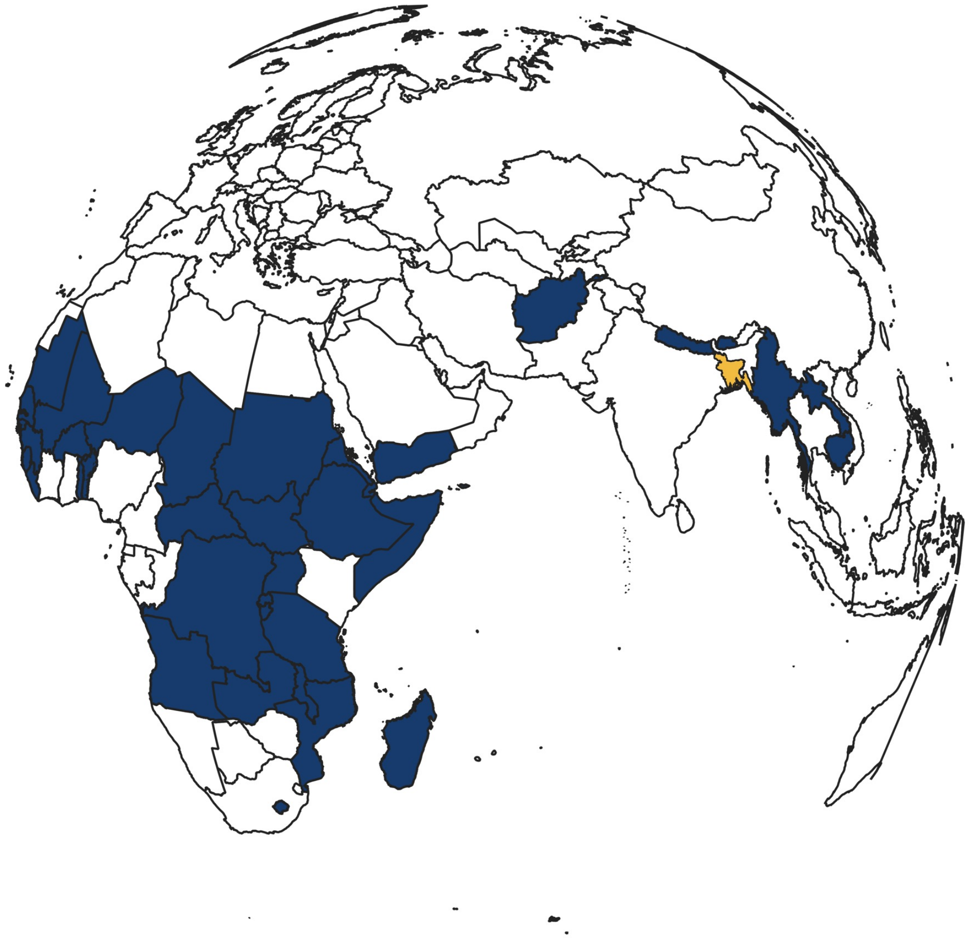
Global Mapping of Exposure and Physical Vulnerability Dynamics in Least Developed Countries using Remote Sensing & Machine Learning



