SAMSELECT: A SPECTRAL INDEX SEARCH FOR MARINE DEBRIS VISUALIZATION USING SAM

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ABSTRACT

This work proposes SAMSelect, an algorithm to obtain a salient three-channel visualization for multispectral images. We develop SAMSelect and show its use for marine scientists visually interpreting floating marine debris in Sentinel-2 imagery. These debris are notoriously difficult to visualize due to their compositional heterogeneity in medium-resolution imagery. Out of these difficulties, a visual interpretation of imagery showing marine debris remains a common practice by domain experts, who select bands and spectral indices on a case-by-case basis informed by common practices and heuristics. SAMSelect selects the band or index combination that achieves the best classification accuracy on a small annotated dataset through the Segment Anything Model. Its central assumption is that the three-channel visualization achieves the most accurate segmentation results also provide good visual information for photo-interpretation. We evaluate SAMSelect in three Sentinel-2 scenes containing generic marine debris in Accra, Ghana, and Durban, South Africa, and deployed plastic targets from the Plastic Litter Project. This reveals the potential of new previously unused band combinations (e.g., a normalized difference index of B8, B2), which demonstrate improved performance compared to literature-based indices. We describe the algorithm in this paper and provide an open-source code repository that will be helpful for domain scientists doing visual photo interpretation, especially in the marine field.

Visual inspection of multi-spectral remote sensing images is central in many disciplines where integrating domain expertise is essential to provide insight into a particular problem. In marine applications, identifying floating matter is challenging due to object heterogeneity, leading to various spectral indices tailored to specific sensors and applications. For example, algal blooms are monitored using indices like the Floating Algae Index (FAI) (Hu, 2009) and Normalized Chlorophyll Index (Mishra & Mishra, 2012), while non-photosynthetic debris is harder to detect due to mixed-pixel composition. Recently, indices such as the Floating Debris Index (FDI) (Biermann et al., 2020) and Plastic Index (Themistocleous et al., 2020) have been introduced. Popular land-indices like the Normalized Difference Vegetation Index (NDVI) are also commonly recommended for marine debris (Biermann et al., 2020), even though they lack bio-physical interpretability in the marine context.

We argue that manual trial-and-error in band visualization has influenced many recent indices. For instance, the popular FDI is a modification of the Floating Algae Index (FAI) (Hu, 2009) but lacks FAI's physical interpretation due to a different scaling factor. This highlights a broader trend of empirically select bands and indices based on photo-interpretation by domain experts. To approximate this expert-driven visual inspection, we use the deep Segment Anything Model (SAM) (Kirillov et al., 2023), wich segments objects-of-interest. SAMSelect then selects the best visualization based on the annotations provided.

1 METHOD

Process. To identify optimal visualizations for marine debris detection, we developed SAMSelect, an automated algorithm that leverages the Segment Anything Model (SAM) (Kirillov et al., 2023)

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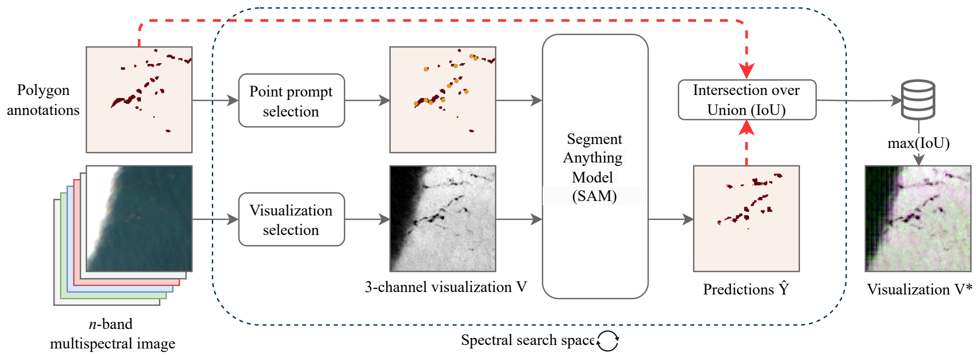


Figure 1: Schematic of the SAMSelect algorithm, automating spectral band selection by maximizing the Intersection over Union (IoU) between SAM-predicted masks and annotated objects.

to select the most effective spectral bands or indices. As illustrated in Figure 1, SAMSelect acts as a proxy for human visual interpretation, effectively exploring a vast space for potential visualizations. By providing annotations of specific features of interest, SAMSelect can be tailored to various remote sensing applications. The algorithm can either exhaustively explore all available spectral bands, or focus on a subset defined by user preferences. This flexibility, combined with its data-driven approach, enables SAMSelect to uncover new insights and validate existing spectral indices.

