Eye of Horus: A Vision-based Framework for Real-time River Water Level Measurement

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Abstract

Hurricanes and tropical storms are among the main causes of floods, which are anticipated to intensify and occur more frequently. Flood inundation mapping (FIM) models provide necessary information about flood extent and loss estimates for decision-makers and planners to protect human lives and mitigate damages. The performance of these models relies heavily on the accuracy and timing of data received from in-situ gauging stations, remote sensing, and more recently crowdsourcing. However, each of these data sources comes with its shortcomings. For example, in-situ measurements at a gauging station provide stream flow data at a certain location, and cannot resolve the spatial distribution of flood. This study aims to introduce a vision-based framework as a new source of hydrologic information for measuring water level in the local stream or river and indicating flood intrusion using Computer Vision and Deep Learning (DL) techniques. For this purpose, time-lapse images captured by surveillance cameras during storm events are fed into DL-based models for the semantic segmentation of the water extent in the images. Three different DL-based approaches represented by PSPNet, TransUNet, and SegFormer were applied and evaluated for the task of semantic segmentation. The predicted masks are then transformed into the water level values by intersecting the extracted water edges, with the 2D representation of a point cloud generated by the Apple iPhone 13 Pro LiDAR sensor of the region of interest. The results were compared with the reference data collected by an ultrasonic sensor. Experimental results show that SegFormer outperformed other DL-based approaches by achieving 99.55% and 99.81% for Intersection over Union (IoU) and accuracy, respectively. Moreover, the highest correlations between reference data and the vision-based approach reached above 0.98 for both the coefficient of determination (R^2) and Nash-Sutcliffe Efficiency (NSE).

1 Introduction

Flood Inundation Mapping (FIM) can protect human lives and prevent further damages if the information needed to plan for evacuation, emergency management, and relief work is provided in a timely manner Gebrehiwot et al. (2019). Flood inundation models are often developed to simulate and predict affected areas and the degree of damage caused by storm events. The inputs for these models commonly come from two main data sources, gauging station network or remote sensing. For example, stream gauges provide in-situ streamflow information (e.g. water height and discharge) at observation sites, such as the United States Geological Survey (USGS) site stations Turnipseed and Sauer (2010). However, gauges cannot provide adequate data about the spatial variation of flow characteristics Lo et al. (2015). This problem is further exacerbated by the fact that stream gauges are not often installed systematically along the waterways Li et al. (2018), and some sites are technically, logistically, and politically difficult to access King et al. (2018). Satellite data and remote sensing can be used to complement in-situ gauge data by providing information at a larger spatial scale Alsdorf et al. (2007). However, seamless monitoring and observation of a fixed region is still a problem due to the limited revisit intervals of satellites, cloud cover, and systematic departures (or biases) Panteras and

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Cervone (2018). Recently, a great deal of attention has been devoted to the concept of crowdsourcing. However, the reliability and confidence level of crowdsourcing methods have been criticized due to the lack of verification Schnebele et al. (2014); Goodchild (2007); Howe (2008). In order to alleviate the mentioned limitations that inherently exist in the current data sources, and to reinforce the idea of real-time monitoring, surveillance cameras are introduced here as a new method to collect flood data. This requires significant investment in Computer Vision (CV) techniques to select appropriate approaches for detecting water on surveillance imageries and translating it into numerical information.

Recent advances in CV provide new techniques needed for processing imagery data for the quantitative measurements of physical attributes from a scene Forsyth and Ponce (2002). So far, however, limited knowledge has been produced on investigating how gathering visual information can be used to estimate physical water parameters using CV techniques. For instance, inspired by the principle of the float method, Tsubaki et al. (2011) used different image processing techniques to analyze images captured by closed-circuit television (CCTV) systems, which are installed for surveillance purposes, to measure the flow rate during flood events. Kim et al. (2011) proposed a method for measuring water level by detecting the borderline between the staff gauge and the surface of water based on image processing of the captured image of the staff gauge installed in the middle of the river. As using images for environmental monitoring became more frequent, several studies investigated the source and magnitude of errors that are common in image-based measurement systems, e.g., the effect of image resolution, lighting effects, perspective, lens distortion, water meniscus Elias et al. (2020), and temperature changes Gilmore et al. (2013), as well as proposed solutions to resolve difficulties originated by poor visibility for better identifying the readings on staff gauges Zhang et al. (2019).

More recently, and after deep learning (DL) became prevalent across a wide range of disciplines, DL-based models have been applied by the water resources community to qualify the visible extent of the water and waterbodies in the images captured by surveillance camera systems for estimating water level Pally and Samadi (2022). Moy de Vitry et al. (2019) used a DL-based approach to detect floodwater in surveillance footage and introduced a novel qualitative flood index (SOFI) to indicate water level fluctuations by calculating the aspect ratio of the area of the water surface that is detected within an image to the total area (pixels) of the image. These types of methods, which are based on a prior assumption and roughly estimate water level fluctuation, cannot be considered as the vision-based alternative for measuring characteristics of streamflow. More systematic studies adopted photogrammetry to reconstruct a high-quality 3D model of the environment with a high spatial resolution to have a precise estimation of real-world coordination while measuring stream flow rate and stage. For example, Eltner et al. (2018, 2021) introduced a method based on Structure from Motion (SfM), and photogrammetric techniques, to automatically measure the water stage using low-cost camera setups.

As the advances in photogrammetry techniques enable 3D surface reconstruction with a high temporal and spatial resolution Westoby et al. (2012), Eltner and Schneider (2015); Eltner et al. (2016) reviewed and analyzed the recent algorithms to build 3D surface models from RGB imagery. However, most of the photogrammetric pipelines are still expensive as they rely on differential global navigation satellite systems (DGNSS), ground control points (GCPs), commercial software, and data processing on an external computing device Froideval et al. (2019). A LiDAR scanner, on the other hand, is commonly available everywhere since the introduction of the iPad Pro and iPhone 12 Pro in 2020 by Apple. This device is the first smartphone equipped with a native LiDAR scanner and offers a potential paradigm shift in digital field data acquisition which puts these devices at the forefront of smartphone-assisted fieldwork Tavani et al. (2022). So far, the iPhone LiDAR sensor has been used in different studies such as forest inventories Gollob et al. (2021) and coastal cliff site Luetzenburg et al. (2021). The availability of LiDAR sensors to build 3D environments, and advancements in DL-based models offer a great potential to produce numerical information from ground-based imageries.

