

# Development of a statistics-based nowcasting model for earthquake-triggered landslides in Taiwan

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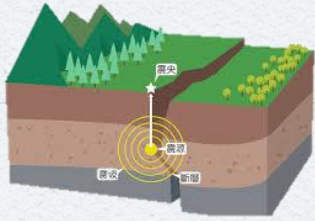
# 1. **Introduction**

# Introduction



Rapid identification of landslides is very important:

1. Assessment of earthquake impacts
2. Hazard mitigation



Earthquake



landslides



fatality

In recent year:

Two kinds of models

physics-based  
of models

statistics-based  
of models

Method

mechanical and  
frictional properties

correlation between key  
driving factors and landslide

Parameters

⊗ more

⊙ less

References

(Jibson et al., 2000);  
(Gallen et al., 2017)

(Nowicki Jessee et al., 2018);  
(Robinson et al., 2018).

# Objectives



Generate the Taiwan landslide susceptibility model



Increase model resolution

In Nowicki 2014, the resolution is about ~1km

While global models have been applied to broad regions, the characteristics of earthquake-triggered landslides could vary with local geologic conditions



In this paper, the resolution increase to 40m





# Process

Based on Nowicki et al., 2014; Nowicki Jessee et al., 2018

To reflect the complicated geomorphic and geologic conditions in Taiwan, he use **high resolution topographic and geologic data** of Taiwan to develop a nowcasting model

1

select **candidate factors** that could highly affect earthquake-triggered landslides

2

Calculate the **correlation coefficient** to determine the factor as a possible variable

4

the best fitting logistic model is defined to **predict the possibility of earthquake-triggered landslides** in Taiwan.

3

test the significance of each variable using a **logistic regression** model and the **goodness-of-fit** criteria

