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Comparison of LAI estimates from high resolution satellite observations using different biophysical processors †

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Abstract: Earth observation provides timely and spatially explicit information on crop phenology and vegetation dynamics that can support decision making and sustainable agricultural land management. Vegetation spectral indices calculated from optical multispectral satellite sensors have been largely used to monitor vegetation status. Besides, techniques to retrieve biophysical parameters from satellite acquisitions, like the Leaf Area Index (LAI), allowed to assimilate Earth observation time series in numerical modelling for the analysis of several land surface processes related to agroecosystem dynamics. More recently, biophysical processors used to estimate biophysical parameters from satellite acquisitions have been calibrated for the retrieval from sensors with different high spatial resolution and spectral characteristics. Virtual constellations of satellite sensors allow the generation of denser LAI time series, contributing to improve vegetation phenology estimation accuracy and consequently enhancing agroecosystems monitoring capacity. This research study compares LAI estimates over croplands using different biophysical processors from Sentinel-2 MSI and Landsat-8 OLI satellite sensors. Results are used to demonstrate the capacity of virtual satellite constellation to strengthen LAI time series to derive important cropland use information over large areas.

Keywords: Leaf Area Index; Earth observation; Sentinel-2; Landsat-8; vegetation phenology

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1. Introduction

Earth observation timely and spatially explicit information on land surface processes, like vegetation dynamics, represents an advanced digital agriculture tool to derive important cropland use information over large areas, supporting decision making and sustainable agricultural land management. Biophysical parameters, as compared with the vegetation spectral indices calculated from optical multispectral satellite sensors, that have been largely used to monitor vegetation status, allows to quantitatively measure vegetation properties. The Leaf Area Index (LAI), a biophysical index defined as one half the total green (i.e., photosynthetically active) leaf area per unit horizontal ground surface area, can be estimated from surface reflectance data acquired by satellite sensors. Vegetation biophysical characteristics, as the canopy structure and photosynthetic capacity, are well described by LAI, that is largely used in agricultural studies [1].

LAI information is widely adopted for crop monitoring and for numerical modelling applications [2], to derive phenological metrics [3], identify and map the main crops types [4], as well as demonstrated to be effective to monitor vegetation dynamics [5] and to map terrestrial natural habitats [6].

A number of techniques, evolved in the past to derive the biophysical variables of vegetation using remote sensing data, can be grouped into four categories [7]: (i) parametric regression methods; (ii) non-parametric regression methods; (iii) physically-based methods, using Radiative Transfer Models (RTMs); (iv) hybrid retrieval methods, combining non-parametric and physically-based approaches.

During the last decades, satellite optical multispectral sensors sensed Earth surface either at medium spatial resolution and high revisit frequency or at high spatial resolution and low revisit frequency. Recently, Copernicus Sentinel-2 satellite constellation, equipped with MSI sensor, allows to sense Earth surface at high spatial, spectral and temporal resolutions, expanding capacity for vegetation status and plant phenology monitoring from time series of biophysical parameters.

The aim of this study is to compare LAI estimates from Sentinel-2 MSI and Landsat-8 OLI satellite data over croplands and other vegetation cover types in a selected test area, using different biophysical processors available in SNAP software, that belong to physically-based estimation methods. Simple linear regression analysis is used to determine linear relationship between different LAI estimates, coefficients and error metrics.

2. Materials and Methods

2.1. Satellite data

Sentinel-2 (S2) satellites images, acquired from September 2017 to December 2019 with cloud cover lower than 90%, were collected for granules 'T32TPP', whose spatial extent corresponds to the test site (Figure 1). The Multi-Spectral Instrument (MSI) sensor onboard S2 satellites is characterized by high spatial resolution (10 m, 20 m and 60 m), high revisit capacity (5 days with two-satellite constellation), and 13 spectral bands from the visible to shortwave infrared. Sentinel-2 MSI L2A data were collected from Theia archive, representing the bottom of the atmosphere (BOA) reflectance, orthorectified, terrain-flattened and atmospherically corrected with MACCS-ATCOR Joint Algorithm (MAJA) [8].