In this paper, a vision-based framework is presented for measuring water levels from time-lapse images. The novel contribution of the proposed framework is using the iPhone LiDAR sensor, as a laser scanner commonly available on consumer-grade devices, for scanning and constructing a 3D point cloud of the region of interest. In the data collection phase, time-lapse images and ground truth water level values were collected using an embedded camera and ultrasonic sensor. The water extent in the captured images was automatically determined with the help of semantic segmentation DL-based models. For the first time, the performance of three different DL-based approaches represented by PSPNet, TransUNet, and SegFormer was evaluated and compared. CV techniques were applied for camera calibration, pose estimation of camera setup in each deployment and 3D-2D reprojection of

point cloud on the image plane. Eventually, K-Nearest Neighbors (KNN) was used to find the nearest projected (2D) point cloud coordinates to the water line on river banks for estimating the water level in each time-lapse image.

2 Literature Review

As this study tries to cover and evaluate a wide range of DL approaches, this section focuses on reviewing different DL-based architectures So far, different DL networks were applied and evaluated for semantic segmentation of the waterbodies within the RGB images captured by still cameras Erfani et al. (2022). All existing semantic segmentation approaches–Convolutional Neural Network (CNN) and Transformer-based– share the same goal to classify each pixel of a given image but differ in the network design.

CNN-based models were designed to imitate the recognition system of primates Shamsabadi et al. (2022), while possessing different network designs such as low-resolution representations learning Long et al. (2015); Chen et al. (2017), high-resolution representations recovering Badrinarayanan et al. (2015); Noh et al. (2015); Lin et al. (2017), contextual aggregation schemes Yuan and Wang (2018); Zhao et al. (2017); Yuan et al. (2020), feature fusion and refinement strategy Lin et al. (2017); Huang et al. (2019); Li et al. (2019); Zhu et al. (2019); Fu et al. (2019). CNN-based models follow local to global features in different layers of the forward pass, which used to be thought of as a general intuition of the human recognition system. In this system, objects are recognized through the analysis of texture and shape-based clues– local and global representations and their relationship in the entire field of view. Recent research, however, shows significant differences exist between the visual behavioral system of humans and CNN-based models Geirhos et al. (2018b); Dodge and Karam (2017); De Cesarei et al. (2021); Geirhos et al. (2020, 2018a), and reveal higher sensitivity of the visual systems in humans to global features rather than local ones Zheng et al. (2018). This fact drew attention to models that focus on the global context in their architectures.

Developed by Dosovitskiy et al. (2020), Vision Transformer (ViT) was the first model that showed promising results on a computer vision task (image classification) without using convolution operation in its architecture. In fact, ViT adopts "Transformers," as a self-attention mechanism, to improve accuracy. "Transformer" was initially introduced for sequence-to-sequence tasks such as text translation Vaswani et al. (2017). However, as applying the self-attention mechanism on all image pixels is computationally expensive, the Transformer-based models could not compete with the CNN-based models until the introduction of ViT architecture which applies self-attention calculations on the low-dimension embedding of small patches originating from splitting the input image, to extract global contextual information. Successful performance of ViT on image classification inspired several following works on Transformer-based models for different computer vision tasks Liu et al. (2021).

In this study, three different DL-based approaches including Convolutional Neural Networks (CNN), hybrid CNN-Transformer, and Transformers-Multilayer Perceptron (MLP) were trained and tested for semantic segmentation of water. For these approaches, the chosen models were PSPNet Zhao et al. (2017), TransUNet Chen et al. (2021) and SegFormer Xie et al. (2021), respectively. The performance of these models is evaluated and compared using conventional metrics.

3 Study Area

In order to evaluate the performance of the Eye of Horus for measuring the water levels in rivers and channels, the setup has been deployed, several times, in Rocky Branch in Columbia South Carolina USA. This creek is approximately 6.5 km long, subjected to rapid changes in water flow, and discharges into the Congaree River Morsy et al. (2016). The observation site is located on part of this creek within the University of South Carolina. Apple iPhone 13 Pro LiDAR sensor was used to scan the region of interest (see Figure 1a). Although there is no official information about the technology and hardware specifications, Gollob et al. (2021) reports the LiDAR module operates at the 8XX nm wavelength and consists of an emitter (Vertical Cavity Surface-Emitting Laser with Diffraction Optics Element, VCSEL DOE) and a receptor (Single Photon Avalanche Diode array-based Near Infrared Complementary Metal Oxide Semiconductor image sensor, SPAD NIR CMOS) based on direct-time-of-flight technology. Comparisons between the Apple LiDAR sensor and other types of laser scanners

including hand-held, industrial and terrestrial have been conducted by several recent studies Mokroš et al. (2021); Vogt et al. (2021). Gollob et al. (2021) tested and reported the performance of a set of eight different scanning apps, and found three applications including 3D Scanner App, Polycam and SiteScape suitable for actual practice tests. The objective of this study is not the evaluation of the iPhone LiDAR sensor and apps' performance. So, according to the experimental trials, 3D Scanner App LABS was used with the following settings: confidence = high, range = 5.0 m, masking = none, and resolution = 5 mm, for scanning and 3D reconstruction processing. The scanned 3D point cloud is shown in Figure 1b.

As the LiDAR scanner settings were set at the highest level of accuracy and computational demand, scanning the whole region of interest at the same time was not possible. So, the experimental region was taken apart into several sub-regions and scanned in multi-step. In order to assemble the sub-regions LiDAR scans, several GCPs were considered in the study area. These GCPs were measured by a total station (Topcon GM Series). Moreover, 13 AruCo markers were installed for estimating extrinsic camera parameters in each setup deployment. Since it was not possible to accurately measure the real-world coordination of AruCo markers by LiDAR scanner, the coordinates of the top-left corner of markers were also measured by a total station. The 3D point cloud scanned for each sub-region was (Affine) transformed into the total station coordinate system, and the real-world coordinates of ArUco markers were appended to the 3D point cloud for the following analyses.

4 Methodology

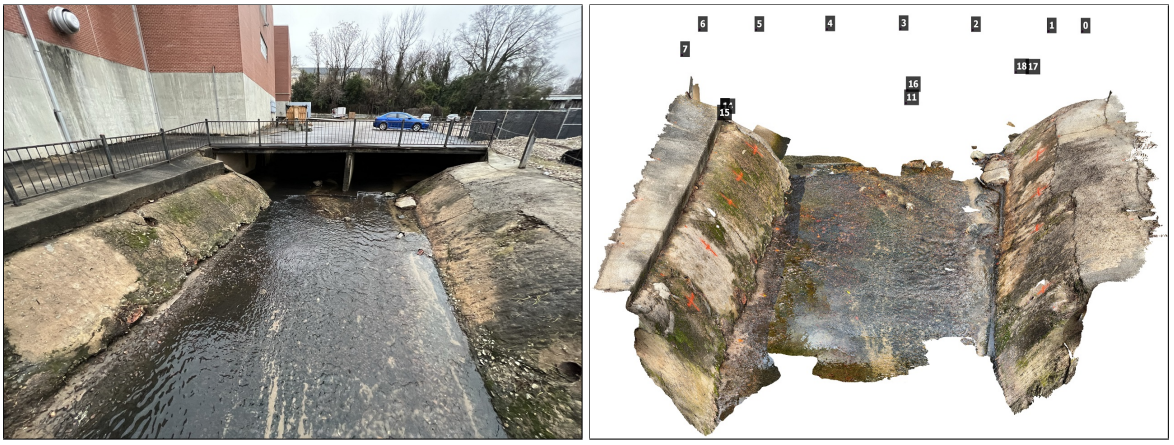
This study includes three main components. The preliminary step is related to the designing of two deployable setups for data collection. These setups include a programmable/ time-lapse camera run by Raspberry Pi and an ultrasonic sensor run by Arduino. After collecting data, the first phase (Module 1) represents the configuration and training of DL-based models for semantic segmentation of water in the captured images. In the second phase (Module 2) CV techniques for camera calibration, spatial resection, and calculating projection matrix are discussed. Finally, in the third phase (Module 3), an ML-based model uses the information achieved by CV models to find the relationships between real-world coordinates of water level in the captured images (Figure 2).

