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A knowledge-based, validated classifier for the identification of aliphatic and aromatic plastics by WorldView-3 satellite data

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Abstract

Although the C-H chains of petroleum derivatives display unique absorption features in the short-wave infrared (SWIR), it is a challenge to identify plastics on terrestrial surfaces. The diverse reflectance spectra caused by chemically varying polymer types and their different kinds of brightness and transparencies, which are, moreover, influenced further by the respective surface backgrounds. This paper investigates the capability of WorldView-3 (WV-3) satellite data, characterized by a high spatial resolution and equipped with eight distinct and relatively narrow SWIR bands suitable for global monitoring of different types of plastic materials. To meet the objective, hyperspectral measurements and simulations were conducted in the laboratory and by aircraft campaigns, based on the JPL-ECOSTRESS, USGS, and inhouse hyperspectral libraries, all of which are convolved to the spectral response functions of the WV-3 system. Experiments further supported the analyses wherein different...
plastic materials were placed on different backgrounds, and scaled percentages of plastics per pixel were modeled to determine the minimum detectable fractions. To determine the detectability of plastics with various chemical and physical properties and different fractions against diverse backgrounds, a knowledge-based classifier was developed, the routines of which are based on diagnostic spectral features in the SWIR range. The classifier shows outstanding results on various background scenarios for lab experimental imagery as well as for airborne data and it is further able to mask non-plastic materials. Three clusters of plastic materials can clearly be identified, based on spectra and imagery: The first cluster identifies aliphatic compounds, comprising polyethylene (PE), polyvinylchloride (PVC), ethylene vinyl acetate copolymer (EVAC), polypropylene (PP), polyoxymethylene (POM), polymethyl methacrylate (PMMA), and polyamide (PA). The second and third clusters are diagnostic for aromatic hydrocarbons, including polyethylene terephthalate (PET), polystyrene (PS), polycarbonate (PC), and styrene-acrylonitrile (SAN), respectively separated from polybutylene adipate terephthalate (PBAT), acrylonitrile butadiene styrene (ABS), and polyurethane (PU). The robustness of the classifier is examined on the basis of simulated spectra derived from our HySimCaR model, which has been developed in-house. The model simulates radiation transfer by using virtual 3D scenarios and ray tracing, hence, enables the analysis of the influence of various factors, such as material brightness, transparency, and fractional coverage as well as different background materials. We validated our results by laboratory and simulated datasets and by tests using airborne data recorded at four distinct sites with different surface characteristics. The results of the classifier were further compared to results produced by another signature-based method, the spectral angle mapper (SAM) and a commonly used technique, the maximum likelihood estimation (MLE). Finally, we applied and successfully tested the classifier on WV-3 imagery of sites known for a high abundance of plastics in Almeria (Spain), Cairo (Egypt), and Accra, (Ghana, West Africa). Both
airborne and WV-3 data were atmospherically corrected and transferred to "at-surface reflectances". The results prove the combination of WV-3 data and the newly designed classifier to be an efficient and reliable approach to globally monitor and identify three clusters of plastic materials at various fractions on different backgrounds.

**Keywords**
Plastic (waste) in the terrestrial environment, aliphatic and aromatic plastics, knowledge-based classifier, spectral analyses, WorldView-3

**1 Introduction**
Plastic litter enters the environment through manifold pathways and has a major deleterious impact on our living space. This phenomenon is of growing concern, and has kindled the idea to investigate the possibilities of monitoring and identification of plastic litter in the terrestrial environment using remote sensing techniques. Plastic products - with the advantages of being lightweight, waterproof, and durable - have become increasingly dominant in the marketplace since their widespread introduction in the 1930s (Feldman, 2008). Global plastic production has quadrupled over the past four decades (Geyer et al., 2017). Improper disposal of plastic waste, along with its longevity and durability, have caused its extensive accumulation in terrestrial and aquatic ecosystems (Derraik, 2002). This has led to a severe damage to wildlife (Browne et al., 2008; Uhrin and Schellinger, 2011) and its habitats (Lebreton et al., 2017). Besides, many plastics can be chemically hazardous in some contexts. More than 50% of plastics are inherently toxic (Lithner and Dave, 2011). Even when not toxic, plastics can absorb and accumulate other pollutants (Teuten et al., 2009; Rochman et al., 2013a). When plastic is exposed to ambient solar radiation, it slowly disintegrates into microplastics and releases greenhouse gases, methane and ethylene, contributing to climate change and global warming effects (Royer et al., 2018; Vishwakarma,
People are, therefore, now paying more and more attention to the impact of plastics on the ecosystem and human health (Lithner and Dave, 2011; Rochman et al., 2013b; Law and Thompson, 2014; Law, 2017). Consequently, it is a challenging future obligation to regularly monitor and detect plastic materials to better identify the sources and pathways of plastic litter and to assess its accumulation over time.

The unique inherent optical characteristics of different types of plastics in the near infrared (NIR) to shortwave infrared (SWIR) allow plastic litter to be sorted automatically by the recycling industry (Huth et al., 1995; Masoumi et al., 2012; Moroni et al., 2015;). With the development and improvement of the SWIR (1.3-2.5µm) imaging technology, remote sensing data with moderate to high temporal, spectral, and spatial resolution bear the potential to be a powerful tool for qualitative and quantitative mapping of plastic occurrences in the environment (Moller et al., 2016). Mapping and quantification of marine and coastal plastic litter based on remote sensing data (NIR, SWIR, TIR) have recently been investigated by a growing number of studies (Moy et al., 2018; Acuña et al., 2018; Garaba et al., 2018; Martínez et al., 2019; Goddijn and Williamson, 2019; Fallati et al., 2019; Themistocleous et al., 2020; Biermann et al., 2020; El Mahrad et al., 2020; Topouzelis et al., 2020). Some authors investigated the detection of plastic greenhouses using statistical classification algorithms based on spectral and textural characteristics (Novelli et al., 2016; Aguilar et al, 2016; Lanorte et al., 2017; Aguilar et al., 2020). Others focused on the differentiation among various plastic types by lab measurement and near-real-time algorithms, which allow the sorting of harvested plastic waste on automated conveyor belts with infrared spectroscopy (Yan and Siesler, 2018; Rani et al, 2019; Sanchez et al., 2020). Most plastic litter ends up in the oceans through miscellaneous routes and is crushed by mechanical wave, forcing it up to nano-sized particles. Approximately 80 percent of ocean plastics originate from land-based sources; the remaining 20 percent are from marine sources (Li et al., 2016).
To prevent further contamination, regular global monitoring of terrestrial plastic debris is of increasing importance. So far, only a few studies have focused on the detection and identification of terrestrial plastics, mostly based on hyperspectral imagers aboard airplanes (Hörig et al., 2001; Kühn et al., 2004; Heiden et al., 2007) and satellites (Wetherley et al., 2017). But airborne sensors are limited in terms of covering larger areas. On the contrary, hyperspectral recordings from space have the disadvantage of low Ground Sampling Distances (GSDs) ≥30 m on account of the limited quantum efficiencies of recent detectors. Therefore, a "super-spectral" instrument such as the DigitalGlobe WorldView-3 system is a suitable solution as tradeoff between spectral and spatial resolution. It can be advantageous to hyperspectral imagers as well as to very high spatial resolution satellite sensors where the latter usually suffer from low repetition rates and missing spectral capabilities. WV-3 data have already been investigated by Asadzadeh and de Souza Filho (2016), delineating the potential to detect hydrocarbon (HC) materials based on simulated imagery. They further proved the data to be capable to unambiguously detect HCs in varying background soils. Some researchers have already proposed knowledge-based indices, such as HI (Kühn et al., 2004), RBD (Asadzadeh and de Souza Filho, 2016), and NDPI, which can be used as one-class classifiers by applying a threshold on the index value, among which NDPI has been proven to have superior performance (Guo and Li, 2020). This index can highlight most of the plastics innovatively by amplifying the significant downward tendency of most plastics along 1570 to 1730 nm and 2165 to 2330 nm, however, it doesn’t cover all the plastic types. Yet, these studies rarely provide a reliable identification of different plastic materials, although this is a major challenge in this context.

