



Project Sunny Lives

Dwelling type Classification and Risk Assessment for Disaster Vulnerability using Satellite Imagery

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Joint work in collaboration with  SEEDS





AI for Good Lab

We are **Data Scientists, Economists, and Data Storytellers** across **four continents**

200+ projects and **100+ papers** published over the past five years

Working together with **subject matter experts (non-profits, academia, and government)**



Leveraging AI and data science to address some of the world's greatest challenges



AI for Good Lab

address **digital inequality** in **underserved communities**



analyze melting glaciers to assess impacts of climate change



better **disaster preparedness & response**

develop low-cost **medical screening** and improve **public health**



wildlife tracking to help **monitor species decline**

support vulnerable communities globally



aid future renewables development

Introduction

- India globally ranked 5th most affected by weather related disasters*
- Over 2 million houses lost every year, only to flood
- Most belong to the economically weaker sections and have no insurance
- **Sustainable Environment and Ecological Development Society (SEEDS):** a non-profit working towards building disaster resilience in low-income areas



Image source: The Guardian

*D. Eckstein, V. Künzel, L. Schäfer, and M. Wings, "Global climate risk index 2020," Bonn Ger., 2019.

Where can ML help?

Dwelling types are good indicator of vulnerability

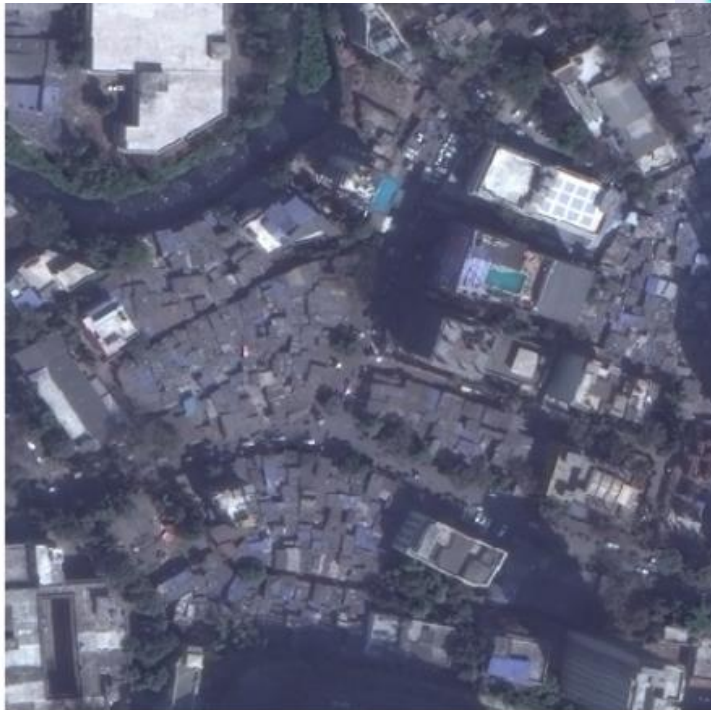
- Dwellings are classified based on roof type, a proxy for the construction material and resilience
- Ground survey is very time-consuming and expensive, machine learning can improve the scalability instead
- Dwellings and their roof type can be identified from high resolution satellite imagery
- Identified dwelling locations and their roof type are used for risk assessment model



Dataset

Satellite Imagery

- 50 cm resolution RGB data from Maxar partnership
- 8 areas of interest (AOIs) were identified by SEEDS from 2 regions in India



