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AUTOMATIC SEAGRASS BANQUETTES DETECTION FROM SURVEILLANCE CAMERA IMAGES WITH DETECTRON2

ABSTRACT: SABATO G., SCARDINO G., KUSHABAHA A., CHIRIVÌ M., LUPARELLI A. & SCICCHITANO G., *Automatic seagrass banquettes detection* from surveillance camera images with Detectron2. (IT ISSN 0391-9838, 2022).

In recent years, machine learning and deep learning methodologies have gained increasing attention in various fields of research, including environmental studies. Some algorithms with deep learning can be used to identify coastal features, detect changes over time, and monitor human activities on the coast, providing important information for sustainable coastal management. This study presents the application of the Detectron2 algorithm for monitoring a beach and verifying the presence or absence of stranded seagrass banquettes from video surveillance system images. The algorithm enables quick and automatic detection of these features, providing a valuable tool for beach managers and researchers alike.

KEY WORDS: Deep Learning, Seagrass, Detection, Beach Monitoring.

RIASSUNTO: SABATO G., SCARDINO G., KUSHABAHA A., CHIRIVÌ M., LUPARELLI A. & SCICCHITANO G., *Rilevamento automatico di banquette di Posidonia con Detectron2 da immagini di telecamere di sorveglianza.* (IT ISSN 0391-9838, 2022).

Negli ultimi anni, metodologie di *machine learning* e di *deep learning* hanno acquisito sempre più attenzione in vari campi di ricerca, compresi gli studi ambientali. Nello specifico, taluni algoritmi di deep learning possono essere utilizzati per identificare alcune caratteristiche delle coste, rilevare i cambiamenti nel tempo e monitorare le attività umane nelle aree di studio, fornendo così informazioni importanti per una gestione sostenibile. Questo studio presenta l'applicazione dell'algoritmo Detectron2 per monitorare una spiaggia e verificare la presenza o l'assenza di banquette di posidonia spiaggiate, il tutto da immagini acquisite da

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This study has been developed within the activities of the RIPARTI project-titled LEUCOTEA (CUP: B83C22004070002, Scientific responsible Prof. Giovanni Scicchitano), which has been proposed by the Department of Earth and Environmental Sciences of the University of Bari "Aldo Moro" in collaboration with CETMA Centro di Ricerca Europeo di Tecnologie Design e Materiali (Dott. Italo Spada). un sistema di videosorveglianza. L'algoritmo consente una rilevazione rapida e automatica delle banquette, pertanto potrebbe risultare uno strumento prezioso sia per i gestori delle spiagge che per i ricercatori

TERMINI CHIAVE: Deep Learning, Posidonia, Rilevamento, Monito-raggio costiero.

INTRODUCTION

In this study we present a deep learning-based system for automatic seagrass banquettes detection that can analyze images from surveillance cameras. This system is capable of quickly and automatically detecting the presence or absence of seagrass banquettes on the analyzed beach, making it a versatile tool for multiple applications.

Posidonia oceanica is a species of marine phanerogam playing an important ecological role in the coastal ecosystem (Cullen-Unsworth & *alii*, 2014), providing habitat and refuge for numerous marine species, protecting the coast from erosion, and contributing to water purification (Waycott & *alii*, 2009).

The stranding of the remains of *P. oceanica* (dead leaves. rhizomes, fibrous remains) is a natural phenomenon that is observed annually on coastlines (fig. 1), especially following autumn and winter storms. The accumulation of stranded biomass, combined with sand, forms structures known as "banquettes" that can reach up to 2 meters in height and stretch for hundreds of meters, depending on the geomorphological setting of the coast (Boudouresque & alii, 2012). In general, banquettes are mainly composed of Posidonia leaves, whose ribbon-like shape and accumulation method give the mass a very compact and elastic lamellar structure, and in some beach systems also sediments and rhizomes can be important and concur in the composition of banquette (Simeone & alii, 2022). However, their elastic nature makes them temporary deposit forms that are easily deformable by the action of incident wave motion. Banquettes, along with their floating fraction, play an important role in the mechanical protection of beaches against erosion (Simeone & De Falco, 2012), hin-

