Introductory to Disaster Risk Management and AI applications

AI for Disaster Risk Management (DRM)

Provided by Mersedeh Tariverdi

From my work in World Bank Group and with our partners' works focusing on International Development Applications

Aug 18th 2026

23 content slides **6 sections** **~90 minutes**

Official Use Only

Quantifying risks for decision making

Intersection of Public Services and Disaster Risk Management

Multi-hazard and cascading risk



Indonesia east flores, 2021

SECTION 01

01

With or without AI?

Data and AI hand in hand ~ from ML for vision ….



AI for Disaster Risk Management

OBJECTIVE Define DRM in plain language and explain why AI matters as climate risks intensify.

- DRM identifies, assesses, and help with interventions designed to reduce risks from natural hazards: floods, earthquakes, cyclones, droughts, wildfires, etc…
- Traditional DRM leaned on manual surveys, physics-based models, and slow data cycles.
- Satellites, social media, sensors, drones, and mobile data now outstrip human analysts (with some caveats!)
- Machine learning finds patterns at scale: making risk information faster, cheaper, and more comprehensive.

IN PRACTICE



05/2016



05/2017



06/2019



03/2025

Climate Change vs. DRM

OBJECTIVE Distinguish climate change as a long-term risk driver from DRM as the practical system for managing shocks.

- Climate change raises the frequency and intensity of hazards — heavier rain, stronger storms, longer droughts.
- It does not decide whether a hazard becomes a disaster — DRM does.
- Warnings, resilient buildings, and recovery resources determine the outcome.
- AI serves both sides: modeling future hazard shifts and improving DRM systems that must work today.

Actuality

Of the top 10 disasters, droughts proved to be the deadliest hazard during the period, causing 650,000 deaths, followed by storms that led to 577,232 deaths; floods, which took 58.700 lives; and extreme temperature events, during which 55,736 died.

(a)	Disaster type	Year	Country	Deaths
1	Drought	1983	Ethiopia	300 000
2	Storm (*Bhola*)	1970	Bangladesh	300 000
3	Drought	1983	Sudan	150 000
4	Storm (*Gorky*)	1991	Bangladesh	138 866
5	Storm (*Nargis*)	2008	Myanmar	138 366
6	Drought	1973	Ethiopia	100 000
7	Drought	1981	Mozambique	100 000
8	Extreme temperature	2010	Russian Federation	55 736
9	Flood	1999	Bolivarian Republic of Venezuela	30 000
10	Flood	1974	Bangladesh	28 700

WMO | Deadliest disasters in the past 50 years.

Official Use Only

The Risk Formula

OBJECTIVE Understand that risk depends on hazard, exposure, and vulnerability — not hazard alone.

Risk = Hazard × Exposure × Vulnerability

- Hazard is the physical event; exposure is who and what is in harm's way.
- Vulnerability is how susceptible people and assets are to harm and how fast they recover.
- AI helps characterize each component and combine them into integrated assessments.

IN PRACTICE

Two districts face the same flood, but informal housing, poor drainage, and weak evacuation access make one far riskier.

SECTION QUIZ

Q If two communities face the same flood depth, what two non-hazard factors most explain differing losses?

A *Exposure — what and who is in harm's way — and vulnerability — how susceptible they are to being harmed.*

Official Use Only

SECTION 02

02

Hazards: What Can Go Wrong, and Where?