The coastal town of Puri

The city of Mumbai including Dharavi slum

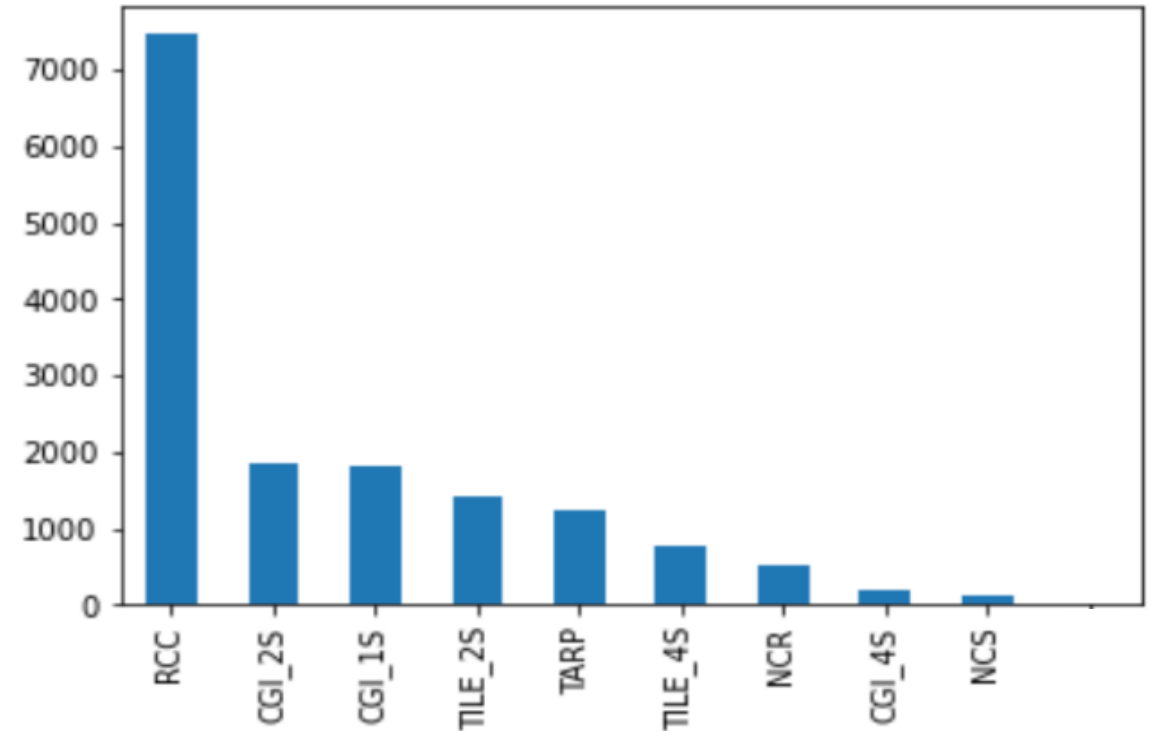


Dataset

Annotations

- All dwelling footprints were identified
- More than 14000 dwellings were annotated and classified into 7 categories (+2 additional types)