Concerning the evaluation of recorded air-, or spaceborne data, various supervised classifiers based on signatures have been reported in the literature. Conventional approaches to chemical agents and soil detection using spectroscopic techniques are discussed by Kruse et
al. (1993) and Kwan et al. (2006). Moreover, popular deep learning algorithms are used for land cover classification (Kwan et al., 2020). All of these methods can be used to classify plastics. The most common household waste consists of five main polymers, including PE, PP, PS, PET, and PVC (Eisenreich and Rohe, 2006; Feldman, 2008; Editor, 2018). For cost-saving reasons, most plastics remain transparent or translucent and thin, introducing the quadratic term of transmittance and the reflectance of background directly below it. Hence, the background has great impact on the apparent reflectance (Kuester and Bochow, 2019). The varying fractions of plastics in relation to different backgrounds further introduce uncertainty into any kind of detection and identification algorithms. Hence, supervised classification methods would require a large number of training pixels, covering all the abovementioned combinations and circumstances. Unsupervised classification algorithms like ISODATA (Tou and Gonzalez, 1974) and K-Means (Wong and Hartigan, 1979), require knowledge about the number of classes in the image to obtain good results; also, they cannot be used to automatically identify materials. Statistically machine learning methods became very popular but have a limited transferability and often require adaption to specific areas and tasks.

The work presented in this paper focuses on the development of a knowledge-based algorithm, evaluating the spectral reflectance signal, which can identify different types or clusters of plastics on various terrestrial backgrounds by the use of the globally operating WV-3 satellite system. As mentioned before, WV-3 is characterized by eight well-placed SWIR bands and a sufficient high spatial resolution for this purpose. To initiate the classifier, we investigated three international spectral libraries, including around 3,600 samples, whereby all spectra were convolved to WV-3 band characteristics using its spectral response function. We iteratively improved the algorithm with lab measurements and simulated spectra, covering a broad range of different, commonly used types of plastics, various levels of
brightness and transparency, detailed fractional coverages of plastic material per pixel, and the interfering reflectance of 12 different background materials. Finally, the developed, signature-based, decision tree type classifier was applied to simulated data, four airborne images recorded in Germany and Spain, and three WV-3 scenes covering known areas of high plastic abundance in Spain (Almeria), West Africa (Accra, Ghana), and Egypt (Cairo) (Fig. 1).

2 Materials

2.1 Laboratory data

2.1.1 Existing spectral libraries

To investigate the potential for the detection and recognition of different plastic materials as well as to mask and separate all other materials from plastics, spectral libraries from JPL-ECOSTRESS (Baldridge et al., 2009; Meerdink et al., 2019), USGS (Kokaly et al., 2017) and our inhouse spectral library (GFZ), were investigated. Only diagnostic spectral signatures located in the NIR and SWIR ranges were selected to ensure credibility for the subsequent spectral resampling. Table 1 lists the details of spectral libraries and categories that were considered in this study. A synthetic scenery of 60-by-60 pixels was generated covering 3,547 spectra of natural surfaces, including 156 samples of different plastics materials. All reflectance data were rescaled into the range of 0 to 100% to facilitate joint analysis.
Table 1. Summary of the spectral libraries used for this study.

<table>
<thead>
<tr>
<th>Spectral library</th>
<th>Number of spectra</th>
<th>Category</th>
</tr>
</thead>
<tbody>
<tr>
<td>ECOSTRESS</td>
<td>1947</td>
<td>Artificial, water, minerals, rocks, soils, vegetation, non-photosynthetic vegetation</td>
</tr>
<tr>
<td>USGS</td>
<td>1436</td>
<td>Artificial, coatings, liquids, minerals, soils, vegetables</td>
</tr>
<tr>
<td>GFZ</td>
<td>164</td>
<td>ABS, EVAC, PE, PBAT, PC, PET, POM, PP, PS, PU, PVC, SAN, PMMA, PA and natural organic materials</td>
</tr>
<tr>
<td>Total</td>
<td>3547</td>
<td></td>
</tr>
</tbody>
</table>

The USGS library (Version 7) contains hyperspectral reflectance data of various materials that cover the wavelength range from the ultraviolet to the far infrared (0.2 to 200 µm). It includes spectra measured in the laboratory, field, and by airborne imaging spectrometers. It contains reflectance spectra from samples of minerals, rocks, and soils as well as of vegetation, microorganisms, and man-made materials, which involves PE, PVC, PET, and PA. The category of organic chemical substances is excluded in this study as their molecular structures are similar to plastics, but rarely disperse in nature. The ECOSTRESS library provides a comprehensive collection of natural and man-made laboratory-derived high-resolution spectra, covering the wavelength range of 0.35–15.4 µm. It includes nearly 2,000 spectra of soils, rocks, minerals, meteorites, vegetation, non-photosynthetic vegetation (NPV), water/snow/ice, and man-made materials. There are two roofing rubbers in the man-made category, which are plastic samples. The PlaMAPP library is an in-house (GFZ) created collection of high-resolution spectra measured in the near infrared and shortwave infrared range (0.97-2.5 µm). It includes five types of household plastics, which cover 95% of the global production of PE, PP, PVC, PET, and PS, as well as nine types of industrial plastics: ABS,
EVAC, PA, PBAT, PC, PMMA, POM, PU, and SAN. These plastics - in accordance with the type of functional groups present in their molecular structure - can be divided into an aliphatic type (without a benzene ring) and an aromatic type (containing a benzene ring), and are listed in Table 2. In total, 3,547 spectral signatures were used to develop and evaluate the classifier.

Table 2. Different plastics sorted by their molecular structure. Materials used for household goods and packaging are marked in bold.

<table>
<thead>
<tr>
<th>Type of Chemical Compound</th>
<th>Plastic types</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aliphatic</td>
<td>PE, PVC, EVAC, PP, POM, PMMA, PA</td>
</tr>
<tr>
<td>Aromatic</td>
<td>ABS, PBAT, PU, PET, PS, PC, SAN</td>
</tr>
</tbody>
</table>

2.1.2 Additional lab measurements

Additional measurements were conducted to derive high-resolution spectra of various plastic types placed on the surfaces of different backgrounds which is required for the development of the classifier. Measurements are conducted under laboratory conditions with an internal measurement protocol (Rogass et al., 2017) with a HySpex SWIR320m-e hyperspectral imager built by Norsk Elektro Optikk (NEO). A H25s light source by HEDLER was used, which is equipped with two 650 Watts tungsten halogen bulbs radiating a near solar-like spectrum. After calibrating the measured digital numbers to radiance using the software HySpex RAD, the conversion to reflectance was accomplished using spectra from a 3-color Zenith® reference panel (albedo: 90%, 50%, 20%), which was placed in every imaged scene. Two scenes were set up, including samples of six plastic materials (HDPE, PVC, PS, PP, PET, and
PBAT), with different optical characteristics like transparent, translucent, opaque-bright, and opaque-dark. Samples were placed on two different soil types viz a bright sandy dry soil and a dark organic dry soil.

2.1.3 The HySimCaR model

To further consolidate the database, it was extended by simulated mixed spectra based on HySpex measurements, using a radiative transfer model HySimCaR (hyperspectral simulation of canopy reflectance, Kuester et al., 2014) that was developed in-house and modified. The model enables the simulation of realistic bidirectional reflectance spectra on the basis of virtual 3D scenarios with Monte Carlo ray-tracing (MCRT) techniques. The spectral reflectances of the mixed samples were calculated by a spectral modeling approach that couples virtual 3D plastic litter scenarios, the geometries of which are linked to the corresponding spectral information (reflectance spectra of background materials, reflectance, and transmittance spectra of plastic materials). Apart from the complexity of varying spectral backgrounds in the terrestrial environment, classification algorithms applied to satellite imagery face the dominance of mixed pixels, causing greater uncertainties in the results of classification approaches. Hence, the fractional cover of the plastic material for the analysis of the mixed pixel problem was calculated directly from the 3D geometry of the virtual littering scenarios. Subsequently, by using the Atmospheric and Topographic Correction (ATCOR) model (Richter and Schläpfer, 2019), all the lab reflectance spectra derived are converted to surface reflectances, as seen by the WV-3 sensor, taking into consideration random noise and atmospheric effects.

