Deep Learning for Flood Monitoring

Dr Varun Ojha

School of Computing, Newcastle University

varun.ojha@ncl.ac.uk

ojhavk.github.io

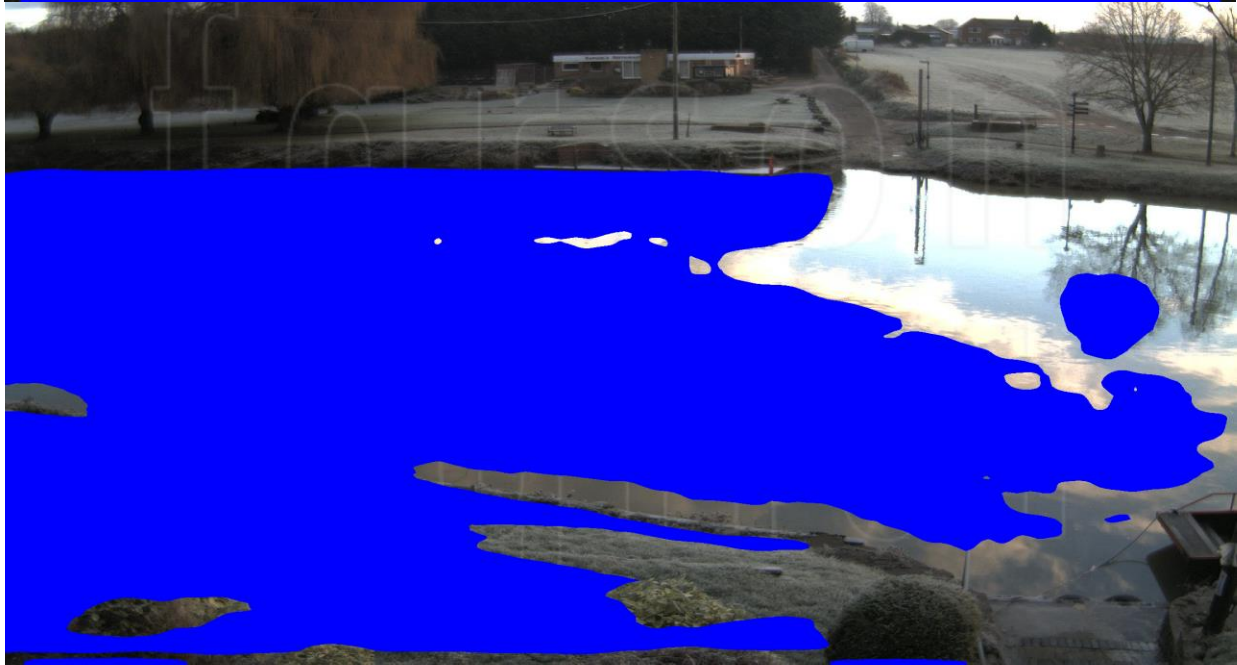
and collaborators

Remy Vandaele and Sarah Dance, University of Reading

at

School of Engineering, Newcastle University

20 May 2024

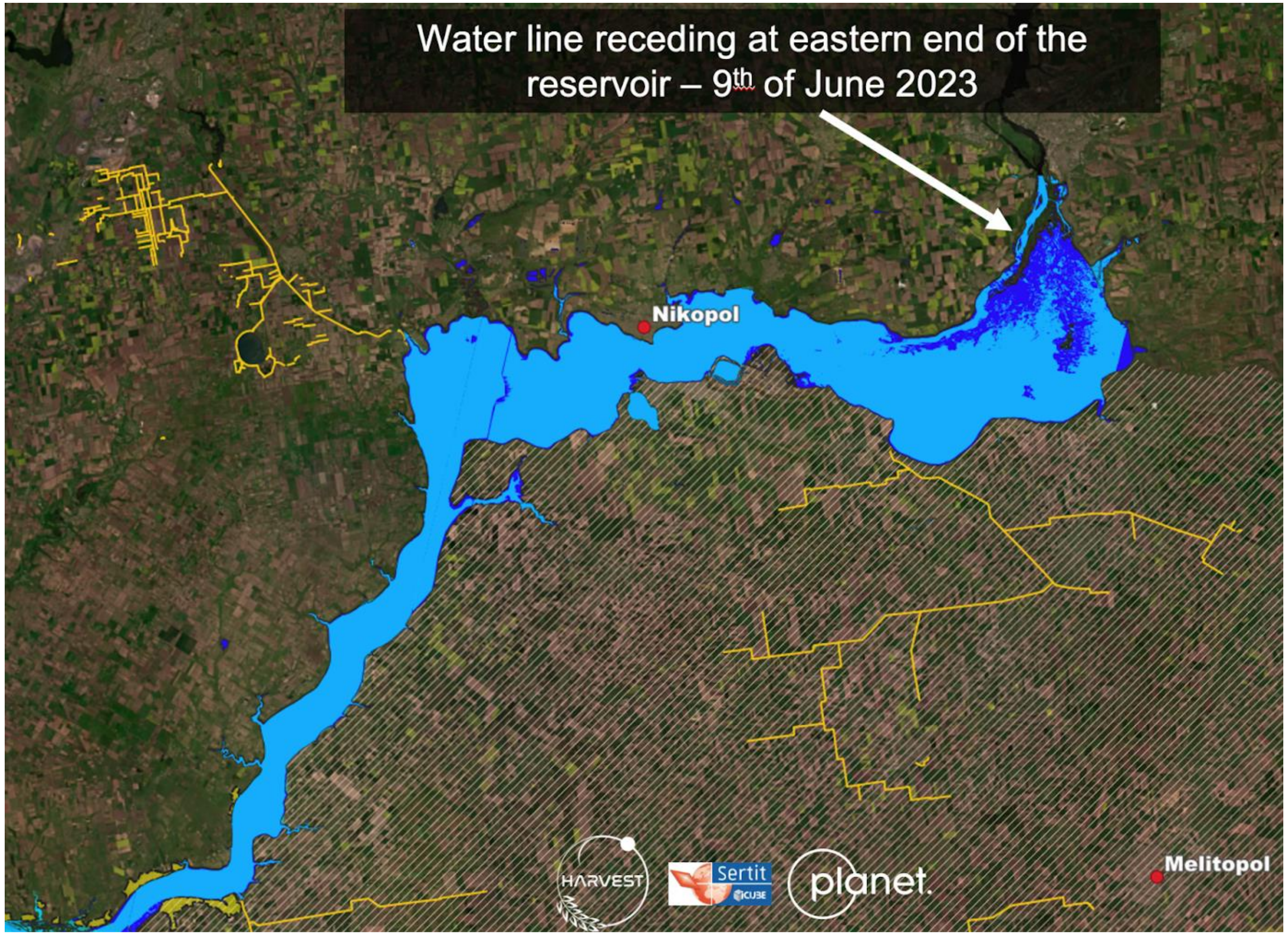


Part 1

Automated river water-level monitoring

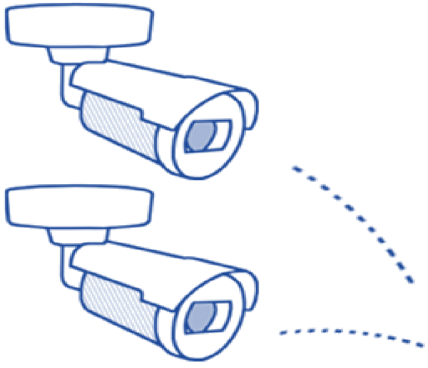
Traditional river water level monitoring

