Predicting sedimentation in Lake Alajuela

MSc. Geomatics thesis

Lars Marinus Langhorst

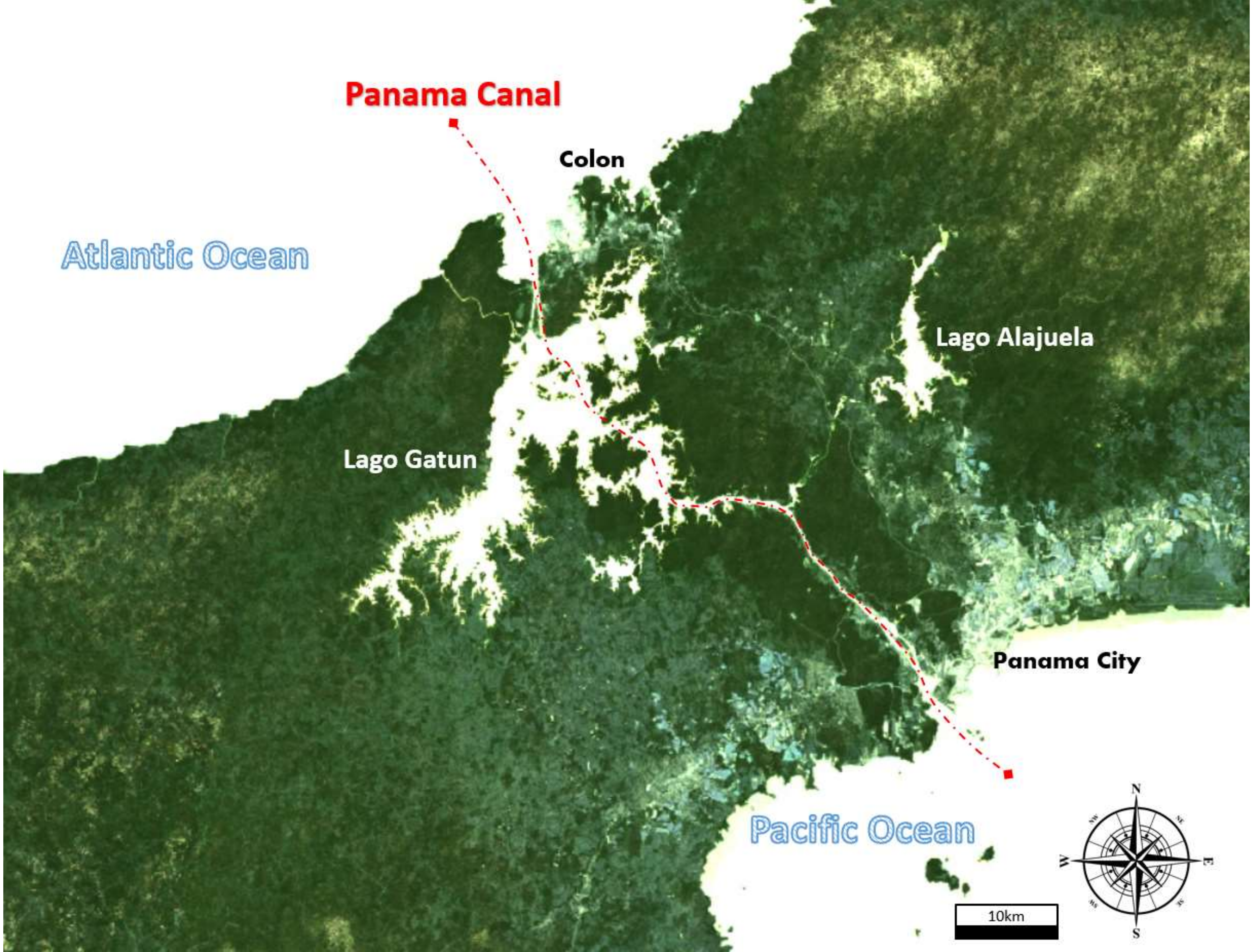
30th June 2022

1st supervisor:

Ken Arroyo Ohori

2nd supervisor:

Hugo Ledoux



Panama Canal
Colon
Atlantic Ocean
Lago Alajuela
Lago Gatun
Panama City
Pacific Ocean
N
S
E
W
10km

352-B2 The Panama Canal. Madden Dam Project. View of Denuded Right Abutment and U.S. FRIGATE taking New Water Supply Pump to Intake. Taken from Point # 1-A. February 2, 1932.

Content

- **Research questions**
- **Background**
- **Methodology**
- **Results**
- **Predictions**
- **Conslusions**

Research questions

Main research question

How to accurately predict sedimentation levels in Lake Alajuela using a Machine Learning method?

Sub-questions

- **Which sedimentation related features can be extracted from the DEM?**
- **Which ML model best predicts sedimentation in a reservoir?**
- **What is the best set of geomorphological and hydrological features to train a ML model for prediction of sedimentation?**
- **What accuracy can be obtained predicting sedimentation in Lake Alajuela?**

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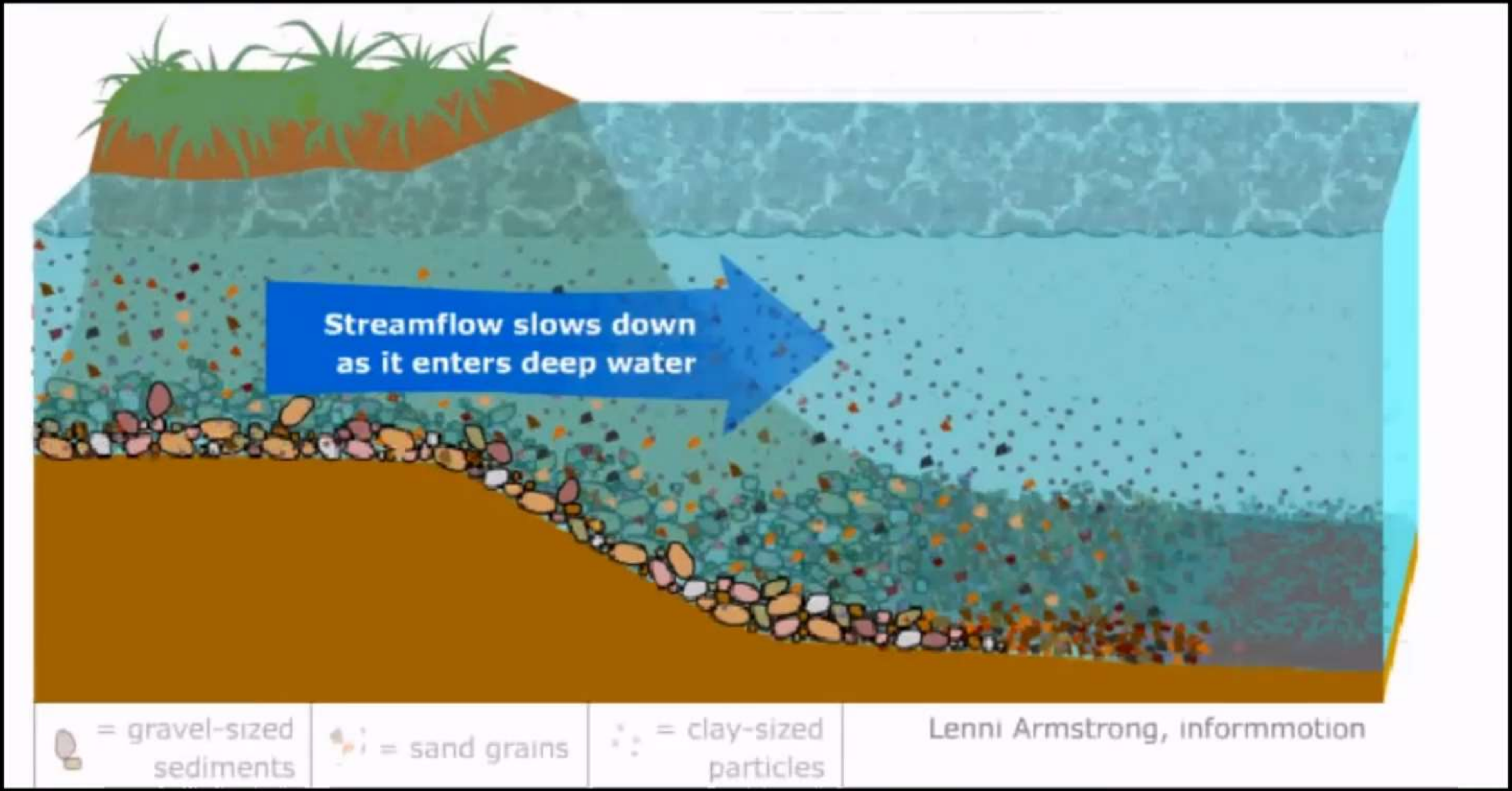
Background

What is sedimentation?

https://www.youtube.com/watch?v=jGhogd0G7_U



Sedimentation modelling – difficult?

”We might have trouble forecasting the temperature of the coffee one minute in advance, but we should have little difficulty in forecasting it an hour ahead.”

Lorenz, 1963

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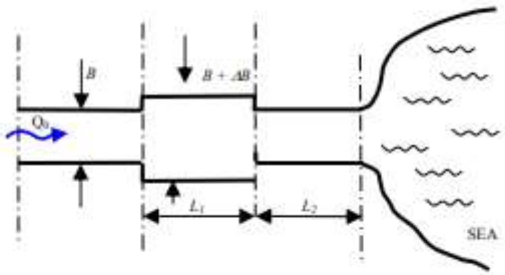
Sedimentation – traditional models

- 1D – **analytical** and **empirical** models
- Primary channel parameters:
  - Width (B)
  - Depth (h)
  - Slope (i)
  - Water discharge (Q)
  - Sediment discharge (Qs)
  - Chezy Coefficient (C)
  - Flow speed (u)
  - Sediment particle size (D)
  - Time and space step (dt/dx)



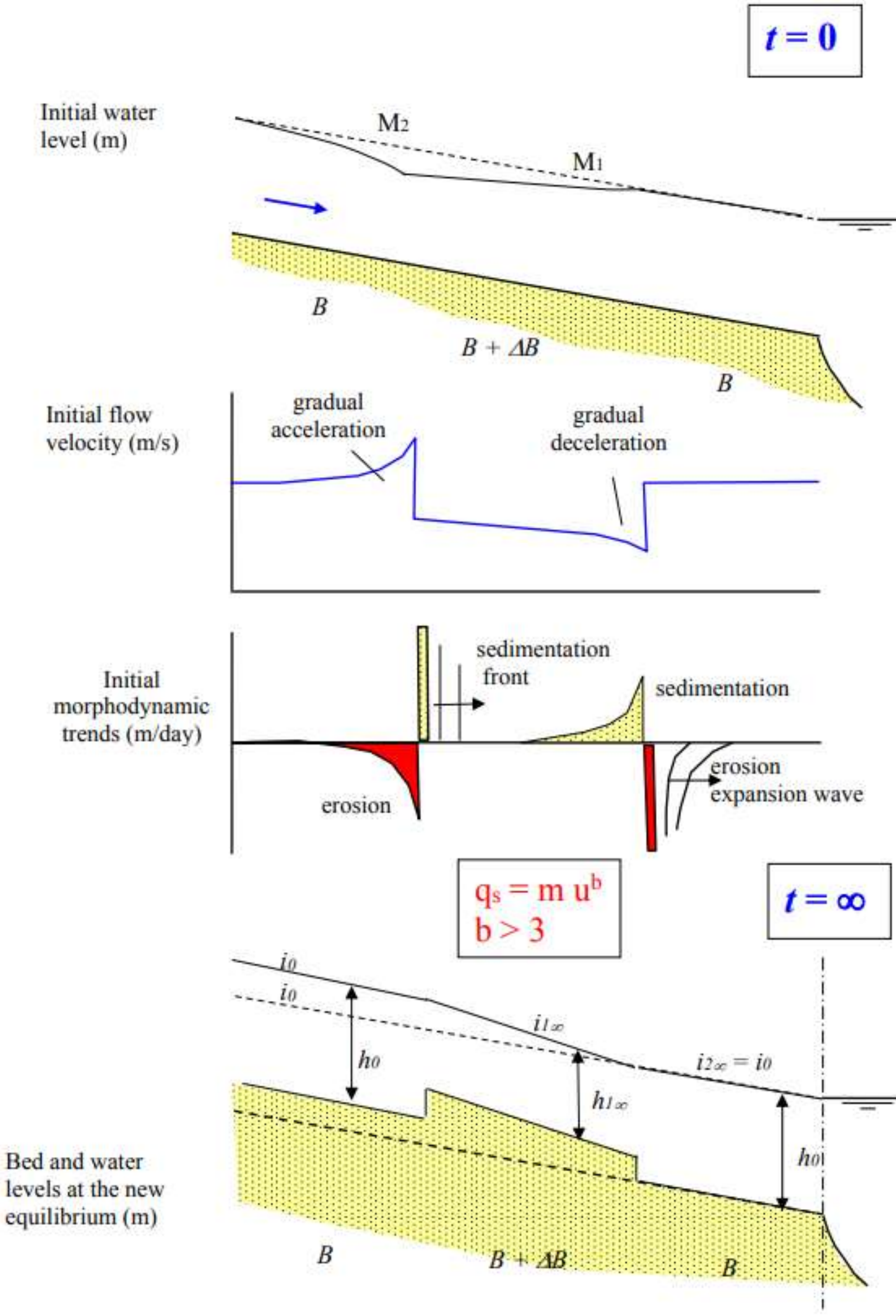
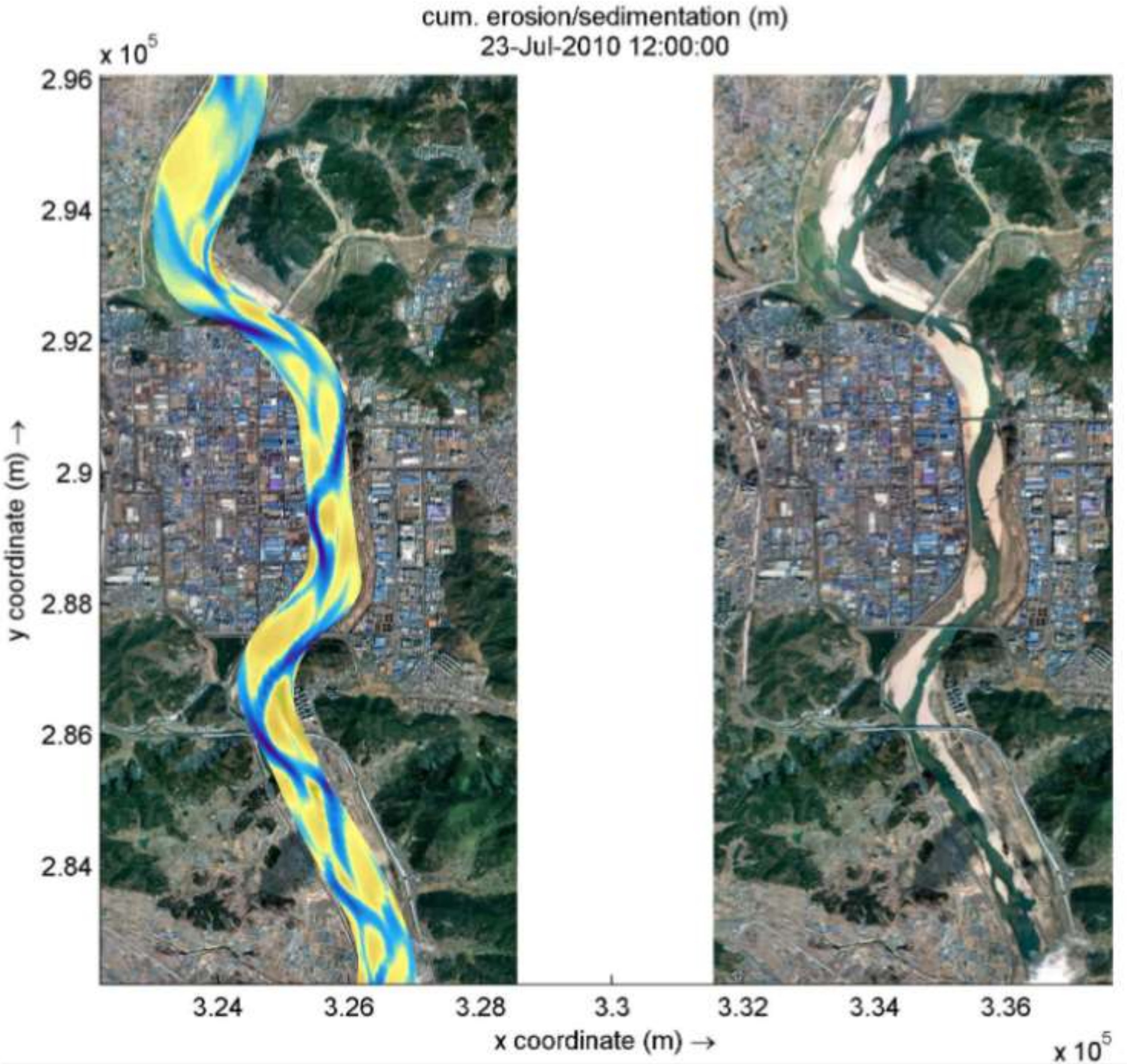


Figure 6.13. Short and long term variations caused by permanent channel widening.

