TRANSFER LEARNING ANALYSIS FOR WILDFIRE SEGMENTATION USING PRISMA HYPERSPECTRAL IMAGERY AND CONVOLUTIONAL NEURAL NETWORKS

Dario Spiller   *Stefania Amici*   *Luigi Ansalone*

School of Aerospace Engineering,
Sapienza University of Rome
Via Salaria 851, Rome 00138, Italy

National Institute of
Geophysics and Volcanology - INGV
Via di Vigna Murata 605, Rome 00143, Italy

Italian Space Agency
ASI
Via del Politecnico snc, Rome 00133, Italy

ABSTRACT

In this work we present a segmentation study of wildfire scenarios using PRISMA hyperspectral data and a methodology based on convolutional neural networks and transfer learning. PRISMA (*Precursore IperSpettrale della Missione Applicativa*, Hyperspectral Precursor of the Application Mission) is the hyperspectral mission by ASI (*Agenzia Spaziale Italiana*, Italian Space Agency) launched in 2019 providing images with a spectral range of 0.4–2.5 µm and an average spectral resolution less than 10 nm. We used the PRISMA hypercube acquired during the Australian bushfires of December 2019 in New South Wales to train a one-dimensional convolutional neural network and perform a transfer learning in the Bootleg Fire of July 2021 in the Fremont-Winema National Forest in Oregon. The generalization ability of the network is discussed and potential future applications are presented.

***Index Terms*—** Wildfires, Convolutional Neural Networks, Transfer Learning, PRISMA, Hyperspectral Imagery

1. INTRODUCTION

Remote sensing (RS) data can help significantly the management of emergency and disaster events, such as wildfires, volcanic eruptions, landslides. In this work, we focus on the analysis of wildfire scenarios, studying the potentialities of the combined use of hyperspectral (HS) data and machine learning (ML). Satellite-based optical RS is a cost-effective way to detect, map, and investigate wildfires [1]. For instance, the assessment of the burned areas was studied by using the National Oceanic and Atmospheric Administration/Advanced Very High Resolution Radiometer (NOAA/AVHRR) and Landsat TM [2], while a near real-time global fire monitoring service is offered by NASA using MODIS and VIIRS data [3].

HS imagery can offer many advantageous features in support to fire detection [4] as it provides the required information in the infrared wavelengths to detect active fires and burnt areas [5]. Previous results investigated EO-1 Hyperion data for fire detection and temperature retrieval over selected Alaskan boreal forest fires [6]. In literature, spectral analyses of wildfire and burning biomass based on the potassium emission signatures have been already performed by using laboratory, airborne and space-borne HS-RS [7], [8], and plumes, clouds and fires have been characterized by using HS images [9].

In this work, HS images from the Italian satellite PRISMA (*PRecursore IperSpettrale della Missione Applicativa*) will be used. The detailed description of PRISMA starting from the initial design phase to the operative service can be retrieved in literature [10]–[13]. PRISMA is the first mission with a highly technological HS camera in a series of planned similar missions [14]–[16], and is proving its potentialities in many research fields such as crop mapping [17], aquatic ecosystem health monitoring [18], forest fire fuel mapping [19], marine plastic litter detection [20], wildfire detection and monitoring [21]. As demonstrated by this non-exhaustive list of studies, PRISMA is offering to the research community new high-quality data paving the way for new applications often based on advanced analysis approaches, from deep learning [22] to quantum ML **Riyokaaz˙2022**.

In this work, we analyse two wildfire scenarios, the first one located in New South Wales, Australia, and happened in December 2019, the second one located in Fremont-Winema National Forest, Oregon, US, and happened in July 2021. Starting from previous promising results combining ML and HS data [17], [21], [23], [24], this work aims to help the advancement of the research with the following contributions:

1. Presenting the potentialities of deep learning methodologies based on 1D convolutional neural networks (CNNs) to catch spectral dependencies in wildfire scenarios.

2. Evaluating the generalization ability of the proposed methodology, performing a transfer learning (TL) in Oregon using a model trained in Australia, i.e., performing inferences in a different ecosystem with respect to the one used for the training.

