



La correzione atmosferica delle immagini Sentinel-2: tecniche e software a confronto

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Starting point

The *identification of plant species* from the integration of Earth Observation (EO) data from different data sources paying special attention to Sentinel 2 mission of the ESA Copernicus Program

 \rightarrow AIM: a continuous, widespread, and updated mapping of the distribution of tree species

In this regard, the research focus has moved from the integration of different EO data to the study of Sentinel 2A images, their limits and potential applications with respect to the identification of plant species.

 \rightarrow AIM: investigate all the possible issues that affect the classification of optical images from Sentinel 2A mission especially in terms of plant species identification.



Data approach

Two main issues have been identified:

- 1 Data characteristics → the limited number of image bands (low spectral resolution) is insufficient to discriminate the spectral signatures of single species due to the lack of spectral differences. Furthermore, due to the limited geometric resolution the problem of mixed pixels occur, i.e. an image pixel covers various objects, reducing the ability to identify single species.
- 2 Data quality → the intrinsic characteristics of Sentinel 2 images such as errors in reflectance values due to atmospheric "noise", topographic features, the presence of cloud and their shadows on ground



Atmospheric correction

Sentinel 2A images (Level-1C) are provided by ESA in Top of Atmosphere (TOA) reflectance. Obviously the effects of atmosphere have to be considered to obtain the Bottom of Atmosphere (BOA) reflectance that is the reflectance value at ground level.

Two main approaches to compute surface reflectance:

- *image based techniques*
- physically based techniques

Both approaches have been tested using respectively:

- Dark Object Subtraction (DOS) model
- Second Simulation of Satellite Signal in the Solar Spectrum (6S) model

Both models have been tested using respectively:

- QGIS v. 2.18.15 (DOS)
- GRASS GIS v. 7.4.0 (6S)
- Arcsi v. 1.4.2 (6S)



Dark Object Subtraction (DOS)

- Based on the lower reflectance value (darker objects) of the image
- It is assumed that the radiance received at sensor from this pixel is almost entirely composed of atmospheric scattering
- The radiance value of this pixel is then subtracted from all pixels
- Being an image-based model, no other input data than bands is required

DOS → QGIS → Semi-Automatic Classification Plugin v. 5.3.11



- The only data input are the image bands and the metadata file
- Applies a DOS1 model (the simplest one)
- It returns corrected .tif file (one for each band) converted in physical value (range 0-1)
- Outliers (reflectance > 1) are set to 1



Second Simulation of Satellite Signal in the Solar Spectrum (6S)

is a Radiative Transfer Model which simulates the effect of the atmosphere on light passing through it.

Being a physically based model, it requires several inputs:

- Geometric configuration of the scene and lighting
 - sensor altitude and geometry,
 - sensing date and bounding box of the image
 - solar irradiance
 - sun position (zenith and azimuth)
- atmospheric measurements
 - o atmospheric profile
 - o aerosol profile
 - o others like Aerosol Optical Thickness (AOT) and Vertical Water Content
- Ground altitude
- Radiance values of the bands scene



$6S \rightarrow GRASS GIS \rightarrow i.atcorr$



It requires lots of input parameters in addition to image band:

- range = the min/max theoretical values the input data can reach (1,10000 outliers are set to 10000)
- elevation map = DEM of the whole area (EU-DEM v1.1 resampled to 10m resolution)
- input values in radiance or reflectance (TOA reflectance)
- rescale = output data range (0,1)
- parameters = text file with 6S parameters

25 --geometrical conditions Sentinel-2A
8 2 10.17 10.29253204 46.04626546 -- month day hh.ddd lon lat ("hh.ddd" is in decimal hours GMT)
2 --atmospheric model=midlatitude summer
1 --aerosols model=continental
0 --visibility [km]
0.470299 --AOT at 550nm
-0.459 --mean target elevation above sea level [km]
-1000 --sensor height (here, sensor on board a satellite)
167 --band number processed (es. 167 blue band Sentinel-2A)

All the parameters have to be manually retrieved and inserted in the txt file!