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dering the action and energy of wave motion and contributing to the stability of beaches (Vacchi & alii, 2017). Moreover, they provide a direct and indirect contribution to the life of animal and plant biocenoses on the beach (Ruju & alii, 2022), as the degradation products of accumulated leaves release large amounts of essential nutrients for the flora and fauna of the entire coastal zone. However, the presence of stranded Posidonia oceanica remains pose an increasingly significant problem. While it is useful to keep them in place to hinder beach erosion and promote productivity in coastal waters, their presence in tourist beach areas can discourage bathers due to the floating residues and odors that develop during bacterial degradation processes. These aspects lead to a decrease in the tourist value of the beach itself, requiring local administrations to remove such deposits to make the beaches more enjoyable (Borrello & alii, 2010). Overall, banquettes are a double-edged sword, providing valuable ecosystem services while also posing challenges for beach management. The fate of banquettes is part of the broader issue of management of stranded biomasses and, in particular, how they should be handled. Public authorities involved have mostly resorted to temporary and emergency solutions, including expensive collection and disposal in landfills (Mossone & alii, 2019). Generally, removal is carried out before summer using mechanical means that remove large amounts of sand along with the leaves, without considering the nature of the coastline being intervened upon (De Falco & alii, 2008). This may accelerate erosion and compromise the integrity of the coastal habitat, forcing local administrations to undertake costly interventions for coastal protection and beach nourishment. Efforts should be made towards a more sustainable and integrated management of stranded biomasses, taking into account both their ecological value and the potential risks associated with their presence on tourist beaches. This requires a greater understanding of the dynamics of biomass accumulation and degradation on beaches, as well as the development of innovative and cost-effective solutions for their management and reuse (Potouroglou & alii, 2017). In the beaches that have been ascertained to be in a critical state of erosion and in protected natural areas, where cleaning and removal operations of Posidonia on the beaches are not systematically carried out as in tourist beaches, but only when necessary and almost exclusively for the removal of anthropogenic waste, mechanical means are not allowed. Therefore, these operations must be carried out using manual tools that do not significantly remove sediment (MATTM-Regioni, 2018). This approach ensures that the natural dynamics of the beach ecosystem are preserved, while still allowing for the removal of waste to maintain the environmental quality of protected areas. It also highlights the need for a case-by-case evaluation of the most appropriate management strategies for coastal areas, taking into account both ecological and socio-economic factors (Borum & *alii*, 2004).

Moreover, the accumulation of *Posidonia oceanica* washed ashore are key indicators of coastal erosion and extreme weather events such as storms or high tides.

Coastal retreat is a consequence of coastal erosion and occurs when the coastline moves inland due to land loss. This phenomenon can have significant environmental consequences, such as the loss of natural habitats, reduction of biodiversity, and increased risk of flooding. Therefore, monitoring coastal erosion and retreat is critical to prevent damage to coastal communities and the environment.

According to the latest report from ISPRA (Istituto Superiore per la protezione e Ricerca Ambientale), 841 km of coastlines in Italy are affected by erosion, accounting for 17.9% of the low-lying Italian coasts (Trigila & *alii*, 2021).

Some studies have been conducted using coastal video-monitoring (Simeone & *alii*, 2013) to assess the marine conditions related to the formation and destruction of banquettes and evaluate their role in the protection of sandy beaches (Gómez-Pujol & *alii*, 2013), but an implementation with deep learning could bring further benefits. The utilization of such a system offers the possibility of having immediate feedback on the effects of atmospheric events occurred. Additionally, it would be possible to perform analyses remotely that would normally require site visits and thereby overcoming associated logistical challenges and the easy creation of information databases.

Machine learning and deep learning are two artificial intelligence techniques that are finding multiple applications in the analysis of beaches. By processing satellite images or video recorded by surveillance cameras, for example, machine learning algorithms can be used to identify and classify various elements of the coastal landscape, such as the presence of *Posidonia oceanica* banquettes or beach morphology based on current and tidal dynamics (Scardino & *alii*, 2022). Furthermore, deep learning allows for the development of highly specialized algorithms for the detection of specific coastal landscape features, improving the accuracy and efficiency of monitoring and analysis systems (Shrestha & Mahmood, 2019). This has a positive impact on beach management, enabling a more accurate assessment of their situation and a timelier response to any emergencies.