4.1 Data Acquisition

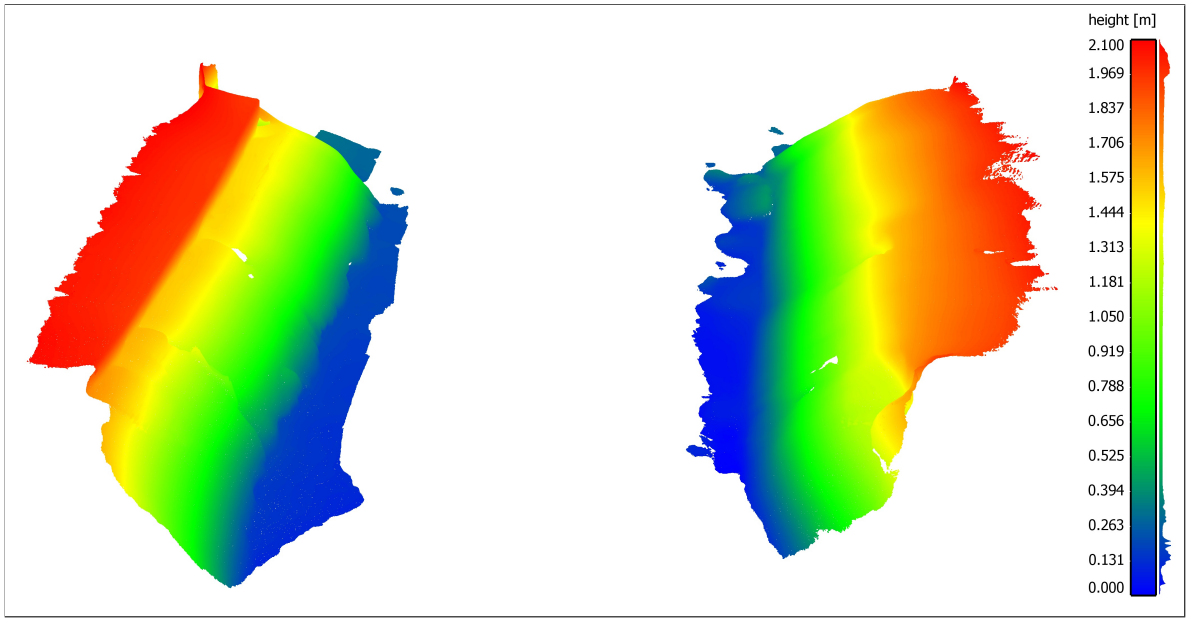
Two different single-board computers (SBC) were used in this study, Raspberry Pi (Zero W) for capturing time-lapse images of a river scene, and Arduino (Nano 3.x) for measuring water level as the ground truth data. These devices were designed to communicate with each other, i.e., to trigger the other to start or stop recording. During capturing time-lapse images, the Pi camera device triggers the ultrasonic sensor for measuring the corresponding water level. The camera device is equipped with the Raspberry Pi Camera Module 2 which has a Sony IMX219 8-megapixel sensor. This sensor is able to capture an image size of 4,256 × 2,832 pixels. In this study, however, the image resolution is set to 1,920 × 1,440 pixels to keep a balance between image quality and the computational cost of following image processing in the next steps. This setup is also equipped with a 1200 mAh UPS lithium battery power module to provide uninterrupted power to the Pi SBC (see Figure 3a).

The Arduino-based device captures the records of water level. The design is based on an unmanned aerial vehicle (UAV) deployable sensor created by Smith et al. (2022). The nRF24L01+ single-chip 2.4 GHz transceiver allows the Arduino and Raspberry Pi to communicate via radio frequency (RF) communication. The chip is housed in both packages and the channel, pipe addresses, data rate, and transceiver/receiver configuration are all set in the software. The HC-SR04 ultrasonic sensor is mounted to the base of the Arduino device and provides a contactless water level measurement. Two permanent magnets at the top of the housing attach to a ferrous structure and allow the ultrasonic sensor to be suspended up to 14 feet over the surface of the water. The microSD card module and DS3231 real-time clock incorporate traditional data logging and allow data to be stored on-device as well as transmitted. The device is powered by a rechargeable 7.4V 1500 mAh lithium polymer battery (see Figure 3b).

The Arduino device waits to receive a ping from the Raspberry Pi device to initiate data collection. The ultrasonic sensor measures the distance from the sensor transducer to the surface of the water. The nRF24L01+ transmits this distance to the Raspberry Pi device and saves the measurement and a



(a) (b)



(c)

Figure 1: Study area at Rocky Branch. (a) View of the region of interest, (b) The scanned 3D point cloud of the region of interest including an indication of the ArUco markers' locations, and (c) The scalar field of left and right banks of Rocky Branch in the region of interest (the colorbar and the frequency distribution of z values for the captured points are shown on the right side).

