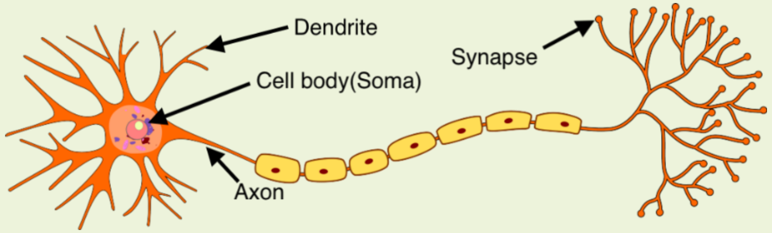
International Conference

Novel Infrastructure Techniques

NITCON - 2025

Narula Institute of Technology

Integration of AI/ML Techniques in Geotechnical Engineering Applications



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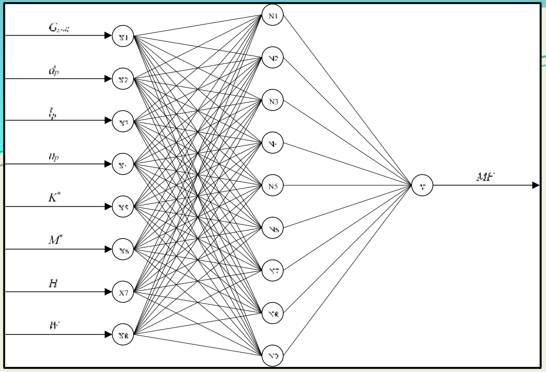

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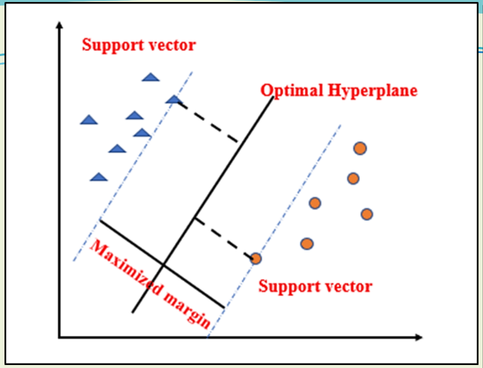
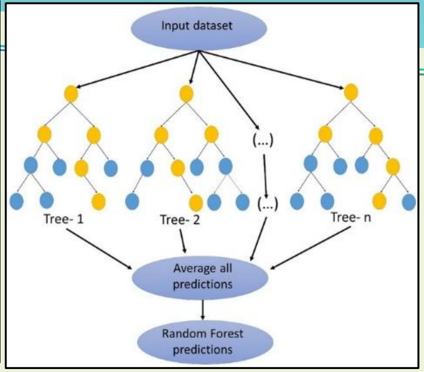


SVM



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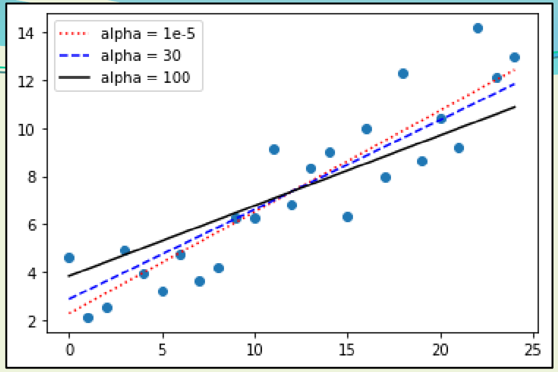

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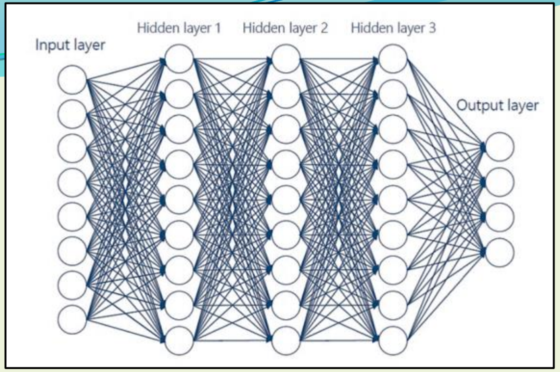
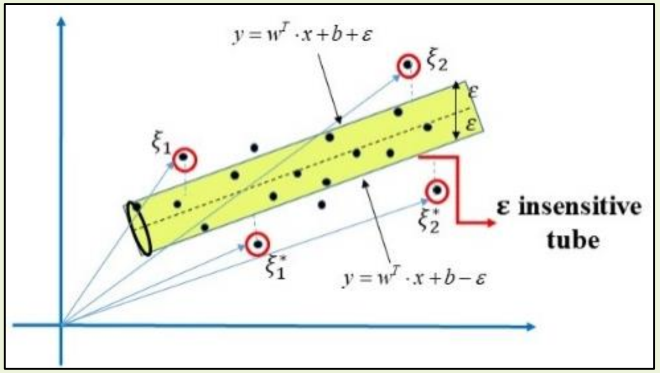


DNN/DL

AI /ML are Data-Driven TOOLS for Mapping and Prediction

Why to use? Where to integrate? Are we intelligently using it?

The PHYSICS and ENGINEERING of the problem is MORE IMPORTANT



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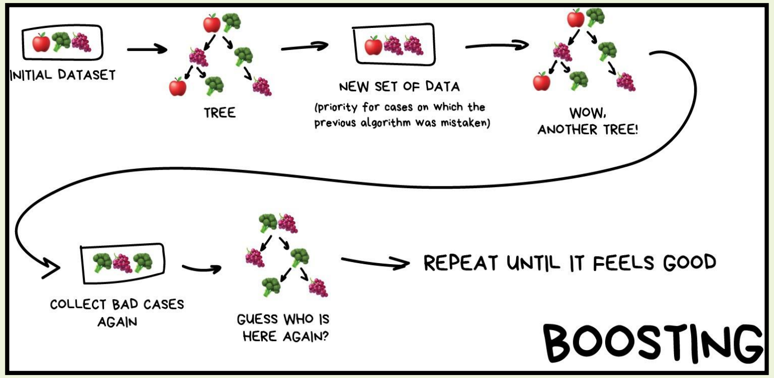
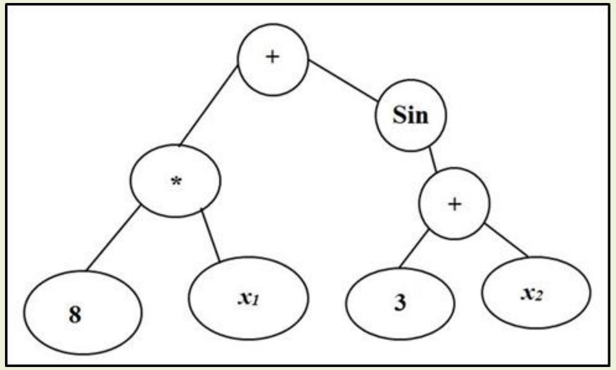
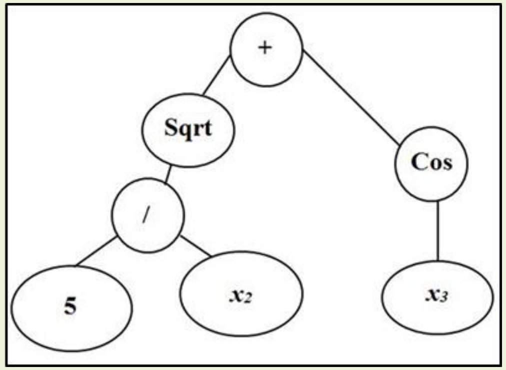
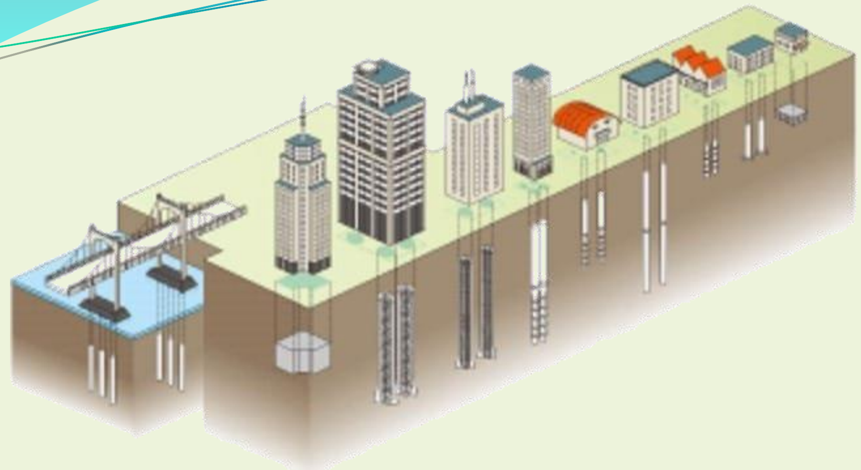


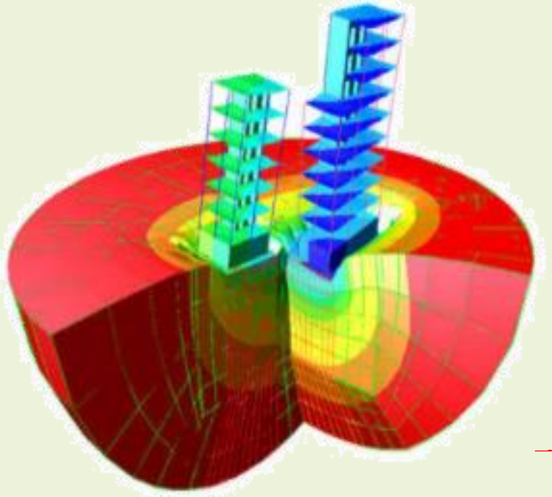
GB/GBRT/XGBOOST

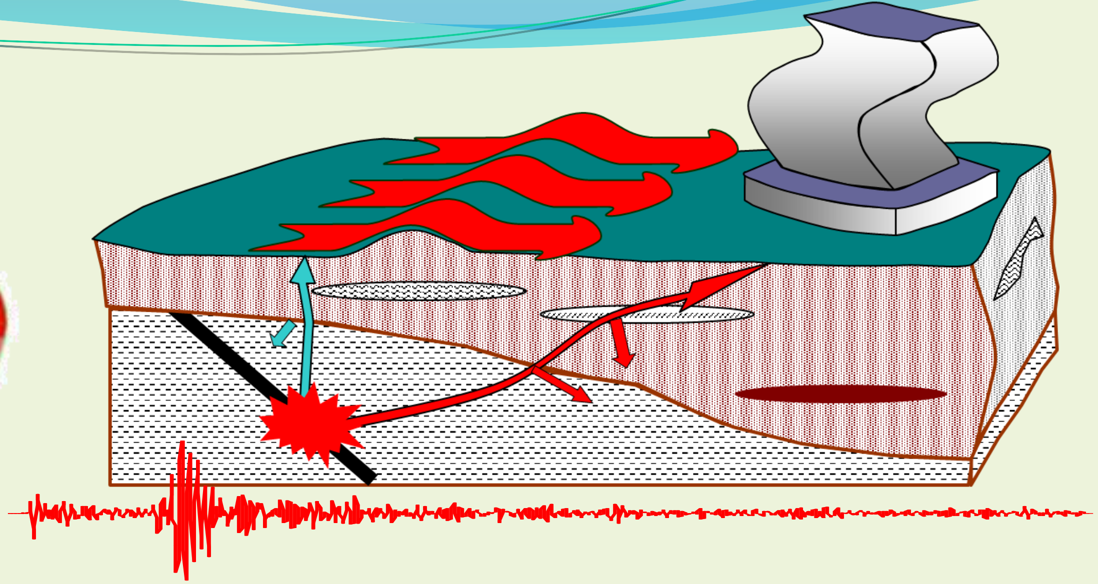




GP/MGGP

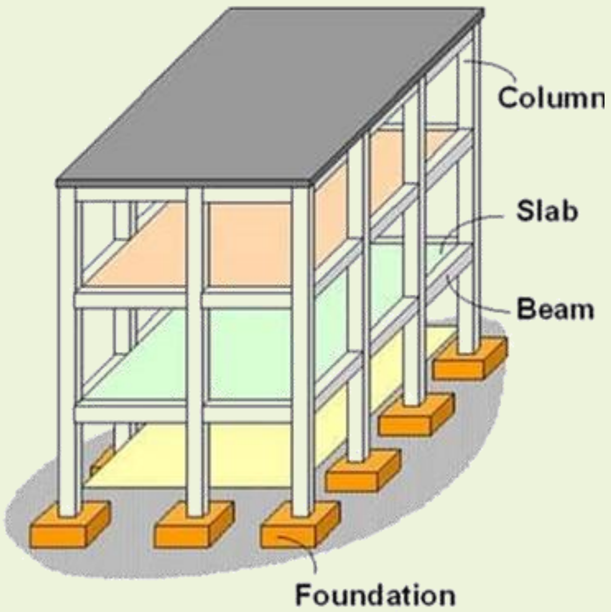


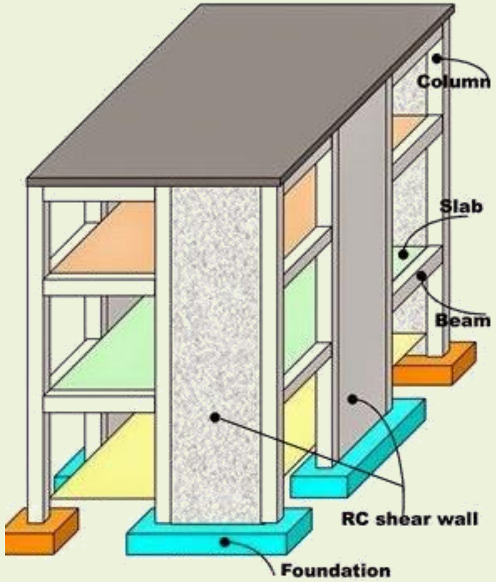




DSSI of RC Buildings on Pile Foundations in Sandy Medium

RC Frame Buildings





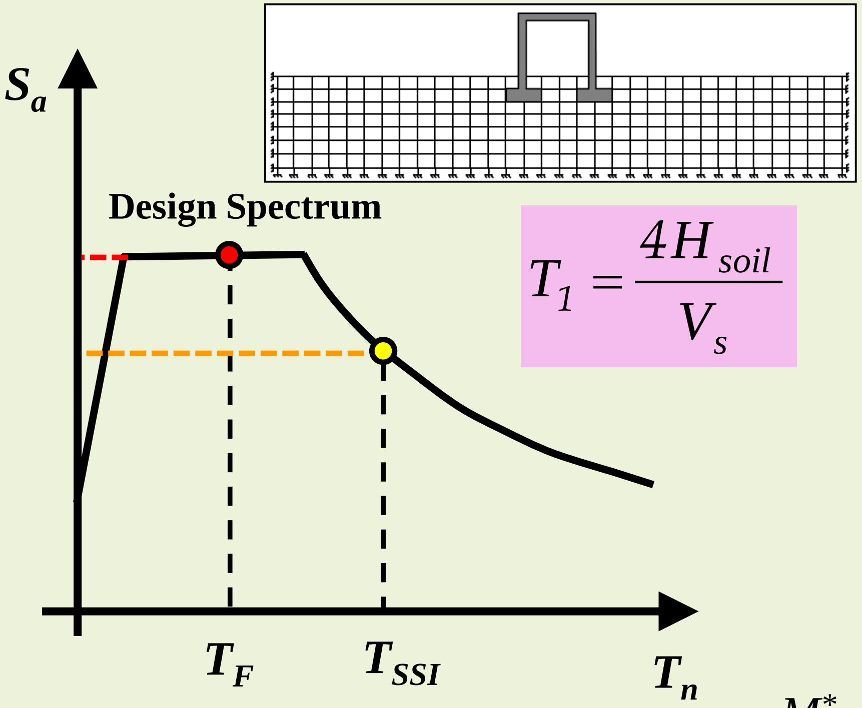
RC Wall-Frame Buildings

Influence of SSI on Natural Period for RC Structures on Pile Foundations

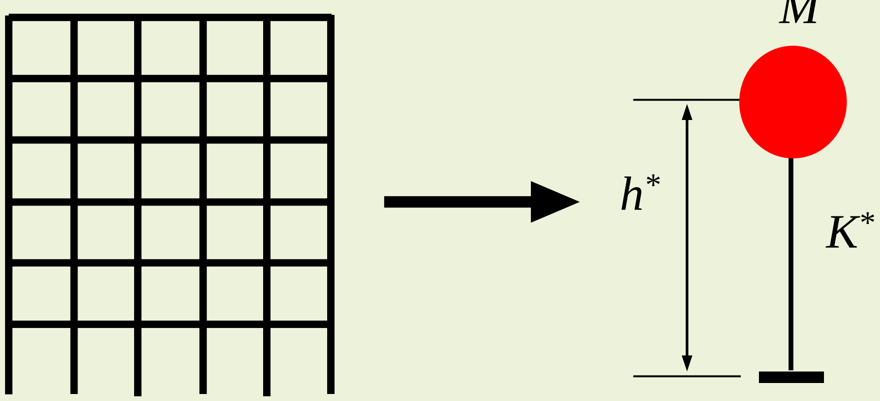
- Assessment of T_{SSI} for shallow foundations is quite common
  - *Shallow footing acts as interface between soil and structure*
  - *Impact of DSSI remains relatively lesser – Conventional fixed-base response analysis*

- Assessment of T_{SSI} for **buildings on pile foundations**
  - *Lumped/equivalent representation of the foundation stiffness*
    - Require the evaluation of impedance functions - Cumbersome
  - *SDOF oscillator*
    - Unsuitable to model non-uniform rocking under vertical members
  - *Rigorous analytical solutions* **(Maravas *et al*. 2007; Medina *et al*. 2013)**
    - Idealized and difficult to use

- Need for data-drivel approach (AI/ML) for T_{SSI} prediction model for building on pile foundation
  - *Incorporate the complex interaction of parameters contributing to SSI*
  - *Develop simple relations between input parameters and outcomes*



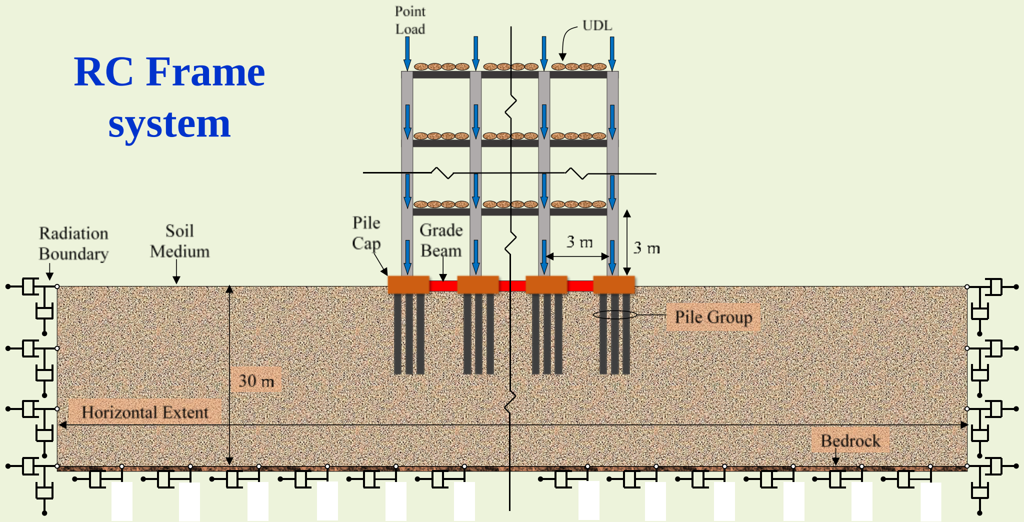
$$T_1 = \frac{4H_{soil}}{V_s}$$



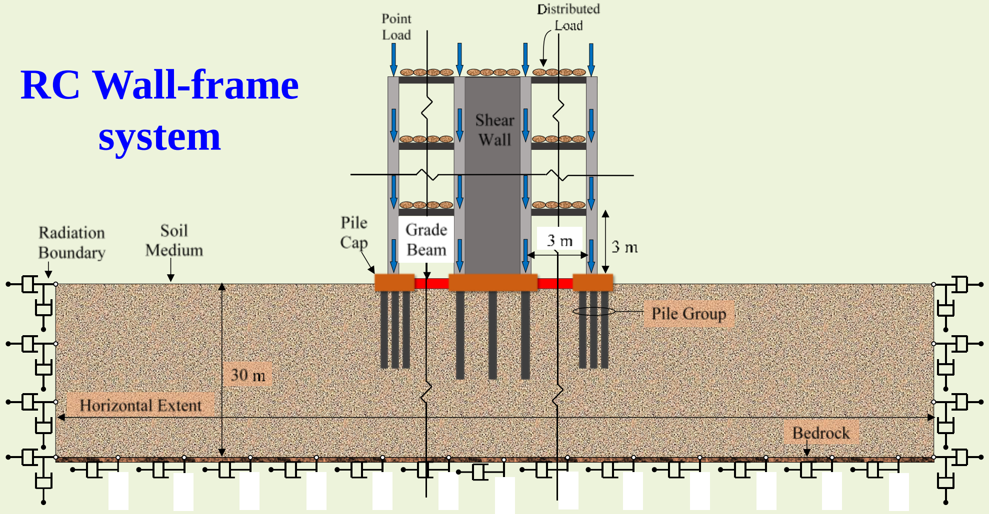
Dynamic SSI (DSSI) Analysis of RC Buildings on Pile Foundations

OPENSEES Modelling

RC Frame system

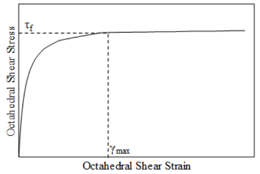


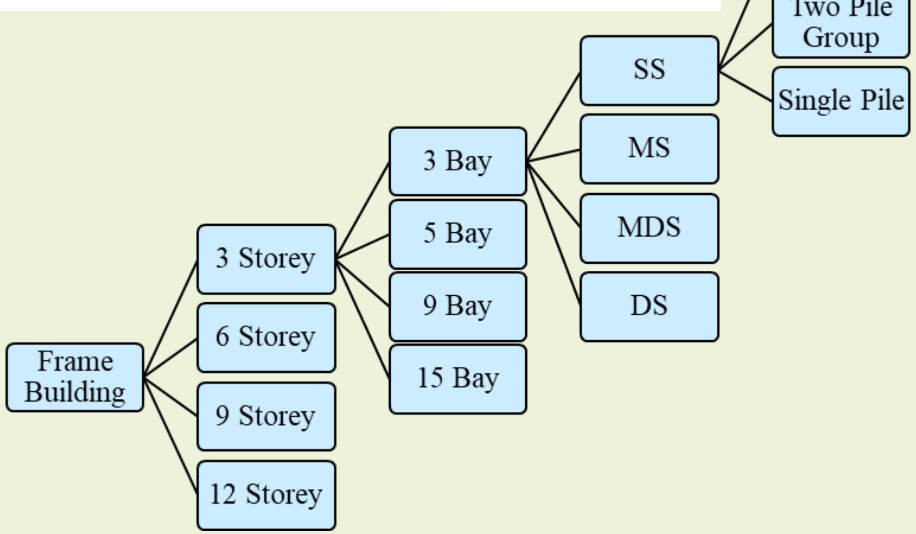
RC Wall-frame system



- Soil domain - 4 noded quadrilateral element
- Structural members and piles - 3dof elastic beam column element
- Storey height and bay widths – 3 m
- Nonlinear soil behavior – Pressure dependent multi yield failure criterion
- Failure criterion - Drucker-Prager yield surfaces (nested yield surface)
- Optimal domain size
  - *Sharma et al.* (FSCE, Springer, 2019)
- Pile groups
  - 3 under columns
  - 6 under shear wall

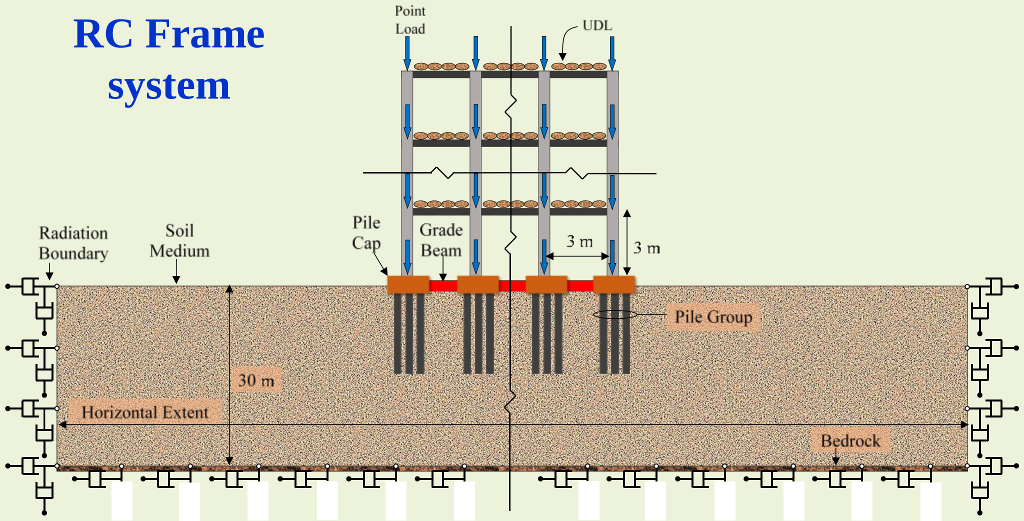
$$\tau = \frac{G\gamma}{1 + \frac{\gamma}{\gamma_r}\left(\frac{p_r'}{p'}\right)^{0.5}}$$





Dynamic SSI (DSSI) Analysis of RC Buildings on Pile Foundations

RC Frame system



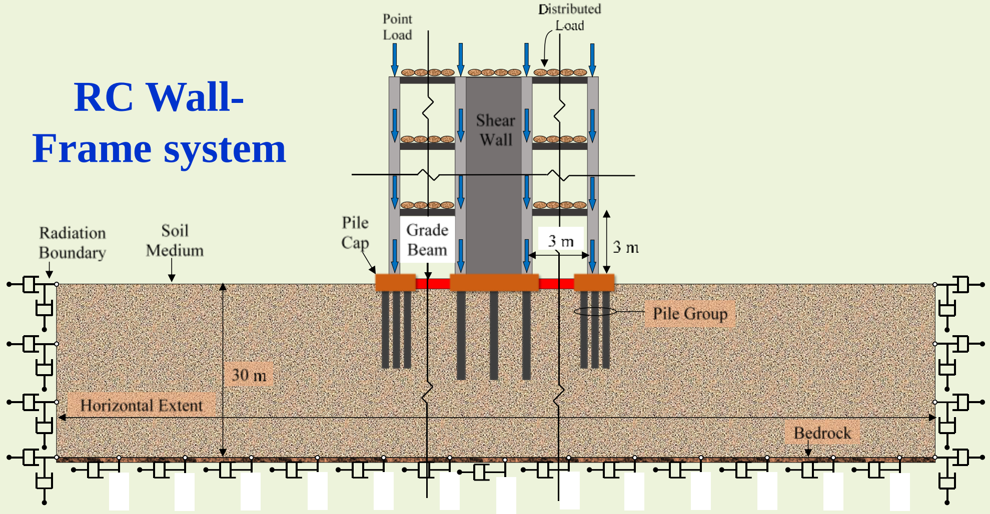
No. of Stories	Loose Sand SS		Medium sand MS		Med. dense sand MDS		Dense sand DS	
	Pile length (m)	Pile dia. (mm)	Pile length (m)	Pile dia. (mm)	Pile length (m)	Pile dia. (mm)	Pile length (m)	Pile dia. (mm)
3	11.0	300	7.0	300	6.5	250	3.5	250
6	12.5	400	7.5	400	5.5	350	4.5	300
9	15.5	450	10.0	450	6.0	400	5.0	350
12	16.5	500	10.5	500	6.5	450	5.0	400

No. of Stories	Storey level	Column					Beam				
		Size (mm×mm)	Main reinf.		Shear reinf.		Size (mm×mm)	Main reinf.		Shear reinf.	
			ϕ (mm)	no.	ϕ (mm)	s_v (mm)		ϕ (mm)	no.	ϕ (mm)	s_v (mm)
3	Upto 3	300×300	12	4+4	8 8	75 170	200×280	20† 20*	2 2	8	100
6	Upto 3	350×350	16	4+4	8 8	75 170	200×350	20† 12*	3 3	8	100
	3 to 6	350×350	16 12	4 4	8 8	75 170	200×350	20† 12*	3 3	8	100
9	Upto 3	450×450	16	4+4	8 8	75 170	250×400	20† 12*	4 3	8	100
	3 to 6	400×400	16 12	4 4	8 8	75 200	250×400	20† 12	4 3	8	100
	6 to 9	350×350	16 12	4 4	8 8	75 220	250×350	20† 12*	3 3	8	100
12	Upto 3	500×500	20 16	4 4	8 8	75 170	250×450	25 16*	3 2	8	90
	3 to 6	450×450	16	4+4	8 8	75 200	250×450	25† 16*	3 2	8	90
	6 to 9	400×400	16	4+4	8 8	75 220	250×400	20† 12*	4 3	8	100
	9 to 12	400×400	16 12	4 4	8 8	75 250	200×350	20† 12*	3 3	8	100

Note: ϕ is rebar diameter, † indicates tensile reinf., ∗ indicates compressive reinf. and reinf. is the abbreviation for reinforcement

Dynamic SSI (DSSI) Analysis of RC Buildings on Pile Foundations

RC Wall-Frame system



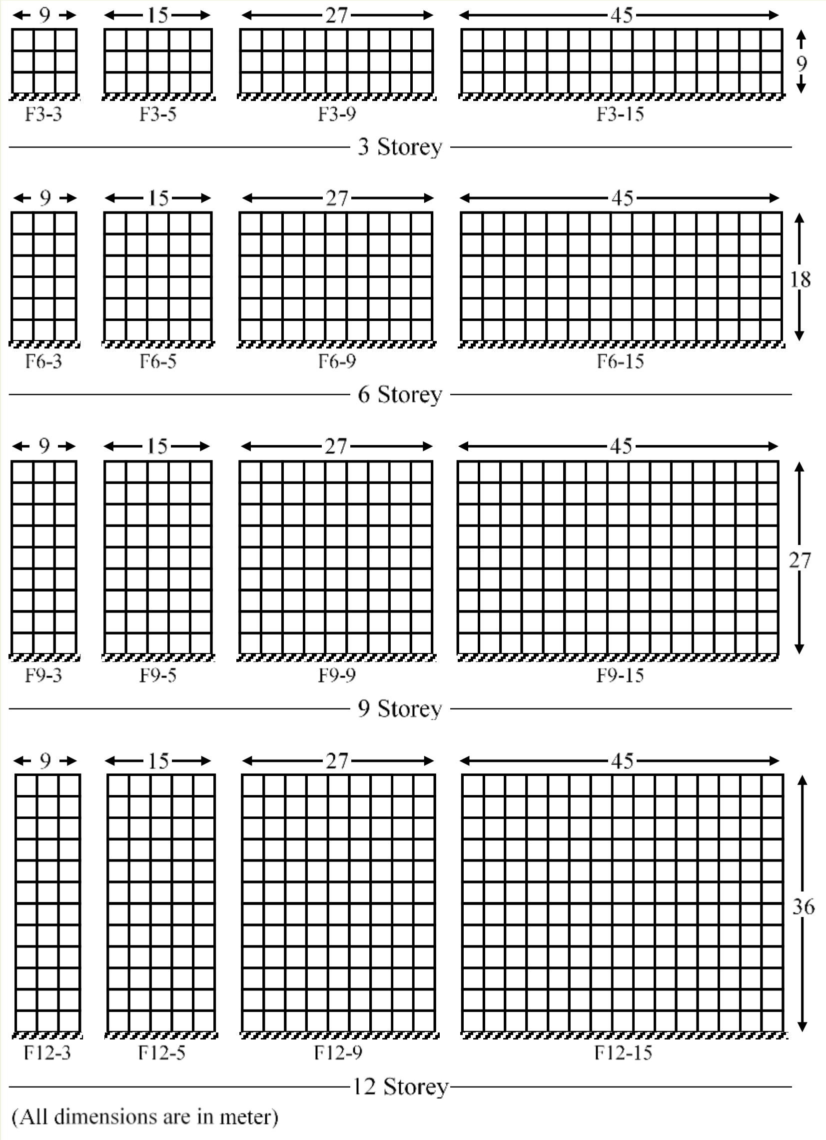
No. of Stories	Loose Sand SS		Medium sand MS		Med. dense sand MDS		Dense sand DS	
	Pile length (m)	Pile dia. (mm)	Pile length (m)	Pile dia. (mm)	Pile length (m)	Pile dia. (mm)	Pile length (m)	Pile dia. (mm)
3	11.0	250	7.0	250	7.5	200	3.5	200
6	12.5	350	8.5	350	6.5	300	6.5	250
9	17.0	400	11.5	400	8.0	350	7.0	300
12	16.5	500	13.5	450	9.5	400	7.0	350

No. of Stories	Storey level	Shear wall details					Boundary element details				
		t_w (mm)	Vertical reinf.		Horizontal reinf.		Size (mm×mm)	Main reinf.		Shear reinf.	
			ϕ (mm)	no.	ϕ (mm)	s_v (mm)		ϕ (mm)	no.	ϕ (mm)	s_v (mm)
3	Upto 1	200	12	10*	12	280	500×500	25 20	4 4	8	100
	1 to 3	200	12	10	12	280	300×300	12 12	4 4	8	100
6	Upto 1	200	12	10*	12	280	500×500	25 20	4 4	8	100
	1 to 3	200	12	10	12	280	350×350	16 16	4 4	8	100
	3 to 6	150	12	10	12	300	350×350	16 12	4 4	8	100
9	Upto 1	200	12	10*	12	260	500×500	25 20	4 4	8	100
	1 to 3	150	12	10	12	260	450×450	16 16	4 4	8	100
	3 to 6	150	12	10	12	300	400×400	16 12	4 4	8	100
	6 to 9	150	12	10	12	300	350×350	16 12	4 4	8	100
12	Upto 1	200	12	10*	12	230	500×500	25 20	4 4	8	100
	1 to 3	150	12	10	12	230	500×500	20 16	4 4	8	100
	3 to 6	150	12	10	12	300	450×450	16 16	4 4	8	100
	6 to 9	150	12	10	12	300	400×400	16 16	4 4	8	100
	9 to 12	150	12	10	12	300	400×400	16 12	4 4	8	100

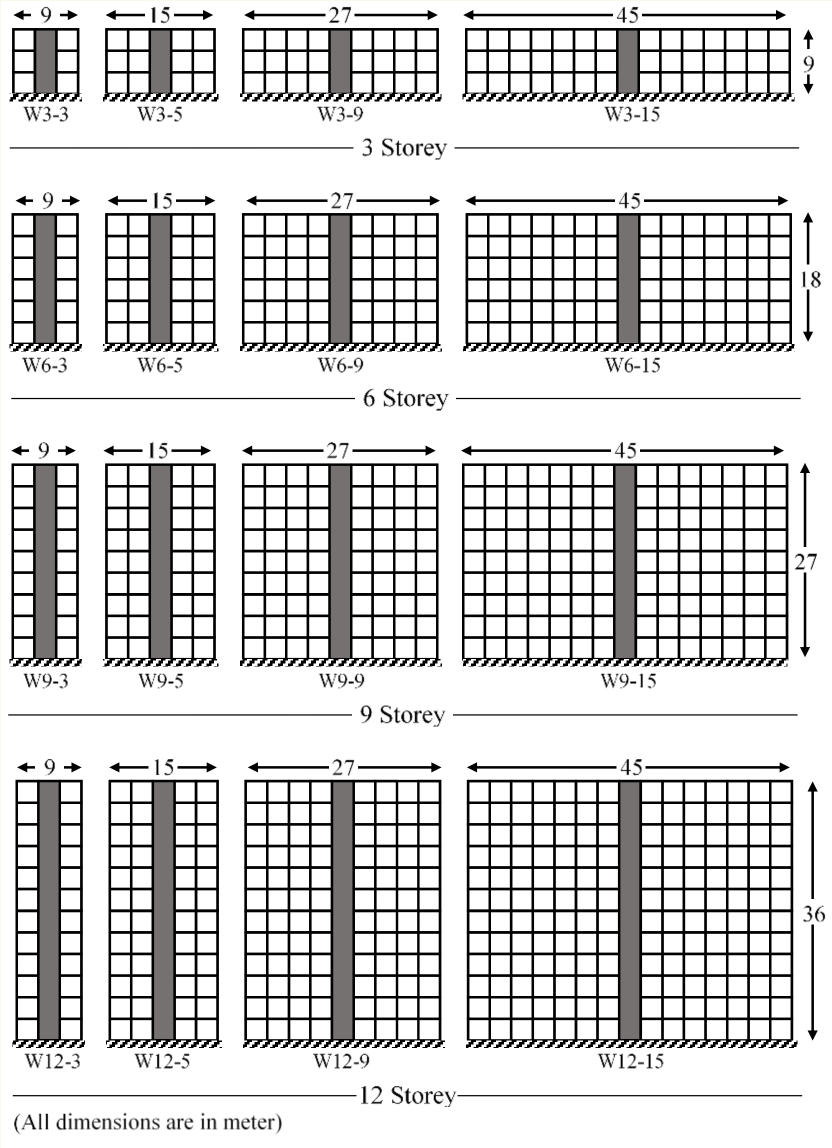
Note: ϕ is rebar diameter, † indicates tensile reinf., ∗ indicates compressive reinf. and reinf. is the abbreviation for reinforcement

Structural Configurations

RC Frame system (F)

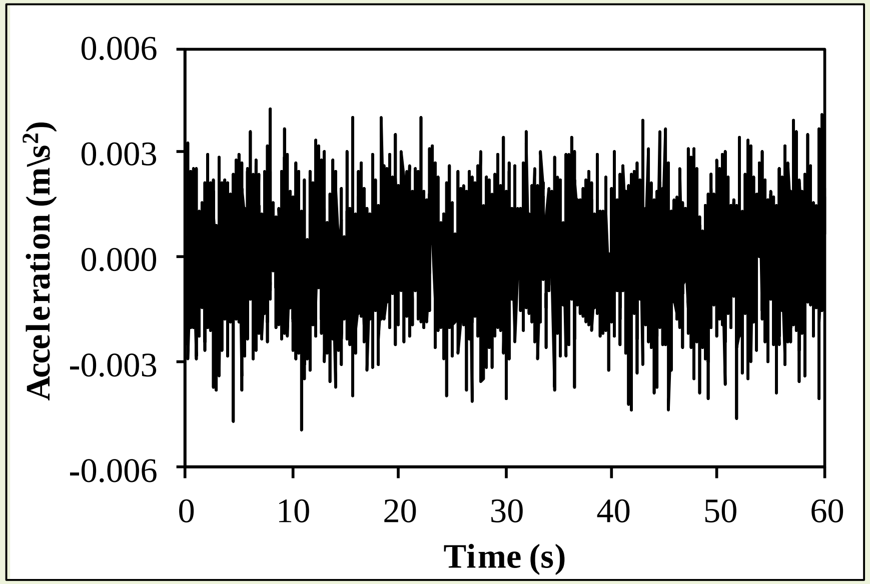


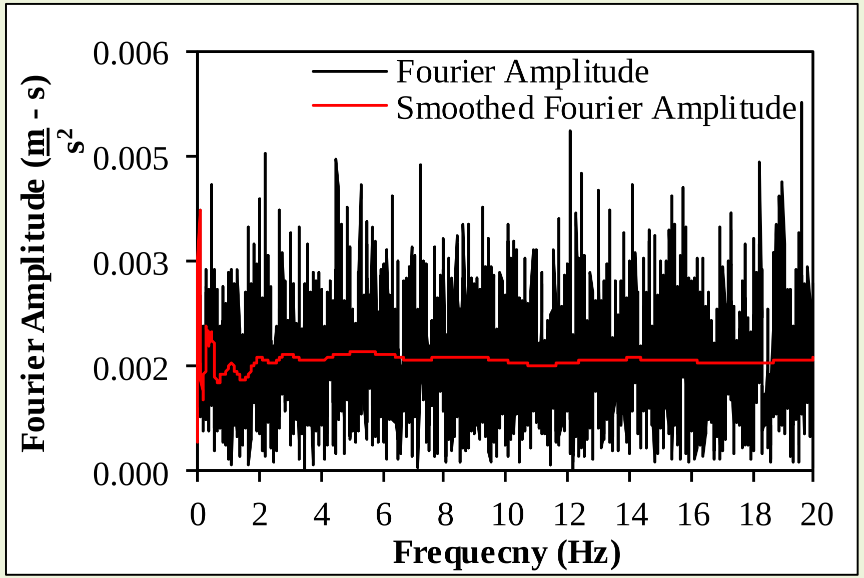
RC Wall-frame system (W)

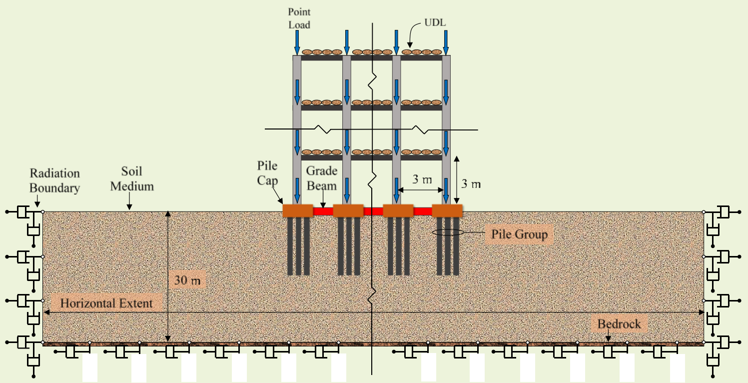


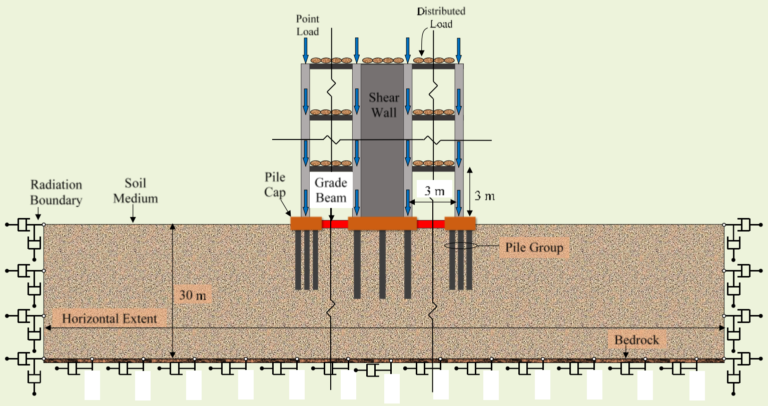
Input Excitation and Output Response

- Natural period of SSI system ⟶ Vibration response
  - ❖ *White noise*
    - Frequency band limited to 0-20 Hz
    - PGA= 0.0005g
  - ❖ *Transfer functions = Output / Input*
  - ❖ ***Modification Factor MF = T_{SSI} /T_F***
    - T_F → Conventional Fixed-base response time period
    - T_{SSI} → Time period influenced by SSI





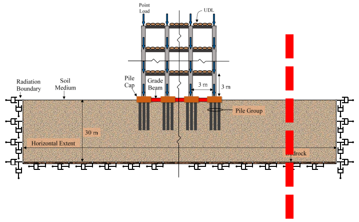


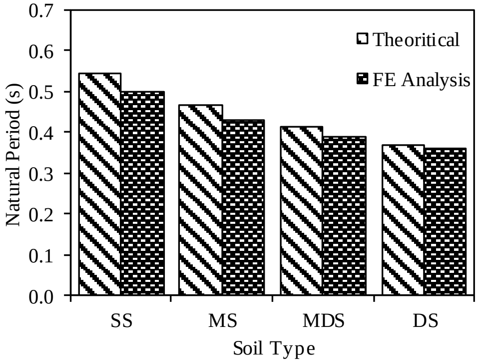


Natural Period of Soil and Structure using Vibrational Analysis

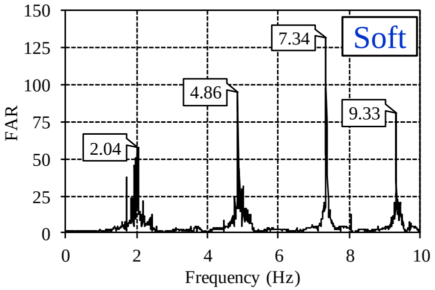
- Transfer functions (Output / Input)
  - Magnitude of response to input motion
  - Fourier Amplitude Ratio Spectrum (FAR)

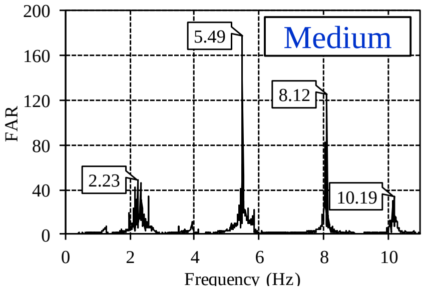
Free-Field Response

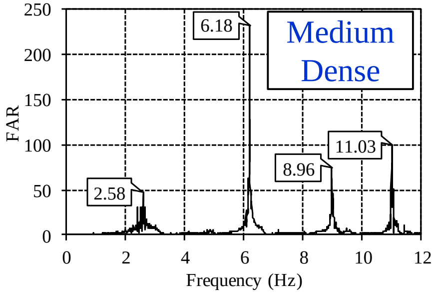


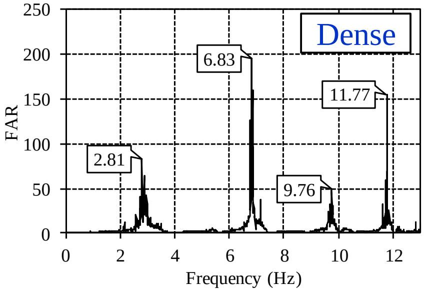


$$T_s = 4.48 \frac{H_s}{v_{sH}}$$





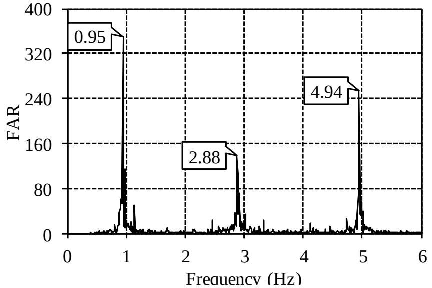




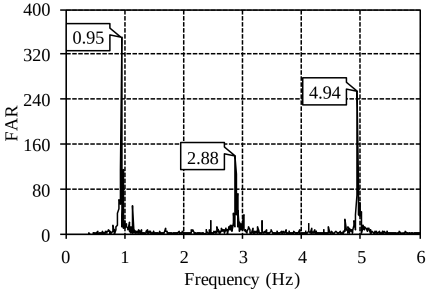
- **Fixed base response at roof level**

RC Frame system (F)

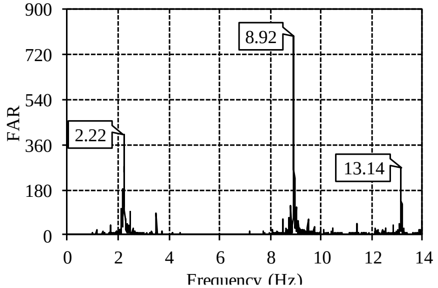
F6-5



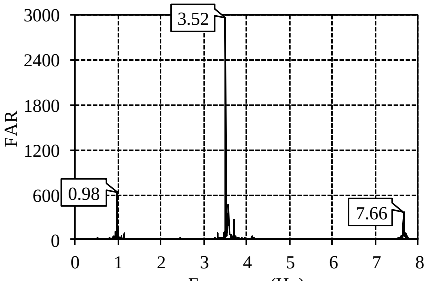
F12-5

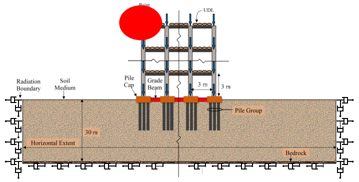


W6-5

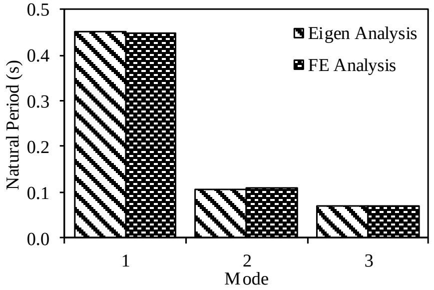


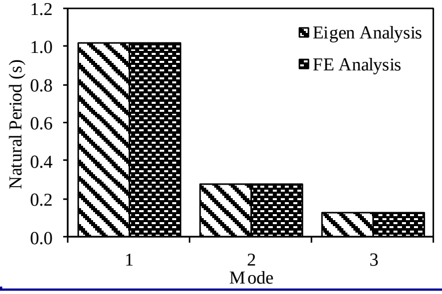
W12-5

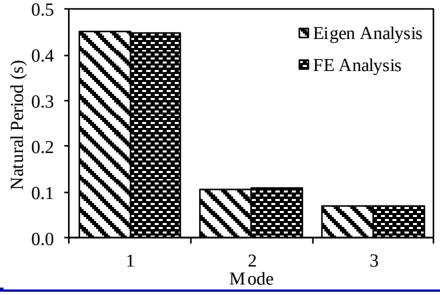


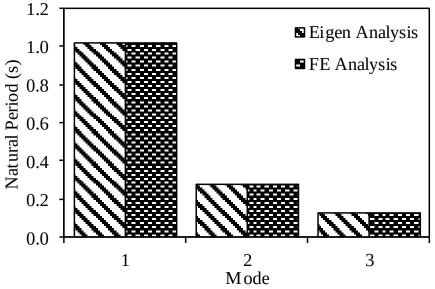


RC Wall-frame system (W)