Detectron2 is a powerful object detection platform, delevoped in Python by Meta, that has been completely revamped from the ground up. It was originally based on maskrcnn-benchmark and has since been implemented in PyTorch. The new modular design of Detectron2 makes it incredibly flexible and extensible, allowing for fast training on single or multiple GPU servers. It offers high-quality implementations of state-of-the-art object detection algorithms, including DensePose and panoptic feature pyramid networks. It also includes numerous variations of the pioneering Mask R-CNN model family (He & alii, 2017), which were also developed by FAIR. The platform's extensible design makes it easy to implement cutting-edge research projects without having to fork the entire codebase. Overall, the system is a highly capable platform that offers advanced object detection capabilities and flexibility in implementation. Its modular design and state-of-the-art algorithms make it an ideal choice for researchers and industry professionals looking to develop cutting-edge computer vision applications (Yuxin Wu & *alii*, 2019).

The analysis of beaches through the use of machine learning and deep learning techniques thus has the potential to improve knowledge of the coastal landscape and support sustainable planning and management of coastal areas, contributing to the protection of the marine environment and increasing the tourism value of beaches.



FIG. 1 - Seagrass banquette.

METHODS

Data Acquisition and Preparation

The initial step involves selecting a coastal area for study. A large number of images are necessary for comprehensive analysis. In our case, the systems were tested using images from a surveillance camera located in Torre Canne beach, in the municipality of Fasano (BR) in the southern region of Puglia, Italy (fig. 2). The images were provided by the "ex Interregional Basin Authority of Puglia". Torre Canne is a hamlet of the municipality of Fasano, located approximately 8 km from the municipal center and about 50 km from Brindisi. During the summer-autumn period, Torre Canne hosts nearly 10,000 inhabitants, while during the winter-spring period, it accommodates around 400 inhabitants. The coastal resort, with its white and fine sandy beaches, falls within the Regional Natural Park of Coastal Dunes from Torre Canne to Torre San Leonardo, established in 2006. It features a typically maritime climate, thanks to the moderating influence of the Adriatic Sea, with less pronounced seasonal temperature variations. The symbol of the hamlet is the lighthouse built in 1929, which illuminates the coastline, the cliffs, and the entire surrounding sea.

Installation

It is necessary to set up the entire Detectron2 script by creating the environment with the necessary and suitable requirements for its proper functioning. For convenience and better performance, we opted to install the system on the Google Colaboratory platform, which provides temporary high-performance workstations (Carneiro & *alii*, 2018).

Image Labeling and Data Augmentation

This step involves labeling the images to create the training dataset. It can be performed using various online annotation systems or software. There are different labeling formats, so it is important to choose the desired output



FIG. 2 - Study area Torre Canne. The webcam location is indicated by white triangle (dataset property of ex Interregional Basin Authority of Puglia).

based on the neural network used. The duration of this process varies since labeling must be manually performed by an operator, and naturally, the more images processed, the more accurate the result will be. In our case for labeling, we used MakeSense (Piotr Skalski, 2019) and CVAT (MIT License, 2018) software tools; afterwards we converted the dataset for Detectron2 using Roboflow (Dwyer B. & *alii*, 2022).

For this work, we used two datasets (tab. 1). To increase it we used augmentation techniques such as horizontal flipping, saturation adjustment, and resizing.