2.2 Sensor systems

2.2.1 Airborne instruments
Data recorded by four push-broom hyperspectral sensors, including the HySpex-VNIR-1600, HySpex-SWIR-320m-e, HySpex Mjolnir S-620 (NEO), and the HyMap sensor (Cocks et al. 1998) were used in this study. The HySpex-VNIR-1600 covers 160 bands in the spectral range of 0.4-1.0 μm, with a spectral resolution of 3.6 nm, while the HySpex-SWIR320m-e operates in the 1.0-2.5 μm range, producing 256 bands with a spectral sampling of 6 nm. Both sensors were mounted on an aircraft with an across-track instantaneous field of view (IFOV) up to 0.185 mrad for the VNIR camera (1600 pixels) and 0.75 mrad for the SWIR camera (320 pixels). The HySpex Mjolnir S-620 is a UAV-based sensor, with an across-track IFOV of 0.54 mrad. It records lines with 620 pixels, covering a range of 1.0-2.5 μm in 300 bands, with a spectral resolution of 5.1 nm. The HyMap imager has an IFOV of 2.0 mrad with 512 pixels in across track direction, covering the range of 0.45-2.48 μm in 128 bands with intervals of 13-17 nm. This sensor can only be used in connection with an aircraft.

2.2.2 WorldView-3 sensor

The WorldView-3 is a high spatial resolution commercial satellite operating in a sun-synchronous orbit, carrying a sensor with moderately broad spectral bands in the VNIR-SWIR (visible, near infrared - short wave infrared) range. In the VNIR, it provides four standard color bands and four additional bands, named coastal, yellow, red edge, and near-IR2. The details of the spectral band configuration are shown in Table 3. The major advancement of the WV-3 system are eight SWIR bands in the 1195-2365 nm atmospheric window. Twelve additional CAVIS (Clouds, Aerosols, Vapors, Ice, and Snow) bands guarantee proper estimates of aerosols and water vapor for atmospheric compensation of the data. The platform operates at an altitude of 617 km. The GSDs at nadir are 0.31 m for the panchromatic band, 1.24 m for the VNIR bands, 3.7 m for the SWIR bands, and 30 m for the CAVIS bands. The swath width of the instrument is 13.1 km, with a descending node at 10:30 a.m. (DigitalGlobe, 2014). Owing
to the onboard fast-reacting "Control Moment Gyros" (CMGs), the off-nadir revisit time is < 1 day. Data provided are already geo-corrected.

Table 3. Spectral band configuration of VNIR and SWIR bands of the WorldView-3 sensor (DigitalGlobe, 2014).

<table>
<thead>
<tr>
<th>Band number</th>
<th>Band name</th>
<th>Wavelength /nm</th>
<th>Band number</th>
<th>Band name</th>
<th>Wavelength /nm</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>coastal:</td>
<td>400-450</td>
<td>9</td>
<td>SWIR 1:</td>
<td>1195-1225</td>
</tr>
<tr>
<td>2</td>
<td>blue:</td>
<td>450-510</td>
<td>10</td>
<td>SWIR 2:</td>
<td>1550-1590</td>
</tr>
<tr>
<td>3</td>
<td>green:</td>
<td>510-580</td>
<td>11</td>
<td>SWIR 3:</td>
<td>1640-1680</td>
</tr>
<tr>
<td>4</td>
<td>yellow:</td>
<td>585-625</td>
<td>12</td>
<td>SWIR 4:</td>
<td>1710-1750</td>
</tr>
<tr>
<td>5</td>
<td>red:</td>
<td>630-690</td>
<td>13</td>
<td>SWIR 5:</td>
<td>2145-2185</td>
</tr>
<tr>
<td>6</td>
<td>red edge:</td>
<td>705-745</td>
<td>14</td>
<td>SWIR 6:</td>
<td>2185-2225</td>
</tr>
<tr>
<td>7</td>
<td>near IR 1:</td>
<td>770-895</td>
<td>15</td>
<td>SWIR 7:</td>
<td>2235-2285</td>
</tr>
<tr>
<td>8</td>
<td>near IR 2:</td>
<td>860-1040</td>
<td>16</td>
<td>SWIR 8:</td>
<td>2295-2365</td>
</tr>
</tbody>
</table>

GSD 1.2 m  GSD 3.7 m

3 Study Areas

To ensure testing and validation of the classifier to be developed in this study for its potential to identify different plastic materials in a real-world environment under various conditions, several regions with miscellaneous surface characters were recorded by aircraft and satellite data.
Fig. 1. Sketch map and detailed coordinates of test sites recorded by aircraft scanners and the WV-3 satellite.

3.1 Sites recorded by airborne instruments

Four selected locations in Germany and Spain (Fig. 1a-d), each characterized by a different landscape, were recorded by the abovementioned airborne instruments. To ensure validity, plastic targets in the airborne datasets were not included in the spectral libraries used for the development of the classifier.

A location - dominated by grassland - was recorded by the HySpex Mjolnir S-620 imager mounted on an UAV on June 13, 2019, at Thyrow, Germany (52°15'04.6"N 13°13'55.7"E, Fig. 1a). The flight altitude was about 30 m, resulting in a GSD of about 3 cm. We placed well-defined and spectrally measured materials on the ground like transparent PET plastic bottles of different size, and large foils made of PBAT, PET, and PE plastic. The geometric processing was conducted with the PARGE software (Schläpfer and Richter, 2002) and the atmospheric correction was done in-house using the SICOR software (Bohn et al., 2020).

The data of the lake location were recorded by the combined HySpex VNIR-1600 and SWIR-320m-e sensors aboard an airplane on February 16 in 2015 at Lake Seddin, Germany.
(52°16'21.4"N 13°03'12.3"E, Fig. 1b). Data were collected at an altitude of 600 m, with a resultant GSD of about 40 cm. HySpex data preprocessing to orthorectified reflectance including co-registration and adaptation of the SWIR sensor to the VNIR was performed with the GFZ in-house processing chain HyPrepAir which is based on procedures described by Brell et al. (2016). Three arrays of white and opaque PS foam boards (fractional covers of 15%, 25%, and 40%) and one blue PE tarpaulin (100% fractional coverage) were set up over the shallow lake water and on its sandy bank. The above described two scenes represent fully controlled experiments and the ground truth map including all the samples is generated accordingly.

A third study area - characterized by an urban landscape - was recorded by the HyMap system from an aircraft. The urban scenery depicts the city of Dresden, Germany (51°6'17.5"N 13°46'6.8"E, Fig. 1c), and was collected on July 7, 2004, with a GSD of 4 m. Ground control for places covered by distinct plastic materials in the resp. regions are maintained by fieldworks using portable spectrometers and GPS devices. Coverages by the respective plastic materials at individual city blocks were digitized manually on-screen using orthorectified aerial photographs of 0.25 m resolution. More than 40 different urban materials including various plastics were identified and mapped based on hyperspectral ground measurements (Behling et al., 2015). For this study, we merged all the found classes into the respective three plastic and one non-plastic cluster, each of them finally comprising more than 250 pixels.

A further area characterized by bare soils and greenhouse agriculture in Almeria, Spain (0°0'38.2"S 10°30'55.5"E, Fig. 1d), was acquired in June 15 using the HyMap system onboard an airplane in 2005, with a GSD of 5 m. This site is dominated by PE plastic sheds utilized as greenhouses for agricultural purposes (Scarascia et al., 2011). Similar to the Dresden dataset, the ground control is conducted by field measurements with portable spectrometers and GPS.
However, due to the lack of diversity of plastics, only greenhouses made from PE were collected for the ground truth map with more than 10,000 pixels.

All these datasets are of L2 level, passing radiometric corrections, atmospheric corrections, and ortho-registration.

3.2 Sites recorded by the WV-3 satellite

Three WV-3 datasets (Fig 1e-g) were selected from regions known for their high abundance of plastic material. One dataset was recorded over Europe (Almeria, Spain), one over West Africa (Accra, Ghana), and one over North Africa (Cairo, Egypt). They were collected in Ortho Ready Standard Level-2A (ORS2A) format, presenting both radiometric and geometric corrections. To retrieve the "at surface reflectance" characteristics of targeted areas, atmospheric corrections were applied using the ATCOR 2 software (Richter and Schläpfer, 2007).

