

Identifying tree characteristics to determine the blocking effects of water conveyance for natural flood management in urban rivers

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Abstract

Plants, especially trees, provide ecological functions but may harm the flood conveyance efficiency of rivers. Understanding the impacts of tree heights, tree areas, and tree locations on flood levels is crucial for floodplain management. This study aims to present a methodology to improve the performance of hydrodynamic modeling by considering plant resistance with the goal of analyzing flood risk reduction strategies that support ecological conservation enhancement. An unmanned aerial vehicle was used to collect floodplain topography, landcover, and tree characteristic data. A modified maximum likelihood classification scheme was developed by incorporating the tree height information to improve the landcover classification. The water-blocking effect of trees, which represents the reduced flood conveyance area, was investigated by establishing tree obstructions in hydrodynamic models. Two hydrodynamic models were established with different tree obstruction setups and Manning's n values, including blocked obstructions (BOs) and conventional high n -values (Adj- n). Among the model setups, the Manning's n values of the trees remained the same as that of the soil in the BO model, in which trees were modeled as blocking obstructions. The n -values of trees were determined to be 0.022 in the BO model and refined to 0.055 in the Adj- n model after the model calibration and verification processes. The results indicated that the simulated flood levels of the BO model were very similar to those of the Adj- n model. The NSE values were 0.98 and 0.97 in the simulations of two historical typhoon events, indicating that the BO model could obtain reliable predictions without altering the n -values. The verified BO model was used to evaluate the degrees of influence of tree heights, tree coverage areas, and tree locations on flood levels. Several nature-based solutions were proposed to analyze the tradeoffs between reducing flood prevention and enhancing wetland restoration using

the verified BO model, suggesting a win-win strategy for natural river management.

KEYWORDS

blocked obstructions, floodplains, natural flood management, unmanned aerial vehicle, vegetation

1 | INTRODUCTION

Urban areas are generally located near large rivers, owing to their inherent industrial and domestic water demands. River floods have become a significant natural hazard concern in subtropical regions (Shih et al., 2019). Flooding is a natural process, but development in floodplains has increased the exposure of people, property, and infrastructure to floods (Dadson et al., 2017). Vegetation development in floodplains is conducive to enhancing ecosystem functions but may also cause adverse effects, such as reduced water conveyance and increased flood risk (Rhee et al., 2008), suggesting tradeoffs between ecological conservation and flood prevention (Shih et al., 2015).

The open-channel flow resistance of vegetated watercourses induced by viscous and pressure drag can be divided into three components: soil grain roughness, form roughness, and vegetative roughness (Wu et al., 1999). The presence of vegetation in a floodplain alters the velocity distribution and flow resistance (Yen, 2002) and has a significant effect on flood levels (Shen et al., 1994). Lee and Shih (2004) indicated that overgrowing trees such as mangroves would increase the flooding risk of urban rivers. Roughness coefficients are typically used to characterize the flow resistance in hydrodynamic model simulations. The flood routing process and mapping results are influenced by several sources of uncertainty, such as the input data and model parameters (Papaioannou et al., 2016). Manning's n value is the primary parameter used in hydrodynamic models, and the choice of this value affects the simulation accuracy and predictive ability of hydrodynamic models. Reducing the uncertainty associated with identifying Manning's n is critical in hydrodynamic and hydrologic modeling (Jain et al., 2004; Kalyanapu et al., 2009; Tung & Yen, 2005). However, estimating Manning's n is an art based on judgment and experience (Chow, 1959; Limerinos, 1970; Philips & Tadayan, 2006). Cowan (1956) developed a procedure to estimate Manning's n by summing the n values of a set of factors, and Arcement and Schneider (1989) presented guidelines for selecting n values for each of these factors. Although these methods are systematic, Kalyanapu et al. (2009) indicated that they require

extensive information on relevant vegetation and topography characteristics and may not be applicable in practice. In addition, many studies have proposed that Manning's n value varies with changing landcover, flow velocity, and water depth, signifying the challenge of determining Manning's n value (e.g., Wu et al., 1999; Yen, 2002).

Furthermore, the flexible stems and varying shapes of plant leaf mass greatly complicate the understanding of flow resistance and the corresponding roughness coefficient (Freeman et al., 2000). Flow resistance, including skin drag, shape drag, and form drag, accounts for the turbulence induced by surface properties, geometrical boundaries, obstructions, and other factors that cause energy losses (Knight et al., 2018). Form drag is caused by the shapes of objects, such as vegetation, hydraulic structures, and the surface geometry of bedforms (Galema, 2009). Many studies have investigated vegetation resistance in theoretical analyses, field surveys, and flume experiments but have scarcely considered the blocking effects of conveyance obstructions in hydrodynamic model simulations (Green, 2005; Mulahasan et al., 2017).

The primary purpose of this study is to use tree height, tree coverage, and tree location information to enhance the performances of hydrodynamic models to enable the analysis of flood risk reduction strategies that support the enhancement of ecological conservation by incorporating field surveys using unmanned aerial vehicles. In addition, the importance of environmental functions around rivers became more clear, allowing reliable predictions of the flood levels caused by vegetation that are of vital significance for flood protection and ecological conservation applications (Crowder & Diplas, 2002; Huang et al., 2012; Li et al., 2019; Nikora, 2010; Shih, 2020). Nature-based solutions (NBSs) are a popular concept in disaster management strategies and are used to build resilient and livable symbiotic environments (Ruangpan et al., 2020). The relevant applications of NBSs include the management of floodplain vegetation (Kiss et al., 2019), urban wetland rehabilitation (Gutman, 2019), and river restoration (Dixon et al., 2016). In this study, several scenario simulations were conducted and discussed using a verified BO model to view the effects of nature-based approaches to river management.

2 | MATERIALS AND METHODS

2.1 | Study area

The Erchung Floodway is located in the Taipei metropolitan area of northern Taiwan (Figure 1). The Erchung Floodway, with a length of approximately 7700 m, a width of 450–700 m, and an area of approximately 4,240,000 m², is a floodway used to divert the flood flows of the main stream of the Tanshui River. The Taipei metropolitan area, which is the largest metropolitan area in Taiwan and includes more than one-third of the total population of Taiwan, deserves special attention with regard to flood prevention measures. A large-scale flood prevention program, namely, the Taipei Flood Prevention System, was implemented in 1963 and completed in 1999 to mitigate flood disasters. The specific goal of this measure was to protect the Taipei metropolitan area against 200-year recurring floods and to reserve a levee with a 1.5-m height as a margin. The Erchung Floodway, a successful measure undertaken as part of the Taipei Flood

Prevention System, was established between 1982 and 1996 to protect residents living in the Taipei metropolitan area. However, its functions may have changed over time due to urban development, such as hydraulic facility construction, natural restoration, riparian vegetation succession, and sediment deposition (Shih et al., 2014). In recent years, the Erchung Floodway has gradually transformed into a metropolitan park. In addition to flood prevention during typhoons, the Erchung Floodway provides multiple functions, such as transportation, leisure, recreation, and ecological conservation.

