BWILD: Beach seagrass Wrack Identification Labelled Dataset

Authors

Jesús Soriano-González[1]*, Elena Sánchez-García[1], Josep Oliver-Sansó[1], Jose David Pérez-Cañellas[1], Francisco Fabián Criado-Sudau[1], Lluís Gómez-Pujol[2], Àngels Fernández Mora[1]

*corresponding author: jsoriano@socib.es

Project members

The iMagine Project - “Beach Monitoring” Use Case:
Àngels Fernández-Mora[1]; Francisco Criado-Sudau[1]; Joaquín Tintoré[1]; Lluís Gómez-Pujol[2].

[1]Balearic Islands Coastal Observing and Forecasting System (SOCIB), 07121 Palma de Mallorca, Spain
[2]Earth Sciences Research Group, Department of Biology, University of Balearic Islands (UIB), Palma, Spain

Overview

BWILD is a dataset tailored to train Artificial Intelligence (AI) applications dedicated to automating beach wrack detection in RGB images. It includes oblique RGB images captured by SIRENA beach video-monitoring systems, along with corresponding annotations in various formats (PNG, XML, JSON). BWILD encompasses data from two microtidal sandy beaches in the Balearic Islands, Spain. The dataset consists of images with varying fields of view (9 cameras), beach wrack abundance, degrees of occupation, and diverse meteoceanic and lighting conditions. The annotations categorise image pixels into five classes: i) Landwards, ii) Seawards, iii) Diffuse wrack, iv) Intermediate wrack, and v) Dense wrack.

1. Content

1.1 Beach wracks

Detached seagrass material may form large litter patches in the surf zone and huge litter banks on adjacent beaches depending on factors like wave exposure, current patterns, and sea level (Gómez-Pujol *et al.*, 2013). Such accumulations are generally referred to as beach wracks (BW), and are common in many coastal areas where extensive seagrass meadows occur, either as sparse wracks or forming wedge structures of few centimetres to several metres in thickness (Fig. 2). It is important to understand the functions of BW on beach dynamics, particularly considering that their removal from sandy shore, to increase the beach exploitation, is a widely diffused practice (Simeone *et al.*, 2013) and could have a strong impact on the beach morphology, particularly on the beach face (Simeone and De Falco, 2012). In this context, beach video-monitoring systems serve as a valuable tool for observing this process on a daily or seasonal basis.

Figure 1. Variable density BW in different Balearic Islands beaches (Spain). Top: Pictures taken on the beach; Bottom: Snapshots from SIRENA beach-video monitoring systems.

1.2 SIRENA coastal video-monitoring observing system

A SIRENA system consists of a set of RGB cameras mounted at the top of buildings on the beachfront (Nieto et al., 2010). These cameras take oblique pictures of the beach (1280×960 resolution), with overlapping sights, at 7.5 FPS during the first 10 minutes of each hour in daylight hours. From these pictures, different products are generated, including snapshots, which correspond to the frame of the video at the 5th minute. In the Balearic Islands, SIRENA stations are managed by the Balearic Islands Coastal Observing and Forecasting System (SOCIB), and are mounted at the top of hotels located in front of the coastline. The present dataset includes data from the SIRENA systems operating since 2011 at Cala Millor (*clm*) and Son Bou (*snb*) beaches, located in Mallorca and Menorca islands (Balearic Islands, Spain), respectively. All latest and historical SIRENA images are available at the *Beamon app* viewer (https://apps.socib.es/beamon).

1.3 BWILD context

The current method for identifying BW from the SIRENA systems in the Balearic Islands involves image-by-image supervision. However, the vast amount of data makes it impractical to label all BW occurrences in every image. BWILD has been developed to address this challenge. Over 3000 masks have been created using oblique RGB images from *snb* and *clm* SIRENA stations. BWILD is provided as a compressed ZIP file (BWILD_v1.0.0.zip) containing RGB images and annotations. The following sections describe the components of BWILD in detail.