3.2.1 Almeria, Spain

The imagery of Almeria, Spain (2°19'29.9"N 36°51'16.1"W, Fig 1e), depicts an agricultural region and was recorded on June 26, 2018. The economy of Almería is mostly dependent on agricultural products, cultivated mainly in the western part of the city. Numerous greenhouses constructed from plastic sheeting produce tons of fruits and vegetables; more than 70% of which are exported to other European countries. About 30,000 tons of plastic waste are created here per year. In places where the soil has become infertile, the greenhouses are abandoned after shredding; these are reported to enter the Mediterranean Ocean (Tremlett, 2013). PE is the preferred plastic type for greenhouses because of its affordability, flexibility, and ease of manufacturing (Scarascia et al., 2011). In this plasticulture area, most targets - such as soils, trees, and the greenhouses - depict a
homogeneous appearance. However, most of the plastics are transparent or translucent with vegetation below.

3.2.2 City of Accra, Ghana, West Africa

The data of Accra (5°32’43.3”N 0°13’4”W, Fig 1f) were acquired on March 3, 2018. In Accra, the area of interest is located at the electronic waste dump site in Agbogbloshie. E-waste has become the fastest growing waste disposal in the world, with an annual growth rate of 3–4%. More than 150,000 tons of electrical appliances consumed worldwide are shipped to Ghana per year (Schluep et al., 2011) via the Port of Tema, located 20 miles east of the Agbogbloshie dump. Furthermore, the urban areas of Accra release about 760,000 tons of municipal solid waste per year (US EPA, 2002). About 80,000 people subsist on the Agbogbloshie dump, living locally or nearby, and suffer from the contaminated environment. Only 15% of e-waste is recycled, of which the most significant constituents are plastics, accounting for up to 20% (Sahajwalla and Gaikwad, 2018).

3.2.3 City of Cairo, Egypt

The imagery of Cairo (30°2’35.1”N 31°16’56.3”E, Fig 1g) was recorded on January 29, 2019. Cairo is a typical urban area, with a compact and heterogeneous distribution of land cover types. The region is covered with garbage from the city center to the countryside, and from the streets to the roofs of the houses. The largest settlement is Mokattam village, with a population of around 30,000 humans, located at the foot of the Mokattam Mountains, next to Manshiyat Naser. The people living here - the Zabbaleen - have served as Cairo's informal garbage collectors since the 1940s, and are a key element of Cairo's waste management system. Some 9,000 tons (Guénard, 2013) of waste are brought here for disposal every day, 80% of which are recycled and turned into sellable raw materials (Woods, 2011). The Zabbaleen live in impoverished conditions, especially as they live among the village's sorted
rubbish and with their livestock. However, they have formed a strong and close-knit community.

4 Methodology

In this study, a classifier was developed based on the physical principles of spectroscopy and tested to automatically identify and cluster different plastic materials in WV-3 data. The general schematic of the overall flowchart for this study is illustrated in Fig. 2. The strategy of spectral resampling to the spectral resolution of WV-3 band filter paths, based on the spectral response functions of the sensor, is presented in Section 4.1. The evaluation of different plastic materials in terms of their spectral characteristics and their molecular structures is discussed in Section 4.2. The rules and routines for the classifier were accordingly developed in Section 4.3, based on the theoretical analyses of the available spectral libraries. Hence, the spectra were sorted into four major clusters consisting of aliphatic plastics and two subgroups of aromatic plastics and non-plastics. Finally, the performance of the classifier to detect different kinds, types, and fractions of plastics was examined by the calculation of confusion matrices on lab, and experimental and airborne data convolved to the WV-3 spectral response in Section 4.4.
Fig. 2. Schematic representation of the study design, including the data used, the data evaluation, the design of the classifier, and the application, TOA: top of atmosphere, BOA: bottom of atmosphere. See text for acronyms.

4.1 Spectral resampling

To obtain a theoretical insight into the capability of the WV-3 instrument for the detection of different plastic materials, all library spectra, all experimentally derived spectra, and all airborne hyperspectral datasets are convolved to the SWIR spectral filter characteristics of the WV-3 sensor. Data with lower spectral resolution are simulated from higher spectral resolution using Eq. 1:

\[
R_i = \frac{\int_{\Delta \lambda} SRF_i(\lambda)R_{\text{lab}}(\lambda)d\lambda}{\int_{\Delta \lambda} SRF_i(\lambda)d\lambda} \quad (1)
\]

where \(R_i\) is the \(i\)th band of the lower resolution data, \(SRF_i(\lambda)\) is the measured spectral response of band \(i\), and \(R_{\text{lab}}(\lambda)\) is a measured radiance or reflectance of the higher spectral resolution.
resolution data (van der Meer and De Jong, 2011). Fig. 3 shows the original high-resolution spectra of all plastic types investigated in this study combined with the resampled spectra.

4.2 Evaluation of the chemical bonds in plastics

Plastics are petroleum derivatives with the backbone of C-H chains and distinctive functional groups. Consequently, they display diagnostic spectral features in the SWIR range. There are further absorption features displayed in the VNIR range (400-1300 nm). However, most of these correspond to electronic transitions between pigment molecules and are excluded from the identification process for this reason. Plastics are polymerized with one-repeat units. Thus, due to their relatively simple molecular structure, their absorption features in the SWIR range are easier to explain than those of natural organic materials. Diagnostic absorption features displayed by plastics in the SWIR range are mainly controlled by the stretching vibration overtones and combination modes of C=O, C-C, and by hydrogen-containing functional groups (X-H), including O-H, N-H, C-H, and others (Schwanninger et al., 2011).

The general absorption features of the C-H bond in plastics (Fig. 3) can be understood based on their mode assignments, including the 1st and 2nd orders of the overtone stretching modes (2ν: 1600-1800 nm, 3ν: 1100-1250 nm) and the combination modes (1νComb: 2150-2500 nm, 2νComb: 1300-1450 nm). The 2nd order of the combination mode is not contemplated in this study as it is masked by the overlay of the 1st overtone of water (O-H) emerging at 1400 nm. This O-H band causes a lack of transparency in the atmosphere and generally prevents access by remote sensing techniques. All spectra of plastics depict a stair-like shape, with inflection points at the 1st overtone and the combination band respectively. This is caused by a gradually decreasing absorptivity toward the higher order of overtones and combination tones.
The C-H bonds in plastics are not isolated but connected with distinct functional groups which have various masses and bond force constants. Due to the anharmonicity and Fermi resonance, vibration frequencies induced by C-H bonds do not fall within the same spectral band in all plastics. These spectral characteristics offer the potential to identify and distinguish between different types of plastic, based on their unambiguous spectral absorption features (Czarnecki et al., 2015; Beć et al., 2018). The correspondence of a spectrum and its vibration mode of C-H bonds is well investigated by both experiments and Density Functional Theory (DFT) simulations (Beć and Huck, 2019; Ma et al., 2019).

Ma et al., (2019) pointed out that the sp hybridization of CC bonds affects the diversity of absorptions for (C-H) substances. Sp hybridization can be described as an entanglement between s and p orbits of the outermost shell of the atom. Consequently, the plastic materials under investigation can be divided into two major clusters: aromatic polymers with benzene rings (sp2 hybridization, Fig. 3a) and aliphatic polymers without benzene rings (sp3 hybridization, Fig. 3b). The sp2 hybridization with a stronger bond force constant can induce a higher absorption frequency than the sp3 hybridization. The raw spectra of plastics without benzene rings produce second overtone absorptions at around 1210 nm and first overtone absorptions at 1730 nm. As far as plastics with benzene rings are concerned, absorptions emerge at higher frequencies in the second overtone range around 1140 nm, while the first overtone absorptions show a "blue shift" to around 1660 nm. In the range of the combination mode, a strong absorption feature appears around 2300 nm among aliphatic plastics, resulting from the combination mode of a C-H stretching and bending vibration. Plastics of the aromatic type have one more broad absorption region related to C-H and C-C stretching vibrations in the combination mode, at around 2130 nm.
Fig. 3. Stacked plot of reflectance spectra of various plastic materials investigated in this study. Laboratory-derived spectra (~1 nm res.) are combined with their respective versions resampled to WV-3 band design. Upward pointing arrows mark bands with diagnostic peaks and downward pointing arrows indicate diagnostic absorption bands. Curves are offset and highlighted in three different colors for clarity.

There are further explainable diagnostic features displaying in the highly resolving lab reflectance spectra sampled at 1 nm intervals like N-H (ν 2: 1517 nm) and C=O (νcomb: 2250 nm).
nm), but these are not unveiled in the simulated WorldView-3 spectra due to the diminished spectral resolution.