River Morphodynamics. Morphological response at the reach scale. A. Crosato. UNESCO-IHE Lecture Note LN0381

Sedimentation – Current Computer models

- 2D and 3D – **numerical** models
- Curvilinear grid



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Where empirical and analytical equations can no longer help us, machine learning may be the answer…

But what is Machine Learning?

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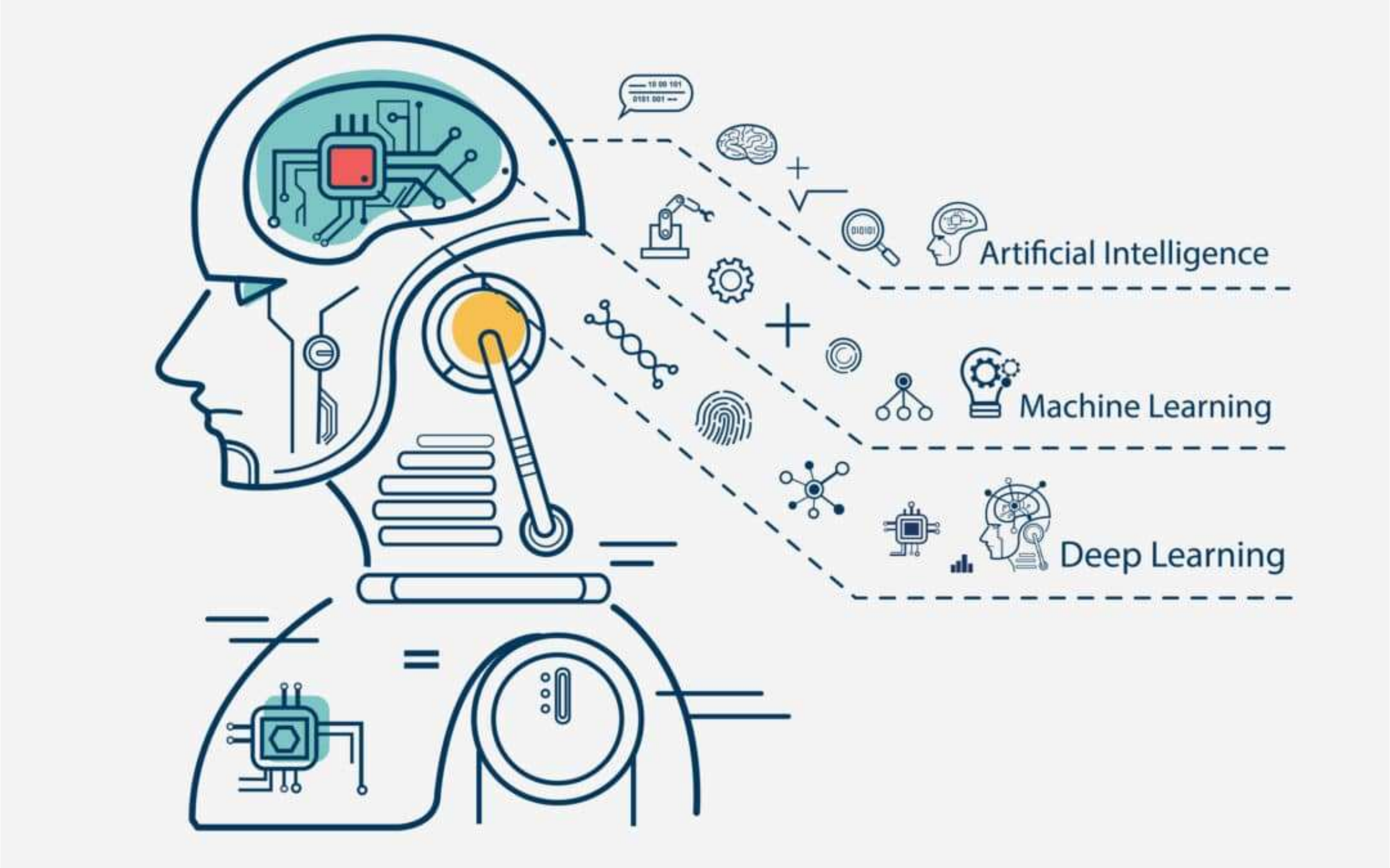
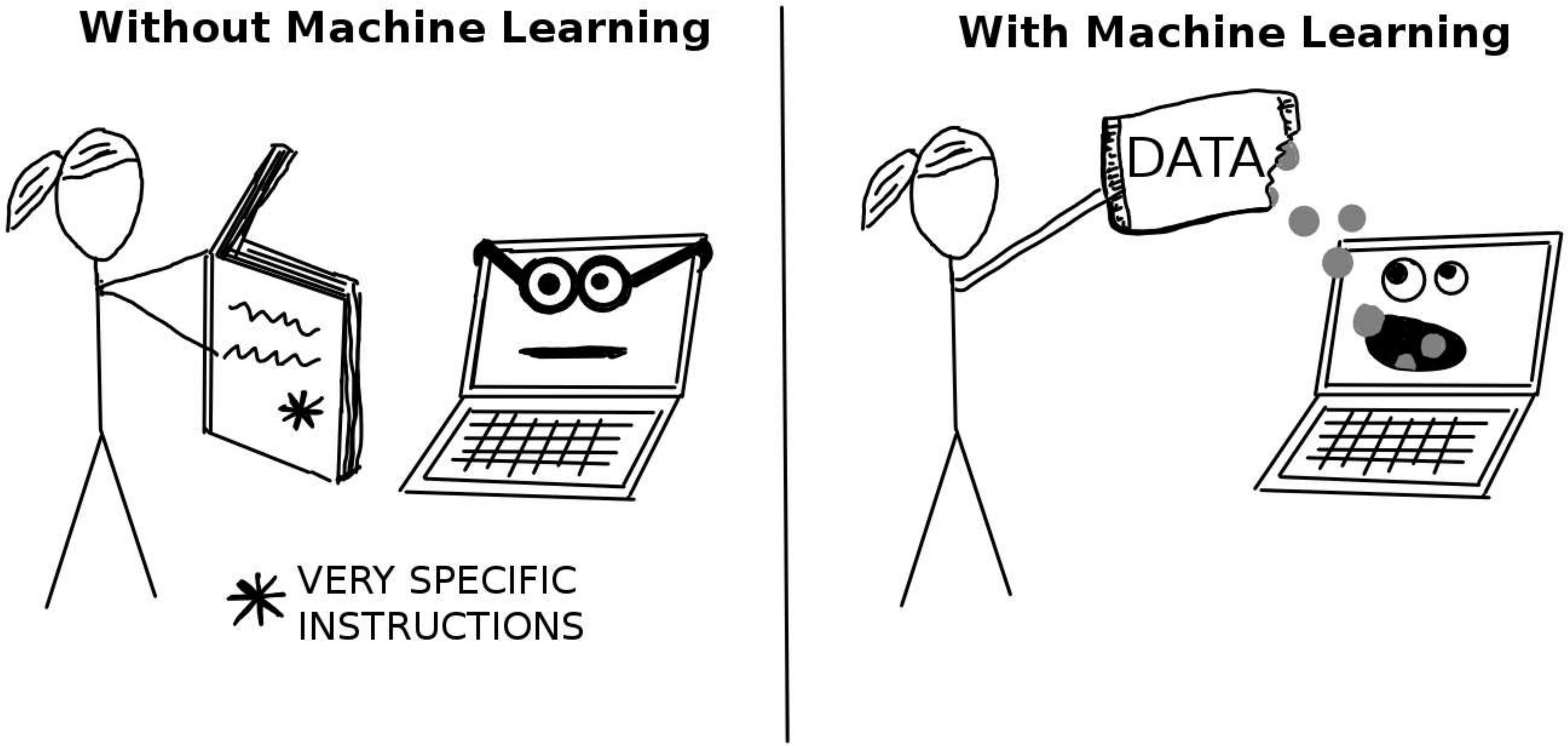
Machine Learning



https://www.atriainnovation.com/en/machine-learning-in-industry/

Machine Learning



https://christophm.github.io/interpretable-ml-book/terminology.html

Machine Learning

Area

$$Y = X1 + X2 + X3 + X4 + \ldots$$

Price of House

Location

Number of floors

Year of construction

Features

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Areas of Study

- Río Chagres
- Río Pequení

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Areas of Study - Río Chagres

- Large discharge changes between seasons
- Main supplier of water
- Average water discharge: 32.2 m^3/s

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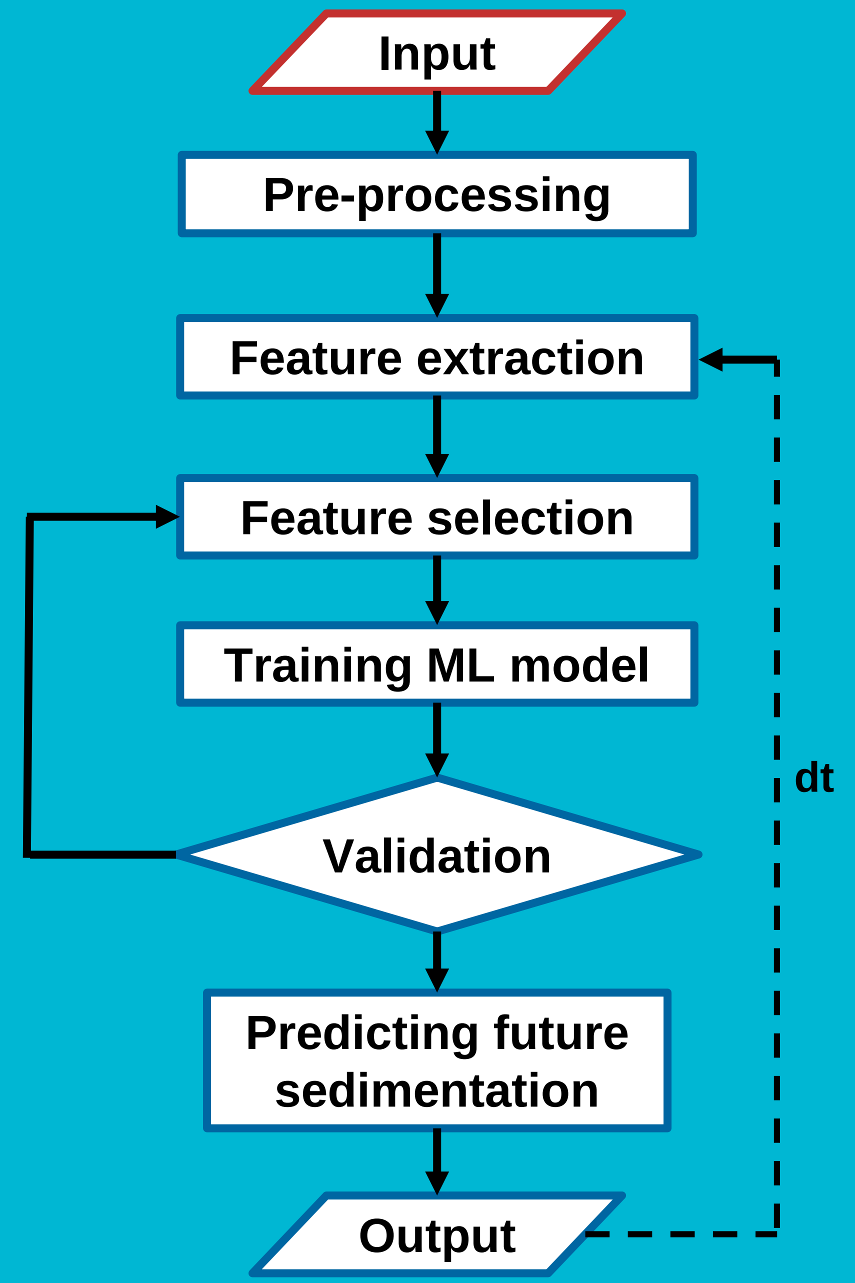
Areas of Study - Río Pequení

- Upper basin erodes during dry season
- Area of study is river mouth into main basin
- Average water discharge: 13.4 m^3/s

Methodology

Input

- Point clouds from bathymetric data
- 1997, 2008, 2012, 2018



Input

- Point clouds from bathymetric data
- 1997, 2008, 2012, 2018

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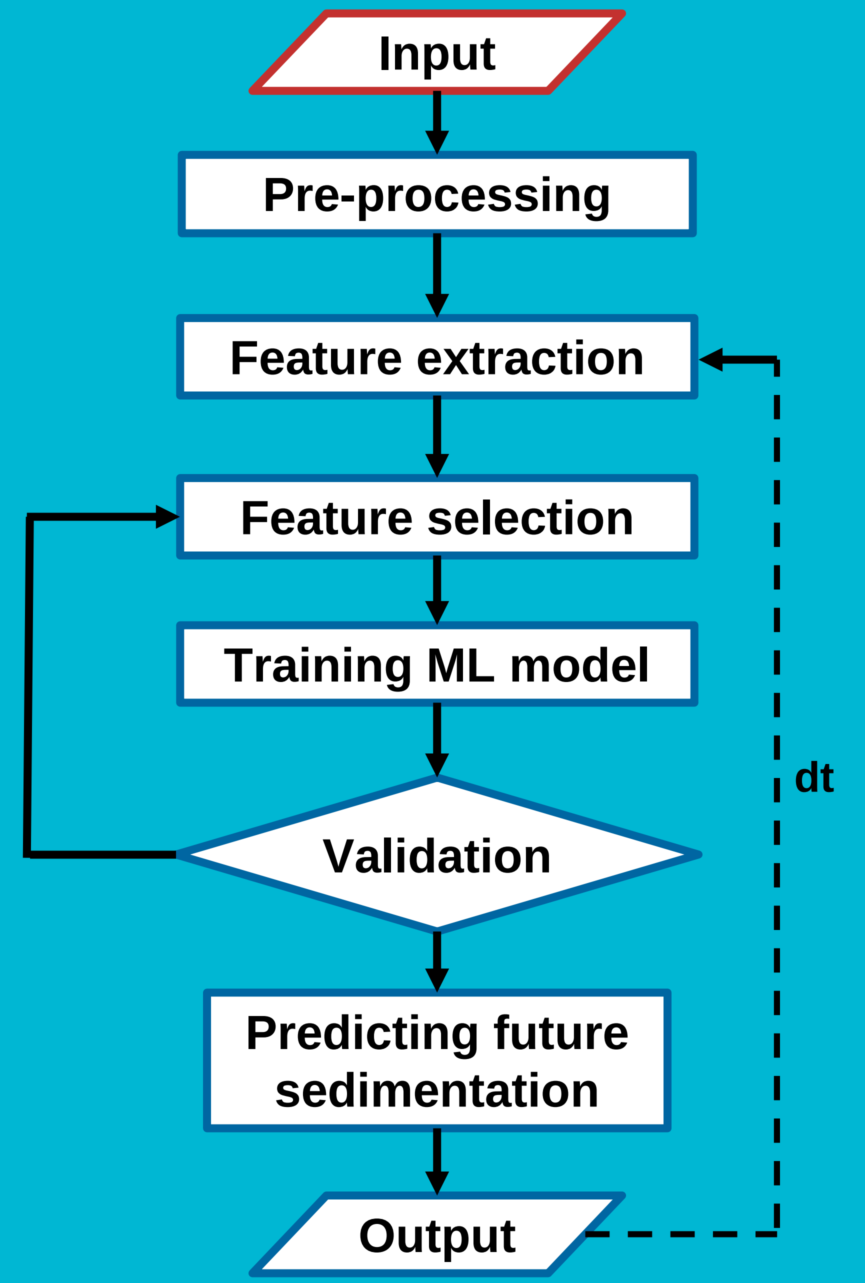
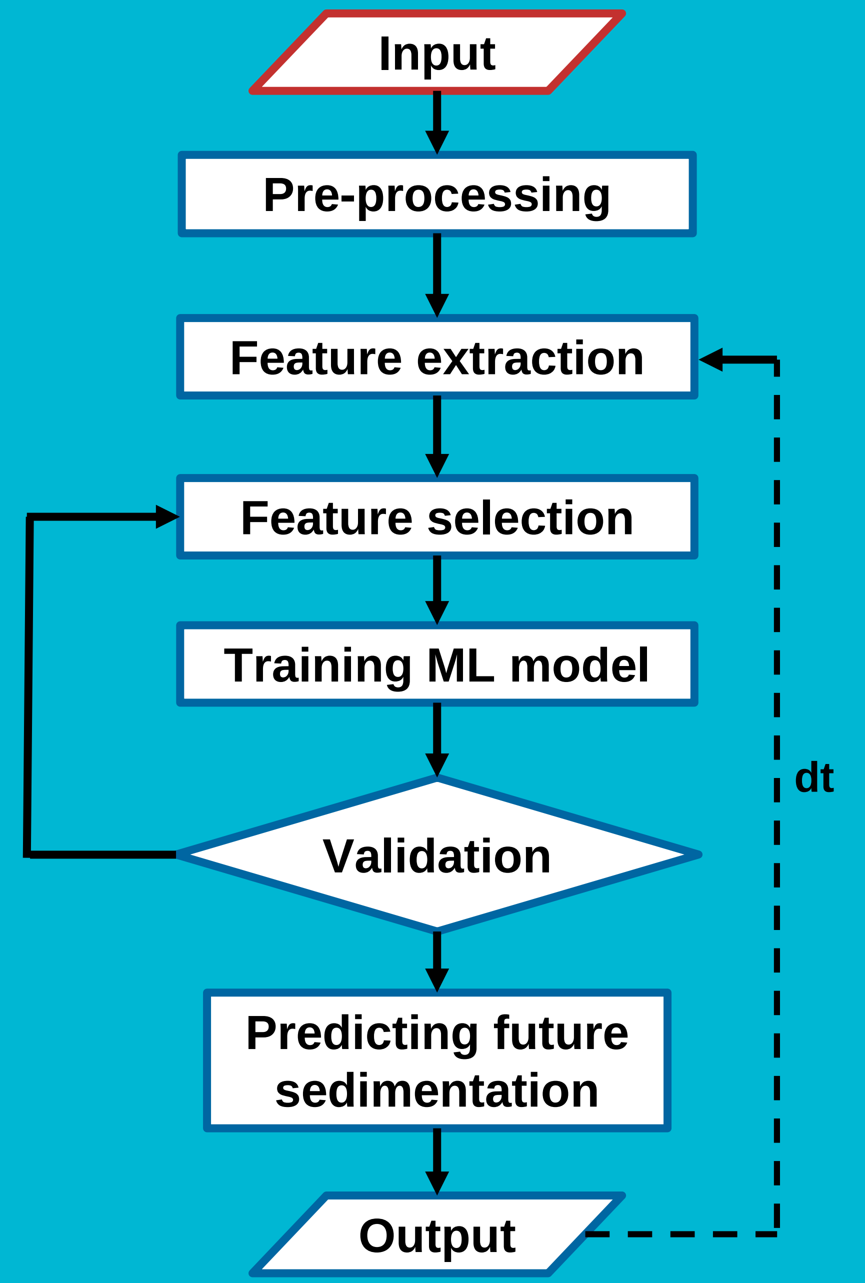


