Deep Learning for Flood Monitoring Challenges

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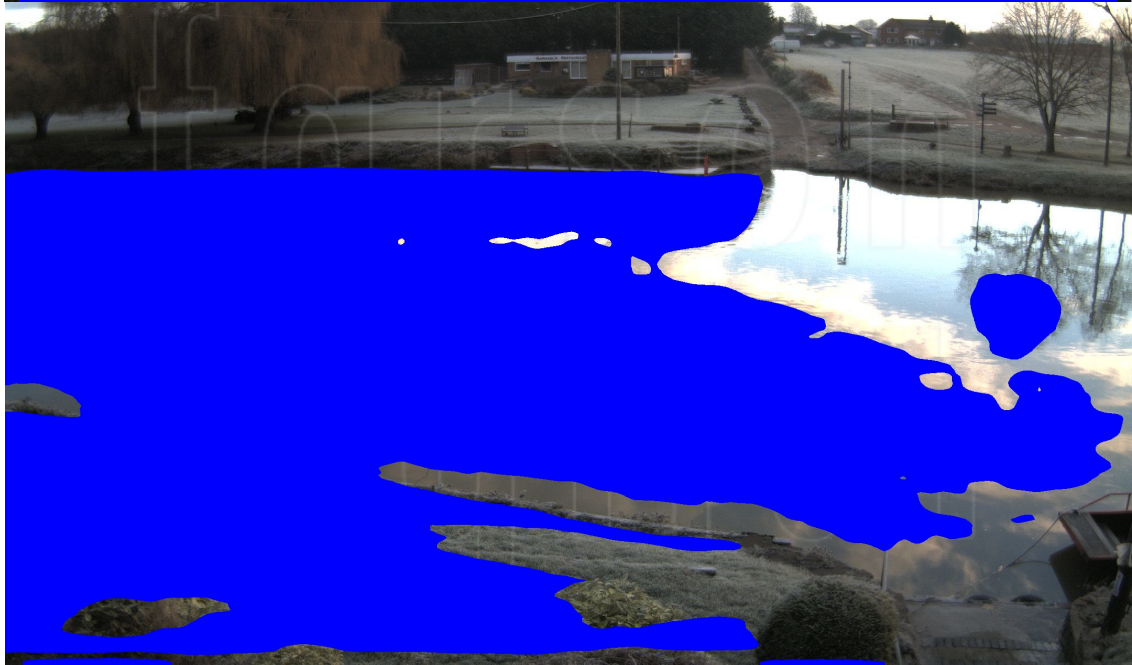
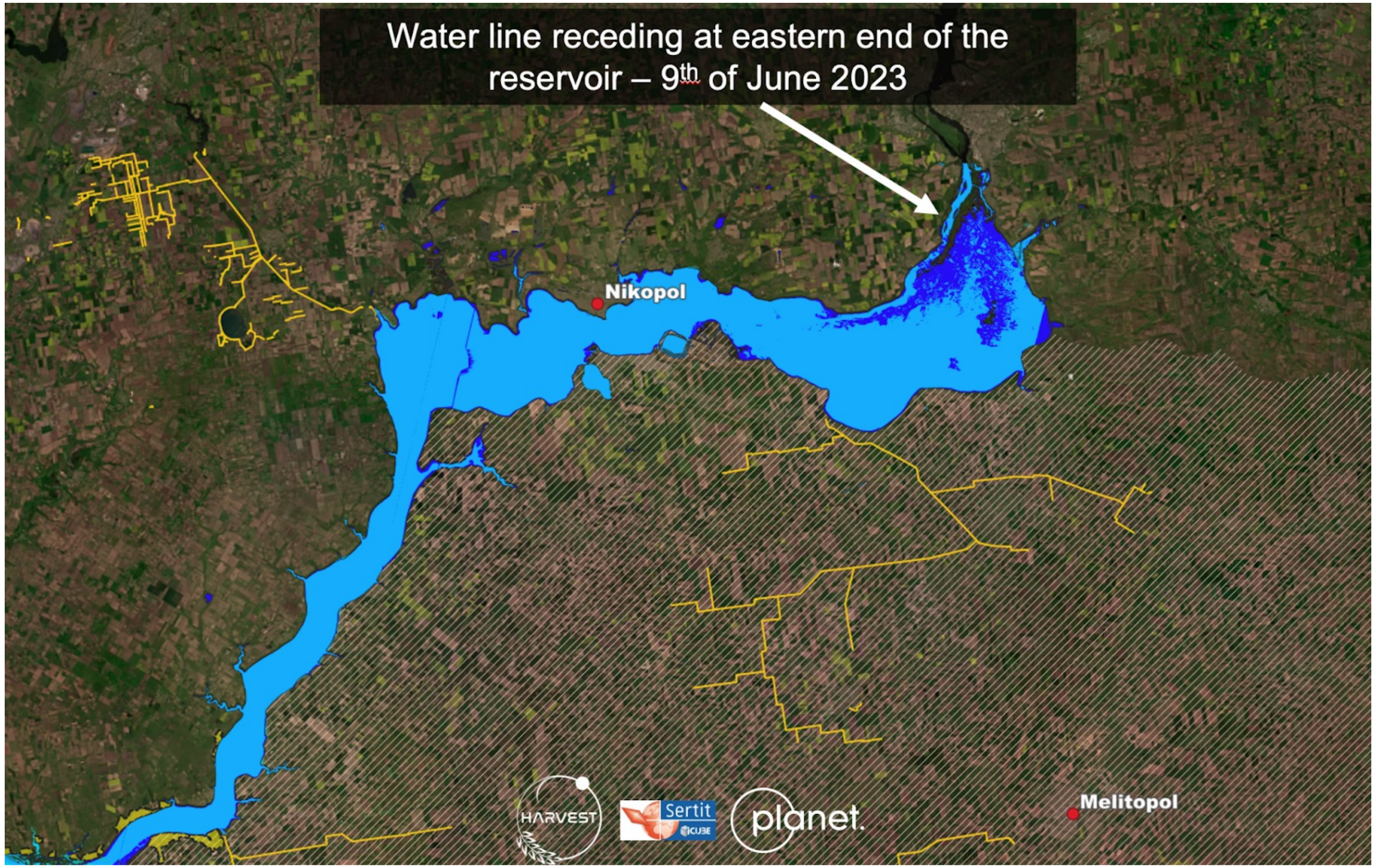


Part 1

river water level monitoring

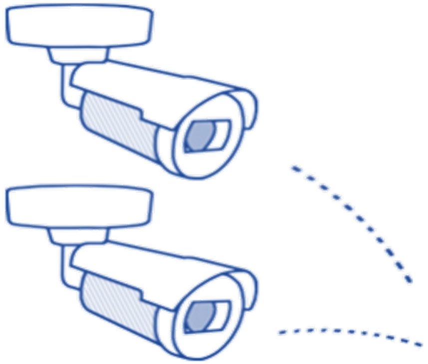
How we currently monitor river water level

