

# Deep Neural Network Utilizing Remote Sensing Datasets for Flood Hazard Susceptibility Mapping

**Bahareh Kalantar**

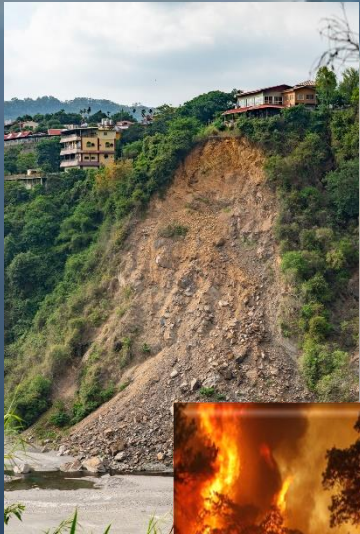
**Research Scientist**

Member in Disaster Resilience Science Team,  
RIKEN AIP

Lead Editor in “Journal of Sensor”

Guest Editor in “Remote Sensing”  
Journal

Associate Editor at “Frontiers in  
Remote Sensing”, Data Fusion  
and Assimilation.







# Objectives

To classify the flood susceptible zones using ANN, DLNN, and PSO-DLNN

To assess and compare the accuracy and reliability of the models based on sensitivity, specificity, the area under curve (AUC), and true skill statistic (TSS) tests

To determine the most important factors influencing the flood occurrence, in the subtropical climate region



