

# Supporting Information for “Discontinuity in fluvial plastic transport increased by floating vegetation”

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## Supporting Information 1: Extended method

### UAV surveys

We used the DJI Phantom 3 UAV, which comes with a FC6310 camera, equipped with a 1/2.3 inch CMOS sensor. The sensor has a maximum resolution of 12.76 megapixels and a camera resolution of 2992 x 3992 pixels. The UAV operated automatically, from take-off to landing. The programming was done with the Drone Harmony app. All images were captured at nadir, i.e. perpendicular ( $90^\circ \pm 0.02^\circ$ ) to the direction of the flight, to facilitate surface calculations. Each flight lasted approximately ten minutes. The UAV imagery analysis involved coverage detection of hyacinths. The pixel area had to be converted to real-ground area, by calculating the ground sampling distance ( $d_g$ )

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[m/pixels], as follows:

$$d_g = \frac{S_w \cdot H_f}{F_l \cdot w_i} \quad (1)$$

Here,  $S_w$  is the sensor width of the camera [m],  $H_f$  is the flight height [m],  $F_l$  is the focal length of the camera [m] and  $w_i$  is the image width [pixels]. All variables as the camera used did not change and the flight height was set at 10 m. A  $d_g$  value of  $3.8 \cdot 10^{-3}$  m/pixel was found.

### Hyacinth and plastic detection with UAV imagery analysis

In this section, we detail the processing steps taken for both hyacinth and plastic detection (Fig. S1). The choice in the RGB threshold values was done by trial and errors over a subset of the imagery dataset. For the hyacinth detection, the same threshold values were applied for all the analyzed images. For the detection of plastic, changes in brightness between images did not allow to use the same threshold values for the entire dataset. A few combinations were therefore retained and tested over batches of images (corresponding usually to the same measurement day). The best fitting threshold values were retained for the batch of images analyzed. For hyacinth detection, images were then blurred with a Gaussian filter, to reduce noise. Noise in hyacinth detection is the result of the configuration of patches. In general, patches were relatively loose (with gaps and holes in-between) with highly irregular edges. Various filter sizes were tested (see Sensitivity analysis in the Validation subsection). Ultimately, a filter size of  $13 \times 13$  pixels was retained for the hyacinth detection. No Gaussian blurring was necessary for the detection of plastic items, as the target objects are of relatively small size and the detection approach sought to maximize edge detection from the background elements rather than reduce noise. For hyacinth detection, a dilate operation was necessary to reduce unnec-

essary details at the edges of patches. A final kernel size of  $17 \times 17$  pixels was selected after trial and errors through visual inspection. A fill in (e.g.: binary closing) operation was performed for both detection approaches. This allows to fill in small gaps within the detected objects of interest. The closing is applied around a circle of a specified diameter [in pixels]. A diameter of 10 pixels was chosen for both hyacinth and plastic detection.

### **Sun glint and false positives with plastic detection**

No recurring distinct shapes of sun glints that could be of use to automatically filter these areas out were recognized throughout the entire UAV imagery dataset. We do not deemed feasible therefore to implement an automatic detection of sun glint and opted for manual removal of sun glint affected area, using a simple cropping operation. The cropping was done by batch of images. In images taken during the same UAV flight and same overpass direction, the area covered by sun glint was generally located in the same region of the images.

## **Validation**

### **Sensitivity analysis for hyacinth detection**

We explored the sensitivity of the output variables for hyacinth abundance [hyacinth coverage and count of patches] to variations in input parameters for the three morphological operations performed (Gaussian blur, dilate and fill-in operations). The sensitivity analysis was performed over a representative subset of the imagery dataset ( $n = 156$  images, 4% of the total number of images analyzed). We performed a Mood's median test to compare the median of the two datasets. The alpha risk value was set at 0.05. We found a  $p\text{-value} > 0.05$  ( $p\text{-value}=0.11$ ), indicating that the null hypothesis is

confirmed and no significant difference can be assumed between the two sample populations.