3. Discussing the possibility to effectively use ML-based methodologies to provide alerts in case of new wildfire.

The rest of the paper is organized as follows. Sec. 2 deals with the description of the area of interest and the HL datacube. In Sec. 3 the classification approach based on CNNs and TL is explained, while in Sec. 4 the results of the proposed analyses are reported. A critical discussion of the output of this study is reported in Sec. 5 and conclusions are provided in Sec. 6.

2. DATA

2.1. Areas of Interest

This study focuses on two different areas, the first one in Australia and the second one in Oregon, USA. The reference labelled pixels used for training, validating, and testing the CNN have been manually identified by analysing the spectral signature of the pixels in the images. With this regard, five classes have been introduced, specifically Fire, Smoke, Burned areas, Vegetation, and Bare soil.

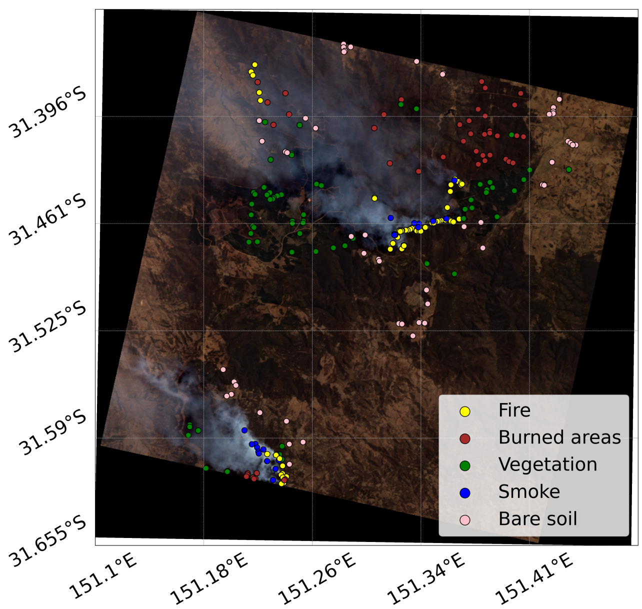

Fig. 1. RGB PRISMA composite image in the Australian AOI with input labelled points.

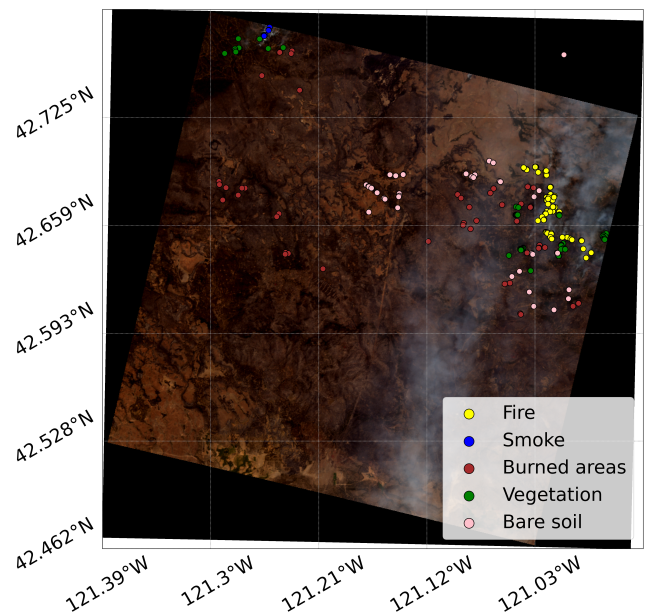

Fig. 2. RGB PRISMA composite image in the Oregon AOI with input labelled points.

2.1.1. *New South Wales, Australia*

The first study area of this paper is in Australia, in New South Wales, about 250 km north of Sydney in the Ben Halls Gap National Park (BHGNP), and it has been previously investigated in [21]. The park is located at a comparatively high altitude that results in generally cool temperatures and high rainfall. However, in late 2019, the simultaneous occurrence of high temperatures and wind speeds, and low relative humidity, produced the conditions for the development of a high-intensity wildfire behavior. The RGB composite of the study area is reported in Fig. 1 along with the labelled points used for training and testing the CNN. As can be seen, two major active wildfires can be identified, a southern one around 151.2 °E, 31.59 °S, and a northern one around 151.3 °E, 31.46 °S. A third smaller active wildfire is located North-West around 151.18 °E, 31.39 °S. The PRISMA image over this area of interest has been acquired on December 27, 2019. The number of labelled pixels identified in the Australia image is reported in the first three rows of Table 1.

