ICOLD European Working Group on Overflow and Overtopping Erosion:

Update on Dam & Levee Erosion Research

Estimation of Coarse-Grained Soils Erosion Rate using Machine Learning

By

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ERDC ENGINEER RESEARCH & DEVELOPMENT CENTER

Embry-Riddle Aeronautical University
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Estimation of Coarse-Grained Soils Erosion Rate using Machine Learning

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BACKGROUND

- Approximately 40% of dam failures are caused by overtopping.
- Started in 2017 to improve on the USACE practice in evaluating flood risk assessment of both dams and levees related to breach by overtopping failures.
  - Understand of soil erodibility, especially non-cohesive materials (sands and gravels) to estimate a realistic time and width of breach.
    - Determination of erodibility parameters of coarse-grained materials
    - Evaluation of the overtopping erosion mechanism of coarse-grained soil mixes; surface erosion versus head-cut erosion
  - Applicability of excess shear erosion model to coarse-grained materials

Delhi Dam, IA, 2010

Winfield –Pin Oak Levee, MO Jun, 2008

STUDY APPROACH

Estimation of Coarse-Grained Soils Erosion Rate using Machine Learning

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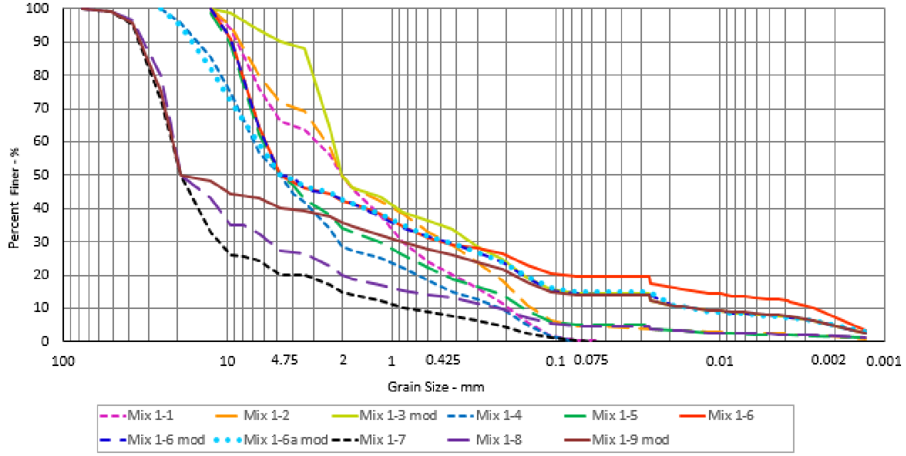
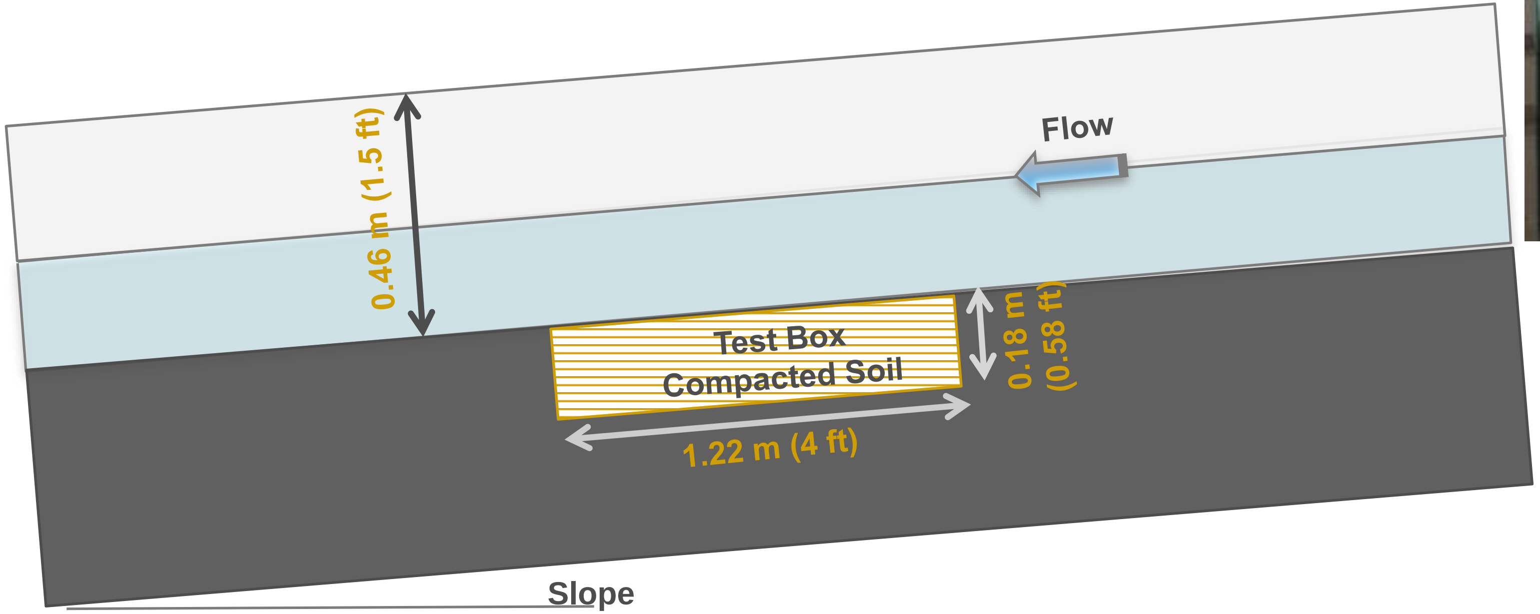
- Design of 12 non-cohesive soil mixes that are grouped by D_{50} and fines content:
  - D_{50}: 2 mm to 50 mm
  - Max size: 5 mm to 150 mm
  - Percent fines: 0 to 15%
  - Clay content: 0 to 5%



- Determine the erosion parameters of the soil mixes by performing box erosion tests. Each soil mix is subjected to different flow rates.
- Use Shallow Water Lidar (SWL) system measurements to capture the erosion progress and rate. SWL uses two laser beams to record water and soil surface simultaneously.
- Perform overtopping erosion tests on 1.2 m (4-ft)- high levee models constructed of the same 12 soil mixes to assess the erosion mechanism (*2nd phase*)