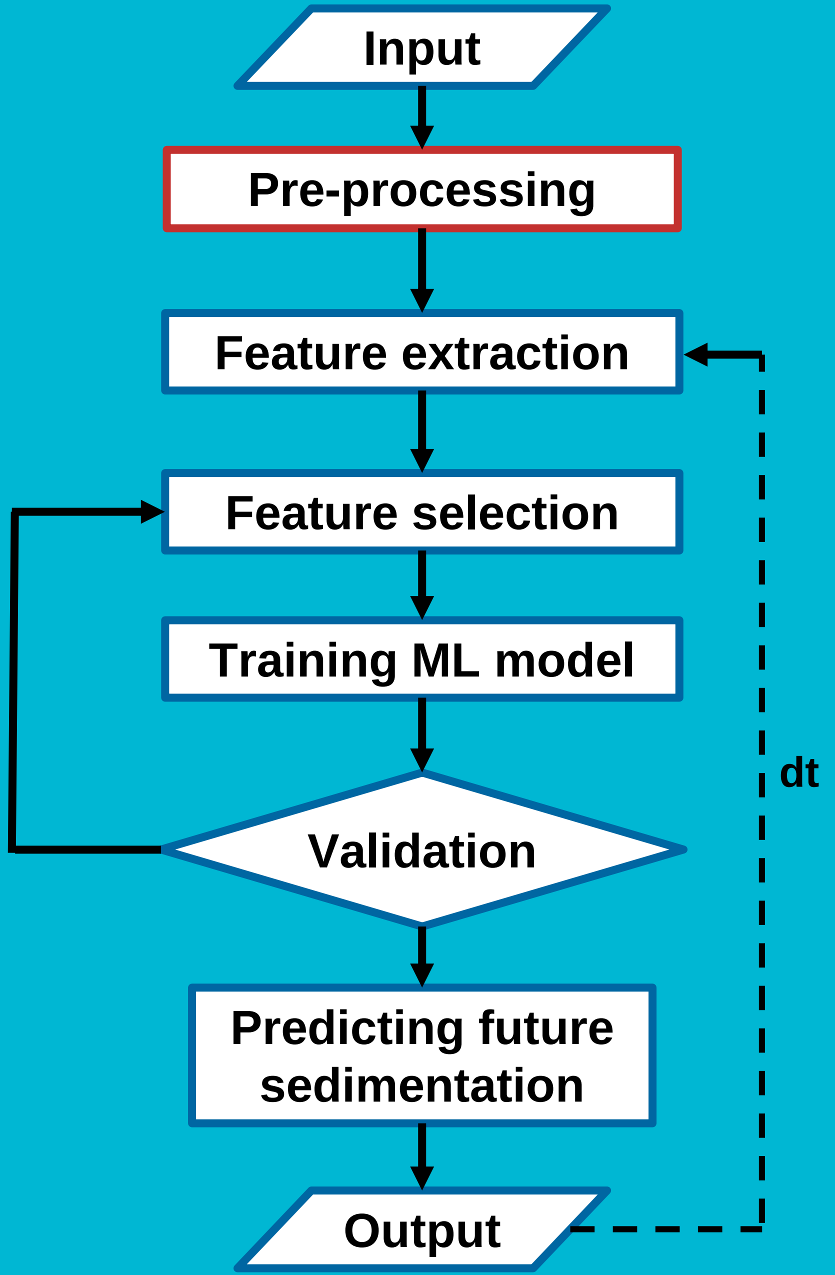
Input

- Point clouds from bathymetric data
- 1997, 2008, 2012, 2018
- Annual rainfall, river flow and dam flow in 2001-2021



Pre-processing

- Filtering
- Clipping
- Triangulating
- Projecting TIN on grid



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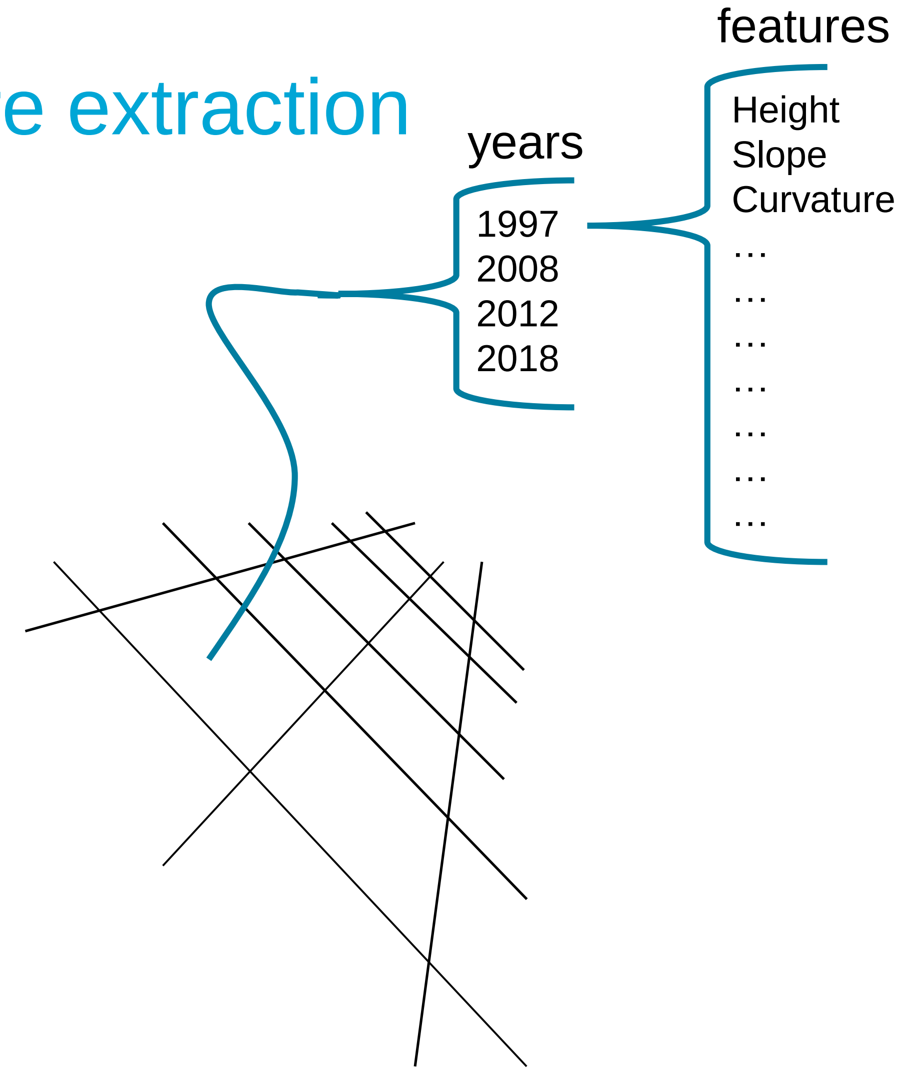
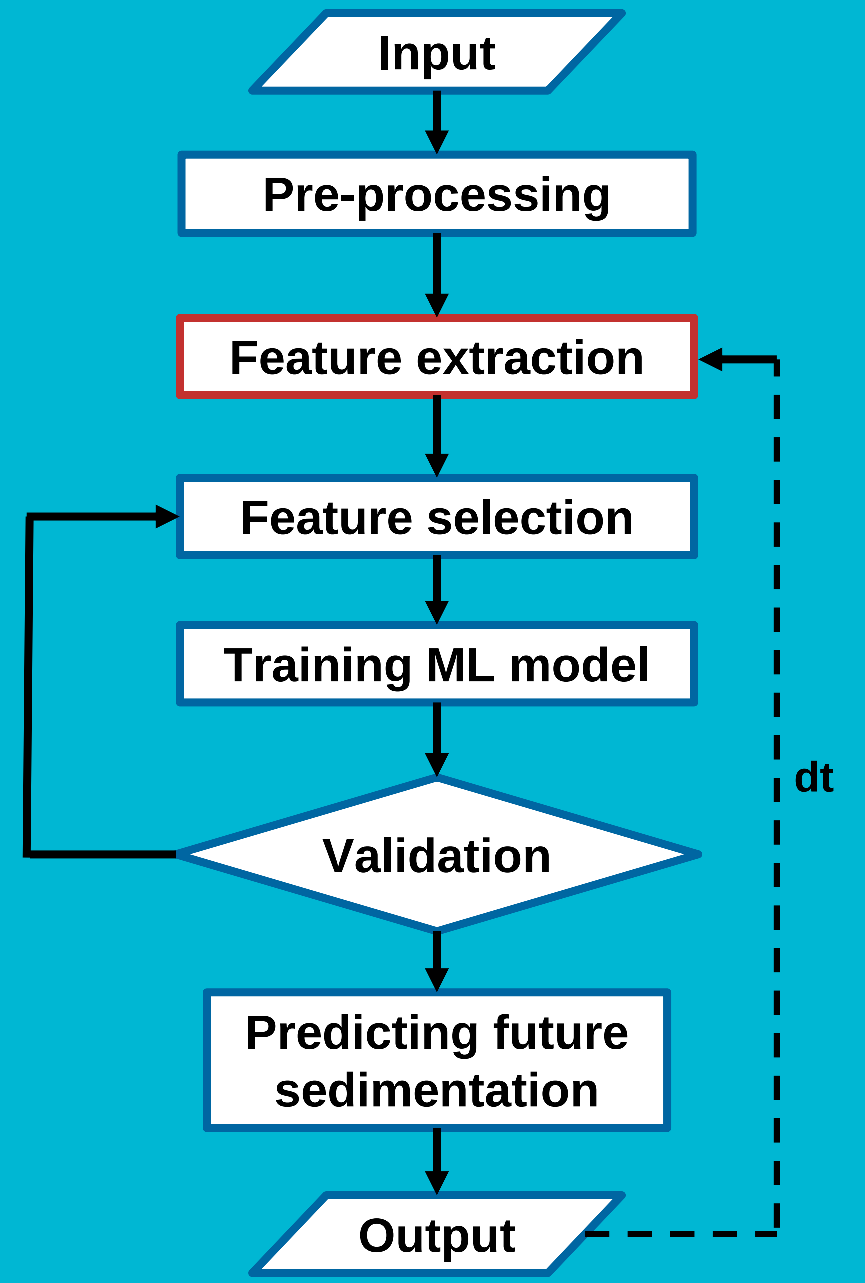
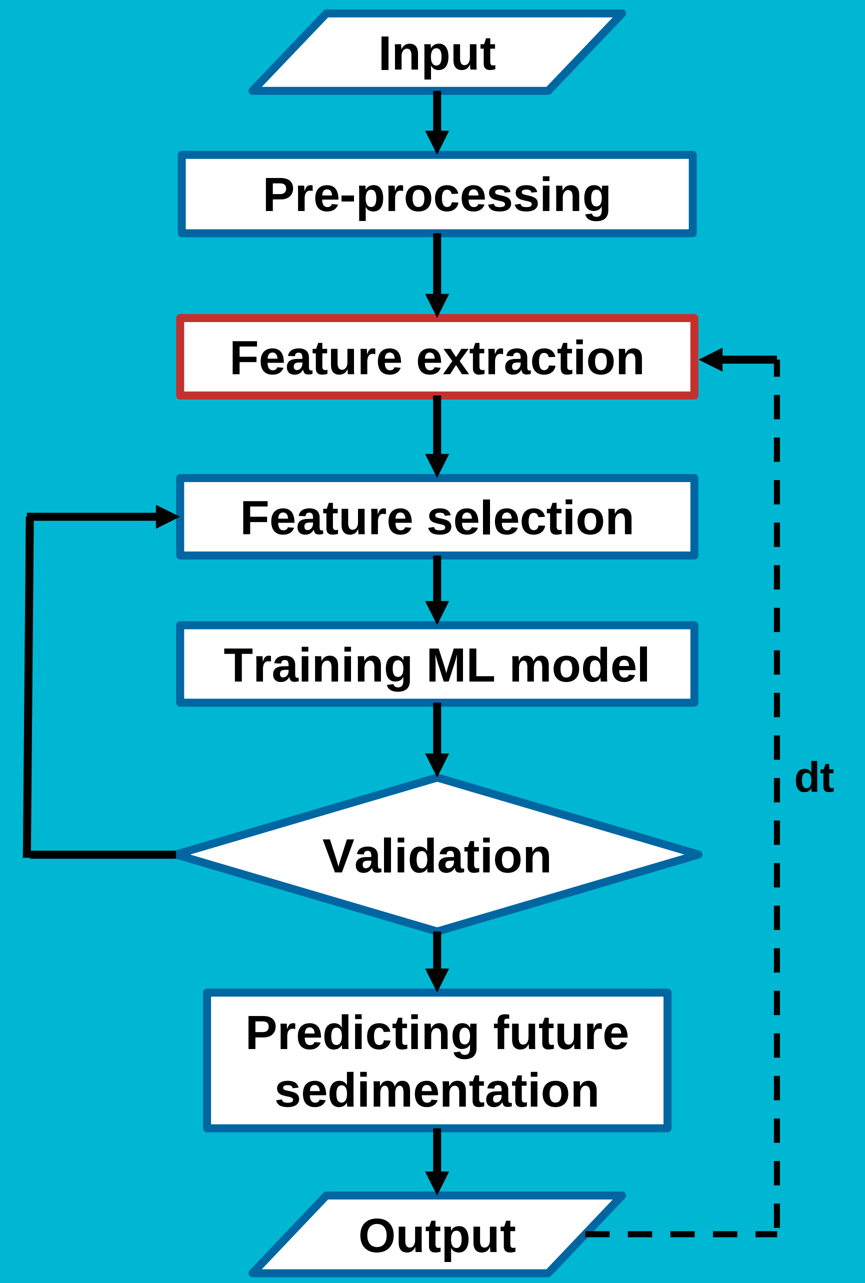
Feature extraction