2.1.2. *Fremont-Winema National Forest, Oregon, USA*

The second study area of this paper is located in the Fremont-Winema National Forest in Oregon (approx. 42.616°N, 121.421°W). Here, the Bootleg Fire started on July 6, 2021, with the cause attributed to lightning. This event gained widespread attention nationwide for two reasons: 1) the Bootleg Fire was co-located with a high-voltage transmission line connecting hydropower from the Pacific North-West to electricity demand centers in Los Angeles, California, and 2) the fire's area expanded incredibly fast. The fire area is a mix of grass/shrub and open to dense timber stands, which previously experienced beetle kill, resulting in concentrations of dry forest fuels[1]. On July 15, airborne data collections were not possible because the Bootleg Fire was generating pyrocumulus along its South-East extent. By the time of the satellite acquisitions on July 17, 2021, the Bootleg Fire was about 1008 km^2, and would not be contained until October 1, 2021 with a final extent of 1,674 km^2. The RGB composite of the study area is reported in Fig. 2 along with the labelled points using testing the TL approach. The number of labelled pixels identified in the Oregon image is reported in the last row of Table 1.

[1]More information can be found at https://inciweb.nwcg.gov/incident/7609/ (visited on May 03, 2022).

2.2. PRISMA Imagery

The PRISMA satellite was launched on 22 March 2019 and holds a HS and panchromatic payload to acquire images with a worldwide coverage. The HS camera works in the spectral range of 0.4–2.5 µm, with 66 VNIR (Visible and Near InfraRed) channels and 173 SWIR (Short-Wave InfraRed) channels. The average spectral resolution is less than 10 nm on the entire range with an accuracy of ±0.1 nm, while the ground sampling distance of PRISMA images is about 5 m and 30 m for panchromatic and HS camera, respectively.

The PRISMA data are made available for free for research purposes by the Italian Space Agency (ASI) [11]. HS and panchromatic data are delivered in HDF5 format in four levels (L):

1. L1, radiometrically corrected and calibrated at-sensor data;
2. L2B, geolocated at-ground spectral radiance product;
3. L2C, geolocated at-surface reflectance product; and
4. L2D, geocoded version of the Level 2C product.

In this work, we used Level 2D data, specifically the image acquired on 2019-12-27, 00:08:27 UTC in Australia, coordinates 31.49°S, 151.30°E, and the image acquired on 2021-07-17, 19:03:35 UTC in Oregon, coordinates 42.63°N, 121.17°W.

Table 1. Number of labelled reference pixels, in Australia and Oregon, used for training and testing the CNN.

Wildfire Location	Usage	0 - Fire	1 - Smoke	2 - Burned areas	3 - Vegetation	4 - Bare soil	Total
Australia, North-East	Train & Val	58	10	30	50	40	188
Australia, South	Test	11	11	9	10	10	51
Australia, North-West	Test	5	0	5	5	5	20
Oregon, North-Wast	Test	72	9	47	50	40	218

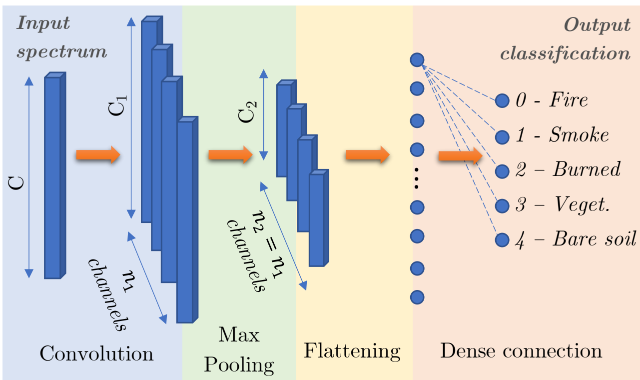

Fig. 3. Architecture of the CNN model for the segmentation analysis.