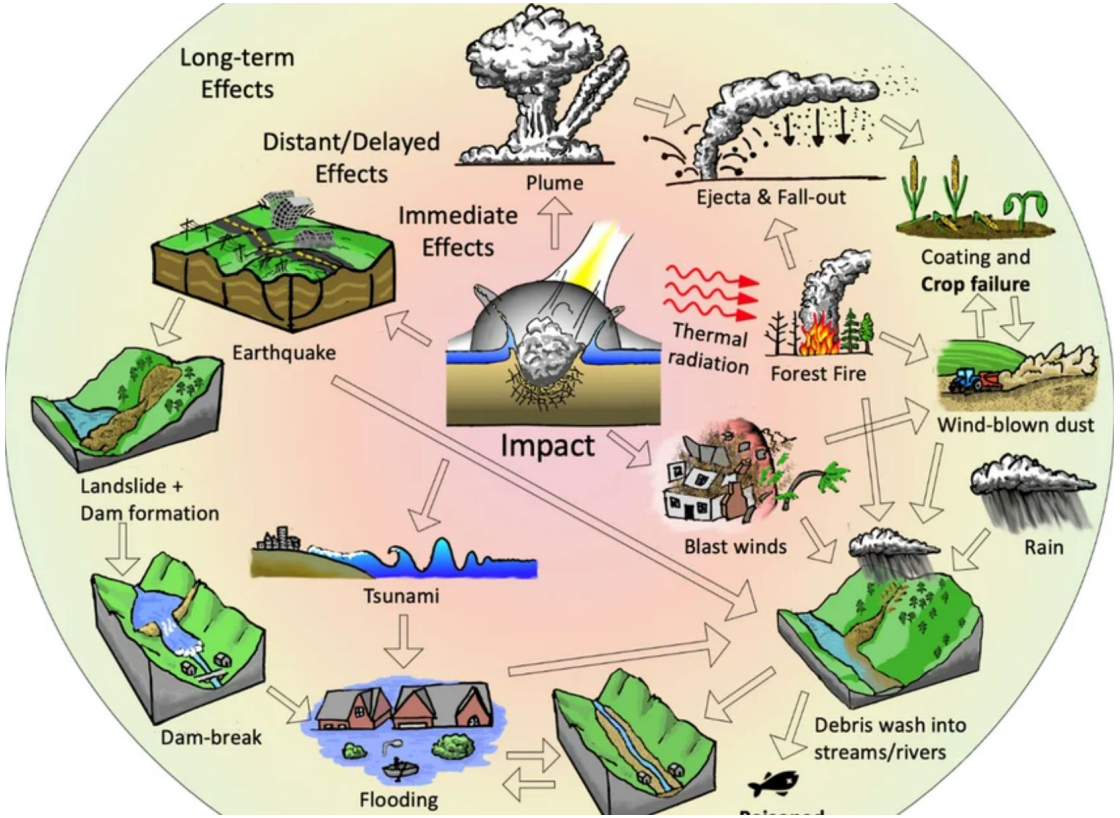
Slides 4–7 · ~20 minutes



Hazards in DRM

OBJECTIVE Identify the main hazard categories: floods, storms, droughts, heat, landslides, earthquakes, and compound events.

- Hydrological: floods and storm surges.
- Meteorological: cyclones, heatwaves, droughts.
- Geophysical: earthquakes, landslides, volcanic eruptions.
- Compound events: two or more hazards together => are increasingly common and hardest to model.
    - There are other risk factors such as fragility of governments and states, violence, and conflicts
    - Other type of shocks (pandemics, finantial, etc.)



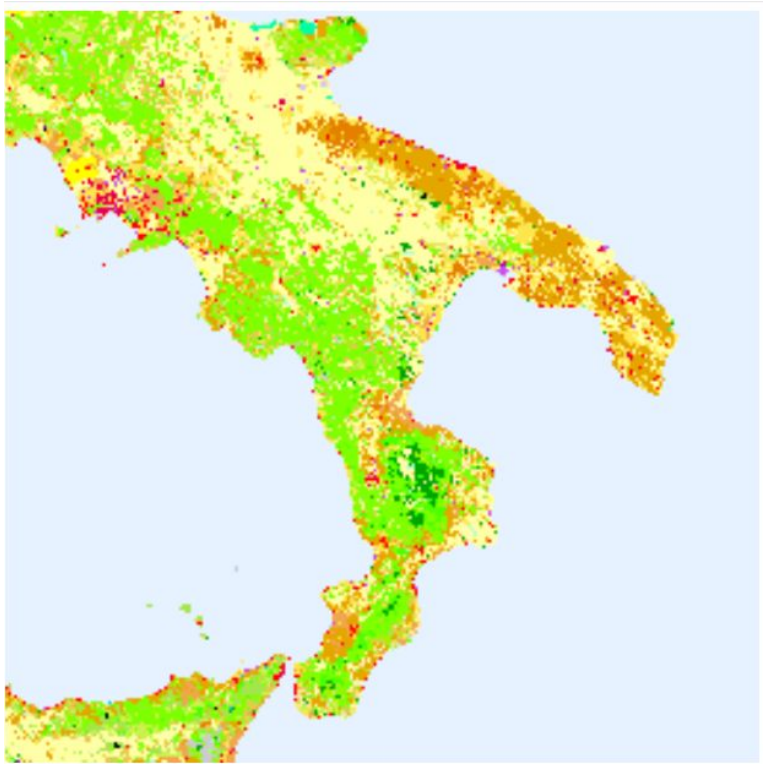
DOI:10.1007/s11069-022-05722-z

Official Use Only

AI for Forecasting

OBJECTIVE Explain how AI improves hazard forecasting by combining satellite, radar, sensor, and weather data.

- ML trained on rainfall, river levels, and imagery produces faster, lower-cost forecasts.
- It excels at very short-range nowcasting, where speed matters most.
- Cyclone impact maps can arrive up to 120 hours before landfall.
- Earlier warning enables anticipatory action and pre-positioned relief.



`ee.ImageCollection("COPERNICUS/CORINE/V20/100m")`

IN PRACTICE

In West Africa, systems fusing real-time satellite and ground-sensor data support flood monitoring and government response.

AI TECHNIQUE

ML flood / cyclone forecasting

Official Use Only

AI for Hazard Mapping

OBJECTIVE Show how machine learning produces higher-resolution hazard maps, especially where traditional data are sparse.

- Static maps of floodplains, shaking zones, and landslide slopes anchor DRM planning.
- Computer vision on satellite and drone imagery cuts mapping cost dramatically.
- Maps can be refreshed far more frequently as conditions change.
- Models trained elsewhere can transfer and fine-tune with limited local data.