Use of river gauge



Use of satellite images

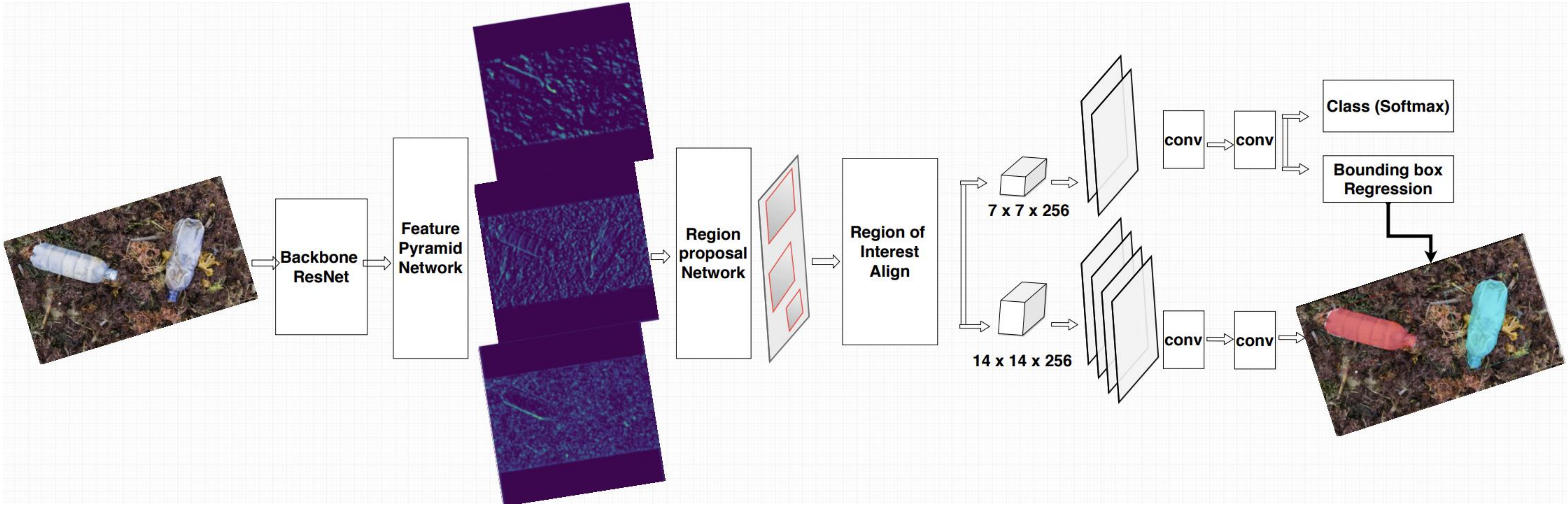
Our approach: use of river cameras



We could use CCTV camera

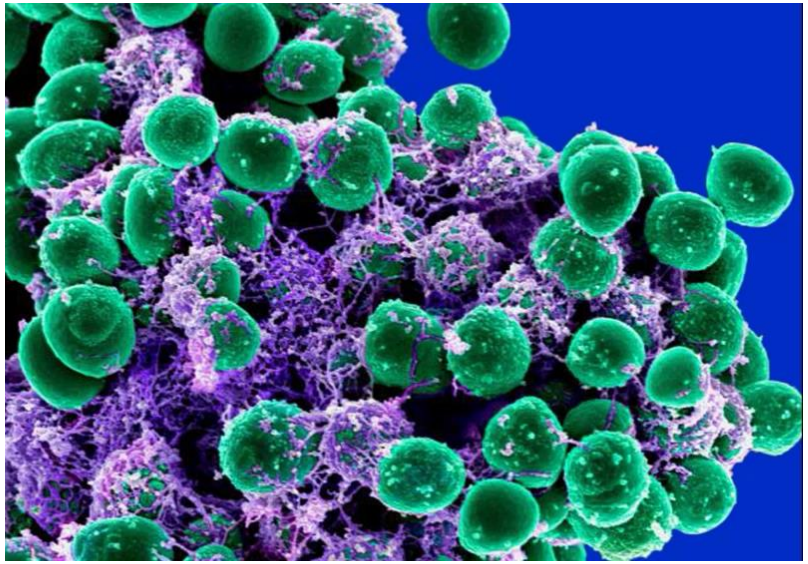
Source/Credit Farson Digital

Deep Leaning Models

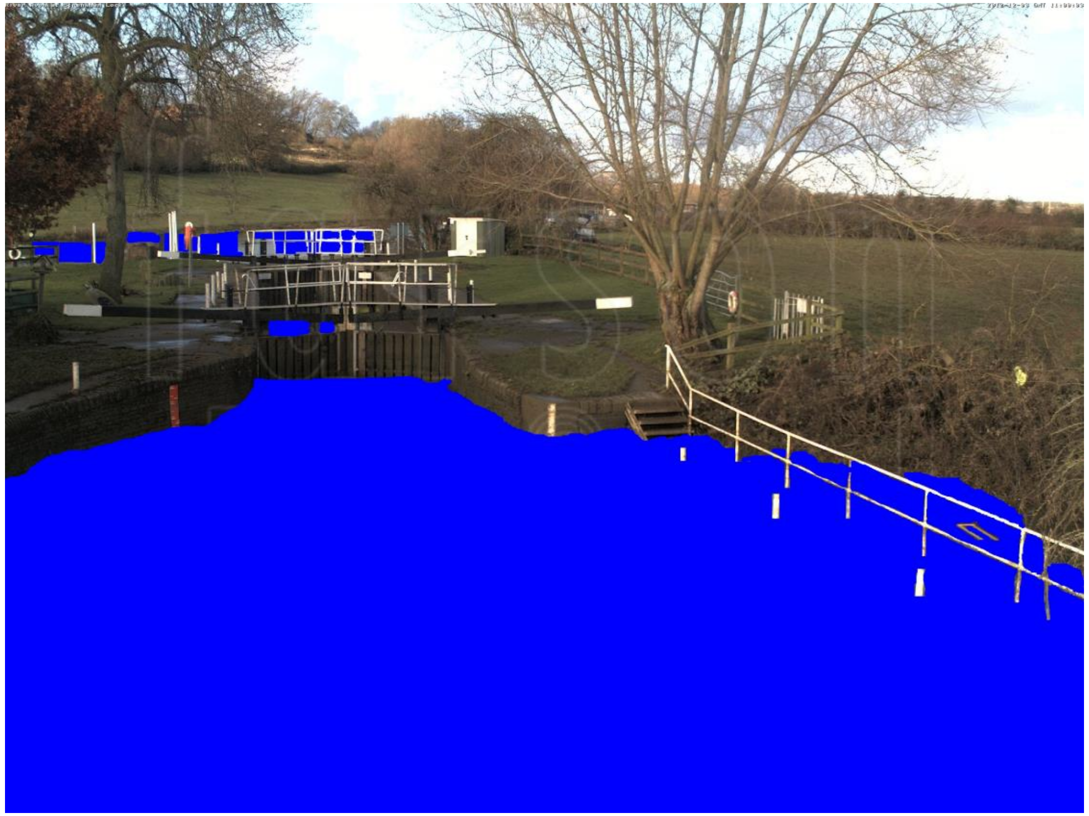


Jaikumar P, Vandaele R, Ojha V (2020) Transfer learning for instance segmentation of waste bottles using Mask R-CNN algorithm 20th Int. Conf. on Intelligent Systems Design and Applications (pp 140–149) Springer (2020)

Deep Leaning Models:
Segment Anything from Meta (2023)



Deep learning for water level estimation

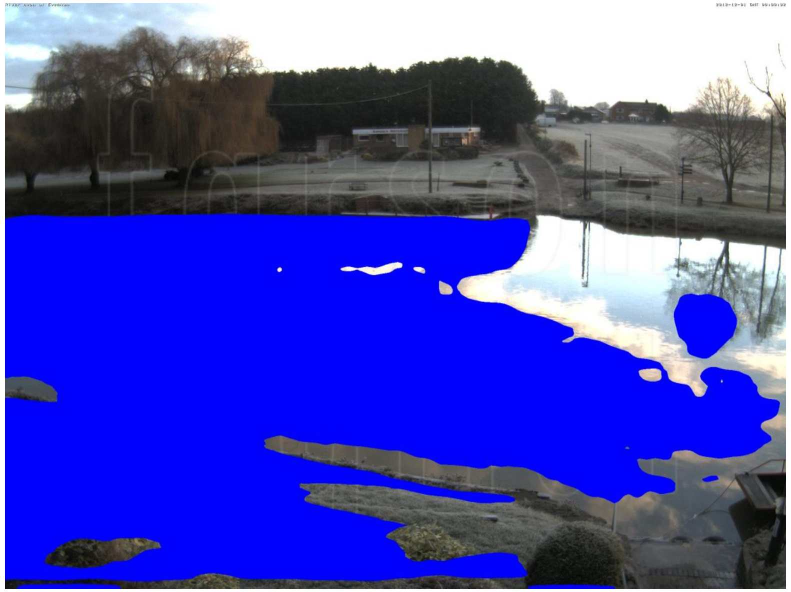


Pixel-wise water segmentation of RGB images for river water-level monitoring or flood monitoring

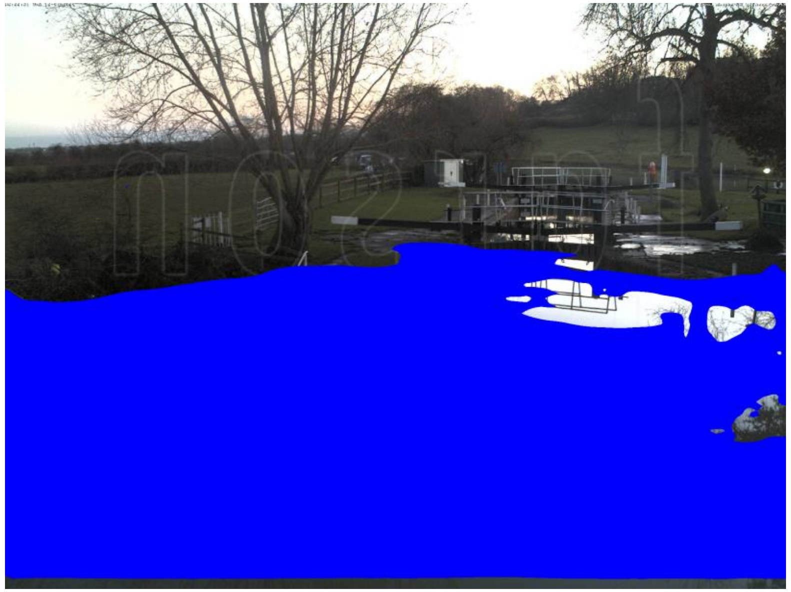
Vandaele, R., Dance, S. L., & Ojha, V. (2020). Automated water segmentation and river level detection on camera images using transfer learning. GCPR

Water semantic segmentation

Challenges with current state of the art water segmentation networks



Water reflection



Varied weather and varied field of view

Shadows and vegetation

And very few to no labelled dataset

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

We used transfer leaning (2020)

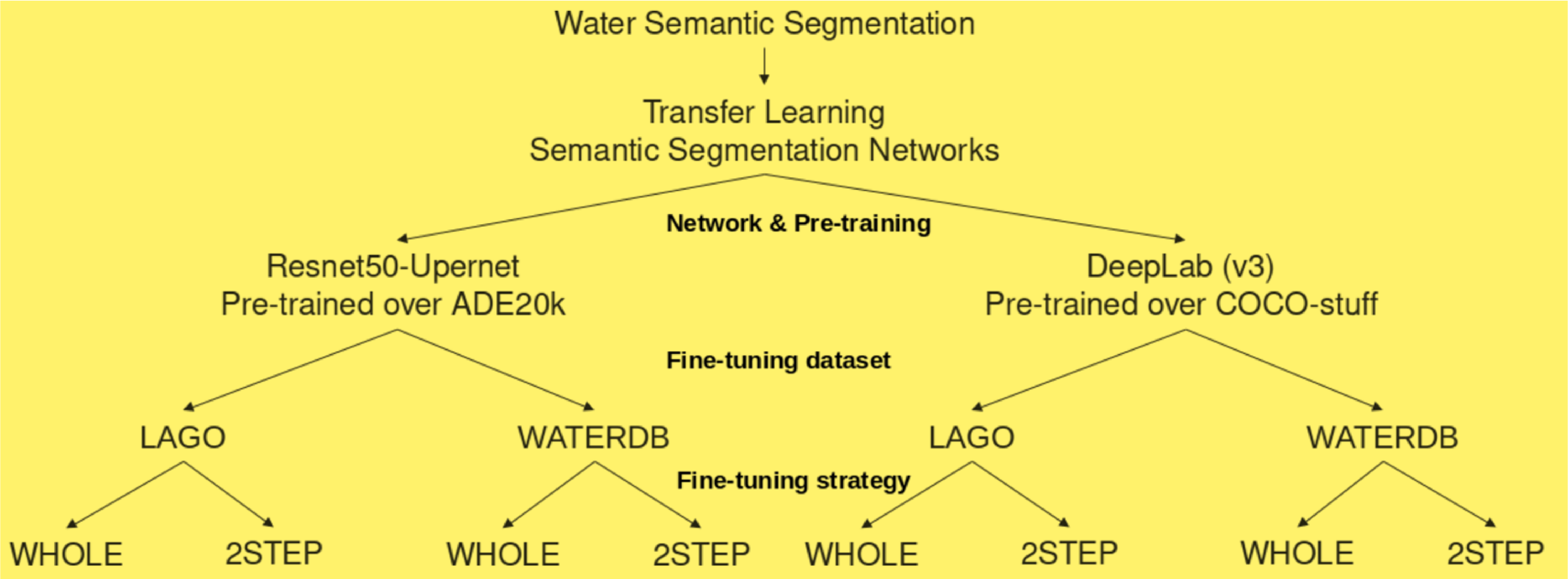
ADE20k samples

COCO-stuff samples

Use transfer learning to harness the predictive power of segmentation networks trained on large databases of natural images

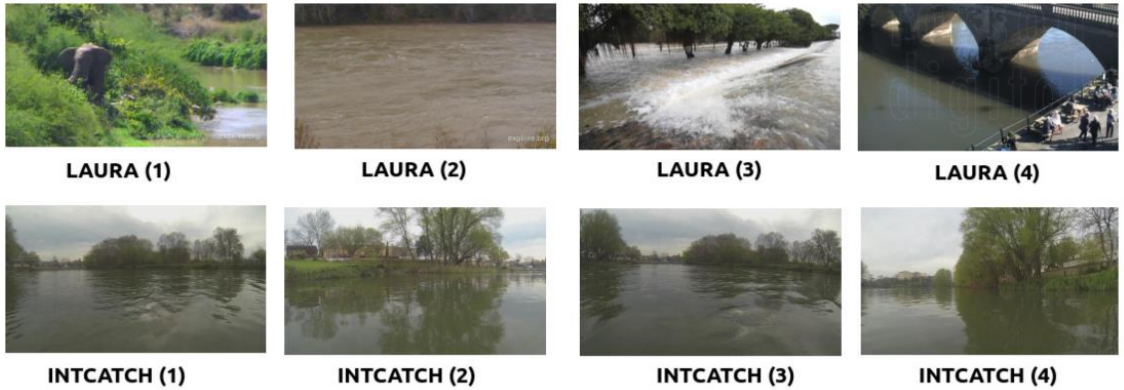
Vandaele, R., Dance, S. L., & Ojha, V. (2020). Automated water segmentation and river level detection on camera images using transfer learning. GCPR

Deep Leaning Modelling



Automated water segmentation
(initial results)

Fine-tuning over the smaller water segmentation datasets.