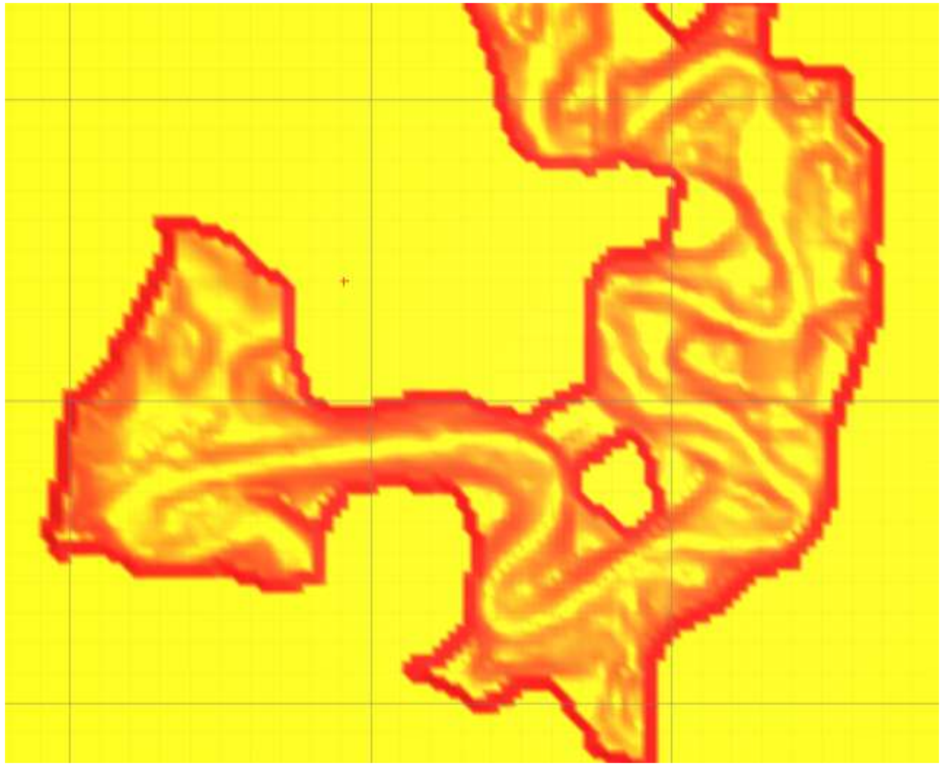
Feature extraction

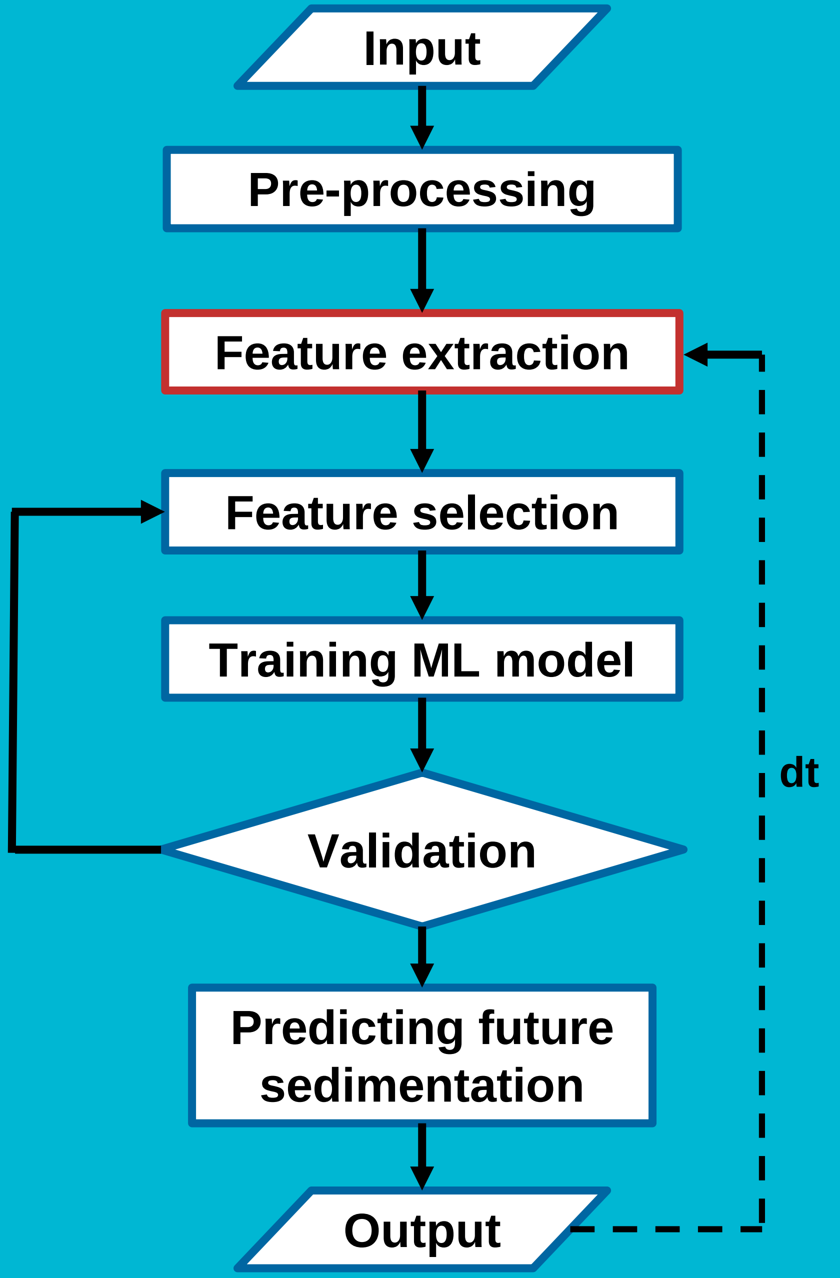
- Basic features



Feature extraction

- Basic features
  - Slope
  - Aspect
  - Height
  - Depth
  - Curvature





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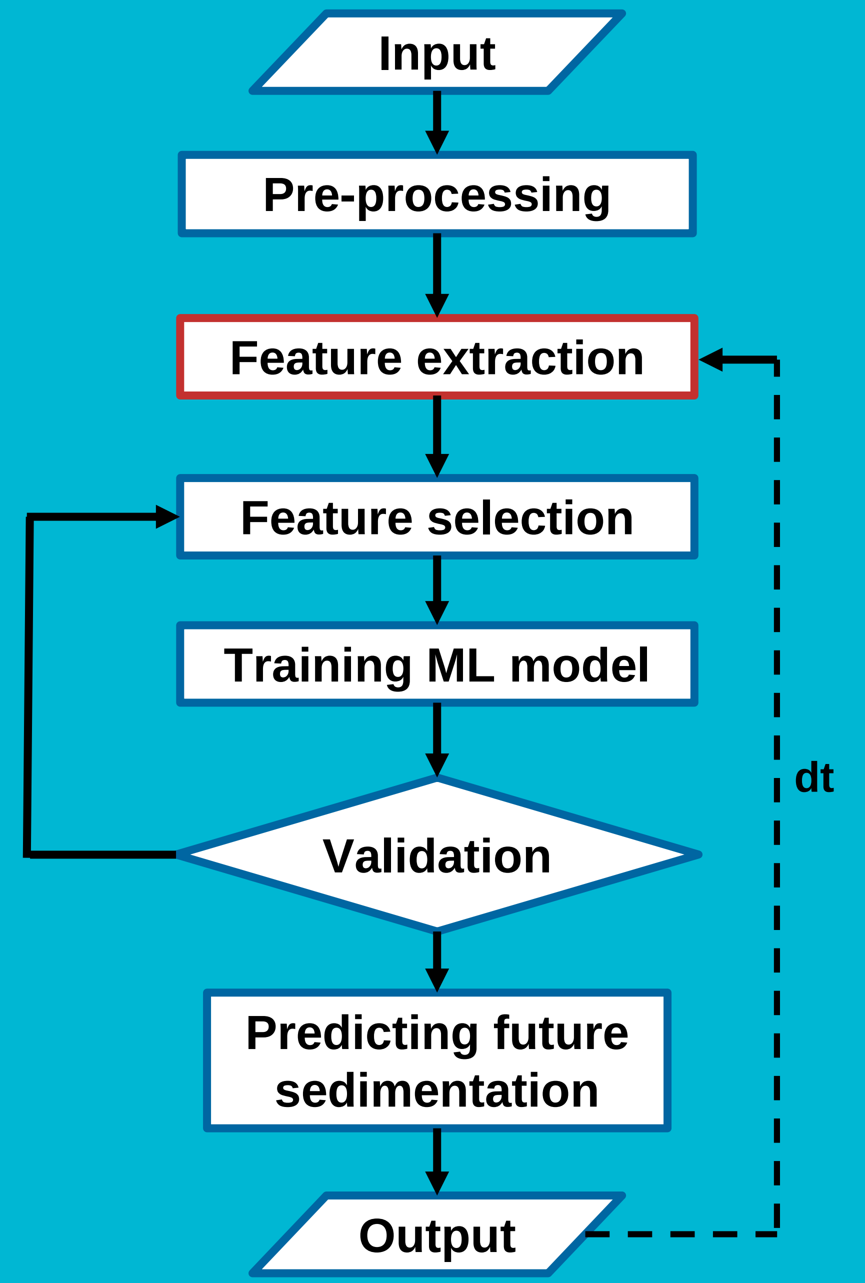
Feature extraction

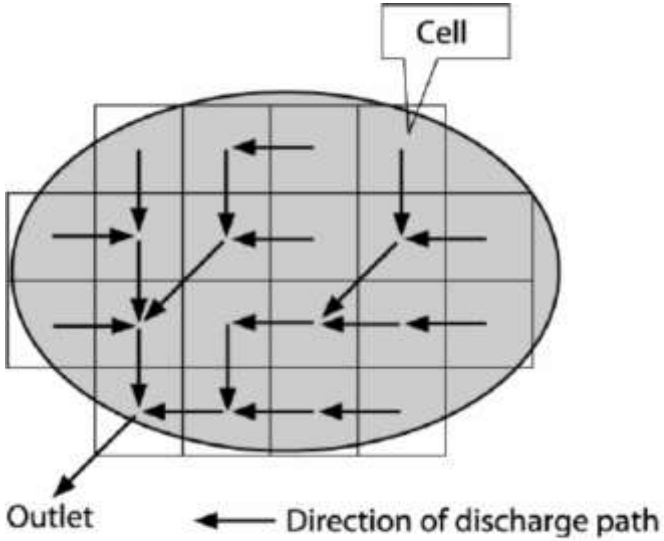
- Basic features
- Computed features:



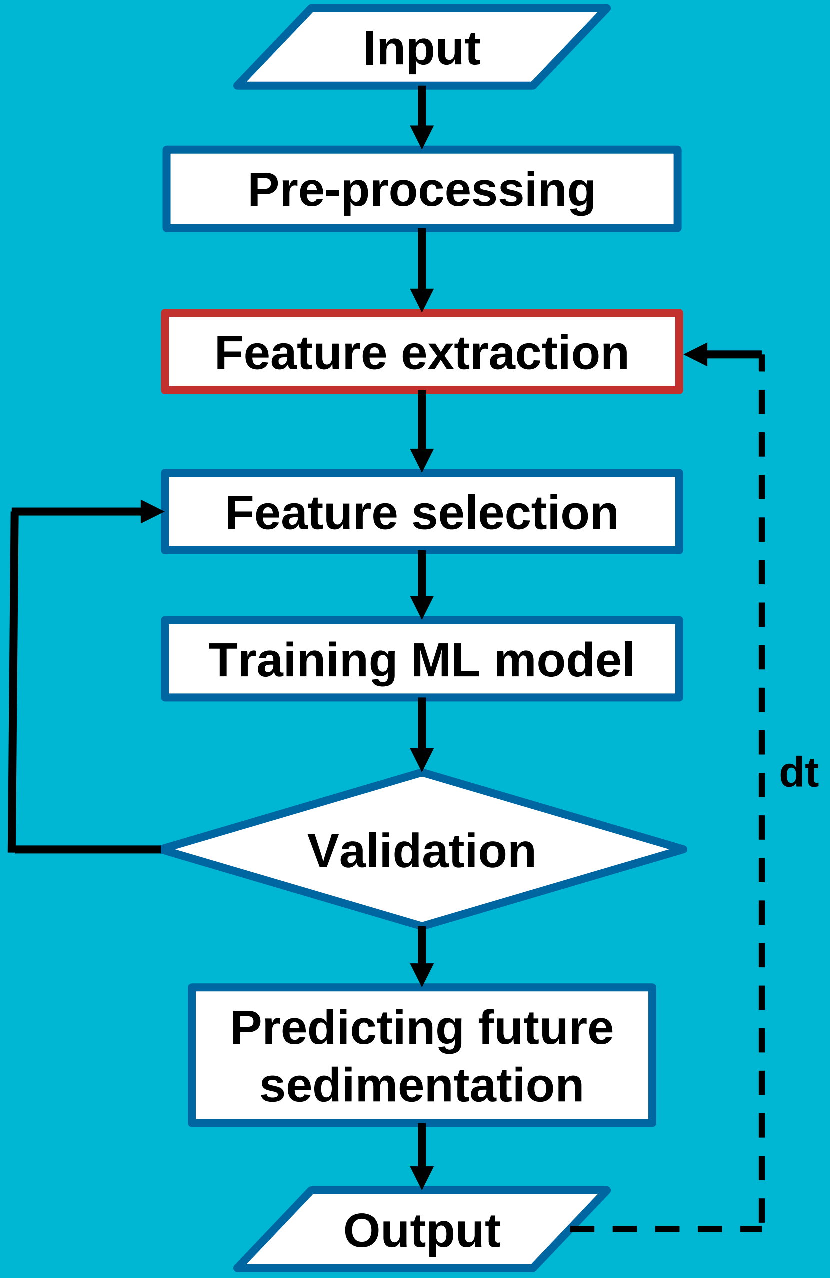
https://www.researchgate.net/figure/Illustration-of-a-grid-cell-based-distribution-runoff-model_fig3_238078019

Feature extraction

- Basic features
- Computed features:
    - Runoff model



https://www.researchgate.net/figure/Illustration-of-a-grid-cell-based-distribution-runoff-model_fig3_238078019