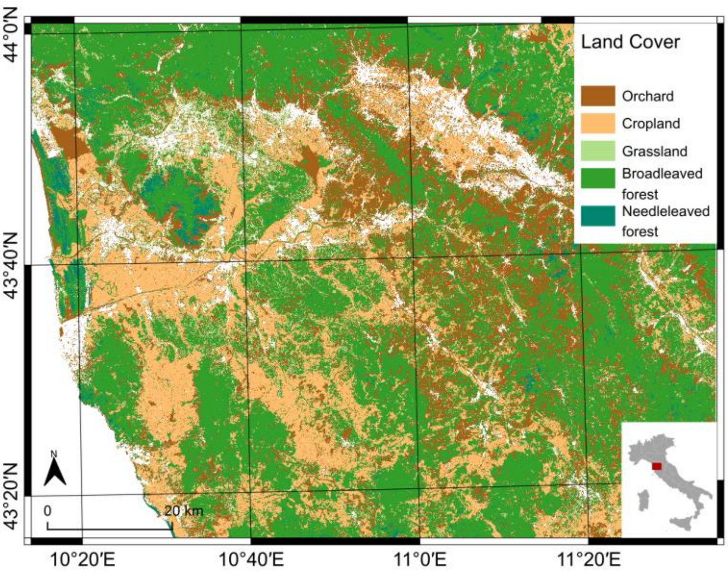

Figure 1. Main vegetation cover in the study area (Italy).

After resampling all spectral bands to 10 m resolution, pixels corresponding to clouds, cloud shadows, snow, water in the product quality flag masks or corresponding to topographic shadows (identified by product quality flags representing the topographic mask and low-sun mask, with the latter considering the pixel aspect, slope, and sun zenith angle) were masked out from further analysis.

Landsat8 (L8) satellites images, acquired from September 2017 to December 2019 with cloud cover lower than 90%, were collected for tiles 'T192030' and 'T193029', which overlay the S2 granule selected as a test site. The Operational Land Imager (OLI) sensor onboard L8 satellite is characterized by high spatial resolution (30 m), medium revisit capacity (16 days), and 9 spectral bands from the visible to shortwave infrared. Landsat8 OLI Collection 2 data were collected from USGS archive, representing the top of the atmosphere (L1TP) and bottom of the atmosphere (L2SR) reflectance, orthorectified, terrain-flattened and atmospherically corrected. Pixels corresponding to clouds, cloud shadows, snow, shadows, water in the product quality flag masks were masked out from further analysis. Bottom of atmosphere reflectances (L2SR), after being stacked with sun and view angles L1TP (using the SNAP processing graph available at https://github.com/ffilipponi/SNAP_L8_C2_BiophysicalLandsat8Op), were correct for changes in illumination due to terrain elevation [9].