IN PRACTICE

In Mozambique, AI flood mapping flags settlements likely to be cut off from roads and services during cyclone season.

AI TECHNIQUE
Computer vision on satellite imagery

https://www.esri.com/en-us/geospatial-artificial-intelligence

Official Use Only

Limits of Hazard Models

OBJECTIVE Recognize that AI does not replace physical models — predictions still need expert validation and clear uncertainty.

- Models fail under distribution shift, rare extremes, or poorly represented physics.
- Uncertainty must be communicated clearly when warnings trigger costly actions.
- Over-reliance on AI without expert validation is a safety-critical risk.
- Responsible use means rigorous validation, transparency, and human oversight.

IN PRACTICE

In small island states, AI can sharpen storm-surge resolution, but local forecasters must still translate warnings communities trust.

SECTION QUIZ

Q **Why is an accurate hazard forecast alone not enough for good DRM decision-making?**

A *Risk also depends on exposure and vulnerability, and forecasts must reach decision-makers in time and in a form they can act on.*

Official Use Only

SECTION 03

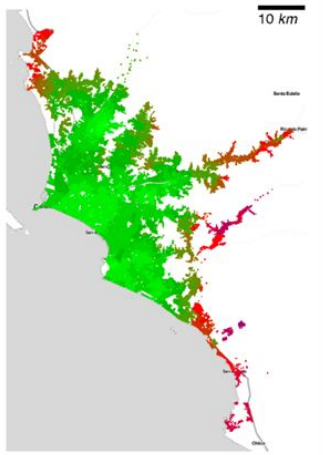
03

Assets & People: Who and What Is in the Way?

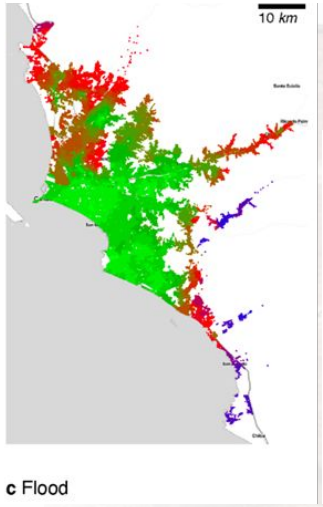


Continuous access to health services | Identifying potential bottlenecks and underserved areas





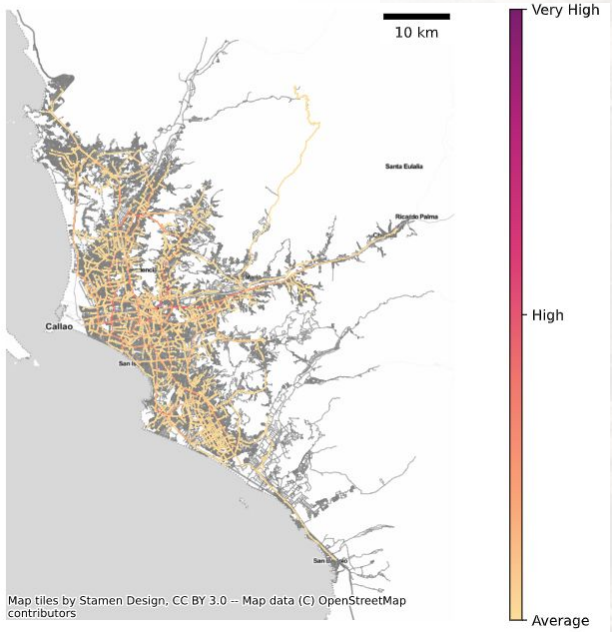
a Undisrupted



c Flood

Time (min.)

- 0 - 10
- 10 - 20
- 20 - 30
- 30 - 40
- 40 - 50
- 50 - 60
- 60 - 70
- 70 - 80
- 80 - 90
- 90 - 100



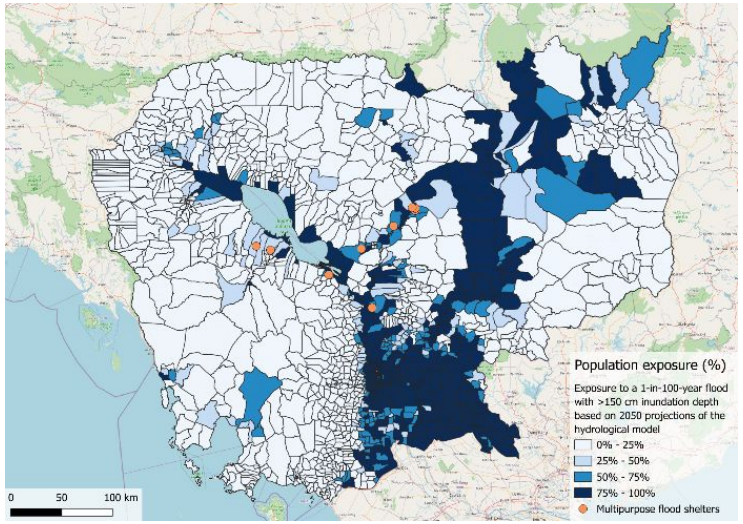


Assets at Risk

OBJECTIVE Define exposure as the people, buildings, infrastructure, and services located in hazard-prone areas.

