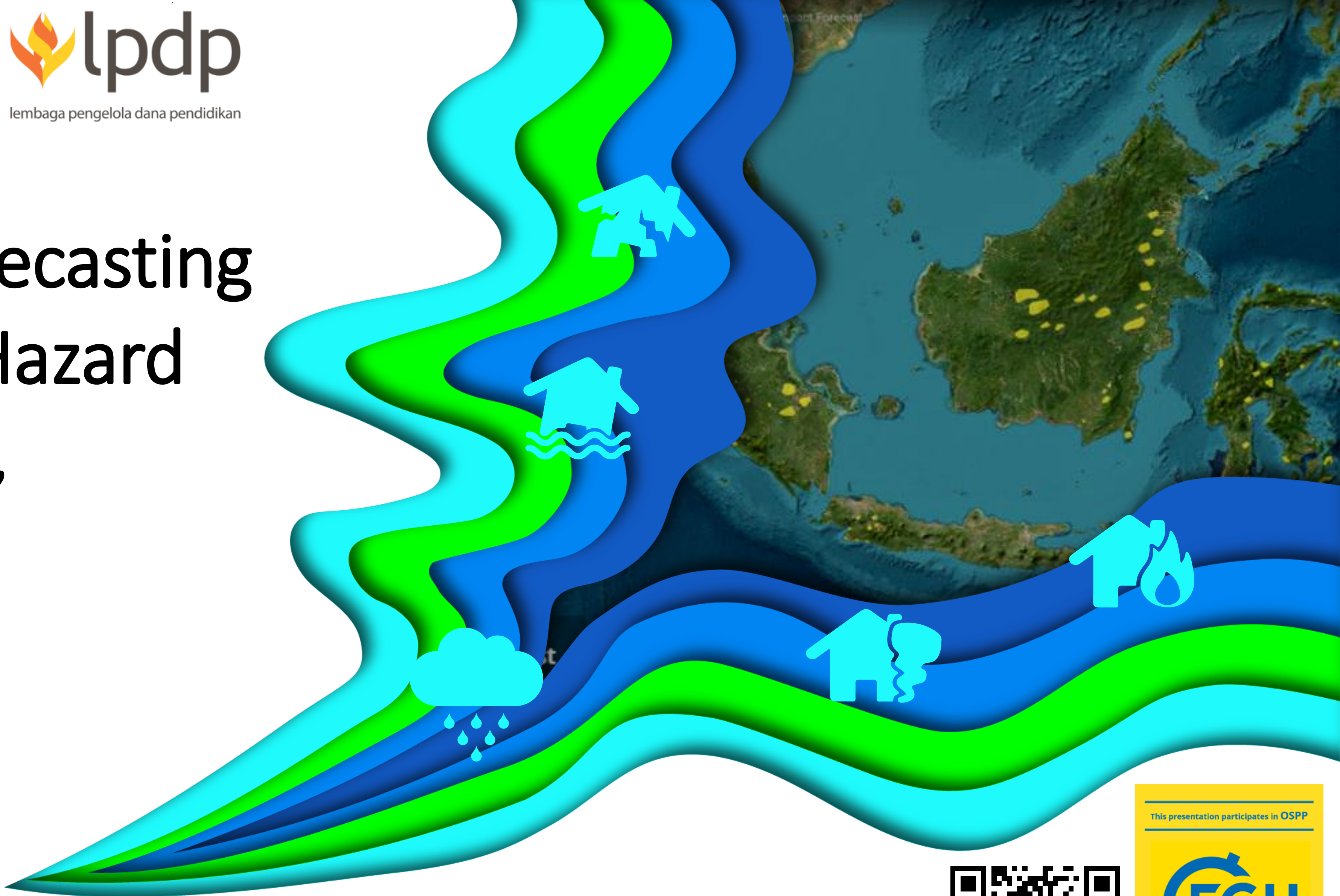
Impact-Based Forecasting Model for Flood Hazard Mitigation in Java, Indonesia



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This presentation participates in OSPP