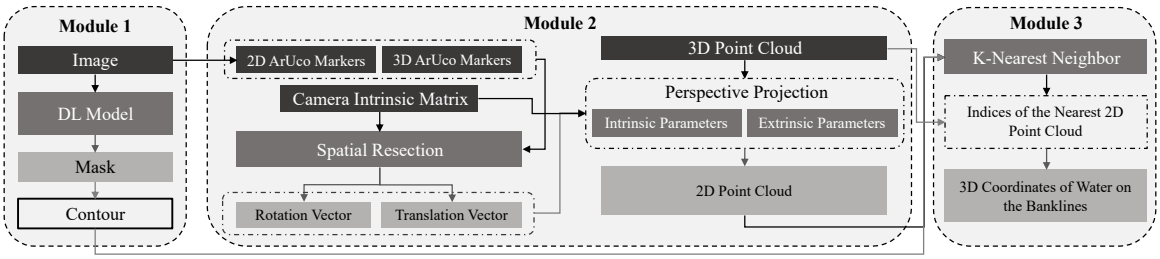
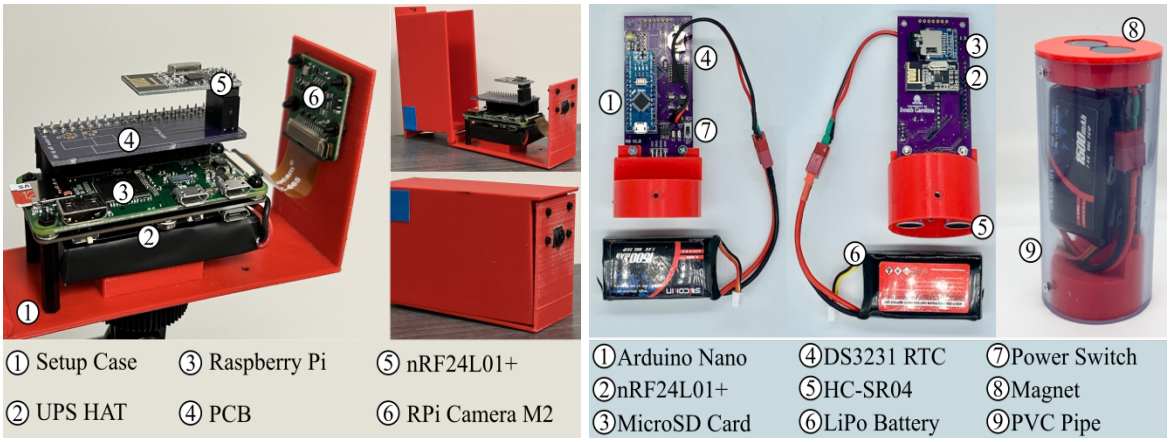


Figure 2: The workflow includes three main modules starting from processing images captured by the time-lapse camera to estimating water level by projecting the waterline on river banks using CV techniques.

time stamp from the real-time clock to an onboard microSD card. This acts as backup data storage, in case transmission to the Raspberry Pi fails. The nRF24L01+ RF transceivers have an experimentally determined range of up to 30 ft which allows flexibility in the relative placement of the camera to the measuring site.



(a) (b)

Figure 3: Data acquisition devices. (a) Beena, run by Raspberry Pi (Zero W) for capturing time-lapse images of the river scene; and (b) Aava, run by Arduino Nano for measuring water level correspondence.

An image dataset for semantic segmentation was developed by collecting images taken from the region of interest during different times of the day and flow regimes. This dataset consists of 1,172 images, and streamflow in the creek is manually annotated for all images. The dataset is split into 812 training, 124 validation, and 236 testing images.

4.2 Deep Learning Model for Water Segmentation

The water extent can be automatically determined on the 2D image plane with the help of DL-based models. The task of semantic segmentation was applied within the framework of this study to delineate the water line on the left and right banks of the river. Three different DL-based models were trained and tested in this study. PSPNet, the first model, is a CNN-based semantic segmentation multi-scale network which can better learn the global context representation of a scene Zhao et al. (2017). ResNet-101 He et al. (2016) was used as the backbone of this model to encode input images into the features. ResNet architecture takes the advantage of "Residual blocks" that assist the flow of gradients during the training stage allowing effective training of deep models even up to hundreds of layers. These extracted features are then fed into a pyramid pooling module in which feature maps produced by small to large kernels are concatenated to distinguish patterns of different scales Minaee et al. (2021).

TransUNet, the second model, is a U-shaped architecture that employs a hybrid of CNN and Transformers as the encoder to leverage both the local and global contexts for precise localization and pixel-wise classification Chen et al. (2021). In the encoder part of the network, CNN is first used as a feature extractor to generate a feature map for the input image, which is then fed into Transformers to extract long-range dependencies. The resulting features are upsampled in the decoding path and combined with detailed high-resolution spatial information skipped from the CNN to make estimations on each pixel of the input image.

SegFormer, the third model, unifies a novel hierarchical Transformer, which does not require the positional encodings used in standard Transformers, and MultiLayer Perceptron (MLP) performs efficient segmentation Xie et al. (2021). The hierarchical Transformer introduced in the encoder of this architecture gives the model the attention ability to multiscale features (high-resolution fine and low-resolution coarse information) in the spatial input without the need for positional encodings that may adversely affect a models performance when testing on a different resolution from training. Moreover, unlike other segmentation models that typically use deconvolutions in the decoder path, a lightweight MLP is employed as the decoder of this network that inputs the features extracted at different stages of the encoder to generate a prediction map faster and more efficiently. Two different variants, including

SegFormer-B0 and SegFormer-B5, were applied in this study. The configuration of the models implemented in this study is elaborated in Table 1. The total number of parameters (Params), occupied memory size on GPU (Total Size) and input image size (Batch Size) are reported in Million (M), Megabyte (MB), and Batch size×Height×Width×Channel (B, H, W, C) respectively.

Table 1: The configuration of models trained and tested in this study.

Model Names	Params (M)	Total Size (MB)	Batch Size (B, H, W, C)	Loss Function	Optimizer	LR
PSPNet	66.2	7,178	2×500×500×3	Binary Cross Entropy	SGD	2.50E-04
TransUNet	20.1	6,017	2×448×448×3	Cross Entropy + Dice	SGD	2.50E-04
SegFormer-B0	3.7	2,217	2×512×512×3	Cross Entropy	AdamW	6.00E-05
SegFormer-B5	82.0	27,666	2×1024×1024×3	Cross Entropy	AdamW	6.00E-05

Models are implemented using PyTorch. In the training procedure, the loss function, optimizer, and learning rate were set for each model individually and according to the preliminary runs having been done for finding hyperparameters. In the case of PSPNet and TransUNet, for instance, the base learning rate was set to 2.5×10^{-4} which was decayed following the poly policy Zhao et al. (2017). For these two networks, stochastic gradient descent (SGD) was considered as the optimizer with a momentum of 0.9 and weight decay of 0.0001. In the case of SegFormer (B0 and B5), a constant learning rate of 6.0×10^{-5} and AdamW optimizer Loshchilov and Hutter (2017) were set for training the networks. In total, networks were trained for 30 epochs, with a batch size of two. The training data, however, were augmented with horizontal flipping, random scaling, and random cropping just for PSPNet and TransUNet.

4.3 Projective Geometry

In this study, CV techniques are used for different purposes. First, CV models were used for camera calibration. They include focal length, optical center, radial distortion, camera rotation, and translation. These parameters provide the information (parameters or coefficients) about the camera that is required to determine the relationship between 3D object points in the real-world coordinate system and its corresponding 2D projection (pixel) in the image captured by that calibrated camera. Generally, camera calibration models estimate two kinds of parameters. First, the internal parameters of the camera (e.g., focal length, optical center, and radial distortion coefficients of the lens). Second, external parameters (refer to the orientation– rotation and translation– of the camera with respect to the real-world coordinate system.