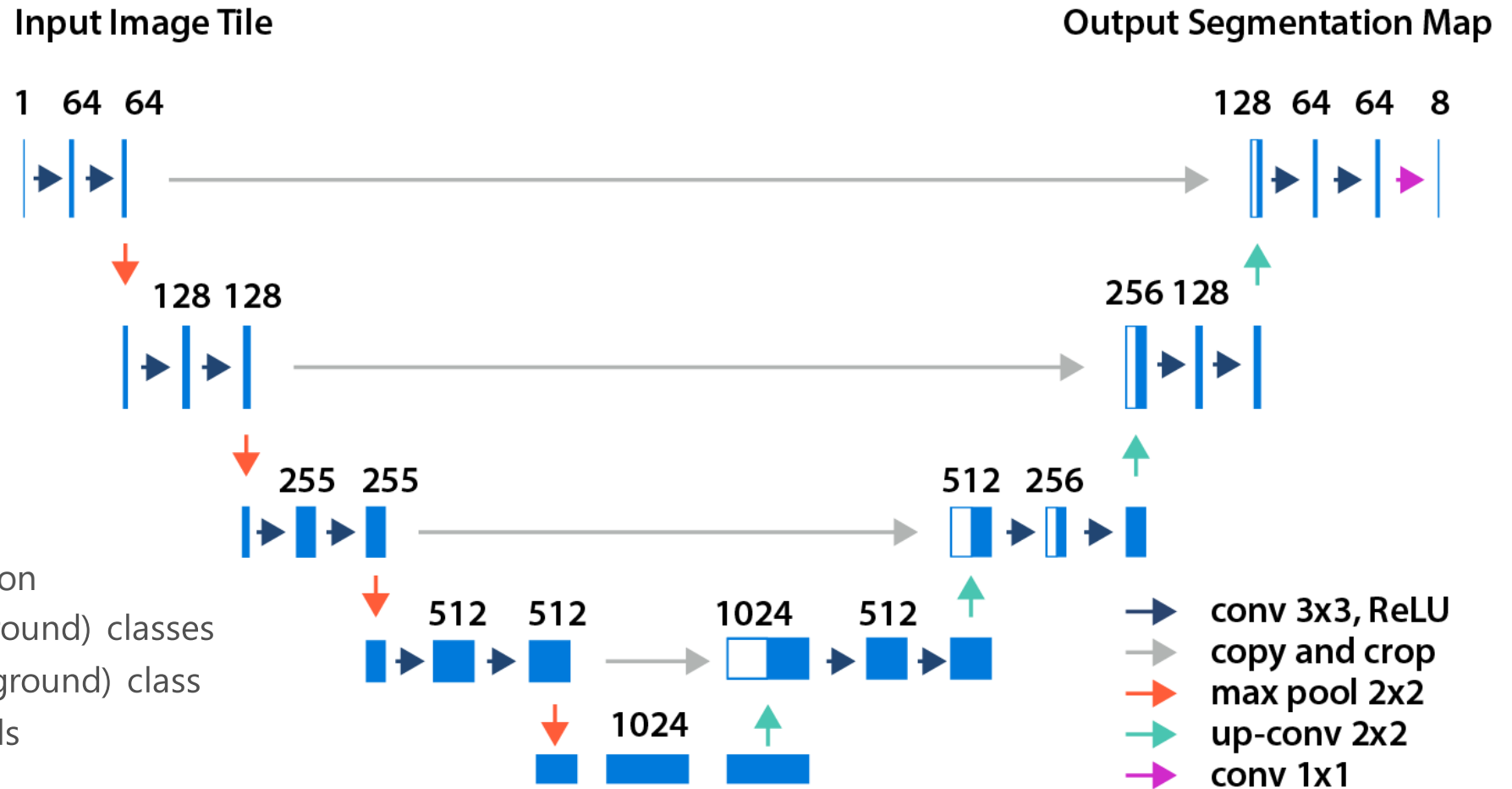
Label Code	Description
CGI_1S	Corrugated Galvanized Iron with 1 Slope
CGI_2S	Corrugated Galvanized Iron with 2 Slopes
CGI_4S	Corrugated Galvanized Iron with 4 Slopes
TILE_2S	Tiled Roof with 2 Slopes
TILE_4S	Tiled Roof with 4 Slopes
TARP	Tarpaulin
RCC	Reinforced Cement Concrete
NCR	No Clear Roof*
NCS	No Clear Structure**

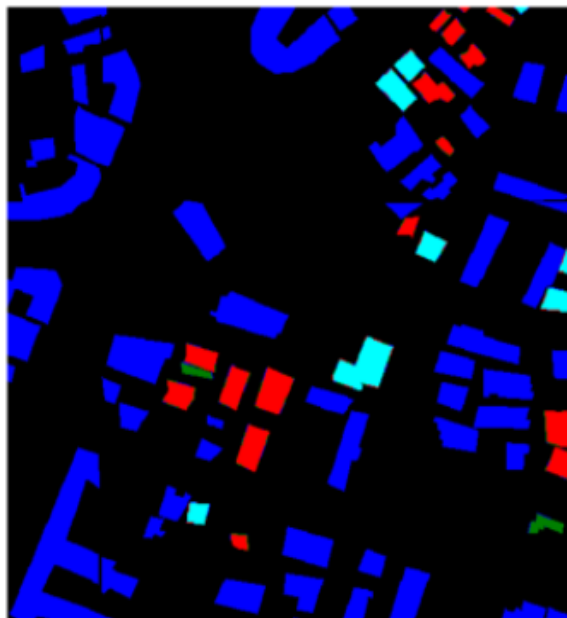
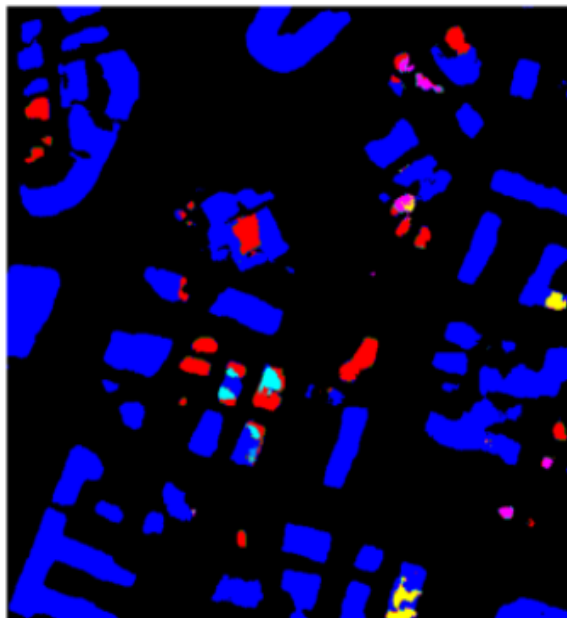