Yet, the spectral resolution in the range of the 1st overtone and combination band is quite sufficient to distinguish aromatic plastics from aliphatic plastics, by clearly evaluating relevant absorptions and peaks as described. Looking further into the details of aromatic plastics, it is found that the position of the absorption peak of the 1st overtone in PBAT, PU, and ABS shifts to longer wavelengths, along with a smoothing effect. The latter is caused by the low spectral resolution of spectra convolved to the WV-3 bandwidths, resulting in the disappearance of the absorption at 1660 nm. Hence, based on the variety of diagnostic absorption features studied, we are theoretically able to separate the investigated plastic materials into at least three different categories namely two clusters of aromatic and one cluster of aliphatic plastics.

4.3 Development of the classifier routines

A knowledge-based decision tree classification method, based on diagnostic absorption features of plastic materials caused by their molecular structure, is developed and applied. Although the basic features can accordingly be extracted, further constraints caused by the limited spectral resolution had to be researched empirically, based on the spectral libraries used.
Fig. 4. Schematic illustration of the Normalized Hydrocarbon Index (NHI) calculation by computing the absorption depth using a convex hull.

The classifier works in several consecutive steps, which are presented in the following. Therefore, a "Normalized Hydrocarbon Index" (NHI) was developed in this study (Fig. 4), based on the HI proposed by (Kühn et al., 2004), which gives the concavity or convexity of a curve at the point $\lambda_B$. The formula is provided in Eq. 2. For $\text{NHI} > 0$, the curve at $\lambda_B$ is concave, the value indicating the relative absorption depth at the given wavelength.

$$\text{NHI} = 1 - \frac{R_B}{R_A + (\lambda_B - \lambda_A) \frac{R_C - R_A}{\lambda_C - \lambda_A}} \quad (2)$$

Fig. 5 illustrates the entire routine of the algorithm and highlights the core theory-based steps in bold black fonts, while the additional empirical constraints are displayed in gray font types. The classifier starts with the separation of the aliphatic from the aromatic hydrocarbons, based on their opposite concavity at 2165 nm. Different routes for aliphatic and aromatic compounds are separated with dashed and solid frames. In the aliphatic group, only a single cluster is extracted while two routes are applied because of the influence of other materials in mixed pixels. Among the two routes, one has stricter requirement on the minimum at 1730 nm while the other gives tolerance to mixed pixels and applies a threshold ($d_1$) of NHI at
1730 nm. Two clusters can be isolated in the aromatic group, based on their distinctive absorption features, such as the minimum at 1660 nm and the maximum at 2165 nm or 2205 nm. For these two clusters, the respective thresholds are introduced to give tolerance to mixed pixels.

To determine suitable threshold values, the evolution of balanced values for the "user’s accuracy" (UAc) and "producer’s accuracy" (PAc), namely the F1-score, was calculated along with the respective thresholds from 0 to 1 in steps of 0.01 (Fig. 6). The figure illustrates that the classifier shows sufficient robustness in clusters 1 and 2, with F1-scores reaching the peak when the threshold is set to 0.02 and 0.05 respectively. For cluster 1, all possible thresholds result in a balanced accuracy of more than 80%, while, for cluster 2, a threshold lower than 0.5 is required to reach such a score. The robustness of the classifier on cluster 3 is relatively less desirable than that of the other two, with the F1-score peaking when the threshold of the classifier is set to 0.02. The F1-score surpasses the 80% level only when the threshold is set to 0.02 and 0.03. A low threshold value makes the classifier more sensitive for spectra, displaying only minor absorption band depth; however, vice versa, it becomes less robust against noise. In this study, the threshold values for clusters 1, 2, and 3 are chosen as tradeoffs between sensitivity and noise to 0.1, 0.05, and 0.02 respectively. Nevertheless, the threshold values for clusters 1 and 2 can be adapted flexibly.
Fig. 5. Flowchart of the developed knowledge-based classifier routine. k: slope; d: input thresholds.
Fig. 6. F1-score versus threshold curves for the three detectable clusters. Red = cluster 1, green = cluster 2, and blue = cluster 3.

4.4 Evaluation of lab and airborne data

The sensitivity of the proposed classifier in respect of varying abundances/fractions of plastics and the respective background materials is assessed on datasets produced by the HySimCaR model (Kuester and Bochow, 2019). In total, the detectability of 39 samples with the most-used plastic types (HDPE, PVC, PS, PP, PET, PBAT) in different physical properties are examined on 12 backgrounds with fractional covers of 0 to 100% in 42 steps. The background materials for the simulation were asphalt, concrete, bright sand, dry soil, wet soil, peat soil, dry grasslands, vital grasslands, vegetated areas, Baltic Sea, River Po, and River Elbe.

Confusion matrices were calculated in accordance with ground truth maps (see details in Section 3.1) to evaluate the potential of the classifier to detect plastics in the lab and airborne datasets. The performance of the classifier is demonstrated using producer’s accuracy (PAc, i.e. precision), user’s accuracy (UAc, i.e., recall) as well as the overall accuracy (OAc). To assess the level of agreement and reliability of the classifier, Cohen’s kappa coefficient was computed. In addition, the F1-score - which calculates the harmonic balance of UAc and PAc - was used to avoid bias from imbalanced ground truth. Due to the problematic of ground
truthing concerned with the totally inhomogeneous substance of the (plastic) garbage at the Accra and Cairo sites recorded by the WV-3, the plausibility of results derived from WV-3 imagery is assessed via ground images instead of mathematical accuracy.

5 Results and Discussion

5.1 Classifier performance for spectral libraries and measured lab data

Table 4 shows the confusion matrix and accuracy metrics for the classification of the spectral libraries (Section 2.1.1.) In general, the PAc exceeds 80% for all classes, and the UAc exceeds 85% for non-plastic and for clusters 1 and 2. The F1-score is above 85% for all classes. More than 99% of the non-plastics can be excluded by the developed classifier, which means on the basis of 3,391 non-plastic samples in total, only 14 samples are falsely recognized as plastics. It is, therefore, noteworthy that the errors arise almost only as false negatives, which are almost equally distributed among the three plastic clusters (10 to 15%). There are only minor misclassifications among the three plastic clusters, which leads to the conclusion that the classifier can separate these three clusters based on lab spectra very well.
Table 4. Confusion matrix based on all spectra in all libraries (see Table 1). The values of the producer’s accuracy are highlighted in bold. N: non-plastic cluster; C1, C2, C3: plastic clusters; UAc: user accuracy; F1: F1-score; OAc: overall accuracy; κ: Kappa coefficient.

<table>
<thead>
<tr>
<th>Spectral library</th>
<th>Ground truth (% accuracy)</th>
<th>UAc</th>
<th>F1</th>
<th>OAc</th>
<th>κ</th>
</tr>
</thead>
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<tr>
<td></td>
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<tr>
<td></td>
<td>C3</td>
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<td>0</td>
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Fig. 7 illustrates the setup of the lab experiments that were conducted. Several plastic materials of different chemical and physical properties were placed on (a) bright sand, and (b) dark soil backgrounds and measured by the HySpex sensor. The top row shows SWIR color composites (a, b) of the setup, while the bottom row depicts the results derived by the developed classifier (c, d). Each column represents a series of samples of one/two type(s) of plastic material with different physical properties. Those selected (PE, PP, PS, PET, and PBAT) represent the three clusters discussed in Section 4.1, and are marked as C1, C2, and C3. The white dashed grid lines are introduced to separate samples with individual parameters. Each row contains materials with the same physical properties like transparency, translucency, and bright/median/dark opacities. The results of the classification clearly show that the black-colored samples in this experiment with average reflectances below 10% cannot be detected. This is on account of the too low reflectivity of the target, leading to an insufficient
signal to noise ratio (SNR) and a severe quenching of the respective absorption features. All other plastic materials are clearly identified at the bright sand background as well as on the dark soil, regardless of their physical properties. There were only a few pixels found omitted within the transparent PP, PET, and PBAT materials, or misclassified when placed on black soil backgrounds. The calculated confusion matrices of the classification results on both backgrounds are given in Table 5. The producer's accuracy of all classes is over 99% on both backgrounds, except for C3 on dark soils. C1 reached 100% on both backgrounds as well as non-plastic on sand. As expected, all accuracy indicators (PAc, UAc, OAc, and F1) yields better results on bright sand than on dark soil, especially C3 with some omitted pixels. In general, both the Cohen's kappa coefficients (κ) are greater than 90%, proving that the classifier is very reliable.