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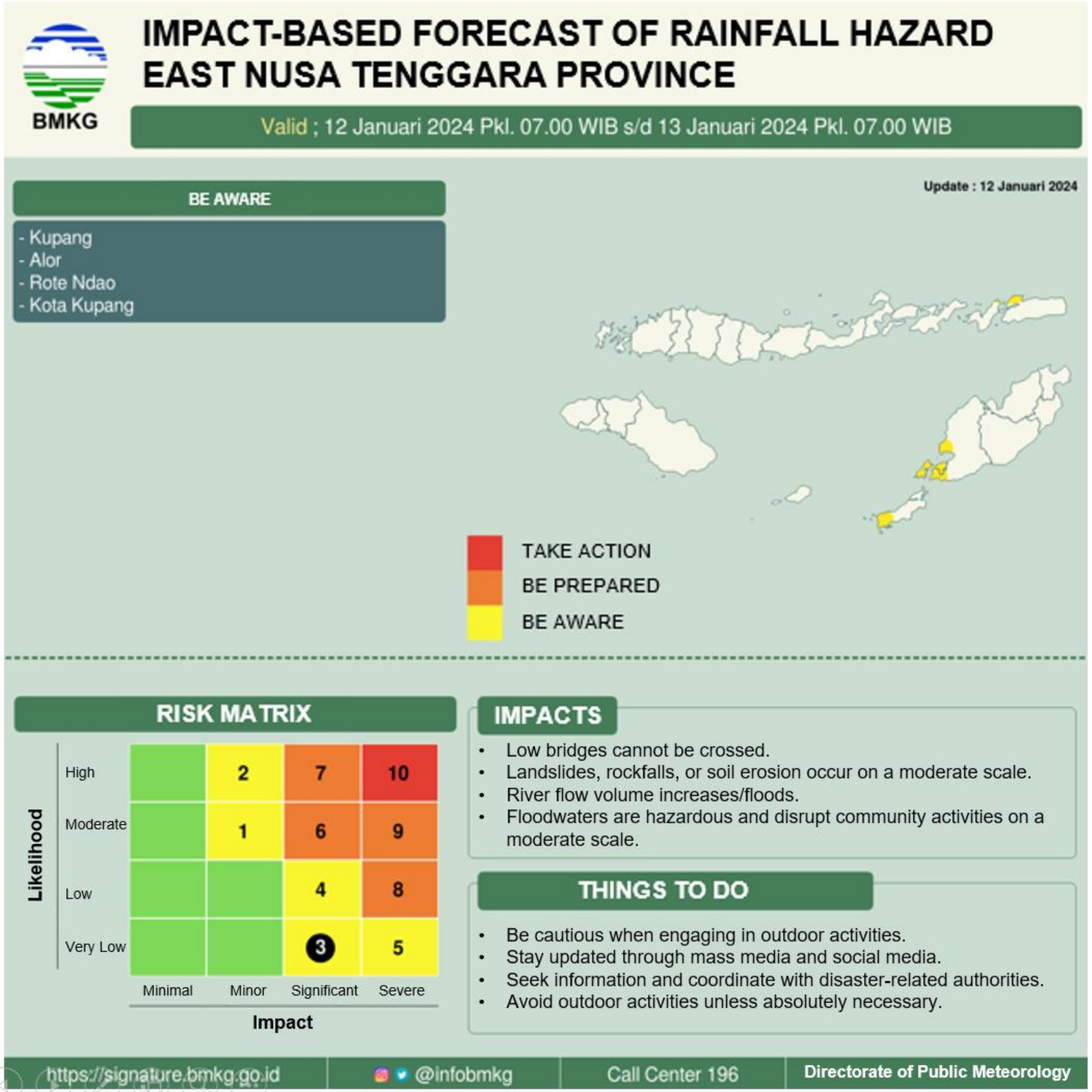