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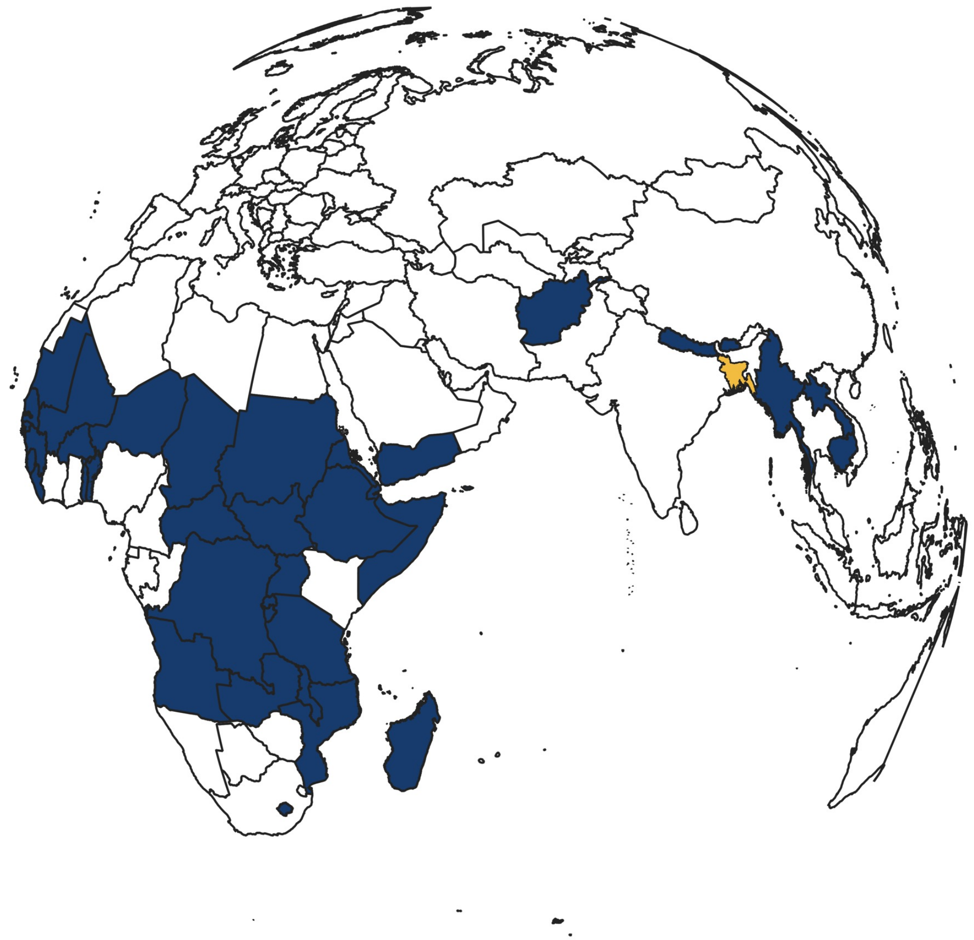
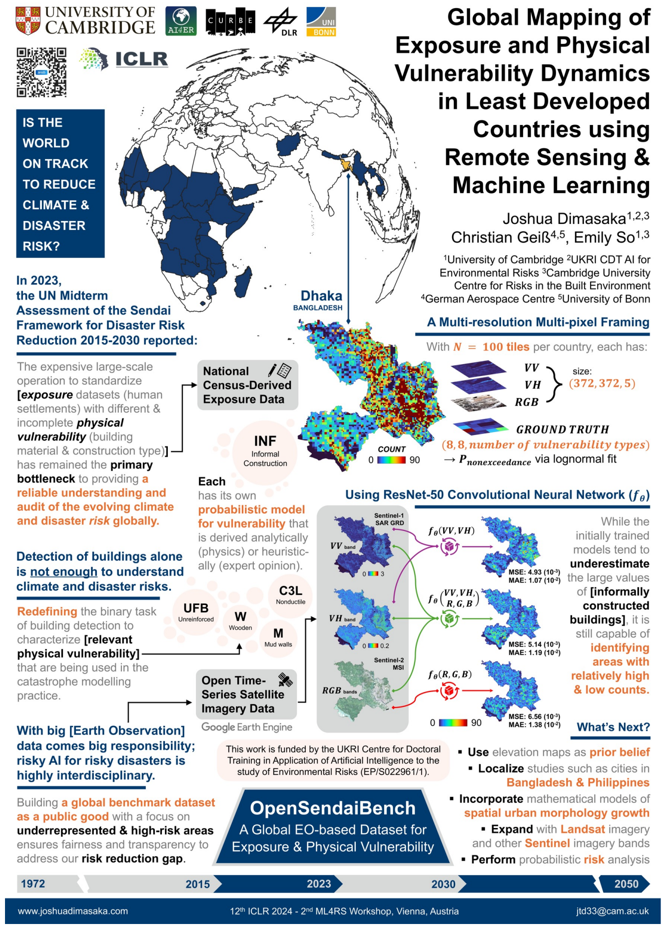


