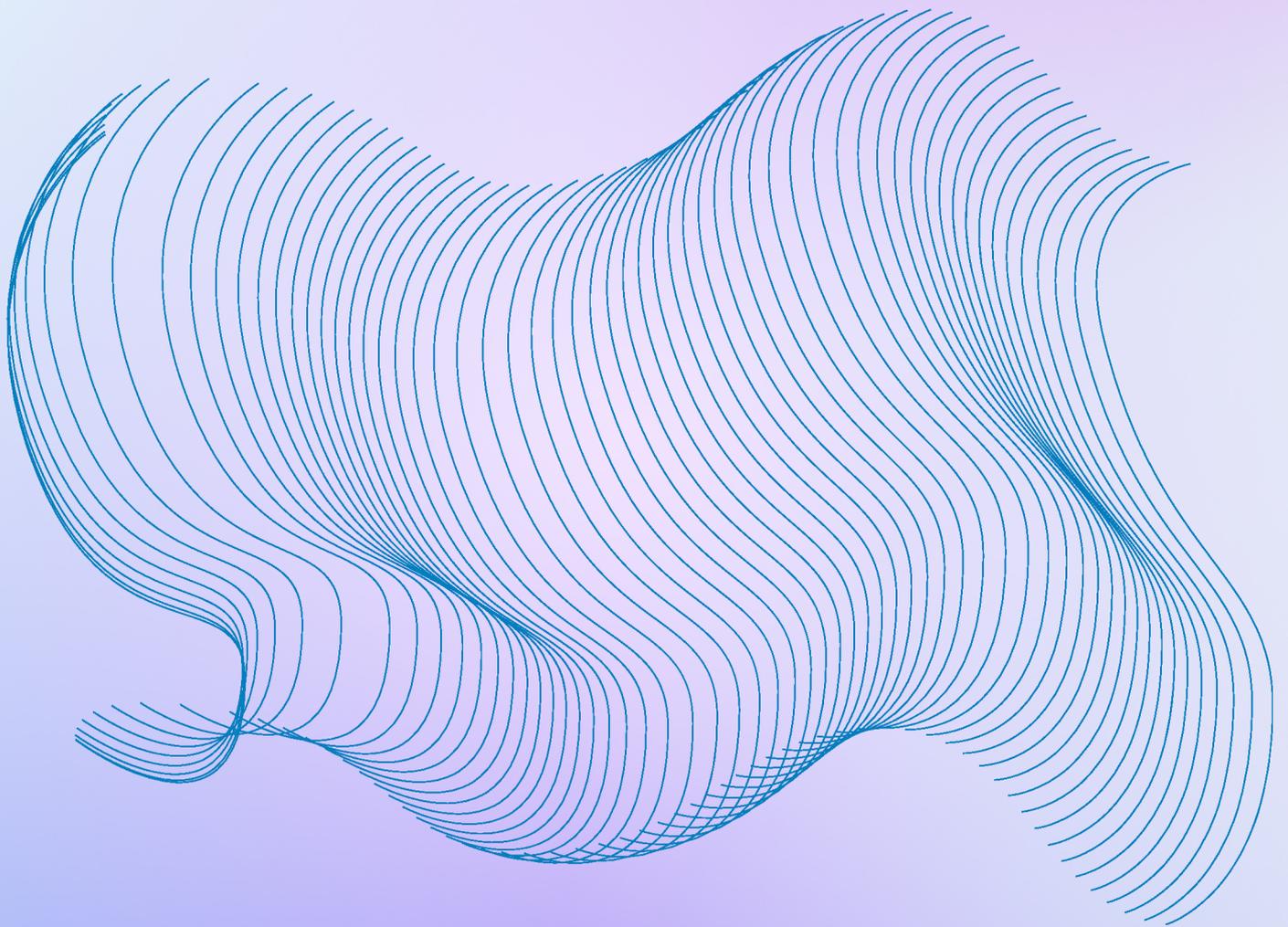