TESTING SETUP



- Width: 0.91 m (3 ft)
- Depth: 0.46 m (1.5 ft)
- Length: 18.3 m (60 ft)
- Slope: -2% to +8%

SHALLOW WATER LIDAR (SWL)

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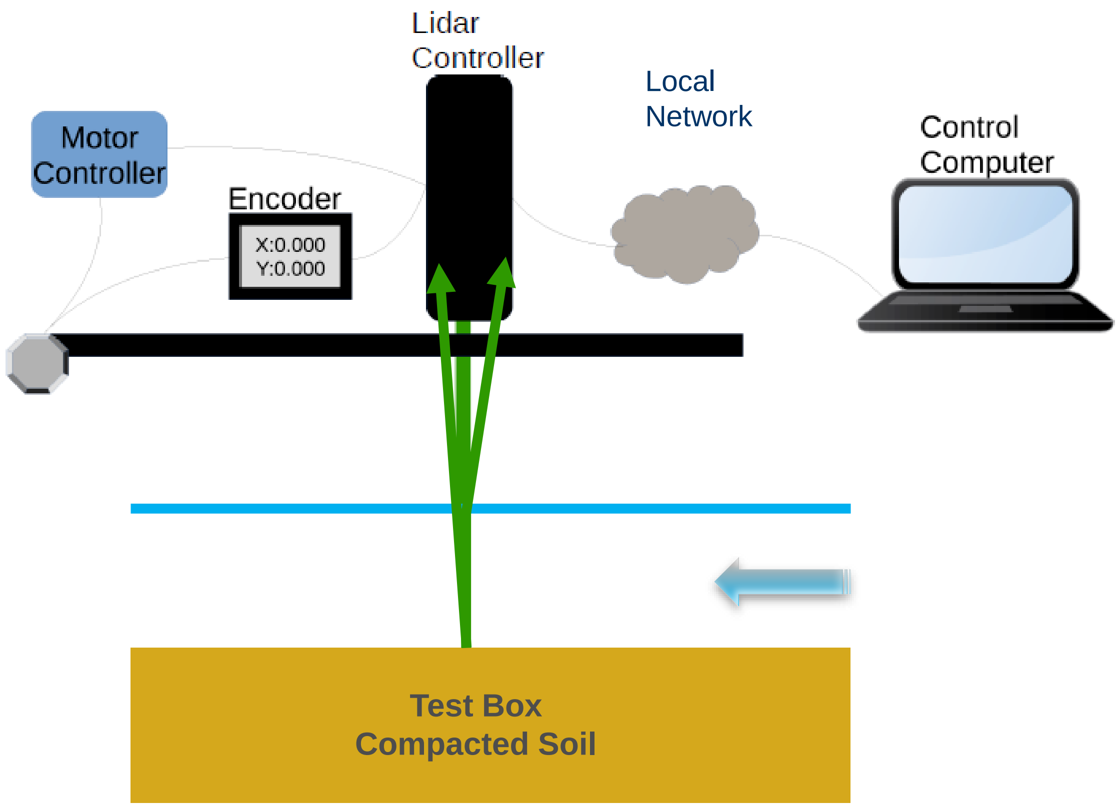

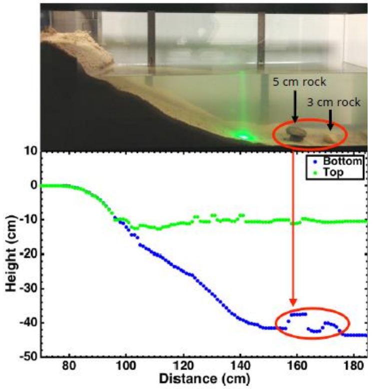

- 8 kHz pulse rate
- Real time measurements
- 1 cm resolution
- Clear and turbid water
- Mounted/Handheld (< 15 lb)

