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Technical Note

Potential Assessment of PRISMA Hyperspectral Imagery for Remote Sensing Applications

Riyaaz Uddien Shaik [1], Shoba Periasamy [2] and Weiping Zeng [1,*]

[1] Super GeoAI Technology Inc., 229-116 Research Drive, Saskatoon, SK S7N3R3, Canada
[2] Department of Civil Engineering, SRM Institute of Science and Technology, Kattankulathur, Chengalpattu 603203, Tamil Nadu, India
* Correspondence: weiping.zeng@supergeo.ai

Abstract: Hyperspectral imagery plays a vital role in precision agriculture, forestry, environment, and geological applications. Over the past decade, extensive research has been carried out in the field of hyperspectral remote sensing. First introduced by the Italian Space Agency ASI in 2019, space-borne PRISMA hyperspectral imagery (PHSI) is taking the hyperspectral remote sensing research community into the next era due to its unprecedented spectral resolution of ≤12 nm. Given these abundant free data and high spatial resolution, it is crucial to provide remote sensing researchers with information about the critical attributes of PRISMA imagery, making it the most viable solution for various land and water applications. Hence, in the present study, a SWOT analysis was performed for PHSI using recent case studies to exploit the potential of PHSI for different remote sensing applications, such as snow, soil, water, natural gas, and vegetation. From this analysis, it was found that the higher reflectance spectra of PHSI, which have comprehensive coverage, have greater potential to extract vegetation biophysical parameters compared to other applications. Though the possible use of these data was demonstrated in a few other applications, such as the identification of methane gases and soil mineral mapping, the data may not be suitable for continuous monitoring due to their limited acquisition, long revisiting times, noisy bands, atmospheric interferences, and computationally heavy processing, particularly when executing machine learning models. The potential applications of PHSI include large-scale and efficient mapping, transferring technology, and fusion with other remote sensing data, whereas the lifetime of satellites and the need for interdisciplinary personnel pose challenges. Furthermore, some strategies to overcome the aforementioned weaknesses and threats are described in our conclusions.

Keywords: Italian Space Agency; hyperspectral imagery; potential assessment; PRISMA; SWOT

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1. Introduction

PRecursore IperSpettrale della Missione Applicativa (PRISMA), a satellite of the Italian Space Agency, carries a hyperspectral sensor that captures a continuum of spectral bands in the range of 400–2500 nm with a spatial resolution of 30 m. The widths of spectral sampling intervals are ≤12 nm. This sensor counts 173 bands within 920–2500 nm in the short-wave infrared (SWIR) portion and 66 bands within 400–1010 nm in the visible near-infrared (VNIR) portion of the light spectrum. A panchromatic camera on PRISMA provides a single band in the wavelength range of 400–700 nm at a 5 m spatial resolution [1,2].

PRISMA hyperspectral imagery (PHSI) has been used for applications such as forest fuel mapping [1]; forest discrimination [2]; burned area mapping [3]; prediction of methane emissions [4]; agricultural applications [5]; the study of geochemical investigations for parameters of soil moisture, soil organic matter, and soil organic carbon [6]; the study of water quality [7]; and geological applications [8,9]. The 'Sviluppo di Prodotti Iperspettrali Prototipali Evoluti' project funded by the Italian Space Agency is developing procedures to map fire presence and fire severity, the extent of fire fuel, urban growth, urban areas, industrial areas, volcanic areas and volcanic parameters, and vegetation. PRISMA proved to be a valuable instrument for the determination of the residual fire severity in an investigated area (ASI | Agenzia Spaziale Italiana). Thus, the PRISMA satellite has wide applicability [10].