3. METHODS

3.1. Architecture of 1D Convolutional Neural Network

The CNN model used in this work is inspired by the one described in [25], it has been already used in [21] and is represented in Fig. 3. The input is the pixel spectral signature, e.g., an array with $C = 230$ elements comprising SWIR and VNIR PRISMA channels (after removal of empty and overlapping channels). The first hidden layer is a one-dimensional (1D) convolutional layer with kernel equal to 3, n_1 =112 filters, same padding, relu activation function, and $l2$ kernel regularizer. It is followed by a max pooling layer with pool size of 2 and stride of 2. After a flattening layer, the result is passed to a fully connected layer of 128 units with *ReLU* activation. The last layer is a dense unit for the multi-class classification with *softmax* activation function. Note that the values of C_1 and C_2 in Fig. 3 depend on the architecture of the network and can be easily evaluated. The model is trained using the Adam optimizer and the *categorical crossentropy* loss function. The whole network has been implemented using Python and Keras. The segmentation analysis is performed by running the model for each pixel in the image.

3.2. Transfer Learning Approach

To test the generalization ability of the proposed classification methodology, the CNN model is trained in the Australian image and then it is tested over the image in Oregon. The challenging operation consists in the fact that the ecosystems captured in the two images are different, and there is no a-priori guarantee that the model can generalize effectively. In this work, we only propose a TL without fine-tuning, which means that the network is not re-trained with some reference pixels from the AOI in Oregon. More detailed analysis considering different TL approaches will be carried out in the future.

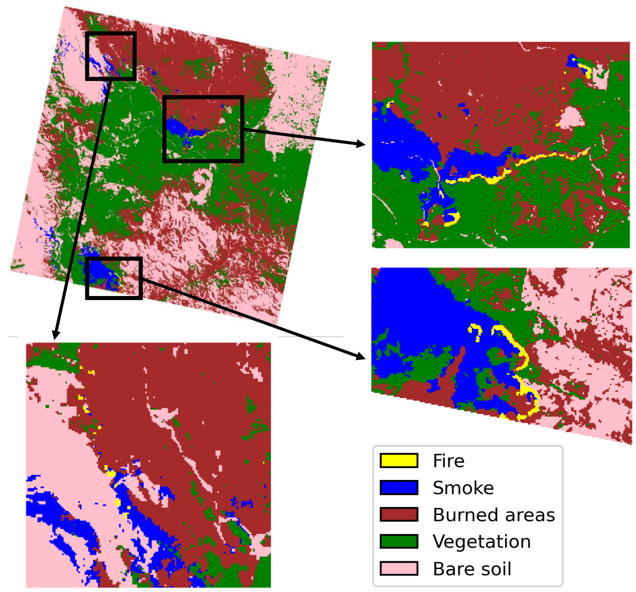

Fig. 4. Segmentation results in the entire Australian AOI and over three zoomed areas around active wildfires.

4. RESULTS

The results are reported separately for the Australian case, where the model has been trained using the dataset over the North-East area, and for the Oregon case.

4.1. Model Training

The results of the model training and testing over the Australian area are shown in Fig. 4. Here, one can appreciate the segmentation results over the entire PRISMA image and in the three selected areas, where it can be seen how smooth and low-noisy is the result. Precision, recall and F1 scores are reported in the first three rows of Table 2. It is worthy to note that the performances over the training area (North-East wildfire) and over the test areas (North-West and South areas) are almost the same, thus proving a perfect generalization ability over near areas.

4.2. Transfer Learning Analysis

The CNN model trained over the North-East wildfire in Australia has been tested over the Oregon labelled points previously shown in Table 1. As can be seen from Table 2, an overall F1 score of 79% has been reached which, even though lower than the F1 values in Australia, represents a really good performance considering that the Oregon

Table 2. Precision, Recall, and F1 scores in the four identified area. The Australia, North-East dataset has been used for training, whereas the others are used as test.

