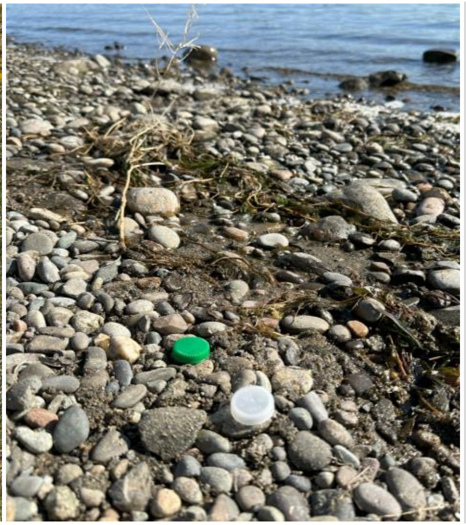
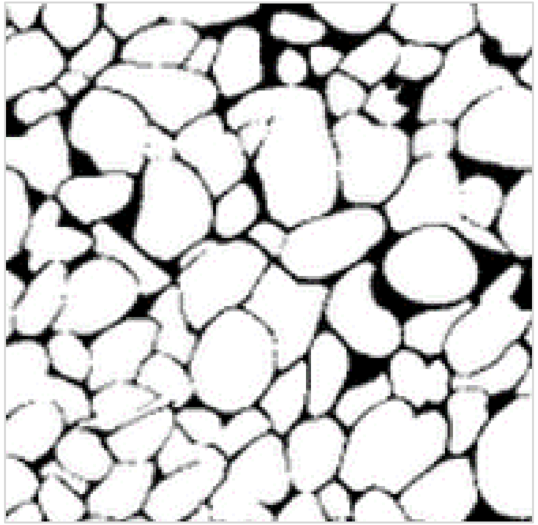
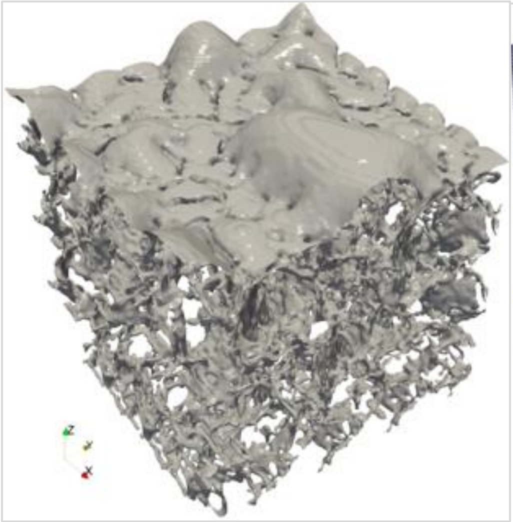
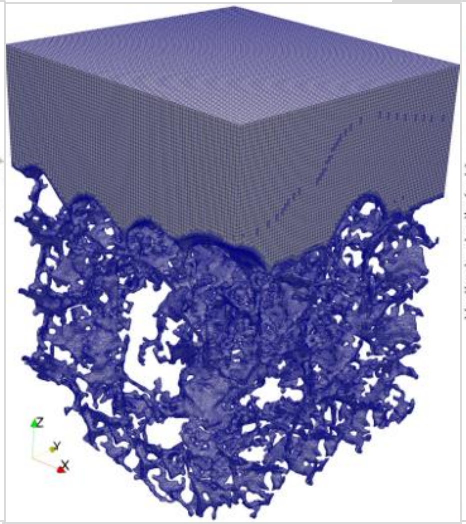
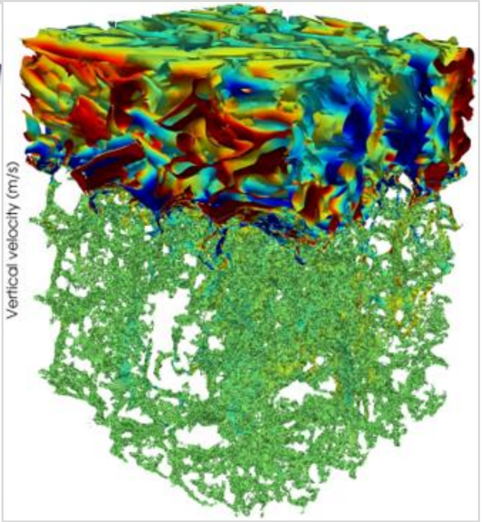
AI-augmented drone observation and multiscale modeling of streambed hydro-biogeochemistry

Yunxiang Chen, Mathematician, PNNL
Jie Bao, Research Engineer, PNNL

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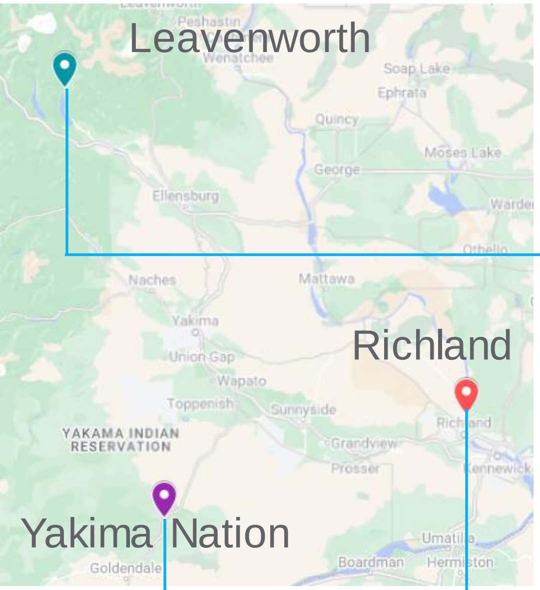
Streams are multiscale and spatial-heterogeneous



Big boulders with small gravels

Rocks under flowing water

Rocks mixed with grass

Streams are interactive hydro-bio-geochemical systems

Geology:
grain sizes
porosity
permeability

- Streambed
- Groundwater
- Static
- Visible

Hydrodynamics:
flow resistance
depth
velocity

- Streambed
- Dynamic
- Invisible

Hydrology:
stream-groundwater exchange flux

- Stream-ground interface
- Dynamic
- Invisible

Biochemistry:
uptake velocity

- Interface
- Dynamic
- Invisible

Strategy for studying such a complex system

Strategy	Static (measure) vs dynamic (model)
	Visible (measure) vs invisible (model)
Hypotheses	Static streambed is visible to drone and can be measured.
	AI can extract streambed features from drone photos/videos.
	Multiscale models can derive dynamic and invisible processes if driven by measured geological data.