Training Model Process and Factors

The step involves training our dataset to enable the system to recognize and segment different areas in an image, according to classes previously annotated. The computation time for the operations depends on various factors, primarily the computing power. Since training models involves Convolutional Neural Network (CNN) and image processing steps, there will be a significant use of resources, especially the CPU or the GPU and the RAM. Moreover, it would be advisable to delegate the process not to simple CPUs but to GPUs which have specialized functional units as the "tensor core" unit, able to execute vectorial mathematical operations, hence a high degree of computing parallelization. This feature also meet the growing demand for higher performance for deep learning (Raihan & alii, 2019). In our case, the features provided by the Google Colab workstation were as follows:

- GPU: NVIDIA Tesla T4 16GB Driver Version: 525.85.12
- CUDA Version: 12.0
- RAM: 12.7 GB

The second factor that influence time and accuracy of the trained model is the setting of the hyperparameters (Yang & Shami, 2020). These are the parameters of a deep learning model that are not directly learned during the training process. Instead, they are manually selected by the user or through automatic hyperparameter search

TABLE 1 - Dataset information

Dataset N.	N. imgs	Classes n.	Class list		N. imgs w/ aug.	Train imgs Val		mgs Test imgs
1	40	5	buildings, sea, sky, sand, and posidonia		96	84 8		3 4
2	49	1	posidonia		117	102	1	0 5
TABLE 2 - Processing parameters used for the training of CNN. Elaboration Dataset N. Processed Imgs Architecture Max_Iter Eval_period Base_LR N_Class Training Time (min)								
1	1	96	mask_rcnn_R_101_FPN_3x	5000	300	0.002	5	39
2	1	96	mask_rcnn_R_101_FPN_3x	8000	500	0.001	5	~ 60
3	2	117	mask_rcnn_R_101_FPN_3x	4000	200	0.002	1	32

techniques and are used to control the behavior of the model during training and its generalization ability. Some examples of hyperparameters include the learning rate, the number of epochs, the batch size, etc. The correct choice of hyperparameters is crucial for obtaining a deep learning model that has good generalization ability and does not suffer from overfitting or underfitting (Zhang & *alii*, 2019).

All the hyperparameters used for the computations are listed in tab. 2.

Testing and Application

Detectron2 model has been trained using a deep learning technique called "transfer learning". It is necessary because training deep learning models requires a lot of computational resources, time, and suitable training data. In addition, often the available training data is limited and not representative of the variety of cases that the model may encounter in a real-world environment. Transfer learning allows the use of deep learning models that have already been trained on large amounts of data and on similar problems to the one being solved. This approach allows the knowledge gained from the pre-trained model to improve the efficiency and accuracy of the model on limited or different training data.

In practice, transfer learning involves using a pretrained deep learning model on a large dataset and updating the last layers of the model on a specific dataset of interest (Zhuang & *alii*, 2021). This approach allows the knowledge gained during the pre-training of the model to improve the model's ability to generalize to new data. The system uses a technique called instance segmentation to perform object detection and segmentation in images. It involves creating a pixel-level mask for each object in an image, allowing for more precise object boundaries and identification of overlapping objects. Both use a two-stage approach for object detection and segmentation. The first stage generates a set of candidate object regions, while the second stage refines these regions and assigns object class labels and pixel-level masks (Hafiz & Bhat, 2020; fig. 3).

These models are trained on large datasets of annotated images, allowing them to learn to recognize and segment objects with high accuracy.

During inference, the models can then be applied to new images to detect and segment objects, such as the coastal features mentioned earlier. After verifying the accuracy of our trained network, it is possible to perform detection and segmentation of selected areas (classes). By submitting an input image, the algorithm can return different colored masks applied to differentiate the various recognized objects and the percentage of accuracy of the recognition.

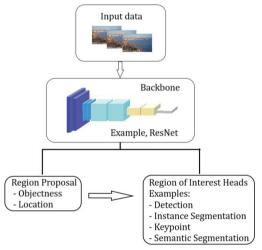


FIG. 3 - Block diagram of CNN used for the detection and segmentation of Posidonia leaves from video frames.

RESULTS AND DISCUSSION

Results indicate that, with a limited test dataset, Detectron2 is already able to perform the detection of the features of interest (figs. 4-6). Posidonia banquette recognition rates as high as 99% directly from the first test, and the processing curves show that the training of the new model has produced excellent results both in terms of accuracy and regarding false positives and false negatives (fig. 7).

We have performed several processing steps with different parameters (tab. 2), and the major differences can be highlighted by comparing the first and the last detection with the Dataset 1.