Optimization objective. SAMSelect finds a visualization $V : \mathbb{R}^D \rightarrow \mathbb{R}^3$ that maps D-channel image $\mathbf{X}$ to a 3-channel visual representation where salient features provided in $\mathbf{Y}$ are visible. It searches for a visualization

$$V^\star = \sum_{\mathbf{X},\mathbf{Y}\in\mathcal{D}} \arg_V \max \left[\text{IoU} \left(\underbrace{\text{SAM}\left(V(\mathbf{X}), \mathbf{p}\right)}_{\hat{\mathbf{Y}}}, \mathbf{Y} \right) \right] \tag{1}$$

that maximizes the Intersection over Union (IoU) over SAM prediction of images in a given visualization SAM$(V(\mathbf{X}), \mathbf{p})$ and their corresponding dense pixel-wise object annotations $\mathbf{Y}$ over a small dataset $\mathcal{D}$ provided by the user. SAM predictions require point prompts $\mathbf{p}$ that we derive from the annotations $\mathbf{Y}$, as detailed later. We implement the maximization by testing an exhaustive search space of possible visualizations.

The **visualization function V** entails two components: 1) a static *histogram normalization* through 1%-99% percentile scaling that we determined experimentally in comparison to histogram equalization and min-max scaling in terms of preserving image details and preventing outlier distortion. 2) *band selection* to determine three visualization channels c_red, c_green, c_blue that we optimize in eq. (1).We consider two families of visualizations:

Band Composites (BC) assign individual spectral bands to each RGB channel. For example, we can assign different Sentinel-2 spectral bands to these three channels by, for instance, constructing true-color like $c_\text{red} \leftarrow b_\text{B4}$, $c_\text{green} \leftarrow b_\text{B3}$, $c_\text{blue} \leftarrow b_\text{B2}$ or NIR false-color $c_\text{red} \leftarrow b_\text{B8}$, $c_\text{green} \leftarrow b_\text{B4}$, $c_\text{blue} \leftarrow b_\text{B3}$. *Spectral Index Composites (SIC)* assign different spectral images to the three available visualization bands $c_\text{red} \leftarrow \text{SI}_1$, $c_\text{green} \leftarrow \text{SI}_2$, $c_\text{blue} \leftarrow \text{SI}_3$. We consider two general forms of Spectral Indices (SIs):

1. *Normalized Difference Indices (NDIs)* are broadly used for vegetation (NDVI) or surface water (NDWI) and can be expressed generally as

$$NDI_{b_1,b_2} = \frac{(b_1 - b_2)}{(b_1 + b_2)} \tag{2}$$

with two bands b_1 and b_2. For Sentinel-2, the popular Normalized Difference Vegetation Index (NDVI) can be expressed as $NDVI = NDI_{B4,B8}$ and the Normalized Difference Water Index (NDWI) can be expressed as $NDI_{B8,B11}$ (Gao, 1996) or $NDI_{B3,B8}$ (McFeeters, 1996).