Use of river gauge



Use of satellite images

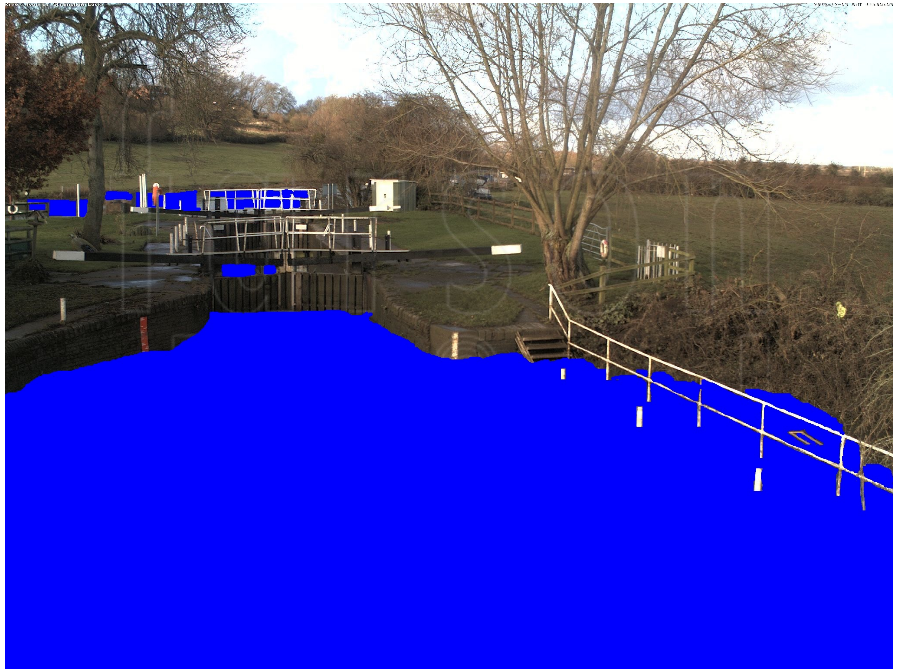
Our approach: use of river cameras



We could use CCTV camera

Source/Credit Farson Digital

Deep Learning for water level estimation

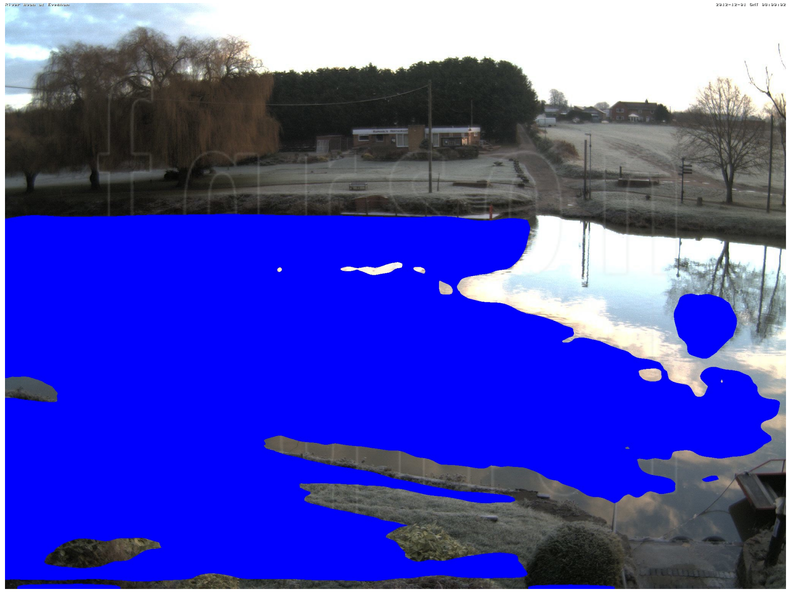


Pixel-wise water segmentation of RGB images for river water-level or flood monitoring

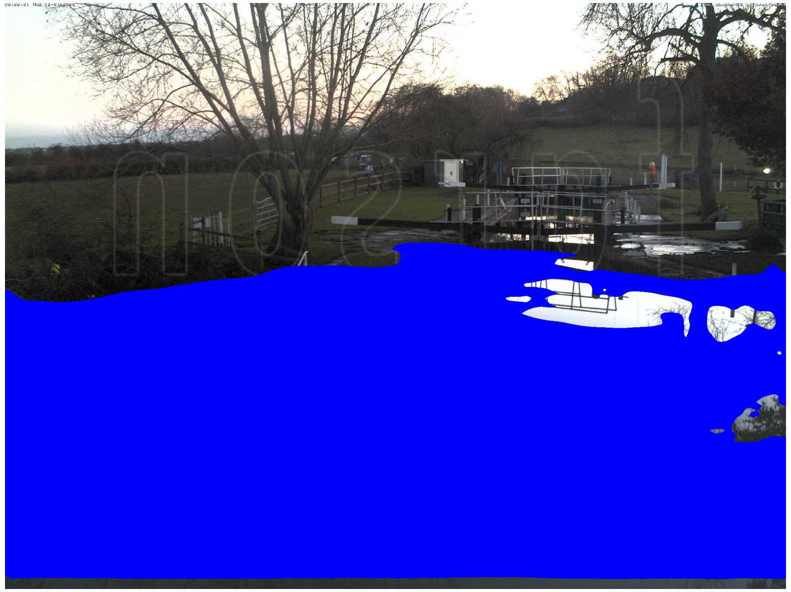
Vandaele, R., Dance, S. L., & Ojha, V. (2020). Automated water segmentation and river level detection on camera images using transfer learning. GCPR

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 can use transfer learning

ADE20k samples

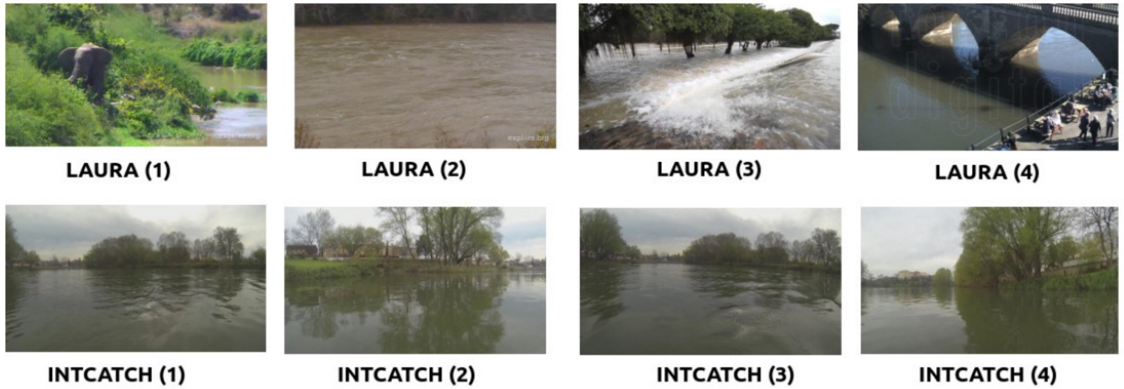
COCO-stuff samples

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

Automated water segmentation

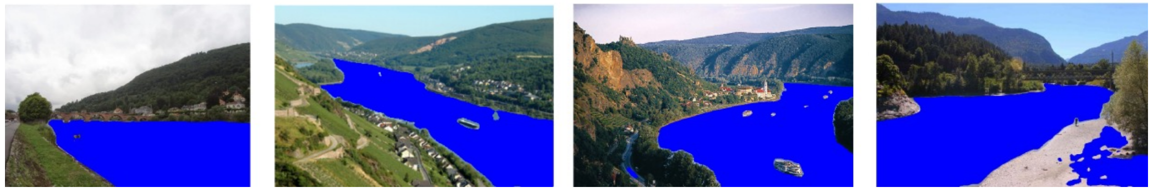
Fine-tuning over the smaller water segmentation datasets.