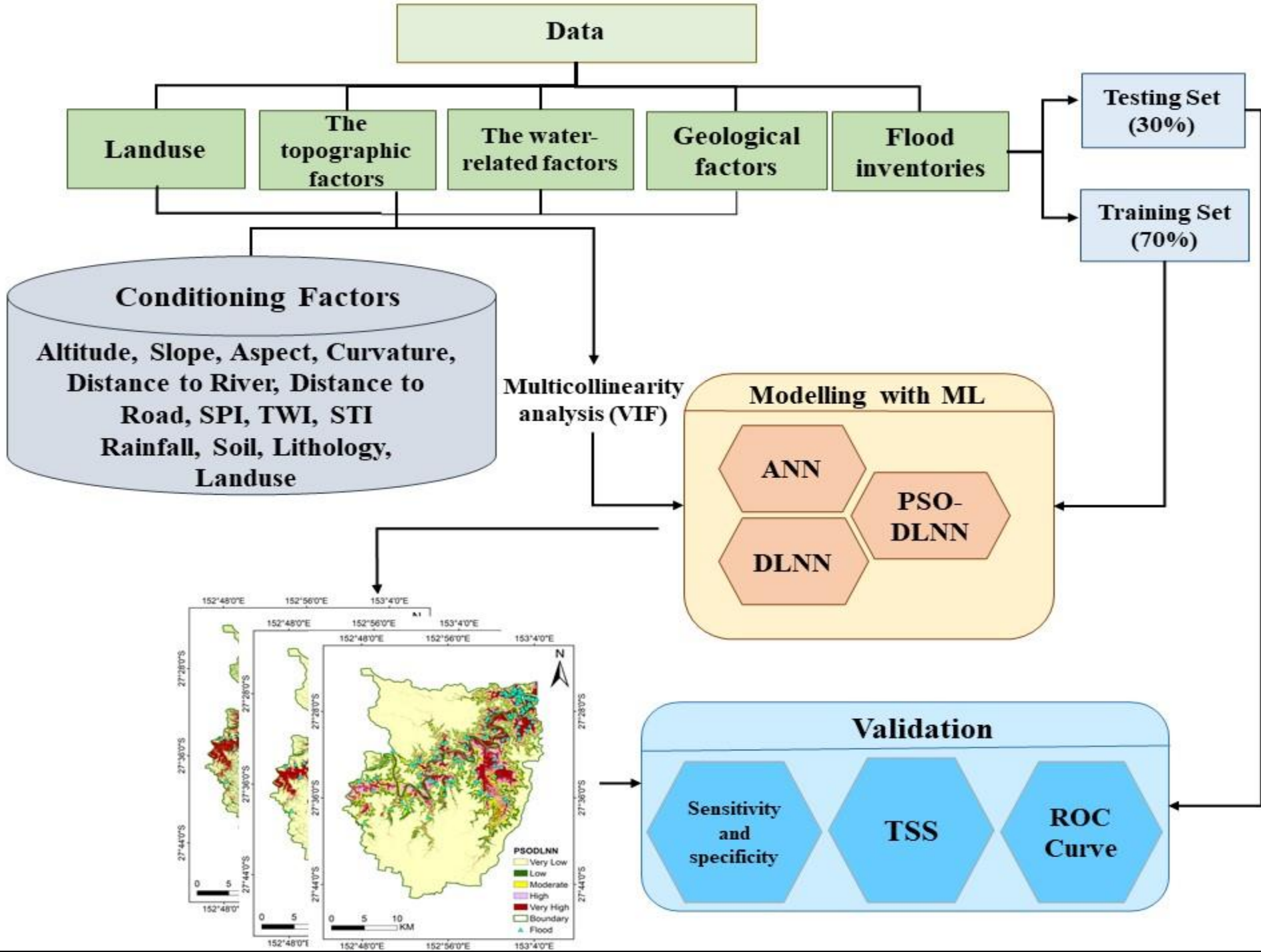
**Altitude: from 0 to 548 m**

**Average temperature: 20.3 °C**  
**128 historical areas from Brisbane floods**

**Annual rainfall of 1168 mm**

**Humid subtropical climate**

**Brisbane**



# Methodology

## Multicollinearity Analysis

Variables	VIF	Tolerance
Altitude	4.52	0.22
Slope	4.1	0.24
Aspect	1.03	0.97
Curvature	1.31	0.76
Distance from river	2.39	0.42
Distance from road	2.13	0.47
Rainfall	2.07	0.48
Land use	1.59	0.63
Lithology	1.38	0.72
Soil	1.99	0.50
SPI	1.15	0.87
TWI	1.69	0.59
STI	4.04	0.25

$$VIF = \frac{1}{1 - R_i^2}$$

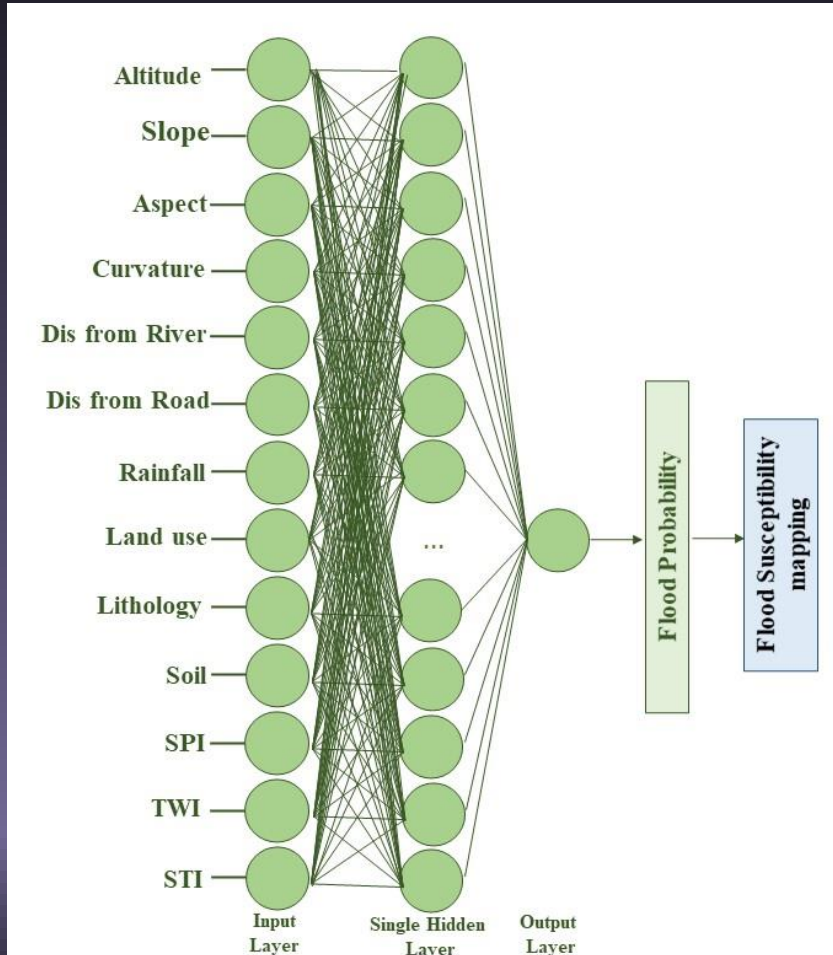
where  $R_i$  is the multi correlation coefficient of  $i^{th}$  factor on the remaining factors