To estimate the camera intrinsic parameters, OpenCV built-in was applied for camera calibration using a 2D checkerboard Bradski (2000). Intrinsic parameters are specific to a camera. The focal length (f_x, f_y) and optical centers (c_x, c_y) can be used to create a camera matrix. The camera matrix is unique to a specific camera, so once calculated, it can be reused on other images taken by the same camera (Equation 1). It is expressed as a 3×3 matrix:

$$camrea\ matrix = \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix} \tag{1}$$

The camera extrinsic parameters were determined using the pose estimation problem which consists in solving for the rotation, and translation that minimizes the reprojection error from 2D-3D point correspondences Marchand et al. (2015). For this purpose, the iterative method was applied which is based on a Levenberg-Marquardt optimization. In this task the function finds such a pose that minimizes reprojection error, that is the sum of squared distances between the observed projections "image point" and the projected "object points." The initial solution for non-planar 3D object points needs at least six points and uses the Direct Linear Transformation (DLT) algorithm.

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \overbrace{\begin{bmatrix} f_x & 0 & c_x & 0 \\ 0 & f_y & c_y & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}}^{\mathbf{K}} \overbrace{\begin{bmatrix} r_{11} & r_{12} & r_{13} & t_x \\ r_{21} & r_{22} & r_{23} & t_y \\ r_{31} & r_{32} & r_{33} & t_z \\ 0 & 0 & 0 & 1 \end{bmatrix}}^{[\mathbf{R}|\mathbf{t}]} \begin{bmatrix} X_w \\ Y_w \\ Z_w \\ 1 \end{bmatrix} \tag{2}$$

Equation 2 represents "Projection Matrix" consisting of two parts– the intrinsic matrix ($\mathbf{K}$) that contains the intrinsic parameters and the extrinsic matrix ($[\mathbf{R} \mid \mathbf{t}]$) that is combination of 3×3 rotation matrix $\mathbf{R}$ and a 3×1 translation $\mathbf{t}$ vector.

2D points are represented with ArUco markers' pixel coordinates on the 2D image plane, and corresponding 3D object points are measured by the total station. Having at least six 3D-2D point correspondences, the spatial position and orientation of the camera can be estimated for each setup deployment. After retrieving all the necessary parameters, a full-perspective camera model can be generated. Using this model, the 3D point cloud is projected on the 2D image plane. The projected (2D) point cloud can represent 3D real-world coordinates of the nearest 2D pixel correspondence on the image plane.

4.4 Machine Learning for Image Measurements

Using the projection matrix, the 3D point cloud is projected on the 2D image plane (see Figure 4). The projected (2D) point cloud is intersected with the water line pixels, the output of the DL-based model (Module 1), to find the nearest point cloud coordinate. For this purpose, K-Nearest Neighbors (KNN) algorithm is used. The indices of the selected points are the same for both the 3D point cloud and the projected (2D) correspondences. So, using the indices of the selected projected (2D) points, the corresponding real-world 3D coordinates are retrievable.

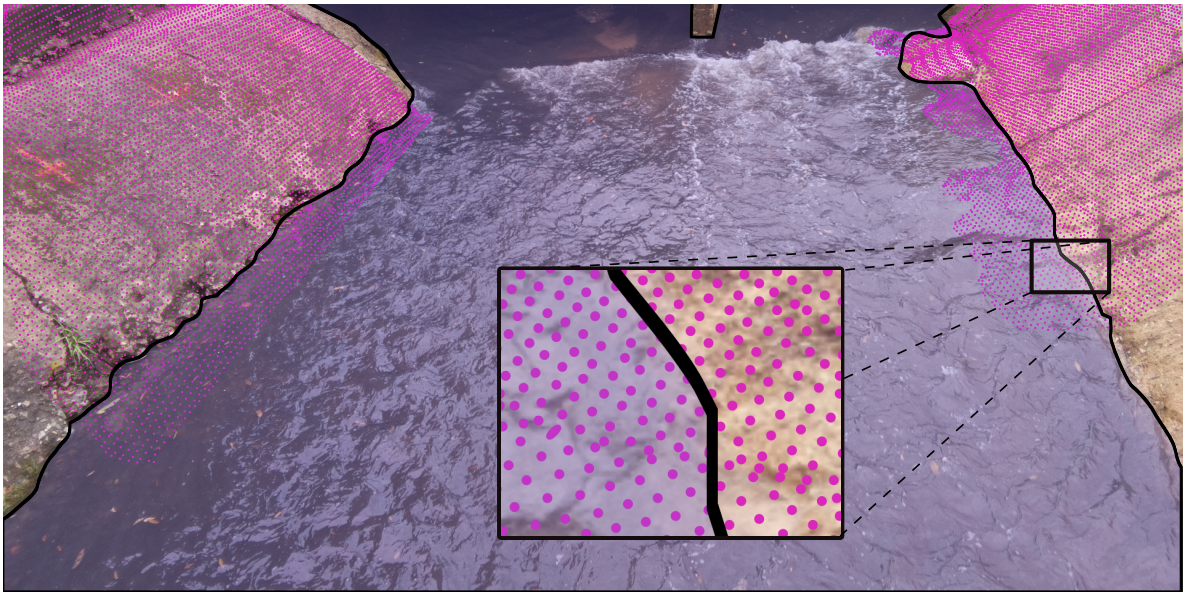


Figure 4: KNN is used to find the nearest projected (2D) point cloud (magenta dots) to the water line (black line) on the image plane.

5 Results and Discussion

The results of this study are presented in two sections. In the first section, the performance of DL-based models is discussed. In the second section, the performance of the proposed framework is evaluated for five different deployments.

5.1 DL-based Models Results

The performance of DL-based models for the task of semantic segmentation is evaluated and compared in this section. Since the proposed dataset includes just two classes, "river" and "non-river", "non-river" was omitted from the evaluation process, and the performance of models is only reported for the "river" class of the test set. The class-wise intersection over union (IoU) and the per-pixel accuracy (ACC) were considered the main evaluation metrics in this study. According to Table 2, both variants of SegFormer, SegFormer-B0, and SegFormer-B5 outperform other semantic segmentation networks on the test set. Considering the models' configurations detailed in Table 1, SegFormer-B0 can be considered the most efficient DL-based network, as it is comprised of only 3.7 Million trainable parameters and occupies just $2,217$ Megabytes of GPU ram during training. Figure 5 shows the four different visual representations of models' performance on the validation set of the proposed dataset. Since the water level is estimated by intersecting the water line on river banks with the projected (2D) point cloud, precise delineation of the water line is of high importance to achieve better results in the following steps. It means estimating the correct location of the water line on creek banks in each time-lapse image plays a more important role than performance metrics in this study. By taking the quality of water line detection into account and based on the visual representations shown in Figure 5, SegFormers' variants still outperform DL-based approaches. Comparing PSPNet and TransUNet in this regard showed PSPNet can delineate the water line more clearly, while the segmented area is more integrated for TransUNet outputs.

