ETH zürich

eawag aquatic research

Localization of sewer assets using street-level images and deep learning

Master Thesis by Dominik Boller
Supervisors: Matthew Moy de Vitry, Dr. João Paulo Leitão, Dr. Jan Dirk Wegner
Head: Prof. Dr. Max Maurer

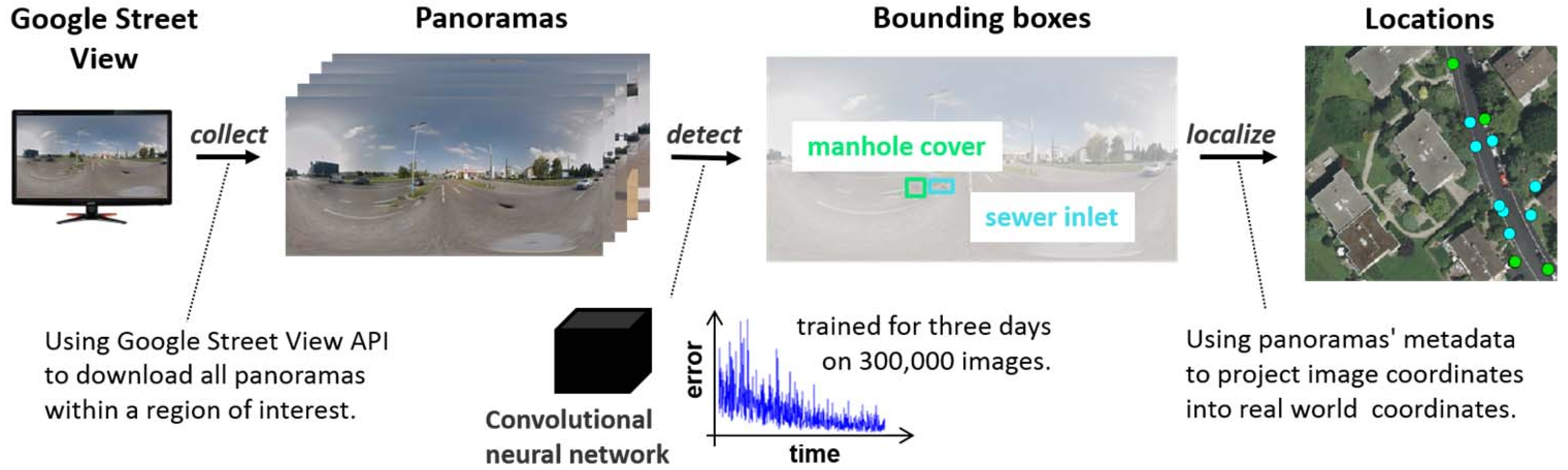
Today, there is a **world-wide lack of information on sewer infrastructure.**

Motivation – lack of knowledge on sewer infrastructure hinders:
- sustainable management.
- mitigation of increasing flood risk.

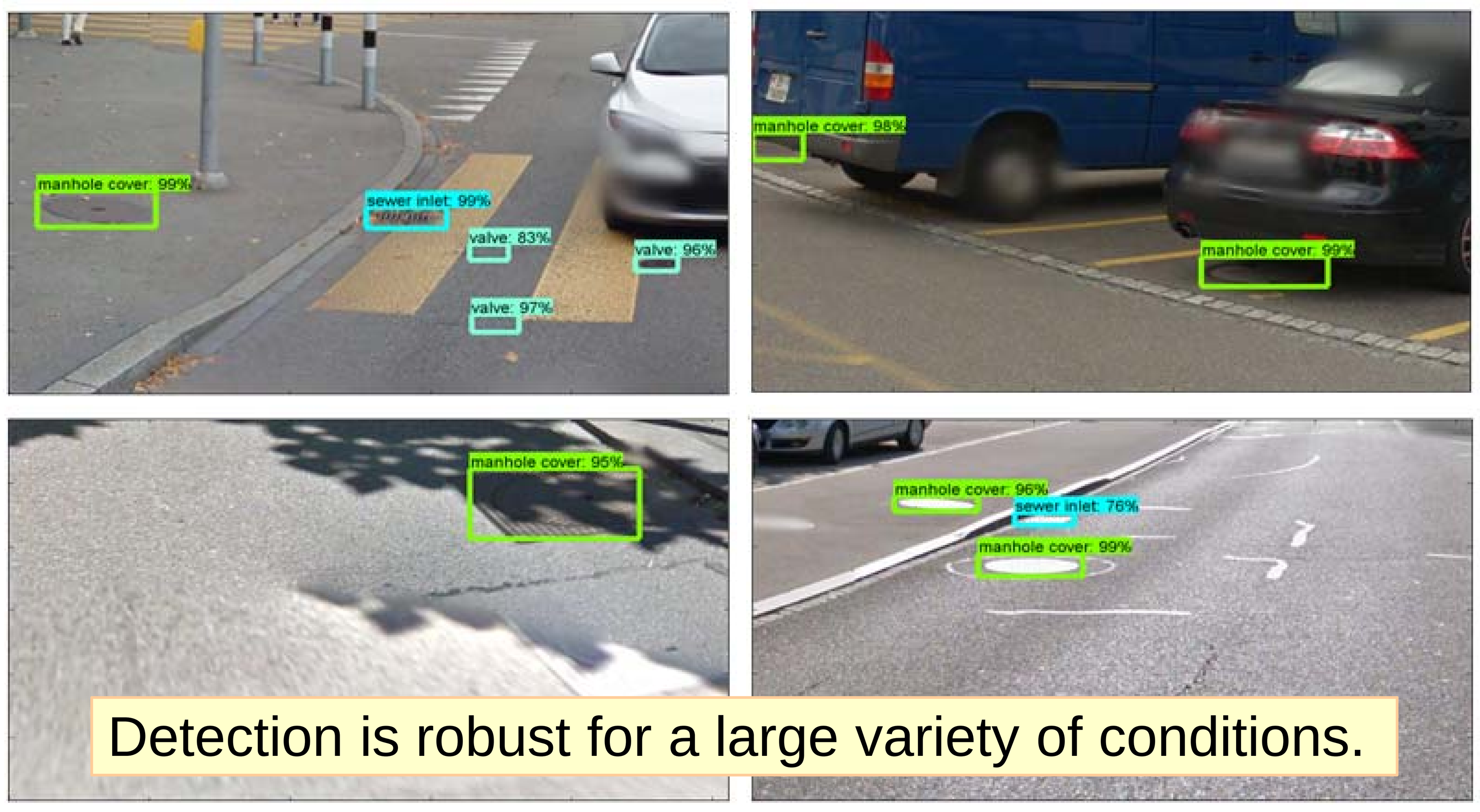
Goal – Localize sewer assets with an approach, which is scalable, low-cost and readily implementable.

Approach – using Google Street View as a data source, which provides:
- free data.
- global coverage.

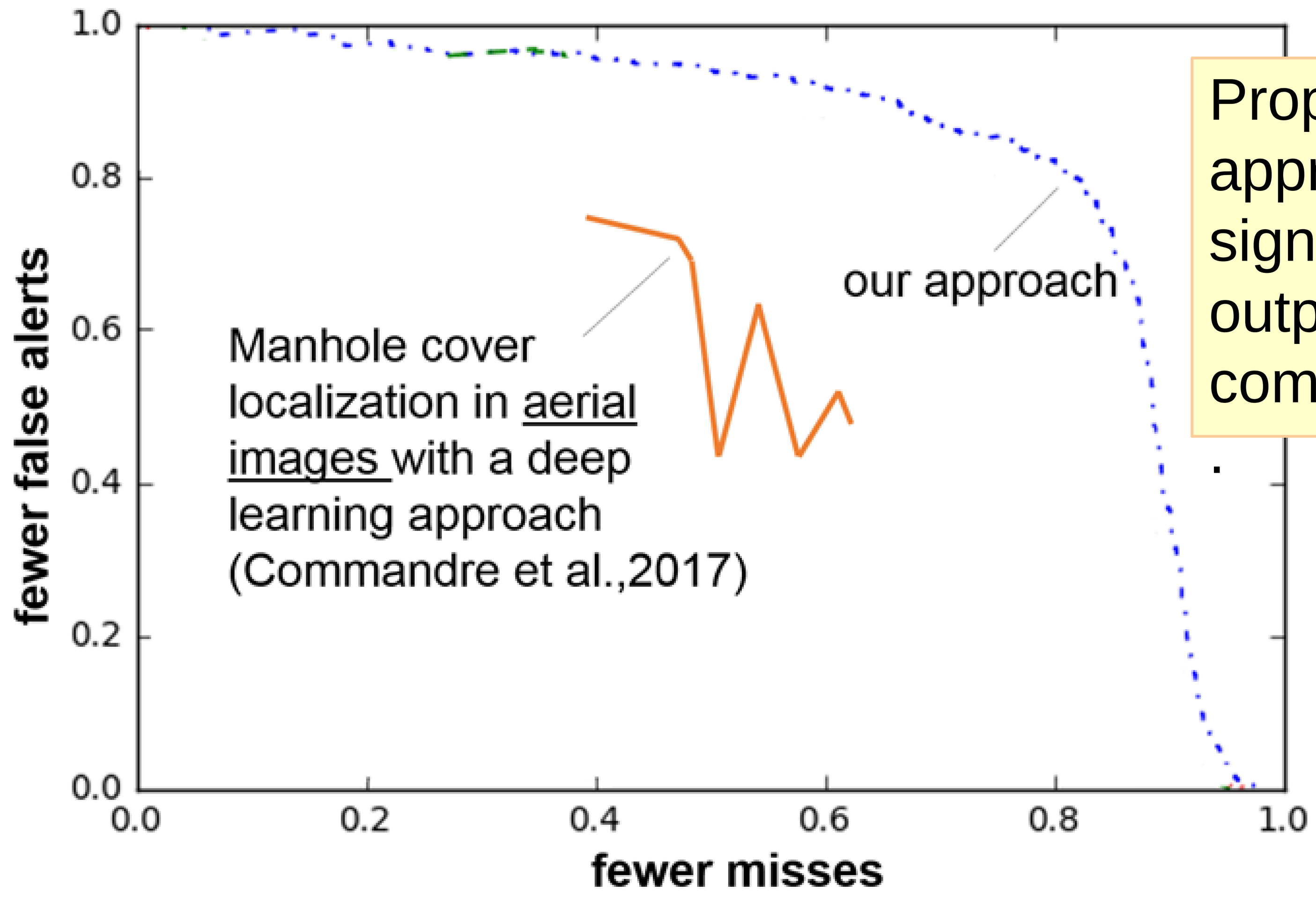
We developed an **automatic framework to localize manhole covers and sewer inlets.**