$$Tolerance = 1 - R_i^2$$

VIF value greater than 5 and the tolerance value less than 0.1

# Methodology

## Artificial Neural Networks (ANN)



$$Out = f\left(\sum_{j=1}^n w_j x_i + \theta_j\right)$$

$f$  is a transfer function

$w_j$  defines the weight vector

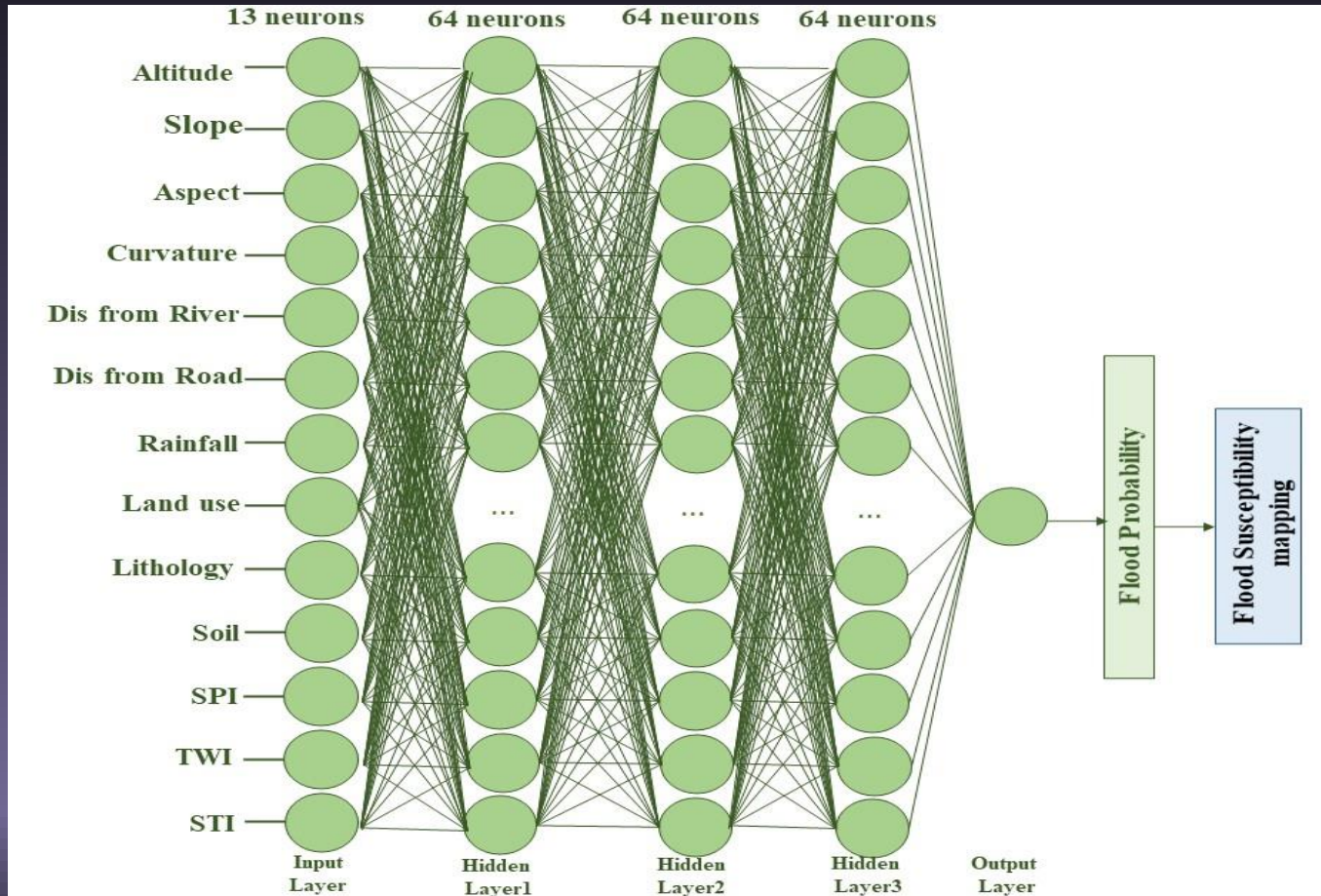
$x_i$  is the node flow (causal factors) from the inputs