AI-augmented observation and modeling framework

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1 Photo/video acquisition

- Smartphones
- Drone

2 AI feature extraction

- YOLO: rock detection AI
- SAM: segmentation AI
- cGAN: 3D pore generation

3 Multi-dimension data generation

- 0D: grain size, porosity, permeability
- 2D: grain size distributions
- 3D: streambed microtopography, subsurface pore structure

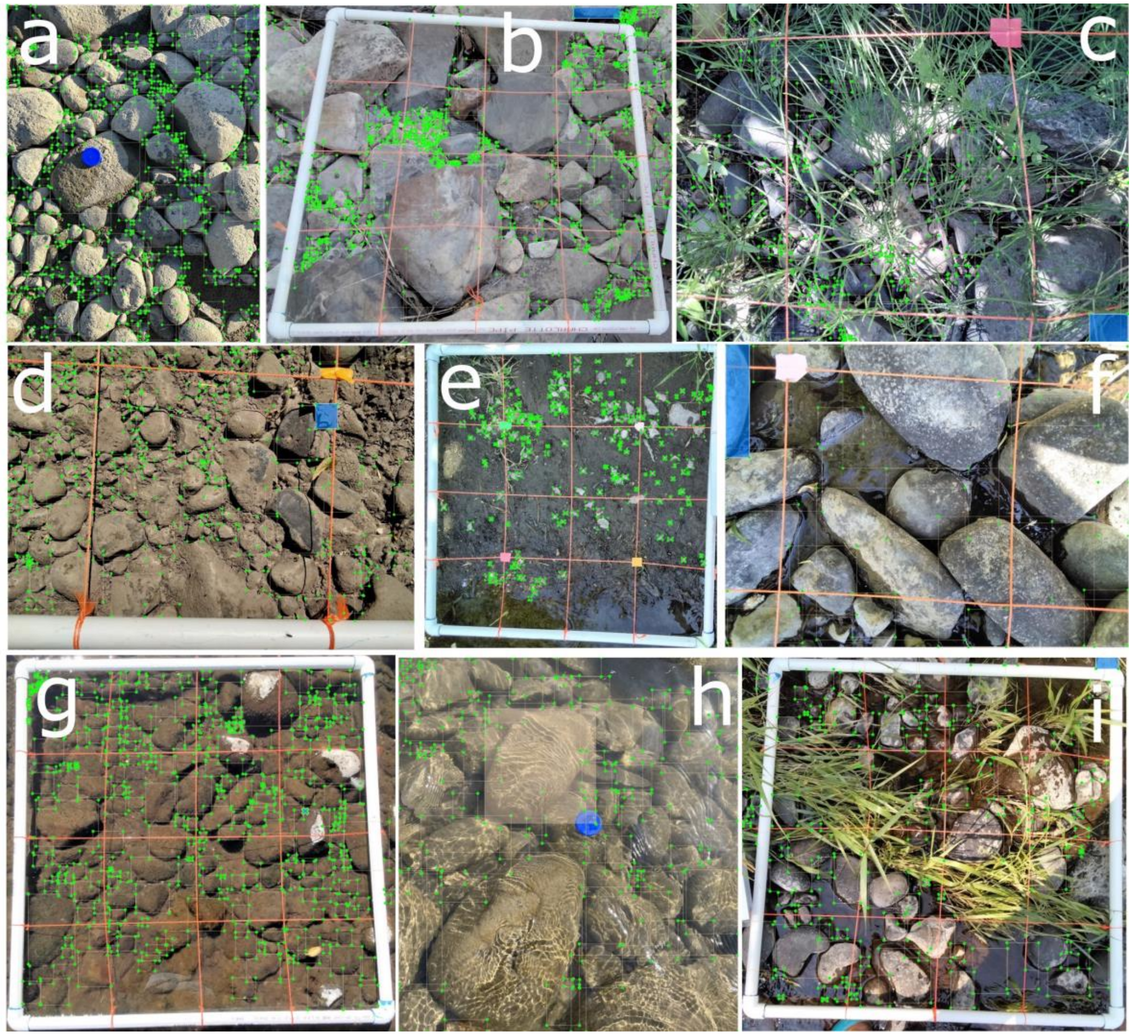
4 Multiscale modeling

- Surface-subsurface coupled model at pore scale
- Watershed scale modeling

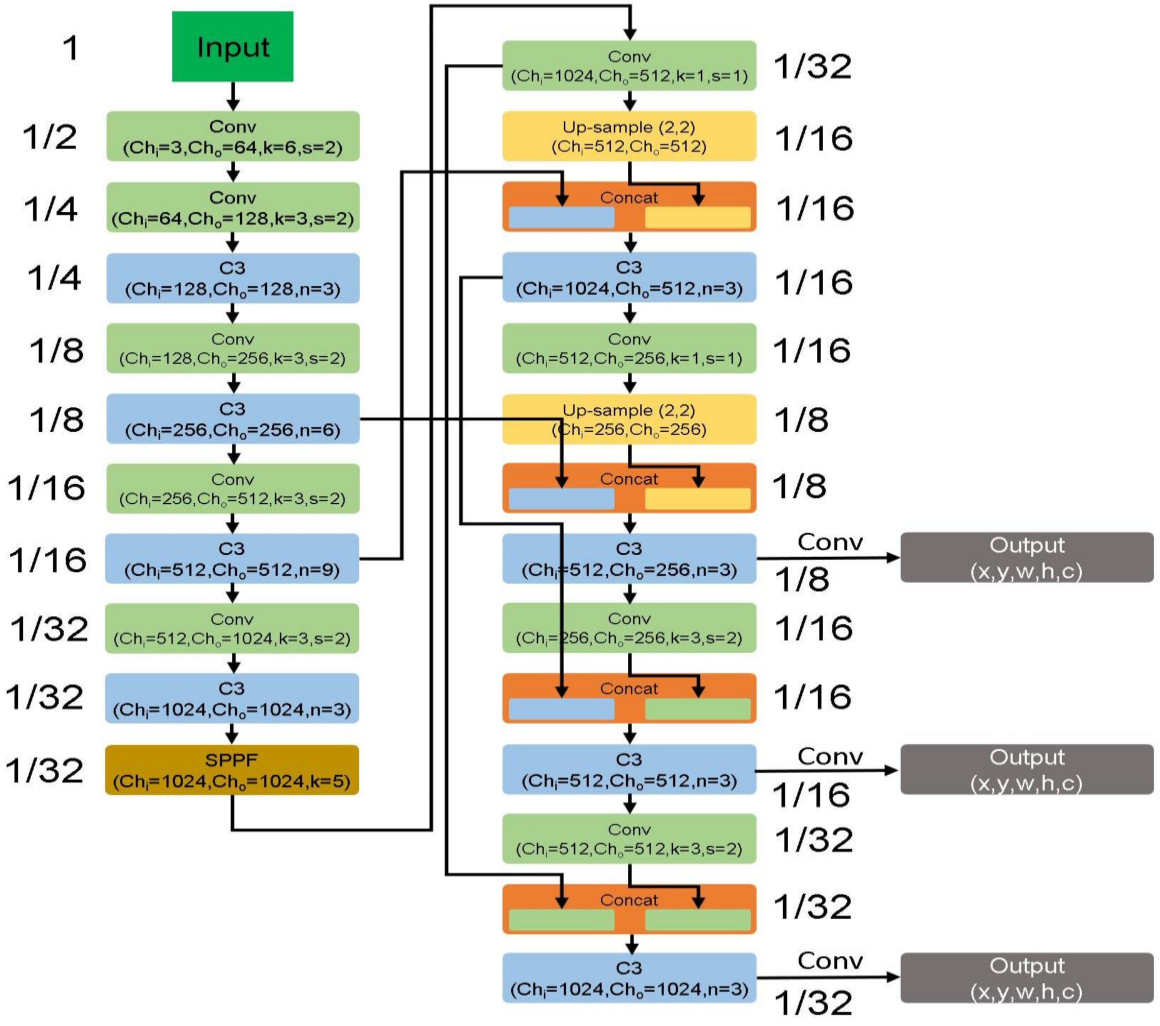
YOLO: AI for detecting rocks from photos