Bibliometric information collected from the literature was augmented using VOS-viewer software (Figure 1) to identify PRISMA applications, techniques, and processing methods. Such maps outline the relationships between existing publications based on the relationships between journals, institutions, types of problems, and the frequency of topic reoccurrences. Reoccurrences of keywords in the reviewed articles are mapped in Figure 1. The links that attach the nodes in Figure 1 indicate connections between them; the shorter the distance between them, the stronger the relationship. Scientometrics is the field of study that concerns itself with measuring and analyzing scholarly literature. A scientometric analysis of the augmented clusters shown in Figure 1 indicates that the "PRISMA" keyword had the most repetitions (repeated 11 times), followed by Sentinel-2 with five occurrences, which indicated articles on multispectral and hyperspectral data fusion. As shown in Figure 1, the other predominant sensors next to PRISMA are HYPSIRI [11] and AVIRIS [11], which are hyperspectral spectrometers. Before the launch of PRISMA, AVIRIS datasets were employed in which these terms reoccurred, and some researchers connected these data with future sensor HYPSIRI. Application domains such as nitrogen content prediction, classification, and agriculture were repeated, which indicates crucial applications for which the sensor is frequently used. Terms such as "classification", "regression", and "dimension reduction" were also used in the PRISMA papers. Dimensional reduction is necessary to reduce the computation load and the time required for computation. The guided image filtering term shown in Figure 1 is an effective noise reduction technique used for hyperspectral data.

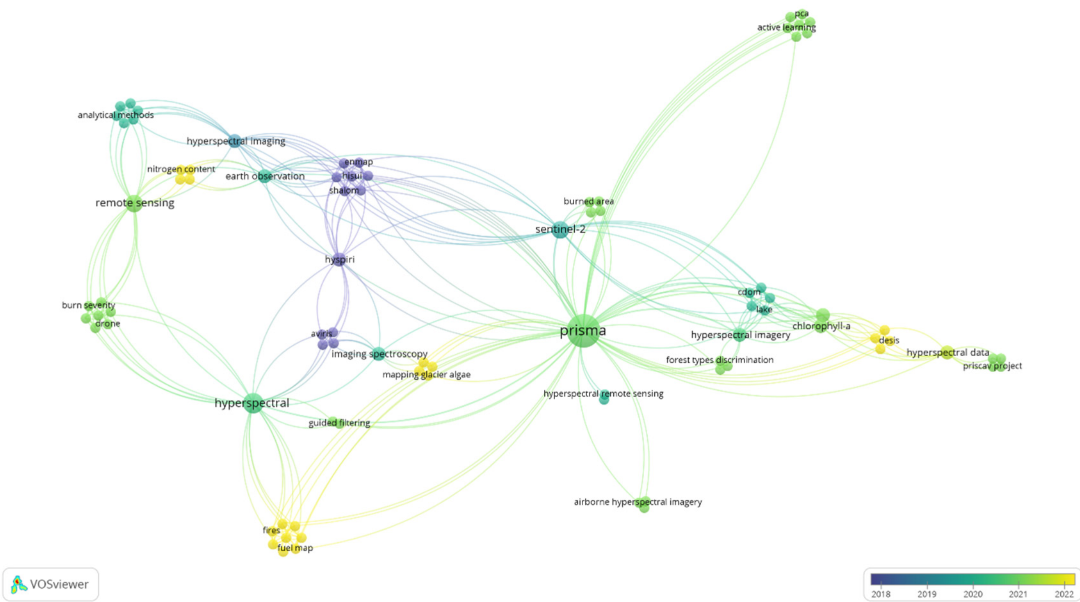

Figure 1. Knowledge mapping (2018–2022): scientometric analysis using VOS-viewer software. The color bar at the bottom right corner denotes the year of the publication. This scientometric analysis considered publications from 2018 to 2022 because the PRISMA satellite launched in 2018.

Figure 2 is based on the results of the scientometric analysis depicted in Figure 1. This analysis is used in various earth observation inventory applications (Figure 1). Riyaaz et al. [1] reported the automatic procedure developed for fuel types in forest fires and concluded that PHSI provides an overall accuracy of around 85%. Their procedure can map fuel types in any part of Europe, and thus assist researchers/policymakers/fire managers in studying fire potential, behavior, emissions, management, effects, and land surface temperature. Sander et al. [11], in their survey, reported that PRISMA data products provide opportunities to further explore linkages between ecosystem properties and fires on both regional and global scales.