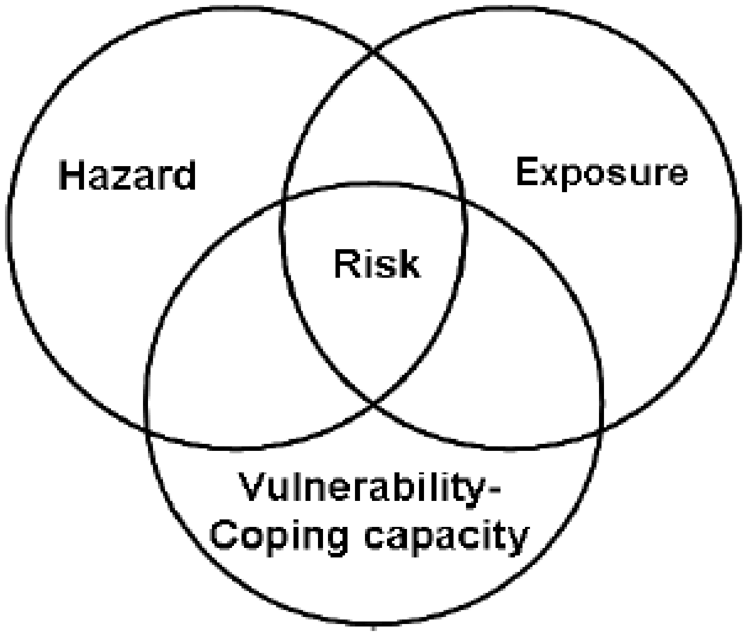

Impact-based forecasting is a **structured advanced method** of integrating **hazard, exposure, and vulnerability** data to identify risk and assist in decision-making, aiming to promote **early action** (WMO,2015)

Previous Study