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

Fine tuning of only water-annotated images of the large datasets

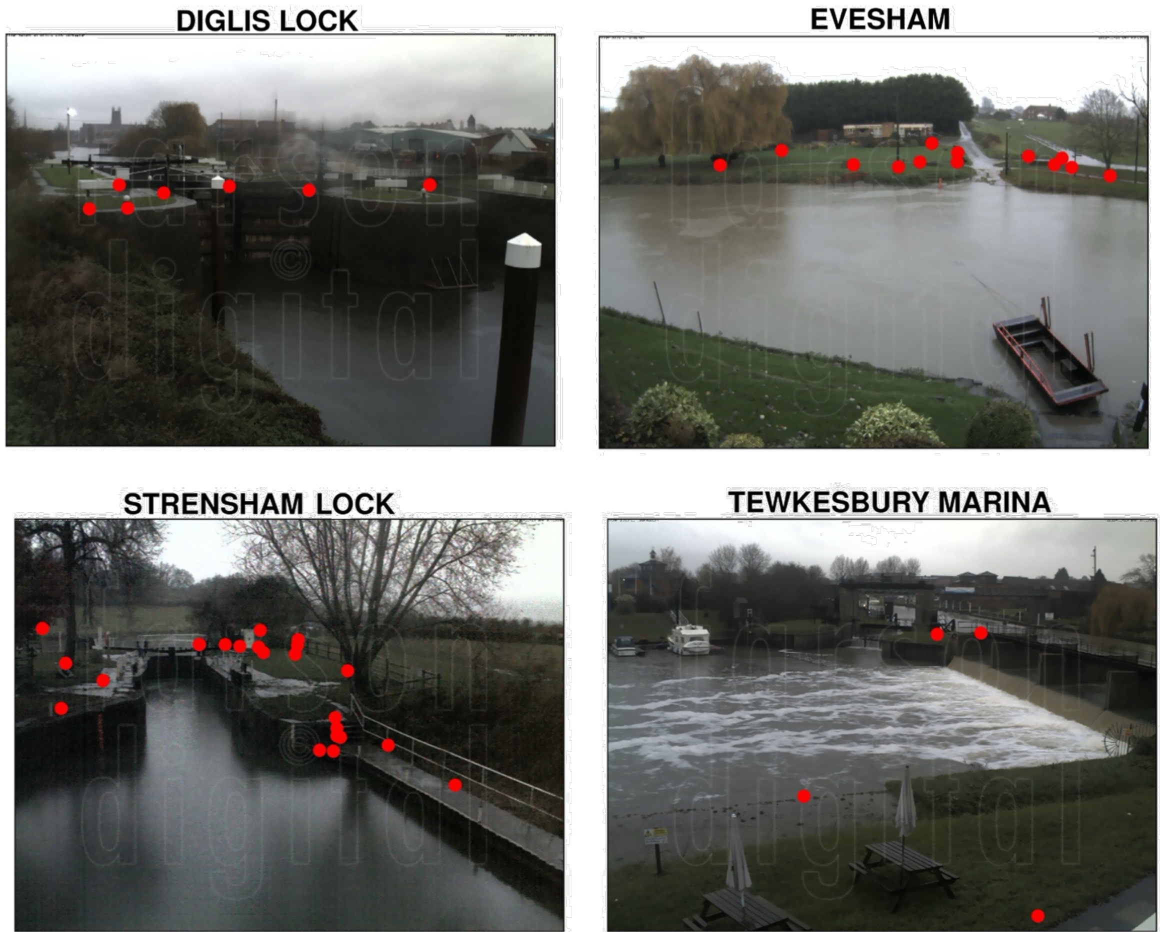


	LAURA data	INTCATCH data
State of the art*	90.2	97.5
Pre-trained	95.5	98.8
Fine-tuning (External data)	96.5	99.5
Fine-tuning (COCO/ADE20k water data)	96.9	99.5

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

Flood monitoring

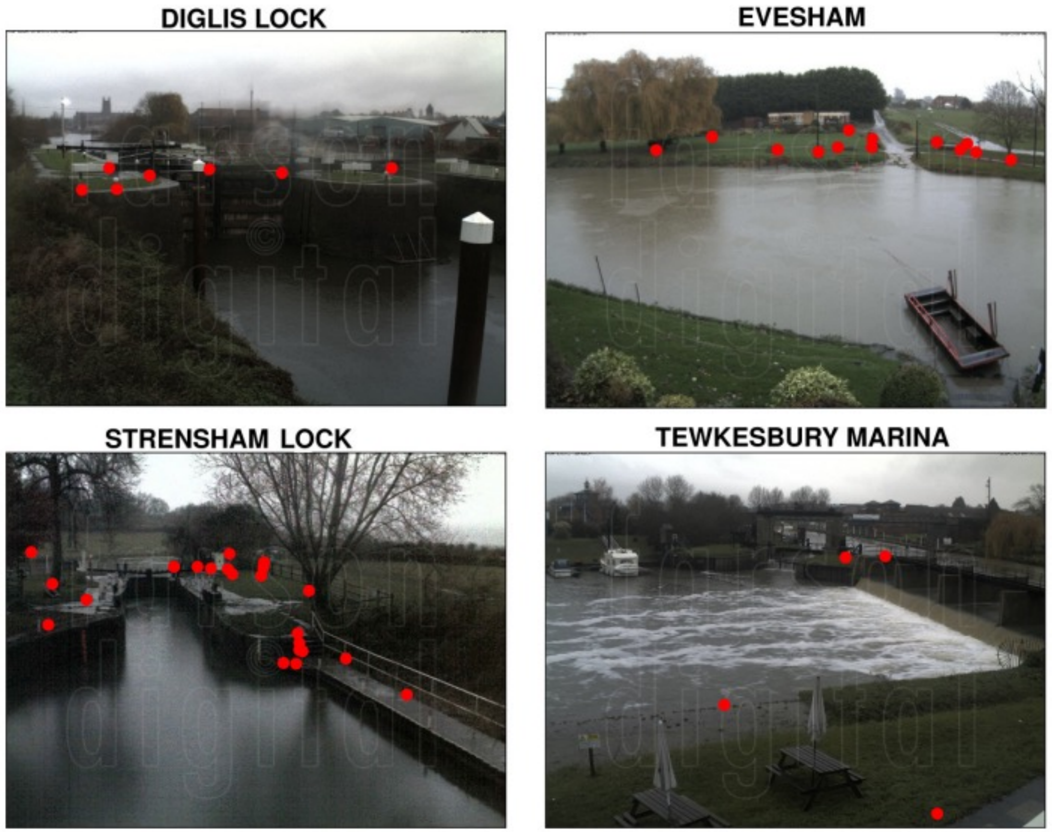
Flood Prediction using Deep Convolutional Neural Network