- Exposure mapping asks a simple question: what is in harm's way?
- It covers buildings, roads, bridges, power, hospitals, schools — and the services they provide.
- Many countries have incomplete, outdated, or ungeoreferenced asset registries.
- AI-assisted mapping is filling that gap — you can't protect what you can't see.

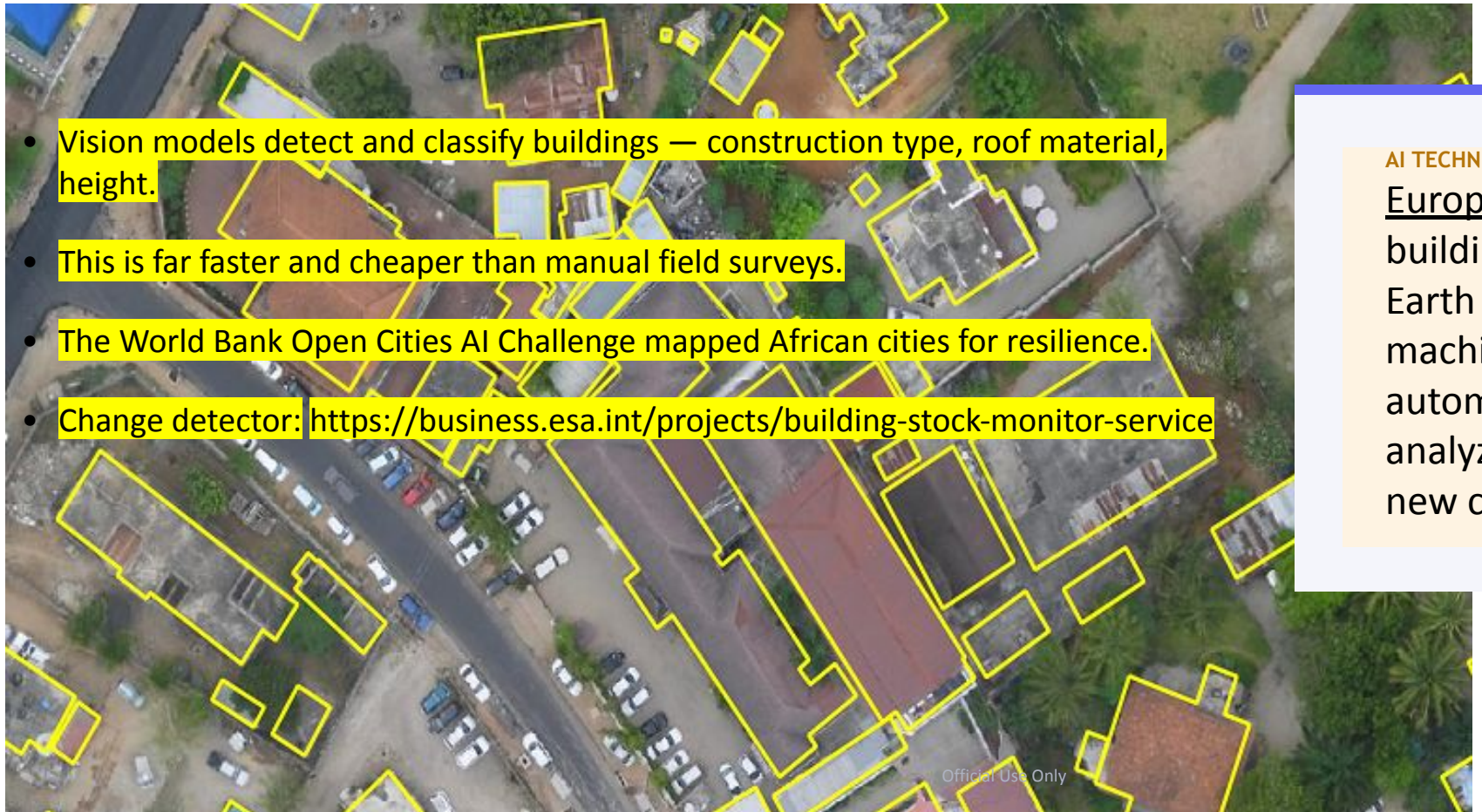
Population exposure to flood hazard and location of existing flood shelters (above), and prioritization of communes according to vulnerability and hazard exposure (below) (Cambodia, WBG report, EP&R)



Official Use Only

AI for Asset Mapping

OBJECTIVE Understand how computer vision extracts building footprints, roads, and critical facilities from imagery.



- Vision models detect and classify buildings — construction type, roof material, height.
- This is far faster and cheaper than manual field surveys.
- The World Bank Open Cities AI Challenge mapped African cities for resilience.
- Change detector: https://business.esa.int/projects/building-stock-monitor-service

AI TECHNIQUE

European Space Agency (ESA) building detection uses satellite Earth observation data and machine learning to automatically map, track, and analyze urban structures and new construction.