Table 2: The performance metrics of different DL-based approaches.

Model Names	IoU (River)	ACC (River)
PSPNet	94.88%	95.84%
TransUNet	93.54%	96.89%
SegFormer-B0	99.38%	99.77%
SegFormer-B5	99.55%	99.81%

Limited by the nature of convolution operations, CNNs typically suffer from architecture-specific issues, including but not limited to locality Geirhos et al. (2018a). As a result, CNN-based networks may even achieve high accuracy on training data, but their performance can considerably decrease on unseen data. At the same time, they perform significantly weaker than Transformer-based networks for detecting semantics that requires combining long- and short-range dependencies. Transformers can relax the biases of DL-based models inducted by Convolutional operations, achieving higher accuracy in localization of target semantics and pixel-level classification with lower fluctuations in varied situations through the leverage of both local and global cues Naseer et al. (2021). Yet, various transformer-based networks may perform differently depending on the targeted task and the network's architecture. TransUNet adopts Transformers as part of its backbone; however, Transformers output single-scale low-resolution features Xie et al. (2021), which may limit the accuracy when multi-scale objects or single objects with multi-scale features are segmented. This problem is addressed on SegFormer variants by introducing a novel hierarchical Transformer encoder that is not only able to output multi-scale features but also relaxes the need for positional encoding in standard Transformer Xie et al. (2021). As a result, Segformer-B0 and -B5 could achieve human-level accuracy– see Figure 5– in the delineation of the water line to the level that the predicted masks are in high agreement with the manually annotated images.

5.2 Water Level Estimation

This section reports the framework performance based on several setup deployments in the field. The performance results are separately shown for the left and right banks and compared with ultrasonic sensor data as the ground truth. The performance of the ultrasonic sensor was evaluated in an individual study Smith et al. (2022) that documented an average distance error of 6.9 mm. Four different efficiency criteria including coefficient of determination (R^2), Nash-Sutcliffe Efficiency (NSE), Root Mean Square Error (RMSE), and Percent bias (PBIAS) were reported in Table 3. R^2, as the most representative metric, emphasizes how much of the observed dispersion can be explained by the prediction. However, if the model systematically over- or under-estimates the results, R^2 will still be close to 1.0 as it only takes dispersion into account Krause et al. (2005). So, NSE, a traditional

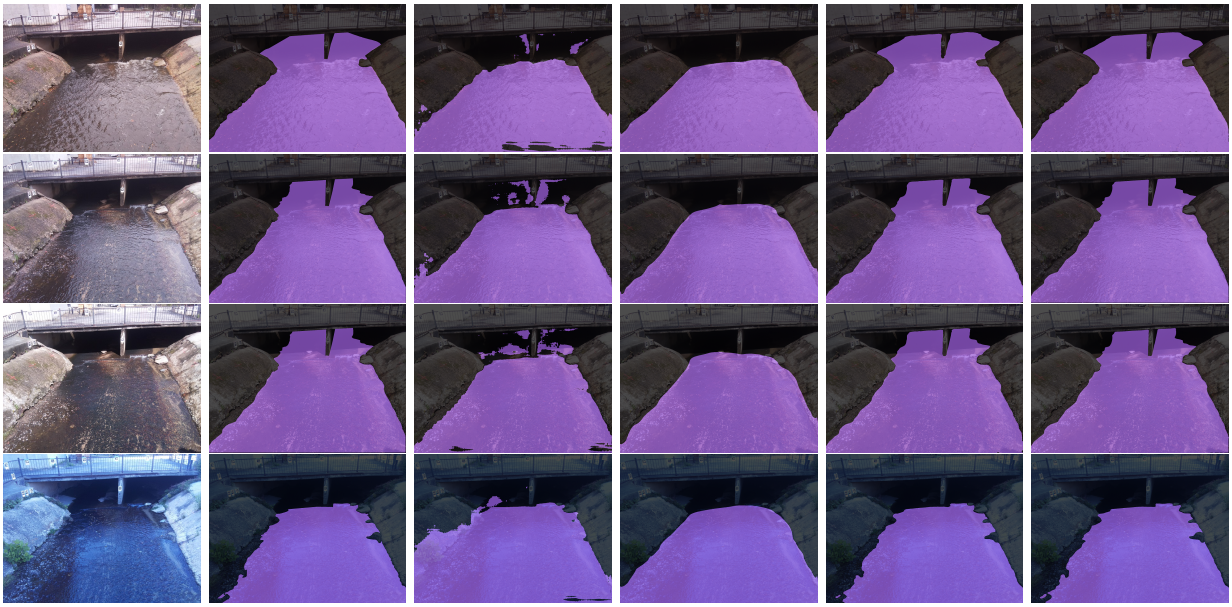


Figure 5: Visual representations of different DL-based image segmentation approaches on the validation dataset.

metric used in hydrology to summarize model performance is also provided. NSE normalizes model performance into an interpretable scale, and NSE equals zero is regularly used as a benchmark to distinguish "good" and "bad" models Knoben et al. (2019). RMSE represents the square root of the average of squares of the errors, the differences between predicted values and observed values. The PBIAS of estimated water level, compared against the ground truth was also used to show where the two estimates are close to each other and where they significantly diverge Lin et al. (2020).

Table 3: The performance metrics of the framework for five different days of setup deployment.

Deployment Date	Position	Metrics			
		R^2	NSE	RMSE	PBIAS
Aug/17/2022	Left Bankline	0.8019	0.5258	0.0409	10.6401
	Right Bankline	0.7932	0.7541	0.0294	-0.4848
Aug/19/2022	Left Bankline	0.7701	0.5713	0.0647	16.1015
	Right Bankline	0.9678	0.9588	0.0201	-3.4752
Aug/25/2022	Left Bankline	0.7690	0.5700	0.0435	-7.7091
	Right Bankline	0.8922	0.8711	0.0238	-1.7738
Nov/10/2022	Left Bankline	0.9461	0.8129	0.0511	-13.1183
	Right Bankline	0.9857	0.9790	0.0171	-1.5210
Nov/11/2022	Left Bankline	0.9588	0.8881	0.0397	-10.3656
	Right Bankline	0.9855	0.9829	0.0155	-1.7987

The setup was deployed on several rainy days. In addition to Table 3, the results of each setup deployment are visually demonstrated in Figure 6. The scatter plots show the relationships between the ground truth data (measured by the ultrasonic sensor), and the banks of the river. The scatter plots visually present whether the camera readings overestimate or underestimate the ground truth data. Moreover, the resulting hydrograph of water level information over time is shown for each deployment separately. Hydrograph is a helpful way to examine how the camera readings can represent the response of a catchment area to a rainfall input as precipitation, i.e., this graph shows how the proposed framework tracks the change in the water level of a stream over time and explains important components of a hydrograph (e.g., rising limb, peak, and recession limb).