*dwellings that do not have a clear view of the roof, but the structure is present

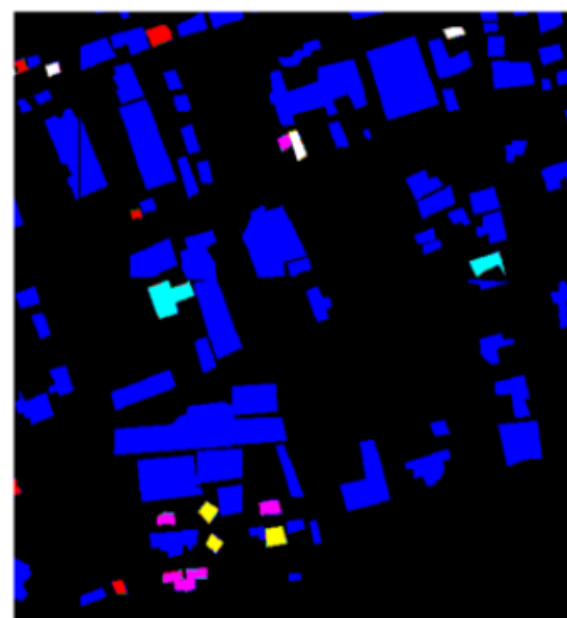
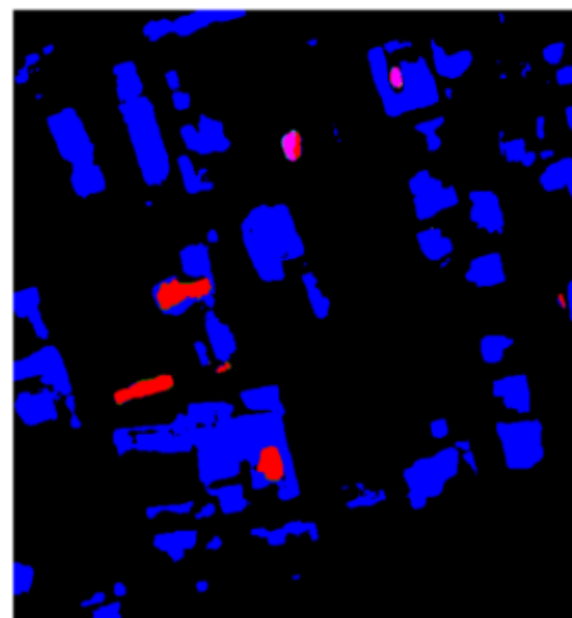
**includes damaged house and houses that cannot be deciphered