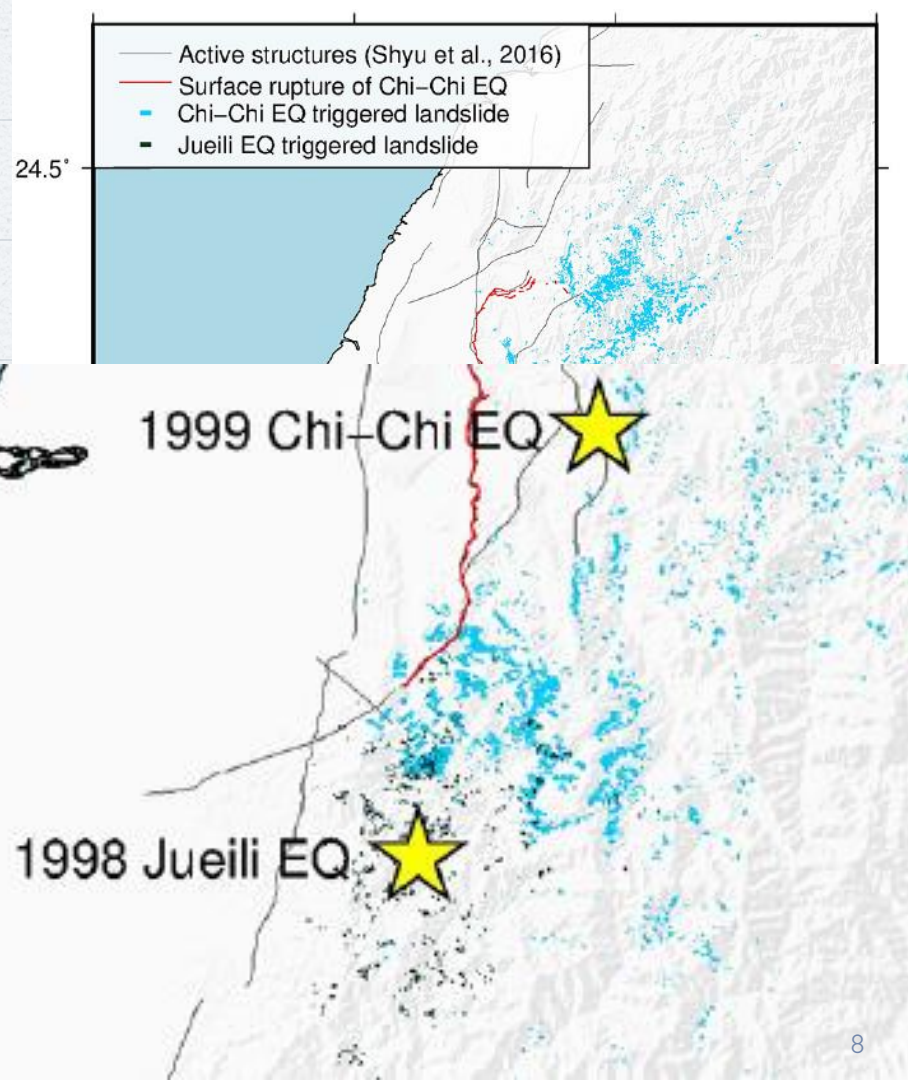


# Study Area

Landslide inventory used in this study:

1. Light blue polygons :  
show landslide distribution of the 1999 Chi-Chi earthquake (Liao and Lee, 2000)
2. Dark blue polygons :  
show landslide distribution of the 1998 Jueili earthquake (Huang and Lee, 1999)

★ Yellow stars denote the epicenters of the two earthquakes.





# Variables

**Seismic property:** quantitative measurements representing ground shaking

**Lithology:** is vital for the delivery of energy and affects the degree of landslides

**Wetness:** is adopted to represent friction of soil for the estimation of landslides (Nowicki et al., 2014).

**Table 1**

Candidate factors for the assessment of earthquake-triggered landslides.

Type	Variable	Reference
Seismic property	PGA	Lin and Tung (2004); Budimir et al. (2015b); Nowicki et al. (2014); Umar et al. (2014); Nowicki Jessee et al. (2018)
	Arias Intensity (AI)	Campbell and Bozorgnia (2012); Liu et al. (2016); Lee et al. (2012); Liu et al. (2015)
	Wave and aspect direction	Khazai and Sitar (2004); Lin and Tung (2004); Meunier et al. (2008); Lee (2012)
Lithology	Lithologic data	Nowicki et al. (2014); Nowicki Jessee et al. (2018)
Topography	Elevation	Lin and Tung (2004); Chang et al. (2007); Umar et al. (2014); Budimir et al. (2015b)
	Aspect	Lin and Tung (2004); Lee and Evangelista (2006); Chang et al. (2007); Umar et al. (2014); Budimir et al. (2015b)
	Curvature	Umar et al. (2014); Budimir et al. (2015b)
	Plan curvature	Chang et al. (2007)
	Profile curvature	Chang et al. (2007)
	Roughness ( $3 \times 3$ )	Budimir et al. (2015b)
	Roughness ( $5 \times 5$ )	Budimir et al. (2015b)
Distance to ridge	Chang et al. (2007); Budimir et al. (2015b)	
Slope angle	Lin and Tung (2004); Chang et al. (2007); Nowicki et al. (2014); Umar et al. (2014); Budimir et al. (2015b); Nowicki Jessee et al. (2018)	
Wetness	CTI	Jibson (1993); Chang et al. (2007); Nowicki et al. (2014); Nowicki Jessee et al. (2018)

**CTI: Compound Topographic Index**

# Choose factor

There are two approaches to examine the impacts on landslides:

## 1. Point biserial Correlation coefficient:

appropriate for assessing relationships between topographic factors and landslides

topographic factors → continuous

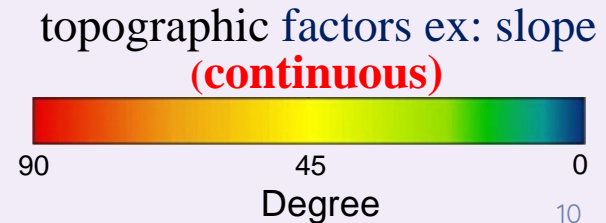
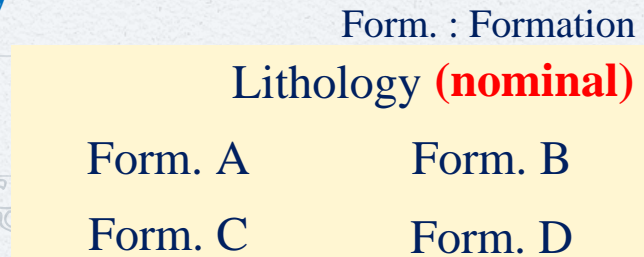
Landslide data → binary