The **object detection performs well**, …

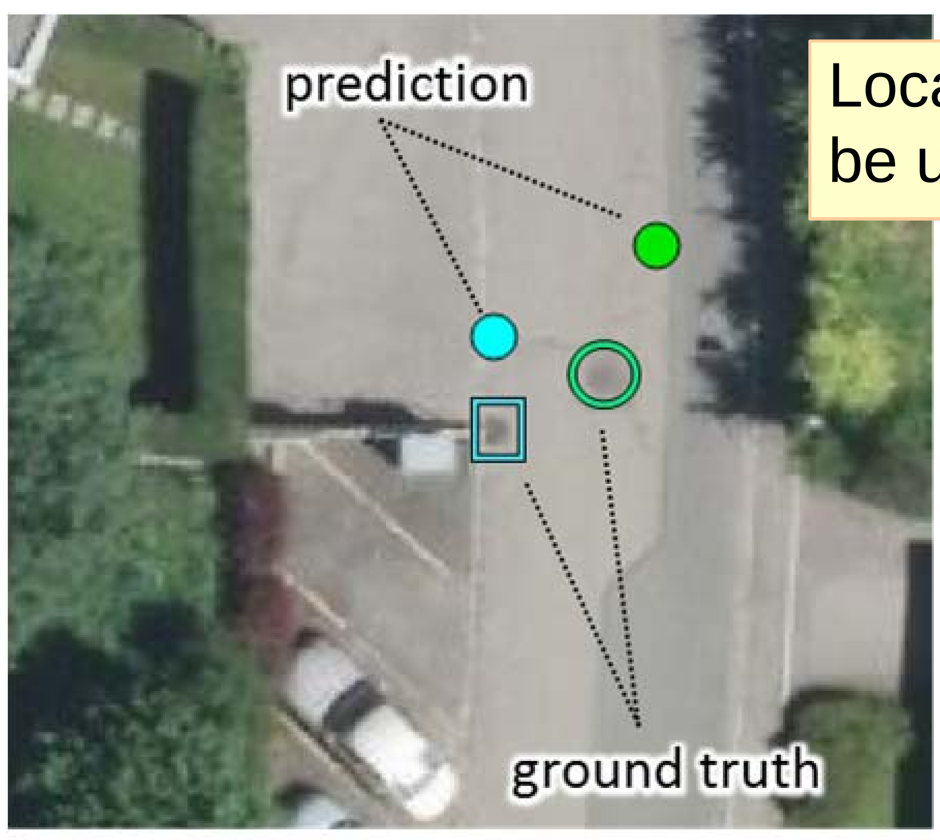


Detection is robust for a large variety of conditions.



Proposed approach significantly outperforms competition

… but the **localization can be improved**.



Localization errors can be up to a few meters.

Possible causes:
- Poor quality of metadata (e.g. position of the camera).
- Algorithmic assumption that the terrain is locally flat may not be applicable everywhere.

Conclusions

- Proposed approach can be readily implemented at a low cost, wherever Google Street View data is available.
- Object detection performance is suitable for practice.
- Future work should focus on improving localization accuracy.

Container-Based Sanitation & Greenhouse Gas Savings – A Methodology

Master Thesis: Daniela Seitz
Supervisors: Nienke Andriessen, Dr. Linda Strande (Eawag)
Raluca Anisie, Mona Mijthab (Mosan)
Head: Prof. Dr. Eberhard Morgenroth

Container-Based Sanitation – A Sustainable Sanitation Service

SDG 6: Sustainable and safe sanitation

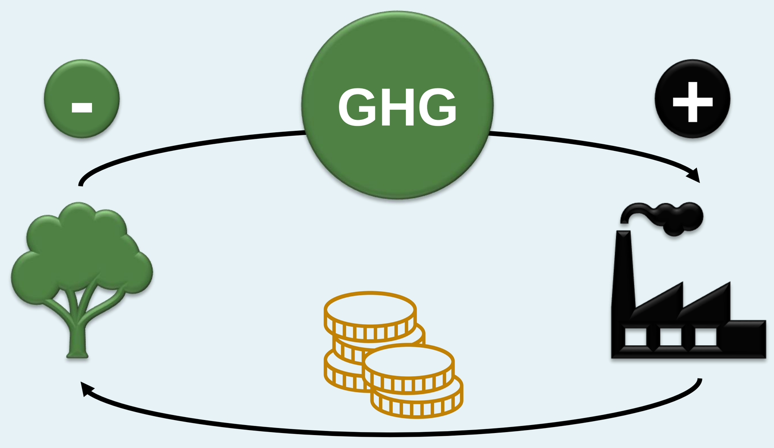
SDG 13: Mitigation of GHG emissions

Container-based sanitation projects integrate the Sustainable Development Goals 6 and 13:

- Replacement of unsafe **baseline** sanitation systems in low- and middle-income countries
- Avoidance of uncontrolled degradation of excreta in the environment that emits CH_4 and N_2O (= GHG) (1)

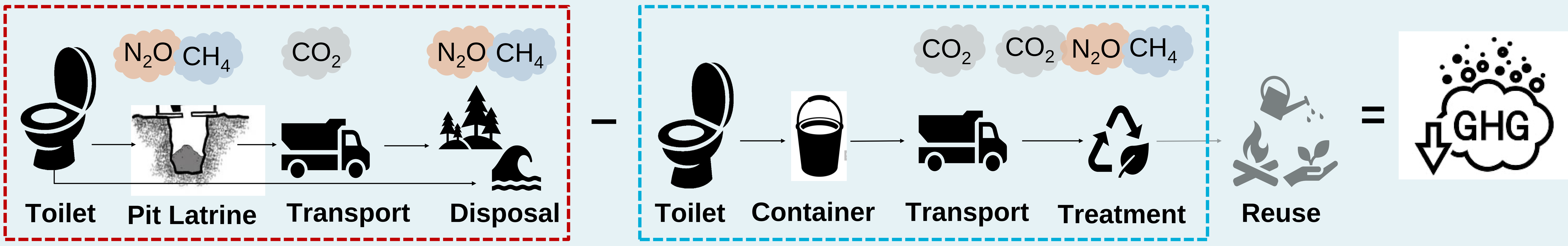
A Methodology for systematic emission quantification and reporting of **GHG savings** could unlock climate financing

Climate financing: purchase of GHG savings by GHG emitter



Development of a Methodology

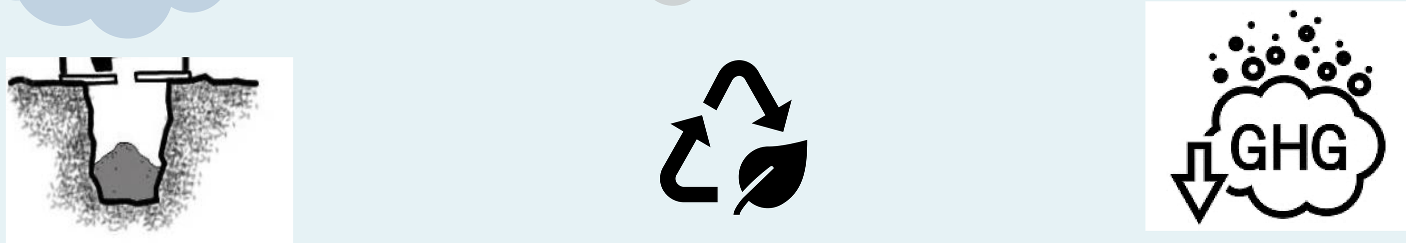
Baseline Emissions – **Project Emissions** = **GHG Savings**



Potential of GHG Savings

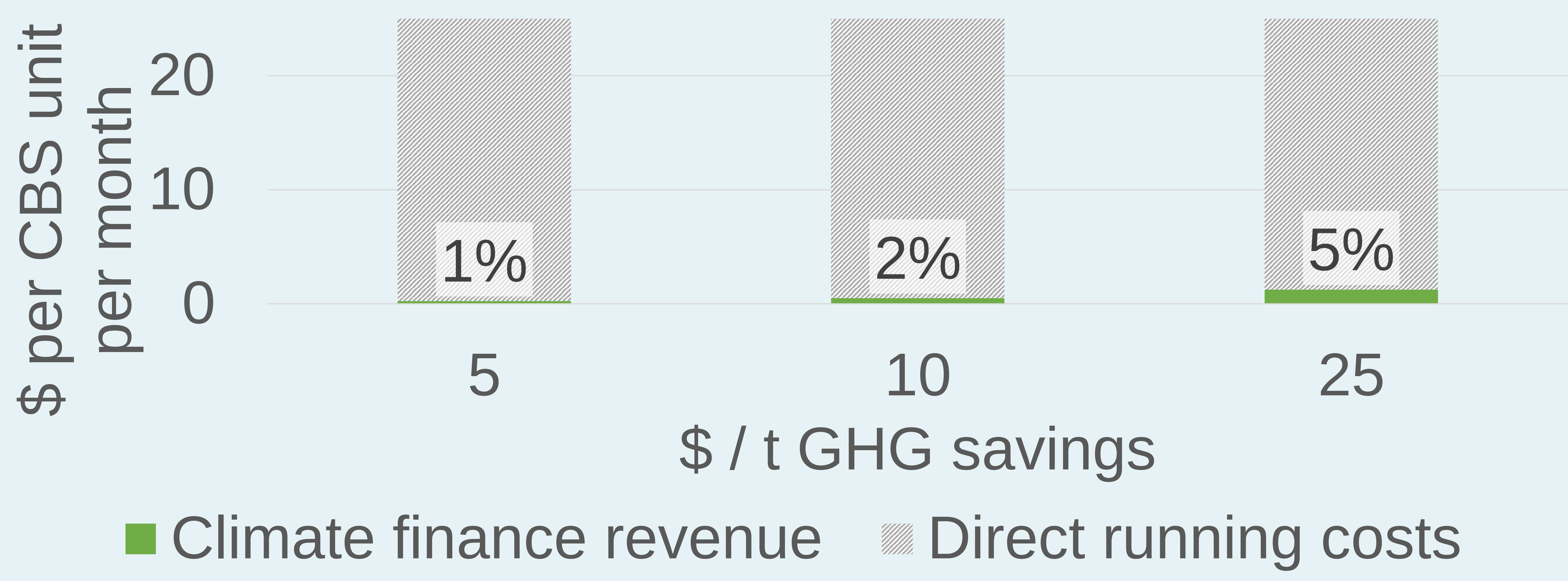
Methodology application → replacing one pit latrine with container-based sanitation (1 year):

0.6 t CO_2-eq – **0.1** CO_2-eq = **0.5** t CO_2-eq



With high uncertainty in the baseline due to:

- Lack of GHG emission studies
- Variability in sanitation systems



Unlocking climate finance revenue could cover a small percentage of direct running costs(2), but other revenue streams are needed to operate sustainable sanitation services!