2. RGB images

BWILD includes oblique RGB images in PNG format, capturing *clm* and *snb* sandy beaches where SIRENA systems operate. Each station is composed of 5 cameras dedicated to beach monitoring, although the furthest-distance camera data of *snb* station (beyond 840 m) is not included in this dataset due to the complexity of identifying features in far distance pixels. Originally, SIRENA images are generated with a resolution of 1280×960 pixels. However, in BWILD, a reduced version of them is provided, presenting cropped images with a uniform resolution of 640×480 pixels. This has been done to make the annotation feasible, keeping at the same time as many different scenarios as possible (*e.g.*, time-periods, distance to camera, meteoceanic and lightning conditions). Therefore, BWILD includes cropped images from 9 different cameras (Fig. 2), in two different elevation sites (*snb:* 41.6 m*, clm*: 46.6 m above mean sea level) with varying fields of view (FOV) achieved through adjustable focal length lenses. This configuration results in each camera capturing information at different spatial scales, with larger focal lengths yielding better resolutions. For example, at the *clm* site, despite the camera's suitable elevation, focal lengths ranging from 5060 pixels (FOV=14.42°) to 1332 pixels (FOV=51.33°) for the five cameras translate to pixel resolutions of 0.2-0.7 m and 4.2-15 m in the cross-shore and long-shore footprint components, respectively, at a distance of 1 km.

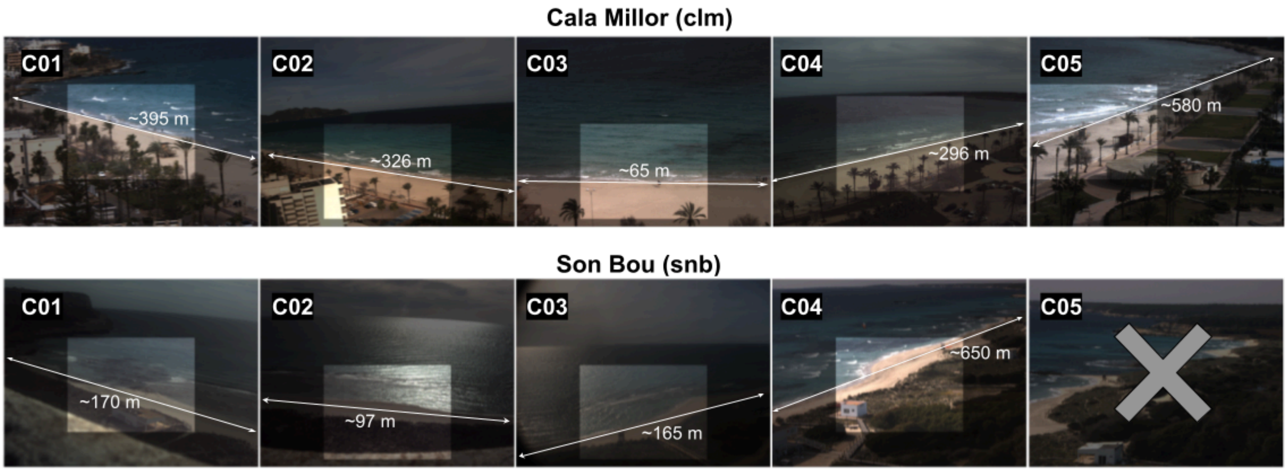

Figure 2. Snapshots from the different cameras (c0X) at *clm* and *snb* SIRENA stations. The approximate length of coastline covered by each image is shown in white. Highlighted areas correspond to the final cropped and labelled regions provided in BWILD.

SIRENA video-monitoring stations employ a standardised naming convention for the images (Fig. 3), which is maintained in the BWILD dataset enabling easy identification and location of specific images based on station and capture time, and facilitating comprehensive analysis and interpretation in further derived works.

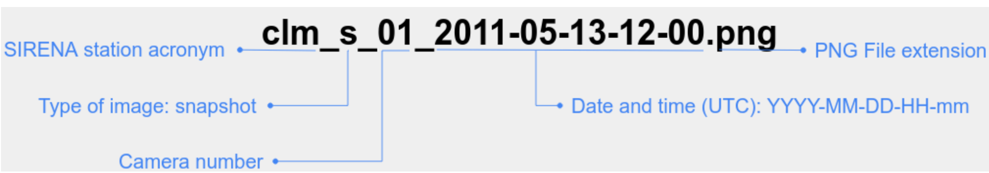

Figure 3. Naming convention structure of SIRENA images exemplified with the filename of a snapshot from *clm* station captured at 12:00 h (UTC) on 13th May 2011.

