510 AN INITIATIVE OF THE NETHERLANDS RED CROSS

Leveraging AI and Big data across the disaster risk management cycle

Opportunities and challenges for the Red Cross

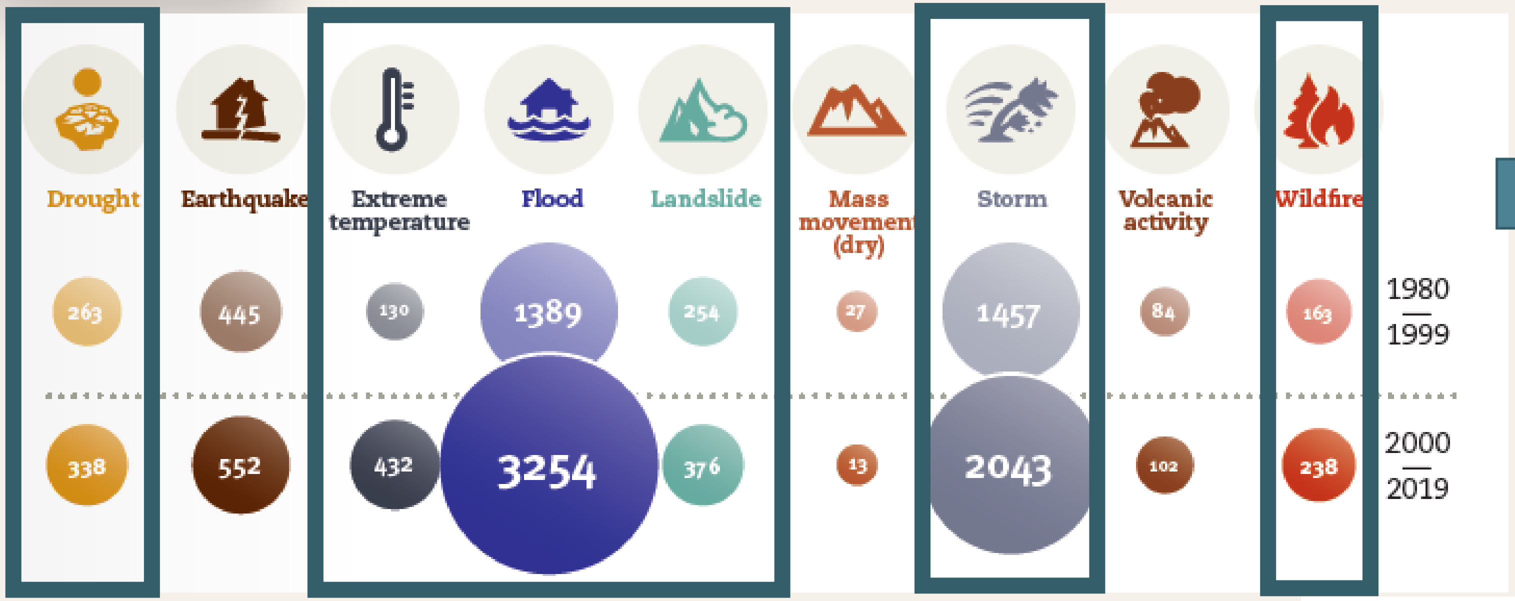
Workshop: Machine Learning for Earth System Modelling and Analytics

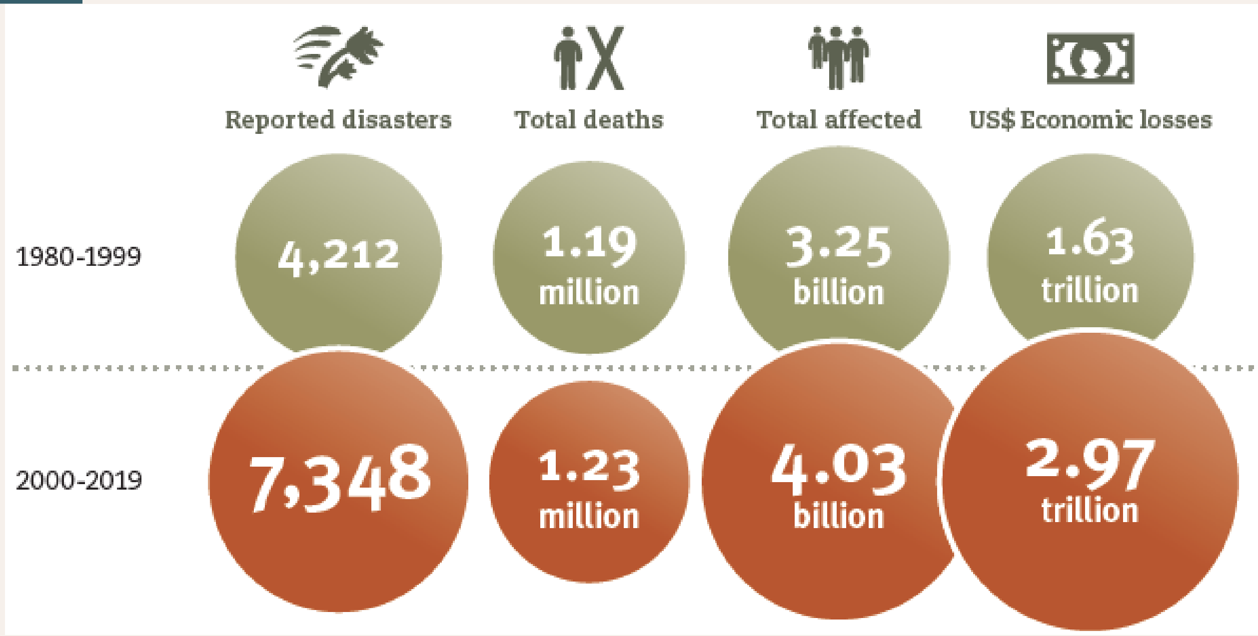
3rd of May 2021

Marc van den Homberg

mvandenhomberg!@redcross.nl

MORE CLIMATE-RELATED DISASTERS, INCREASED IMPACT

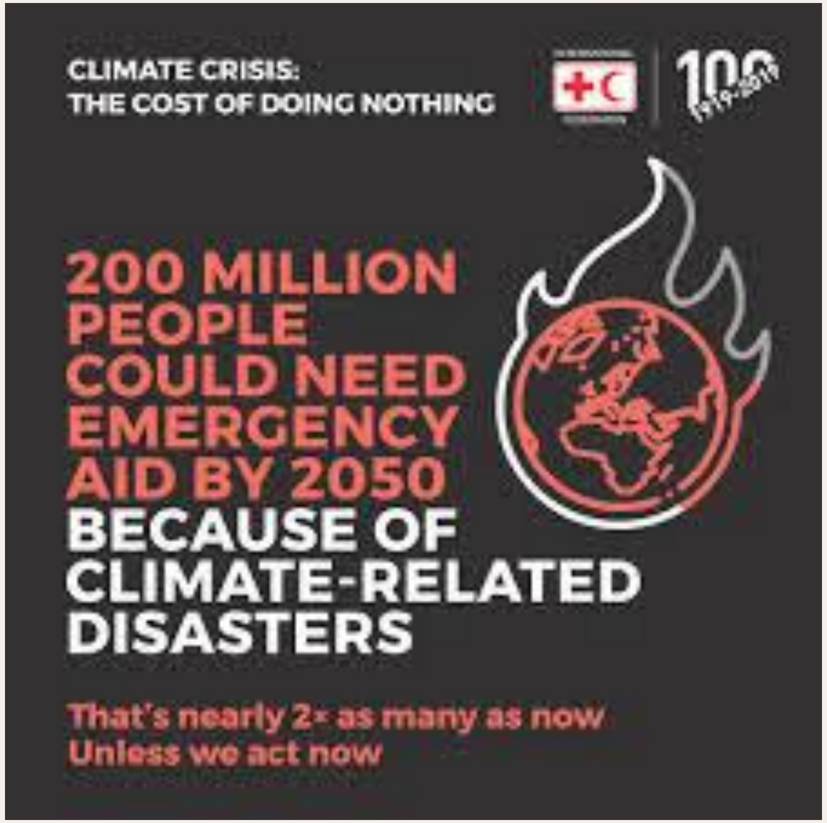


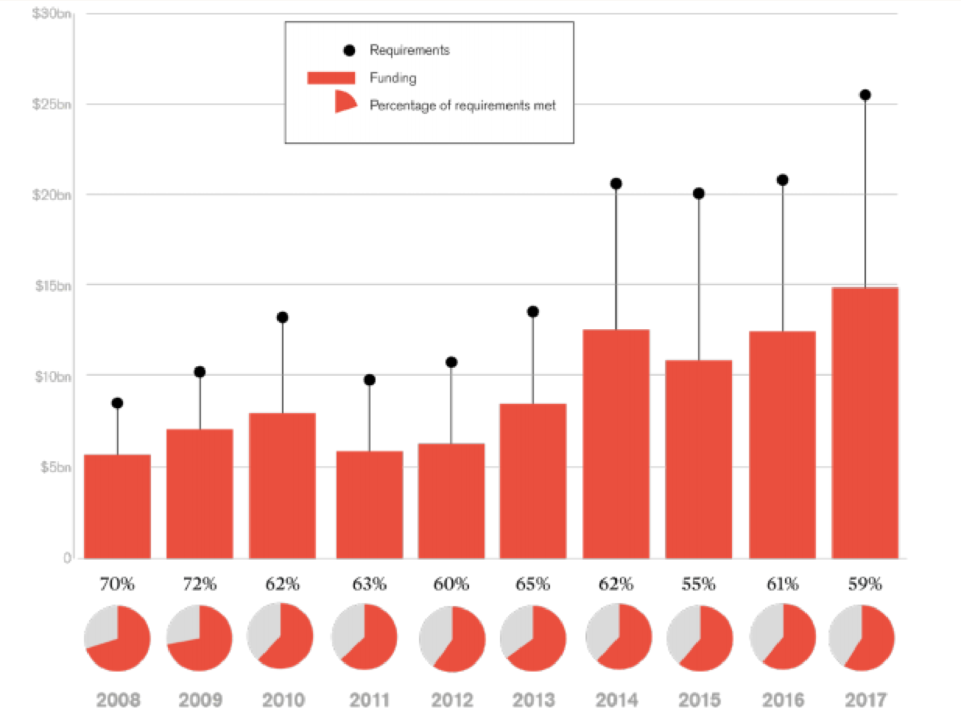


Human costs of disasters, an overview of the last 20 years,
CRED (EM-DAT) and UNDRR

THE COST OF DOING NOTHING & FUNDING GAP

- Climate change a double threat to vulnerable communities
  - More extreme weather events
  - Climate change's macroeconomic impacts reduce resilience among world's poorest, leaving them less able to manage shocks





- Funding does not meet the requirements

The state of the humanitarian system. London: Overseas Development Institute (2018)

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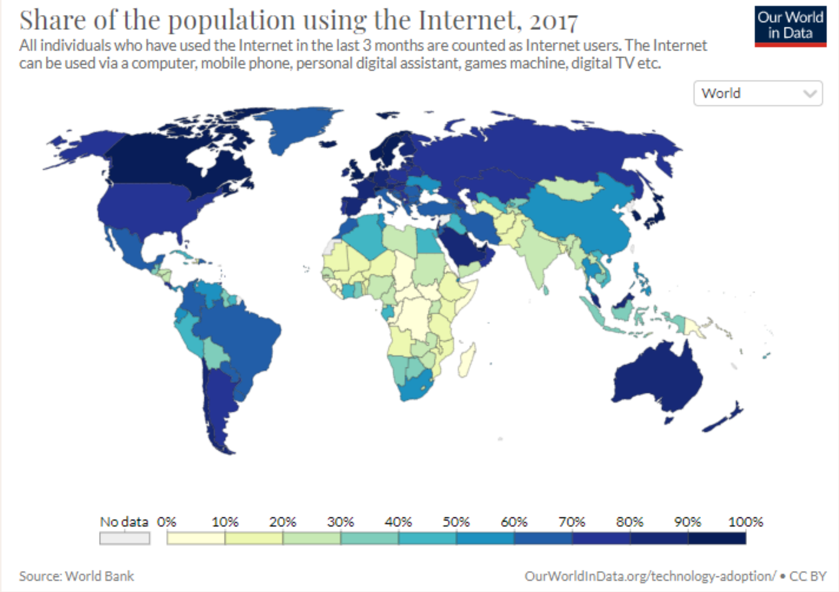
DIGITAL AND DATA REVOLUTION

- Increasing digitization: mobile phones, Internet of Things etc
- Rapid increase in Small & Big data

- Digital divide
  - Unequal internet access
  - Data illiteracy
  - Data capacity gap
  - Data poverty