Common teals *Anas crecca* are one of the most abundant duck species in the world. They breed in temperate Eurasia and migrate to the Mediterranean region and to Asia in the winter. The largest wintering population in and around the study area consisted of approximately 10,000 individuals in 2000 (Li et al., 2009), but the population was found to have significantly reduced to approximately 2500 individuals by 2007 (Fang et al., 2008). In recent years, the Tanshui River wetlands have become a significant terrestrial area due to sediment deposition, resulting in a reduction in common teals since their habitat preferences may have been negatively affected. The effect of sediment deposition also influences the flood diversion capacity of the Erchung Floodway and might increase the flood level of the Tanshui River. According to Hsu et al. (2014), creating bare mudflats and open-water areas helps attract common teals. Excessive trees may reduce the habitat quality of common teals. Therefore, the influences of various tree coverage areas and locations in the study area on the flood levels and habitat preferences of common teals were analyzed and discussed.

2.2 | Hydrodynamic modeling simulation

2.2.1 | Overview of HEC-RAS

A one-dimensional model, the Hydrologic Engineering Centers River Analysis System (HEC-RAS 5.0), was used in this study to estimate the bypass flow of the Erchung Floodway. The model was developed by the United States Army Corps of Engineers based on the energy equation shown in Equation (1) (Brunner, 2016). In this model, the essential input data requirements include the river bathymetry network (river connectivity, cross-sectional geometry, reach lengths, and energy loss coefficients), hydraulic data (upstream flow and downstream water level data), and tree data, which are represented by blocked obstructions (BOs). In addition, the conveyance obstruction function in the model allows the user to



FIGURE 1 Location map of the study area. The blue lines represent the cross-sections provided by the Water Resource Agency in Taiwan, while the red lines represent the cross-sections investigated in this study using UAV techniques

define cross-sectional areas that are permanently barred from conveying flow. The BOs decrease the flow area and add additional wetted perimeters where the water comes in contact with the obstacle. We used the tree height, coverage, and location, all of which were investigated using the UAV surveys, to transform the BO data in the model. The relevant energy equation is shown as follows:

$$Z_2 + Y_2 + \frac{\alpha_2 V_2^2}{2g} = Z_1 + Y_1 + \frac{\alpha_1 V_1^2}{2g} + h_e \quad (1)$$

where Z is the elevation of the main channel inverts, Y is the depth of the cross-sections, V is the cross-sectional average velocity, α is the velocity weighting coefficient, g is the gravitational acceleration, and h_e is the energy head loss. The energy head loss can be calculated as shown in Equation (2):

$$h_e = L\bar{S}_f + C \left| \frac{\alpha_2 V_2^2}{2g} - \frac{\alpha_1 V_1^2}{2g} \right| \quad (2)$$

where L is the discharge-weighted reach length, as shown in Equation 3, $\bar{S}_f$ is the representative friction slope between two sections and can be calculated by applying Manning's formula, C is the expansion or contraction loss coefficient, and α_1 and α_2 represent energy correction terms. The discharge-weighted reach length is calculated as follows:

$$L = \frac{L_{lob}\bar{Q}_{lob} + L_{ch}\bar{Q}_{ch} + L_{rob}\bar{Q}_{rob}}{\bar{Q}_{lob} + \bar{Q}_{ch} + \bar{Q}_{rob}} \quad (3)$$

where L_{lob} , L_{ch} , and L_{rob} represent the cross-sectional reach lengths specified for the flows in the left overbank, main channel, and right overbank, respectively, and $\bar{Q}_{lob}$, $\bar{Q}_{ch}$, and $\bar{Q}_{rob}$ represent the arithmetic averages of the flows between sections for the left overbank, main channel, and right overbank, respectively.

2.2.2 | Boundary conditions and roughness coefficient

In the HEC-RAS model, the cross-sectional bathymetry of the Tanshui River system in 2019 was adopted as the topography data: the upper boundary at T36A was considered for Dahan Creek, H10A for Hsindian Creek, and K11A for Keelung River. The downstream boundary is located at T00, which is the river mouth of the Tanshui River, as shown in Figure 1. An orthographic projection was adopted to consider the crossing areas where the directions of the bridges are diagonal with the main stream path. Topographical data and tree obstruction

data were collected via UAV investigations in this study to represent the primary study area, that is, Erchung Floodway.

The flood levels of two typhoon events, Krosa and Aere, were simulated to validate the model by refining the model parameters and performing an accuracy assessment. The flood control resulting from the designed NBS scenarios that consider the habitat quality of the common teal is based on the simulation analysis of the flood flow with a 200-year return period. The 200-year flood was considered our simulation scenario because it represents a flood-protection standard for the Tanshui River. The flow discharges of the 200-year floods were 13,200, 10,300, and 1500 m³/s for Dahan Creek, Hsindian Creek, and Keelung River, respectively, whereas the flood level at the river mouth, at the same 200-year recurrence standard, was 3.05 m.

In this study, steady-state flow simulations were conducted, and the water levels and water depths did not change with time in each simulation. The Manning's resistance coefficient for vegetation was estimated in conformity with the Cowan (1956) method for additive resistance. This method consists of incorporating roughness additions for various surface irregularities and vegetation. We established two models with different tree obstruction setups and Manning's n value, using BO and adjusted n -value (Adj- n) methods. In the BO model, Manning's n value of each landcover type was determined by using UAV data, and the land cover types included open water, soil grain, concrete paving, and grass. The Manning's n value of tree patches was set as that of the underlying soil type, as the roughness caused by trees was replaced by the effects of BOs. According to the recommendations of Arcement and Schneider (1989), the selected Manning's n values for the four landcover types were input to the HEC-RAS model. In the Adj- n model, the initial n value of trees was set as 0.040, and the value was refined to optimize the hydrodynamic simulation results. The n values of the other four landcover types remained constant during the model calibration and verification processes in both models. We calculated the proportion of pixels occupied by different landcover types in the area of interest, as illustrated in Figure 2. The roughness coefficients of each cross-section were obtained using an area-weighted average method, as shown in Equation (4):

$$n = \frac{\sum_{i=1}^k n_i \times p_i}{\sum_{i=1}^k p_i} \quad (4)$$

where n_i represents the roughness of a pixel and p_i indicates the number of pixels in a given landcover type. The

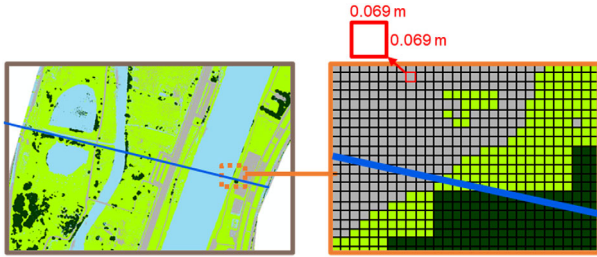


FIGURE 2 Schematic plot of determining the total roughness of a cross-section by cumulating the Manning's n value of each landcover type in the study of interest

n values of the open water, soil grain, concrete paving, and grass landcover types were set as 0.020, 0.022, 0.015, and 0.025, respectively.

