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Contents

Session 1 – Information Extraction

Comparison of Sentinel-1 and ALOS AW3D30 DSM Potentials in a Mountainous Topography.....	1
--	---

Oil Spill Classification Based on Dark Spot Detector and Wind Parameters Estimation on SAR Data.....	5
--	---

Session 2 – Land and Geology

Clear-Cuts Mapping Using LANDSAT NDVI Time Series.....	8
--	---

Chlorophyll Estimation in Mediterranean <i>Quercus Ilex</i> Tree Canopies with Hyperspectral Vegetation Indices at Leaf and Crown Scales.....	11
---	----

Crop-Specific Phenomapping by Using Dense, High-Resolution Landsat and Sentinel Time-Series: A Case Study in Ukraine.....	14
---	----

High-Resolution WorldView-2 Dune Systems Sparse Vegetation Monitoring, By Modeling Leaf Optical Properties and Directional Reflectance of the Vegetation.....	18
---	----

NASA CYGNSS-Reflectometer and SMAP-Radiometer Functional Correlation Over Land Surfaces.....	21
--	----

Session 3 – Sensors and Electromagnetics

The FLEX Mission as Example of Multiplatform Remote Sensing: Scientific Opportunities and Implementation Challenges.....	24
--	----

Atmospheric Correction of Landsat-8 VNIR Bands Using Drone Imagery as Reflectance Reference.....	28
--	----

Session 4 – Water and Ice

Drone Hyperspectral System for Monitoring Coastal Bathing Water Quality.....	32
Multi-Index Image Differencing Method for Flood Water Detection.....	35

Session 5 – Signal Processing

Improving Forest Carbon Maps: Modeling Approaches from High-Resolution To National Scale.....	38
Extended Random Jumps: A New Spatial-Spectral Classification Algorithm for Hyperspectral Remote Sensing Images.....	41
Exploring NDVI Data Continuity between Landsat 8 OLI and Sentinel-2A MSI in a Temperate Forest District.....	45
Wind Speed Estimation Enhancement using SAR Despeckling from C-Band Sentinel-1 Images.....	48

Poster Session

Hydrological Multitemporal Study of the Mountain Region in the State of Rio de Janeiro (Brazil) Through Satellite Data and In-Situ Data.....	51
High Resolution Bathymetry of Littoral Zones Based on Very High Resolution WorldView-2 Images.....	56
Differential Tomography Model to Deal with Temporal Decorrelation of Volumetric Media.....	59

COMPARISON OF SENTINEL-1 AND ALOS AW3D30 DSM POTENTIALS IN A MOUNTANIOUS TOPOGRAPHY

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Abstract

In space-borne remote sensing, correct three dimensional (3D) modelling of the Earth surface is one of the most significant goals. Up to date, several synthetic aperture radar (SAR) and optical space missions were realized to achieve the digital elevation data in global coverage. In this study, we aimed to compare the potentials of digital surface models (DSM) derived from recently released and freely available Sentinel-1 and ALOS Prism data. To demonstrate the potentials of the DSMs in difficult topographic conditions, a mountainous area was preferred for the analysis. The name of ALOS Prism's global DSM is ALOS World 3D 30m (AW3D30) having 1 arc-second (~30 m) grid interval. Accordingly, 30 m gridded Sentinel-1 DSM was generated by interferometric processing utilizing interferometric wide (IW) swath SAR pairs. The comprehensive potential analysis of the DSMs was realized with model-to-model based comparison with the photogrammetric reference DSM. The influence of terrain slope was presented for different elevation groups separately using thresholds for tangent of terrain inclination. Height differences from the reference DSM were visualized by color-coded height error maps. Vertical profiles in randomly selected sections and contour lines showed the morphologic characters of the DSMs and the correlation levels with the reference.