https://doi.org/10.1007/978-981-97-0740-9_24

Chapter 24
On the Development of the Impact-Based Forecast Model in Indonesia

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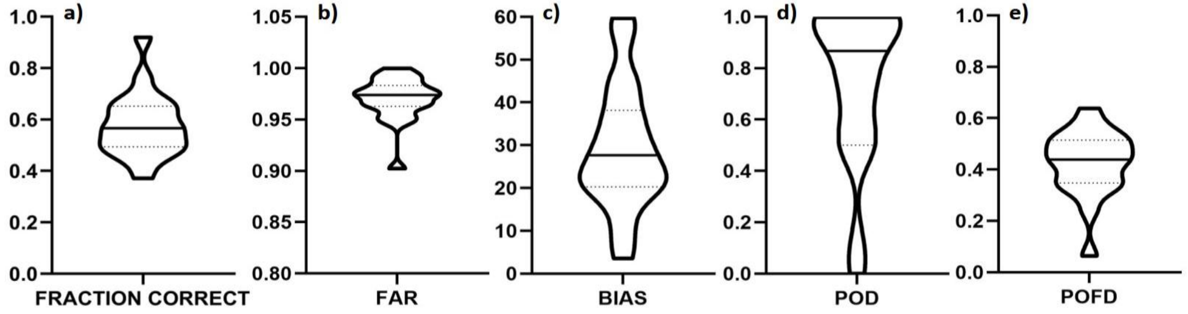
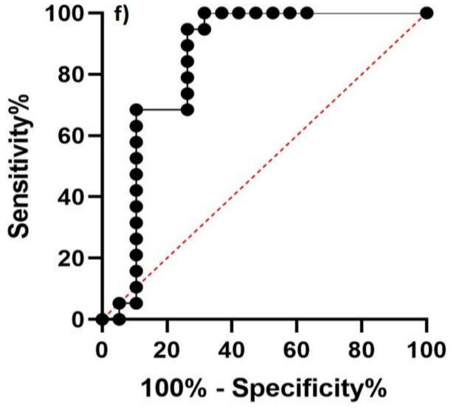
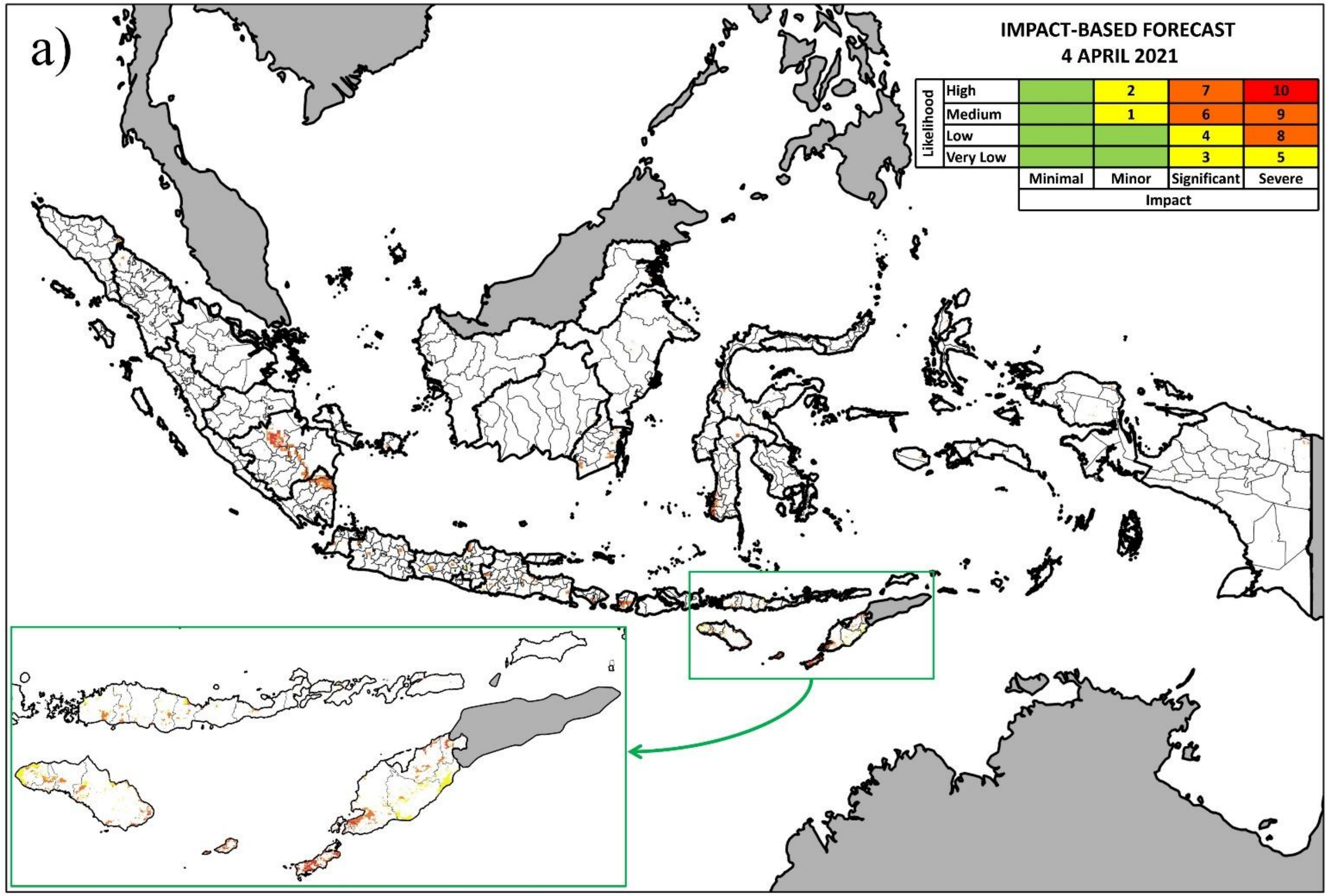