As can be seen from the outputs on the same dataset (figs. 4-5), by increasing the training parameters, the algorithm improves the precision of detection, managing to detect even smaller-sized banquettes. We conducted tests with Dataset 2 as well, which was labeled only with the Posidonia class, and the result was similar to the first (fig. 6).

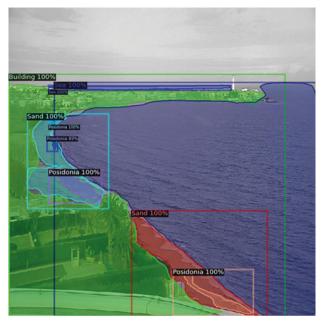


FIG. 4 - Output Detection 1.

In this case, it works with distant images always from the same perspective, which leads to a close correlation of applicability to the environment with which it was trained.

The results of detection depend on various factors, such as the image quality and the complexity of the objects present in the image. In general, convolutional neural networks have proven to be very effective in object segmentation in many applications. However, it is important to note that detection with CNNs is a computationally intensive process and requires a lot of computing power. Additionally, the CNN must be trained on a representative set of image data to achieve the best possible results. In any case, some of the benefits that can be obtained from such systems include:

- 1. Precision: CNN can identify objects in an image with high precision and create binary masks that accurately identify the area of each object.
- 2. Efficiency: thanks to the parallel processing capability of convolutional neural networks, CNN detection can be performed efficiently on large amounts of data.
- 3. Automation: CNN can automate the process of identifying and segmenting objects in an image, reducing the need for human intervention.
- 4. Customization: CNN detection can be customized to fit the specific needs of the application, for example, by training the CNN on a representative set of image data to achieve the best possible results.

However, from the evidence, it can be concluded that training the model is sufficient to implement and correlate it to the new environment. Training is necessary only once, after which it will be possible to perform detection on all the images we have inserted for recognition.

By using a temporal denomination for the images with a daily frequency, for example, it will be possible to determine the presence or absence of the banquettes and also

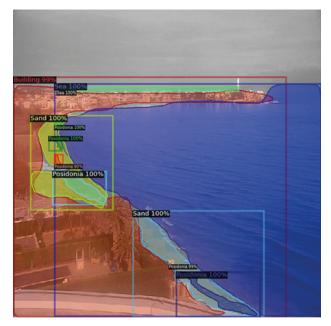
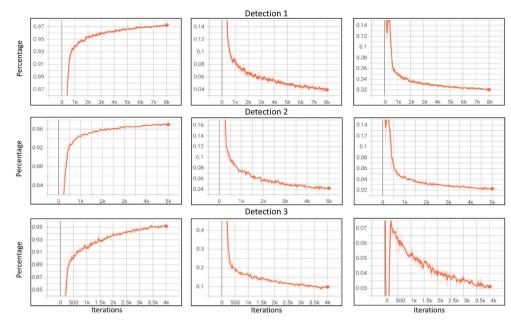


FIG. 5 - Output Detection 2.



FIG. 6 - Output Detection 3.

monitor their dynamics. One of the benefits of using systems like this is to reduce the workload on the operator who has to manually analyze and view the images and to obtain almost instantaneous results. The future development could be involved in the automatic detection of the areal coastal features, in order to quantify continuously the coastal changes (Yang & *alii*, 2020) and the accumulation of Posidonia (Paquier & *alii*, 2020; Tomasello & *alii*, 2022). Furthermore, this approach could be relevant to integrate the assessment of mass balance in the mobile coastal systems (Scardino & *alii*, 2020), in order to model the high frequency in the coastal dynamic.



All of this is in a continuous monitoring vision of a beach and evaluation of coastal erosion, marine ecosystem health, and tourist use of the areas of interest. The field of application is diverse and could be of interest especially for those institutions that deal with research, conservation, and monitoring of beaches.

