at the same time put them at risk (Stucke, M. E., 2017). To analyze movements, we need some information from data but don't need highly personal information. Aggregation can be used to avoid identification and keep the data anonymous. However, problems can appear when there is a small population in a specific area. The movements make it easy to identify the individuals, such as when you have particular trips to places or at specific hours. Differential Privacy (DP) can solve this problem, by adding some noise to the data without modifying the aggregations; it only makes it more challenging to identify specific individuals. DP should be used carefully because, in some cases, it can generate over-representation and think who will be most affected when this is used to make decisions (Stucke, M. E., 2017)(Kerry, C., 2020).

We are in a period of datification which requires us to reimagine and rethink data management. There are three new data responsibilities:

1. Traditional data responsibility (avoid harm and misuse of data): basic notions of privacy and existing regulation
2. Responsibility to provide access to data and resulting insights. For example, provide data for a clear public interest, such as for humanitarian purposes.
3. Responsibility to take action based on the insights of the data. Move from "data intelligence" to "actionable intelligence."

We also need new partnerships to unlock domain expertise. To scale data collaboratives, we need to make them more systematic, sustainable (lowering transaction costs and new funding mechanisms), and responsible. There is a need for better tools to identify questions that can be answered through data (participatory science of inquiry) and place the minimum data we need to answer questions.

A key role we need to invest in is "Data Stewards," individuals in public and private organizations that understand the opportunity costs, align incentives, engage the broader public, and nurture collaborations around data sharing.
New sharing agreements in a more streamlined and ethical council can provide independent decision-making around certain data decisions.

There is a baseline to share information in a humanitarian crisis in the European Data Act. This can be used as a guide for other regions/ country regulations to improve the use of data.

Community Mapping & Civil Society Participation

According to SocialTic technology is essential, but community participation is necessary to build accurate and practical maps. A combined approach between EO, AI, and community mapping can be used to transform data collection into actionable datasets for communities. It involves local capacity building and solid ethical frameworks. In the end, nobody knows the local landscape better than the local people.

When working with communities, it is crucial for the community to adopt/ see the importance of the mapping exercise. If a community felt that a survey wasn't done correctly, the project´s adoption could be at risk. During a community mapping project, there can be barriers mainly around technological capabilities and skills; language barriers could also be a problem (most tools are implemented in English). Also, communities should be seen not only as data generators but also as data insights consumers.

The Digital Earth Partnership (DEP) combines EO data and services with community mapping to enhance the resilience of vulnerable countries and communities to climate change & natural hazard disasters. It is a way to accelerate a partnership toward proactive risk management and climate change adaptation. The objective of Open Cities is to generate data for aggregated local risk management, involving active local and open mapping communities. In Addition, it aims to generate missing data for public policy and create and strengthen the long-term capacity to sustain this information flow. To date, Open Cities projects have been developed in partnership between the World Bank and HOT in several cities in Africa and Southeast Asia. They are now starting in Latin America and the Caribbean: Saint Lucia, Jamaica, Dominica, Mexico, and Guatemala.

From 2021, HOT is developing new operations in Latin America to create an open Mapping Center in this region. In this context, the project's goal was to identify partnerships with long-term potential and initiate collaboration with available mapping communities in the area. While providing support to advance the development or their consolidation, in collaboration with the risk prevention and sustainable development sector, to better match opportunities with needs and complement different agendas and, in particular, community plans.

Landscape Analysis

After the workshop, participants role-played as emergency response stakeholders under two scenarios (hurricane and earthquake). The main goal of the exercise was to identify key questions and analysis requirements for data analysts to answer during the emergency response phase. On the second day, the group did a capability assessment to identify gaps and action points considering the questions and needs identified on the first day.

Day 1

Under a disaster scenario, there is good coordination regarding the National Emergency Committee at the Federal level to address the crisis. But there is a lack of communication with other institutions and civil society.

Fortunately, there is not a lack of political willingness but a lack of awareness and existing networks of mobility data before a disaster.

Most of the data needed for DRM is provided by INEGI (Demographic and socioeconomic characteristics) and CENAPRED (risk maps, Atlas Nacional de Riesgo). The group identified missing data that could be useful for DRM, such as origin-destination location to map displacements and monitor resettlements, building status to assess damages, historical records of evacuation patterns (internal displacement matrix), and stratified by income, and other variables for informing modeling efforts. A question that arises is; How do we retain the memory of an event for building upon that knowledge for future events.

Another identified gap is how the ongoing event is communicated with civil society organizations. There are different agencies with different types of activities that are not coordinated.

Day 2

Participants completed a systematic mapping exercise to identify stakeholders and data agreements that need to be made.

The following table shows the institutions identified. One key observation is the need for analytical capacity, and this need can be addressed by creating curricular/ training courses around (data science) and internships.

Academic (DS or DRM programs)	Government agencies	Private sector	NGO	Others
UNAM (Instituto de Geografia) UTR (Aguascalientes) Escuela Nacional de Ciencias de la Tierra ITAM TEC (Escuela de Gobierno) ENAPROC IIMAS CIMAT Instituto Mora Youth Mappers	CENAPRED INEGI CONAGUA INECC SEMARNAT SEDEMA SEMAR Guardia Nacional CNPC Comité de Emergencias	META Google AWS Twitter Telefonica AT&T America Movil	HDX NASA NOAA SENTINEL	Donors Volunteers

The data agreements should be made between the Private sector and INEGI and then INEGI can pipe the data to agreements with Academic organizations.

A key focal point would be the Instituto de Ciencias de la Tierra from Instituto de Geografia(UNAM) ; they are partners with INEGI (laboratorio de Ciencia de Datos) and CENAPRED. Also, if the SDGs are included, it would be easier to have a project with INEGI since they are in charge of giving follow-up to the SDGs indicators.

Instead of starting with a massive undertaking, it is more viable to start with a pilot project and start from there to provide technical support. CENAPRED suggests we start with a project related to earthquakes.

Next Steps

- Identify specific people and create a directory of the network (name, university, contact details)
- Data agreements between data providers and academic partners.
- Include new data in the risk models (simulations)
- Include / merge Meta`s data to the Atlas Nacional de Riesgo

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