$\theta_j$  represents a threshold value or bias



# Methodology

## Deep Learning Neural Networks (DLNN)

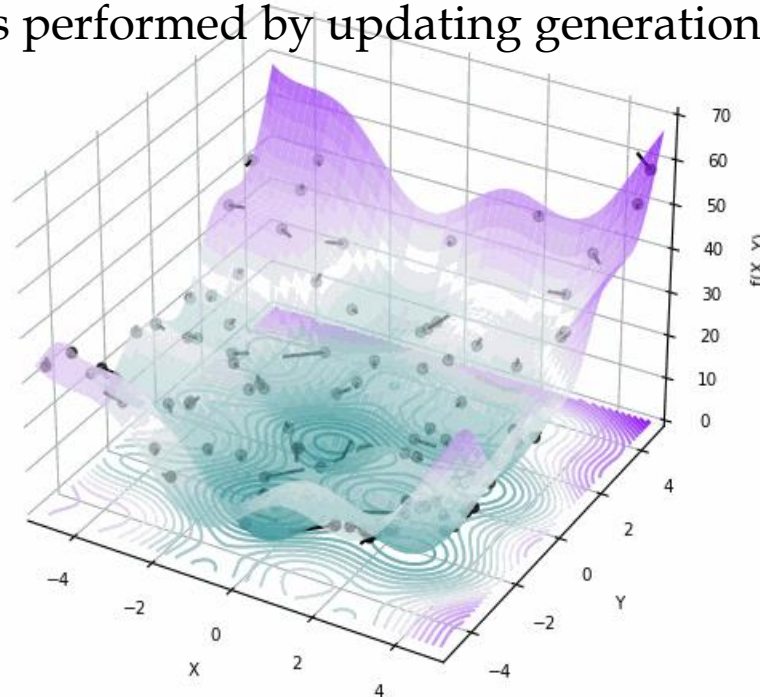


# Methodology

## Optimized DLNN via particle swarm optimization (PSO)

PSO is a population-based optimization technique.

The system is initialized with a population of random solutions, and the search for the optimal solution is performed by updating generations.



No	Parameter	Model		
		ANN	DLNN	PSO-DLNN
1	Input nodes	13	13	13
2	Output nodes	2	2	2
3	Activation	-	'relu'	'relu'
4	Function	-	'Sigmoid'	'Sigmoid'
5	reluLeak	-	0.01	0.01
6	Eta	-	0.8	0.8
7	Hidden layer unit	1	3	3
8	Iteration	1000	500	500
10	Phi	-	-	4.1
11	phi1	-	-	2.05
12	Phi2	-	-	2.05
13	W	-	-	0.73
14	C1	-	-	1.49
15	C2	-	-	1.49