CONCLUSIONS

In this study, we introduced a deep learning-based system, specifically the Detectron2 framework, for the automatic detection of *Posidonia oceanica* seagrass banquettes in surveillance camera images. Stranded remains of *Posidonia oceanica* are becoming an increasingly significant issue. While it is beneficial to leave them in place to prevent beach erosion and enhance productivity in coastal waters, their presence in tourist beach areas can deter swimmers due to the floating debris and unpleasant odors that arise during bacterial degradation. These factors contribute to a decrease in the beach's tourism appeal, forcing local authorities to remove the debris to make the beaches more enjoyable.

The findings suggest that, even with a limited test dataset, the Detectron2 algorithms are capable of accurately detecting the target features. In fact, the recognition rates for Posidonia banquettes were as high as 99% from the first test. Moreover, by increasing the training parameters, the algorithm can improve the precision of detection, allowing for the identification of even smaller-sized banquettes.

The accuracy of object detection results depends on several factors, including image quality and the complexity of objects in the image. In general, convolutional neural networks, such as those used in Detectron2, have demonstrated high effectiveness in object segmentation across various applications.

FIG. 7 - Processing curves for the training; Detection 1 with: a) Accuracy; b) False negative; c) False positive; Detection 2 with d) Accuracy; e) False negative; f) False positive; Detection 3 with g) Accuracy; h) False negative; i) False positive.

The incorporation of deep learning technology could vield even more advantages. The implementation of such a system would provide the opportunity for real-time feedback on the impacts of atmospheric events. Moreover, it would enable remote analysis that would typically require on-site visits, thereby overcoming logistical obstacles and facilitating the creation of comprehensive information databases. Utilizing systems like this could also alleviate the workload of operators who would otherwise need to manually analyze and review images, enabling almost instantaneous results. This can facilitate continuous monitoring and evaluation of coastal erosion, marine ecosystem health. and tourist use of areas of interest. The applications for this technology are diverse and could be especially beneficial for institutions involved in research, conservation, and monitoring of beaches.

REFERENCES

- BORRELLO P., DE ANGELIS R., PALLOTTINI E., SACCOMANDI F., CAPPUCCI S., AGUZZI L., CASTELLI S., PARODI V., CUNEO C., UNGARO N., SIR-CHIA B., SERENA F., MANCUSI C., BINI A., VIACAVA J. & BOVINA G. (2010) - Formazione e gestione delle banquettes di Posidonia oceanica sugli arenili. ISPRA - Istituto Superiore per la Protezione e la Ricerca Ambientale, Manuali e linee guida 55/2010.
- BORUM J., DUARTE C., KRAUSE-JENSEN D. & GREVE T.M. (2004) European seagrasses: an introduction to monitoring and management. EU project Monitoring and Managing of European Seagrasses (M&MS) EVK3-CT-2000-00044.
- BOUDOURESQUE C.F., BERNARD G., BONHOMME P., CHARBONNEL E., DI-VIACCO G., MEINESZ A., PERGENT G., PERGENT-MARTINI C., RUIT-TON S., TUNESI L. (2012) - Protection and Conservation of Posidonia oceanica Meadows. RAMOGE and RAC/SPA, Tunis, 202 pp.
- CARNEIRO T., MEDEIROS DA NOBREGA R.V., NAPOMUCENO T., BIAN G.B., DE ALBUQUERQUE V.H. & FILHO P.P.R. (2018) - Performance Analysis of Google Colaboratory as a Tool for Accelerating Deep Learning Applications. IEEE Access, 6, pp. 61677-61685. doi: 10.1109/AC-CESS.2018.2874767

