Estimation of Floating Plastic Debris Surface in Inland Waters using Spectral Unmixing with Multispectral Data

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***Abstract*—Unlike hard classification from medium-resolution sensors, spectral unmixing at sub-pixel level offers improved accuracy in estimating the total surface occupied by a material of interest within a given area. While in ideal cases imaging spectrometer data should be utilized for this purpose, we propose to use a limited number of fixed classes in order to perform spectral unmixing from multispectral data to address the specific challenge of estimating the surface area covered by floating plastic debris in inland waters. In that context, working with multispectral data is motivated by extended opportunities to identify and monitor narrow water channels for variable plastic appearances, in terms of extended coverage, spatial and temporal resolution.**

***Index Terms*—Plastic debris, inland water, spectral unmixing, Earth observation**

I. Introduction

The Mediterranean Sea is an accumulation zone of plastic debris with a mass of up to 3000 tons of floating material estimated in 2015 [1]. Plastic debris is the origin of microplastic, decomposed e.g. by sun radiation and mechanical force. The Nile river belongs to the most polluted rivers draining into the Mediterranean Sea [2]. Monitoring plastic debris thereby enables to estimate the volume of accumulated plastic and plastic washed away by flood waters. On a global level, Lebreton et al. [3] simulated a discharge ranging from 1.15 to 2.41 million metric tons of plastic entering the oceans from rivers and thereby underscored the importance of fluvial systems as transport medium. Hence, gathering further information on the areas affected by accumulation of plastic debris is valuable for enabling cleaning activities before entering the sea or being decomposed into microplastics. Research on plastic debris using remote sensing data, particularly for sea and inland water surfaces, gained prominence in 2019, primarily focusing on floating plastic detection from single optical images [4]. Notably, only a few studies address inland waters, relying on airborne and UAV data [5]. Free-access Copernicus Sentinel missions provide a basis for this research. For rivers, studies have demonstrated the feasibility of using Sentinel-1 and Sentinel-2 images for detecting floating macro plastic on clear water surfaces. Those studies applied indices such as the floating debris index (FDI) introduced in [6]; in some cases additionally in combination with other indices such as the normalized difference vegetation index (NDVI). The area affected by plastic debris can then be estimated as the total surface of pixels detected as plastic in the scene. Nevertheless, there is a relevant limitation: the accuracy in the estimation of the total area of detected pixels in Sentinel-2 data is limited by their pixel size, covering 100 m^2 if only bands at 10 m resolution are considered, and 400 m^2 if the full spectrum is used, including the short wave infrared bands. In the case of inland waters, in particular narrow water channels, affected pixels are often only partially covered by plastic debris. In such scenarios, even if plastic is correctly detected, the total surface may be largely overestimated. For example, a study in [7] reports an overestimation of more than 100% for the area covered by correctly detected solar panels in a region with highly mixed image elements. In the cited paper, an almost perfect estimation is achieved when using instead spectral unmixing techniques, yielding the percentage of each pixel which is covered by the material of interest.

So far, spectral unmixing has been used in most cases in the frame of imaging spectrometer data analysis, as the number of available spectral bands should exceed, ideally by far, the number of target materials on ground (with associated spectra usually known as endmembers) in order to have reliable results. As the endmembers matrix must be inverted in the unmixing process, linearly dependent endmembers make the process mathematically unstable. In this paper, we propose to use a limited number of fixed classes in order to perform spectral unmixing from multispectral data for the specific problem of estimating floating plastic debris surface in inland waters. As for inland waters a ground sampling distance (GSD) of 10 meters is of great advantage, we propose the use of the four bands at this GSD only in Sentinel-2. We restrict the number of materials to the ones usually found in inland waters, considering water, plastic, vegetation, and soil/urban. As the related endmembers exhibit spectra which are assumed to be linearly independent, the number of endmembers does not exceed the number of available spectral bands and the spectral unmixing process can be carried out.

II. Spectral Unmixing

The process of spectral unmixing (SU) decomposes the spectrum associated with a pixel in an image as a combination of spectra belonging to pure materials, usually known as endmembers. The fraction of a given endmember within the image element is its abundance [8]. In this paper we use linear spectral unmixing, in which the aforementioned combination is assumed to be linear, and the portion of a pixel (amount of surface) belonging to a given material to be directly proportional to its abundance.