Dataset 1: 75 water-segmented images dataset from Lopez-Fuentez et al., 2017

Dataset 2: 39 water-segmented images dataset from Steccanella et al., 2018

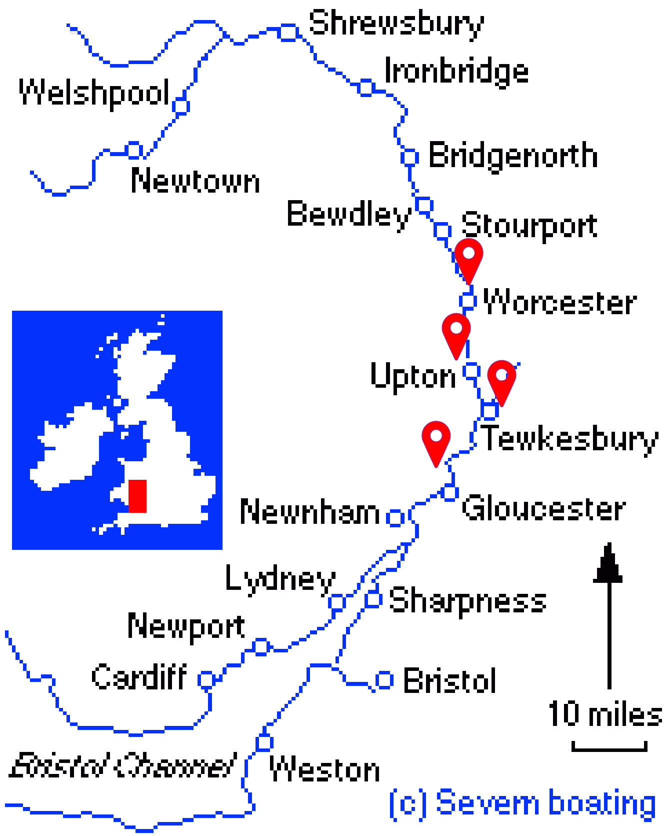
ADE20k dataset			COCO-stuff dataset		
	Training	Test		Training	Test
water	709	75	river	2113	90
sea	651	57	sea	6598	292
river	320	26	water-other	2453	79
waterfall	80	9			

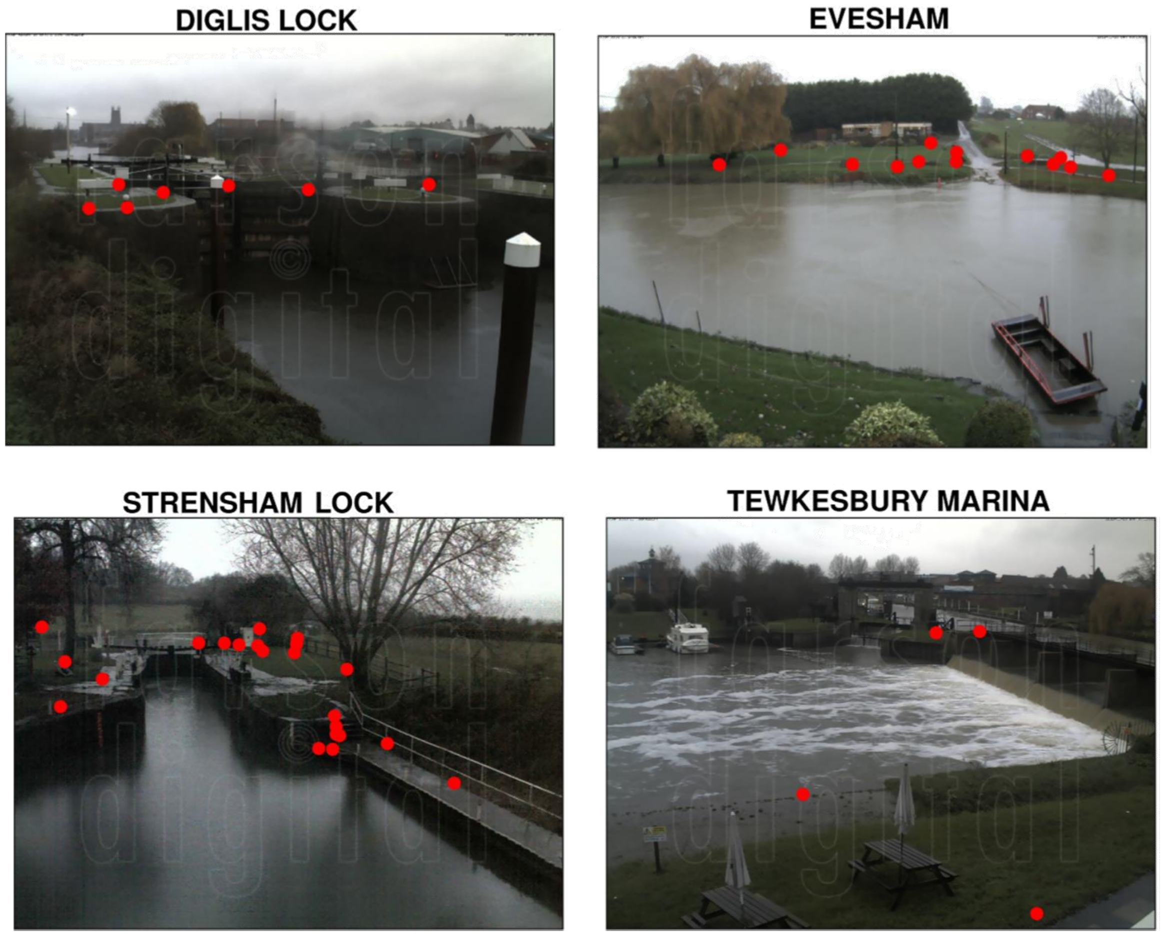
	LAURA data	INTCATCH data
State of the art*	90.2%	97.5%
Pre-trained	95.5%	98.8%
Fine-tuning (External data)	96.5%	99.5%
Fine-tuning (COCO/ADE20k water data)	**96.9%**	**99.5%**

* ResNet50 with UpperNet decoder on COCO stuff and DeepLab (V2 om ADE20k data)

Flood monitoring
(real world test bench)

Flood monitoring using deep convolutional neural network



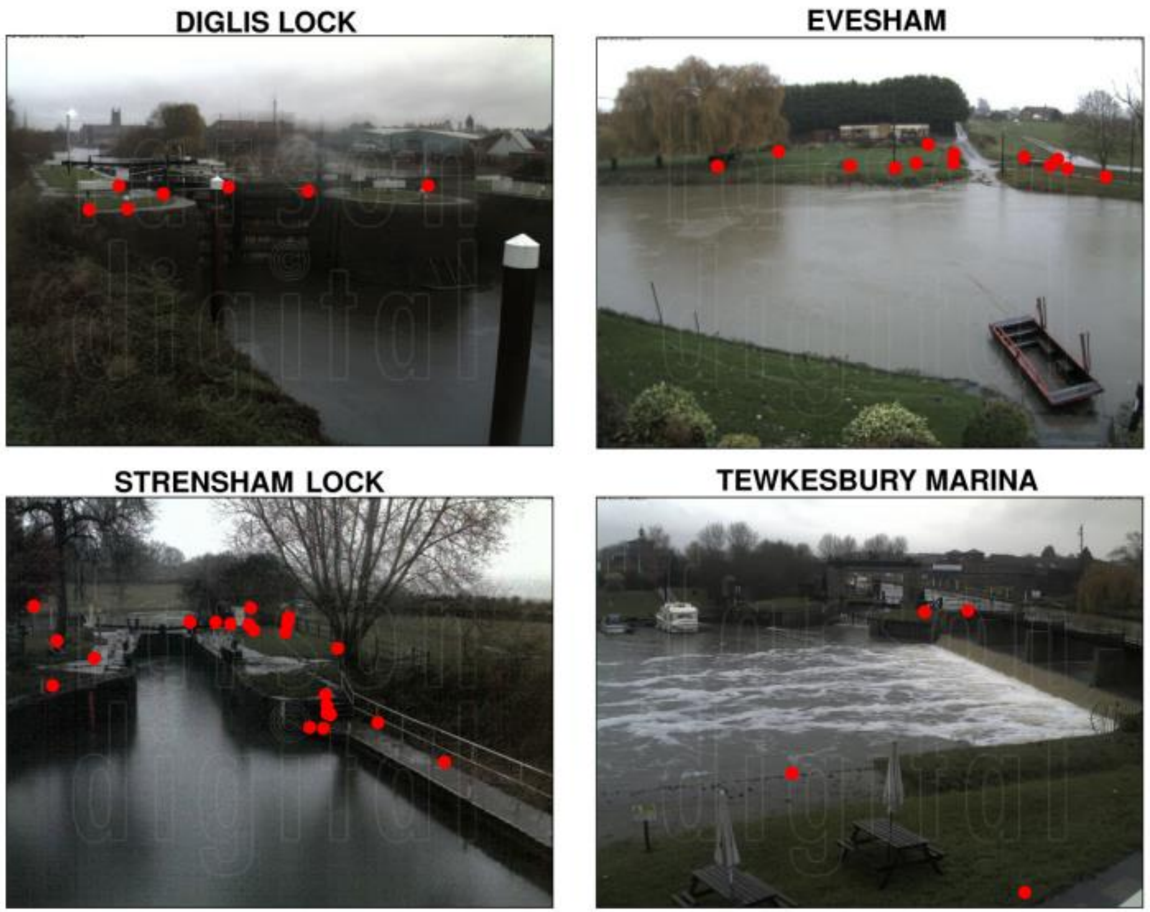


Customized dataset: Landmark annotation of waterline

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

River water level detection

(real world test results)



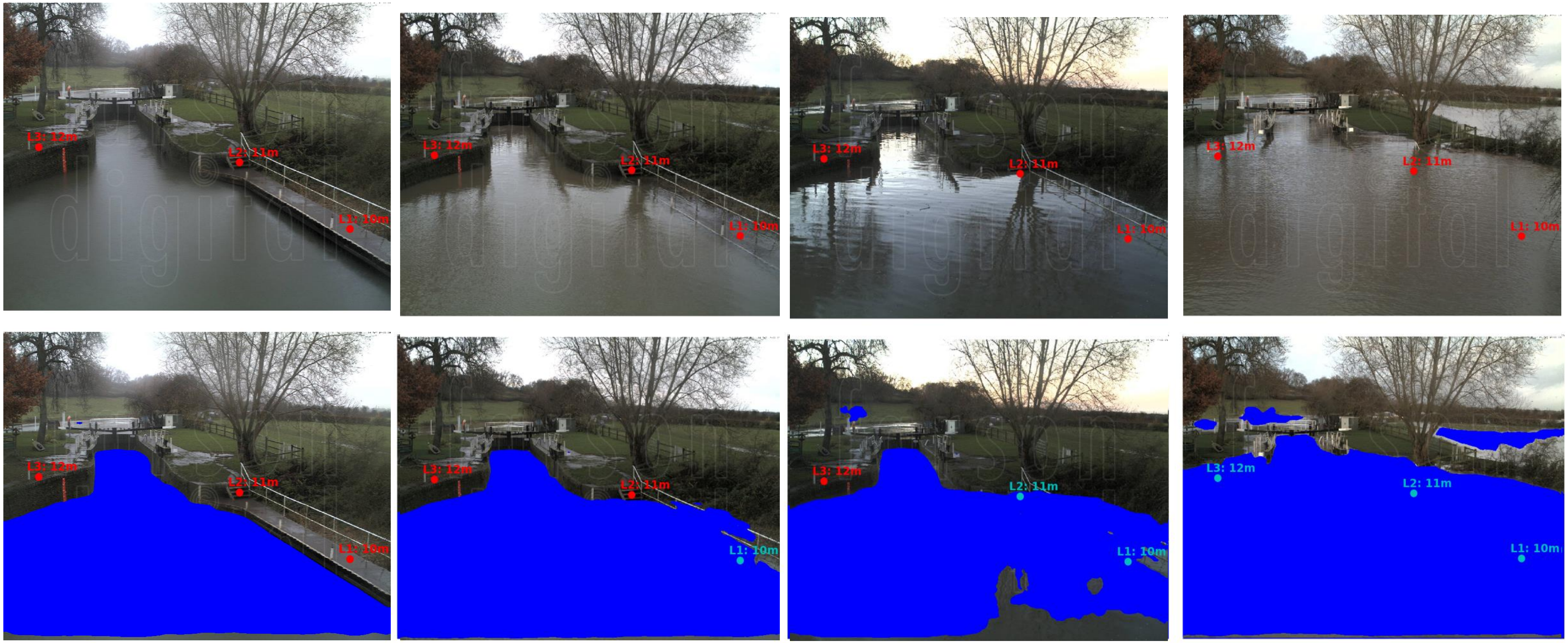
Flood Monitoring

Method	Accuracy on River Camera data
Pre-trained	87.4%
Fine-tuning (COCO/ADE20k water data)	**91.3%**

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

Automated flood monitoring

(time-series sequence of images (video) of river.)