## 2. Cramer's V:

used to examine the relationship between lithology data and landslide data.

Lithology type → nominal

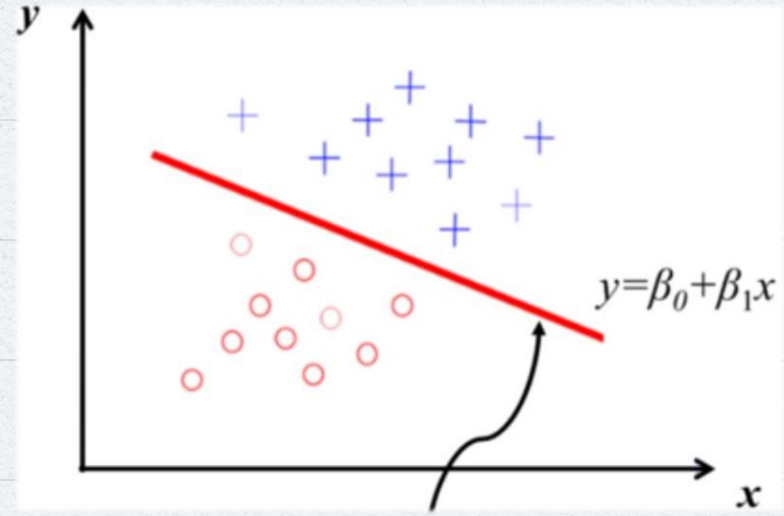
Landslide data → binary



# Logistic Regression

$$\textit{susceptibility} = \frac{e^y}{1 + e^y}$$

Sample points are randomly selected on landslide and non-landslide areas



Find a line that distinguishes two groups

To determine the most significant variables, approaches including:

1. Akaike information criteria (AIC)
2. area under the receiver operating curve (AUC)

$$y = a_0 + \sum_{k=1}^n a_k x_k$$

$a_0$ : constant intercept

$a_k$ : weight of factor

$x_k$ : the value of factor

$n$ : number of factor

3.

# Result

# Determination of variables

Coefficient values  $>0.1$  or  $<-0.1$   
→factor has a strong correlation  
with landslide occurrences  
(Nowicki Jessee et al., 2018).

**Table 2**  
Correlation coefficient between each variable and earthquake-triggered  
landslides.

Type	Variable	Coefficient	p-Value
<b>Seismic property</b>	PGA	<b>0.72</b>	0.00
	Arias Intensity (AI)	<b>0.61</b>	0.00
	Wave and aspect direction	0.06	0.00
<b>Lithology</b>	Lithologic data	<b>0.36</b>	0.00
<b>Topography</b>	Elevation	0.05	0.00
	Aspect	0.02	0.00
	Curvature	-0.06	0.00
	Plan curvature	-0.06	0.00
	Profile curvature	0.06	0.00
	Roughness (3 × 3)	<b>0.44</b>	0.00
	Roughness (5 × 5)	<b>0.45</b>	0.00
	Distance to ridge	-0.02	0.00
	Slope angle	<b>0.43</b>	0.00
	<b>Wetness</b>	CTI	-0.09

## Six Factors:

1.PGA

2.Arias Intensity

3.Lithology

4.Roughness(3 × 3)

5.Roughness(5 × 5)

6.Slope angle

**Bold coefficient values  
denote a more significant  
correlation.**



# The nowcasting model of earthquake-triggered landslide

randomly select 2500 pixels on non-landslide areas and another 2500 pixels on landslide areas as the training data.

