Automated river-level monitoring through river camera images and deep learning

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Current river monitoring solutions

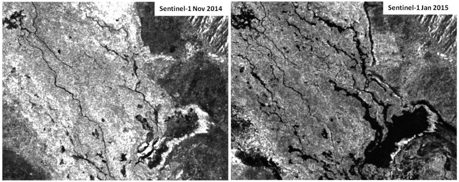
River gauges

Pro: Steady water-level data stream

Con: Lacks flexibility (cost, location)

Hard to observe a flood event at an ungauged location

SAR images



Pro: Flexible solution

Con: At best, $\sim$1 image every few days

Can miss the rising limb of a flood and flash flood events

Our solution

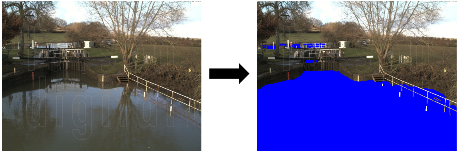
River cameras

Steady image stream: *CCTV live cameras*
Flexible solution: *cheap & easy to install and maintain*

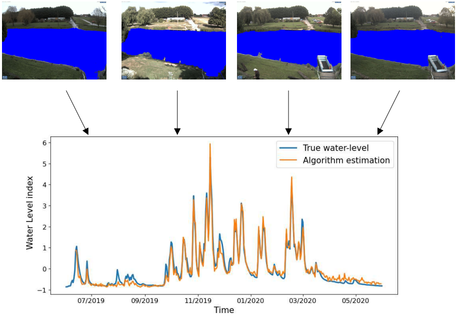
How to transform the images into quantitative data?

Proposition 1

Part 1. Water segmentation.
Extraction of the water pixels from the images.



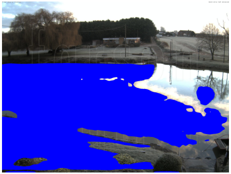
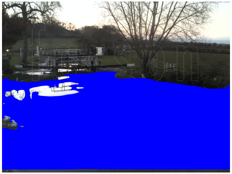
Part 2. Transformation of the water segmentation into river level data.



Proposition 1, part 1. Water segmentation

Challenge

Typical deep learning networks offer unsatisfying results for water segmentation

- Problems with water reflection, shadows, weather,...
- Segmentation networks trained from scratch
  - Small water segmentations datasets ($\pm$200 images)

Proposition 1, part 1. Water segmentation
Method

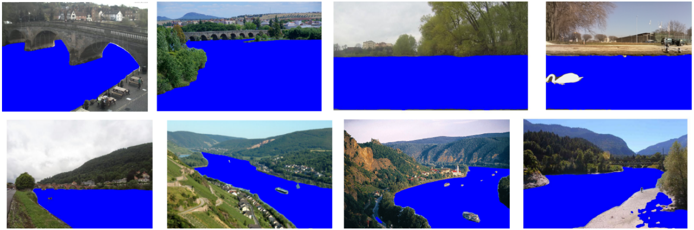
Our idea: use transfer learning to harness the predictive power of segmentation networks trained on large databases of natural images

ADE20k samples

COCO-stuff samples

Proposition 1, part 1. Water segmentation

Results



	Accuracy (%)	
	(1)	*(2)*
SotA	90.2	97.5
Our method	96.9	99.5

(1) 75 water-segmented images dataset from *Lopez-Fuentez et al., 2017*
(2) 39 water-segmented images dataset from *Steccanella et al., 2018*

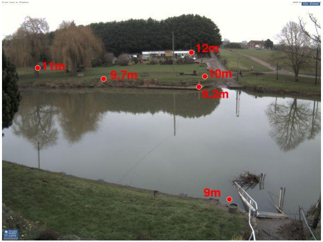
Vandaele, R., Dance, S. L., & Ojha, V. (2020). Automated water segmentation and river level detection on camera images using transfer learning. DAGM Conference.

Part 2. Extraction of river level data

Methods

1. SOFI index: % *of water pixels in a region of the image.*

2. LBWLE index: *height of the highest landmark reached by water*



Proposition 1, part 2. Extraction of river level data

SOFI index results

Test set. 4 Farson Digital cameras captured between 01/06/2019 and 31/05/2020, annotated with gauge data:

Camera name	# images	Distance to gauge station (m)
Diglis Lock	3081	94
Evesham Lock	3012	120
Strensham Lock	3067	820
Tewkesbury Marina	3147	1112

Performance criterion. Pearson Correlation Coefficient ρ:

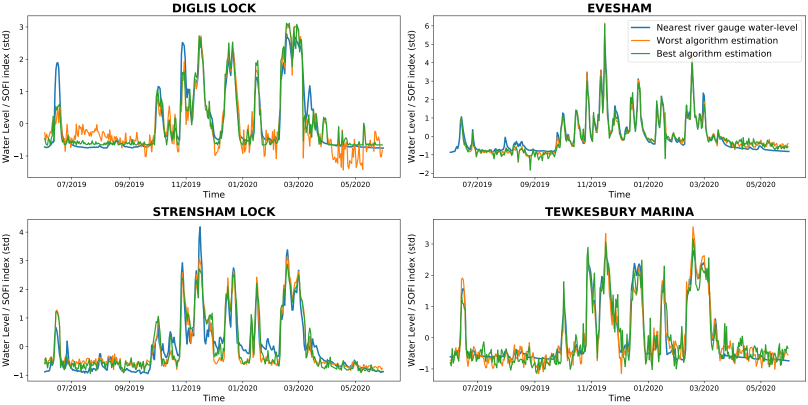
$$\rho = \frac{\sum_i^N (w_i - \bar{w})(g_i - \bar{g})}{\sqrt{\sum_i^N (w_i - \bar{w})^2}\sqrt{\sum_i^N (g_i - \bar{g})^2} \qquad (1)$$

w_i is the gauge water level, g_i the estimated water level.