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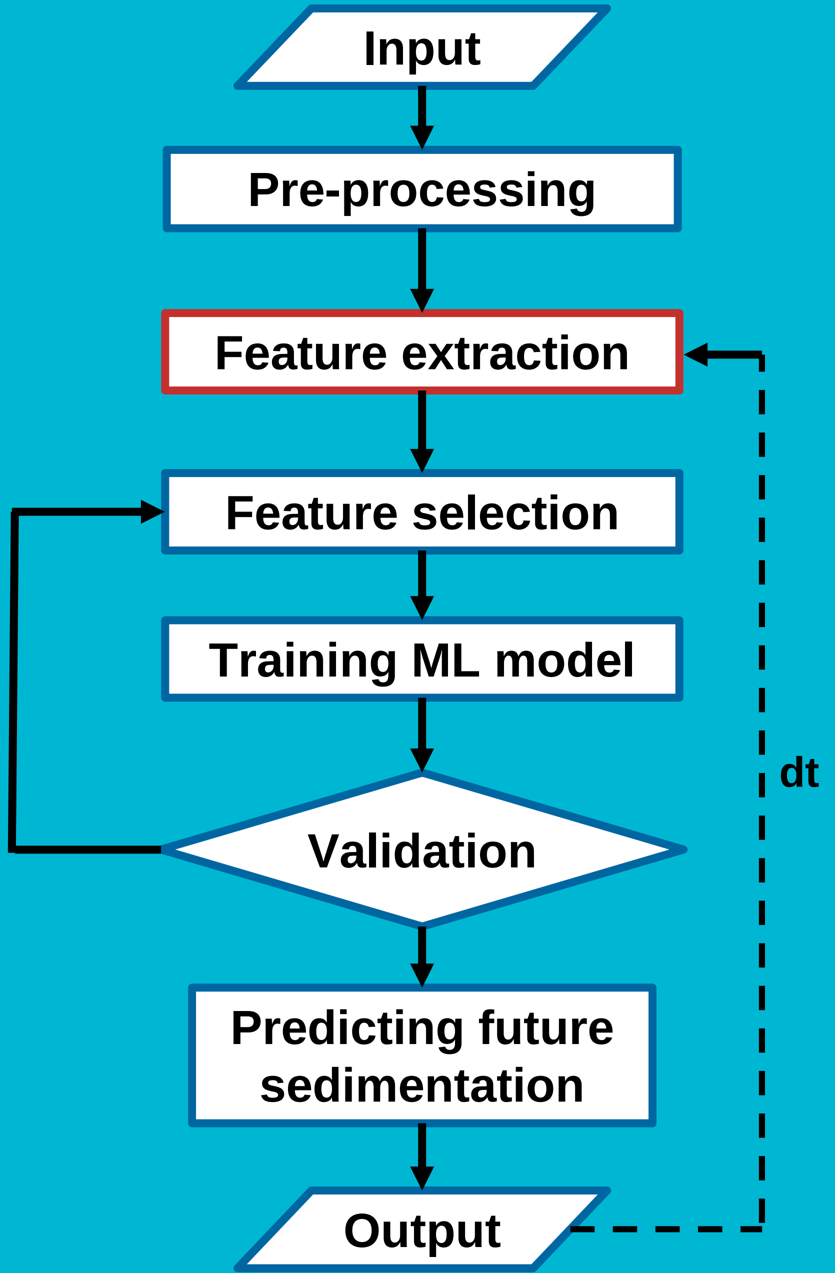
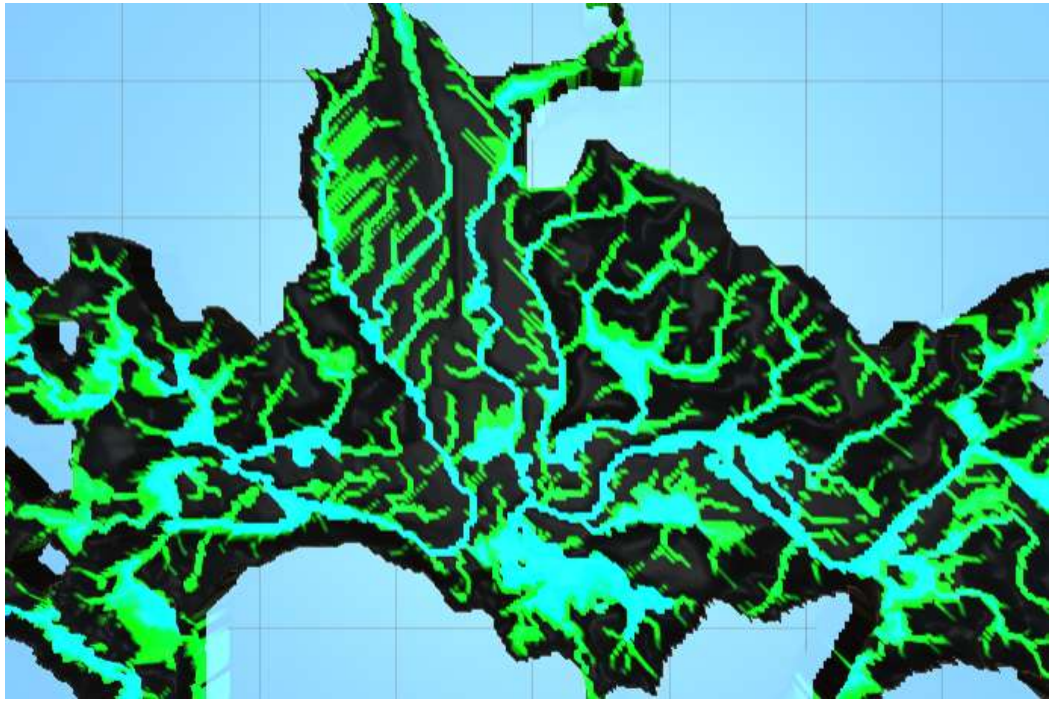
Feature extraction

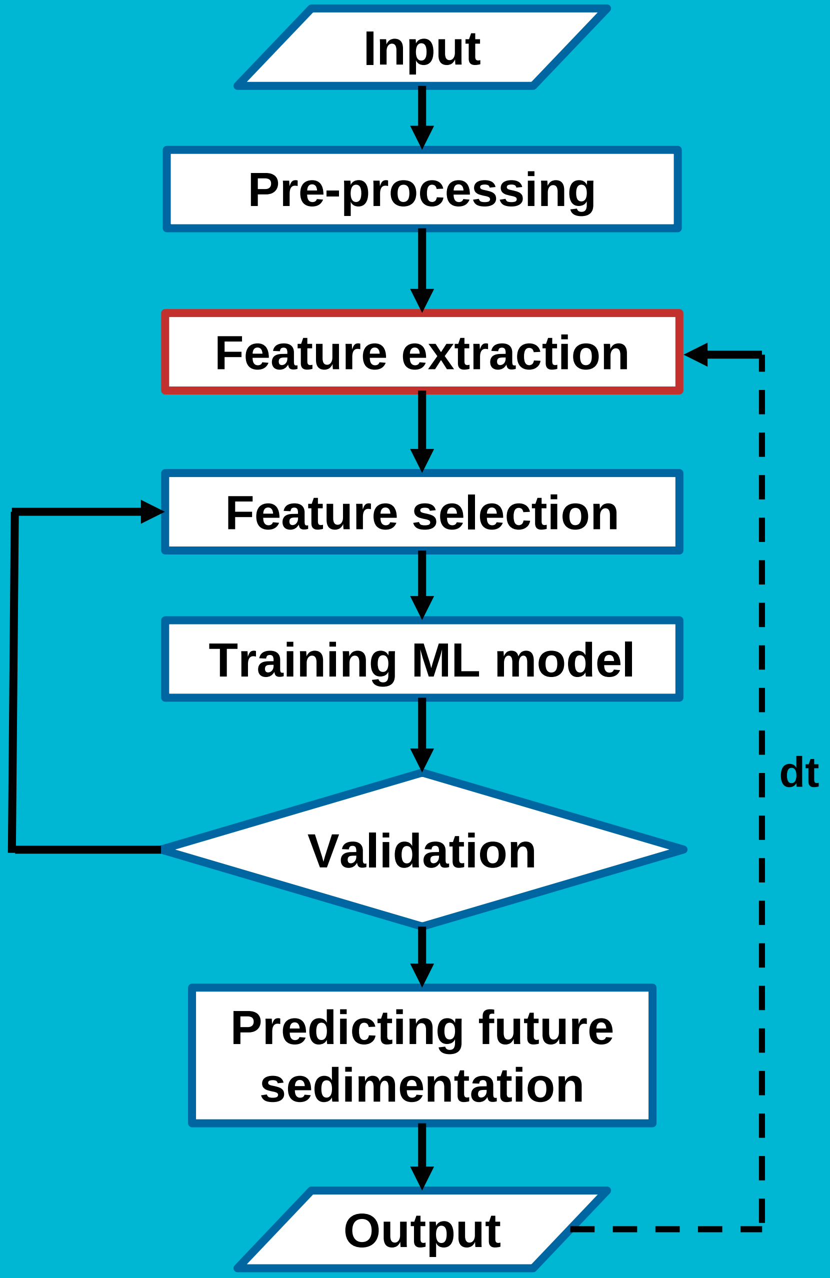
- Basic features
- Computed features:
  - Runoff model



Feature extraction

- Basic features
- Computed features:
  - Runoff model





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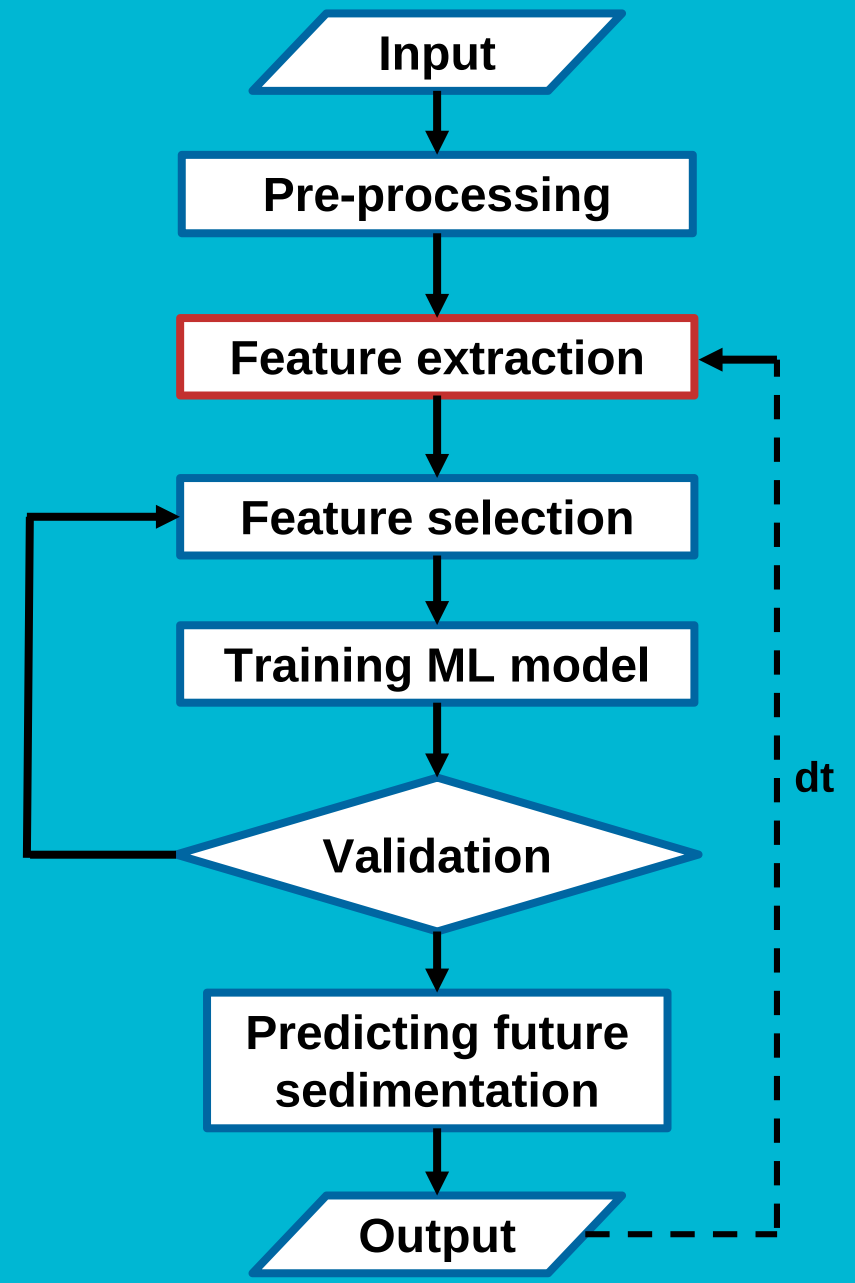
Feature extraction

- Basic features
- Computed features:
  - Runoff model
  - Folow Path

0	0	1	0	0	1	0
0	0	2	0	1	2	0
0	1	2	3	2	1	0
0	2	4	3	3	0	0
0	6	5	3	2	1	0
8	6	4	3	1	0	0



Feature extraction

- Basic features
- Computed features:
  - Runoff model
  - Folow Path

0	0	1	0	0	1	0
0	0	2	0	1	2	0
0	1	2	3	2	1	0
0	2	4	3	3	0	0
0	6	5	3	2	1	0
8	6	4	3	1	0	0

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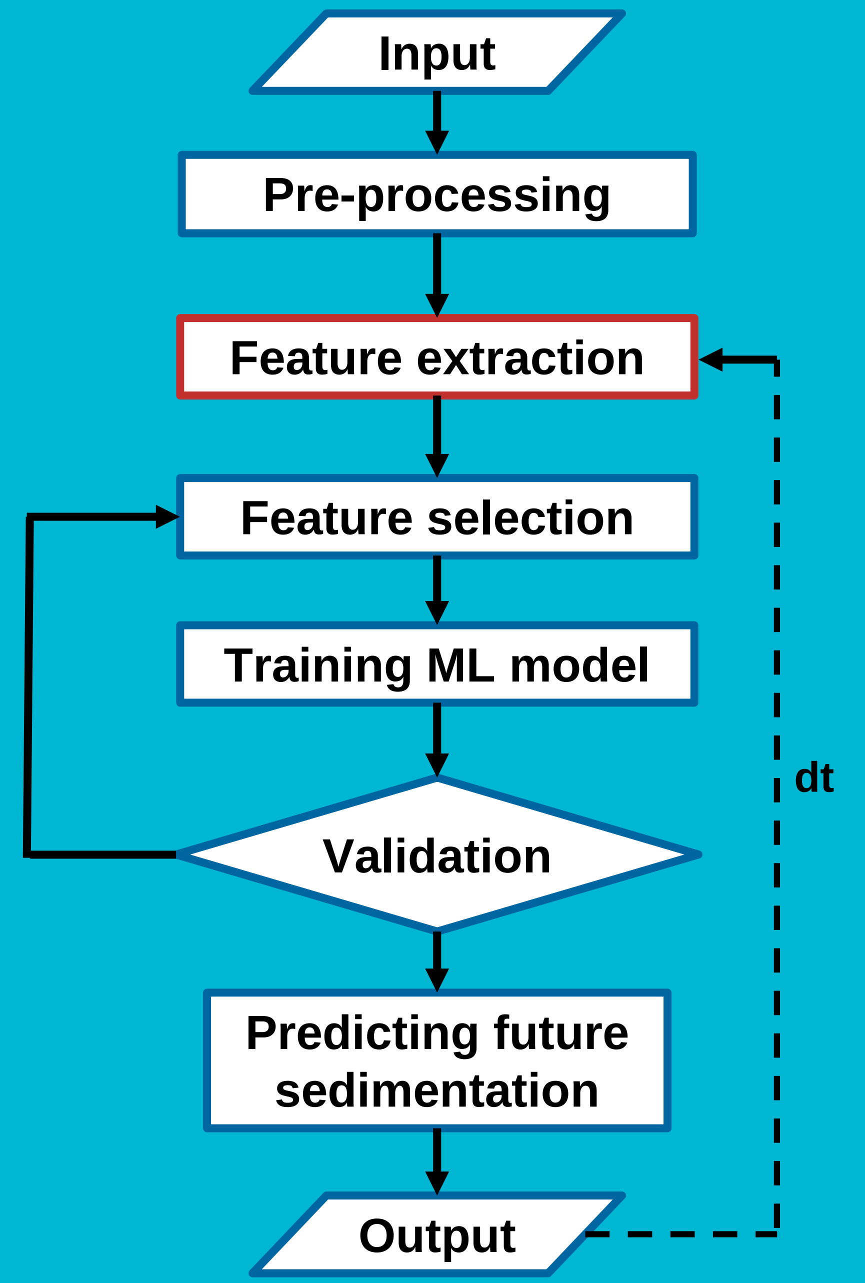
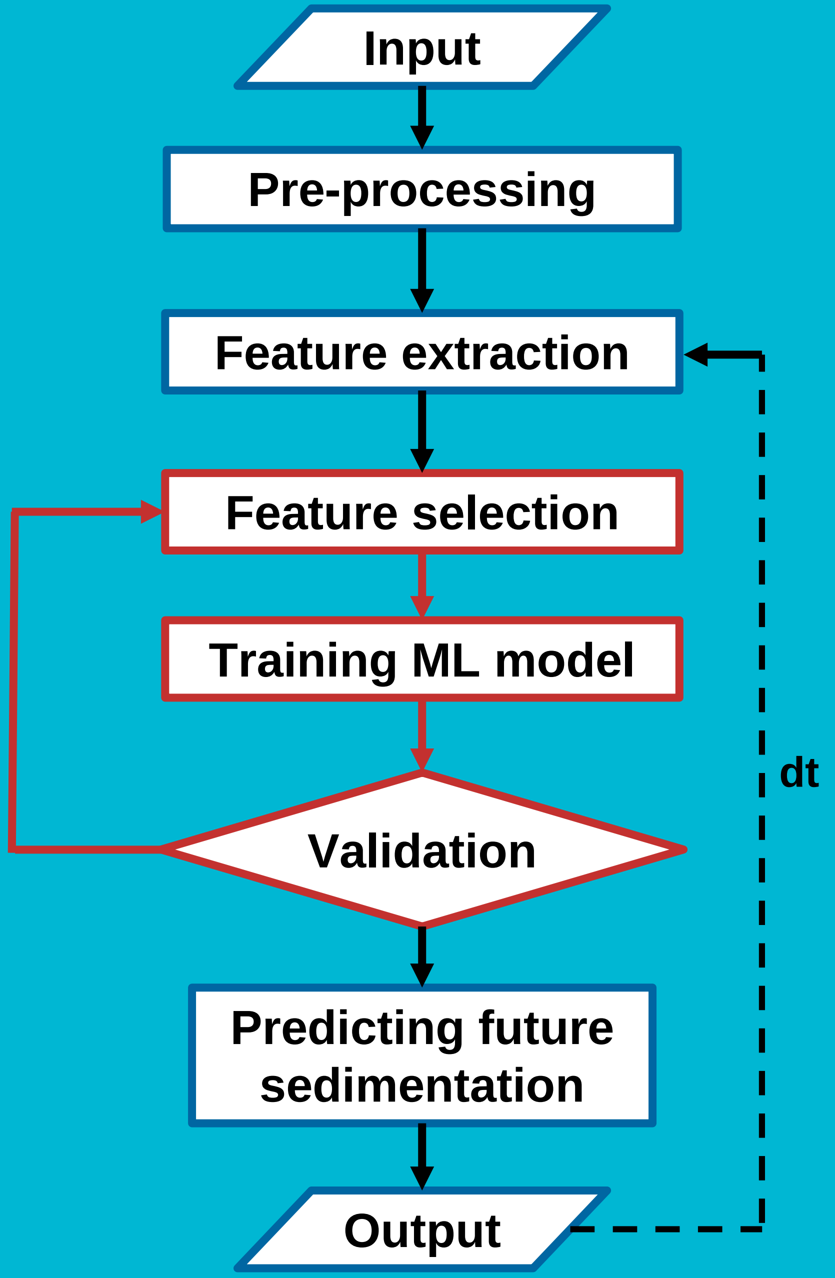