References

1. Montgomery, I., et al., *Supporting the Shift to Climate Positive Sanitation*, in *Climate change mitigation from container-based sanitation systems*, CBSA, Editor. 2020, CBSA.
2. Holder, M. *Research: Carbon offset prices set for ten-fold increase by 2030.* 2021 [07.06.2021 22.08.2021]; Available from: https://www.businessgreen.com/news/4032443/research-carbon-offset-prices-set-fold-increase-2030.

ETH zürich

eawag
aquatic research

Efficient Fertilizer Production from Urine – Developing a Novel Nitrite Sensor

Master Thesis: Livia Britschgi
Supervision: Bastian Etter, Carina Doll
Head: Prof. Dr. Kai M. Udert

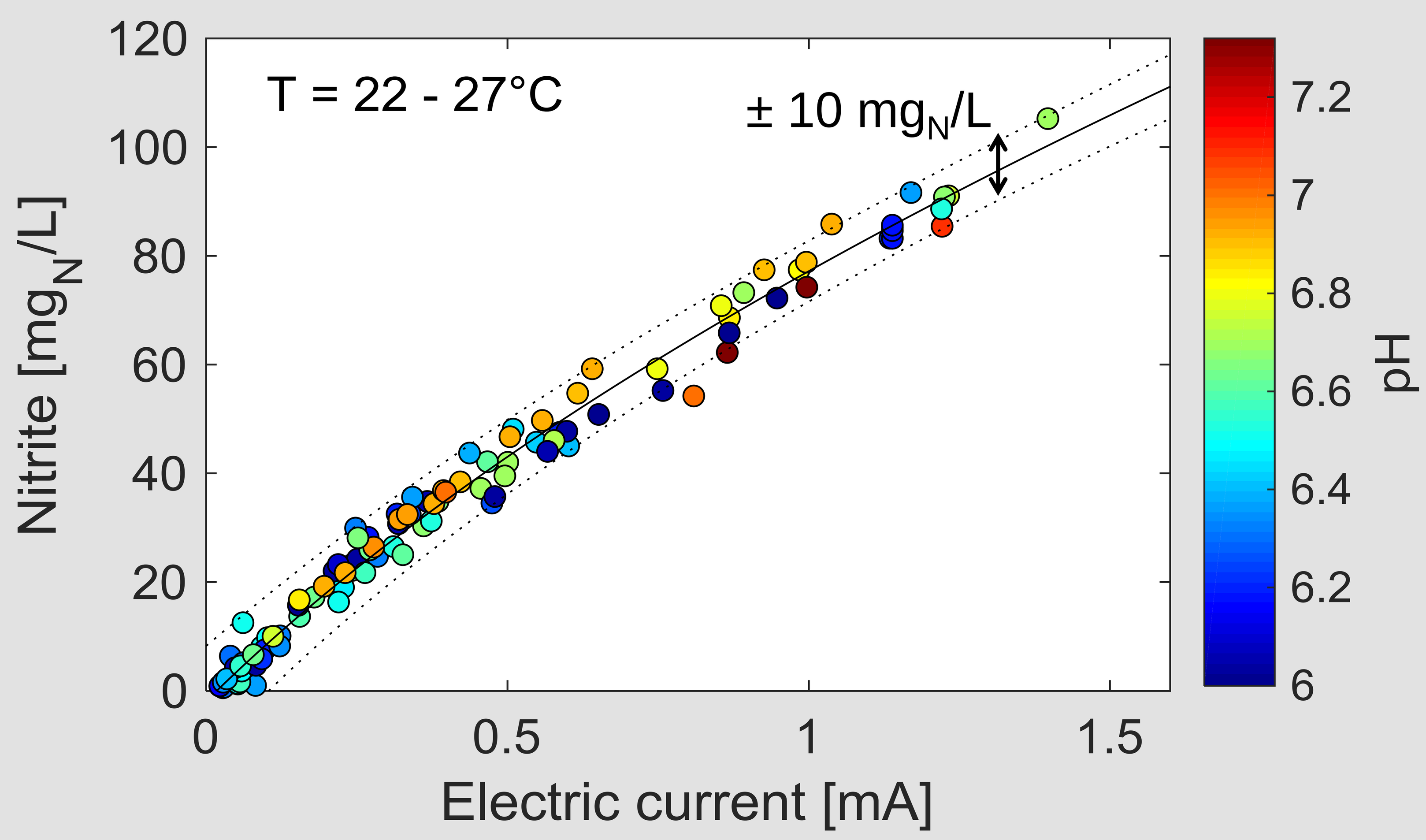
Motivation

- Nitrification is the critical step in the process of fertilizer production from urine.
- Nitrite accumulation can cause nitrification failure.
- Prevention: continuous nitrite measurement
- One approach is an electrochemical sensor.

Hypothesis

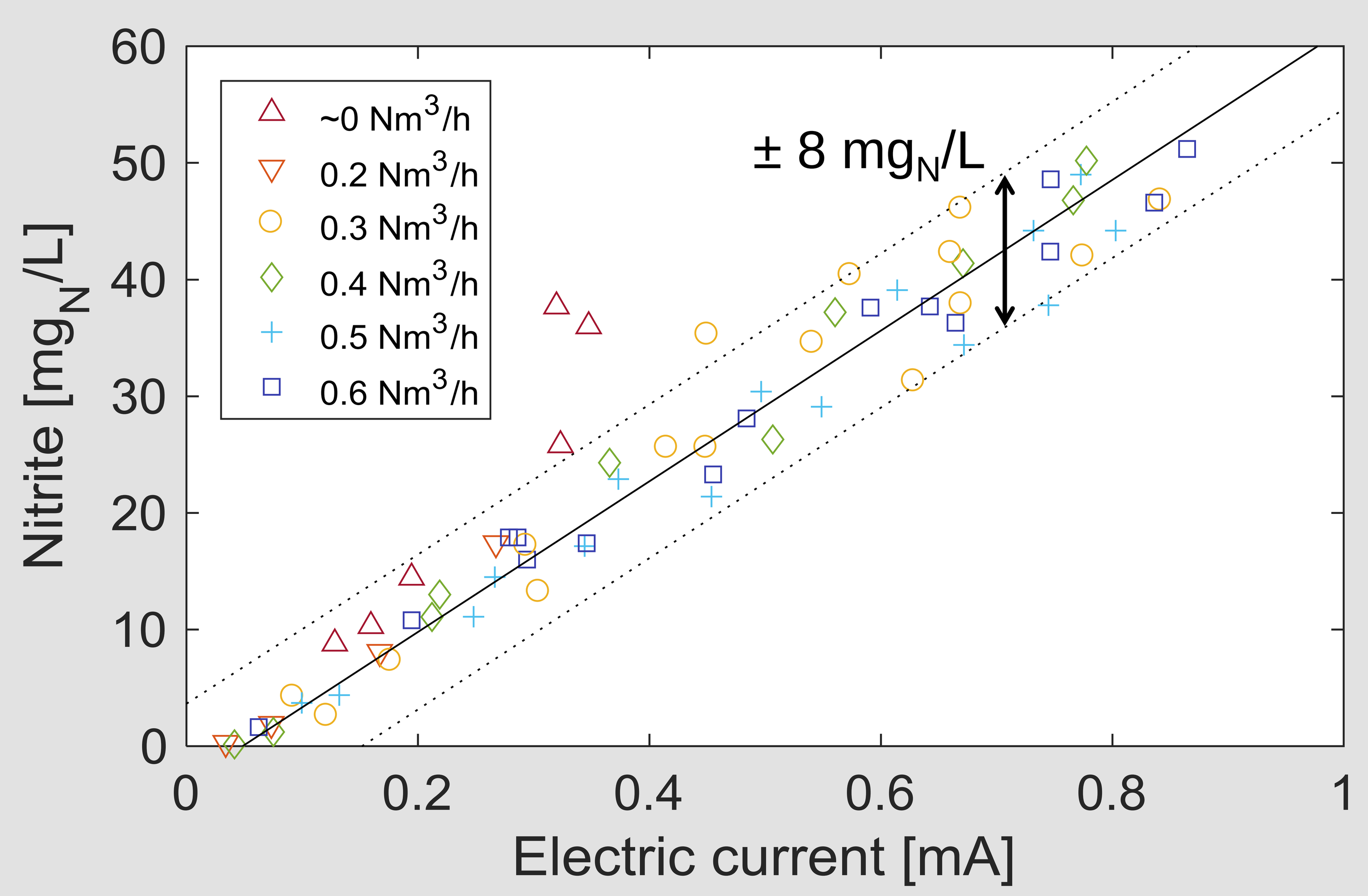
1. The electrochemical nitrite sensor is sensitive to distortions such as temperature, pH and aeration.
2. The nitrification performance and robustness can be increased with the help of the electrochemical nitrite sensor.

Temperature and pH



➡ The influence of temperature and pH is negligible in the assessed range.