The spectrum of a pixel $\mathbf{p}$ with b bands is then expressed as the linear combination of n reference spectra $\mathbf{S} = [s_1, s_2, \ldots, s_n] \in \mathbb{R}^{b\times n}$, weighted by n scalar fractional abundances $\mathbf{x} = [x_1, x_2, \ldots, x_n]^T \in \mathbb{R}^{n\times 1}$, plus a residual vector $\mathbf{r} \in \mathbb{R}^{b\times 1}$;

$$\mathbf{p} = \sum_{i=1}^{n} x_i s_i + r = \mathbf{S}\mathbf{x} + \mathbf{r} \tag{1}$$

Here, $\mathbf{r}$ represents the portion of the signal which cannot be represented using the spectral library $\mathbf{S}$ composed by the selected endmembers, due to the library being incomplete, noise, and other sources of error. The problem in Eq. 1 may be solved through a set of linear equations using least squares approaches [8], usually enforcing at least the non-negativity constraint in order to avoid having meaningless negative abundances for some material.

Spectral unmixing usually needs three steps: estimation of the number of materials present in the scene, creation of the spectral library, and abundance estimation. In the end, the sum of the abundances for an endmember related to a material of interest in an image subset can be easily converted to the total surface occupied by that material. For our purposes, our main interest lies in estimating the abundance of the plastic material in sensitive areas.

While multispectral sensing from medium-resolution sensors has largely succeeded at classifying entire pixels, spectral unmixing at sub-pixel level may offer improved accuracy in estimating the total surface occupied by floating plastic debris. For example, relying on the detection of plastic from Sentinel-2 images would limit the approximation of the total surface to the size of the single detected pixels, which cover 100 m^2 on ground if only bands at 10 m resolution are considered, or 400 m^2 if also bands at 20 m are included in the analysis. For small water channels, such approximation could yield a large overestimation of the surface occupied by floating plastic.

Spectral unmixing is usually carried out using imaging spectrometer data, as its applicability is limited by spectral resolution of the sensor, as the number of endmembers n should not to be larger than the number of available spectral bands m: the matrix $\mathbf{S}$ should be orthogonal, as it needs to be inverted in order to mathematically solve Eq. 1, and therefore the problem becomes overdetermined if $n > m$.

Nevertheless, it would be desirable to study plastic accumulations with high temporal and spatial resolution, as dynamics of plastic accumulation phenomena are rapidly changing, and small water channels may be considerably smaller than the GSD of typical spaceborne hyperspectral sensors (usually in the order of 30 m).

As stated, it is anyway difficult to apply spectral unmixing to multispectral data. Such hindrance is more severe at a GSD of $10m$, for which only 4 bands are available for Sentinel-2, as accumulations of debris rarely span a full pixel if bands at $20m$ are employed. For the same reason, data-driven semi-automatic endmember extraction algorithms trying to identify pure pixels are hard to apply in our case. The mentioned restrictions would not apply to data having both high spectral and spatial resolution, such as airborne imaging spectrometer data, which are not available in our case.

In order to tackle this problem, we force the spectral library to be composed by a limited number of relevant macro-classes, including the plastic endmember. The selected endmembers must be easily separable according to their spectral features: as mentioned, if these are highly correlated the endmembers matrix would become non-orthogonal, the inversion needed unstable, and the estimated fractions $\mathbf{x}$ highly sensitive to random error [9]. Therefore, in practice our library is composed by the spectra of pre-selected classes containing water, vegetation, and bare soil / urban structures, in addition to plastic, pushing the process to its very limits and requiring an assessment of the stability of its results.

III. Results

We assume in this section to have a binary mask identifying the plastic in the scene at the same resolution of the sensor, which can be obtained with one of the aforementioned methods, e.g. by thresholding the FDI in a sensitive area. In our case, we use an automatic multitemporal-based method which will be described in a paper currently under preparation. The most straight-forward analysis estimates then the total number of pixels covered by new accumulation of plastic, and considering the total surface as the total area of these pixels.

The plastic endmember is selected as the average of the highest reflectance pixels within the plastic mask. The training area collection step for the other classes (water, vegetation, and soil/urban) can be either manual or automatic. In the case of manual selection, the process is relatively inexpensive to carry out, as all the mentioned classes are easy to identify in a true color or false color representation of the acquired scenes at 10 m GSD. An alternative is an automatic endmember selection step, which uses instead the maximum values in the same scene subset of NDVI to select a representative pixel for vegetation, and does the same for water (highest NDWI) and soil/urban (highest band ratio of red over green outside of detected plastic). Thus, the number of classes is not larger than the available Sentinel-2 spectral bands, and the spectra are not linearly dependent, making the unmixing process mathematically feasible.