Keywords: Sentinel-1, ALOS Prism, AW3D30, Digital Surface Model, Potential

1.Introduction

Digital Surface Models (DSMs) represent the terrain elevation, in simple form of three dimensional. Models are used in variety of disciplines and generated by many techniques like Photogrammetry, Airborne Laser Scanning (ALS) and InSAR. Active and passive sensing technologies enable both accurate and well-represented 3D surface [3],[4],[5]. Optical Sensing another words Passive Sensing rapidly increase the influence on computer vision, modelling and virtual reality [6]. With the effective satellite mission observe earth surface become popular after millennium. Additionally, active sensing also case that generating DSM without ground based measurements. Recently, studies on software and hardware have made sensors more efficient and productive. The developments of integrated sensing systems in satellite are revolutionary. Satellites become micro and cube [7].

In this study photogrammetric DSM used as reference to ALOS World 3D (AW3D) which produced by Japan Aerospace Exploration Agency (JAXA) and Sentinel-1 DSM that generated from InSAR pair which produced by ESA. Both tested models are freely available on internet.

Study area and materials described in section 2. Section 3 methodology, explained how the study was organized and done. Section 4, represent visual and analytic results. Finally, section 5, conclusion was mentioned.

2.Study Area and Materials

The study area is whole city center and around of Zonguldak, Turkey and surroundings; it has a rolling up to mountainous topography with elevations up to 530 m. above sea level. The area cover on country and rough terrain can be seen in figure 1. Also frequency distribution of elevation presented in figure 2.

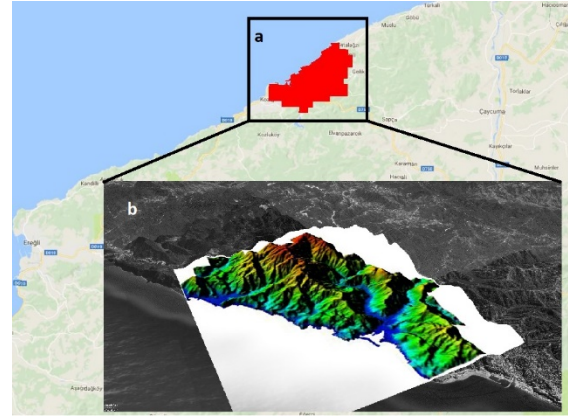


Figure.1 a) Test area in Zonguldak b) rough terrain

As a reference model produced in 2005 by the Municipality of Zonguldak 10m. resolution photogrammetric DSM is used.

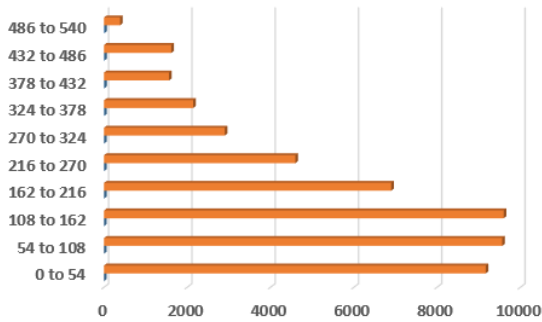


Figure.2 Elevation distribution on study area

For Sentinel-1 mission data are collected by Sentinel-1A satellite. InSAR-pair, master is date January 28th and slave February 9th, respect to that information temporal baseline calculated as 11 day.

Table.1 Characteristics of the used Sentinel-1A master and slave InSAR-pair

Characteris tics	S-1A_IW master image	S-1A_IW slave image
sensor ID	SAR-C	SAR-C
sensor mode	Interferometric wide	Interferometric wide
master (d-m- y)/slave(d-m- y)	28-JAN-2018	09-FEB-2018
polarization mode	dual polarization	dual polarization
polarization channel	VH+VV	VH+VV
pass direction	descending	descending
scene size	185 km x 250 km	185 km x 250 km