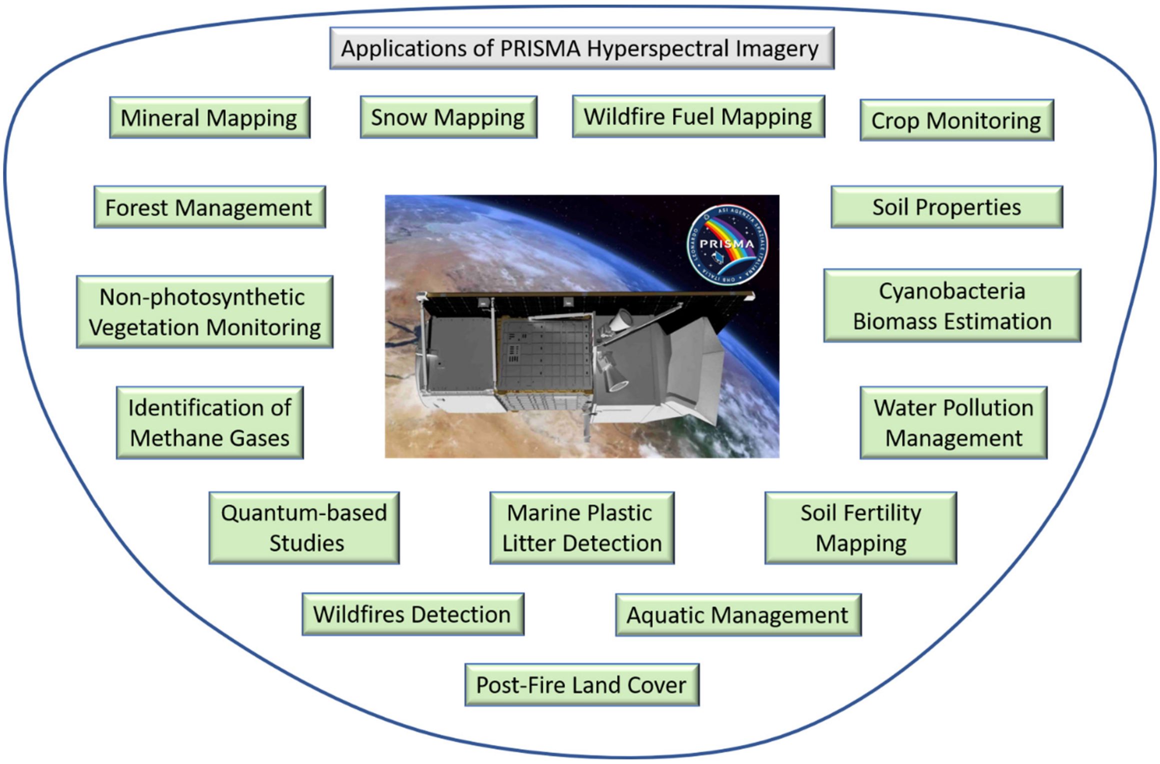

Figure 2. Applications of PRISMA Hyperspectral Imagery.

In a study conducted to map burned areas [3] using PHSI and Sentinel-2—a constellation of two polar-orbiting satellites—sensors data demonstrated that the combined use of optical and hyperspectral datasets enabled the detection of burned areas in a complex background with an overall accuracy of 98%. Lazzeri et al. [12] conducted multitemporal mapping of post-fire land cover using PRISMA, Sentinel-2, and unmanned aerial vehicles (UAVs) in Portugal and Italy. It was demonstrated that due to the ability to capture imagery in a broader wavelength range, the hyperspectral sensors on UAVs are more beneficial than PRISMA or Sentinel-2. Due to its ability to detect and classify nonphotosynthetic vegetation [13], PRISMA was found to be suitable for studying crop residues; however, senescent vegetation had not yet been harvested, and crop residues were not well distinguished. The study added that PRISMA is not designed to quantify cellulose abundance or to evaluate differences among species. Bohn et al. [14] used PHSI to estimate glacier ice surface properties, such as crystal size, algae concentration, and liquid water content. Niroumand-Jadidi et al. [7] compared the results of PRISMA and Sentinel-2 in a study of water quality and reported that an atmospheric correction algorithm developed for PRISMA did not improve the results of either method. Bresciani et al. [15] compared hyperspectral data from PRISMA and the Earth-sensing imaging spectrometer (DESIS) used by the German Space Agency (DLR) for aquatic applications. They reported that more data for training and validating would improve the results for both technologies. Kokal et al. [16] compared PRISMA with LANDSAT-9 in land cover classification using a support vector machine classifier and obtained overall accuracies of 89.33% for LANDSAT-9 and 92.33% for PRISMA. As LANDSAT-9 has a spectral resolution of 20–180 nm and PRISMA has a spectral resolution of $\leq$12 nm, it was concluded that the higher spectral resolution of PRISMA accounted for its slightly better results.