Chen, Y. et al, Quantifying streambed grain sizes and hydro-biogeochemistry using YOLO and photos, WRR, in review.

AI data preparation:
- ✓ 61 photos from diverse environments
- ✓ 36 photos with 11,977 labels for training
- ✓ 5 photos with 954 labels for validation
- ✓ 20 photos with 4,020 labels for testing



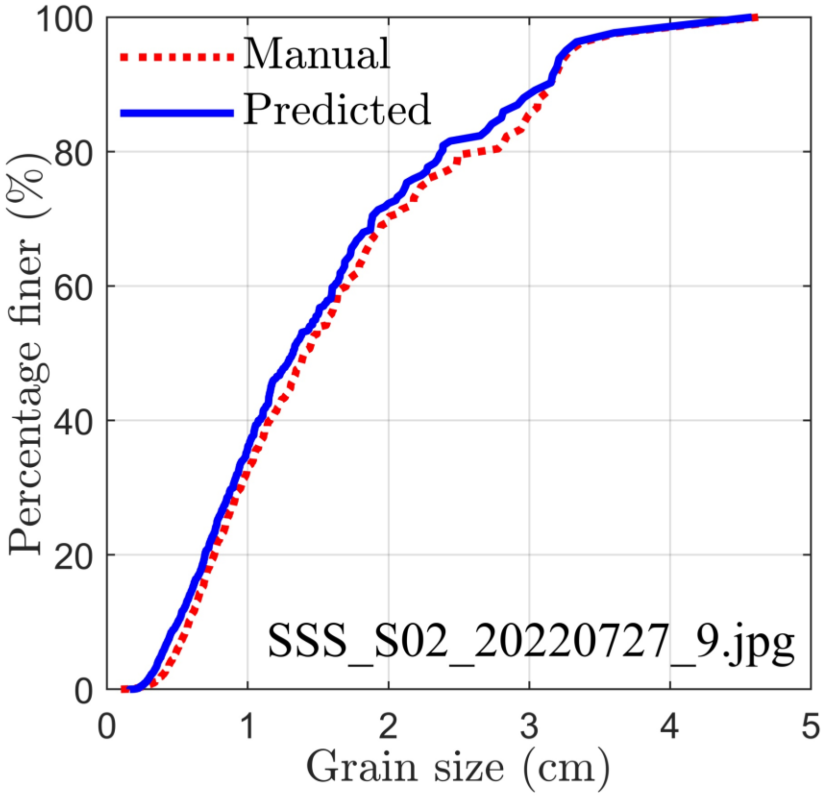
AI neural network structure:
- Input: photos/videos (jpg, png, avi, mp4)
- Output: labels (centroid, width, height, class)



YOLO: accuracy in detecting grain sizes

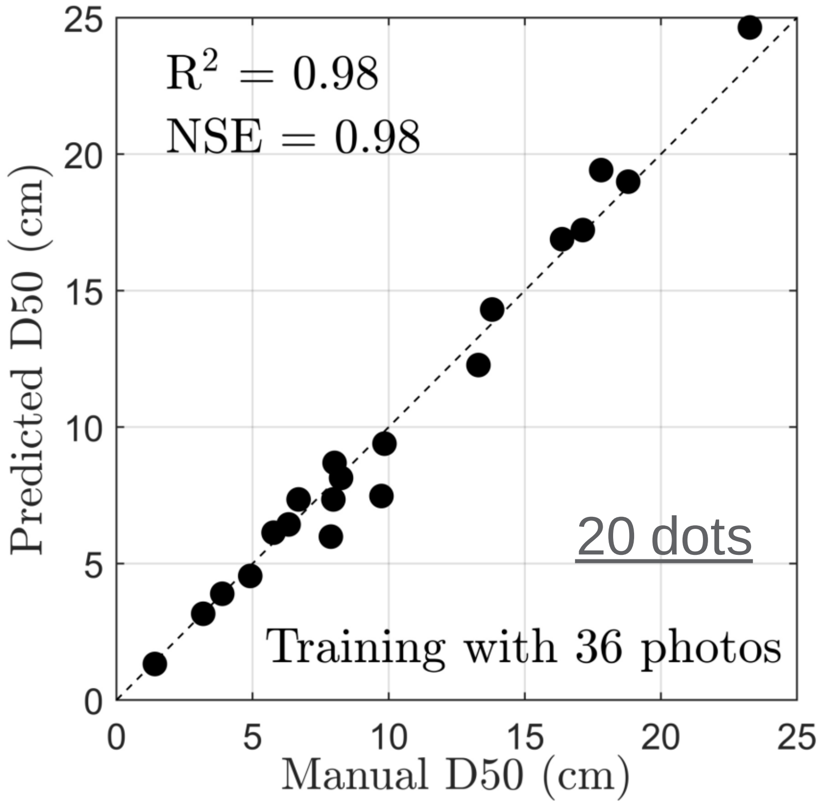
Results evaluated based on 20 testing photos