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



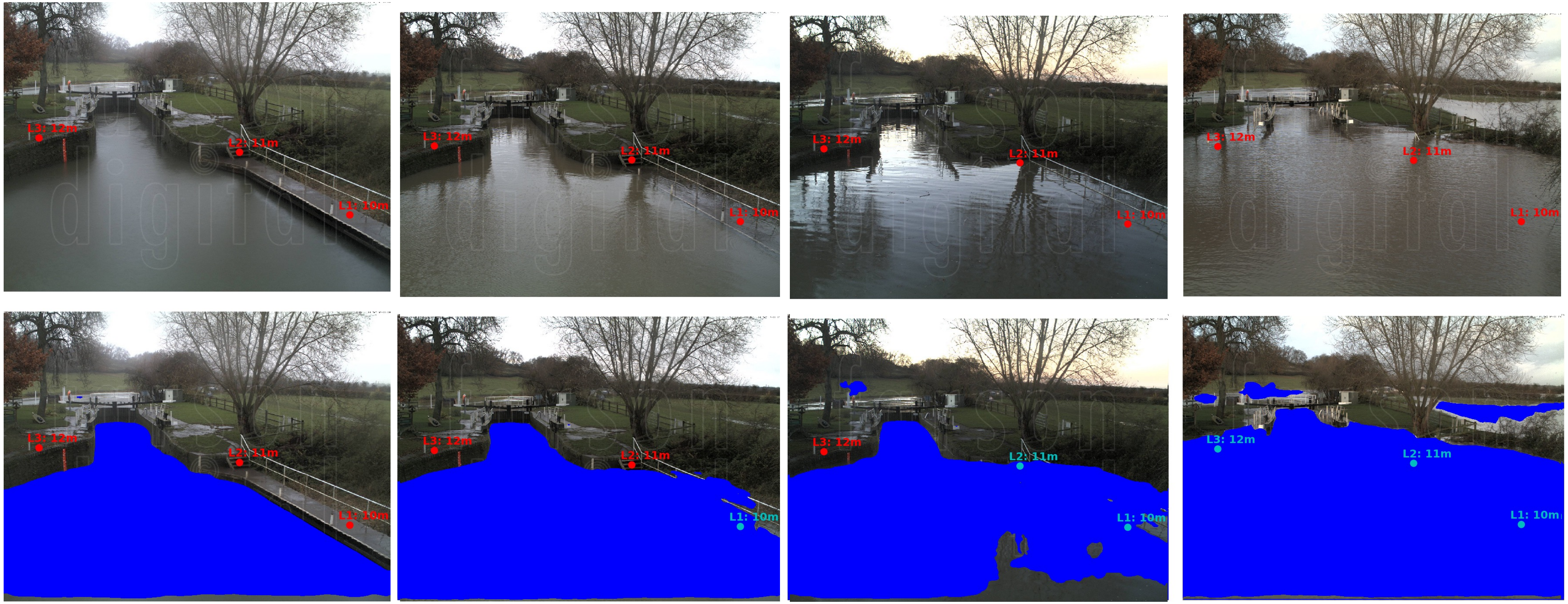
Method	Accuracy on River Camera data
Pre-trained	87.4
Fine-tuning (COCO/ADE20k water data)	91.3

Flood Monitoring

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 of river.

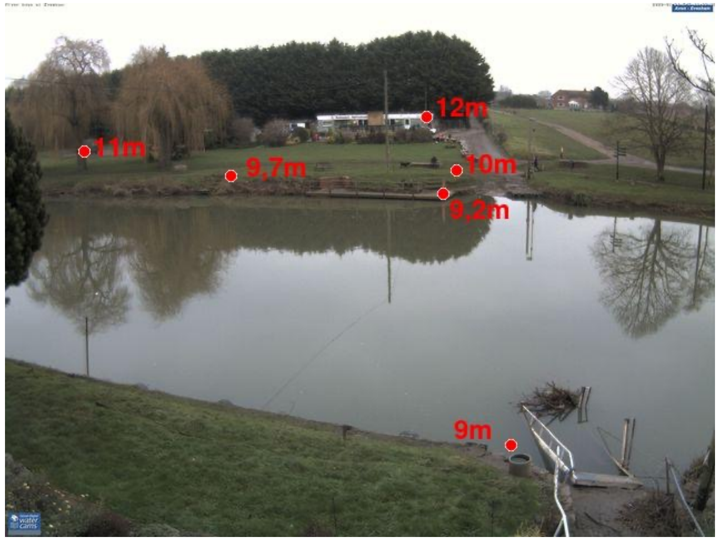


T1: Water level < 10m | T2: 10m < Water level < 11m | T3: 11m < Water level < 12m | T4: 12m < Water level

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

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



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

Extraction of river level data (of 2 weeks image streams)

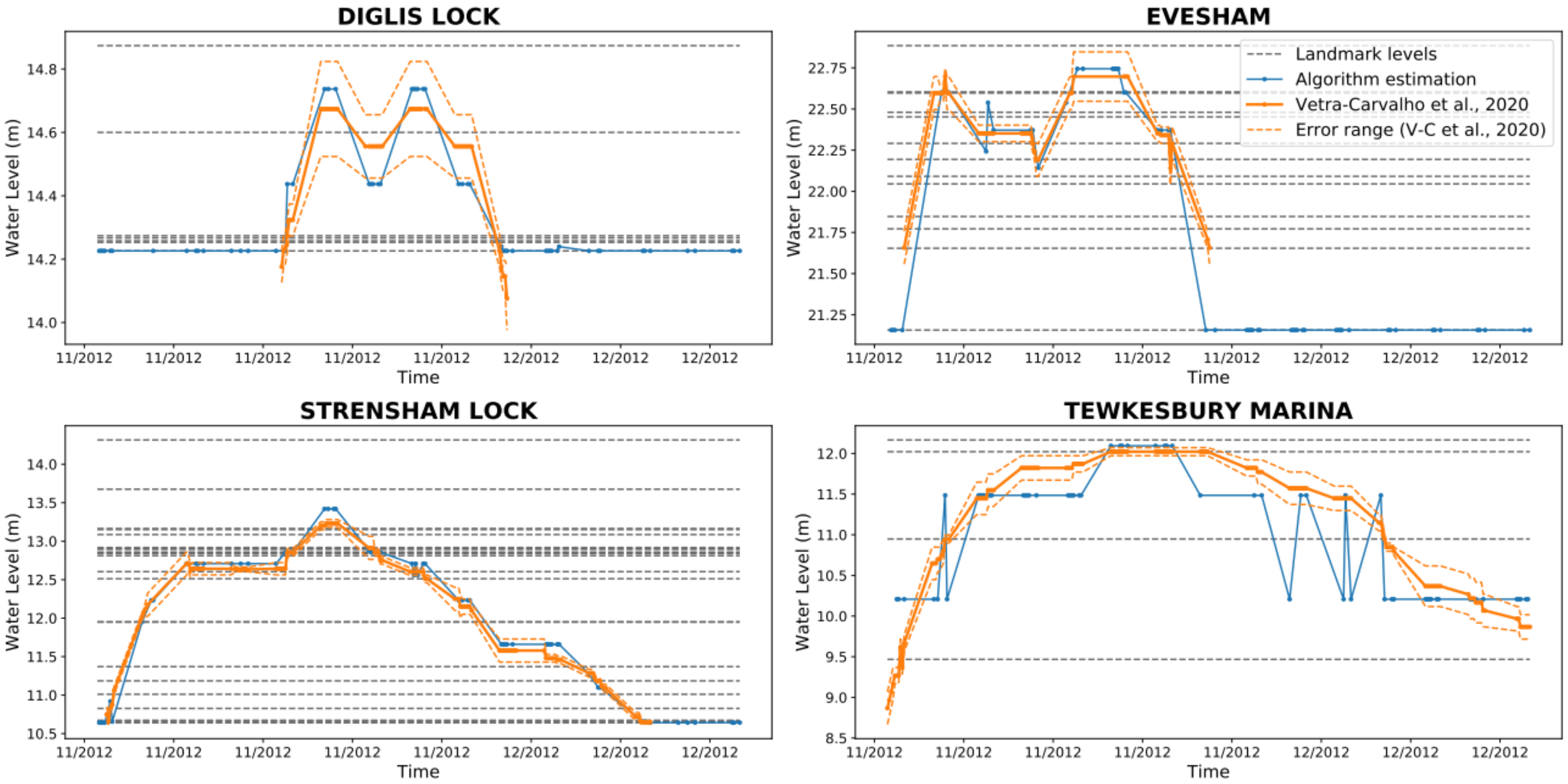
Test set. 4 Cameras captured images during a 2-week flood event in 2012:

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

Extraction of river level data

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

where
TP pixels flooded predicted as flooded
TN pixels unflooded predicted as unflooded
FP pixels unflooded predicted as flooded
FN pixels flooded predicted as unflooded



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

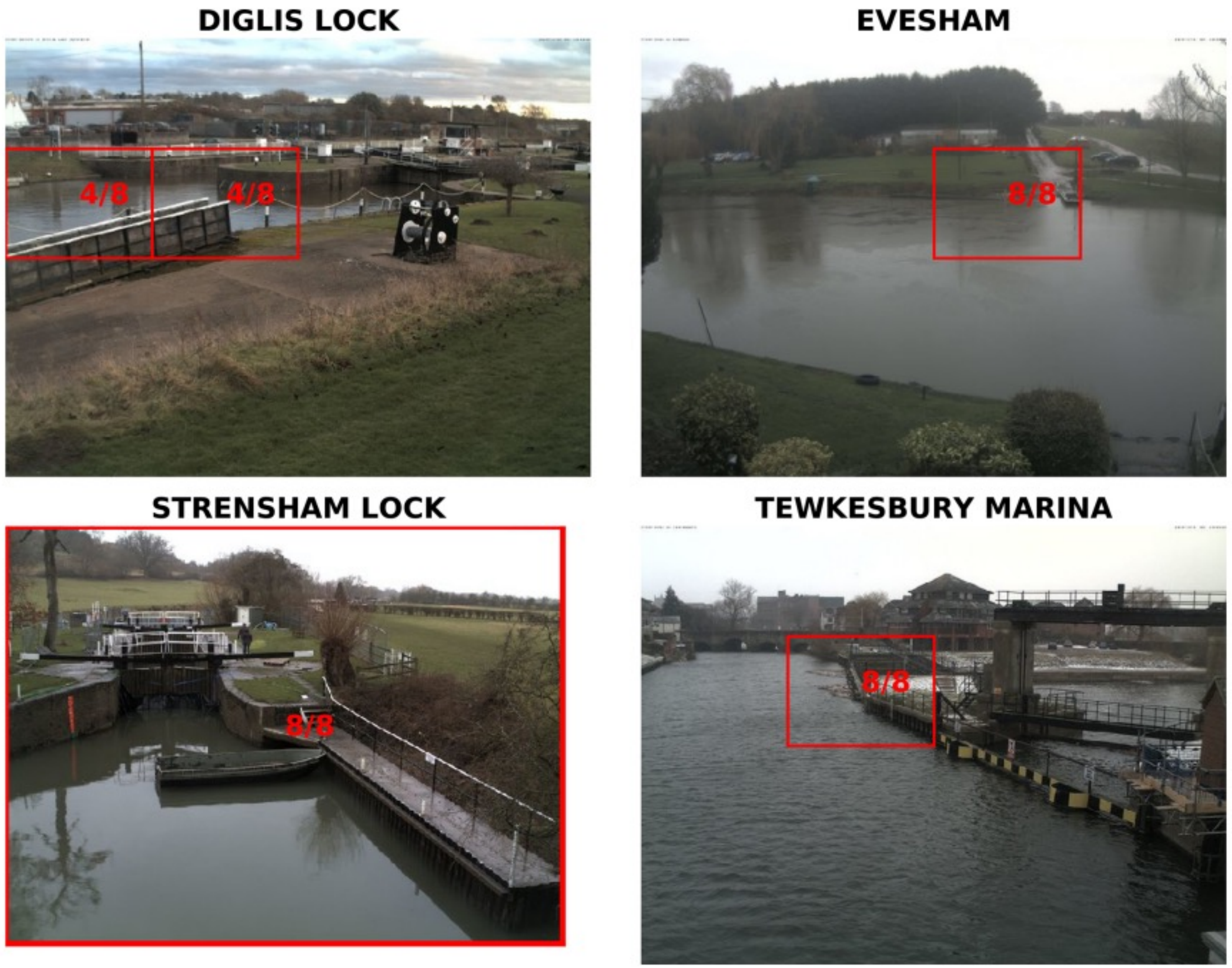
Extraction of river level data (of 1 year image streams)

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

Extraction of river level data (1 Year)