2. *Spectral Shape Indices (SSI)* are used predominantly in marine applications, such as the Floating Algae Index (Hu, 2009) and the Floating Debris Index (Biermann et al., 2020). In a general form, these indices compare the reflectance at a center band b_c with an linearly interpolated "virtual" band b_c' by subtraction $SSI_{b_\ominus,b_c,b_\oplus} = b_c - b_c^{'}$. The linear interpolation involves bands left $b_\ominus$ and right $b_\oplus$ of the center band

$$b_c^{'} = b_\ominus + (b_\oplus - b_\ominus) \cdot \frac{\lambda_{b_c} - \lambda_{b_\ominus}}{\lambda_{b_\oplus} - \lambda_{b_\ominus}} \tag{3}$$

at their wavelengths $\lambda_{b_\ominus}$, λ_{b_c}, $\lambda_{b_\oplus}$. For instance, the Floating Algae Index (FAI) using Sentinel-2A data can be expressed as $SSI_{B4,B8,B11} = B8 - (B4 + (B11 - B4) \cdot \frac{832.8\text{nm} - 664.6\text{nm}}{1613.7\text{nm} - 664.6\text{nm}})$.

Search Space. Using Sentinel-2 L2A data and conducting an exhaustive search space across all twelve spectral bands, SAMSelect evaluates 1,646 visualizations through the four visualization modules: BC (220), NDI (66), SSI (220), and SIC (1,140). The higher count for SIC reflects its broader range of possible combinations, as it uses the top-10 most informative NDI and SSIs rather than the spectral bands.

2 Data and Study Sites

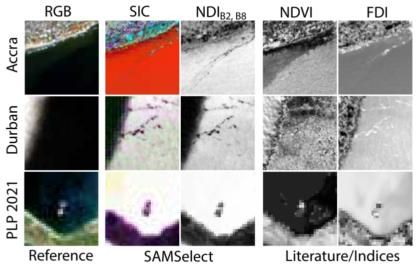
We developed and evaluated SAMSelect visualizations on Sentinel-2 imagery with across three study sites. Accra, Ghana faces significant waste management challenges (Dyck et al., 2016), with an estimated 140-380kg entering the ocean daily from the Odaw River (Pinto et al., 2023). Sentinel-2A imagery from 31st of October, 2018, captures two types of marine debris, waste outwash and *Sargassum spp*. Durban, South Africa experienced severe flooding from 18-22 April, 2019, leading to extensive plastic accumulation in the harbor (Biermann et al., 2020). Sentinel-2B imagery from 24th of April captures this debris despite cloud and haze, providing a realistic post-flood scenario for SAMSelect testing.Plastic Litter Project (PLP), Greece deploys artificial plastic targets in the Gulf of Gera (Papageorgiou et al., 2022). We use the initial Sentinel-2 overpass with both targets visible on the 21st of June, 2021, to assess SAMSelect's ability to generalize its visualizations to verified plastic targets.

3 Results

Applying the SAMSelect algorithm yields two different Spectral Index Composites (SIC) for Accra and Durban: SIC_Accra is composed of $c_\text{red} \leftarrow \text{NDI}_{B2,B8}$, $c_\text{green} \leftarrow \text{SSI}_{B1,B8,B11}$, $c_\text{blue} \leftarrow \text{SSI}_{B2,B8,B11}$. SIC_Durban is composed of $c_\text{red} \leftarrow \text{NDI}_{B2,B8}$, $c_\text{green} \leftarrow \text{NDI}_{B1,B8A}$, $c_\text{blue} \leftarrow \text{NDI}_{B3,B8}$. That SAMSelect yields different spectral index composites is likely due to the varying composition of visible debris both locations. As an easy-to-compute single single indices, we find that the Normalized Difference Index $\text{NDI}_{B2,B8} = \frac{B2-B8}{B2+B8}$ consistently produced most salient visualizations across both Accra, Durban and the PLP2021 targets, as can be see in fig. 2a. This result is notable given that the blue band is not a commonly used in marine debris detection, but has precedence in a similar Rotation-Absorption Index (RAI) (Loos et al., 2012) for oil slick detection. For visualizations on the Plastic Litter Project data, we use SIC_Durban, as the few pixels of deployed targets are too few to run the SAMSelect algorithm.