# Methodology

## Evaluation methods

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

$$\text{TSS} = \text{Sensitivity} + \text{Specificity} - 1$$

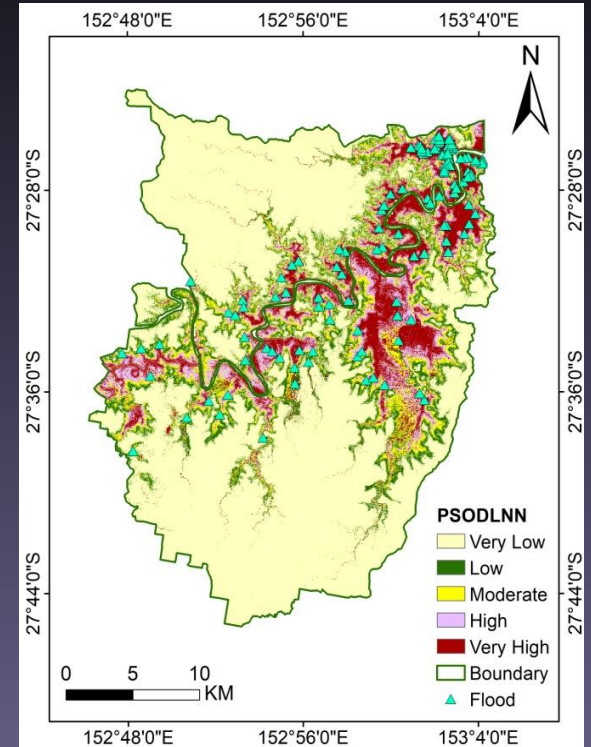
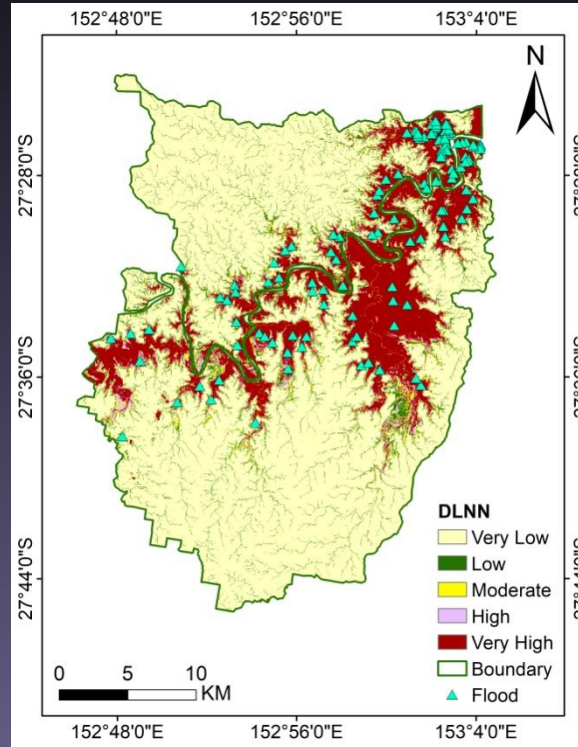
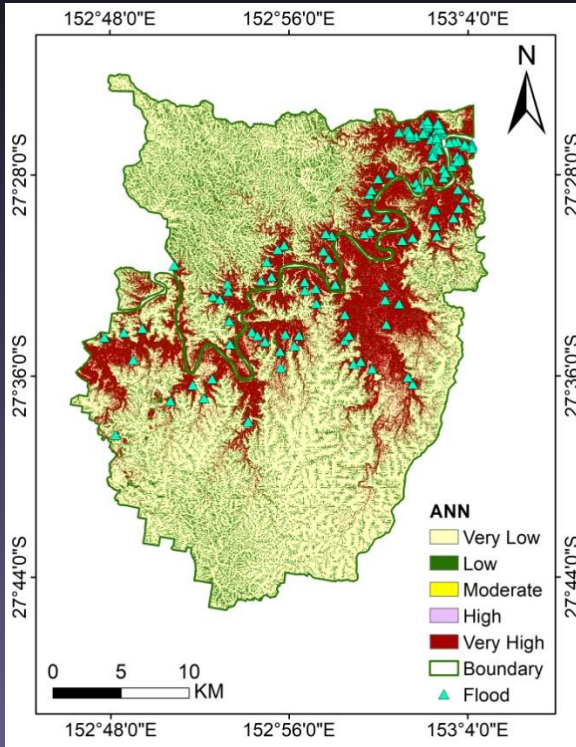
TP = true positive