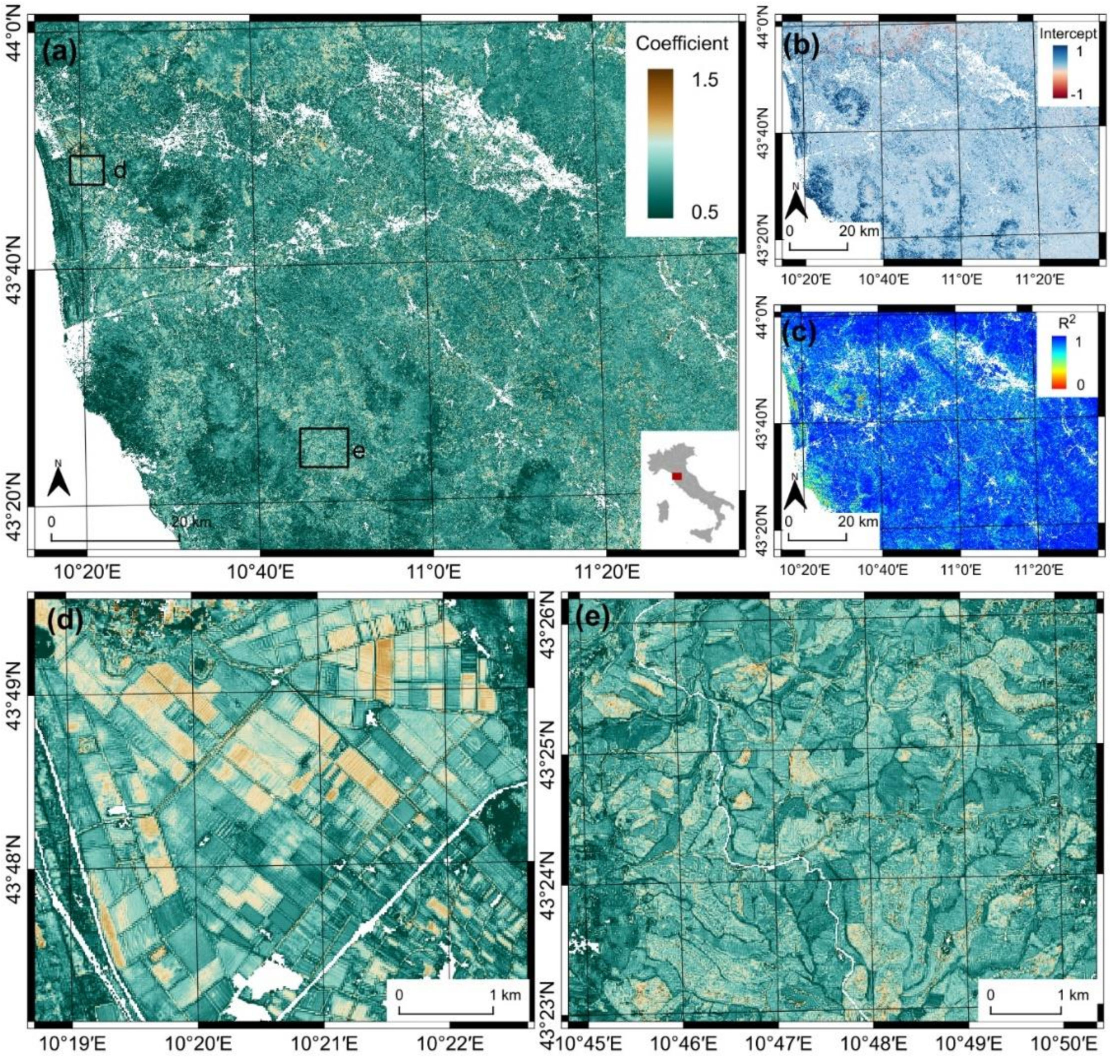

Figure 2. Spatially explicit linear regression results: (a) linear regression coefficient; (b) linear regression intercept; (c) coefficient of determination; (d) spatial detail of linear regression coefficient over plain croplands; (e) spatial detail of linear regression coefficient over hilly croplands.

2.2. Biophysical parameters estimation

Leaf Area Index (LAI) was estimated from surface reflectance data using the biophysical processors [10] available in SNAP software version 8, based on trained neural networks, recently updated to version 3.0 with newly calibrated coefficients. Apart from recalibrated coefficients, the newly introduced features are the support for L8 OLI sensor, the optional use of S2 spectral bands at 10 m spatial resolution only (specifically those at green (B3), red (B4) and near-infrared (B8) wavelengths), and the computation of the biophysical parameters by the use of spectral response of each satellite sensor.

2.3. Comparison of LAI estimates

Three sets of LAI estimates (S2; S2 using the 10 m processor; L8) were stacked in large multidimensional datacubes, after applying an image co-registration step [11] do deal with weak spatial coherence of Sentinel-2 time series processed using processing baselines *01.xx* and *02.xx* [12]. Copernicus Land Monitoring Service datasets were used to generate a vegetation land cover map, used for subsequent analysis.

A linear regression model has been created for each combination of unique pairs from the three LAI sets, using the entire datacubes as dependent and independent variables. Model has been generated for both spatial and temporal dimensions, the latter without the use of an intercept value. Additionally, separate models have been created for the following land cover classes: all vegetated pixels; croplands; grasslands; broadleaved forest; needleleaved forest. Regression coefficients and coefficient of determination (R^2) were computed for each model, together with Root Mean Square Error (RMSE).

In order to perform the comparison between S2 and L8 LAI estimates, S2 datacubes were resampled to fit 30 m spatial resolution, using average resampling statistics, and only synchronous acquisitions were used.

All the procedures used to analyse data were performed using GDAL libraries, R, GRASS GIS and SNAP software.

3. Results and Discussions

Spatially explicit linear regression results are shown in Figure 2. Croplands resulted in a regression coefficient close to 1, while forested areas resulted in higher intercept value and consequently lower regression coefficient. High coefficient of determination values demonstrates the robustness of the linear regression model.