1. Grain size distribution (GSD)



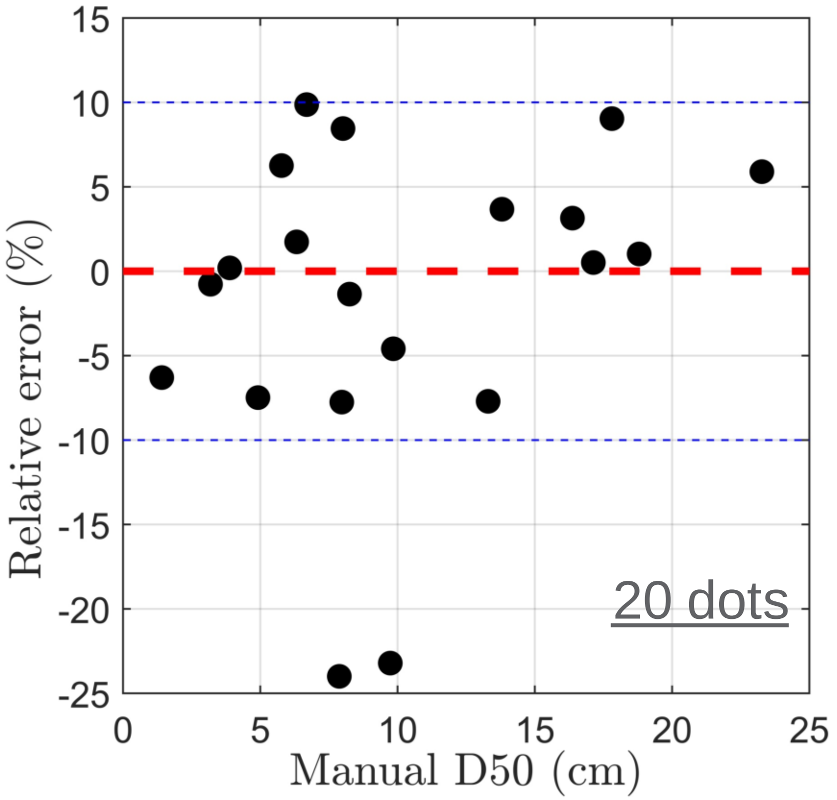
- ✓ AI predicted GSD is very close to manual measurements.

2. Median grain size D50



- ✓ AI predicted D50 accuracy:
- R^2 = 0.98
- NSE = 0.98

3. Relative error (%)

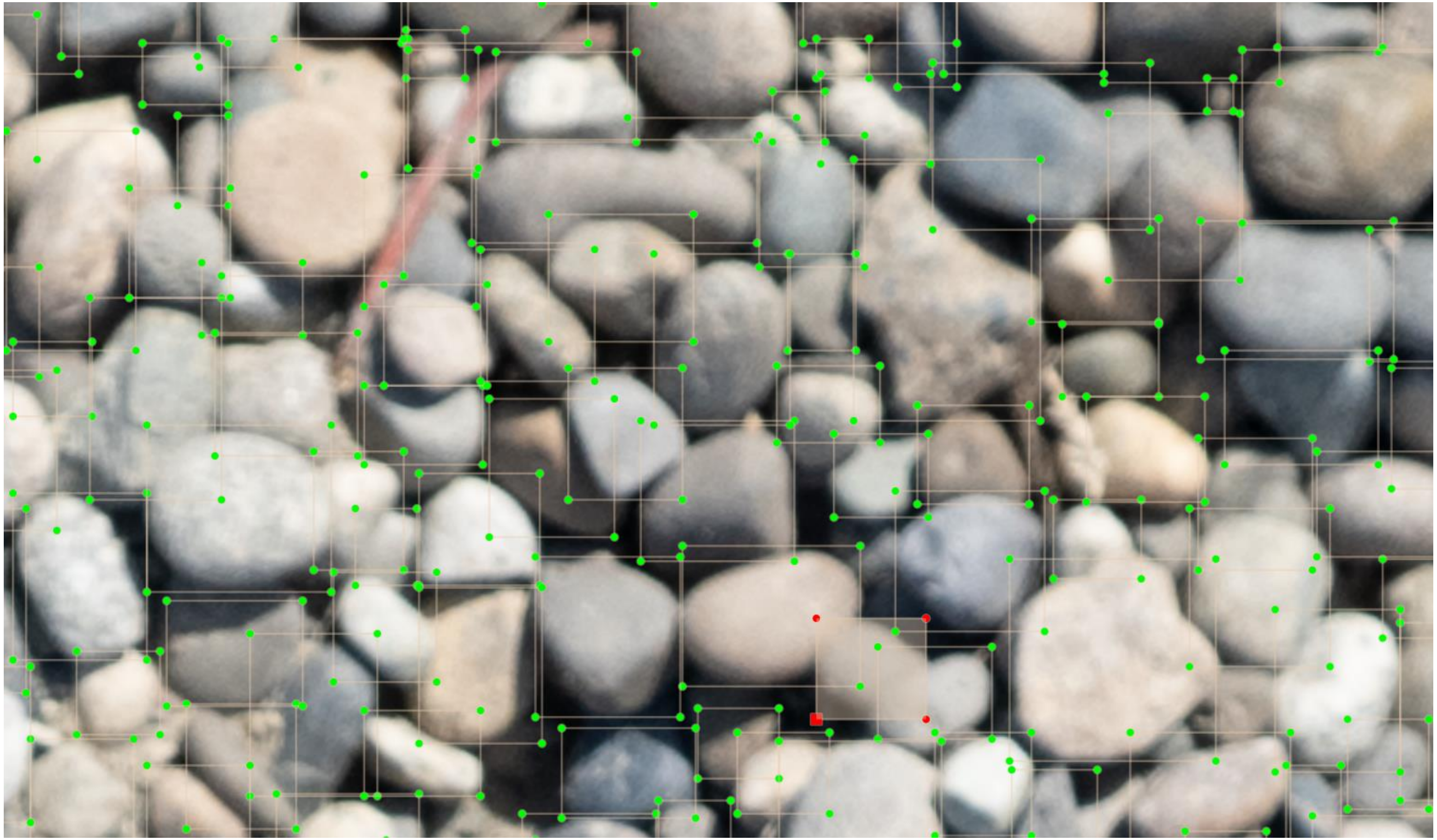


- ✓ 90% of the data show relative error less than 10%.
- ✓ Mean absolute relative error: 6.65%

YOLO: application for drone photos/videos

- dimension 3840x2160
- 24 photos per second
- Minimum 0.18 mm
- Drone height 0.5-10 m

~10,000 photos
Highly efficient!



It takes a few seconds to identify thousands of sediments in a single drone photo;
It takes an hour to extract grain size distributions for 10,000 photos.