As Table.1 indicated that sensor mode in used and freely available Interferometric Wide (IW) which in sensed C band (5.6 cm). Each image has three Swaths (IW1,2,3) and each swath has 9 Bursts. In the study IW1 were used for generation DSM. IW mode images were captured by Terrain Observation with Progressive ScanSAR (TOPSAR). ScanSAR mode is capable of steering beam in range direction, additionally TOPSAR mode electronically steered from backward to forward in the azimuth direction for each burst. TOPSAR mode replaces the conventional ScanSAR mode by resulting more homogeneous image quality throughout the swath. [1],[9],[10]

Table.2 ALOS AW3D specifications

	ALOS AW3D
Launch Date	24-JAN-2006
Sensor	Prism
Geometric Res.	2.5 m
Grid Spacing	~30 m
Datum	WGS84
Coverage	Global
Accuracy	5 m std
Radiometric Res.	16 bit GeoTIFF
Data Spectrum	2006-2011

Ver. and Ver. Date	1.1 and 6-MAR- 2017
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AW3D Global is recently freely available and more up to date DSM which data was perceived between 2006 to 2011 by ALOS PRISM sensor. First free DSM published around 30 m. sampling in 2016 version 1.0 with some gaps. Revision 1.1 came up March 2017 gaps filled with interpolation [8].

3.Methodology

This part describes flow of generation and validation DSM. Basically, Global Mapper and Surfer softwares used for visualization of DSMs, Contours and Height Error Maps. BLUH produced and created by Karsten Jacobsen for academic software was used for validation of DSMs.

3.1 DSM Generation of Sentinel-1 InSAR

Coregistration, master and slave images should be identified and imported the swath of interest individually. Study area is totally covered by IW1 that's why only IW1 was coregistered. After selecting the IWs, the information of the satellite orbit during the acquisition is automatically applied. Orbit information are given in two ways as precise and restituted. The next step in coregistration is the back-geocoding where a coarse DSM is needed to establish the cartographic system. For this the SRTM DSM was used, as provided by SNAP. In the interferogram generation, phase each SAR image pixel depends on the difference in orbit paths of the two SAR scenes to the considered resolution cell [4],[8].

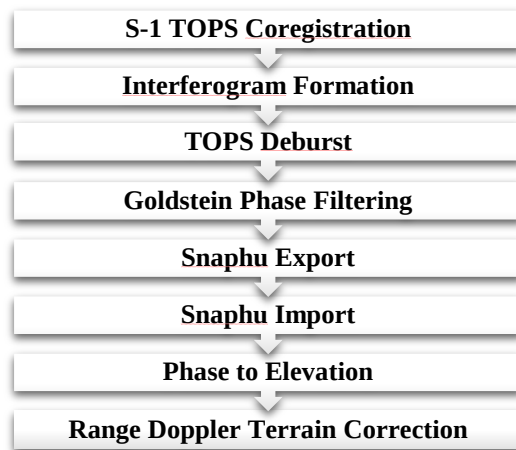


Figure 3. DSM generation from Sentinel-1

After interferogram generation and flattening, TOPS are de-bursted and filtered by Goldstein algorithm. The filtering is followed by phase unwrapping, done by applying statistical-cost mode section selected as TOPO using the initial mode Minimum Cost Flow by Snaphu software of Stanford University. Snaphu export was used in SNAP to see the unwrapped phase. Afterwards, the unwrapped phase converted to elevation and geocoding was performed by the Range Doppler. In the end we have 30 m. spacing for Sentinel-1 generated DSM. Figure.3 is a flow of processing steps which refer above.

3.2 DSMs Shift and Analyze

The first thing to do in order to compare the accuracy of DSMs relative to each other is to ensure that images are superimposed on top of each other. It is not possible to analyze on two separate non-overlapping images. An accuracy analysis of the height of a spot can only be done if the planimetric is in the same place in both DSMs. If the point indicated different values in two surface models planimetric coordinates that pointed out skewness of models [2],[5]. Figure 4 has steps of flow which explained in this sub-section.