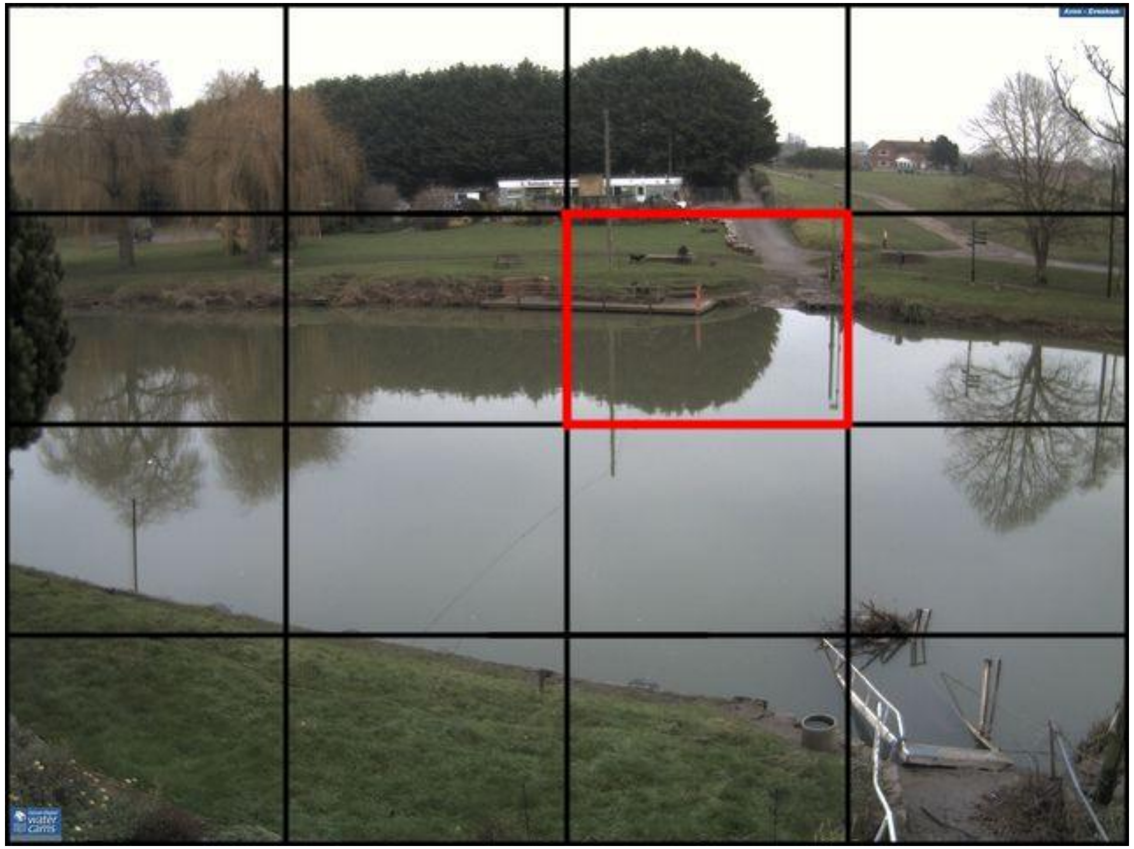


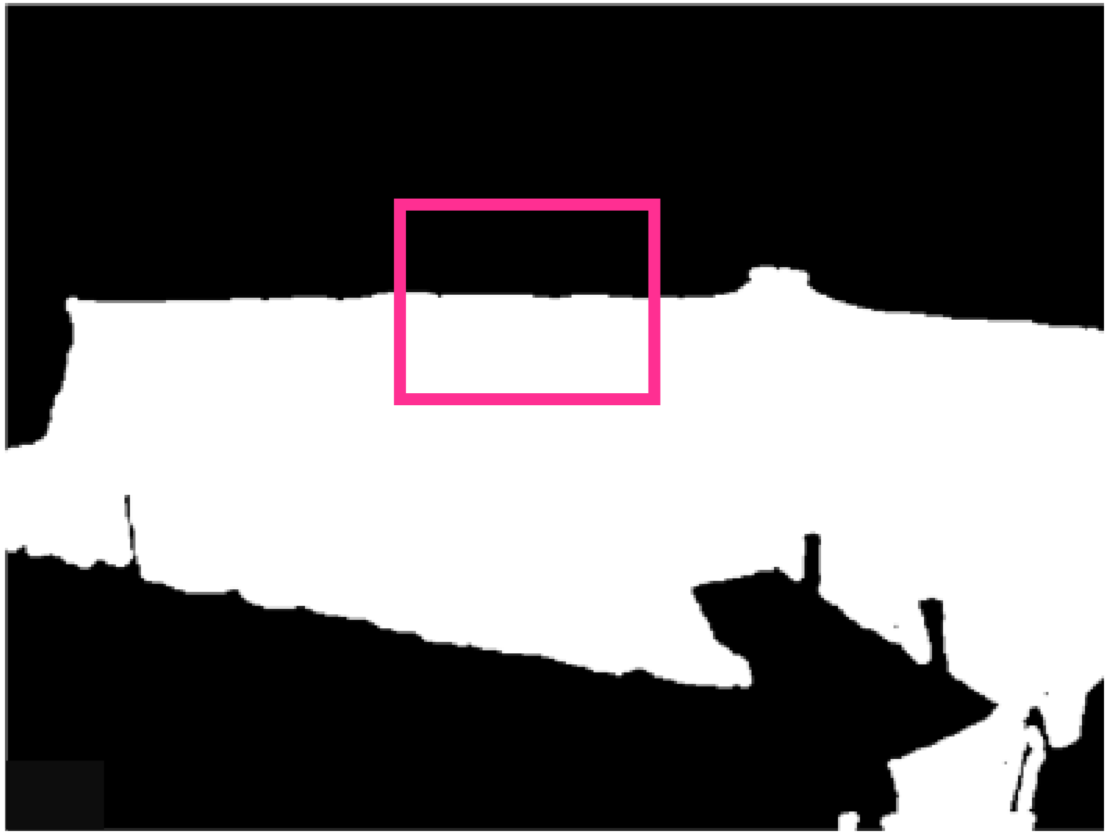
T1: Water level < 10m | T2: 10m < Water level < 11m | T3: 11m < Water level < 12m | T4: 12m < Water level

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

Flood monitoring using % pixels flooded

(towards generalisation for real world practical use: method 1)





Static observer flooding index
(SOFI) index: % of water pixels in a region of the image flooded

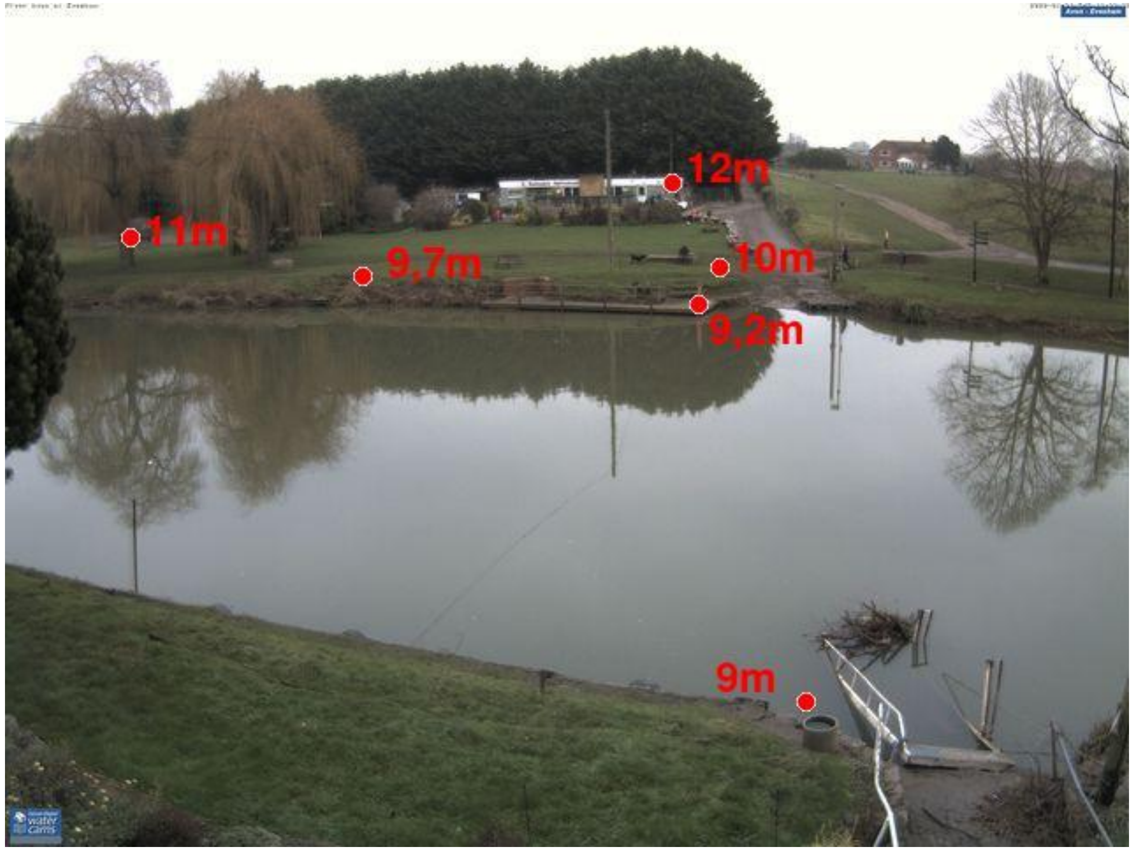
Vandaele, Dance, and Ojha, (2021), Deep learning for automated river-level monitoring through river camera images, *Hydrology and Earth System Sciences*

Flood monitoring using water level

(towards generalisation for real world practical use: method 2)

Increasing height ($h_i < h_{i+1}$)

Landmark index i	Landmark height h_i	Flood state F_i
10	14.21 m	0
9	13.22 m	0
8	13.01 m	0
7	12.91 m	0
6	12.75 m	1
5	12.65 m	0
4	12.13 m	0
3	12.11 m	0 (unflooded)
2	11.67 m	1
1	11.24 m	1 (flooded)



Water level index: height of the highest landmark reached by water

Vandaele, Dance, and Ojha, (2021), Deep learning for automated river-level monitoring through river camera images, *Hydrology and Earth System Sciences*

Real world river level test data (of 2 weeks image streams)

Test set. 4 Cameras captured images during a 2-week flood event in 2012:

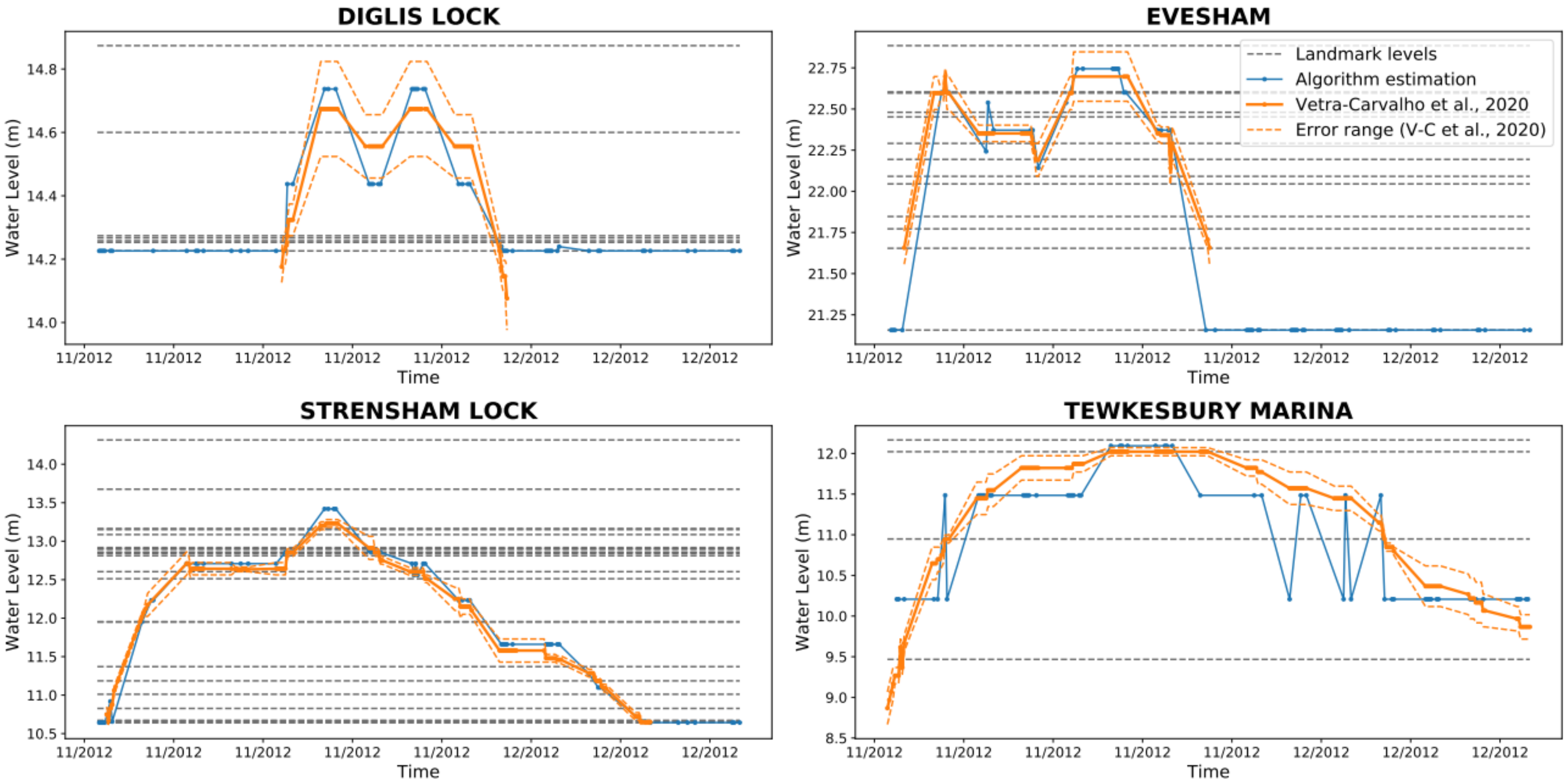
Camera name	# images	# landmarks	% flooded landmarks
Diglis Lock	141	7	24.11
Evesham Lock	134	13	30.94
Strensham Lock	144	24	37.15
Tewkesbury Marina	138	4	43.66

Vandaele, Dance, and Ojha, (2021), Deep learning for automated river-level monitoring through river camera images, *Hydrology and Earth System Sciences*

River level test data (of 2 weeks) results

$$\mathit{Blanace\ Accuracy} = 0.5\frac{TP}{TP+TN} + 0.5\frac{FP}{FP+FN}$$

where
$\boldsymbol{TP}$ pixels flooded predicted as flooded
$\boldsymbol{TN}$ pixels unflooded predicted as unflooded
$\boldsymbol{FP}$ pixels unflooded predicted as flooded
$\boldsymbol{FN}$ pixels flooded predicted as unflooded



The **Balanced Accuracy** criterion is computed as **the average of the true positive rates and the true negative rates**

	Diglis Lock	Evesham Lock	Strensham Lock	Tewkesbury Marina
Blance Accuracy	**0.94**	**0.98**	**0.94**	**0.97**

Real world river level test data (of 1 year image streams)

Test set. 4 Cameras captured images 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

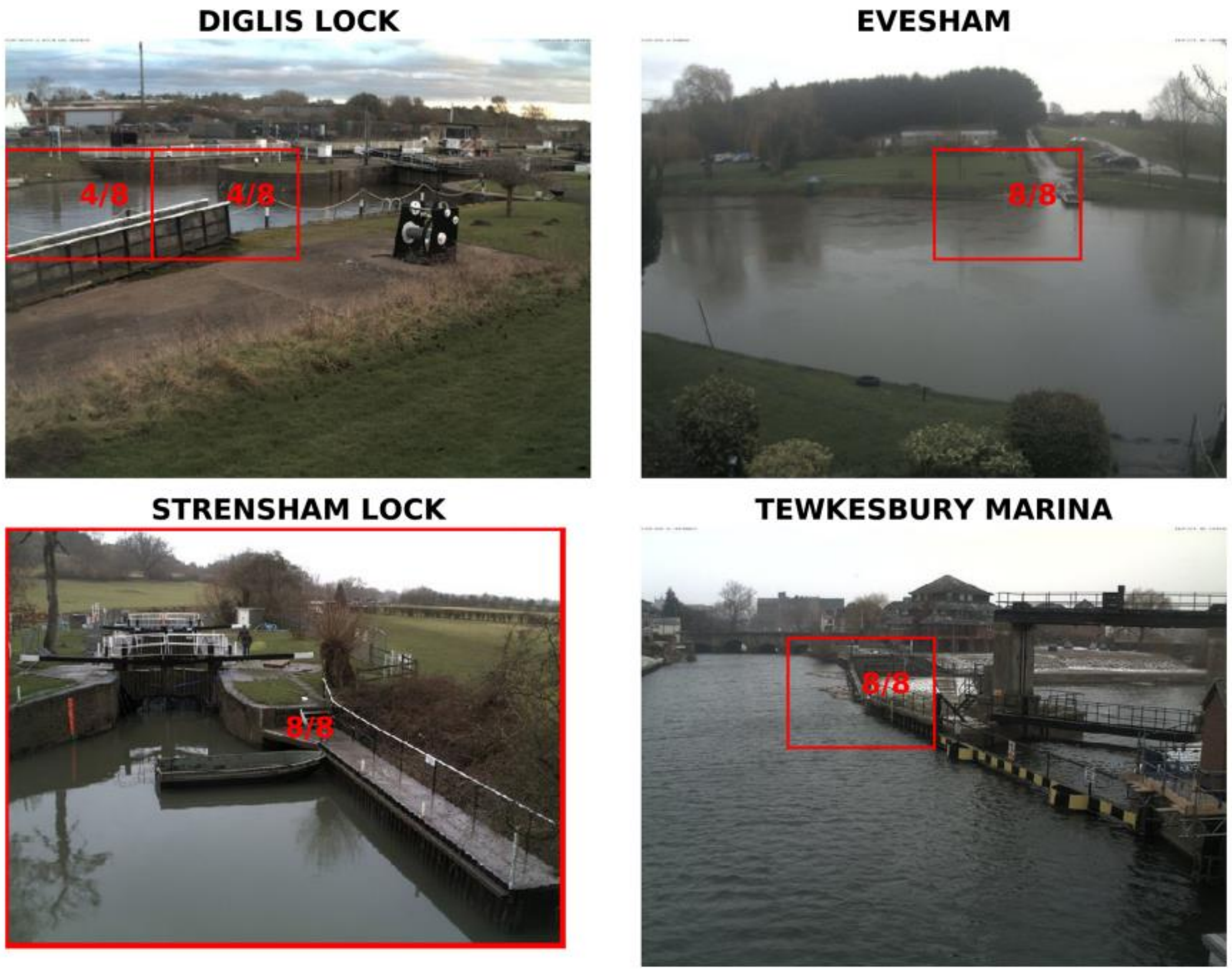
Optimization of best image window for river level information extraction

SOFI index/Water level estimation from the window selected by majority voting from 8 trained nets that offers best correlation

Correaltion

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

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

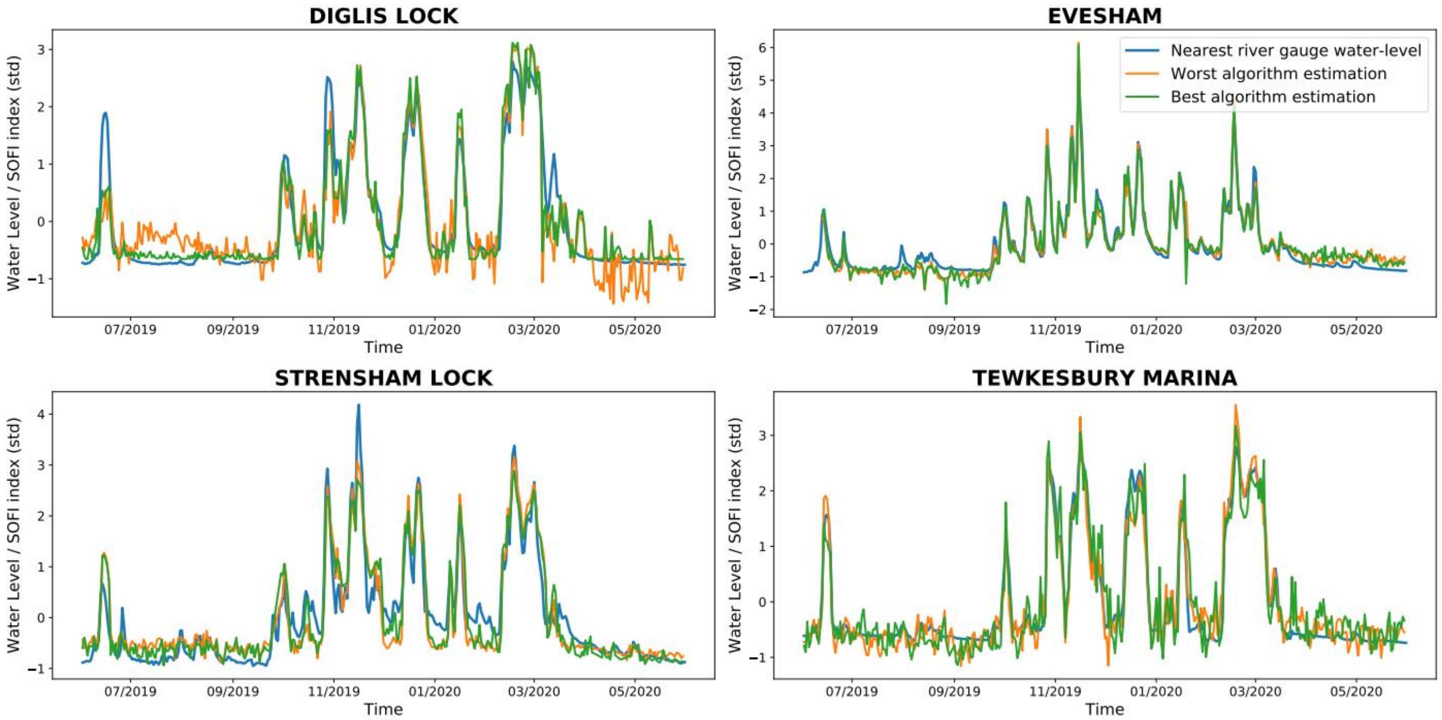


River level test data (1 Year) results

Correaltion

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

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



	Diglis Lock	Evesham Lock	Strensham Lock	Tewkesbury Marina
$Correlation$	**0.94**	**0.98**	**0.94**	**0.97**

Extrapolation and Gneralisation?