SAM: segmenting rocks from drone photos

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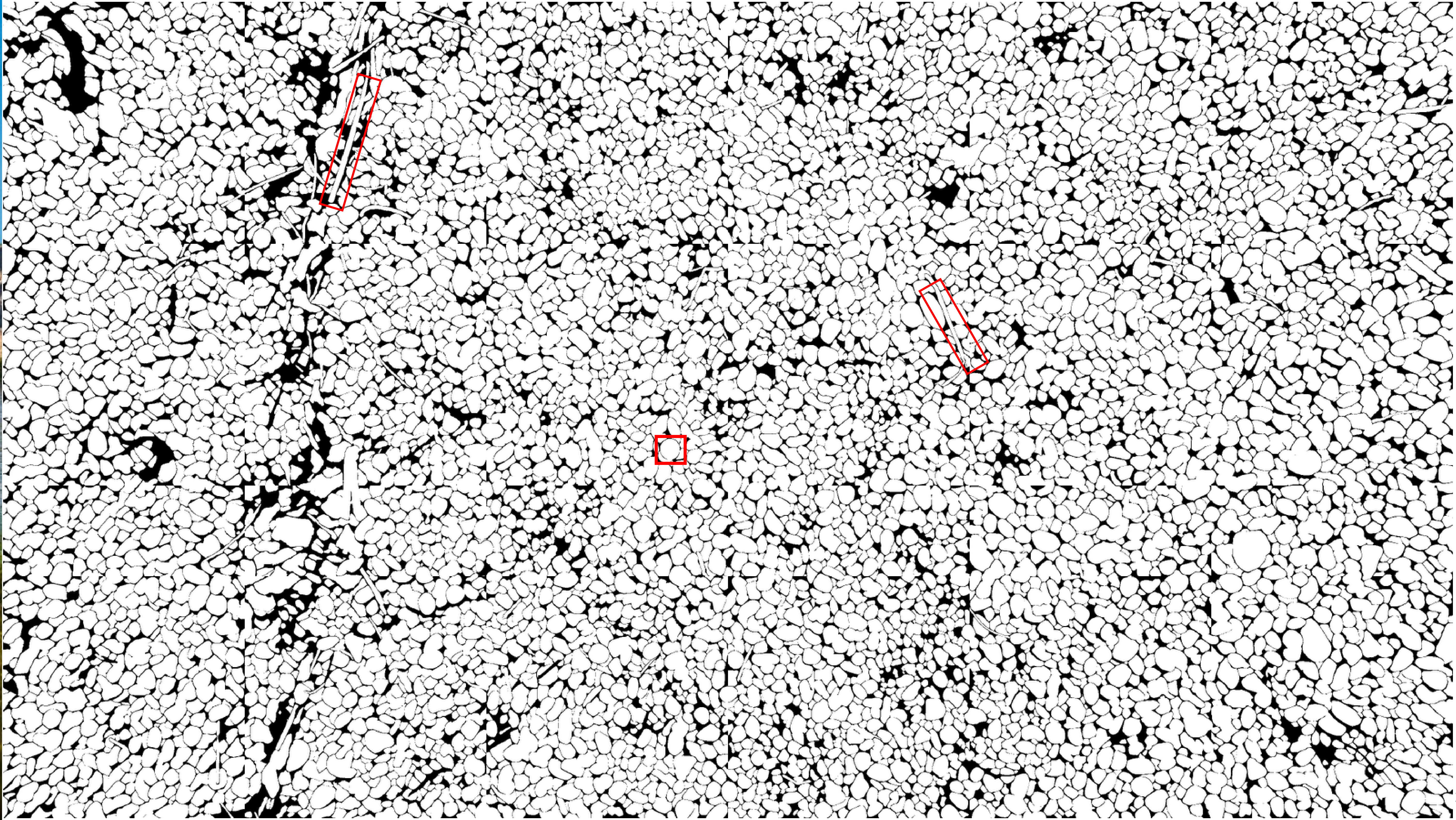
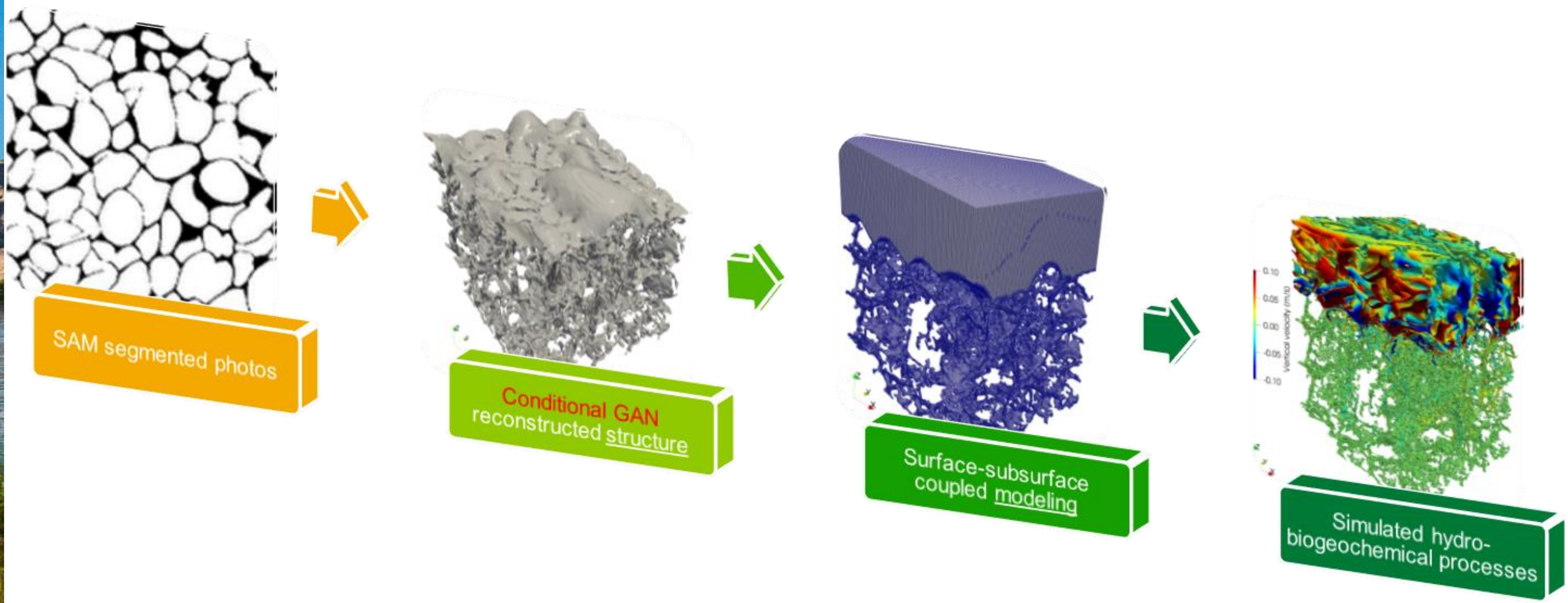