Lower AIC      Higher AUC



Best model

**Table 3**

A test of the best-fit model.

Variable	AIC	AUC
PGA + Roughness (5 × 5) + Lithology + PGA*Slope + PGA*Roughness (5 × 5)	83,706	0.9435
PGA + Roughness (5 × 5) + PGA*Roughness (5 × 5) + Lithology	83,717	0.9434
PGA + Slope + PGA*Roughness (5 × 5) + Lithology + PGA*Slope	83,872	0.9433
PGA + Slope + Lithology + Roughness (3 × 3)	88,680	0.9361
PGA + Slope	93,471	0.9296
Arias Intensity + Roughness (5 × 5) + Lithology	97,639	0.7939

The final equation of this model is:

$$y = -3.469336 + 6.252418 X_{PGA} + 11.67491 X_{Roughness(5 \times 5)} - 6.624769 X_{Lithology} - 0.6799484 X_{PGA*Slope} + 11.71126 X_{PGA*Roughness(5 \times 5)} + \epsilon \quad (5)$$

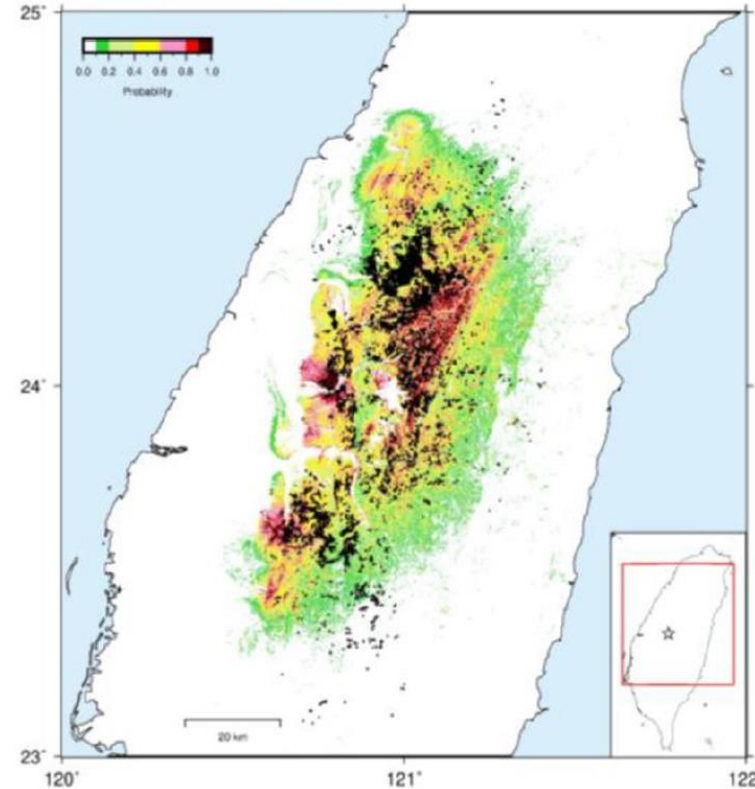
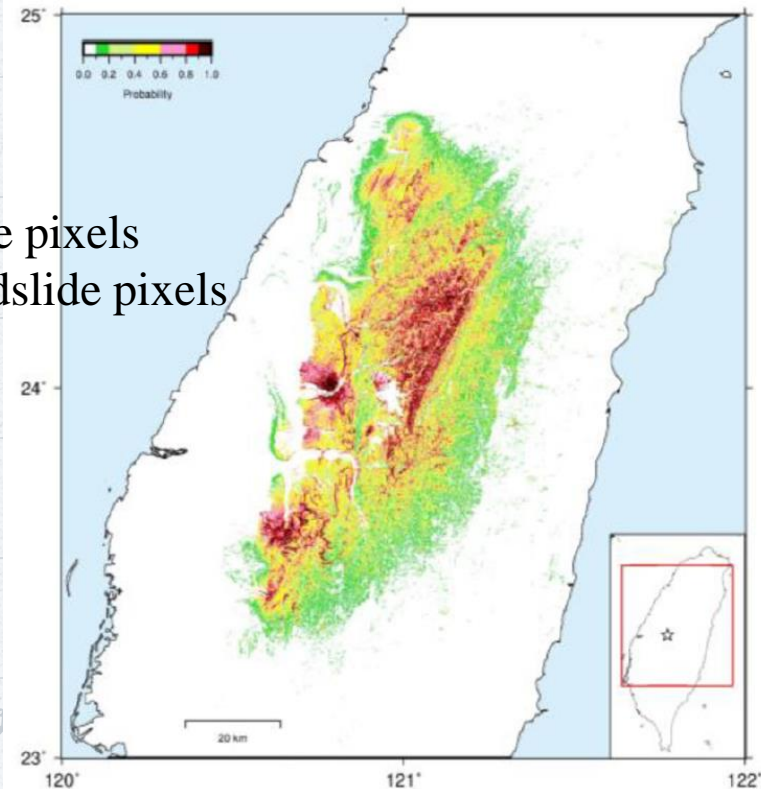
$$\text{Prob}_{stable \rightarrow landslide} = \frac{e^y}{1 + e^y}$$