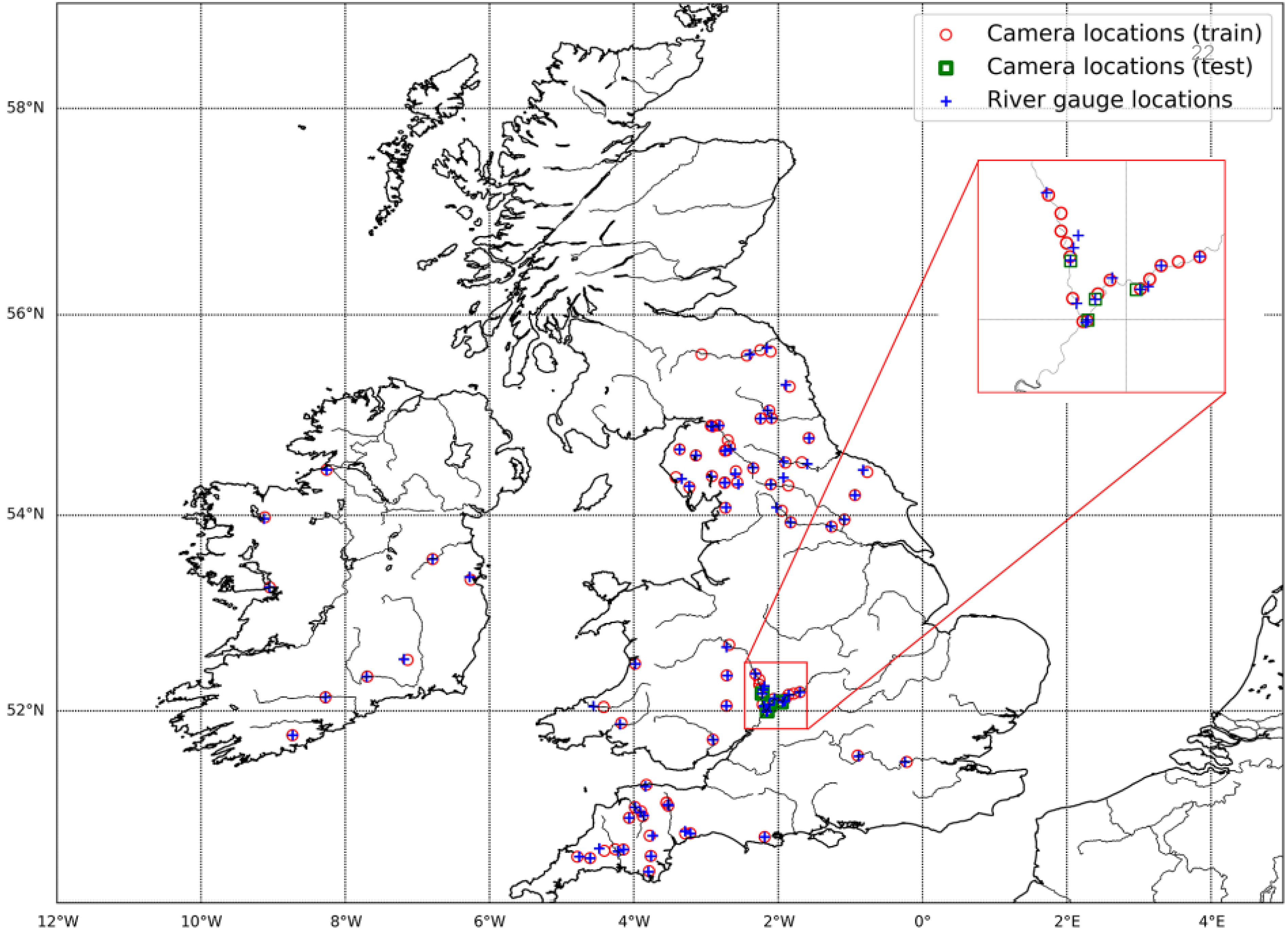
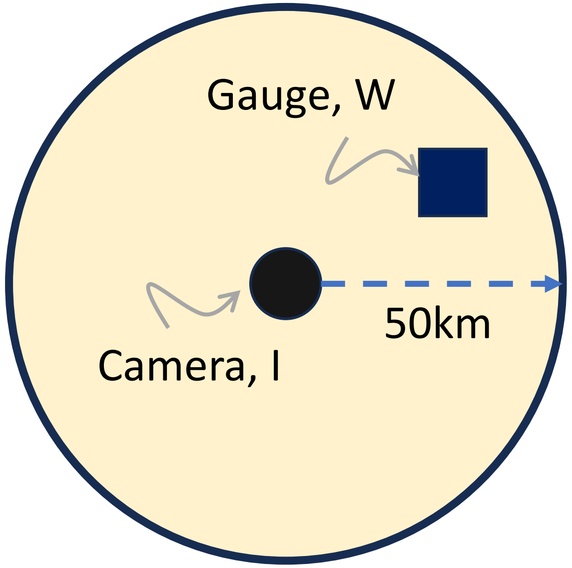
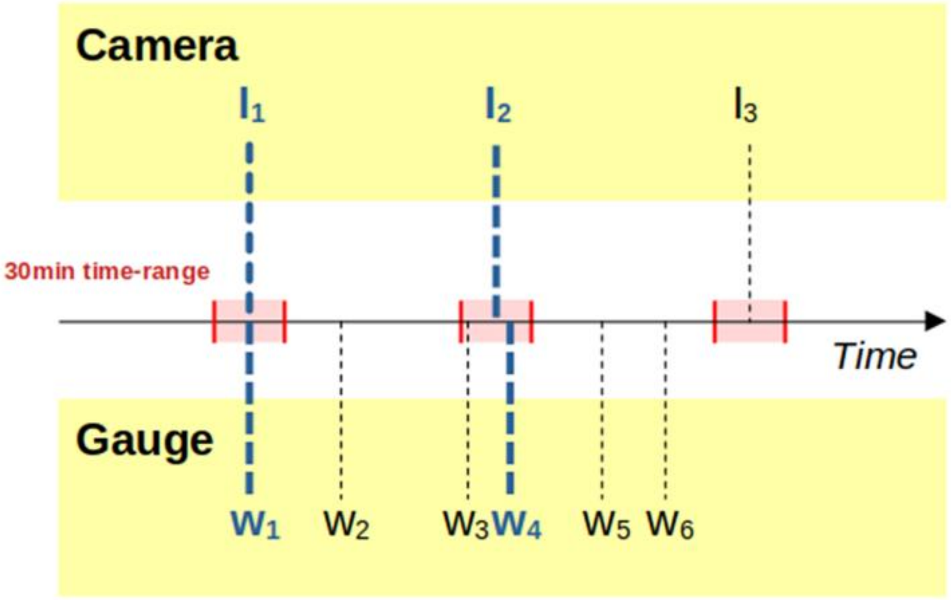


Image Regression

- Creation of a large dataset of **32,715 images annotated with river levels**:
    - Matching of a camera with a river gauge (closest gauge > 50km)
    - Matching of an image with a gauge measurement
    - 95 camera locations across UK and Northern Ireland consist of **32,715 images**

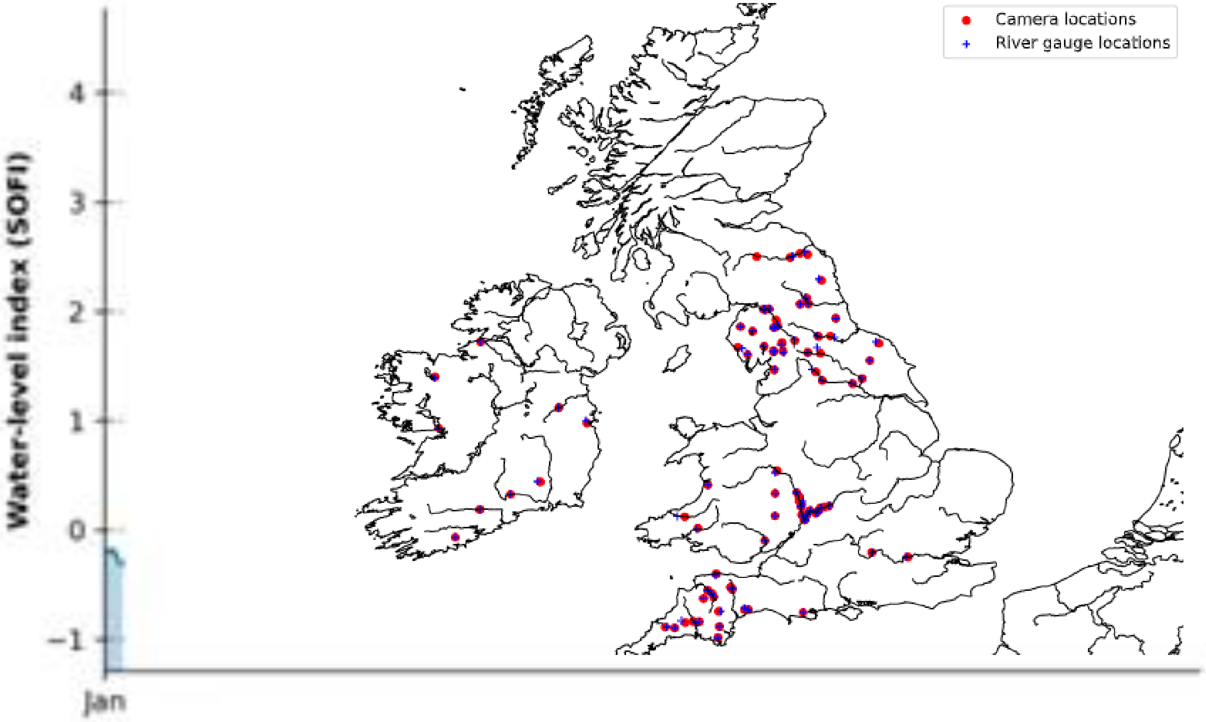




Vandaele, R., Dance, S L, & Ojha, V (2023) Calibrated river-level estimation from river cameras using convolutional neural networks, *Environmental Data Science*

Flood tracking

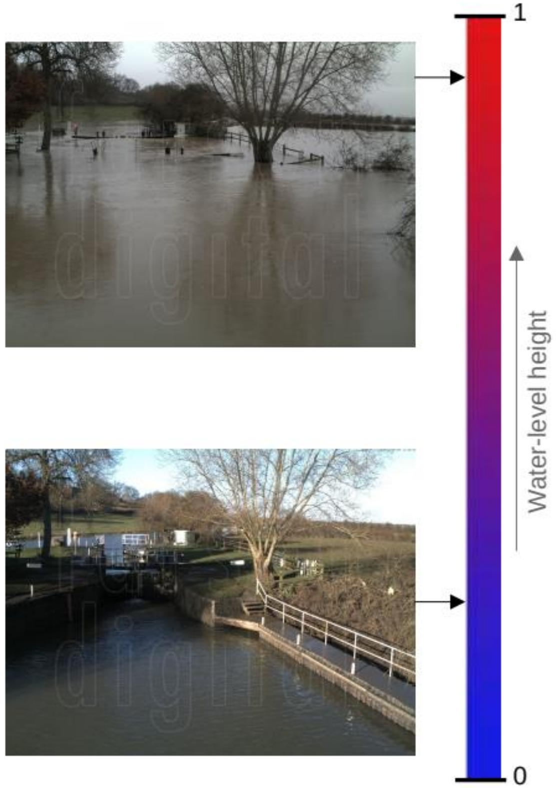
Vandaele, Dance, and Ojha, (2021) *Hydrology and Earth System Sciences*



