A Generalized Tool for Wave-by-Wave Estimation of Nearshore Wave Breaking Dissipation from Optical Imagery

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Wave breaking is one of the most relevant forcing mechanisms on the nearshore, which is strongly related to its dissipation (Holman and Haller, 2013). Its quantification from direct data synoptically over large domains is difficult, and remote sensing systems may add into this regard.

However, the problem is compounded because estimating dissipation on a wave-by-wave basis requires the coupling of two largely independent steps. First, the identification of the breaking portion of the wave, and next, the use of a proper dissipation model that can use some of the parameters provided by the remote sensing platform. Finally, there is the problem of how to validate these results.

The first two steps were tested by Diaz et al. (2018), using as input for the wave breaking identification prior results based on sensor fusion. These were coupled with the model by Duncan (1981), which uses as input geometrical parameters that are easily obtainable from remote sensing platforms once the areal coverage of breaking is estimated. While promising, these results were obtained using expensive equipment that required at least two remote sensing systems to address wave breaking identification. The use of two remote sensing systems was required to remove in conjunction, spurious signals on each sensor that otherwise are difficult to discriminate from the signal of interest.

The maturity reached by machine learning algorithms, has allowed its application to the nearshore environment to estimate several wave parameters. Among recent work, Sáez et al. (2021) trained and validated a Convolutional Neural Network (CNN) to detect wave breaking based solely on optical images, thereby removing the need to use two sensors. Sáez et al. (2021) used the same baseline data as Díaz et al. (2018) to perform the training.

Yet, one of the relevant questions is whether a CNN model that was determined at a given location and under certain conditions, can be used elsewhere with similar results. Typically, it can be expected that such extrapolation would yield inaccurate results. However, it is possible to develop a process, known as transfer learning, where the network is trained incrementally using new datasets.

In this work, a novel tool for transfer learning is presented. The benefits of this application are several. First, it is designed to be used with any kind of footage, such as movies or time series of drones, that can be uploaded by the user. Next, it does not require the user to be proficient in machine learning or a large computational capacity to apply the method. The expertise and capabilities of the user in qualitatively identifying wave breaking patterns are used to provide feedback to the network regarding its performance during the training process (Human-In-The-Loop). A loop system is included so the user is presented with different network models that allow to adapt the network learning to the new environmental conditions. The result is that the previous network version, using as baseline that of Sáez et al. (2021) is continuously updated to predict wave breaking patterns over an increasing range of conditions and situations. Moreover, by incrementally improving from prior data the computing times. For instance, the full training of the network model using 1000 images required 3-4 hours (using Google Colab, GPU environment), whereas this application does it in roughly 30 seconds.

As a final step, the dissipation estimates can be an output of the new network. The model was applied in two different locations with different wave and environmental conditions and by different users.

The first example of this is shown in Fig. 1, where the model was implemented at Quintero, Valparaíso, Chile. The second example is presented in Fig. 2 which corresponds to estimation of the energy dissipation rate in Plage Rive Droite, Palavas-les-flots, France. In these figures, it is possible to see that the network segments areas of active breaking successfully and realistic energy dissipation rate fields are obtained. In both examples, panels b and c, show the energy dissipation rate decomposed in the cross-shore and along-shore component, respectively.

As mentioned, the method was developed using Google services, including Google Drive for storing the dataset and saving results, and Google Colab for executing the codes related to the method. Therefore, the method can be easily applied by any user.

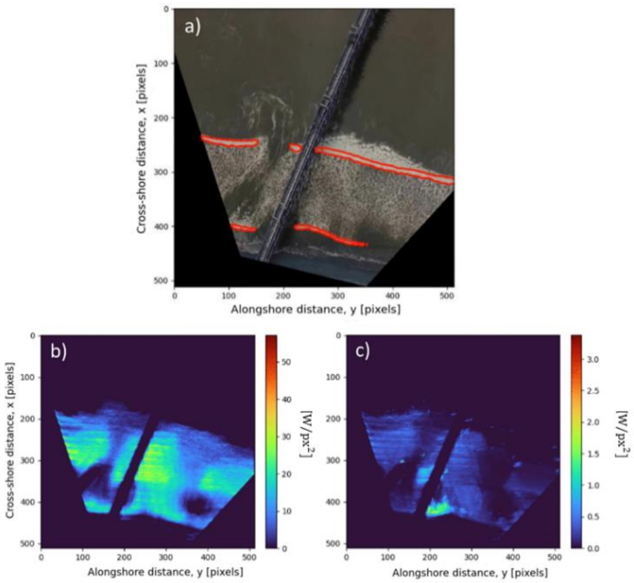

Figure 1 – a) video image and mask, b) energy dissipation rate in direction perpendicular and c) parallel to the shore at Quintero Beach, Valparaíso, Chile.

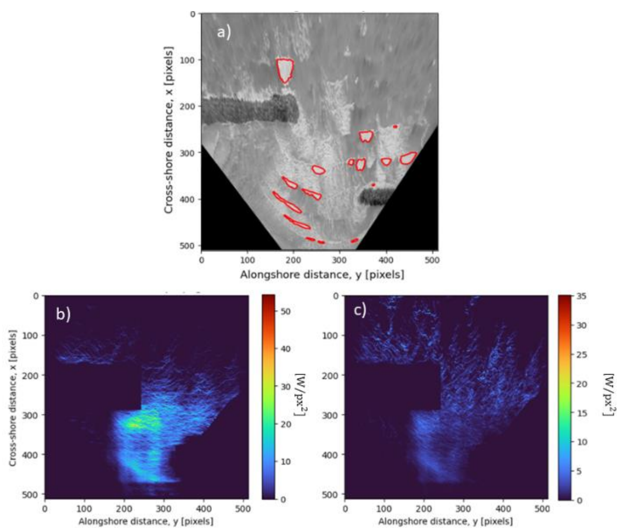

Figure 2 – a) video image and mask, b) energy dissipation rate in direction perpendicular and c) parallel to the shore at Plage rive droite, Palavas-les-flots, France.

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