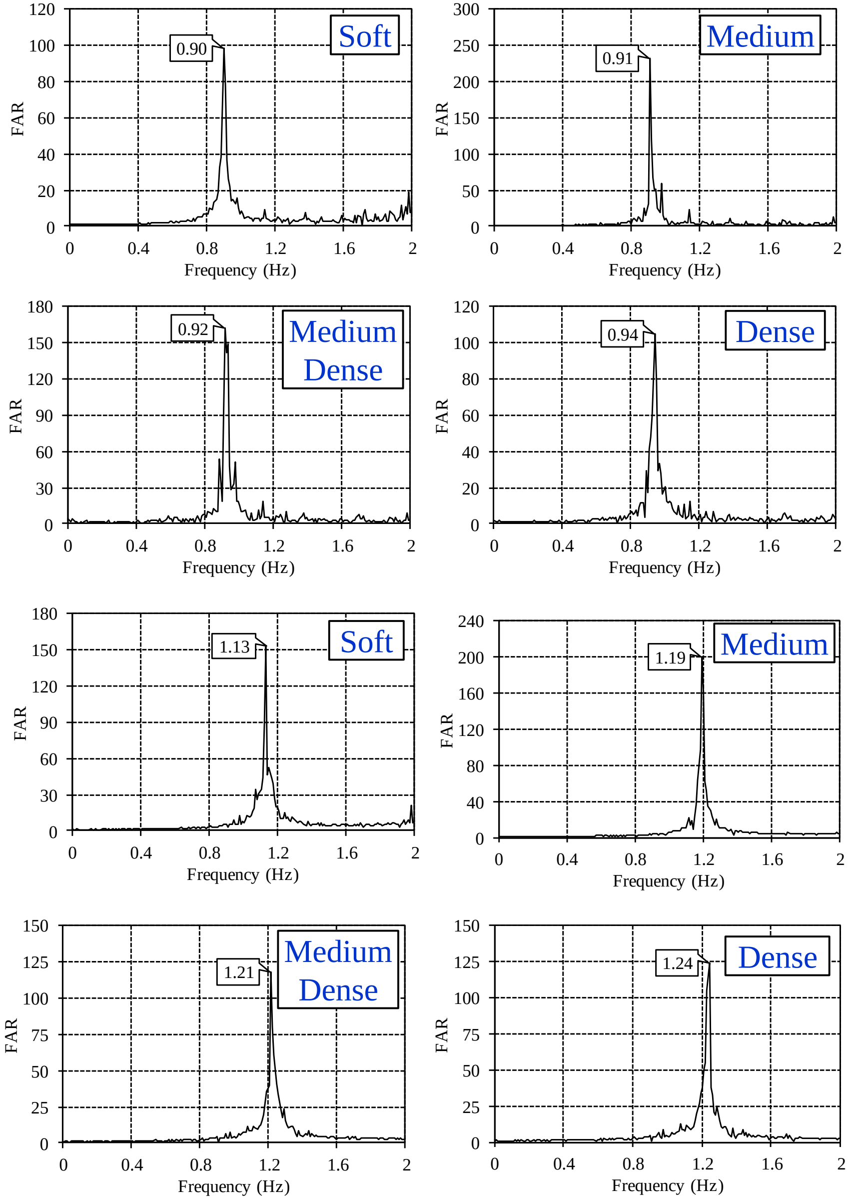




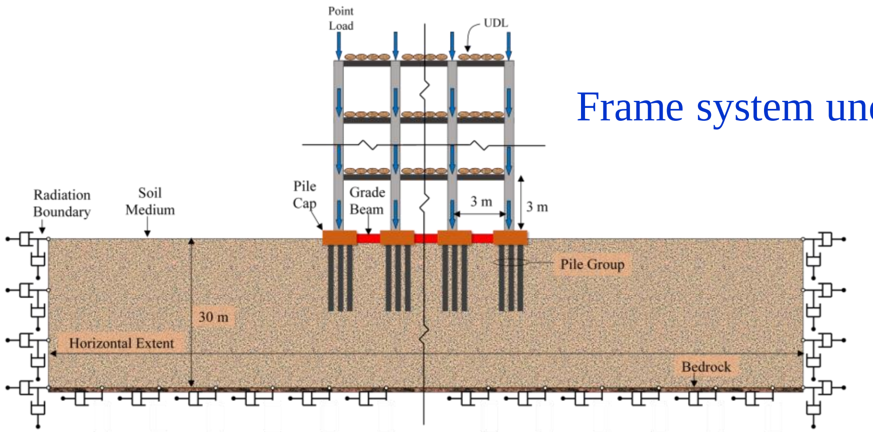




Effective Natural Period (T_{SSI})

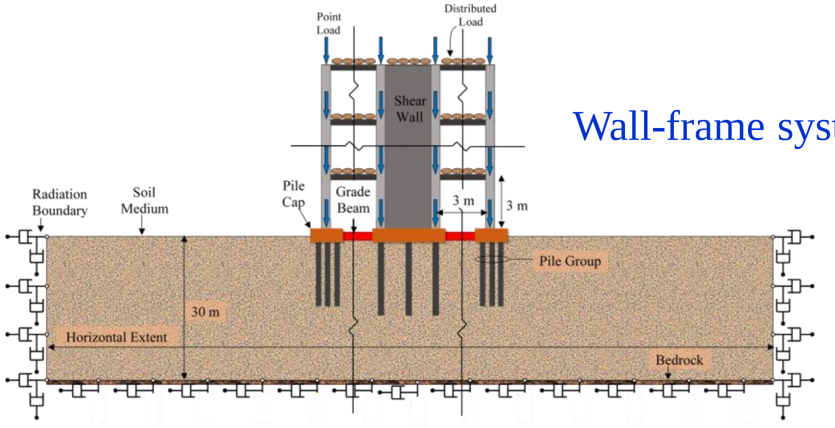


- Transfer functions (Output / Input)
  - Magnitude of response to input motion
  - Fourier Amplitude Ratio Spectrum (FAR)



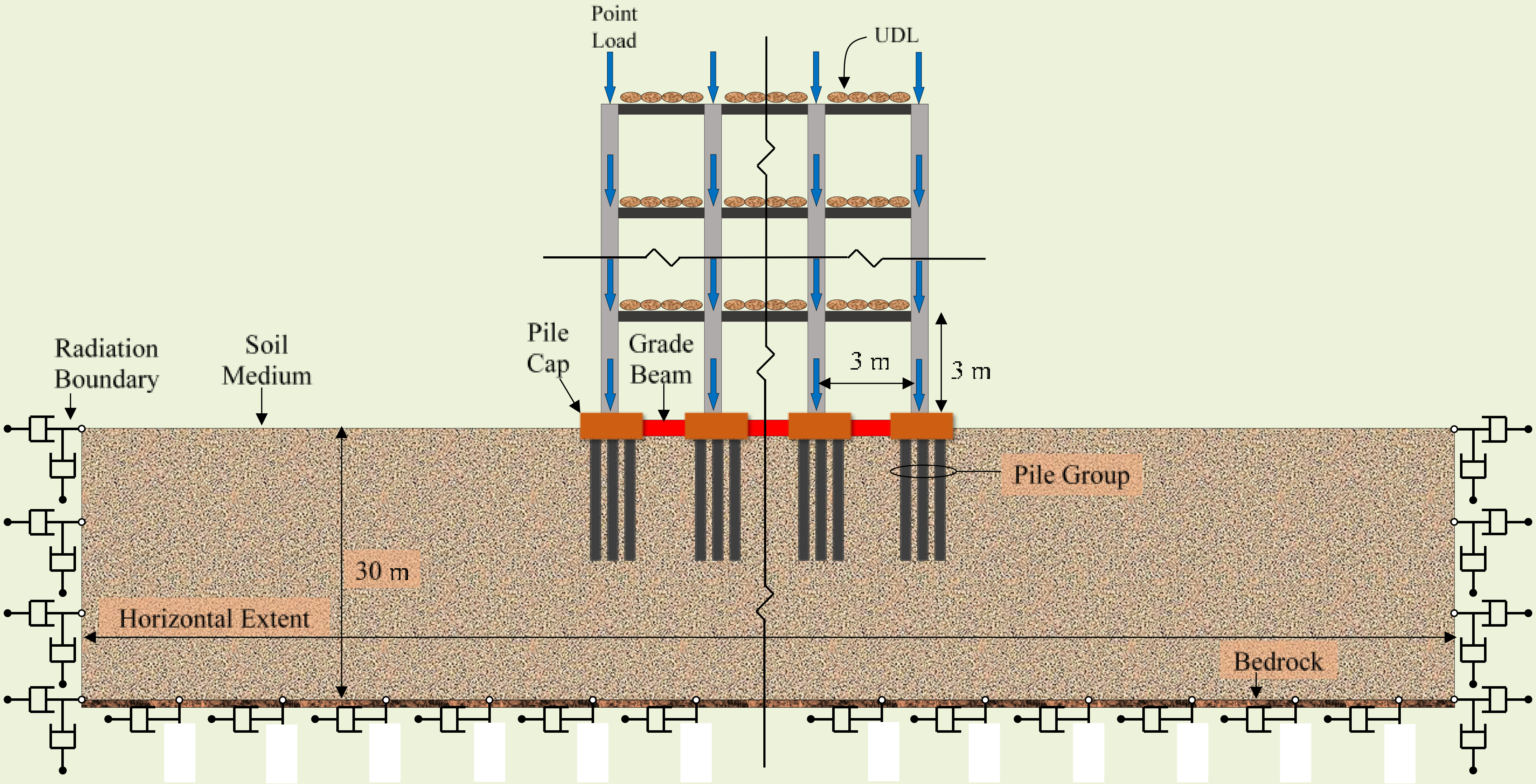
Frame system under SSI

$$MF = T_{SSI} / T_F$$

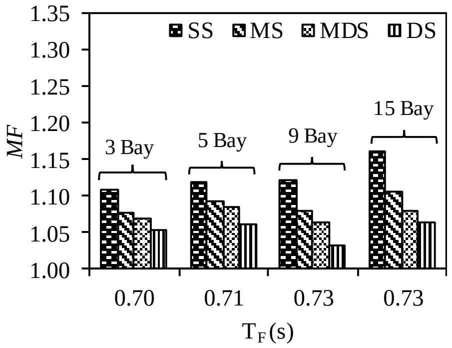


Wall-frame system under SSI

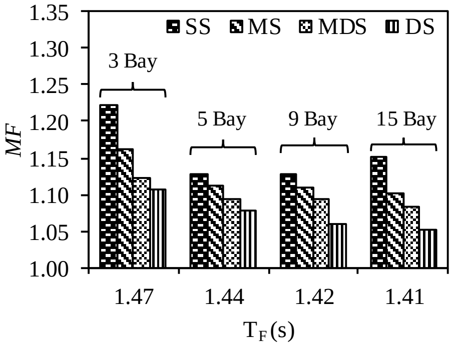
MF for RC Frame Structure



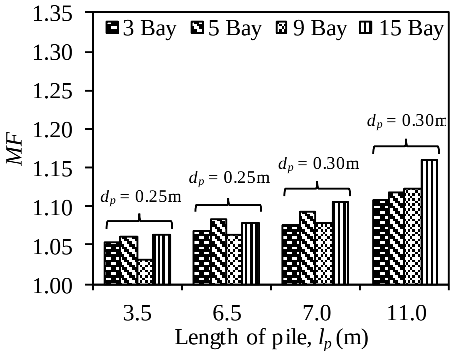
Parametric analysis of *MF*: Frame System



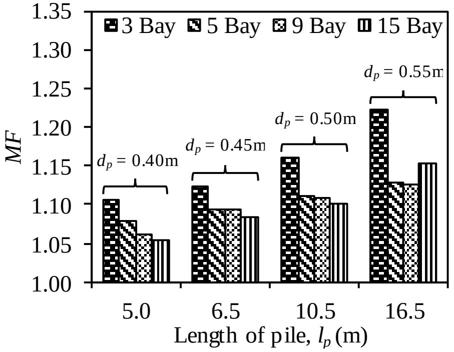
3 Storeyed



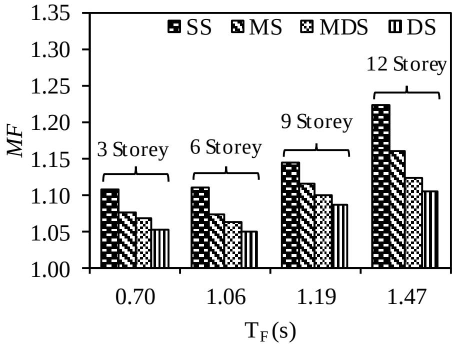
12 Storeyed



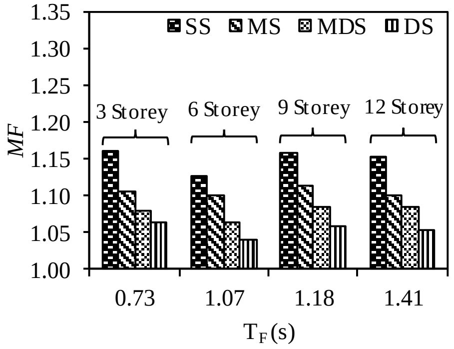
3 Storeyed



12 Storeyed



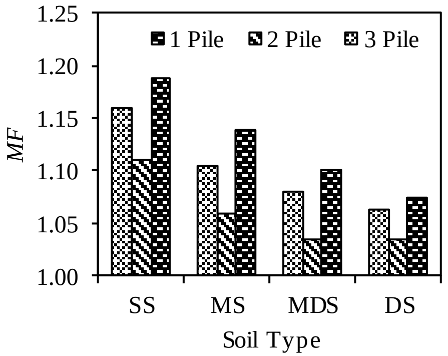
3 Bay



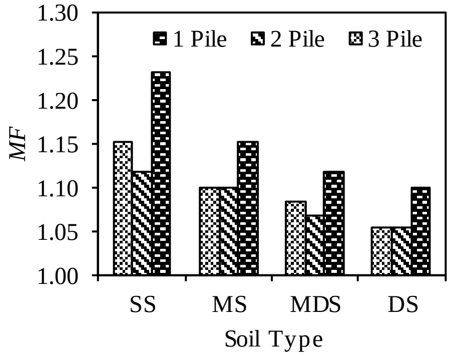
15 Bay

Relative flexibility of pile

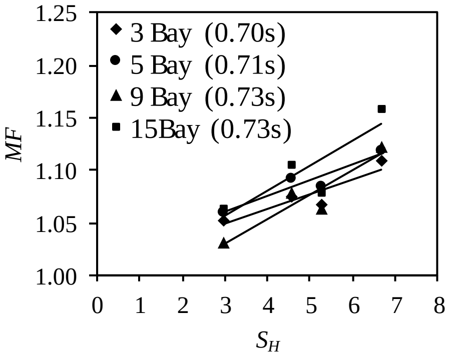
$$S_H = (l_p / d_p)(E_p / E_s)^{-0.25}$$



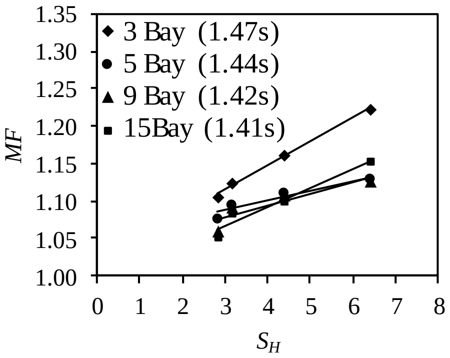
3 Storied 15 Bay



12 Storied 15 Bay



3 Storeyed



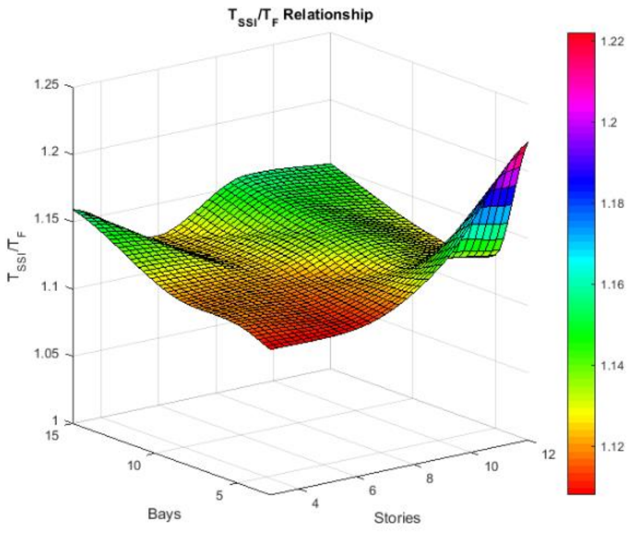
12 Storeyed

Parametric analysis of *MF*: Frame System

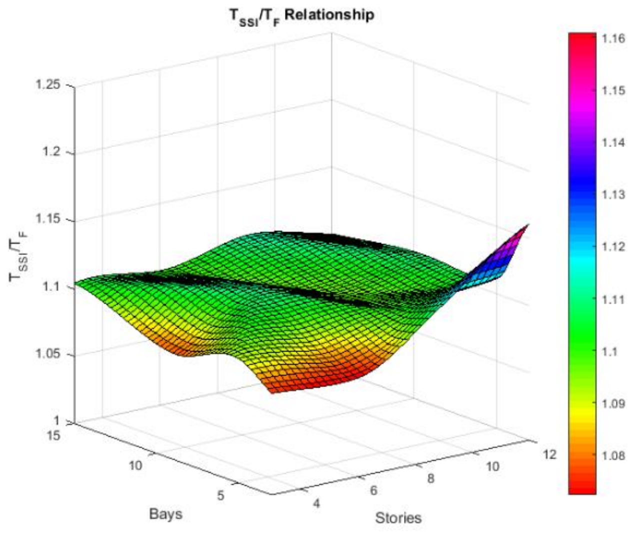
- Height of the structure, H
- Width of the structure, W
- Effective Stiffness of the structure, K^*
- Modal mass of the structure, M^*
- Relative stiffness of the piles, T
- Soil properties (G_{soil})
- Stiffness of the pile cap

$$\frac{H}{W} \uparrow$$

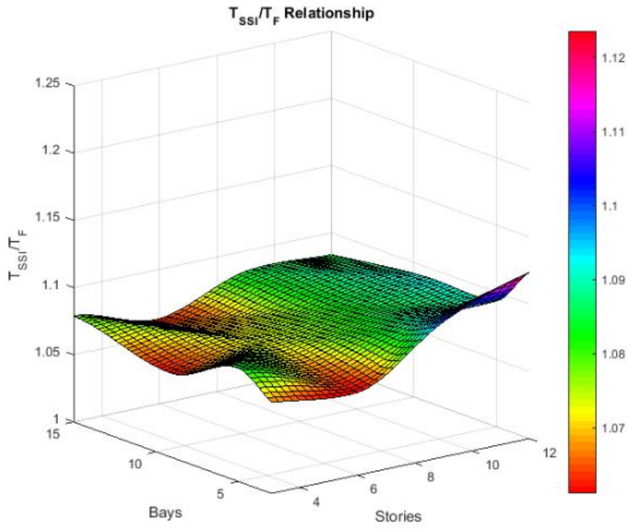
$$\frac{T_{SSI}}{T_F} \uparrow$$



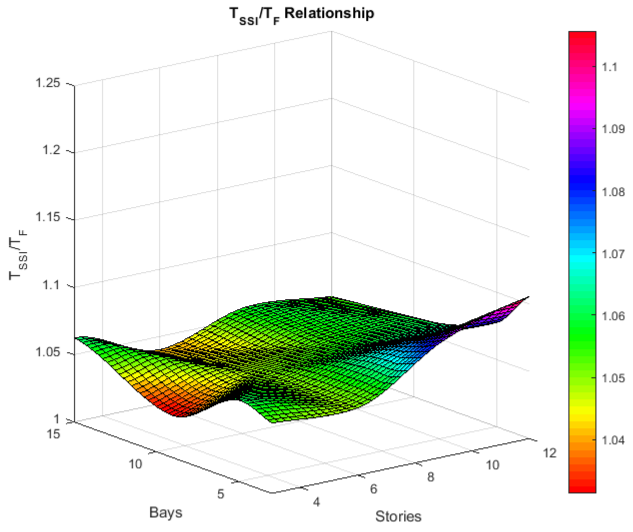
Soft Soil



Medium Soil



Medium Dense Soil



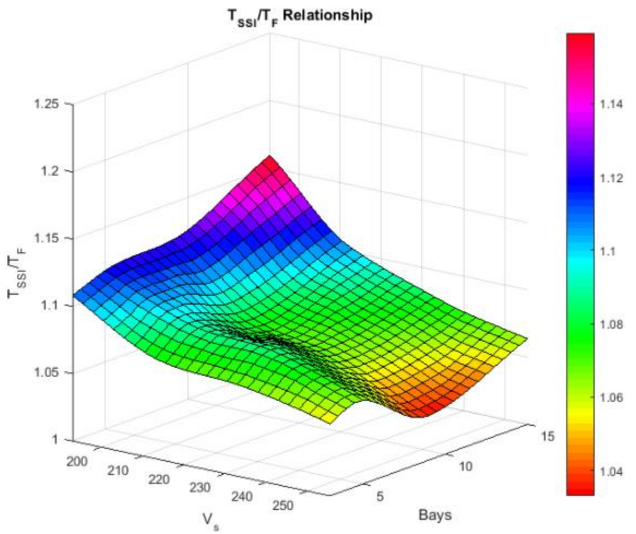
Dense Soil

Parametric analysis of *MF*: Frame System

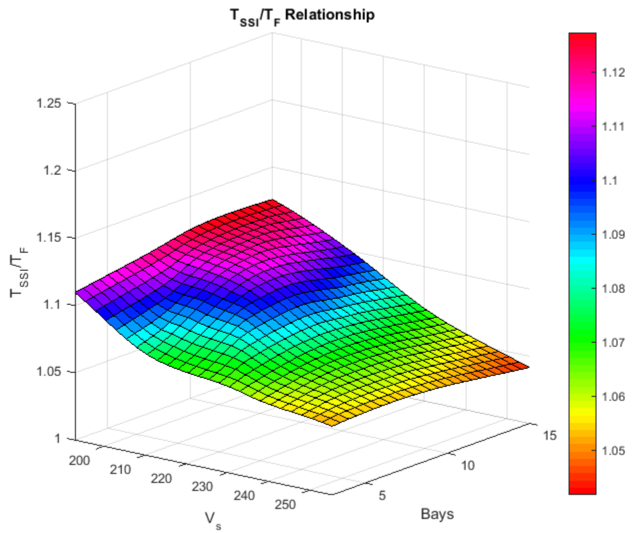
- Height of the structure, *H*
- Width of the structure, *W*
- Effective stiffness of the structure, *K**
- Modal mass of the structure, *M**
- Relative stiffness of the piles, *T*
- Soil properties (G_{soil})
- Stiffness of the pile cap

$G_{soil} \downarrow$

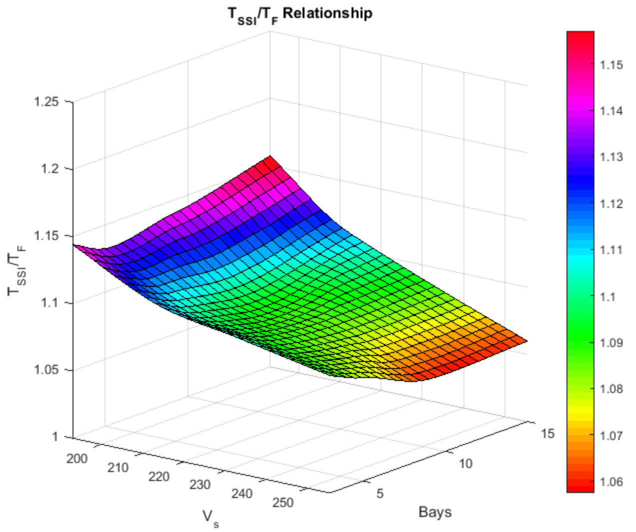
$\frac{T_{SSI}}{T_F} \uparrow$



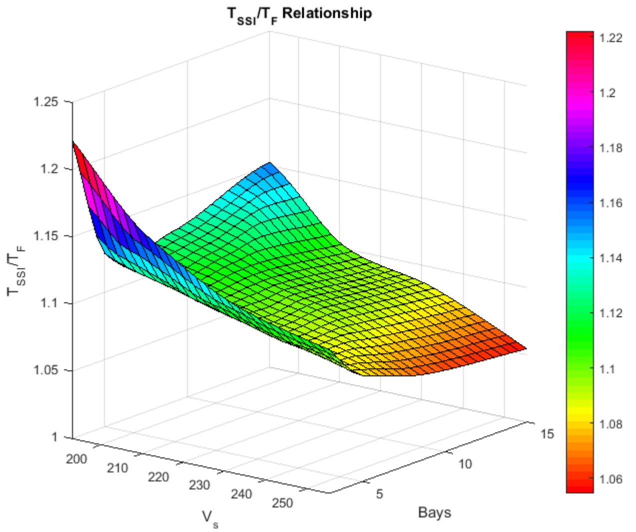
3 Storey



6 Storey



9 Storey

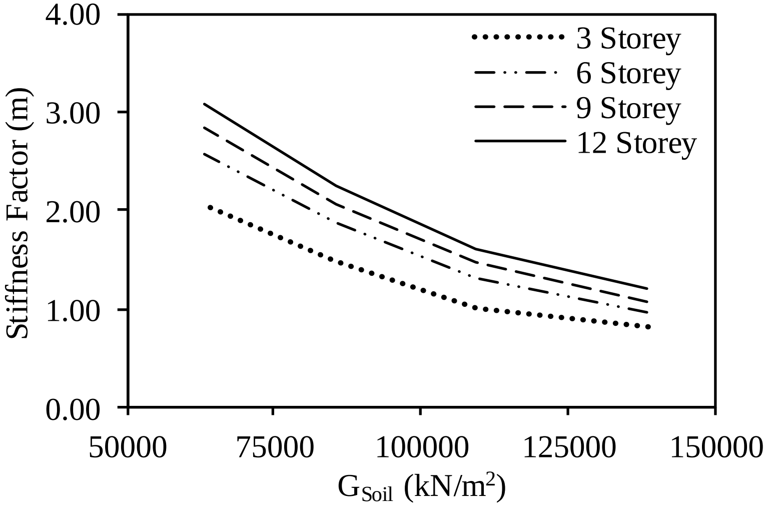


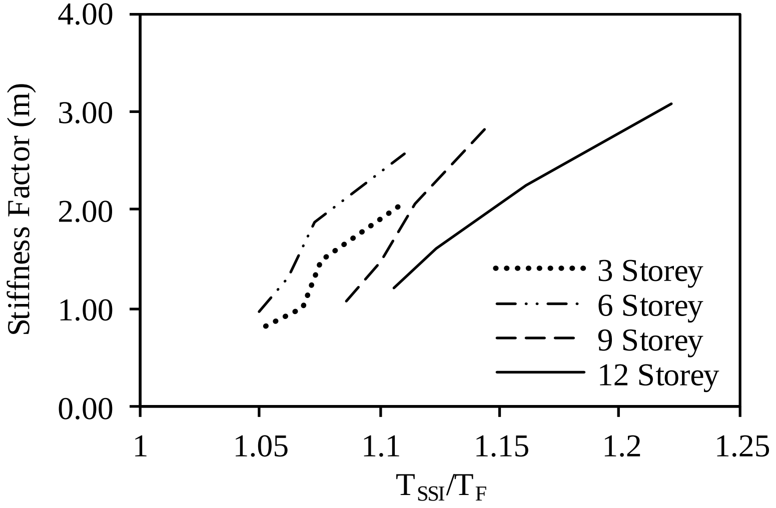
12 Storey

Parametric analysis of *MF*: Frame System

- Height of the structure, H
- Width of the structure, W
- Effective stiffness of the structure, K^*
- Modal mass of the structure, M^*
- Relative stiffness of the piles, T
- Soil properties (G_{soil})
- Stiffness of the pile cap

$$T = \sqrt[5]{\frac{EI_p}{\eta}}$$

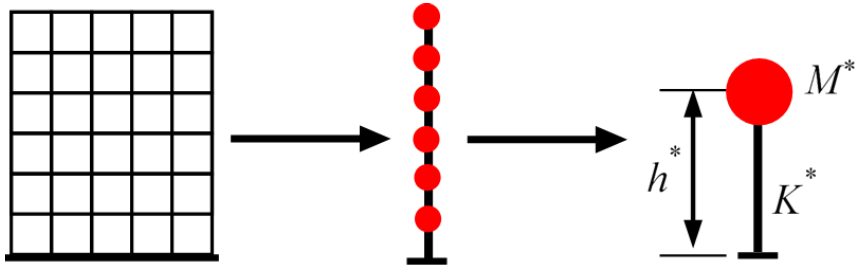




$G_{soil} \downarrow$ $\quad T \uparrow$ $\quad \dfrac{T_{SSI}}{T_F} \uparrow$

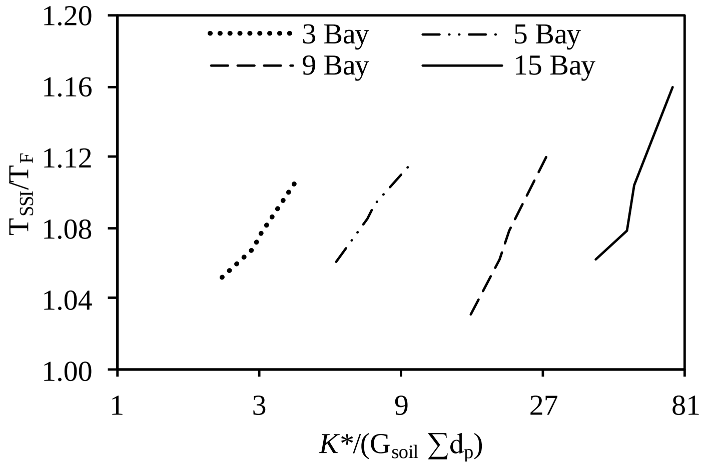
Parametric analysis of *MF*: Frame System

- Height of the structure, H
- Width of the structure, W
- Effective stiffness of the structure, K^*
- Modal mass of the structure, M^*
- Relative stiffness of the piles, T
- Soil properties (G_{soil})
- Stiffness of the pile cap

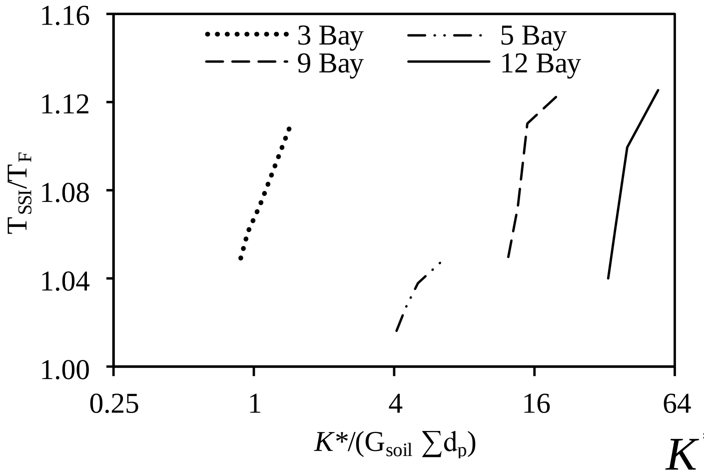


$$K^* = \left(\frac{2\pi}{T_F}\right)^2 M^* \qquad M^* = \Gamma_1 L_1^h$$

$$\Gamma_1 = \frac{\{\phi_1\}^T [M] \{i\}}{\{\phi_1\}^T [M] \{\phi_1\}} \qquad L_1^h = \{\phi_1\}^T [M] \{i\}$$

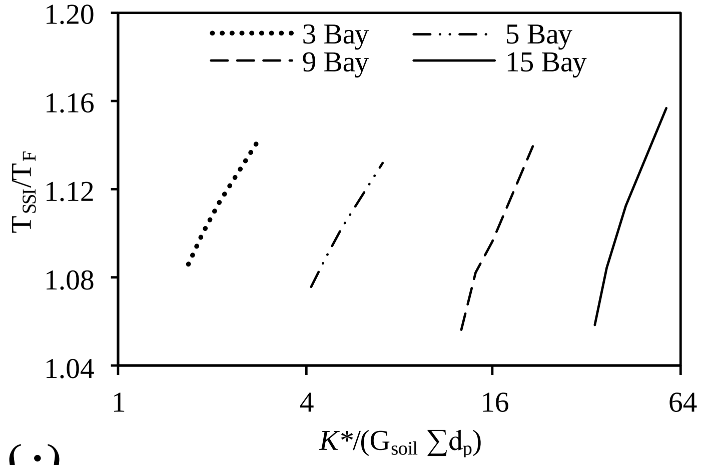


3 Storey

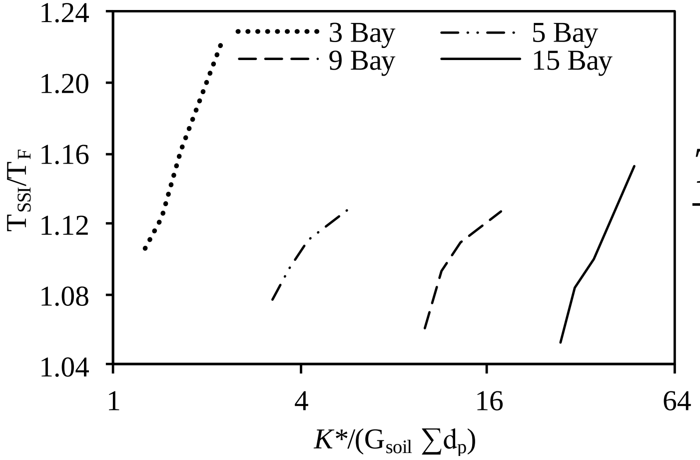


6 Storey

$$\frac{K^*}{G_{soil}\sum d_p} \uparrow$$



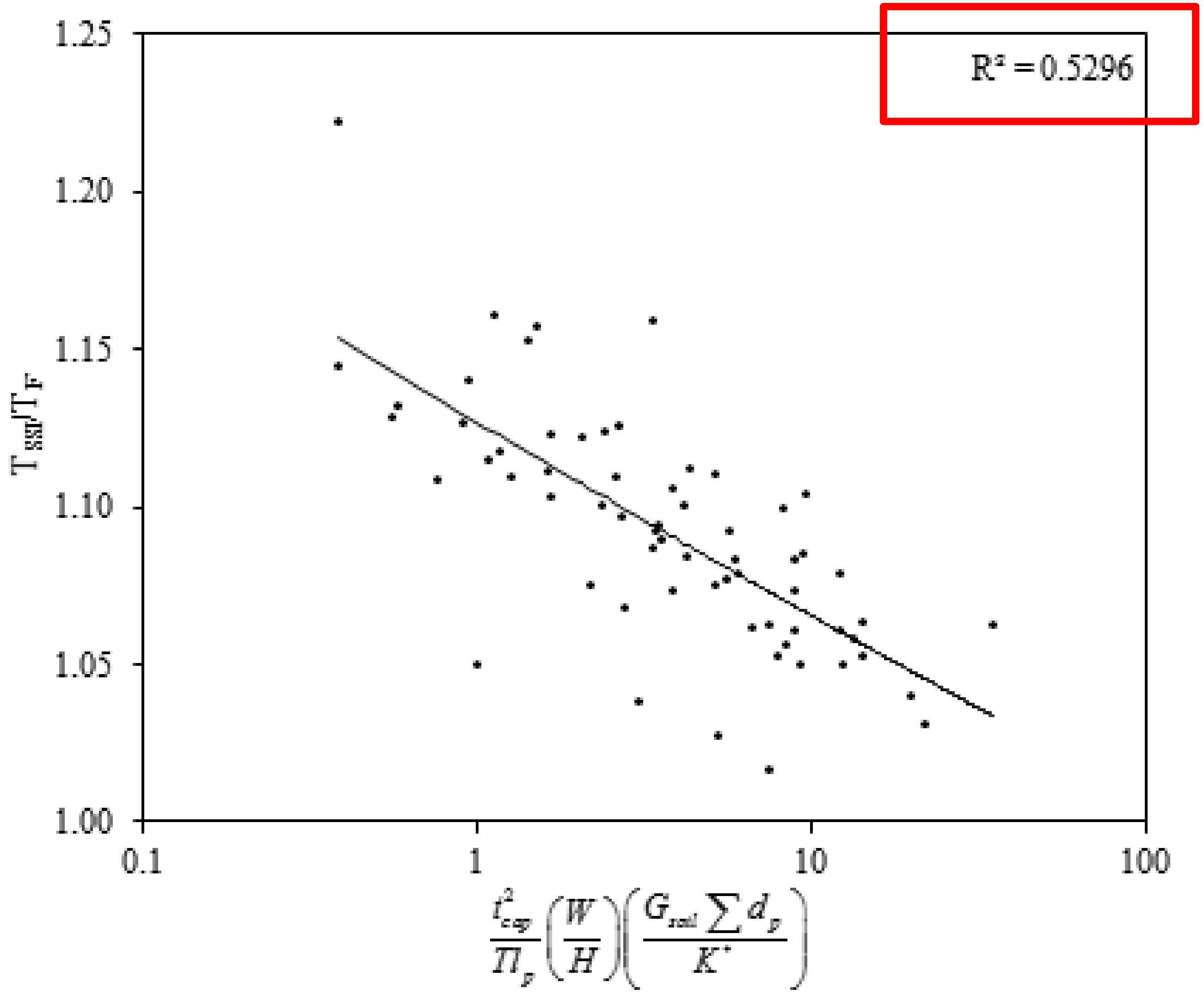
9 Storey



12 Storey

$$\frac{T_{SSI}}{T_F} \uparrow$$

Non-Dimensional Relationship of T_{SSI} and T_F : Frame System

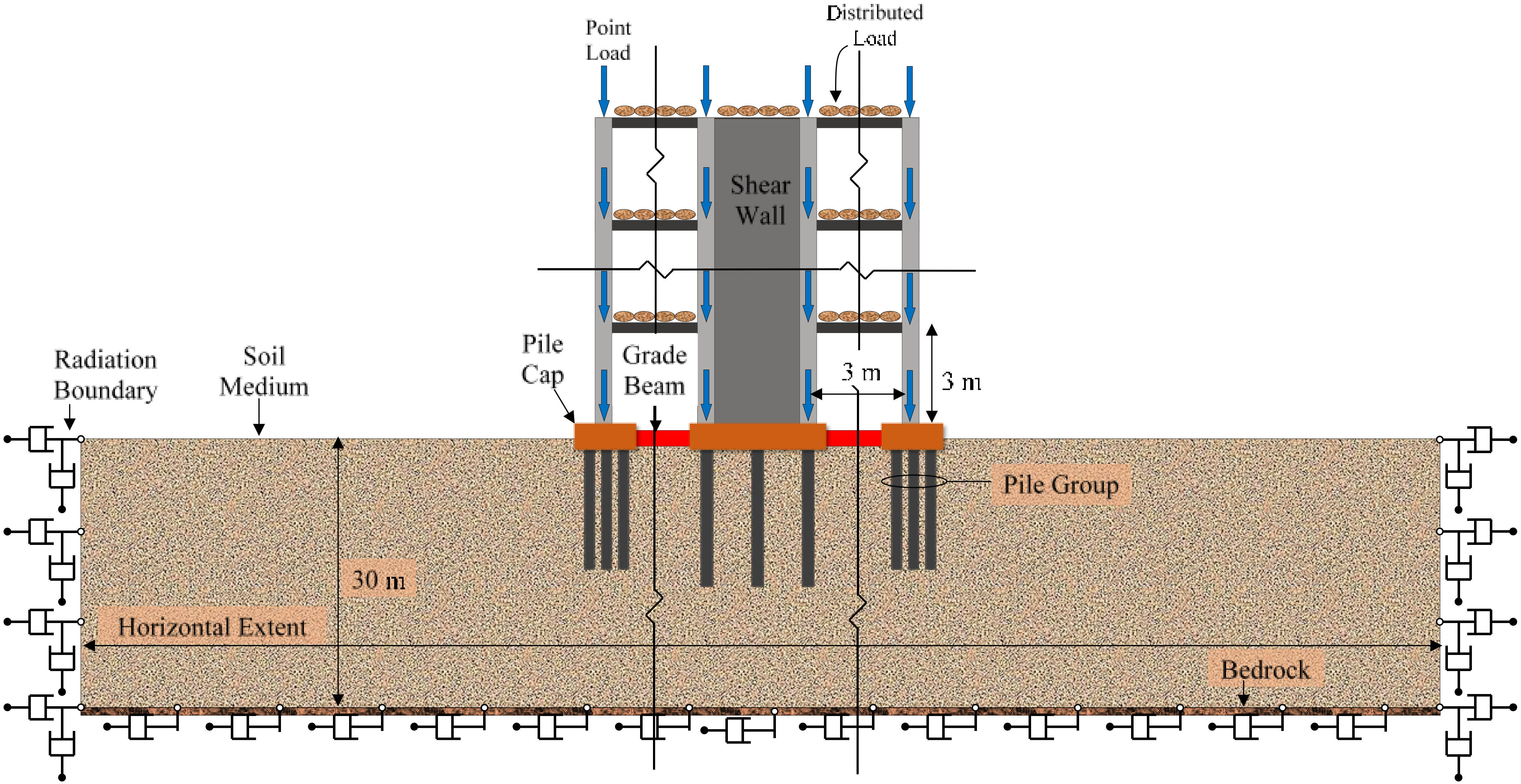


$$T_{SSI} = 1.127\, T_F \left[\frac{Tl_p}{t_{cap}^2} \left(\frac{H}{W} \right) \left(\frac{K^*}{G_{soil} \sum d_p} \right) \right]^{0.024}$$

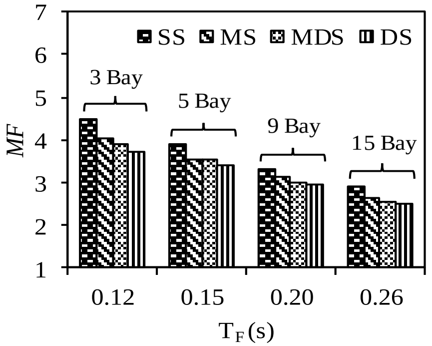
Large scatter

Poor capability in capturing the simultaneous influences of parameters on T_{SSI}/T_F

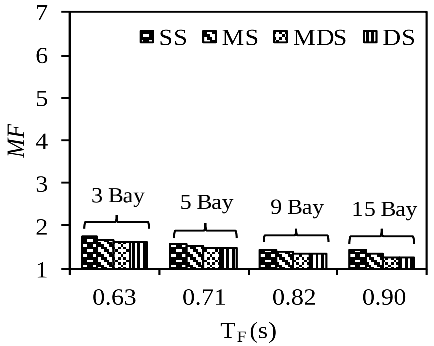
MF for Wall-Frame Structure



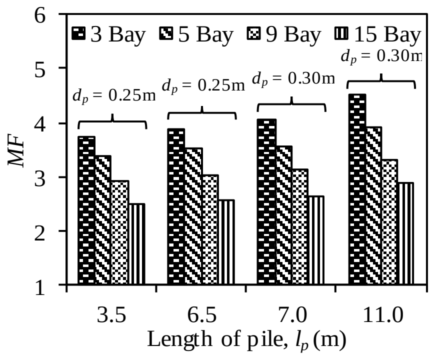
Parametric analysis of *MF*: Wall-frame System



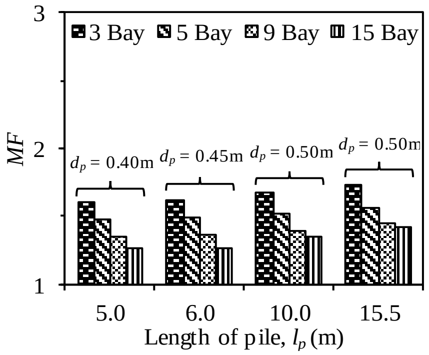
3 Storeyed



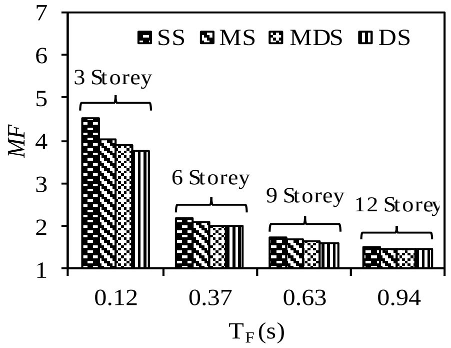
9 Storeyed



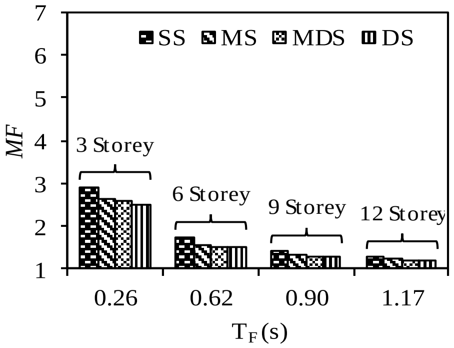
3 Storeyed



9 Storeyed



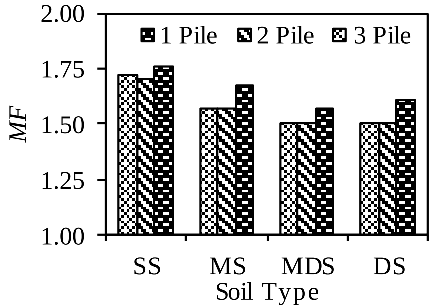
3 Bay



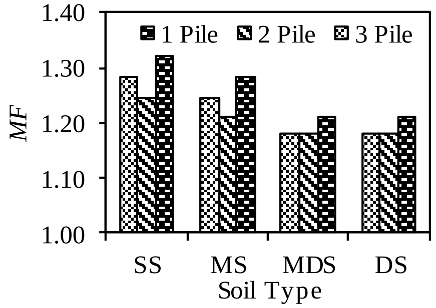
15 Bay

Relative flexibility of pile

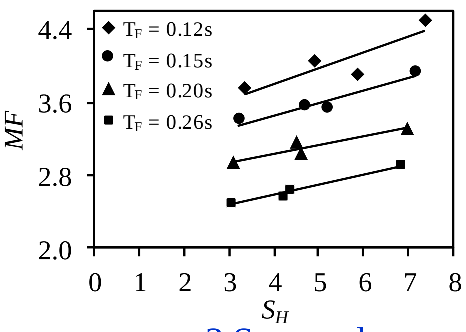
$$S_H = (l_p / d_p)(E_p / E_s)^{-0.25}$$



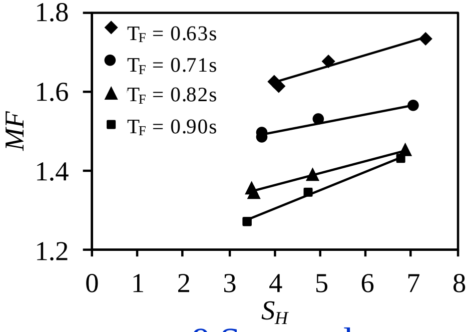
6 Storied 15 bay



12 Storied 15 bay



3 Storeyed



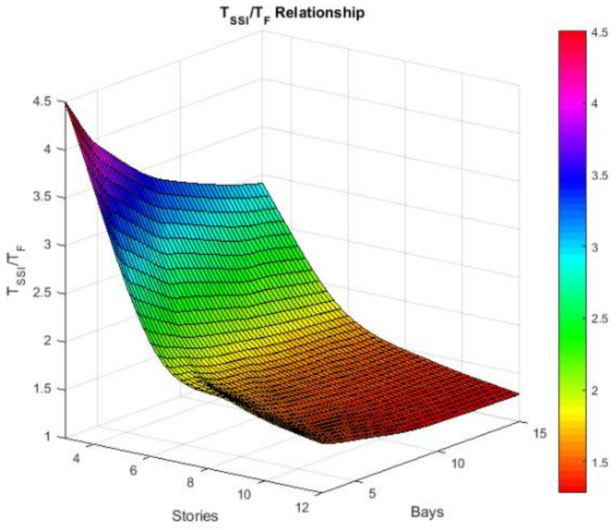
9 Storeyed

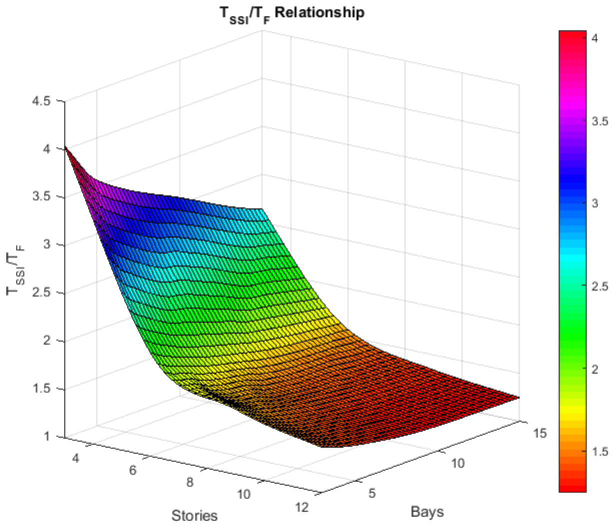
Parametric analysis of *MF*: Wall-Frame System

- Height of the structure, *H*
- Width of the structure, *W*
- Effective Stiffness of the structure, *K**
- Modal mass of the structure, *M**
- Relative stiffness of the piles, *T*
- Soil properties (G_{soil})
- Stiffness of the pile cap
- Shear wall – Column area ratio

$$\frac{H}{W} \downarrow$$

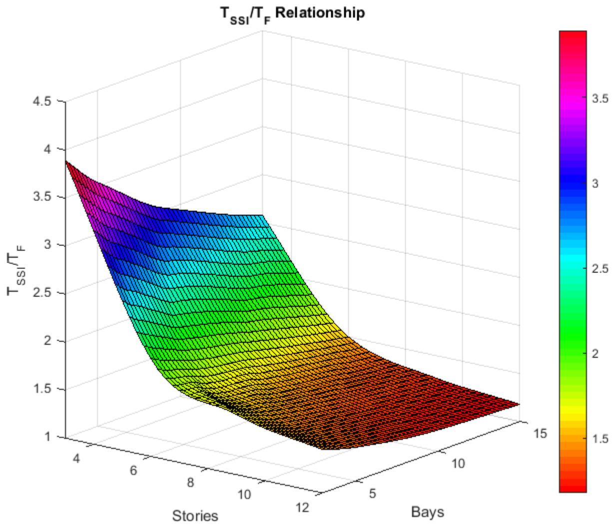
$$\frac{T_{SSI}}{T_F} \uparrow$$

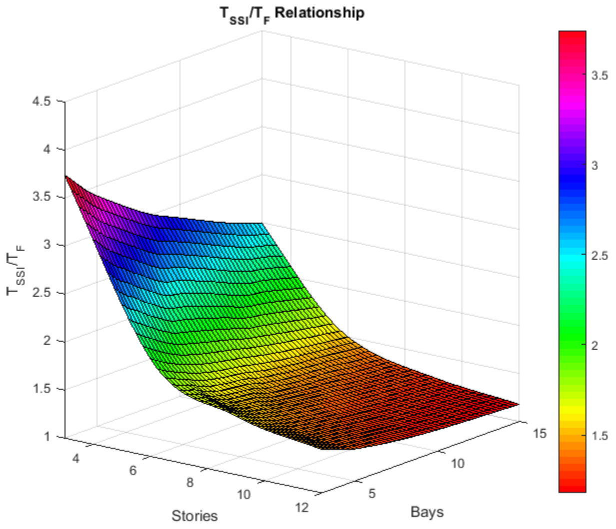




Soft Soil

Medium Soil





Parametric analysis of *MF*: Wall-Frame System

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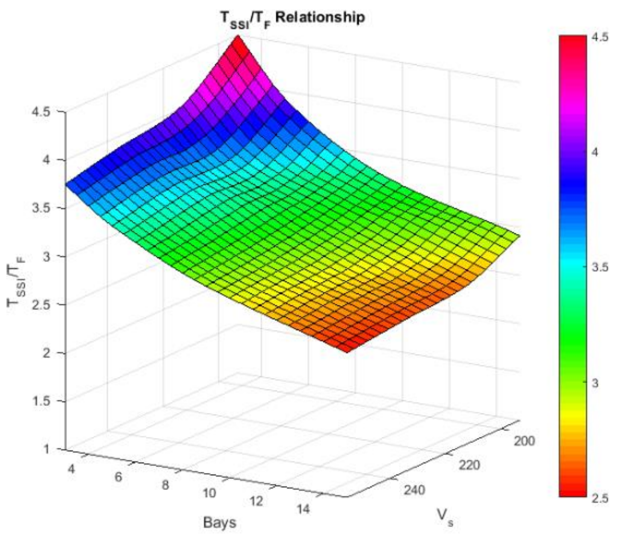
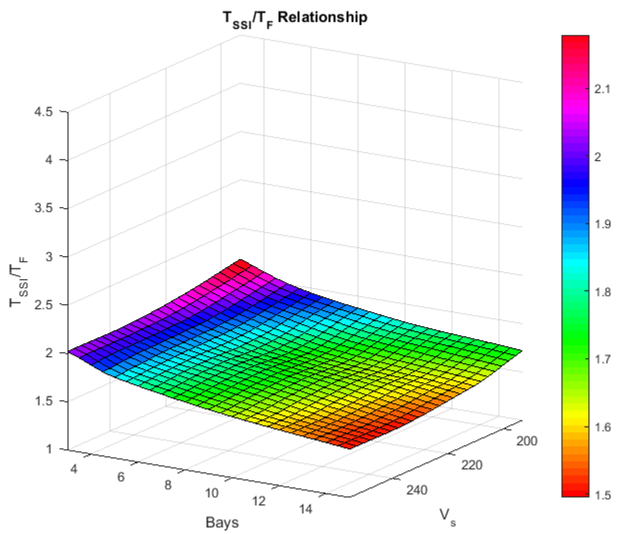
- Relative stiffness of the piles, *T*
- Soil properties (G_{soil})
- Stiffness of the pile cap
- Shear wall – Column area ratio