Wildfire Location	Precision	Recall	F1
Australia, North-East	0.98	0.98	0.98
Australia, South	0.98	0.98	0.98
Australia, North-West	1.00	0.95	0.97
Oregon, North-East	0.85	0.79	0.79

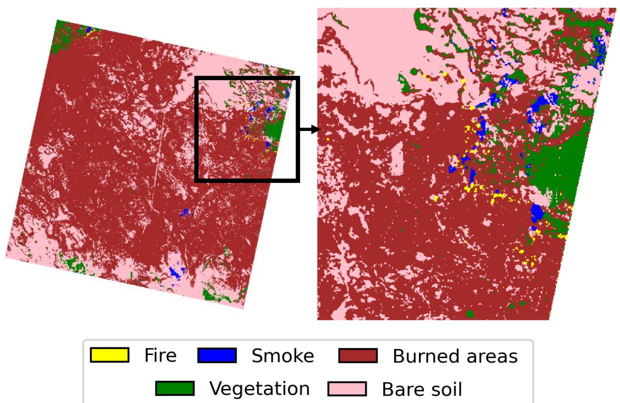

Fig. 5. Segmentation results in the entire Oregon AOI and over one zoomed area around active wildfires.

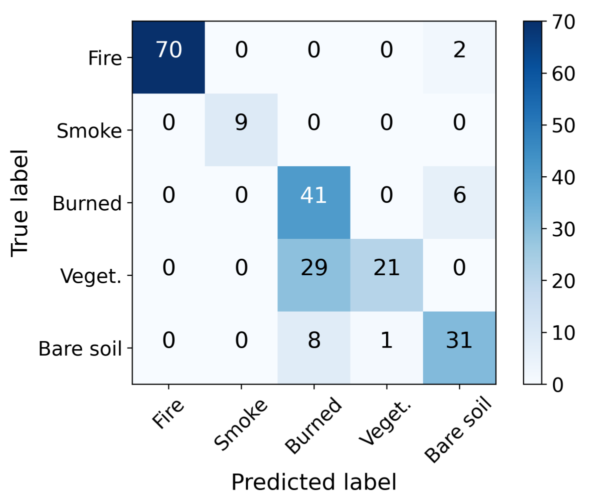

Fig. 6. Confusion matrix for the Oregon transfer learning test case.

ecosystem is completely different from the Australian one[2]. From the confusion matrix in Fig. 6, we can highlight that active fires and smoke classes are perfectly recognized, whereas higher confusion is noted among the other classes. The segmentation results are shown in Fig. 5.

[2]Note that, using all the labelled Australian points as training data, the F1 score only improves to 80%.

5. DISCUSSIONS

The results reported in this paper prove a very important fact. To correctly detect wildfires with a CNN-based approach using PRISMA data, we do not need neither very deep models nor big quantity of data. With a relatively small network and few very good quality input data, our methodology successfully passed our TL challenge in Oregon. Indeed, several comments are in order. First, the F1 value in Oregon is in line with many previous segmentation studies. Second, looking at the reported confusion matrix, one can note that active fires and smoke classes are detected with an accuracy of 100%. As the correct detection of wildfires is of preeminent importance in case of emergency and disaster management, this result clearly suggest that our approach can be successfully used in future applications. Third, it is noteworthy that our successful result is mainly due to the very high quality of the PRISMA data, in terms of signal-to-noise ratio, spectral resolution, spectral interval, etc. The very precise and unique spectral response of wildfires captured by PRISMA allows us to properly recognize active fires in different areas of the world, even in images that were never seen by the network. Finally, it is relevant to note that we demonstrated that very good segmentation results can be achieved with a small network and a small amount of training data. Dealing with complex HS data does not mean that the model must be very deep to reach good perfomances, as well as it does not imply that a very big training dataset is to be used. On the contrary, dealing with good HS data, as the PRISMA ones, enables the usage of relatively small networks and relatively small training dataset.