IS THE WORLD ON TRACK TO REDUCE CLIMATE & DISASTER RISK?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Sentinel-1 SAR GRD
VV band
0
3
VH band
0
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RGB bands
$f_\theta(VV, VH)$
MSE: 4.93 (10^{-3})
MAE: 1.07 (10^{-2})
$f_\theta\binom{VV, VH,}{R, G, B}$
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MAE: 1.38 (10^{-2})
0
90
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1972
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www.joshuadimasaka.com
12th ICLR 2024 - 2nd ML4RS Workshop, Vienna, Austria
jtd33@cam.ac.uk


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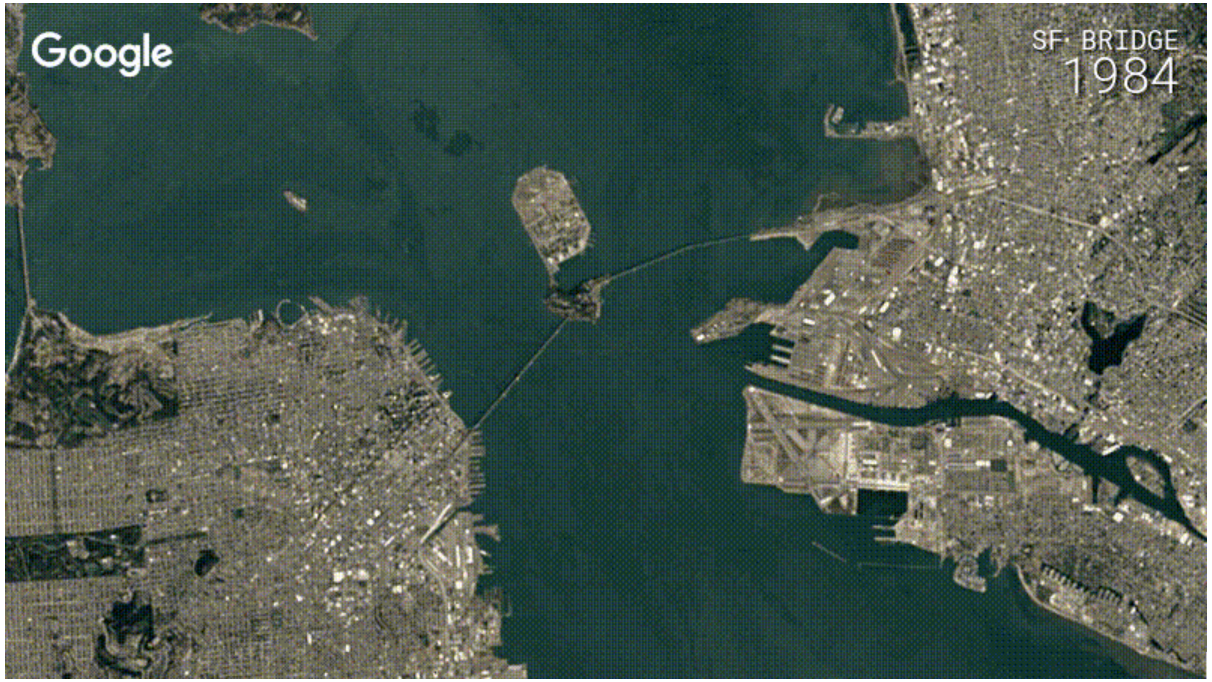

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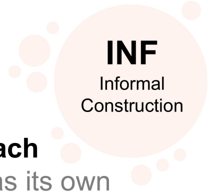

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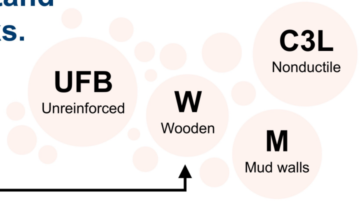

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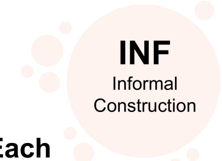

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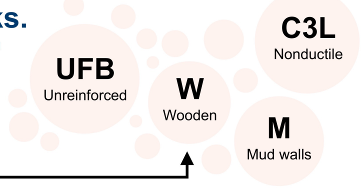