2.2.3 | Conveyance obstructions

Vegetation causes changes in flow resistance and water conveyance, resulting in increased water levels compared with those in unvegetated areas (Cowan, 1956). Plants, particularly trees that stand firmly during water inundation, indicate the effects of blocked water conveyances and wetted perimeters on drag friction (Knight et al., 2018). Nepf (1999) proposed that the bulk plant drag coefficient is a function of the product of the projected plant area per unit volume and the stem diameter. Conveyance obstructions, such as buildings and healthy trees, decrease flow areas and add additional wetted perimeters where waters come into contact with the obstructions (Brunner, 2016). Conveyance obstructions define the cross-sectional areas that are permanently blocked from conveying flows. This study assumed that a firm tree was seen as rigid vegetation that blocked water conveyance. We used the conveyance obstruction function in the HEC-RAS model to create BOs on each cross-section. In the model, users can determine the heights and widths of BOs using several rectangles. This study used UAV technology to investigate the tree heights and tree coverage areas to set up the BO data in HEC-RAS. Equation (5) was used to calculate the width of the BOs. The cross-sectional vegetation blockage factor can be determined by using Equation (6) (Green, 2005). The formula of Equation (5) is shown as follows:

$$W_{BOs} = \frac{A_{tree}}{H_{tree}} \quad (5)$$

where W_{BOs} , A_{tree} , and H_{tree} represent the obstruction width, tree coverage area, and tree height, respectively. The obstruction height is the tree height. The cross-sectional blockage factor was calculated as follows:

$$B_{BOs} = \frac{A_{BOs}}{A} \quad (6)$$

where A_{BOs} and A represent the area of obstructions and the total conveyance area in a given cross-section. The values of A_{BOs} and A were determined using the simulation results of the BO model and the Adj- n model.

2.3 | Landcover and topography investigation

2.3.1 | UAV technology used to obtain a digital terrain model

Yalcin (2019) suggested that advances in remote sensing technology have led to the generation of high-resolution digital models that significantly improve the accuracy of hydrodynamic modeling. Unmanned aerial vehicle (UAV) photography has been widely utilized in several hydrological studies on topographic measurements and natural hazard monitoring (Colomina & Molina, 2014; Feng et al., 2015; Langhammer et al., 2017; Serban et al., 2016). A DJI Phantom 4 pro with a FOV84 camera mounted on a gimbal and equipped with a 24-mm DJI lens was used in this study to conduct flight operations to generate a digital surface model (DSM) and an orthophoto, as shown in Figure 3. The autonomous flights operated on 35 predefined flight paths at an altitude of 250 m above ground level with an average speed of approximately 15 m/s using a remote control connected to a smartphone. More than 1000 geotagged images covering the study area obtained forward overlapping of 80% and 60%, and side directions were also obtained. The ground sample distance of 6.9 cm/pixel represents the size of the object space corresponding to each pixel in the image.

In addition, a total of 10 ground control points (GCPs) were developed throughout the targeted mapping area for image georeferencing (Kung et al., 2011; Mendes et al., 2015). The GCPs were added to the orthophotos to perform aerial triangulation for calibration. This study uses the structure-from-motion technique proposed by Tomasi and Kanade (1993) to obtain the digital terrain model (DTM). Pix4D (Version 3.2.23) was used to convert the UAV orthophotos and point clouds to generate a digital surface model (DSM) and a digital elevation model (DEM). The DEM was employed to create the cross-sectional topographies in the HEC-RAS hydrodynamic model (blue lines in Figure 1). The underwater topography of each cross-section was obtained by interpolating the cross-sections investigated by the Water Resources Agency (WRA) (red lines in Figure 1). The heights of the ground objects calculated using the difference between