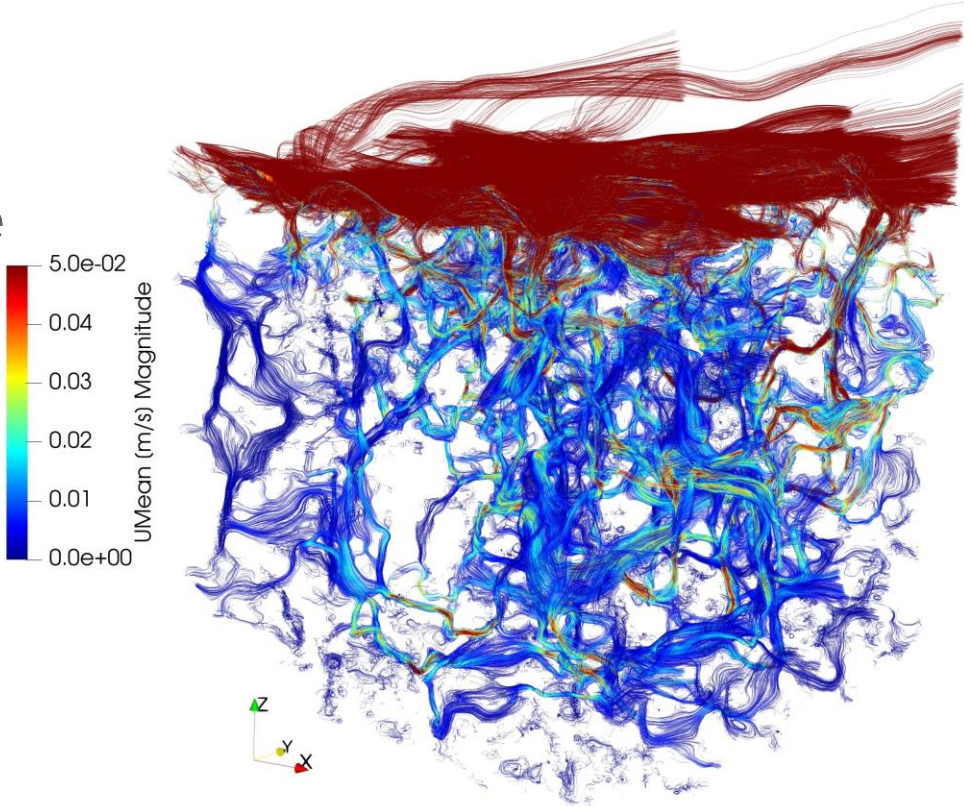
Next direction 1: photo-driven pore-scale modeling



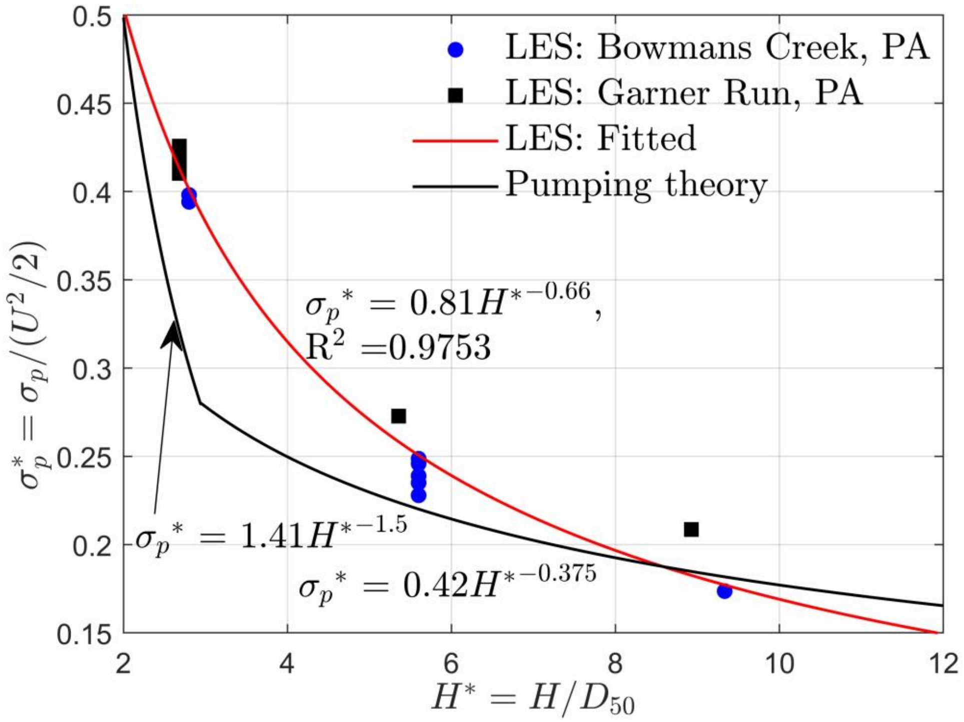
Now, we can build surface-subsurface coupled pore-scale modeling technology from drone photos/videos with the help of AI.

Next direction 1: demonstration for interface processes

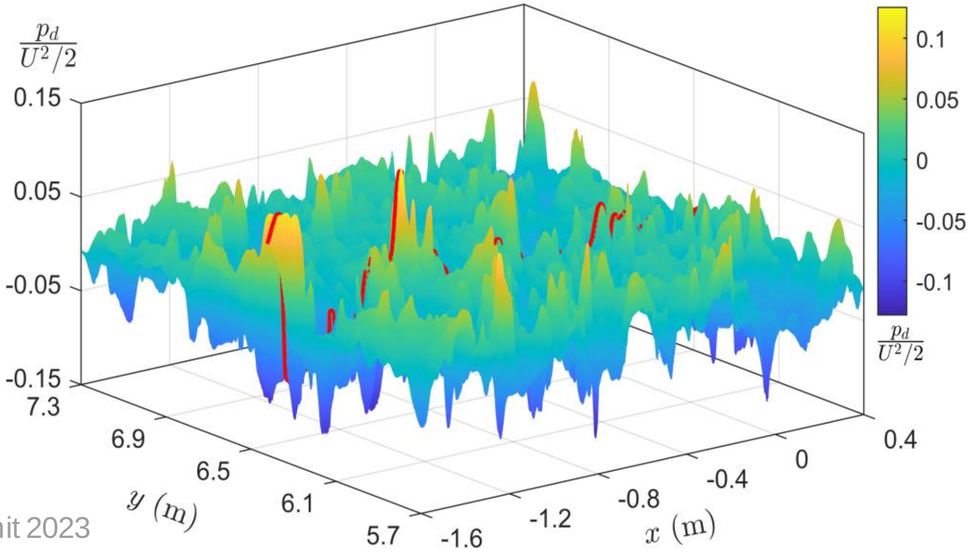
Details at surface-subsurface interface: velocity