Proposition 1, part 2. Extraction of river level data

SOFI index results

	Diglis Lock	Evesham Lock	Strensham Lock	Tewkesbury Marina
$\rho_{\text{Best network}}$	0.94	0.98	0.94	0.97



Part 2. Extraction of river level data

LBWLE index results

Test set. 4 Farson Digital cameras captured during a 2-week flood event in 2012.

Location	#images	# landmarks	% flooded landmarks
Diglis Lock	141	7	24.11
Evesham Lock	134	13	30.94
Strensham Lock	144	24	37.15
Tewkesbury Marina	138	4	43.66

Performance criterion. Balanced Accuracy (landmark classification):

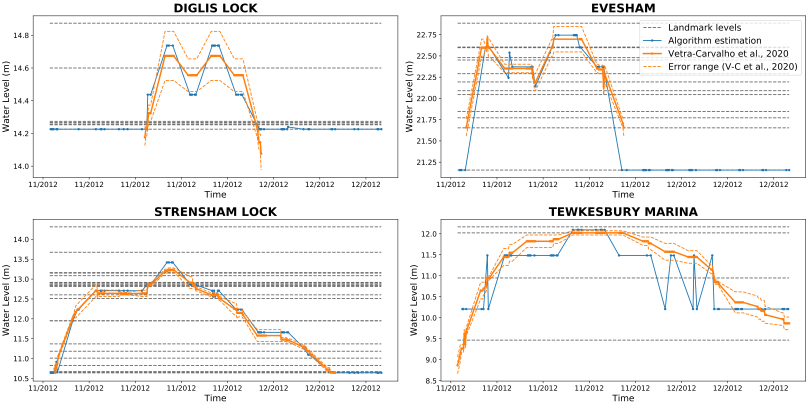
$$BA = 0.5 \times \frac{A}{A + D} + 0.5 \times \frac{B}{B + C} \tag{2}$$

A is the number of true positives, B of false positives, C of false negatives and D of true negatives.

Proposition 1, part 2. Extraction of river level data

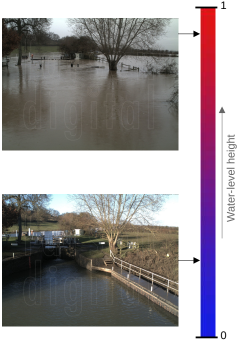
SOFI index results

	Diglis Lock	Evesham Lock	Strensham Lock	Tewkesbury Marina
$BA_{\text{Best network}}$	0.95	0.97	0.91	0.95

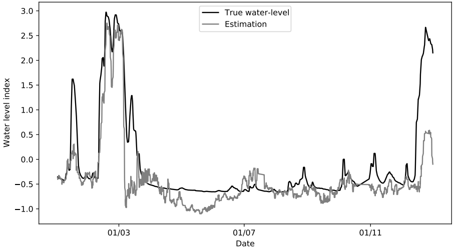


Proposition 2. Image regression

1. Creation of a large dataset of 32,715 images annotated with river levels



2. Training of a deep regression network on this dataset to estimate the calibrated river level



Vandaele et al., 2022. Environmental Data Sciences (submitted)

Proposition 2. Image regression

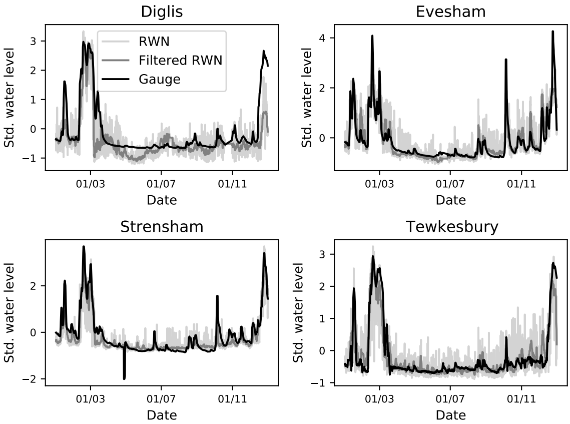
Creation of the dataset

1. Matching of a camera with a river gauge
   - Closest gauge to the camera
   - Camera removed when the closest gauge > 50km
   - Manual inspection of the matching quality
   - Started with 163 cameras from Farson Digital and 10.000+ gauges from EA, OPW, NRW and SEPA.
2. Matching of an image with a gauge measurement
   - The matching was made according to their timestamp
   - The closest measurement within 30mins from the image timestamp was selected
3. Final dataset
   - 95 cameras, 32,715 images
   - Test dataset and performance criterion similar to Slide 9

Proposition 2. Image regression

Results

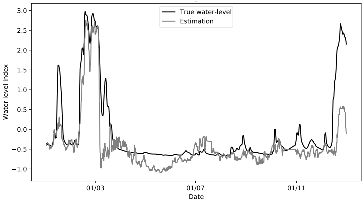
	Diglis Lock	Evesham Lock	Strensham Lock	Tewkesbury Marina
$\rho_{\text{Best network}}$	0.8	0.94	0.87	0.86



... but independent from the field of view of the camera!

Future steps

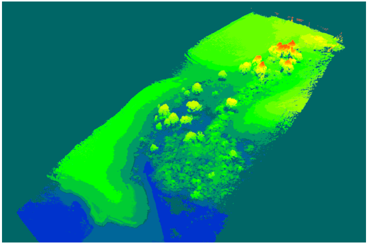
1. Improve the accuracy of the image regression network



- Robust-to-noise training
- Use additional information (segmentation, temporality)

2. Extract absolute river water-levels (in meters above sea-level)

- Integrate LiDAR DSM data
- Image registration, heterogeneous networks,...



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