2.1 Image selection

The SIRENA repository at SOCIB includes more than 250,000 snapshots from each *clm* and *snb* stations. The goal of image selection is to minimise the volume of data requiring labelling while ensuring the dataset encompasses a comprehensive range of scenarios that AI applications will encounter in practice. To achieve this, the following steps were taken:

(i) Image screening: Filtering of invalid images including corrupted files and images with poor visibility or quality (e.g. in Fig. 4). A suite of simple Python functions was developed to assess images based on the following criteria:

- Minimum file size and readability.
- Ensure non-empty image with three channels and multiple colours.
- Evaluate brightness levels for excessive darkness.
- Assess RGB channel correlation.
- Identify images with excessive sun glint.
- Check homogeneity by comparing row variance.

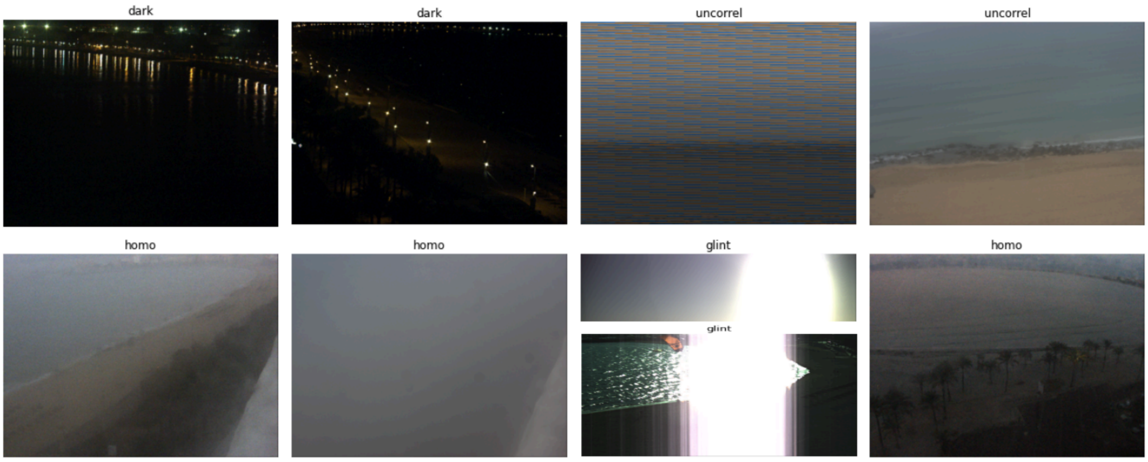

Figure 4. Examples of invalid images, including dark, homogeneous (homo), uncorrelated (uncorrel) and glinted (glint) captures.

(ii) Image clustering: With the aim of minimizing the impact of different numbers of images at various stations, the influence of image geometries (e.g., FOV, image components, and features), and the variability of external factors across years (weather, anthropic structures, etc.) on the clustering process, unsupervised classification of *clm* and *snb* images was conducted separately for each station-camera-year combination (hereafter referred to as 'cases') for the period 2011-2022. In-house Python functions were employed to preprocess the images within each 'case', determine the optimal number of clusters using statistics derived from the Silhouette method, perform k-means clustering, and generate a per-case comma-delimited file containing the paths of valid images, the cluster number assigned to each image, and the centroid distance of each image. Since all images included in each case-wise classification task were captured from the same station and camera, the lightning condition was one of the most influential factors in the clusterization (e.g. in Fig. 5).

(iii) Selection of final images: The classification results in the previous step were combined with an existing database of absence/presence of BW in *clm* and *snb* images. The database contains the date and cameras in which BW were present at noon (12:00h UTC). This database was created over time in the University of the Balearic Islands by examining daily images from various cameras in both SIRENA stations (Gómez-Pujol *et al*., 2019). Since different areas, captured by different cameras, may be more prone to BW accumulation, BW presence was prioritized over the uniformity in the number of images for different stations, cameras, and years. After the automated selection, images underwent manual screening to eliminate misclassified images from the filtering stage and were cropped as seen in Fig. 2.