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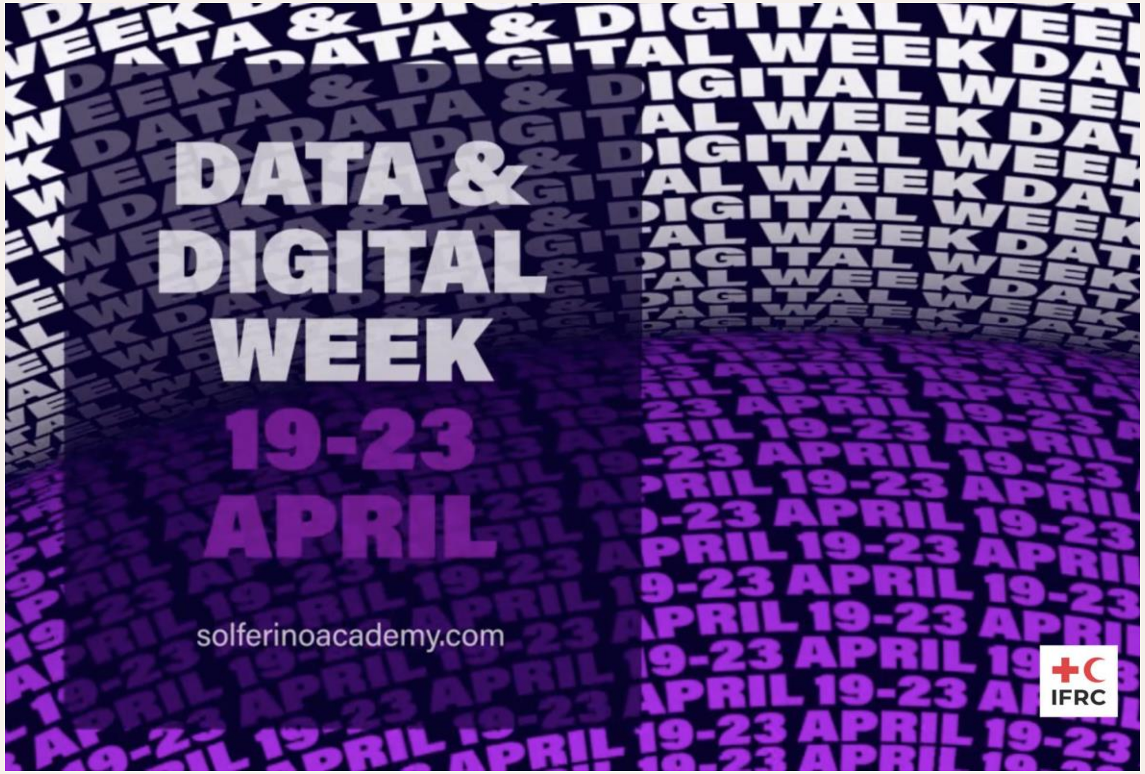
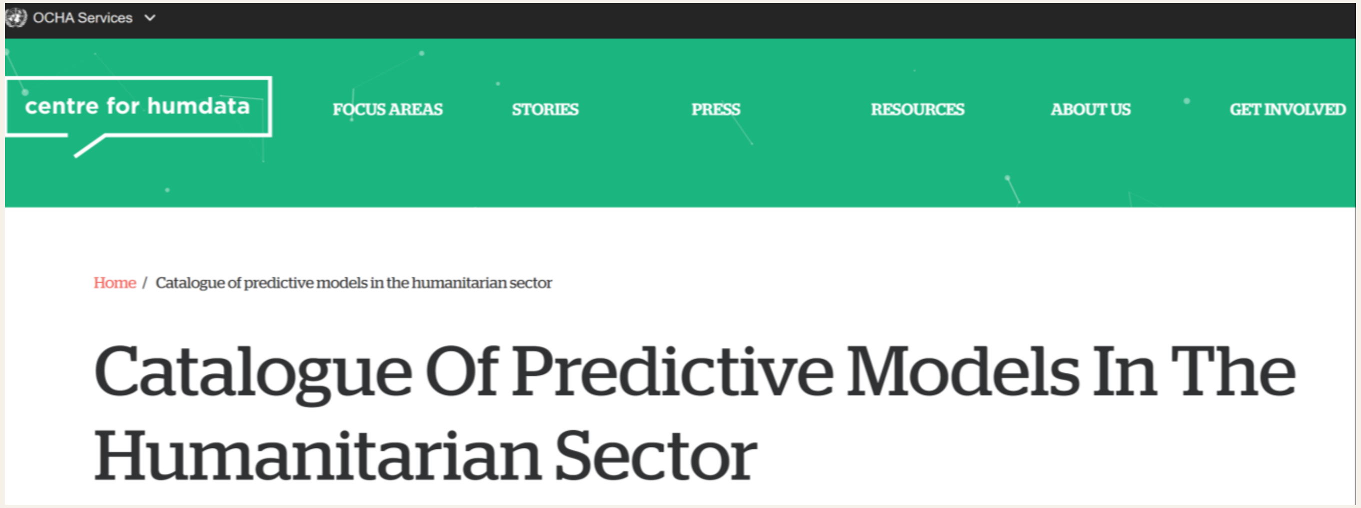
WHAT IS/CAN BE THE ROLE OF AI AND BIG DATA IN DISASTER RISK MANAGEMENT?





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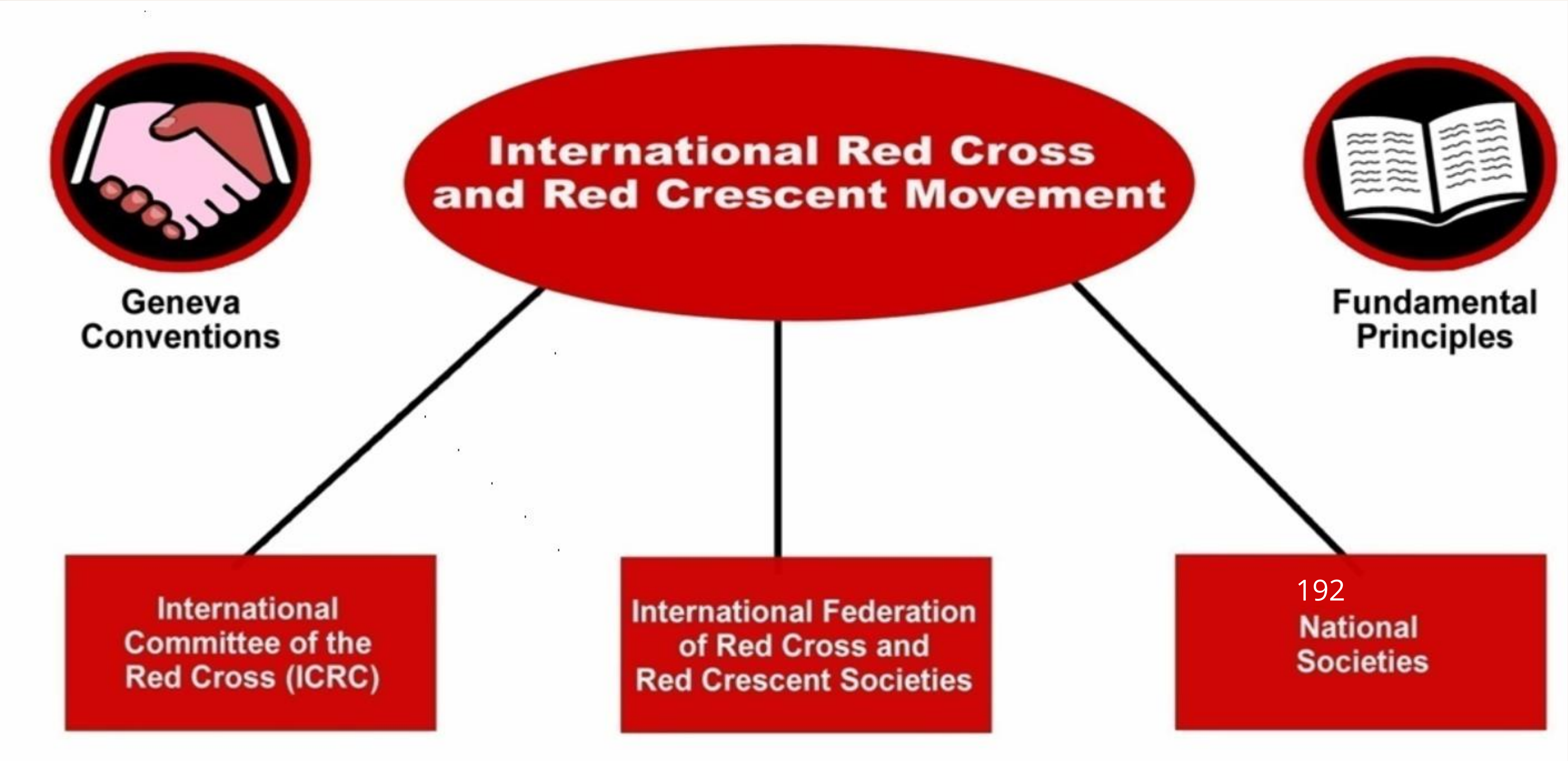
GLOBAL, LOCAL AND BIG DATA IN THE RED CROSS RED CRESCENT MOVEMENT

INTRODUCING THE RED CROSS MOVEMENT



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RED CROSS RED CRESCENT RESEARCH CENTERS

RC3

science connected for humanity

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RED CROSS RED CRESCENT RESEARCH CENTERS

International Federation of Red Cross and Red Crescent Societies
Global First Aid Reference Centre

Belgian Red Cross

croix-rouge française
PIROI
GESTION DES CATASTROPHES center

Psychosocial Centre
International Federation of Red Cross and Red Crescent Societies

Climate Centre

FONDATION croix-rouge française
Pour la recherche humanitaire et sociale

ICHA International Center for Humanitarian Affairs
At the Kenya Red Cross Society
Inquire • Understand • Influence

CADRIM
Red Cross Caribbean Disaster Risk Management Reference Centre

Evidence-based by CEBaP

Livelihoods Centre
knowledge creation | knowledge sharing | knowledge networking
International Federation of Red Cross and Red Crescent Societies

Global Disaster Preparedness Center

GAP

INTERNATIONAL FEDERATION

ICRC
Centre for Operational Research and Experience
CORE

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510 million square kms
total surface of the earth.

We aim to help every **national society** in need **anywhere.**

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Our purpose is to improve **speed, quality** & cost-**effectiveness of humanitarian aid** by using & creating **data & digital** products.

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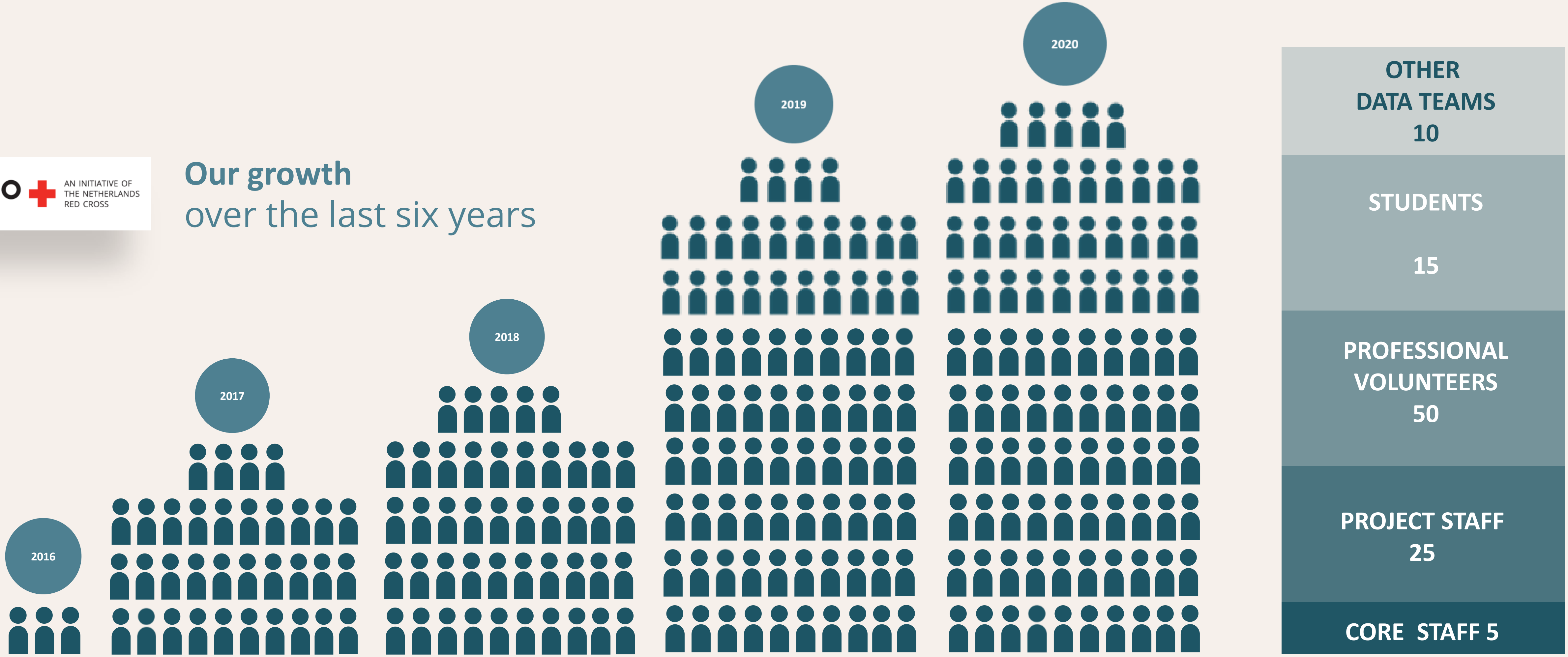
Our growth
over the last six years



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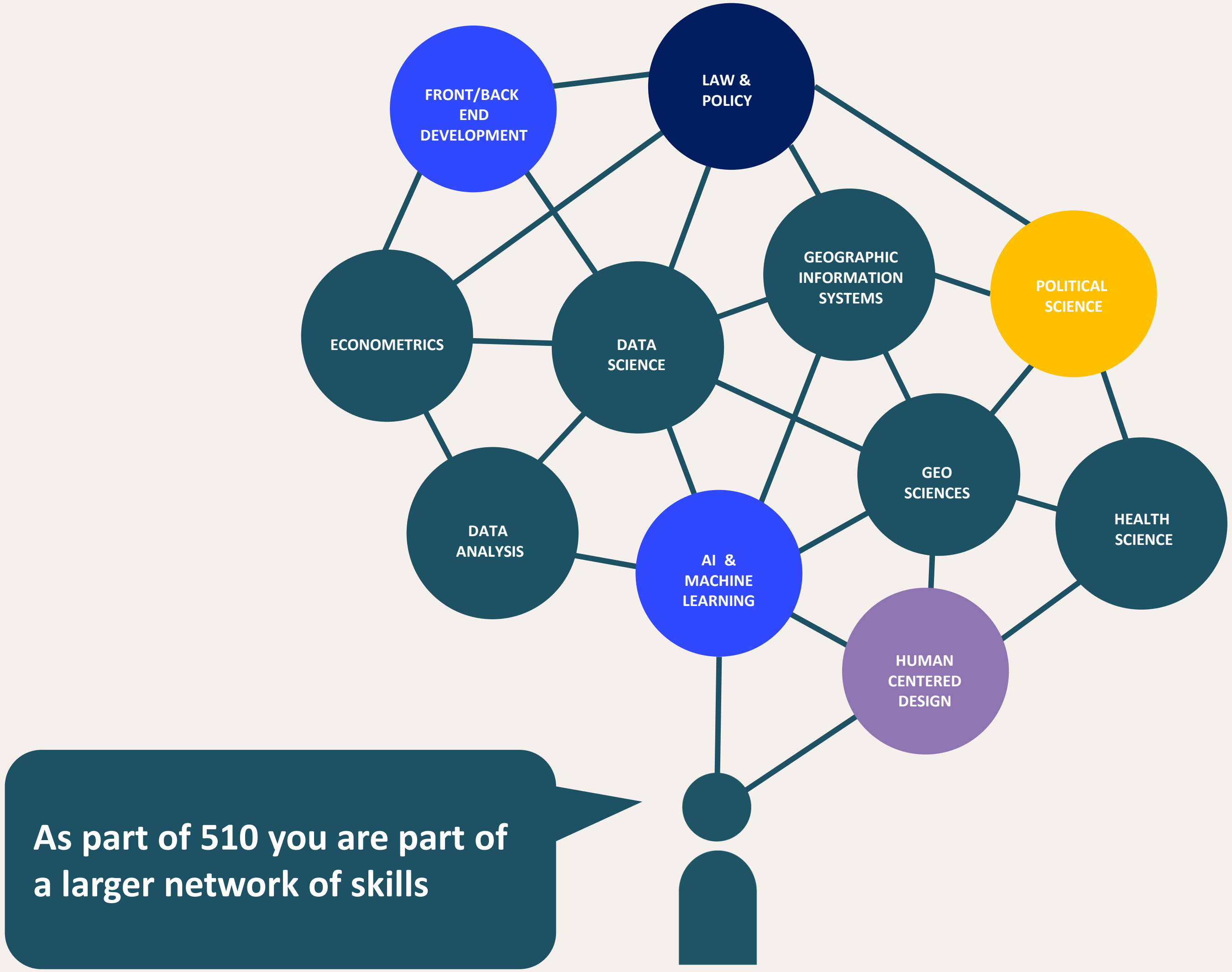
Our team skills are cross-pollinated