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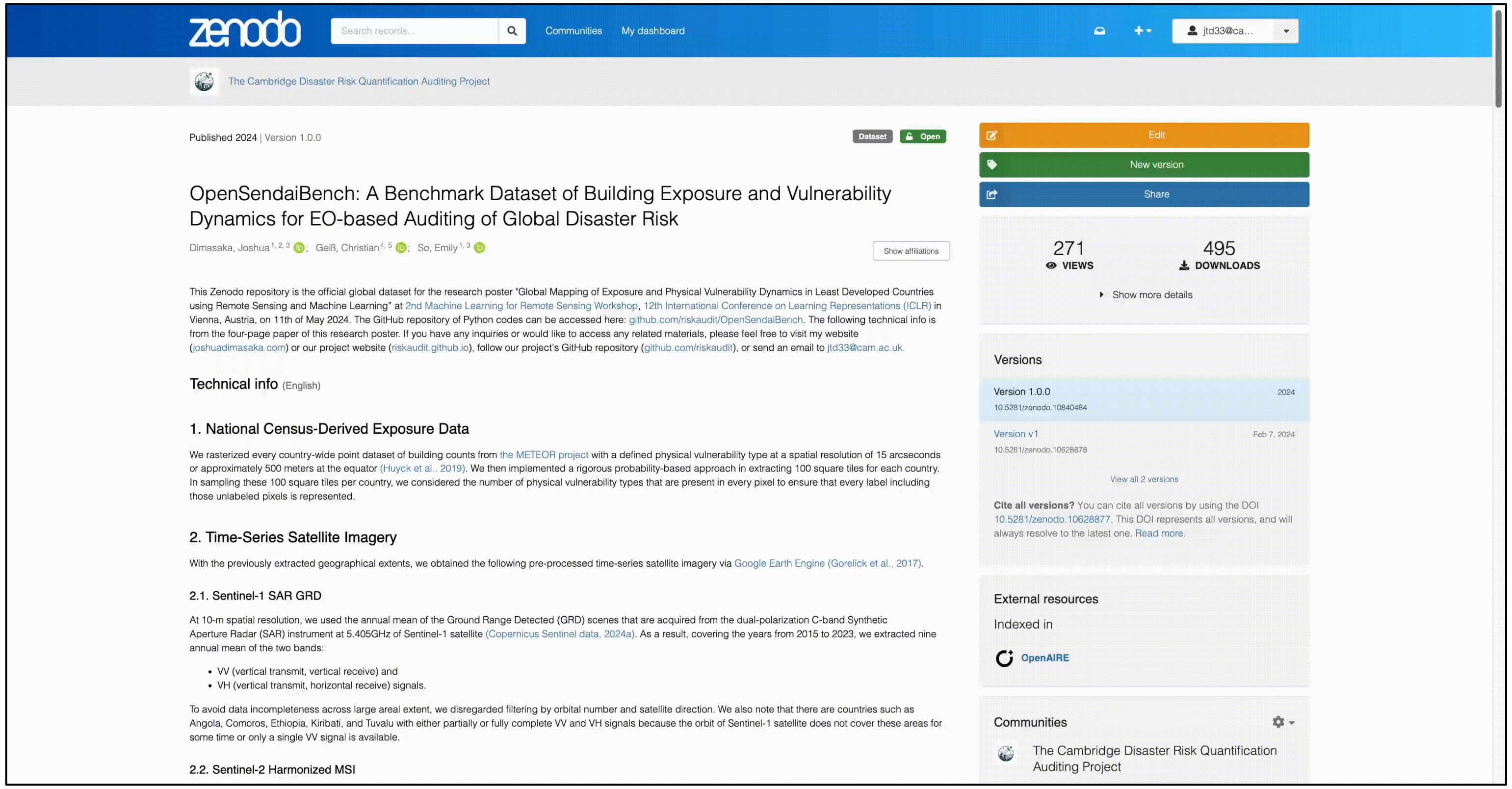
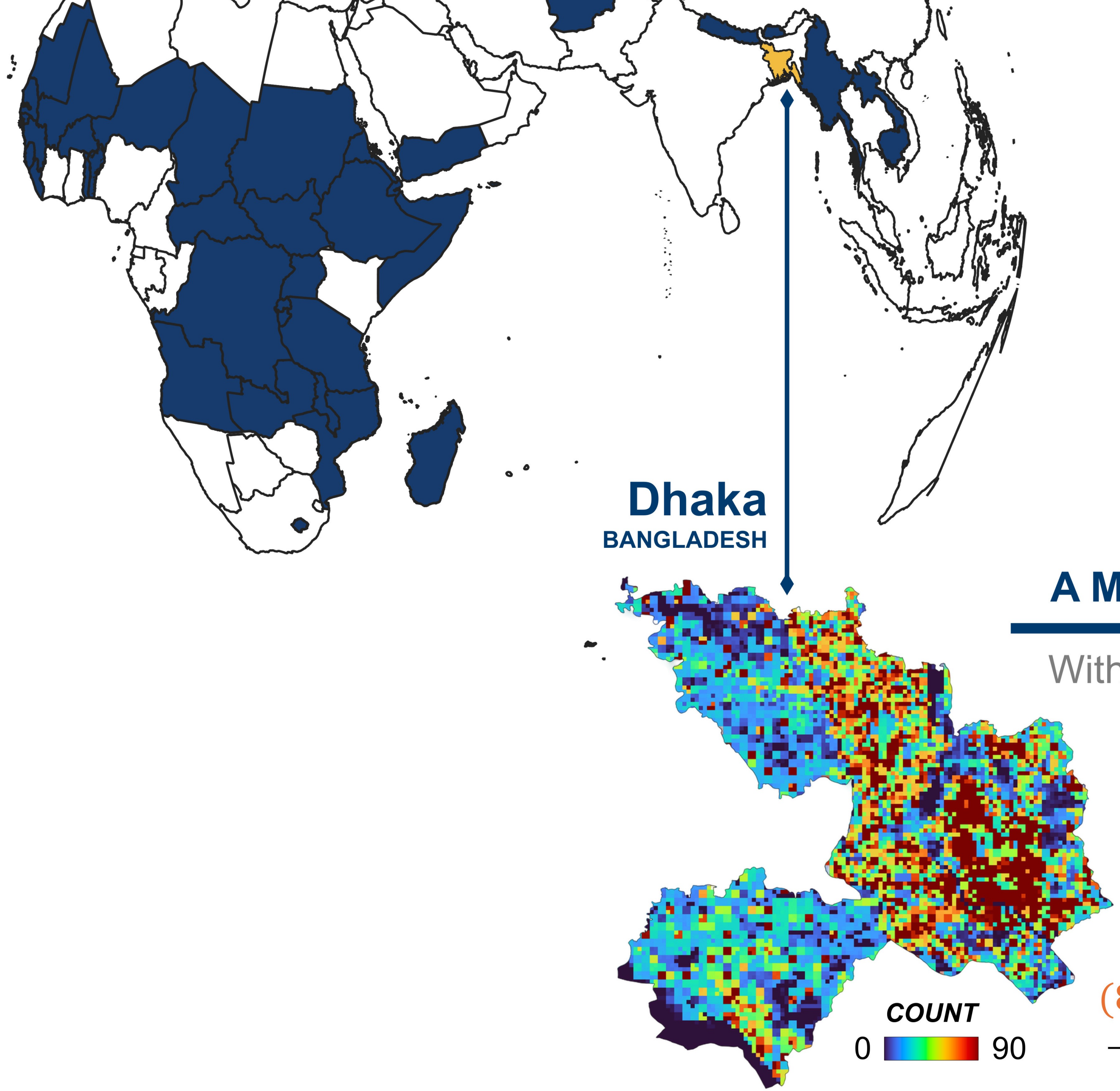