Aeration



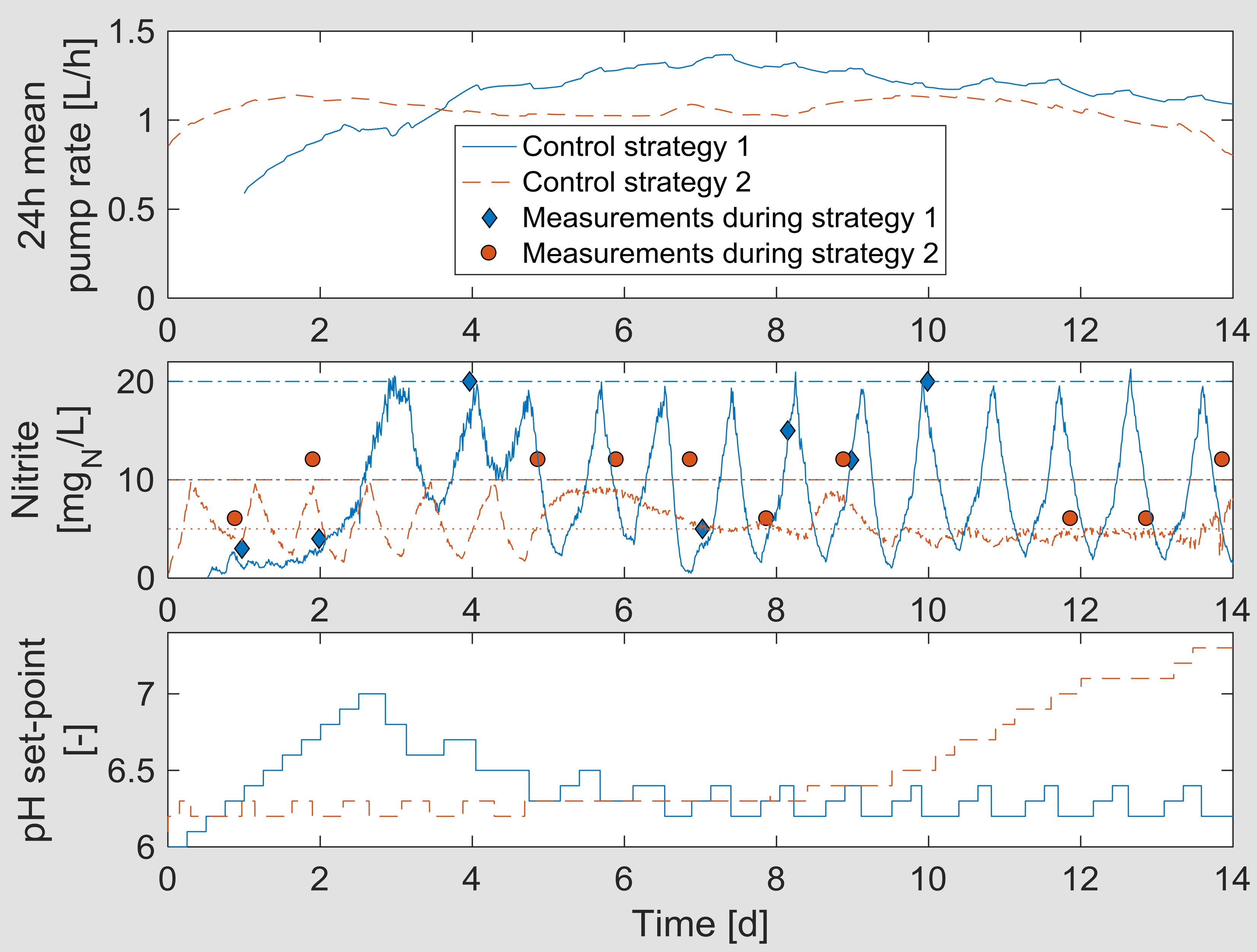
➡ The influence of aeration is negligible, as long as the nitrification reactor is continuously aerated.

Nitrification Control Including the Electrochemical Nitrite Sensor

- Urine feed control based on pH in nitrification reactor:
  - Urine feed start: pH ↑ (due to high pH in urine)
  - Urine feed stop: pH ↓ (due to nitrification)

- If $NO_2^- < NO_{2\,min}^-$ for 6h → pH set-point ↑
- If $NO_2^- > NO_{2\,max}^-$ once → pH set-point ↓

	Control strategy 1	Control strategy 2
$NO_{2\,min}^-$ [mg$_N$/L]	10	5
$NO_{2\,max}^-$ [mg$_N$/L]	20	10
pH set-point ↑	+0.1	+0.1
pH set-point ↓	-0.2	-0.1
Time interval [h]	6	6



➡ No clear conclusions can yet be drawn from the test of the 2 control strategies.
➡ However: the electrochemical nitrite sensor is suitable for the support of nitrification control.

➡ Nitrite accumulation can be prevented by including the sensor in the control strategy.
➡ The optimal operation strategy needs to be found in order to maximize the process performance.

ETH zürich

eawag aquatic research

Estimate Sediments from Temperatures in Gully Pots

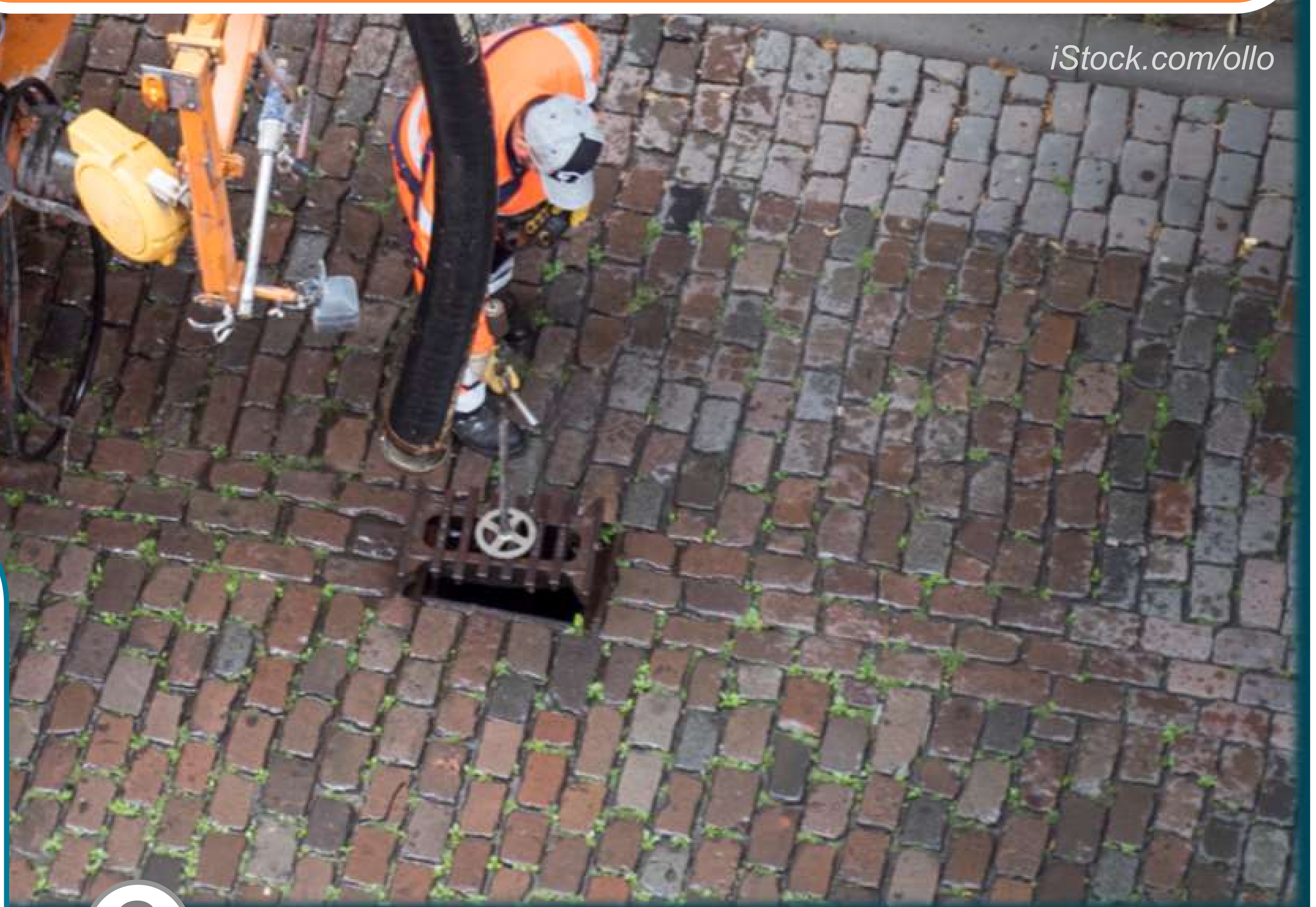
Master Thesis: Lenard Fuchs
Supervisor: Dr. Manuel Regueiro-Picallo, Dr. Jörg Rieckermann
Head: Prof. Dr. Max Maurer

The Problem: Sediment in Sewers

- Reduced capacities in sewers → Flood risk
- Pollutants adsorb onto sediments → Pollution

Solution: Remove Sediments

- Currently: cleaned out periodically
- But cleaning costs time and money
- **Temperature Sensors → clean when needed!**



1 Methodology

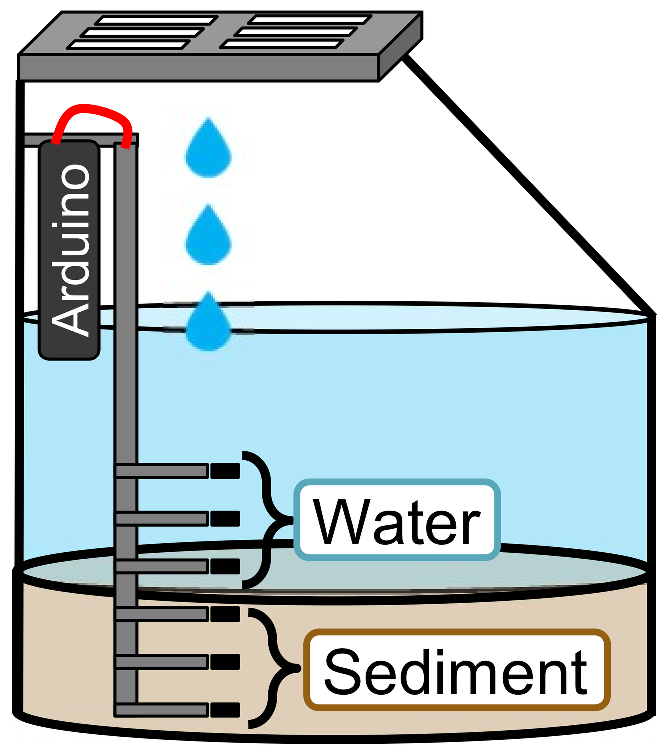
Core Idea

1. Rain pours into gully
2. Water temp. changes quickly
3. Sediment temp. changes slower

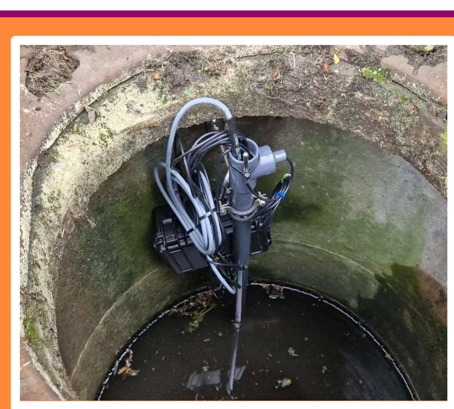
Slower change → more sediment

Surrogate Model

- Find rain events
- Find sensors in sed. and water
- **→ Rough estimation**
- Compute features during event
  → Final sediment estimation