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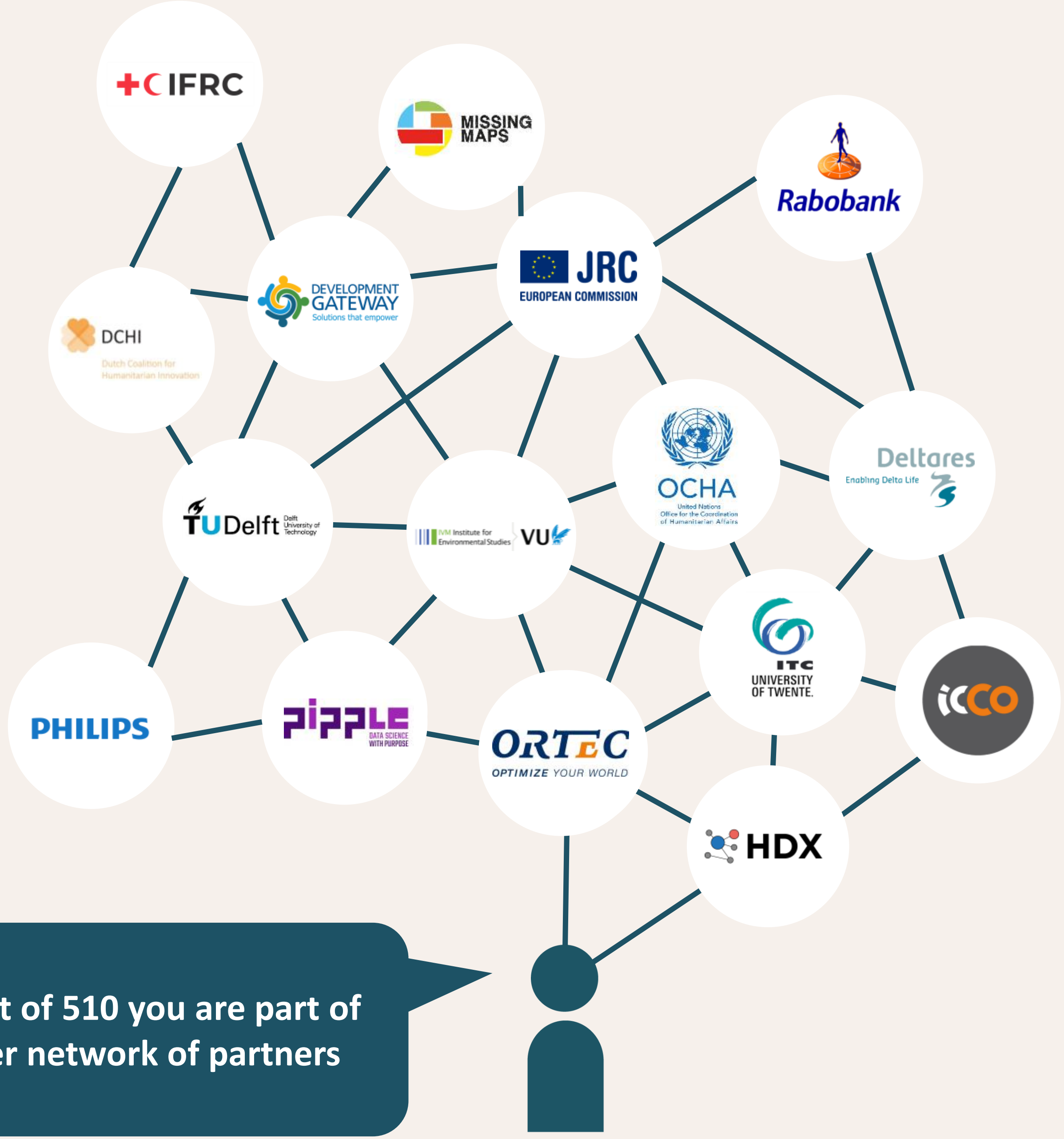
Our network of partners
help us move our purpose forward



As part of 510 you are part of a larger network of partners

We support national societies (NS)

So far, we have supported 36

DATA CAPACITY GAP: CREATING DATA TEAMS WITHIN OTHER NATIONAL SOCIETIES

- 10 by the end of 2020

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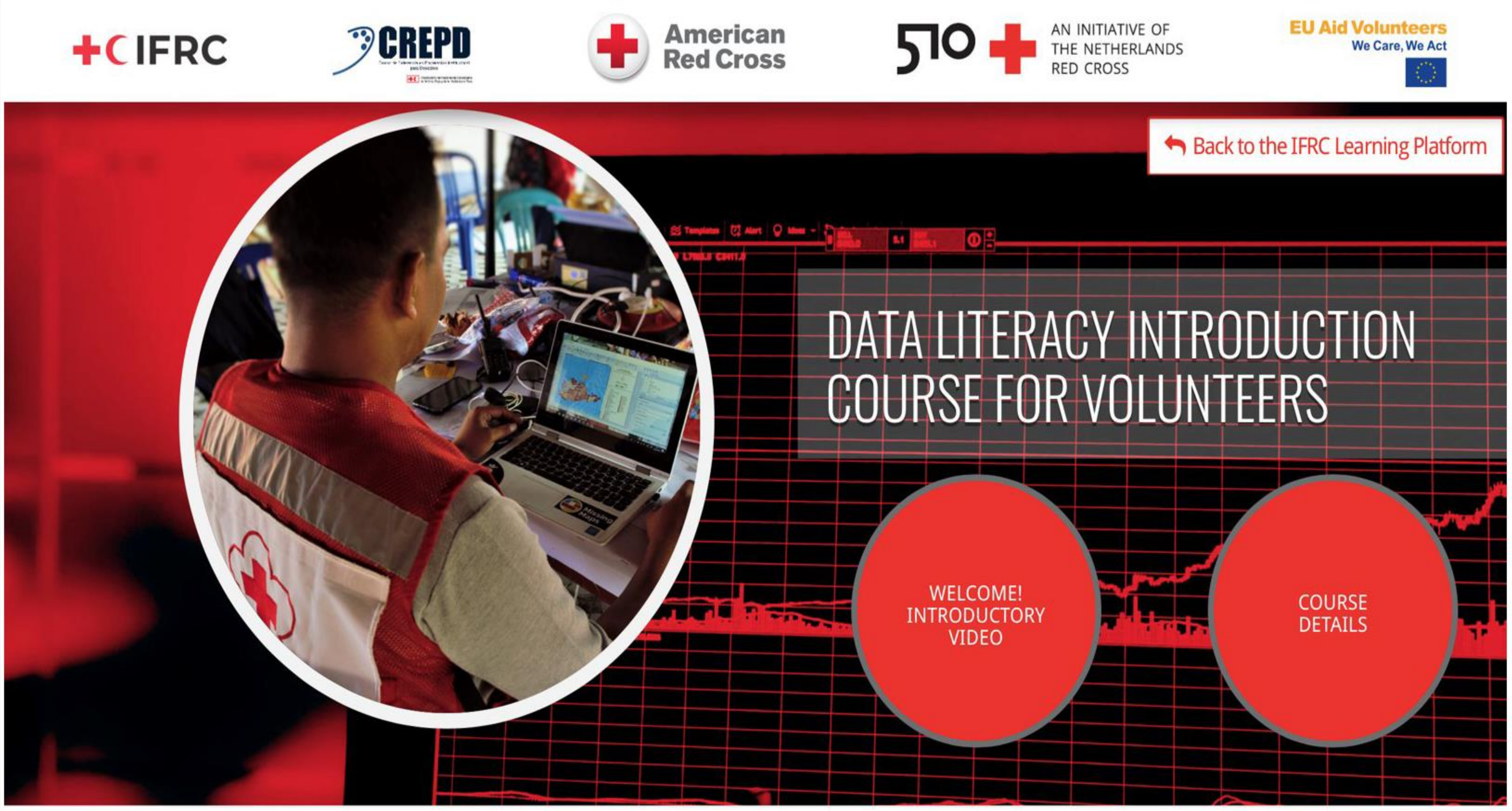
MALAWI RED CROSS SOCIETY DATA TEAM

MALAWI RED CROSS SOCIETY

DATA LITERACY FOR RED CROSS VOLUNTEERS



LEVERAGING AI & BIG DATA ACROSS DISASTER RISK MANAGEMENT CYCLE

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DIGITAL RISK ASSESSMENT	PREDICTIVE IMPACT ANALYTICS	EMERGENCY DATA SUPPORT	DIRECT DIGITAL AID
CRA COMMUNITY RISK ASSESSMENT	IBF IMPACT BASED FORECAST	DISASTER MAPS	121 CASH BASED AID
ERA EPIDEMIC RISK ASSESSMENT	IMPACT ASSESSMENT TOOLS	DAMAGE ASSESSMENT TOOLS	
LANDSCAPE RESTORATION	POPULATION MOVEMENT TOOLS	POPULATION MOVEMENT TOOLS	

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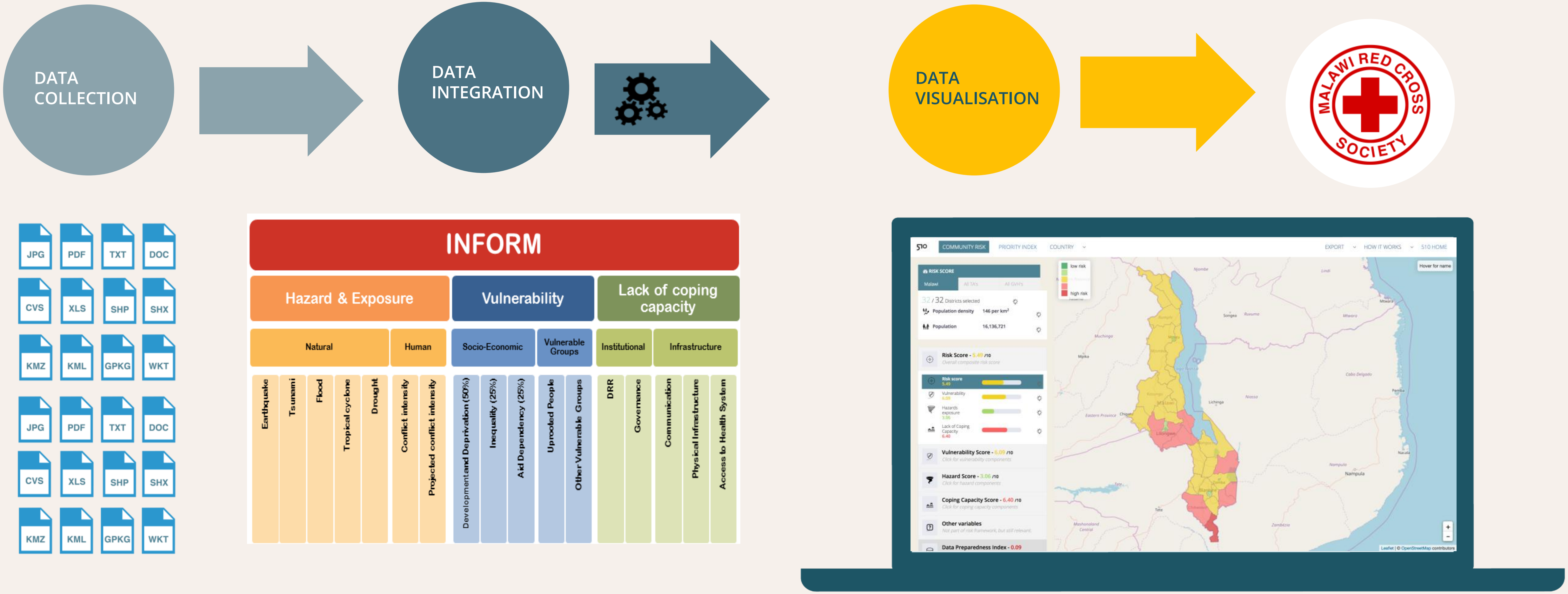
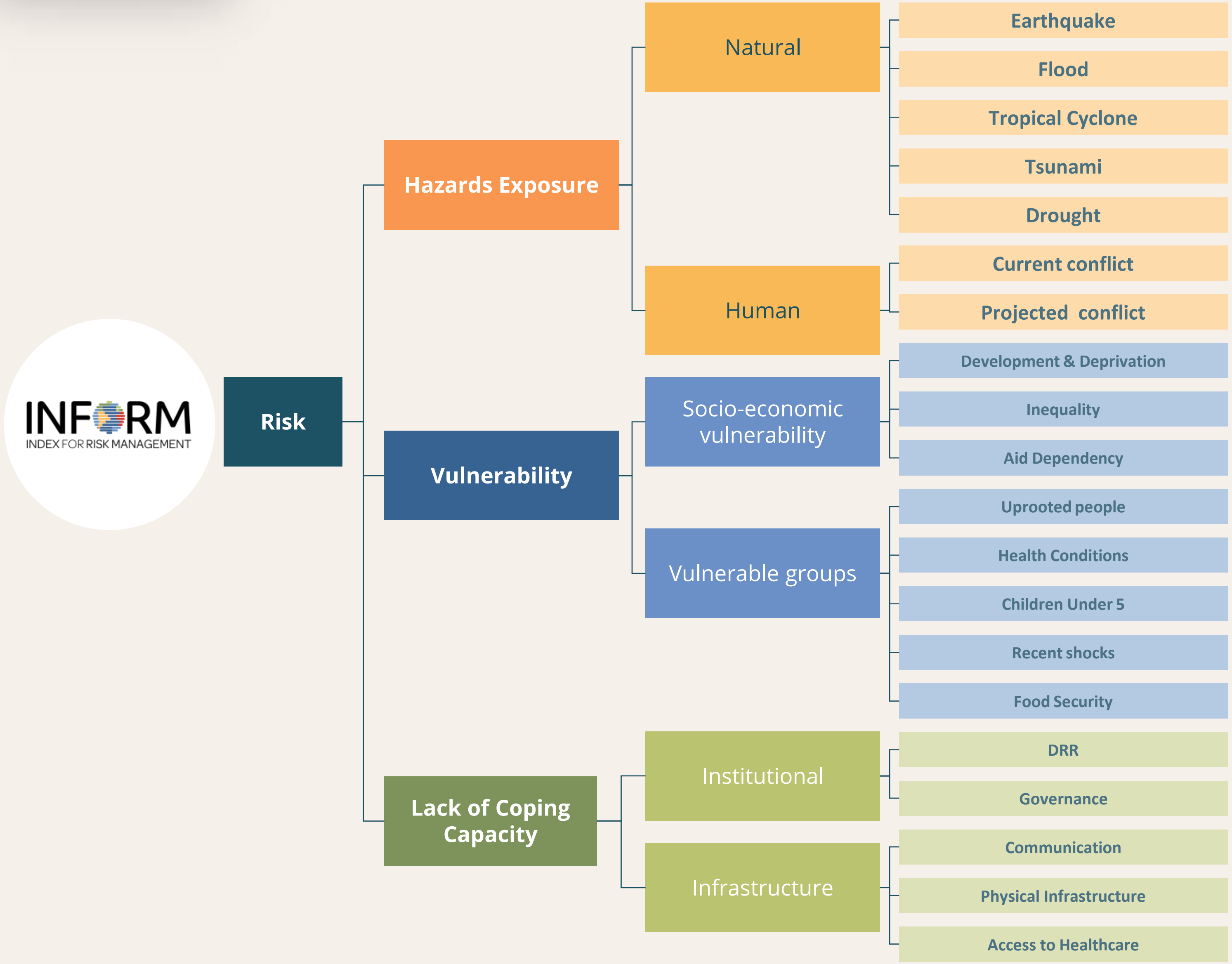
DIGITAL RISK ASSESSMENT