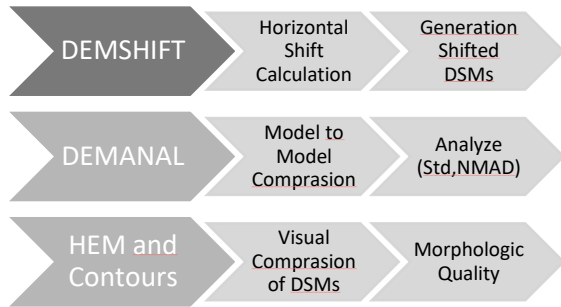


Figure.4 DSMs shift analyze and generation of diff models

Reference, Sentinel-1 and ALOS AW3D compliance were analyzed. The maximum height difference between the dissonant points is taken as 50 m. The points exceeding 50 m are being handled by the program in order not to make a blunder. Horizontal shifts have been eliminated using cross correlation method based on spatial correlation. When performing a quality assessment, a model-based comparison with a precise reference model will be more effective and a method that will work with each pixel. The vertical accuracy of a DSM can be defined using many different criteria. In practice, the mean square height differences (RMZE) or standard deviation (SZ) of height differences between the model tested and the reference model are used as the criterion for accuracy. In the study, SZ, which has a 68% probability degree, was used as the main evaluation criterion.

The absolute vertical accuracy, which is equal to the standard deviation of the sum of the squares of the height differences, is usually given as a function of the terrain slope, as well as related to the terrain slope. The relation between absolute vertical accuracy and land slope is given in Equation (5.1). Equation b is the product factor of the land slope, and α is the slope of the land. In absolute vertical accuracy analysis, a two-step process was performed to obtain the final result.

$$\text{absolute vertical accuracy } SZ = a + b \times \tan(\alpha) \quad (5.1)$$

In addition to the Normalized Median Absolute Deviation (NMAD) SZ, the second absolute accuracy indicator is used. If the height differences between the tested model and the reference model show a normal distribution, NMAD has a MAD of 1.48 multiplication factor and 68% probability (same as SZ). A situation in which NMAD is large, SZ, is an indication that the height differences are performing anomalous dispersion.

4.Results

4.1 DSM Accuracy

While the horizontal shift error detected in S-1A is about 39 m in the X and 24 m in the Y directions. The error amount in AW3D DSM m in X direction 14m. and Y 2m. direction. Table 3 contain that shift parameters in planimetric. After generating and calculating shifted DSMs, we achieve main step of absolute vertical accuracy assessment.

Table.3 Horizontal shift calculated values

Reference DSM	Shifted DSM	ΔX	ΔY
DSM (10m)	S-1A (30m)	39.42 m	-23.84 m
	AW3D (30m)	13.61 m	-2.28 m

Table 4 indicate the calculation results as S-1A for all terrain tilts 5.2 m., on zero slope 4.2 m. in SZ. Also NMAD values respectively all terrain tilts and zero slope are 4.0 m and 3.8 m. On the other hand, AW3D SZ little higher values as 5.5 m. for all terrain tilts and 4.0 m. zero slope. For NMAD indicators 4.7 all-terrain tilts and 3.2 m. on zero slope.

Table.4 Absolute vertical accuracy values

Ref. DSM	Tested DSM	SZ (m)		NMAD (m)	
		SZ all terrain tilts	SZ $\alpha < 0.1$	NMAD all-terrain tilts	NMAD $\alpha < 0.1$
DSM (10m)	S-1A (30m)	5.178 + 5.627 $\times \tan(\alpha)$	4.172	3.978 + 7.290 $\times \tan(\alpha)$	3.742
	AW3D (30m)	5.465 + 5.001 $\times \tan(\alpha)$	4.044	4.684 + 5.953 $\times \tan(\alpha)$	3.182

On the Figure of frequency distribution about vertical accuracies is shown as 5th which we could able to see all terrain tilts.

