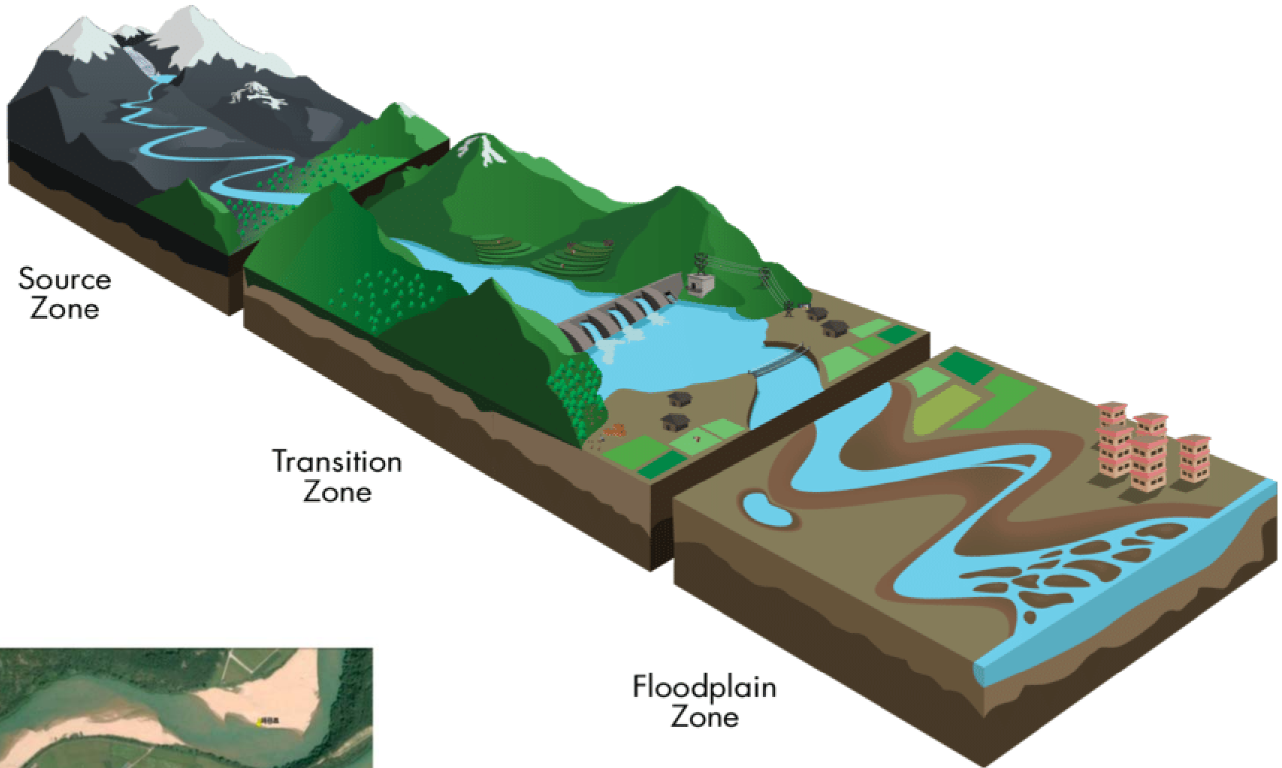
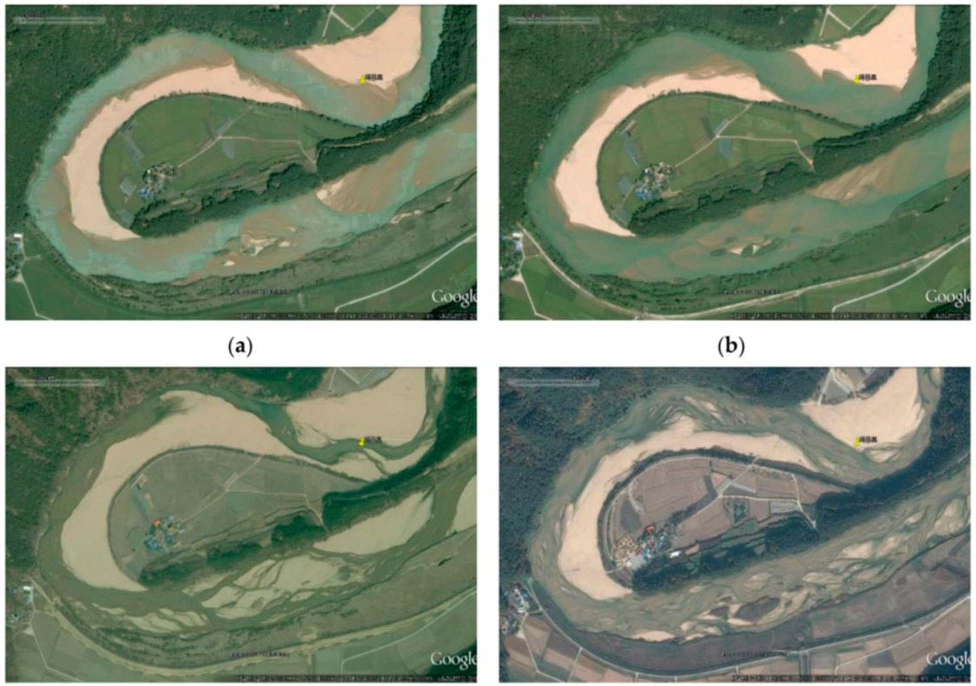
ML Applications for River Hydromorphology

Motivation

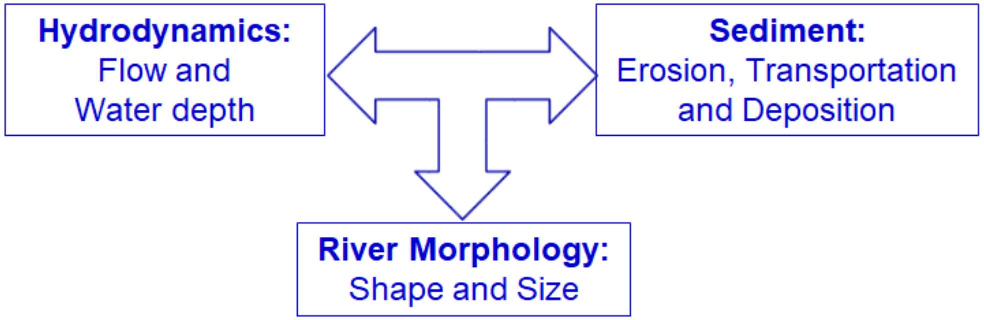
River responds to changes in geohydrological and hydromorphological factors

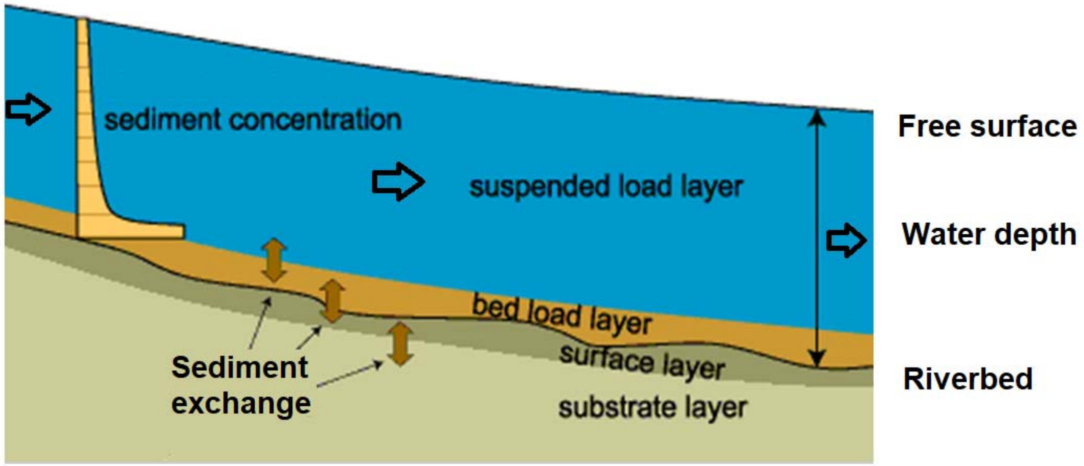


https://www.nps.gov/subjects/geology/fluvial-landforms.htm



(a) (b) (c) (d)





Commonly used approaches for hydromorphology:

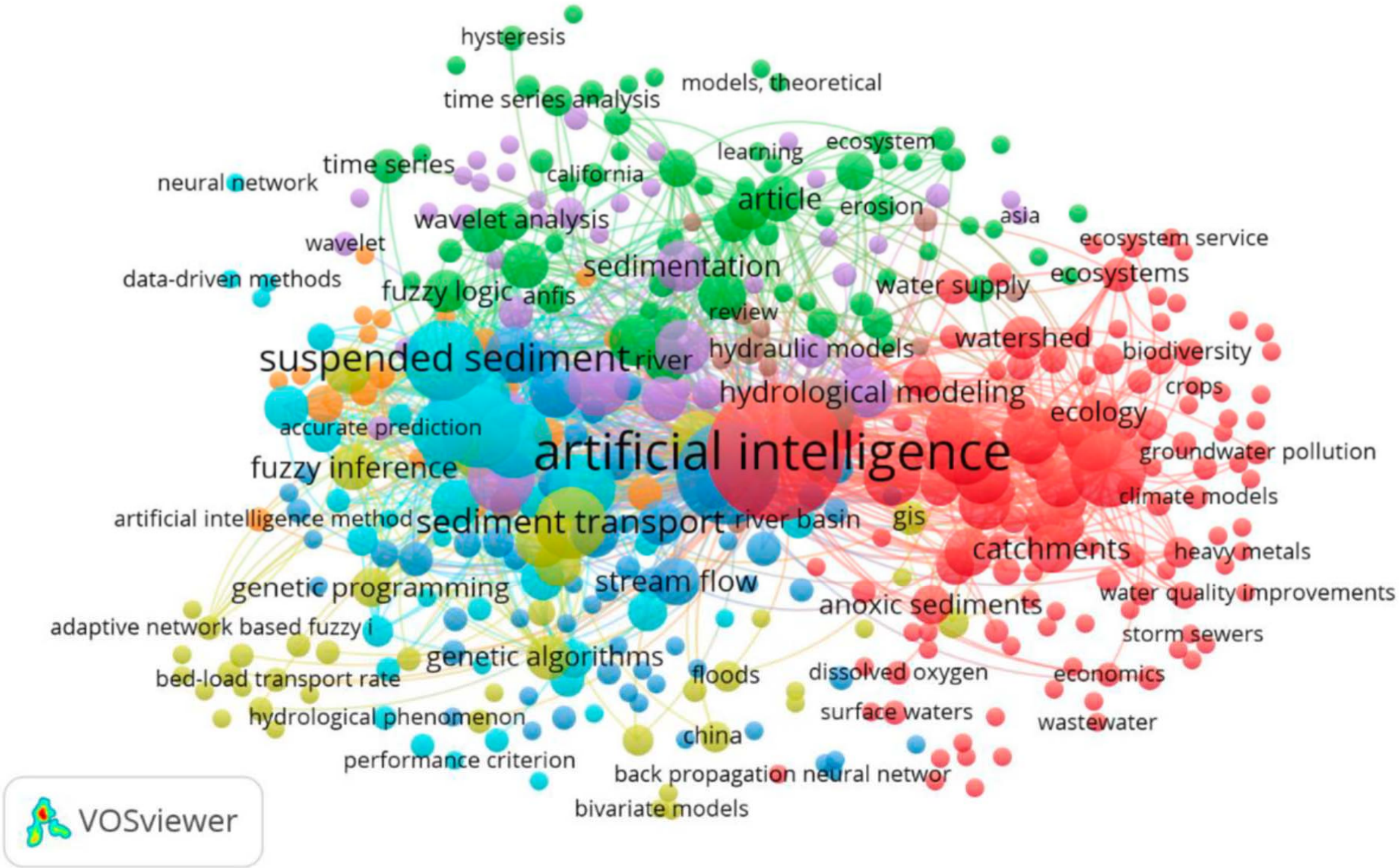
- Physical based or deterministic models: physical laws
- Empirical models: observed data and predefined relationship