COMMUNITY RISK ASSESSMENT: DATA FRAMEWORK



https://dashboard.510.global/#!/

van den Homberg, M., Visser, J., & van der Veen, M. (2017). Unpacking Data Preparedness from a humanitarian decision making perspective: toward an assessment framework at subnational level. In Proc. Information Systems for Crisis Response and Management (ISCRAM) Conference, http://idl.iscram.org/files/marcvandenhomberg/2017/1995_MarcvandenHomberg_etal2017.pdf

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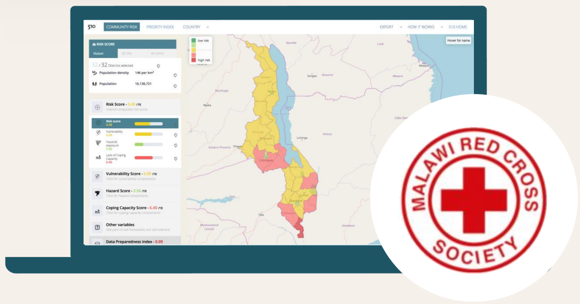
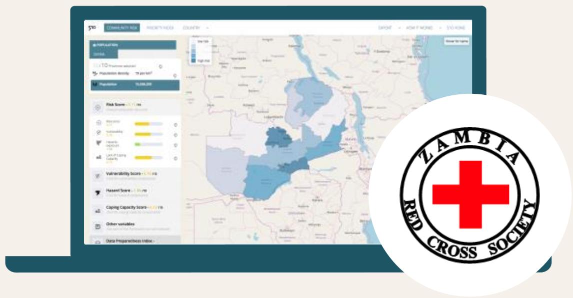
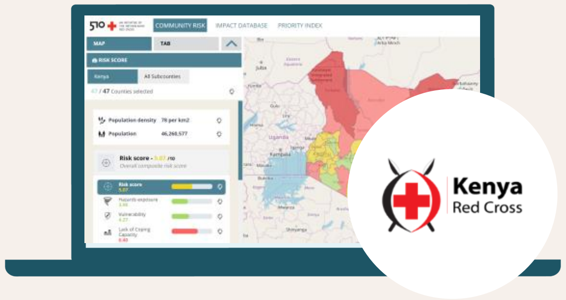
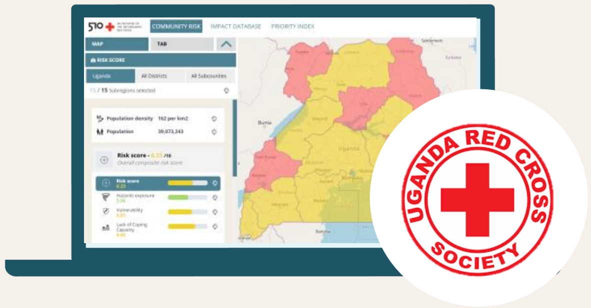
WHERE WE UNDERSTAND & IDENTIFY RISK

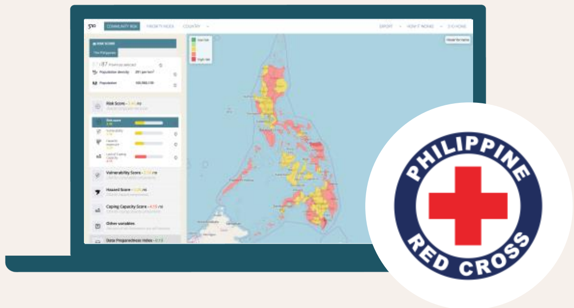
https://dashboard.510.global

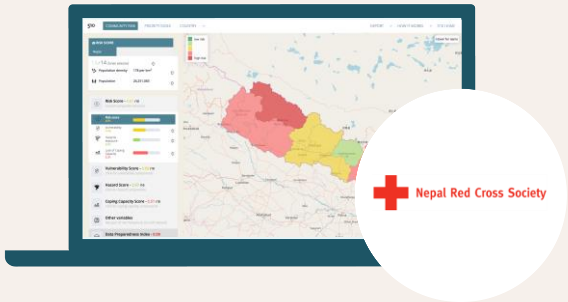


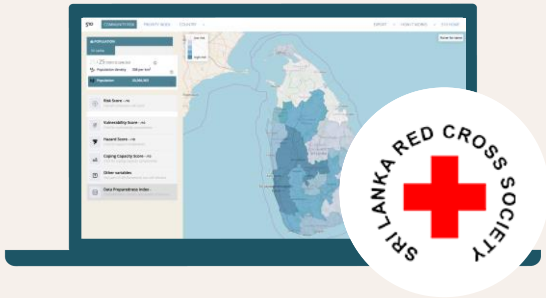


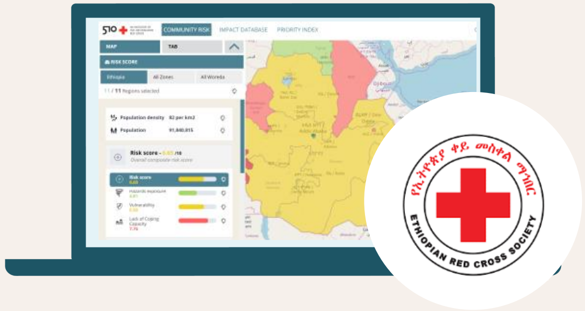


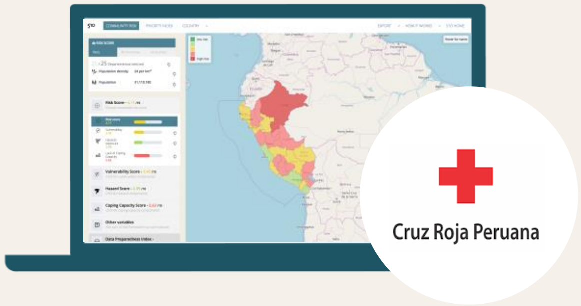


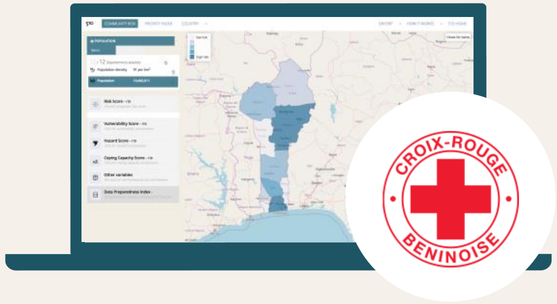


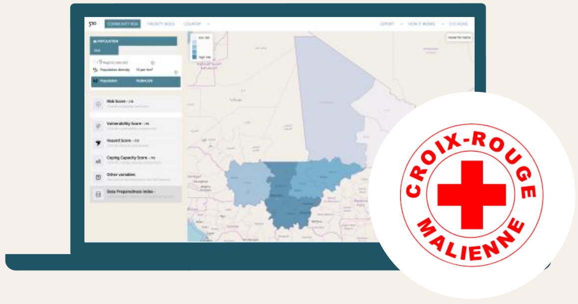












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COMMUNITY RISK ASSESSMENT : DATA GRANULARITY

INFORM INDEX FOR RISK MANAGEMENT

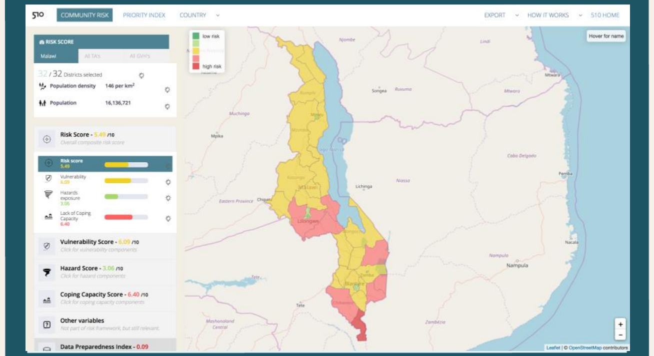
Risk	Category	Indicator	32 DISTRICTS	367 TRADITIONAL AUTHORITIES	9133 GROUP VILLAGE HEADS	
Hazards Exposure	Natural	Earthquake	Yes	Yes	No	
		Flood	Yes	Yes	Yes	Flood risk
		Tropical Cyclone	-	-	-	
		Tsunami	-	-	-	
		Drought	Yes	Yes	Yes	Drought risk
	Human	Current conflict	No	No	No	
		Projected conflict	No	No	No	
Vulnerability	Socio-economic vulnerability	Development & Deprivation	Yes	Yes	Yes	Poverty incidence
		Inequality	No	No	No	
		Aid Dependency	No	No	No	
	Vulnerable groups	Uprooted people	No	No	No	
		Health Conditions	No	No	No	
		Children Under 5	Yes	No	No	
		Recent shocks	No	No	No	
		Food Security	Yes	No	No	
Lack of Coping Capacity	Institutional	DRR	No	No	No	
		Governance	No	No	No	
	Infrastructure	Communication	Yes	No	No	
		Physical Infrastructure	Yes	Yes	Yes	Travel times to facilities
		Access to Healthcare	Yes	Yes	No	

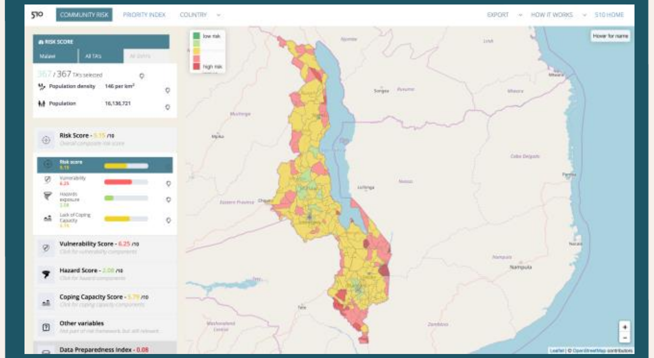
COMMUNITY RISK ASSESSMENT : DATA GRANULARITY

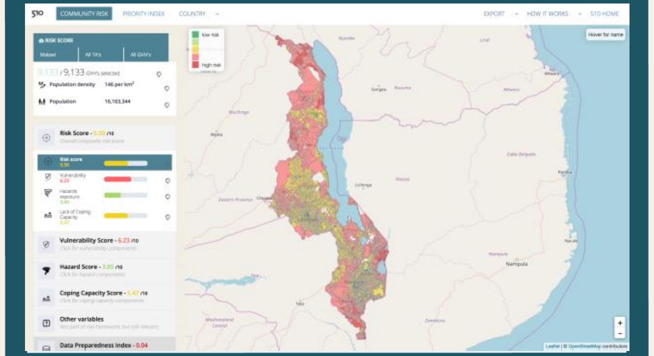
32 DISTRICTS

367 TRADITIONAL AUTHORITIES

9133 GROUP VILLAGE HEADS



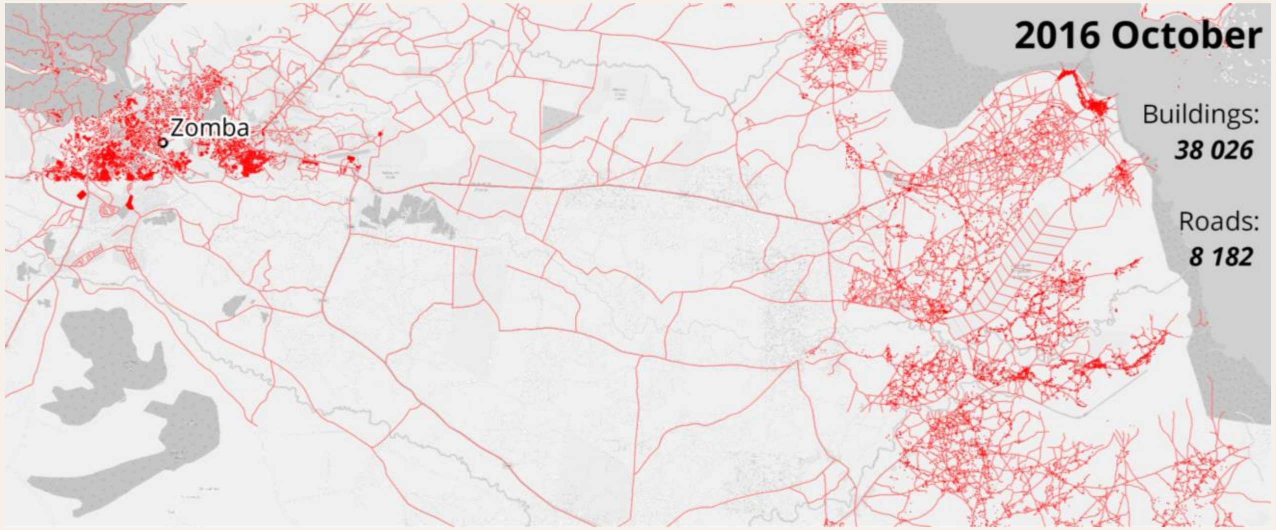




https://dashboard.510.global

HOW DO WE EXPAND RISK DATABASE?