Fig. 7. Images of the laboratory experiment. Various plastic materials of different physical properties were measured by the HySpex sensor placed on bright sand (a) and dark soil (b) backgrounds. Results of the classification for (a) are shown in (c), and for (b) depicted in (d). C1=PE/PP; C2=PS/PET; C3=PBAT. TP:
SWIR-bands of the HySpex sensor were convolved to spectral characteristics of the WV-3 spectral bands. Bands 1730 nm, 1570 nm, and 2205 nm coded RGB.

Table 5. Confusion matrices of classified plastic materials measured during a lab experiment on bright sand and dark soil backgrounds. The values of the producer’s accuracy are highlighted in bold. N: non-plastic cluster; C1, C2, C3: plastic clusters; UAc: user accuracy; F1: F1-score; OAc: overall accuracy; κ: Kappa coefficient.

<table>
<thead>
<tr>
<th>Classes</th>
<th>Ground truth (% accuracy)</th>
<th>N</th>
<th>C1</th>
<th>C2</th>
<th>C3</th>
<th>UAc</th>
<th>F1</th>
<th>OAc</th>
<th>κ</th>
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</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>C1</td>
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<td>b. Soil</td>
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<td></td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>N</td>
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<td>C2</td>
<td>C3</td>
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<td>1087</td>
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The omission of transparent samples results from the low reflectance of the dark soil with averages of around 25%. According to Miller et al., 1992, the apparent reflectances of non-opaque materials over background substances can be derived from Eq. 3, where $A$ is the apparent reflectance, $r$ and $t$ are the real reflectance and transmittance of the target, and $rb$ is the reflectance of the background.

\[ A = r + t^2 rb \]  

Only the light that is not absorbed by an object can be reflected or transmitted. Hence, both transmittance and reflectance spectra of an object show the same absorption band positions and can be used to identify and ideally quantify the respective material. For highly transparent or translucent samples, the reflectance is very low; the identification of an object is mainly dependent on its transmittance, given by the second term of Eq. 3. Since the transmittance is less than 1, its square will be much smaller, and the magnitude of the background reflectance will determine whether the object will have enough apparent reflectance to be recognized. Besides, the shape of the background reflectance also influences the apparent reflectance. In summary, a material with a higher transparency will have a greater transmittance in the wavelength range with low absorption, and its apparent reflectance is proportional to the background reflectance. Hence, backgrounds have notable influences on the apparent reflectance, especially for transparent and translucent plastics, which are the most common plastics on the market. The analyses in relation to the lab experiments demonstrate that all three clusters of plastics can be differentiated well and separated from non-plastic materials, indicating that the classifier designed shows the expected performance. As for the classification of the spectral libraries, the only errors represent false negatives, which can be attributed to the low apparent albedo of the dark samples.
5.2 Classifier performance for simulated HySimCaR datasets

As a next step, the classifier was applied to simulated datasets, which include 39 samples on 12 different backgrounds, with 42 steps of surface cover fractions in the range of 0-100%. Based on the conclusions drawn in Section 5.1, no black opaque sample is considered in this assessment. To better visualize the results, a heatmap was generated (Fig. 8). The x and y axes represent different types of backgrounds and various samples of plastic materials. The backgrounds include two artificial materials (asphalt and concrete), four bare soils sorted from bright to dark and wet, three surfaces covered with vital and dry vegetation, and three water bodies. Plastic materials are grouped in accordance with their optical behavior, as transparent, translucent, and opaque. The translucent and opaque samples are further grouped into bright, median, and dark species. The names of the samples are labeled in three colors, where red, green, and blue respectively represent clusters 1, 2, and 3. The heatmap depicts the detectable fractional covers of the respective materials by the level of saturation of the blue color and guided by a color bar. I.e., the value on row i and column j indicates that from this fractional cover, the classifier is able to identify the i\(^{th}\) sample on the j\(^{th}\) background. According to the color bar, the less saturated the blue color, the lower the detectable fraction per pixel, and the higher the detectability of the particular plastic material on the respective backgrounds. The cross 'x' implies that the i\(^{th}\) sample on the j\(^{th}\) background is not detectable.
Fig. 8. Display of detectable fractional covers of 39 individual plastic materials with different physical properties on 12 different backgrounds. The strength of saturation of the respective blue color marks the percentage of plastic parts per pixel that is detectable. The less saturated the blue color, the lower the detectable fraction per pixel and the higher the detectability of the particular plastic material on the respective backgrounds. X: Undetectable. Abbreviations of plastic materials belonging to cluster 1=red, cluster 2=green, and cluster 3=blue.
On asphalt and concrete, almost all the translucent plastics can be identified at a relatively low fractional coverage. Among the transparent and opaque plastics, the transparent PBAT and PET samples and the two opaque dark PET samples could not be detected. The classifier exhibits a similar performance for most plastics on dry bright sands and dry soils. In contrast to other backgrounds, the detectability for all transparent plastics decreases when placed on darker soils or wet and peat soils, while it does not vary much for translucent and opaque plastic materials. On vegetated backgrounds, the classifier's detection ability is generally lower for nearly all types of plastic materials, where some remain completely unidentifiable. For transparent plastics, there is a significant increase in the detectability at dry grass as compared to vital grass and vegetated canopies. Translucent and opaque plastics are also difficult to detect on areas covered by vital vegetation, which is especially obvious for medium and dark samples as well as for the white opaque PVC. As for the three bodies of water, most of the transparent plastics could not be identified because of the strong absorption of water in the SWIR wavelength range. Surprisingly, most translucent and opaque plastics can be identified, especially cluster 1 materials, even at very low abundances. It is also of interest to note that the brightness of the samples on the water surface has a relatively large influence on the detectability, as the minimum abundance to identify bright and medium samples is generally lower than that of dark ones. However, in this simulation study, it was assumed that the plastic objects float on the water surface and are not covered by water at all.

Overall, the classifier is able to detect plastics at relatively low abundances below 10% when located on top of artificial materials, bright sand, and water, while a higher fractional cover is required for successful identification over dark soil and vegetated surfaces. For those samples with similar optical properties, more fractional coverage is usually expected to recognize the second and third clusters of plastics as compared to the first cluster. In
summary, the classifier shows a robust performance for the recognition of a majority of plastic materials at various fractional covers on most backgrounds, but also depicts inadequacy in recognizing transparent plastics on top of water bodies.

5.3 Classifier performance for airborne and WorldView-3 imagery

A further test for the developed classifier to detect plastics is carried out on four airborne hyperspectral datasets convolved to WV-3 spectral properties, acquired in Germany and Spain. The ground truth map and the classification results are highlighted in Fig. 9. The non-plastics, and the plastic clusters 1, 2, and 3, are represented as patches in yellow, red, green, and blue. Table 6 presents the confusion matrices of the classification results for an urban site (Dresden), a grassland area (Thyrow), a lake and its shore (Seddin), and a greenhouse farming region (Almeria). The urban and grassland sites contain all three clusters of plastics while in the remaining two sites, only two clusters of plastics are present. The user accuracies of all classes exceeded 97% in the urban and grassland areas, and theproducer's accuracy reaches more than 95% for all classes except the second cluster of plastics in Dresden. For the first cluster of plastics, present in all scenes, the classifier performs best in the Thyrow area - with a F1-score over 98% - and worst for the Almeria site (with a F1-score of 94.6%).

This is in accordance with the conclusions obtained in the previous section, based on the simulated data. The plastic covers of the greenhouses in Almeria are mostly translucent and on top of vegetation, where the classifier performs in a less robust manner at low fractional covers. Another reason for the less good result in identifying the plastic sheds of the Almeria site may be found in whitewashing procedures taking place in June where greenhouses are not necessarily cultivated. This procedure, done to prepare for the next season by reducing the radiation penetrating the plastic sheds, can mask the optical properties of the plastic.
The producer’s accuracies of the classification results for the second cluster of plastics are 97%, 93%, and 88% respectively for grassland, lake, and urban areas. It is further noticeable that the kappa coefficients of all four scenes exceed 0.9, illustrating the performance quality of the classifier. The results also depict that there is no omission for the three plastic clusters, and the user’s accuracies of the backgrounds all reach more than 95%, while the producer’s accuracies all achieve 99%. The accurate identification of the second cluster of plastics over the lake surface suggests that the classifier also holds great potential to be applied to monitor floating non-transparent litter in the ocean. In summary, the classifier is well capable of identifying defined clusters of plastic in both homogeneous and heterogeneous areas, even when the used hyperspectral airborne data are resampled to the moderate spectral resolution of the WV-3 satellite.