During installation


After installation


Inside the gully

2 Event Analysis

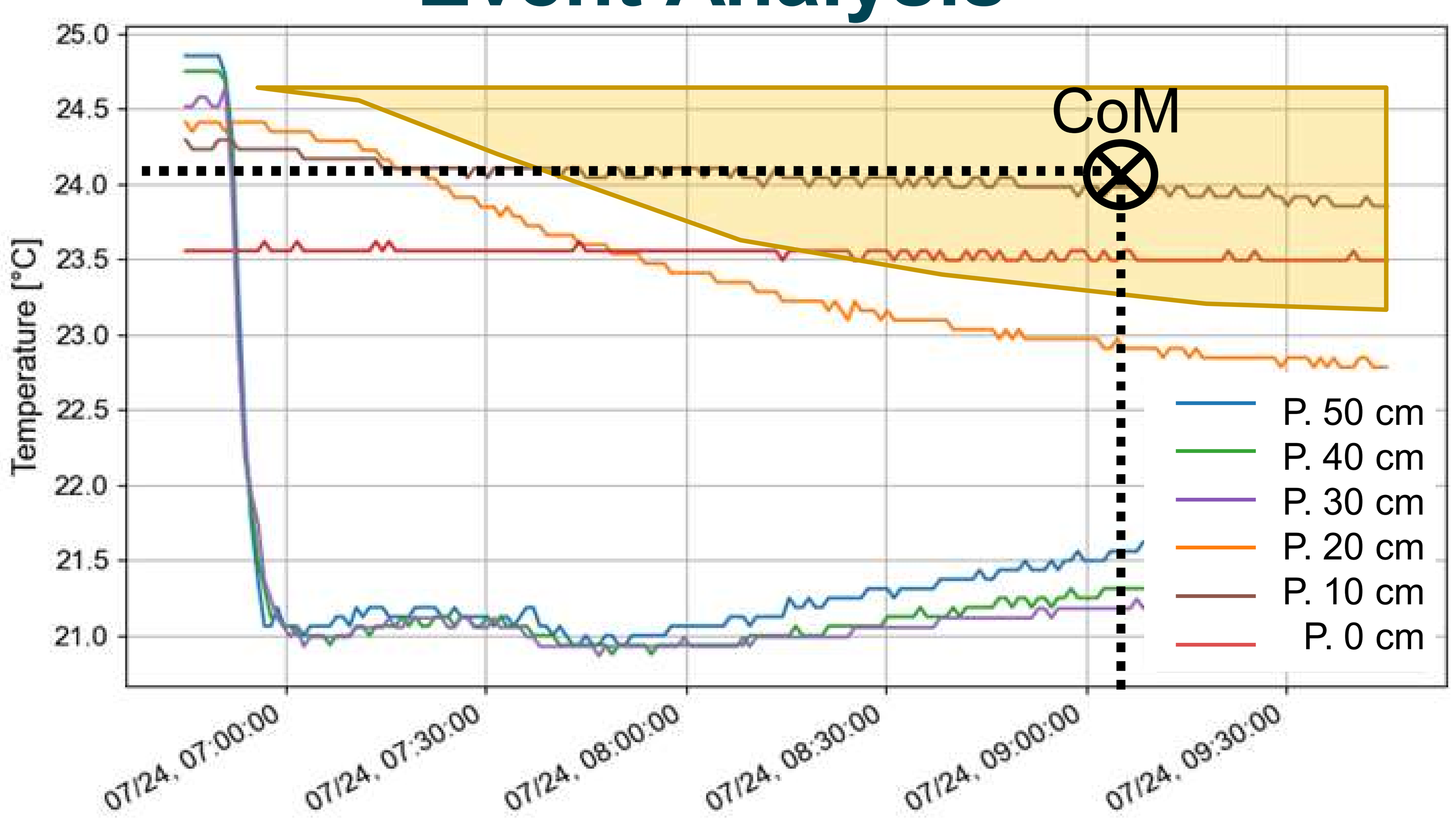


Fig 1: Temperatures measured by each sensors at different positions (P) above the gully bottom at eawag Dübendorf.

- Sensors at 0, 10 and 20 cm cool down slowly
  → Sensors are in the sediment → Rough estimation
- Center of mass (CoM) = Data feature used

3 Sediment Depth Estimations

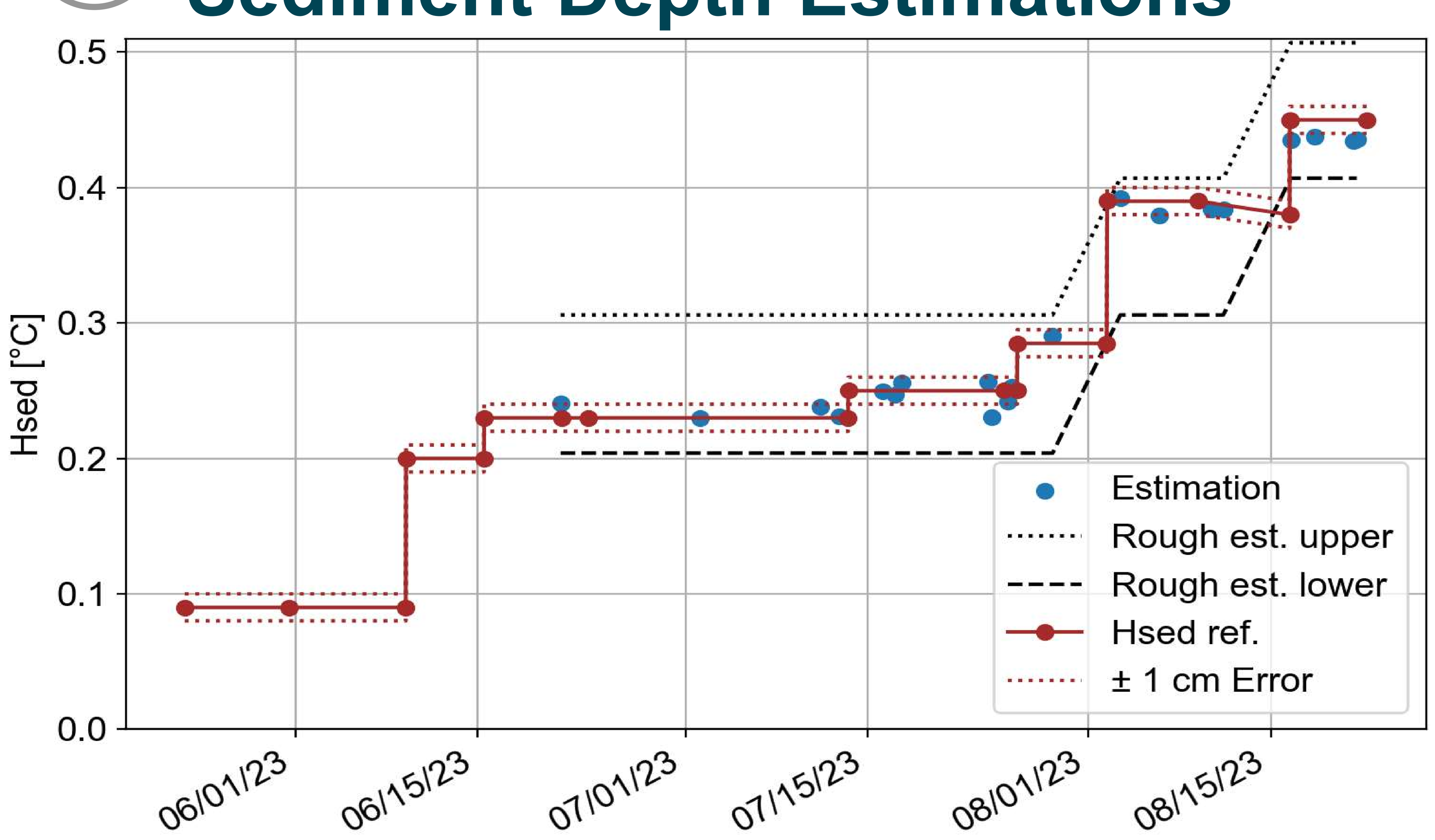


Fig 2: Sediment estimations from sensor for different events (blue) compared with manual measurement (red), rough estimation from sensor positions (dashed)

- Sediments added manually → Reference increases
- Rough estimation from sensor positions (dashed)
- Final estimation using Surrogate Model (blue)

→ Estimation accuracy ≈ reference measurements

4 Conclusions

1. **Estimation accuracy ≈ reference measurements**
2. The **more water** is inside a gully the more rain is needed to change the temperature **→ fewer events**
3. Data stored locally, next steps:
   → Wireless transmission

ETH zürich

eawag aquatic research

What can CCTVs* be used for other than crime prevention and road traffic control?