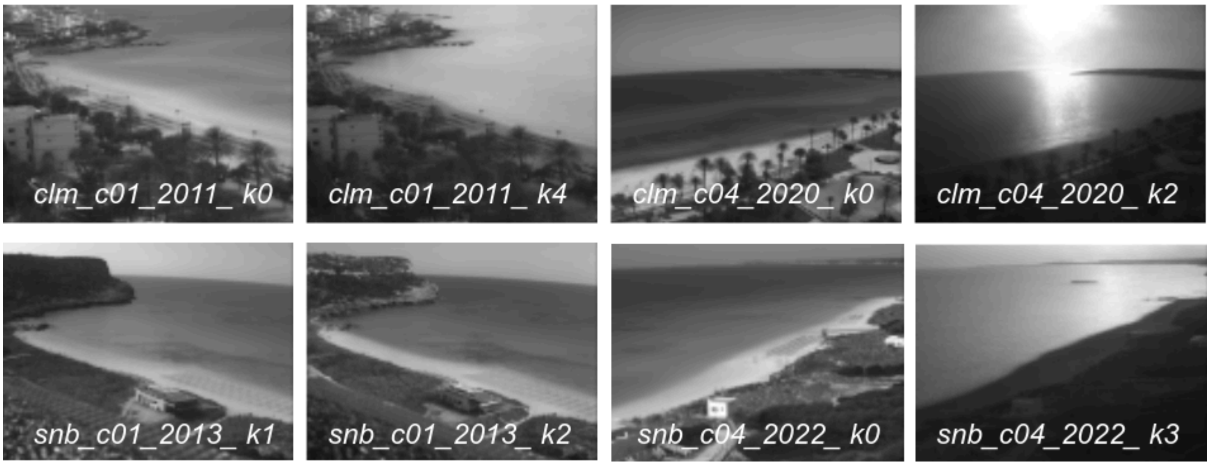

Figure 5. Examples of median grayscale images derived from different clusters in *clm* and *snb* stations. IDs in the images stand for station_camera_year_clusterID.

3. Labels and Masks

3.1 Labels

In the BWILD dataset, pixels are categorised into five labels of interest (Table 1 and Fig. 6).

Table 1. BWILD labels and description.

Label	Description
landwards*	Pixels that are towards the landside with respect to the shoreline
seawards*	Pixels that are towards the seaside with respect to the shoreline
diffuse wrack	Pixels that potentially resembled beach wracks based on colour and shape, yet the annotator could not confirm this with certainty, were denoted as ‘diffuse wrack’
Intermediate wrack	Pixels with low-density beach wracks or mixed beach wracks and sand surfaces
Dense wrack	Pixels with high-density beach wracks

*The choice of "Landwards" and "Seawards" labels in the BWILD dataset is deliberate, aiming to provide more nuanced information than the generalistic "Land" and "Water" labels. This decision recognizes that pixels on both sides of the shoreline may include diverse elements such as rock outcrops, beachgoers, buildings, and vessels, which do not neatly fit into generalistic categories.

3.2 Image labelling: Computer Vision Annotation Tool (CVAT)

The BWILD dataset has been labelled using CVAT, the Computer Vision Annotation Tool (CVAT.ai Corporation, 2023). CVAT is a free interactive video and image comprehensive annotation tool for computer vision. It can be deployed locally or used online at *https://www.cvat.ai*. CVAT emphasises user-friendliness, adaptability, and compatibility with a range of formats and tools, presenting a well-designed data management system and an intuitive labelling interface (Fig. 7) with multiple functionalities to ease navigation across the dataset, speed up labelling, and export the generated masks.