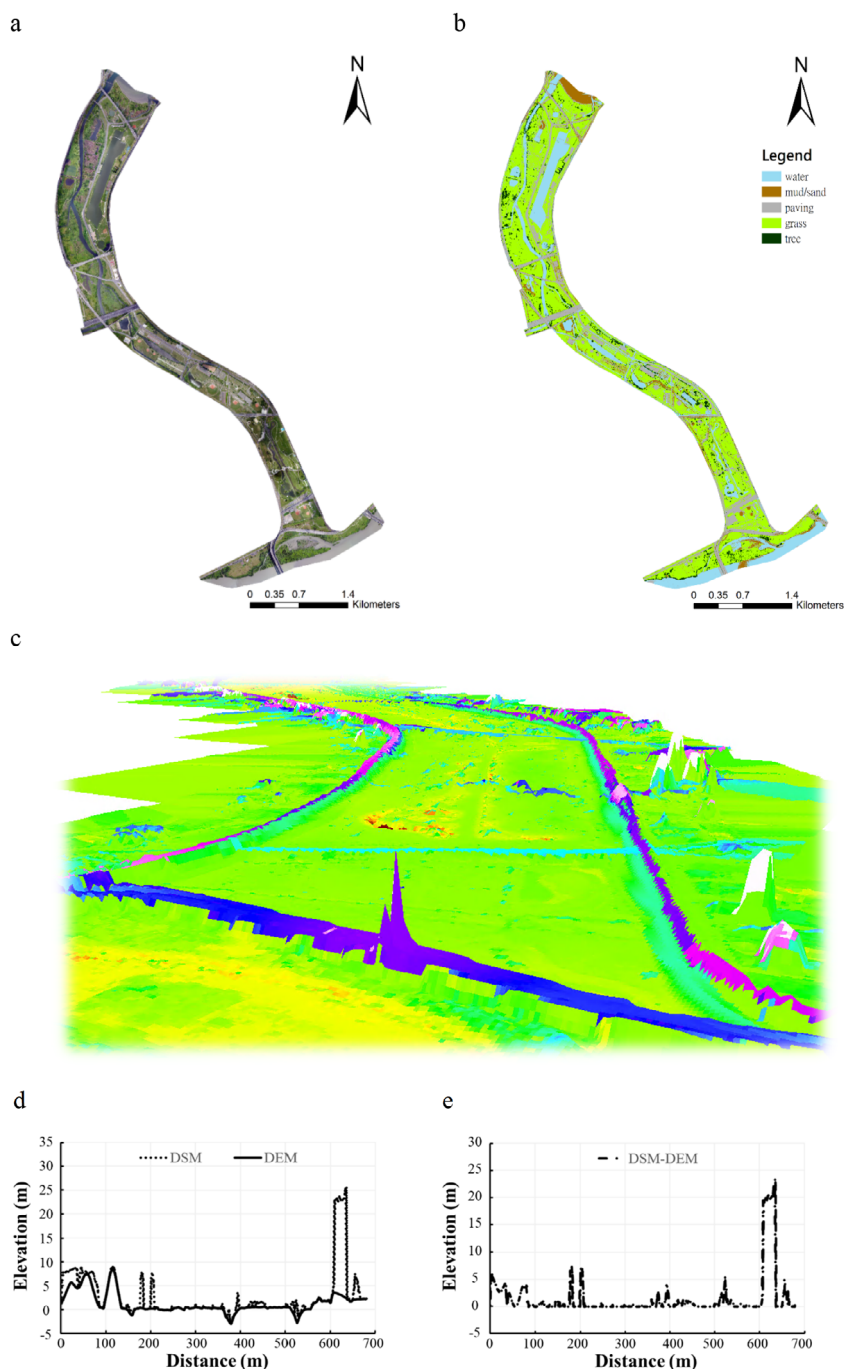


FIGURE 3 Results of the UAV surveys of this study: (a) Orthophoto, (b) landcover classification, (c) digital surface model (DSM), (d) development of a horizontal cross-section, and (e) obstructions in the HEC-RAS model

the DSM and DEM were used to obtain the BO information in HEC-RAS.

2.3.2 | Modified MLC method used to identify landcover

We developed a modified MLC method (MMLC) to integrate the maximum likelihood classification (MLC) results and tree height information to enhance the landcover interpretation. The first step is to use the

MLC method to classify four landcover types, including water, soil, paving, and plants. The landcover classification was performed on the orthophotos using the MLC tool in ArcGIS software (Wolf & Dewitt, 2000). The second step was to separate the grass and trees from the plant patches. The significant difference between trees and grass is the plant height. Through the DSM and DEM models established in this study, the plant height could be calculated. Thus, the height of plants was used as a criterion to discriminate between grass and trees.

In addition, 30 trees in different locations were investigated using a Nikon Laser Forestry Pro II laser rangefinder. The tree heights were measured from the bottom of the trunk to the top of the canopy by considering the average value of three measurements obtained at different positions. The data measured by the rangefinder were compared to verify the accuracies of the tree heights calculated by the terrain models obtained from the UAV surveys.

2.4 | Evaluation of model performance

2.4.1 | Landcover classification

McNemar's test is a nonparametric statistical test used for paired comparisons; this test was also used in this study to compare the performances of the MMLC and MLC results (McNemar, 1947). In addition, an error matrix was developed in a specific table layout to assess the performance of the MMLC method according to the suggestion of Lillesand et al. (2004). The evaluation of the error matrix reveals the tree-height benchmark for the best MMLC classification. Each row of the matrix represents the instances within a predicted class, and each column represents the instances in an actual class (Stehman, 1997). The user's accuracy (UA), overall accuracy (OA), and Kappa coefficient (KA), which were calculated from the error matrix, were used in the accuracy assessment of the georeferenced data. The UA indicates the percentage of classification results that are identical to known features and is calculated by considering the total number of correct classifications for a particular class and dividing it by the row total, as shown in Equation (7). The OA represents the exact percentages of all categories in the error matrix, as shown in Equation (8). The KA is generated from a statistical test and is used to evaluate the accuracy of a classification, as shown in Equation (9). The value of the KA is between -1 and 1 , and a value closer to 1 indicates a higher classification accuracy. A negative KA value suggests that the classification accuracy is significantly worse than random results (Foody, 1992). The three equations can be expressed as follows:

$$UA_j = \frac{N_{jj}}{N_{+j}} \times 100\% \quad (7)$$

$$OA = \left(\frac{1}{N} \sum_{i=1}^M N_{ii} \right) \times 100\% \quad (8)$$

$$KA = \left[\frac{\left(N \sum_{i=1}^M N_{ii} \right) - \left(\sum_{i=1}^M N_{i+} N_{+i} \right)}{N^2 - \left(\sum_{i=1}^M N_{i+} N_{+i} \right)} \right] \quad (9)$$

where N and M represent the total cell probability and the total number of land cover types, respectively, and N_{i+} , N_{+j} , and N_{ij} indicate the row and marginal column proportions and the individual cell probability of the error matrix, respectively.

2.4.2 | HEC-RAS model and tree height

The simulated water depth by HEC-RAS and the estimated tree heights from the UAV survey were compared with the measured values in terms of the Nash–Sutcliffe efficiency coefficient (NSE), as shown in Equation 10. In accordance with Ritter and Muñoz-Carpena (2013), $NSE \geq 0.90$ is classified as an excellent simulation, whereas NSE values ranging from 0.80 to 0.90 indicate a good simulation and those ranging from 0.65 to 0.80 indicate an acceptable simulation. The NSE can be calculated as follows:

$$NSE = 1 - \frac{\sum_{i=1}^N (O_i - P_i)^2}{\sum_{i=1}^N (O_i - \bar{O})^2} = 1 - \left(\frac{RMSE}{SD} \right)^2 \quad (10)$$

where N is the number of samples, O_i and P_i represent the samples (of size N) containing the observations and model estimates, respectively, $\bar{O}$ is the mean of the observed values, RMSE is the root mean square error, and SD is the standard deviation of the observations.