OpenSendaiBench

A Global EO-based Dataset for Exposure & Physical Vulnerability

1972 2015 2023 2030 2050



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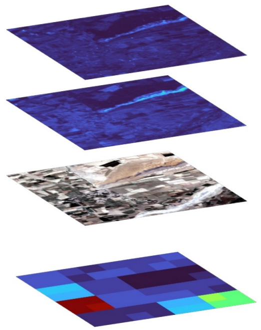

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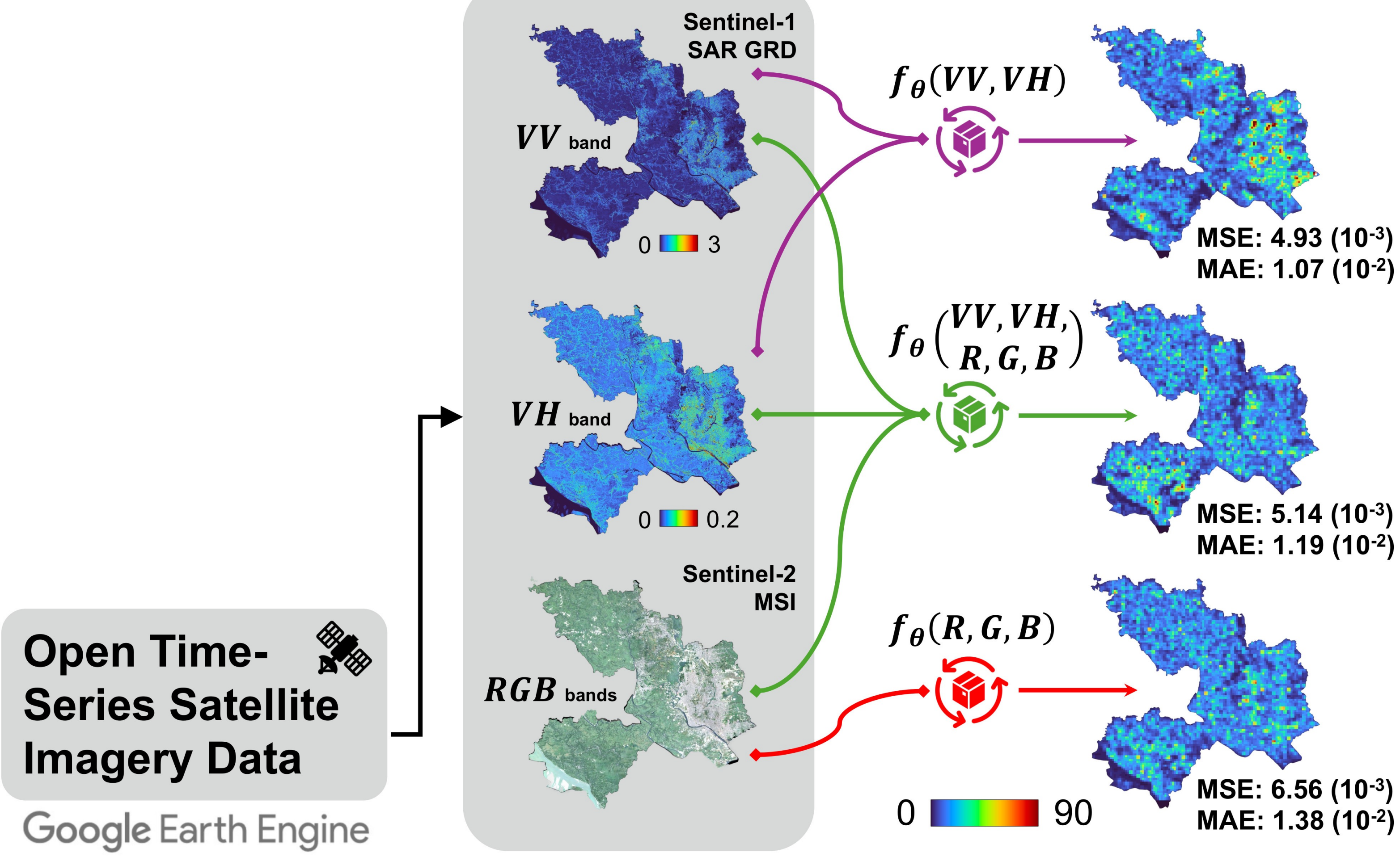