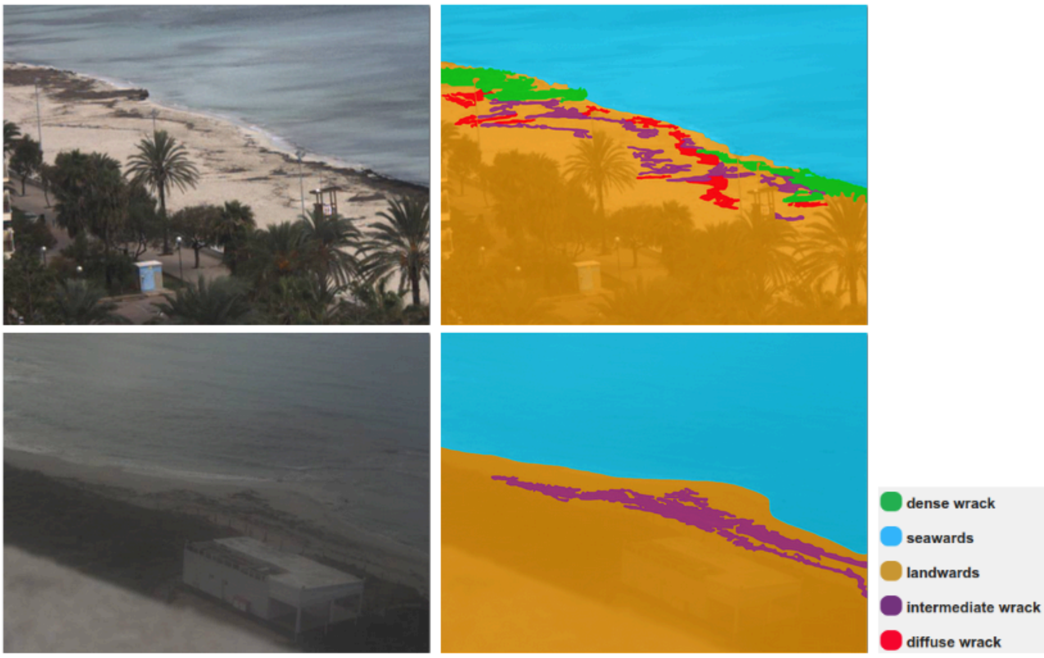

Figure 6. Examples of annotated images at *clm* (top) and *snb* (bottom).

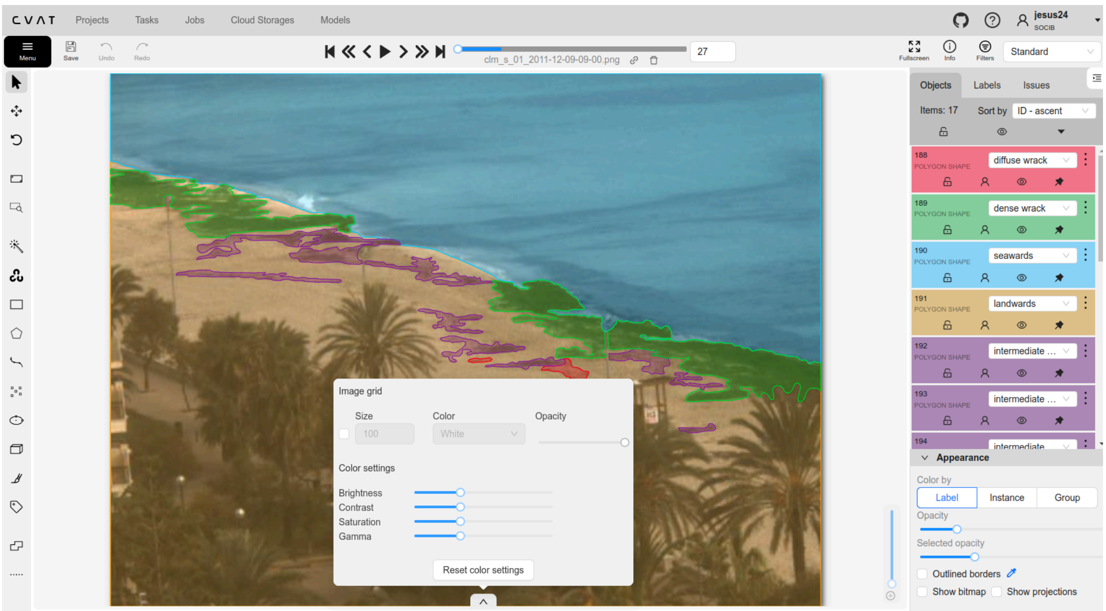

Figure 7. Main CVAT online user interface (*https://app.cvat.ai*). Top: Header and top panel; Left: Controls sidebar; Right: Objects sidebar; Center: Workspace; Bottom drop-down: Image grid and colour settings controls.