From the literature search of PRISMA research, it was identified that, in a few studies, strengths and weaknesses were explicitly discussed, while threats and opportunities were overlooked. Meanwhile, other studies may be useful for explaining threats and opportunities, while ignoring other parameters. Many studies have explicitly reported the working potential of PRISMA for their applications. However, to the best of our knowledge, no comprehensive study quantitatively consolidates this information via a SWOT strategy to bring out the potential of PRISMA images. This comprehensive study is essential for researchers working on a hyperspectral remote sensing cluster to understand the importance of these newly launched data and their range of applications. The SWOT analysis is the process of evaluating the interrelations between external and internal factors of a system to extract strengths, weaknesses, opportunities, and threats; it is a mixed evaluation (subjective–objective) [17–19]. Combining these analysis strategies will provide a comprehensive update and a detailed assessment of the situation. Strengths and weaknesses are internal elements connected to the objectives and performance of satellite data [19]. At the same time, opportunities and threats are external elements that consider features facilitating the establishment of businesses and hindering achievable goals, respectively [20]. In this study, a SWOT analysis was conducted for PHSI and further strengthened by examining the internal and external factors reported in the various case studies. The objectives of this study are as follows: (i) bibliometric analysis of publications on PHSI focusing on applications; (ii) SWOT analysis with case studies from the literature, which includes the technical defects of this imagery. SWOT analysis has remained one of the best ways to assess the potential of any system, and there is no research available that contains a SWOT analysis of PHSI. We believe this comprehensive study with a SWOT analysis would help the remote sensing community to better understand the potential of PHSI.

2. Materials

2.1. PRISMA Hyperspectral Products

PRISMA products are divided and subdivided according to their utility. Level 0 provides raw data in binary files, including instrument and satellite ancillary data (e.g., cloud cover percentage). Level 1 consists of radiometrically and geometrically calibrated hypercubes and panchromatic radiance images in the higher atmosphere. Level 2 consists of four sub-levels: L2A, L2B, L2C, and L2D. Images of geolocated on-ground radiance (L2B), geolocated reflectance (L2C), and geolocated and geocoded on-ground reflectance images (L2D) are provided [2,21].

Land cover mapping and cloud masking are available in the Level 1 product. This includes atmospheric constituents such as aerosols, thin cloud optical thickness, and water vapor. Details of PRISMA products are provided in the PRISMA specifications document. Levels 1 and 2 are generated on demand and released in hierarchical data format (release 5, HDF5). Level 2 products can be georeferenced with or without ground control points (GCP), according to user preference and GCP availability [2,21].

In June 2019, following the launch of the PRISMA satellite, hyperspectral data were released for public use. Since hyperspectral imagery is useful for various applications, it has become a particular interest of remote sensing researchers to exploit the fullest potential of these data. Hence, since 2019, these data have been employed in various applications, as shown in Figure 2. Environment for Visualizing Images (ENVI) is a software application used to process and analyze geospatial imagery. ENVI recently released an add-on ENVI-PRISMA toolkit that can ease the processing of PRISMA hyperspectral imagery (PHSI). Additionally, ImaACor software was developed for atmospherically correcting both multispectral and hyperspectral imagery. The evaluation of this software using PRISMA data has proven it to be a value-added software that researchers can use to process PRISMA L1 data and conduct atmospheric corrections independently.

The preprocessing steps of the PRISMA imagery commonly applied for all the applications include (1) georeferencing; (2) correction of georeferencing; (3) removal of noisy lines and bands, since more than 20% of bands are affected; (4) conversion from radiance to reflectance for L1 and L2B PRISMA products; (5) Masking of pixels that are unnecessary to the study using PRISMA L1 land cover map.

2.2. Assessment of PRISMA

This section explains SWOT components in detail, which were obtained using the assessment of PRISMA hyperspectral data.