G_{soil} ↓

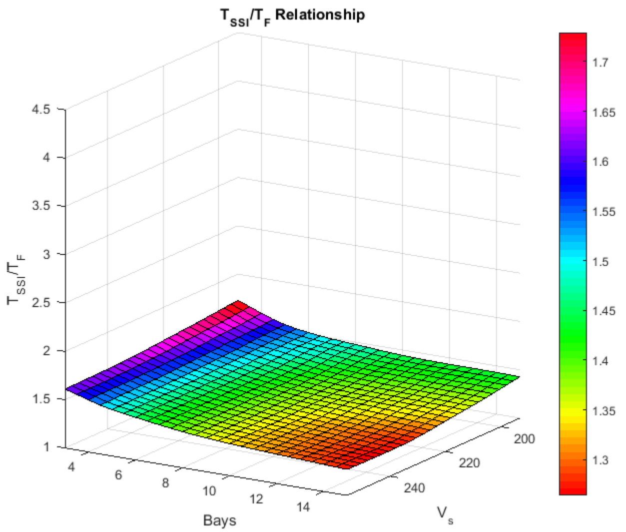
$\frac{T_{SSI}}{T_F}$ ↑

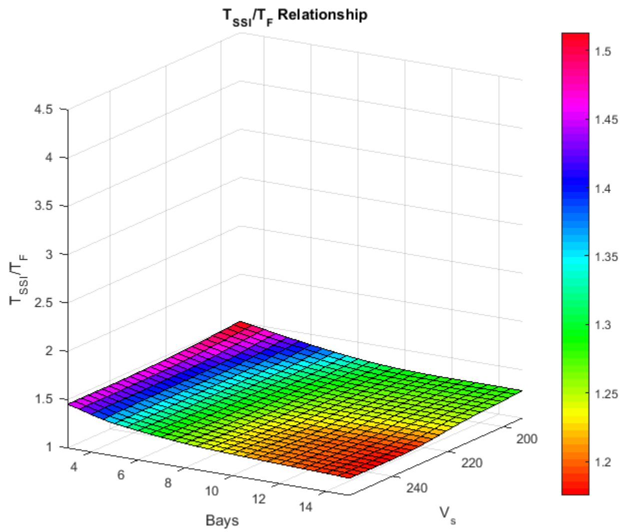


3 Storey



6 Storey



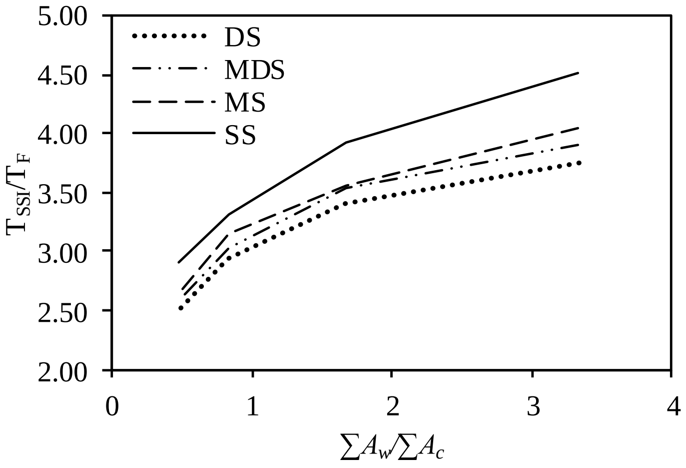


Parametric analysis of *MF*: Wall-Frame System

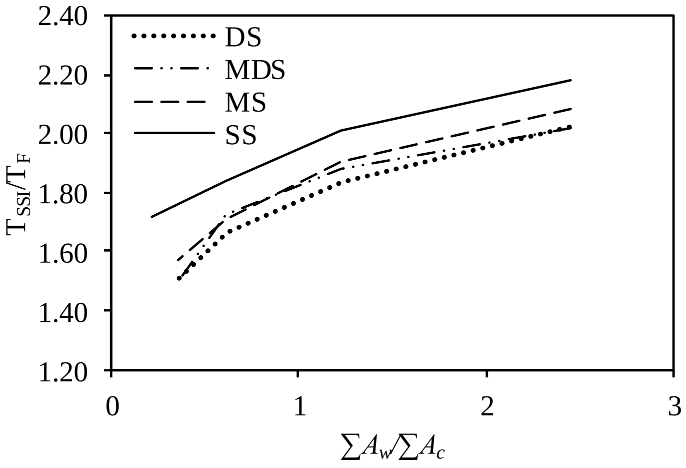
- Height of the structure, H
- Width of the structure, W
- Effective Stiffness of the structure, K^*
- Modal mass of the structure, M^*
- Relative stiffness of the piles, T
- Soil properties (G_{soil})
- Stiffness of the pile cap
- Shear wall – Column area ratio

$$\frac{\sum A_w}{\sum A_c} \uparrow$$

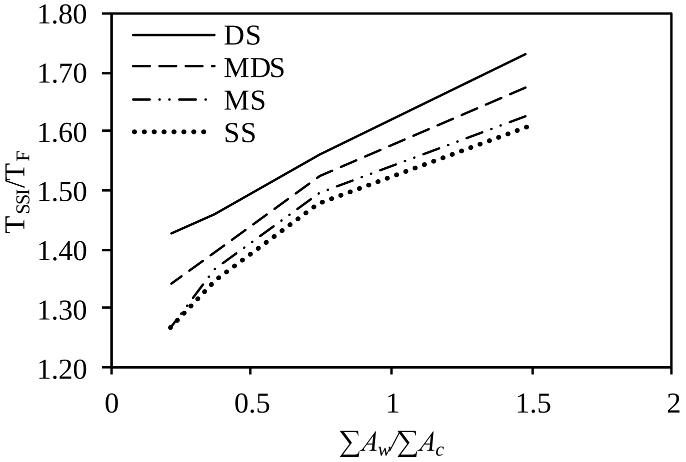
$$\frac{T_{SSI}}{T_F} \uparrow$$



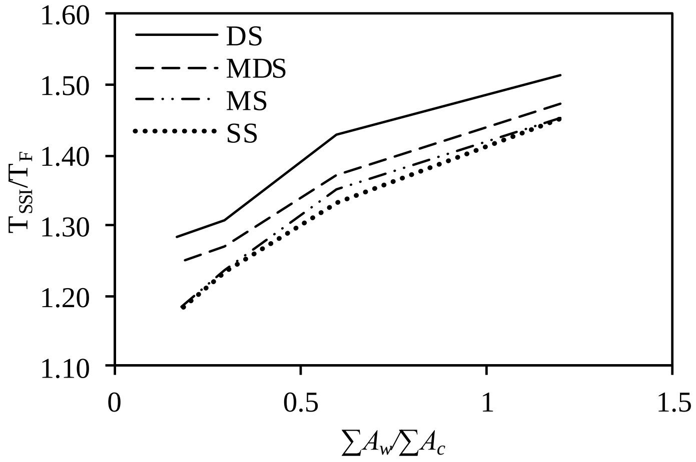
3 Storey



6 Storey

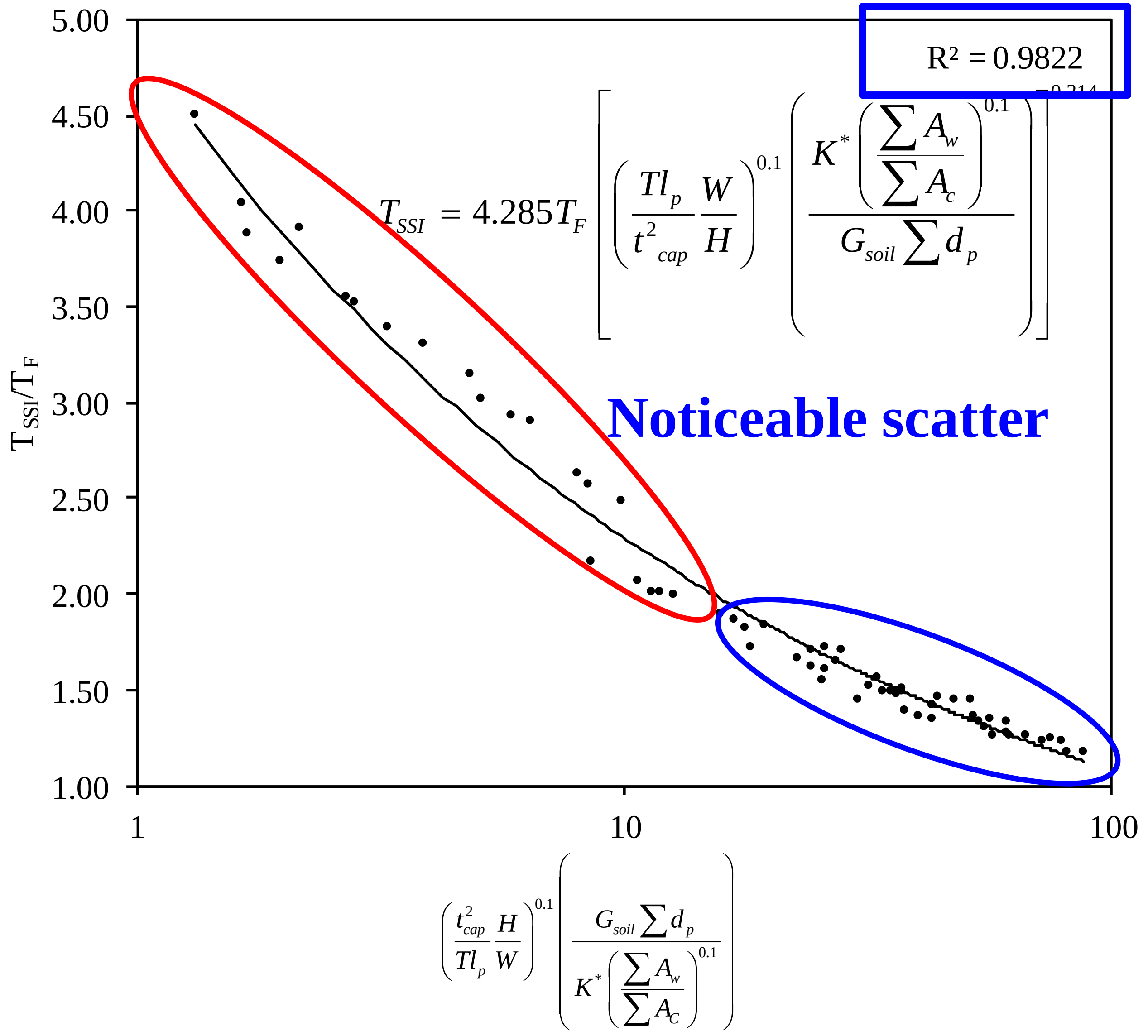


9 Storey



12 Storey

Non-Dimensional Relationship of T_{SSI} and T_F : Wall-Frame System

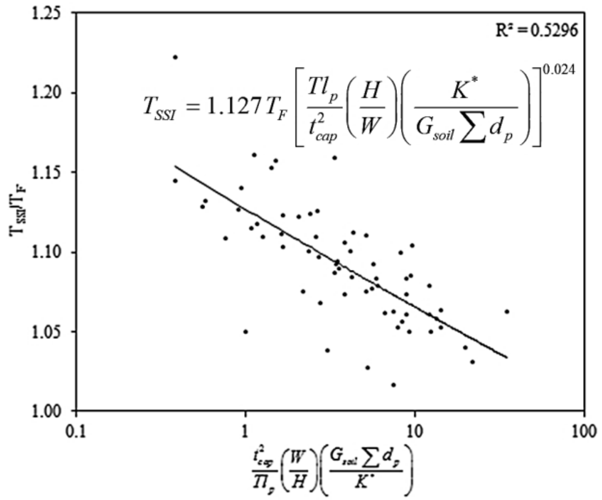


- Non-dimensional relationship
  - H → Height of structure
  - W → Width of structure
  - K^* → Effective stiffness of structure corresponding to first mode of vibration
  - $\sum A_w$ → Total wall area in the considered direction
  - $\sum A_c$ → Total column area in the considered direction
  - $\sum d_p$ → Summation of the diameter of the piles in the considered direction
  - G_{soil} → Representative shear modulus of the soil

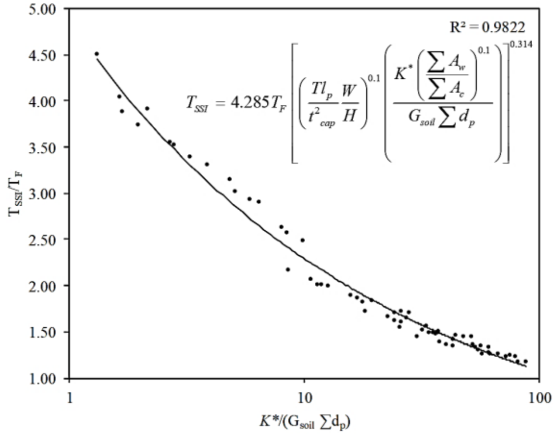
Poor capability in capturing the simultaneous influences of parameters on T_{SSI}/T_F

Necessity of Predictive Relationship

- Structural, soil and pile foundation parameters influence *MF*
  - Complex Interaction
- For effective prediction of *MF*
  - Need a model capable of capturing complex interaction



- Artificial Neural Network (ANN) approach
  - Gained popularity over the last decade
    - ❑ Ability to capture and predict complex interaction
      - ➢ Mapping of Input and Output data, which in turn is generated from the numerical simulation of a physical problem

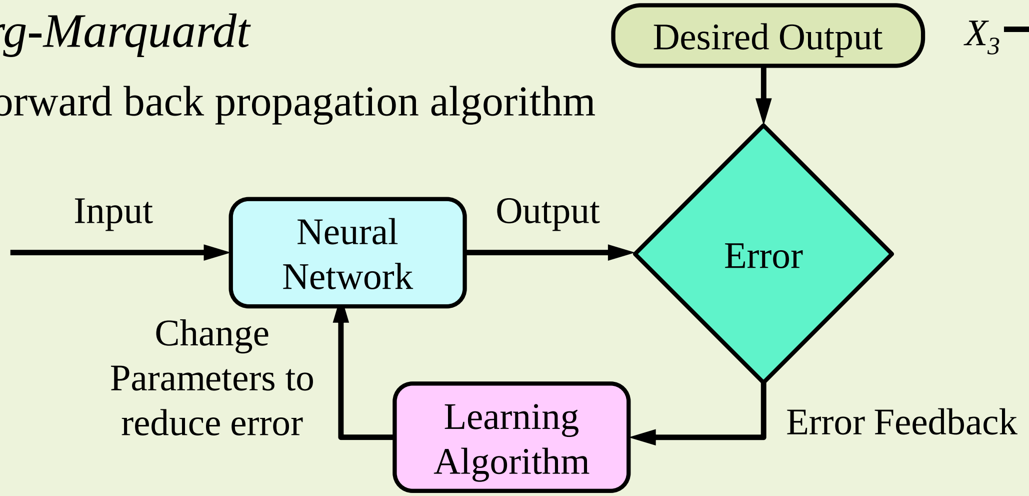


- Employ ANN for prediction of
  - $MF \longrightarrow T_{SSI} = T_F \times MF$

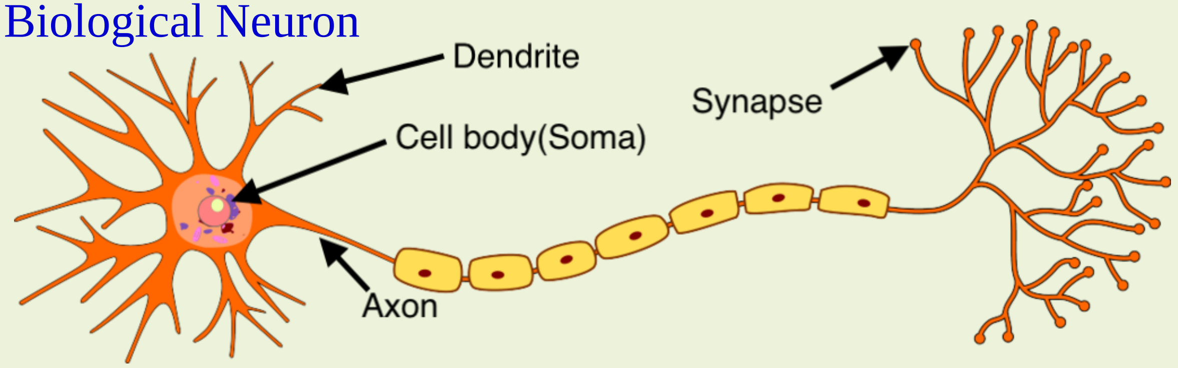
Artificial Neural Network

- Artificial Neural networks
  - *Analogous to biological neural network in humans*
  - *Several simple yet highly interrelated processing elements*
    - Termed as artificial neurons
    - Capable of deciphering complex relationships involving multiple input and output parameters
    - Ability to generalize and infer relationships from unseen data

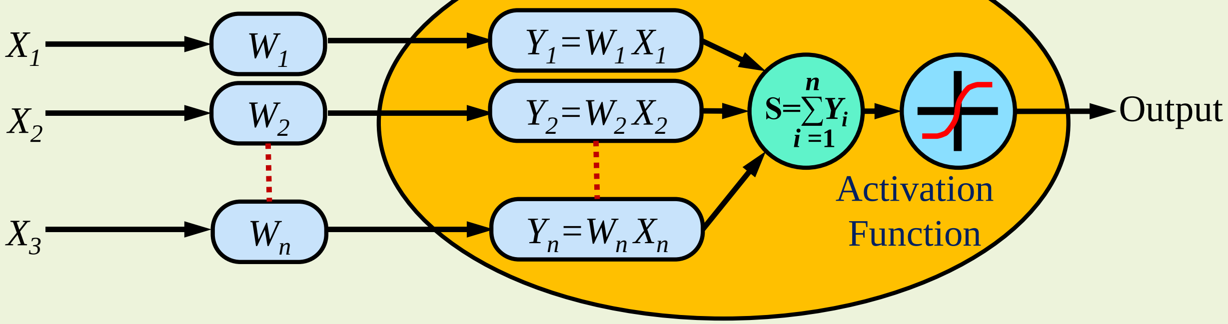
- To train the ANN model, a learning rule is required
  - *Levenberg-Marquardt*
    - Feed forward back propagation algorithm

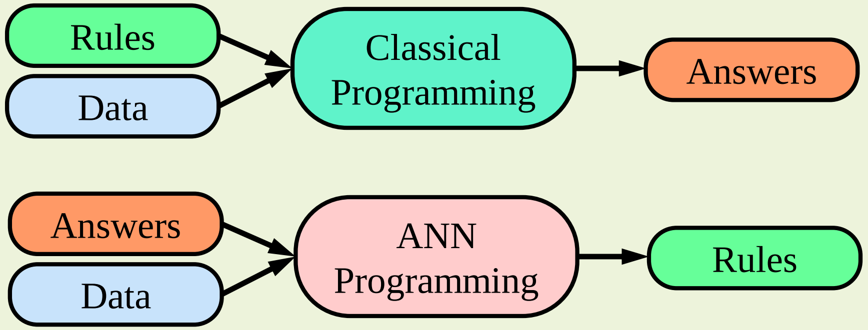


Biological Neuron



Artificial Neuron





Modelling ANN Architecture

- Normalization
  - Input and Output

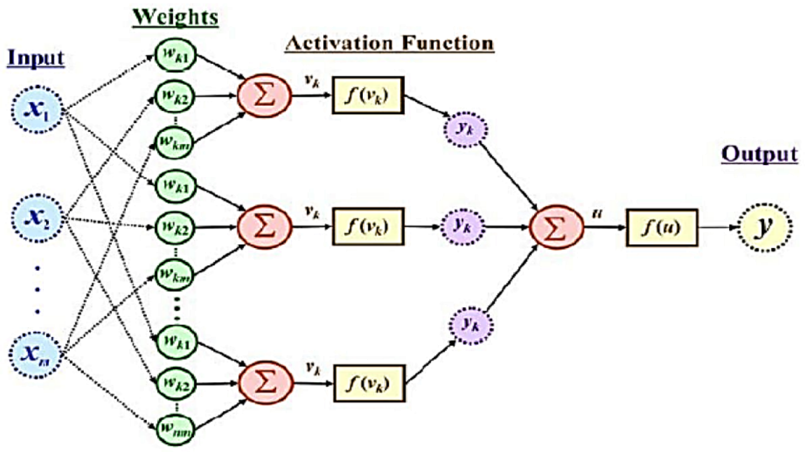
$$X_n = \frac{2(X - X_{\min})}{(X_{\max} - X_{\min})} - 1$$

where, X_n is the normalized value, X_{max} and X_{min} is the maximum and minimum value of the variable X

- Selection of optimum number of hidden neurons based on MSE

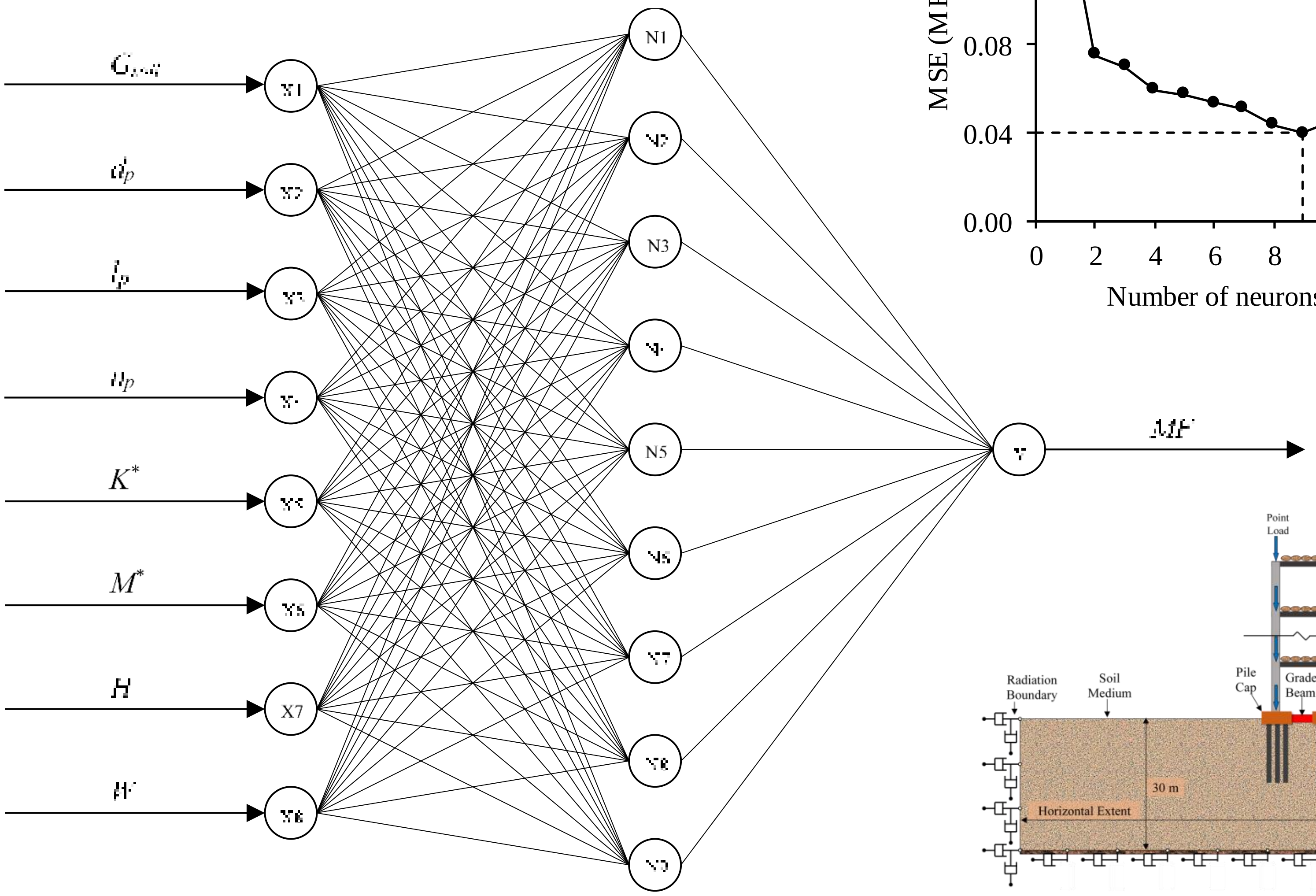
$$MSE = \frac{\sum_{i=1}^{n} (MF_{simulated} - MF_{predicted})^2}{n}$$

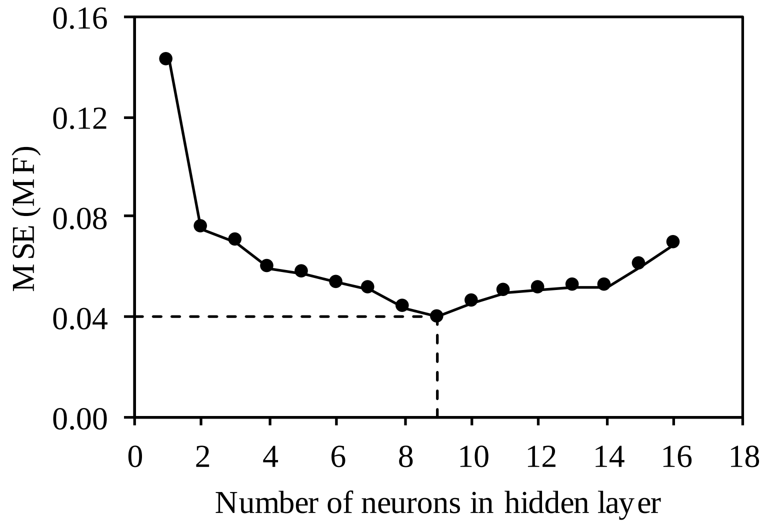
where, MSE is the mean of the squared error obtained from the dissimilarities in the simulated and predicted output $MF_{simulated}$ and $MF_{predicted}$ respectively and n is the number of data points



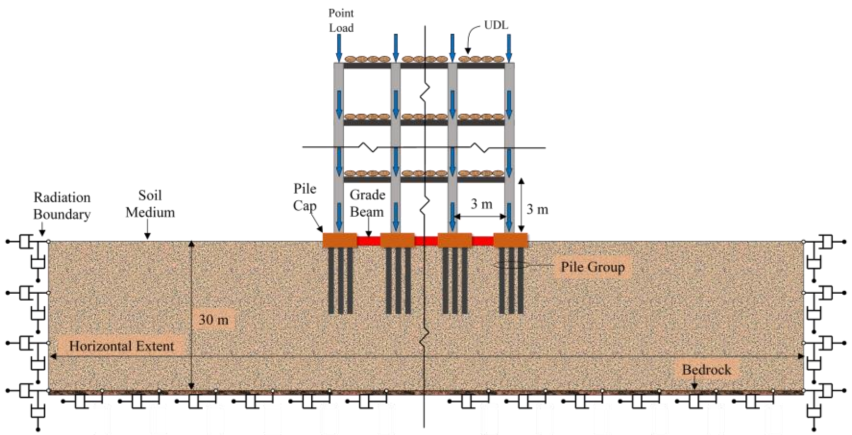
ANN Architecture for *MF*: Frame System

8-9-1 ANN Architecture



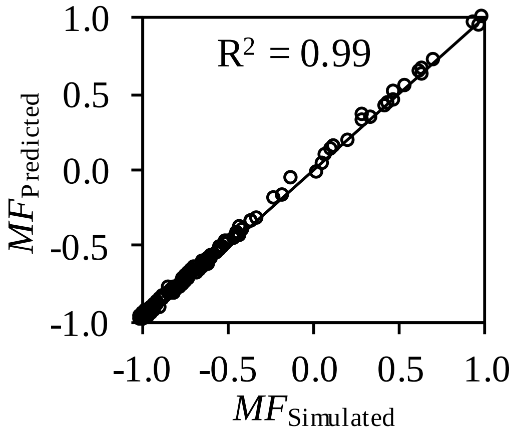


$$T_{SSI} = T_F \times MF$$

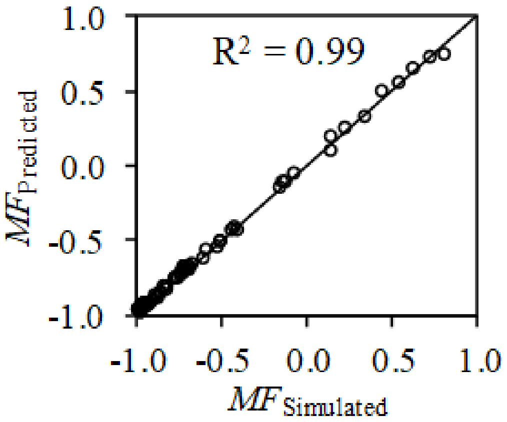


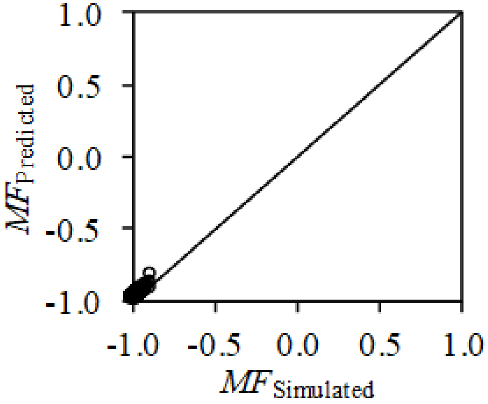
Performance of ANN model for *MF*: Frame System

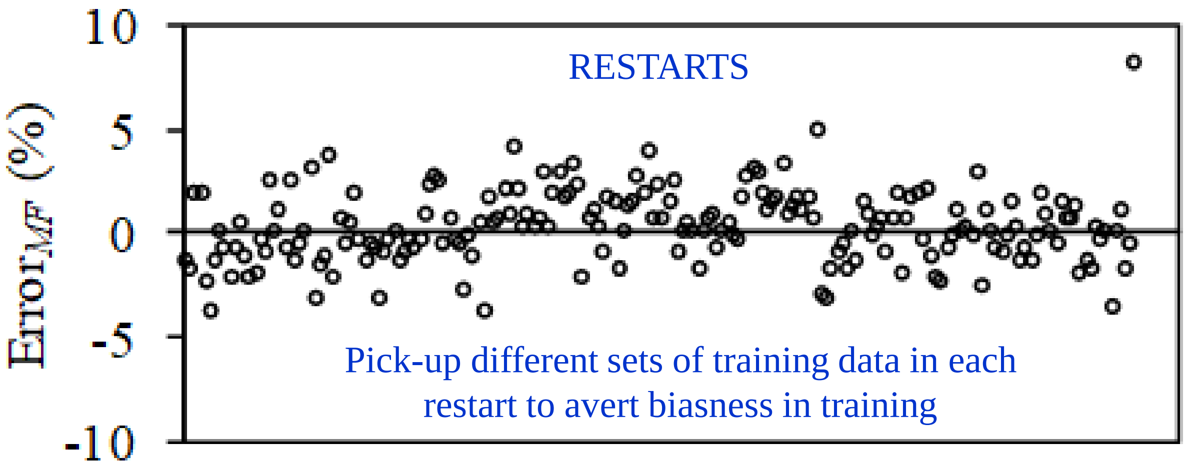
Training using
70% of total data



Validation (to check overfitting) and Testing (to check robustness)
using 30% of total data







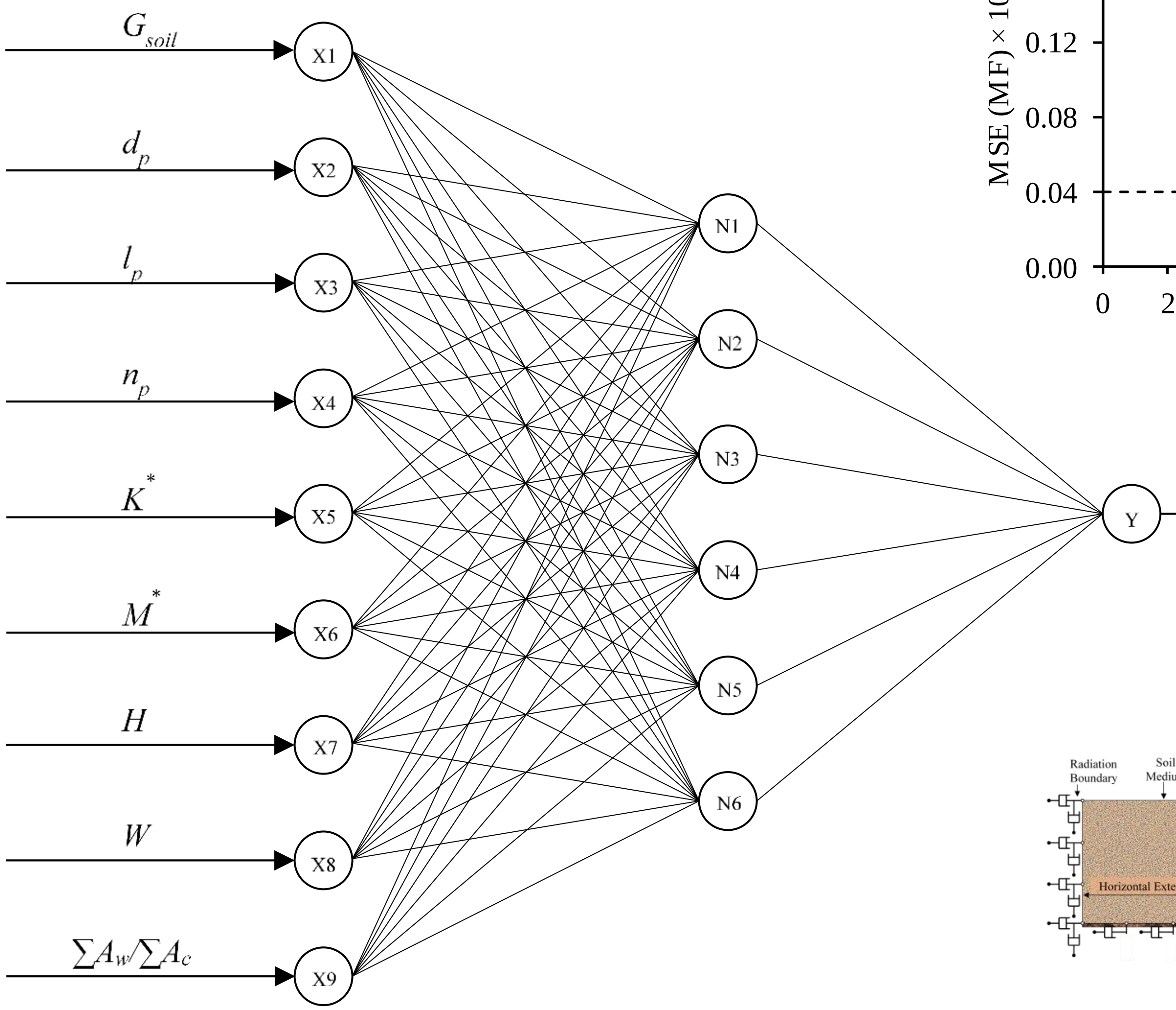
$$MF_n = f_{lin}\left\{b_0 + \sum_{j=1}^{n}\left[w_{HO}^{j}\; f_{sig}\left(b_{hj} + \sum_{k=1}^{N} w_{IH}^{j} X_k\right)\right]\right\}$$

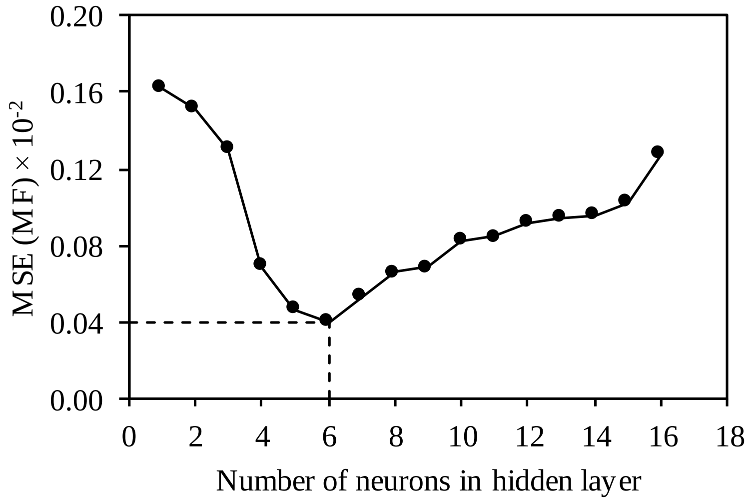
$$MF = 0.5(MF_n + 1)(MF_{\max} - MF_{\min}) + MF_{\min}$$

$$MF_{max} = 1.23,\ MF_{min} = 1.02$$

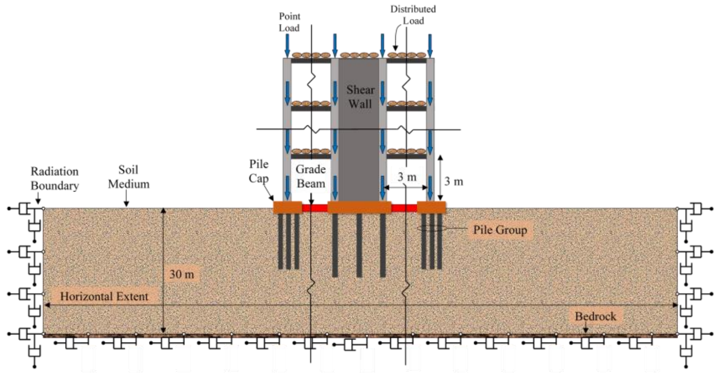
ANN Architecture for *MF*: Wall-Frame System

9-6-1 ANN Architecture



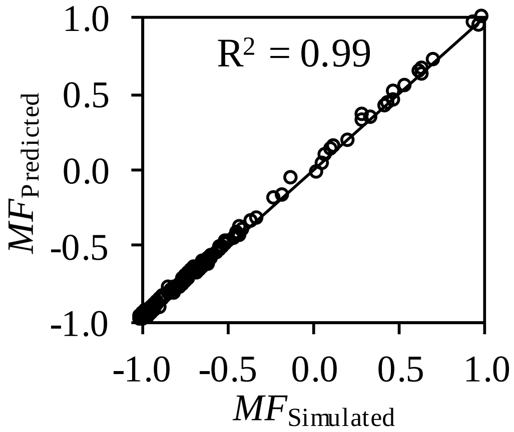


$$T_{SSI} = T_F \times MF$$

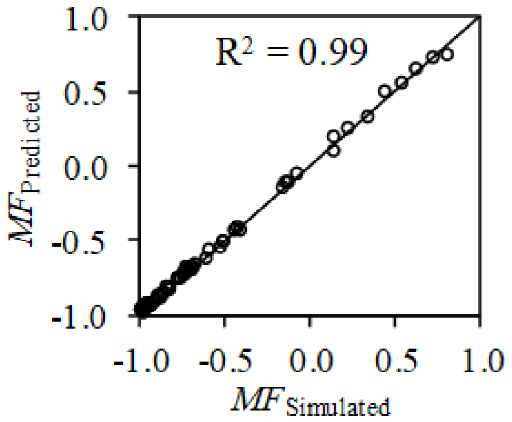


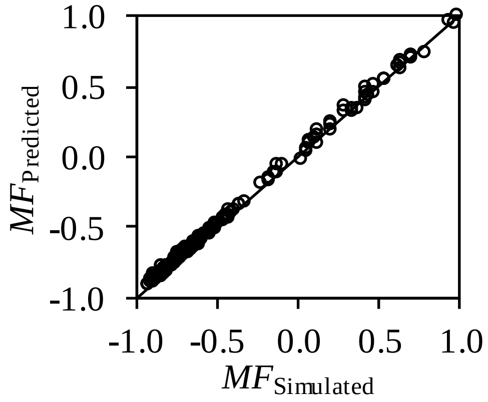
Performance of ANN model for *MF*: Wall-Frame System

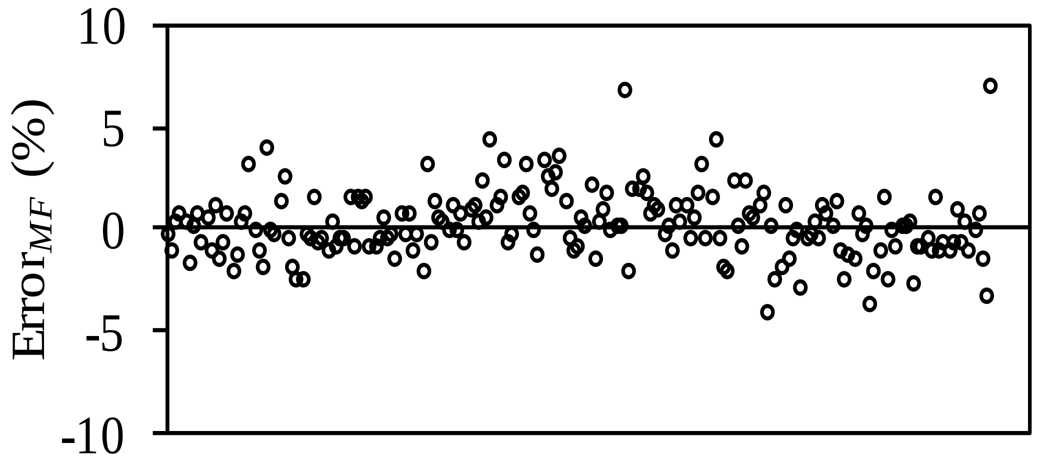
Training using
70% of total data



Validation and Testing using
30% of total data







$$MF_n = f_{lin}\left\{b_0 + \sum_{j=1}^{n}\left[w_{HO}^{j}\; f_{sig}\left(b_{hj} + \sum_{k=1}^{N} w_{IH}^{j} X_k\right)\right]\right\}$$

$$MF = 0.5(MF_n + 1)(MF_{\max} - MF_{\min}) + MF_{\min}$$

$$MF_{max} = 4.5,\; MF_{min} = 1.18$$

ANN-based Predictive Mathematical Relationship

$$MF = 0.5(MF_n + 1)(MF_{\max} - MF_{\min}) + MF_{\min}$$

$$MF_n = f_{lin}\left\{ b_0 + \sum_{j=1}^{n}\left[w_{HO}^{j}\, f_{sig}\left(b_{hj} + \sum_{k=1}^{N} w_{IH}^{j} X_k \right)\right]\right\}$$

- MF_n → Normalized estimate of MF
- MF_{max} → Maximum estimate of MF
- MF_{min} → Minimum estimate of MF
- f_{sig} → Tan-sigmoid transfer function
- f_{lin} → Linear transfer function
- b_0 → Bias at the output layer
- b_{hj} → Bias at the j^{th} neuron of the hidden layer
- w_{IH} → Weight of the input-hidden neuron
- w_{HO} → Weight of the hidden-output neuron
- N → Total number of input variables (9)
- n → Total number of neurons in the hidden layer (6)

$$MF_n = 0.21 + B_1 + B_2 + B_3 + B_4 + B_5 + B_6$$

$$B_1 = -0.97\left(\frac{e^{A_1} - e^{-A_1}}{e^{A_1} + e^{-A_1}}\right) \qquad B_2 = -0.41\left(\frac{e^{A_2} - e^{-A_2}}{e^{A_2} + e^{-A_2}}\right)$$

$$B_3 = 0.18\left(\frac{e^{A_2} - e^{-A_2}}{e^{A_2} + e^{-A_2}}\right) \qquad B_4 = 0.25\left(\frac{e^{A_4} - e^{-A_4}}{e^{A_4} + e^{-A_4}}\right)$$

$$B_5 = 0.04\left(\frac{e^{A_5} - e^{-A_5}}{e^{A_5} + e^{-A_5}}\right) \qquad B_6 = -0.44\left(\frac{e^{A_6} - e^{-A_6}}{e^{A_6} + e^{-A_6}}\right)$$

ANN-based Predictive Mathematical Relationship

$$MF = 0.5(MF_n + 1)(MF_{\max} - MF_{\min}) + MF_{\min}$$

$$MF_n = 0.21 + B_1 + B_2 + B_3 + B_4 + B_5 + B_6$$

$$MF_n = f_{lin}\left\{b_0 + \sum_{j=1}^{n}\left[w_{HO}^{j}\, f_{sig}\left(b_{hj} + \sum_{k=1}^{N} w_{IH}^{j} X_k\right)\right]\right\}$$

$$B_1 = -0.97\left(\frac{e^{A_1} - e^{-A_1}}{e^{A_1} + e^{-A_1}}\right)$$

$$A_1 = 0.01G_{Soil} - 0.2d_p - 0.1l_p - 0.04n_p - 0.67K^* + 0.54M^* + 0.45H + 0.14W - 0.14A_r + 1.31$$

$$B_2 = -0.41\left(\frac{e^{A_2} - e^{-A_2}}{e^{A_2} + e^{-A_2}}\right)$$

$$A_2 = 0.16G_{Soil} + 0.12d_p + 0.2l_p + 0.09n_p - 1.81K^* - 0.02M^* - 0.73H - 0.13W - 0.76A_r - 2.32$$

$$B_3 = 0.18\left(\frac{e^{A_2} - e^{-A_2}}{e^{A_2} + e^{-A_2}}\right)$$

$$A_3 = 0.38G_{Soil} + 0.3d_p + 0.34l_p + 0.28n_p - 0.11K^* - 0.96M^* - 1.03H + 0.004W + 0.47A_r - 0.65$$

$$B_4 = 0.25\left(\frac{e^{A_4} - e^{-A_4}}{e^{A_4} + e^{-A_4}}\right)$$

$$A_4 = 0.52G_{Soil} + 0.61d_p + 0.4l_p + 0.28n_p - 0.67K^* - 0.08M^* - 0.22H - 0.47W + 0.45A_r + 1.33$$

$$B_5 = 0.04\left(\frac{e^{A_5} - e^{-A_5}}{e^{A_5} + e^{-A_5}}\right)$$

$$A_5 = -0.86G_{Soil} - 0.09d_p + 0.87l_p - 0.17n_p + 0.1K^* - 0.59M^* + 0.45H + 1.15W + 0.14A_r - 1.35$$

$$B_6 = -0.44\left(\frac{e^{A_6} - e^{-A_6}}{e^{A_6} + e^{-A_6}}\right)$$

$$A_6 = 1.34G_{Soil} + 0.34d_p - 0.25l_p + 0.47n_p - 1.13K^* - 0.38M^* - 0.86H + 0.52W - 0.06A_r + 2.67$$

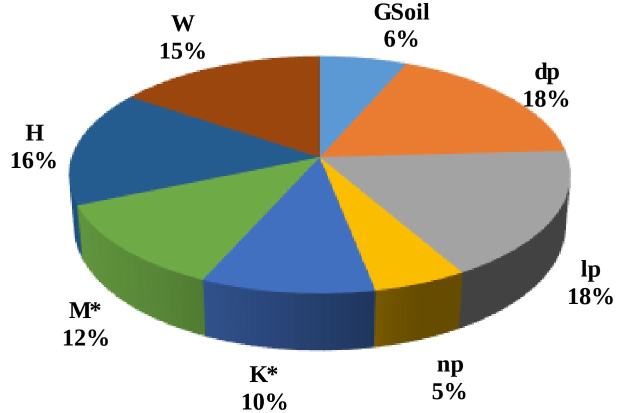
Importance Ranking: Garson's Sensitivity Analysis

$$\text{Relative Importance}_{Xm} = \sum_{j=1}^{n} \frac{\left| {}^{m}w_{IH}^{j} \right|}{\left(\sum_{k=1}^{N} \left| {}^{k}w_{IH}^{j} \right| \right) \left| w_{HO}^{j} \right|}$$

Xm is the m^{th} input variable for which the relative importance is to be obtained, w_{IH} is the input-hidden weight, w_{HO} is the hidden-output weight, N is the total number of input variables and n is the total number of neurons in the hidden layer

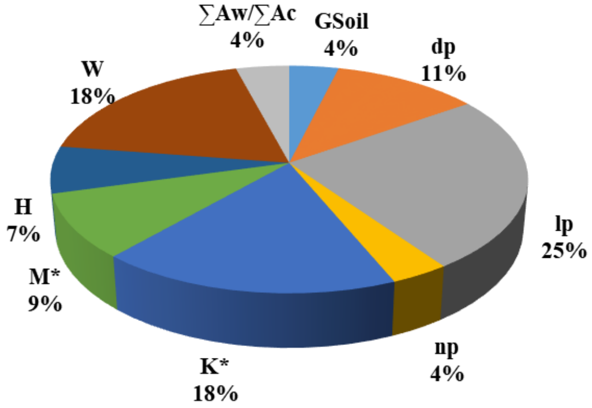
RC Frame system (F)

Input Variable		Outcome of Garson's Sensitivity Analysis		
		Relative Importance	Relative importance (%)	Rank
X1	G_{Soil}	1.04	6.50	7
X2	d_p	2.80	17.60	1
X3	l_p	2.79	17.56	2
X4	n_p	0.84	5.26	8
X5	K^*	1.56	9.76	6
X6	M^*	1.90	11.93	5
X7	H	2.53	15.90	3
X8	W	2.47	15.49	4



RC Wall-frame system (W)

Input Variable		Outcome of Garson's sensitivity analysis		
		Relative Importance	Relative importance (%)	Rank
X1	G_{Soil}	0.953	3.85	8
X2	d_p	2.829	11.41	4
X3	l_p	6.192	24.98	1
X4	n_p	0.860	3.47	9
X5	K^*	4.417	17.82	3
X6	M^*	2.279	9.19	5
X7	H	1.655	6.68	6
X8	W	4.576	18.46	2
X9	$\sum A_w/\sum A_c$	1.028	4.15	7



Effective Natural Period: Past Studies

Past Study	Expression	Remark
Veletsos and Meek [5]	$T_{SSI} = T_F \sqrt{1 + \frac{K^*}{K_x} + \frac{K^* H^2}{K_\phi}}$	Analytical equation developed for surface footings. Most widely used and adopted by seismic code e.g. ATC 3.
Gazetas [6]	$T_{SSI} = T_F \sqrt{1 + \frac{K^*}{K_x} + \frac{K^* H}{K_{x\phi}} + \frac{K^* H^2}{K_\phi}}$	Semi-empirical relation with additional sway rocking component.
Kumar and Prakash [7]	$T_{SSI} = T_F \sqrt{1 + \frac{60}{H}\left(\frac{K^*}{K_x} + \frac{K^* H^2}{K_\phi}\right)^{1.5}}$	Semi-empirical relationship proposed specifically for structure on pile foundation