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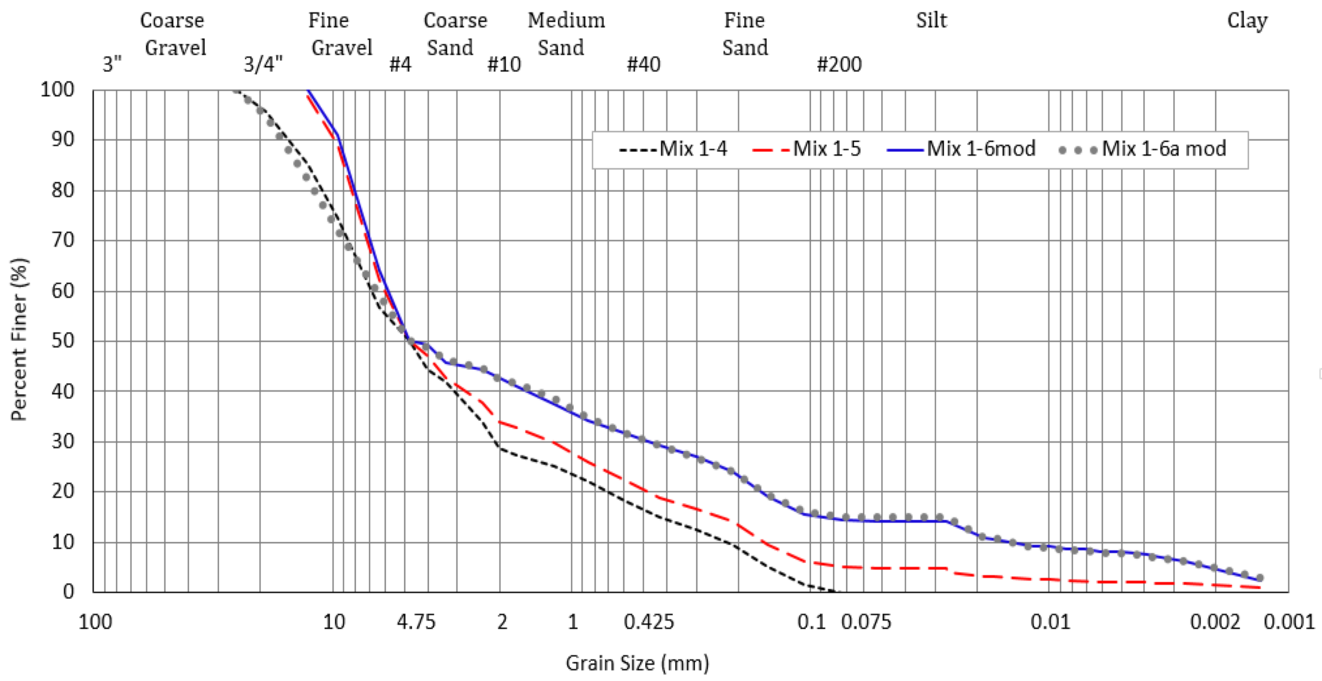
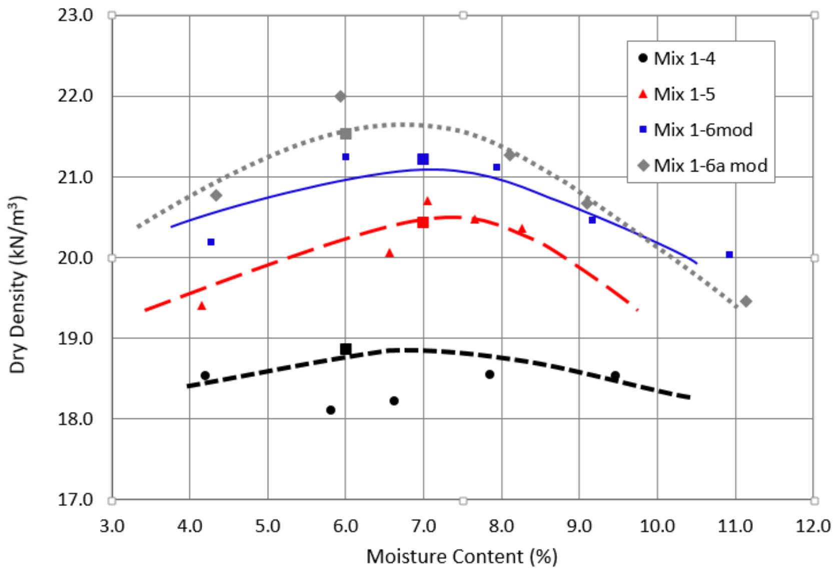
SHALLOW WATER LIDAR (SWL)

Soil mix compacted in the test box

SOIL MIX PROPERTIES



Grain size distribution



Compaction curves for soil mixes using standard Proctor test (ASTM D-698).

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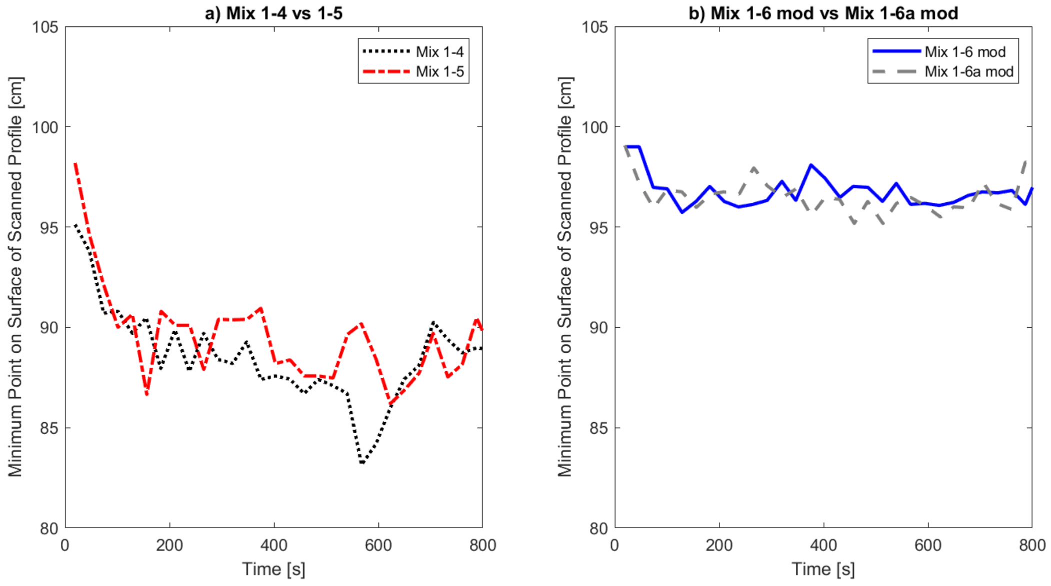
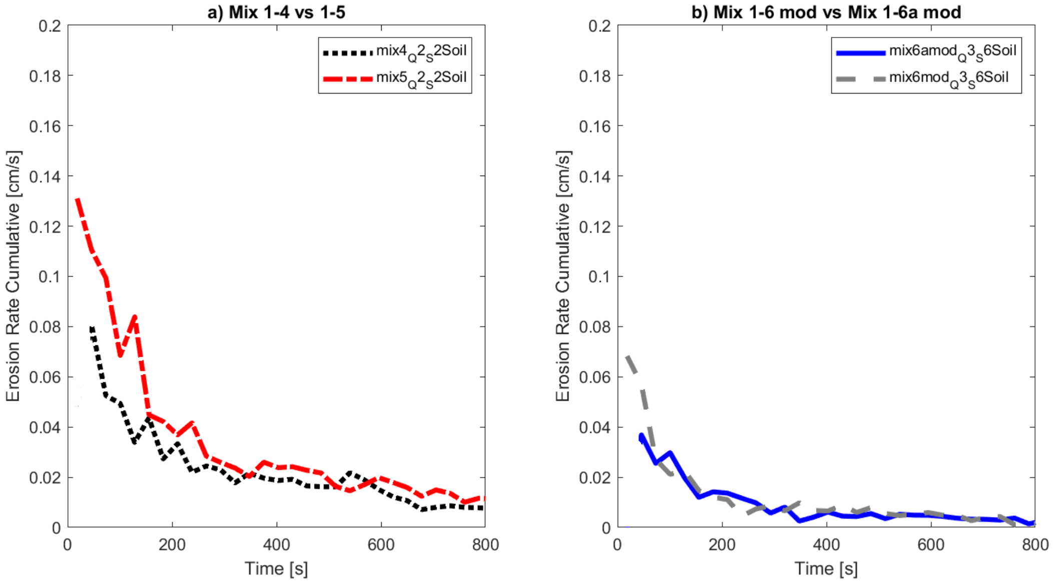
TEST RESULTS



Maximum erosion with time. (a) mix 1-4 and 1-5, (b) mix 1-6 mod and 1-6a mod.