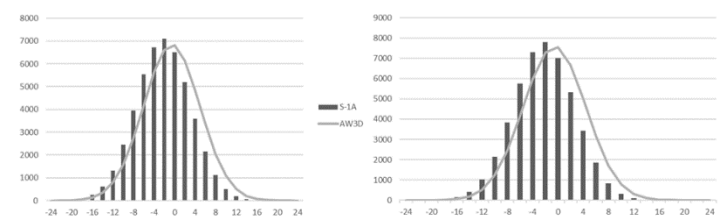


Figure.5 Frequency distribution of on left standard deviation and right graphic NMAD

Height error maps have been produced to support calculated values and plotted graphics.

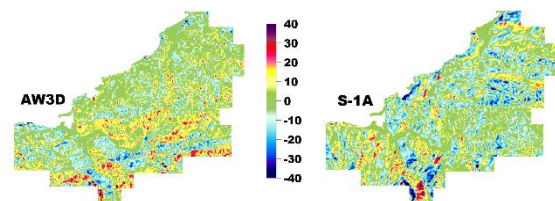


Figure.6 Height Error Maps of study area

Figure 6 is showed and supported the accuracy assessments. As on zero slope AW3D DSM is better then S-1A. For all terrain tilts S-1A have the drop on AW3D.

4.2 Morphologic Quality

The accuracy of the points in the height models is only one aspect of the quality of the DSMs, the spacing is also important, both of which lead to morphological quality, appearing on the contour lines.

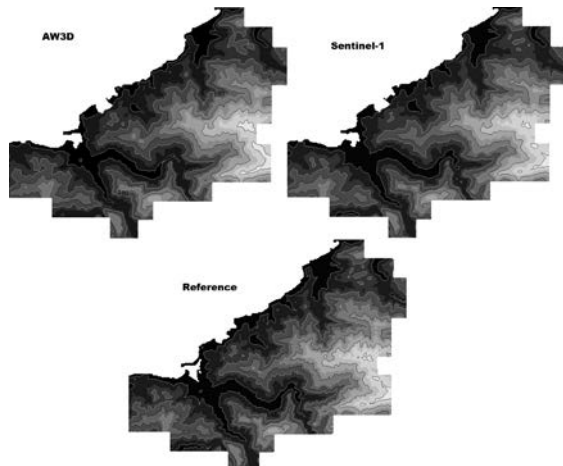


Figure.7 Shows the contours for all DSM used

Reference, S-1A and AW3D DSMs were respectively 10, 30 and 30 meters. Figure.7 shows the contours for all DSM used. Especially Reference DSM has more details due to grid spacing.

Conclusion

Analyzes were performed on a model-based digital surface model reference produced from photogrammetry-derived data. In the analyzes, the horizontal and vertical accuracies of the digital surface model obtained from the Sentinel-1A fit were tried to be explained in detail. Vertical absolute accuracy was determined. When the results are examined, it is seen that the digital surface model obtained from Sentinel-1A conforms better with the reference model and the accuracy level of all terrain tilts is higher than the AW3D. However, it should come to the mind that the data obtained from the ALOS satellite in the period 2006-2011. Additionally, on slope zero where terrain tilts lower then 0.1 AW3D seem better on the case of the datasets.

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OIL SPILL CLASSIFICATION BASED ON DARK SPOT DETECTOR AND WIND PARAMETERS ESTIMATION ON SAR DATA

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ABSTRACT

This paper tackles the oil spills monitoring using satellite Earth Observation tools based on Synthetic Aperture Radar (SAR) sensors. The proposed processing scheme is composed by a dark spot detector and the discrimination of false positives using, in both stages, instantaneous wind field information. The detector implements an adaptive threshold to provide a robust performance against speckle noise and wind conditions. Focusing on the typical evolution of the elongated slicks, a classification is performed. Results obtained with a SAR image acquired by TerraSAR-X over the Gulf of Mexico and the co-registration with weather forecast, confirm the suitability of the proposed methodology.