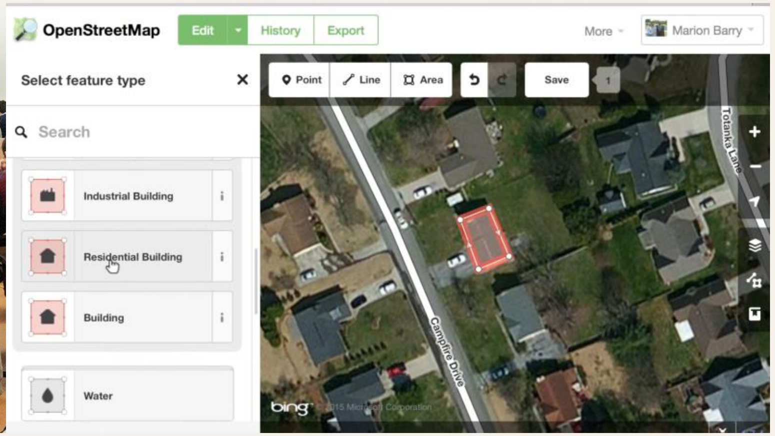
OPENSTREETMAP STARTING POINT



MAPATHONS

Manual tracing and labelling of buildings in aerial imagery.
Lots of commitment of many volunteers but:

Labour-intensive
Time-consuming
Quality depends on skills volunteer



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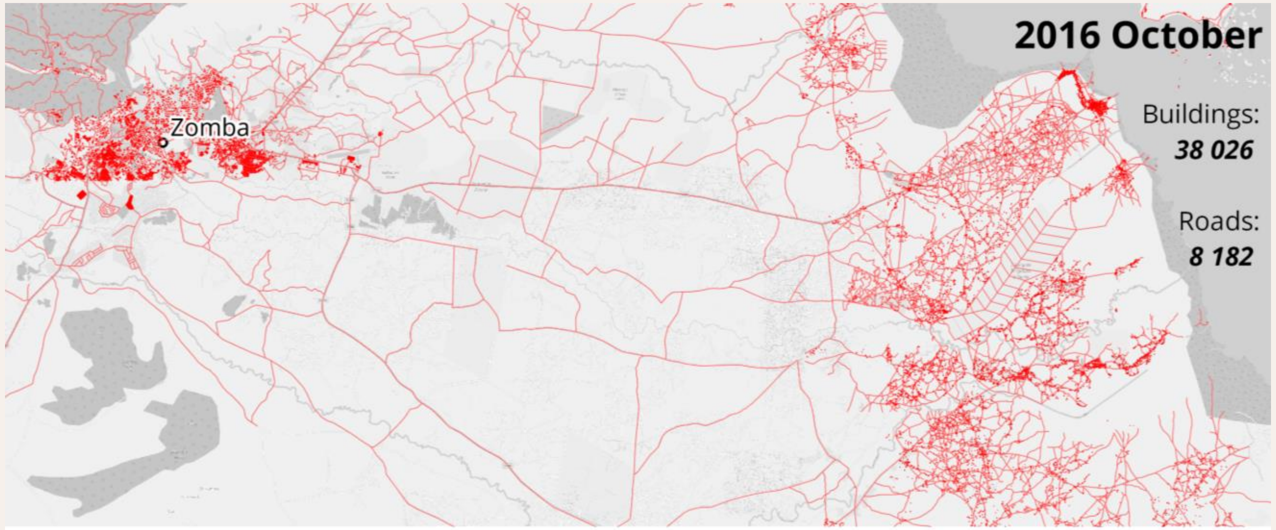
HOW DO WE EXPAND RISK DATABASE?

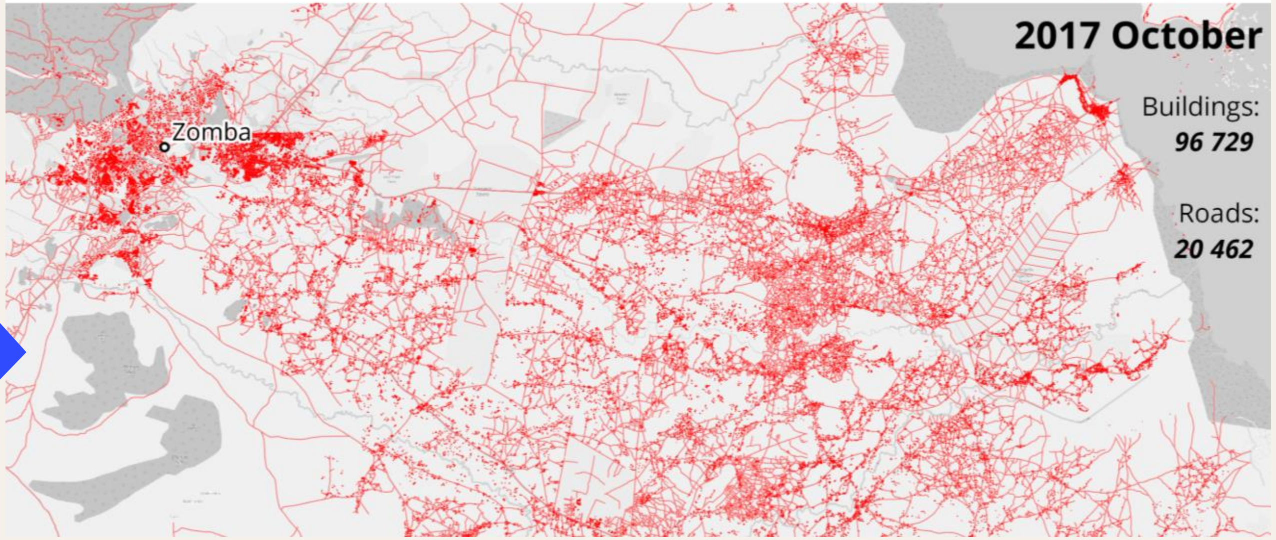
Missing Maps

OPENSTREETMAP STARTING POINT



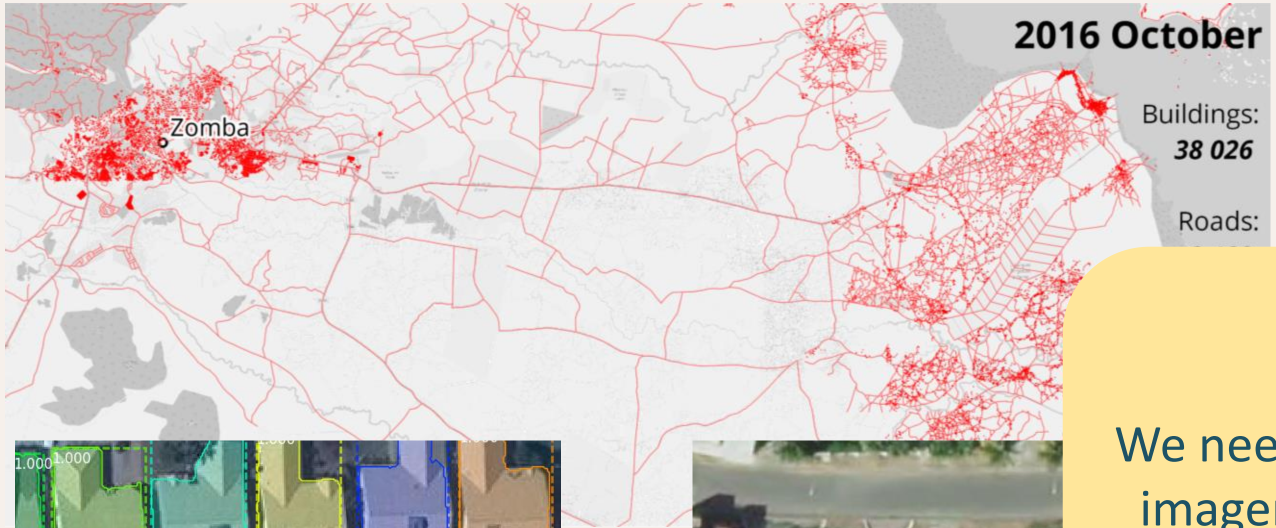
AFTER MAPATHON

Population, infrastructure, natural resources, assets are added



HOW DO WE EXPAND RISK DATABASE?

OPENSTREETMAP STARTING POINT



AUTOMATIC MAPPING

of areas using convolutional neural networks
Classification of roof shape is successful; roof material not yet...
Availability of high resolution aerial imagery key

Segmentation

Classification

We need high resolution imagery for automatic mapping to work better!

PREDICTIVE IMPACT ANALYTICS: CURRENT SITUATION

€ € €

Humanitarian funding for response

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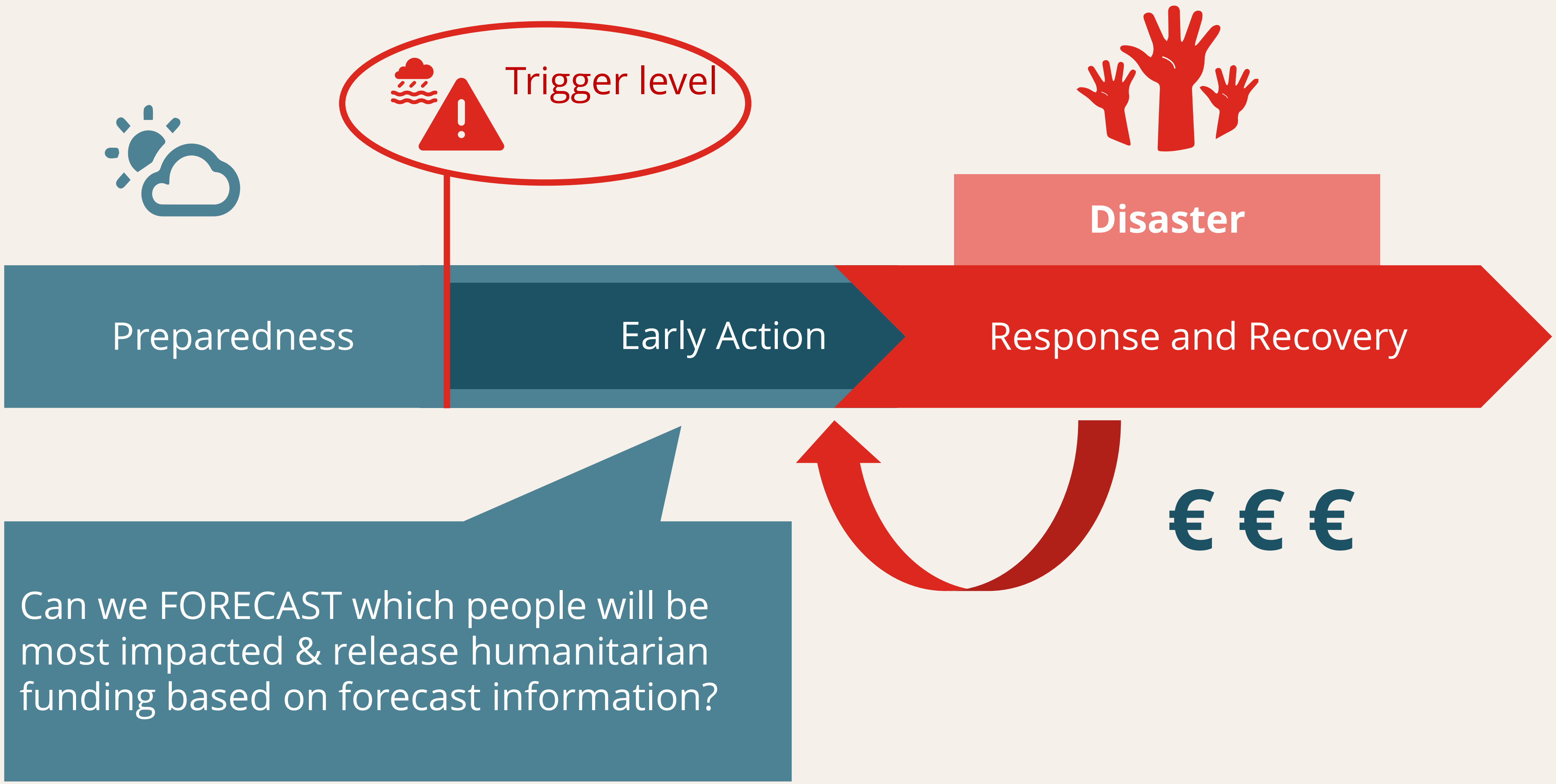
PREDICTIVE IMPACT ANALYTICS: EARLY WARNING EARLY ACTION FORECAST-BASED FINANCING



PREDICTIVE IMPACT ANALYTICS: TRIGGER DEVELOPMENT FOR FORECAST-BASED FINANCING

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Early warning system

- Risk knowledge
- Detection, monitoring, analysis & forecasting of hazard & it's impact
- **Warning dissemination & communication**
- **Preparedness and response capabilities**

TRIGGER DEVELOPMENT

STEP 1: Expand risk database

STEP 2: Inventory of forecasts

STEP 3: Create Impact Database

STEP 4 A: Composite Index approach

STEP 4 B: Elementary modelling

STEP 4 C: Statistical modelling

Impact based forecast

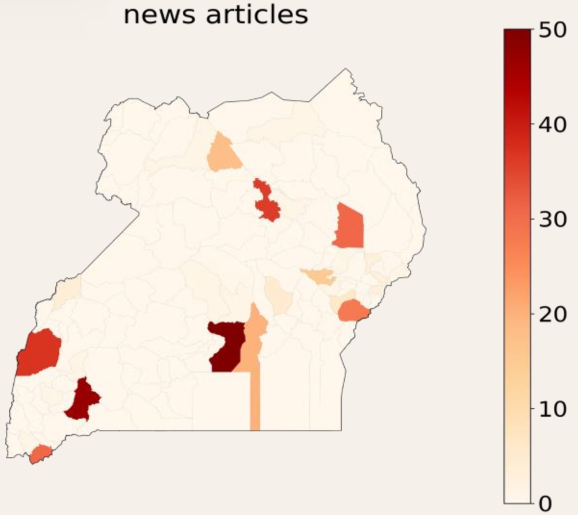
STEP 5: Generate impact-based forecasting intervention map

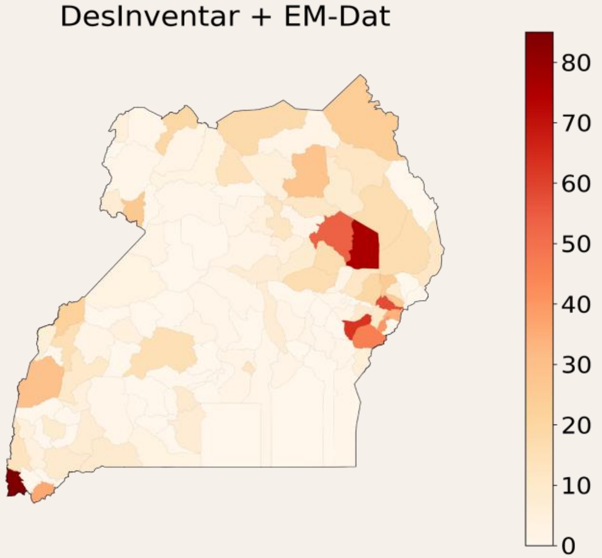
STEP 3: CURRENT IMPACT DATABASE

		SOURCES	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
IMPACT	DATA FROM LOCAL & NATIONAL LEVEL	DMMU												
	DATA FROM GLOBAL REPOSITORIES	EM DAT												
		DESINEVNTAR												
		HUMANITARIAN DATA EXCHANGE												