Modeling



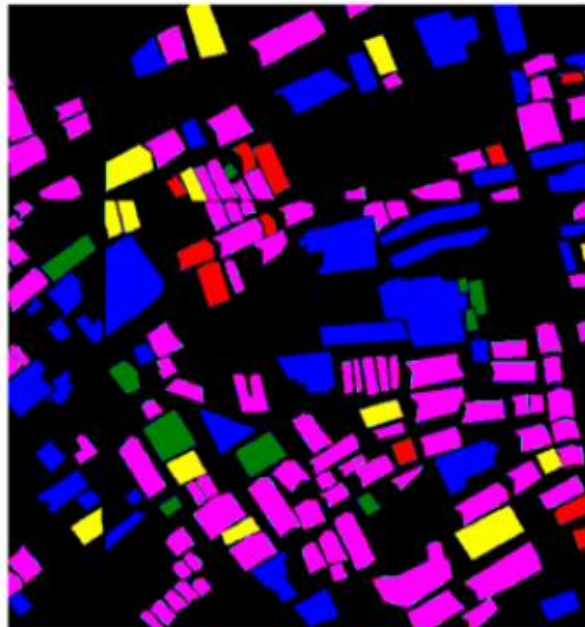
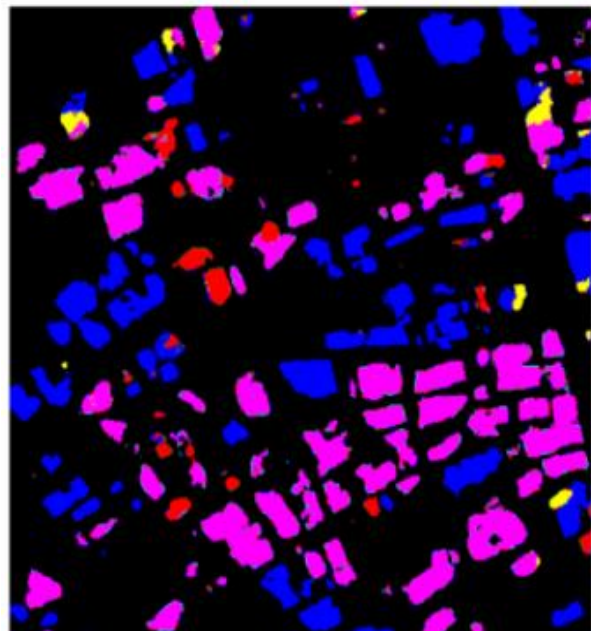


(Left column): predicted label
(Middle): ground truth
(Right): input imagery

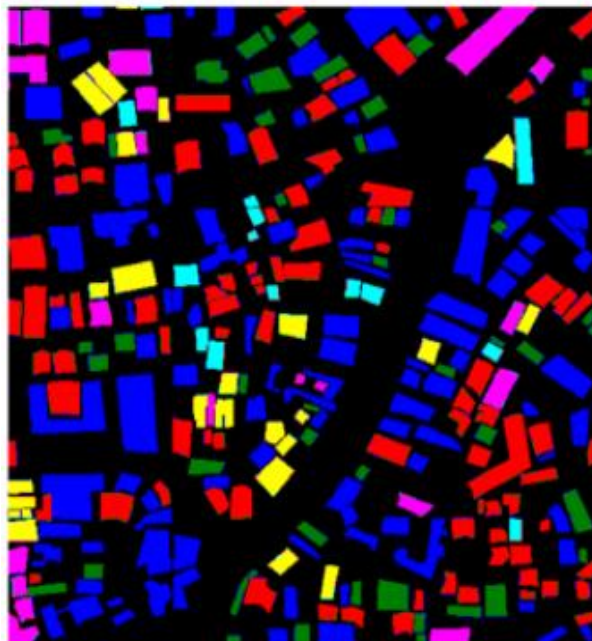
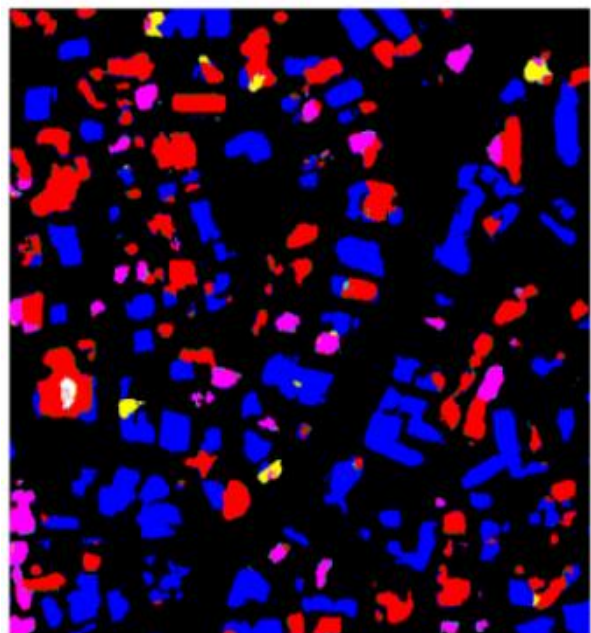