3.3 Masks

The BWILD dataset not only provides ready-to-use data but also facilitates the modification and redefinition of labels, allowing users to customize the dataset to their specific needs. To this end, images and labels in different annotation formats (described below) are provided in separate folders. Additionally, the BWILD_V1.0.0.zip file includes the label_constructor_5_classes.txt file. This file facilitates the creation of a project in CVAT preserving the label IDs and colours employed during BWILD's creation. The hierarchical structure of the main zip file is presented in Fig. 8.

CVAT for images

This is the native CVAT annotation format. It supports all CVAT annotation features, so it can be used to make data backups, and create projects by importing datasets directly to CVAT. Annotations in 'CVAT for images' format are provided in a single XML file.

Segmentation Mask

Annotation format created by CVAT engineers and used in the training of models for tasks like semantic segmentation, instance segmentation, and panoptic segmentation. Annotated images in the 'Segmentation Mask' format consist of PNG masks.

COCO

A widely-used machine learning structure for tasks involving object identification and image segmentation. The 'COCO' format includes all annotations in a single JSON file compatible with projects that employ bounding boxes or polygonal image annotations.

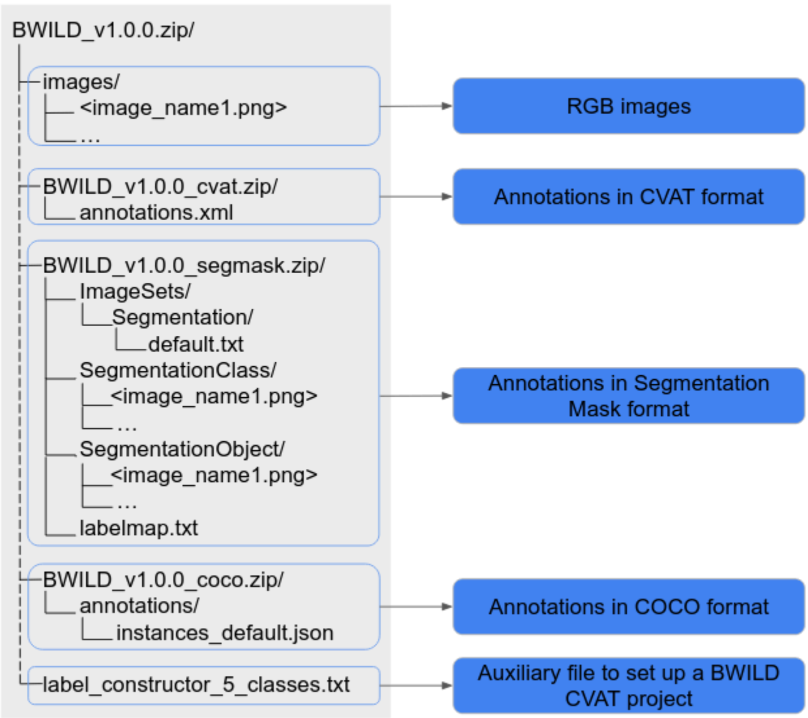

Figure 8. Hierarchical structure of the BWILD_v1.0.0.zip file containing the BWILD dataset. Readers are referred to https://docs.cvat.ai/docs/manual/advanced/formats for more information on the different annotation formats.

4. BWILD_v1.0.0 descriptors

BWILD_v1.0.0 comprises 3286 labelled images distributed unevenly across *clm* and *snb* SIRENA stations and cameras (Fig. 9 and Table 2).

