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## Preliminary analysis of the potentialities of the Segment Anything Model (SAM) in the segmentation of Sentinel-2 imagery for water reservoir monitoring

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Water reservoirs play a crucial role in the supply of freshwater, agricultural irrigation, hydroelectric power generation, and various industrial applications. However, their existence is increasingly threatened by water stress, due to growing water demand, water pollution, and impacts of climate change, including intensified and prolonged droughts. To address this challenge, a sustainable management of water resources is essential, relying on continuous and accurate monitoring of water reservoirs. Modern Earth Observation technologies offer an effective, frequent, and costefficient means for monitoring water basins.

This study focuses on evaluating the potential of the Segment Anything Model (SAM) network (Kirillov et al., 2023), released by Meta AI in April 2023, for segmenting water reservoirs through the processing of satellite images. SAM aims to serve as a foundational segmentation model capable of generalising its segmentation abilities in a zero-shot manner across diverse tasks. Unlike traditionally supervised learning, zero-shot learning enables a model to recognize objects or features it has never seen during the training. Notably, SAM's application to satellite imagery, a type of images for which it was not specifically trained, poses a unique challenge.

In this work, SAM was applied to Sentinel-2 multispectral imagery using a "prompt click" approach, where a water-class pixel was pre-selected for each input image. Google Earth Engine facilitated temporal aggregation of Sentinel-2 images on the interest period (from 01/01/2019 to 31/12/2019), creating four RGB median images, one for each three-month period. SAM was independently applied to investigate each of these four sub-periods.

Validation was carried out in the Genoa port area to minimise the influence of temporal water level variations, which in turn produce water area changes. Indeed, the use of a port area made it possible to consider a single reference mask for the different sub-periods analysed, greatly simplifying the validation procedure.

The validation phase revealed SAM's superior performance in coastlines with regular shapes and undisturbed water (Fig. 1 and Tab. 1), while port areas, characterised by irregular shapes, higher activity and turbidity, yielded less satisfactory results (Fig. 2 and Tab. 2).

In conclusion, this study highlighted SAM's limitations, primarily related to the specific nature of satellite images, vastly different from the training data. Limitations include SAM's training on threeband (R,G,B) and 8-bit images: the first one has led to the impossibility of using all the 13 bands of Sentinel-2 multispectral images and the second one caused the need to reduce the radiometric resolution of the Sentinel-2 images (from 16 bit to 8 bit), both resulting in information loss. Despite these limitations, SAM demonstrated effective segmentation capabilities, especially in simpler and less disturbed coastal areas, comparable to water segmentation algorithms based on spectral indices. Future improvements could be achieved through fine-tuning on satellite images, and applying SAM to high-resolution ones.



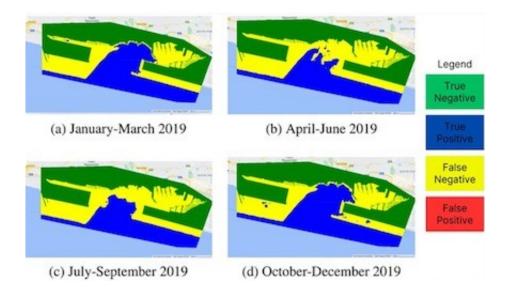
(c) July-September 2019

(d) October-December 2019

Fig.1

Temporal range	Accuracy	Precision	Recall	F1 score	IoU
January-March	0,998	0,998	0,997	0,997	0,994
April-June	0,998	0,998	0,996	0,997	0,994
July-September	0,997	0,999	0,994	0,996	0,992
October-December	0,996	1,000	0,988	0,994	0,988

Tab.1



## Fig.2

Temporal range	Accuracy	Precision	Recall	F1 score	IoU
January-March	0,731	1,000	0,540	0,702	0,540
April-June	0,669	1,000	0,434	0,606	0,434
July-September	0,672	1,000	0,439	0,610	0,439
October-December	0,730	1,000	0,538	0,700	0,538

## Tab.2

## References:

Kirillov, A., Mintun, E., Ravi, N., Mao, H., Rolland, C., Gustafson, L., Xiao, T., Whitehead, S., Berg, A. C., Lo, W.-Y. et al., 2023. Segment anything. arXiv preprint arXiv:2304.02643.