Official Use Only

People at Risk

OBJECTIVE Explain how exposure includes where people live, work, travel, and shelter — not just where assets are.

- Risk to people depends on when and where they are, which shifts constantly.
- A 3 a.m. flood hits homes; the same flood at noon hits the commercial core.
- Mobile plus census data with ML estimate population by time of day.
- Migration, displacement, and informal growth shift exposure beyond static census data.

IN PRACTICE

In Manila or Dhaka, daytime and nighttime population maps diverge sharply, one static map misrepresents actual exposure.

AI TECHNIQUE

Mobile data + census fusion

Mobile phone call detail records (CDRs) to infer mobility patterns within cities and across regions at high spatial and temporal resolution.

Official Use Only

Dynamic Exposure

OBJECTIVE Recognize that exposure changes over time because of urbanization, migration, and seasonal livelihoods.





SECTION QUIZ

Q What is the difference between exposure mapping for assets and for people?

A *Assets are fixed structures in hazard zones; people mapping must track where and when populations actually are — making it far more dynamic.*





AI TECHNIQUE

Big data trend analysis
Satellite change detection (fig Maxar technologies)

- Urbanization pushes populations into hazard-prone areas.
- Climate-driven migration and seasonal labor move people between places.
- Static census-based maps systematically underestimate exposure.
- Change detection on time-series imagery enables near-continuous monitoring.

Critical Use Only

SECTION 04

04

Vulnerability: Who Is Most at Risk of Harm?

Slides 12–15 · ~15 minutes



What Vulnerability Means

OBJECTIVE Define vulnerability as susceptibility to harm, and how fast people and assets recover (resilience).

- Vulnerability is distinct from exposure.
- A reinforced hospital in a floodplain is exposed but not very vulnerable.
- An earthen-walled settlement on the same plain is exposed and highly vulnerable.
- Two dimensions — physical (structure) and social (coping capacity) — are both mappable with AI.

IN PRACTICE

Poor drainage, weak housing, and limited savings make the same flood far worse in low-income neighborhoods.

Official Use Only

Social Vulnerability

OBJECTIVE Identify social factors that shape impacts: poverty, age, disability, health, gender, and access to services.

- Social vulnerability is the capacity to anticipate, cope, resist, and recover.
- Income, assets, social capital and similar provide reserves to absorb losses.
- Age, disability, and health shape the ability to evacuate or survive.
- Social networks and service access complete the picture — factors compound.

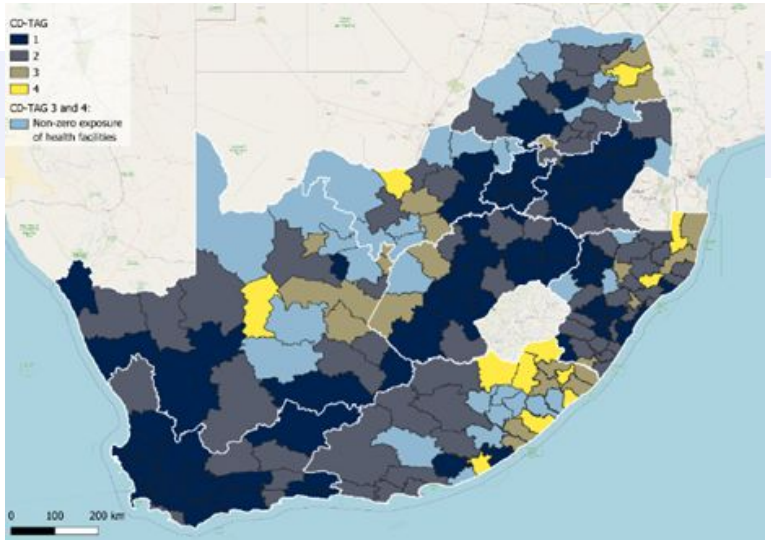
IN PRACTICE

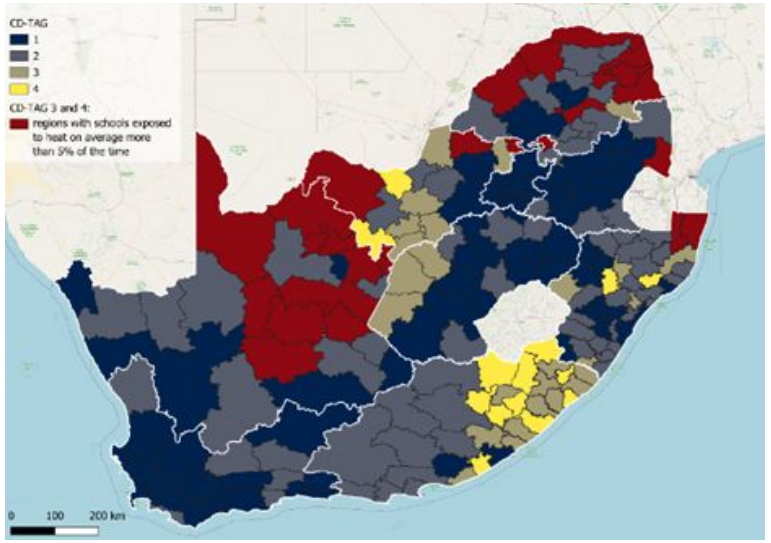
Poor road access, fragile housing, steep slopes, and no formal emergency services create high flood-mortality risk.