- CULLEN-UNSWORTH L.C., NORDLUND L.M., PADDOCK J., BAKER S., MCK-ANZIE L.J. & UNSWORTH R.K.F. (2014) - Seagrass meadows globally as a coupled social–ecological system: Implications for human wellbeing. Marine Pollution Bulletin, 83 (2), 387-397. doi: 10.1016/j.marpolbul.2013.06.001
- DE FALCO G., SIMEONE S. & BAROLI M. (2008) Management of beachcast Posidonia oceanica seagrass on the Island of Sardinia (Italy, Western Mediterranean). Journal of Coastal Research, 24 (4C), 69-75.
- DWYER B., NELSON J., SOLAWETZ J., & Alii (2022) Roboflow (Version 1.0). [Software] Link: https://roboflow.com.
- GÓMEZ-PUJOL L., ORFILA A., ÀLVAREZ-ELLACURÌA A., TERRADOS J. & TINTORÉ J. (2013) - Posidonia oceanica beach-cast litter in Mediterranean beaches: A coastal videomonitoring study. Journal of Coastal Research, 165, 1768-1773. doi: 10.2112/SI65-299.1
- HAFIZ A.M. & BHAT G.M. (2020) A survey on instance segmentation: State of the art. International Journal of Multimedia Information Retrieval, 9 (3), 171-189. doi: 10.1007/s13735-020-00195-x
- HE K., GKIOXARI G., DOLLAR P. & GIRSHICK R. (2017) Mask R-CNN. 2017 IEEE International Conference on Computer Vision (ICCV), Venice: IEEE, 2980-2988. doi: 10.1109/ICCV.2017.322
- MATTM-Regioni (2018) Linee guida per la difesa della costa dai fenomeni di erosione e dagli effetti dei cambiamenti climatici. Versione 2018
 Documento elaborato dal Tavolo Nazionale sull'Erosione Costiera MATTM-Regioni con il coordinamento tecnico di ISPRA, 305 pp.
- MIT License (2018) CVAT Computer Video Annotation Tool. [Software] Link: https://www.cvat.ai.
- MOSSONE P., GUALA I. & SIMEONE S. (2019) Posidonia banquettes on the mediterranean beaches: To what extent do local Administrators' and Users' perceptions correspond? In: GARGIULO C. & COPPI C. (Eds.), Planning, nature and ecosystem services, 225-234. FedOAPress, Naples. doi: 10.6093/978-88-6887-054-6
- PAQUIER A.-É., LAIGRE T., BELON R., BALOUIN Y., VALENTINI N. & MUGICA J. (2020) - Video Monitoring of Posidonia oceanica Banquettes on Pocket Beaches, Northern Corsica. XVI^{èmes} Journées Nationales Génie Côtier – Génie Civil Le Havre, 682 pp. doi: 10.5150/jngcgc.2020.075
- POTOUROGLOU M., BULL J.C., KRAUSS K.W., KENNEDY H.A., FUSI M., DAFFONCHIO D., MANGORA M.M., GITHAIGA M.N., DIELE K. & HUXHAM M. (2017) - Measuring the role of seagrasses in regulating sediment surface elevation. Scientific Reports, 7 (1), 11917. doi: 10.1038/ s41598-017-12354-y
- RAIHAN M.A., GOLI N. & AAMODT T.M. (2019) Modeling Deep Learning Accelerator Enabled GPUs. 2019 IEEE International Symposium on Performance Analysis of Systems and Software (ISPASS), Madison, WI, USA: IEEE, 79-92. doi: 10.1109/ISPASS.2019.00016
- RUJU A., BUOSI C., COCO G., PORTA M., TROGU D., IBBA A. & DE MURO S. (2022) - Ecosystem services of reed and seagrass debris on a urban Mediterranean beach (Poetto, Italy). Estuarine, Coastal and Shelf Science, 271. doi: 10.1016/j.ecss.2022.107862.
- SCARDINO G., SABATIER F., SCICCHITANO G., PISCITELLI A., MILELLA M., VECCHIO A., ANZIDEI M. & MASTRONUZZI G. (2020) - Sea-level rise and shoreline changes along an open sandy coast: Case study of Gulf of Taranto, Italy. Water, 12 (5), 1414. doi: 10.3390/w12051414
- SCARDINO G., SCICCHITANO G., CHIRIVÌ M., COSTA P.J.M., LUPARELLI A. & MASTRONUZZI G. (2022) - Convolutional neural network and optical flow for the assessment of wave and tide parameters from video analysis (LEUCOTEA): An Innovative Tool for Coastal Monitoring. Remote Sensing, 14 (13), 2994. doi: 10.3390/rs14132994