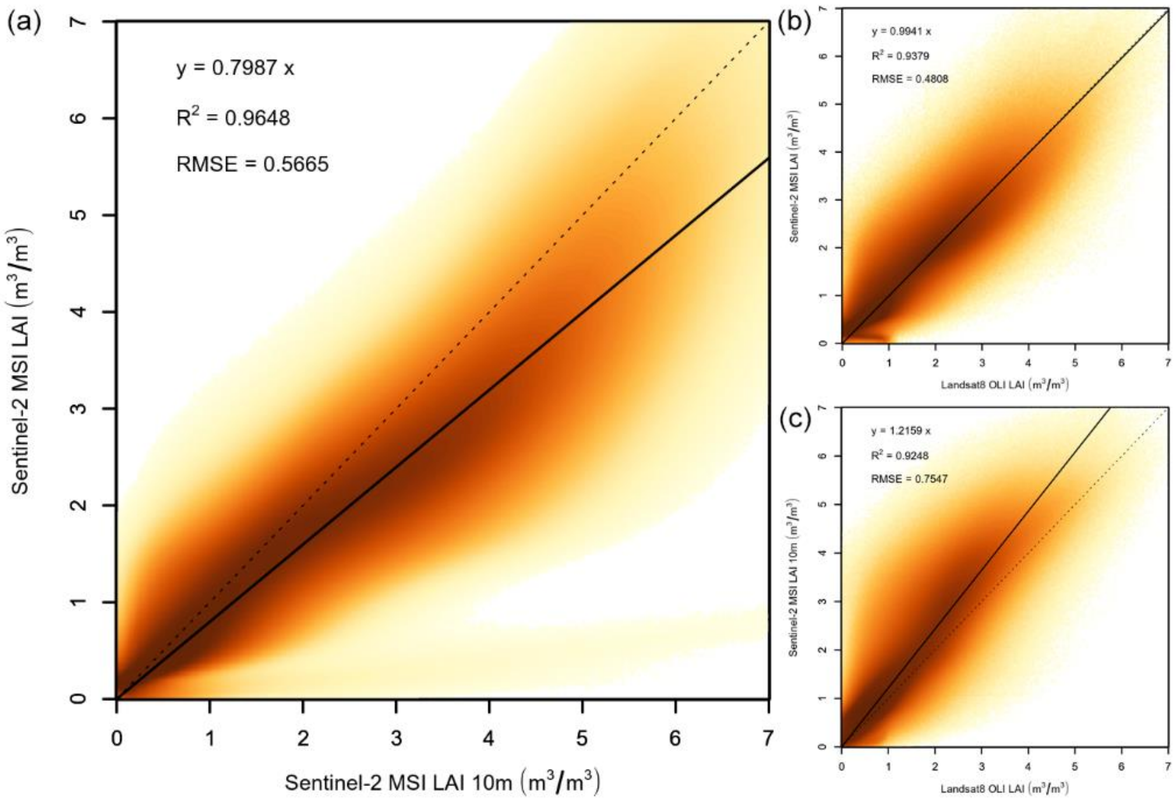

Figure 3. Density scatterplot showing linear relationship for the three LAI sets.

LAI biophysical processor calibrated on S2 spectral bands at 10 m spatial resolution overestimates LAI values, as compared with biophysical processor calibrated on S2 full spectrum and with biophysical processor calibrated on L8 (Figure 3). LAI estimates from biophysical processor calibrated on L8 has strong linear relationship with LAI estimates from model calibrated on S2 full spectrum. These evidences demonstrate how red-edge and short-wave infrared spectral reflectances provide key information related to vegetation status, that complements plant photosynthetic activity revealed from visible and near-infrared wavelengths.