For each morphological parameter, we calculated the change in output values for the count of patches and mean and median coverage area [%], based on changes in input parameters [%]. Changes in input parameters were computed for approximately -50, -30, -10, 10, 30 and 50%. Given that kernel sizes have to be odd numbers, small deviations from the above-mentioned changes in input were sometimes necessary to fulfill this requirement. Ultimately, we expressed the sensitivity in terms of slope factor [%], calculated as the ratio between the change of output and the change of input parameters:

$$s = \frac{c_o}{c_i} \quad (2)$$

Here,  $c_o$  is the change in output parameter and  $c_i$  in input parameter. The sensitivity analysis results (Table S1) show that the dilate parameter is the most sensitive, with a higher dilate kernel leading to a lower number of patches and higher hyacinth coverage.

### Assessment of plastic detection

We assessed the accuracy of our detection approach of floating plastic items by manually labelling items on a subset of our dataset ( $n = 273$ , 10% of the image dataset used for plastic detection). This validation set of images was selected randomly, using the sample function in Python. We again performed a Mood's median test to compare the median of the two datasets and test whether the validation set can be considered representative of the entire imagery dataset. We found a p-value  $> 0.05$  (p-value=0.22), indicating that the null hypothesis is confirmed and no significant difference can be assumed between the two sample populations.

We manually identified and counted all floating items, irrespective of their size, on the validation set. An accuracy ratio [%]  $a_r$  was computed for each image, as follows:

$$a_r = 100\% - \frac{|c_d - c_m|}{c_m} \cdot 100\% \quad (3)$$

Here,  $c_d$  is the total number of floating items detected with the detection approach on a given image and  $c_m$  the total number of floating items manually labelled. The overall accuracy ratio [%] was computed as the mean of accuracy ratios per image. We found an overall accuracy ratio of 75%. The number of floating items was found to be exactly the same between the validation and our detection approaches for 52% of the images ( $n = 141$ ). For 37% of the images ( $n = 102$ ), the detection approach underestimated the number of floating items when compared with the manual labelling. Only for a minority of the images (11%,  $n = 31$ ) the detection approach overestimated the number of floating plastic items.