# The nowcasting model of earthquake-triggered landslide

After the development of the logistic regression model, we test this model on the Chi-Chi Earthquake.

140,000 landslide pixels  
140,000 non-landslide pixels



# The nowcasting model of earthquake-triggered landslide

We vary the threshold of landslide probability from 0.1 to 0.9 in the interval of 0.1. If the probability of each pixel is higher than the threshold, the pixel is counted as a landslide pixel.

susceptibility

0.3



Non-Landslide pixel

Assume Threshold = 0.5

0.8



Landslide pixel





# The nowcasting model of earthquake-triggered landslide

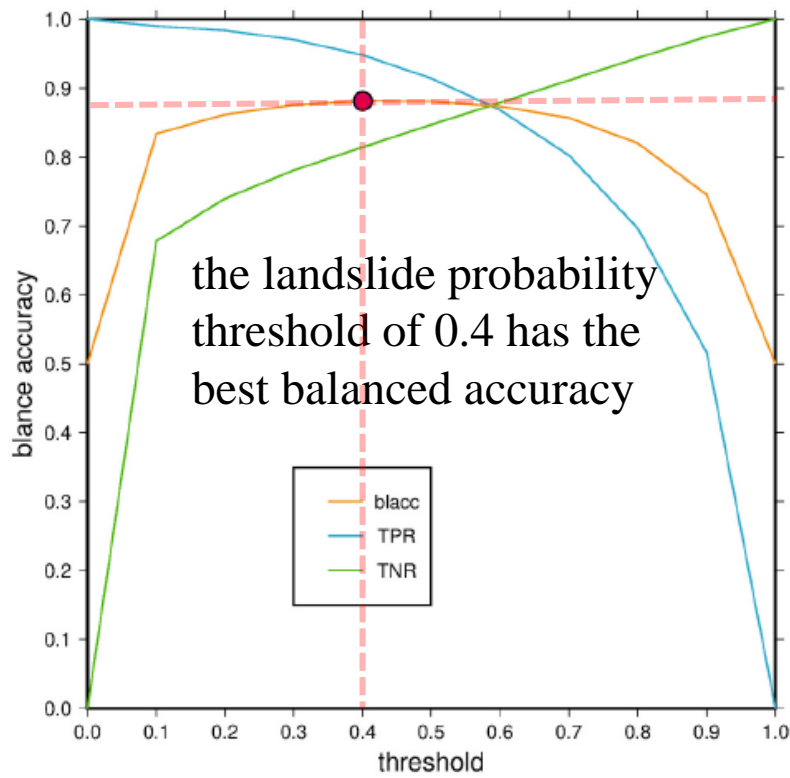


Fig. 4. Balanced accuracy of the nowcasting model based on Chi-Chi earthquake. Blacc: balanced accuracy; TPR: true positive rate; TNR: true negative rate.