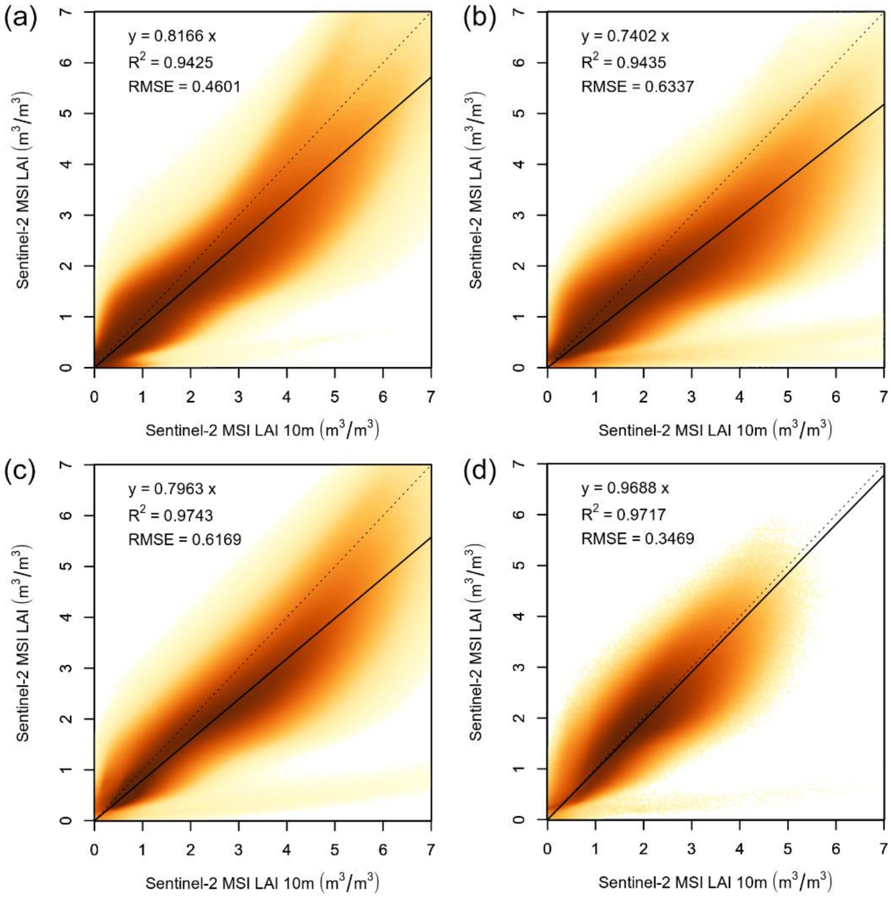

Figure 4. Density scatterplot showing linear relationship for LAI estimated using the two Sentinel-2 MSI models calibrated on different band sets for main land cover classes: (a) croplands; (b) grasslands; (c) broadleaved forests; (d) needleleaved forests.

LAI biophysical processor calibrated on S2 spectral bands at 10 m spatial resolution overestimates LAI values for the different plant functional types (Figure 4). Overestimation has been found to be higher for grasslands and lower for needleleaved forests. Further improvements require in situ measurements to complement the linear relationship analysis with the evaluation of accuracy metrics.

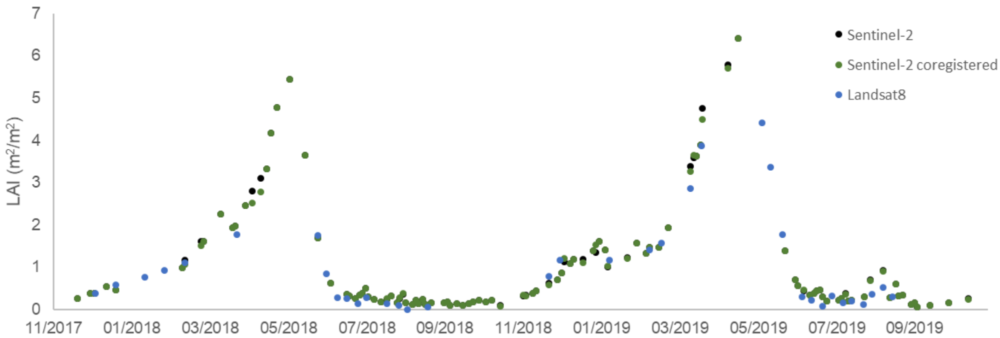

Figure 5. LAI time series for a winter cereal pixel.

Plot in Figure 5 shows how LAI estimates from multiple satellite sensors, with unbiased linear relationship, can constitute denser time series from virtual satellite constellation, contributing to improve temporal analysis, like vegetation phenology estimation, and consequently enhancing agroecosystems monitoring capacity. Weak spatial coherence of Sentinel-2 acquisitions over time requires an image co-registration procedure to be applied in order to reduce shaky time series [12].