AI TECHNIQUE

Mixed data types and classification => Nighttime lights + poverty proxies

Compound hazard CD-TAG for healthcare sector with a focus on flood exposure (above), and education sector with focus on extreme heat (below) (WBG report, South Africa)



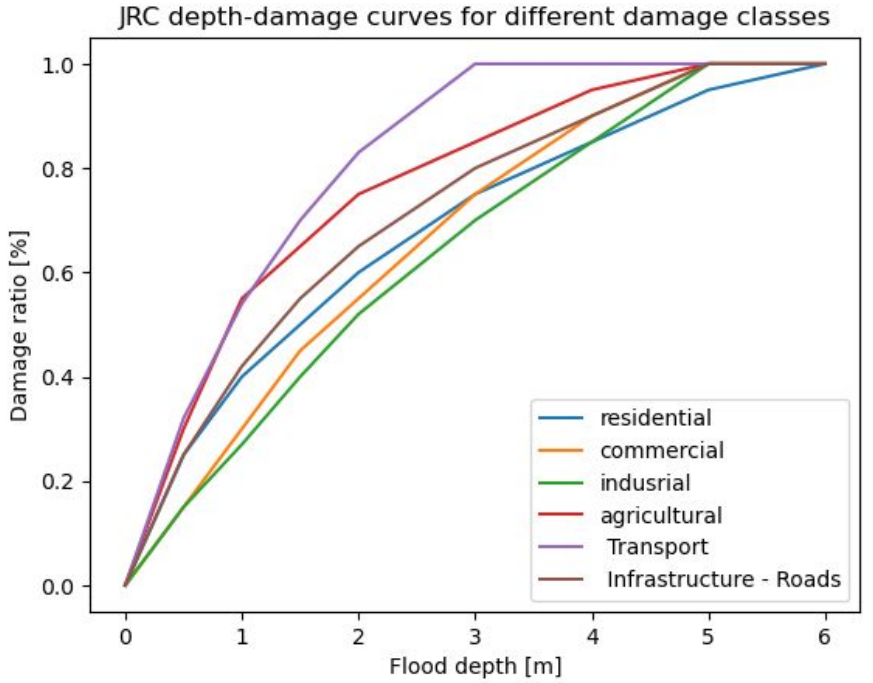


Official Use Only

Asset Vulnerability

OBJECTIVE Explain physical vulnerability of buildings — how design, materials, and maintenance affect damage levels.

- Vulnerability curves link hazard intensity to expected damage.
- Catastrophe models use them to turn hazard maps into loss estimates.
- Damage varies enormously by construction type, quality, age, and maintenance.
- The same quake ruins unreinforced masonry but spares well-designed reinforced concrete.



Sample of curves: https://handbook.climaax.eu/resources/FAQ/vulnerability_curves.html

IN PRACTICE

In cyclone-prone Madagascar, schools with light roofing and weak roof-wall links fail at lower wind speeds.

AI TECHNIQUE

ML damage curves from surveys

Official Use Only

AI for Vulnerability Assessment

OBJECTIVE Show how AI estimates social and physical vulnerability from imagery, surveys, records, and damage data.

- Satellite poverty proxies — nightlights, roofs, road density — estimate status at high resolution.
- They flag which neighborhoods lack the resources to recover.
- ML on past damage surveys learns hazard-to-damage relationships.
- That learning transfers to places without prior damage records.

IN PRACTICE

After repeated Pakistan floods, pre/post imagery refines damage probabilities by housing type; the same applies in conflict zones.

AI's role in vulnerability identification within DRM is transformative in scale and speed, but its accuracy and fairness depend entirely on whether the communities at greatest risk are centered in how the data is collected, how the models are trained, and how the outputs are used.

SECTION QUIZ

Q **A neighborhood is highly exposed to flooding but has strong housing, drainage, and services — is it necessarily highly vulnerable?**

A *No. High exposure does not mean high vulnerability. The same flood causes little damage in a resilient area and catastrophe in a fragile one.*