TN=true negative

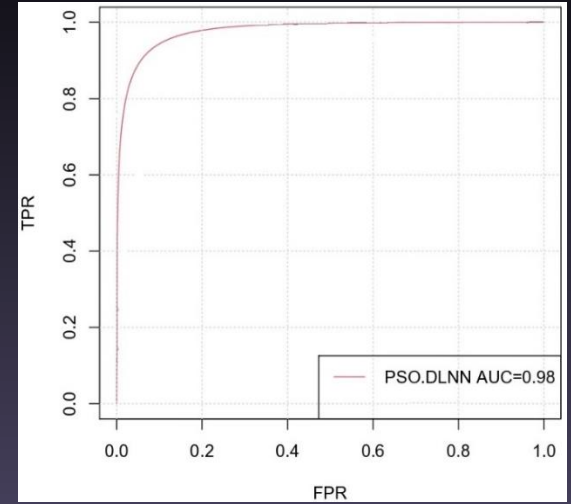
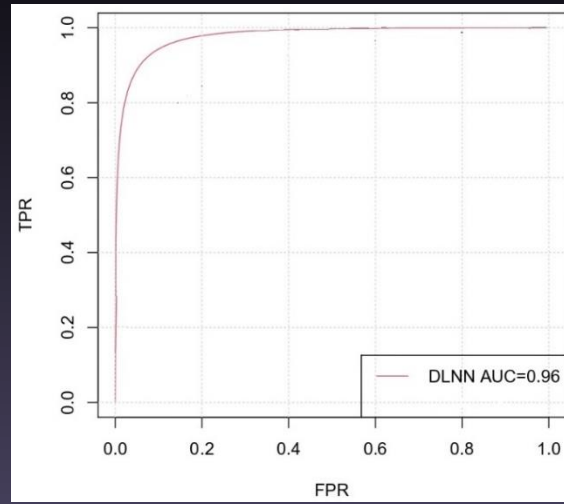
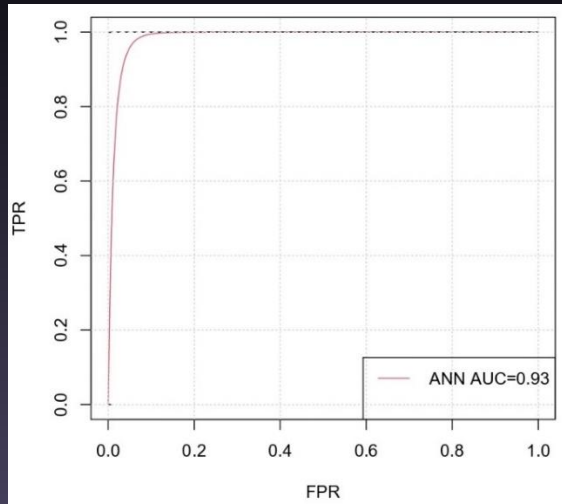
FN= false negative