Table 6 a-d. Confusion matrices of four classified airborne data sets. The values of the producer’s accuracy are highlighted in bold. N: non-plastic cluster; C1, C2, C3: plastic clusters; UAc: user accuracy; F1: F1-score; OAc: overall accuracy; κ: Kappa coefficient.
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<thead>
<tr>
<th>Ground truth (% accuracy)</th>
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<th>F1</th>
<th>OAc</th>
<th>κ</th>
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<td></td>
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<tr>
<td>N</td>
<td>C1</td>
<td>C2</td>
<td>C3</td>
<td></td>
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<tr>
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<td>C2</td>
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<tr>
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Fig. 9. Color composites of convolved SWIR bands recorded by the airborne hyperspectral instruments HySpex (a, b) and HyMap (c, d), displaying various plastic materials on four different background surfaces. a: Grasslands (Thyrow, DE); b: Lake and shore (Seddin, DE); c: Soils (Almeria, ES); d: Urban surfaces (Dresden, DE). Ground truth targets marked with the resp. cluster materials and non-plastics are depicted in (a, b, c, and d). Classified clusters are displayed in (e, f, g, and h) underlain by color composites of SWIR bands convolved to WV-3 spectral response. Bands 1730 nm, 1570 nm, and 2205 nm coded RGB.

Finally, the classifier was applied to three WV-3 datasets to examine its potential for identification of the three plastic clusters and their separation from different background materials. The three recorded WV-3 scenes are displayed as color composites and as panchromatic bands both superimposed by the results of the classifier (Fig. 10). In the first column the sites of Almeria (Fig. 10a), Accra (Fig. 10d), and Cairo (Fig. 10g) are displayed in overview mode based on SWIR bands, while the second column (Fig 10b, e, h) shows enlarged sections of the respective imagery merged with the panchromatic band of WV-3 (0.31 m GSD) for a more detailed inspection. For plausibility assessment, photographs of the sceneries are
displayed in the third column. As expected, plastic materials of cluster 1 are most widely
distributed in the three regions, especially in the area of Almeria, where PE or PVC plastics
are generally used for greenhouse sheds (Scarascia et al., 2011). The classification layer
reproduces nearly exactly the shapes of the greenhouse sheds and depicts no to minor
misclassifications for soils and vegetated areas in the surrounding (Fig. 10a, b). The
classification result of the Accra site (Fig. 10d, e) shows mainly plastic materials of clusters 1
and 2. The local waste mainly consists of worldwide discarded electronic devices, which
contain a wide variety of plastic materials (Guénard, 2013). The enlarged view focuses on the
Korle Lagoon fed by the Odaw river, where the dumped, floating trash is dammed by a levee,
located in the middle at the bottom of the image (Fig. 10e). Further visual verification can be
made comparing the situation depicted by the imagery with a corresponding local
photograph of the levee in a southerly direction (Fig. 10f, Amasaba, 2014). The photograph
of the inhomogeneous waste also illustrates the difficulty of collecting meaningful ground
truth data for validating the result of the classification. For further inspection, Google Maps
(https://goo.gl/maps/XiUWK7HiWyyf38yT7), and photos uploaded by people to the Web
can be consulted.

The classification result of the vicinity of Mansheya Nasir in Cairo (Fig. 10h), displays plastic
materials belonging to all clusters with greater emphasis on cluster 1. The area - known as
"garbage city" - is home of the Zabbaleen people who recycle 80% of the waste in Cairo. They
sort the gathered plastic materials and usually store the plastic garbage in residential areas
on the roof of their houses as illustrated by the ground photograph (Fig 10i, McGlinch, 2009).

Inspection of the panchromatic image superimposed with the classification result already
reveals this situation (Fig. 10h). The classification layer marks all three clusters of plastic
mainly on the top of the resolved houses, further marks the artificial lawn of two larger soccer
fields (https://goo.gl/maps/9nK4SkkcYBpMyXHK7) in the top-middle of the image and
shows no or only minor misclassifications in the areas of the vegetated park in the image center nor on the shoulder of the rocks in the east. For further inspection use Google Street View images (https://goo.gl/maps/gPCWNgsN76uRtGVz9) and media reports (e.g., atlasobscura.com/places/garbage-city). The results further indicate the potential of the developed classification routine for the detection of different plastic materials at lower spatial resolutions, as provided by satellite recordings.

Fig. 10. Classification of plastic materials in WorldView-3 data of (a-c) Almeria, Spain, (d-f) Accra, Ghana, West Africa and (g-i) Cairo, Egypt. Left column (a, d, g): SWIR color composites with
superimposed classification result; SWIR-bands 1730 nm, 1570 nm, 2205 nm coded RGB. Middle column (b, e, h): Panchromatic images with superimposed classification results. Right column (c): high-resolution real color merge; (f, i): Local photographs. Classification result: Red = c1 - aliphatic group, green = c2 - aromatic group (PET, PS, PC, SAN), blue = c3 - aromatic group (PBAT, ABS, PU).

5.4 Comparison to commonly used algorithms

There is an increasing high number of various algorithms used for supervised or unsupervised classification of remotely sensed data. Although all the different methods are not comparable, we like to demonstrate how other commonly used algorithms perform in comparison to our spectra-based approach. Therefore, we chose two supervised classifiers embedded within the ENVI/IDL environment. One is the Spectral Angle Mapper (SAM) developed by Kruse et al. (1993) another the Maximum Likelihood Estimation (MLE) published by Richards, (1999). Three of our scenes were used for the testing, including the lab experiment on the sandy background (Fig 7a), and the airborne recordings of Thyrow and Dresden (Fig. 9a, d). In each of these scenarios all three clusters of plastics are present, and all sites are fully controlled by ground truthing. The ground truth maps were divided into two parts for training and testing respectively. Pixels of non-plastics are not included in the training datasets due to the huge interclass variation. We did not apply the algorithms to the real WorldView-3 datasets on account of already discussed ground truth issues.

SAM is a signal-based spectral classification method that matches pixels to reference spectra using an n-D angle. The algorithm determines the spectral similarity between two vectorized spectra (reference and unknown) by calculating the angle between them. Pixels with smaller angles are more likely to match the reference spectrum while pixels further away than the specified maximum angle threshold in radians are not classified. A primary advantage of this method is the insensitivity to illumination conditions. It is further notable that reference spectra used by SAM can come from spectral libraries or need to be extracted directly from
the respective image. Using spectra of libraries as training data is more comparable to our
classifier, but to understand the optimal performance of SAM, we also used the training part
of the images as reference data set. The performance was evaluated by calculating the F1-
score of the classification result at a series of maximum angle thresholds in steps of 0.01
ranging from 0 to pi/2 (~1.5). Fig. 11a-c show the F1-scores of the three sites versus threshold
curves obtained from the classification results using the spectral library as training data. The
three plastic classes and the one non-plastic class are represented by graphs in different
colors. It demonstrates that the performance of SAM is highly influenced by the threshold
value. When a proper threshold is selected, the F1-score of non-plastics and cluster 1 plastics
can be higher than 90%, whereas cluster 2 and cluster 3 plastics score lower than 80% in any
case. Especially in the Dresden scene, the cluster 3 plastic cannot be identified. Fig. 11d-f
depict the results using spectral samples generated from image data based on our ground
truth maps. The results are dissimilar to those in Fig. 11a-c, which illustrates that the choice
of training data also has a significant impact on the results. Both approaches of SAM
calculations indicate that the optimal threshold value varies with the respective scenarios
and classes.

