Global Mapping of Exposure and Physical Vulnerability Dynamics in Least Developed Countries using Remote Sensing & Machine Learning

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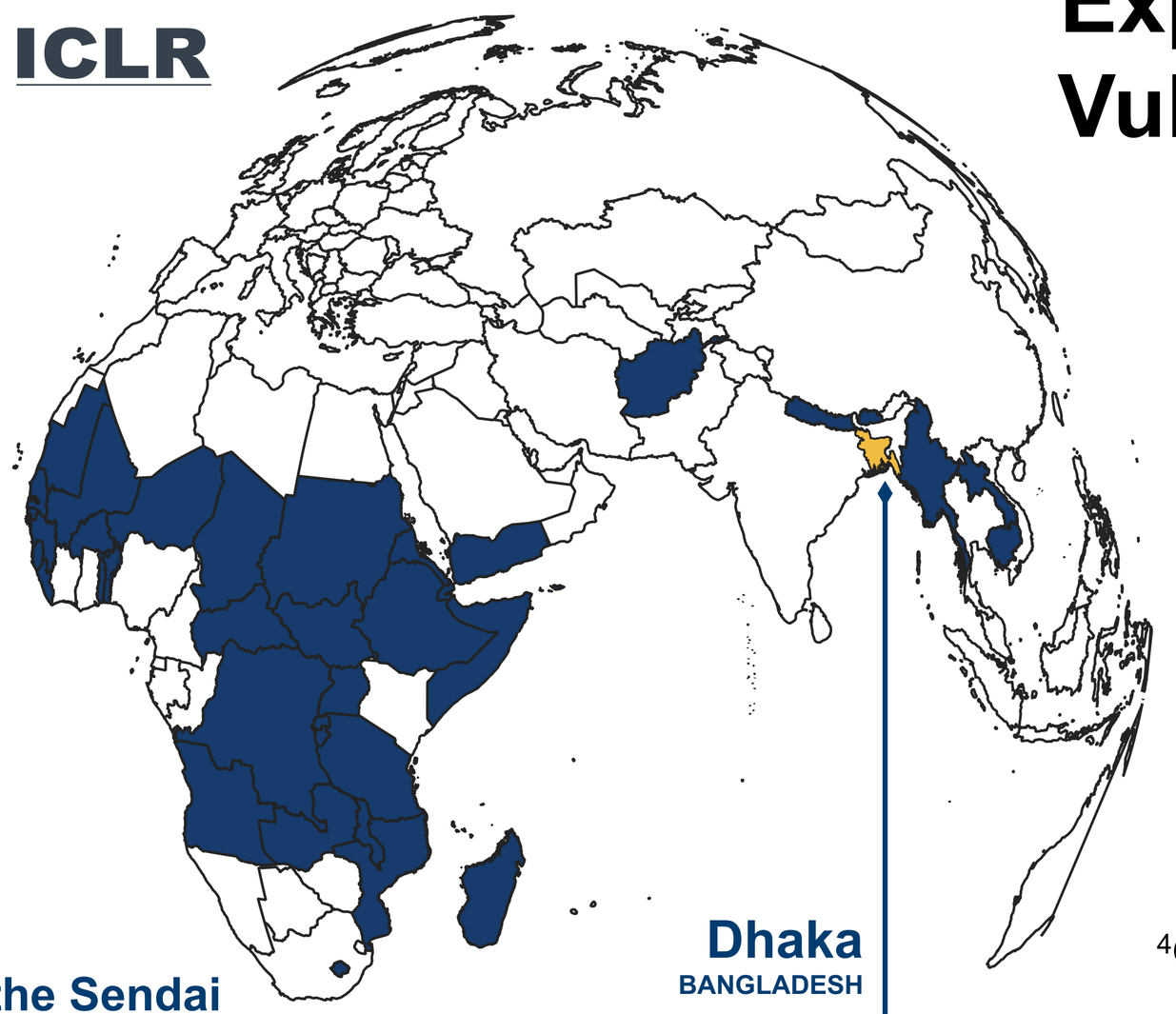
IS THE WORLD ON TRACK TO REDUCE CLIMATE & DISASTER RISK?



In 2023, the UN Midterm Assessment of the Sendai Framework for Disaster Risk Reduction 2015-2030 reported:

The expensive large-scale operation to standardize [***exposure*** datasets (human settlements) with different & incomplete ***physical vulnerability*** (building material & construction type)] has remained the **primary bottleneck** to providing **a reliable understanding and audit of the evolving climate and disaster *risk* globally.**

Detection of buildings alone is not enough to understand climate and disaster risks.

Redefining the binary task of building detection to characterize **[relevant physical vulnerability]** that are being used in the catastrophe modelling practice.

With big [Earth Observation] data comes big responsibility; risky AI for risky disasters is highly interdisciplinary.