3. Conclusion

A comparison of LAI estimates from Sentinel-2 MSI and Landsat-8 OLI satellite data over croplands and other vegetation cover types, using different biophysical processor has been presented. Results from linear regression analysis demonstrates a general underestimation of LAI biophysical processor calibrated on S2 spectral bands at 10 m spatial resolution, as compared with biophysical processor calibrated on S2 and L8 full spectrum. The biophysical processor calibrated on the full spectrum provides stronger linear relationships between LAI estimated from S2 MSI and L8 OLI satellite sensors, encouraging the use of estimated biophysical parameters time series from virtual satellite constellation, to derive important cropland use information over large areas.

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References

1. De Peppo, M.; Dragoni, F.; Volpi, I.; Mantino, A.; Giannini, V.; Filipponi, F.; Tornato, A.; Valentini, E.; Nguyen Xuan, A.; Taramelli, A.; Ragaglini, G. Modelling the ground-LAI to satellite-NDVI (Sentinel-2) relationship considering variability sources due to crop type (Triticum durum L., Zea mays L., and Medicago sativa L.) and farm management. Proc. SPIE 11149, *Remote Sensing for Agriculture, Ecosystems, and Hydrology XXI*, **2019** 111490I. https://doi.org/10.1117/12.2533446.
2. De Peppo, M.; Taramelli, A.; Boschetti, M.; Mantino, A.; Volpi, I.; Filipponi, F.; Tornato, A.; Valentini, E.; Ragaglini, G. Non-parametric statistical approaches for Leaf Area Index estimation from Sentinel-2 data: a multi crop assessment (submitted).
3. Filipponi, F.; Smiraglia, D.; Agrillo E. Earth Observation for Phenological Metrics (EO4PM): temporal discriminant to characterize forest ecosystems (manuscript in preparation).
4. Filipponi, F., Smiraglia, D., Mandrone, S., Tornato, A. Cropland mapping using Earth Observation derived phenological metrics. *Proceedings* **2021**, *68* (accepted).
5. Filipponi, F.; Manfron, G. Observing Post-Fire Vegetation Regeneration Dynamics Exploiting High-Resolution Sentinel-2 Data. *Proceedings* **2019**, 18, 10. https://doi.org/10.3390/ECRS-3-06200.
6. Agrillo, E.; Filipponi, F.; Pezzarossa, A.; Casella, L.; Smiraglia, D.; Orasi, A.; Attorre, F.; Taramelli, A. Earth Observation and Biodiversity Big Data for Forest Habitat Types Classification and Mapping. *Remote Sens.* **2021**, *13*, 1231. https://doi.org/10.3390/rs13071231.
7. Verrelst, J.; Rivera, J.P.; Veroustraete, F.; Muñoz-Marí, J.; Clevers, J.G.P.W.; Camps-Valls, G.; Moreno, J. Experimental Sentinel-2 LAI estimation using parametric, non-parametric and physical retrieval methods – A comparison. *ISPRS Journal of Photogrammetry and Remote Sensing* **2015**, *108*, 260–272, https://doi.org/10.1016/j.isprsjprs.2015.04.013.
8. Hagolle, O.; Huc, M.; Desjardins, C.; Auer, S.; Richter, R. MAJA Algorithm Theoretical Basis Document. Available online: https://doi.org/10.5281/zenodo.1209633 (accessed on 7 December 2017).
9. Meyer, P; Itten, K. I. ; Kellenbenberger, T.; Sandmeier, S.; Sandmeier, R., 1993. Radiometric corrections of topographically induced effects on Landsat TM data in an alpine environment. *ISPRS J. Photogramm. Remote Sens.*, **1993**, 48, pp. 17–28.
10. Weiss, M.; Baret, F. S2 ToolBox Level 2 Products: LAI, FAPAR, FCOVER. 2016. Available online: https://step.esa.int/docs/extra/ATBD_S2ToolBox_L2B_V1.1.pdf (accessed on 31 March 2021).
11. Scheffler, D.; Hollstein, A.; Diedrich, H.; Segl, K.; Hostert, P. AROSICS: An Automated and Robust Open-Source Image Co-Registration Software for Multi-Sensor Satellite Data. *Remote Sens.* **2017**, *9*, 676. https://doi.org/10.3390/rs9070676.
12. Filipponi, F. Exploitation of Sentinel-2 Time Series to Map Burned Areas at the National Level: A Case Study on the 2017 Italy Wildfires. *Remote Sens.* **2019**, *11*, 622. https://doi.org/10.3390/rs11060622.