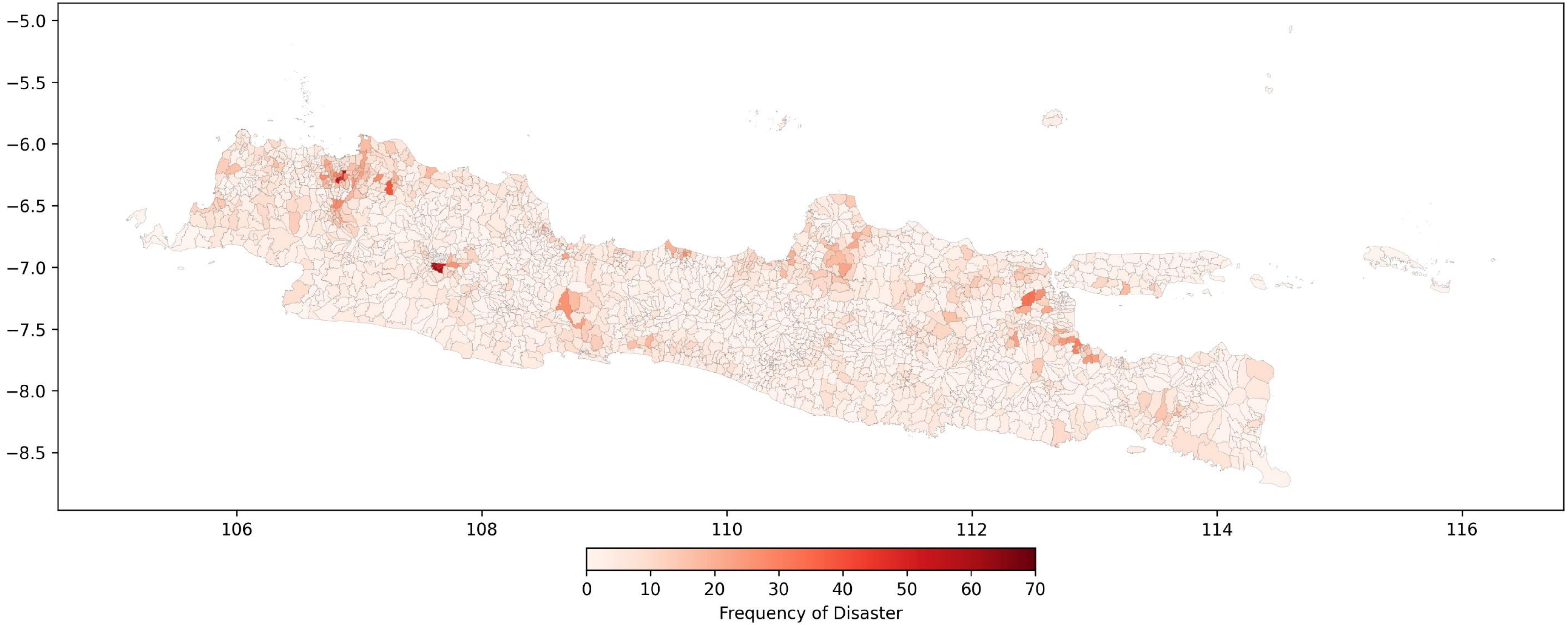


Area Under Curve (AUC)	0.8449
Standard Error	0.07254
95% Confidence Interval	0.7072 to 0.9870
P-Value	0.0003



	Minimal	Minor	Significant	Severe	Total
Number of disasters	102	52	9	9	172
Predicted	76	34	8	9	127
Unpredicted	26	18	1	0	45
Correctly classified	0	0	5	8	13
Misclassified	102	52	4	1	159

Frequency of All Flood Disasters (2014 - 2023)



Vulnerability & Capacity

- The vulnerability and capacity data were directly used from InaRISK by Indonesian National Disaster Management Agency (BNPB)

Type of Vulnerability	Percentage Weight
Social Vulnerability	40%
Physical Vulnerability	25%
Economic Vulnerability	25%
Environmental Vulnerability	10%

Regional Capacity Parameters	Percentage	Classification		
		Low (0 – 0.333)	Medium (0.334 – 0.666)	High (0.667 – 1.000)
Regional Resilience	40%	0 – 0.40	0.41 – 0.80	0.81 - 1
Community Preparedness	60%	<0.33	0.34 – 0.66	0.67 - 1

	Social Vulnerability Parameters	Percentage	Classification		
			Low (0 – 0.333)	Medium (0.334 – 0.666)	High (0.667 – 1.000)
E	**Population Density**	60%	<5 pop/ha	5 - 10 pop/ha	>10 pop/ha
	Vulnerable Group Ratio	40%			
V	Gender Ratio (10%)		>40	20 - 40	<20
V	Vulnerable Age Group Ratio (10%)		<20	20 - 40	>40
V	Disabled Population Ratio (10%)				
V	Poor Population Ratio (10%				
E	Total Population (10%)				

	Physical Vulnerability Parameters	Percentage	Classification		
			Low (0 – 0.333)	Medium (0.334 – 0.666)	High (0.667 – 1.000)
V	**Houses Damage Loss**	40%	<400 mill	400 – 800 mill	>800 mill
V	**Public Facilities Damage Loss**	30%	<500 mill	500 mill – 1 Bill	>1 Bill
V	**Crisis Facilities Damage Loss**	30%	<500 mill	500 mill – 1 Bill	>1 Bill

	Economic Vulnerability Parameters	Percentage	Classification		
			Low (0 – 0.333)	Medium (0.334 – 0.666)	High (0.667 – 1.000)
E	**Gross Regional Domestic Product**	40%	<100 mill	100 – 300 mill	>300 mill
E	**Productive Land**	60%	<50 mill	50 – 200 mill	>200 mill

	Environmental Vulnerability Parameters	Classification			
		Low (0 – 0.333)	Medium (0.334 – 0.666)	High (0.667 – 1.000)	Midpoint (min+(max-min/2))
E	**Protected Forest Damage**	<20 Ha	20 – 50 Ha	>50 Ha	35
E	**Natural Forest Damage**	<25 Ha	25 – 75 Ha	>75 Ha	50
E	**Mangrove Forest Damage**	<10 Ha	10 – 30 Ha	>30 Ha	20
E	**Shrubs Damage**	<10 Ha	10 – 30 Ha	>30 Ha	20
E	**Swamps Damage**	<5 Ha	5 – 20 Ha	>20 Ha	12.5