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

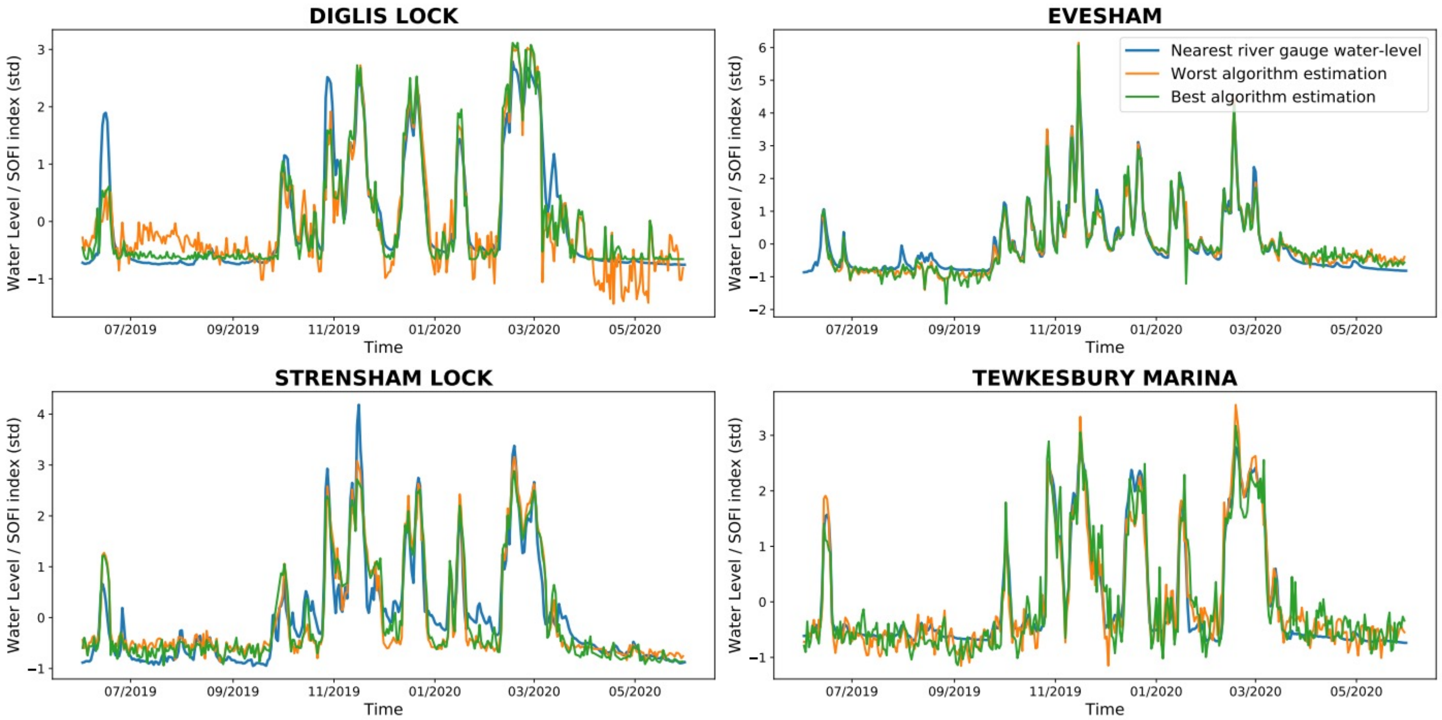


Extraction of river level data

$$Correaltion$$

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

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**

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**

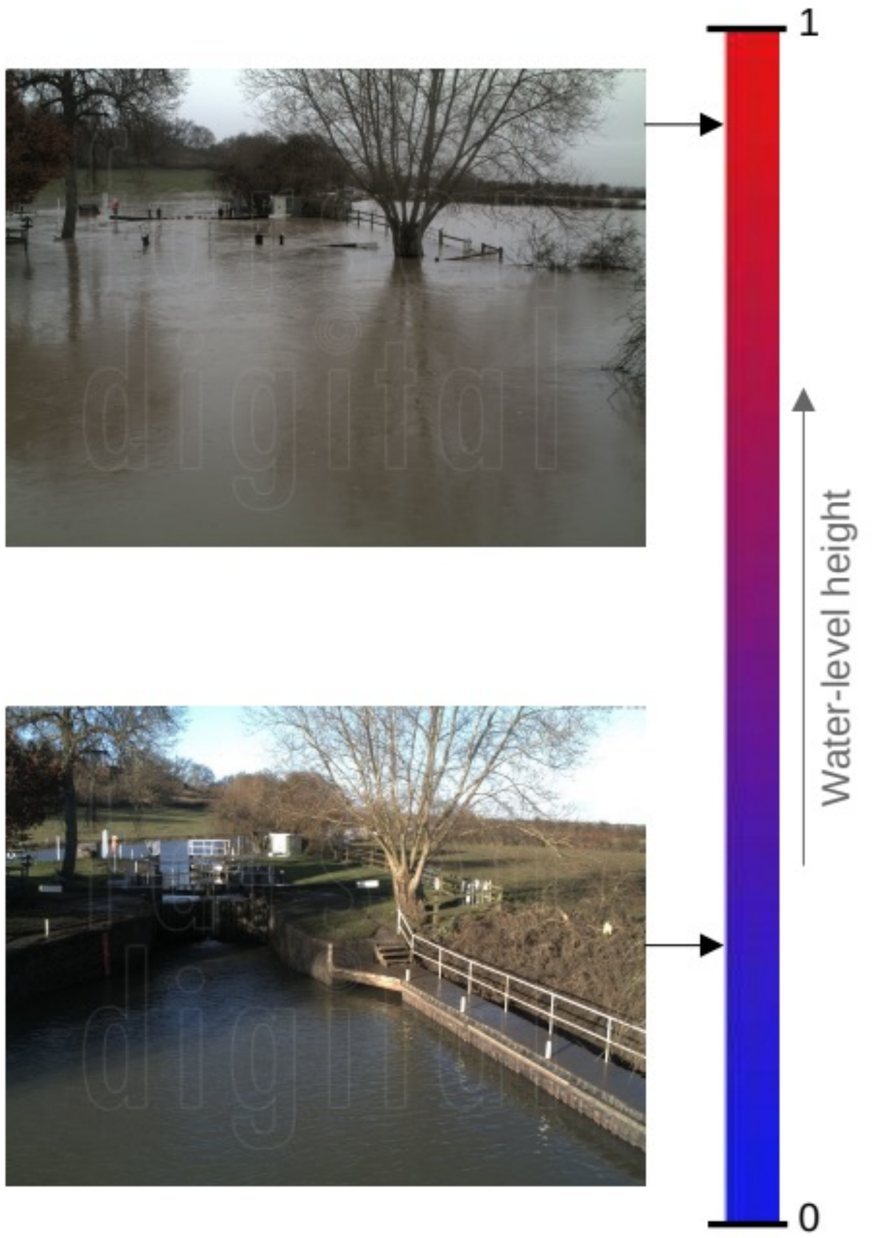
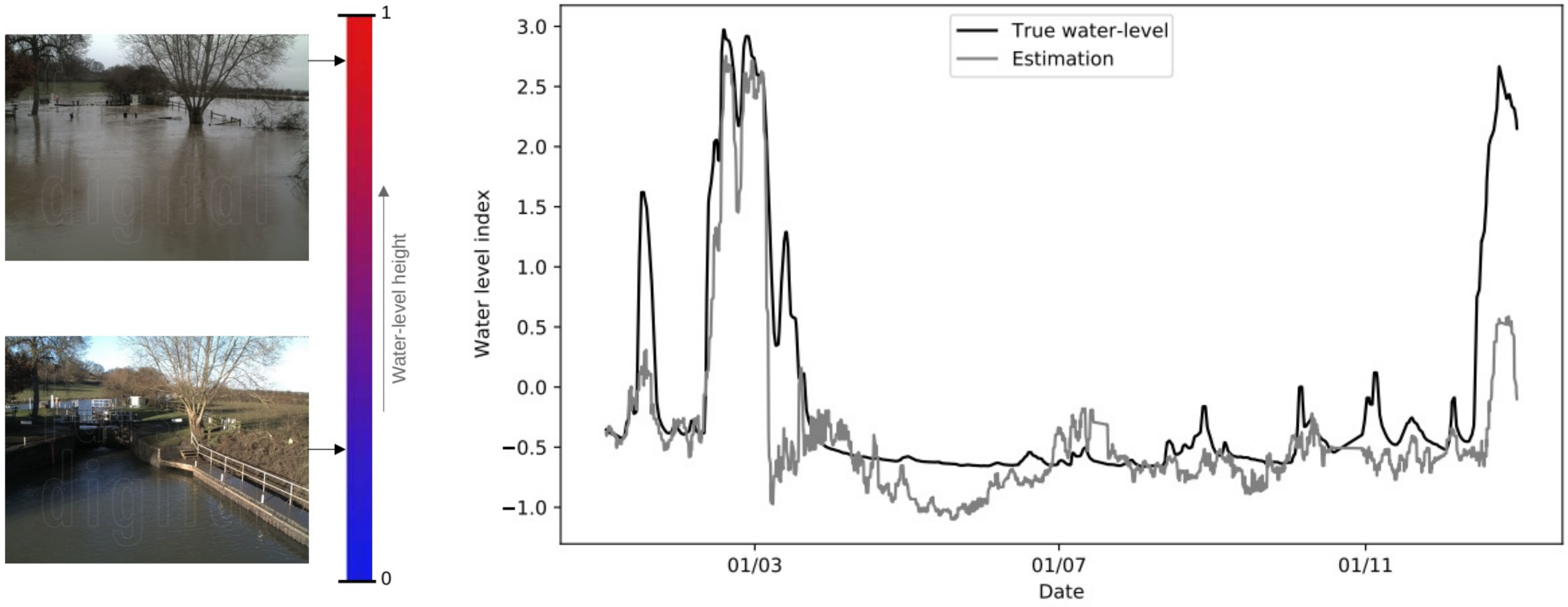