$\Rightarrow$ A nonlinear partial differential equations system with initial and boundary conditions

- Numerical methods
- Model parameters need to be calibrated

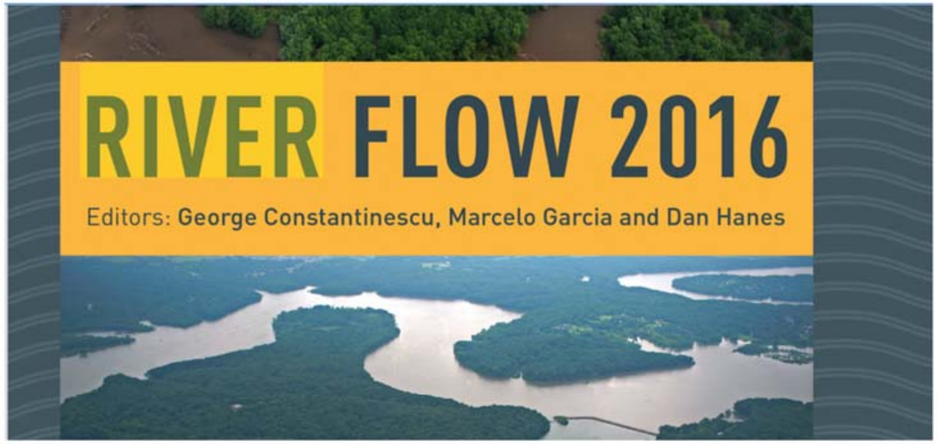
ML approaches for hydromorphology:

- Explore complex nonlinear relationship from data set
- Save CPU-time and improve predictive accuracy



Frequently used keywords on river sediment prediction employing artificial intelligence / Machine learning models

Example 6.1



Application of artificial neural networks for river regime

M.D. Bui[1], D. Huber[1], K. Kaveh[1], A.M. da Silva[2], P. Rutschmann[1]

- An alluvial stream does not accept any channel form provided for it by humans or nature. Instead, it creates the stable or regime channel, which, under ideal conditions, does not vary with time.
- Conventional regime models:
  - ✓ establish the relationship between the geometry of a stable channel (width, depth and slope) and the external controls (water discharge and sediment load).
  - ✓ are almost empirical methods (need prior knowledge about the nature of the relationships among the data) and have restricted ranges of application.
- Artificial neural networks (ANN):
  - ✓ learn from data examples to capture the subtle relationships among the data, even if the underlying relationships are unknown or the physical meaning is difficult to explain.
  - ✓ have proven a high tolerance against data sample errors.

➢ Develop an optimal ANN model for regime channel characteristics.

Data

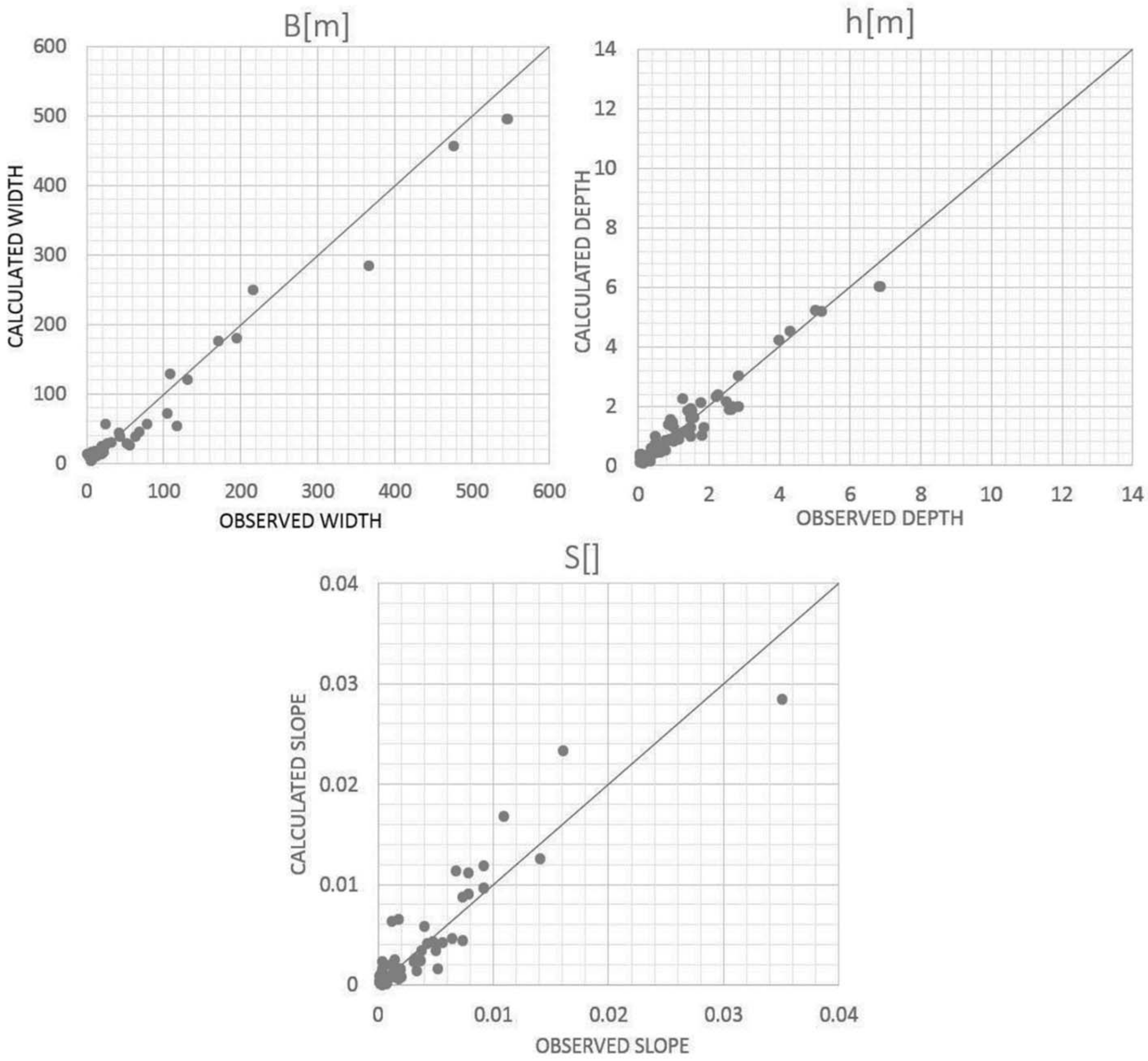
- The regime channels are assumed to be of the “R-type” (Yalin and da Silva, 2001), and thus determined by the bankfull discharge (*Q*) and the grain size *D*.
- A data set of 509 observations collected by different authors has been divided randomly into three subsets: 70% for training, 5% for validating,15% for testing.

Limit	h(m)	B(m)	S(-)	D(m)	Q(m^3/s)
lower	0.018	0.3475	35×10^{-6}	55×10^{-6}	0.0037
upper	20.12	1381.40	0.06	0.1758	42468.9

- Since the different behavior of sand- and gravel-bed channels regarding the grain size a distinction is necessary: D_1 for sand and D_2 for gravel.
- Since the difference between max and min water discharge as well as the variation of its observation accuracy is very large, the dataset is divided into two groups concerning the discharge: Q_1 for Q < 2 m^3/s and Q_2 for the rest.

Designed network

- The ANN architecture was modified by changing the number of hidden layers and its neurons, the initial weights, as well as the type of the transfer function (>70 models).
- An optimal model was determined based upon evaluating the difference and correlation between the predicted values and the desired outputs.



Model evaluation

- Performance indices of various methods for the testing data set: ANN is compared against the Thermodynamic Entropy Theory (Yalin and da Silva, 2001) and the Stability Theory (Julien and Wargadalam,1995).

		B[m]	h[m]	S[-]
ANN	**RMSE**	17.7	0.3	0.0019
	R	0.990	0.970	0.929
Yalin & da Silva	**RMSE**	37.9	1.2	0.0053
	R	0.935	0.897	0.866
Julien & Wargadalam	**RMSE**	37.2	2.5	0.0050
	R	0.930	0.886	0.842

Explicit ANN-based equations

$$B = LW^{B} \times \text{tansig}\left(IW^{B} \times \begin{bmatrix} Q_1 \\ Q_2 \\ D_1 \\ D_2 \end{bmatrix} + \vec{b}^{B} \right) + c^{B}$$

$$h = LW^{h} \times \text{tansig}\left(IW^{h} \times \begin{bmatrix} Q_1 \\ Q_2 \\ D_1 \\ D_2 \\ B \end{bmatrix} + \vec{b}^{h} \right) + c^{h}$$

$$S = LW^{S} \times \text{logsig}\left(IW^{S} \times \begin{bmatrix} Q_1 \\ Q_2 \\ D_1 \\ D_2 \\ B \\ h \end{bmatrix} + \vec{b}^{S} \right) + c^{S}$$

1. Width

IW^B			
2.6327	1.4804	2.0225	0.8001
-1.0993	0.3084	-0.3891	-11.2784
-1.8314	0.4307	-0.6335	1.2994

b^B
-5.2570
-0.9797
-0.8232

LW^B		
0.9812	-1.3047	0.7187

c^B
0.4983

2. Depth

IW^h				
-0.4594	-3.5012	-0.9682	-4.1823	-14.9311
0.0933	4.8028	0.1385	-0.6239	4.4082
-0.4844	3.4161	-0.5985	7.2029	1.1162
1.8294	-2.8268	-5.5373	5.9407	-0.9678
1.7722	2.1540	-0.7601	-1.4467	0.6633

b^h
-1.5036
1.1708
1.1566
-0.7627
1.6919

LW^h				
-3.6283	-2.4068	1.7721	0.2590	-2.3036

c^h
-0.4131

3. Slope

IW^S					
11.6941	-10.0254	12.8639	3.9292	-2.2914	1.6707
4.7240	0.7294	4.7956	1.9810	-4.4402	1.2225
42.8973	-0.4062	-3.9882	-8.7085	21.3059	75.8515
-3.3486	5.6306	5.3187	5.7861	8.0982	-10.8346

LW^S			
-0.7132	2.3945	-0.8971	-6.9980

b^S
-9.9386
-5.4758
0.5517
-10.5947

c^S
0.8905

Conclusion

- An explicit neural networks formulation has been developed using sigmoidal shaped activation functions and optimal weights obtained from training processes.
- The ANN based model is found to be capable of predicting channel regime characteristics in a range given for the minimum and maximum data used in network training and validation process.
- The estimations by the ANN model were clearly better than those of two conventional approaches, with lower error (RMSE) and higher correlation coefficient (R).
- The analytical equations obtained by the ANN can also easily be applied for estimating the regime characteristics in other hydromorphological conditions.