If the threshold is set to a low value (e.g., 0.1), it may generate many false alarms, but instead, it avoids the occurrence of missing events.

$$\text{Balance accuracy} = \frac{\text{TPR} + \text{TNR}}{2}$$

Table 5

Balanced accuracy under various threshold of probability.

Threshold	TPR	TNR	Balanced accuracy
0.0	1.00000	0.00000	0.50000
0.1	0.99017	0.67818	0.83417
0.2	0.98383	0.73980	0.86181
0.3	0.97040	0.78101	0.87570
0.4	0.94812	0.81460	0.88136
0.5	0.91435	0.84710	0.88072
0.6	0.86844	0.87883	0.87363
0.7	0.80283	0.91146	0.85715
0.8	0.69960	0.94394	0.82042
0.9	0.51654	0.97461	0.74558

TPR: true positive rate; TNR: true negative rate.

# The nowcasting model of earthquake-triggered landslide

Use Chi-Chi earthquake (1999) model



Put into Jueili earthquake(1998)

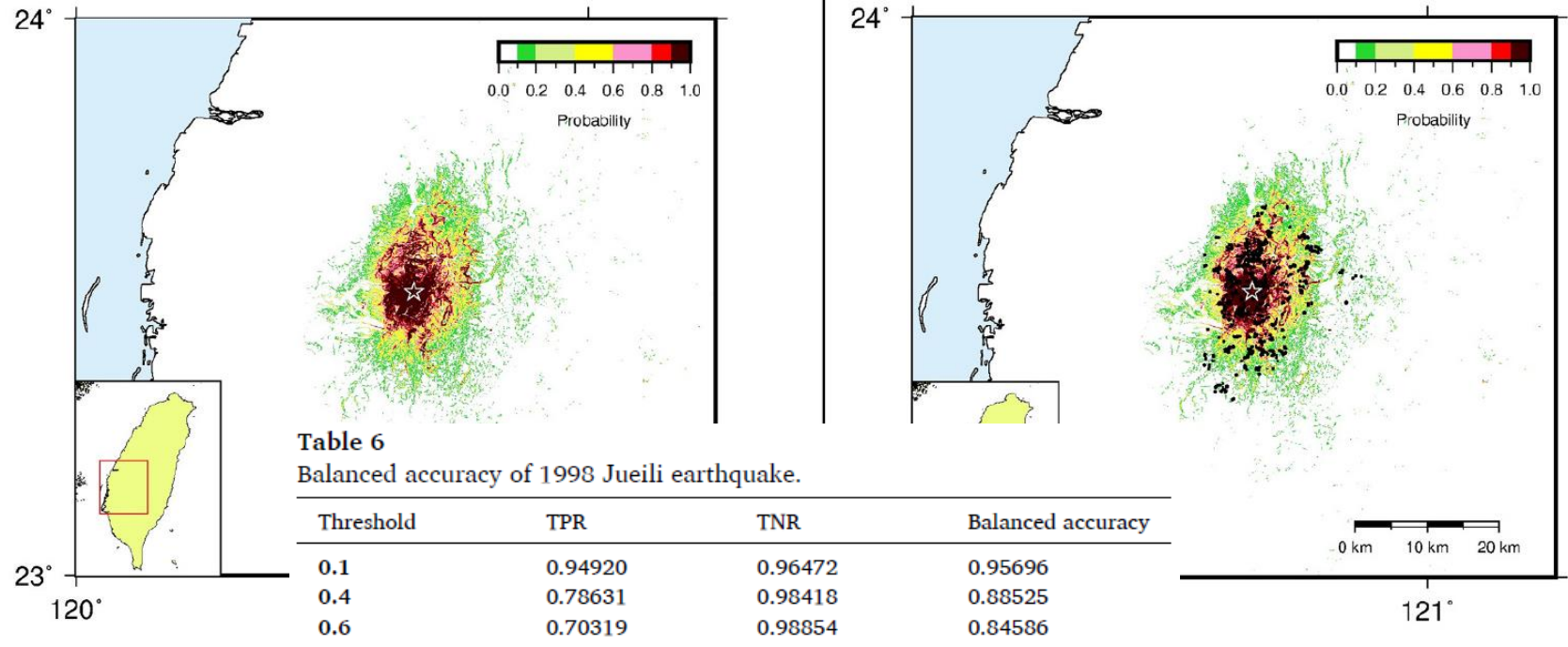


Fig. 5. Probability of landslides triggered by the 1998 Jueili earthquake. Black polygons are mapped landslides from Huang and Lee (1999).