Categories

	0 not_house
	1 RCC
	2 CGI_1S
	3 CGI_2S
	4 CGI_4S
	5 TILE_2S
	6 TILE_4S
	7 TARP



(Left column): predicted label
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Categories

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Risk Score Model

Inputs

1. Waterbodies
2. Road Network
3. TWI
4. Elevation
5. Vegetation
6. Impervious Surface
7. Landslide Risk
8. Building Footprints

Data
Pre-Processing

Intermediate
Calculations

Analytical
Hierarchical
Process

Reclassification of
the score from 1 to 5

Outputs

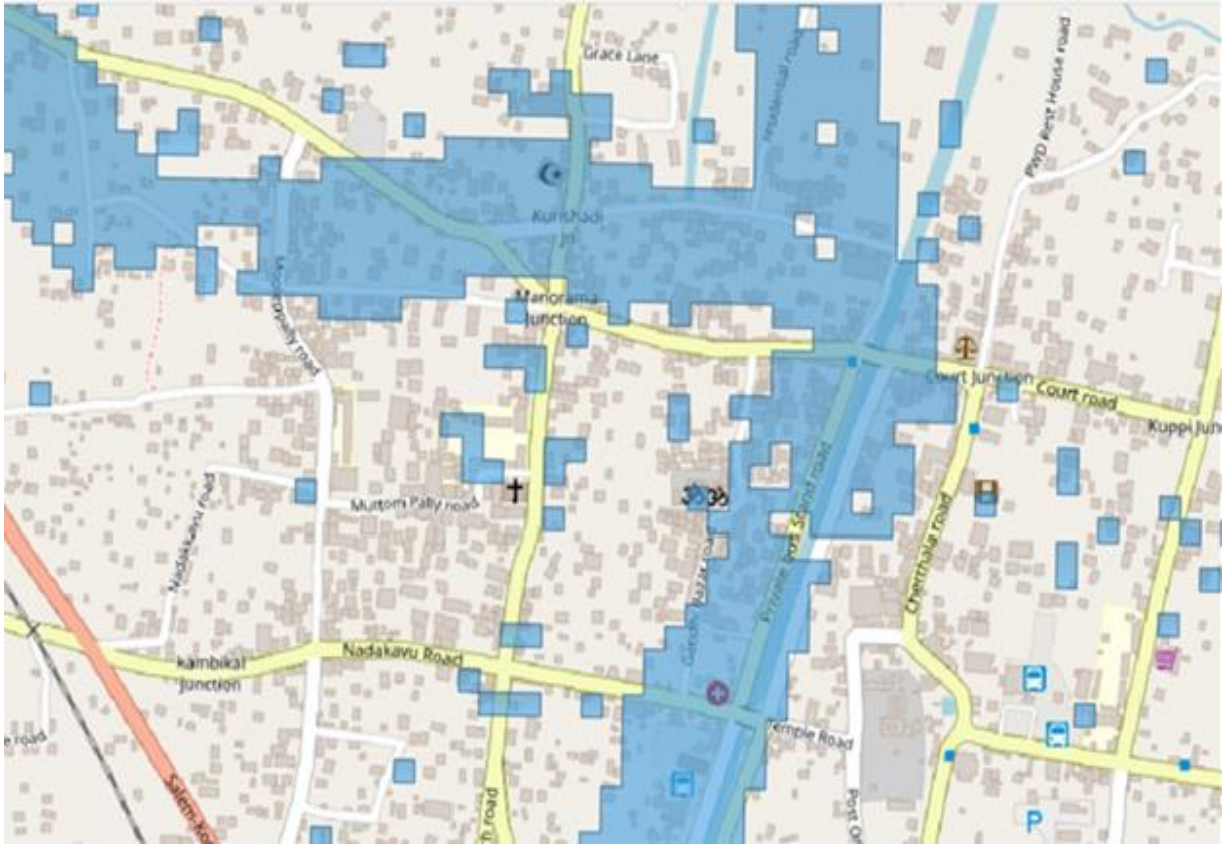
1. 30m Raster with risk zones
2. GeoJSON o/p of footprints with risk of scores for each