Strengths

PRISMA offers global coverage [1], with a spectral resolution of 12 nm, spectral bands of >230 nm, and a spatial resolution of 30 m [22,23]. PRISMA provides more information about the Earth's surface than the planned hyperspectral sensor HYPSIRI [11] (which is due to be launched in 2024) and the earlier hyperspectral sensor AVIRIS [11]. The VIS-SWIR channels of PRISMA have a high spectral resolution that can be integrated with a panchromatic camera [24,25]. PRISMA has a higher potential than Sentinel-2 for mapping the quality parameters of water [7]. PRISMA's SWIR channel offers a higher separability than the SWIR channel on Sentinel-2 [2,12]. In the 2000–2200 nm range, the Earth's nonphotosynthetic vegetation cover can be examined using PRISMA [13,26,27]. Reflectance spectra (400–2500 nm) can indicate ng fuel types [15], water aquatic systems [26], the classification of different types of agricultural land cover [5], and forest cover [2], as well as provide an improved distinction between coniferous and broadleaved trees [2,28]. The discrimination between two and five forest categories by 40% and 102%, respectively, is improved by PRISMA [2].

The PRISMA sensor combines a hyperspectral sensor with a medium-resolution panchromatic camera [21]. PRISMA is available in three products: L0, L1, and L2 (please refer to Section 2) [1,21]. A hyperspectral image simulator (HSIS) is included in the PRISMA system so that the performance of L1 and L2 PRISMA processors can be evaluated [29]. PRISMA HDF5 images can be opened with the EnMap Toolbox. PRISMA proved to be a valuable instrument for the determination of the residual fire severity in the investigated area [30].

PRISMA's spectral resolution and its large number of channels, ranging from visible to short-wave infrared "SWIR", enables a better estimation of the abundance of major atmospheric constituents, and an efficient removal of atmospheric effects on the acquired images [31]. PRISMA matches well with the MODTRAN simulation [32] of high atmospheric conditions. PRISMA top-of-atmosphere (TOA) radiances of Level 1 (L1) products are consistent with the values expected to be observed over water targets [26]. The standard products L1 and L2 are suitable for the retrieval of biophysical parameters [32]. The product Level 2D is reported to be effective for the mapping of burned areas [3]. PRISMA data can be used for the quantitative analysis of CH_4 plumes [4]. PRISMA represents a unique orbiting source of hyperspectral data to investigate and analyze geophysical/geological phenomena [8]. PRISMA data can assist with soil organic content applications [6,33], as well as detecting and identifying natural and anthropogenic disasters in vegetation, which makes them useful in post-disaster management [33].

Weaknesses

✓ Lack of phenological data [6];
✓ Atmospheric correction is not developed for aquatic applications [7];
✓ PRISMA data were only tested at the parcel scale, which is not sufficient for distinguishing between non-agricultural vegetation and crop leftovers [23,34];
✓ The PRISMA sensor cannot scan at the required angles because there is no scanning mechanism onboard [24];
✓ As vegetation cover is dynamic and fast-changing, timely image acquisitions strongly influence the performance of the PRISMA application. The temporal resolution of PRISMA is an issue [12];
✓ A contiguous spectral response might not detect aliasing between adjacent but different materials. If there is a time lag between scene acquisitions, varying atmospheric

and illumination conditions might have a considerable impact on the acquired image [2];
- ✓ More than 20 bands will contain greater than 50% noise [1];
- ✓ Irregular noisy bands broaden temporal resolution [1];
- ✓ Selected bands can have irregular noise values [28];
- ✓ The spatial resolution of PRISMA data is insufficient for precision farming applications [5].

Opportunities:

- ✓ Future algorithms for the routine mapping of vegetation traits from operational spaceborne sensors will be defined [23];
- ✓ The PRISMA-based retrievals agree well with those of Sentinel-2 (high consistency in top-of-atmosphere radiance), mainly the total suspended matter (TSM) maps [7];
- ✓ The Coeff (a univariate quadratic function of wavelength), computed from average PRISMA spectra per land parcel, is a significant index for obtaining accurate results with the object-based classification of crops' single parcels. The main advantage of object-based classification over per-pixel classification is faster computation [13];
- ✓ PRISMA's mission aims to demonstrate in-orbit qualification of a state-of-the-art hyperspectral imager, validate end-to-end data processing, and enable environmental monitoring and risk prevention [24];
- ✓ The combined hyperspectral and panchromatic products enable the recognition of geometric features that provide detailed information about the chemical composition of substances on the Earth's surface [31];
- ✓ Unmanned aerial vehicles equipped with UAV platforms and a hyperspectral sensor, and used with PRISMA, can enable the acquisition of ground truth. The PRISMA image can be co-registered with a Sentinel-2 image [12];
- ✓ PRISMA has better discrimination and a more complex nomenclature system than Sentinel-2; the two can be combined to study the physiochemical and geometric features of a target, contributing to forest analysis, precision agriculture, water quality assessment, and climate change research [2];
- ✓ Automatic procedures can be applied to develop fuel maps of any part of Europe [1];
- ✓ Procedures developed for PRISMA will be used globally [28];
- ✓ Ongoing research will improve PRISMA images [5];
- ✓ PRISMA data might be fused with data from a panchromatic camera or with satellite data from Landsat and ASTER (advanced spaceborne thermal emission and reflection) [35];
- ✓ The standard nearest-neighbor method proved to be the most robust on the PRISMA scene [27].