FP = false positive

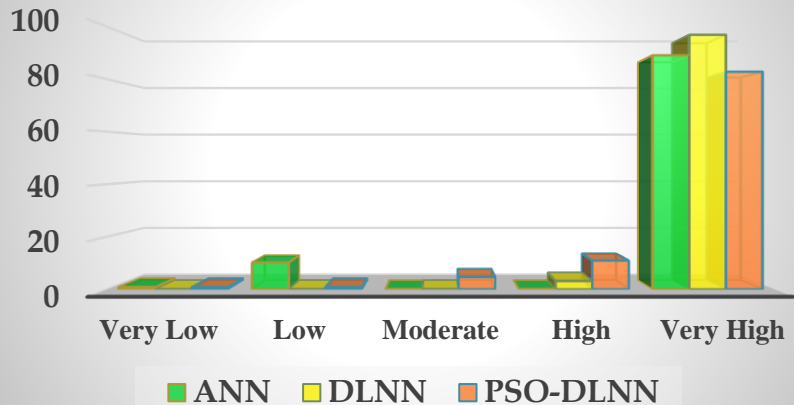
# Results



# Results



## Flood Density Graph



Models	Stage	Evaluation Tests			
		Sensitivity	Specificity	TSS	AUC
ANN	Train	0.98	0.96	0.94	0.98
	Validation	0.94	0.85	0.79	0.93
DLNN	Train	0.99	0.87	0.86	0.98
	Validation	0.86	0.85	0.71	0.96
PSO-DLNN	Train	0.99	0.89	0.88	0.99
	Validation	0.92	0.98	0.90	0.98

# Results

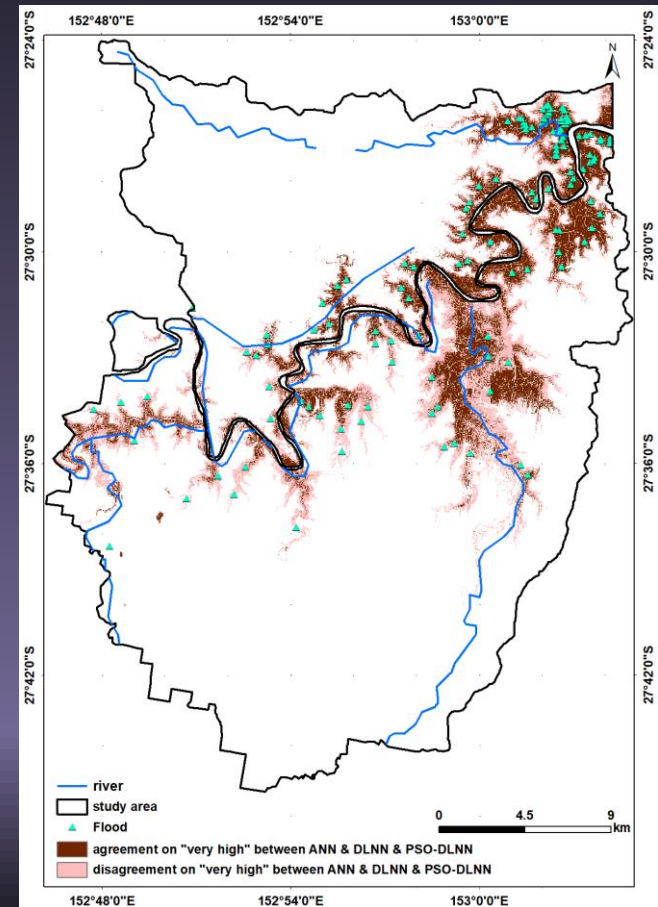
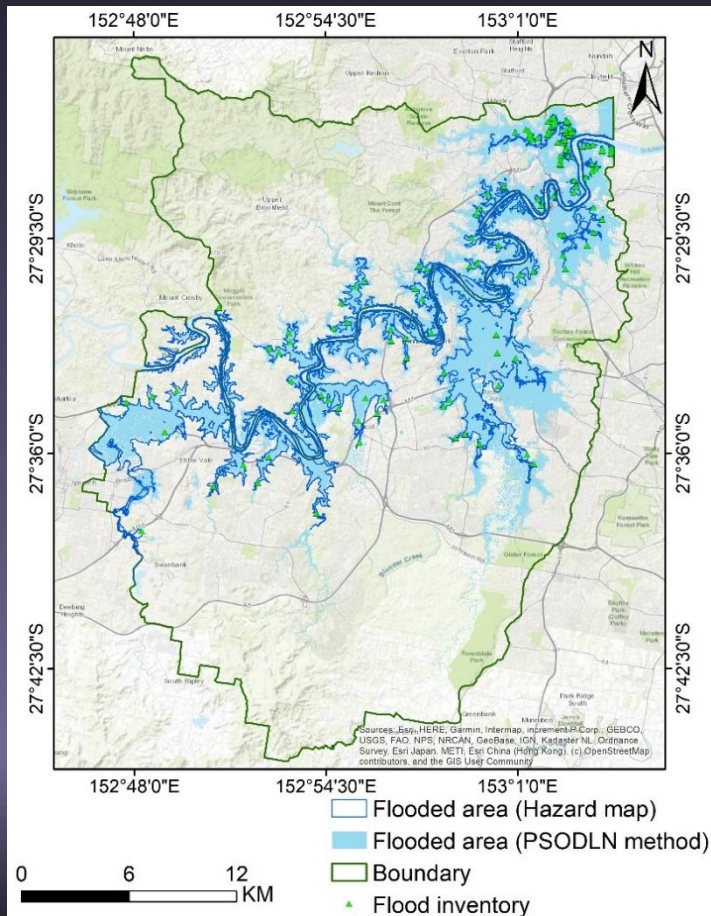
Variable importance analysis derived from PSO-DLNN model.