3 | RESULTS AND DISCUSSION

3.1 | Performances of tree height estimations and landcover type identifications

We compared the 30 tree heights measured from the rangefinder and those calculated using the DSM and DEM models built from UAV aerial photos, as illustrated in Figure 4a. The heights of the trees measured by the rangefinder were used as the observed data, and the heights of the ground objects obtained from the UAV survey were used as the estimated data. The observed and estimated tree heights (mean $\pm$ SD) were 8.38 ± 1.88 m and

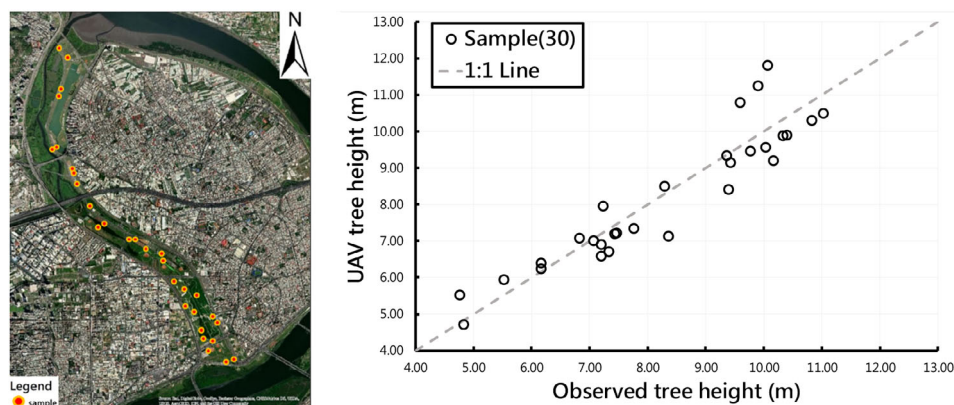


FIGURE 4 Performance of the calculated tree heights with the DSM and DEM built from the UAV survey: (a) Distribution of 30 sampling points for observing the tree heights in the field, and (b) comparison of the UAV-estimated and field-observed tree heights

8.38 ± 2.03 m, respectively, as illustrated in Figure 4b. The calculation results show that the validity coefficient, NSE, is 0.85, which represents a good estimation. Therefore, the tree heights estimated from the UAV data were employed to enhance the landcover classification performance and establish the BOs in HEC-RAS.

We investigated the real landcover types for a comparison to assess the performances of the MLC and MMLC methods. McNemar's test revealed that the interpretation accuracies of the MMLC and MLC methods were 85% and 72%, respectively, showing significant differences ($\alpha = 0.05$). The MLC differentiation between trees and grass was not ideal, as shown in Appendix Figure A1 and Table A1. The error matrix was established, and the OA, UA, and KA were calculated to acquire the best tree-height benchmark classification accuracy, as shown in Figure 5a,b. The results show that the OA of the image in which the tree heights were not added in the classification was 72.02%. However, the UA in the tree category was 21.25%, and the KA was 0.62, indicating that the classification results should be improved. We thus assessed the tree heights, ranging from 1.5 to 7.0 m, for which the MMLC method could obtain the best classification result. After adding the tree height data for the auxiliary interpretation, the OA, UA, and KA values increased, as shown in Table 1 and Tables A2–A13. When the tree heights were between 3.0 and 3.5 m, the OA and KA values were the highest, at 84.89% and 0.77, respectively. In contrast, the best UA value, 72.65%, was found at a tree height of 5.5 m. The MMLC results revealed a significant classification improvement through the incorporation of the tree heights.

We further analyzed the influences of different tree heights on the classification performance of the tree coverage ratio. Shih et al. (2014) found that the roughness in the upper reach of a floodway is the most sensitive to flood levels. Thus, we compared the results obtained for the entire area and the upstream area, as shown in Figure 5c,d. The results revealed that the best

performances when estimating the tree coverage ratios in the whole region and upstream area were obtained when the corresponding tree heights were set at 3.0 and 3.5 m. The calculated and measured tree coverage ratios were 5.60% and 5.51% across the entire area, respectively, when the tree height was set to 3.0 m. The calculated and measured tree coverage ratios were 4.42% and 4.46%, respectively, when the tree height was set to 3.5 m, representing the best landcover classification improvement.

3.2 | Hydrodynamic model development and validation

3.2.1 | Model development

The Erchung Floodway is a part of the Tanshui River system. Cross-sectional data collected from the WRA in Taiwan were used to develop the HEC-RAS model of the Tanshui River system, as shown in the red lines in Figure 1. The longitudinal distances between adjacent cross-sections were approximately 200 and 700 m, indicating the limited precision of the hydrodynamic data. Therefore, in this study, the DEM model obtained using UAV aerial photography were used to increase the number of cross-sections, as shown in the blue lines of Figure 1. The WRA cross-sections were used to interpolate the underwater topography. After the completion of this interpolation, the cross-section spacing was between 10 and 100 m, as shown in Figure 6a. The longitudinal distributions of each cross-section and the horizontal cross-sections in the HEC-RAS model are shown in Figure 6b,c. The tree height, tree width, and tree location in each section calculated by the DSM and DEM were used to create obstruction data in the HEC-RAS model, as shown in Figure 6d. As the upper limit of the number of obstructions that can be input by HEC-RAS is 20, it is necessary to organize the tree data in each cross-section. When the heights of different but adjacent trees do not