Threats:

- ✓ Lack of reference data for model training leads to a decrease in PRISMA accuracy [23];
- ✓ The one-day time gap between PRISMA and Sentinel-2 leads to differences in their atmospheric corrections [7];
- ✓ PRISMA is not designed to quantify cellulose abundance or to evaluate species differences [13];
- ✓ Hyperspectral images should be used with caution when evaluating burned areas after wildfires because of the elapsed time from event to image acquisition [12];
- ✓ The presence of many shadow areas, where tall and short trees are mixed, can alter the results of separability analysis [2];
- ✓ Unlike Sentinel-2 data, PRISMA images cannot be downloaded in a cloud platform [1];
- ✓ Irregular noisy bands can lead to inaccuracies in PRISMA images [1];
- ✓ The number of noisy bands, the georeferencing, and the levels of data are not yet standardized in PRISMA [28];
- ✓ As the data and parameters that can be retrieved from PRISMA are often fed into physical models, it is crucial to ensure an extremely accurate radiometric accuracy

during the mission lifetime. The COVID-19 pandemic affected the data measurement plan. Further analyses are necessary to confirm the results obtained using PRISMA extreme viewing geometries, including new land cover targets for the spring/summer period when agricultural soil is not plowed [32];

✓ PRISMA-Sentinel-2 data fusion procedures are being tested to search for the best-performing procedure in the PRISMA-Sentinel-2 framework. Sentinel-2 and PRISMA images acquired with very low time differences might not be available [36].

2.3. SWOT Matrix

Table 1 shows a strength, weaknesses, opportunities, and threats (SWOT) matrix created for PHSI. This matrix depicts the positives and negatives of the internal and external factors of a system and determines the strengths, weaknesses, opportunities, and threats of PHSI.

Table 1. SWOT Matrix.

Technology	Internal	External
Positives	**Strengths:** ✓ Better accuracy for various applications; ✓ Possibility of automation using machine learning; ✓ Can be extended to any location on Earth; ✓ PRISMA toolkit in ENVI for easy processing; ✓ PRISMA processing can be carried out using EnMap; ✓ Spectral shape is in the 2.0–2.2 m range; ✓ Operations in the VIS-SWIR channels can be optically integrated with a panchromatic camera; ✓ PRISMA provides a level 2D product that is atmospherically corrected, georeferenced, and geolocated; ✓ PRISMA provides a land cover map with a Level 1 product.	**Opportunities:** ✓ PRISMA saves time and costs via avoiding field-based measurements; ✓ PRISMA technology can be transferred between organizations and research labs; ✓ PRISMA image fusion with multispectral, radar; LiDAR is possible.
Negatives	**Weaknesses:** ✓ PRISMA is an on-demand technology and its acquisition is not easy; ✓ The availability of archived data is limited; ✓ Revisiting time is equal to ~16 days; ✓ Temporal resolution is low; ✓ A long processing time and high computational power are required; ✓ Unstable noisy bands are present in the data; ✓ Unstable deadlines are present in some bands; ✓ Lack of accurate atmospheric corrections for aquatic applications; ✓ A residual coherent horizontal pattern of noise and a diagonal pattern of about 630 lines, with a periodic disturbance at ~0.3–0.4 cycles/pixel.	**Threats:** ✓ Interdisciplinary knowledge is required for processing PRISMA data; ✓ The lifetime of the PRISMA satellite is unknown.

2.4. Discussion

The strengths, weaknesses, opportunities, and threats of PRISMA are discussed below.