Master Thesis: Simon Kramer
Supervisors: Matthew Moy de Vitry, João P. Leitão, Kris Villez, Jan Dirk Wegner
Head: Prof. Max Maurer

*** Closed-Circuit Television or surveillance camera**

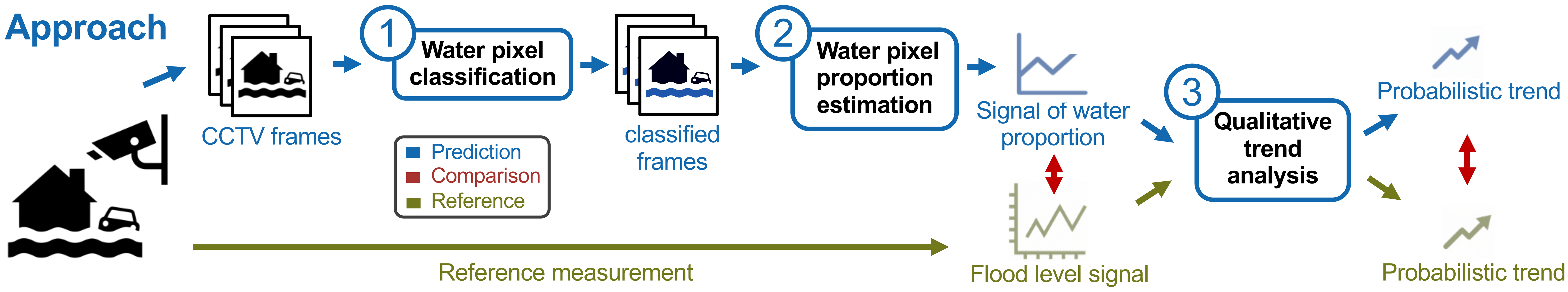
Motivation

- Risk of flooding is expected to increase due to climate change and urbanization.
- No dedicated urban flood monitoring sensor networks.
- CCTV market is strongly growing!

Goal

Design and evaluate a data processing approach to extract flood trends from varietal CCTV videos by means of convolutional neural networks and qualitative trend analysis.

Approach



1 Water pixel classification

Classification is conducted with convolutional neural network U-Net from Ronneberger (2017). It is trained with 1200 social media images.

Mean classification accuracy for six tested CCTVs:
Augmented: 80% +/- 5%
Fine tuned: 97% +/- 2%

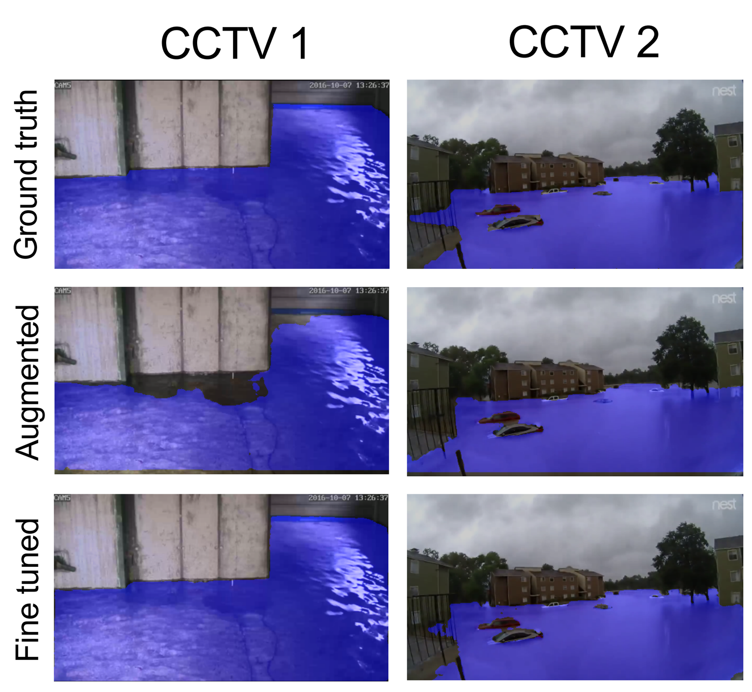


Fig. 1: Water classification performance of two CCTVs. Augmented: trained with augmented images, Fine tuned: trained on specific CCTV.

➡ **Water detection is reliable for varietal CCTV videos.**

2 Water pixel proportion estimation

Proportion of water pixels to total number of pixels is estimated for each classified frame.

The correlation with the flood level signal is increased with improved water pixel classification.

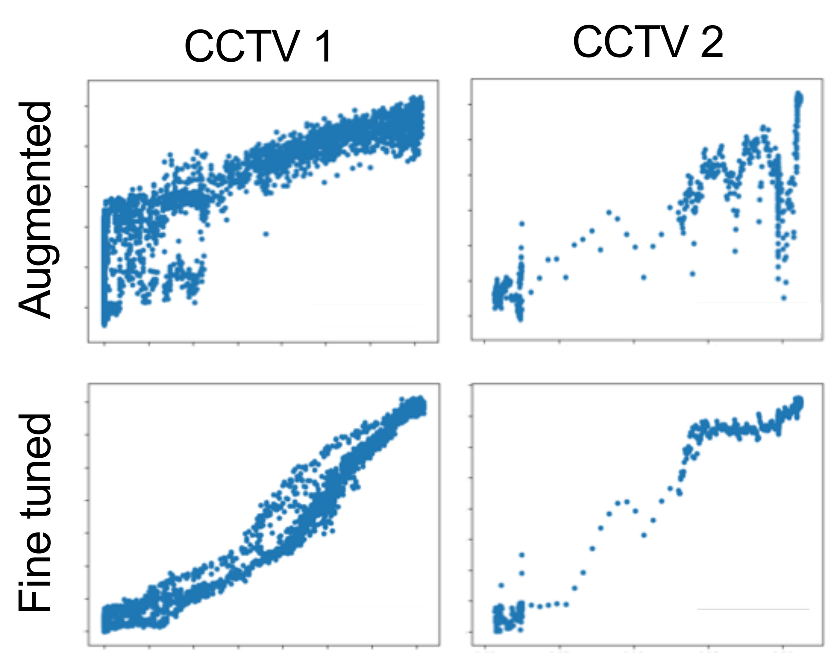


Fig. 2: Relationship between reference flood level (x-axis) and water proportion in images (y-axis) for augmented and fine-tuned water classification.

➡ **Water pixel proportion is a useful proxy for flood level because correlation between them is high.**

3 Qualitative trend analysis

- Probabilistic trend classification of reference signal and water proportion signal conducted on basis of qualitative state estimator (QSE) from Thürlimann et al. (2015).
- Method needs to be adapted to signal characteristics:
  - Addition of trend classes for absence of flooding and absence of change in flood level.
  - Automated parameter adaption to be applicable to different flood event lengths and signal noises.
- Accuracy of trend information is ensured by discarding partition of the trend signal with indecisive classification.

➡ **Agreement between predicted and reference trend for the six tested CCTV is 80% +/- 10%.**

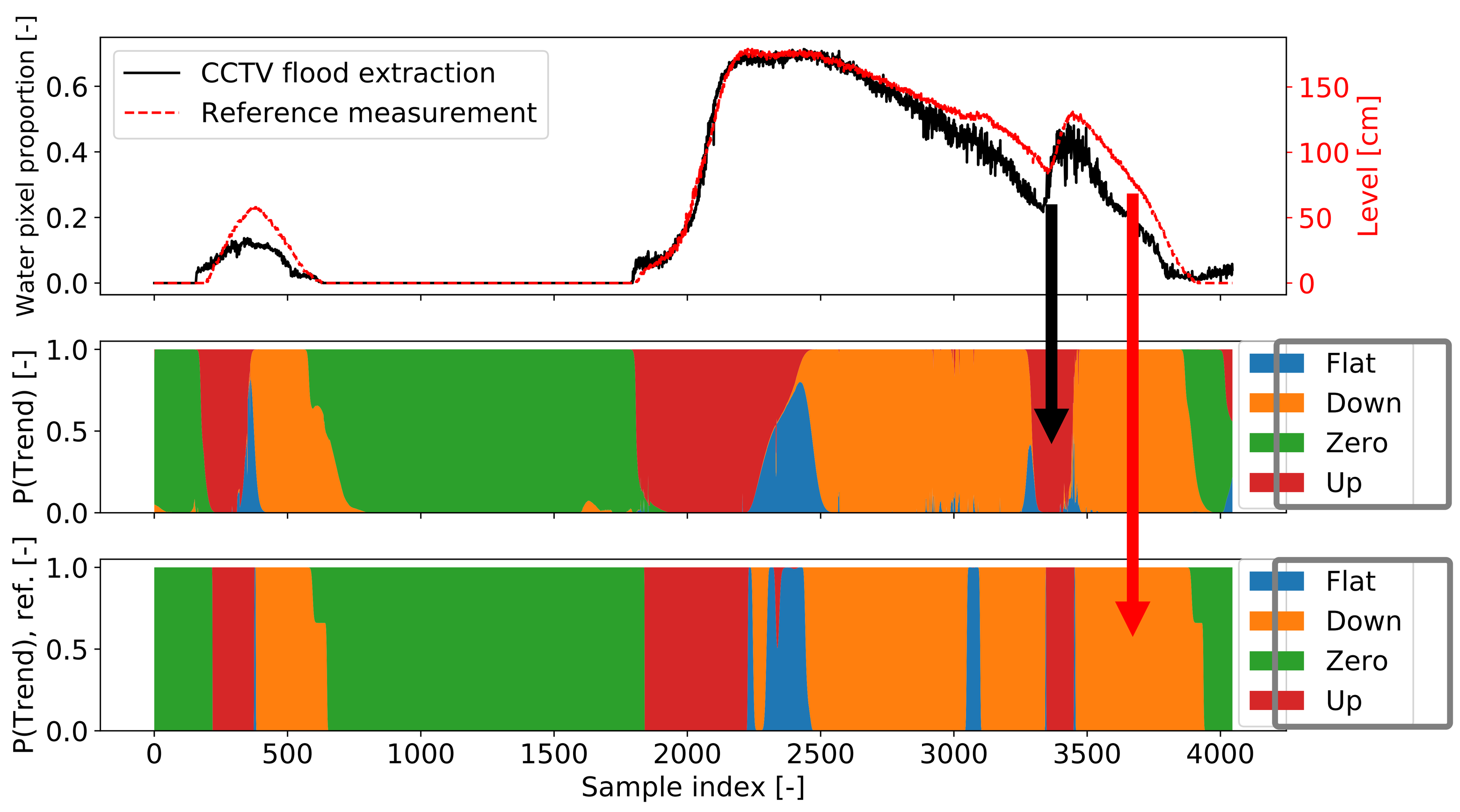


Fig. 3: Trend class probabilities P(Trend) of water pixel proportion extracted from CCTV 1 with fine-tuned classifier compared to trend class probabilities of reference flood level.

Conclusion

CCTV videos can also be seen as a **new reliable flood data source** with a potential use in **trend-based flood model calibration, flood prediction, and flood risk mapping.**

ETH zürich

eawag aquatic research

Should aerobic granular sludge (AGS) models consider different granule size classes?