- SHRESTHA A. & MAHMOOD A. (2019) Review of deep learning algorithms and architectures. IEEE Access, 7, 53040-53065. doi: 10.1109/ ACCESS.2019.2912200
- SIMEONE S. & DE FALCO G. (2012) Morphology and composition of beachcast Posidonia oceanica litter on beaches with different exposures. Geomorphology, 151-152, 224-233. doi: 10.1016/j.geomorph.2012.02.005
- SIMEONE S., DE MURO S. & DE FALCO G. (2013) Seagrass berm deposition on a Mediterranean embayed beach. Estuarine, Coastal and Shelf Science, 135, 171-181. doi: 10.1016/j.ecss.2013.10.007
- SIMEONE S., PALOMBO A.G.L., ANTOGNARELLI F., BRAMBILLA W, CONFORTI A. & DE FALCO G. (2022) Sediment budget implications from Posidonia oceanica banquette removal in a starved beach system. Water, 14, 2411. doi: 10.3390/w14152411
- SKALSKI P. (2019) Make Sense. [Software] Link: https://www.makesense.ai.
- TOMASELLO A., BOSMAN A., SIGNA G., RENDE S.F., ANDOLINA C., CIL-LUFFO G., CASSETTI F.P., MAZZOLA A., CALVO S., RANDAZZO G., SCARPATO A. & VIZZINI S. (2022) - 3D-Reconstruction of a giant Posidonia oceanica beach wrack (banquette): Sizing biomass, carbon and nutrient stocks by combining field data with high-resolution UAV photogrammetry. Frontiers in Marine Science, 9. doi: 10.3389/ fmars.2022.903138
- TRIGILA A., IADANZA C., LASTORIA B., BUSSETTINI M. & BARBANO A. (2021) - Dissesto idrogeologico in Italia: pericolosità e indicatori di rischio, Edizione 2021. ISPRA, Rapporti 356/2021
- VACCHI M., DE FALCO G., SIMEONE S., MONTEFALCONE M., MORRI C., FERRARI M. & BIANCHI C.N. (2017) - Biogeomorphology of the Mediterranean Posidonia oceanica seagrass meadows: Posidonia Oceanica meadows and coastal geomorphological processes. Earth Surface Processes and Landforms, 42 (1), 42-54. doi: 10.1002/esp.3932.
- WAYCOTT M., DUARTE C.M., CARRUTHERS T.J.B., ORTH R.J., DENNISON W.C., OLYARNIK S., CALLADINE A., FOURQUREAN J.W., HECK K.L., HUGHES A.R., KENDRICK G.A., KENWORTHY W.J., SHORT F.T. & WILLIAMS S.L. (2009) - Accelerating loss of seagrasses across the globe threatens coastal ecosystems. Proceedings of the National Academy of Sciences, 106 (30), 12377-12381. doi: 10.1073/pnas.0905620106.
- WU Y., KIRILLOV A., MASSA F., LO W.Y. & GIRSHICK R. (2019) Detectron2. [Software] Link: //github.com/facebookresearch/detectron2.
- YANG L. & SHAMI A. (2020) On hyperparameter optimization of machine learning algorithms: Theory and practice. Neurocomputing, 415, 295-316. doi: 10.1016/j.neucom.2020.07.061.
- YANG T., JIANGDE S., HONG Z., ZHANG Y., HAN Y., ZHOU R., WANG J., YANG J., TONG X. & KUC T. (2020) - Sea-land segmentation using deep learning techniques for Landsat-8 OLI Imagery. Marine Geodesy, 43, 1-25. doi: 10.1080/01490419.2020.1713266.
- ZHANG H., ZHANG L. & JIANG Y. (2019) Overfitting and underfitting analysis for deep learning based end-to-end communication systems. 2019 11th International Conference on Wireless Communications and Signal Processing (WCSP), Xi'an, China: IEEE, 1-6. doi: 10.1109/WCSP.2019.8927876.
- ZHUANG F., QI Z., DUAN K., XI D., ZHU Y., ZHU H., XIONG H. & HE Q. (2021) - A comprehensive survey on transfer learning. Proceedings of the IEEE, 109 (1), 43-76. doi: 10.1109/JPROC.2020.3004555.

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