The first deployment was done on Aug 17, 2022 (see Figure 6a). The initial water level of the base flow and some parts of the rising limb were not captured in this deployment. Table 3 showed the performance results of the right bank are better than those of the left bank. R^2 for both banks was about 0.80 showing a strongly related correlation between the water level estimated by the framework and ground truth data. Figure 6a shows how the left and right banks perform during the rising limb, right bank still underestimated the water level in this time span. Moreover, results showed, both left and right banklines were able to capture the peak water level; however, during the recession limb, the left bank overestimated the water level.

The second deployment was done on Aug 19, 2022. In this deployment, all segments of the hydrograph were captured. According to Table 3, the performance of the right bank was better than the left one, more than 0.95 was reported for R^2 and NSE of the right bankline. Figure 6b shows during the rising limb and crest segment both banks estimated the water level similar to ground truth. During the recession limb, the right bank water level estimation kept coincident with ground truth, while the left bank overestimated the water level. The third deployment was on Aug 25, 2022. This time water level of the recession limb and the following base flow were captured (see Figure 6c). The right bank with R^2 of 0.89 performed better than the left bank. This time left bank underestimated the water level over the recession limb, but during the following base flow, the water level was estimated correctly by both banks.

Results noted that the left bank cannot perform as well as the right bank. Field investigation showed that the effect of stream erosion on the concrete coating of the left bank surface was more severe compared with the right bank, and iPhone LiDAR did not scan inside the patches and holes existing on the concrete surface. Considering the mechanism that the KNN algorithm adopts to find the nearest (2D) point cloud coordinates to the water line, the selected points for these locations (patches and holes) cannot represent the corresponding real-world coordinates. Figure 7 illustrates the box plot and scatter plot of the water level estimated by the framework for a time-lapse image captured at 13:29 on Aug 19, 2022. According to this figure, existing patches and holes on the left bank surface have caused instability in water level estimation along the region of interest. The box plot of the left bank (Cam-L-BL) is comparatively taller than that of the right bank (Cam-R-BL) which implies the estimated water level is spread over larger values. Moreover, the scatter plot demonstrates the major oscillations along the present flow regime.

After analyzing the initial results, the deployable setups were modified to enhance the quality of data collection. The programming code of the Arduino device (Aava) was modified to measure five different records for water level, each time it is triggered by the camera device (Beena), and transmit the average distance to the Raspberry Pi device. This modification decreased the number of noise spikes in the measured data and let better comparison between camera readings and ground truth data. The case of the camera device (Beena) was redesigned to protect the single board against rain without requiring an umbrella which makes the camera setup unstable in stormy weather and causes a decrease in the precision of measurements. Moreover, an opening is incorporated into the redesigned case to connect an external power bank to the camera setup to enhance the running time. Finally, the viewpoint of the camera was subtly shifted to the right to adjust the share of the river banks on the camera's field of view.

The results of setup deployments (on Nov 10, 2022, and Nov 11, 2022) demonstrated that setup modification has significantly enhanced the results of the left bank (Table 3). NSE improved from around 0.55 for the first three setup deployments to more than 0.80 for those deployments which were done after setup modifications. Figure 8 shows banks performances during all segments of the hydrograph and the peaks are captured by the right banklines on both deployment dates. There is no effect of noisy spikes on both camera readings and ground truth data. The right bank still underestimated the water level during the rainstorms.

6 Conclusion

This study introduced Eye of Horus, a vision-based framework for measuring water-related parameters, e.g., water level, from real-time images captured during flood events. Time-lapse images and real water level correspondences were collected by Raspberry Pi camera and Arduino HC-SR05 ultrasonic sensor, respectively. Moreover, Computer Vision and Deep Learning techniques were used for semantic segmentation of water surface within the captured images and for reprojecting the 3D point cloud