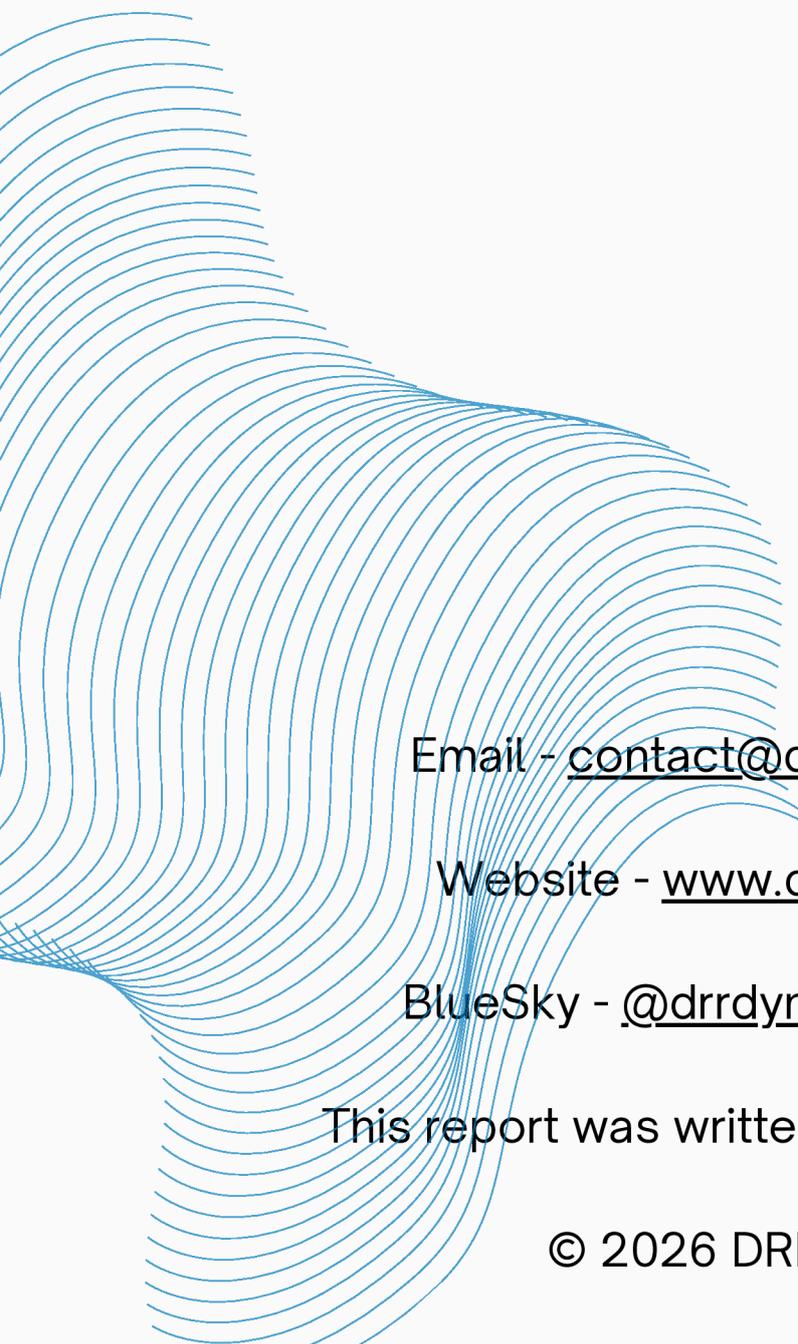