Master Thesis by Akanksha Jain
Supervisor: Dr. Nicolas Derlon
Head: Prof. Dr. Eberhard Morgenroth

Introduction

Aerobic granular sludge (AGS) comprises of dense, microbial aggregates (granules) and flocs. It is a relatively new treatment technology with several advantages including excellent settleability, high biomass retention, and simultaneous nutrient removal is single tank. Modelling of AGS technology is being improved and developed further and the Eawag AGS model presents itself as a relevant model for these systems.

Motivation

- Granule size in the model governs the surface area available (Fig.1), which has important implications for microbial activities in mass transport limited granules.
- Currently, Eawag AGS model assumes one fixed size & volume of granules. Having multiple granule size classes will incur additional model complexity.

→ Can this assumption of uniform granule size adequately represent reality?

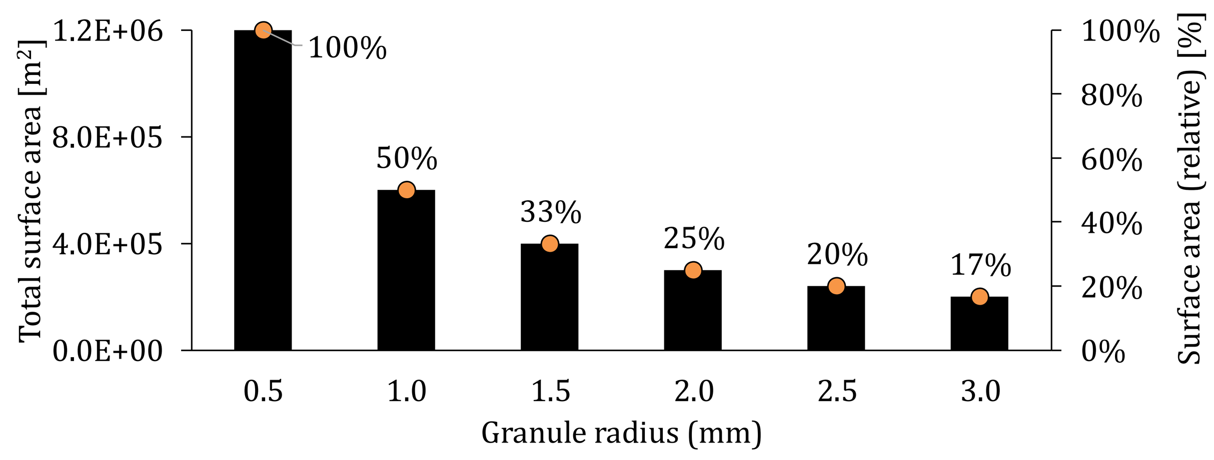
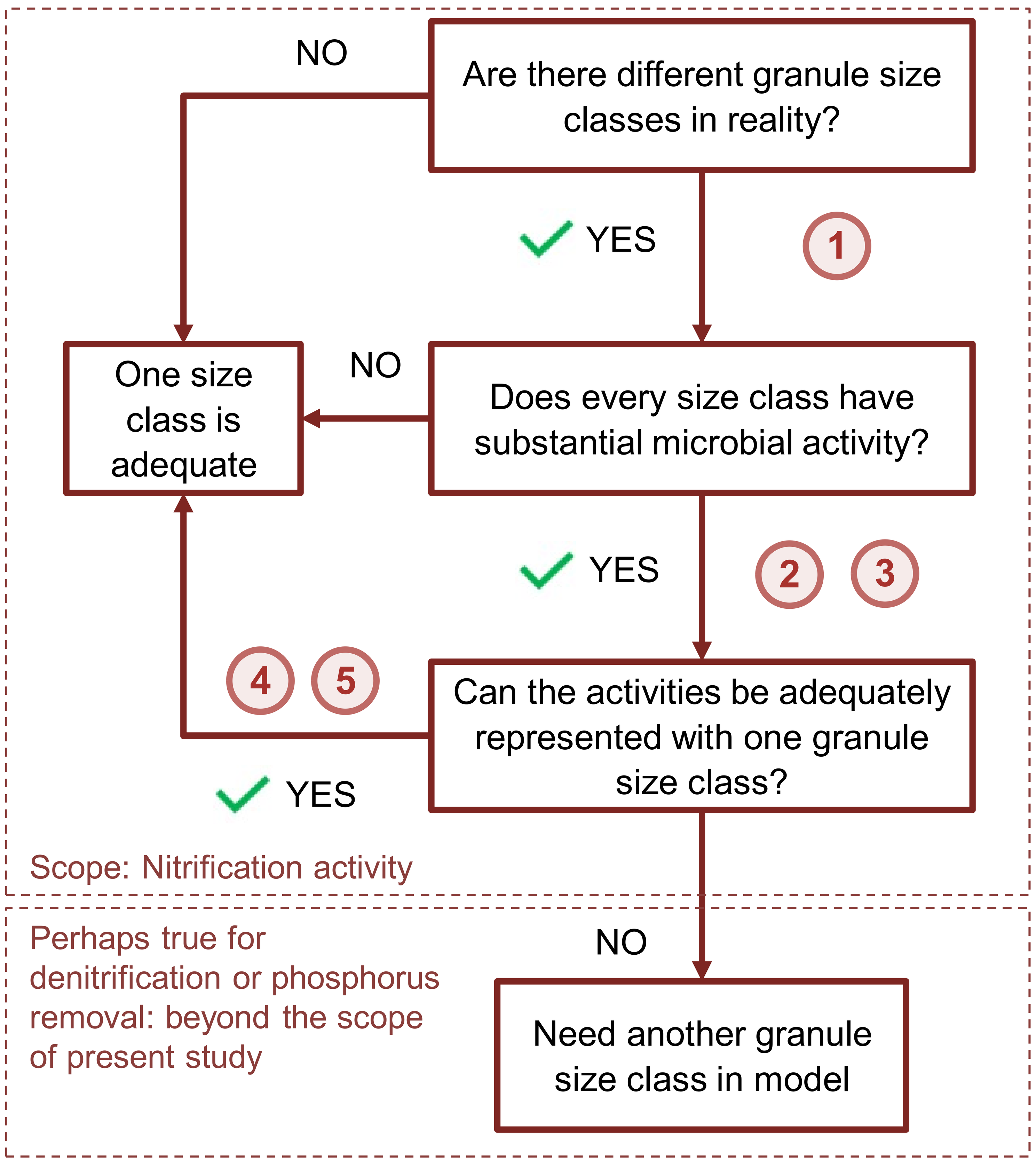


Fig. 1: shows how the total surface area available changes when the granule radius in the Eawag AGS model is changed from 0.5 to 3.0 mm.

Approach



Methods:

1) Sieving and measuring total suspended solids (TSS)
2) Batch tests to observe NH_4-N removal activity
3) Combining results (1) & (2) to check if a size class can be excluded from consideration due to low activity
4) Sensitivity analysis with granule radius. If model not sensitive, this has implications for decision on adding a size class.
5) Based on interpretations of results

1 What granule size classes are present within AGS in reality?

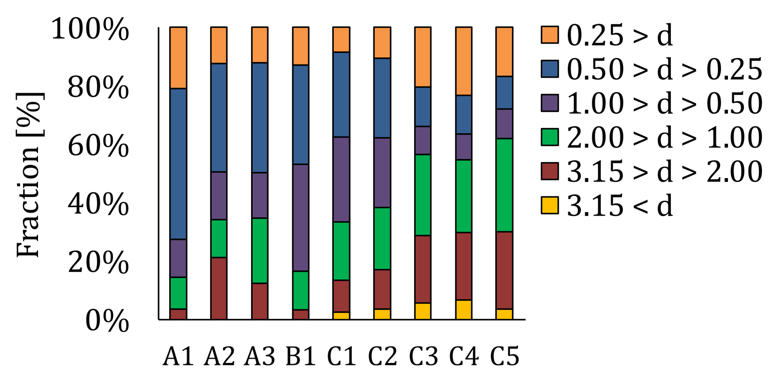


Fig. 2: TSS-based proportions of granule size classes at different treatment plants (A1-3, B1, C1-5).

➢ Highly heterogenous sludge

2 What is the microbial activity of different size fractions in AGS?

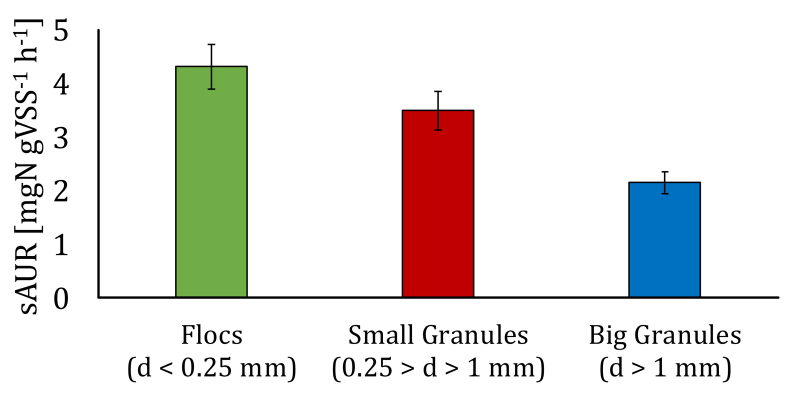


Fig. 3: The specific ammonia uptake rates (sAUR) measured for different size fractions in AGS.

➢ Big granules have lowest activity

3 What is the contribution of each size class to overall activity?

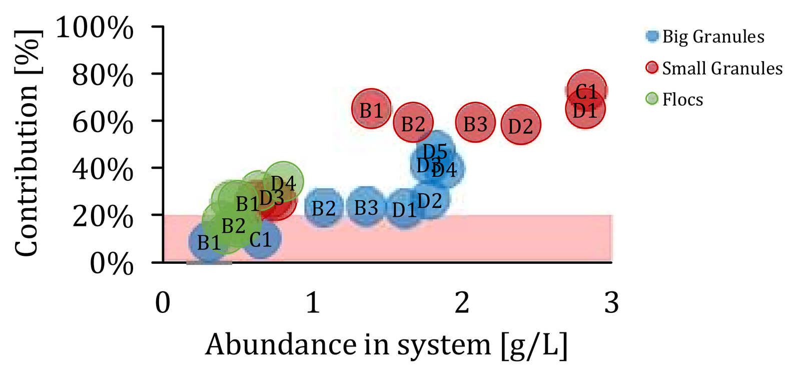


Fig. 4: Contribution of each size fraction to overall activity at different treatment plants (A1-3, B1, C1-5).