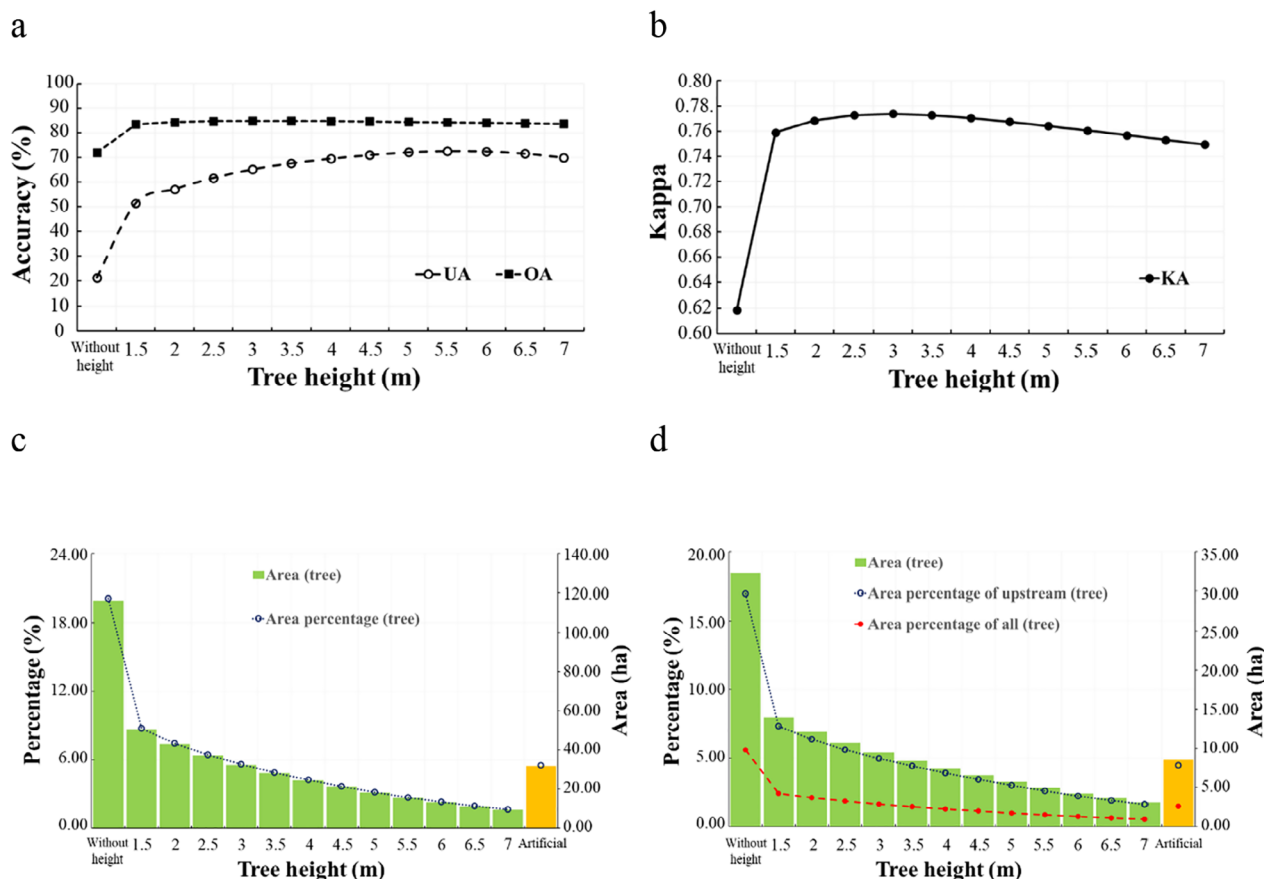


FIGURE 5 Performance of landcover classification: (a) User's accuracy (UA) and overall accuracy (OA), (b) kappa coefficient (KA), (d) tree coverage ratios of the whole region, and (e) the upstream in variant tree heights

TABLE 1 Flood diversion of Erchung Floodway in various ratios and locations of tree removal compared with that in the current situation

Scenarios	Q_b (m ³ /s) ^a	Description
BOs_100%	6546	Original situation
BOs_0%	7117	Complete removal of trees
BOs_MD	6807	Removing the trees upstream
BOs_UD	6802	Removing the trees midstream
BOs_UM	6587	Removing the trees downstream
BOs_U	6841	Leaving the trees upstream
BOs_M	6848	Leaving the trees midstream
BOs_D	7091	Leaving the trees downstream

^aFlood diversion of floodway representing flood protection capacity.

change, the trees are categorized in the same obstruction by averaging the tree heights and summing the tree widths. If the number of obstructions in the cross-section exceeds 20, the average height and the summation of the widths of the two adjacent obstructions are considered. The comprehensive cross-sections and corresponding tree

obstructions of each cross-section are presented in Appendix Figure A2.

3.2.2 | Model validation

To validate the developed HEC-RAS model with the addition of tree obstructions that can accurately reflect the hydraulic characteristics of the Erchung Floodway, the historical water levels were compared with the results of the model simulation. Typhoon Aere was used to calibrate the riverbed and floodplain roughness values in the model, while Typhoon Krosa was employed for the model verification, as shown in Figure 7. The figure demonstrates three kinds of data, namely, the measured water level (circle dots), the BO simulation results (BO model; solid line), and the simulation results obtained by adjusting the n value (Adj- n model; dotted line). The setup of the BO simulations was consistent with that described in the previous method section. Trees react as BOs, and the n values of trees were set to be the same as those of the underlying soil. In the Adj- n model, tree obstructions were not considered. In this model, we