The MLE assumes that the statistics for each class in each band are normally distributed and
calculates the probability of a given pixel belonging to a specific class. Each pixel is assigned
to the class that has the highest probability, namely, the maximum likelihood. If the highest
probability is smaller than the specified threshold, the pixel remains unclassified. Due to the
necessity of distributed information, only spectra derived from the image data could be used
as training data. Similarly, we examined the performance of MLE by calculating the F1-score
of the classification result at a series of probabilities ranging from 0% to 100%. Fig. 11g-i
display the result based on the same ground truth maps used for the SAM calculations. It
implies that the performance of the MLE does not meet the demand at all three scenarios.
Comparing the results derived from these three scenes with our knowledge-based classifier (Lab-sand: Table 5a; Thyrow: Table 6b; and Dresden: Table 6a), the F1-scores for each class is above 0.9 when using the same ground truth maps, thus, indicating a superior performance. The evaluation of our classifier also demonstrates its robustness, i.e., the scenario and classes
have little effect on the results and no training data is needed. The SAM performs moderately
by the use of spectral library data but unsatisfactorily like the MLE approach if image data is
to be used as a reference. In the latter case, the accuracy of the classification is highly
dependent on ground truthing, but this was very carefully accomplished for the selected
scenes. The field check becomes all the more complicated when the focus is on plastic waste
where a meaningful mapping is almost unfeasible (see photographs of Fig. 10). This is to some
extent also true for popular algorithms like machine learning and deep learning as they also
rely on training datasets and require parameter tuning.

Certainly, statistically based classifiers provide a convenient and general option for nearly
every material once reliable training data are available. As for the here developed classifier,
one has to carefully examine the spectral behavior of the targeted material with its physical
background, which may take some efforts. But once the classifier is designed, it’s trustful and
robust and no pre-knowledge of the areas under consideration is needed.

5.5 Final assessment of the developed classifier routine

The performance of the classifier in detecting different plastic materials was evaluated on
various backgrounds, including grasslands, water bodies, farming regions, and urban areas,
which are common scenarios in terrestrial remote sensing. The classifier obtained decent
results at relatively low fractions of plastics on all background materials and, so, provided an
efficient and transferable concept for the global detection of plastics. Once set up by the
respective spectral properties of the targeted material, it operates in an autonomous mode,
and can be further combined with other exogenous data. All the requisite thresholds for the
classifier are applied to indices or ratios and never directly to the reflectance values. This
contributes to the transferability and robustness of the classifier and its results, and makes it
unsusceptible to BRDF effects and artifacts introduced by atmospheric corrections.
However, with all advantages of the newly developed classifier, there are also a few limitations to be mentioned. In the present form it is dedicated to detect different types of plastic with a high accuracy and cannot detect any other materials. The principle scheme can be adapted to nearly any other materials, but with a different setup based on the respective spectral properties. Concerning the detectability of plastics, it is not sensitive enough to reveal black plastics with an averaged reflectance below 10%. In this case, hyperspectral thermal sensors are the first choice, since the fundamental vibrations of C-H bonds are located in the thermal infrared range (TIR), providing better preconditions for diagnosis as the emission of dark materials is generally high in this wavelength region. Furthermore, organic polymers with chemical compositions similar to plastics may be misclassified. For example, asphalt - as a type of methyl petroleum derivative - displays very similar reflectance spectra to that of plastic cluster 1. Although asphalt can be excluded by increasing the threshold value, pixels containing lower abundances of plastic would then not be identified as such. Therefore, the choice of threshold values needs to be balanced properly. Moreover, PBAT transparent samples of the simulated data could not be identified on the surface of the bright sand, which seems to be not quite consistent with the results obtained from our laboratory data. However, one possible influencing factor that we have not yet considered is the thickness. For thin plastics, the light travels a rather short distance inside the material, which reduces the spectral absorption depth and, so, makes them unrecognizable for the classifier. The spectral absorption depth is positively proportional to the thickness, and, thus, it is important to consider the effect of thickness for quantitative studies of plastics with transparent or even translucent materials. We have also not explicitly considered the degradation of plastics, which is usually accompanied by the breakage of chemical bonds, although a part of the samples used for the lab experiments and simulation study has been collected in the environment. This may lead to classification failure, although the developed
classifier is constructed on the absorption features of the C-H bonds. For future research, it is planned to explore the quantification ability as well as further improvements of the classifier after considering the thickness and degradation phenomena of plastics, to broaden its application to other targets, and utilize the classifier to fuse with multi-source data to achieve additional intelligent recognition functions.

6 Conclusion

The results of this study clearly demonstrate that a worldwide identification and separability of terrestrial plastics with different chemical and physical properties is feasible by the use of WorldView-3 satellite imagery. The core element of this study is the newly-developed, decision tree style, knowledge-based classifier which was exclusively built to detect and identify most common plastics materials of the aliphatic and aromatic groups. The detectability of three distinct plastic clusters is totally based on theoretical considerations concerning the detailed spectral characteristics of plastic materials in connection with their molecular structure. No training data is needed and no statistical approaches have to be accomplished. The algorithm can be adapted to further specific targets, but needs a new setup according to the spectral characteristics of the respective materials. The first cluster to be identified is the aliphatic group, comprising PE, PVC, EVAC, PP, POM, PMMA, and PA. The second and third clusters are diagnostic for the aromatic group, including PET, PS, PC, and SAN, separated from PBAT, ABS, and PU respectively. The non-plastic cluster comprising nearly all other natural and man-made materials is defined by the majority of spectra in the databases used. The hit ratio of the classifier is significantly high, and its robustness is proven by comparative analyses to SAM and MLE approaches and by our HySimCaR radiative transfer model which was used to calculate the influence of different factors like material characteristics, backgrounds, and fractional covers. The validation of the results based on spectra, the experiments conducted, and the modeled data was accomplished by the
calculation of various error measures using confusion matrices. Concerning the airborne data, the validation is based on controlled field experiments and intensive field checks. But ground truth for plastics, especially for plastic waste cannot always be conducted in detail due to its nature and fast temporal relocation. However, when finally applying our classification scheme to the WorldView-3 datasets, the results appear reasonable and of similar significance to those of laboratory experiments and airborne investigations.

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**List of Figure Captions**

**Fig. 1.** Sketch map and detailed coordinates of test sites recorded by aircraft scanners and the WV-3 satellite.

**Fig. 2.** Schematic representation of the study design, including the data used, the data evaluation, the design of the classifier, and the application, TOA: top of atmosphere, BOA: bottom of atmosphere. See text for acronyms.

**Fig. 3.** Stacked plot of reflectance spectra of various plastic materials investigated in this study. Laboratory-derived spectra (~1 nm res.) are combined with their respective versions resampled to WV-3 band design. Upward pointing arrows mark bands with diagnostic peaks and downward pointing arrows indicate diagnostic absorption bands. Curves are offset and highlighted in three different colors for clarity.

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Fig. 8. Display of detectable fractional covers of 39 individual plastic materials with different physical properties on 12 different backgrounds. The strength of saturation of the respective blue color marks the percentage of plastic parts per pixel that is detectable. The less saturated the blue color, the lower the detectable fraction per pixel and the higher the detectability of the particular plastic material on the respective backgrounds. X: Undetectable. Abbreviations of plastic materials belonging to cluster 1=red, cluster 2=green, and cluster 3=blue.

Fig. 9. Color composites of convolved SWIR bands recorded by the airborne hyperspectral instruments HySpex (a, b) and HyMap (c, d), displaying various plastic materials on four different background surfaces. a: Grasslands (Thyrow, DE); b: Lake and shore (Seddin, DE); c: Soils (Almeria, ES); d: Urban surfaces (Dresden, DE). Ground truth targets marked with the resp. cluster materials and non-plastics are depicted in (a, b, c, and d). Classified clusters are displayed in (e, f, g, and h) underlain by color composites of SWIR bands convolved to WV-3 spectral response. Bands 1730 nm, 1570 nm, and 2205 nm coded RGB.
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Fig. 11. F1-score versus threshold curves for three selected test sites. SAM classification results based on training data from the spectral library (a-c); and from ROIs (d-f). MLE classification results using training data from ROIs (g-i). Black = non-plastics, red = cluster 1, green = cluster 2, blue = cluster 3.
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Table 5. Confusion matrices of classified plastic materials measured during a lab experiment on bright sand and dark soil backgrounds. The values of the producer’s accuracy are highlighted in bold. N: non-plastic cluster; C1, C2, C3: plastic clusters; UAc: user accuracy; F1: F1-score; OAc: overall accuracy; \( \kappa \): Kappa coefficient.

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