Calculation of zonal
statistics for each
building footprint

Risk Score Model

Risk Score	Description
1	No Risk of Flooding
2	Low Risk of Flooding
3	Moderate Risk of Flooding
4	High Risk of Flooding
5	Water Island

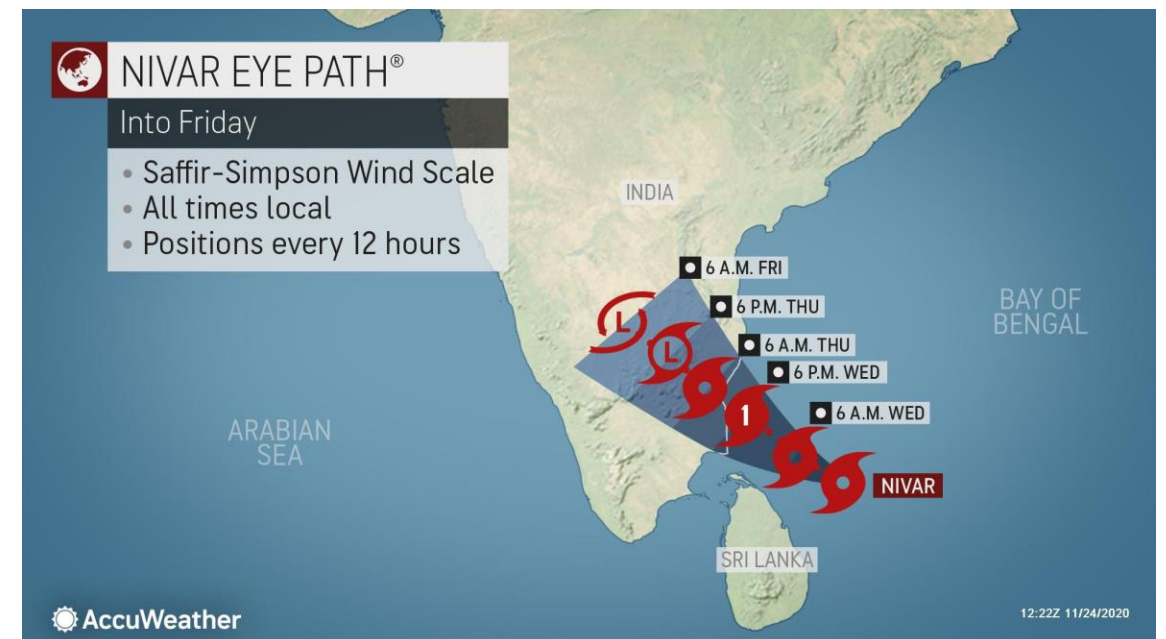
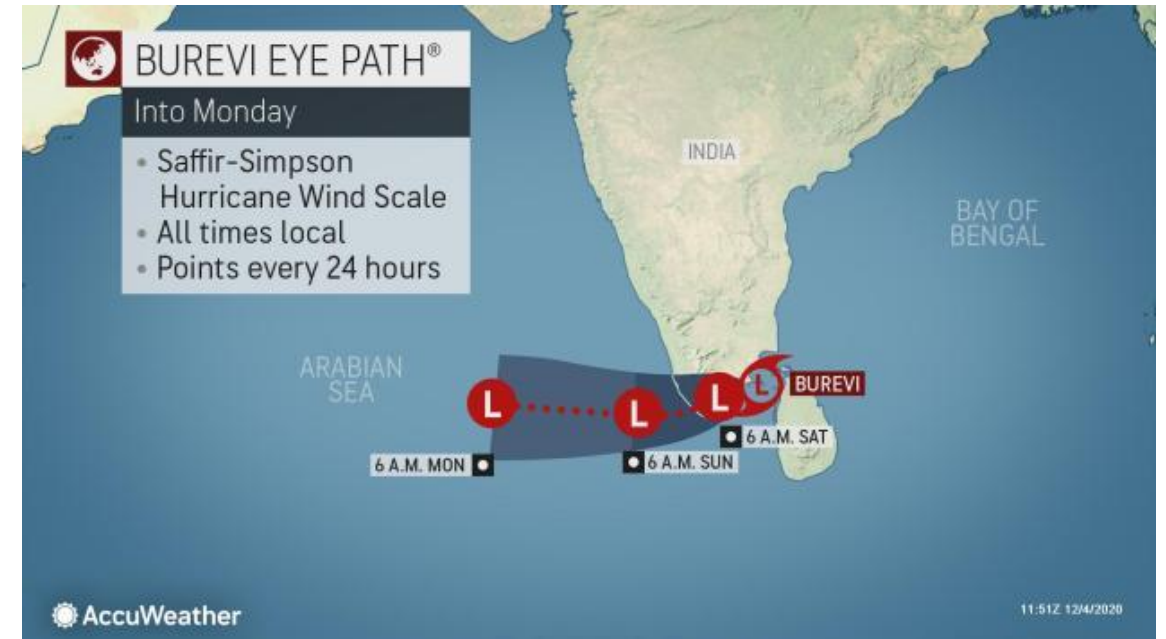
Moderate to high-risk zones (with score 3 or above) in a region in Northern Kerala shown in blue