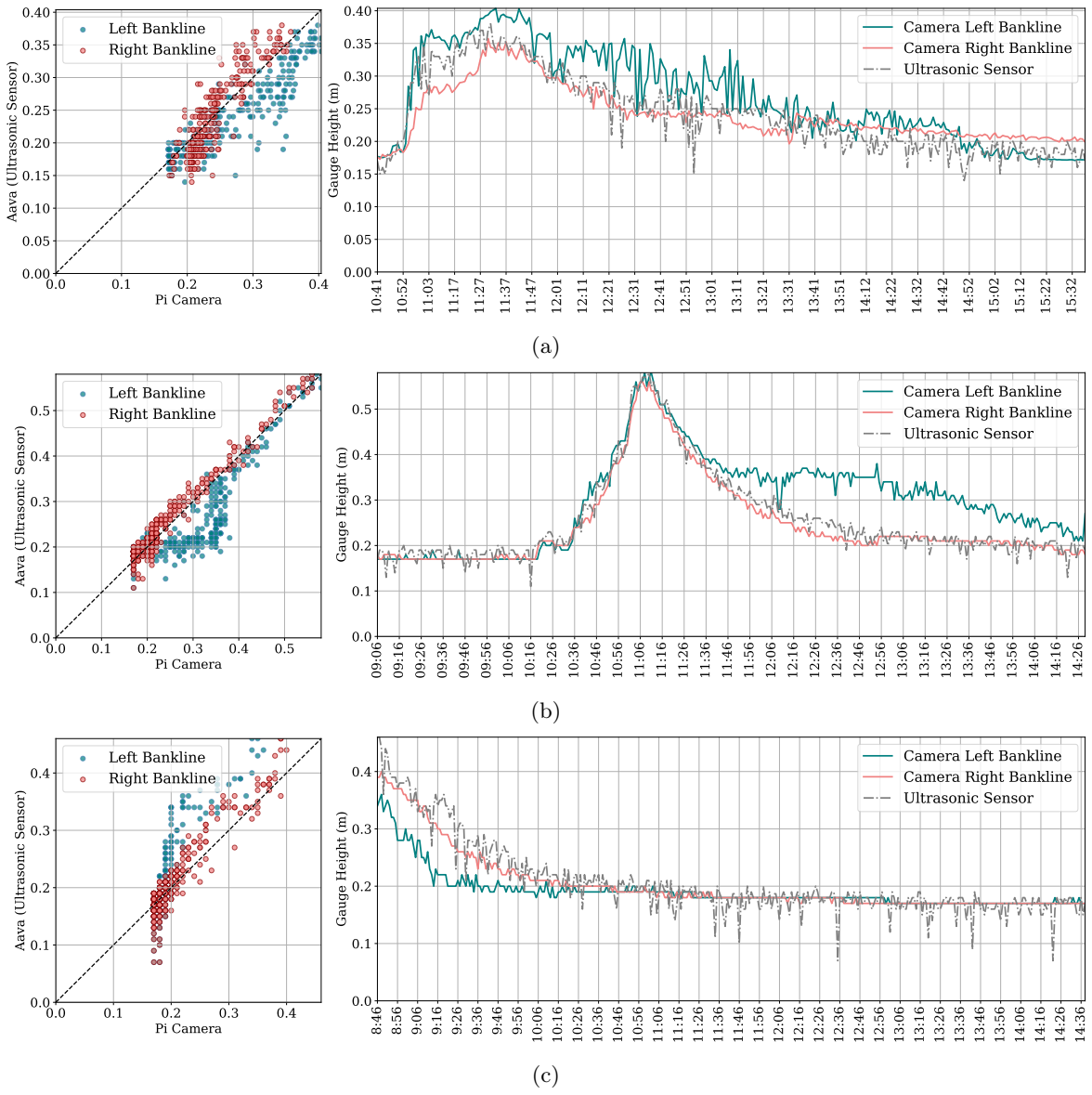


Figure 6: Scatter plot and time series plot for estimated water level by the proposed framework and measured by the ultrasonic sensor for setup deployment on (a) Aug 17, 2022 (b) Aug 19, 2022, and (c) Aug 25, 2022.

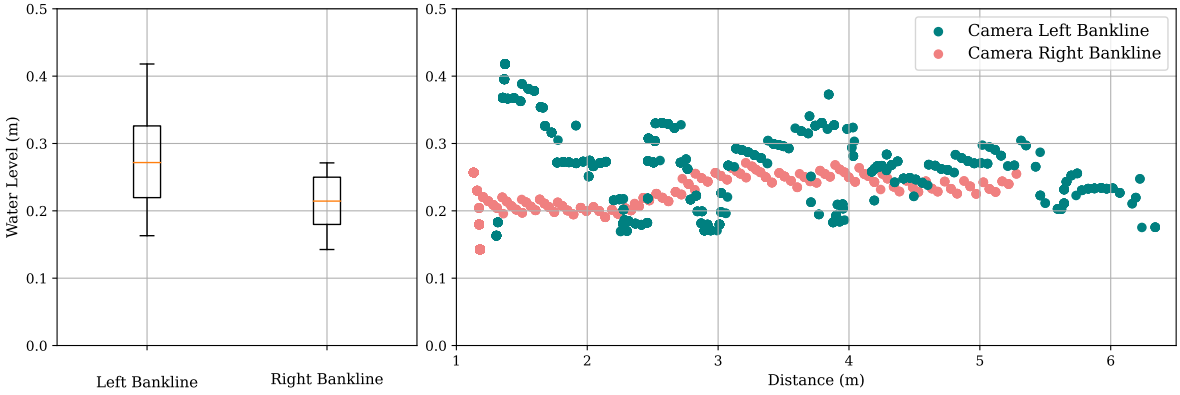
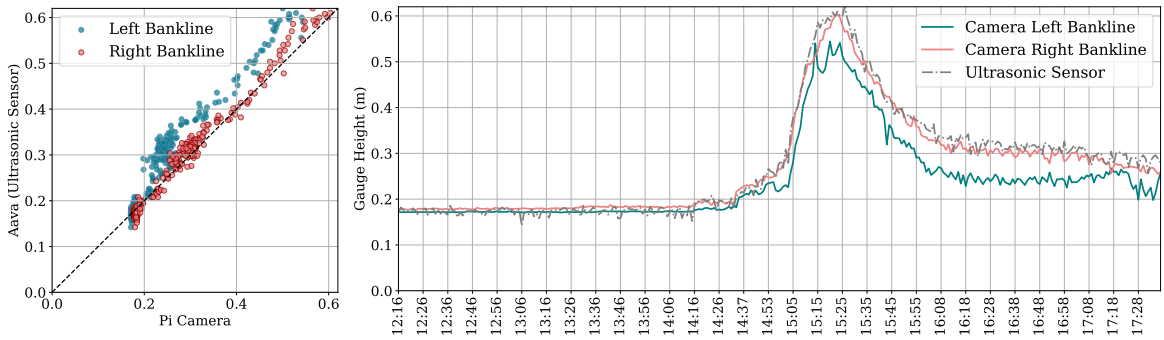
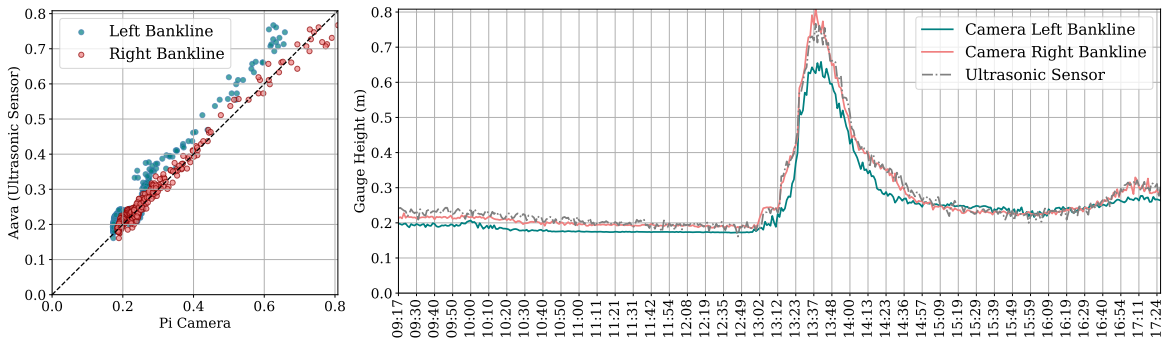


Figure 7: Water level fluctuation along both left and right banks for the flow regime for an image captured at 13:29 on Aug 19, 2022.



(a)



(b)

Figure 8: Scatter plot and time series plot for estimated water level by the proposed framework and measured by the ultrasonic sensor for setup deployment on (a) Nov 10, 2022, and (b) Nov 11, 2022.

constructed with an iPhone LiDAR scanner, on the (2D) image plane. Eventually, the K-Nearest Neighbor algorithm was used to intersect the projected (2D) point cloud with the water line pixels extracted from the output of the Deep Learning model, to find the real-world 3D coordinates.

Such a vision-based framework can be considered as a new alternative for obtaining the hydro-climate data, to attenuate the shortages and limitations which are inherently associated with the current data collection and real-time monitoring systems. For instance, modern hydrological models consider geometric properties of flow channels for estimating discharge routing parameters, stage, and eventually flood inundation maps. So, the determination of bankfull characteristics is one of the current challenges, as a majority of streams have degraded or down-cut, through natural processes or induced by civilization. The visual sensing approach is a reliable way for measuring stream depth and water velocity and determining instantaneous streamflow at bankfull stage.

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