Erosion rate with time. (a) mix 1-4 and 1-5, (b) mix 1-6 mod and 1-6a mod.

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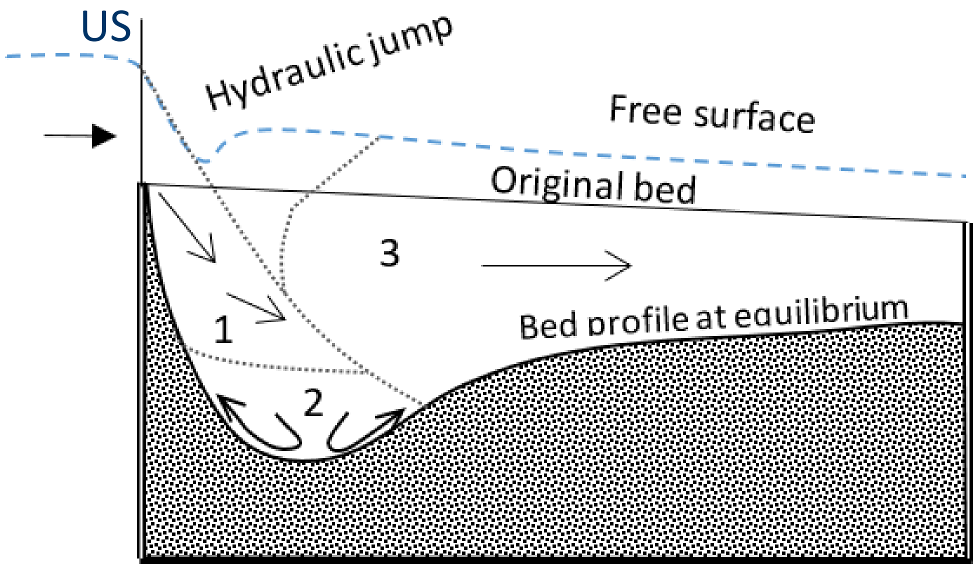
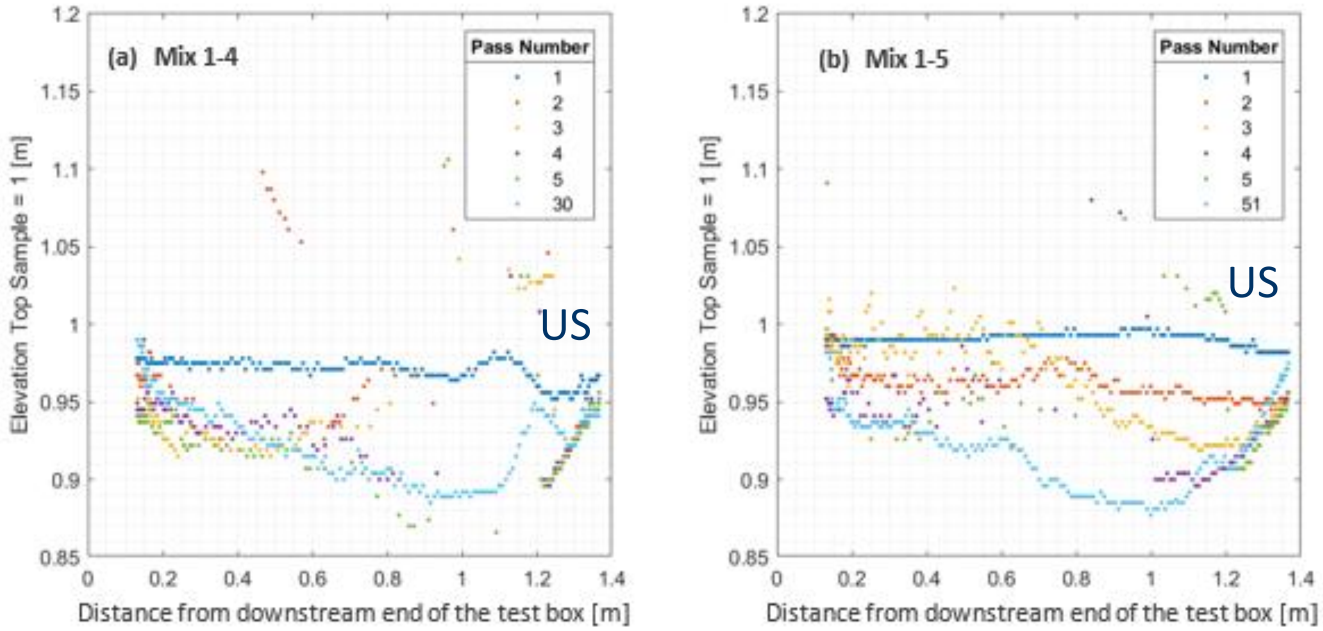


Definitional sketch of scour hole within the test box (after Meftah et al. 2020)