Index Terms— SAR, Oil Spill Detection, Oil Spill Classification, Wind Data, Multi-resolution

1. INTRODUCTION

An oil spill is the release of a liquid petroleum hydrocarbon into the environment. Oil spilt into the oceans every year due to human malpractice causes or natural seeps can have disastrous consequences for society, economically, environmentally, and socially.

Satellite Earth Observation (EO) tools can be used for remote sensing tasks in open ocean surface due to the capability of providing wide area coverages. Spacecraft on-board Synthetic Aperture Radars (SAR) produce high-resolution imagery acquired under any weather and light condition [1]. SAR data is not an optical image and its interpretation has to consider phenomena such as inherent speckle noise, Doppler effect due to moving targets and ambiguities.

Radar backscatter values from oil spills are very low appearing as dark spots in SAR images [2]. However, these values are very similar to backscatter values from very calm sea areas and other natural phenomena named look-alikes. The general scheme for oil spills monitoring is composed of dark spots detection, features extraction and oil spill discrimination. The detection stage can be based on intensity adaptive

thresholding [2], exploiting the edge information [3] or spectral analysis [4].

The detection performance is highly dependent on the wind conditions. Low sea states are associated with sea clutter that produces low contrast with respect to the oil spill (minimum wind speeds of 3 knots). High sea clutter returns can lead to detection losses inside the wave troughs (maximum wind speed of 20 knots) [5]. In this paper, wind information, texture parameters and adaptive thresholding technique are considered to detect and classify dark spots. Texture parameters are estimated at multiple scales, considering the complexity of SAR data [6], to declare blocks that can include dark spots and require a detailed analysis. These blocks are thresholding attending to local sea clutter statistics, the block size, and the wind intensity. The classification is focused on elongated detected slicks, and a preliminary discrimination in function of its orientation is performed. The validation of the proposed solution is carried out using a ScanSAR image collected by TerraSAR-X [7] confirming the ability to map oil spill candidates.

2. OIL SPILL DETECTION AND CLASSIFICATION

For the considered purpose, the most important step is the dark spot detector, because once oil spills are omitted in this stage, they will never be detected in the following steps. The detection scheme is based on textural parameter estimations at different resolutions and a adaptive thresholding technique. The wind field information is also used to discriminate elongated detected dark spots which orientations can not be associated with moving source or wind dynamics.

2.1. Homogeneity indicator

The homogeneity indicator is based on a local texture measurement: the Power-to-Mean Ratio ($PMR = \frac{\sigma}{\mu}$, where σ and μ are the standard deviation and mean value of the samples amplitude, respectively). A low value of PMR denotes an homogeneous area with low contrast that can be associated with the absence of dark spots in the patch under study. PMR values are calculated for different resolutions or patch sizes to

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improve the characterization of the textural information [6]. From now on, PMR_P denotes the PMR estimated in blocks consisting of $P \times P$ pixels. The patches with a PMR_P higher than the mean PMR_P ($\overline{PMR_P}$) of the whole image will be considered in following steps.

2.2. Adaptive thresholding

The intensity threshold is determined taking into account both false alarm requirements and a sea clutter statistical model. One of the most adopted models for high-resolution SAR sea-clutter is the Generalized Gamma Distribution (GGD): $f(x|k, \nu, \sigma) = \frac{|\nu|k^k}{\sigma\Gamma(k)} \left(\frac{x}{\sigma}\right)^{k\nu-1} e^{-k(\frac{x}{\sigma})^\nu}$ [8]. The GGD parameters are k , σ and ν , the shape, scale and parameters respectively. These parameters are locally estimated considering a patch centered in the previously selected blocks. The patch size will be a compromise solution between estimation error and local characterization.