<b>Variables</b>	<b>Importance</b>
Altitude	100
Slope	33.05
Aspect	1.32
Curvature	16.55
Distance from river	55.44
Distance from road	29.21
Rainfall	9.31
Land use	22.63
Lithology	11.29
Soil	1.74
SPI	0
TWI	18.77
STI	39.69

# Discussion

Comparison of flooded area predicted by PSO\_DLNN method and hazard map.

Agreement and disagreement flood susceptibility for the "very high" class simulated by ANN, DLNN, PSO-DLNN.





# Conclusion

- The significance of the conditioning factors analysis for the region highlighted that *altitude*, *distance from river*, *sediment transport index (STI)*, and *slope* played the most important roles, whereas stream power index (SPI) did not contribute to the hazardous situation.
- The best accuracies by AUC were evaluated in PSO-DLNN (**0.99** in training and **0.98** in testing datasets), followed by DLNN and ANN.
- Therefore, the *optimized PSO-DLNN* proved its robustness to compare with other methods.



Article

# Deep Neural Network Utilizing Remote Sensing Datasets for Flood Hazard Susceptibility Mapping in Brisbane, Australia

Bahareh Kalantar <sup>1,\*</sup>, Naonori Ueda <sup>1</sup>, Vahideh Saeidi <sup>2</sup>, Saeid Janizadeh <sup>3</sup>, Fariborz Shabani <sup>4</sup>,  
Kourosh Ahmadi <sup>5</sup> and Farzin Shabani <sup>6,7</sup>

<sup>1</sup> RIKEN Center for Advanced Intelligence Project, Goal-Oriented Technology Research Group, Disaster Resilience Science Team, Tokyo 103-0027, Japan; naonori.ueda@riken.jp

<sup>2</sup> Department of Mapping and Surveying, Darya Tarsim Consulting Engineers Co. Ltd., Tehran 14578-43993, Iran; saeidi@daryatarsim.com

<sup>3</sup> Department of Watershed Management Engineering, College of Natural Resources, Tarbiat Modares University, Tehran 15119-43943, Iran; janizadehsaeid@modares.ac.ir

<sup>4</sup> Department of Civil Engineering, Kermanshah Azad University, Kermanshah 67189-97551, Iran; fariborz.shabani1977@gmail.com

<sup>5</sup> Department of Forestry, Faculty of Natural Resources and Marine Sciences, Tarbiat Modares University, Tehran 15119-43943, Iran; kourosh.ahmadi@modares.ac.ir

<sup>6</sup> Global Ecology and ARC Centre of Excellence for Australian Biodiversity and Heritage, College of Science and Engineering, Flinders University, GPO Box 2100, Adelaide, SA 5001, Australia; farzin.shabani@flinders.edu.au

<sup>7</sup> Department of Biological Sciences, Macquarie University, Sydney, NSW 2109, Australia

\* Correspondence: bahareh.kalantar@riken.jp; Tel.: +81-362252482

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