Classifiying Disaster

Date of Event	Incident	Location	Regency	Province	Chronology & Documentation	Reason	Die	Lost	Wounded	Damaged House	Submerged House	Damaged Public Facilities
2024-11-17	FLOOD	Ec. Teunom Gp. Rambong Payong Gp. Pasie Timon Gp. Pasie Geulima Gp. Great Gp. Blang Baro District. Pasie Raya Gp. Tuwie Kareung Gp. High Island	ACEH JAYA	ACEH	Documentation	• Triggered by high intensity rain accompanied by strong winds which resulted in flooding	0	0	0	0	78	0

- The classification of the impact that I have used is derived from The WCSSP WP3 MEIT project: Focus Group Discussion Survey Questions between BMKG (Met Services) – BPBD (Regional DMA) – University College London (in Purnama et al., 2024)

Impacts	Minimal	Minor	Significant	Severe
The number of people affected (e.g. injured, displaced, evacuated)	0 - 999	1.000-50.000	50.001 – 201.000	> 201.000
The number of people dead	0	0	1-27	> 27
The number of neighborhoods (RT) with several houses damaged or destroyed.	0 - 99 RT	100 – 350 RT	351 – 999 RT	> 1.000 RT
The number of flood sections or bridge closed	0 - 9	10 - 25	26 - 74	> 75
The number of public buildings affected (e.g. schools, hospitals, government or religious)	0 - 9	10 – 79	80 - 229	> 230

Why Cube Root?

Scale Normalization (Similar to Geometric Mean)

When multiplying three components like H, V, and 1−C, the result can become extremely small or large depending on their values. Taking the cube root brings the value back to a more balanced or representative scale. This is similar to the geometric mean, which for three variables is defined as:

$$GM = (x.y.z)^{1/3}$$

Geometric mean is often used when combining factors that interact multiplicatively and may have different scales, so the final result stays within a comparable range to the inputs.

Avoiding Scale Distortion

Without the cube root, the product H×V×(1−C) can be too small (e.g., 0.02 × 0.3 × 0.1 = 0.0006), even if all the components are relatively "high". This can make the impact score unintuitive. The cube root “tames” extreme values and keeps the impact score more proportional and interpretable across regions or time.

Preserving Dimensional Consistency

If the goal is to ensure the final score I remains within a [0,1] range, like the inputs, and represents a kind of “weighted average,” then using the cube root helps keep the result consistent with that range and interpretable.

Multi-class Cost Matrix

Table 2. The cost matrix for a binary class classification.

		Predicted Class	
		Negative $f(x) = -1$	Positive $f(x) = +1$
Actual class	Negative $(y = -1)$	$C(-1,-1) = C_{TN}$	$C(+1,-1) = C_{FP}$
	Positive $(y = +1)$	$C(-1,+1) = C_{FN}$	$C(+1,+1) = C_{TP}$

Source: Yoo et al (2024)

Table 12. Misclassification cost matrix on lending club.

		Prediction						
		A	B	C	D	E	F	G
Actual	A	0	0.0089	0.0166	0.0241	0.0303	0.0365	0.0443
	B	0.0333	0	0.0073	0.0144	0.0203	0.0262	0.0336
	C	0.0530	0.0211	0	0.0070	0.0128	0.0184	0.0256
	D	0.0684	0.0376	0.0172	0	0.0056	0.0112	0.0182
	E	0.0789	0.0489	0.0291	0.0123	0	0.0055	0.0124
	F	0.0851	0.0568	0.0380	0.0222	0.0106	0	0.0070
	G	0.0856	0.0608	0.0443	0.0304	0.0202	0.0109	0

Source: Wang et al (2019)

EXAMPLE

Actual →	No Disaster	Minimal	Minor	Significant	Severe
Predict ↓					
No Disaster	0	50	100	500	1000
Minimal	10	0	50	250	500
Minor	20	5	0	100	250
Significant	50	20	10	0	100
Severe	100	50	20	10	0

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lembaga pengelola dana pendidikan

Thank You!