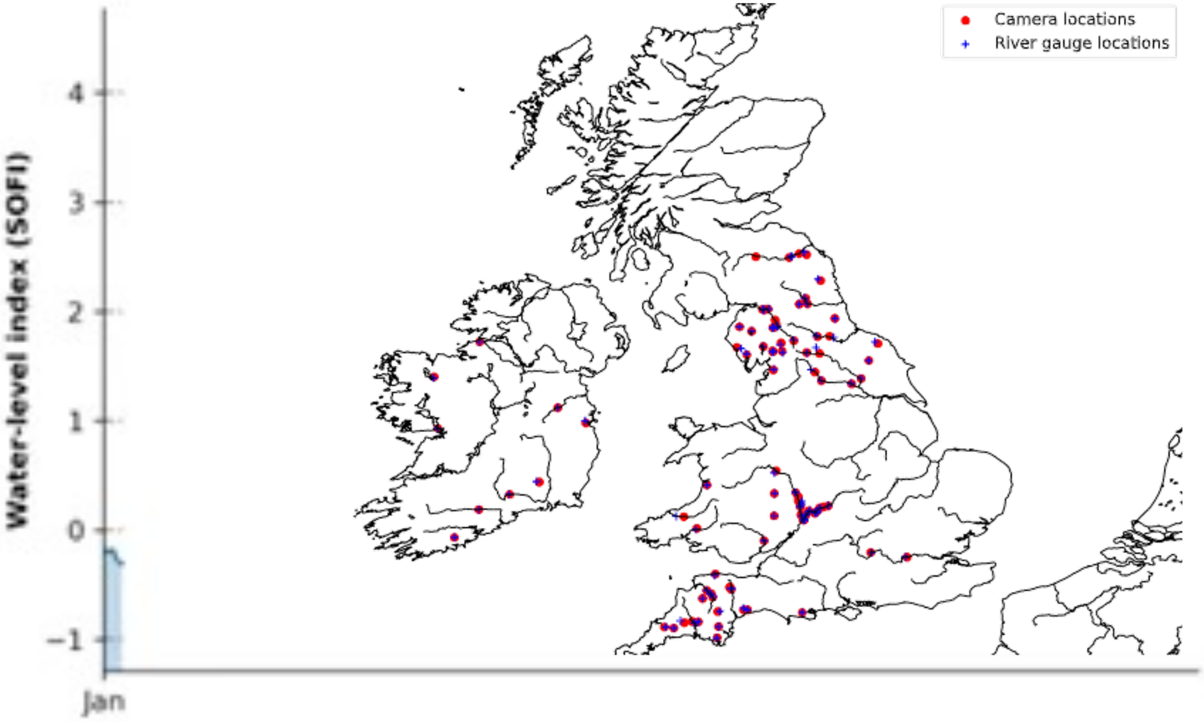
Image Regression: Estimation

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



Flood tracking

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

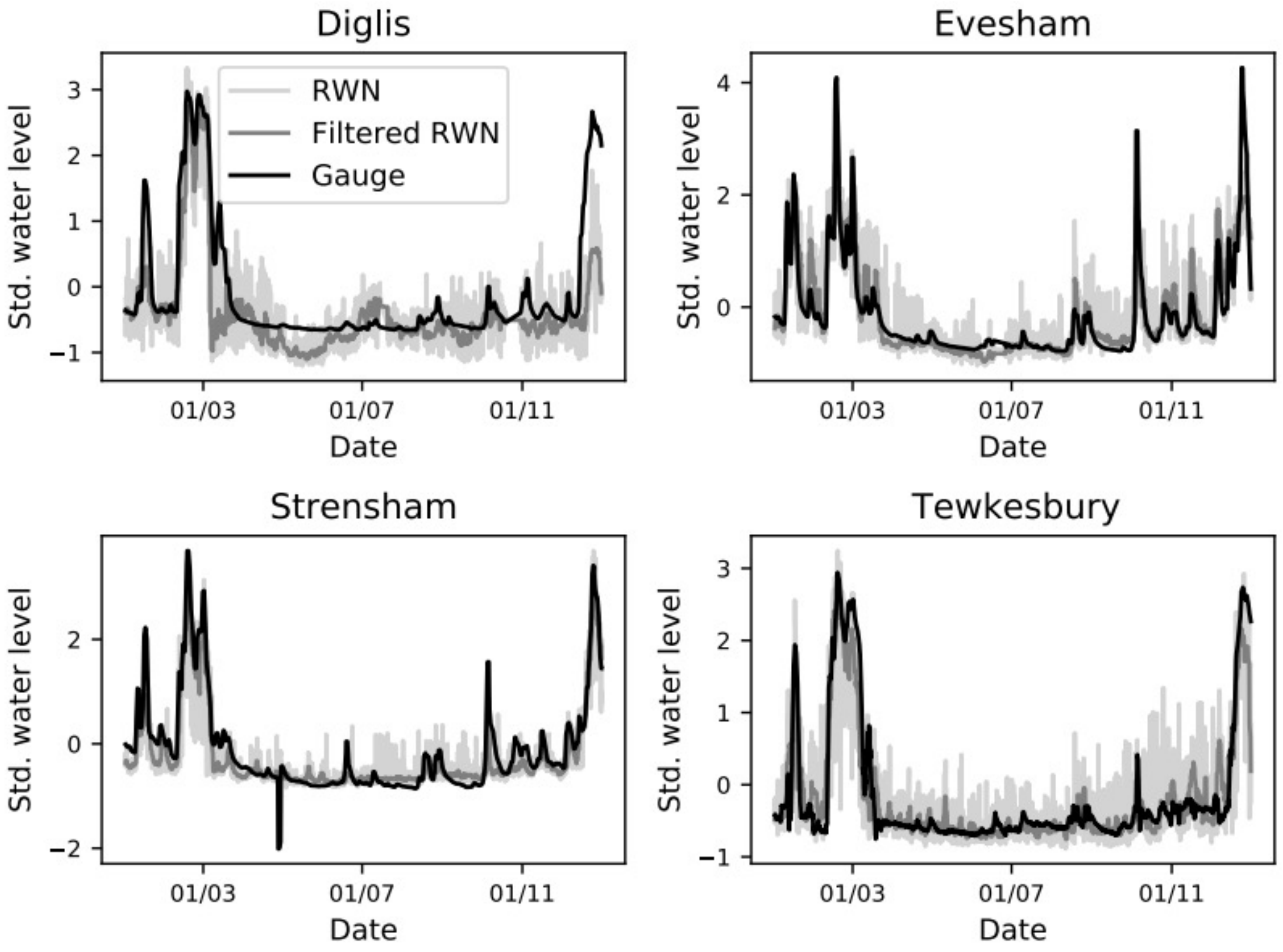


We achieve 94% accuracy in correctly predicting real flood events.