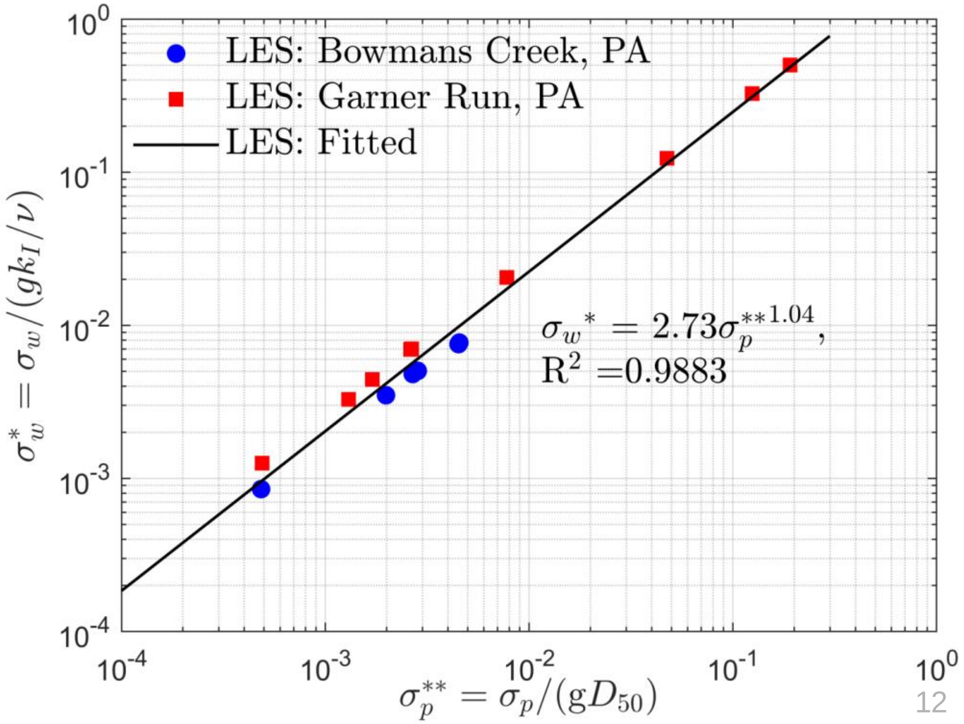
σ_p: standard deviation of dynamic pressure at interface



Dynamic pressure



σ_w: standard deviation of vertical velocity at interface



Direction 2: photo-driven watershed HBGC parameterization

Chen, Y. et al, Quantifying streambed grain sizes and hydro-biogeochemistry using YOLO and photos, WRR, in review.

Hydrodynamics: Friction factor

$$\sqrt{\frac{8}{f}} = \frac{U}{u_\tau} = \frac{c_1 c_2 H/D_{84}}{\sqrt{c_1^2 + c_2^2 (H/D_{84})^{5/3}}}$$

Hydrology: Manning coefficient

$$n = \frac{D_{84}{}^{1/6}}{20.4}$$

Hydrology: surface-subsurface exchange flux magnitude

$$\sigma_{HEF} = c_2 \frac{g k_I}{\nu} \frac{U^2}{2 g D_{50}} \left(\frac{H}{D_{50}}\right)^{c_4}, k_I = c_5 D_5^2$$

Biochemistry: stream nitrate uptake velocity

$$u_f = 0.17 \boldsymbol{u_\tau} Sc^{-2/3} * c_6 [\mathrm{NO_3}^-]^{c^7}$$

Uncertainty estimation: r means relative error

$$r_{50} = \sqrt{r_{50p}{}^2 + r_{SC}{}^2} \qquad r_{84} = \sqrt{r_{84p}{}^2 + r_{SC}{}^2}$$

$$r_f = 2\{1 - \frac{5}{6}[1 + \frac{c_1^2}{c_2^2}(\frac{H}{D_{84}})^{-5/3}]^{-1}\}\sqrt{r_H^2 + r_{84}^2}$$