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The Alan Turing Institute

COLOURING CITIES RESEARCH PROGRAMME

GEM GLOBAL EARTHQUAKE MODEL working together to assess risk

EMI Earthquakes and Megacities Initiative

LUNGSOD QUEZON PILIPINAS

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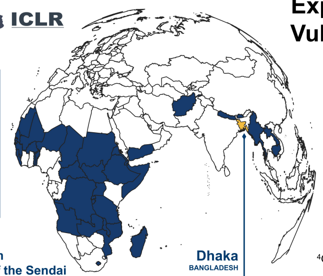

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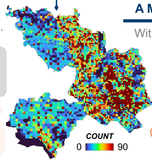

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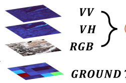

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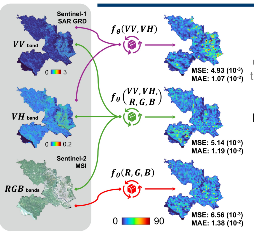

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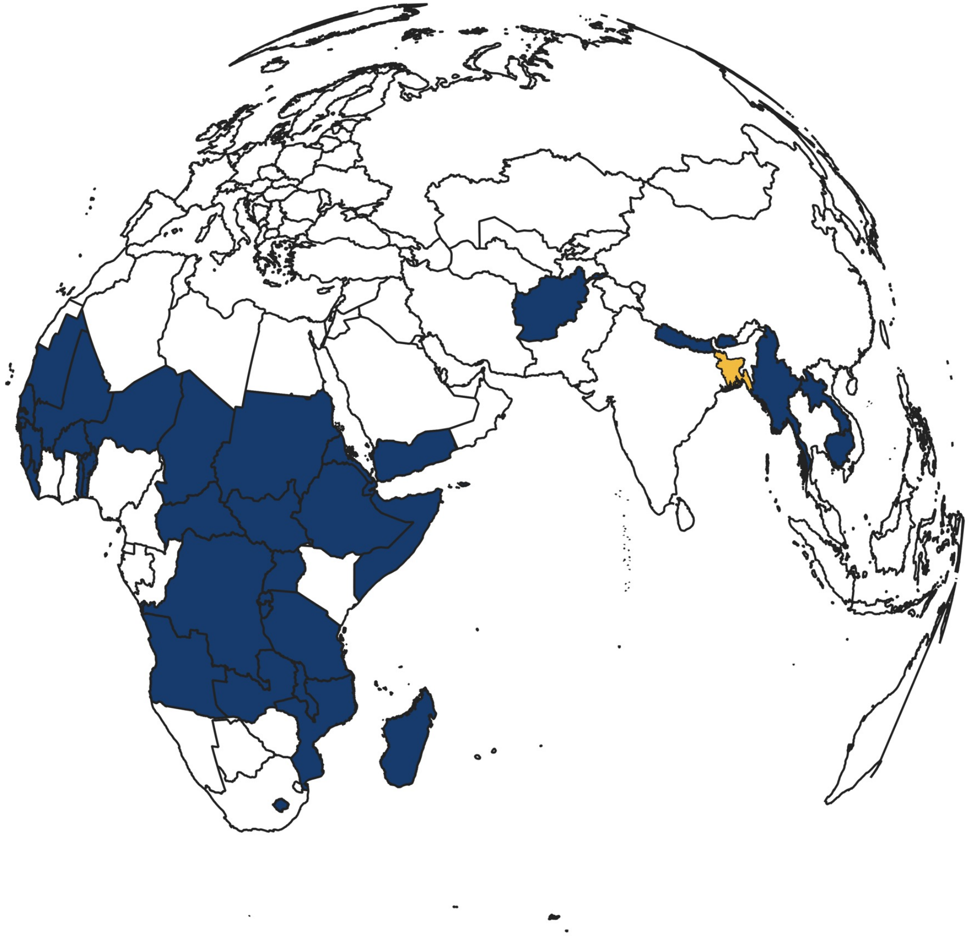
open SENDAI BENCHMARK VERSION 1.0.0
zenodo



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