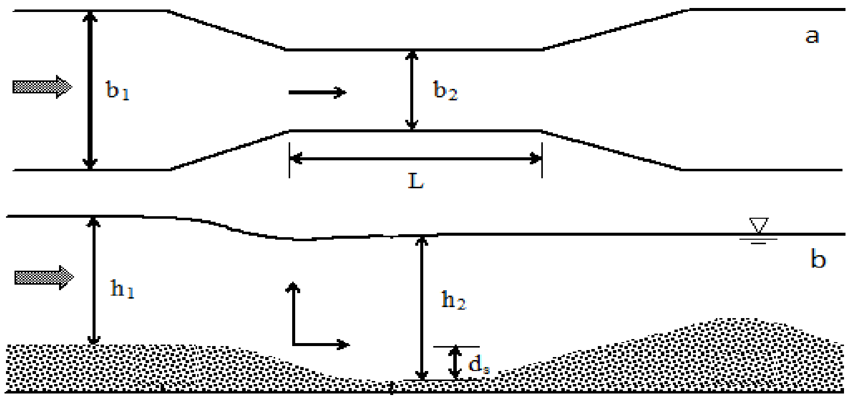
Journal
Journal of Applied Water Engineering and Research ›
Volume 3, 2015 - Issue 2

Example 6.2

Original Articles

Contraction scour estimation using data-driven methods

Minh Duc Bui, Keivan Kaveh, Petr Penz & Peter Rutschmann



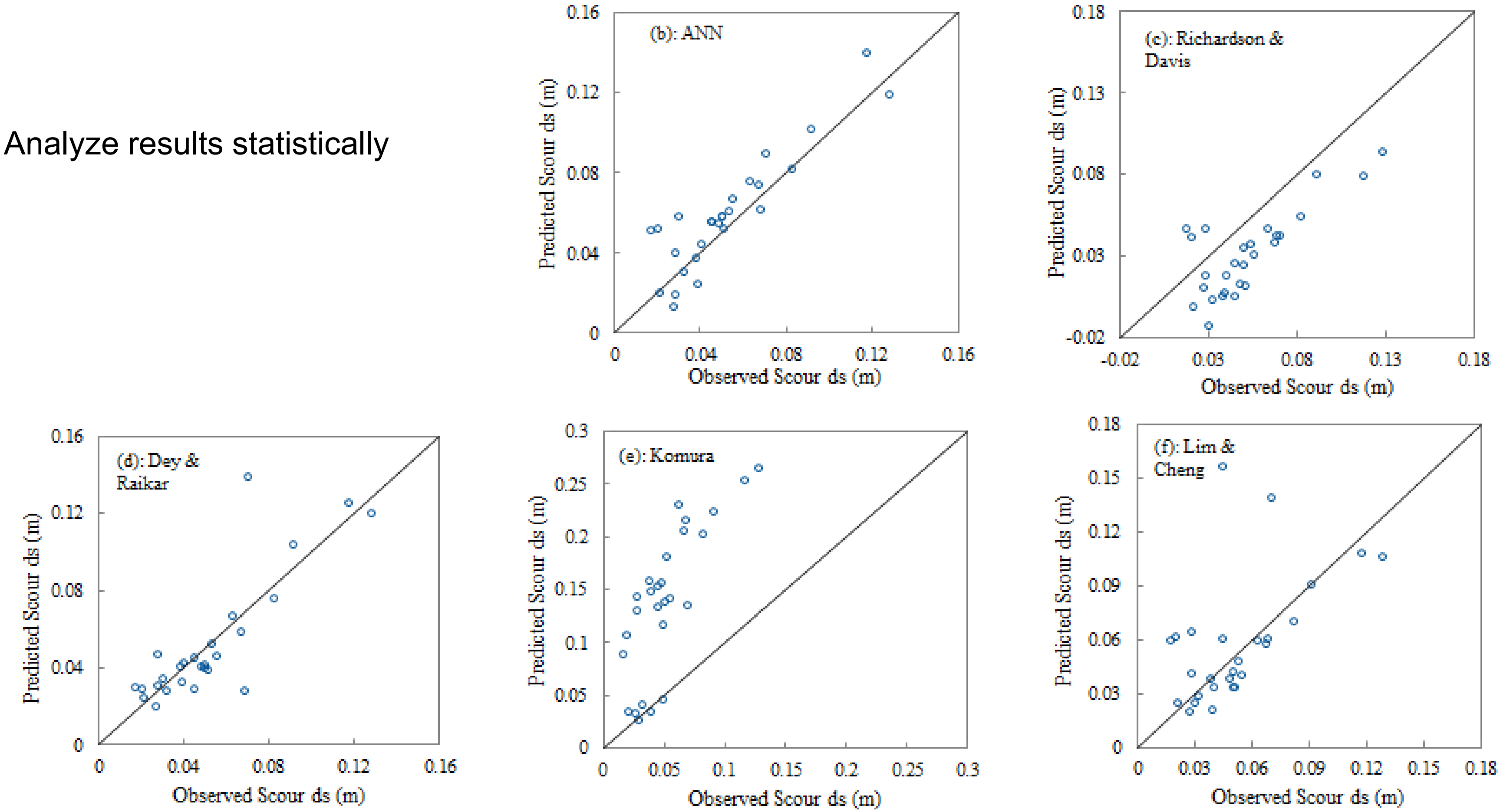
$$\bar{d}_s = \frac{d_s}{b_1};\ \bar{d} = \frac{d_m}{b_1};\ \bar{h} = \frac{h_1}{b_1};\ \bar{b} = \frac{b_2}{b_1};\ \overline{Fr} = \frac{v_1}{\sqrt{\Delta g d_m}};\ \Delta g = \left(\frac{\rho_s - \rho}{\rho}\right) g$$

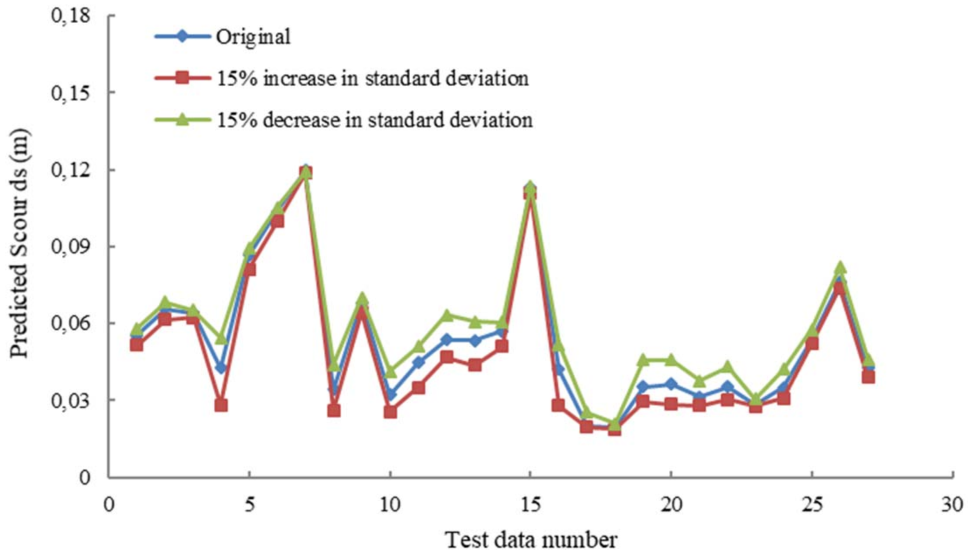
$$\bar{d}_s = F\left(\bar{d}, \overline{Fr}, \bar{h}, \bar{b}, \sigma_g\right)$$

- 182 measured data sets for the equilibrium depth of contraction scour
- Inputs and Output
- Feedforward Multilayer Perceptron (MLP)
- Training and Test: Trial-and-Error

	ANN	Dey & Raikar	Richardson & Davis	Komura	Lim & Cheng
R	0.965	0.836	0.853	0.790	0.748
RMSE [m]	0.015	0.035	0.054	0.170	0.048
MAE [m]	0.006	0.013	0.028	0.084	0.016

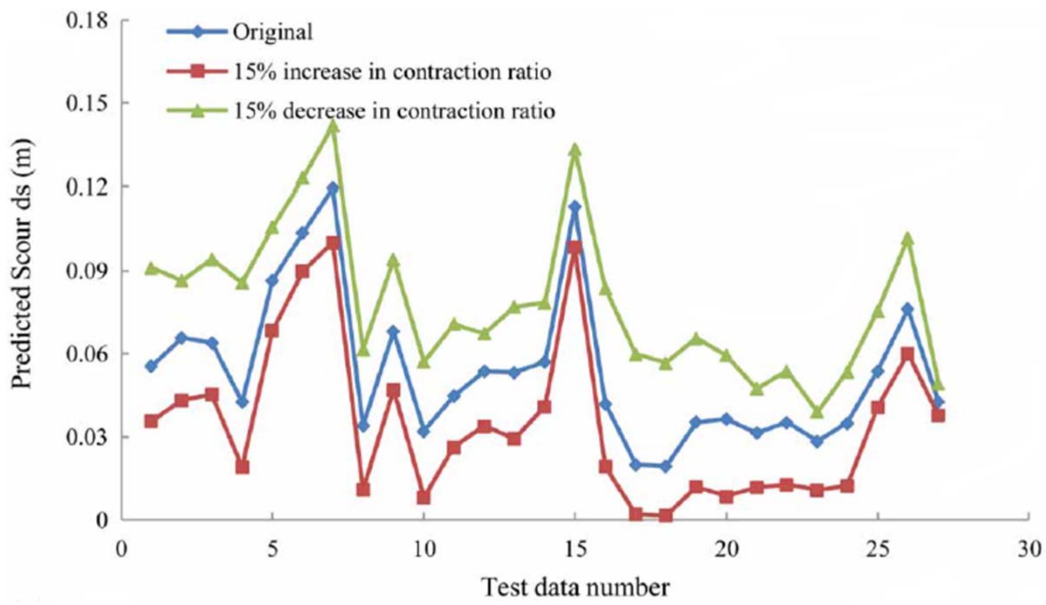
Analyze results statistically





The importance of the individual input parameters was checked with a sensitivity analysis:

- The contraction ratio is the most sensitive parameter, followed by the impact of the formation of the armoring layer for non-uniform sediments.



$$\left(\overline{d_s}\right)_{pr} = LW^{2,1} \times \text{tansig}\left(IW^{1,1} \times \begin{bmatrix} \overline{d} \\ \overline{Fr} \\ \overline{h} \\ \overline{b} \\ \sigma_g \end{bmatrix}_{pr} + b^1 \right) + b^2$$