Strengths

A major strength of PRISMA hyperspectral imagery is its accuracy in detecting wildfire fuel types [37,38]. It is possible to detect all the available fuel types in the area of interest due to PRISMA's high number of spectral bands and support of machine learning approaches [1,39,40]. Only vegetation in broad categories, such as shrublands, grasslands, broadleaf forests, and coniferous forests, can be detected using multispectral data [41–44]. LiDAR can detect hyperspectral data, but there is a lack of LiDAR sensors nationwide [45–48]. At present, actively operating spaceborne hyperspectral sensors include

PRISMA, DESIS—a dynamic line rating Earth-sensing imaging spectrometer platform of the International Space Station that is attached to a multiple-user system for Earth sensing (MUSES) [15,30]—and the recently launched EnMAP [30] (the hyperspectral satellite of the German Aerospace Centre). Few comparative studies have been performed that compare the data among these sensors. In one example, a study on crop classifications using PRISMA and DESIS concluded that PRISMA yielded substantially higher classification accuracies because of its higher signal-to-noise ratio [49].

PRISMA is one of the satellites that have global coverage. The algorithm developed for one region can be implemented in other parts of the world to extract wildfire fuel types. Many other hyperspectral sensors have limited coverage, such as the Airborne Imaging Spectrometer (AIS) [50], Airborne Hyperspectral Scanner (AHS) [51], Airborne Imaging Spectrometer for different Applications (AISA) [52], Airborne Reflective Emissive Spectrometer (ARES) [53], Airborne Prism Experiment (APEX) [54], Airborne Visible/Near-Infrared Imaging Spectrometer (AVIRIS) [55], Hyperspectral Digital Imagery Collection Experiment (HYDICE) [56], Digital Airborne Imaging Spectrometer (DA-IS-7915) [57], Hyperspectral Mapper (HyMap) [58], Operational Modular Imaging Spectrometer (OMIS) [59], and Multispectral Infrared and Visible Imaging Spectrometer (MIVIS) [60].

Algorithms for vegetation indicators [61], water quality [62], fire severity mapping [12], forest fire front mapping, volcanic parameters estimation [63], urban mapping [64], fuel mapping [65], and material detection were developed under the framework of "Sviluppo di Prodotti Iperspettrali Prototipali Evoluti", which is funded by the Italian Space Agency [64]. Each algorithm provides input for one specific region on Earth. Additionally, a recent study on analyzing marine mucilage [66], sugarcane leaf area index [67], wildfire detection [68], and cyanobacterial estimation [69] using PRISMA was published. Aside from its applicability in many fields, automation is necessary for continuous monitoring in any application and is particularly essential for disaster management [1], which is possible with PRISMA due to its global availability.

A strength of PRISMA is its panchromatic camera. This camera provides panchromatic sharpening, a technique that combines the high-resolution detail from a panchromatic band with the low-resolution color information of other bands, usually only visible bands. Panchromatic images reduce the spatial resolution to 5 m. For instance, Maria et al. [25] detected plastic litter using PRISMA panchromatic image resolution.

Weaknesses

PRISMA is an on-demand technology, and the acquisition of data for a specific date is not easy due to the high traffic of requests. Easy and automatic access to data is essential for the management of disasters, such as wildfires, earthquakes, etc. Moreover, an analysis cannot be performed for the complete desired region due to the limited availability of data in the archive. Figure 3 shows the PRISMA images available for Italy. PRISMA also requires cloud environments such as DIAS (Data and Information Access Services), provided for the Sentinel family, to automatically download images [70].

The revisiting time of the PRISMA satellite is ~16 days, which is another constraint on data gathering. The PRISMA-Second Generation satellite, which is due to be launched in 2024, will make PRISMA more accessible. The processing of PRISMA data is time-consuming due to a large number of bands (239). Processing data using machine learning techniques takes more time than processing data with a multispectral [3], synthetic aperture radar (SAR) [24]. Data from the dynamic line rating (DLR) Earth-sensing imaging spectrometer (DESIS) are captured only in the visible and near-infrared (VNIR) regions [49].

To automate data processing for a complete region, high computation power is required. Virtual machines, such as the EarthConsole G-BOX [71] provided by European Space Agency (ESA), can be accessed to process this hyperspectral imagery. Hyperspectral data have unstable, noisy bands in the hypercube. PRISMA data have dead/noisy lines on some of the bands in the hypercube, as illustrated in Figure 4. A procedure for removing the dead and noisy lines using linear/nonlinear interpolation is described in [1]. According to the literature, most of the applications apply some machine/deep learning techniques to predict the required parameters using PRISMA. Data regarding the desired region of interest are required to train artificial intelligence techniques. However, data are often scarce, which is a major weakness of data processing [72].