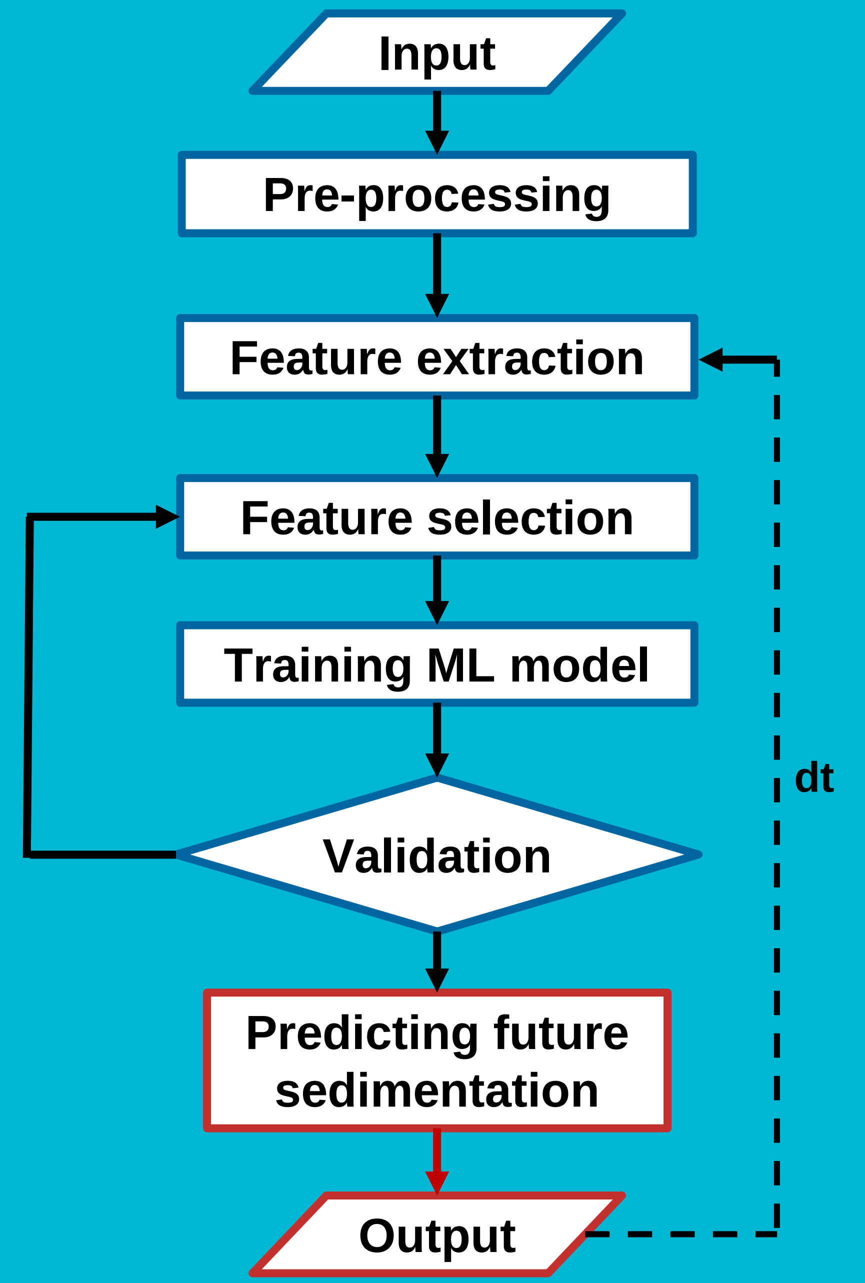
Model training and validation

Training data: 1997-2008 and 2008-2012
Testing data: 2012-2018



Predictions

- New output = sedimentation levels + previous hieght map
- Features extracted for new DEM



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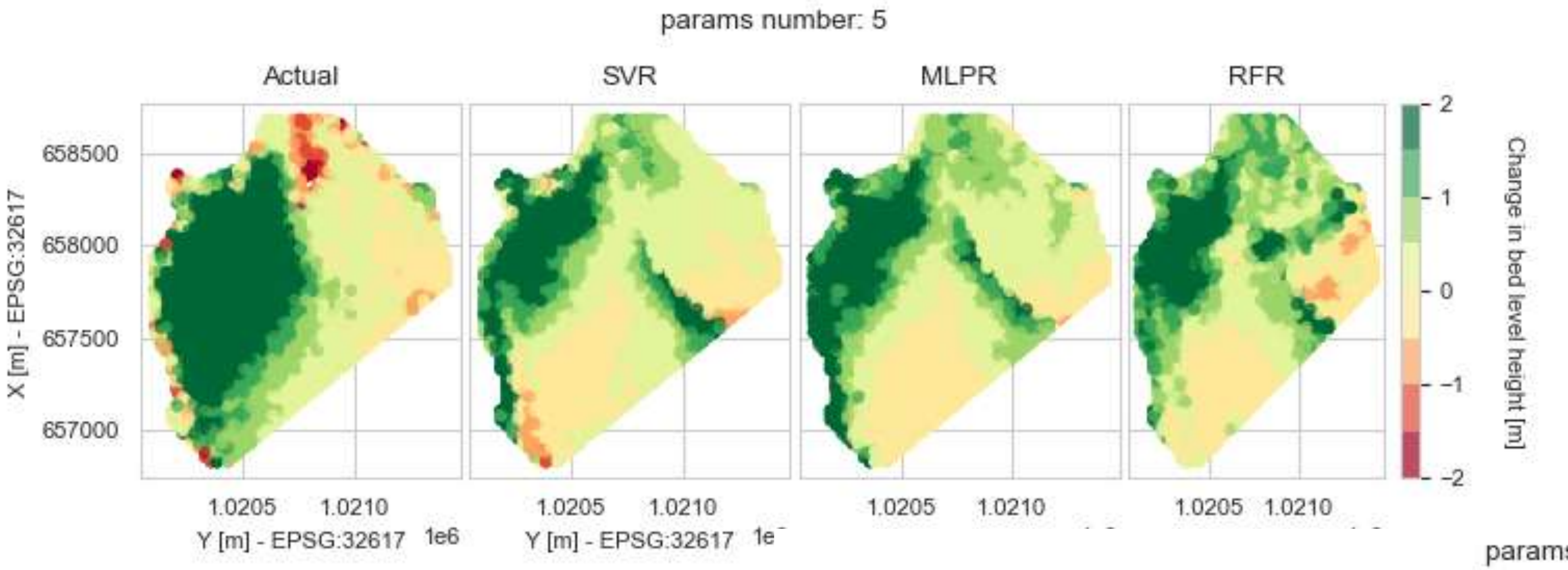
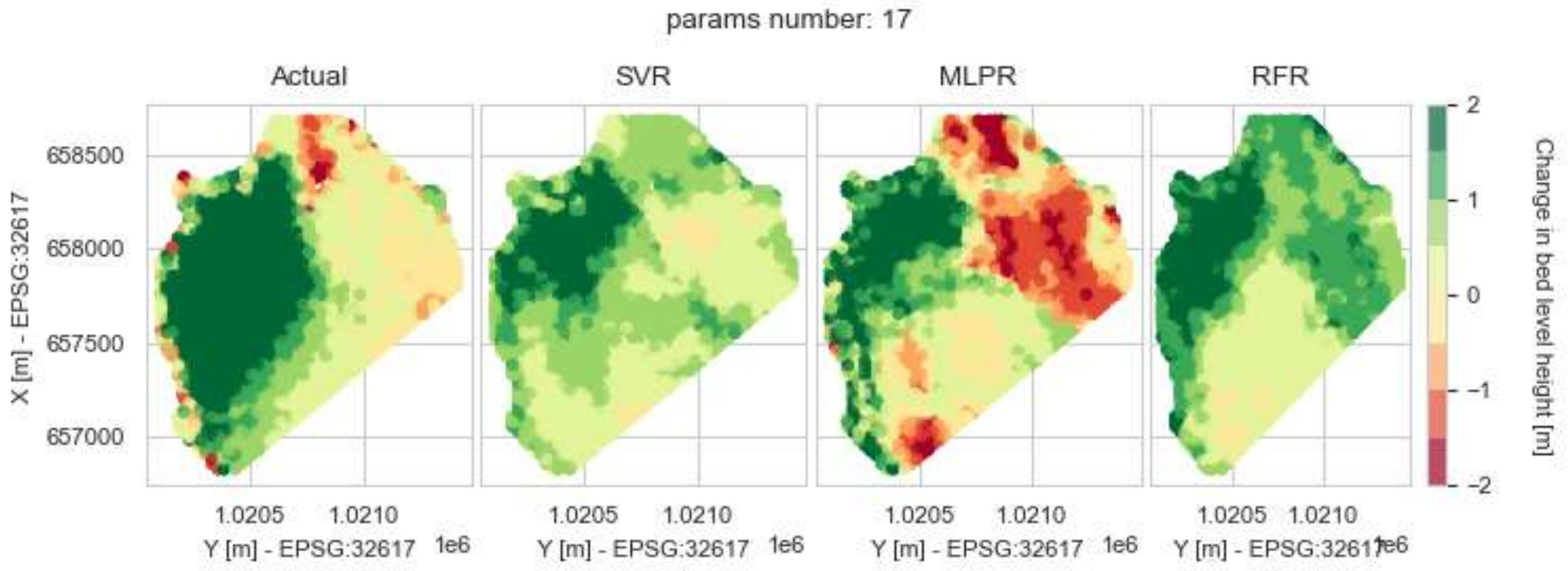
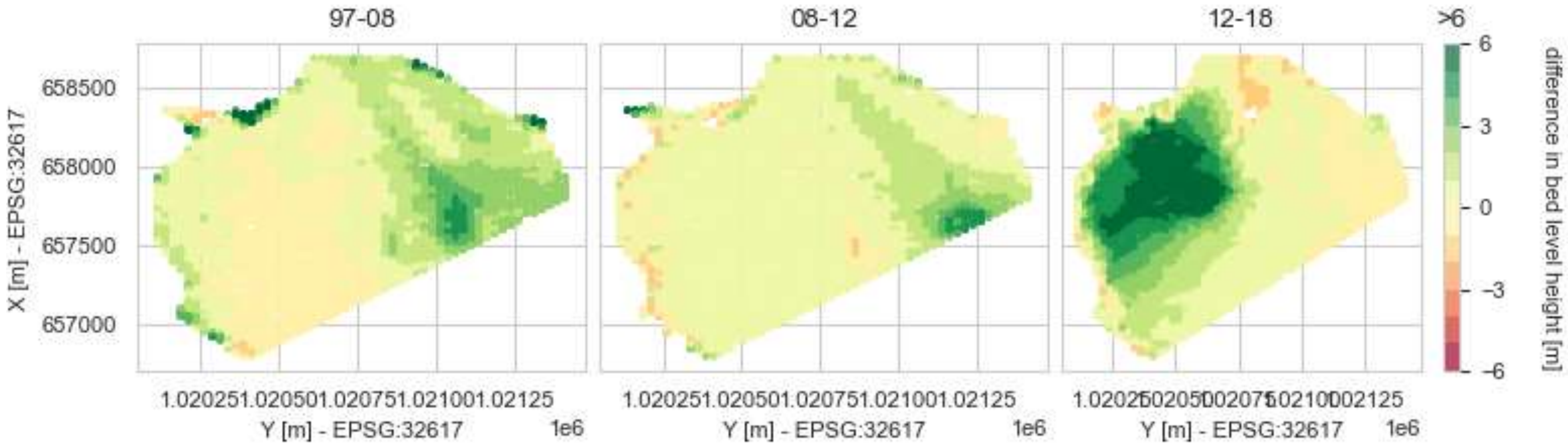
Results

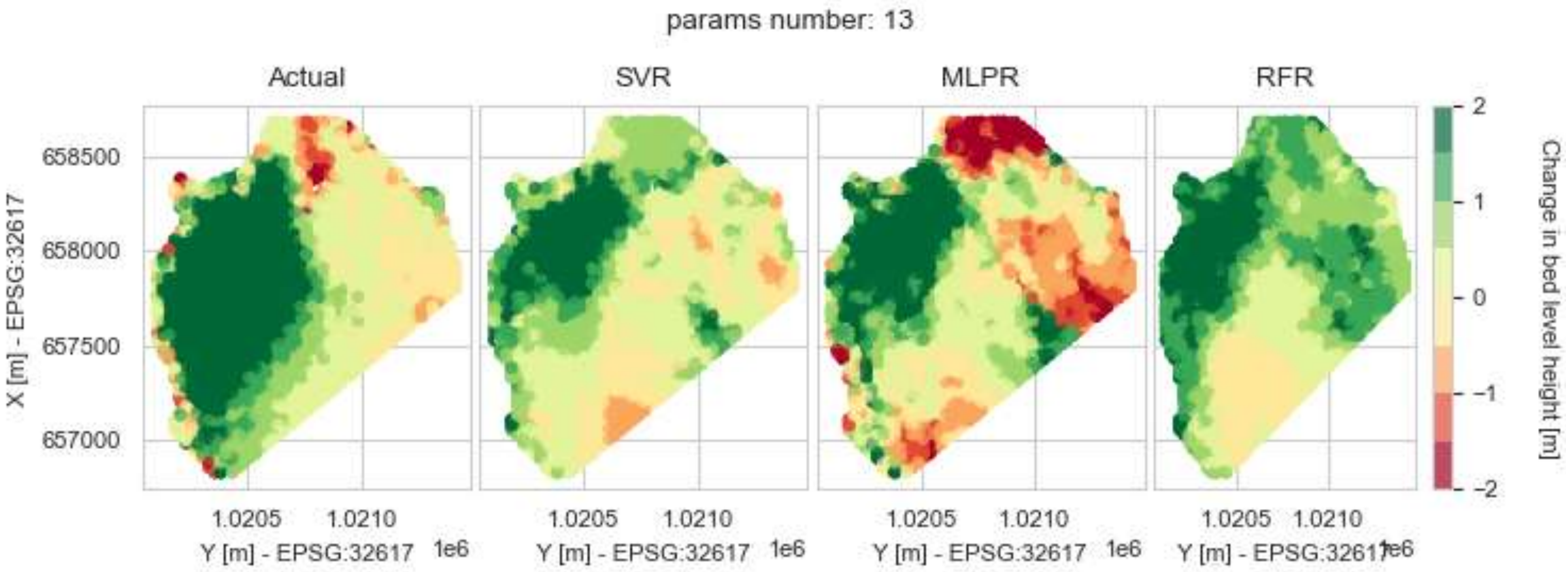
Test Results – Feature and Model Selection