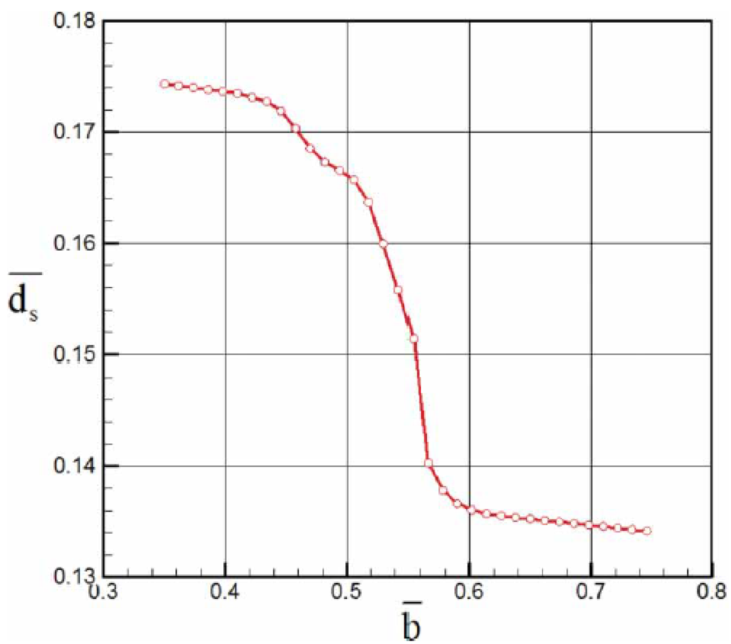
$$\mathrm{IW}^{1,1} = \begin{bmatrix} -61.7540 & 0.7590 & 16.0804 & -2.2736 & -1.3754 \\ -36.1590 & -1.9702 & -18.4141 & 3.2689 & 3.0961 \\ 12.5222 & -0.0331 & -14.5885 & 8.0144 & -0.2061 \\ 112.9620 & 1.4127 & 2.7952 & -5.7359 & -1.0236 \\ -26.4800 & 0.0029 & 13.6386 & 8.1508 & -0.0300 \\ 128.5200 & -1.6282 & 8.8843 & -0.1999 & 0.2204 \\ -65.1840 & -1.1853 & -12.4488 & -0.9877 & -0.6407 \end{bmatrix},$$

$$\mathrm{LW}^{2,1} = [0.0276 \quad -0.0258 \quad -0.0726 \quad 0.0241 \quad -0.0312 \quad 0.2775 \quad -0.0295],$$

$$\vec{b}^{\,1} = \begin{bmatrix} 2.1017 \\ 1.7659 \\ -0.0878 \\ 0.1017 \\ -7.2220 \\ 4.7620 \\ 3.9530 \end{bmatrix},$$

$$b^2 = [-0.1876].$$

- The trained network maps non-linear input-output relationships in complex systems.
- In the form of a matrix equation.



Physical suitability of the ANN-based model

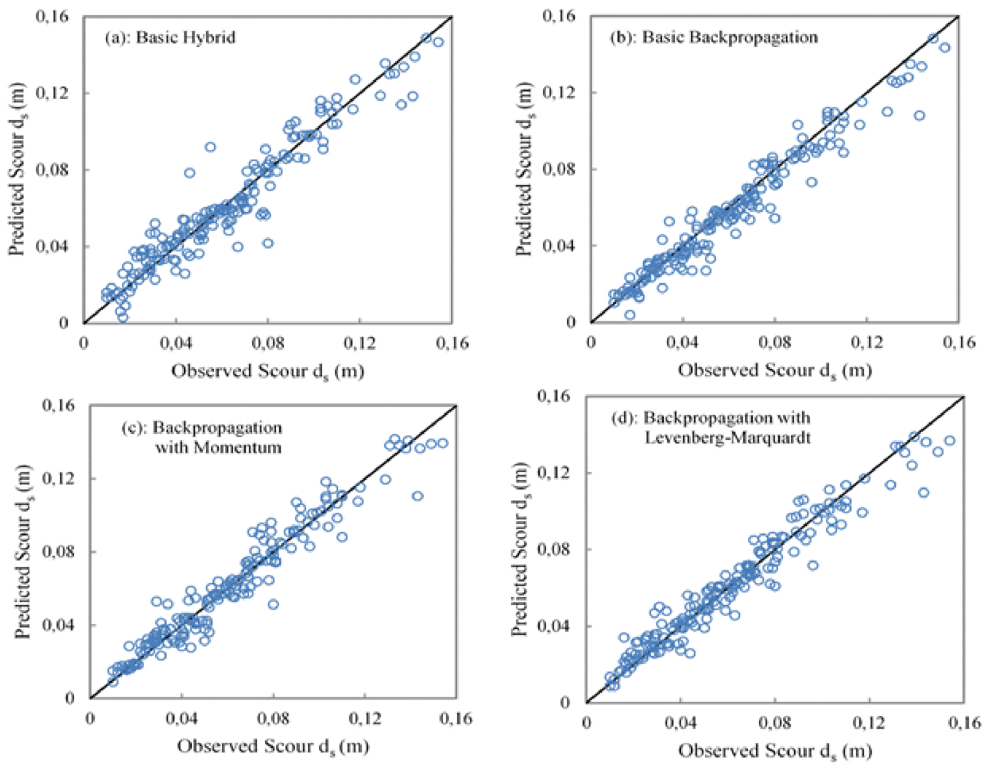
IOSR JOURNAL OF MECHANICAL AND CIVIL ENGINEERING (IOSR-JMCE)
e-ISSN: 2278-1684,p-ISSN: 2320-334X, Volume 14, Issue 3 Ver. V. (May - June 2017), PP 18-32
www.iosrjournals.org

Performance Analysis Of Different Model Architectures Utilized In An Adaptive Neuro Fuzzy Inference System For Contraction Scour Prediction

Minh Duc Bui[1], Keivan Kaveh[1], Peter Rutschmann[1]
[1](Institute of Hydraulic and Water Resources Engineering, Technical University of Munich, Germany)

Testing different ANFIS networks and training methods.

⇒ Using the zero-order Takagi-Sugeno model with 4 bell-shaped membership functions for each input, the Levenberg-Marquardt algorithm for training yields best results for contraction scour depth.



Example 6.3

Article

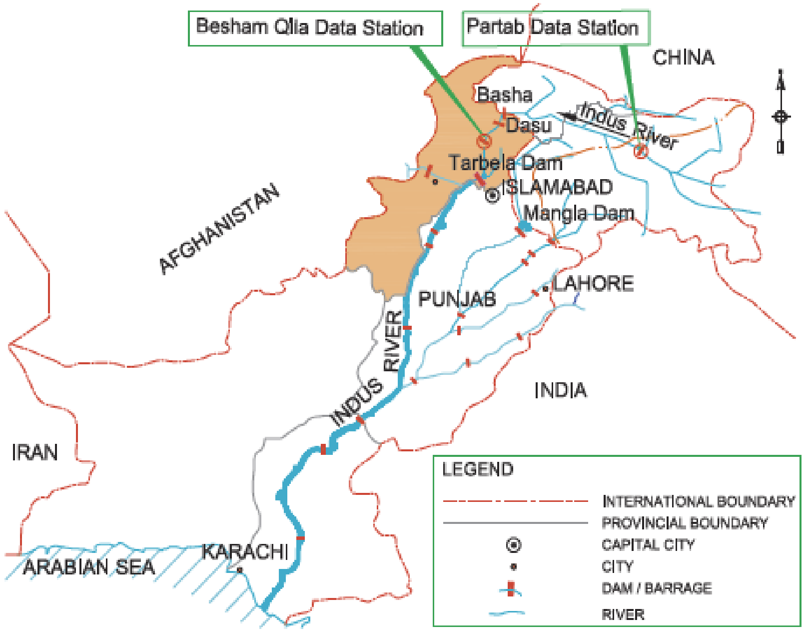
Variability and Trend Detection in the Sediment Load of the Upper Indus River

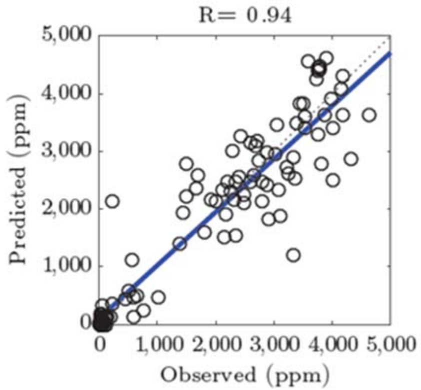
Sardar Ateeq-Ur-Rehman *, Minh Duc Bui and Peter Rutschmann

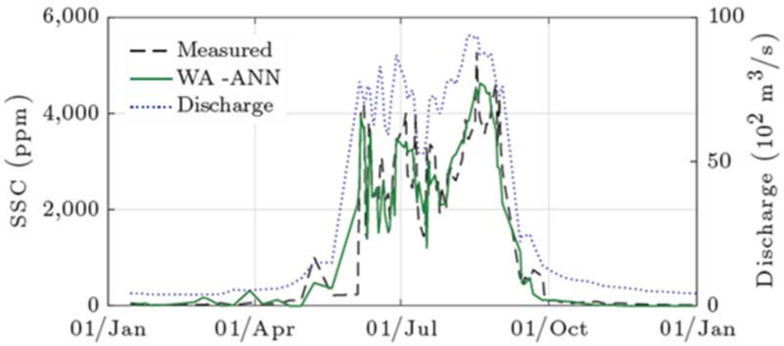
- Estimation of the sediment load for boundary conditions in numerical models.
- Very difficult to estimate accurately in an area with a strong hysteresis phenomenon and a disproportionate spatio-temporal trend between water runoff and suspended sediment rate.
- Development of an ANN model combined with Discrete Wavelet Transform (WAANN).

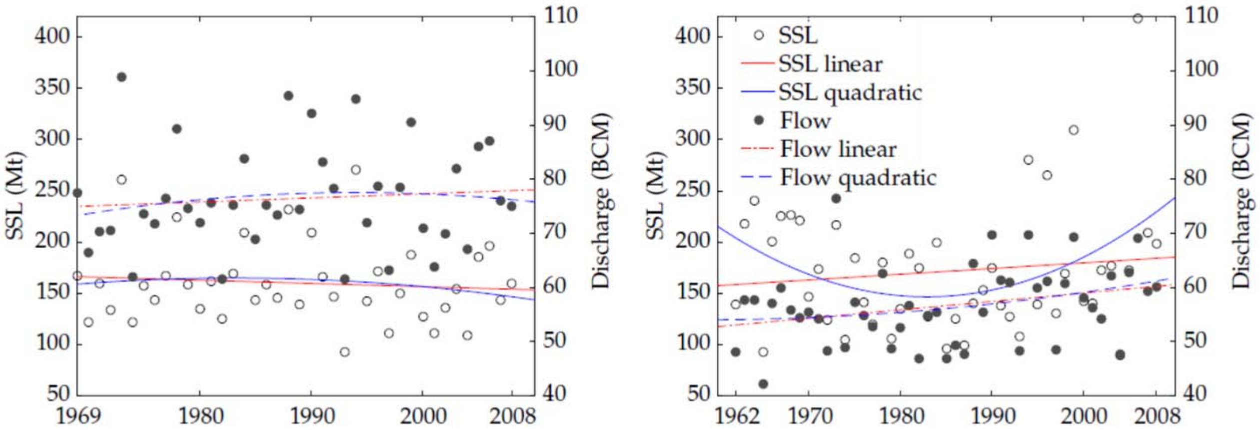
$$f_i = A_{M,i} + \sum_{m=1}^{M} \sum_{n=0}^{(2^{M-m}-1)} W_{m,n} 2^{\frac{m}{2}} \Psi\left(2^{-m} i - n\right)$$

$$f_i = A_{M,i} + \sum_{m=1}^{M} D_{m,i}$$









(a) Besham Qila (b) Partab Bridge

- WA-ANN gives good results for the extraordinary events and fills the gap between the intermittent measurements of the suspended sediment concentration (SSC).
- Analysis of the temporal change in sediment transport rates (SSL) and water runoff using non-parametric trend tests.