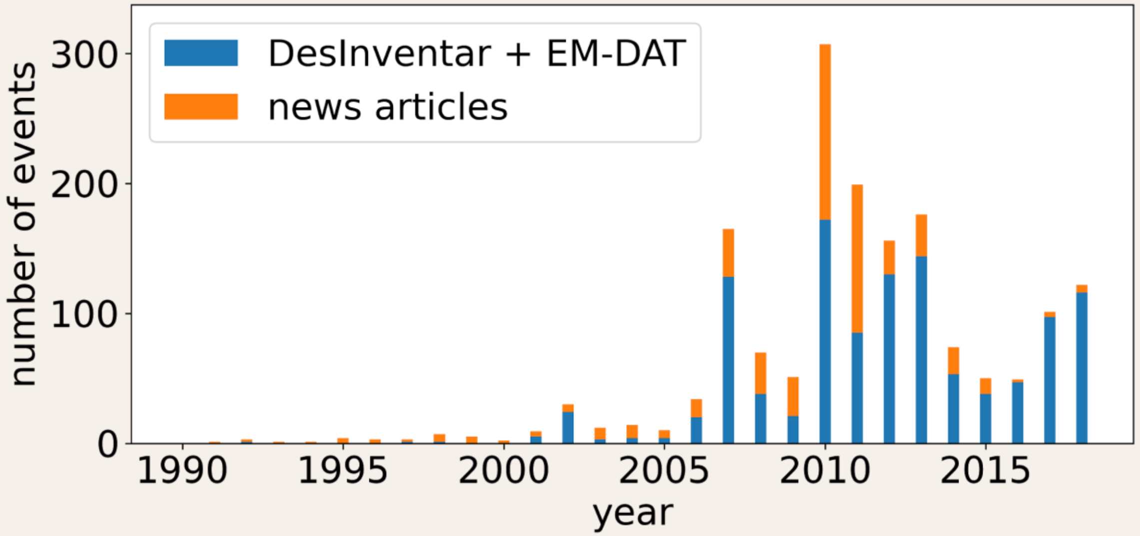
We are missing data with sufficient spatial and temporal resolution

STEP 3: 510s NEWS IMPACT MINER





Web scraping and Natural Language Processing Example for Uganda



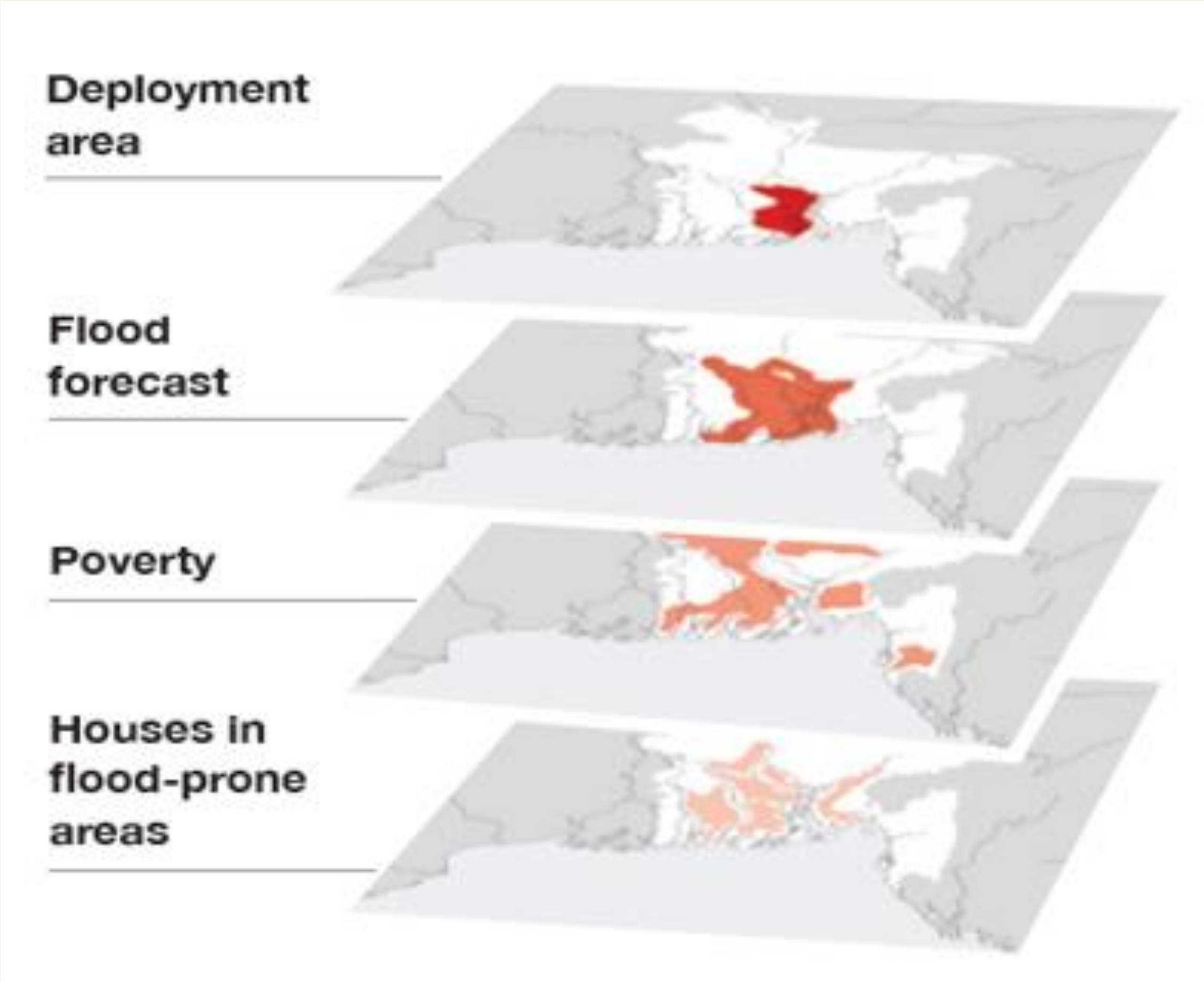
- *Text Mining of Loss Data*, Jacopo Margutti et al., EGU2020
- Enriching impact data by text mining digital media, GAR paper 2022, under review

STEP 3: HOW DO WE EXPAND IMPACT DATABASE?

		SOURCES	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
IMPACT	DATA FROM LOCAL & NATIONAL LEVEL	DMMU												
	DATA FROM GLOBAL REPOSITORIES	EM DAT												
		DESINEVNTAR												
		HUMANITARIAN DATA EXCHANGE												
	DATA FROM DIGITAL RESOURCES USING DATA & TEXT MINING	DIGTIAL NEWSPAPER REPOSITORIES												
		DISASTER RELIEF EMERGENCY FUNDS												
		SOCIAL MEDIA												

Text mining can be used to extract impact data from new sources (social media, online newspaper repositories) but fusing with other sources has to be done with care given potential biases and risk of duplications

STEP 4: COMPOSITE INDEX APPROACH



STEP 4: COMPOSITE INDEX APPROACH FOR CYCLONE


www.ifrc.org
Saving lives, changing minds.

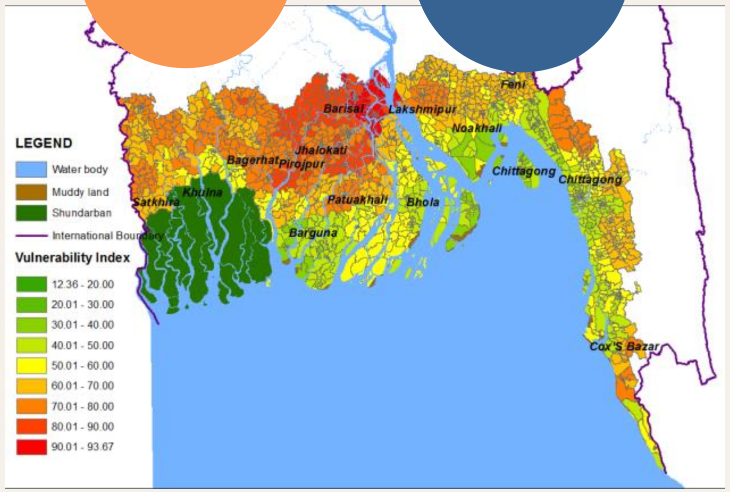
Bangladesh: Cyclone
Early Action Protocol summary

International Federation of Red Cross and Red Crescent Societies

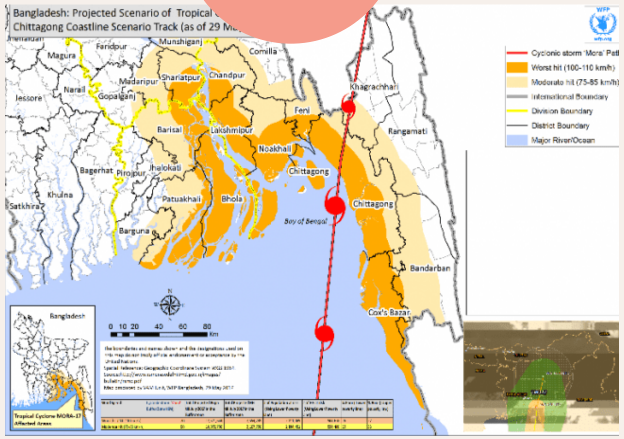
EAP APPROVED **December 2018**	**20,000 of people** to be assisted **Amount Swiss francs: 182,996**	EAP timeframe **5 Years** Early Action timeframe **1Month**

EXPOSURE

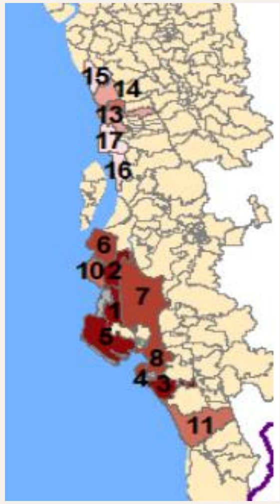
VULNERABILITY



HAZARD FORECASTED



PRIORITY MAP

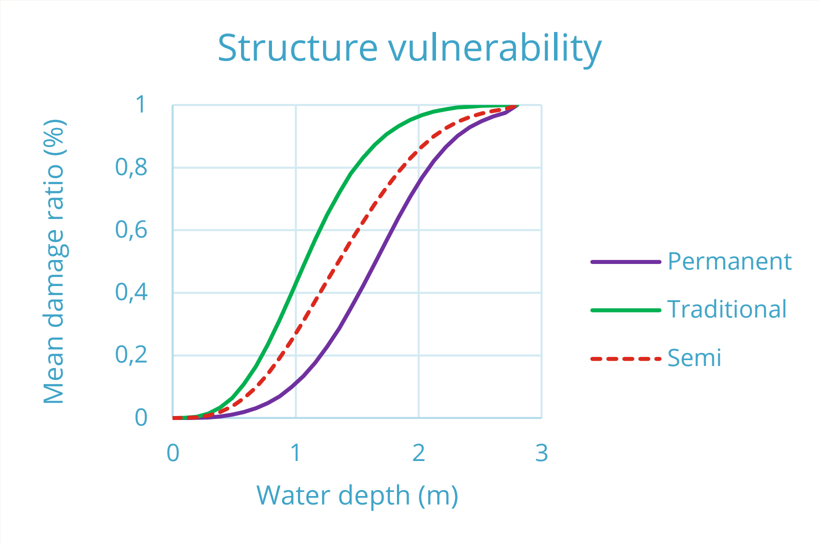


STEP 4: ELEMENTARY MODELLING FOR FLOODS

Wouters, L., et al.: Improving flood damage assessments in data scarce areas by retrieval of building characteristics through UAV image segmentation and machine learning – a case study of the 2019 floods in Southern Malawi, Nat. Hazards Earth Syst. Sci. https://doi.org/10.5194/nhess-2020-417, in review, 2021

1. Extract & classify structures (drone)

2. Estimate flood depth and extent from hydrological model (forecast) or SAR Sentinel 1 and Digital Elevation Model (response)



3. Determine –for each building- damage from damage curve based on flood depth. Sum over all buildings in area

Inez Gortzak, Marc van den Homberg, Jacopo Margutti, Christopher Beddow, Maarten van Aalst

Characterising housing stock vulnerability to floods by combining UAV, Mapillary and survey data - A case study for the Karonga district in Malawi

EGU General Assembly 2021

OBJECTIVE

Identifying the most vulnerable households (socially & physically)

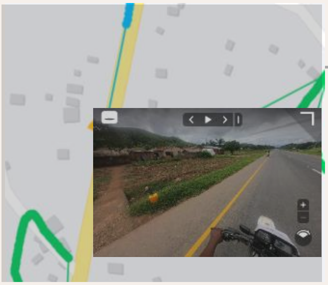
DATA & METHODOLOGY

Combining datasets to increase the number of vulnerability attributes

UAV imagery

Remote sensing (OBIA)

Rooftop material



Mapillary imagery

Machine learning + camera data

Wall material

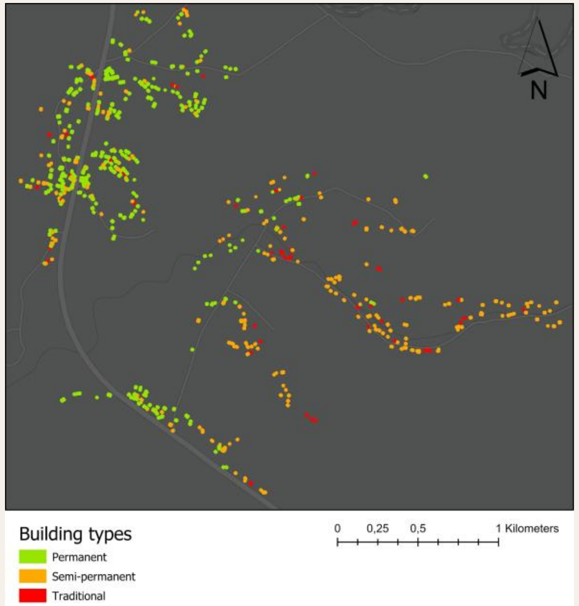
Survey data

Normalising indicator values

Social vulnerability index based on: health, wealth, education, age, household size