Video Credit: Remy Vandaele

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

trash screen monitoring

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

Binary Classifier

Blockage score

$> T$ **Blocked** trash screen

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

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

Trash screen monitoring: Anomaly Detection

Anomaly Detection

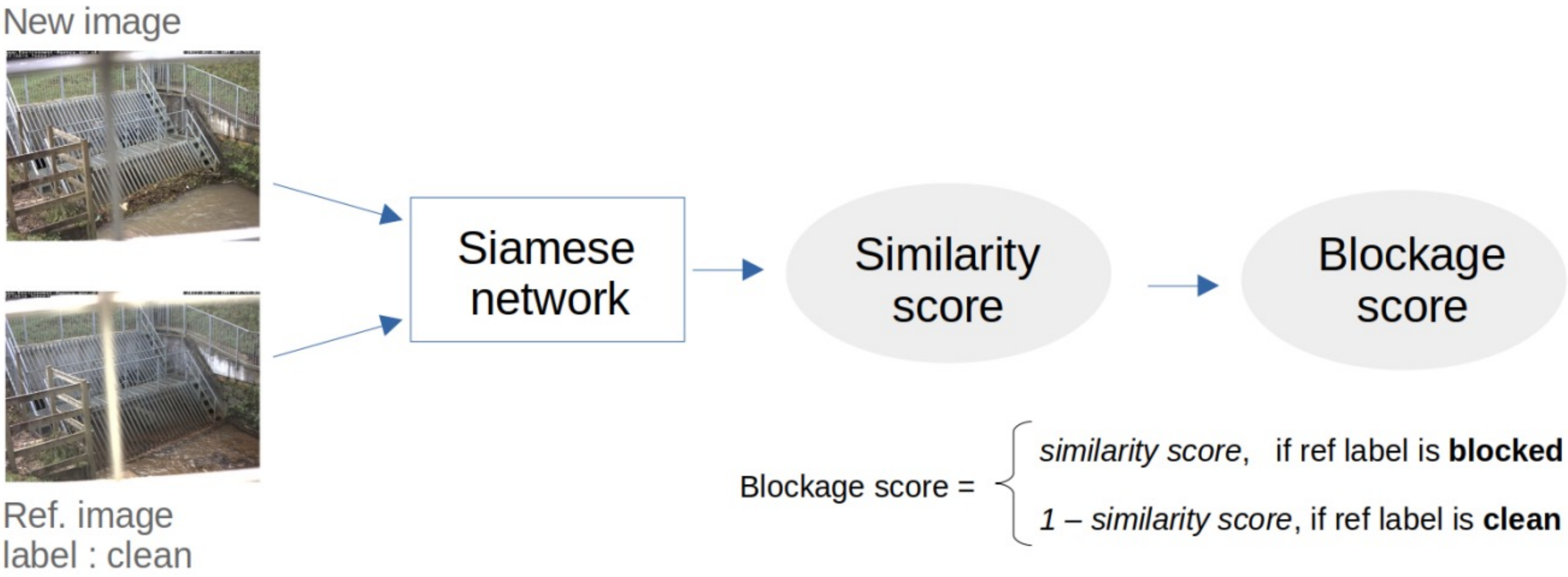
Blockage score

> T → **Blocked** trash screen

≤ 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



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

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

Evaluation

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

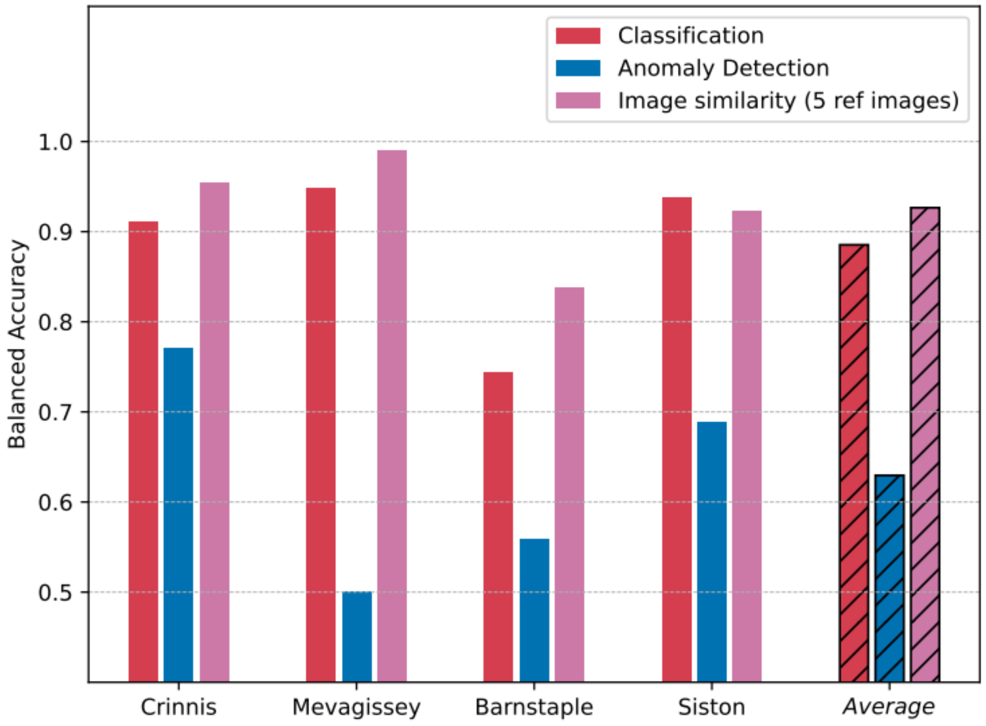
Crinnis

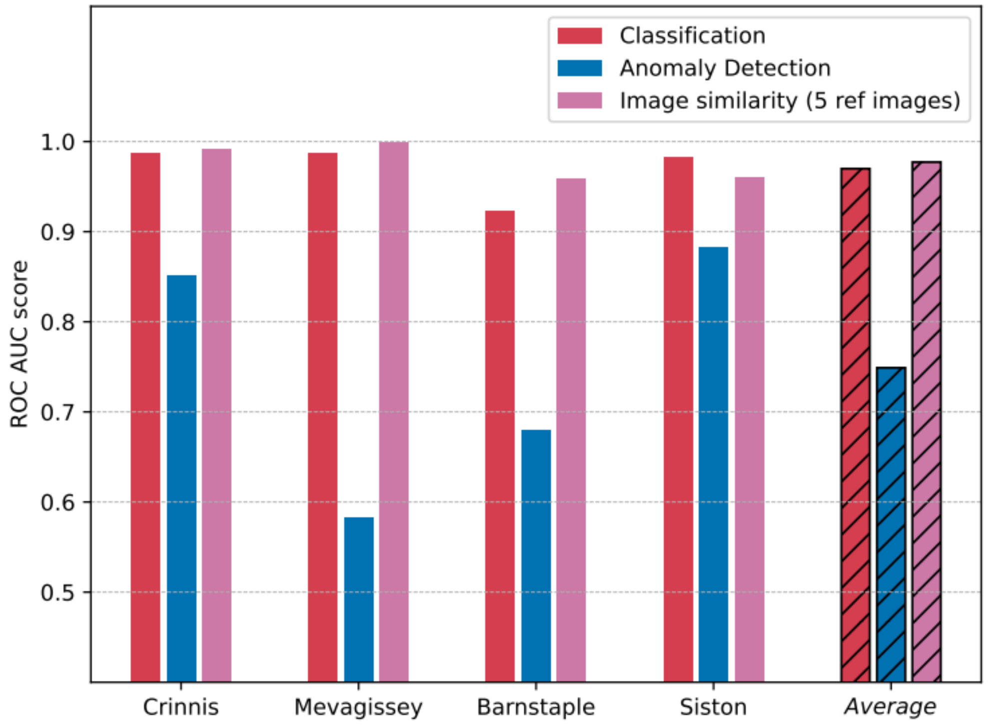
Mevagissey

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

References

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- 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)
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