Official Use Only

SECTION 05

05 Risk Quantification => Putting It All Together for Across the DRM Cycle: Before, During, After

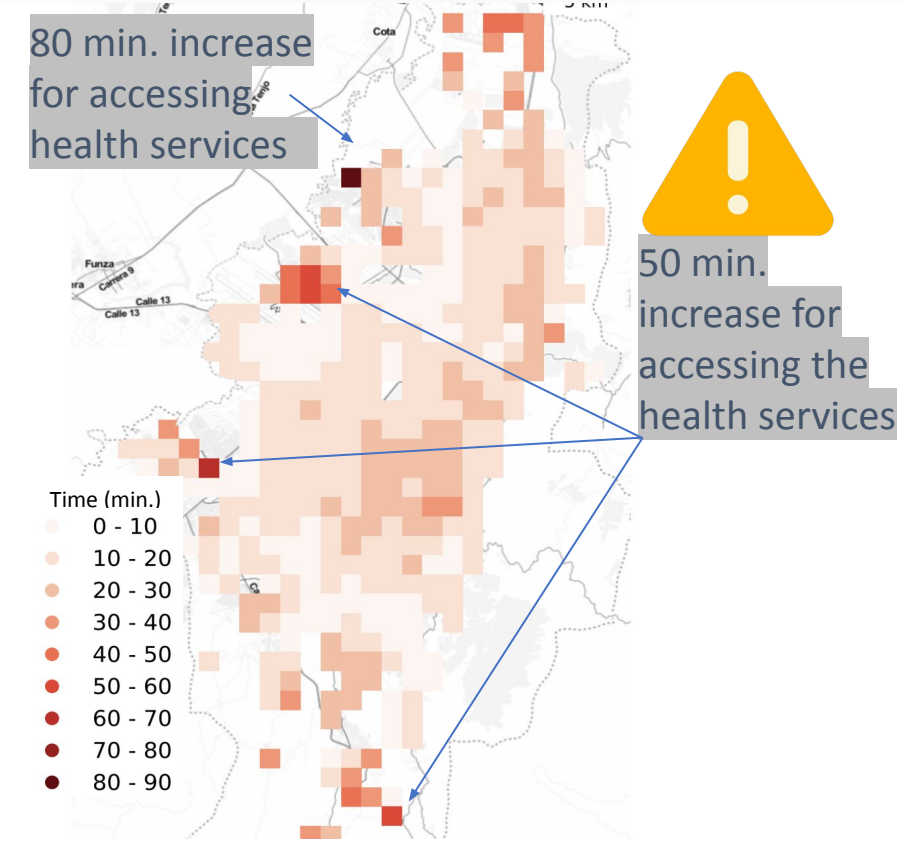


From Layers to Risk

OBJECTIVE Combine hazard, exposure, and vulnerability into a practical risk assessment framework.

- Risk quantification is the integration step ~ very much debated on what is risk to whom for what purpose
- Overlay hazard, exposure, and vulnerability to find hotspots where all three coincide => methods and thresholds are important
    - **Bias analysis, areas with lack of information would be underrepresented, population with less digital footprint would be less visible**
- Hotspots guide barriers, house-reinforcement targeting, and supply pre-positioning.
- AI improves every input layer and helps handle cross-layer uncertainty.

Change in access time of health services (WBG, Peru)



Official Use Only

Risk Quantification Basics

OBJECTIVE Understand simple risk metrics: expected annual loss, probable maximum loss, casualties, disruption, displacement.

- Expected Annual Loss (EAL): average yearly loss across many event sizes.
- Probable Maximum Loss (PML): worst case at a return period (e.g., 1-in-100-year).
- Impact metrics: casualties, people displaced, disruption days, economic loss.
- Probabilistic catastrophe models simulate thousands of scenarios — AI accelerates them.

IN PRACTICE

Estimating expected annual flood losses to roads and clinics in a secondary Mozambique city justifies drainage budgets.

AI TECHNIQUE
Probabilistic catastrophe modeling

Official Use Only

AI for Loss Estimation

OBJECTIVE Explain how AI supports loss and damage estimation when historical data are incomplete or slow to collect.

Data Acquisition: Collect coordinate-registered pre-disaster (baseline) and post-disaster GeoTIFF or high-resolution optical imagery.
Localization: Use automated segmentation or building footprints to identify structures and road networks.
Change Detection: Feed dual-temporal inputs into Siamese or dual-attention neural networks to filter out false changes like weather or lighting shifts.
Classification: Categorize structural integrity into standard tiers: *No-Damage, Minor-Damage, Major-Damage,* or *Destroyed*.

IN PRACTICE

AI post-flood imagery speeds housing-damage estimates, enabling faster shelter and cash targeting.

AI TECHNIQUE
Pre/post imagery damage classification

Official Use Only

Future Risk Under Climate Change

OBJECTIVE Show how AI tests future risk under different climate and development scenarios, including urban growth.

- AI enables scenario analysis: sea-level rise, population change and movement, upgraded codes.
- A big field now: **ML downscaling produces higher-resolution projections for local risk models.**

SECTION QUIZ

Q What is the practical difference between mapping today's flood exposure and quantifying future flood risk

? **A** *Exposure mapping describes the current state; risk quantification estimates the probability and magnitude of future losses for planning and investment.*

Official Use Only

Decisions Before Disasters

OBJECTIVE Show how AI-informed risk analysis supports prevention, preparedness, and anticipatory action.

- The highest-value use of DRM is reducing risk before disasters strike.
- Prevention: identify where to invest in risk reduction.
- Preparedness: optimize early-warning systems and response plans.
- Anticipatory action: forecast-based financing releases funds before impact.

IN PRACTICE

Triggering early cash or livestock support before drought deepens in the Horn of Africa protects livelihoods that can't be recovered.