RESULTS

Physical vulnerability map



COMBINED WITH DAMAGE CURVES:
Flood damage scenarios

COMBINED WITH SOCIAL VULNERABILITY MAP:
Improved vulnerability targeting

CONCLUSION

Workflow for local scale physical & social vulnerability assessment

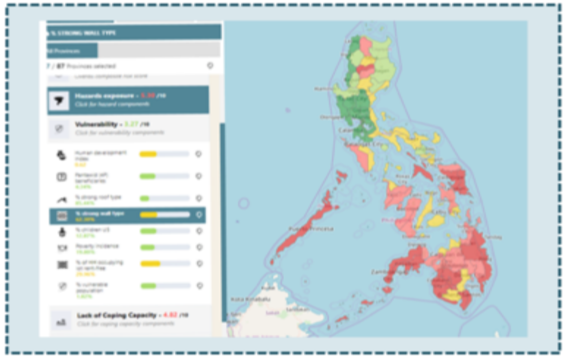
Building a bridge between datasets + increasing data value

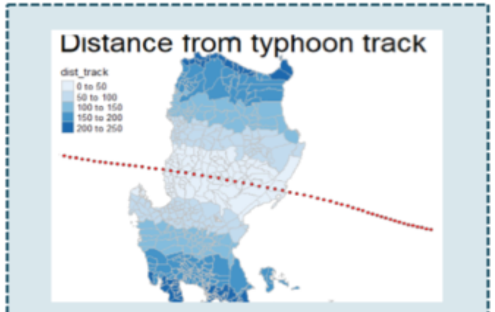
Locating the most vulnerable households for risk reduction measures

STEP 4: MACHINE LEARNING FOR TYPHOON EARLY ACTION PROTOCOL

Explanatory variables (all per municipality)

Exposure and vulnerability indicators		Hazard indicators	
Roof ty	Poverty	Rainfall	Typhoon path
Wall ty	Etc.	Wind speed	





Historical typhoons

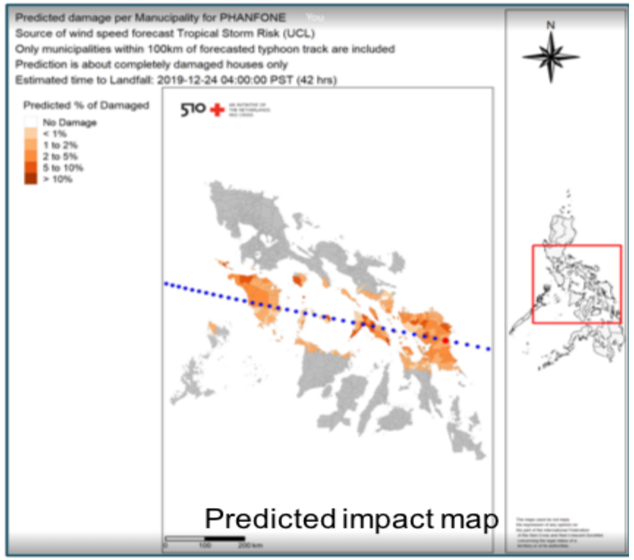
Forecast Typhoon

MODEL

Variable to be explained

Impact indicators

damaged houses (by mun.)



Predicted impact map

Aklilu Teklesadik et al.

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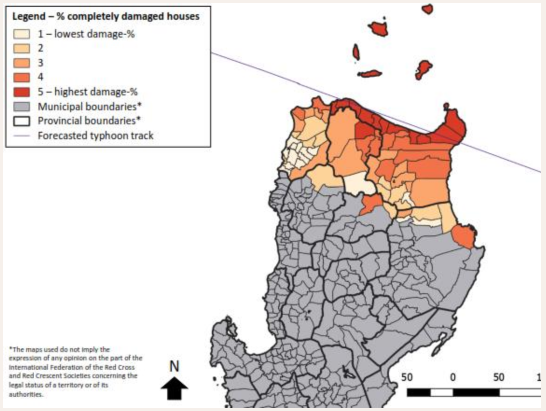
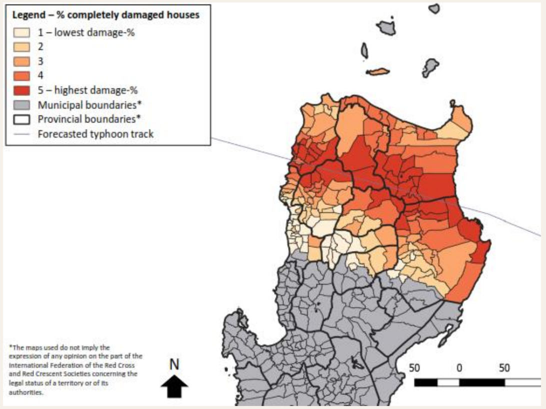
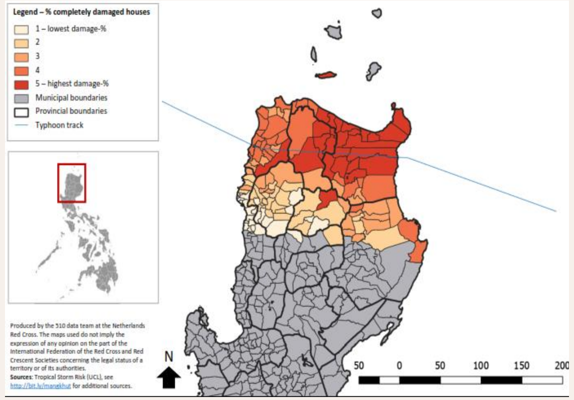
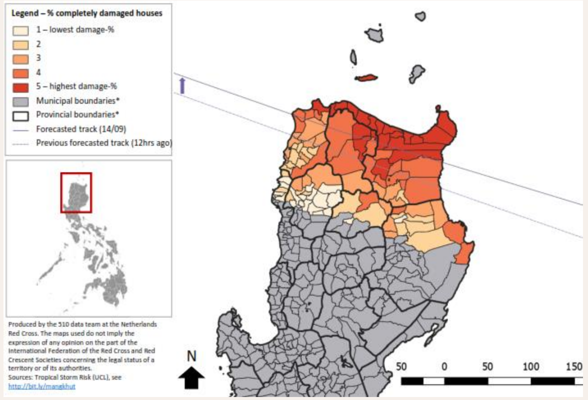
TYPHOON TRIGGER MODEL: RESULTS

72 hours | 48 hours | 24 hours | 6 hours after









Hazard	Forecasts typhoon + historical typhoon events	Typhoon that made landfall
Exposure		
Topography		
Vulnerability		

Forecast skill and Machine Learning performance metrics

Machine Learning performance metrics

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STEP 4: TYPHOON TRIGGER MODEL: OPERATIONAL WORKFLOW

1. Retrieve active typhoon name and location form GDACS
2. Check if any of this events are in Philippines Area of Responsibility
3. Download Rainfall + typhoon track data Via API (ECMWF, NOAA and UCL-TSR)
4. Preprocessing script model input- wind field for grid points
5. Run prediction model, make maps
6. Send email to relevant stakeholders

Philippine Red Cross uses the trigger since end of 2019 for activations:

- Tisoy 2019 (small scale)
- Ulysses 2020
- Goni (2020), but missed/not triggered due to rapid genesis

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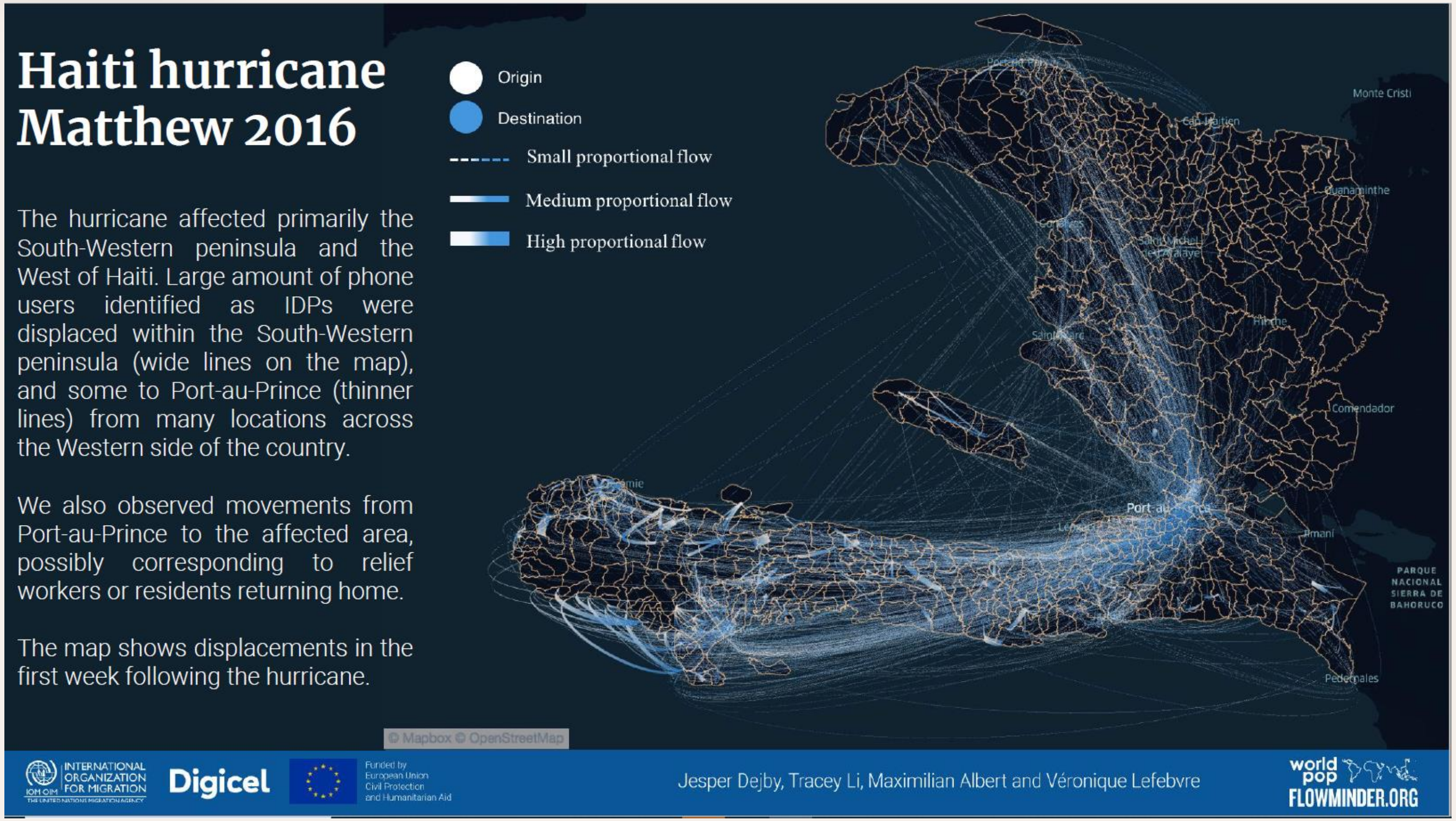
STEP 4: POPULATION MOVEMENT FORECASTING??



- Ikea Foundation Innovative Approaches to Response Preparedness
- Feasibility study
- How does the mobility behaviour of a population change right before, during, and after a flood, and can we predict that change, using Call Detail Record data?

The Netherlands Red Cross | Climate Centre | 510 AN INITIATIVE OF THE NETHERLANDS RED CROSS | BritishRedCross | Kenya Red Cross | IKEA Foundation

EMERGENCY DATA SUPPORT:
SURGE INFORMATION MANAGEMENT SUPPORT

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Remote support

Deployed

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REMOTE SUPPORT

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DEPLOYED: WE COLLECT DATA FROM THE FIELD

DRONE LAUNCH IN MALAWI

Tamas Marki @tmarki · 25 oct. 2018

This is how you launch a mapping **drone**! The data team of @MalawiRedCross with support from @510global are mapping topography in Chikwawa to have a better view on flood risk in the Shire catchments, funded by @eu_echo. @RodeKruisVL @RodeKruis @EUinMalawi @ECHO_CESAfrica

3 11

https://twitter.com/i/status/1055437783010029568

DRONES IN ST MAARTEN: BEFORE AND AFTER

https://www.510.global/before-after-irma/

AUTOMATING DAMAGE ASSESSMENTS

- Emergency responders immediately need to know:
  - WHERE are the people in need
  - HOW BAD is the situation → the scale of the damage
- How can we do it?
  - By going to the field and surveying → often impossible, takes weeks/months for large areas
  - By manually checking satellite imagery → too slow if affected area is large

- Or by ? Jacopo Margutti (Netherlands Red Cross): Automated Damage Assessment

Parallel Session B:

Extreme Events and Impacts

Valentijn, T., Margutti, J., van den Homberg, M., & Laaksonen, J. (2020). Multi-hazard and spatial transferability of a cnn for automated building damage assessment. *Remote Sensing*, *12*(17), 2839.

ACCOUNTABILITY IN "DIGITAL HUMANITARIANISM"

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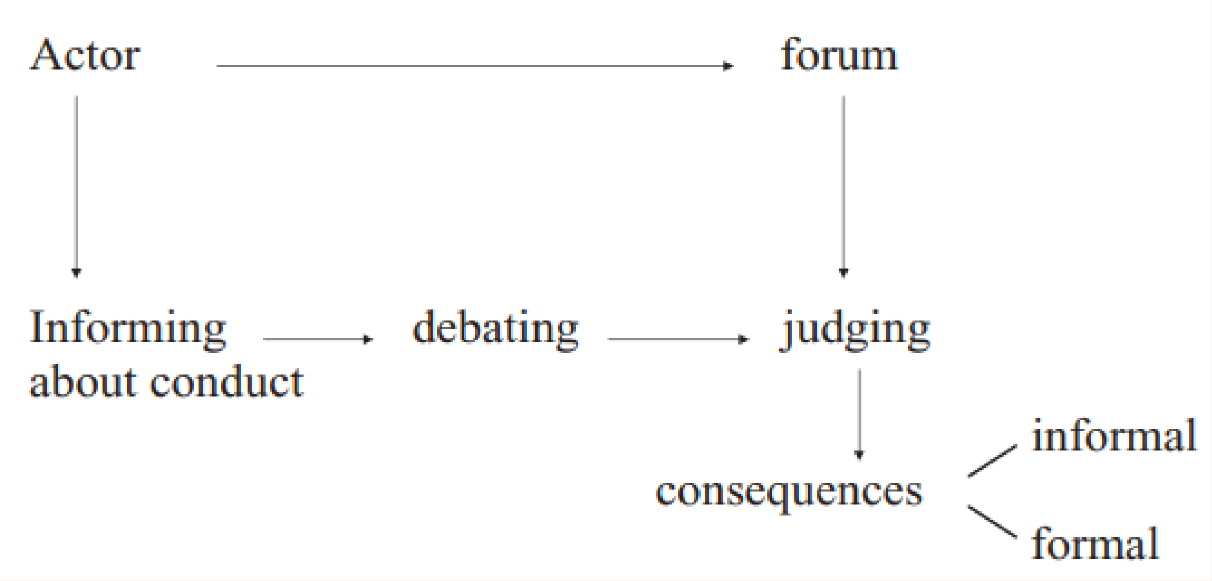
AI for triggers in anticipatory action:

- What if the trigger is missing out on people?
- What if each humanitarian organization has a different trigger?
- …

van den Homberg, M., Gevaert, C., and Georgiadou, Y. "The changing face of accountability in humanitarianism: Using artificial intelligence for anticipatory action." Politics and Governance 8, no. 4 (2020): 456-467.