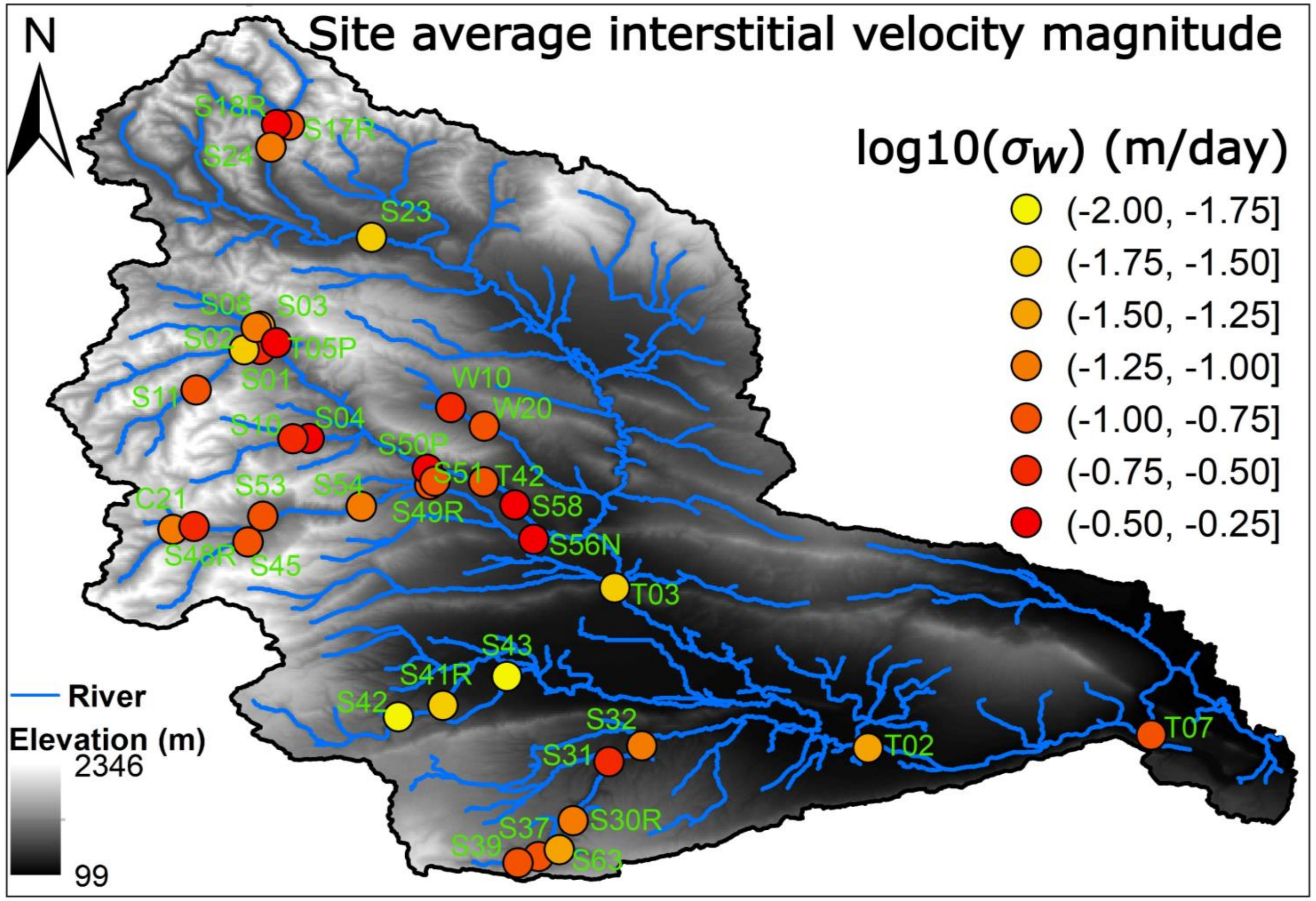
$$r_n = \frac{r_{84}}{6}$$

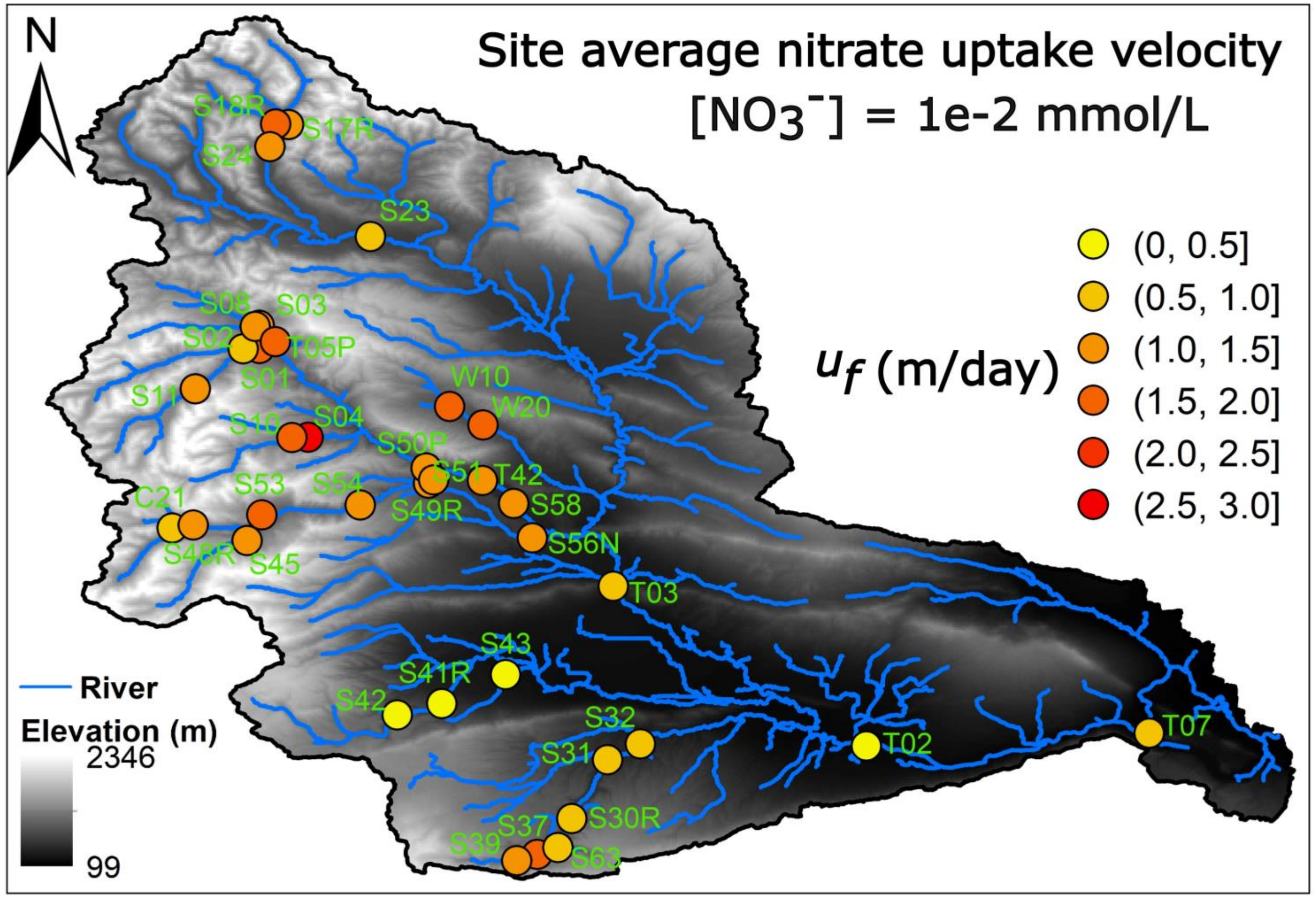
$$r_{HEF} = \sqrt{4 r_U^2 + (1 - c_4)^2 r_{50}^2 + c_4^2 r_H^2}$$

$$r_{uf} = \sqrt{r_U^2 + r_f^2/4 + c_7^2 r_{NO3-}^2}$$

- D5/D50/D84 can be derived from photos/videos with AI;
- Depth H, velocity U, and nitrate concentration need measurements or estimated from regional/global models;
- r_H, r_U, r_{NO3-} are measurement uncertainty of depth, velocity, and nitrate concentration.

Direction 2: demonstration at the Yakima River Basin, WA





- Key riverbed hydro-biogeochemical parameters can be estimated from photos at watershed scale;
- Watershed scale model can be constrained with photo-derived parameters.

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IAEA International Atomic Energy Agency Atoms for Peace

Take-away:

The integration of drone, AI, and modeling provides a new solution to study river hydro-biogeochemistry at both pore and watershed scale.