A.I. in Inclusive DRR

The basics.



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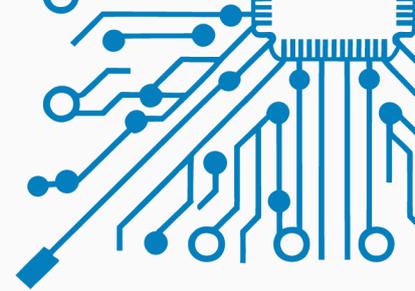
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Artificial intelligence (AI) is increasingly presented as the future of disaster risk reduction. Governments, UN agencies and private sector partners are investing in predictive models, automated damage assessments and algorithm-driven decision systems.

The language of innovation, efficiency and scale is everywhere.

As conversations increasingly focus on expanding and accelerating the use of AI in disaster systems, there is a more fundamental question that risks being overlooked: *before exploring further avenues of progress, are the systems we are building inclusive enough to be implemented responsibly in the first place?*

Only once we understand how these systems function can we assess what they mean for marginalised communities.



The basics: What is AI in practical terms?

Artificial intelligence is not a single tool. It is a broad term used to describe computer systems that can perform tasks which normally require human judgement. In disaster contexts, this usually means recognising patterns in large datasets and using those patterns to generate predictions or recommendations.

Most of the AI used in disaster risk reduction relies on machine learning. Machine learning systems are trained using historical data. The system analyses examples from the past, identifies statistical patterns and then applies those patterns to new data.

For example, imagine a model trained on 20 years of rainfall data, river levels and recorded flood events. The system identifies which combinations of rainfall intensity, soil saturation and river flow have previously resulted in flooding. When new rainfall data is added, the system estimates the probability of flooding based on those learned relationships.

The system does not “understand” floods. It identifies correlations in data.

This distinction matters. AI systems are only as good as the data they are trained on and the assumptions built into their design.

Where is AI currently being used in DRR?

AI applications in DRR generally fall into several categories.

Hazard forecasting. Machine learning models are used to refine predictions of floods, droughts, landslides and storms by combining meteorological data with satellite imagery and historical records.

Exposure and risk mapping. AI can analyse satellite images to identify informal settlements, changes in land use or infrastructure vulnerabilities.

Damage assessment. After a disaster, image recognition systems can classify damaged buildings more quickly than manual surveys.

Anticipatory action. Predictive models can trigger early cash transfers or pre-positioning of supplies when certain thresholds are met.

Targeting and prioritisation. Algorithms can support decisions about which communities or households receive assistance first.

In each of these areas, the promise is speed, scale and efficiency. In a world where disasters are increasing in frequency and intensity, this promise is attractive.



Why are DRR actors drawn to AI?

Disaster risk reduction operates under pressure. Climate change is altering hazard patterns. Urban populations are growing. Budgets are constrained. Expectations for rapid response are high.

AI offers several perceived advantages.

First, processing power. Large volumes of data can be analysed quickly. This is particularly valuable when integrating meteorological data, satellite imagery and demographic information.

Second, consistency. Automated systems can apply the same criteria across large geographical areas, reducing variation in decision-making.

Third, predictive capacity. AI can identify patterns that may not be immediately visible to human analysts.

Fourth, optimisation. Resource allocation models can help agencies distribute limited funding or supplies more strategically.

These benefits are real. However, they are technical benefits. Disaster risk reduction is not only technical. It is social, political and deeply shaped by inequality.

Inclusion begins with visibility

To understand the inclusion implications of AI, we must start with a basic feature of how these systems work: they rely on data.

AI models are trained on datasets that reflect existing governance systems. These datasets might include census data, social protection registries, insurance records, mobile phone data, health records or satellite imagery.

But not everyone is equally visible in these systems.

Some people are absent from official registries. Undocumented migrants may avoid formal registration. People experiencing homelessness may not have fixed addresses. Informal workers may not appear in employment records. Gender and sexual minorities in hostile legal environments may avoid disclosure.

When AI systems are trained on incomplete or biased data, they reproduce those gaps. The model does not know who is missing. It treats the available data as reality.

Inclusion, therefore, is not an add-on consideration. It is embedded in the data foundation.

If the baseline dataset underrepresents certain communities, the model's predictions and recommendations will reflect that underrepresentation.



Assumptions built into systems

AI systems do not only reflect data gaps. They also reflect design assumptions.