Video Credit: Remy Vandaele

Regression-Water Net: Estimation

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



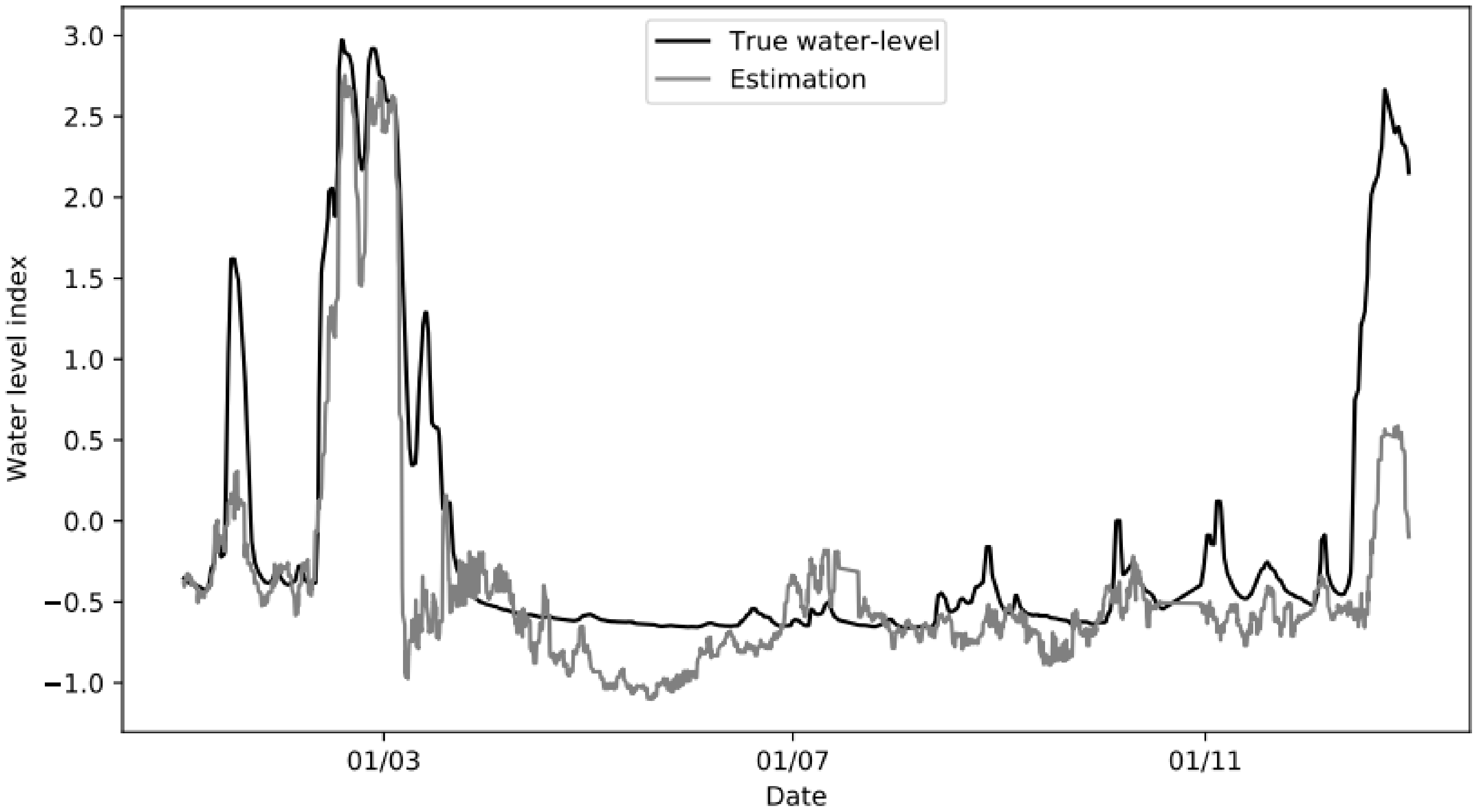
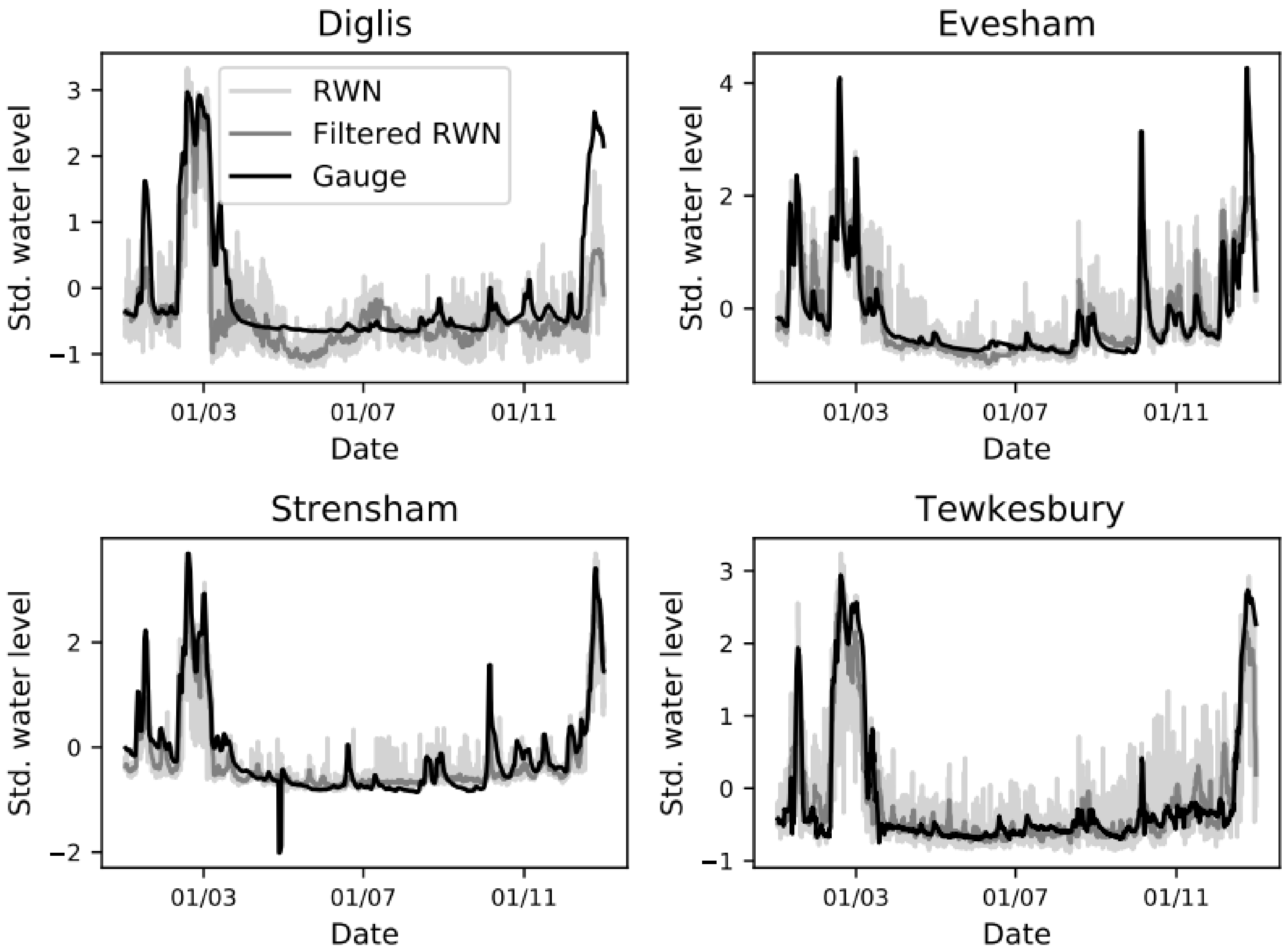


Image regression

	Correlation between actual and estimation
Diglis Lock	**0.8**
Evesham Lock	**0.94**
Strensham Lock	**0.87**
Tewkesbury Marina	**0.86**



Part 2

Automated Trash Screen Blockage Detection: Actional Flood Risk Management

Trash screen monitoring

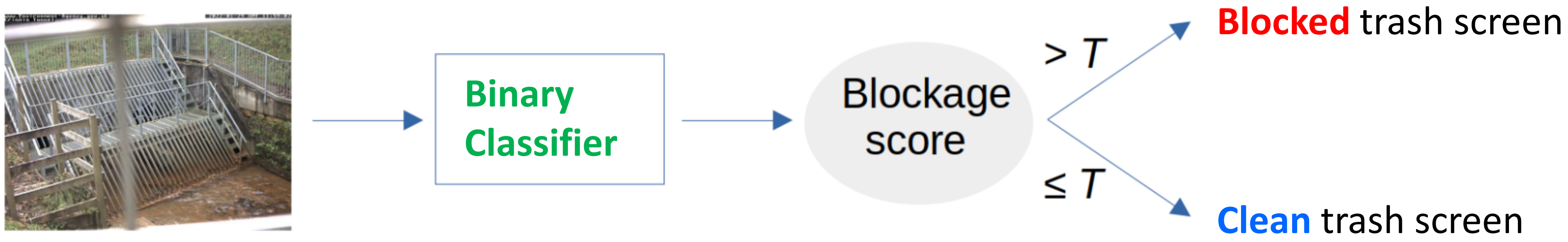
Trash screens prevent debris from entering critical parts of river networks but debris buildup can lead to floods Clean trash screen Blocked trash screen

Clean trash screen

Blocked trash screen

54 trash screens with CCTV camera feed: 80,452 images downloaded over 10 months

Trash screen monitoring: Binary classifier



- Advantage – Could give high accuracy
- Disadvantage – Manual data labelling is required
- ResNet-50 backbone
- Blockage score (softMax)

Trash screen monitoring: Anomaly Detection

Anomaly Detection

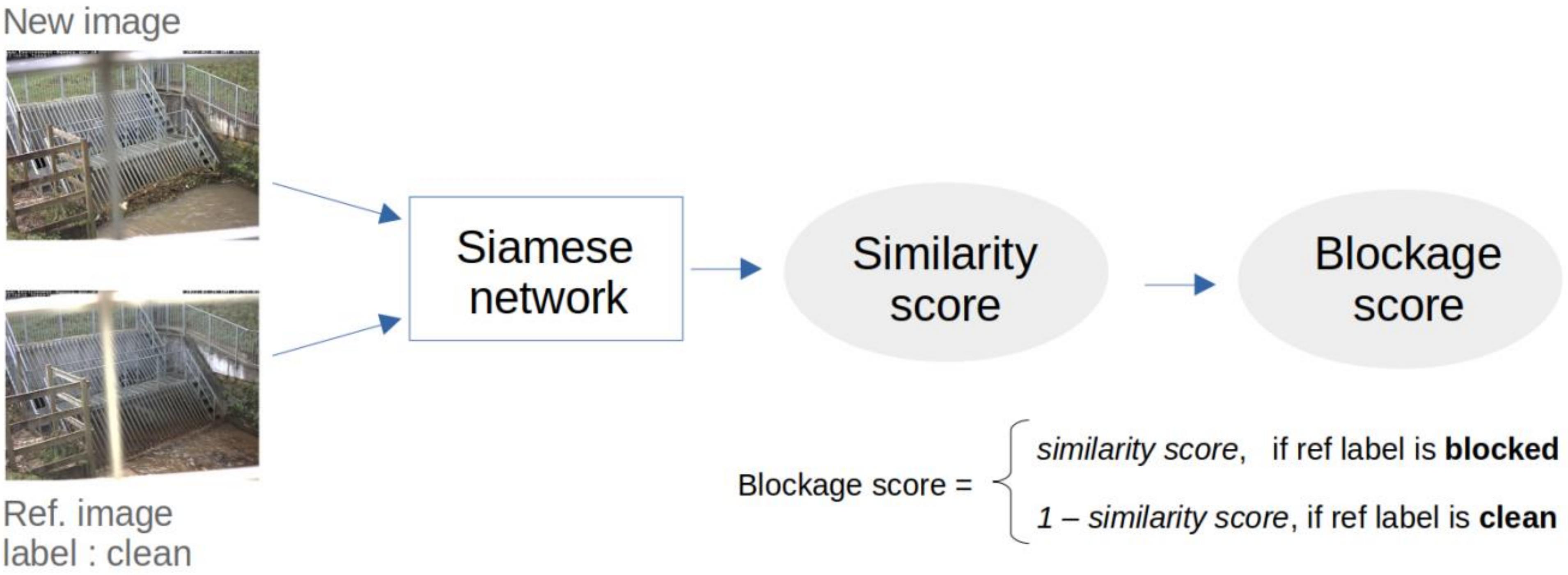
Blockage score

$> T$ **Blocked** trash screen

$\leq T$ **Clean** trash screen

- Advantage – No manual data labelling is required
- Constraint – Trash should be an anomaly
- Images are represented by a vector of features extracted from a pre-trained network
- A multivariate Gaussian fits the training vectors with parameters
- Anomaly score is the *Mahalanobis distance between a multivariate gaussian and a new data*