Figure 3. PRISMA images available for Italy.

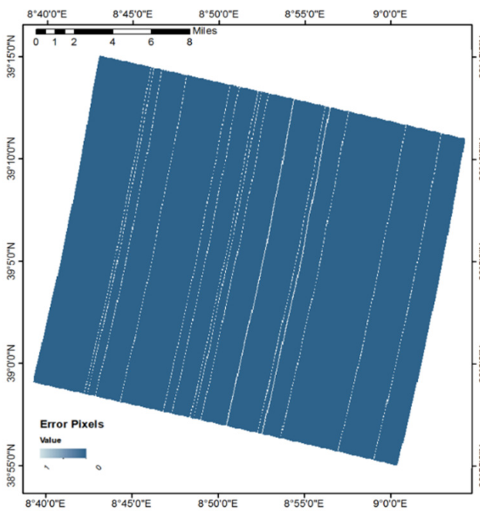

Figure 4. Noisy lines on PHSI.

Opportunities

PRISMA hyperspectral data are available from any part of Earth and can be accessed by anyone from anywhere upon registration. Open access algorithms developed for various applications can be used when needed. Once an algorithm/procedure is developed, it can be transferred among institutions and research centers. Technology transfer has become easier since PRISMA data became globally available. In some cases, image fusion with remote sensing data, such as multispectral, radar, and LiDAR data, can help to extract the desired results. For example, LiDAR data can help to determine whether forest vegetation is prone to catching fire [73,74]. Nicola et al. [36] fused PRISMA data with Sentinel-2 data to enhance the spatial resolution to 10 m. Anis et al. [75] developed a soil fertility map of northern Morocco by fusing PRISMA and GIS data.

Challenges

Hyperspectral data processing is an interdisciplinary field, and personnel who process these data need to be familiar with their applications and with machine/deep learning. Artificial intelligence techniques are essential for the processing of hyperspectral data. Procedures developed for the PRISMA satellite will be useful over the lifetime of the satellite (5–7 years) if there is no degradation in the sensor. However, the Italian Space Agency has announced the launch of PRISMA-SG, which could extend the use of procedures developed for PRISMA.

Future Scope for PRISMA

Although the applicability of PRISMA has been demonstrated for almost all land and ocean applications, it is yet to be tested for applications regarding oil spills, defense, soil pollution, and climate change. Furthermore, a few recent studies highlighted that using deep learning approaches and composite kernels significantly enhances the classification accuracy of hyperspectral data products after fusing them with LiDAR data [76,77]. Hence, PRISMA hyperspectral imagery and LiDAR data fusion, using extinction profiles and quantum machine learning [77] or a deep convolutional neural network [78], have excellent future scope in classification applications.

3. Conclusions

Hyperspectral imagery plays a vital role in precision agriculture, forestry, environment, and geological applications. In the present study, SWOT analysis was performed for PHSI, using recent case studies in which the potential of PHSI was exploited for different remote sensing applications, such as mineral mapping, snow mapping, wildfire fuel mapping, crop monitoring, forest management, non-photosynthetic vegetation mapping, the identification of methane gases, quantum-based studies, wildfire detection, marine plastic litter detection, post-fire land cover, aquatic management, soil fertility mapping, water pollution management, soil properties study, and cyanobacterial biomass estimation. The significant strength parameters of PHSI have enhanced reflectance spectra and improved spatial resolution, therefore making PHSI more suitable for studying vegetation biophysical parameters compared to other applications. The major weakness of PRISMA is the very high computational time required to process a huge amount of data using complex machine learning models. Furthermore, PRISMA data have limited availability, and atmospheric interference results in noisy bands that require computationally intensive processes. The significant advantage of PRISMA data is the technology transfer and fusion with other remotely sensed images, such as optical remote sensing data, LiDAR, and SAR, which make these data applicable for a wide range of applications and able to obtain reliable results without atmospheric interferences. Data acquisition is mainly hindered by the lifetime of PRISMA, and data processing is made challenging due to the requirement of interdisciplinary personnel.

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