Test Results – Feature and Model Selection





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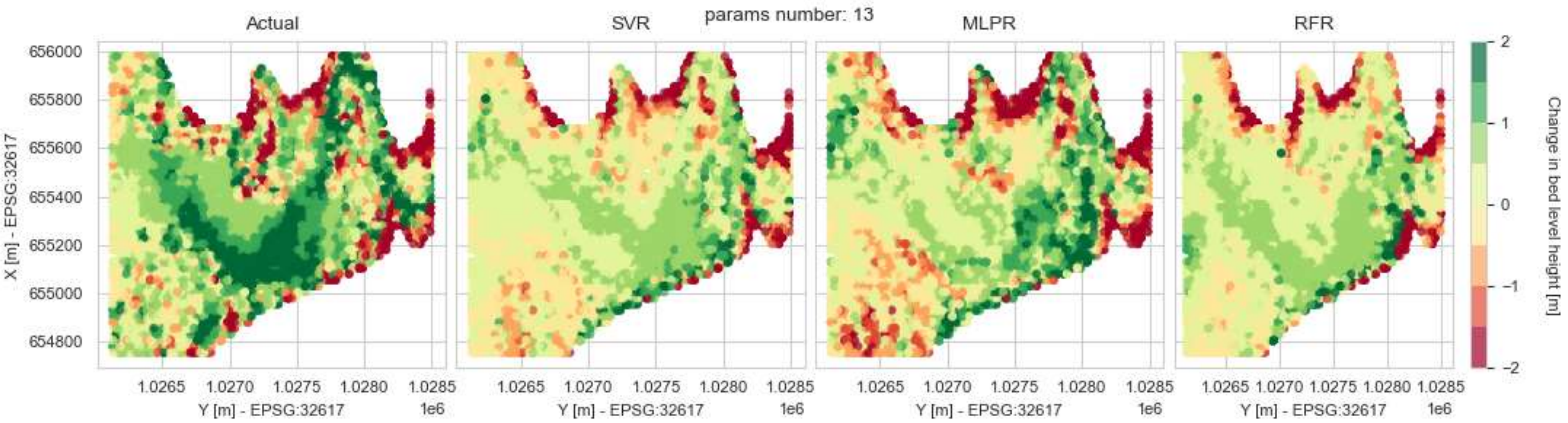
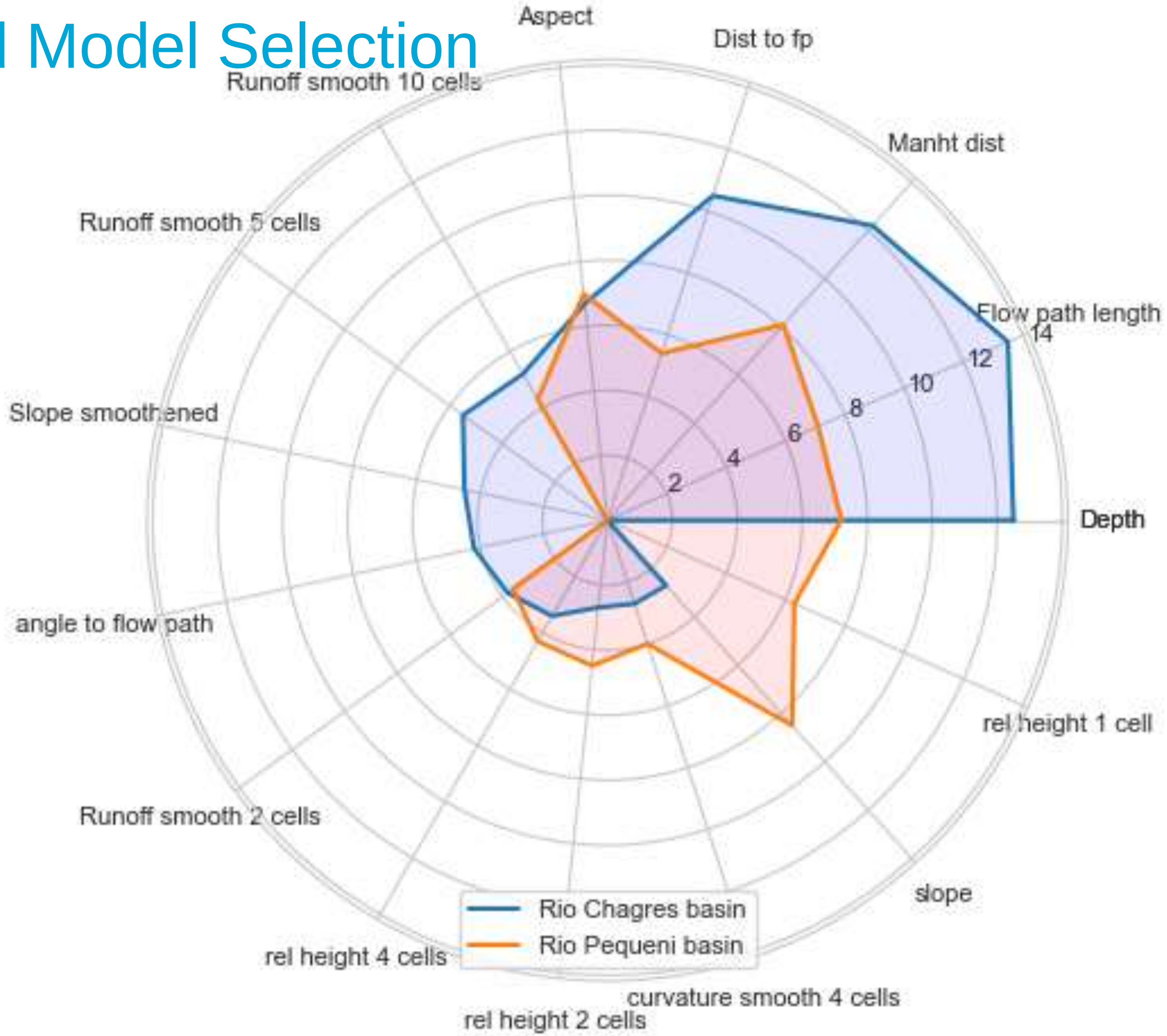
Test Results – Feature and Model Selection



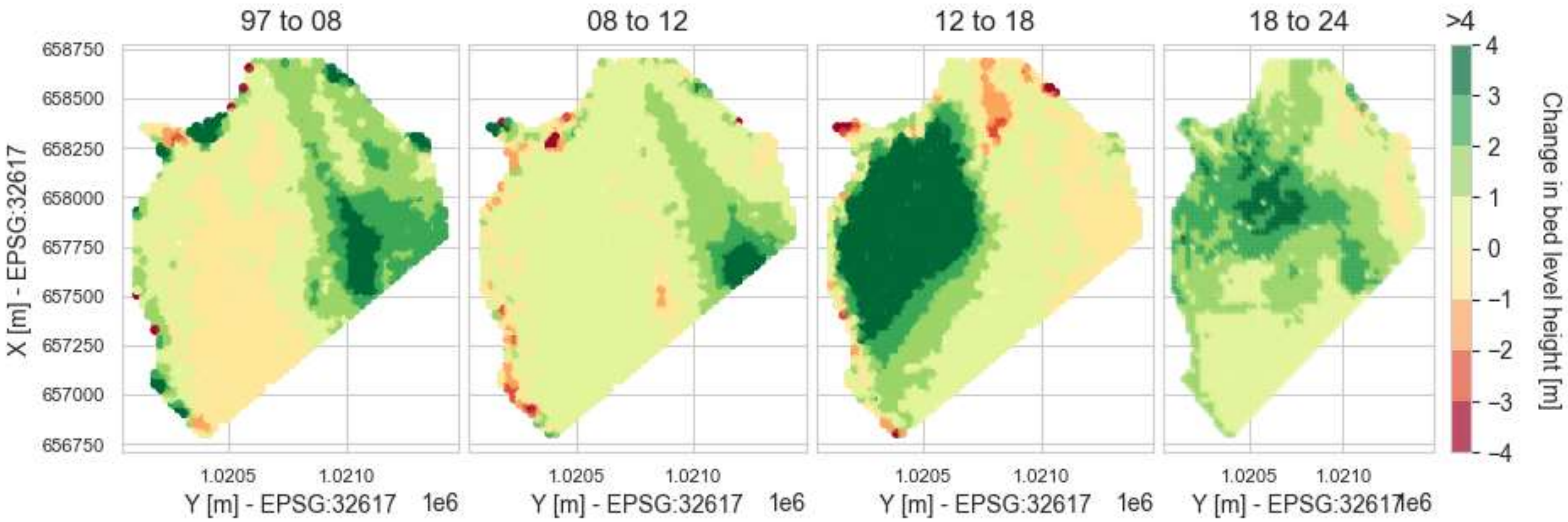
Test Results – Feature and Model Selection