International Journal of Sediment Research 32 (2017) 340–350

Contents lists available at ScienceDirect

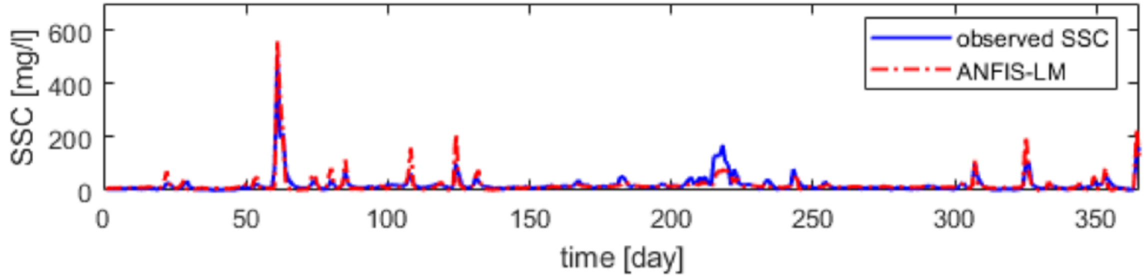
International Journal of Sediment Research

journal homepage: www.elsevier.com/locate/ijsrc

Original Research

A comparative study of three different learning algorithms applied to ANFIS for predicting daily suspended sediment concentration

Keivan Kaveh*, Minh Duc Bui, Peter Rutschmann

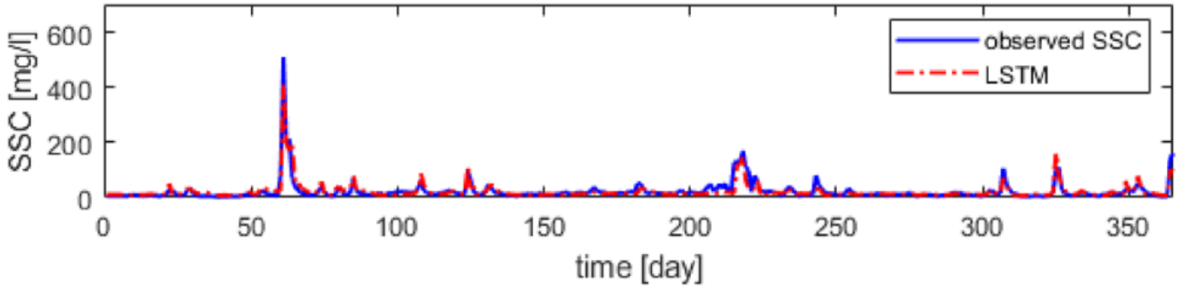


Engineering with Computers
An International Journal for Simulation-Based Engineering
ISSN 0177-0667
Engineering with Computers
DOI 10.1007/s00366-019-00921-y

ORIGINAL ARTICLE

Long short-term memory for predicting daily suspended sediment concentration

Keivan Kaveh[1] · Hamid Kaveh[2] · Minh Duc Bui[1] · Peter Rutschmann[1]

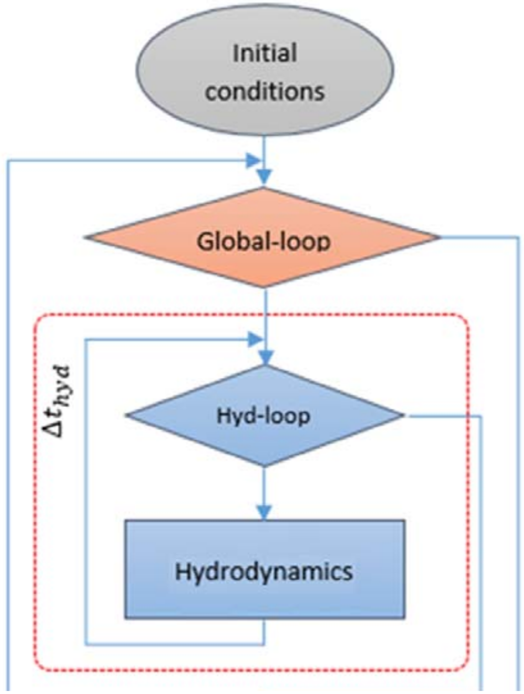


Example 6.4 New concept for hydromorphological modelsystems

$$\frac{\partial z_b}{\partial t} = -\frac{1}{1-p}\frac{\partial q_b}{\partial x}$$

$$\frac{\partial z_b}{\partial t} + C(z_b)\frac{\partial z_b}{\partial x} = 0 \qquad C(z_b) = \frac{1}{1-p}\frac{\partial q_b}{\partial z_b}$$

- Using Empirical Formulas to Calculate Sediment Transport Rates in Exner's Equation :
  - The results of the different formulas often vary widely.
  - In many cases unsatisfactory morphological changes are predicted.

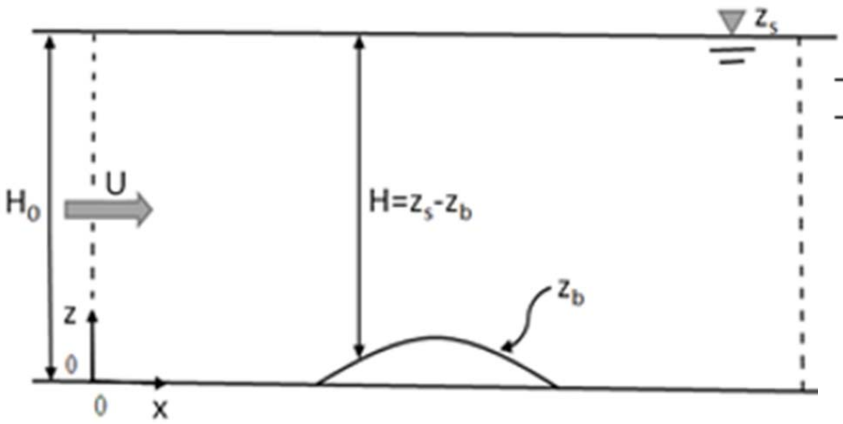


IAHR AIRH
Supported by CEDEX
IAHR 2015

E-proceedings of the 36th IAHR World Congress
28 June – 3 July, 2015, The Hague, the Netherlands

Integrating artificial neural networks into hydromorphological model for fluvial channels

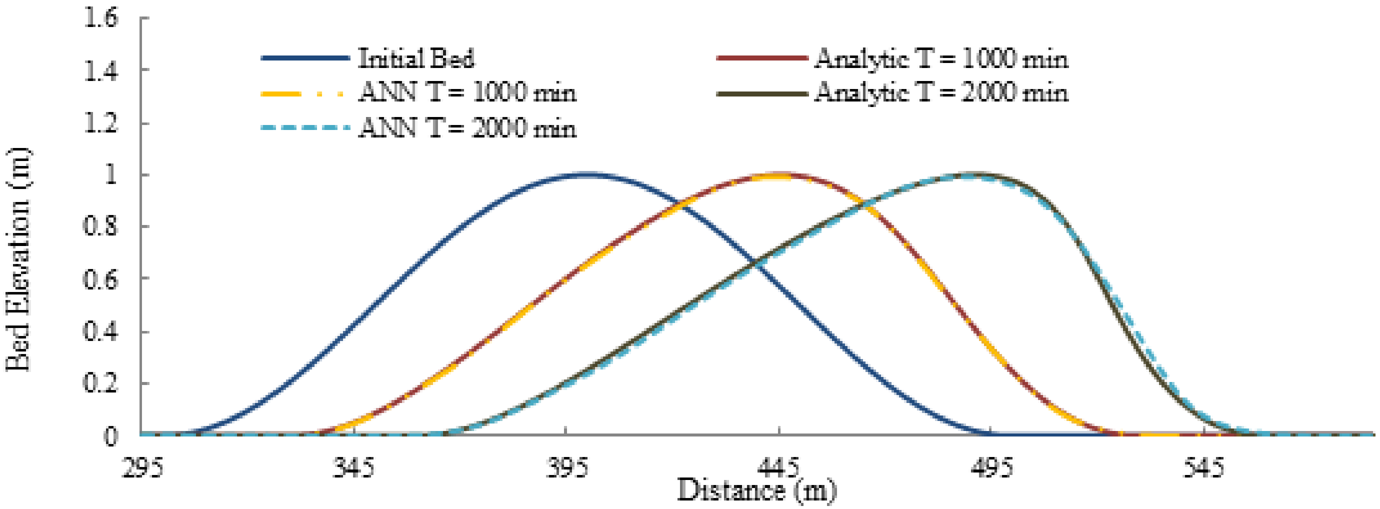
MINH DUC BUI [1], KEIVAN KAVEH [2] & PETER RUTSCHMANN [3]



Test case	Test parameters		ANN
Sinusoidal	$Q = 9m^3/s$, $T = 42min$, $W = 190$, $H = 0.9$	R	0.999938
		RMSE	0.004196
		MAE	0.003382
Gaussian	$Q = 7m^3/s$, $T = 47min$, $W = 0.0009$, $H = 0.7$	R	0.999946
		RMSE	0.002789
		MAE	0.001772
Fractional	$Q = 11m^3/s$, $T = 33min$, $W = 190$, $H = 0.55$	R	0.997888
		RMSE	0.008145
		MAE	0.003714

$$z_{bi}^{(n+1)} = LW^{2,1} \times \text{logsig}\left(IW^{1,1} \times \begin{bmatrix} z_{bi}^{n} \\ z_{b(i-1)}^{n} \\ U_i^{n} \\ U_{(i-1)}^{n} \end{bmatrix} + \vec{b}^1 \right) + b^2$$

→ Stable numerical solution with a large time step (3000 times larger than using conventional numerical methods)



Advances in Engineering Software 132 (2019) 18–28

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Integration of artificial neural networks into TELEMAC-MASCARET system, new concepts for hydromorphodynamic modeling

Keivan Kaveh*, Minh Duc Bui, Peter Rutschmann

Institute of Hydraulic and Water Resources Engineering, Technische Universität München, Arcisstraße 21, D-80333 München, Germany

A new concept for sediment transport in gravel bed rivers

water MDPI

Article

Combination of Discrete Element Method and Artificial Neural Network for Predicting Porosity of Gravel-Bed River

Van Hieu Bui [1,2,*], Minh Duc Bui [1] and Peter Rutschmann [1]

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water MDPI

Article

The Prediction of Fine Sediment Distribution in Gravel-Bed Rivers Using a Combination of DEM and FNN

Van Hieu Bui [1,2,*], Minh Duc Bui [1] and Peter Rutschmann [1]

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Motivation: Limitations of current models

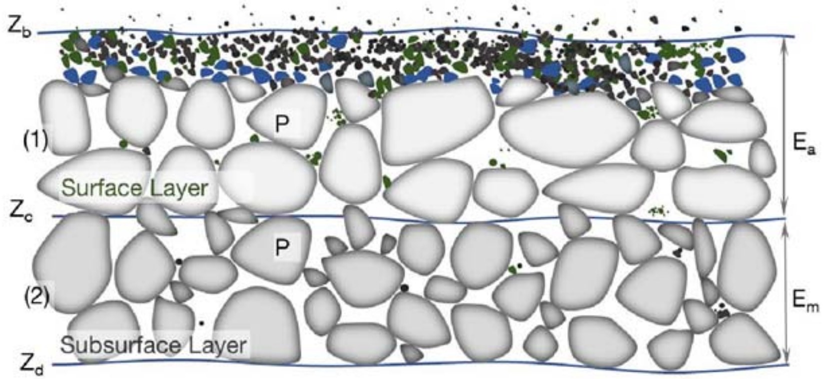
- Consider the porosity as a constant
- Fine sediment exchange in the voids contributes on morphological changes
- Neglect the fine sediment exchange between layers

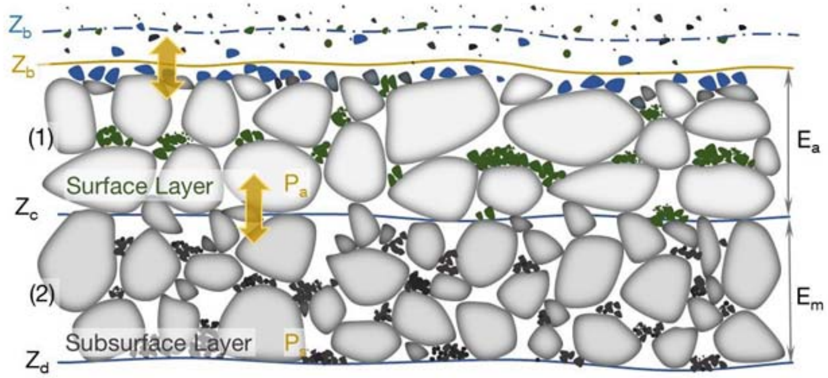
⇒ Develop a framework combining the Discrete Element Method (DEM) and Machine Learning (ANN) to predict the porosity and fine sediment distribution.