T_{SSI} = Natural period of the structural system under the influence of SSI

T_F = Fixed base natural period of the superstructure

H = Effective height of the superstructure

K^* = Effective stiffness of the superstructure under fixed base condition

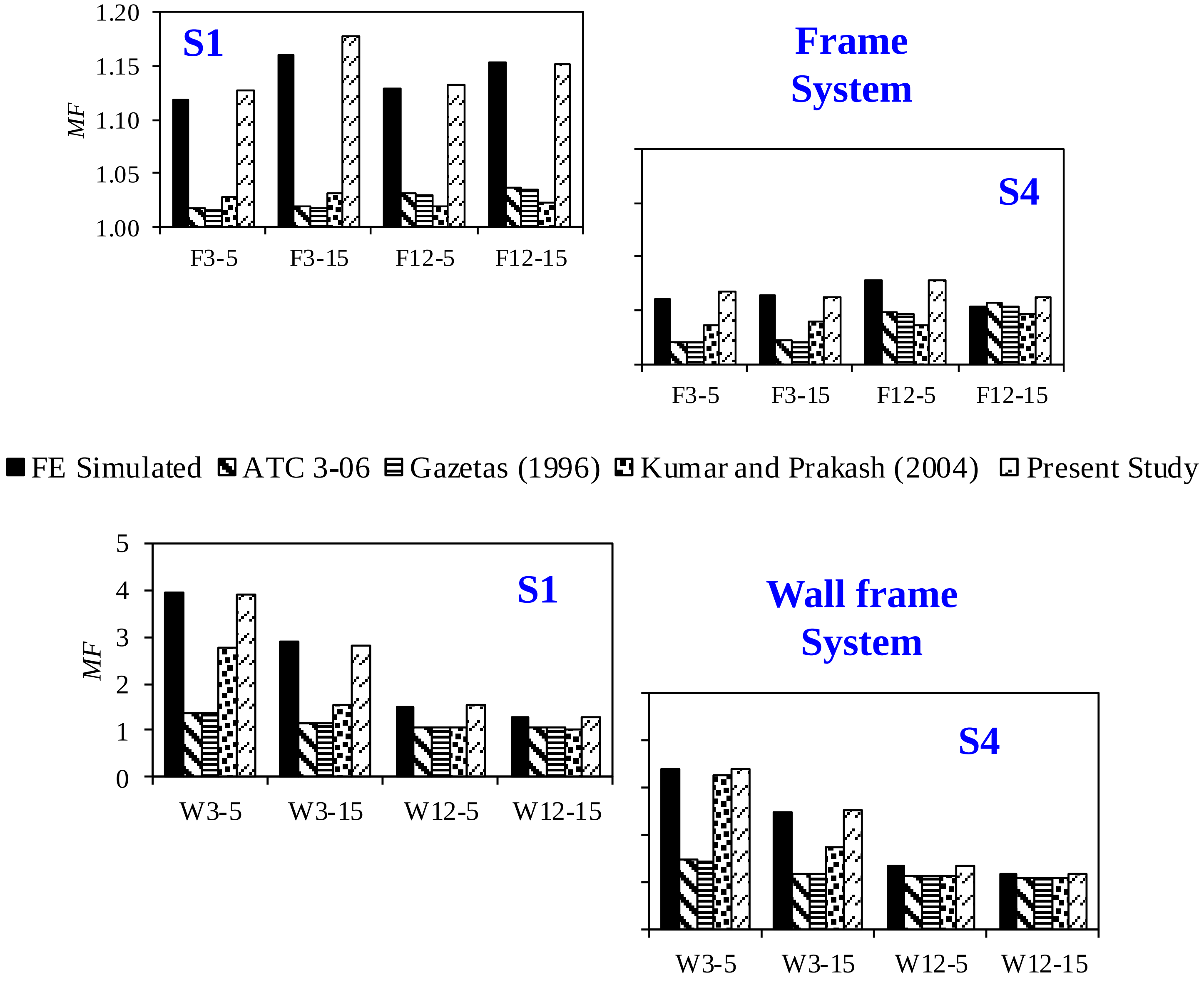
K_x = Lateral stiffness of the foundation

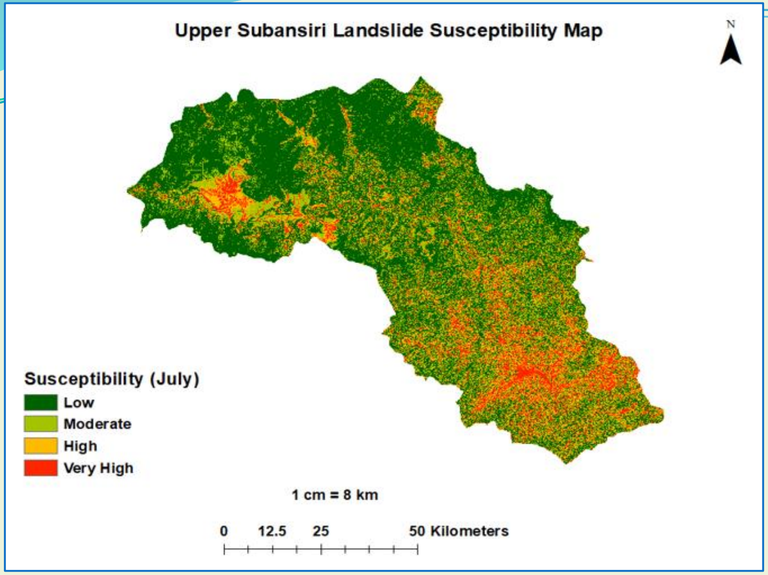
K_ϕ = Rotational stiffness of the foundation

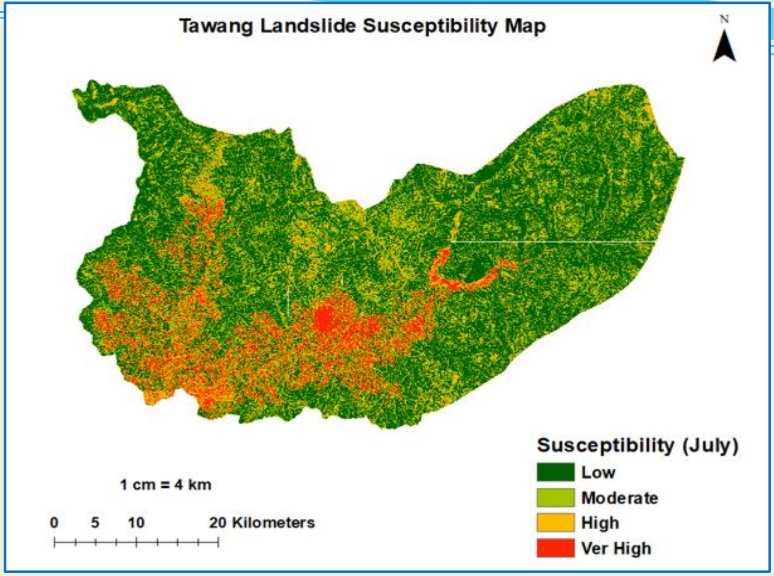
$K_{x\phi}$ = Coupled sway rotational stiffness of the foundation

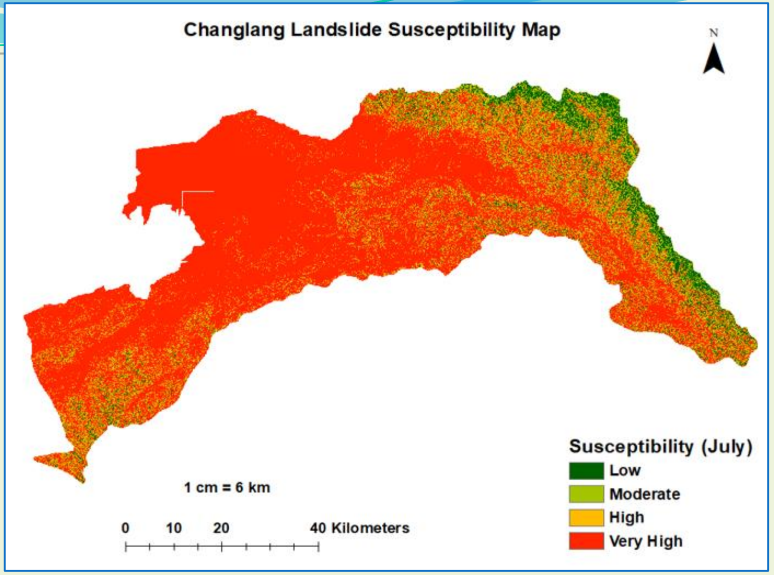
Comparison with Past Literature

- Estimates of *MF* using proposed model
  - Compared with previously proposed relationships
- Relationship proposed in ATC 3 and Gazetas (1996) provides lower estimates
  - Shallow foundation
- Relationship proposed by Kumar and Prakash (2004)
  - Better, developed for pile foundations
  - Simplified model, limited
- Estimates using ANN model
  - Close agreement with FE simulated values
  - Can be used for prediction of effective natural period

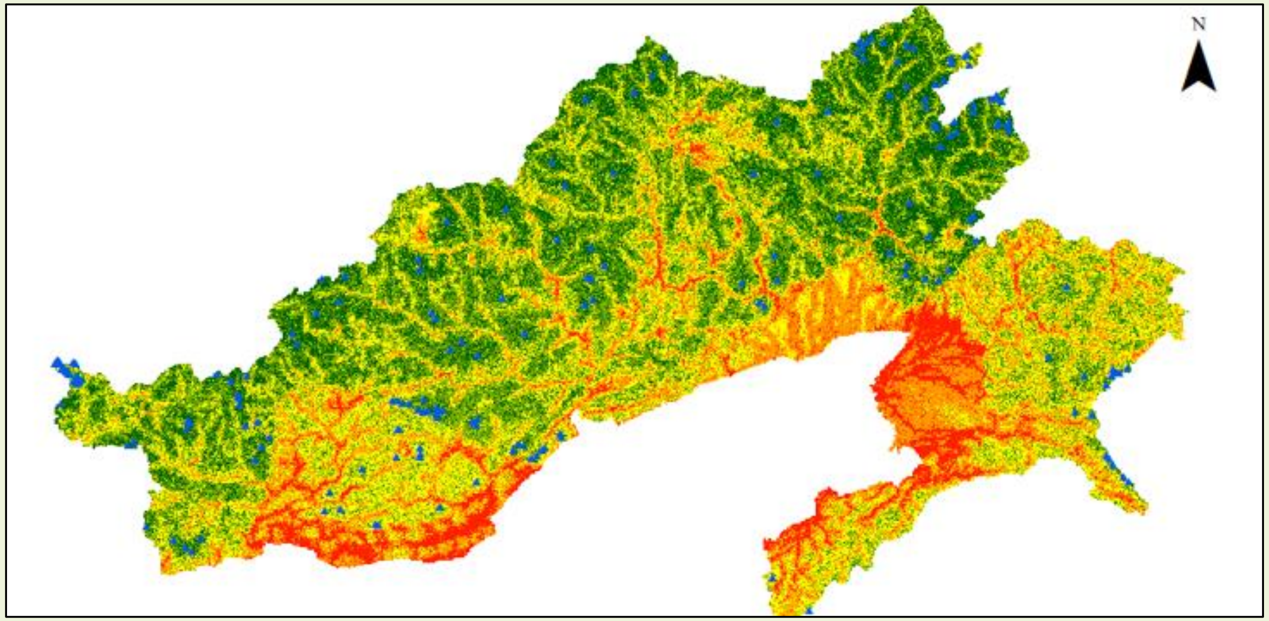








Application of ML in Landslide Susceptibility Mapping



Some Major Landslides In India

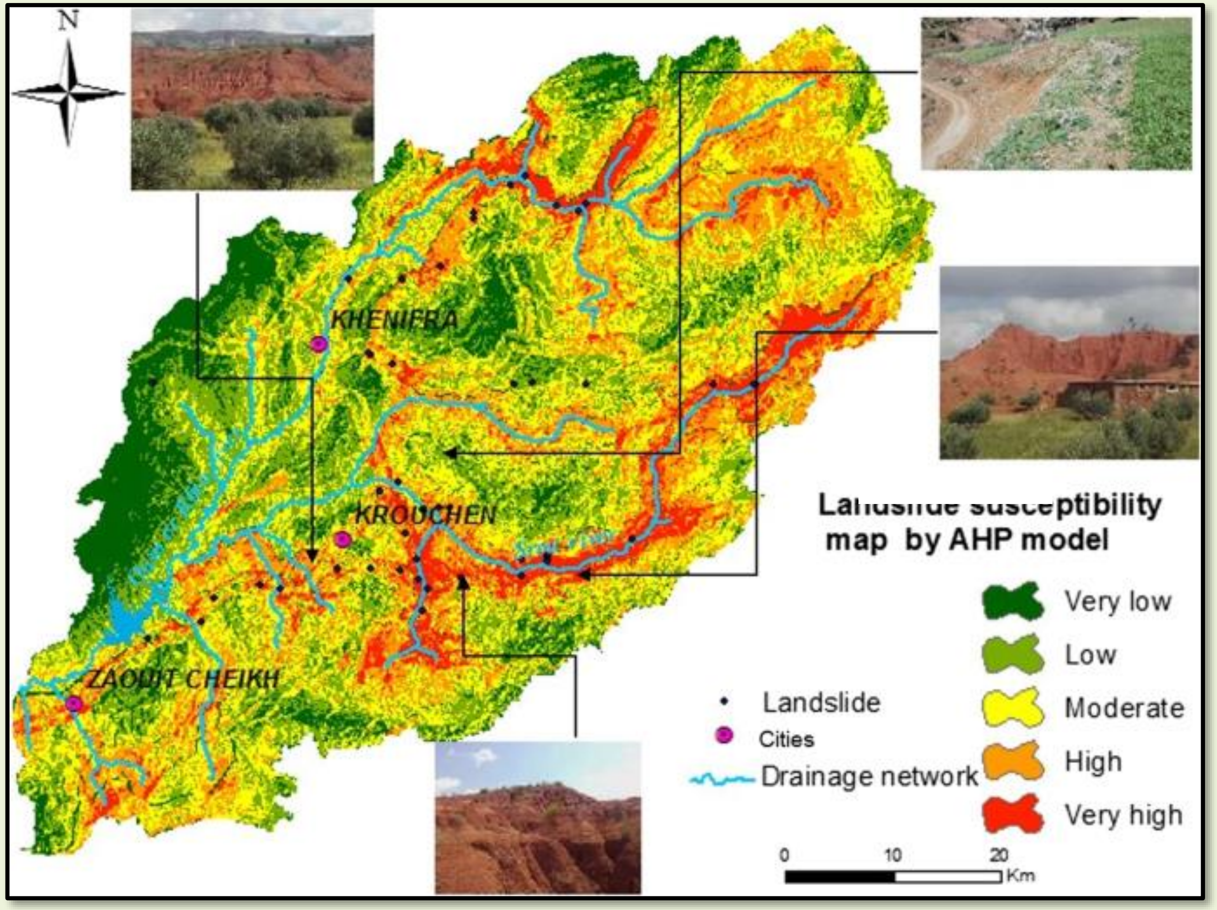
Kohima Landslide in Nagaland	August, 1993	500 people died, 200 houses destroyed; Damage to 5km road stretch.
Leh landslide in , J&K	6 August 2010 due to cloud burst	145 killed, > 2,500 people affected and became homeless.
Malin landslide in Maharashtra	30^{th} July 2014 due to Heavy rainfall	151 people died, and more than 100 were missing.
Kuwari landslide in Uttarakhand	10th March 2018 due to Heavy rainfall	More than 400 people died, and 106 houses perished.
Pettimudi landslide in Kerala	6th August 2020 due to Heavy rainfall	80 people died, and many casualties occurred.
Tupul landslide in Manipur	30 June 2022 due to Heavy rainfall	30 Indian Army personnel and 31 civilians were among the deceased

Landslide Susceptibility Mapping (LSM)

- Likelihood of a landslide occurrence across a given geographic area.

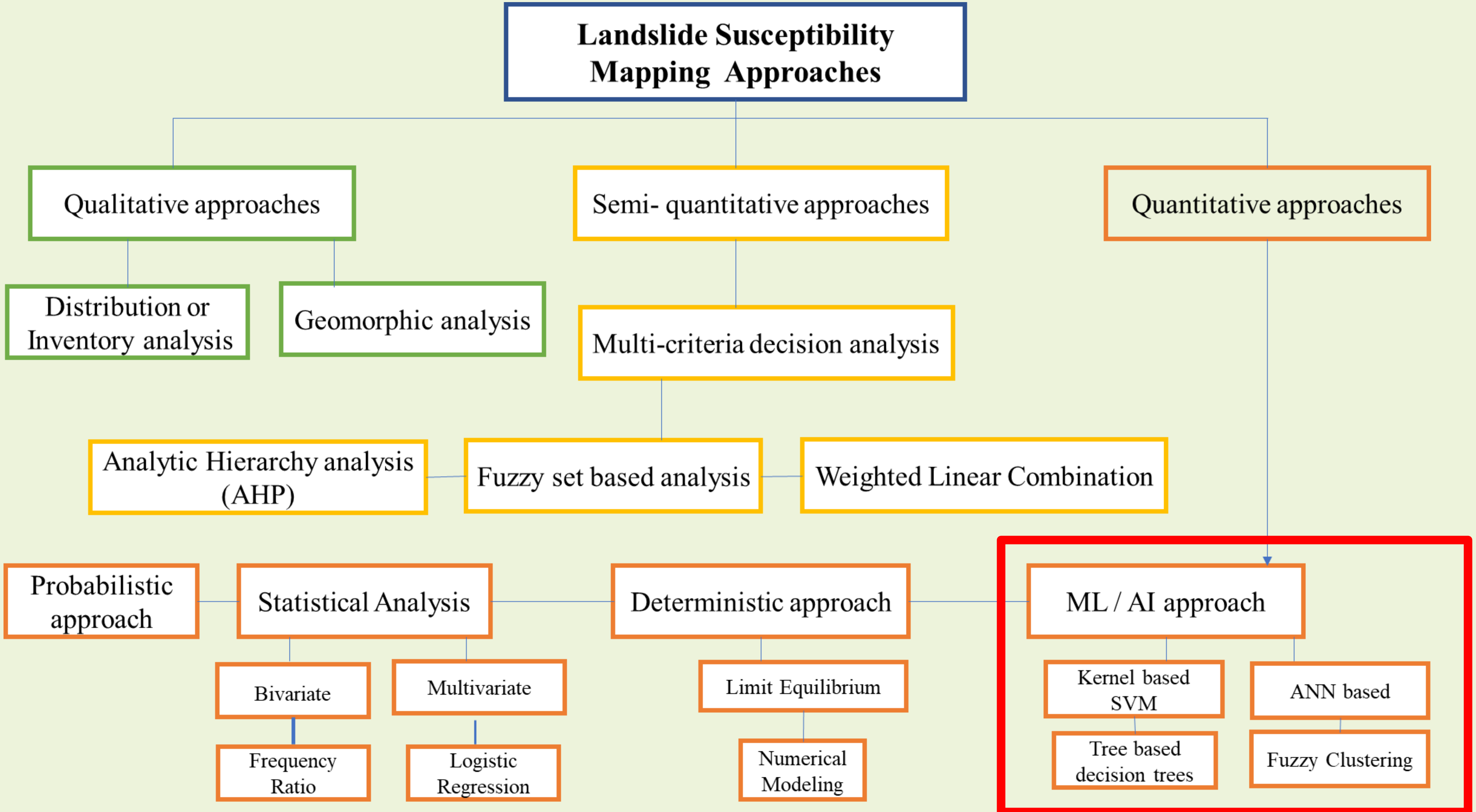
- Aiding to assess landslide-susceptible areas
  - Predict landslides
  - Decrease the damage caused by landslides.

- Aim of landslide susceptibility mapping
  - Provide a better understanding of the potential risks associated with landslides in a particular region
  - Support decision-making processes related to land use planning, engineering design, and emergency management.



A Typical Landslide Susceptibility mapping
(Pham et al. 2017)

Techniques of Landslide Susceptibility Mapping



Remote Sensing based Rainfall Induced Landslide Assessment Methods

Qualitative methods

Involve the visual interpretation and expert judgment of the features of the terrain to identify areas that are susceptible to landslides.

(Theiry et al., 2014; Das et al., 2011).

- **Expert Opinion**
- **Field Mapping**
- **Photo interpretation**

Quantitative methods

Involve the use of statistical and mathematical models to map the relationships between landslide occurrence and various terrain attributes.

(Pardeshi et al., 2013; Marrapu & Jakka, 2014).

- **Deterministic Approach**
- **Geological Approach**
- **Statistical Approach**
- **Machine Learning Approach**
- **Hybrid Approach**

Deterministic Approach:

Is a traditional, analytical approach that relies on mathematical equations to determine the stability of slopes.

(Das et al., 2020; Singh et al., 2016; Sarkar et al., 2020).

- **Infinite slope stability method**
- **Limit equilibrium method**
- **Finite element method (FEM)**

Limitations

- **Simplified assumptions**
- **Scalability**
- **Flexibility**
- **Limited data availability**

Geological Approach

Involves assumption that landslides occur in areas with specific geological characteristics.

Approach involves identifying those geological factors that control the occurrence of landslides, such as the type and structure of rocks, geological history, and soil properties.

(Magliulo et al., 2008; Pavel et al., 2010; Gorum et al., 2008).

- **Geomorphological Mapping**
- **Soil Analysis**
- **Geophysical Survey**

Limitations

Limited Spatial Coverage
Limited Data Availability
Lack of consideration of other factors e.g. weather, land use

Statistical Approach

Assume that the relationships between the landslide occurrence and the terrain attributes can be represented by mathematical functions.

(Wubalem & Meten, 2020; Hemasinghe et al., 2018; Batar et al., 2021; Getachew & Meten,2021; Arabameri et al., 2019; Tahn et al., 2019).

- **Logistic regression (LR)**
- **Weight of evidence**
- **Multiple Regression**
- **Frequency ratio method**

Limitations

- **Lack of Causality**
- **require large datasets**
- **Assumption of linearity**
- **Limited ability to incorporate expert knowledge**

Machine Learning Approach

Data-driven methods

Various ML algorithms, such as: ANN involve the development of a network of artificial neurons that can learn from the data to predict susceptibility.

Decision trees involve the development of a tree-like structure. SVMs involve the development of Hyperplane.

(Pourghasemi et al., 2013; Huang et al., 2018; Nefeslioglu et al., 2009; Park et al., 2018; Selamat et al., 2022; Saha et al., 2022

- **Support Vector Machines (SVM)**
- **Decision Trees**
- **Artificial Neural Networks (ANNs)**

Limitations

- **Dependence on quality and quantity of input data:**
- **Less Interpretability: black boxes**
- **Flexibility:**
- **Limited data availability:**

Hybrid Approach

Uses multiple susceptibility assessment methods to take advantage of their strengths and overcome their weaknesses.

Developed by combining statistical methods with ML methods or by geomorphic approach or Expert based.

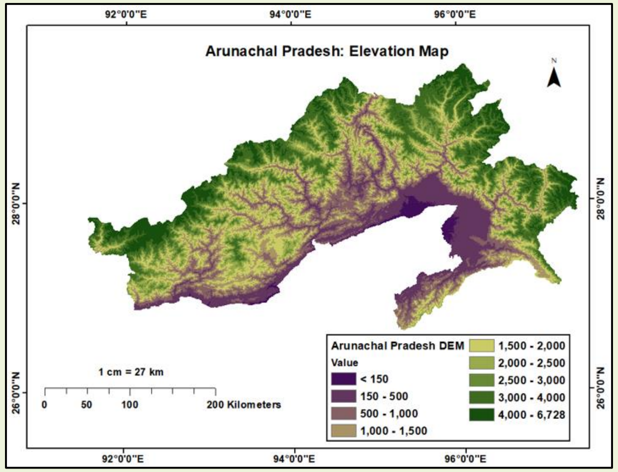
(Shit et al., 2016; Leonardi et al., 2016; Jazouli et al., 2019).

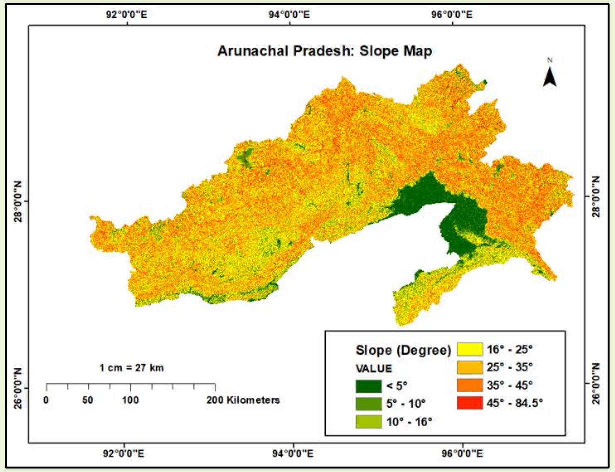
- **Weighted overlay analysis**
- **Fuzzy logic**
- **Analytic hierarchy process (AHP)**

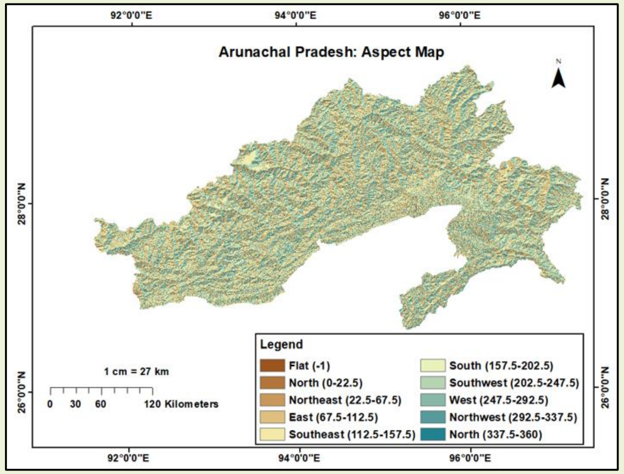
Limitations

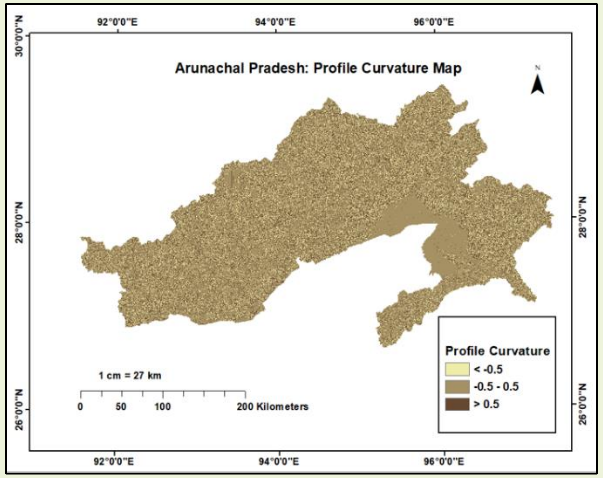
- **Lack of Causality:**
- **require large datasets**
- **Assumption of linearity**
- **Limited ability to incorporate expert knowledge:**

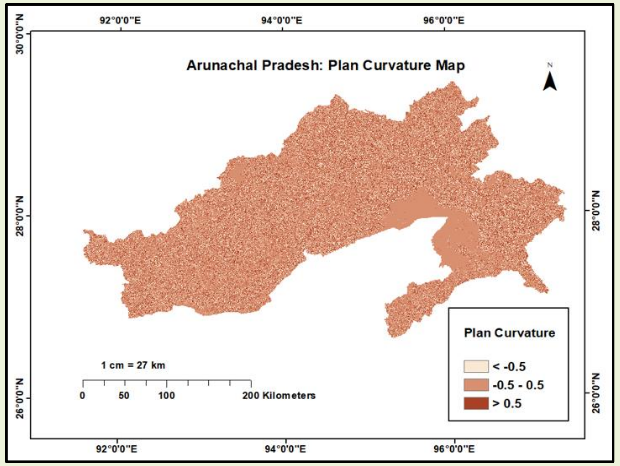
Landslide Conditioning Factors for LSM Maps

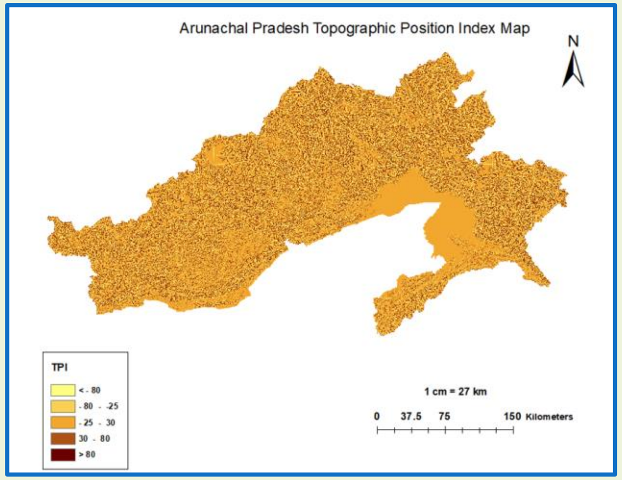


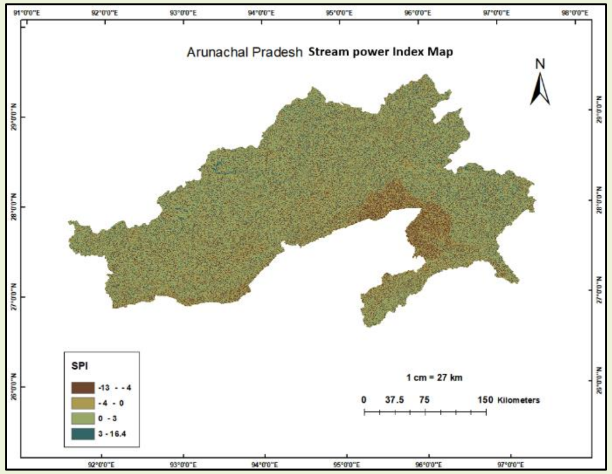


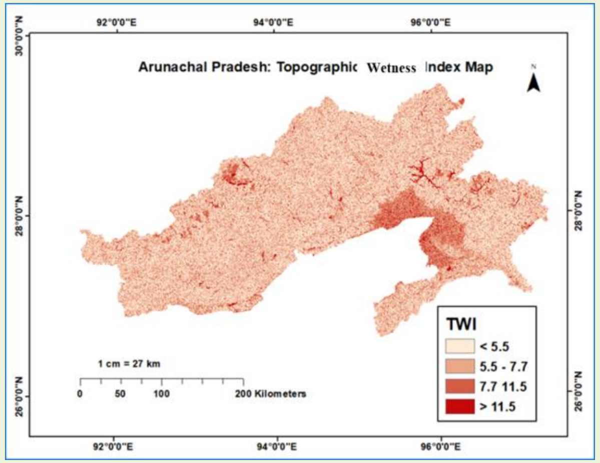


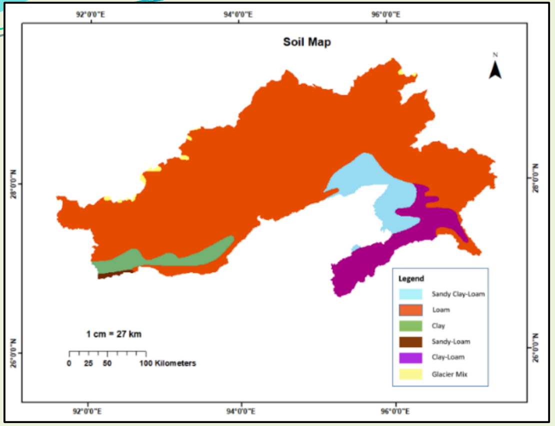


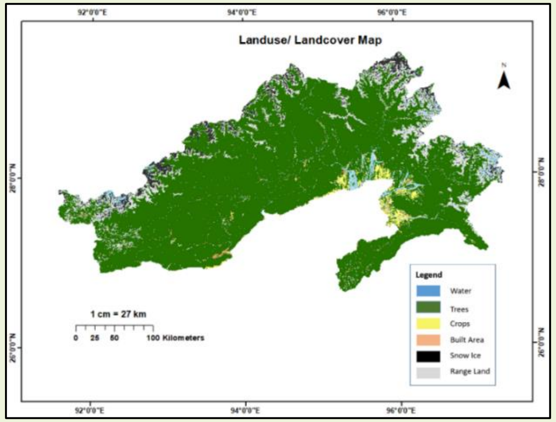


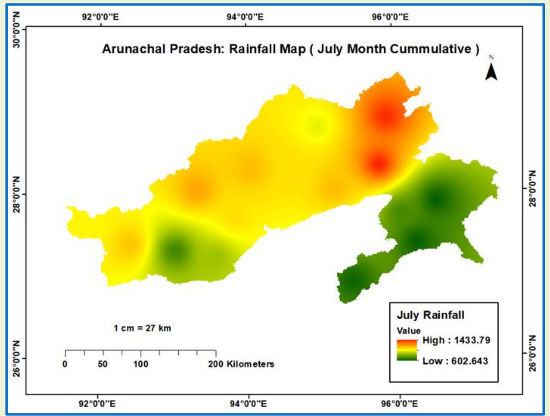




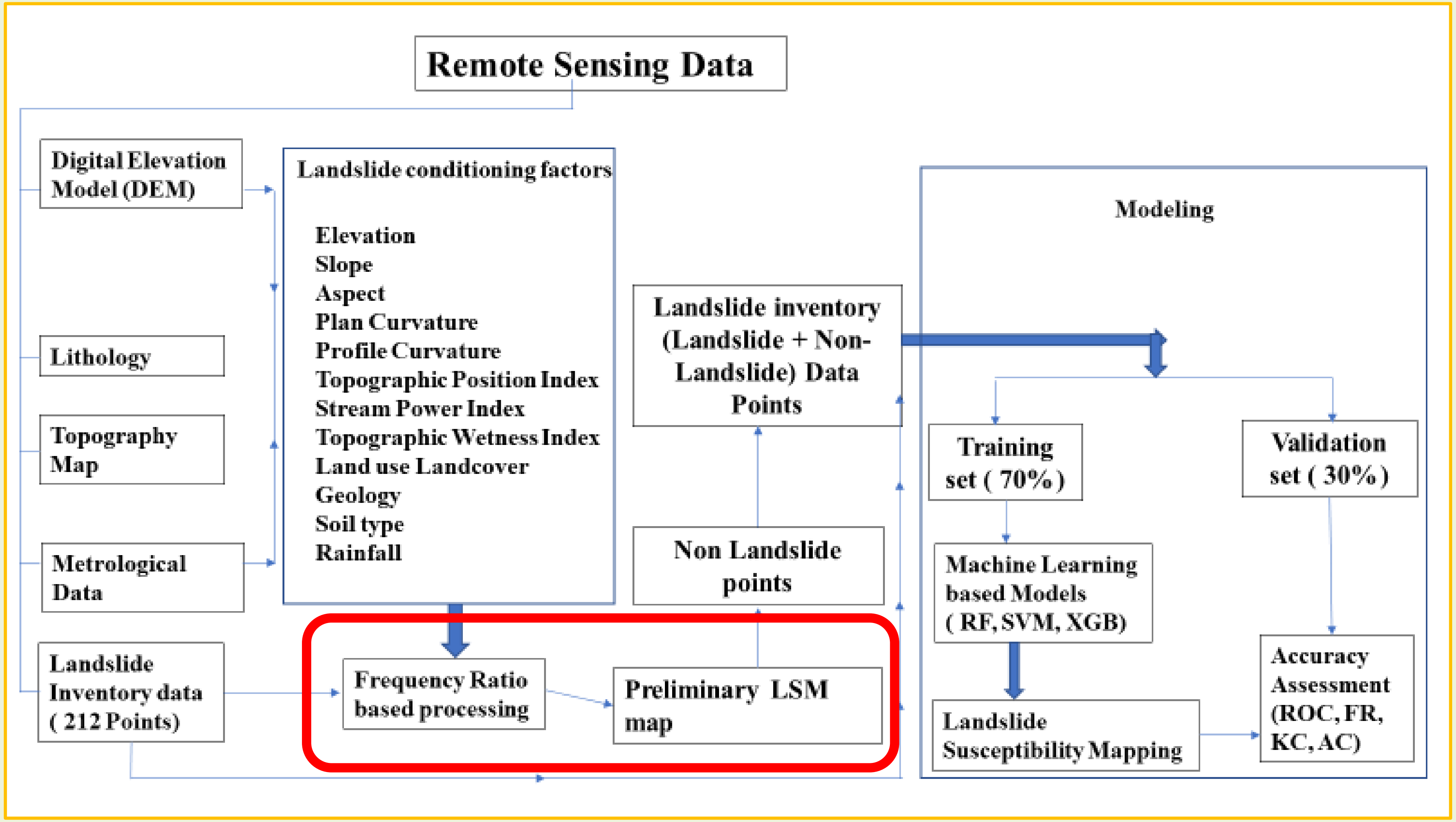








Landslide Conditioning Factors and Maps



Preliminary LSM using Frequency-Ratio Approach

- Frequency Ratio (FR)
  - *A ratio of the probability of presence and absence of landslide occurrences for each landslide conditioning factor class*
  - *Higher FR value*
    - Stronger observed spatial relationship between the landslide occurrence and landslide conditioning factor

$$FR = \frac{P_i}{PL_i} = \frac{N_i^{pix}/N}{N_i^{Lpix}/N^L}$$

P_i = Percentage of pixels in each landslide conditioning factor class

PL_i = Percentage of landslide pixels in each landslide conditioning factor class

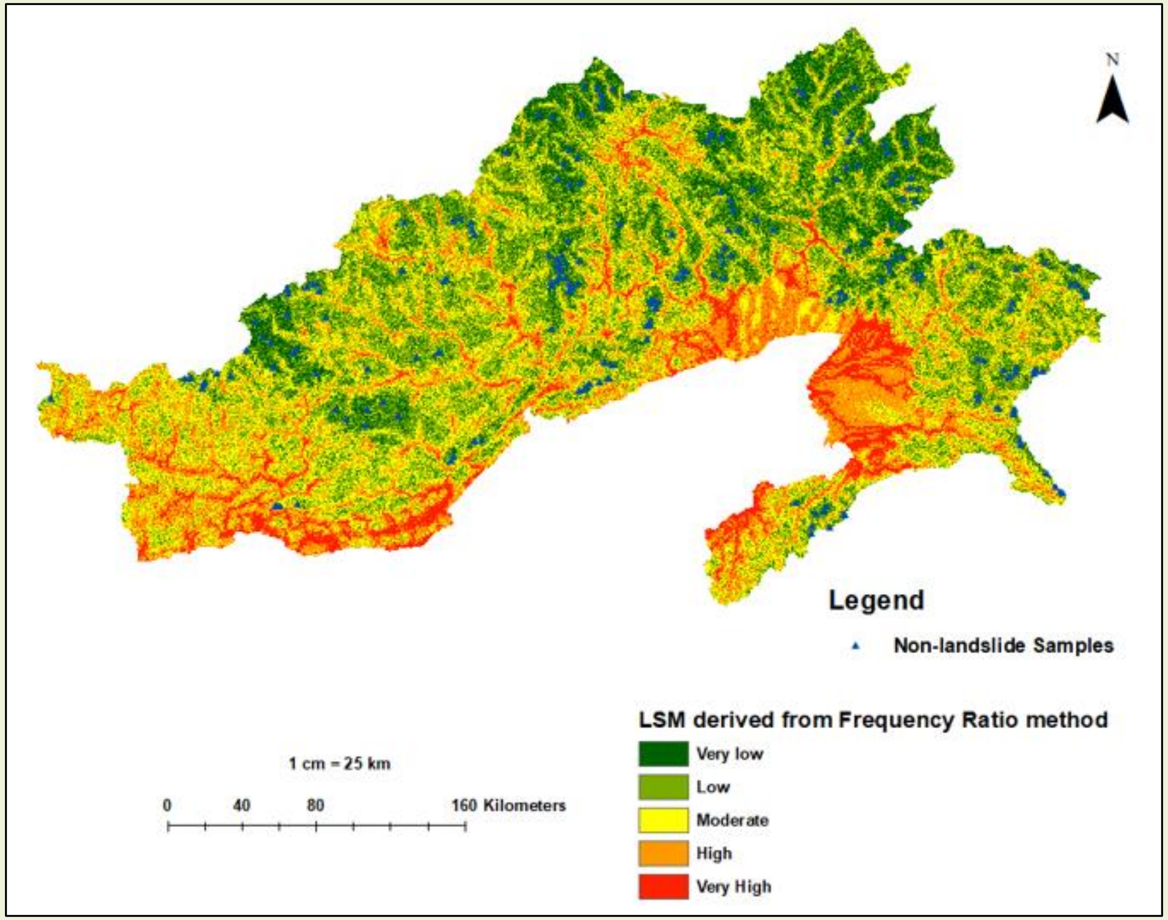
N_i = Number of pixels in each landslide conditioning factor class

N = Number of all pixels in total the study area.

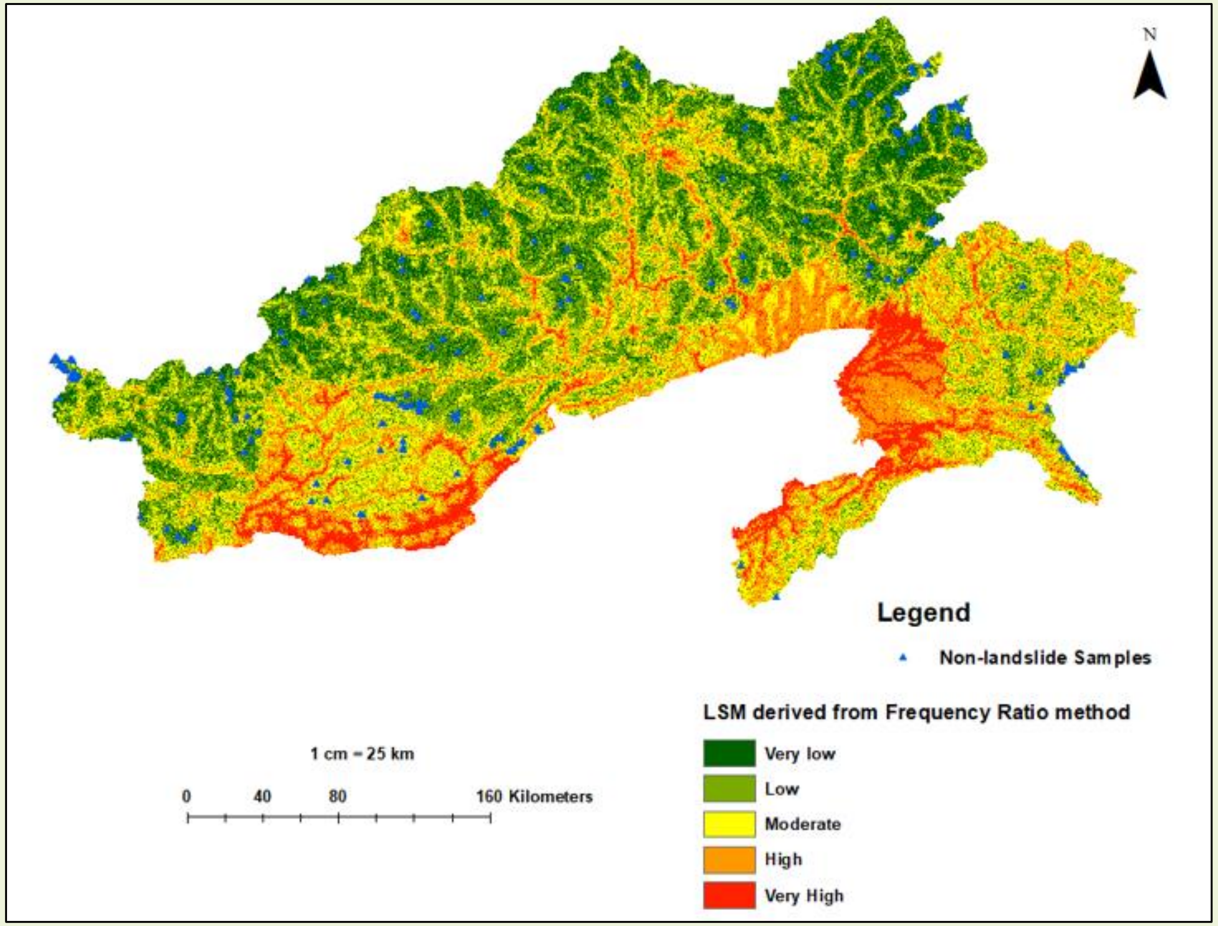
N^L = number of all landslide pixels in total the study area

SN.	Factors	Class	No. of Landslide	Landslide %	Area (No. of Pixel)	Area (%)	FR	Normalization
1.	Slope (Degree)	<5° (Gentle - Slope)	20	9.43	6715510	7.37	1.28	0.50
		5°-10° (Moderate Slope)	27	12.73	4558428	5.0	2.54	1.00
		10° - 16° (Strong Slope)	28	13.2	8355556	9.2	1.44	0.57
		16° - 25° (Very Strong Slope)	43	20.28	20580225	22.6	0.90	0.35
		25°-35° (Extreme slope)	49	23.11	27568745	30.3	0.76	0.30
		35° - 45° (Steep Slope)	34	16.03	17607238	19.3	0.83	0.33
		>45° (Very Steep Slope)	11	5.18	5751399	6.3	0.82	0.32
		Summation	212		91137101	100		

Preliminary LSM using Frequency-Ratio Approach



July



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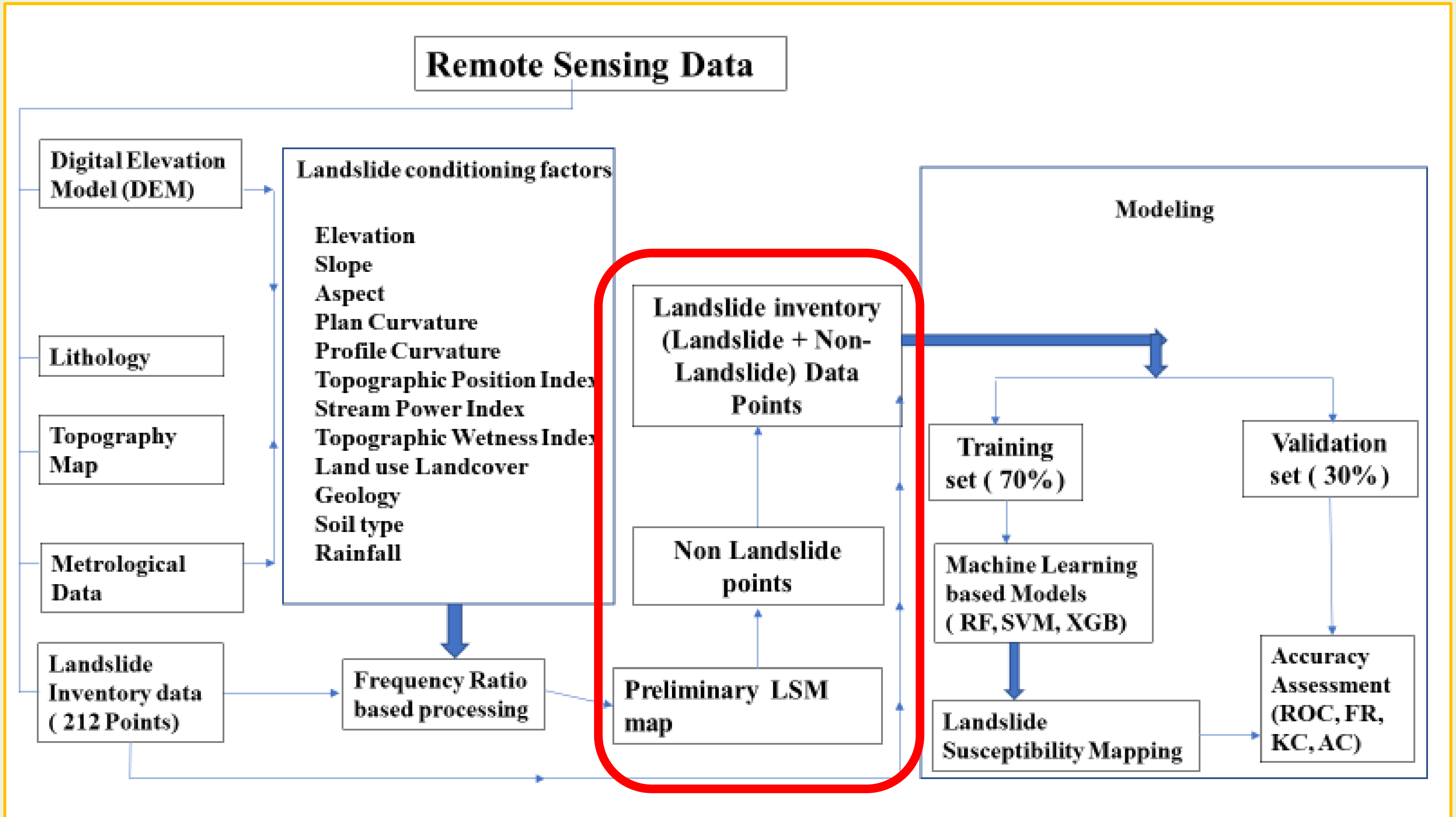
Landslide Conditioning Factors and Maps



Machine Learning Techniques (MLTs)

Advantages over other LS assessment methods

1. **Increased accuracy**: ML models have shown higher accuracy in predicting landslide susceptibility compared to traditional methods, such as empirical or statistical models. Because ML models can handle complex and non-linear relationships between the input variables and landslide occurrence.

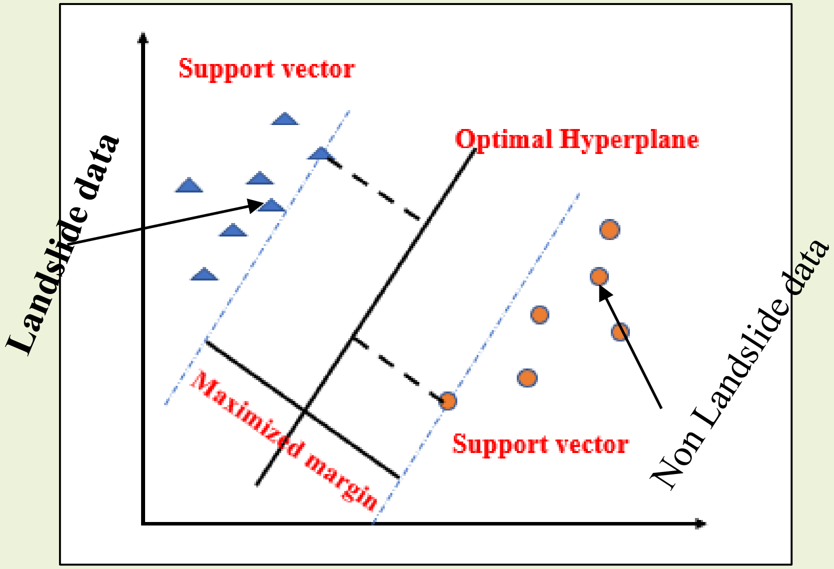
2. **Flexibility**: ML models are flexible and can accommodate a wide range of input data, including topography, geology, climate, land use/land cover, and other. This makes them suitable for analyzing different types of landscapes and regions.

3. **Scalability**: ML models can be applied to large areas or regions, making them suitable for regional-scale landslide susceptibility mapping.