- Río Chagres basin: 14 features
- Río Pequení basin: 12 features

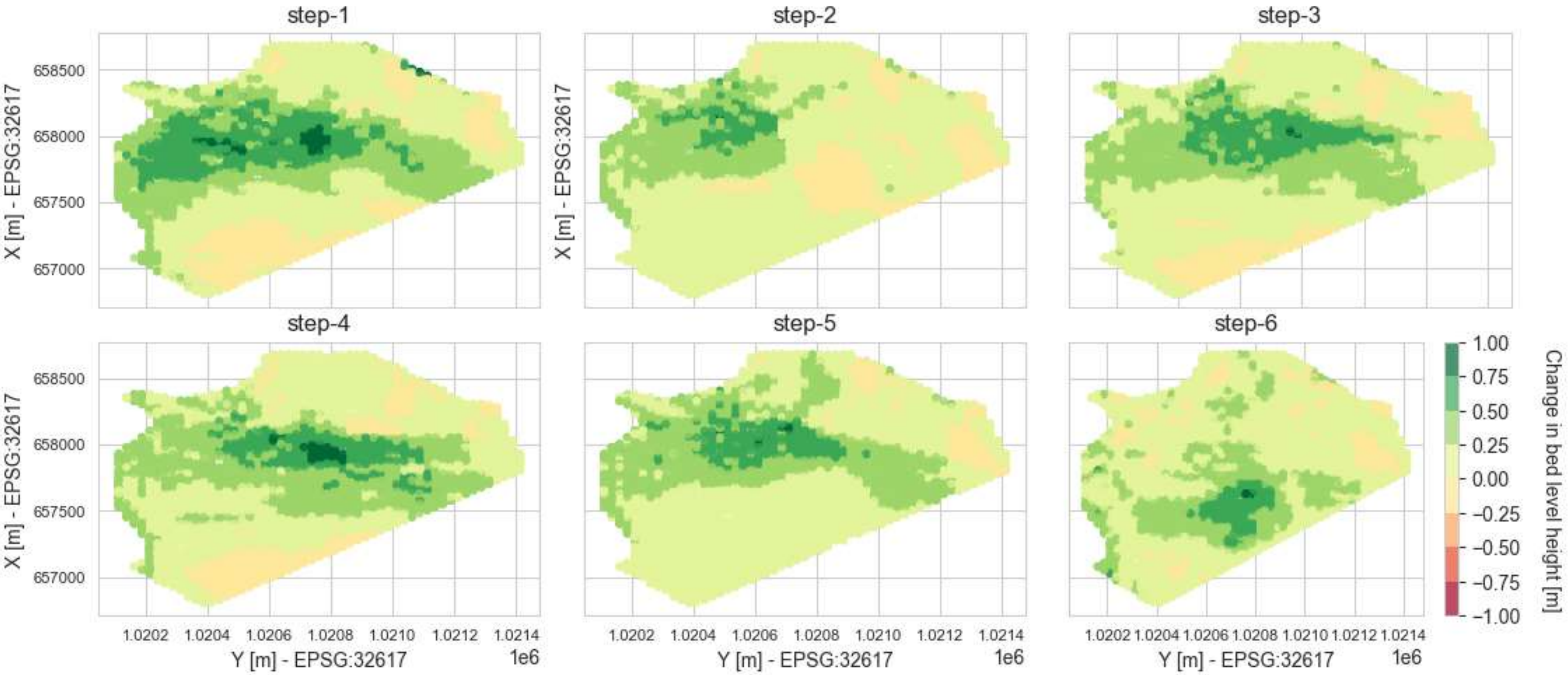


Predictions

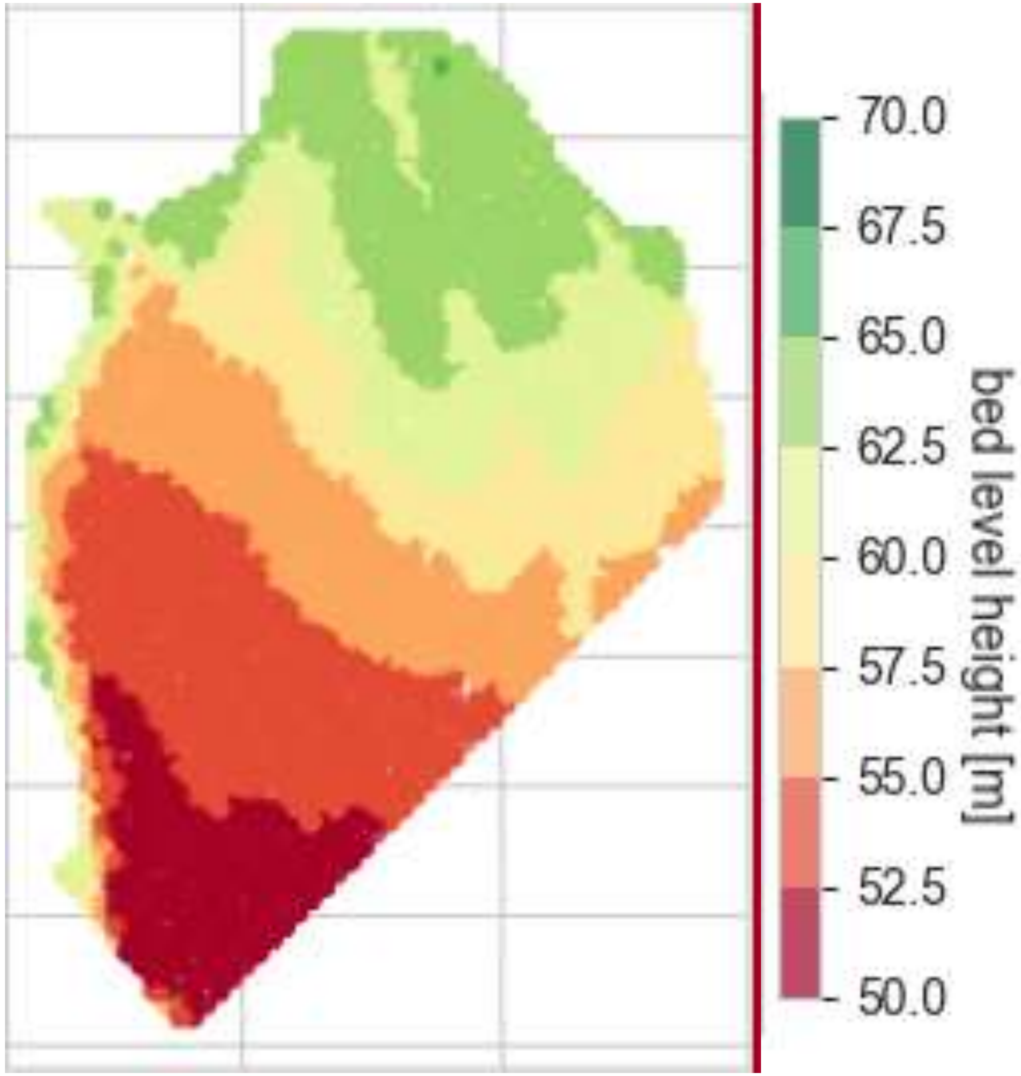
Predictions - Río Chagres



Predictions - Río Chagres



Predictions - Río Chagres



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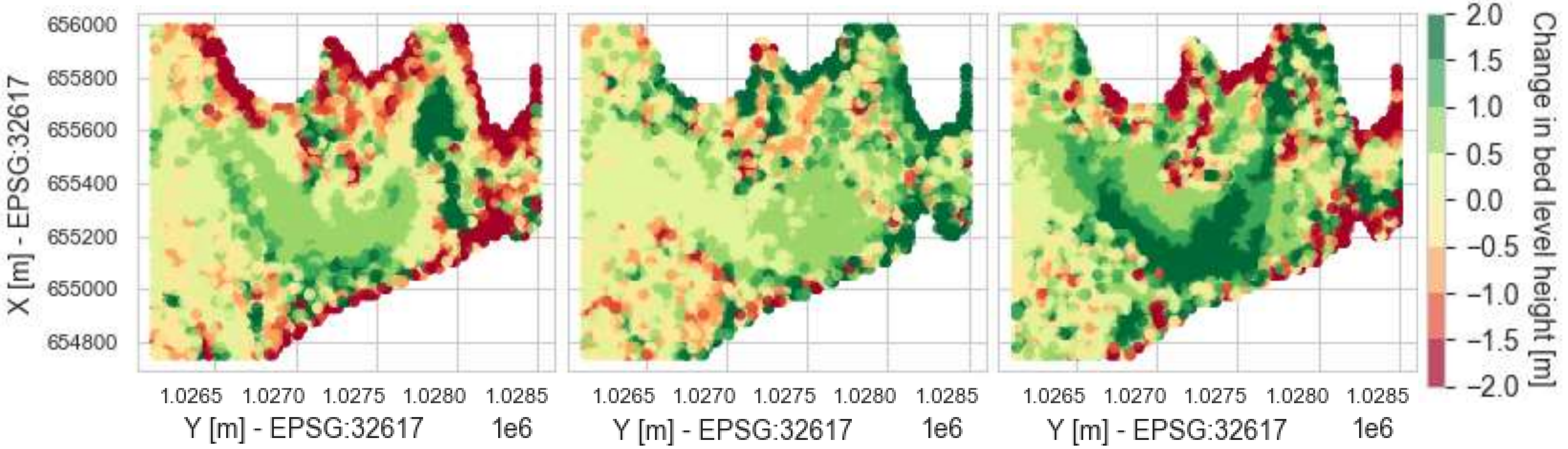
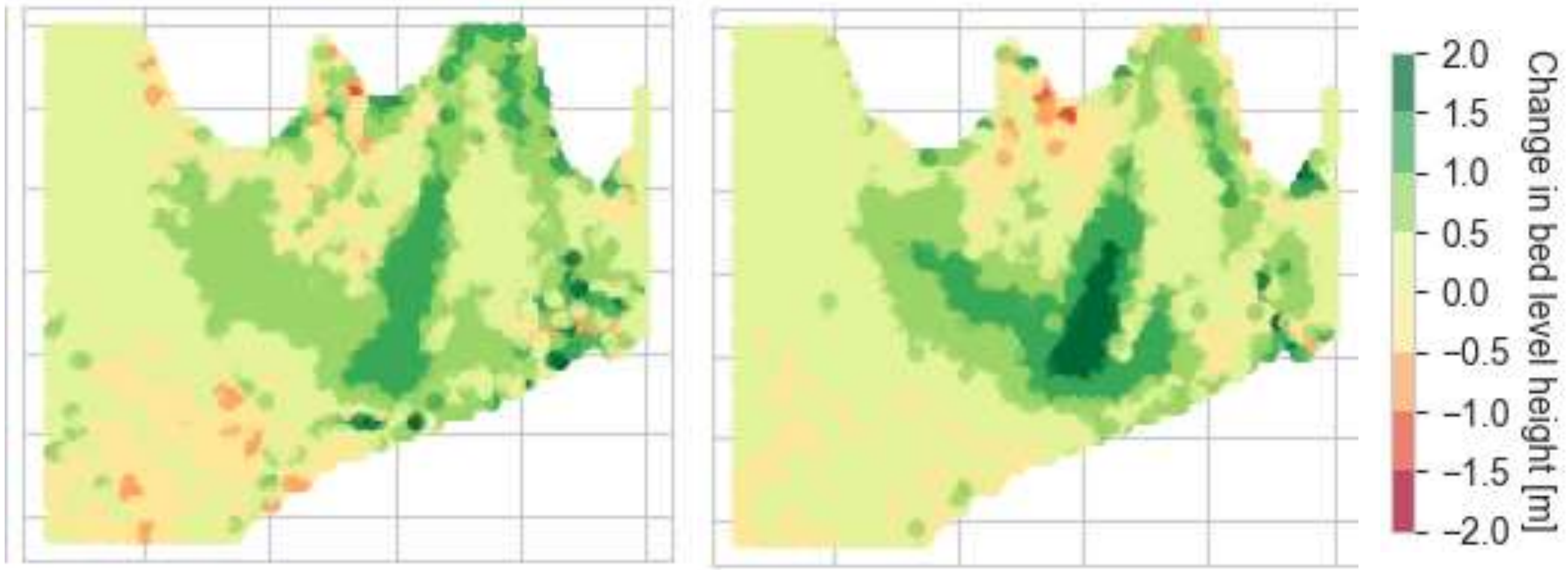
Predictions - Río Pequení





Predictions

Analysed prediction for 2024:

- Río Chagres basin: 3000 – 4000 m^3 new sediment

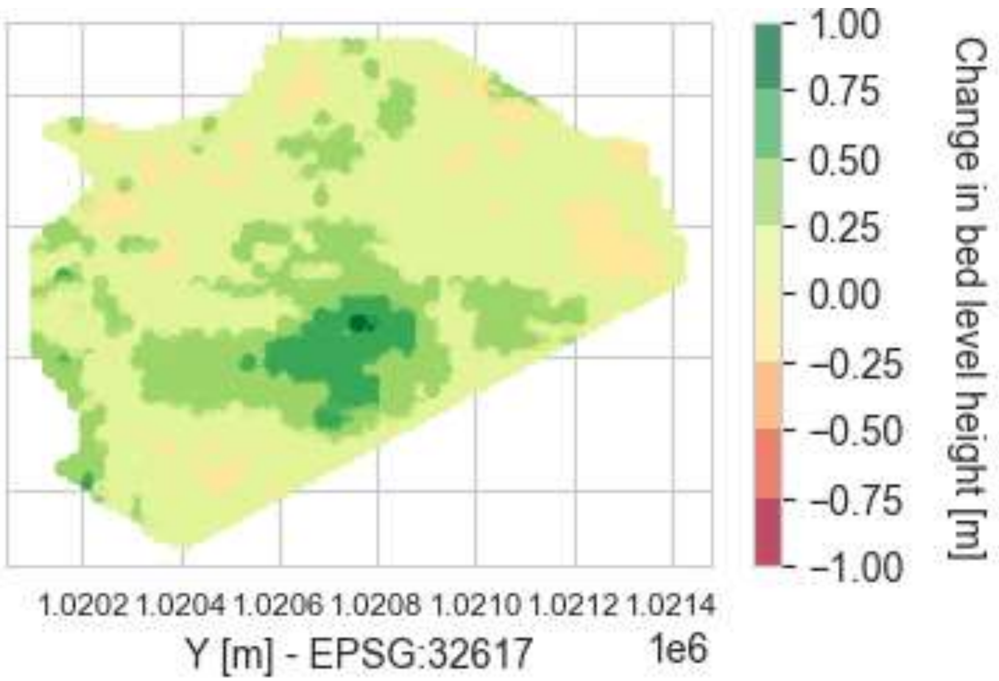
Predictions

Analysed prediction for 2024:

- Río Chagres basin: 3000 – 4000 m^3 new sediment

Location of sediment front:

- Río Chagres basin: Moved to center and 500 meters away from river mouth



Predictions

Analysed prediction for 2024:

- Río Chagres basin: 3000 – 4000 m^3 new sediment
- Río Pequiní basin: 1400 – 1800 m^3 new sediment

Location of sediment front:

- Río Chagres basin: Moved to center and 500 meters away from river mouth

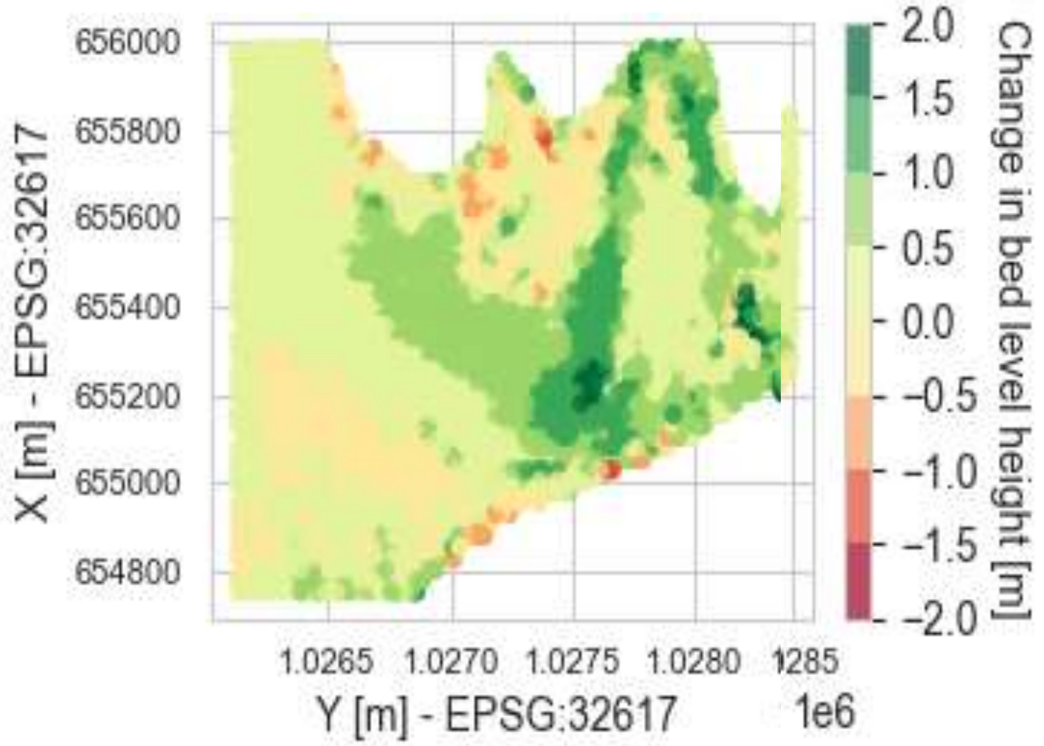
Predictions

Analysed prediction for 2024:

- Río Chagres basin: 3000 – 4000 m^3 new sediment
- Río Pequiní basin: 1000 – 2000 m^3 new sediment

Location of sediment front:

- Río Chagres basin: Moved to center and 500 meters away from river mouth
- Río Pequení basin: Main deposition in higher position of river mouth curve



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Conclusions – Answers to research questions

How to accurately predict sedimentation levels in Lake Alajuela using a Machine Learning method?

- Which sedimentation related features can be extracted from the DEM?
- Which ML model best predicts sedimentation in a reservoir?
- What is the best set of geomorphological and hydrological features to train a ML model for prediction of sedimentation?
- What accuracy can be obtained predicting sedimentation in Lake Alajuela?

Conclusions - Contributions

- Prediction of morphological process with runoff-features
- Time steps in prediction using ML model
- Morphological processes in Lake Alajuela + predictions

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Conclusions - Limitations

- Available Data
- Runoff model failure
- Data cleaning

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Conclusions - Recommendations

- Larger variety in data on temporal range with depth data
- Step-wise morphology predictions with machine learning model and runoff features with improved flow path computation

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Special thanks to:

Supervisors:

Ken Arroyo Ohori

Hugo Ledoux

Co-reader:

Giorgio Agugiaro

From the Panama Canal:

Fernando Bolivar

Jaime Rodriguez

Javier Huertas

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Thank you for your attention

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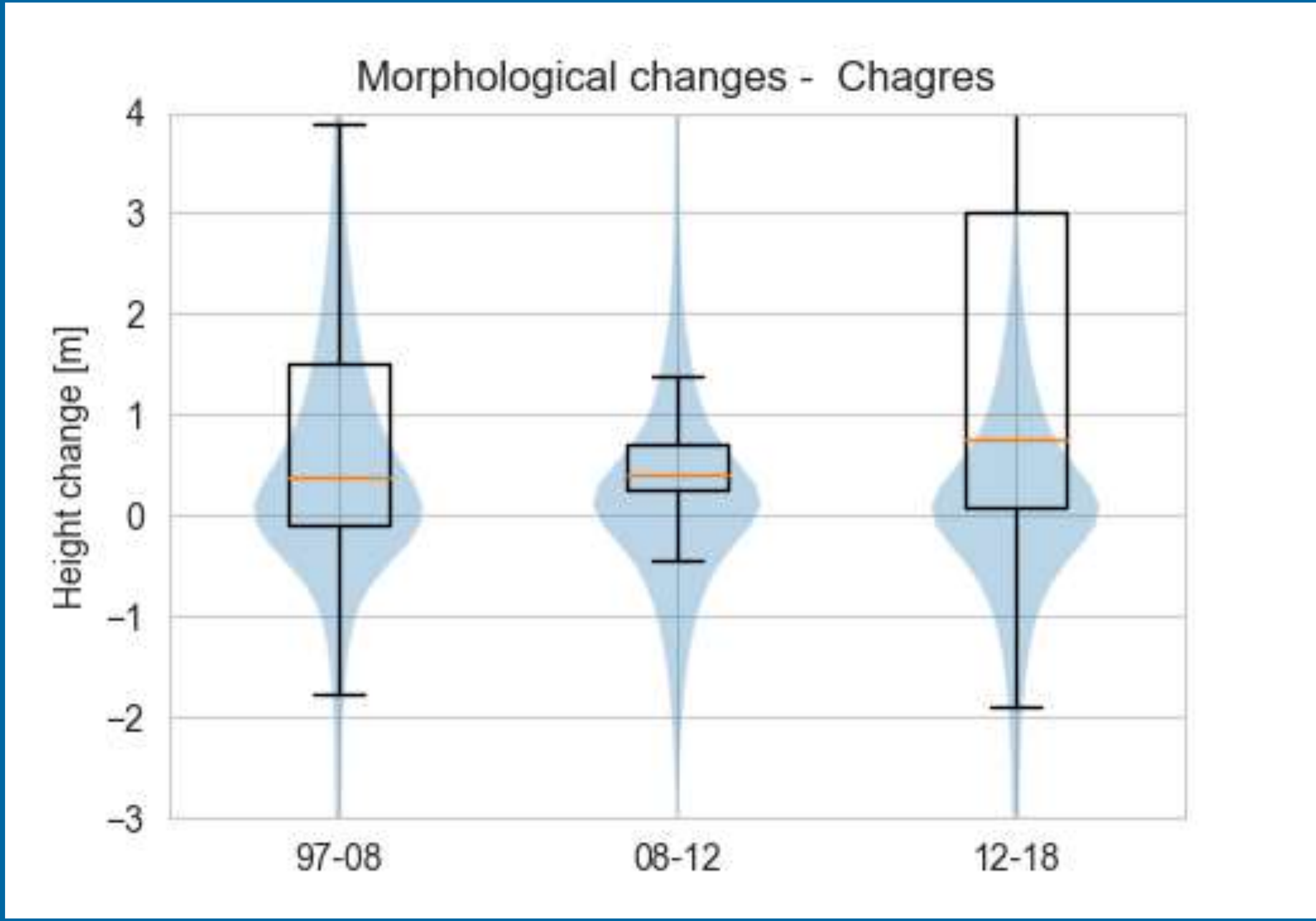
Morphological changes - Chagres
Height change [m]
4
3
2
1
0
−1
−2
−3
97-08
08-12
12-18

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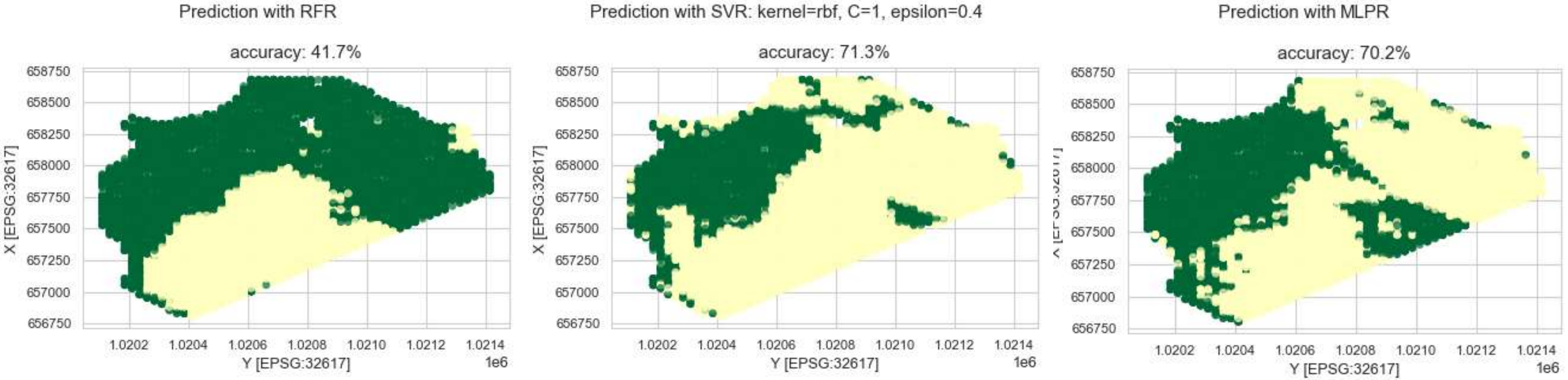
no. of features	18	17	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1
SVR	1.63	1.77	1.74	1.73	1.52	1.53	1.52	1.52	1.53	1.51	1.51	1.5	1.49	1.51	1.62	1.63	1.63	1.7
MLPR	2.16	1.83	1.81	1.88	1.53	1.54	1.53	1.54	1.51	1.56	1.46	1.42	1.43	1.45	1.56	1.58	1.58	1.7
RFR	1.59	1.64	1.65	1.64	1.53	1.58	1.59	1.59	1.6	1.59	1.59	1.59	1.64	1.59	1.62	1.57	1.68	1.8

no. of features	18	17	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1
SVR	0.877	0.822	0.822	0.822	0.827	0.812	0.800	0.802	0.807	0.806	0.798	0.794	0.798	0.808	0.817	0.835	0.824	0.800
MLPR	0.937	0.867	0.867	0.872	0.846	0.826	0.805	0.816	0.839	0.802	0.781	0.783	0.782	0.786	0.797	0.796	0.786	0.803
RFR	0.819	0.814	0.814	0.811	0.815	0.807	0.810	0.820	0.826	0.833	0.882	0.919	0.937	1.274	1.254	1.074	1.413	1.723



Prediction with RFR
accuracy: 41.7%
Prediction with SVR: kernel=rbf, C=1, epsilon=0.4
accuracy: 71.3%
Prediction with MLPR
accuracy: 70.2%
X [EPSG:32617]
Y [EPSG:32617]
658750
658500
658250
658000
657750
657500
657250
657000
656750
1.0202
1.0204
1.0206
1.0208
1.0210
1.0212
1.0214
1e6

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