For example, many social protection systems assume stable households with clear documentation. If an AI model is built to prioritise households based on property ownership records or tax data, people outside those systems may be invisible.

Early warning systems increasingly rely on mobile phone networks. If alerts are sent primarily through smartphone apps or SMS systems, those without reliable phone access may not receive them.

Risk models often use formal infrastructure maps. Informal settlements that are poorly mapped may appear less exposed than they actually are.

These are not technical errors. They are the result of designing systems around formal governance structures.

Hyper-marginalised groups, by definition, often sit outside or at the edges of those structures. If AI is layered onto systems that already struggle to recognise them, automation can entrench exclusion.

Automation and decision-making

Another basic feature of AI systems is that they can influence decisions at scale.

If a predictive model determines which districts are high risk and should receive anticipatory cash transfers, that model shapes resource distribution. If an algorithm ranks communities based on vulnerability scores, those rankings influence prioritisation.

Automated systems can create distance between decision-makers and affected populations. When outputs are presented as data-driven, they may appear objective.

However, objectivity is not guaranteed. AI models are built by people who choose which variables to include, how to define risk and what outcomes to optimise.

For example, a model designed to minimise financial losses may prioritise economically productive areas. A model focused on infrastructure damage may overlook social vulnerabilities.

Without transparency and accountability, automated decision-making can obscure value judgements rather than eliminate them.

The digital divide

The digital divide is another foundational issue.

Digital systems assume access to devices, connectivity and digital literacy. In many contexts, access is uneven. Women and girls may have less access to mobile phones. Rural communities may experience limited connectivity. Older persons may have lower digital literacy.

If disaster systems shift towards app-based registration, biometric verification or online feedback platforms, participation may require digital access.

AI-driven systems often intensify reliance on digital data streams. If inclusion is not deliberately addressed, those already marginalised in digital spaces may be further excluded in disaster systems.

Why inclusion must shape the debate from the start

The purpose of raising these issues is not to argue against AI. It is to argue that inclusion cannot be treated as a secondary consideration.

If AI is framed purely as a technical upgrade, inclusion risks being discussed only after deployment, when exclusion patterns are already embedded.

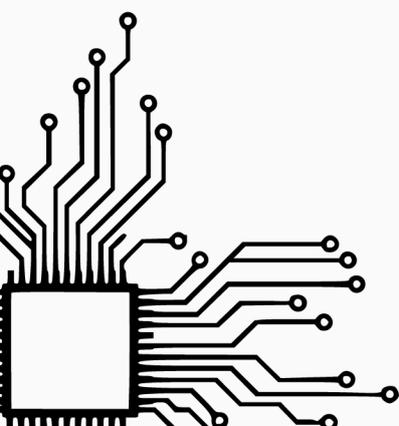
A more responsible approach begins with questions such as:

- Who is represented in the training data?
- Who is missing, and why?
- What assumptions about households, identity and access underpin the system?
- How can individuals challenge automated decisions?
- What non-digital pathways remain available?

These are basic governance questions. They are not specialist concerns.

Disaster risk reduction has long recognised that risk is socially constructed. Exposure and vulnerability are shaped by inequality, discrimination and power relations. AI systems operate within those same structures.

If we accept that disaster risk is not neutral, we must also accept that AI systems used to manage that risk are not neutral.



Artificial intelligence offers tools that can strengthen disaster risk reduction. It can improve forecasting, accelerate damage assessments and support anticipatory action.

But these tools do not exist in isolation. They are embedded in governance systems that already struggle to see and support hyper-marginalised communities.

Understanding the basics of how AI works makes one point clear: these systems learn from existing data and operate within existing assumptions. If those foundations are unequal, automation will not correct them.

Inclusion is not a separate conversation to be added once systems are built. It must shape how we design, train, deploy and govern AI in disaster contexts from the outset.

The real question is not whether AI belongs in disaster risk reduction. It is whether we are willing to align its adoption with the principles of equity and accountability that inclusive DRR has long argued for.

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