There are still some research points to be addressed in the future. For instance, a more detailed analysis of the TL methodology is required. In this study, we only reported the results having used as training dataset only a portion of the available labelled pixels in the Australian image (for consistency and for brevity). Even though we already tested that using all the available Australian labelled pixel for the training does not improve consistently the performances in Oregon, we will investigate other research opportunities related to the way the TL is applied. For instance, a comparison between the approach described in this paper with a *fine-tuning* approach, where the network is re-trained for few epochs using labelled pixels from the new Oregon area, would highlight how much the results can be improved when using a model with a bit of direct knowledge of the inference area.

6. CONCLUSION

In this paper, we have use PRISMA hyperspectral data to perform a segmentation analysis over wildfire scenarios. First, we trained a convolutional neural network in an image acquired in Australia, in 2019, over the bushfires in New South Wales. The training and testing over the Australian region performed successfully, reaching precision, recall, and F1 scores close to one. Second, we performed a transfer learning study by studying the results of the model inferences over an image acquired in Oregon, in 2021, over the Bootleg Fire. Here, the precision of our model is 85%, whereas recall and precision are around 80%. These results demonstrate the feasibility of our approach, especially because in the Oregon test case the classes *active fire* and *smoke* are recognized with an accuracy of 100%.

7. REFERENCES

[1] P. Barmpoutis, P. Papaioannou, K. Dimitropoulos, *et al.*, "A review on early forest fire detection systems using optical remote sensing," *Sensors*, vol. 20, no. 22, 2020. DOI: 10.3390/s20226442.

[2] C. Domenikiotis, A. Loukas, and N. R. Dalezios, "The use of NOAA/AVHRR satellite data for monitoring and assessment of forest fires and floods," *Natural Hazards and Earth System Sciences*, vol. 3, no. 1/2, pp. 115–128, 2003. DOI: 10.5194/nhess-3-115-2003.

[3] D. Davies, G. Ederer, O. Olsina, *et al.*, "NASA's Fire Information for Resource Management System (FIRMS): Near Real-Time Global Fire Monitoring Using Data from MODIS and VIIRS," *NASA Technical Reports GSFC-E-DAA-TN73770*, 2020.

[4] S. Veraverbeke, P. Dennison, I. Gitas, *et al.*, *Hyperspectral remote sensing of fire: State-of-the-art and future perspectives*, 2018. DOI: 10.1016/j.rse.2018.06.020.

[5] A. Barducci, D. Guzzi, P. Marcoionni, *et al.*, "Comparison of fire temperature retrieved from SWIR and TIR hyperspectral data," *Infrared Physics Technology*, vol. 46, no. 1, pp. 1–9, 2004, Workshop on Advanced Infrared Technology and Application. DOI: 10.1016/j.infrared.2004.03.001.

[6] C. F. Waigl, A. Prakash, M. Stuefer, *et al.*, "Fire detection and temperature retrieval using eo-1 hyperion data over selected alaskan boreal forest fires," *International Journal of Applied Earth Observation and Geoinformation*, vol. 81, pp. 72–84, 2019. DOI: 10.1016/j.jag.2019.03.004.

[7] S. Amici, M. J. Wooster, and A. Piscini, "Multi-resolution spectral analysis of wildfire potassium emission signatures using laboratory, airborne and spaceborne remote sensing," *Remote Sensing of Environment*, 2011. DOI: 10.1016/j.rse.2011.02.022.

[8] A. Vodacek, R. L. Kremens, A. J. Fordham, *et al.*, "Remote optical detection of biomass burning using a potassium emission signature," *International Journal of Remote Sensing*, vol. 23, no. 13, pp. 2721–2726, 2002. DOI: 10.1080/01431160110109633.

[9] M. K. Griffin, S. M. Hsu, H. h. K. Burke, *et al.*, "Characterization and delineation of plumes, clouds and fires in hyperspectral images," in *International Geoscience and Remote Sensing Symposium (IGARSS)*, 2000. DOI: 10.1117/12.410349.

[10] L. Candela, R. Formaro, R. Guarini, *et al.*, "The PRISMA mission," in *International Geoscience and Remote Sensing Symposium (IGARSS)*, 2016. DOI: 10.1109/IGARSS.2016.7729057.