4. **Automated feature selection**: ML models can automatically select the most relevant input features or variables for predicting landslide susceptibility. This reduces the need for expert knowledge and subjective selection

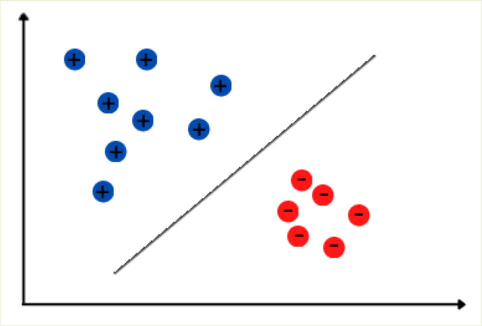
Support Vector Machine (SVM)

(a)



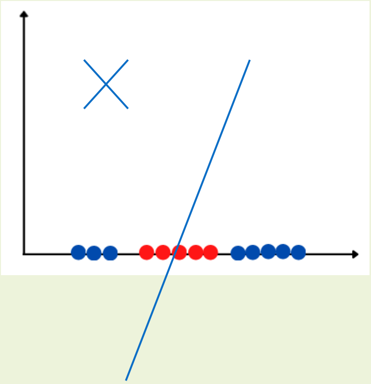
(b)

Linearly separable data

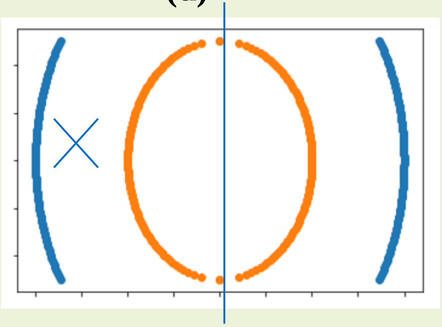


Non-Linearly separable data

(c)

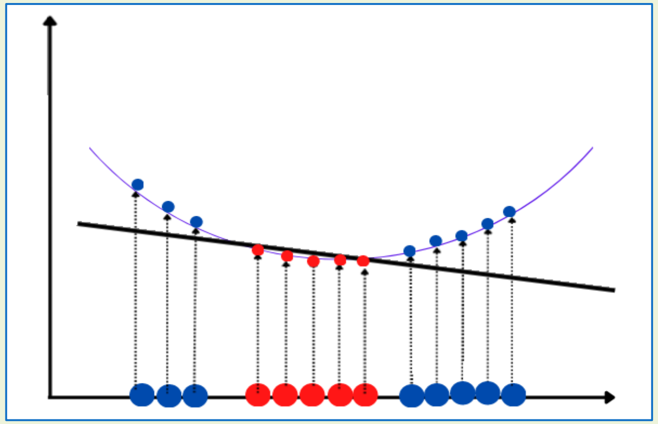


(d)

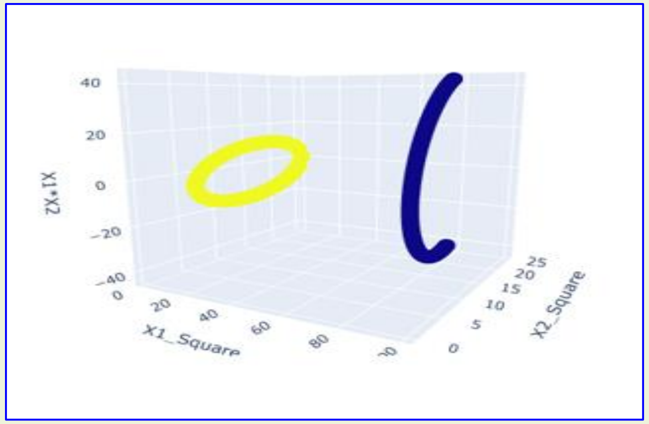


Converting Non-linear separable dataset into High dimension and then solving them

(e)



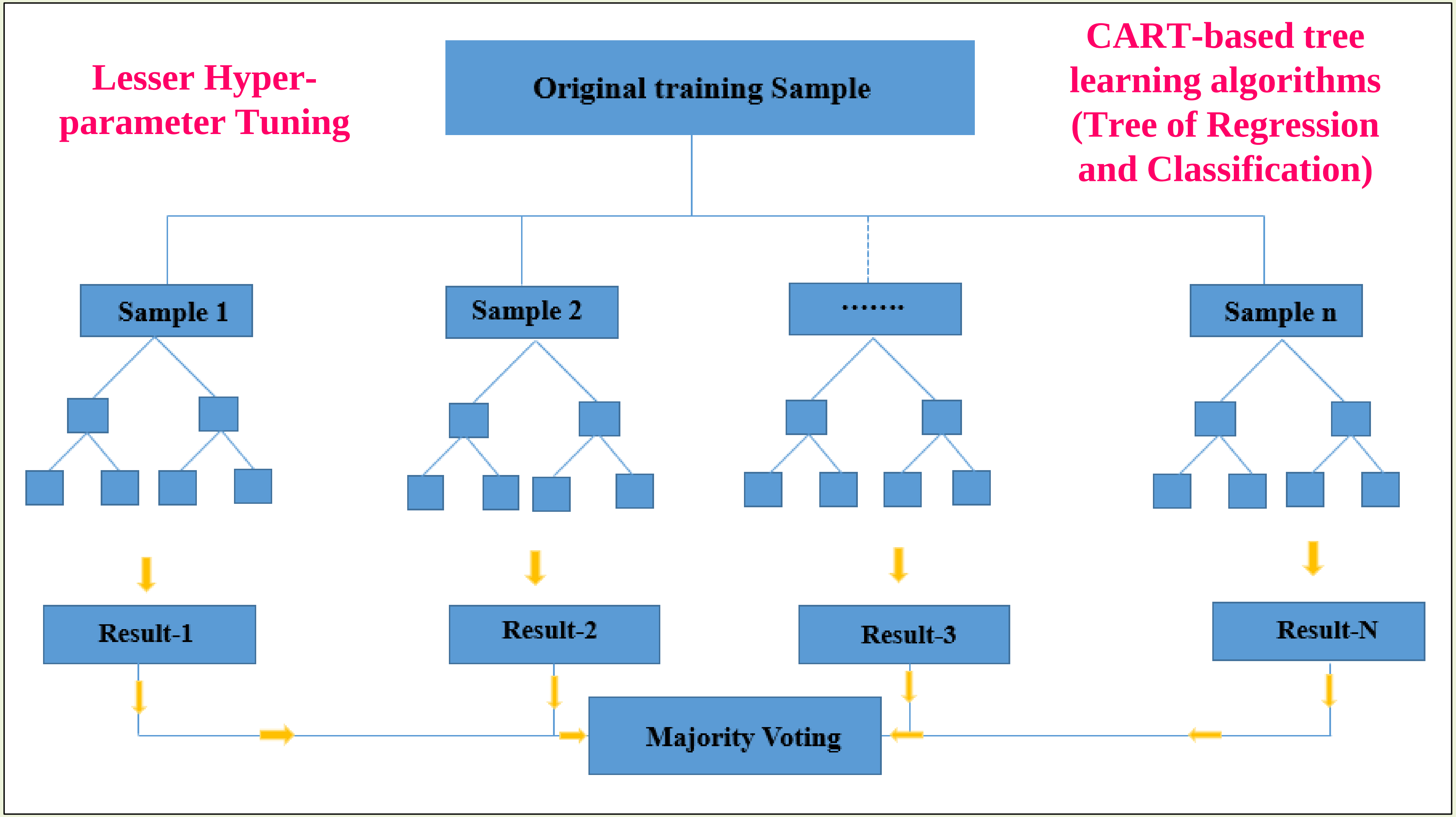
(f)



Limitation

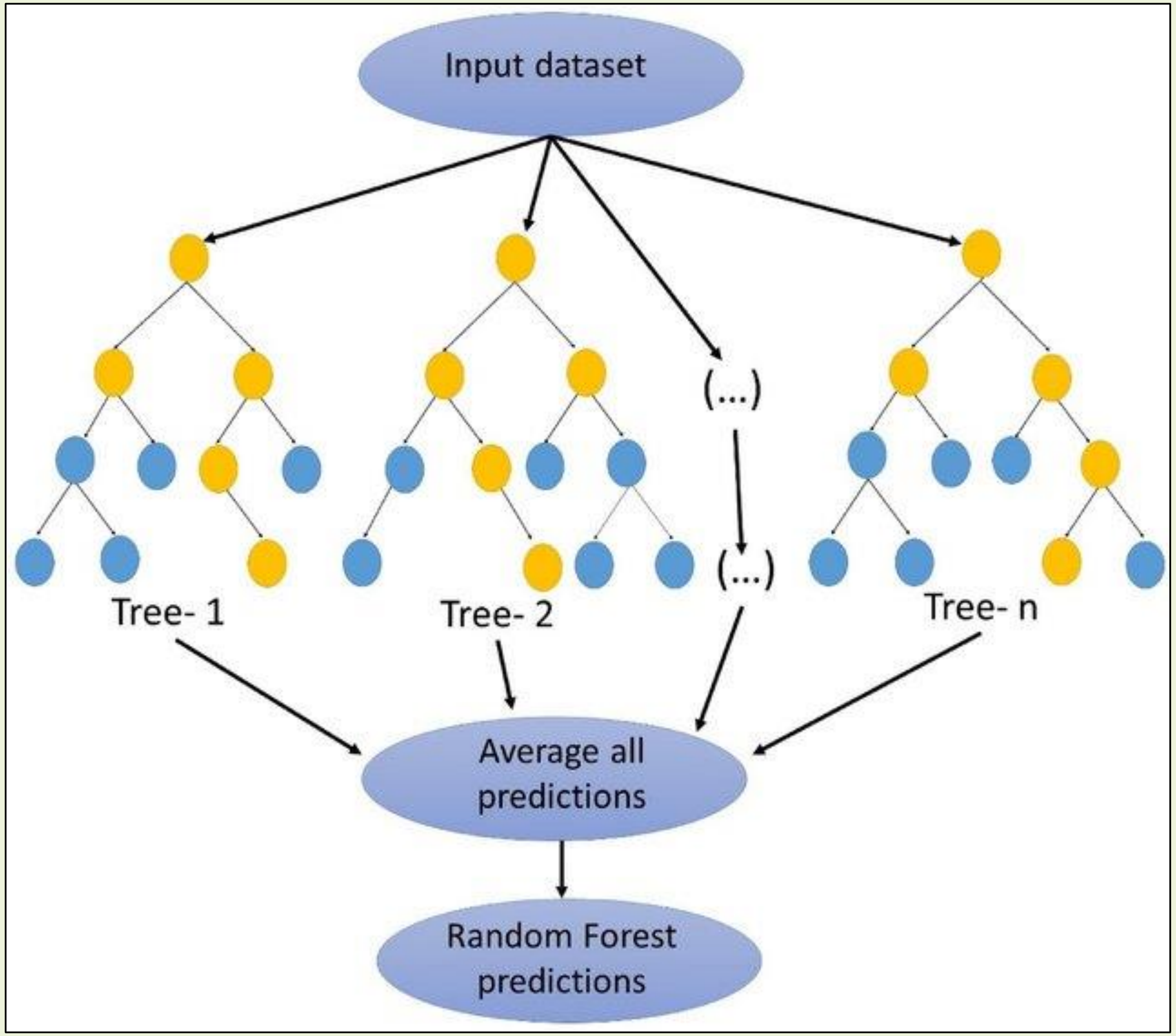
Parameter tuning, computational intensity, limited binary classification, and difficulty in interpreting the model for non-linear kernels

Random Forest (RF) : Bagging Ensemble Strategy



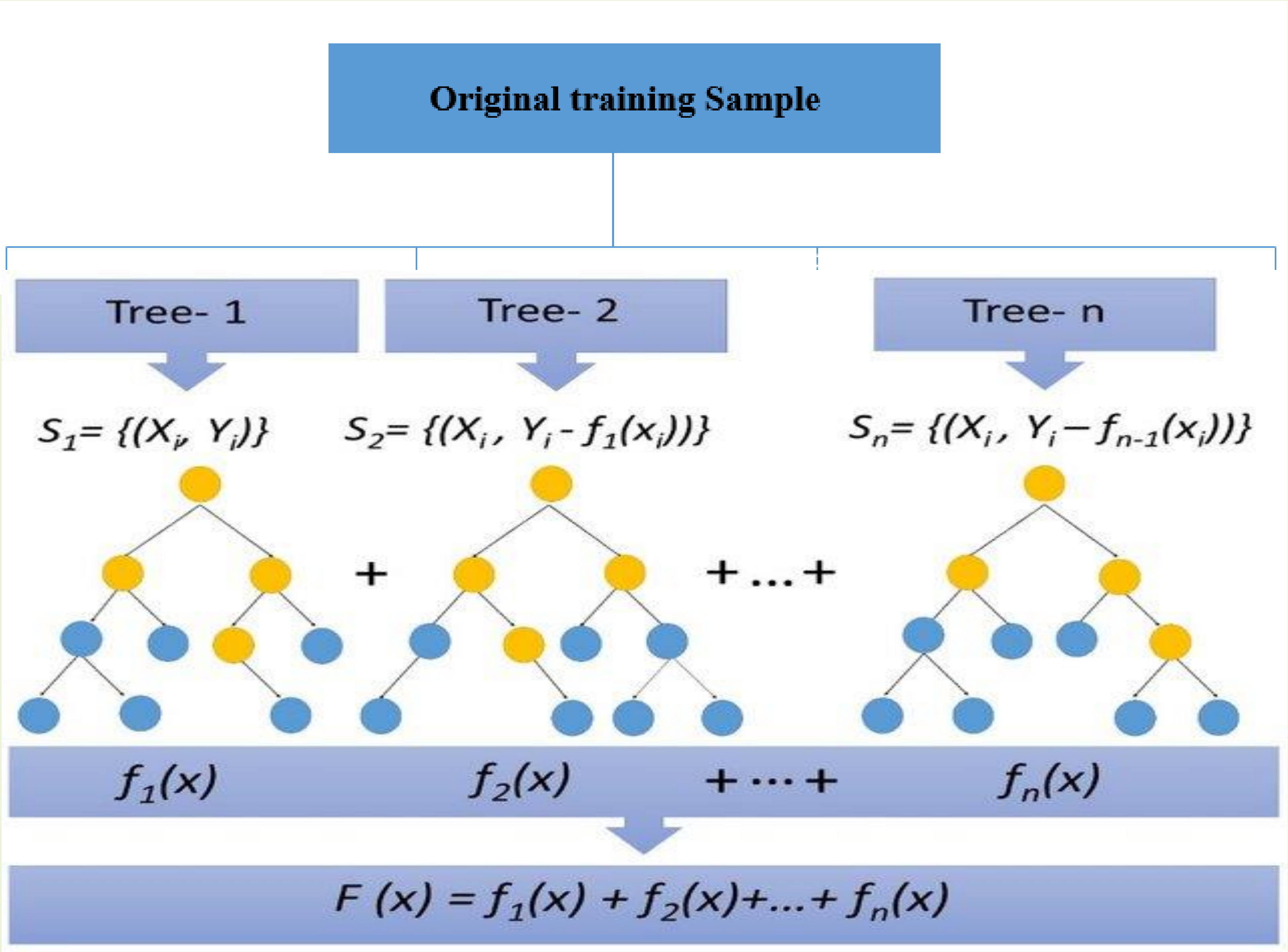
Random Forest (RF) : Bagging Ensemble Strategy

Lesser Hyper-parameter Tuning

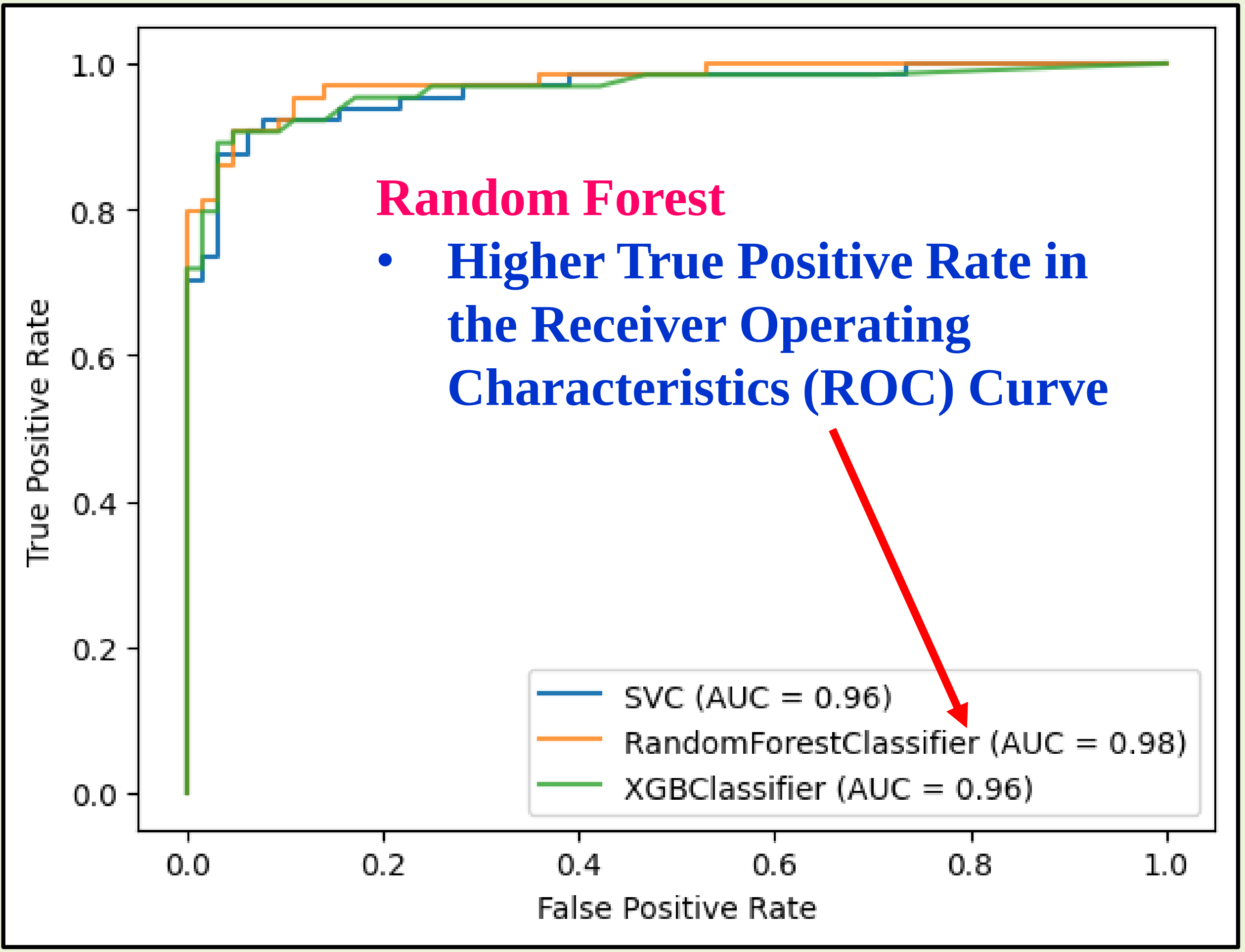


CART-based tree learning algorithms (Tree of Regression and Classification)

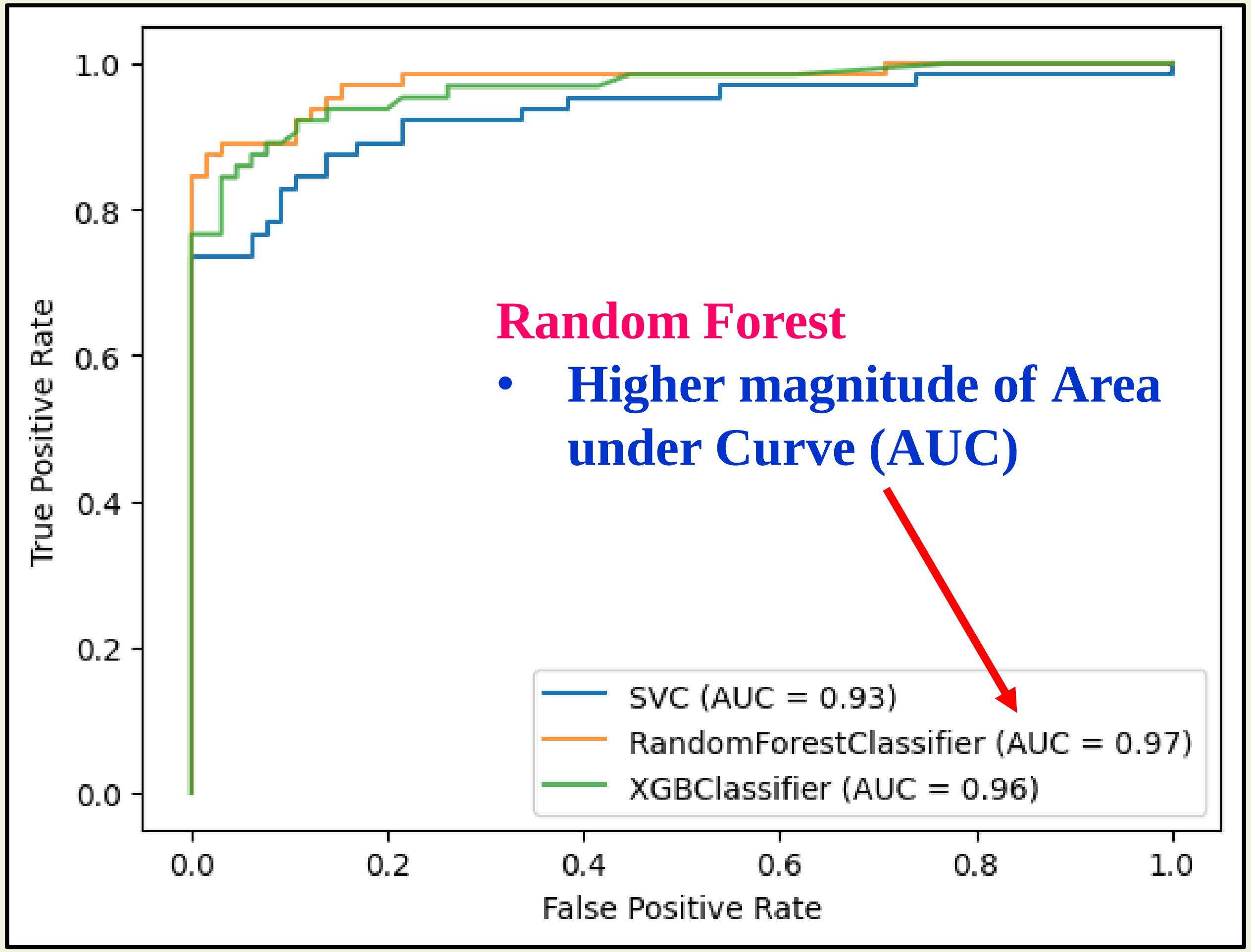
Extreme Gradient Boosting (XGBoost)



Accuracy Assessment: ROC Curve Analysis with AUC Score of ML models

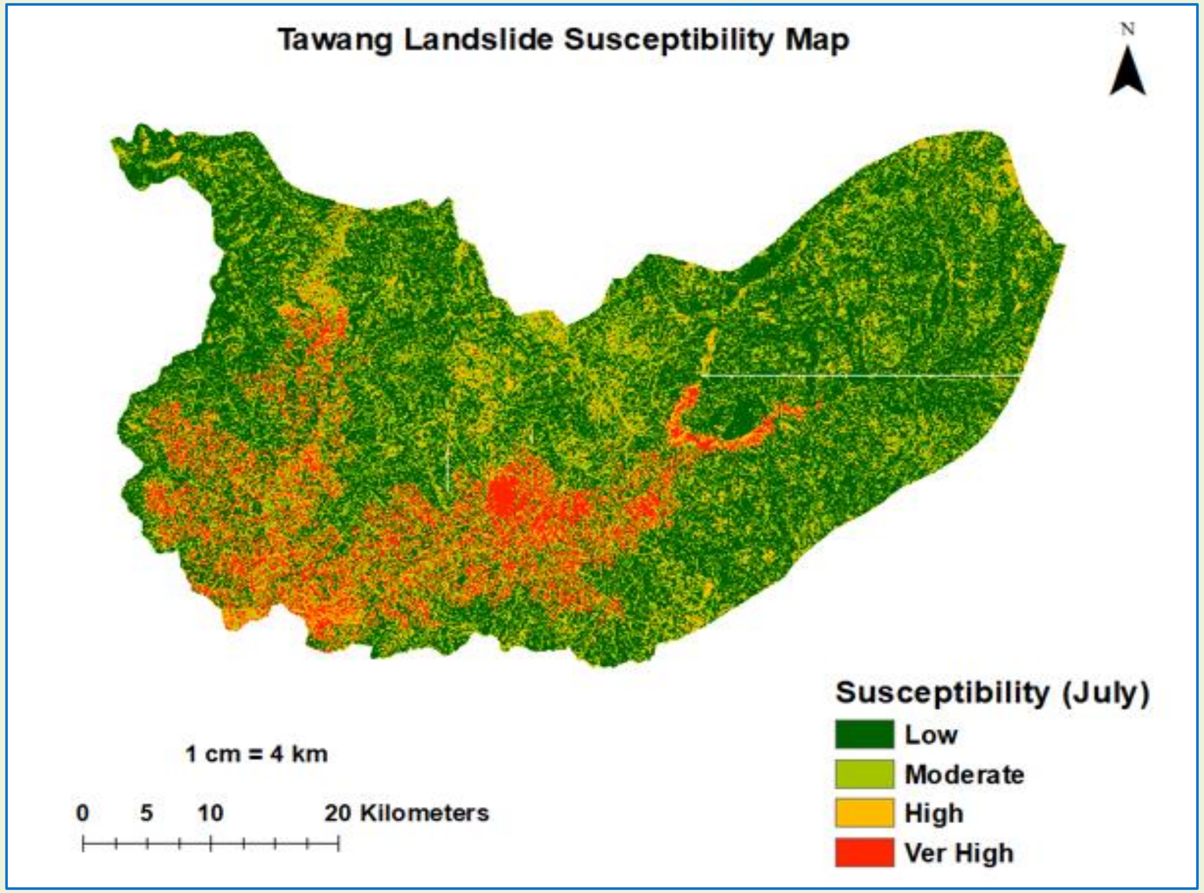


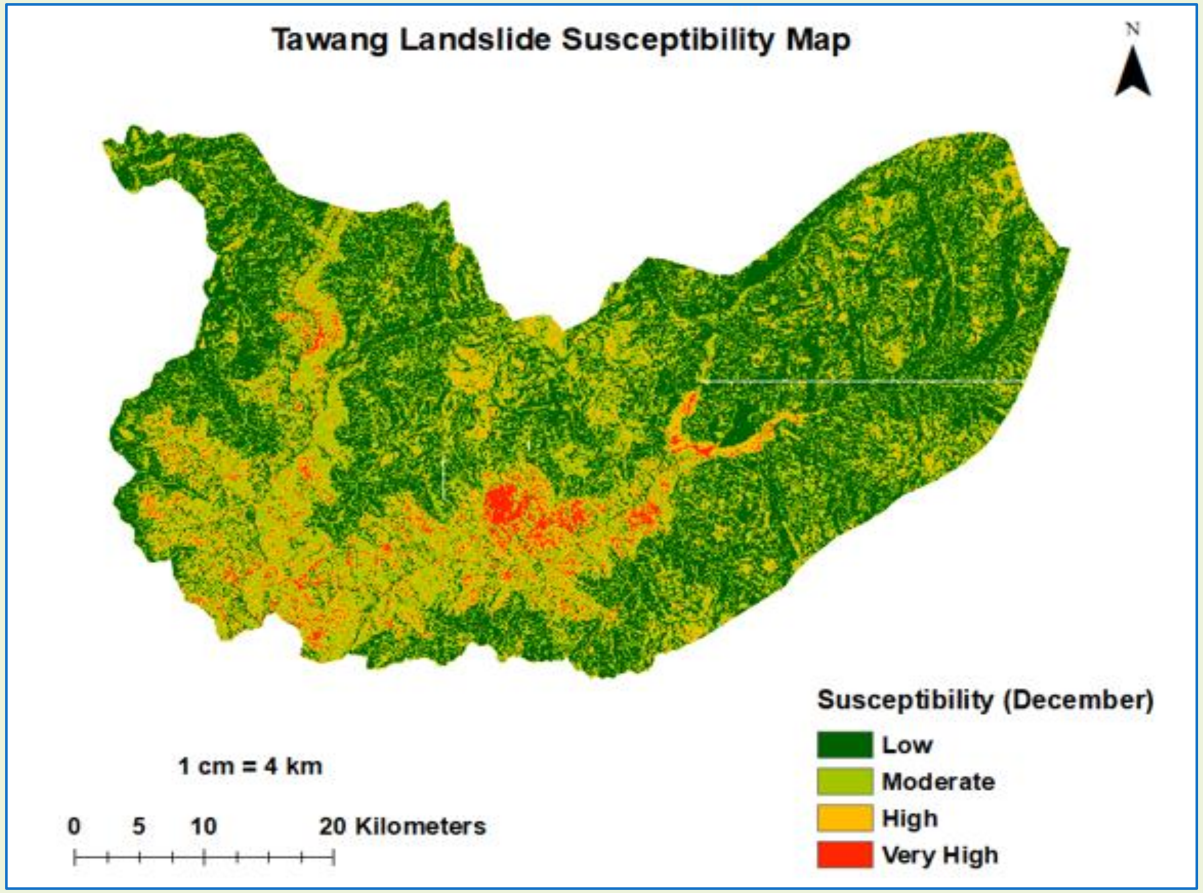
July



December

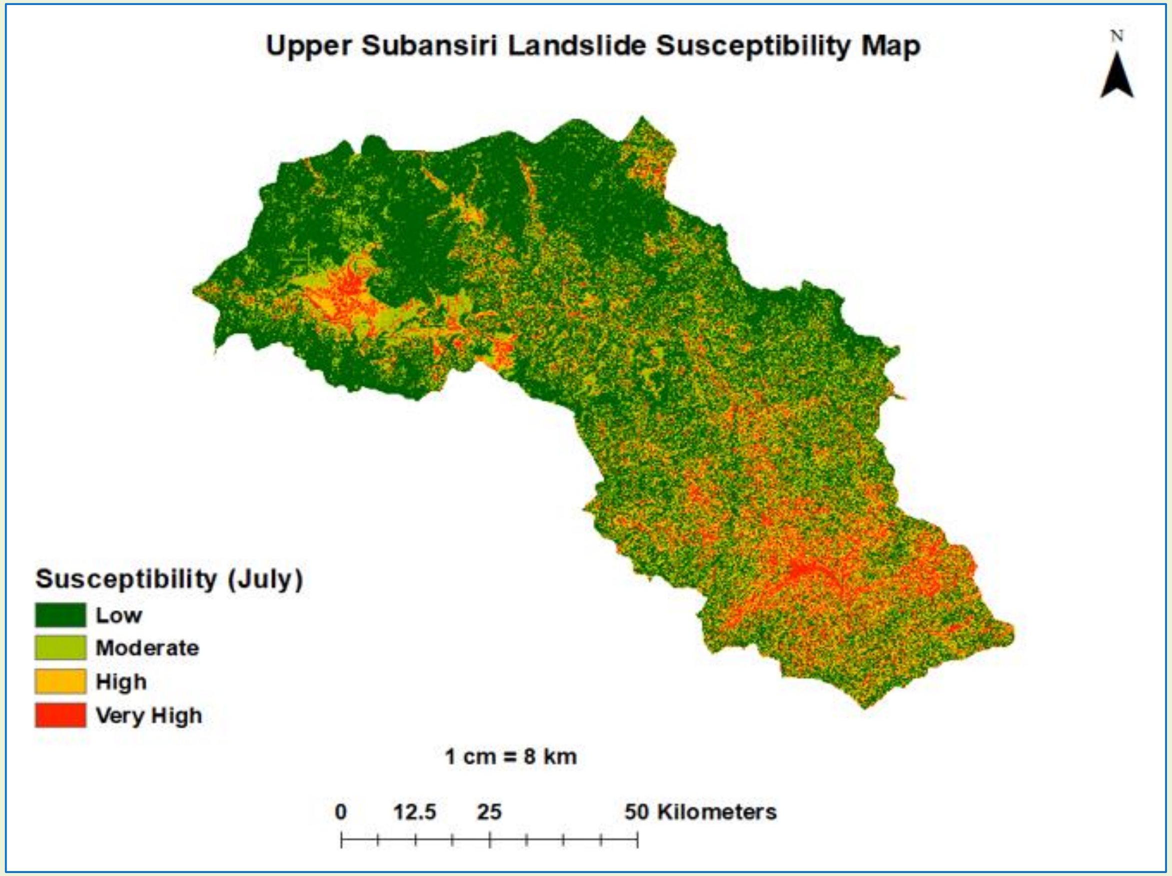
Final Landslide Susceptibility Map: Tawang, AP

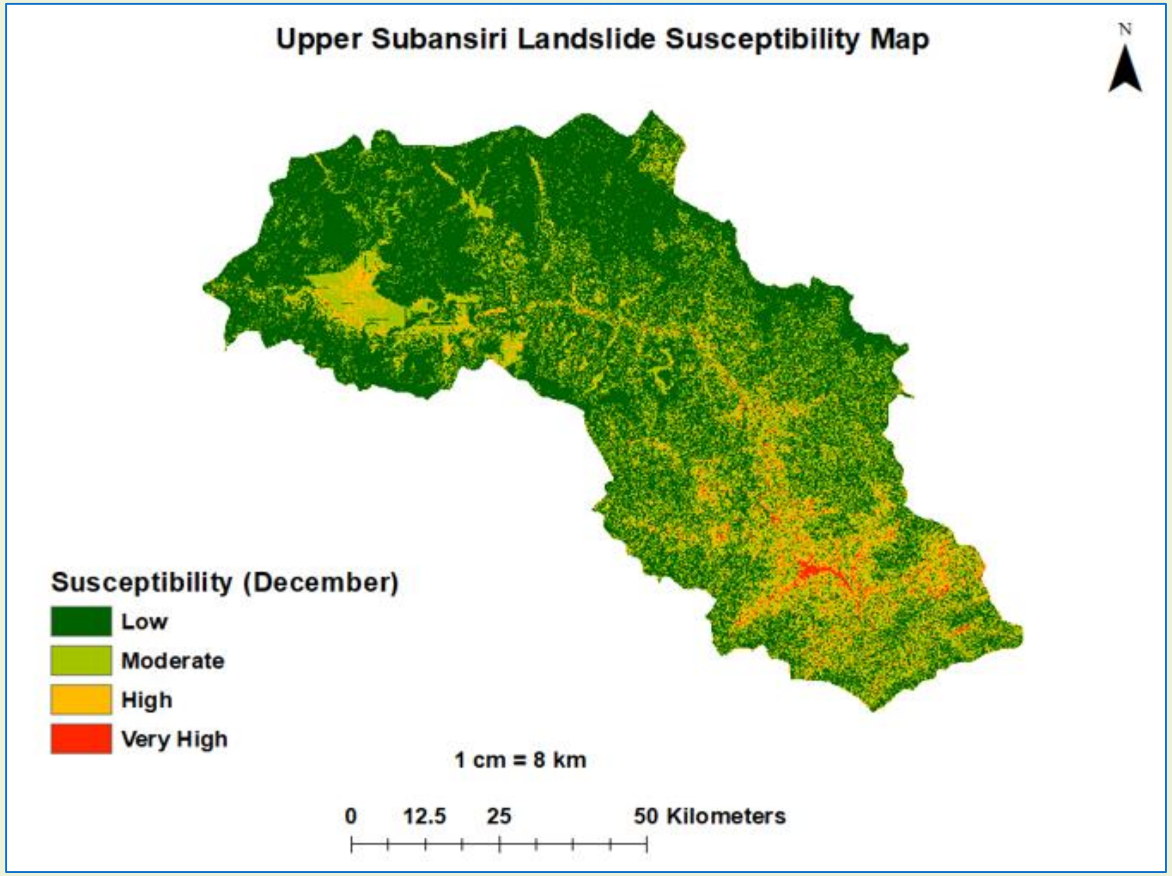




July **December**

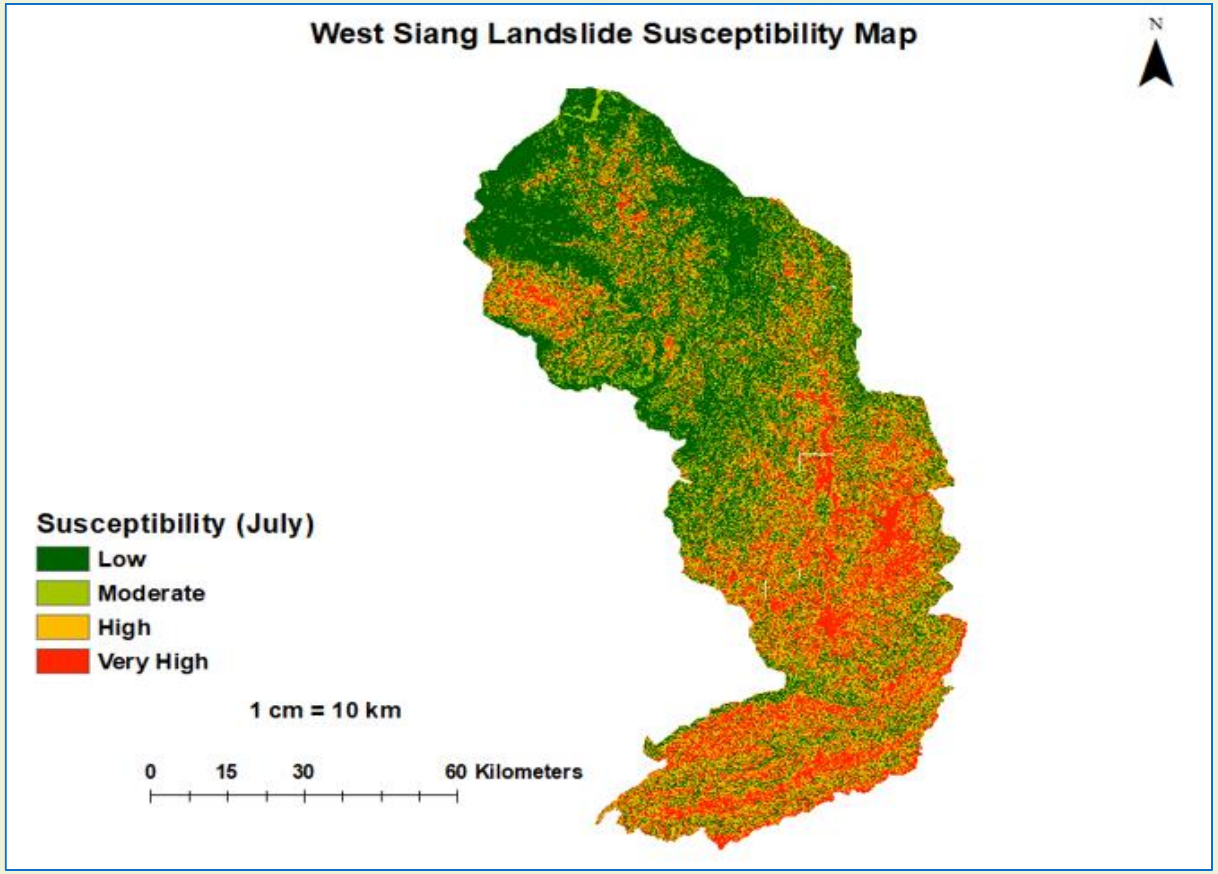
Final Landslide Susceptibility Map: Upper Subansiri, AP



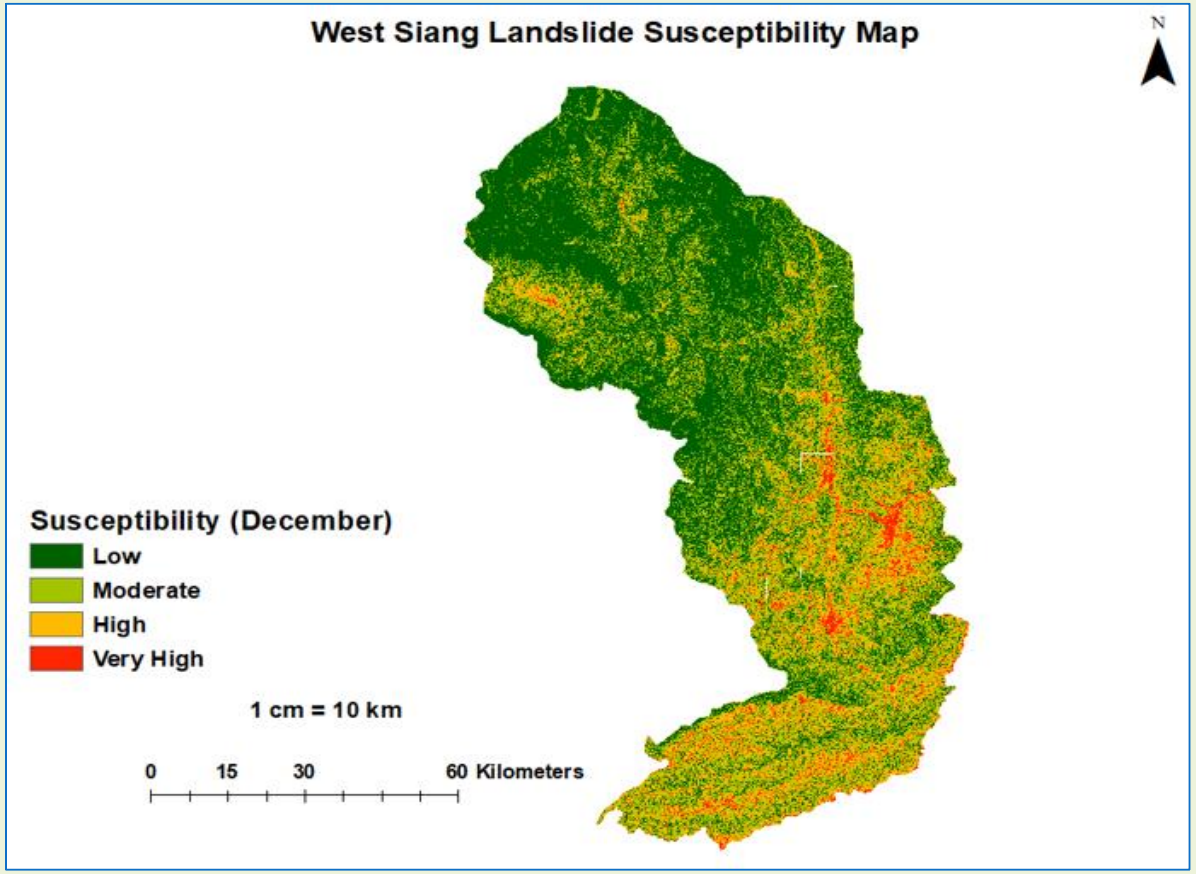


July **December**

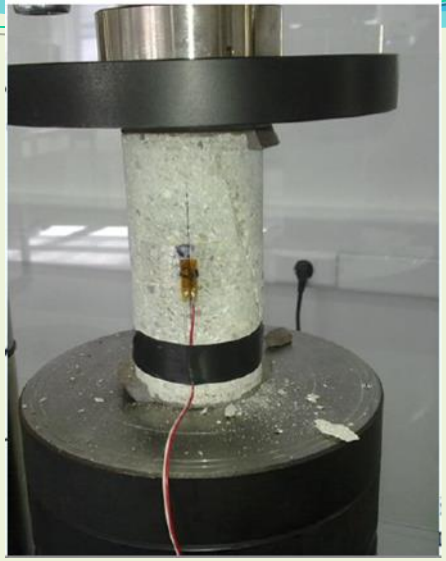
Final Landslide Susceptibility Map: West Siang, AP



July



December



Application of ML in Tunneling and Tunnel Boring

Tunnel Boring

- Tunnel Boring Machine (TBM)
  - Sensitive to adverse **geotechnical conditions**
    - **Rock bursting**, **spalling**, **squeezing**, **high water inflow**

- Rock bursting
  - Spontaneous and violent **failure of rock** due to **high stresses**
- Squeezing
  - Reduction in cross-section of tunnel

- TBM Penetration rate and its prediction
  - Essential for time planning, cost control and choice of excavation
  - Estimation affected by geological, geomechanical and machine design factors
  - Considering correlation among parameters is critical

Source: Verman *et al*. 2018

Performance Parameters of TBM

- **Penetration rate (PR)**
  - *Ratio of excavation distance to the operating time during tunnel construction and generally expressed in m/h or mm/min*

$$\mathrm{PR} = \frac{\text{Distance bored}}{\text{TBM boring time}} = \frac{L}{T_b}$$

- **Advance rate (AR)**
  - *Average speed of advancement of the tunnel and expressed in rings per day or m/day or m/shift*

$$\mathrm{AR} = \frac{\text{distance bored}}{\text{shift time}} = \frac{L}{T_{sh}}$$

- **Utilization Index (UI)**
  - *The percentage of time in boring (T_b) per unit shift time(T_{sh}) and expressed in percent*
  - *The shift time includes TBM boring time and down time (T_d) during operations of excavation*

$$\mathrm{UI} = \frac{\text{TBM boring time}}{\text{Shift time}} \times 100 = \frac{T_b}{T_{sh}} \times 100$$

$$T_{sh} = T_b + T_d$$

Factors Affecting Performance of TBM

- **Machine design factors**
  - Thrust force
  - Cutter head Torque
  - Specific energy
  - Cutter head power
  - Cutter head RPM
- **Rock properties**
  - Strength
  - Brittleness
  - Abrasiveness
  - Fracture frequency
  - Hardness
  - Orientation of joints and faults
- **Geotechnical conditions**
  - Spalling
  - Rock bursting
  - Squeezing
  - Swelling
  - High water inflow

Application of AI in Tunnel Boring

SL NO	REFERENCE	OBJECTIVE	METHODOLOGY	CONCLUSION
1	Neaupane and Adhikari (2006)	Predicting the surface settlement caused by tunneling	Artificial Neural Networks	R^2 – 0.881 on testing set with 15% sum squared relative error
2	Suwansawat and Einstein (2006)	Predicting the surface settlement caused by tunneling	Artificial Neural Networks	The effect of machine type on the ANN model improved performance of training and testing sets
3	Santos and Celestino (2008)	Predicting the surface settlement caused by tunneling	Artificial Neural Networks	The importance of dimensionless input was highlighted by showing the improvement in quality of results
4	Javad and Narges (2010)	Predicting the Penetration rate of TBM	Artificial Neural Networks	The model with dataset from three different tunnel projects showed good agreement with desired ones
5	Eftekhari et al. (2010)	Predicting the Penetration rate of TBM	Artificial Neural Networks	A two layer feed forward network obtained R^2 – 0.83 on testing set

Application of AI in Tunnel Boring

SL NO	REFERENCE	OBJECTIVE	METHODOLOGY	CONCLUSION
6	Mahdevari et al. (2013)	Predicting the cumulative convergence due to squeezing	Support Vector Regression	R^2 improved from 0.936 to 0.97 compared to ANN
7	Mahdevari et al. (2014)	Predicting the Penetration rate of TBM	Support Vector Regression	R^2 - 0.9903 and 0.95 for training and testing datasets. Capable of avoiding overfitting
8	Kohestani et al. (2017)	Predicting the maximum surface settlement caused by tunneling	Random forest	RF outperformed ANN in terms of model simplicity, robustness
9	Zhou et al. (2017)	Predicting the surface settlement caused by tunneling	Random forest	Smaller dataset resulted in high R^2 and low RMSE. Large datasets will improve model precision
10	Armaghani et al. (2017)	Predicting the Penetration rate of TBM	PSO-(ANN) ICA-(ANN)	R^2 - 0.912 and 0.905 for respective hybrid intelligent models. Superior in comparison with simple ANN

Dataset from Tunnel Projects

- Datasets from three different tunnel projects **(Javad and Narges 2010)**
  - **The Queens Water Tunnel, USA**
  - **The Karaj-Tehran Water Tunnel, Iran**
  - **The Gilgel Gibe II Hydroelectric project, Ethiopia**
- Dataset has 185 examples
  - 3 input variables
  - 1 output variable
- Geological strength parameters of rock are used as explanatory variables:
  - Unconfined Compressive Strength (UCS)
  - Rock Quality Designation (RQD)
  - Distance between planes of weakness (DPW)
- Penetration rate of TBM is the response variable

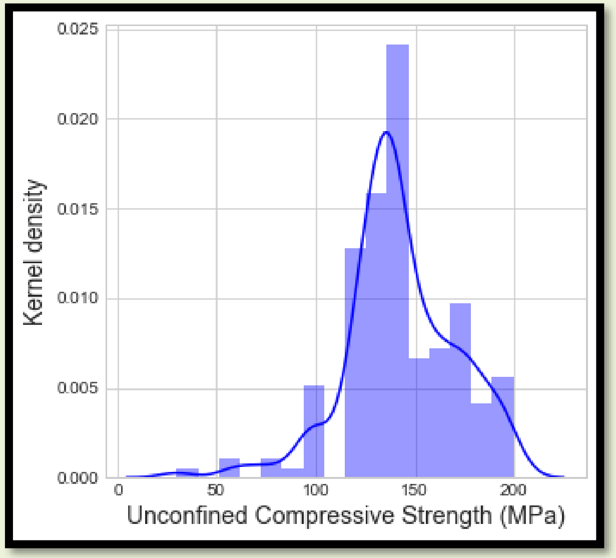
No.	Tunnel station	UCS (MPa)	RQD	DPW (m)	Measured ROP (m/h)
65	Queens (USA)	120.7	99.28	0.8	1.94
66	Queens (USA)	180.7	90.98	0.2	3.04
67	Queens (USA)	130.1	99.28	0.8	1.85
68	Queens (USA)	137.5	99.81	1.6	1.50
69	Queens (USA)	176.8	99.81	1.6	1.88
70	Gilgel Gibe II (Ethiopia)	100.0	69.90	0.09	3.30
71	Queens (USA)	145.5	99.28	0.8	2.35
72	Gilgel Gibe II (Ethiopia)	120.0	49.32	0.06	2.99
73	Queens (USA)	160.3	99.28	0.8	1.91
74	Queens (USA)	131.0	97.35	0.4	1.78
75	Queens (USA)	135.2	99.81	1.6	1.27
76	Queens (USA)	137.0	99.81	1.6	2.05
77	Queens (USA)	119.0	99.81	1.6	1.68
78	Queens (USA)	153.4	99.28	0.8	1.94

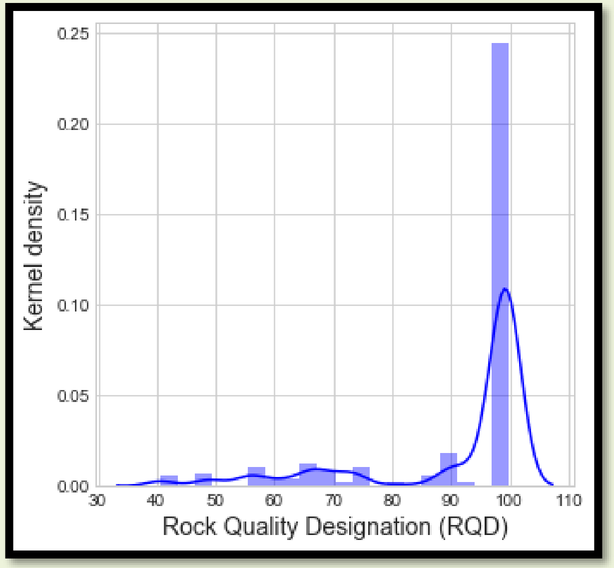
Small part of the dataset

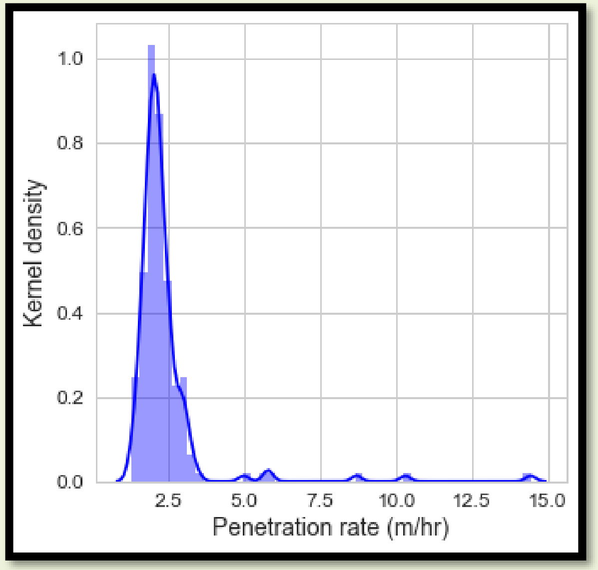
Exploratory Data Analysis

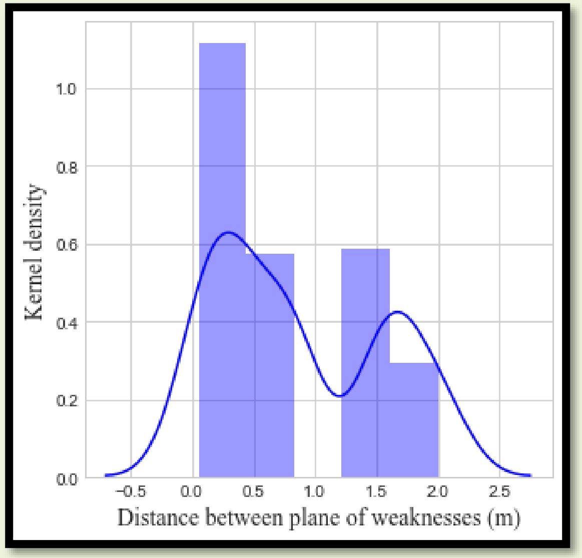
- Process of performing initial investigations on the data
  - Discover patterns, spot anomalies, summary statistics
    - UCS shows more concentration of data points near its mean value
    - RQD is negatively skewed with a tail on the left side of distribution
    - DPW shows a bell shaped curve with two distinct peaks
    - PR is positively skewed with a tail on the right side of distribution