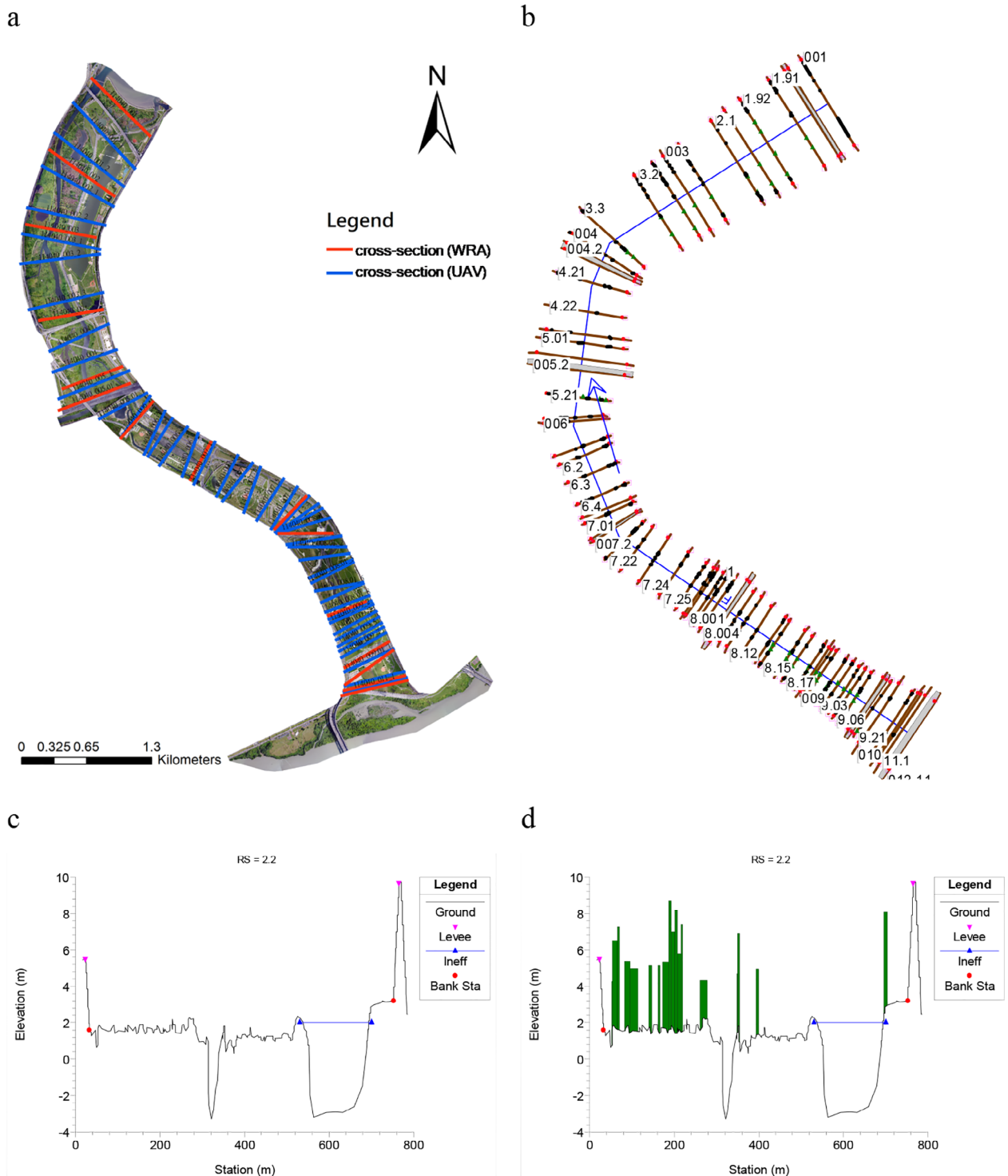


FIGURE 6 (a) Location of each cross-section, (b) schematic of allocating cross sections in HEC-RAS, (c) a horizontal cross-section without tree obstructions (Adj- n method), and (d) a horizontal cross-section is incorporating tree obstructions (BOs method)

refined the n -values of trees and retained the same n -values of the other landcover types as those used in the BO model to obtain the optimum simulation results. The average n value of each cross-section was calculated according to Equation (4). The results indicated that the

simulated results of the BO model were very similar to those of the Adj- n model, which was consistent with the HEC-RAS modeling conducted in the vegetative resistance experiments of Freeman et al. (2000) (Shih and Chen, unpublished data). The n -values of trees were

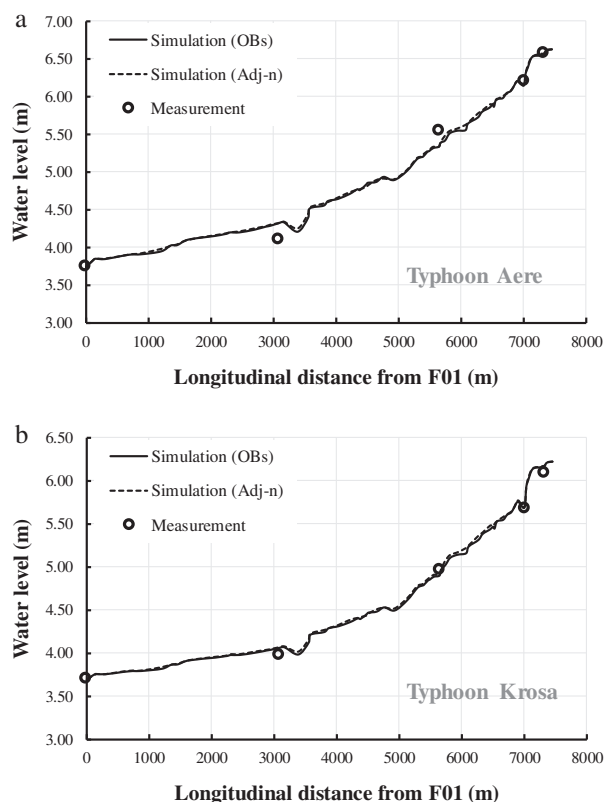


FIGURE 7 Model validations by comparing the water levels of HEC-RAS model simulation and filed measurement: (a) Typhoon Aere in 2004, (b) Typhoon Krosa in 2007

determined to be 0.022 and 0.055 in the BO model and the Adj- n model, respectively. The blockage factors ranged from 0% to 20.8% ($6.8 \pm 5.7\%$) and from 0% to 19.8% ($7.1 \pm 5.7\%$) in the simulations of Typhoons Aere and Krosa, respectively, representing the spatial hierarchy of plant coverages in the floodway. In addition, compared with the measured water levels, the NSE values obtained in the BO method simulation were 0.98 and 0.97 for Typhoons Aere and Krosa, respectively, indicating reliable simulations. The n -values were not adjusted in the calibration process or the verification process. This suggests that the BO method can be used to obtain reliable simulation results without altering the n -value. In addition, our study suggests that the flooding effect caused by trees blocking water conveyances reduces the difficulty of determining the roughness coefficient of the study area. The proposed model in which the BO method was incorporated was used as the basis for the subsequent simulation analysis of the corresponding scenarios. Nature-based solutions were proposed to discuss the tradeoffs between reducing flood diversion measures (cost) and enhancing wetland restoration measures (benefit).

The tree obstruction model presented in this study to identify flow characteristics considers the effects

of tree obstructions on the hydraulic radius (Cheng & Nguyen, 2011) and conveyance area (Mulahasan et al., 2017). Although this research was generally successful, some errors occurred in the flood level simulations. The possible sources of modeling errors result from the following factors. (1) Flow hydraulics: the backwater effects, turbulent wakes from one tree trunk on other trees, and mixing on the lateral shear layers between the channel and floodplain flows were not considered well in our model simulation, possibly leading to the underestimation of energy loss (Knight et al., 2018). Future studies may evaluate these physical processes through two- or three-dimensional model simulations. (2) Plant characteristics: Wu et al. (1999) found that the vegetation roughness decreased with increasing water depth under submerged conditions. Green (2005) proposed the cross-sectional vegetation blockage factor to represent the influence of complex plant structures on flow resistance; these plant structures included the root system, branch stiffness, leaf flexibility, and canopy extension. In this study, trees were simplified to rectangles, which may cause the wetted perimeter and friction loss to be underestimated. Future studies should consider resistance coefficients for complex tree structures, including the canopy, leaves, stems, and root systems. The interactions between the bending parts of vegetation and water surfaces might increase the resistance coefficient. (3) Landcover types: the UAV used in this study investigated the landcover types in 2019 and then converted the landcover types to the corresponding Manning's n values. However, the data used for the model calibration and verification were the flood levels recorded during Typhoon Aere in 2004 and Typhoon Krosa in 2007. After inspection, we discovered that some of the landcover types were inconsistent among 2004, 2007, and 2019, as shown in Appendix Figure A3; these inconsistencies may have contributed to the modeling errors.