⇒ Analyze the bed characteristics by using the developed algorithms and applying the image processing.

⇒ Build a new numerical model for bed variation of gravel-bed rivers considering porosity variation and exchange flux of fine sediment between two layers.

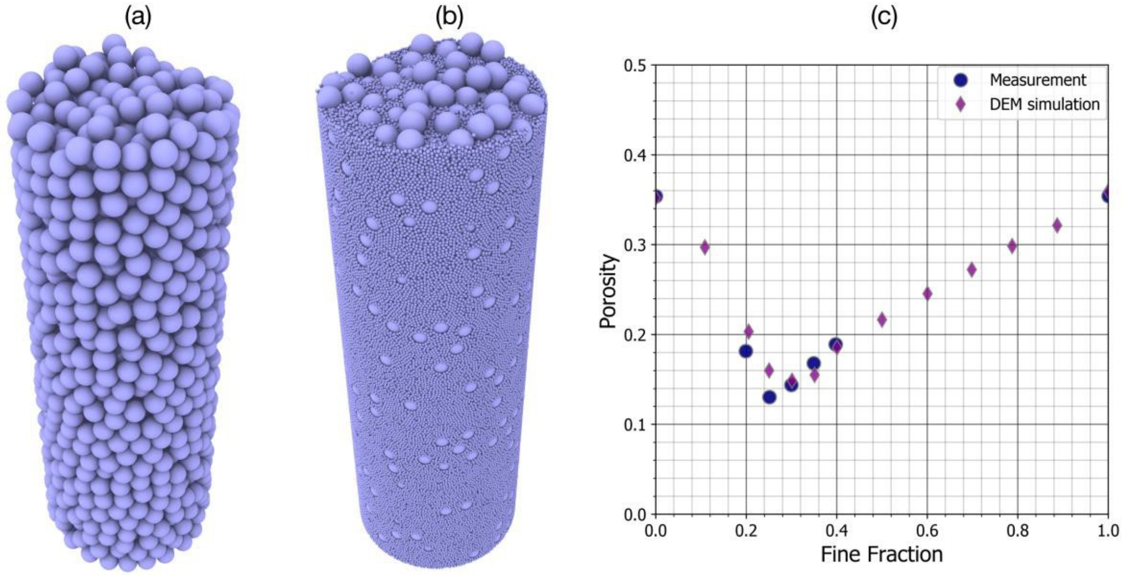
⇒ Verify the combine framework of DEM and ANN and to test the new bed variation model.

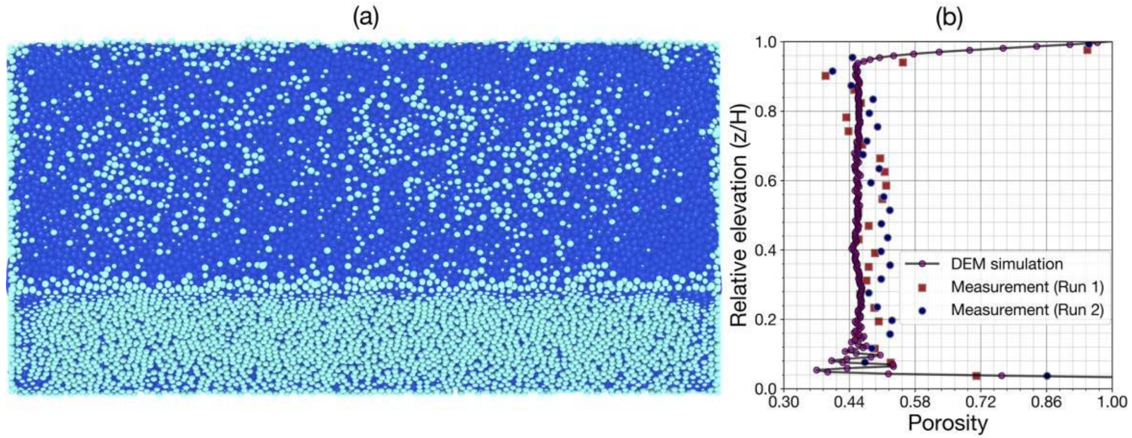




Verification of DEM porosity simulations

- Samples
  - Pure gravel (a): 1864 grains porosity 0.3520
  - Fine fraction 0.4003 (b): porosity 0.1856, 355891 grains.
- Gravel bed
  - Flume filled by uniform gravel with D = 8 mm with the experimental porosity.
  - Porosity obtained from DEM simulations in comparison with the porosity measurement of Navaratnam, Aberle et al. (2018).



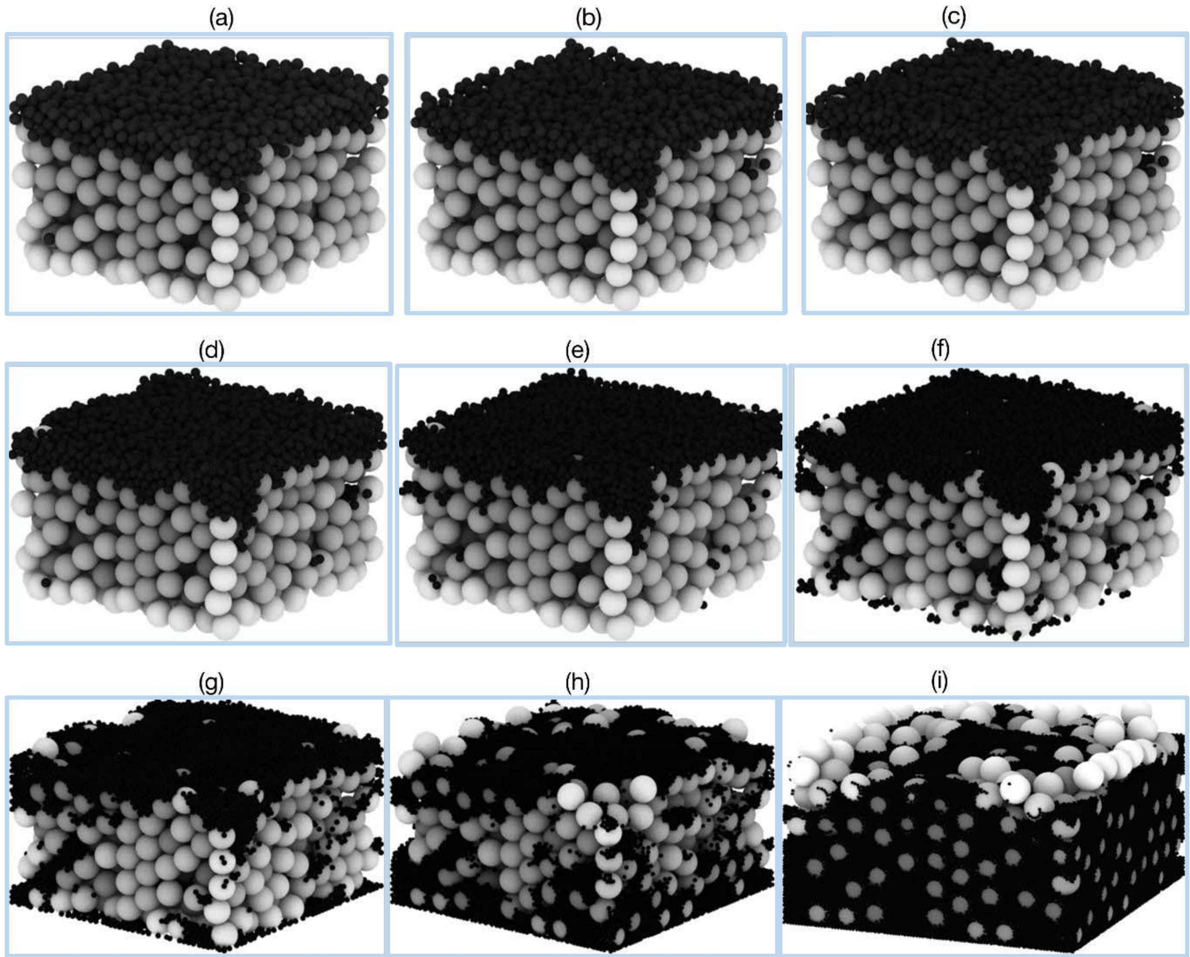


DEM simulation of fine sediment exchange rates

- Different ratios (d/D): 0.45, 0.414, 0.4, 0.35, 0.3, 0.25, 0.20, 0.15, 0.10

  - (d_m/D_m) Larger than 0.45 impossible to get infiltration
  - 0.414, 0.40, 0.35, 0.30 bridging
  - 0.25, 0.20, 0.15 partially impeded percolation