Soil surface profiles with each loop

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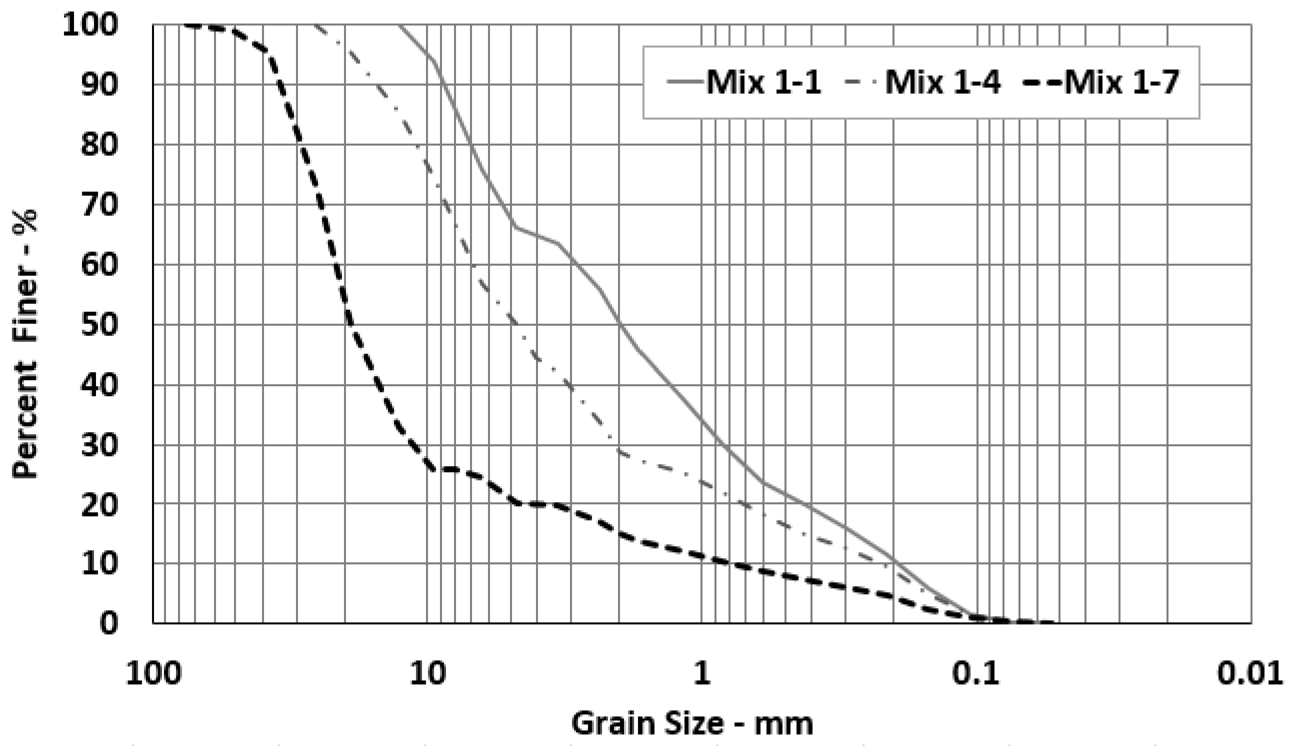
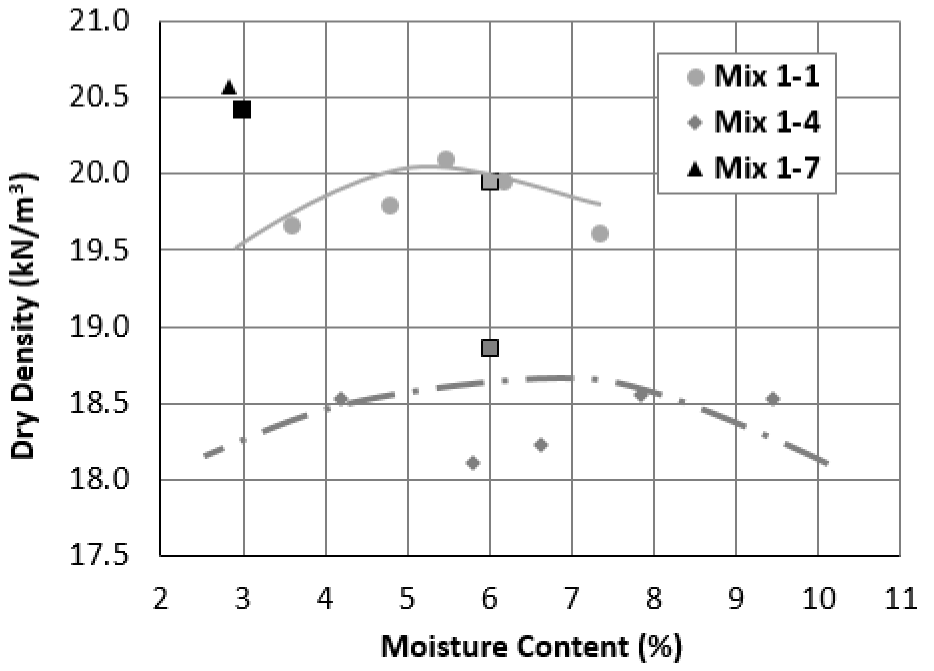
SOIL MIX PROPERTIES



Grain size distribution



Compaction curves for soil mixes using standard Proctor test (ASTM D-698).