- (Algorithmic) Accountability
  - Who is the **actor**?
    - Organization who initiates the early actions?
    - Algorithm developer?
    - …
  - Who is the **forum** that judges the actor?
    - To be affected people?
    - Donor?
    - Scientific/validation committee?
  - What are the **consequences** and for whom?



Bovens, M. (2007). Analysing and assessing accountability: A conceptual framework. European Law Journal, 13(4), 447–468

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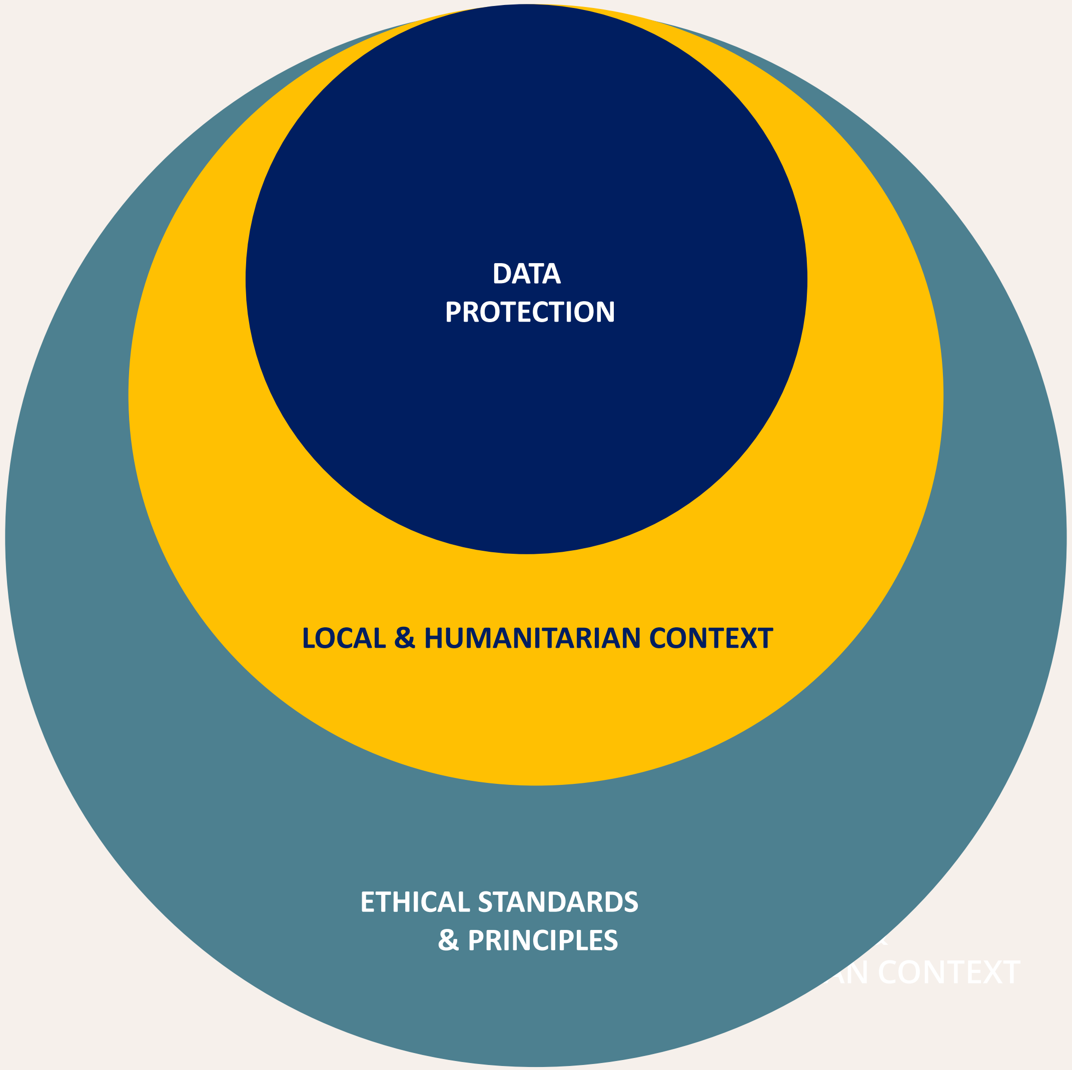
DATA RESPONSIBILITY PRINCIPLES

- PURPOSE SPECIFICATION
- MINIMIZATION
- DATA QUALITY
- RESPECT FOR THE RIGHTS OF THE DATA SUBJECT
- DATA SECURITY
- DO NO HARM
- LEGITIMATE AND LAWFUL USE



https://www.510.global/data-responsibility-v2-2/

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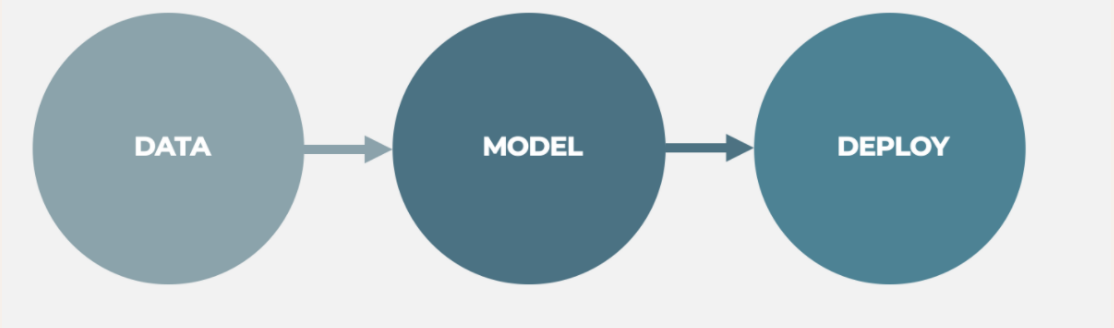
RESPONSIBLE ARTIFICIAL INTELLIGENCE

- Tool to calculate FACT score (Fairness, Accountability, Confidentiality and Transparency)



- https://rodekruis.github.io/responsible_ai/#/

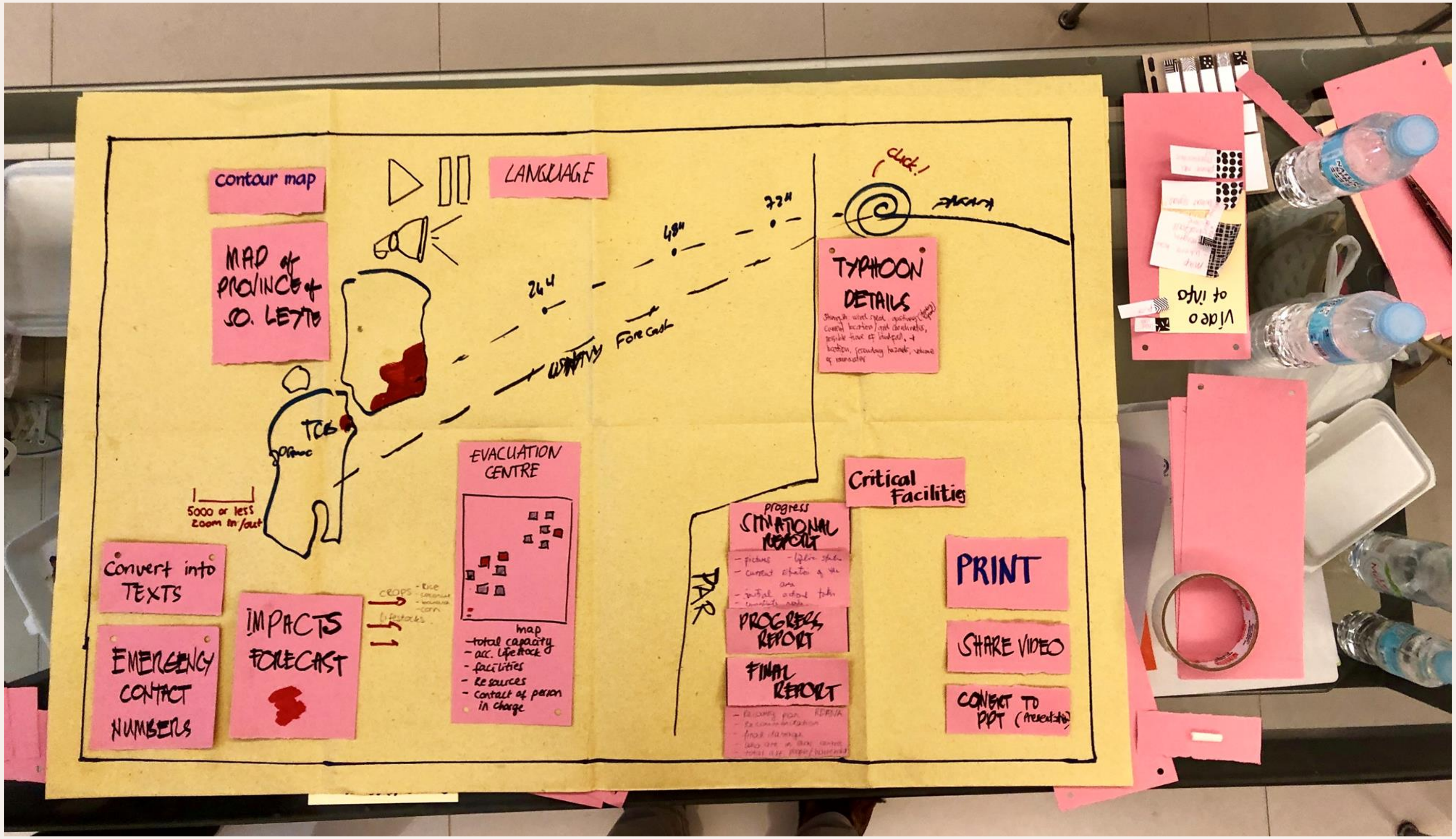
What is bias in geo-spatial data?

Project with ITC, Caroline Gevaert et al.:

- Disastrous Information: Embedding “Do No Harm” principles into innovative geo-intelligence workflows for effective humanitarian action
- VENI project “Bridging the gap between Artificial Intelligence and society: Developing responsible and viable solutions for geospatial data”

Responsible AI for DRM, https://opendri.org/wp-content/uploads/2021/05/ResponsibleAI4DRM.pdf

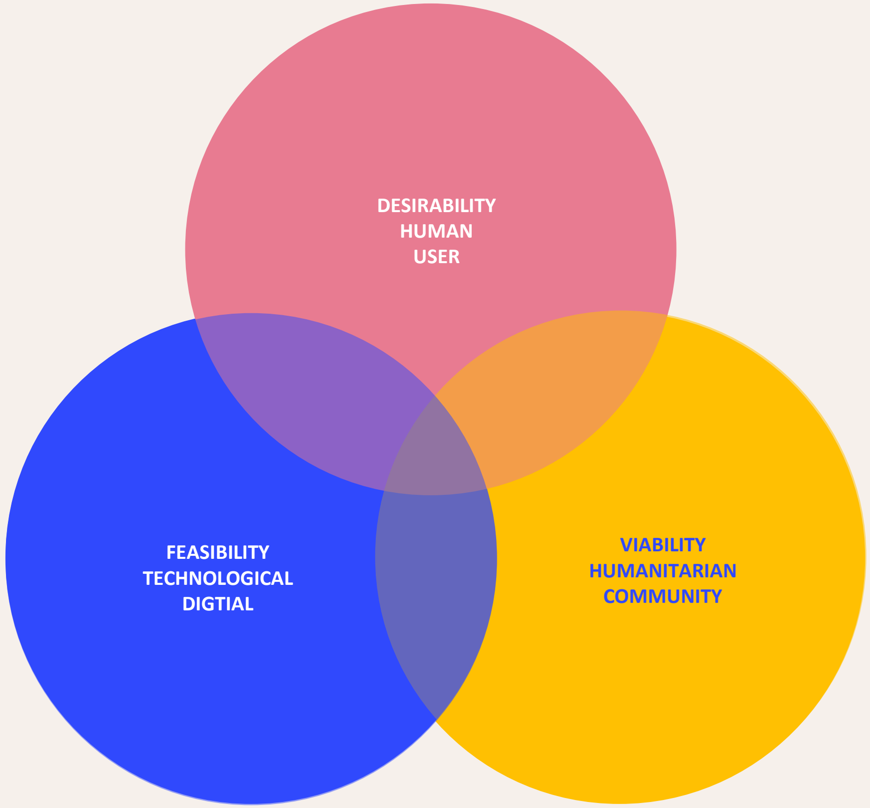
HUMAN CENTERED DESIGN



Bierens, S., Boersma, K., & van den Homberg, M. J.C. (2020). The legitimacy, accountability, and ownership of an impact-based forecasting model in disaster governance. Politics and Governance, 8(4), 445-455. https://www.cogitatiopress.com/politicsandgovernance/article/view/3161

HUMAN CENTERED DESIGN

DESIRABILITY HUMAN USER	1: CO-DESIGNS 2: CLUSTERING & SPECIFICATIONS 3: USER ACCEPTANCE TESTING
VIABILITY HUMANITARIAN COMMUNITY	3: COMMUNITY ENGAGEMENT 4: PEST ANALYSIS & ENVIRNOMENT MAP
FEASIBILITY TECHNOLOGICAL DIGTIAL	5: SYSTEM SPECIFICATIONS 6: FRONT & BACK END DEVELOPMENT 7: SOFTWARE ARCHITECTURE



HUMAN CENTERED DESIGN

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CHALLENGES: MULTIPLE GAPS

Humanitarian needs > funding

Digital divide

North-South power inequalities

Shifting accountability

Data gaps: missing primary data, high resolution satellite imagery

Between disciplines (data scientist vs DRR expert)

Between system levels (global, national to local)

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OPPORTUNITIES: BRIDGING MULTIPLE GAPS

Create data capacity locally

Anti-disciplinarity ☺

Use Big data & AI to enrich (but not replace) Small Data

Human centred design: put the user first

Upscale and downscale between global, national and local levels

Build accountability in geo-intelligence workflows

TO CONCLUDE

- Transitions at global level
  - More climate extremes, increased vulnerability
  - Digital and data revolution
- Challenges in the form of multiple gaps
- Opportunities to partially close some of these gaps
  - Use AI & big data across disaster risk management cycle, but hand in hand with:
    - Initiating and supporting local data capacity development
    - Putting the user first via human centered design
    - Building in accountability
    - Working transdisciplinary