➢ All size fractions have a non-trivial (>20%) contribution to overall activity

4 How sensitive is the model to changes in granule size?

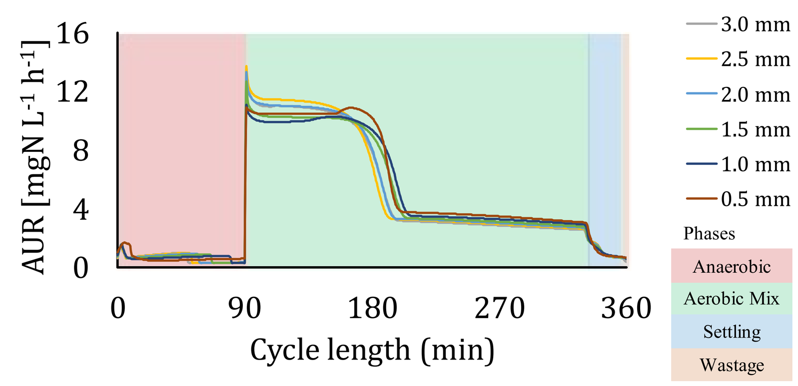


Fig. 5: Total ammonia uptake rates (AUR) predicted by the model for different granule radii (0.5 to 3.0 mm)

➢ Not very sensitive

5 How can different granule size classes be represented without incurring additional model complexity?

➢ Use an effective diameter.

$$A_{eff} = \frac{\sum(MLSS_i \times A_i)}{\sum MLSS_i} \qquad D_{eff} = \sqrt{\frac{A_{eff}}{\pi}}$$

where,
i = granule size classes
A_{eff} = effective area
D_{eff} = effective diameter
MLSS = biomass concentrations in g_{TSS} L^{-1}

Conclusion

Nitrification activity is expected to be sufficiently represented in the Eawag AGS model with a single granule size class having an effective diameter (D_{eff}).

Can self-assessment be used to predict faecal sludge accumulation rates?

Master Thesis: Lia Weinberg
Supervisor: Samuel Renggli
Head: Prof. Dr. Kai Udert

Study area: Kohalpur, Nepal

1. Self-assessment

- Household members answer questionnaire by themselves.
- Questionnaire is programed into a tablet.
- Can be distributed online for efficient data collection.

2. Quantity measurements

- Knowledge about faecal sludge quantities is crucial to design treatment plant.
- Quantities depend on many factors, they are highly variable and therefore, need to be obtained specifically for each location.
- Here defined as faecal sludge accumulation rates: volume of sludge per person and time.

Fig. 1: Household member filling out self-assessment on tablet.

Approach

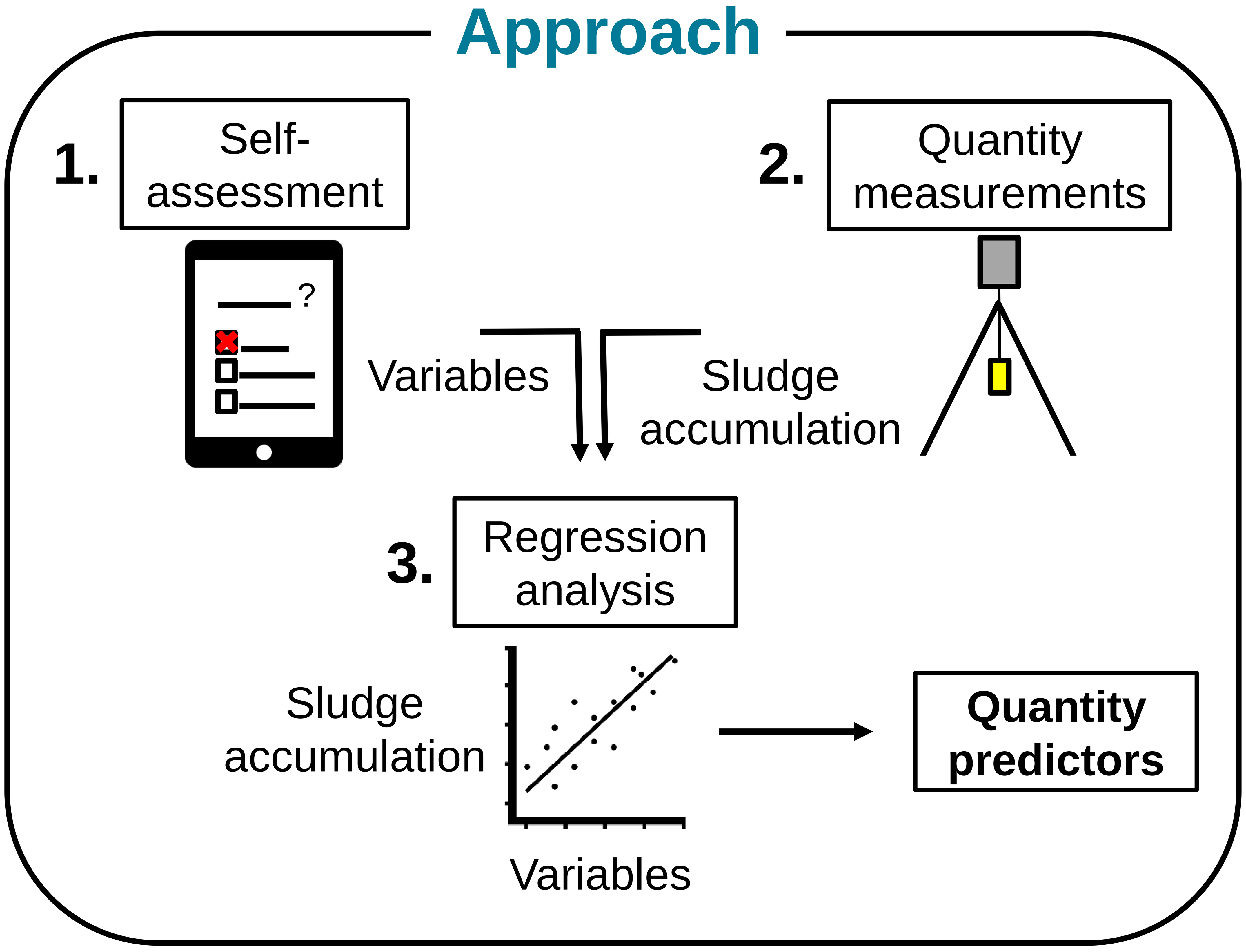


Fig. 2: Measuring sludge volumes inside containment.

3. Regression analysis

- Possible trends were found between sludge accumulation rates and the variables last emptied sludge (Fig. 3a) and containment age (Fig. 3b) → these two variables can possibly predict sludge accumulation rates.
- Containment age can be self-assessed but last emptied sludge cannot.

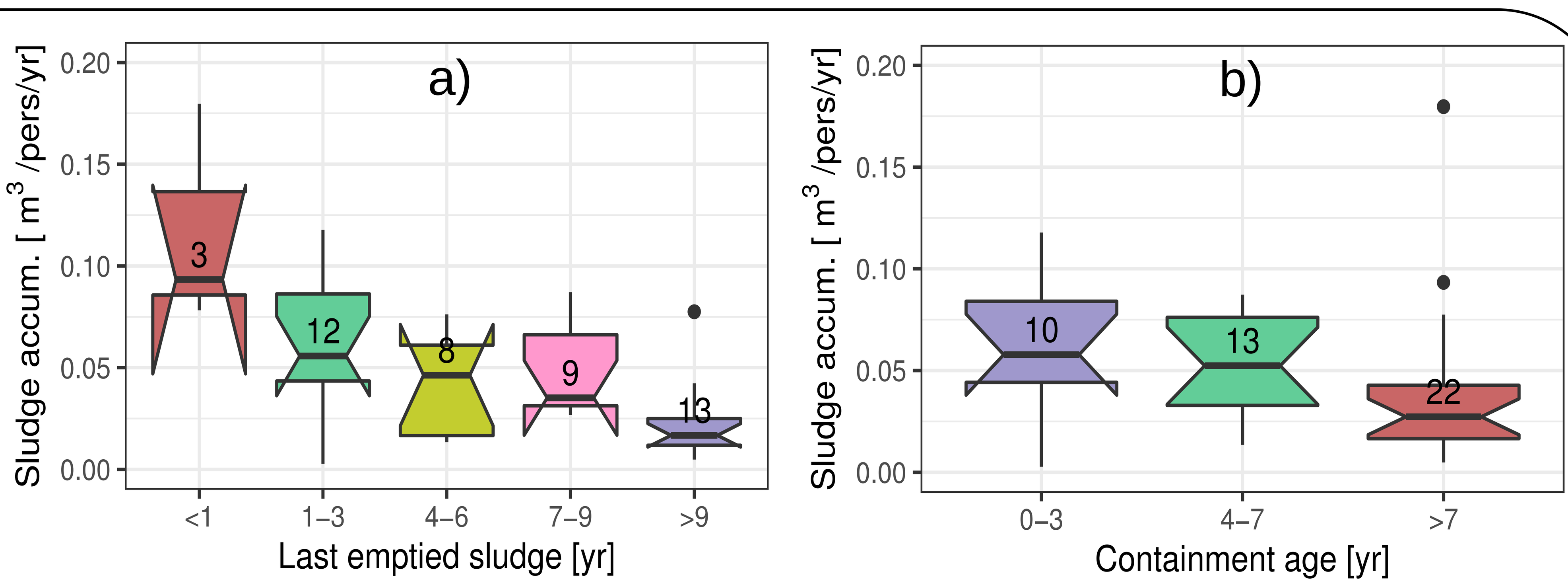


Fig. 3: Regression between sludge accumulation rate and last emptied sludge (a) and containment age (b). Numbers above median line represent sample size of respective subgroups.

Conclusions

Self-assessment can be used as a data collection method. Better data could be obtained by asking questions more precisely and having better translations.

In Kohalpur, containment age can be both self-assessed and possibly predict sludge accumulation rates.

The results found in this study are context-specific for Kohalpur, Nepal. This study does not present a list of predictors that can be applied to other places in the world, but rather an approach on how to find them.