Variable	UCS	RQD	DPW	PR
count	185	185	185	185
mean	142.71	91.04	0.87	2.33
std	27.79	15.42	0.67	1.32
min	30.00	40.6	0.05	1.27
25%	129.15	90.98	0.3	1.85
50%	139.30	99.28	0.8	2.09
75%	159.77	99.81	1.6	2.43
max	199.70	99.88	2.0	14.43

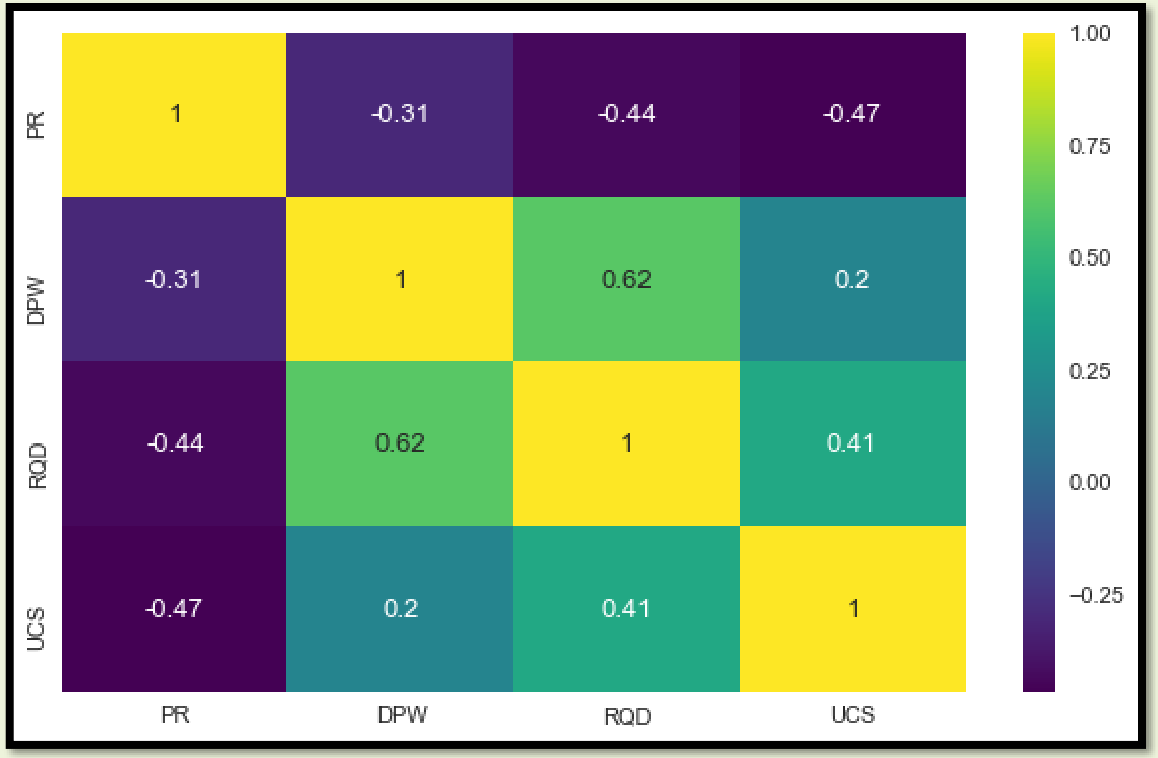






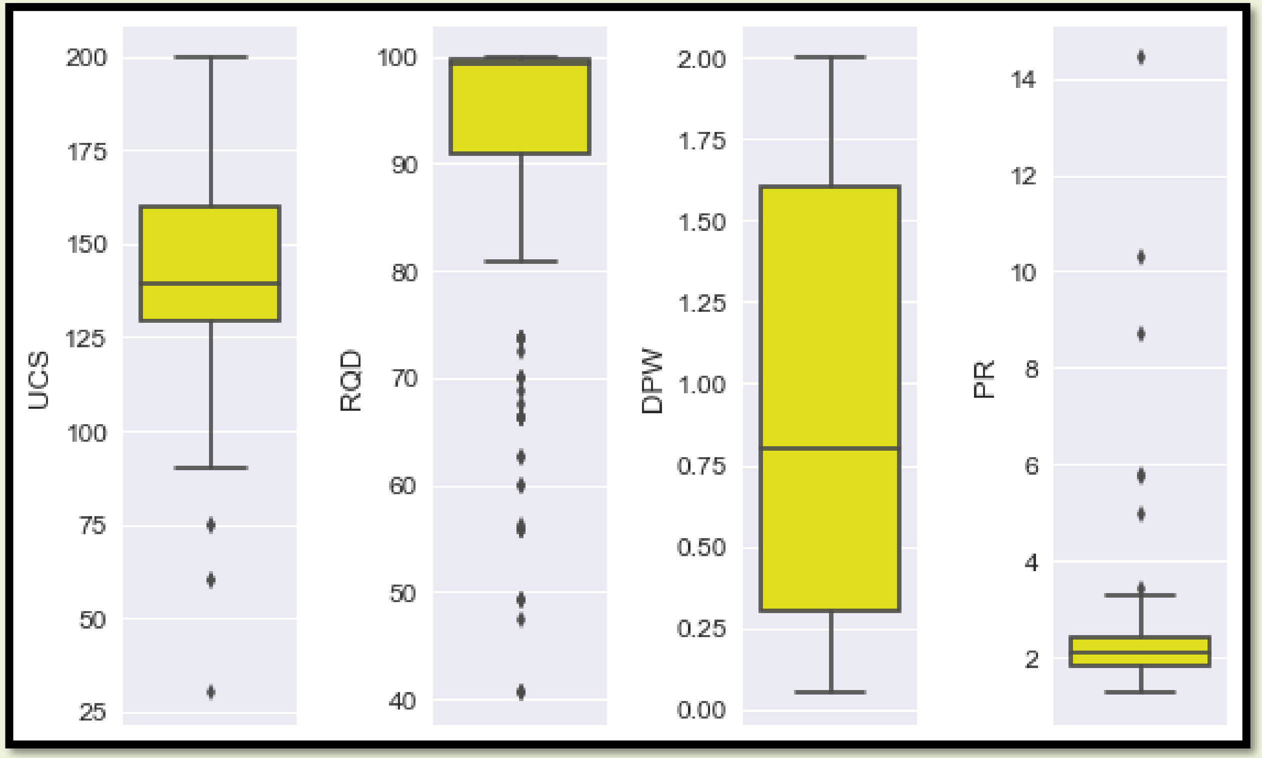


Exploratory Data Analysis



Correlation Matrix

Relationship between variables



Box-and-Whisker Plot

Distribution of quantitative data

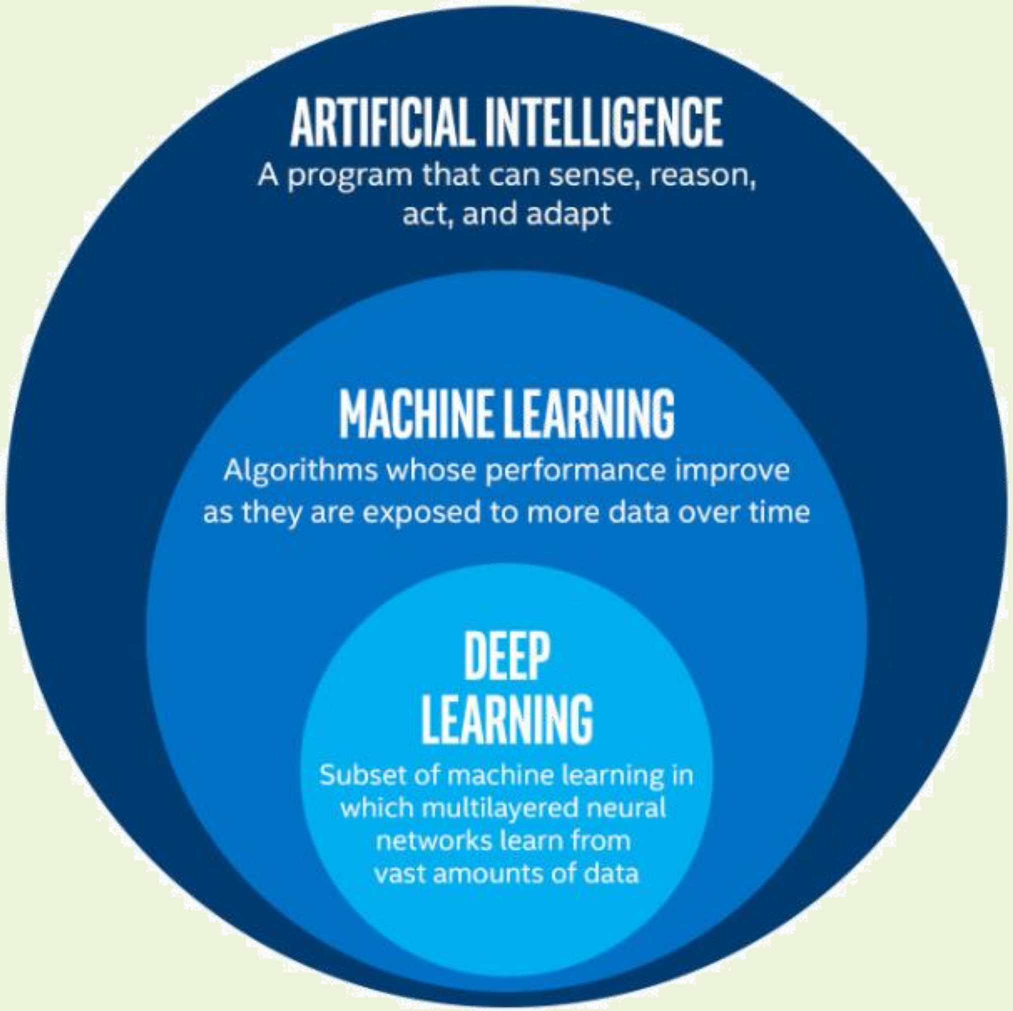
Whiskers extend to show rest of the distribution (max and min values)

Artificial Intelligence (AI) – Machine Learning (ML) – Deep Learning (DL)

- Deep Learning (DL)
  - Extracts features or attributes from raw data
- Machine learning (ML)
  - Each instance in a dataset is described by a set of features or attributes

- Data representations are hard-coded as a set of features in ML algorithms
  - Need feature selection/extraction

- DL methods: algorithm constructs representations of the data automatically
  - DL methods have many nuances and unexplained phenomenon than classic ML methods



Adopted ML Algorithms

ARTIFICIAL NEURAL NETWORKS

RANDOM FOREST

GRADIENT BOOSTING

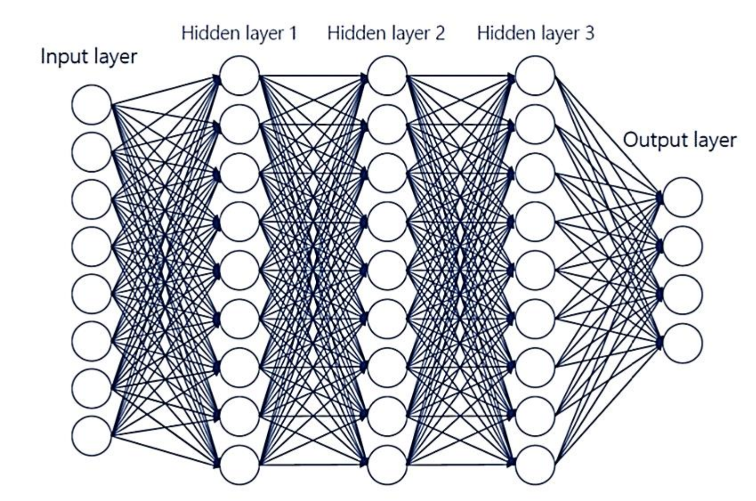
DNN: Multi-layered Perceptron (ANN-MLP)

- '**MinMaxScaler**' method from sklearn library is used for data normalization in range (0 to 1)
- The entire dataset is then divided into training, validation and testing sets
- '**train_test_split**' method from sklearn library is utilised to split the dataset
  - About **20%** of the dataset is set aside as testing set and the rest as training set
  - About **15%** of the training data is kept as validation set
- Within the hidden-layers and in output layer, the "**ReLU**" activation function is used
- The "**Adam**" optimizer is used as learning algorithm with a user defined learning rate for training
- **Mean Squared Error** (MSE) is used as loss metric and **correlation coefficient** (R^2) as evaluation metric

Training parameters	Magnitude and Nomination
Training Function	Adam Optimizer
Transfer Function a. Hidden layer 1 b. Hidden layer 2 c. Output layer	 a. Relu (linear) b. Relu (linear) c. Relu (linear)
Performance Function	'mse' (Mean square error)
Epochs	1000
Number of neurons in input layer	3
Number of hidden layers	3
Number of neurons in hidden layer1	12
Number of neurons in hidden layer2	9
Number of neurons in hidden layer3	5
Number of output layers	1

Optimal Architecture of MLP

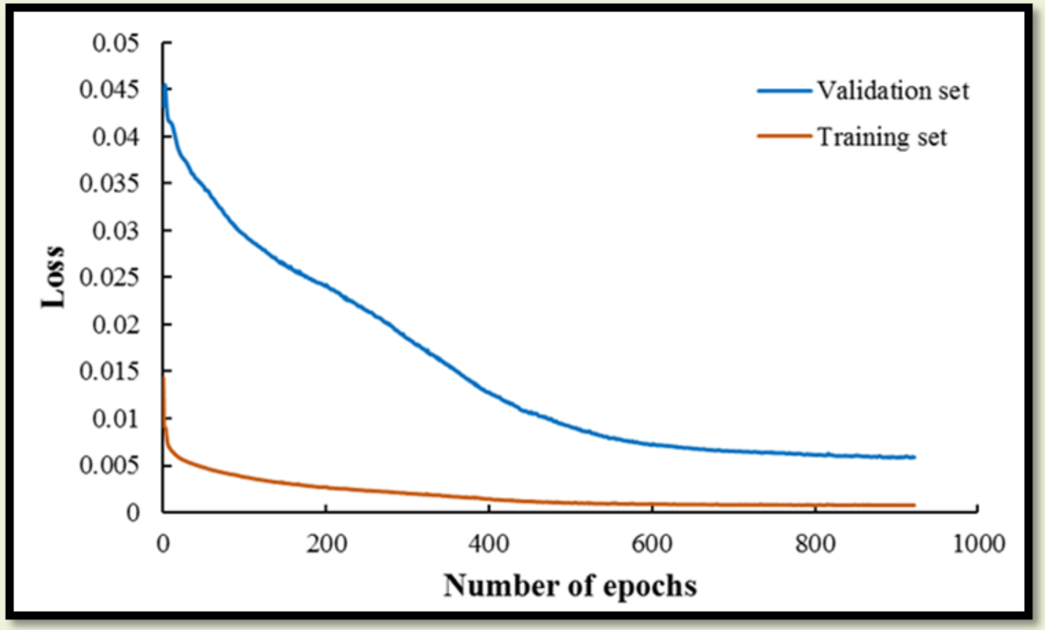
- A trial and error procedure is used to identify the best network
- Several network topologies are examined
- The target network is
  - Minimum error for training set and a generalized solution which performs well with the testing set
- The errors suggest that the network with 3-(12-9-5)-1 architecture shows optimum model performance

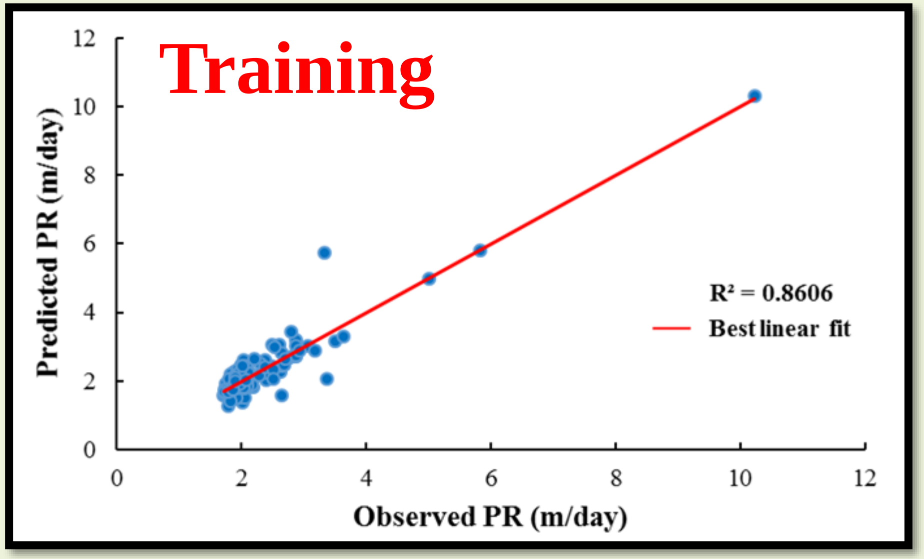


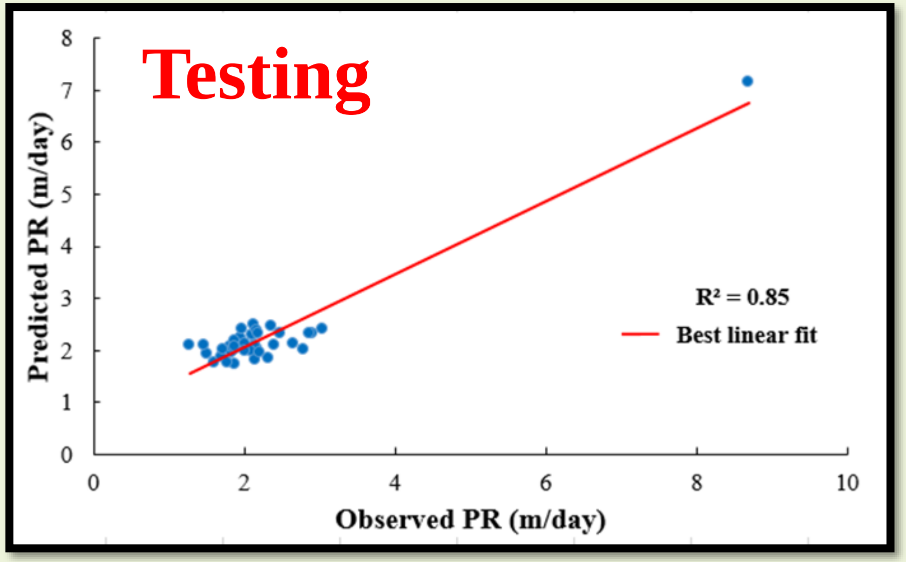
$R^2 < 0.95$??

Model	MSE train	MSE validation	MSE test	R^2 train	R^2 test
3-5-4-1	0.0027	0.002	0.61	0.51	0.64
3-8-9-1	0.0012	0.0074	0.35	0.71	0.72
3-5-5-4-1	0.003	0.0026	0.80	0.43	0.36
3-7-5-3-1	0.0019	0.018	0.39	0.67	0.69
3-7-7-3-1	0.001	0.01	0.27	0.82	0.83
3-8-7-4-1	0.0025	0.02	0.56	0.56	0.55
3-9-6-4-1	0.0012	0.003	0.27	0.83	0.82
3-9-7-3-1	0.00095	0.007	0.20	0.84	0.79
3-9-8-4-1	0.00088	0.012	0.18	0.83	0.85
3-10-9-4-1	0.0012	0.0116	0.182	0.86	0.81
3-11-11-9-1	0.00084	0.0075	0.19	0.86	0.80
3-13-9-3-1	0.001	0.007	0.195	0.83	0.84
3-12-9-5-1	0.00079	0.0059	0.176	0.86	0.85
3-15-12-7-1	0.00083	0.009	0.21	0.84	0.81
3-18-17-8-1	0.00074	0.0075	0.182	0.85	0.84
3-25-24-8-1	0.00075	0.0085	0.19	0.86	0.84

ANN-MLP based Prediction of PR of TBM

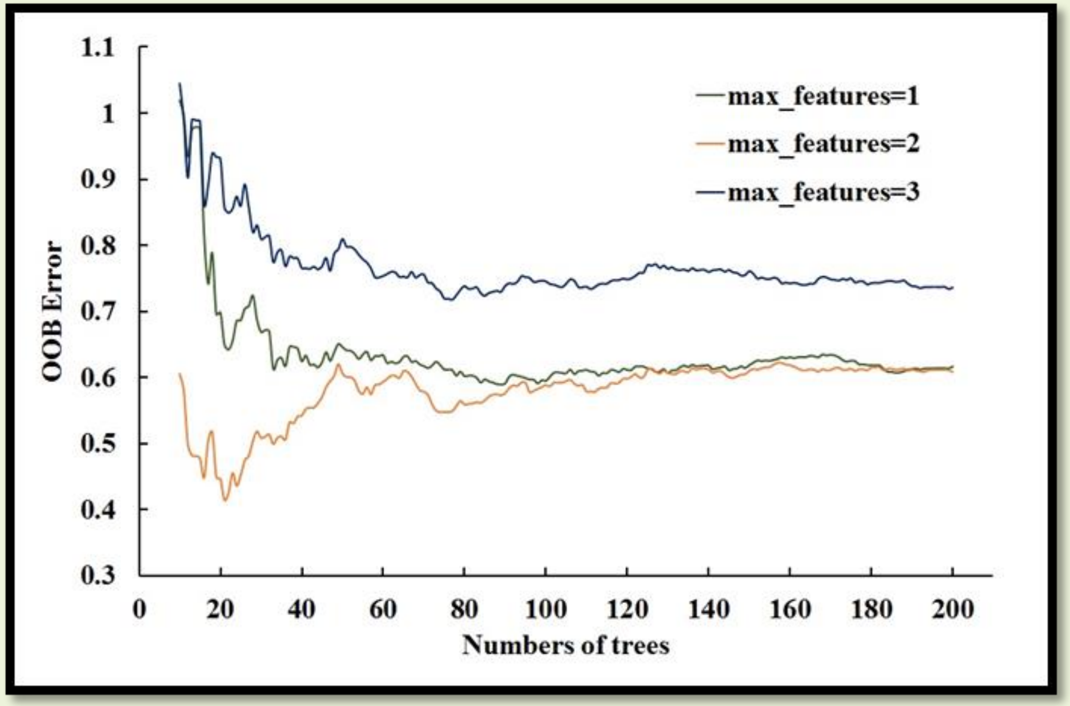


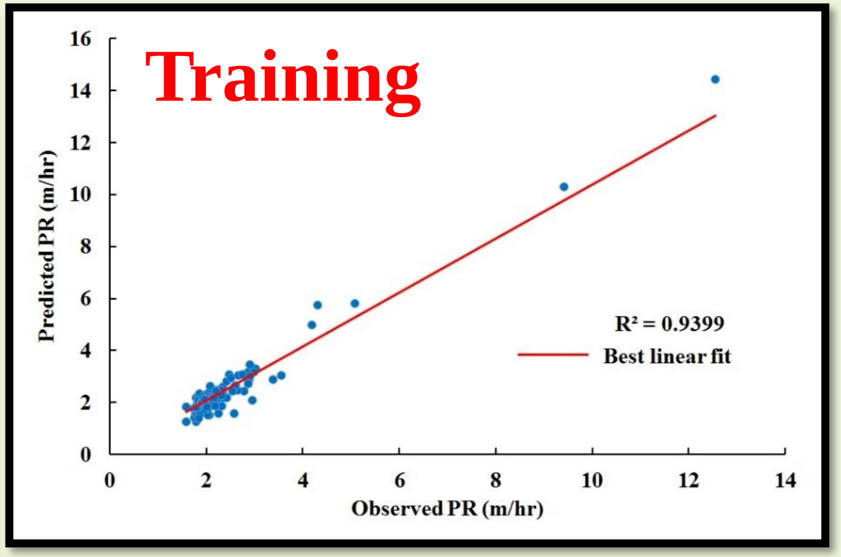


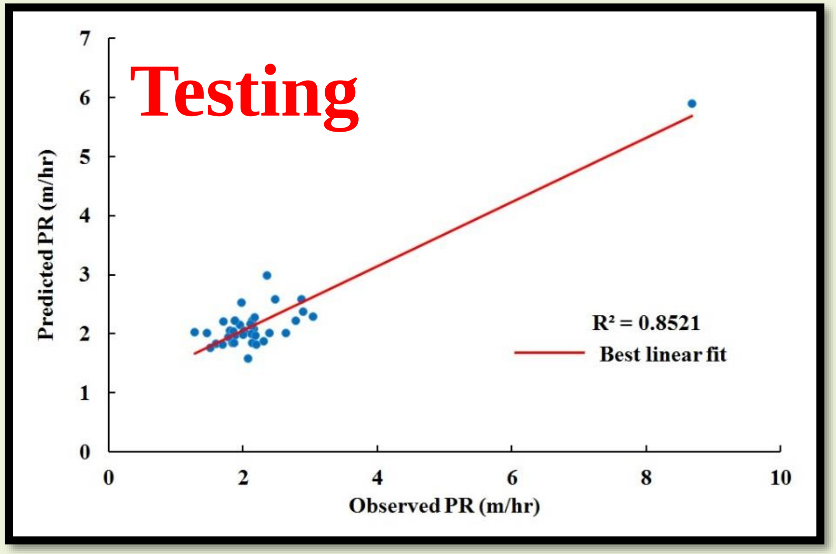


Approach	R^2Test	MSE Training	MSE Validation	MSE Testing
PYTHON	0.85	0.00079	0.0059	0.176
MATLAB Javad and Narges (2010)	0.939	0.0083	0.0158	0.1081

Random Forest (RF) based Prediction of PR of TBM







Datasets	R^2	MSE
Training set	0.9399	0.12
Testing set	0.8521	0.33

Tuning parameters	Default values
n_estimators	User defined
max_features	Number of features
max_depth	None
min_samples_leaf	1
criterion	MSE
Bootstrap	True
min_samples_split	2

Work Flow of Gradient Boosting Regression Tree (GBRT)

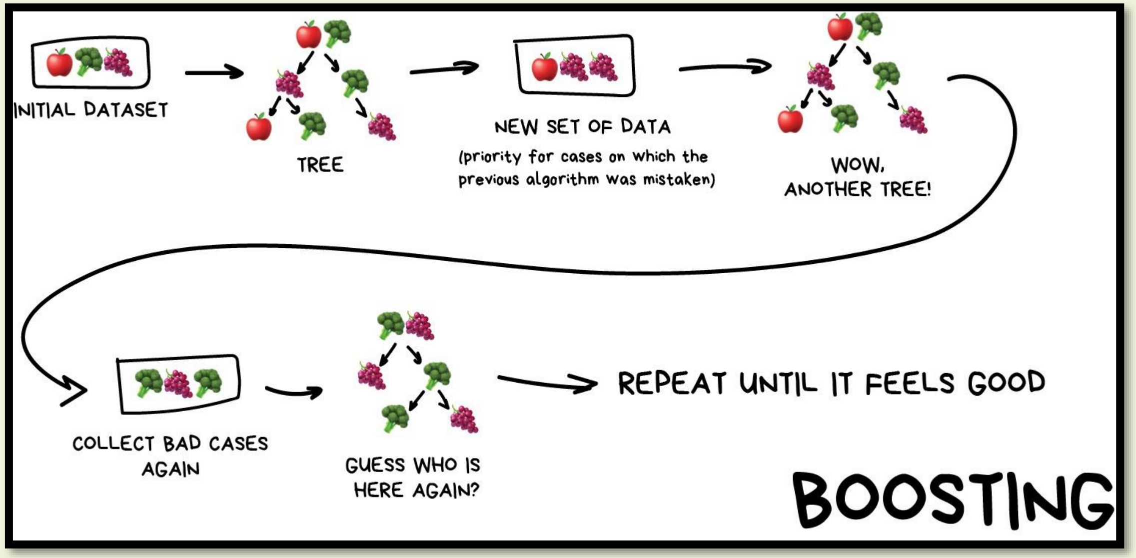
Create a decision tree on known response values

Make Predictions

Calculate errors (Residuals)

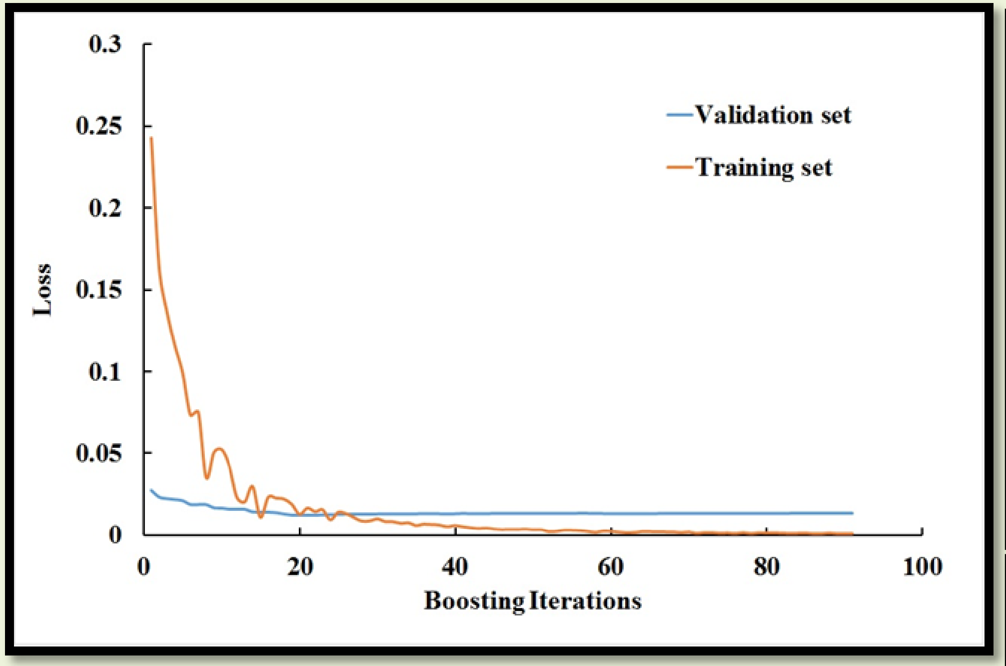
Fit new tree using errors as response values

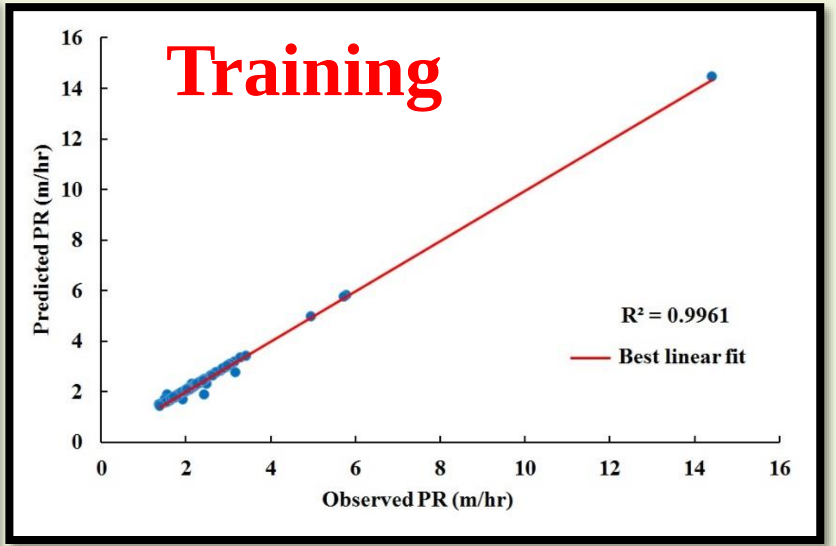
Combine new tree with tree from previous iteration

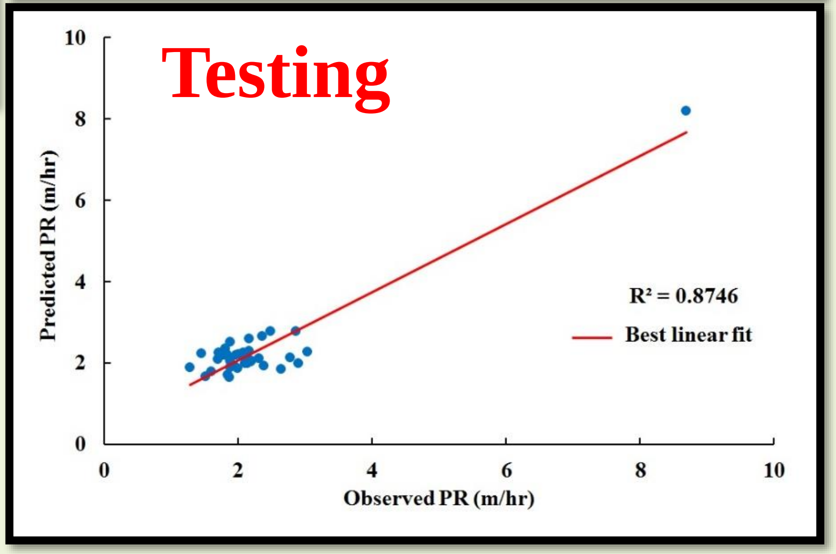


- **Tuning parameters**
  1. Number of trees
  2. Maximum depth of each tree
  3. Subsample
  4. Learning rate
  5. Loss function

GBRT based Prediction of PR of TBM



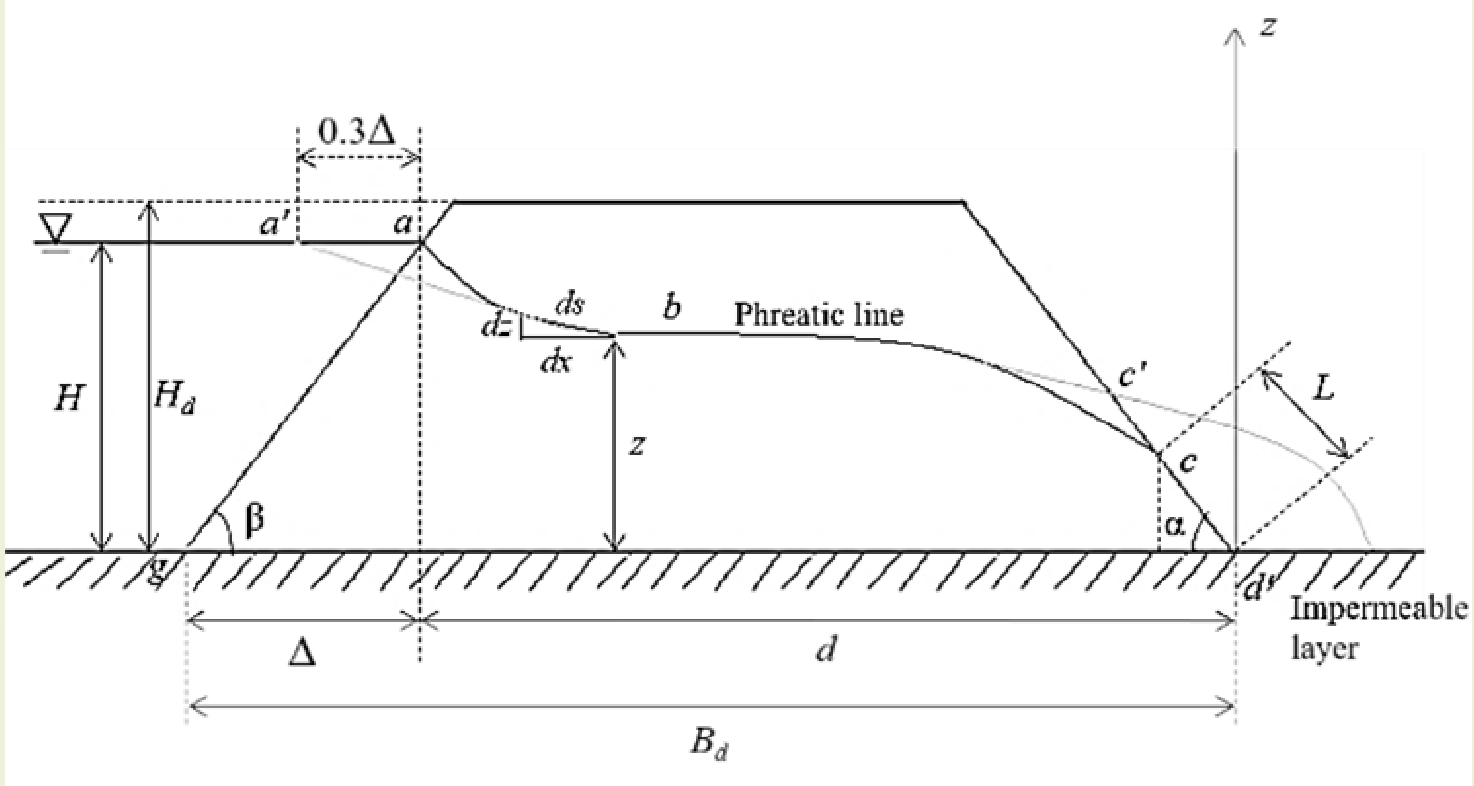




Datasets	R^2	MSE
Training set	0.9961	0.01
Testing set	0.8746	0.16

Tuning parameters	Default values
n_estimators	100
learning_rate	0.1
max_depth	3
criterion	friedman mse
subsample	1.0

Choose more than one estimator to judge the efficacy of one model over the other



Application of ML in Filter Dimensioning in Earthen Embankment

Schaffernak Seepage Analysis

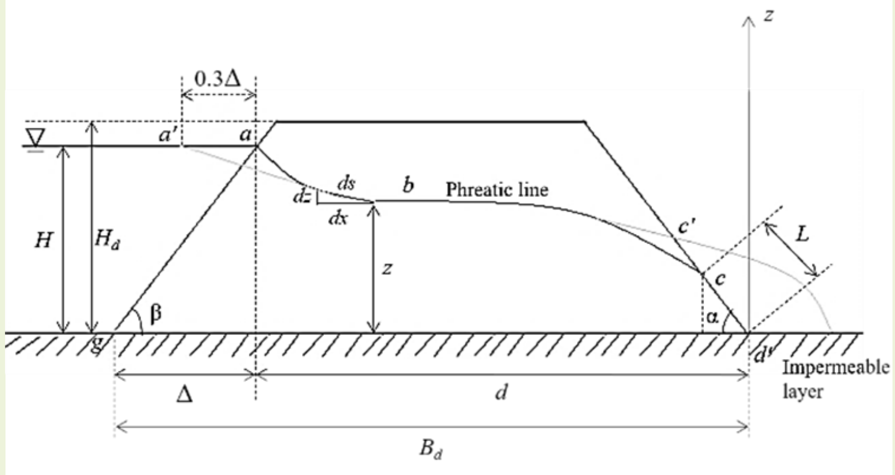
- Filter dimension and exit discharge as per schaffernak analysis:

$$L = \frac{d}{\cos\alpha} - \sqrt{\frac{d^2}{\cos^2\alpha} - \frac{H^2}{\sin^2\alpha}} \qquad q = kL\sin\alpha\tan\alpha$$

Exit discharge, $q_{nD} = \left(\frac{L\sin\alpha}{H_d}\right)\tan\alpha$

Filter height, $F_{HN} = \frac{L\sin\alpha}{H_d} = \left[\left(\frac{d}{H_d}\right)\tan\alpha - \sqrt{\left(\frac{d}{H_d}\right)^2\tan^2\alpha - \left(\frac{H}{H_d}\right)^2}\right]$

Filter width, $F_{WN} = \frac{L\cos\alpha}{b_d} = \left(\frac{H_d}{b_d}\right)\left[\left(\frac{d}{H_d}\right) - \sqrt{\left(\frac{d}{H_d}\right)^2 - \left(\frac{H}{H_d}\right)^2\left(\frac{1}{\tan^2\alpha}\right)}\right]$



Schematic diagram for Schaffernak's analysis

$$\left(\frac{d}{H_d} = \frac{B}{H_d} + \left(\frac{1}{\tan\alpha} + \frac{1}{\tan\beta}\right) - 0.7\left(\frac{H}{H_d}\right)\left(\frac{1}{\tan\beta}\right)\right)$$

$$\left(F_{HN}, F_{HN}, q_{nD}\right) = f\left(\alpha, \beta, \frac{H}{H_d}, \frac{B}{H_d}\right)$$

Data Generation for Filter Dimensioning

Training and Test dataset:

Parameter	range	interval	Total data point
Upstream slope (α)	$5^\circ - 90^\circ$	15°	7
Downstream slope (β)	$5^\circ - 90^\circ$	15°	7
B/H_d	0.1-1.5	0.1	14
H/H_d	0.1-1.0	0.1	10

Total dataset = $7 \times 7 \times 14 \times 10 = 6860$

Training dataset = 80% (6860) = 5488

Test dataset = 20% (6860) = 1372

Validation dataset:

Parameter	range	interval	Total data point
Upstream slope (α)	$15^\circ - 75^\circ$	random	500
Downstream slope (β)	$15^\circ - 75^\circ$	random	500
B/H_d	0.36-0.84	random	500
H/H_d	0.46-0.79	random	500

Validation dataset = 500

$$\left(\alpha, \beta, \frac{H}{H_d}, \frac{B}{H_d}\right) \longrightarrow \boxed{\text{ML model}} \longrightarrow \left(F_{HN}, F_{HN}, q_{nD}\right)$$

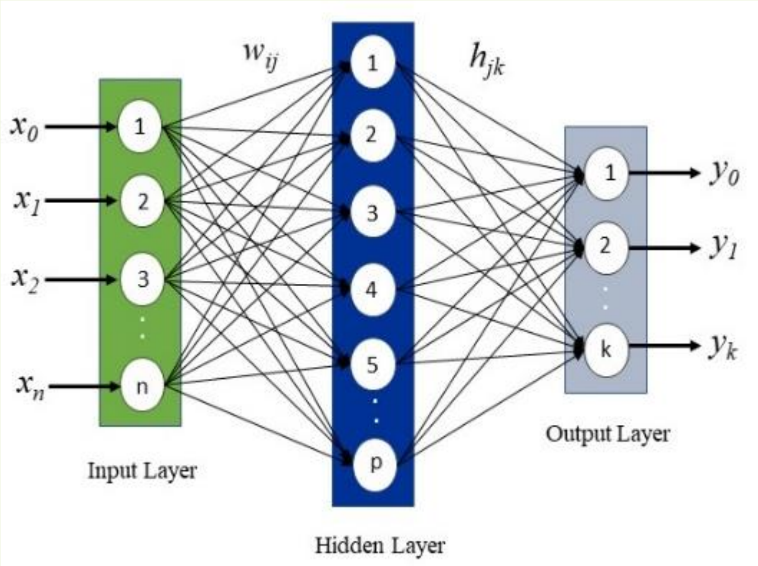
Input feature (4)

Training

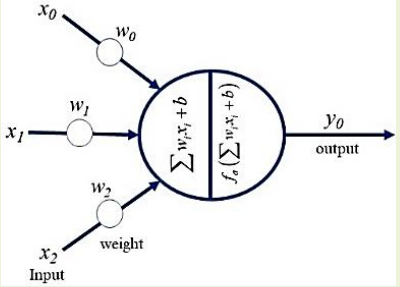
Output feature (3)

Multilayer Perceptron (MLP)

- Working principle of MLP model is similar to that of feed-forward backpropagation neural network.



MLP model



Artificial neuron

The input and output for neurons of hidden layer:

$$s_j^{input} = w_{0j}x_0 + w_{1j}x_1 + \ldots + w_{nj}x_n = \sum_{i=0}^{n} w_{ij}x_i \qquad (1)$$

$$s_j^{output} = f_a^{hidden}(s_j^{input} + b_j^{hidden}) \qquad (2)$$

The input and output for neurons of output layer:

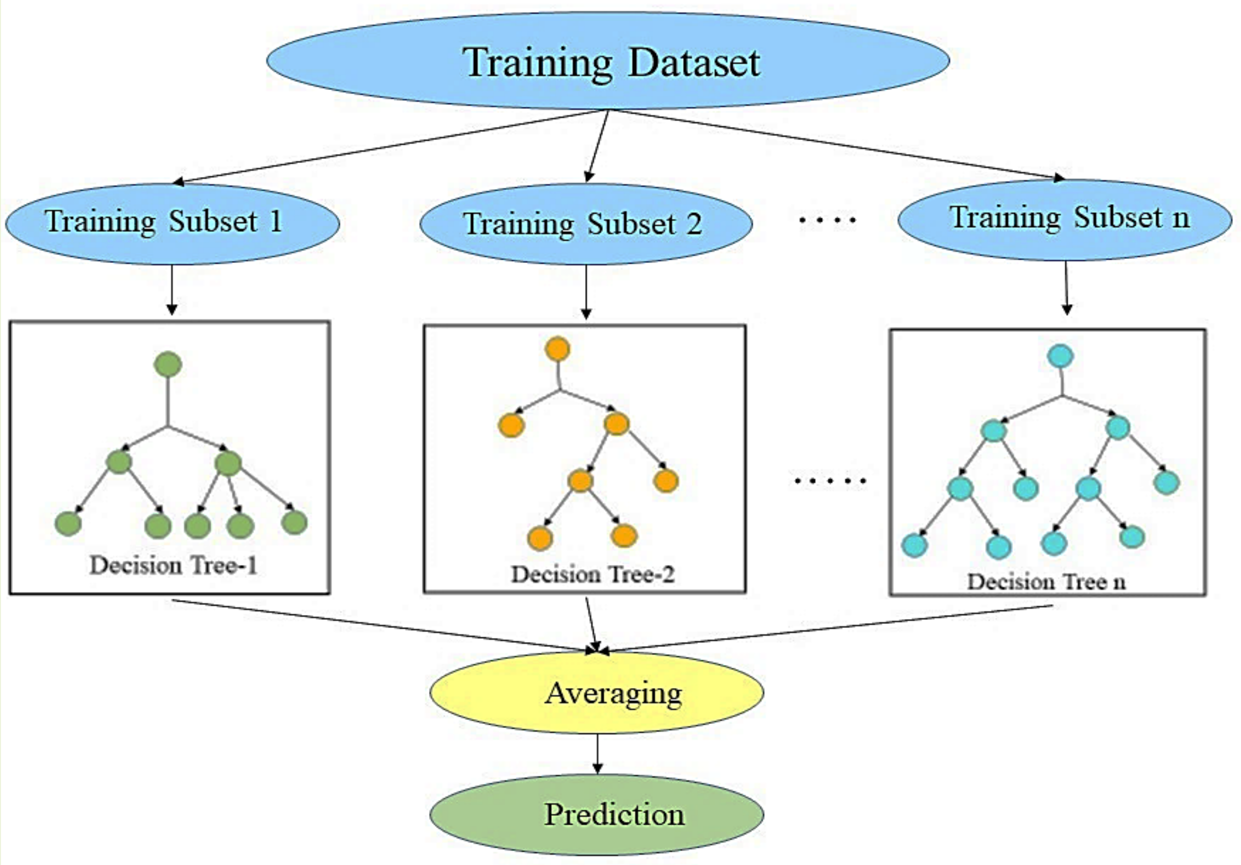
$$y_k^{input} = h_{0k}s_0^{output} + h_{1k}s_1^{output} + \ldots + h_{pk}s_p^{output} = \sum_{j=0}^{p} h_{jk}s_j^{output} \qquad (3)$$

$$y_k^{output} = f_a^{output}(y_k^{input} + b_k^{output}) \qquad (4)$$

The cost or loss function for MLP is: $$L = \frac{1}{2}\sum_i \sum_k \left\| f_a^{output}\left(\sum_{j=0}^{p} h_{jk}s_j^{output} + b_k^{output}\right) - y_k^{\mathrm{Target}} \right\|^2 \qquad (5)$$

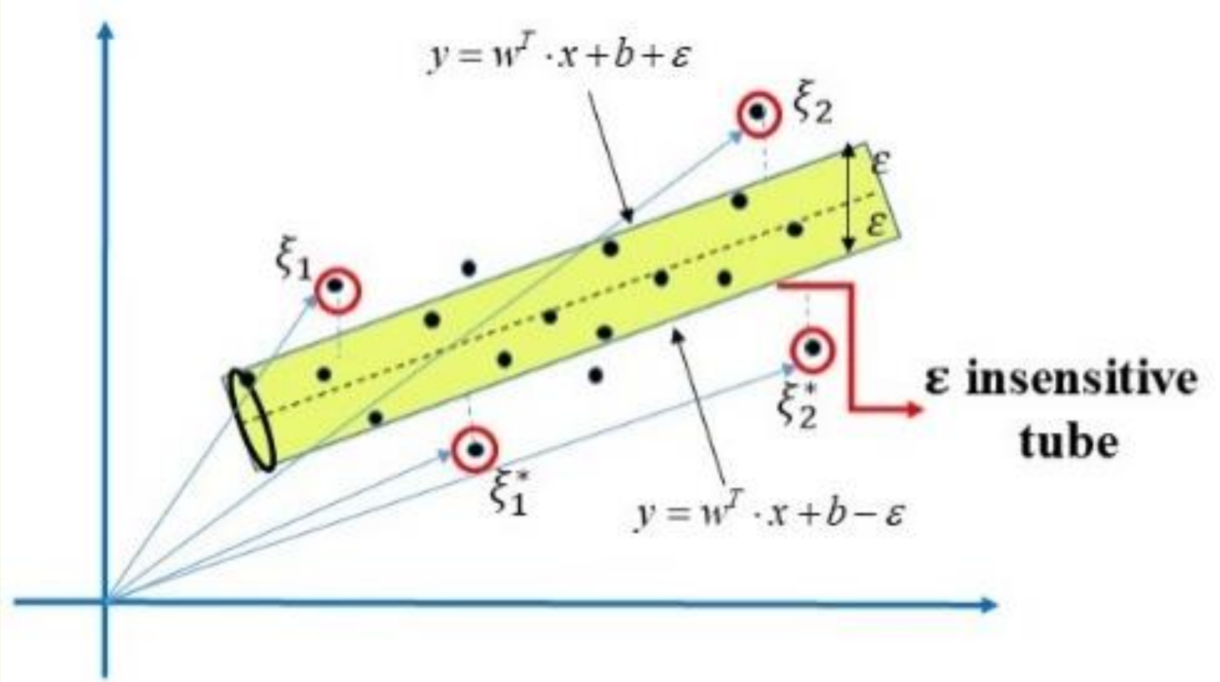
Random Forest (RF)

- RF is an ensemble learning technique that makes use of a set of decision trees for predictive analysis.
- Each tree is trained independently with a subset of the input data called the bootstrap dataset.
- Bootstrap datasets are prepared from the original dataset by random selection from an original dataset with repetition.
- The results are predicted based on the average predictive value of each tree.