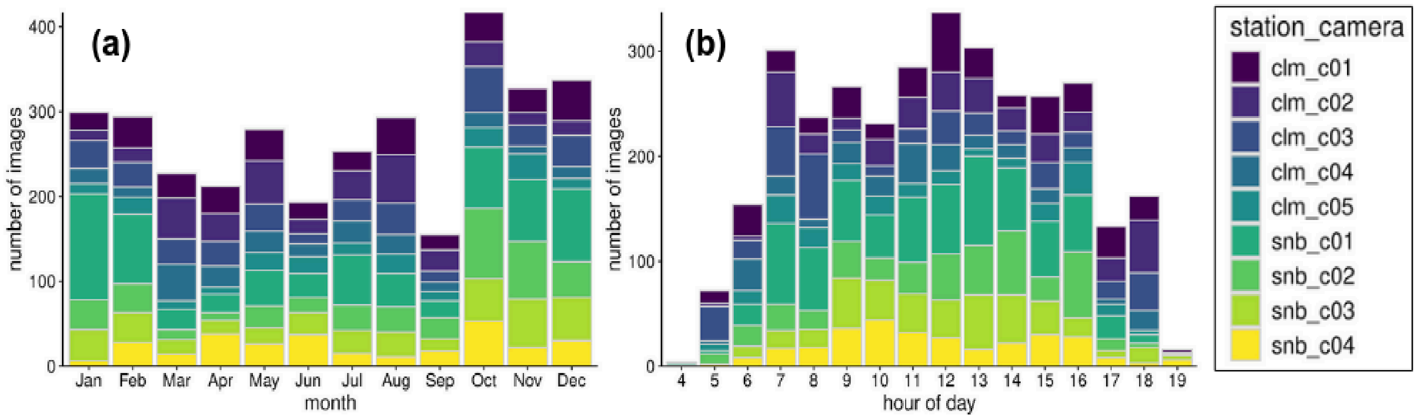

Figure 9. Temporal distribution of BWILD images across SIRENA stations and cameras: (a) monthly; (b) hourly.

Table 2. Counts by SIRENA station and camera (*station*_c0x), including the total number of images, the number of images with no wracks (NW), and the number of images including DfW (diffuse wrack), IW (intermediate wrack), or DnW (dense wrack).

***station*_camera**	**Images count**	**NW**	**DfW**	**IW**	**DnW**
*clm*_c01	372	152	154	144	183
*clm*_c02	355	141	113	90	166
*clm*_c03	356	133	62	80	179
*clm*_c04	239	79	79	108	118
*clm*_c05	204	40	57	123	106
*snb*_c01	672	59	349	461	379
snb_c02	412	71	215	231	189
*snb*_c03	378	94	158	198	190
*snb*_c04	298	93	121	146	151
Total	3286	862	1308	1581	1661

4. Usage

4.1 Licence and citation

BWILD is licensed under the Creative Commons Attribution licence (CC-BY-4.0), enabling its redistribution and reuse with proper credit. Users are required to cite the dataset according to the provided DOI and reference in the Zenodo repository (Soriano-González *et al*., 2024).

4.2 Applications and usage suggestions

The BWILD dataset stands as a resource for advancing the automation of BW detection from SIRENA cameras and analogous beach imaging systems. The diverse annotation formats offered in BWILD can be applied to a wide range of applications, including object detection and segmentation, and simplify the interaction with the dataset, making it more user-friendly. With the 'CVAT for images' format, users can seamlessly import datasets directly into the CVAT tool. This enables users tailoring the provided masks in BWILD to their specific requirements and application scenarios, and export the dataset in formats different from those delivered in the present dataset. In the same line, the widely adopted 'COCO' format has spurred the creation of open tools and codes designed to transform annotations from the 'COCO' format into other ones, easing the conversion of the dataset to be used in different applications.

4.3 Dataset limitations and relevant notes

Variable presence of BW across different beach segments and seasons impose a variable distribution of images across different SIRENA stations and cameras (Fig. 9). Users of BWILD dataset must exercise caution, recognizing this distribution variance, to ensure a nuanced interpretation of results and to address potential biases in their applications.

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iMagine

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