- Smaller than 0.1 statistic percolation



DEM simulation of fine sediment exchange rates

- Different ratios (d/D): 0.45, 0.414, 0.4, 0.35, 0.3, 0.25, 0.20, 0.15, 0.10
  - (d_m/D_m) Larger than 0.45 impossible to get infiltration
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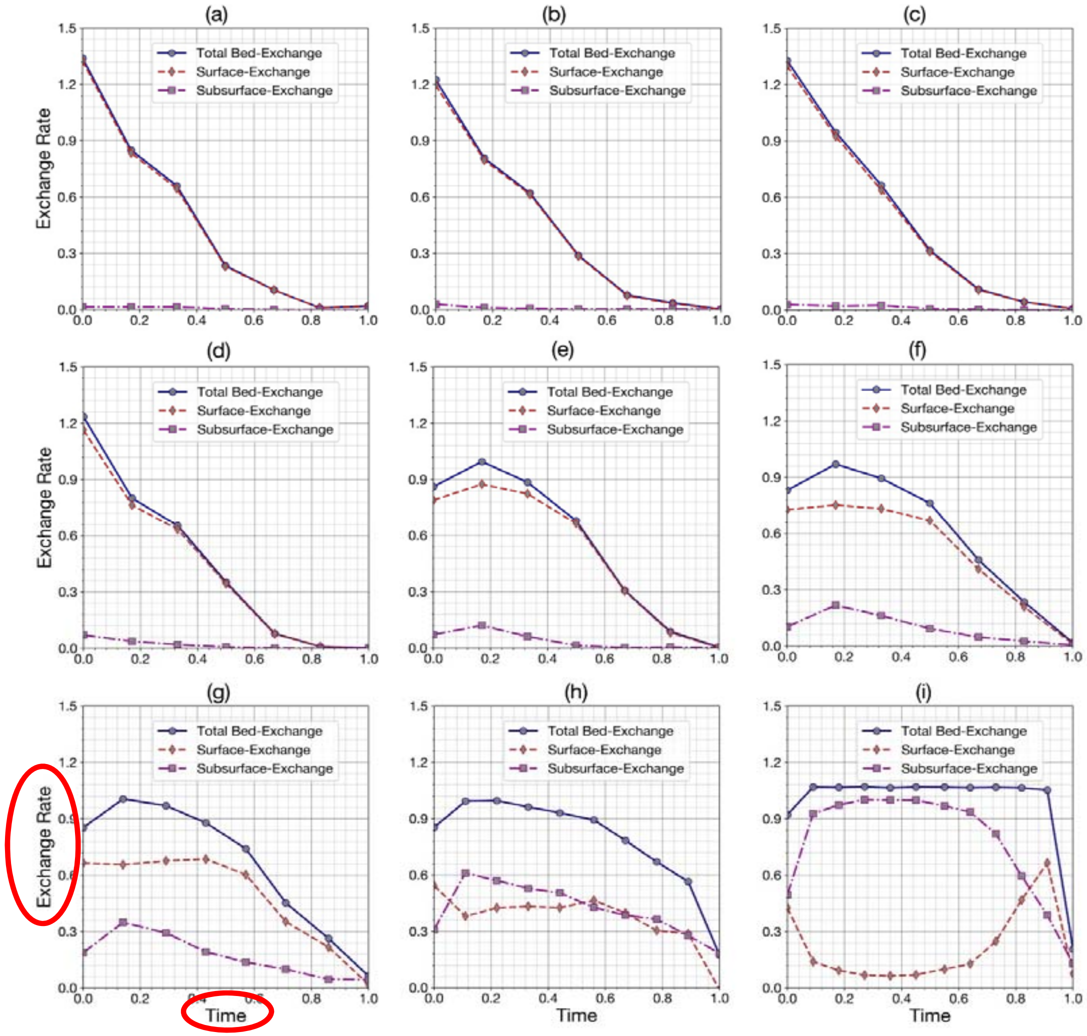


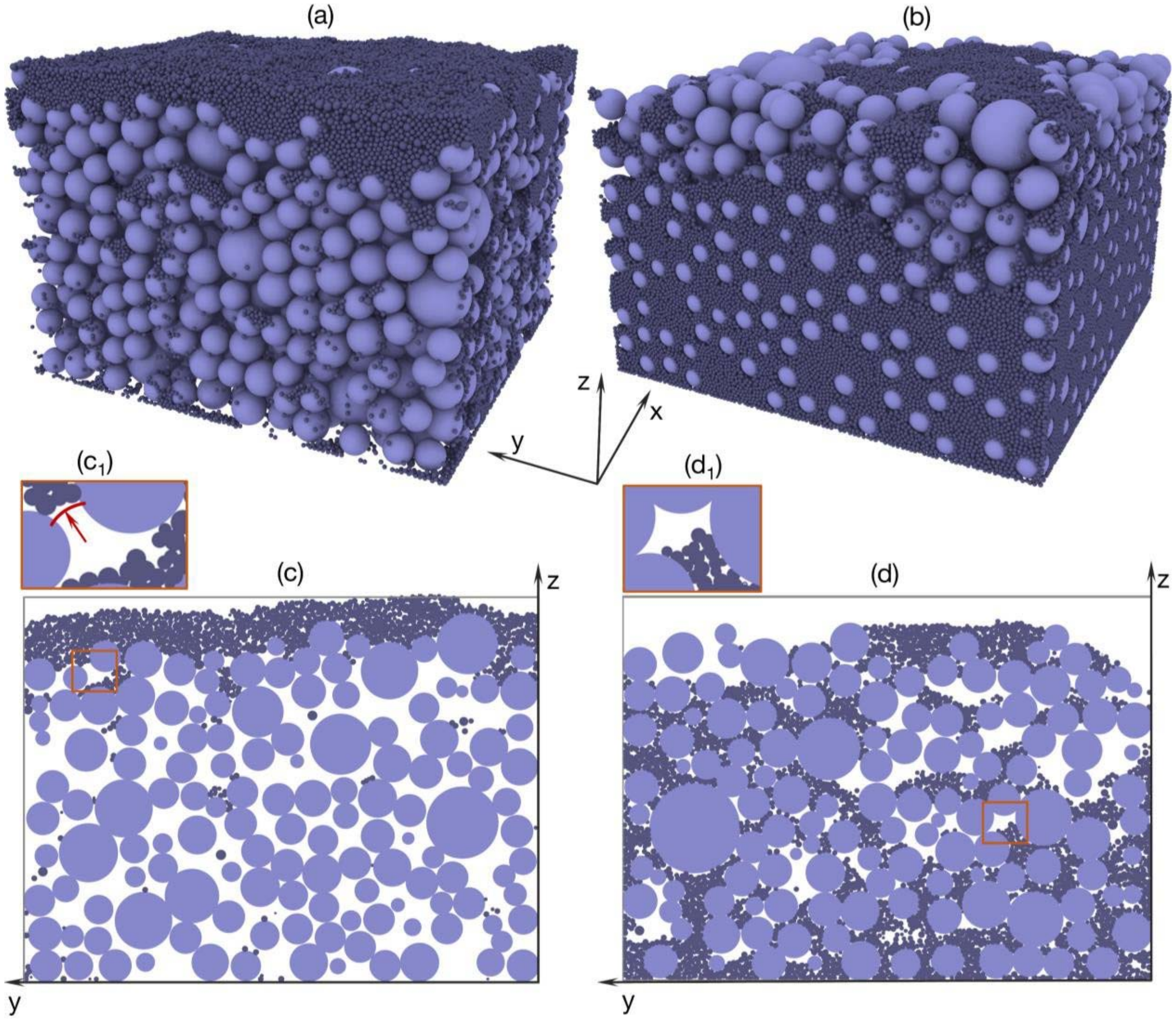
DEM simulation of the infiltration process

Bridging (a):

- Fine grains connect to build the ‘bridge’ across gravels

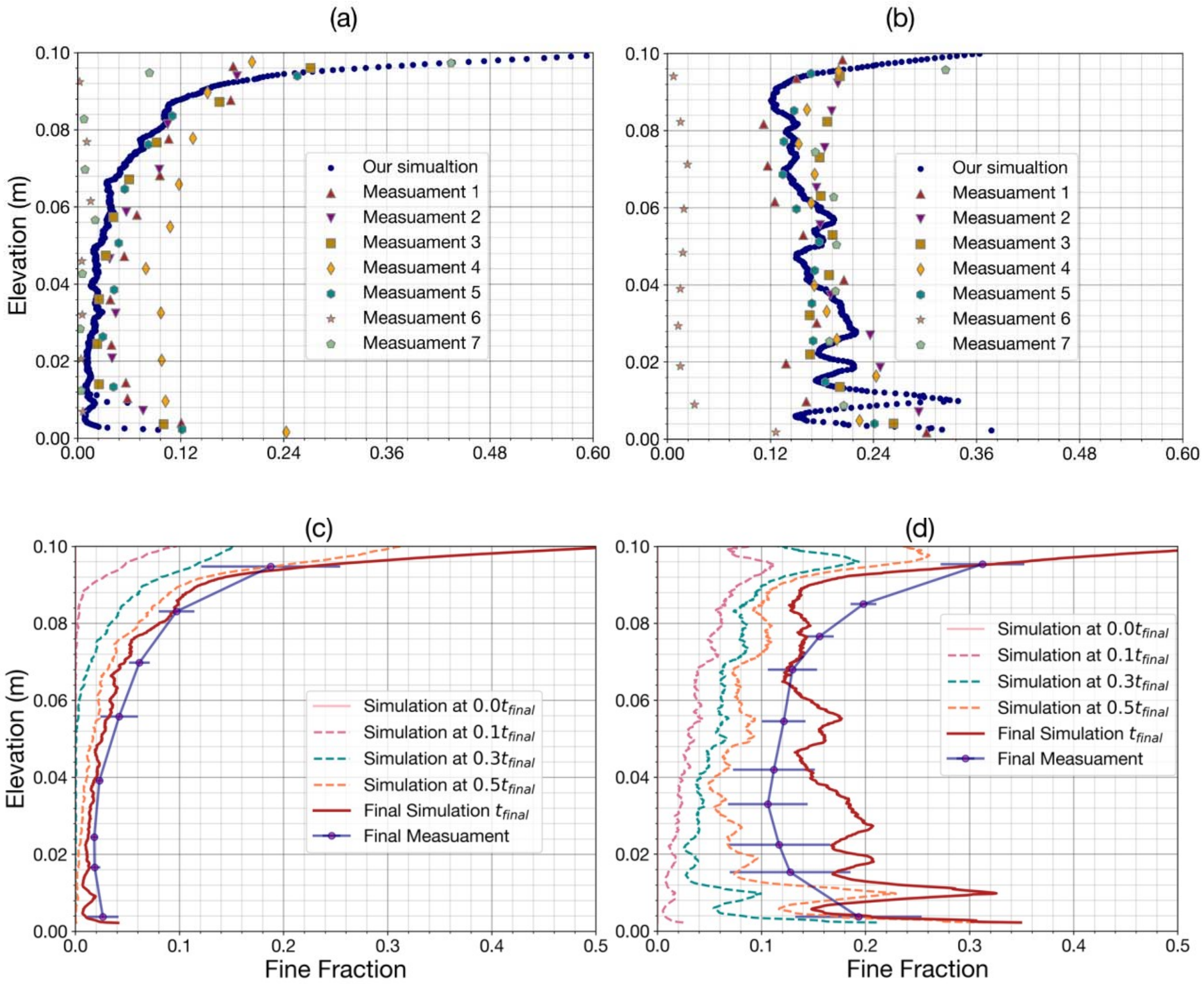
Percolation (b)