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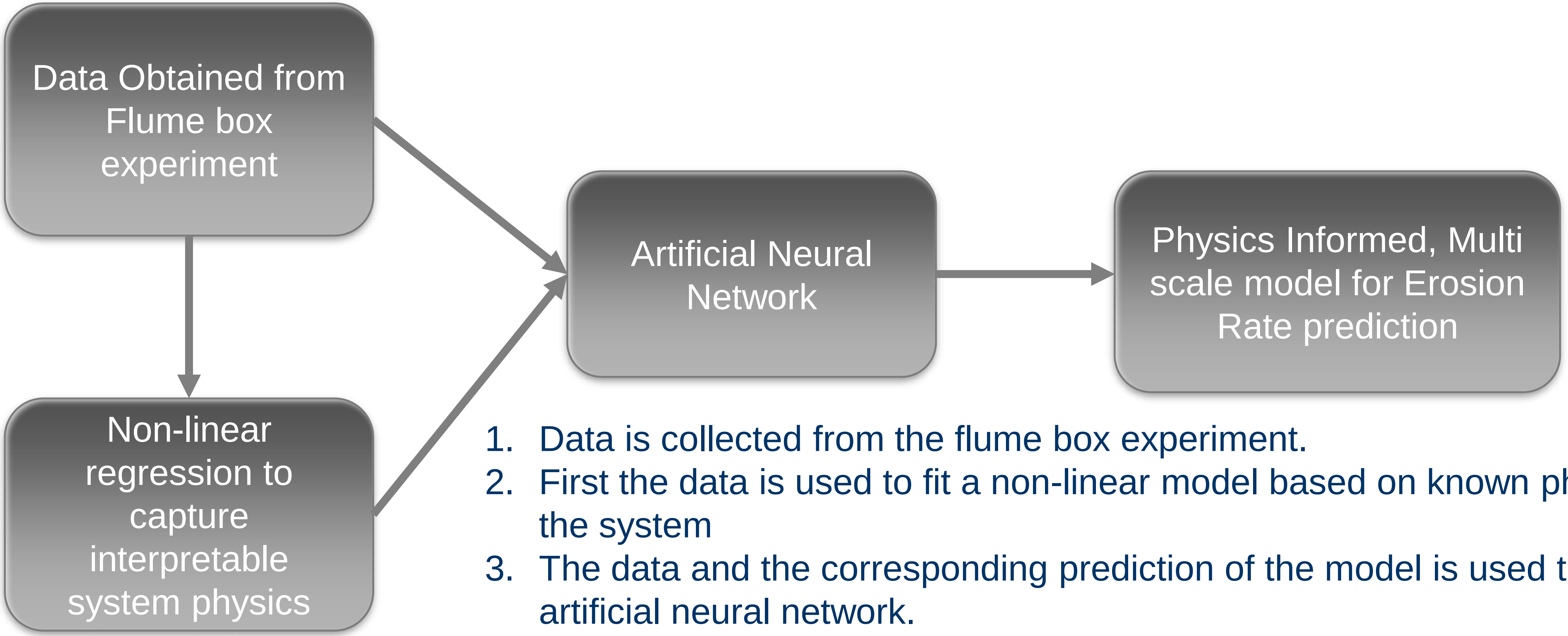

1. Data is collected from the flume box experiment.
2. First the data is used to fit a non-linear model based on known physics of the system
3. The data and the corresponding prediction of the model is used to train an artificial neural network.
4. Less data, aided by low resolution system physics.

NON-LINEAR REGRESSION

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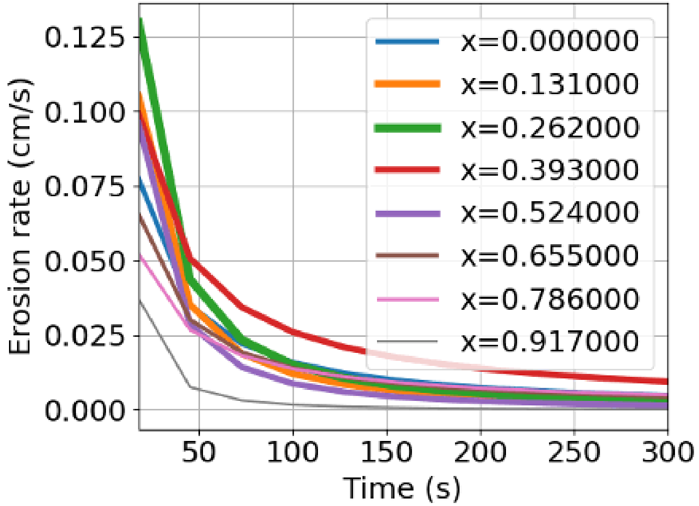
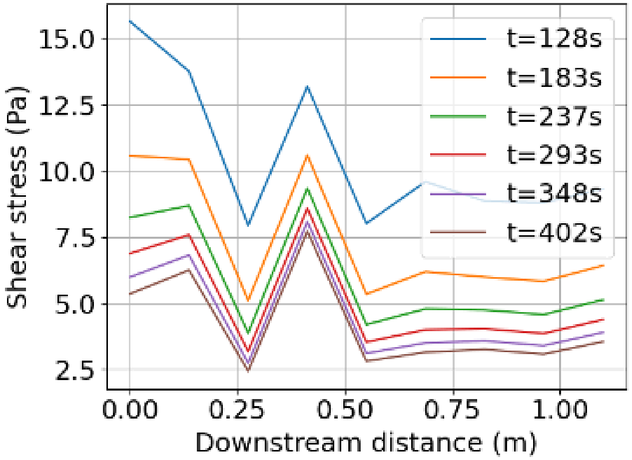
1. The mid-section (section 5) of the box was chosen to analyze erosion behavior
2. Data is divided into bins both temporally and spatially and average of each bin is considered as the representative value.
3. To image the evolution of the soil and water surfaces with respect to time using the Levenberg-Marquardt algorithm (Levenberg 1944).
4. To choose the best model, a series of competing models were tested for each zone and the model which yielded the least R2 error was chosen.





$$Erosion\ rate = \frac{Change\ in\ height\ of\ soil}{Time\ taken}$$

$$\frac{u}{\sqrt{(\tau/\rho_w)}} = \frac{1}{\kappa}\ln(30z/k_s)$$

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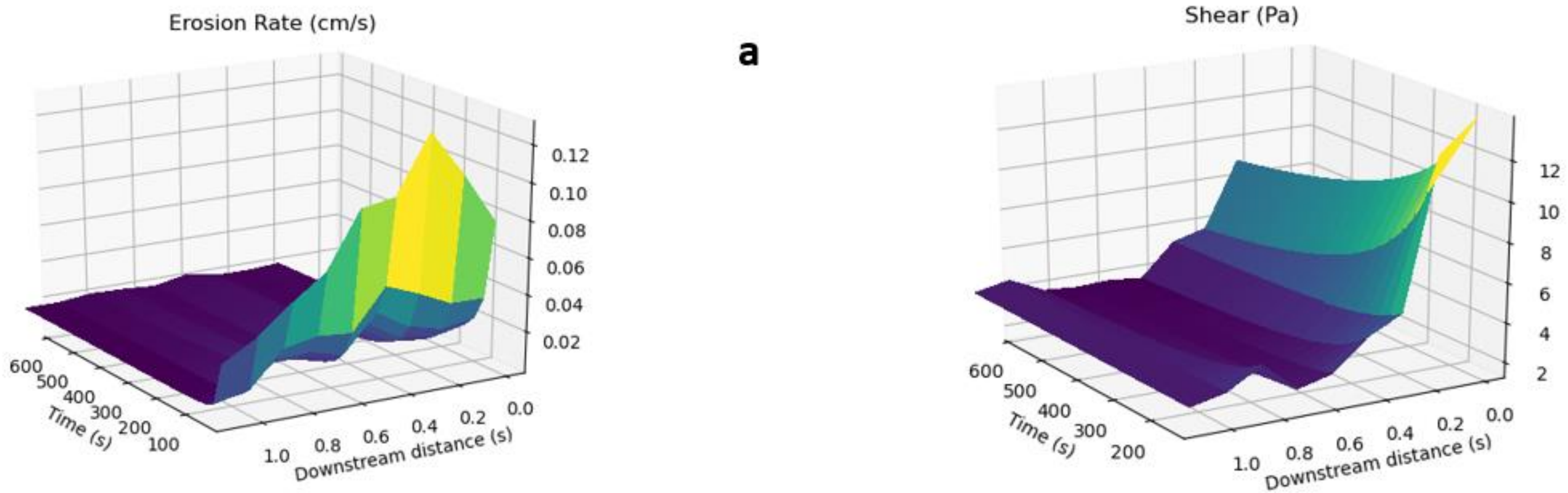
TEST RESULTS