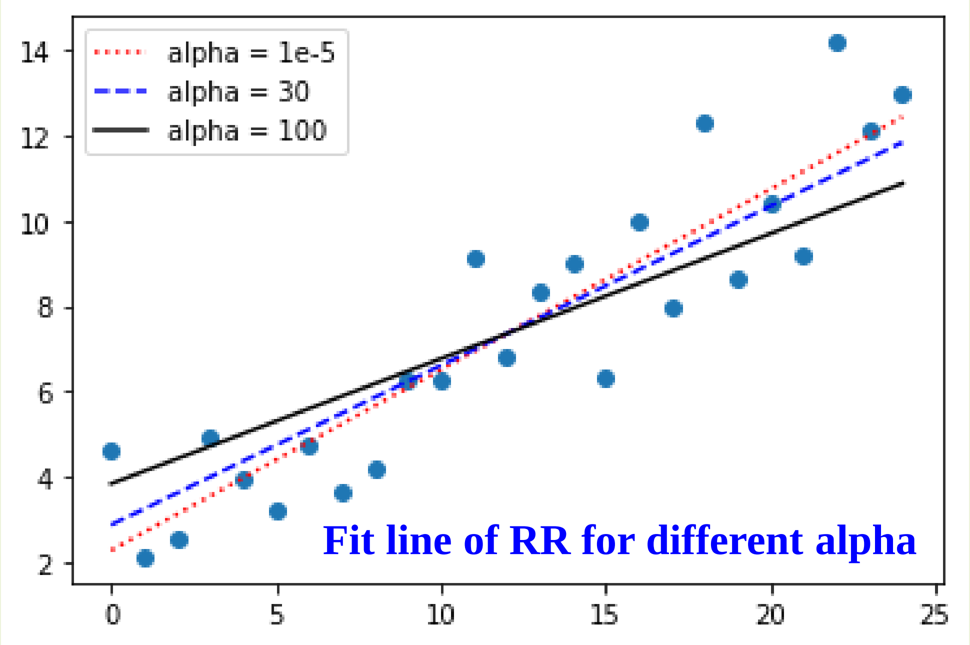
Support Vector Regression (SVR)

- Support vector machine (SVM) is a statistical learning-based ML tool that uses kernel to map low dimension function into high-dimension space where it classifies data using an SVM classifier.
- The principle of SVR is similar to SVM.
- SVR confines error within the fit tube and considers error estimation for data lying outside the tube.
- The objective function of SVR: $$Obj = \min\left[\frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}\left(\xi + \xi^*\right)\right]$$



Ridge Regression (RR)

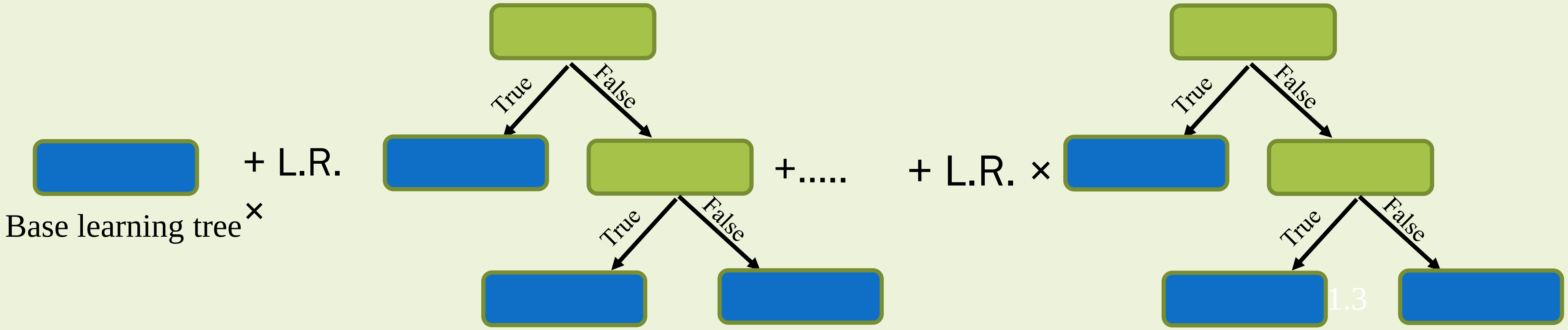
- Ridge Regression (RR) is a **regularization technique that analyses multiple regression when the data suffers from multicollinearity**.
- Multicollinearity leads to overfitting, which is reduced by adding a penalty term in the least square cost function.
- The model equation for Ridge Regression (RR) is: $y_k = \alpha_0 + \sum_{i=1}^{n} \alpha_1 x_k^i \Rightarrow Y = X\theta + \alpha_0$
- The least square cost function is given as: $L = \|Y - X\theta\|^2 - \lambda \|\theta\|^2$



Fit line of RR for different alpha

Xtreme Gradient Boosting (XGBoost)

- XGBoost is a decision tree-based ensemble learning technique that involves sequential addition of trees in each iteration to the base learning tree to minimize the objective function.



- The objective function of XGBoost is:

$$Obj = \left[\sum_{i=1}^{n} L(y_i, p_i) \right] + \gamma T + \frac{1}{2} \lambda O_{value}^2$$

Training Loss measures how well model fits on training data

Regularization, measures complexity of trees

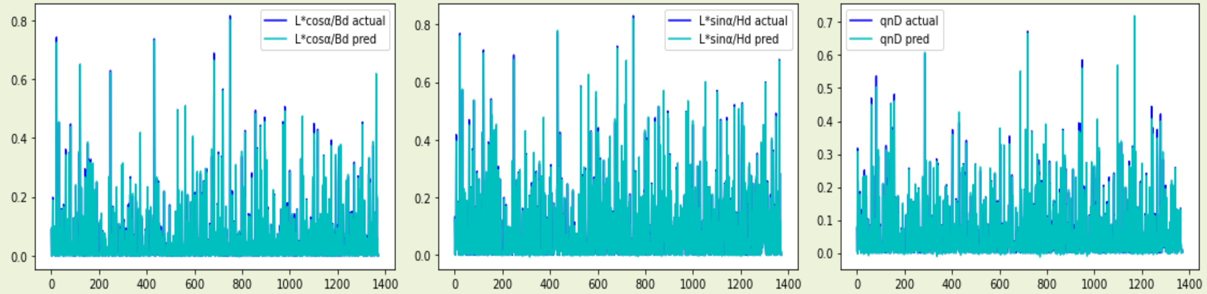
Application of DL and ML Techniques

Output Parameter	Test Data R^2	Test Data RMSE	Test Data MAE (%)	Validation Data R^2	Validation Data RMSE	Validation Data MAE (%)	Model
	1.00	1.513×10^{-05}	0.233	0.91	2.639×10^{-04}	1.200	XGBoost
	1.00	2.896×10^{-05}	0.225	0.92	2.452×10^{-04}	1.158	RF
$L^*(\sin\alpha)/H_d$	0.86	2.385×10^{-03}	3.755	0.45	1.594×10^{-03}	3.551	MLP
	0.67	6.038×10^{-03}	5.592	0.67	9.339×10^{-04}	2.839	RR
	0.36	9.920×10^{-03}	8.425	-0.37	3.904×10^{-03}	5.839	SVR
	1.00	2.029×10^{-05}	0.251	0.89	1.891×10^{-04}	0.861	XGBoost
	1.00	2.587×10^{-05}	0.199	0.90	1.710×10^{-04}	0.826	RF
$L^*(\cos\alpha)/B_d$	0.76	2.438×10^{-03}	3.737	0.26	7.729×10^{-04}	2.170	MLP
	0.54	5.478×10^{-03}	4.916	0.302	1.162×10^{-03}	3.281	RR
	0.05	9.022×10^{-03}	8.487	-0.5	6.165×10^{-03}	7.058	SVR
	1.00	2.471×10^{-05}	0.273	0.90	2.571×10^{-04}	1.174	XGBoost
	0.99	8.206×10^{-05}	0.243	0.91	2.433×10^{-04}	1.194	RF
q_{nD}	0.62	3.091×10^{-03}	3.581	0.21	2.602×10^{-03}	4.387	MLP
	0.37	6.394×10^{-03}	4.824	0.58	1.102×10^{-03}	2.214	RR
	0.20	9.553×10^{-03}	7.727	-0.20	3.114×10^{-03}	4.954	SVR

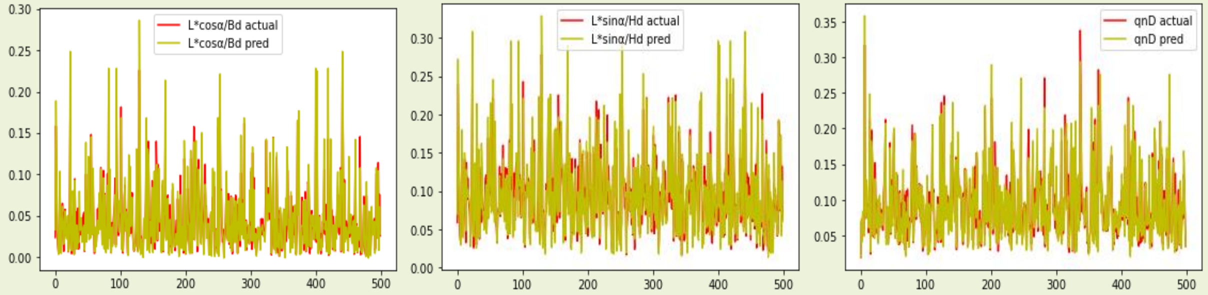
- XGBoost shows best fitting for test data, Random Forest shows best fitting for training data, and SVR shows the poorest fit.
- Root Mean Square Error (RMSE) for all three-output parameters is minimum for XGBoost for test data, and for synthetic data, it is minimum for Random Forest.
- Mean Absolute Error (MAE %) for all three-output parameters is minimum for Random Forest for both test data and synthetic data, while it is maximum for SVR.

Results and Discussion

XGBoost

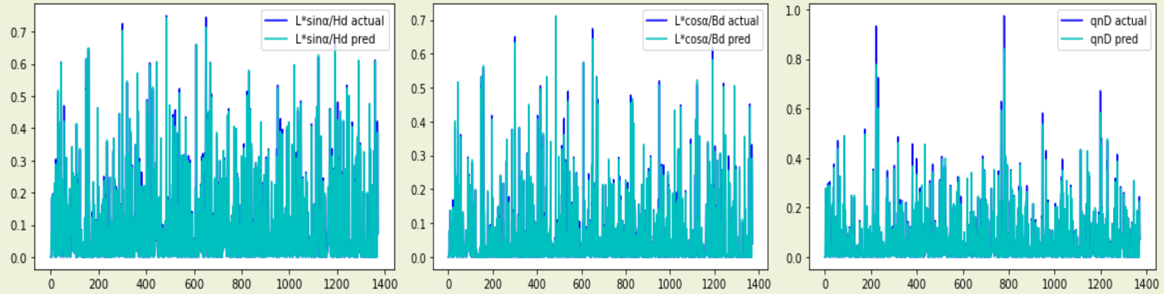


Comparison between actual and predicted output for test data

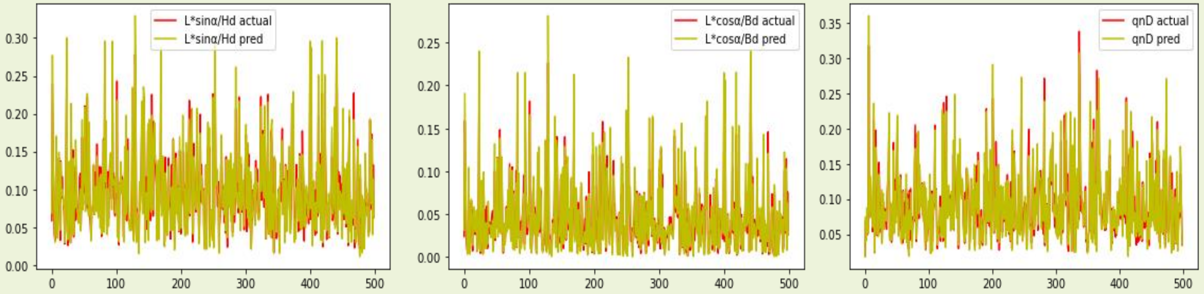


Comparison between actual and predicted output for validation data

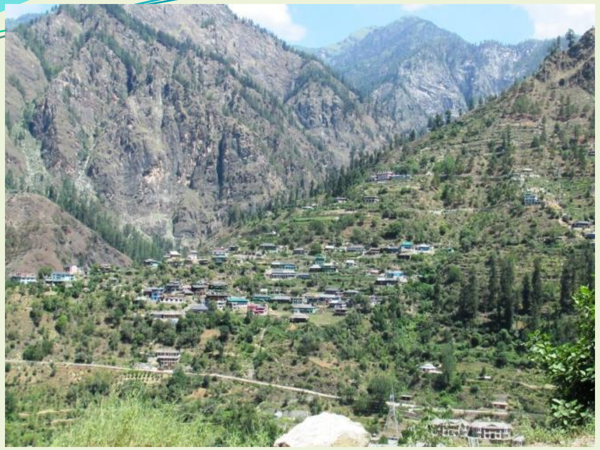
Random Forest



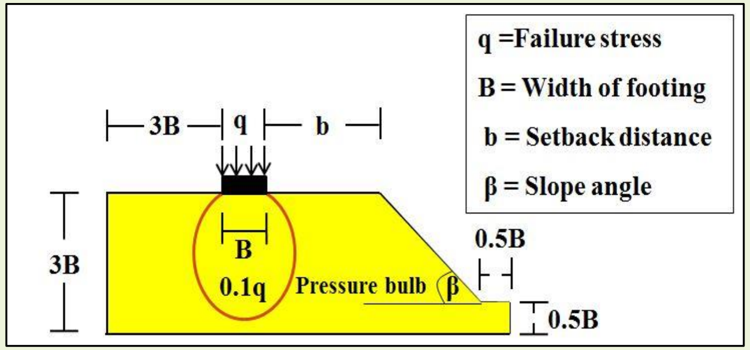
Comparison between actual and predicted output for test data

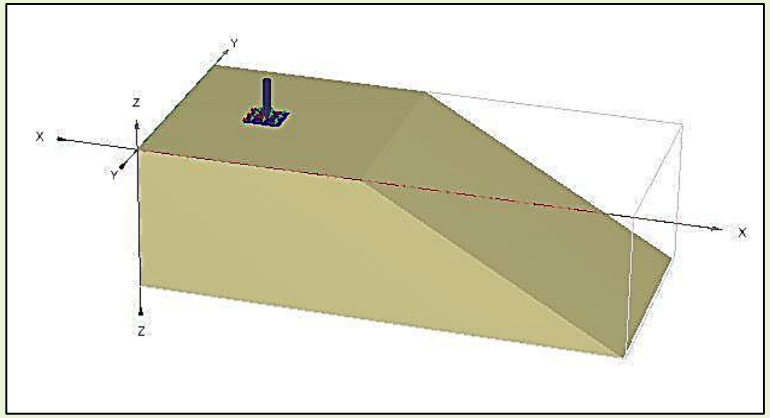


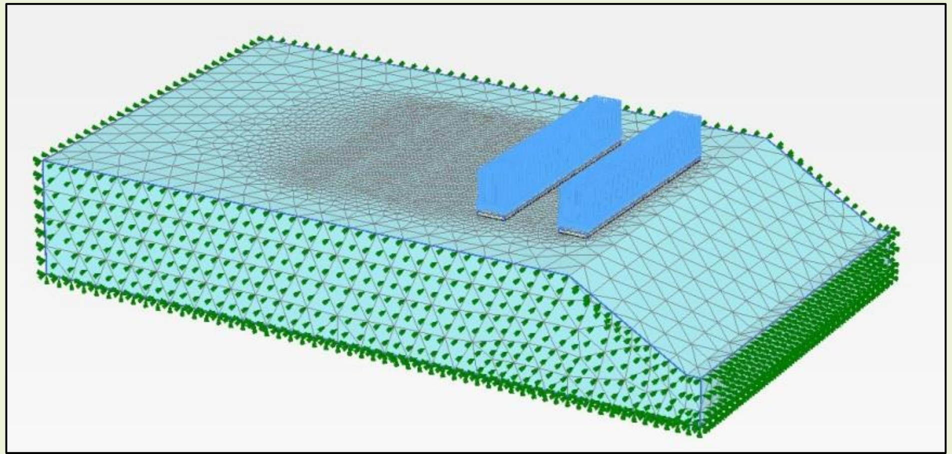
Comparison between actual and predicted output for validation data



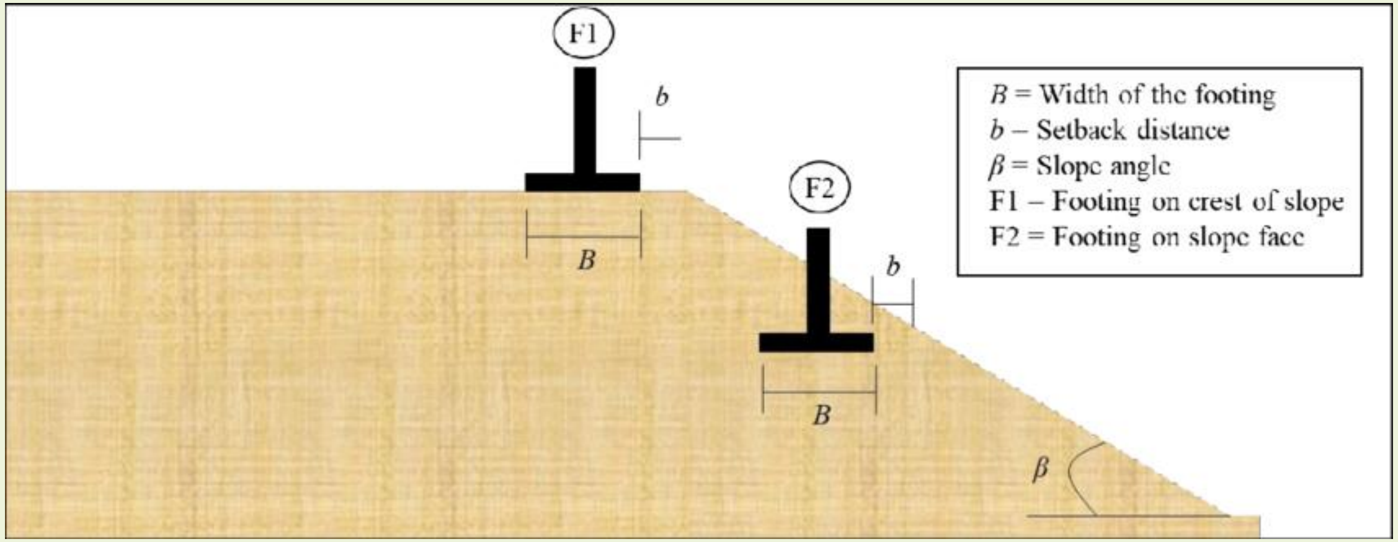
Bearing Capacity of Foundation on Slopes

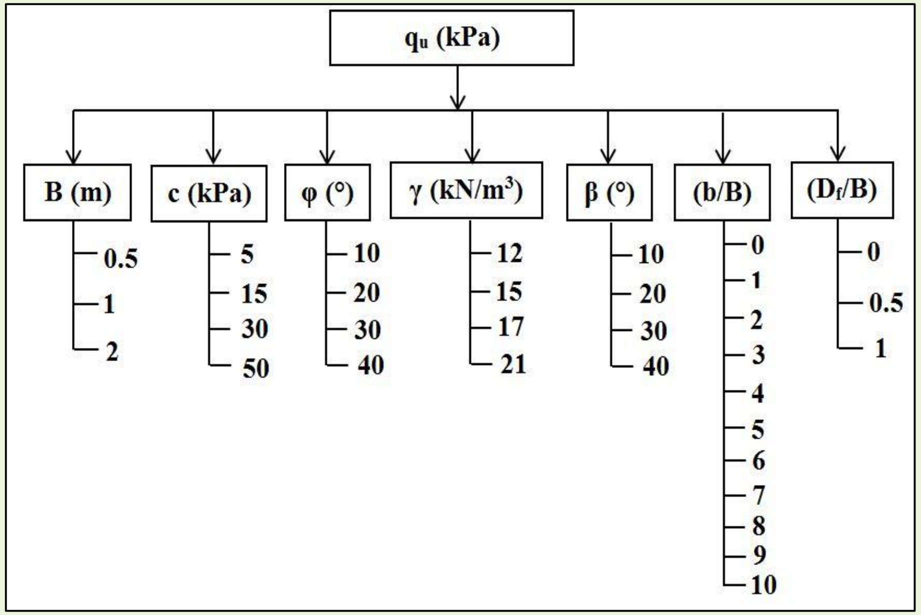


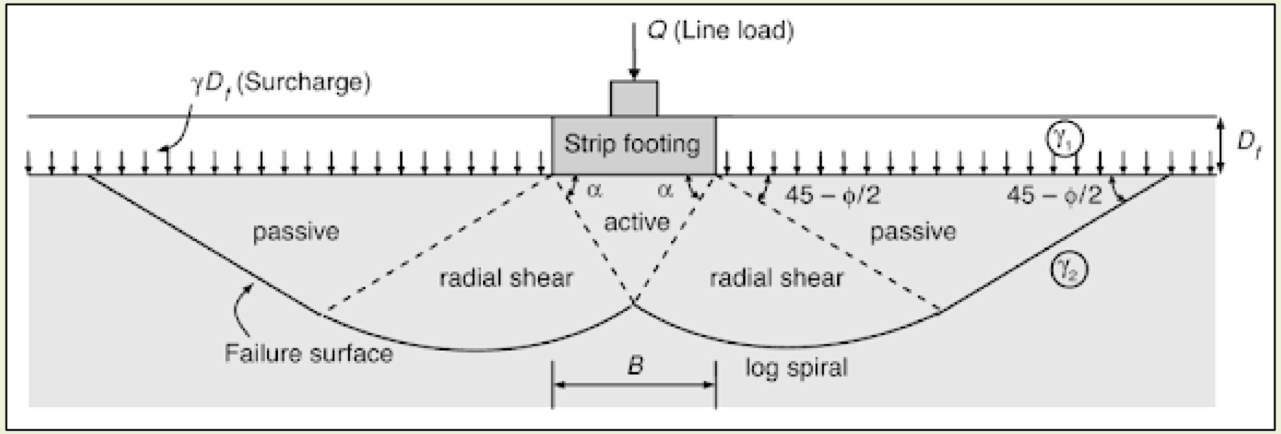


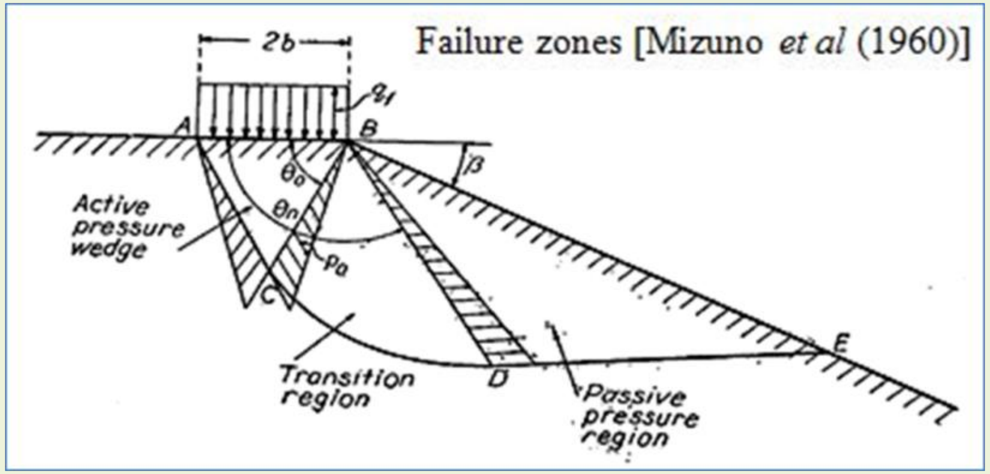


Bearing Capacity of Foundation on Slopes





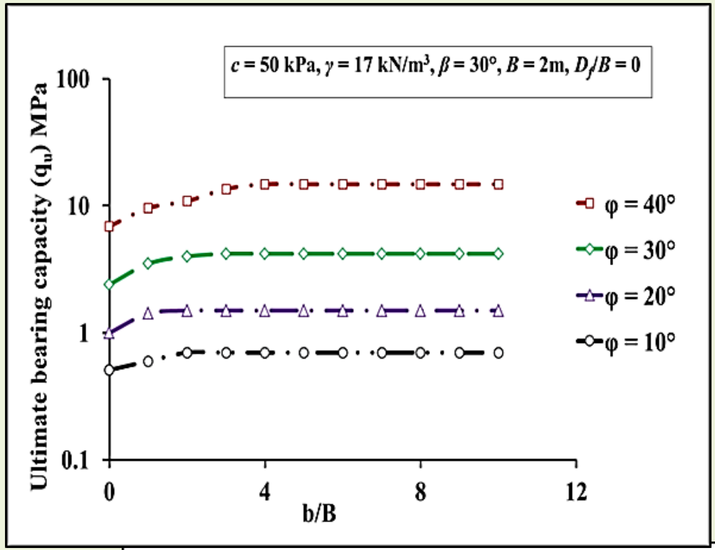


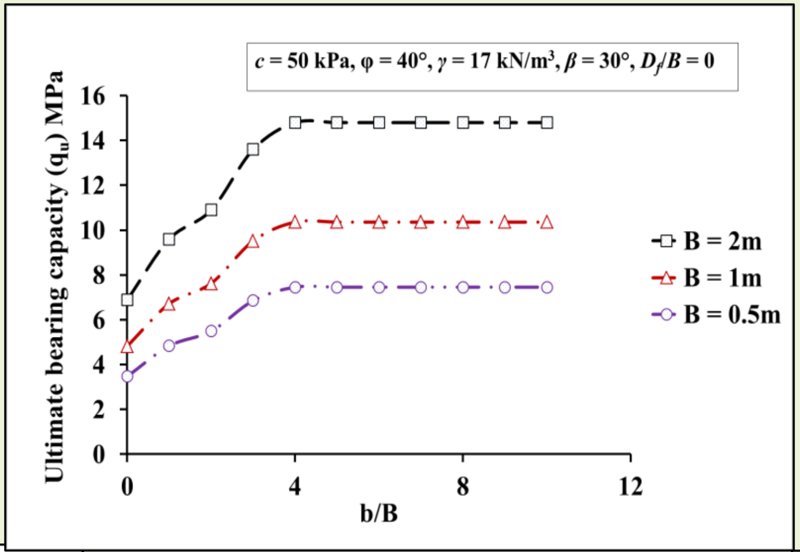


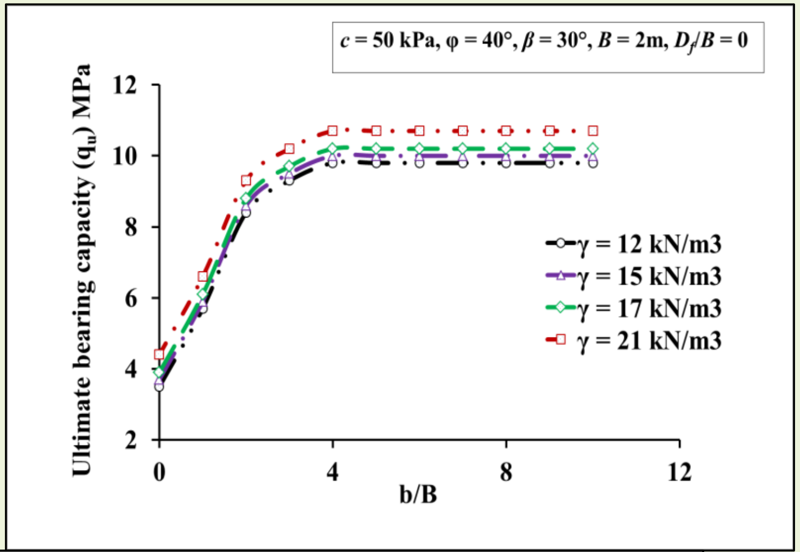
Failure zones [Mizuno et al (1960)]

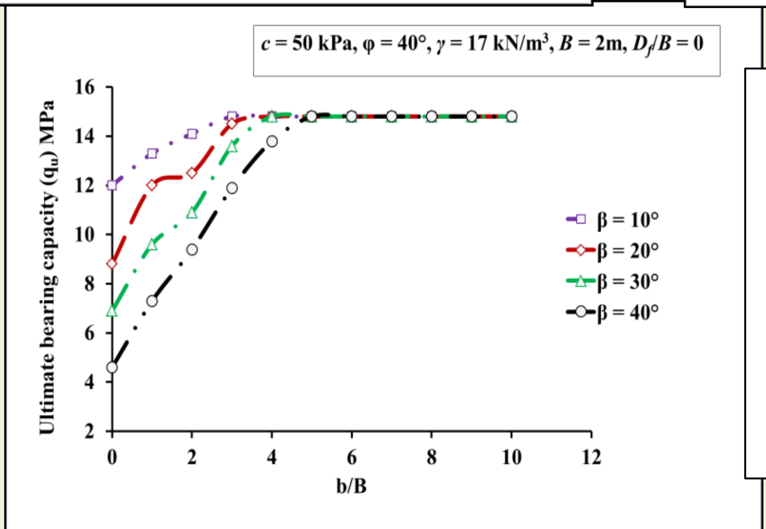
Bearing Capacity of Foundation on Slopes

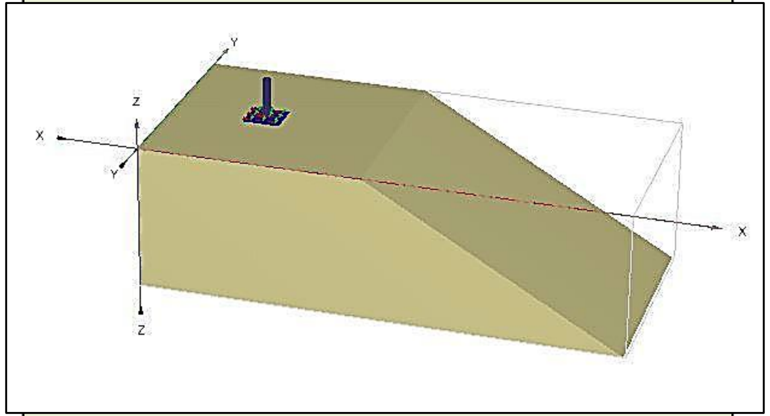
Single Square Footing on Crest of a Marginal Soil Slope

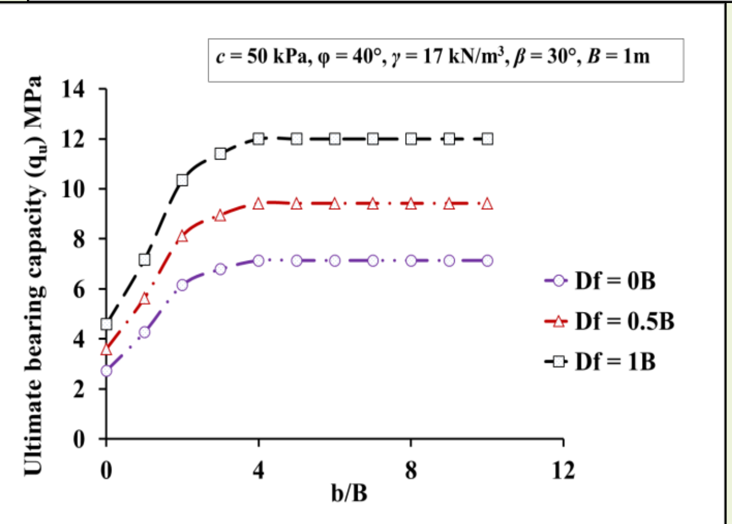






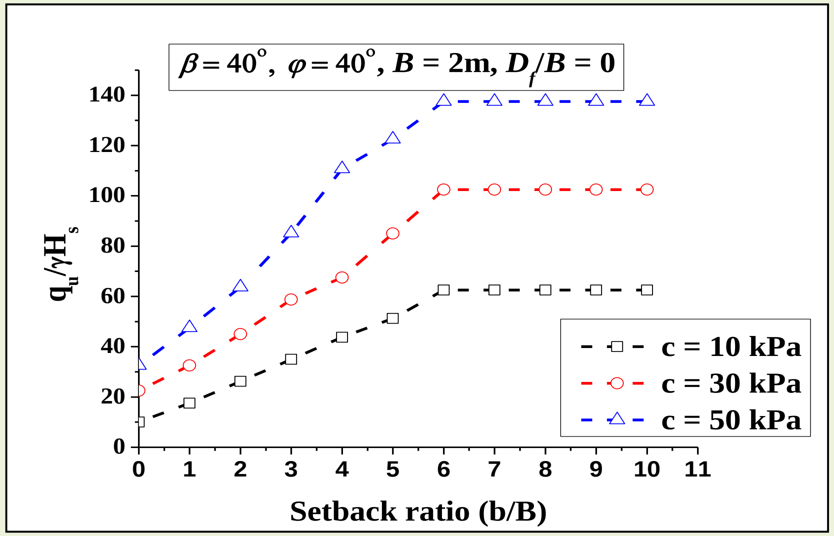


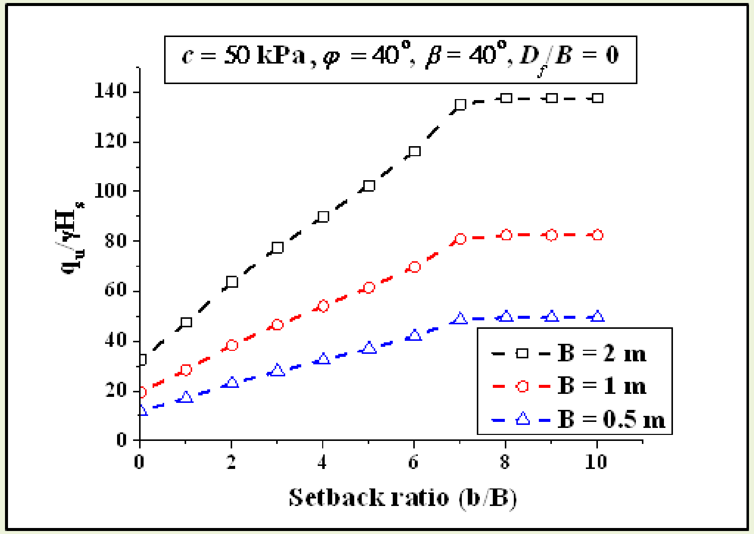


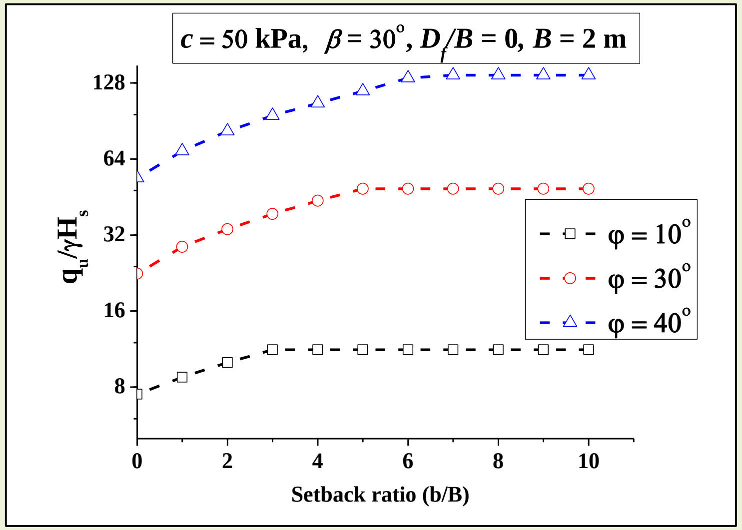


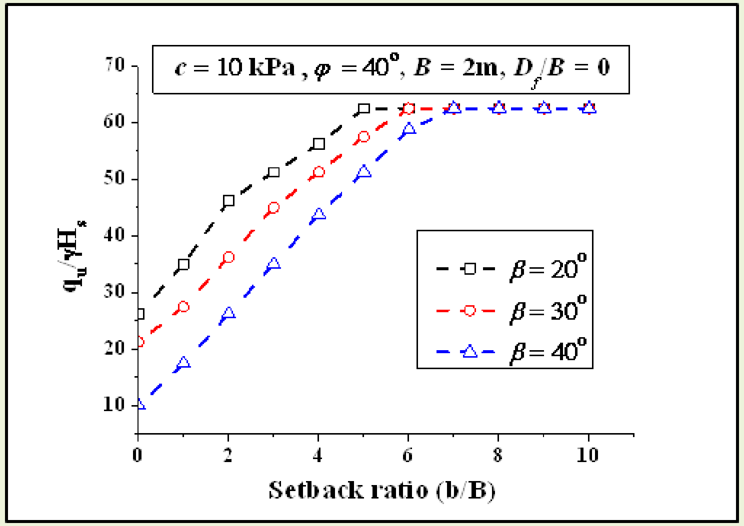
Bearing Capacity of Foundation on Slopes

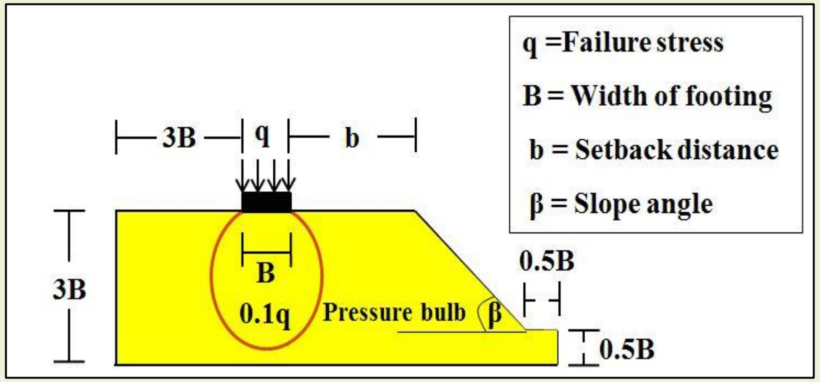
Single Strip Footing on Crest of a Marginal Soil Slope

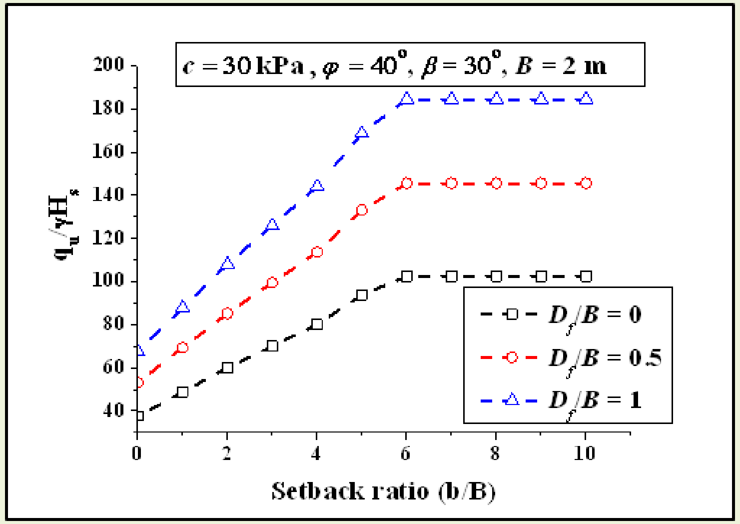






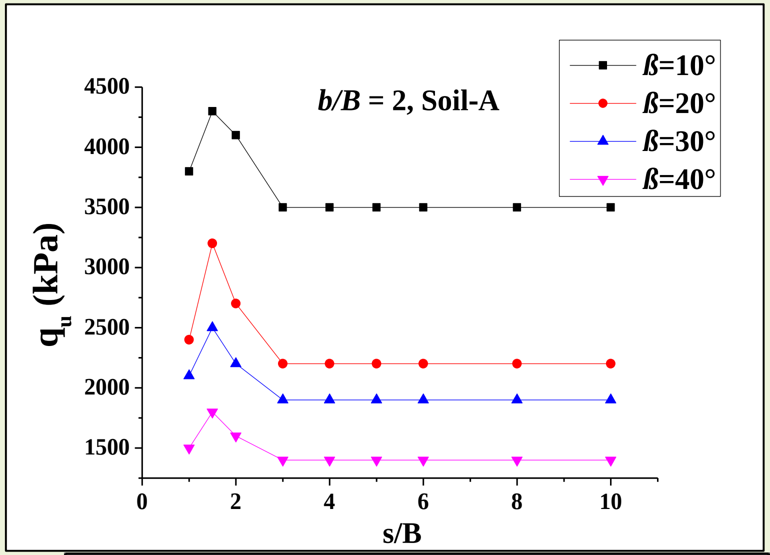


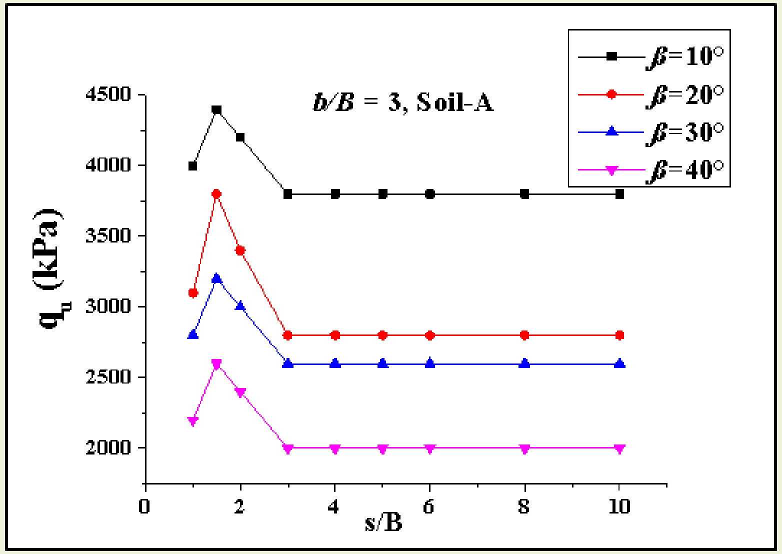


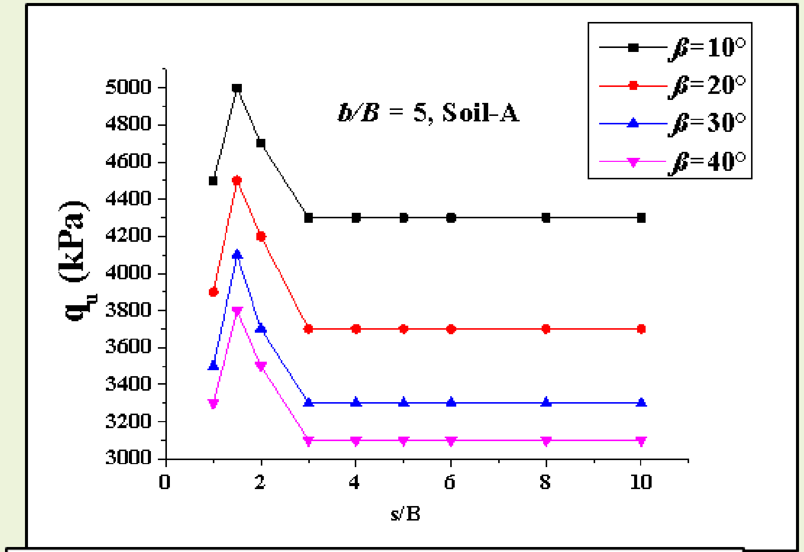


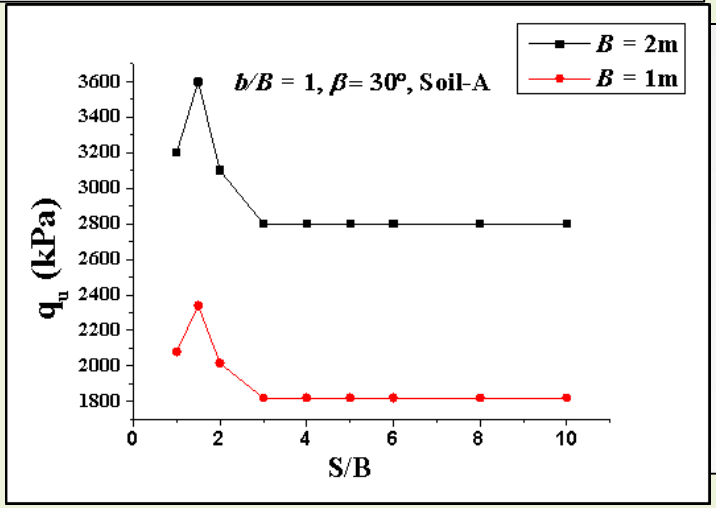
Bearing Capacity of Foundation on Slopes

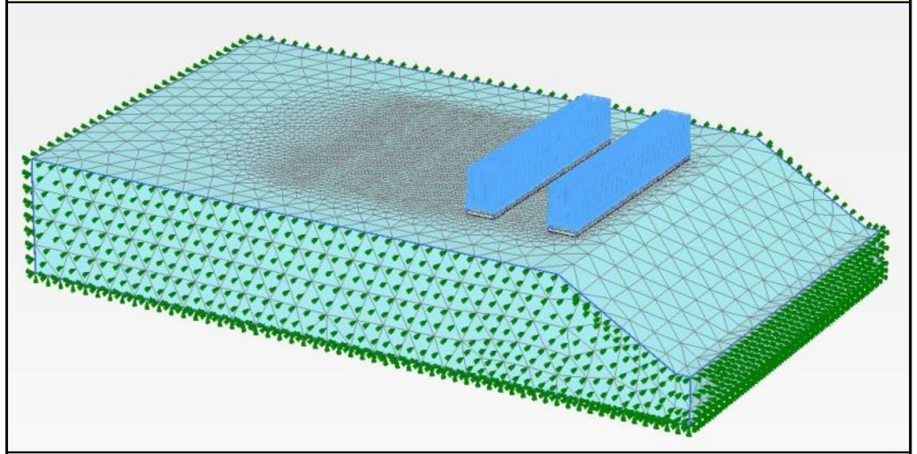
Interfering Strip Footings on Crest of a Marginal Soil Slope

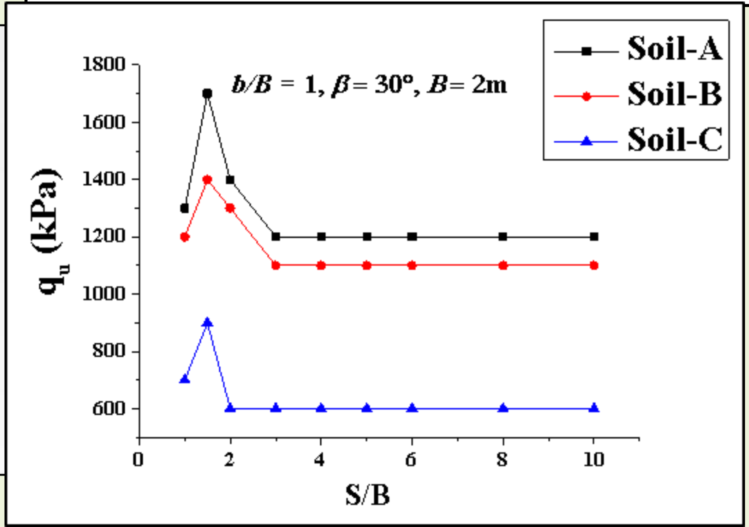






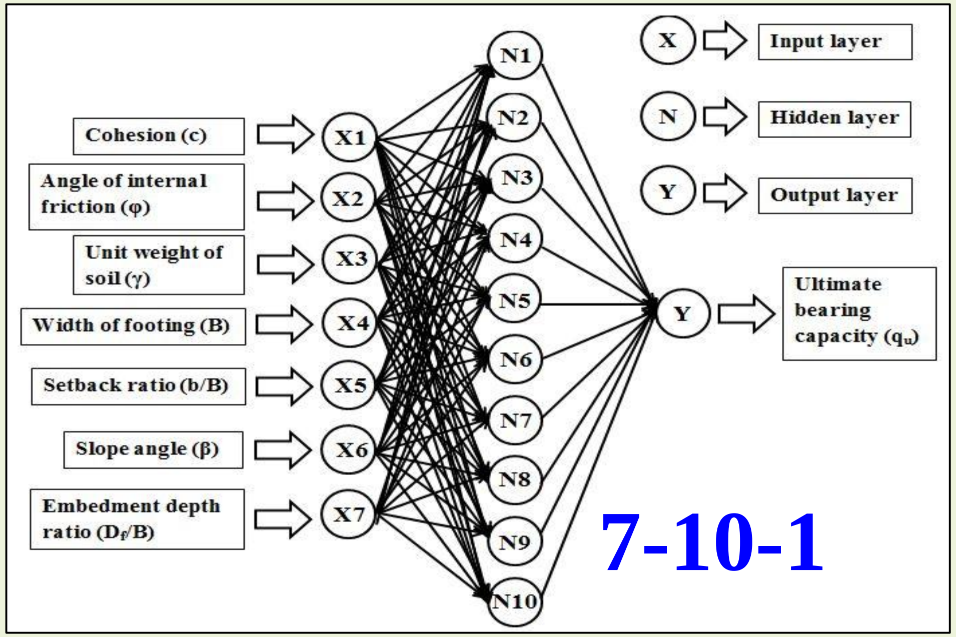






Bearing Capacity of Foundation on Slopes: Application of ANN

- **Normalization of data**
  - ❖ Input
  - ❖ Output
    - ❑ $$P_i^n = \frac{2(P_i^a - P_i^{\min})}{(P_i^{\max} - P_i^{\min})} - 1$$ **(Rukhaiyar et al. 2017)**
    - ❑ P_i^a **and** P_i^n **are before and after normalization magnitude**
    - ❑ $P_i^{\max}$ **and** $P_i^{\min}$ **are the maximum and minimum magnitude**
- **ANN**
  - ❖ Architecture
- **Network**
  - ❖ Feed-forward cum back-propagation
- **Training function**
  - ❖ Levenberg-Marquardt's
- **Number of neurons in hidden layer**
  - ❖ Varied to achieve minimum MSE

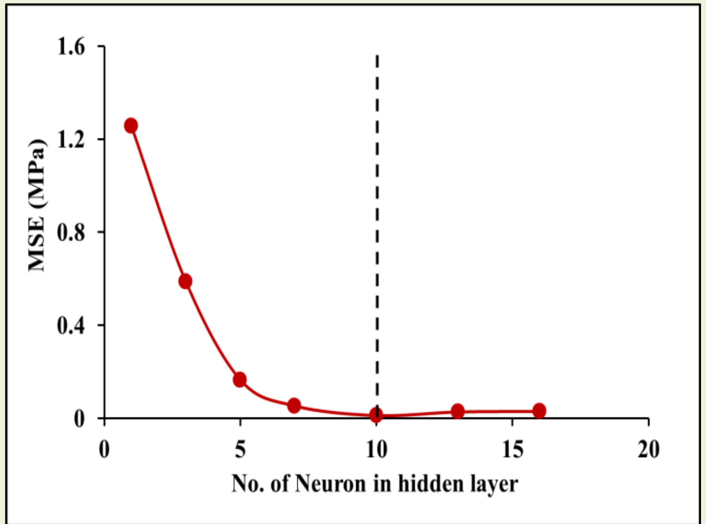


$$MSE = \frac{1}{N_d} \sum_{i=1}^{N} (O_{Simulation} - O_{ANN})^2$$

N_d = Number of data

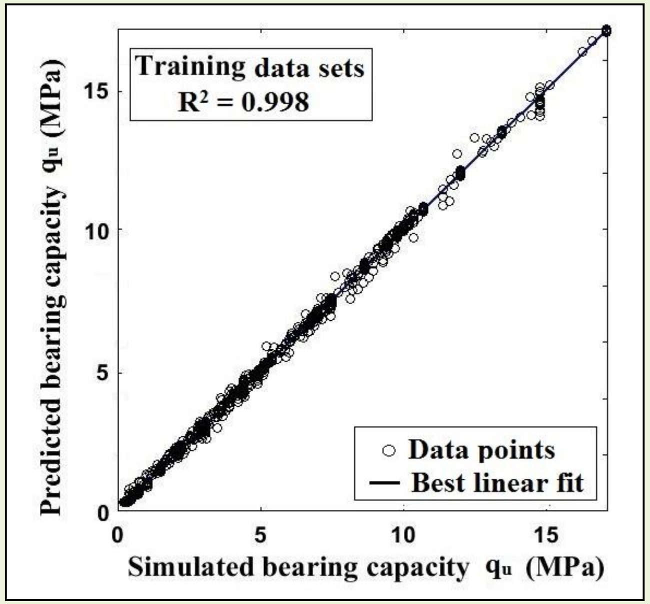
$O_{Simulation}$ = Numerically simulated values