Trash screen monitoring: Image similarity



$$\text{Blockage score} = \begin{cases} \textit{similarity score}, & \text{if ref label is } \textbf{blocked} \\ 1 - \textit{similarity score}, & \text{if ref label is } \textbf{clean} \end{cases}$$

- The similarity score (softMax) can be transformed in a blockage score

Evaluation

46 training cameras, 4 validation cameras, 4 test cameras -> 80K images

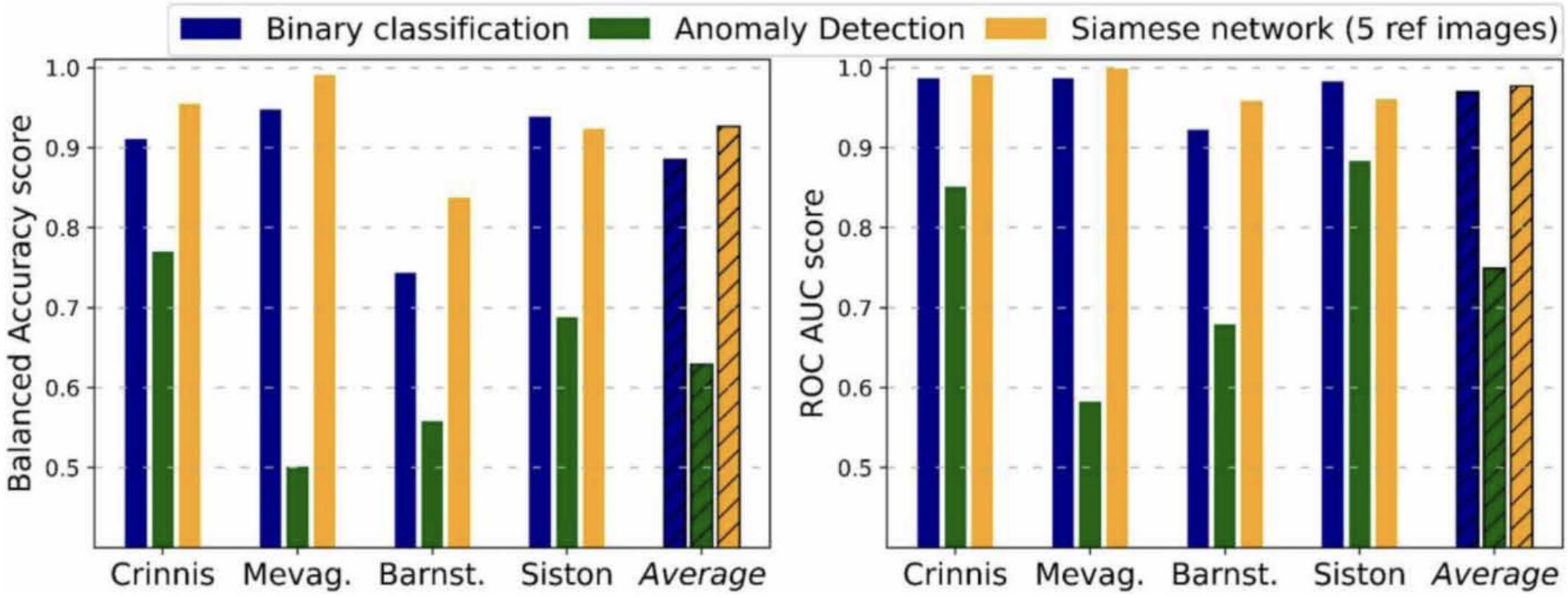
Crinnis

Mevagissey

Barnstaple

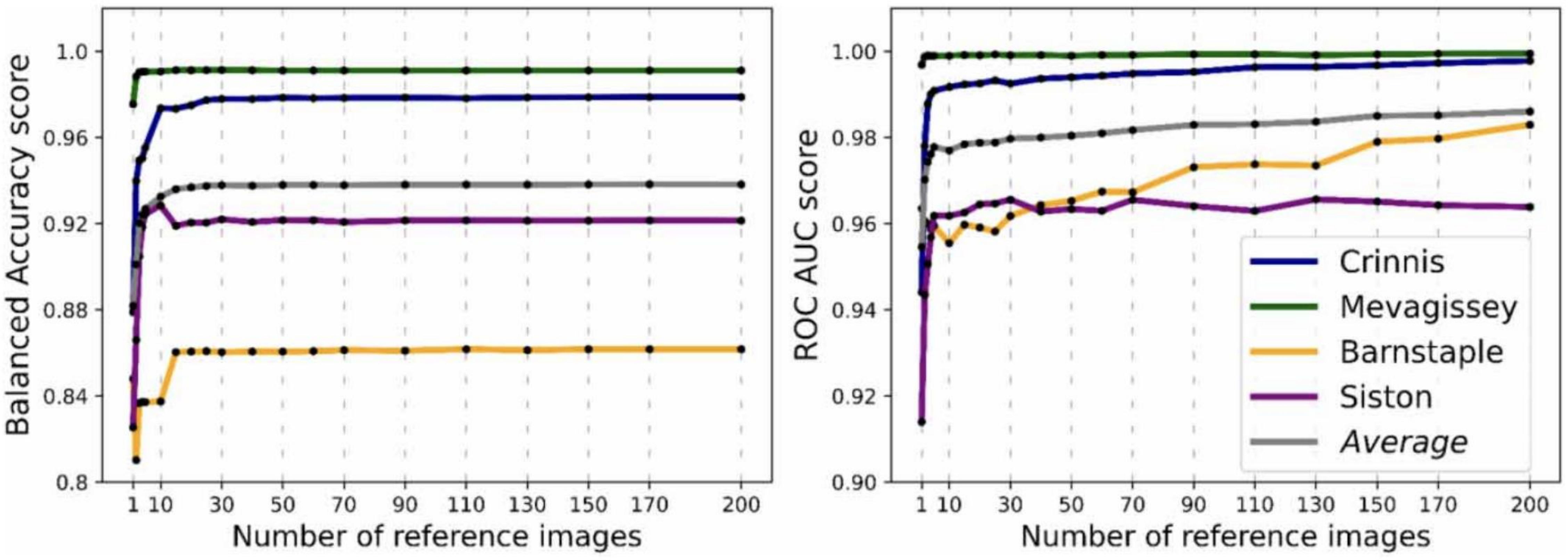
Siston

Blockage detection results



- Binary classifier and image similarity have Balanced Accuracy and ROC AUC scores > 0.9 for 3 of the 4 locations
- Anomaly Detection has the worst results
- The Siamese network (image similarity) obtains the best results with only 5 reference images

Influence of the number of reference images on the performance of the Siamese network



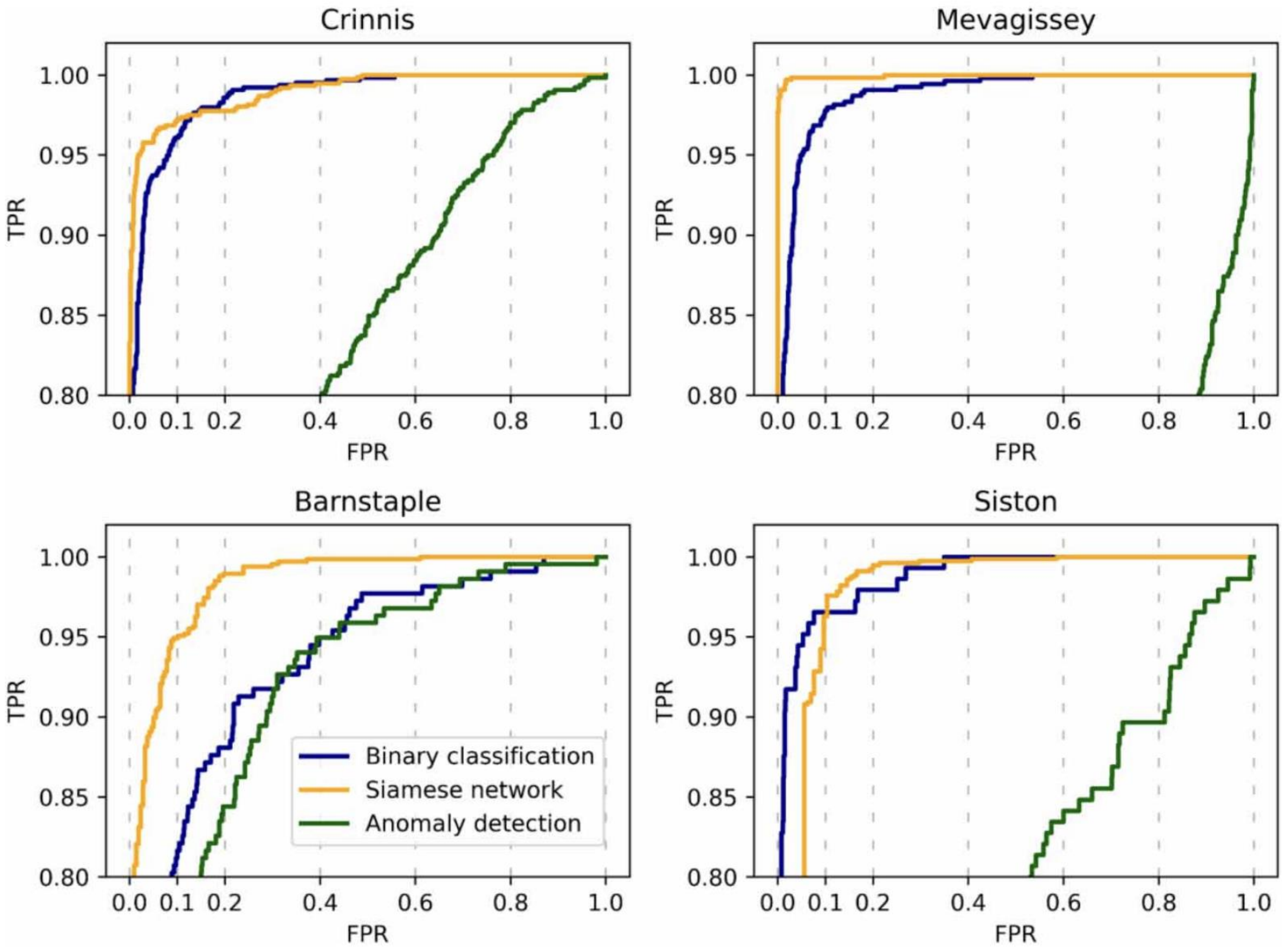
ROC

=>

Maximise the true positive rates (TPR)

Minimise the false positive rates (FPR)

ROC is TPR vs FPR



…in detail…

- Calibrated river-level estimation from river cameras using convolutional neural networks
  Environmental Data Science, Cambridge University Press (2023)
  Vandaele, R., Dance, S. L., & Ojha, V.

- Deep learning for automated river-level monitoring through river camera images: an approach based on water segmentation and transfer learning
  Hydrology and Earth System Sciences 25(8) 4435–4453 (2021)
  Vandaele R, Dance SL, Ojha V

- Automated water segmentation and river level detection on images using transfer learning
  42nd DAGM German Conference on Pattern Recognition, DAGM GCPR, Tubingen, Germany, *Proceedings 42* (pp 232–245) Springer, LNCS (2020)
  Vandaele R, Dance SL, Ojha V

- Deep Learning for Automated Trash Screen Blockage Detection Using Cameras: Actionable Information for Flood Risk Management
  Journal of Hydroinformatics, (2024)
  Vandaele, R., Dance, S L, & Ojha, V