6S → GRASS GIS → i.atcorr

```
25 --geometrical conditions Sentinel-2A
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```

- Month, day, hh.ddd, lon and lat \rightarrow metadata files
- Atmospheric and aerosol model → Arcsi
- Mean elevation \rightarrow from input DEM map
- AOT at 550nm → AERONET (Aerosol Robotic Network) data at different wavelengths thus interpolated to obtain AOT at 550nm using Py6S, a python interface to 6S

If AOT value must be related to the investigated area and to sensing date/time of the images → not always available !!



6S → ARCSI

- It requires only the metadata file and a DEM (EU-DEM v1.1) as input data
- Atmospheric and aerosol model are automatically retrieved
- It allows to estimate automatically the AOT value from the image:
 - It estimates the surface reflectance in the blue channel by using a simple DOS model;
 - Taking this estimated reflectance as input, 6S is then numerically inverted to identify the AOT value, which provides a surface reflectance value as close to that estimated from DOS as possible;
 - Once the AOT value has been estimated it has been used to parameterise and run 6S to build a Lookup Table (LUT) at elevation steps of 100 m and apply this to produce surface reflectance.

Arcsi doesn't normalize the outliers thus reflectance values > 1 can occur!!



Results – RGB composites





RGB GRASS image

Since May 2017 Sentinel 2 images are also provided by ESA in BOA reflectance (Level-2A). **Obviously these images have been considered** but from the related metadata file emerged that the final surface reflectance is computed using the same model parameters for each hemisphere. This lead to a rough simplification of the final reflectance results for all analysed images.





Results and comparisons



Histogram of blue bands (reflectance value > 1)



Results and comparisons



Histogram of blue bands



Results and comparisons



Histogram of blue bands (L1C and L2A)



Histogram of blue bands (L1C and GRASS)



Histogram of blue bands (L1C and QGIS)



Histogram of blue bands (L1C and Arcsi)



Results – Correction differences for Blue bands

L1C - L2A 0.00 -0.10 -0.20 L1C - GRASS 0.10 0.00 -0.10 -0.20





L1C - Arcsi



Results – Correction difference statistics for all bands



Mean and standard deviations of the correction with respect to all bands



Results – Classification Approach







- 10 bands used (10-20 m res)
- Supervised classification
- Maximum Likelihood
- Same training areas (10 for each class)



Cloud masked using mask from L2A





Results – Classification Approach



- Accuracy assessment using Kappa Analysis
- Same validation areas (10 for each class)

Both classification and accuracy assessment have been performed using GRASS GIS

Results – Classification Approach

Cats 1 2 3 4	% Commission 0.147080 3.101044 13.467598 24.478054	% Ommission 1.543596 0.701516 21.051200 18.066702	Estimated K 0.997820 0.948338 0.838454 0.725371	Ca 1 2 3 4	ats % Com 0.165 3.519 15.56 17.24	mission 523 8844 59049 9653	% Ommi 1.7462 0.6659 15.733 22.085	ssion 30 555 6488	Estimated 0.997547 0.941361 0.813247 0.806469		
Kappa	Kappa Var	iance	Ka	Kappa Kappa Variance							
0.909	964 0.000001		O	0.915520 0.000001							
0bs C	orrect Total	0bs % 0bserv	ed Correct	01	bs Correct	: Total	Obs	% Obser	ved Correct		
14509	7 154766	93.75250	4	14	45710	15476	6	94.1485	866		

K analysis L2A

Cats	% Comm	nission	% Ommission	Estimated K	Cats	% Commis	ssion %	Ommission	Estimated K	C	ats	% Commission	% Omn	115510n	Estimated K
1	0.1470	194	1.553529	0.997820	1	0.146988	3 1.	482011	0.997822	1		0.170985	1.410	0493	0.997466
2	3.0170	103	0.704749	0.949738	2	3.045849	5 0.	696667	0.949258	2		3.297188	0.682	1119	0.945071
3	13.767	1087	17.415119	0.834862	3	14.46652	25 15	.729159	0.826472	3		13.871257	17.77	12512	0.833612
4	20.596	5127	19.071399	0.768924	4	18.68702	23 20	.842994	0.790343	4		20.892615	20.33	87673	0.765597
Kappa Kappa Variance			Kapp	Kappa Kappa Variance					Kappa Kappa Variance						
0.917003 0.000001			0.91	0.918610 0.000001					0.914906 0.000001						
Obs Correct Total Obs % Observed Correct			Obs	Obs Correct Total Obs % Observed Correct					Obs Correct Total Obs % Observed Correct						
14585	7	154766	94.24356	8	1460	34	154766	94.3579	34	1	45638	3 1547	66	94.1020	64

K analysis QGIS

K analysis L1C

K analysis GRASS

K analysis Arcsi

Thank you for your attention!