[11] R. Guarini, R. Loizzo, C. Facchinetti, *et al.*, "PRISMA hyperspectral mission products," in *International Geoscience and Remote Sensing Symposium (IGARSS)*, 2018. DOI: 10.1109/IGARSS.2018.8517785.

[12] R. Loizzo, R. Guarini, F. Longo, *et al.*, "PRISMA: The Italian hyperspectral mission," in *International Geoscience and Remote Sensing Symposium (IGARSS)*, 2018. DOI: 10.1109/IGARSS.2018.8518512.

[13] R. Loizzo, M. Daraio, R. Guarini, *et al.*, "PRISMA Mission Status and Perspective," in *International Geoscience and Remote Sensing Symposium (IGARSS)*, 2019. DOI: 10.1109/IGARSS.2019.8899272.

[14] E. Carmona, J. Avbelj, K. Alonso, *et al.*, "Data processing for the space-based DESIS hyperspectral sensor," in *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, 2017. DOI: 10.5194/isprs-archives-XLII-1-W1-271-2017.

[15] L. Guanter, H. Kaufmann, K. Segl, *et al.*, *The EnMAP spaceborne imaging spectroscopy mission for earth observation*, 2015. DOI: 10.3390/rs70708830.

[16] J. Nieke and M. Rast, "Towards the copernicus hyperspectral imaging mission for the environment (CHIME)," in *International Geoscience and Remote Sensing Symposium (IGARSS)*, 2018. DOI: 10.1109/IGARSS.2018.8518384.

[17] D. Spiller, L. Ansalone, F. Carotenuto, *et al.*, "Crop Type Mapping Using PRISMA Hyperspectral Images and One-Dimensional Convolutional Neural Network," in *2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS*, 2021, pp. 8166–8169. DOI: 10.1109/IGARSS47720.2021.9554175.

[18] M. Bresciani, C. Giardino, A. Fabbretto, *et al.*, "Application of New Hyperspectral Sensors in the Remote Sensing of Aquatic Ecosystem Health: Exploiting PRISMA and DESIS for Four Italian Lakes," *Resources*, vol. 11, no. 2, 2022. DOI: 10.3390/resources11020008.

[19] R. U. Shaik, G. Laneve, and L. Fusilli, "An Automatic Procedure for Forest Fire Fuel Mapping Using Hyperspectral (PRISMA) Imagery: A Semi-Supervised Classification Approach," *Remote Sensing*, vol. 14, no. 5, 2022. DOI: 10.3390/rs14051264.

[20] M. Kremezi, V. Kristollari, V. Karathanassi, *et al.*, "Pansharpening PRISMA Data for Marine Plastic Litter Detection Using Plastic Indexes," *IEEE Access*, vol. 9, pp. 61 955–61 971, 2021. DOI: 10.1109/ACCESS.2021.3073903.

[21] D. Spiller, L. Ansalone, S. Amici, *et al.*, "Analysis and detection of wildfires by using prisma hyperspectral imagery," *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. XLIII-B3-2021, pp. 215–222, 2021. DOI: 10.5194/isprs-archives-XLIII-B3-2021-215-2021.

[22] S. T. Seydi, M. Hasanlou, and J. Chanussot, "DSMNN-Net: A Deep Siamese Morphological Neural Network Model for Burned Area Mapping Using Multispectral Sentinel-2 and Hyperspectral PRISMA Images," *Remote Sensing*, vol. 13, no. 24, 2021. DOI: 10.3390/rs13245138.

[23] A. Piscini and S. Amici, "Fire detection from hyperspectral data using neural network approach," in *Remote Sensing for Agriculture, Ecosystems, and Hydrology XVII*, 2015. DOI: 10.1117/12.2194911.

[24] S. Amici and A. Piscini, "Exploring PRISMA Scene for Fire Detection: Case Study of 2019 Bushfires in Ben Halls Gap National Park, NSW, Australia," *Remote Sensing*, vol. 13, no. 8, 2021. DOI: 10.3390/rs13081410.

[25] W. Hu, Y. Huang, L. Wei, *et al.*, "Deep convolutional neural networks for hyperspectral image classification," *Journal of Sensors*, 2015. DOI: 10.1155/2015/258619.