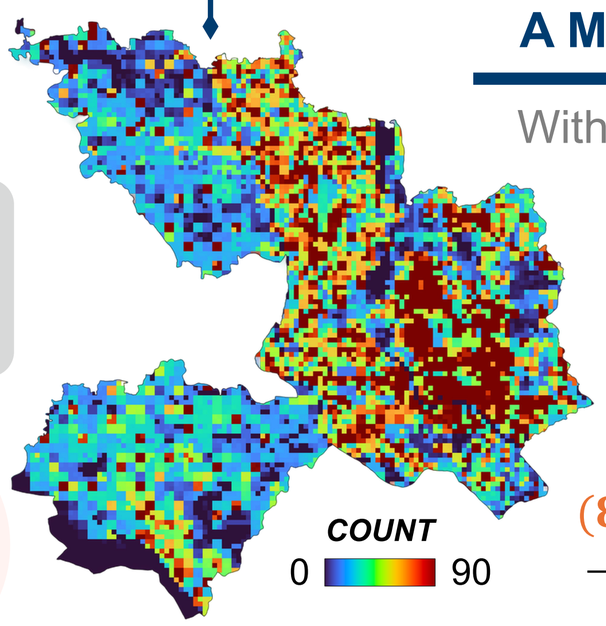
Building **a global benchmark dataset as a public good** with a focus on **underrepresented & high-risk areas** ensures fairness and transparency to address our **risk reduction gap**.

National Census-Derived Exposure Data

Open Time-Series Satellite Imagery Data
Google Earth Engine

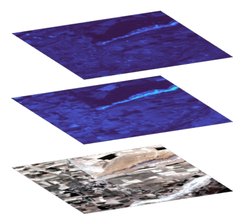
Each has its own **probabilistic model for vulnerability** that is derived analytically (physics) or heuristically (expert opinion).

INF Informal Construction
UFB Unreinforced
W Wooden
C3L Nonductile
M Mud walls



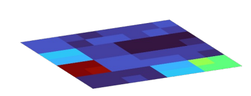
A Multi-resolution Multi-pixel Framing

With $N = 100$ **tiles** per country, each has:



VV
VH
RGB

size: $(372, 372, 5)$

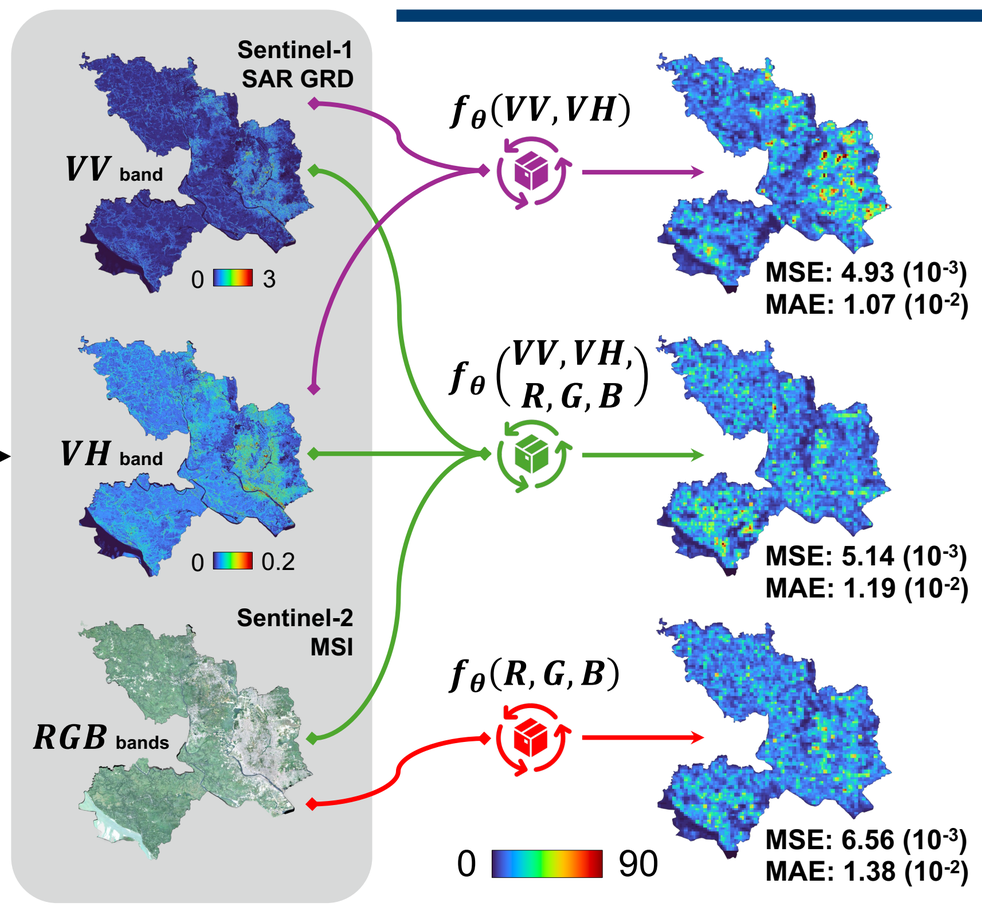


$GROUND\ TRUTH$

$(8, 8, number\ of\ vulnerability\ types)$

$\rightarrow P_{nonexceedance}$ via lognormal fit

Using ResNet-50 Convolutional Neural Network (f_θ)



While the initially trained models tend to **underestimate** the large values of **[informally constructed buildings]**, it is still capable of **identifying areas with relatively high & low counts.**

What's Next?

- **Use** elevation maps as **prior belief**
- **Localize** studies such as cities in **Bangladesh & Philippines**
- **Incorporate** mathematical models of **spatial urban morphology growth**
- **Expand** with **Landsat** imagery and other **Sentinel** imagery bands
- **Perform** probabilistic **risk** analysis

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OpenSendaiBench
A Global EO-based Dataset for Exposure & Physical Vulnerability

1972 — 2015 — 2023 — 2030 — 2050