3.3 | Implications of natural floodplain management in urban rivers

To determine the spaces that were sensitive to tree obstructions in the studied floodway, simulations of several scenarios were conducted, as shown in Table 1. Shih et al. (2014) found that changes in land use and increases in river roughness due to human activities affected the flood diversion capacity of a watercourse. A decrease in the flow diversity of the floodway increased the flood level of the main stream of the Tanshui River. The authors further suggested removing a portion of the vegetation or decreasing the tree heights and tree coverage. This study tested the findings and suggestions of Shih et al. (2014), who reported that the flood diversion

amount of a floodway could be increased after the vegetation is removed. We considered the 200-year return period flood level for the sensitivity analysis. In this analysis, the upper, middle and lower reaches of the floodway were cleared of trees. The differences in flood diversion were compared between the scenarios with and without tree obstructions. Under the condition that the floodway vegetation was removed entirely, the flood diversion amount increased to 571 m³/s. A sensitivity analysis of the roughness reduction effects on the upper, middle, and lower reaches of the floodway was conducted to explore the most sensitive section. The results revealed that the roughness reduction effect of the flood channel showed the following descending ranking: upstream > midstream >> downstream; this ranking is consistent with the conclusions of Shih et al. (2014). Owing to flood disasters that have intensified with rapid urbanization and climate change and threaten sustainable development, an integrated approach to flood risk management is required. Floodplain hydraulics are significant concerns, particularly in terms of various vegetation characteristics, such as the vegetation type, coverage ratio, density, height, and canopy. Compared with the difficulty of determining Manning's n value in conventional numerical simulations, our new method can quickly determine the degrees of influence of various planting locations and coverage ratios on flooding risks. This indicates the practical advantages of the method developed in this study for flood management.

In this study, several NBS scenarios were proposed in which the flood prevention ability of the studied floodway was not reduced to analyze the tradeoffs between the flood diversion capacity and the ecological benefits

associated with the habitat restoration of common teals (*A. crecca*). The habitat suitability values of common teals were calculated according to the suggestion of Hsu et al. (2014). A total of 12 sets of simulated scenarios in three categories were designed for comparison with the current situation, as shown in Table 2 and Appendix Figure A4. The sensitivity analysis conducted in this study found that removing the trees in the upper and middle reaches of the floodway could result in the most significant flood protection effects. Rhee et al. (2008) found that vegetation in rivers plays essential roles in improving and restoring the river environment and suggested that, apart from adding high esthetic value to revetments, vegetation can be used as an environmentally friendly levee protection method. Therefore, when setting up NBS strategies, we tried our best to preserve trees. The premise of retaining large trees is that they will not increase the risk of flooding but will increase ecological functions. The NBS scenario simulation results revealed that the flood diversion resulting from leaving the upstream trees was higher than that resulting from removing the upstream trees. Nevertheless, the flood diversion was the highest under the NBS2 scenario, and that under the NBS1 + 2 + 3 scenario was the lowest. The flood diversion capacities obtained in the 12 NBS plans were higher than that calculated for the current situation. This finding indicates that the proposed NBSs could satisfy the dual requirements of flood protection and ecological conservation.

Furthermore, the population of metropolitan Taipei has increased by approximately 0.4 million people over the past two decades, indicating the increased pressure of urban development on natural environments. Population

Scenarios		Q_b (m ³ /s) ^a	Description
BOs	NBS		
BOs_MD	NBS1	6708	Removing the trees upstream
	NBS2	6754	
	NBS3	6719	
	NBS1 + 2	6658	
	NBS2 + 3	6657	
	NBS1 + 2 + 3	6575	
BOs_D	NBS1	6992	Leaving the trees downstream
	NBS2	7031	
	NBS3	7006	
	NBS1 + 2	6933	
	NBS2 + 3	6933	
	NBS1 + 2 + 3	6826	

TABLE 2 Flood diversion of Erchung Floodway in various scenarios with the combination of tree removal in upstream and midstream, and the corresponding NBS for wetland restoration

^aFlood diversion of floodway representing flood protection capacity.

growth and improved living standards have created new challenges and increased the vulnerability of society and the environment to flood hazards (Dang et al., 2011). The New Taipei City Government has used the Erchung Floodway not only as a flood-prevention measure but also as a natural park by establishing recreational facilities. This kind of multifunction application should be used with caution when operating in floodplains to avoid raising the risk of flooding. As vulnerability and exposure increase, disaster risk might further increase. Our research suggests that BOs, such as hydraulic structures and trees that block water conveyance, should be minimized in the upstream floodway. If the obstacle removal planning is appropriate, we believe it may play a role in conserving biodiversity and establishing ecosystem-based disaster risk reduction approaches (Hooke, 2000).

Dadson et al. (2017) reported that it is neither practical, cost-effective, nor politically feasible to relocate communities, property, or economic activities away from areas prone to flooding. Although potential inundation maps have been used as references to set up nonstructural strategies for mitigating flood hazards (Chen et al., 2013; Murphy et al., 2003; Shih et al., 2019), structural measures are essential to decrease flooding risks. Conventional engineering methods are often criticized for significantly damaging the ecological environment, although they effectively prevent flood hazards. The natural stabilizing functions of the environment have long been neglected by humans, causing ecosystems to shrink, weaken, or disappear. Our study suggests a practical reference regarding alternative options for initiating or revising the natural flood management of an urban river, as indicated by Dadson et al. (2017) and Sanjou et al. (2018). The approach provided in this study is suggested for inclusion in enhancing flood inundation maps (Shih et al., 2019) and real-time flood inundation predictions (Ouyang, 2018); the incorporation of this novel approach could strengthen the resilience to flooding hazards in urban areas.

4 | CONCLUSION

This research examines the landcover types and tree blocking effects that impact river flood levels using numerical model simulations by incorporating UAV surveys. We conducted a UAV survey of the Erchung Floodway to collect high-resolution orthophotos and a georeferenced DSM and DEM. The tree heights were calculated and included in the MMLC methodology to improve the performance of the landcover classification. The bathymetry obtained from the DEM data and the BOs obtained from the tree data in each cross-section were used to establish the hydrodynamic model to simulate the flood levels and flood diversion

capacity of the Erchung Floodway. After considering the decreased conveyance area effect resulting from the presence of trees, the Manning's n value of the tree patches was significantly reduced from 0.055 to 0.022. We suggest that the method described herein can help determine a suitable n -value for trees in practical simulations using hydrodynamic models. The riverbed roughness set by the HEC-RAS model with the addition of BOs could accurately reflect the flow characteristics of the floodway. When the floodway trees were wholly removed, the amount of flood diversion increased significantly, indicating an opportunity for the wetland restoration of duck habitats. Future studies should consider the resistance coefficients of complex tree structures, as the interactions between the bending parts of vegetation and water surfaces might increase the value of the resistance coefficient.

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CONFLICT OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY STATEMENT

Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

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SUPPORTING INFORMATION

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