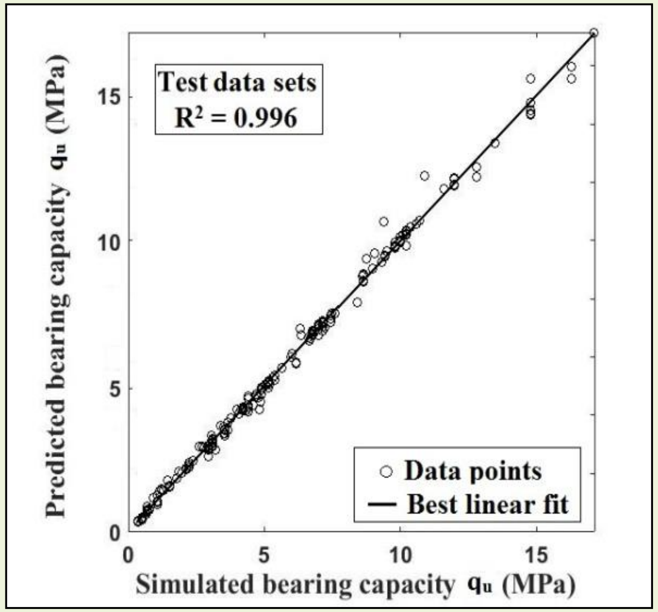
O_{ANN} = Predicted values of the same entity

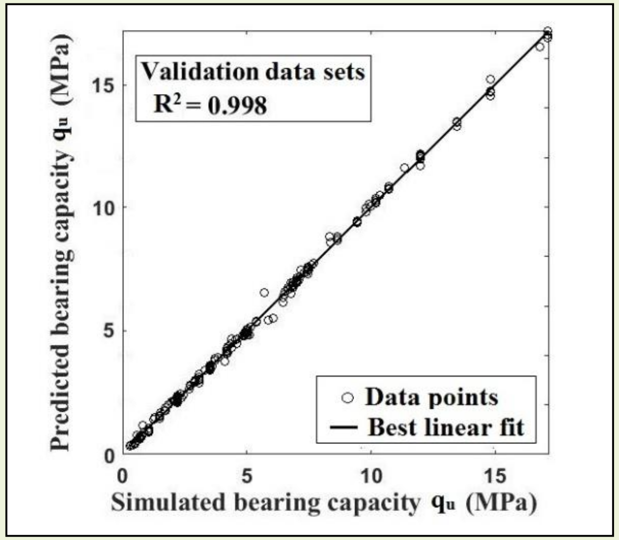


Bearing Capacity of Foundation on Slopes: Application of ANN

- **ANN architecture**
  - ❖Training
  - ❖Testing
  - ❖Validation
    - ❑80% of the total data
      - ➢ *used for training*
    - ❑20% of the total data
      - ➢ *Validation of the ANN architecture*
    - ❑Training dataset
      - ➢ *Further divided, where*
    - ❑70% of the data
      - ➢ *Used for actual training*
    - ❑Remaining 30% of the data
      - ➢ *Used as the testing*
      - ➢ *Das and Basudhar 2006*







Bearing Capacity of Foundation on Slopes: Application of ANN

- **Table**
  - Weight
  - Biases

Input-Hidden weights

N / X	Hidden N1	Hidden N2	Hidden N3	Hidden N4	Hidden N5	Hidden N6	Hidden N7	Hidden N8	Hidden N9	Hidden N10
c (X1)	0.55	-0.67	-0.26	0.84	-0.54	0.95	0.58	-3.58	0.004	-0.12
ϕ (X2)	-0.56	-0.33	8.43	1.30	-0.64	-7.25	1.27	-5.25	-0.29	-0.91
γ (X3)	0.32	0.03	0.02	0.16	-0.09	0.03	0.09	-0.75	-0.01	0.04
B (X4)	0.24	0.11	0.15	0.46	-0.52	-0.06	0.46	4.79	-0.13	-0.13
b/B (X5)	1.45	0.0008	2.05	0.14	0.07	-1.74	-0.51	2.64	0.02	2.01
β (X6)	-0.38	-0.01	-0.47	-0.04	-0.01	0.51	0.11	-0.67	0.004	-0.46
D_f/B(X7)	1.30	0.57	-0.66	0.72	-0.35	0.66	0.42	6.50	-0.09	-0.05

Biases

Hidden layer biases (b_{hN})	Output layer biases (b_O)
1.16	-0.61
-0.48	
-0.66	
-2.16	
1.34	
0.03	
-1.79	
-5.15	
-0.03	
3.03	

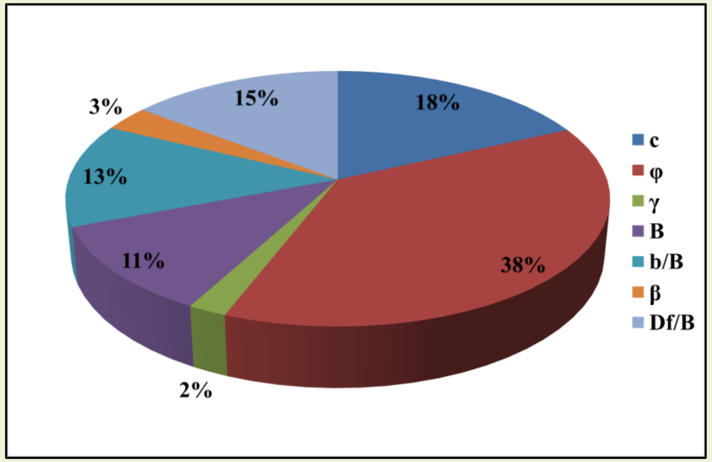
Hidden-Output weights

N / Y	Hidden N1	Hidden N2	Hidden N3	Hidden N4	Hidden N5	Hidden N6	Hidden N7	Hidden N8	Hidden N9	Hidden N10
Output	0.06	-2.16	0.52	1.91	2.01	0.53	0.83	2.32	-3.58	0.97

Bearing Capacity of Foundation on Slopes: Application of ANN

$$Input_X = \sum_{N=1}^{10} \frac{|Hidden_{XN}|}{\sum_{Z=1}^{7} |Hidden_{ZN}|}$$

(Garson's sensitivity algorithm)

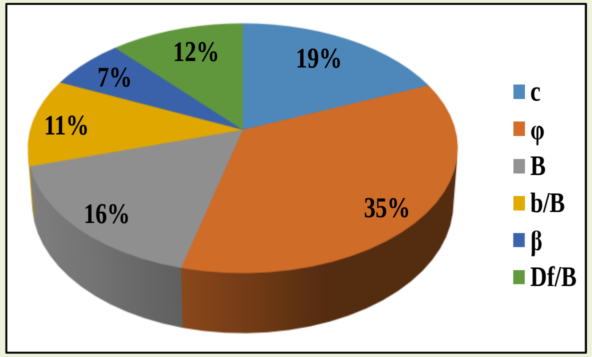


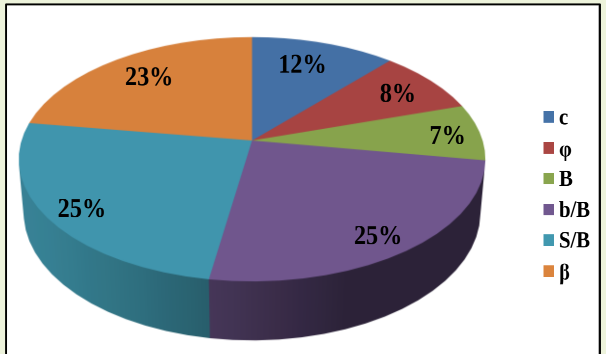
Square footing

Product of the input-hidden and hidden-output connection weights

N / Z	Hidden N1	Hidden N2	Hidden N3	Hidden N4	Hidden N5	Hidden N6	Hidden N7	Hidden N8	Hidden N9	Hidden N10
c (X1)	0.04	1.45	-0.13	1.61	-1.09	0.50	0.48	-8.31	0.02	-0.12
ϕ (X2)	-0.04	0.71	4.40	2.49	-1.29	-3.83	1.06	-12.18	1.03	-0.88
γ (X3)	0.02	-0.07	0.01	0.31	-0.19	0.02	0.08	-1.73	0.02	0.04
B (X4)	0.02	-0.24	0.08	0.87	-1.04	-0.03	0.38	11.10	0.48	-0.12
b/B (X5)	0.09	0.0018	1.07	0.26	0.14	-0.92	-0.43	6.13	-0.07	1.94
β (X6)	-0.02	0.03	-0.24	-0.08	-0.01	0.27	0.09	-1.55	0.01	-0.45
D_f/B (X7)	0.08	-1.23	-0.34	1.37	-0.69	0.35	0.35	15.09	0.32	-0.05

Strip footing





Interfering strip footing

Bearing Capacity of Foundation on Slopes: Application of ANN

Predicting Expression for Square footing on slope

$$\left(\frac{q_u}{\gamma H_s}\right)_n = f_{Sig}\{b_O + \sum_{N=1}^{h}[w_N f_{Sig}(b_{hN} + \sum_{i=1}^{m} w_{iN} X_i)]\}$$

$$A_1 = 0.55(c) - 0.56(\varphi) + 0.32\gamma + 0.24(B) + 1.45(b/B) - 0.38(\beta) + 1.30(D_f/B) + 1.16$$

$$A_{10} = -0.12(c) - 0.91(\varphi) + 0.04\gamma - 0.13(B) + 2.01(b/B) - 0.46(\beta) - 0.05(D_f/B) + 3.03$$

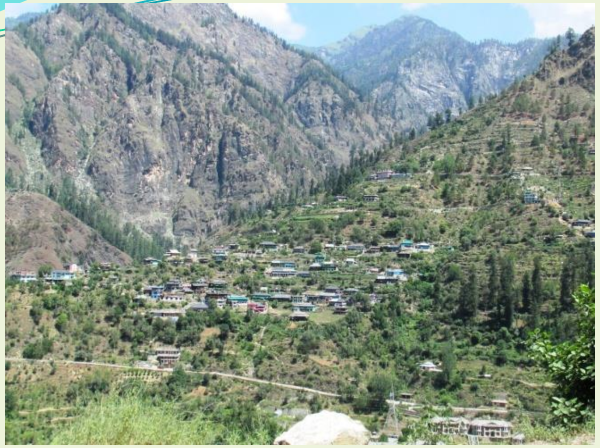
$$B_1 = 0.06\left(\frac{e^{A_1} - e^{-A_1}}{e^{A_1} + e^{-A_1}}\right)$$

$$B_{10} = 0.97\left(\frac{e^{A_{10}} - e^{-A_{10}}}{e^{A_{10}} + e^{-A_{10}}}\right)$$

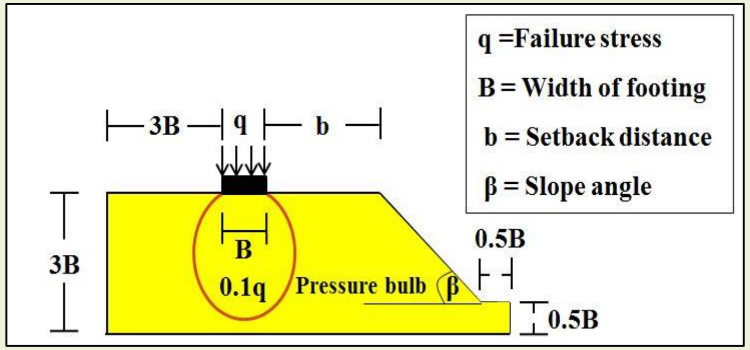
$$C_1 = -0.61 + B_1 + B_2 + B_3 + B_4 + B_5 + B_6 + B_7 + B_8 + B_9 + B_{10}$$

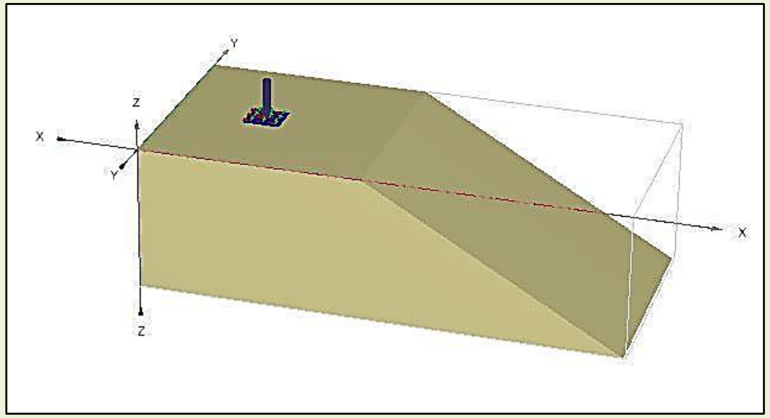
$$(q_u)_n = \left(\frac{e^{C_1} - e^{-C_1}}{e^{C_1} + e^{-C_1}}\right)$$

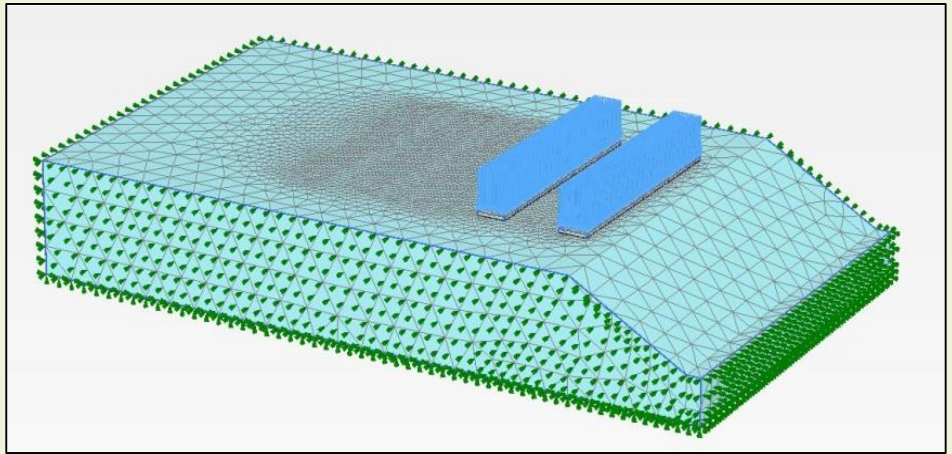
$$(q_u) = 0.5[(q_u)_n + 1][(q_u)_{max} - (q_u)_{min}] + (q_u)_{min}$$



Bearing Capacity of Interacting Foundation on Slopes : GIGO

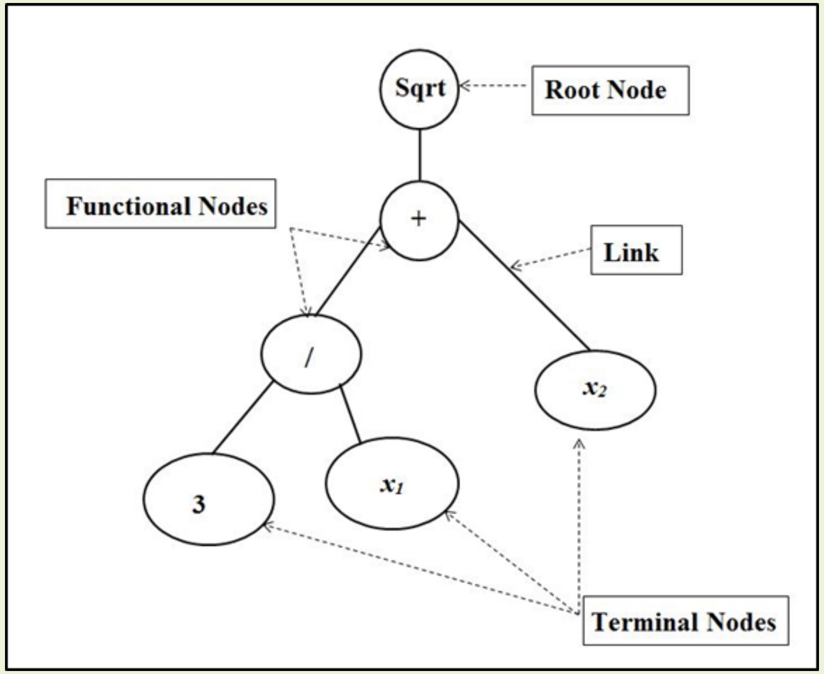






Bearing Capacity of Foundation on Slopes: Application of MGGP

- Genetic programming (GP)
  - *Based on the Darwinian principle of natural selection*
  - *Symbolic optimization method that generates programs to execute a problem*
    - Outcomes are revealed in terms of tree structures
  - *A hierarchical tree structure*
    - Comprises functions and terminals
  - *A function set consists*
    - Typical programming operations
    - Typical mathematical functions
    - Simple arithmetic operations
    - Domain-specific operators
    - Logical functions
    - Any other necessary mathematical operators



Typical tree structure of a GP model representing

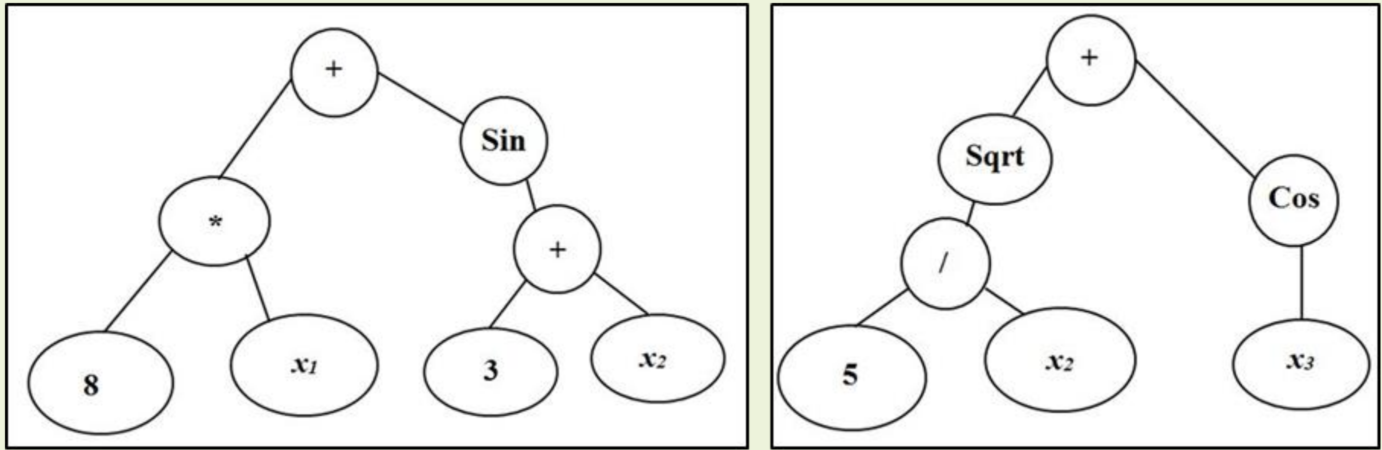
$$f(x) = \sqrt{(3/x_1 + x_2)}$$

Bearing Capacity of Foundation on Slopes: Application of MGGP

- Multi-Gene Genetic programming (MGGP)
  - *Every symbolic model (i.e. every tree of GP) in* ***MGGP is a weighted linear arrangement of the outputs from a huge quantity of trees***
  - *Model comprises nonlinear algebraic and trigonometric operators*
    - **Linear with regard to the individual operators associated with the coefficients w_0, w_1 and w_2**
      - Assessed with aid of least squares method
  - *Large number of population and generations are realized along with other* ***algorithm parameters***
    - Build method
    - Maximum depth of individual gene
    - Maximum number of genes
    - Mutations, crossover and the direct crossover (M-C-D) probabilities
    - Direct and Elite fractions

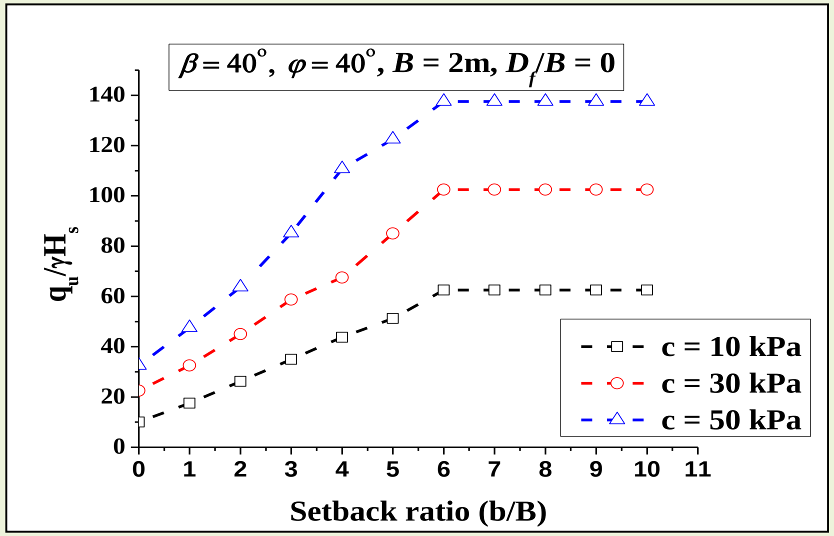
Typical tree structure of a MGGP model representing

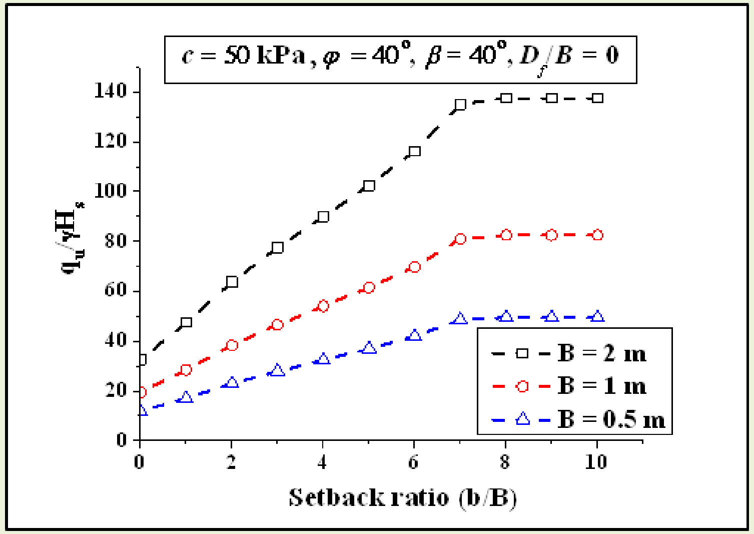
$$y = w_0 + w_1\left[8x_1 + \sin\left(3 + x_2\right)\right] + w_2\left[\sqrt{5/x_2} + \cos\left(x_3\right)\right]$$

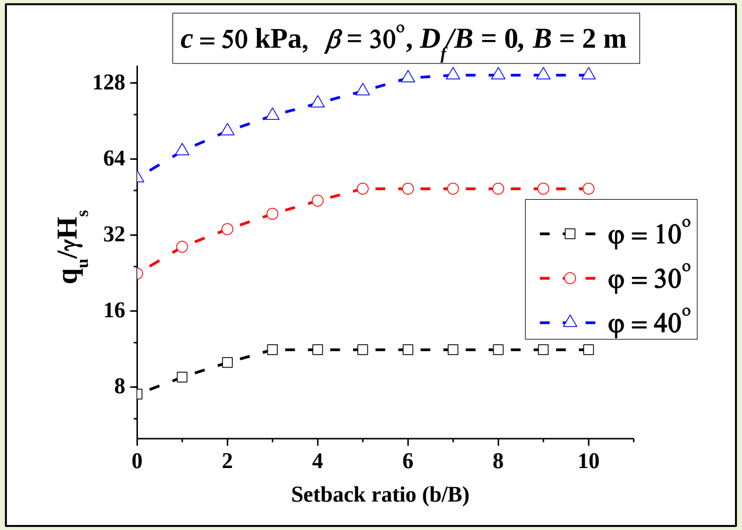


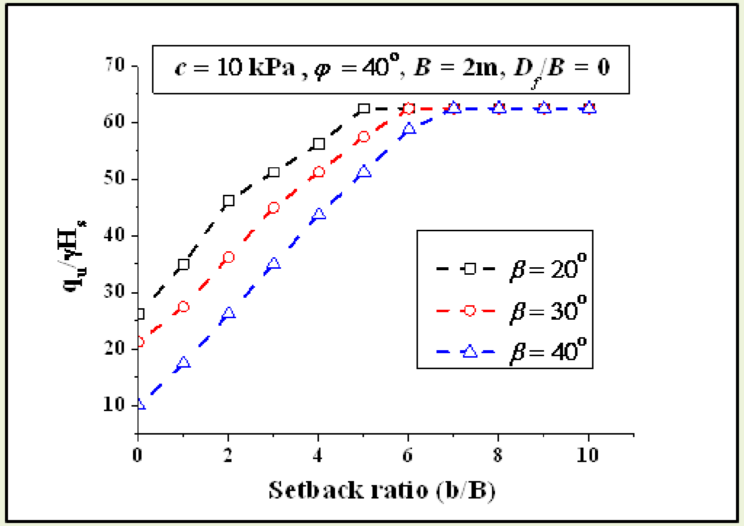
Bearing Capacity of Foundation on Slopes

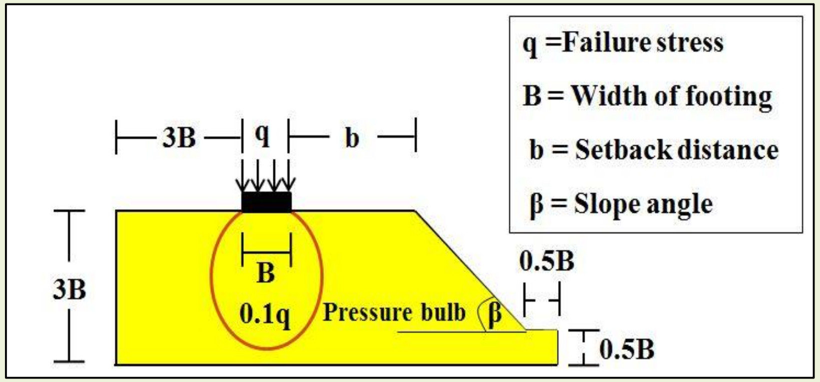
Single Strip Footing on Crest of a Marginal Soil Slope

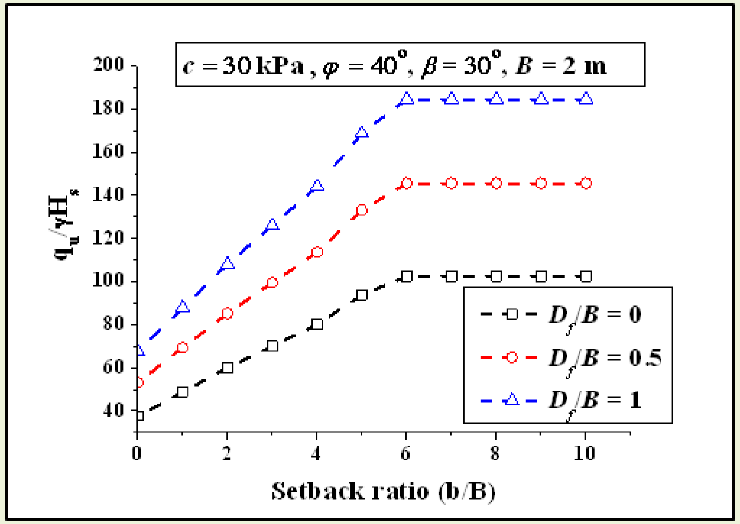












Bearing Capacity of Foundation on Slopes: Application of MGGP

Single Strip Footing on Crest of a Marginal Soil Slope

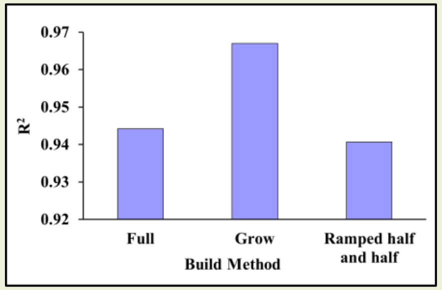
Ranges of input parameters used in the study

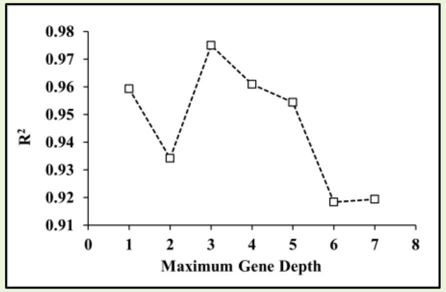
Input parameters	MGGP notation	Range
c (kPa)	X_1	10-80
φ (°)	X_2	10-40
B (m)	X_3	0.5-2
b/B	X_4	0-10
β (°)	X_5	10-40
D_f/B	X_6	0-1

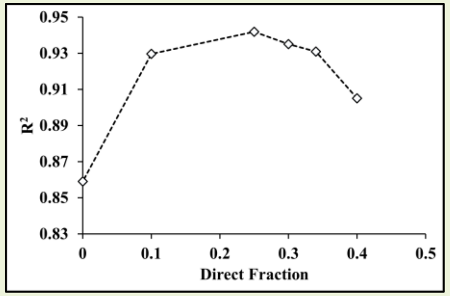
Optimal algorithm parameters used in MGGP

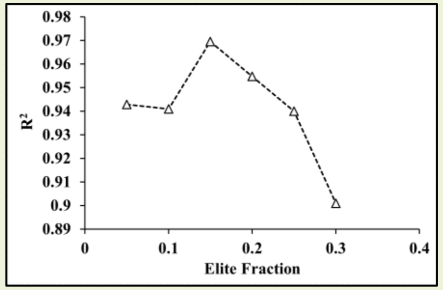
Parameters	$q_u/\gamma H_s$ predictor
Build method	Grow
Maximum depth of individual gene	3
Maximum number of genes	5
M-C-D probabilities	0.3
Tournament size (%)	100
Elite fraction	0.15
Population size	750
Number of generations	50

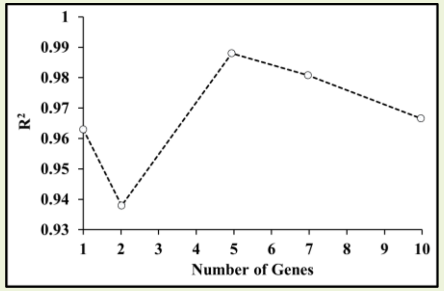
$$\frac{q_u}{\gamma H_s} = \left[8.01 - 41.72X_3 + \frac{3797X_3}{X_2^{\,2}} + X_1X_3e^{-1.352\times10^{-3}X_2^2X_3} + 0.246\frac{X_2^3X_3}{X_5^2} + 0.021X_2^2X_3X_6 + 9.6\times10^{-5}X_3X_4X_5 \right]$$

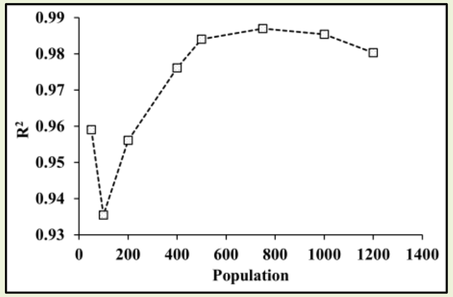


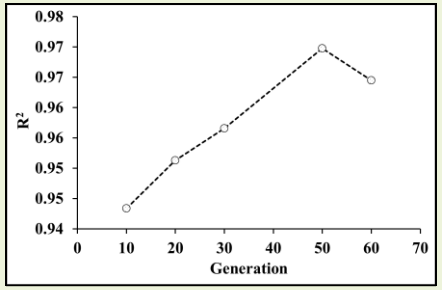










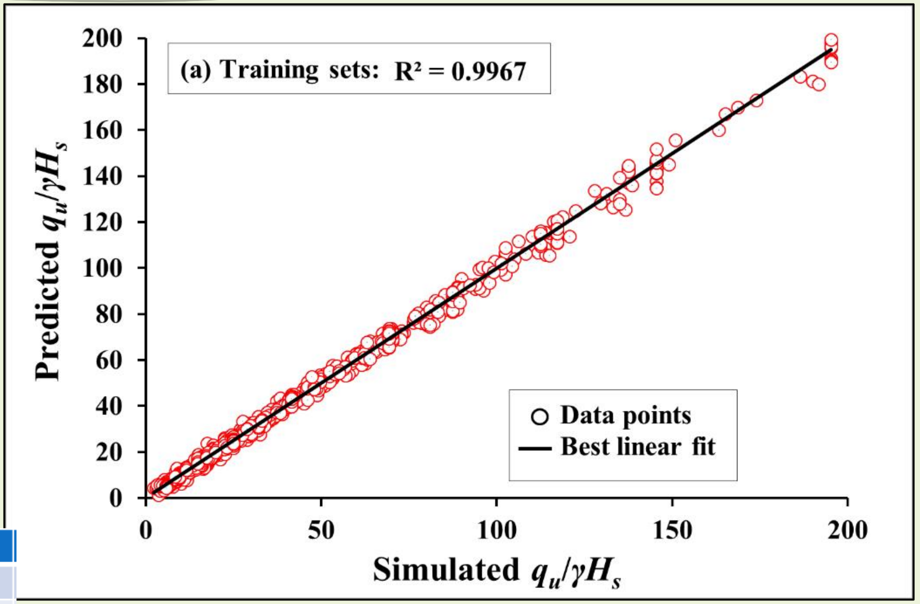


Bearing Capacity of Foundation on Slopes: Performance of MGGP model

Single Strip Footing on Crest of a Marginal Soil Slope

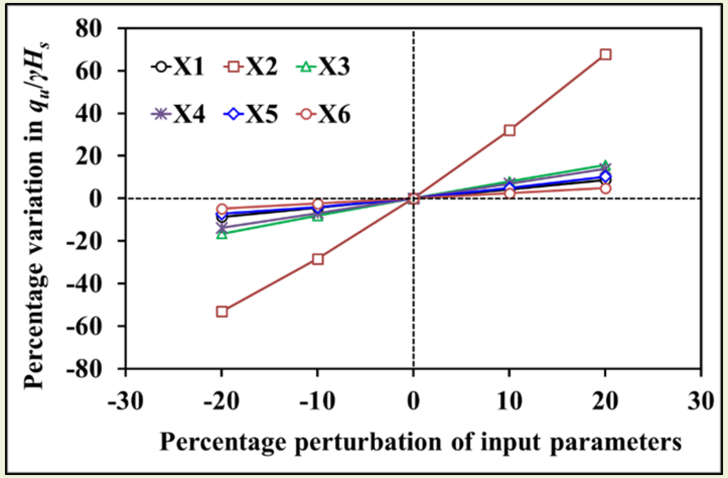
Statistical evaluator	Training	Testing
coefficient of regression (R^2)	0.996	0.997
Nash–Sutcliffe efficiency (NS)	0.996	0.997
Index of Agreement (d)	0.999	0.999
Modified Index of Agreement ($d_{Modified}$)	0.995	0.991

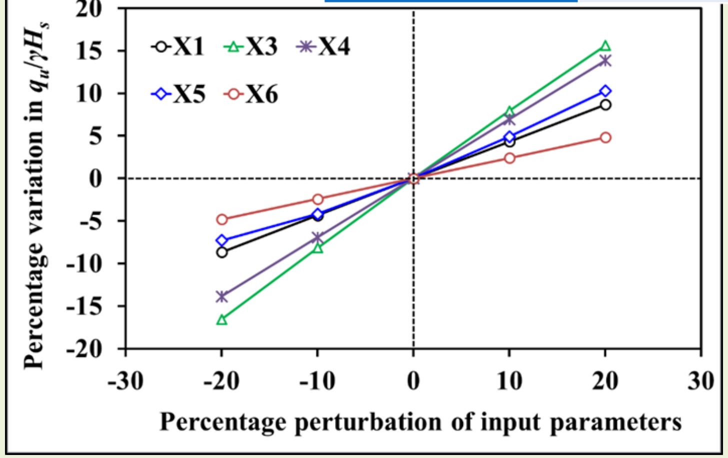
Multiple Statistical Evaluators

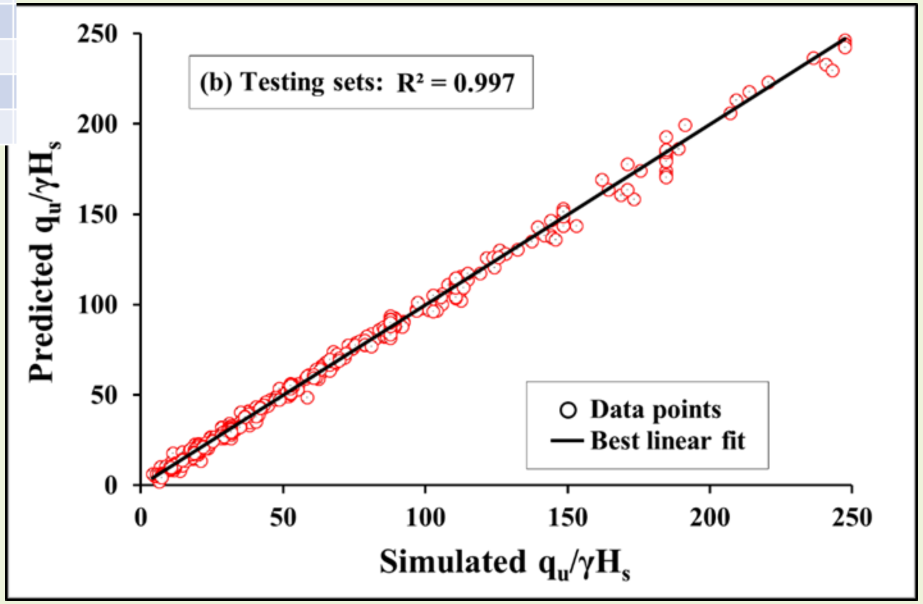


Input parameters	MGGP notation
c (kPa)	X_1
φ (°)	X_2
B (m)	X_3
b/B	X_4
β (°)	X_5
D_f/B	X_6

Sensitivity Analysis: Local Perturbation





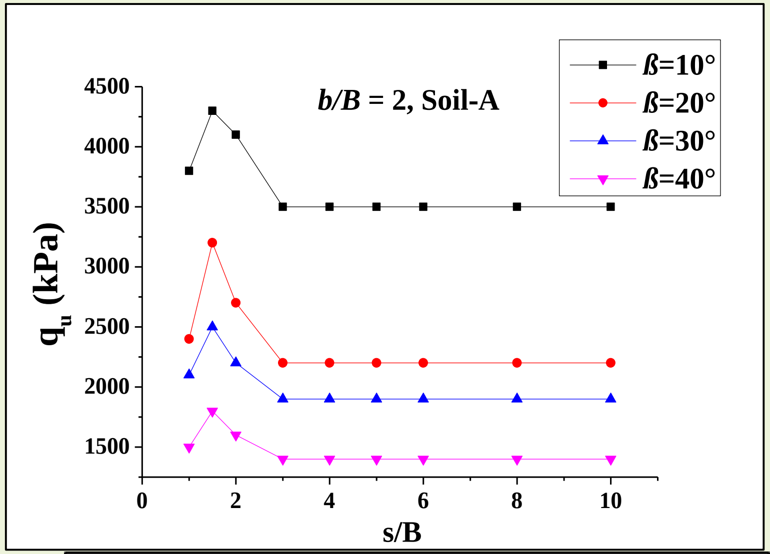


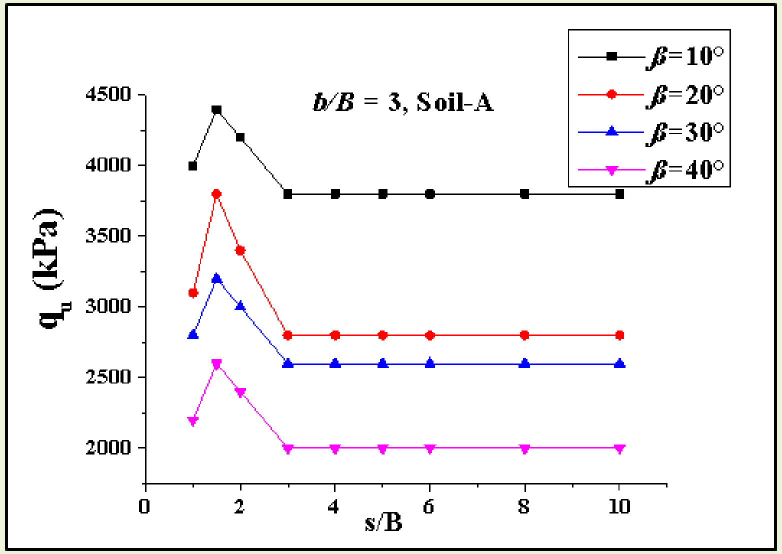
GIGO

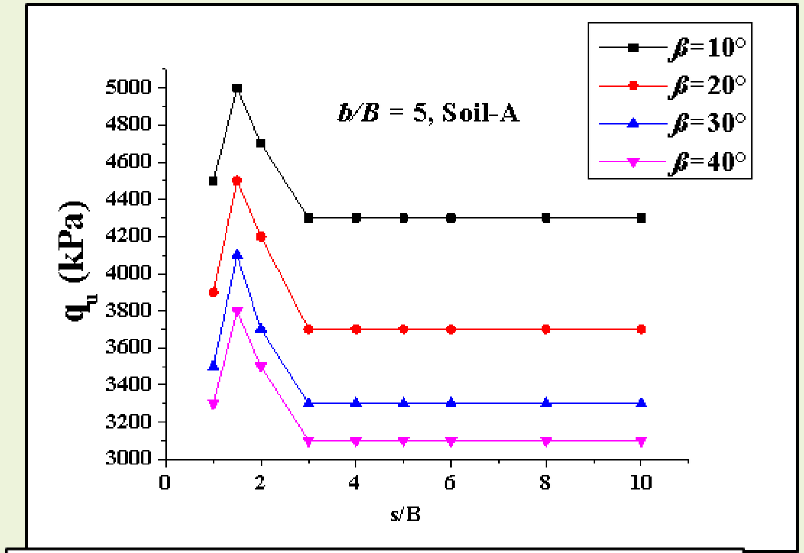
Bearing Capacity of Foundation on Slopes

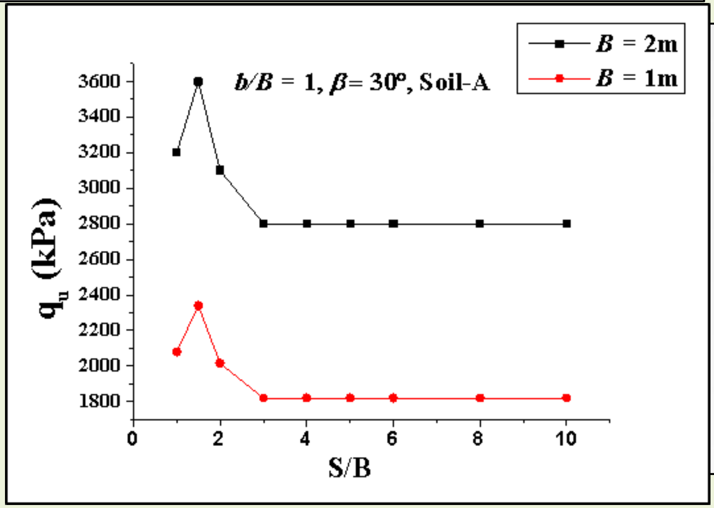
Be Cautious

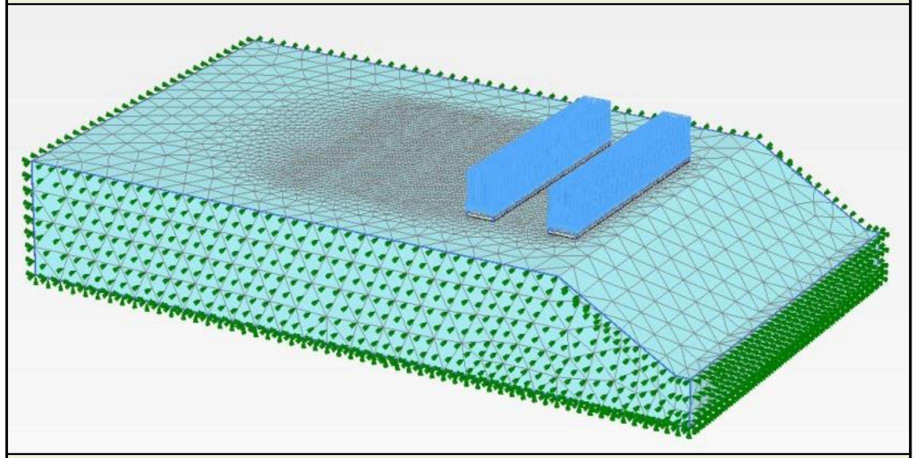
Interfering Strip Footing on Crest of a Marginal Soil Slope

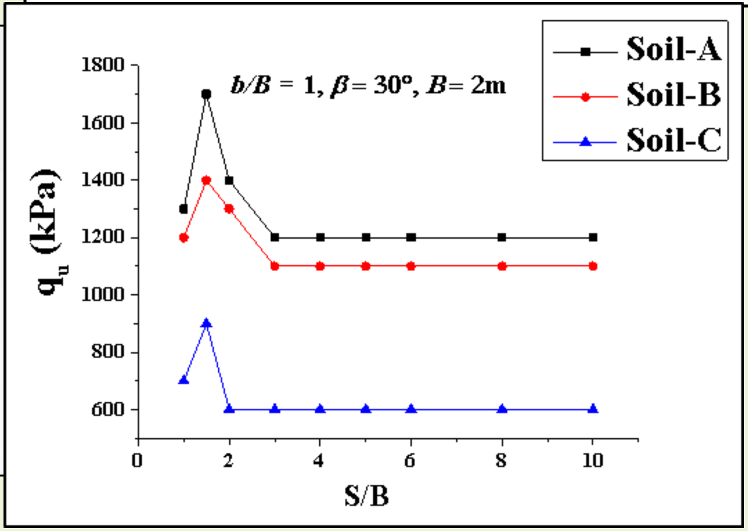






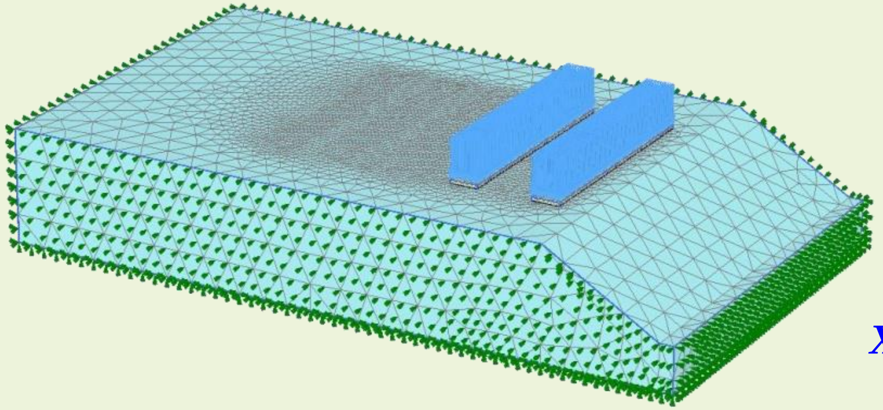






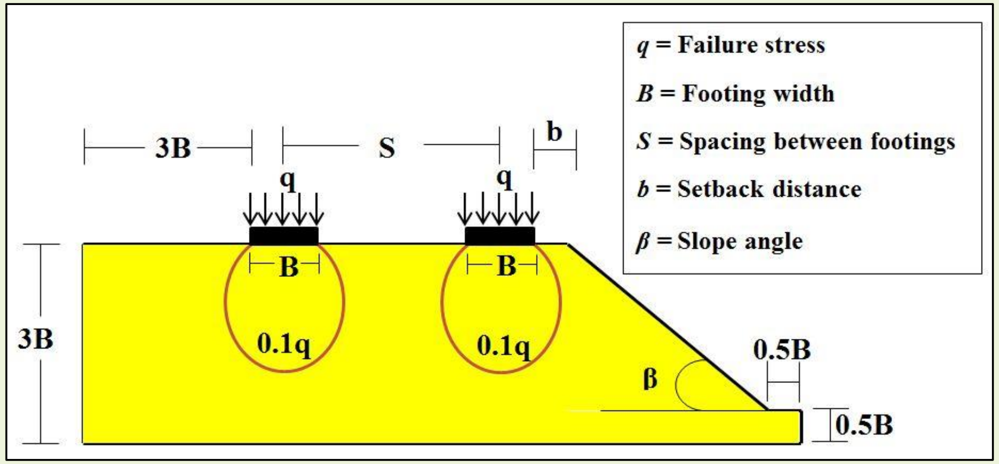
Bearing Capacity of Foundation on Slopes: Performance of MGGP Model

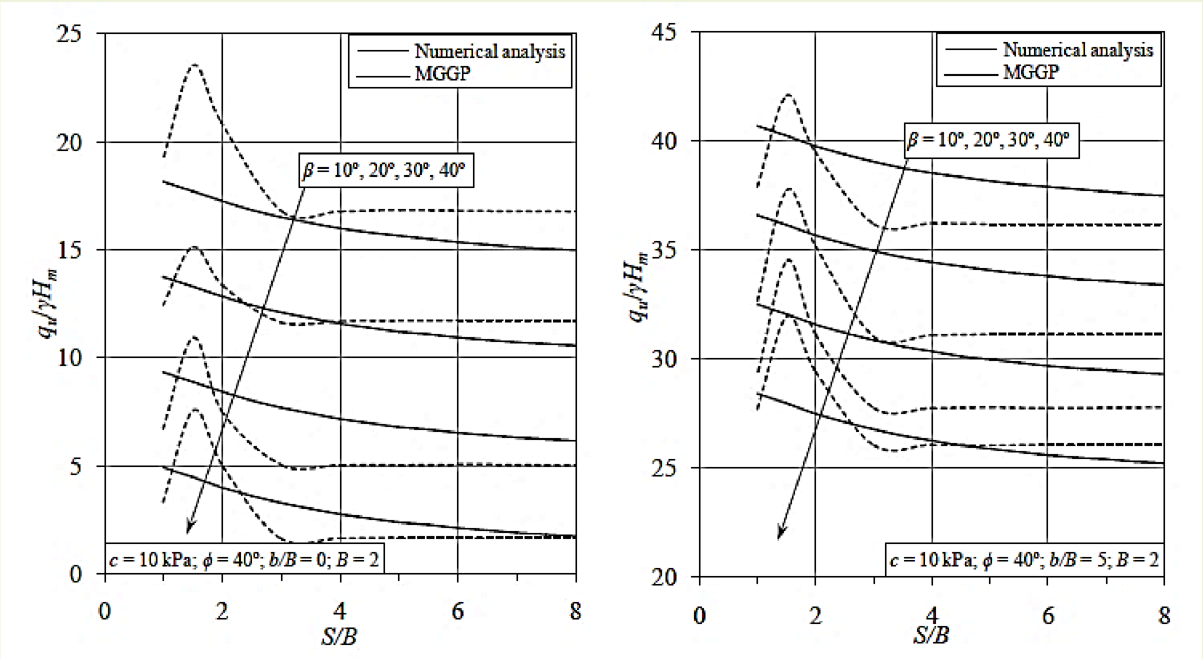
Interfering Strip Footing on Crest of a Marginal Soil Slope



$$q_u/\gamma H_m = \left[0.015X_2X_4e^{X_3} - 0.441X_6 - 4.959e^{-\left(\frac{2.764}{X_5}\right)} - 3.595\times10^{-7}e^{0.203X_1} + \frac{0.0013X_1X_4X_6}{X_3} + 22.9 \right]$$

X_1 = Cohesion (c), X_2 = Angle of internal friction (φ), X_3 = Width of footing (B), X_4 = Setback distance ratio (b/B), X_5 = Spacing ratio (S/B) and X_6 = Slope angle (β)





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Be Cautious

Artificial Intelligence is Required for Advancement

BUT IN THE PROCESS

Are we Ourselves Demeaning our Natural Intelligence???

AI/ML Techniques are finally Mathematical Representations of Physical Problems

Why to use AI/ML in Engineering Problems?
Where to integrate AI/ML in Engineering Problems?
Are we intelligently using AI/ML or blindly following a black-box?

Acknowledgement

- **Organizers of the Event**
  - *A platform to discuss interesting issues related to the application of artificial intelligence in traditional geotechnical engineering*
- **A special appreciation to the contributors**
  - *The workforce to bring out the intricate findings*





- **All those researchers who laid the foundation of present day discussions**

Thank You for Patient Hearing

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