# Conclusion

1

2

Correlation coefficient between each variable and earthquake-triggered landslides.

Type	Variable	Coefficient	<i>p</i> -Value
Seismic property	PGA	<b>0.72</b>	0.00
	Arias Intensity (AI)	<b>0.61</b>	0.00
	Wave and aspect direction	0.06	0.00
Lithology	Lithologic data	<b>0.36</b>	0.00
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	Distance to ridge	-0.02	0.00
	Slope angle	<b>0.43</b>	0.00
Wetness	CTI	-0.09	0.00

2

In Jueili earthquake(1998),  
when threshold=0.1  
→balance accuracy =0.95

**Table 6**

Balanced accuracy of 1998 Jueili earthquake.

Threshold	TPR	TNR	Balanced accuracy
<b>0.1</b>	<b>0.94920</b>	<b>0.96472</b>	<b>0.95696</b>
<b>0.4</b>	<b>0.78631</b>	<b>0.98418</b>	<b>0.88525</b>
<b>0.6</b>	<b>0.70319</b>	<b>0.98854</b>	<b>0.84586</b>

3

Increase resolution from 1km to 40m



THANK YOU

# Appendix



## Cramer's V

Pearson's chi-squared test

$$Cramer's V = \frac{\sum \frac{(O_i - E_i)^2}{E_i}}{N \times [\min(n,m)-1]}$$

$O_i =$  observed value

$E_i =$  expected value

$n =$  number of column

$m =$  number of row

$N =$  Number of samples

$$\sum \frac{(O_i - E_i)^2}{E_i} =$$

$$\frac{(2 - 2.66)^2}{2.66} + \frac{(18 - 17.33)^2}{17.33} + \frac{(2 - 1.33)^2}{1.33} + \frac{(8 - 8.66)^2}{8.66}$$

Cramer's V	
0-0.4	Lowly correlated
0.4-0.7	Moderately correlated
0.7-1	Highly correlated



## observed value

	Positive	Negative	Total
vaccine	2	18	20
No vaccine	2	8	10
Total	4	26	30



## expected value

	Positive	Negative	Total
vaccine	$20 * \frac{4}{30}$ <b>= 2.66</b>	$20 * \frac{26}{30}$ <b>= 17.33</b>	20
No vaccine	$10 * \frac{4}{30}$ <b>= 1.33</b>	$10 * \frac{26}{30}$ <b>= 8.66</b>	10
Total	4	26	30

# Appendix



## Point biserial Correlation coefficient

Student	A	B	C	D	E	F	G	H	I	J
gender	1	0	1	1	0	1	1	0	1	0
Score	76	58	74	67	65	68	71	69	66	61

$p = \text{ratio of gender 1}$

$q = \text{ratio of gender 2}$

$$\sigma_{score} = 5.48$$

$$\overline{gender_1} = 70.33$$

$$\overline{gender_2} = 63.25$$

Correlation coefficient	
0-0.4	Lowly correlated
0.4-0.7	Moderately correlated
0.7-1	Highly correlated

$$r = \frac{\overline{X_p} - \overline{X_q}}{\sigma_x} \sqrt{pq} = \frac{70.33 - 63.25}{5.48} \sqrt{\frac{6}{10} * \frac{4}{10}} = 0.633$$









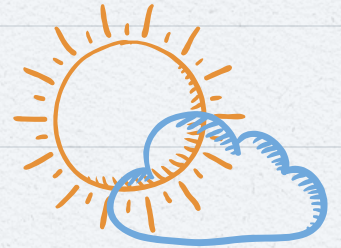
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