Variation of erosion rate and shear stress with respect to space and time for **mix 1**

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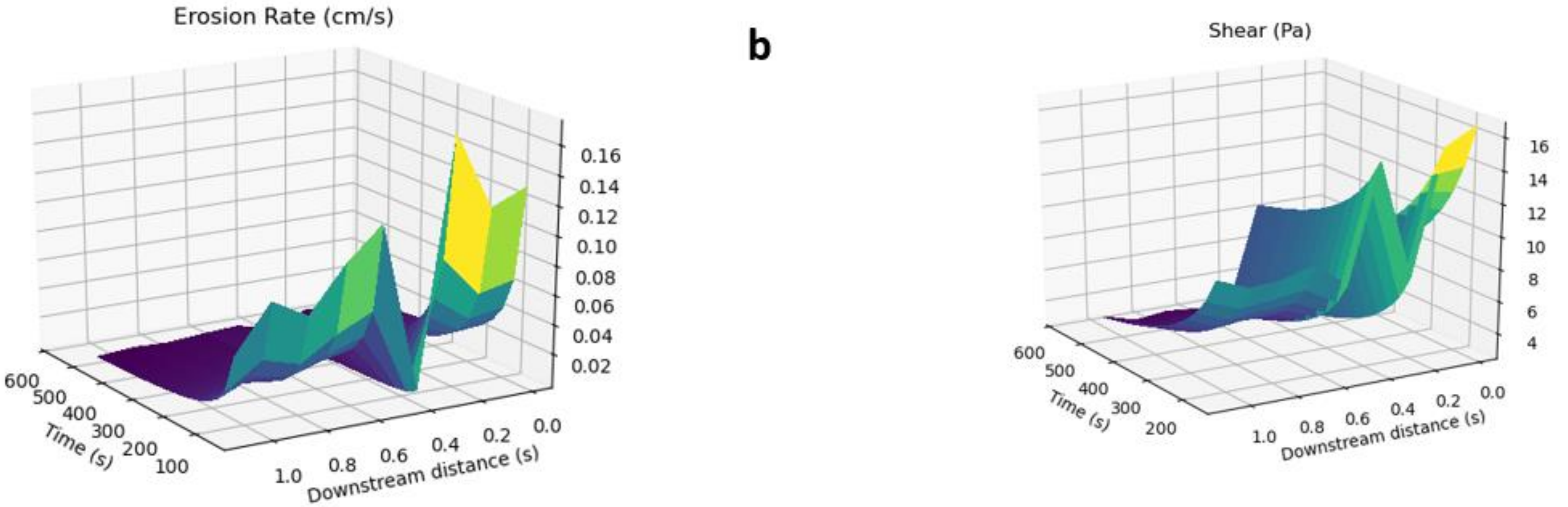

Variation of erosion rate and shear stress with respect to space and time for **mix 4**

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Summary of soil mix properties and test conditions

Mix	D_{50} (mm)	D max (mm)	Fines Content (%)	USCS	wc%	Dry Density (kN/m3)	Flow Rate (m^3/sec)	Slope %	Initial Average Bed Shear (Pa)	Initial Average Velocity (m/sec)	Initial Erosion Rate (cm/sec)
1-1	2	13	0	SW	6	19.9	0.061	2	16.9	1.4	0.077 (0.13)
1-4	5	25	0	GW	6	18.9	0.057	2	15.8	1.37	0.081 (0.175)
1-5	5	13	5	GW-GC	7	19.6	0.057	2	15.8	1.37	0.131
1-6 mod	5	13	15	GC	7	21.2	0.09	6	37.4	2.1	0.068
1-6a mod	5	25	15	GC	6	21.5	0.09	6	37.4	2.1	0.037
1-7	20	75	0	GP	3	20.4	0.057	2	15.8	1.37	0.02 (0.03)

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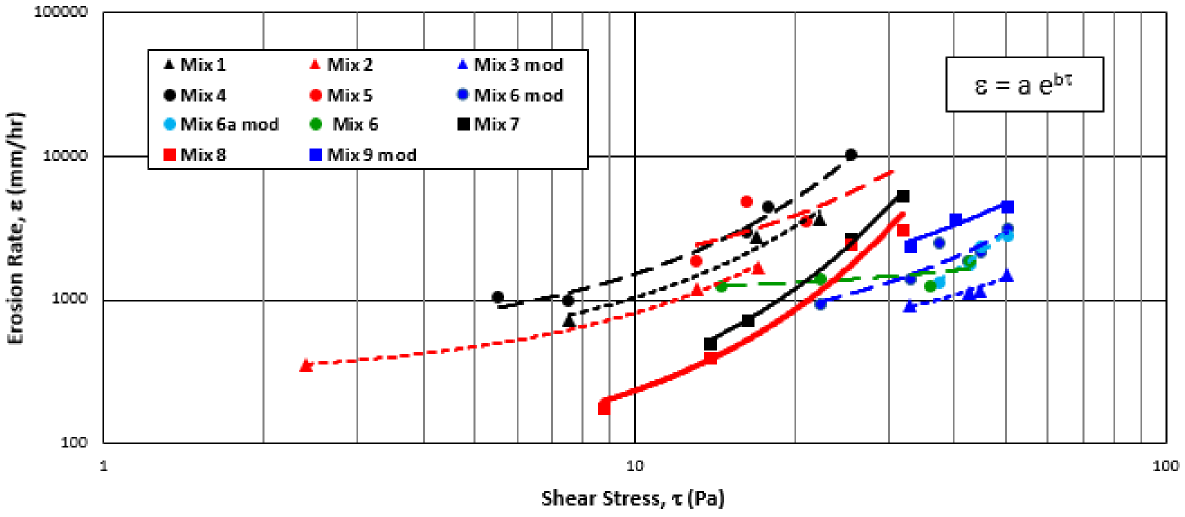