Model Deployment

Deployment

- The model was used in two regions in Dec 2020
 - Northern Kerala for Cyclone Burevi
 - Tamilnadu for Cyclone Nivar
- After the disasters, a small subset of houses were surveyed to collect data on actual damage, and was found to be >80% accurate for assessing risk





Impact

Better disaster preparedness

- *Before*: A set of disconnected information (weather forecast, warnings, water release from dams)
- *Now*: An overall risk map based on expected flooding and damage caused, can be obtained quickly prior to the disaster

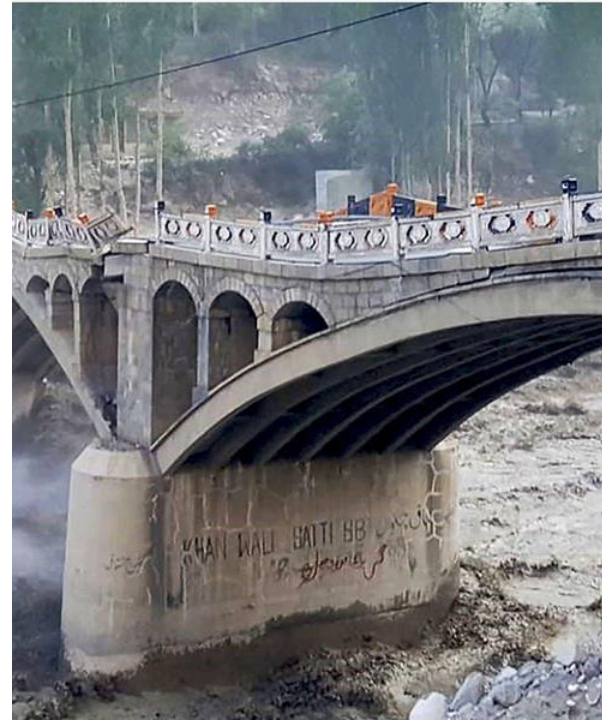
Impact

- **Short term:** can take necessary actions on at a community/neighborhood level
 - such as evacuation, allocation of resources
 - to minimize the loss and provide relief
- **Long-term:** identify vulnerable regions and work towards risk reduction
 - by strengthening of buildings
 - improving water and sanitation management



What next?

- More labelled data collection and improved modeling can improve dwelling type classification
- Current model focused on urban landscape, might be adapted to rural areas
- Similar approach can be extended to other disasters (such as earthquakes, extreme heatwave)





Thank you.