AI TECHNIQUE
Forecast-based financing triggers

Official Use Only

Decisions During Disasters

OBJECTIVE Explain how AI supports situational awareness, routing, shelter planning, and emergency prioritization.

- Responders need rapid, accurate situational awareness.
- AI on real-time imagery, social media, and sensors maps the evolving picture.
- ML routing finds the best paths around disrupted road networks.
- These capabilities are nascent in many developing contexts but growing fast.

IN PRACTICE

Real-time flood image analysis in West Africa flags inundated areas and blocked routes for faster rescue deployment.

Official Use Only

Decisions After Disasters

OBJECTIVE Understand how AI accelerates damage assessment, recovery prioritization, and model updating after events.

- Priorities: rapid damage assessment, recovery planning, and learning.
- Automated damage classification replaces weeks of survey with hours.
- ML needs-assessment cross-references damage with population and vulnerability.
- Every event is a chance to update the underlying risk models.

IN PRACTICE

After a Malawi cyclone, AI damage assessment targets reconstruction funds — with satellite maps available within 72 hours.

AI TECHNIQUE
AI-assisted needs targeting

Official Use Only

SECTION 06

06 Responsible and Actionable AI



SECTION 06 · RESPONSIBLE and ACTIONBLE AI

Choosing High-Value Use Cases and build foundations for scale up

OBJECTIVE Prioritize AI use cases by data availability, decision relevance, institutional capacity, and equity impact.

- Data availability: is there enough quality data to train and validate?
- Decision relevance: does the output improve a specific risk-reducing decision?
- Institutional capacity: can the agency maintain and interpret it?
- Equity impact: does it reach the most vulnerable, or only the already-served?

SECTION QUIZ

Q In a resource-constrained country, what makes an AI DRM use case high priority — technical sophistication or decision usefulness

? **A** *Decision usefulness. Simpler tools that inform real decisions made by real institutions reduce more risk than advanced tools that don't.*

Official Use Only

Responsible AI in DRM

OBJECTIVE Identify governance risks: bias, opacity, data gaps, exclusion, privacy, and overconfidence in automation.

- Models can encode the biases in their training data — undercounting poor or informal areas.
- Opacity — the black-box problem — obscures why a model produced an output.
- Data gaps leave the highest-risk populations least represented.
- Privacy risks arise from mobility, financial, or health data; overconfidence is a recognized danger.

IN PRACTICE

A model trained only on formal neighborhoods underperforms in informal settlements — precisely where vulnerability is highest.

Official Use Only

Human-Centered Implementation

OBJECTIVE Understand why AI outputs must combine with local knowledge, frontline institutions, and trusted warnings.

- AI generates outputs; humans make decisions.
- The chain runs from model to community member, official, engineer, and finance minister.
- Every link needs communication, trust-building, capacity, and community validation.
- Local knowledge frequently reveals AI errors that would otherwise cause harm.

IN PRACTICE

In small island states, warnings using unfamiliar language or geography go unheeded — even when the forecast is technically accurate.

Official Use Only

Recap and Discussion

OBJECTIVE Explain AI's role across the core chain: hazards + assets and people + vulnerability → risk → better decisions.

AI improves every step of this chain — but works best when embedded in functional institutions, validated with local knowledge, and designed to reach the most vulnerable.

- Characterize the hazard: what could happen, where, how intensely.
- Map exposure of assets and people in harm's way.
- Assess vulnerability — susceptibility to harm.
- Quantify risk and support better decisions across the before / during / after cycle.

In class activity

Closing activity: each participant picks one AI DRM use case for their context and names its data, decision, and institutional needs.

SECTION QUIZ

Q What is one reason a technically accurate AI model can still fail in DRM practice?

A Many: outputs not communicated in an actionable form; not validated locally; institution lacks capacity; vulnerable groups excluded from data; or no human oversight.

Official Use Only

REFERENCE

AI Use Cases by DRM Component

DRM Component	AI Application	Developing-Country Example
Hazard — Forecasting	ML flood / cyclone forecasting	Anticipatory action before drought, Horn of Africa
Hazard — Mapping	Computer vision on satellite imagery	Flood-zone mapping in Mozambique
Exposure — Assets	Building detection & classification	Open Cities AI mapping, West African cities
Exposure — People	Mobile data + census fusion	Dynamic population mapping in Dhaka
Exposure — Dynamic	Satellite change detection	Informal settlement growth, East Africa
Vulnerability — Physical	ML damage curves from post-event surveys	Housing damage prediction after Pakistan floods
Vulnerability — Social	Nighttime lights + poverty proxies	Social vulnerability mapping in Freetown
Risk Quantification	Probabilistic catastrophe modeling	Expected annual flood losses in Dar es Salaam
Post-Disaster Assessment	Pre/post imagery damage classification	Cyclone damage mapping in Malawi
Anticipatory Action	Forecast-based financing triggers	Drought cash-transfer triggers in Kenya
Recovery Prioritization	AI-assisted needs targeting	Reconstruction fund allocation in Nigeria

Official Use Only