## Supporting Information 2: Rainfall and freshwater discharge at the Saigon river

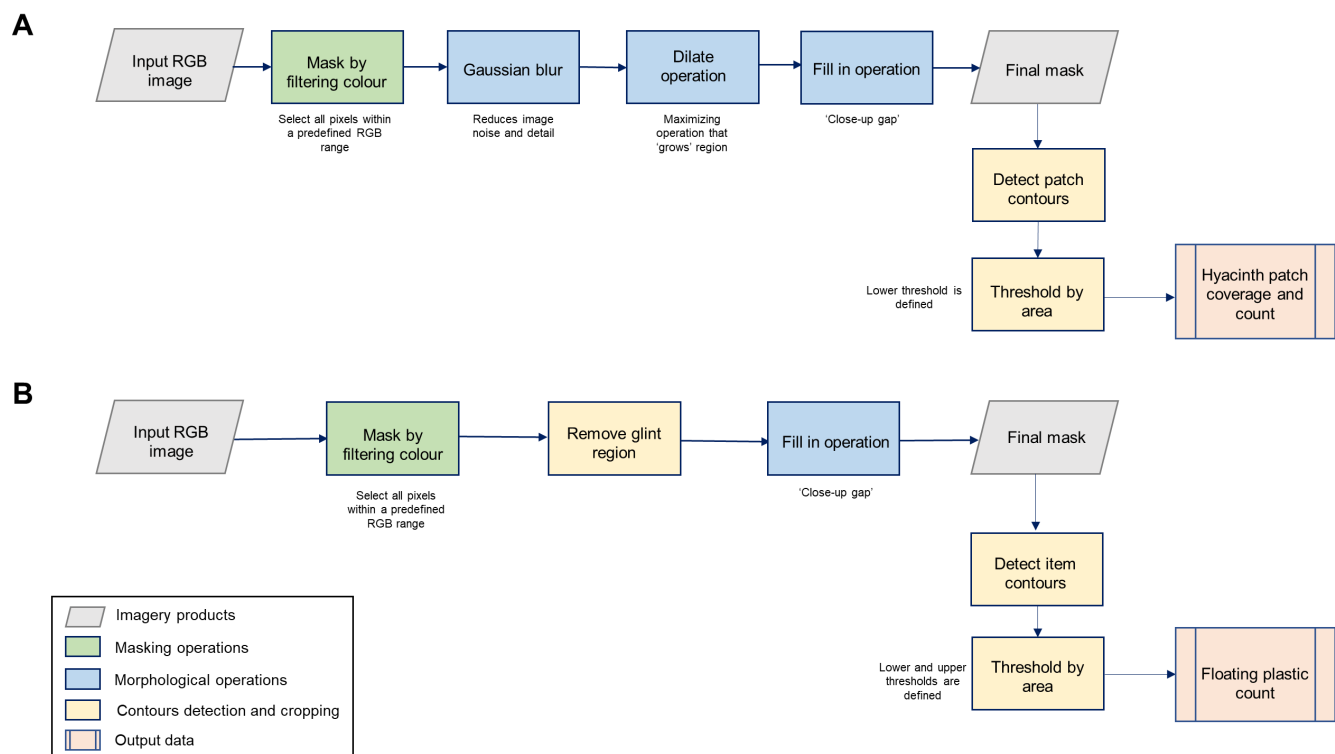


Figure S1: Processing steps to detect: A. Hyacinth patches and B. Floating plastic items.

Table S1: Sensitivity analysis for input parameters (morphological operations) in hyacinth detection on UAV images. This table reports the slope factor  $s$ , expressed in %.

	Dilate	Gaussian	Closing
Hyacinth patch	-54	-21	-5
Mean hyacinth coverage	55	25	4
Median hyacinth coverage	64	28	12

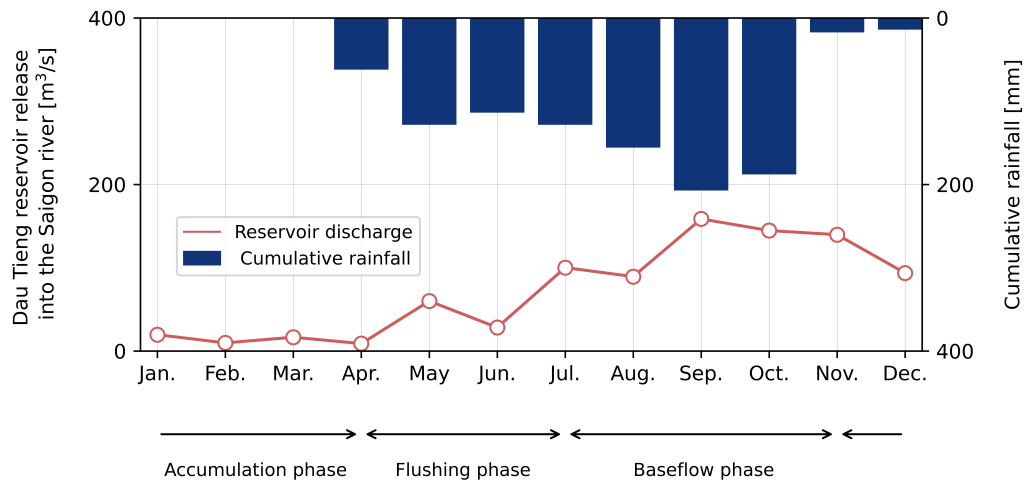


Figure S2: Monthly rainfall and freshwater discharge at the Saigon river, for the year 2021. The rainfall data was monitored at the Mc ãnh Chi station in District 1, Ho Chi Minh City. The freshwater discharge (mean values) from the Dau Tieng reservoir into the Saigon river was measured at the Tây Ninh station. The three phases indicated refer to plastic transport/hyacinth coverage phases, as conceptualized in section 4.2.