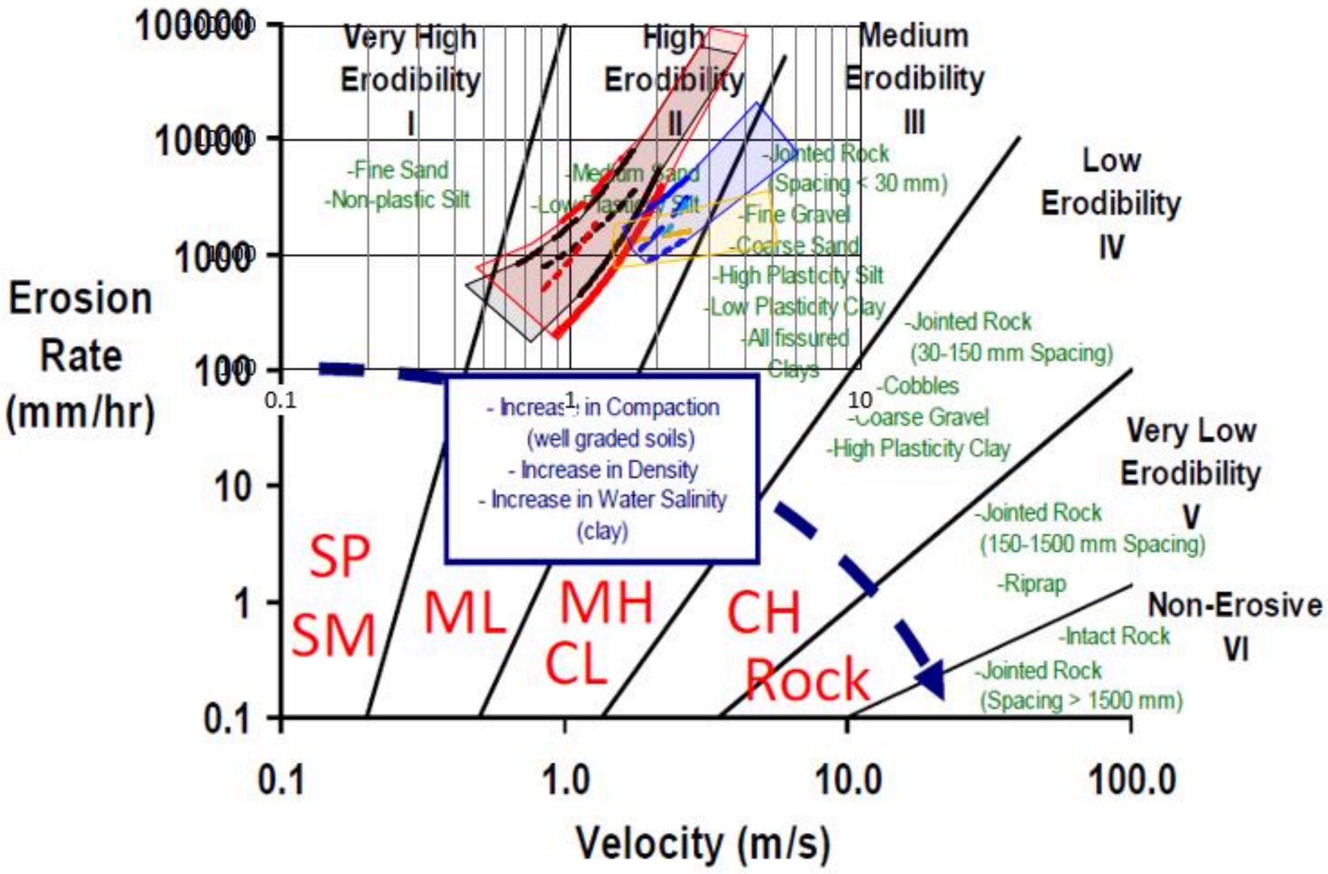

HEC 18- Erosion rate vs. velocity for a wide range of geomaterials (Briaud et al. 2011)

TEST RESULTS

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Slope 2%
Q= 0.057 m^3/sec (2 cfs)

Mix 4 – zero% fines
max size = 25 mm (1 in)

Mix 5 – 5% fines, 2% clay
max size = 12.5 mm (1/2 in)

CONCLUSIONS

- Erosion rate significantly decreases with time. This reduction could not be calculated if the erosion measurements were not taken at small time intervals from the beginning of the test using SWL.

- The initial erosion rate and the level of reduction over time is affected not only by D_{50}, but also by the fines content and the coarser portion of the soil mix:
  - Compared to mixes with similar coarser portion and D_{50} , increased fines and clay content (from zero to 15%) causes the erosion rate to decrease by one half
  - For the same clay content, the larger the coarse portion of the soil mix, the slower the initial erosion rate is. Erosion rate decreased by one half when the max size increased from 13 mm to 25 mm
  - The initial erosion rate is reduced by almost 4 times when the D_{50} increased from 2 mm to 20 mm

- The erosion rate was shown to be strongly correlated to the acting bed shear nonlinearly. The bed shear temporal and spatial variation was calculated using the soil and water profile images as were obtained by processing the SWL data using machine learning techniques. This ensured careful nonlinear regression by not overfitting on noisy data.

- Further data processing is needed to fine-tune and quantify the erosion rate at different acting bed shear along the full soil profile.

Comments

Questions ?