3.1 Qualitative comparison of visualizations

In fig. 2a, we show SAMSelect-derived indices (SIC, $\text{NDI}_\text{B2,B8}$) with NDVI and the Floating Debris Index (Biermann et al., 2020), which are commonly used to interpret floating marine debris. It can be seen that marine debris are difficult to identify in true-color, while they become significantly more distinguishable using spectral indices. We find that NDVI in particular struggles with reliable target identification due to a combination of normalization and limited ability to penetrate the thin haze present in the Durban scene, while the FDI visualizations highlight marine debris. the $\text{NDI}_{B2,B8}$ found by SAMSelect provides more pronounced contrast between the target features and the surrounding marine waters. This is particularly notable in the Plastic Litter Project 2021 (PLP) targets, which are clearly identifiable with the SAMSelect derived indices, while only one of both targets are clearly delineated in NDVI, FDI.



(a) Visualizations of Sentinel-2 images from Accra, Durban, and the Plastic Litter Project. SAMSelect-derived indices (here SIC and NDI$_B 2B8$) produced more salient visualizations compared to literature indices NDVI, and FDI.

Viz V	**Accra**		**Durban**	
	Bands	IoU	Bands	IoU
NDVI	B8, B4	18.7	B8, B4	9.6
FDI	B6, B8, B11	27.7	B6, B8, B11	23.2
PCA	PC1, PC2, PC3	21.3	PC1, PC2, PC3	11.3
NDI	B2, B8	36.3	B2, B8	39.5
SSI	B2, B8, B11	41.7	B8A, B9, B11	15.1
BC	B3, B5, B8A	36.7	B3, B8, B8A	29.6
SIC	B1,2,8,11	**45.8**	B1,2,3,8,8A	**42.0**

(b) Summary of the best scoring results from the spectral index search space derived from SAMSelect, showcasing the four main visualization methods NDI, SSI, BC, SIC. These visualizations are compared against the literature-based indices of NDVI, FDI (Biermann et al., 2020), and a Principal Component Analysis (PCA).

3.2 Quantitative Comparison to Established Indices

In section 3, we compare the SAMSelect-identified three-channel Spectral Index Composition (SIC) and Band Composite (BC) with the best-performing identified SSI and NDI single-channel indices and compare them to the established NDVI, FDI indices and a PCA. As metric, we report the IoU of the Segment Anything Model (Kirillov et al., 2023) using the visualizations as inputs on annotated polygons of marine debris of the Sentinel-2 scenes in Accra and Durban.

Overall, the results demonstrate a quantitative improvement over established indices NDVI and FDI, with segmentation scores increasing within a range of 8.6% to 23%. In Durban, NDI$_{B2,B8}$ showed even greater improvements, with a 29.9% increase over NDVI and a 16.3% increase over FDI, though SSI$_{B2,B8,B11}$ performed less effectively in this region. Comparatively, PCA-based composites produced results similar to NDVI and FDI but had lower segmentation scores than those identified by SAMSelect.

The visualizations found by SAMSelect demonstrated consistent segmentation performance, with differences among the methods ranging from 2.5% to 9.9%, except for the subpar performance of SSI in Durban. Generally, assigning individual spectral bands to the RGB channels in BC resulted in similar or decreased segmentation performance compared to single-channel indices like NDI and SSI. This suggests that single-channel indices may be more effective at isolating marine debris features from surrounding water. However, assigning individual NDI and SSI indices to RGB channels using the SIC approach resulted in a slight performance increase over single-channel visualizations, with improvements of 4.1% in Accra and 2.5% in Durban. Notably, the SIC achieved the highest segmentation performance, with scores of 45.8% in Accra and 42% in Durban, which is due to the efficient compression of four (Accra) and five (Durban) spectral bands in three visualization channels.

4 Discussion and Conclusion

In this letter, we propose the SAMSelect algorithm as a tool that can automatically discover the optimal band combination for visualizing objects of interest in any multispectral scene. By simply providing an image and corresponding annotations, SAMSelect can identify the band combination that maximizes agreement between SAM predictions and the annotations. In the case of marine debris, SAMSelect has consistently selected the NDI$_{B2,B8}$ combination which outperformed existing indices like NDVI and FDI. This suggests that this combination is particularly effective for distinguishing marine debris from other objects in the scene. While our experiments focused on marine debris detection in Sentinel-2 imagery, SAMSelect is applicable to a wide range of terrestrial and marine applications with other multispectral sensors, such as PlanetScope and Landsat.

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