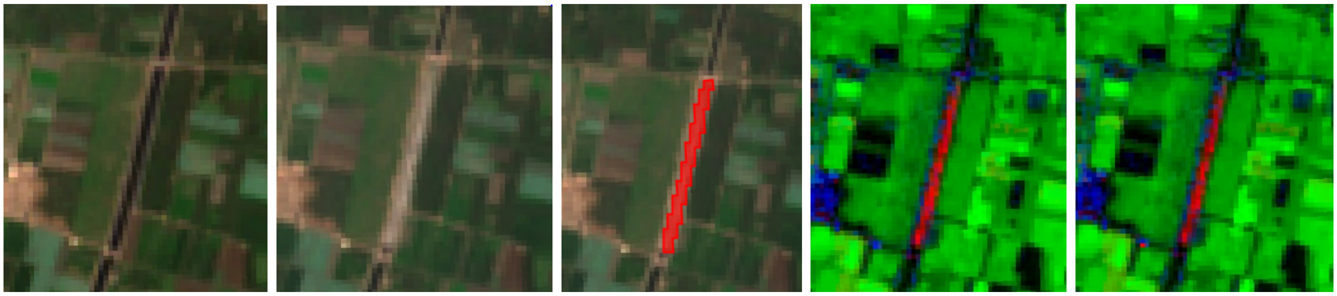

Fig. 1. Spectral unmixing quantification of floating debris for a tributary of the Nile river. From left to right: plastic-free true color composite of Sentinel-2 image from the 17th of July 2020; water channel exhibiting accumulation of plastic debris acquired few days earlier (true color composite of Sentinel-2 image from the 12th of July 2020); same image with overlaid mask for detected plastic; results of spectral unmixing applied on the image acquired on the 12th of July 2020, with manual and automatic endmember selection, respectively. For unmixing results, only the abundance of three materials is represented: plastic in red, vegetation in green, urban in blue.

TABLE I
PLASTIC SURFACE ESTIMATED THROUGH HARD CLASSIFICATION AND SPECTRAL UNMIXING (SU) WITH MANUAL AND AUTOMATIC SELECTION OF THE ENDMEMBERS (MANUAL AND AUTO), RESPECTIVELY.

	Classification	SU (manual)	SU (auto)
m^2	8410	5669	4929

Fig. 1 reports a case of study on a small tributary of the river Nile, in Egypt, for an image acquired on the 12th of July 2020. The reported Sentinel-2 subsets show how accumulated plastic debris is released downstream and disappears from the scene. Additionally, the available mask for pixels containing plastic debris is reported. As mentioned, estimating the area by simply summing the area defined by the mask can lead to a large overestimation. For spectral unmixing results, a composite of three abundance maps only is reported, quantifying the percentage of each pixel covered respectively by plastic (red), urban (blue), and vegetation (green). In this case there is no validation data, but the unmixing results reported show how the concentration of plastic is found to be higher in the center of the river and mixed with soil/road and vegetation on the border of the river, which we consider to be a realistic arrangement. The estimated area of plastic is 8410 m^2 if the full plastic mask is considered, and is then reduced to 5669 m^2 for the spectral unmixing results. The case of spectral unmixing using automatically extracted endmembers yields results where plastic is sometimes confused with soil/urban, with the red area appearing therefore less bright in the figure. In this case, the estimated area of 4929 m^2 could therefore be an underestimation of the affected area. Results are summarized in Table I. The images were processed in a Google Earth Engine environment [10], using the built-in *unmix* function for abundance quantification given a spectral library, and enforcing the non-negativity constraint in the associated least-squares-based solver.

IV. CONCLUSIONS

Spectral unmixing demonstrated to be useful for estimating the area covered by a material of interest in a scenario presenting a relevant degree of mixture in the image elements. In order to achieve unmixing for multispectral data, the endmembers must be carefully selected in order to be as few as possible, not linearly dependent, and be able to represent the main materials found in the area of interest. Results presented on plastic surface quantification on a tributary of the river Nile in Egypt suggest that more accurate surface estimation can be obtained with respect to a hard classification of the area occupied by pixels in which plastic was detected. The analysis results in an assessment of the extent of the floating plastic debris, which could be refined with local sample measurements for estimating the plastic debris volume.

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