- Increase of fine fractions near the flume bed



Verification of DEM models

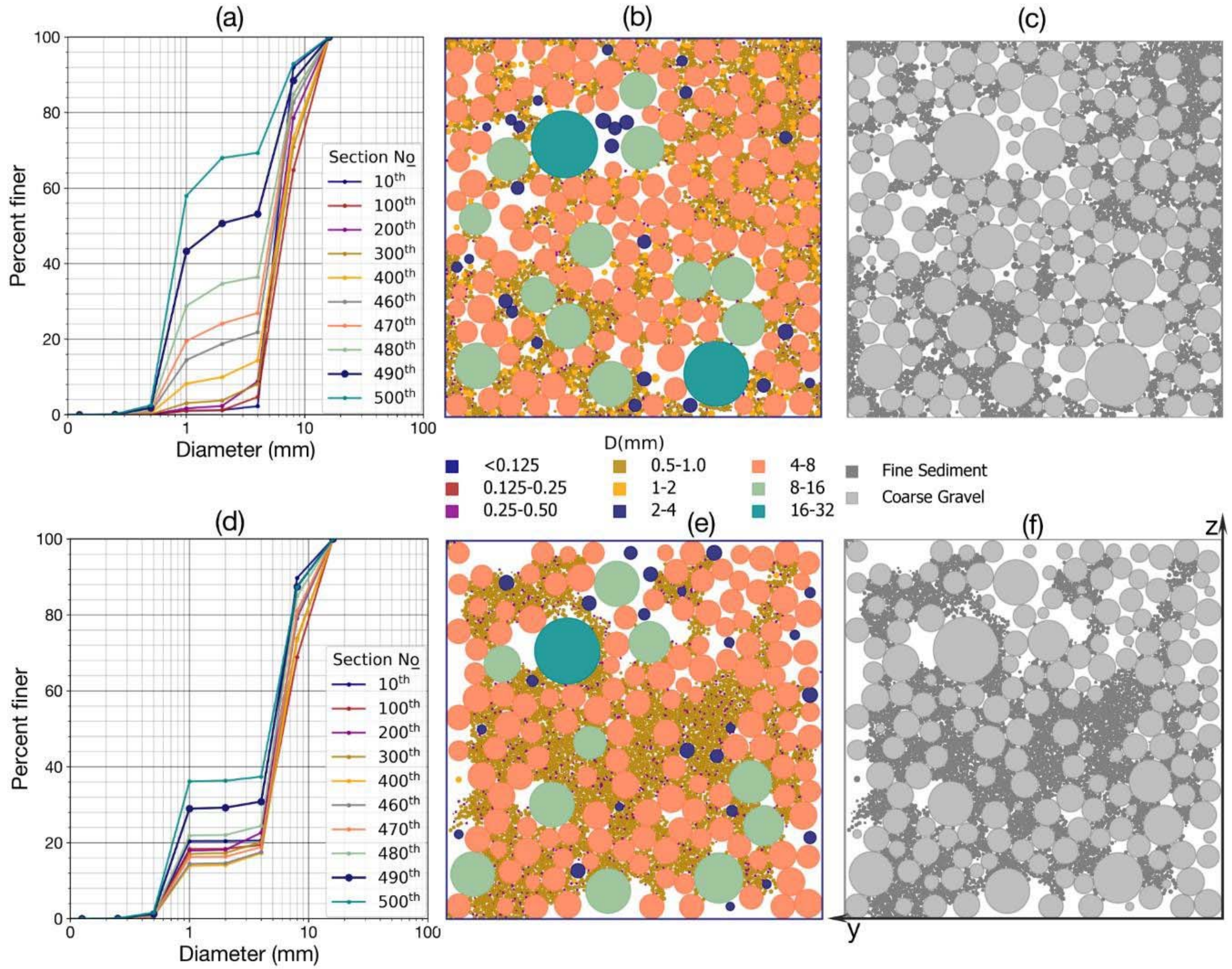
- Fine sediment distribution
- Compare with Gibson (2009) (a, b) and Gibson (2010) (c, d)
- Good results in bridging.
- The wall effects on amplitude of wave distribution.
- Acceptable agreement (percolation)



DEM based data

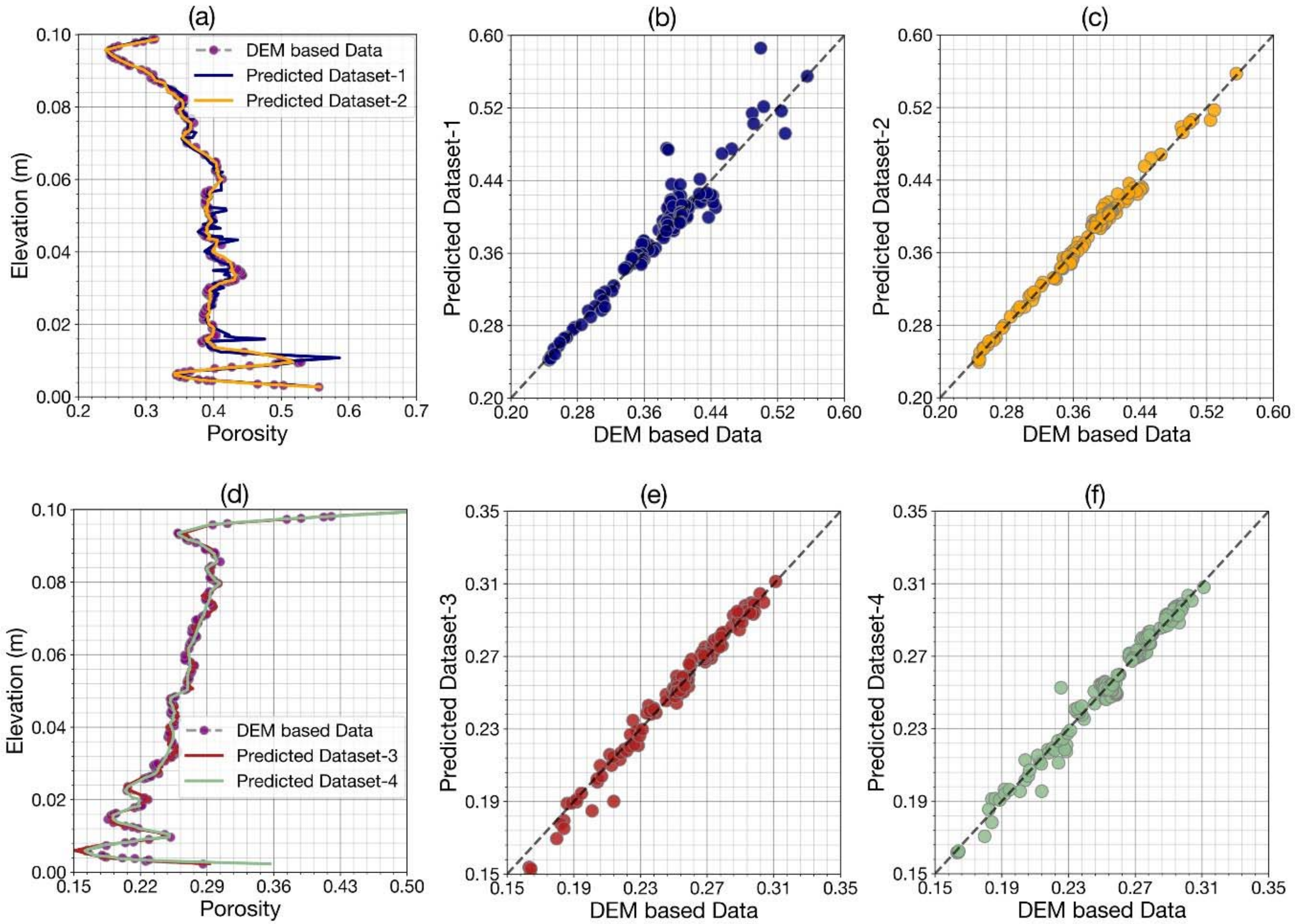
500 cross sections
z- direction for

- Uniform fine sediments (2 size classes)
- Non-uniform fine sediment (9 size classes)
- Bridging and percolation



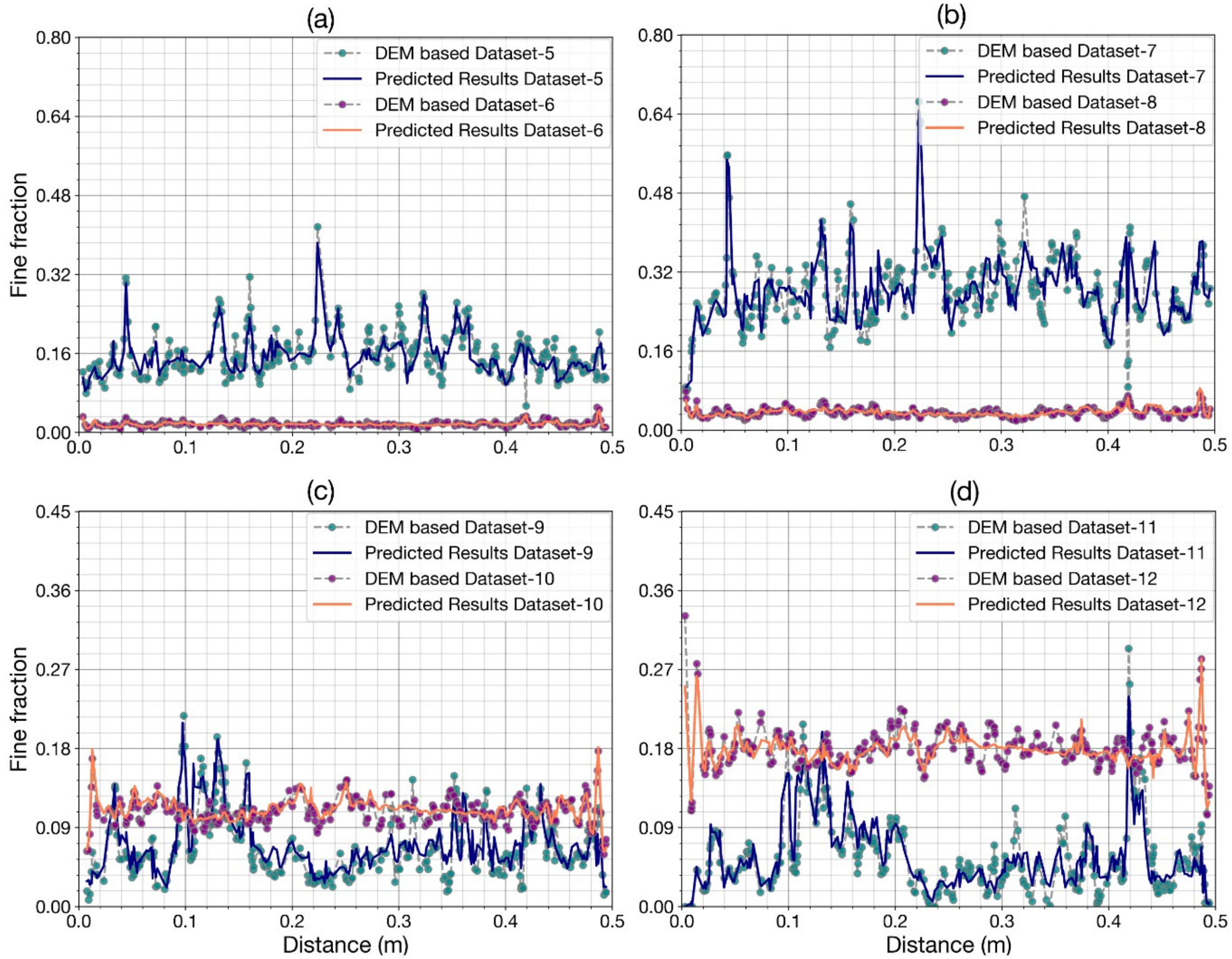
Porosity prediction - (z-direction)

- Bridging (a,b,c)
  Percolation (d,e,f)
- 500 samples were used to train the ANN
- Classification in 2 size classes and 9 size classes



Fine fraction prediction

- The bed was divided in two layers.
- In some points, the FNN gave poor results.
- Acceptable results in whole domain.
- The framework DEM and FNN is successful in predicting sediment distribution



Notes

- Using appropriate network architectures and training processes, the ML models can be developed for different sediment problems.
- Comparing with the observed data, the performance of the ML models are significantly better than those of traditional approaches with lower error and higher correlation coefficient.
- The equations obtained from the ML can also be easily applied to estimate the properties of sediment transport under other hydromorphological conditions.
- A coupling of ML methods with numerical models provides promising results.
- ML can become a useful tool for sediment transport calculation and modelling hydromorphological processes.