The false alarm requirements are proposed to be dependent on the multi-scale analysis and on the wind intensity. $P_{FA}^{P,BS}$ will denote the desired false alarm probability for a given block size (P) and Beaufort wind force scale (BS) [9]. The dependence on P allow to avoid a speckle filtering stage, and the dependence on BS allow a robust design against different contrast conditions associated with the instantaneous wind intensity. Indeed only four BS values ($BS = 2$ Light Breeze to $BS = 5$ Fresh Breeze) are associated with wind conditions that allow oil spill detectability (wind speed between 3-20 knots) [5]. The final output is a binary segmented image where the oil candidates are stand out clearly.

2.3. Tail Oil Slicks

Some typical slick shapes found in SAR imagery are: tail slicks (narrow or linear slicks that can be straight, slightly bent or angular) or wide slicks (with a not clear delineation and a difficult relation with temporal wind data). This work is focused in tail slicks that can be released from a moving source, so the development of the slick shape is influenced by the vessel speed and direction, or can be spilt from a fixed point source, so it is assumed to move with 3% of the wind speed and 15° to the right of the wind direction [10].

To select the tail slicks, the flattening values of the ellipses that have the same second-moments as the detected dark spots are considered. For each dark spot with a flattening close to the unity, the orientation is estimated and a potential moving target source is searched. Using the current wind direction, the movement dynamic of the ship-source and the extracted orientations, the oil spill classification is performed.

3. RESULTS

The oil spill detector and classifier is evaluated with a SAR image acquired by TerraSAR-X over the Deepwater Horizon

BS/P	128	64	32
2	0.1	0.05	0.01
3	0.2	0.06	0.02
4	0.3	0.07	0.03
5	0.4	0.08	0.04

Table 1. Desired $P_{FA}^{P,BS}$ values for adaptive thresholding stage

oil spill (also referred to as the Gulf of Mexico oil spill), a disaster that began on April 20th, 2010 (Figure 1(a)). The considered SAR product is a geo-coded radiometrically enhanced one that considers vertical polarization. The selected imaging mode is ScanSAR with a illuminated area of 23,826km² and a pixel spacing of 8.25m [7]. Only the results of this image are presented as representative ones to confirm the capability of the proposed scheme.

In Figure 1(b), wind data, interpolated for the illuminated area at the collection time of the SAR image, is depicted. This information is provided by the Global Forecast System of the National Centers for Environmental Prediction [11].

128x128; 64x64 and 32x32 blocks are used to implement multi-scale PMR estimation. The first iteration declares 128x128 blocks whose $PMR_{128} > \overline{PMR_{128}}$, and are candidates to contain dark spots. A second and a third iterations are performed over the non-selected blocks with lower resolution using PMR_{64} and PMR_{32} estimations, respectively. Different thresholds associated with the desired $P_{FA}^{P,BS}$ are determined using local GGD parameters corresponding to 2,048x2,048 windows centered at the declared blocks, and interpolating the wind speed data to the geo-referenced blocks. Table 1 details the assumed $P_{FA}^{P,BS}$ values based on the experimentation with SAR images with oil spills.

In Figure 1(c), the local sea clutter and wind intensity dependent threshold map are presented, while Figure 1(d) depicts the classified image with the following results: 23 dark spots (white, red and green ones), with a minimum area big enough to be dangerous of 0.3 km² [5], are detected; of which 9 (red and green ones) can be considered tail slicks with a flattening higher than 0.7; of which 7 (green ones) are candidates to contain oil because the orientation is close to 15° to the right of the wind direction. The Gulf of Mexico is known to be exploited for its oil by mean of offshore floating drilling rigs that can be considered as fixed point pollution sources.

4. CONCLUSIONS

In this paper, a dark spot detector and a oil spill classification using instantaneous wind information and SAR data is considered. SAR systems are suitable EO tools, although the automatic interpretation is a complex task. Oil spills on SAR images appear as dark spots, although other phenomena can give false oil spill positives or look-alikes.

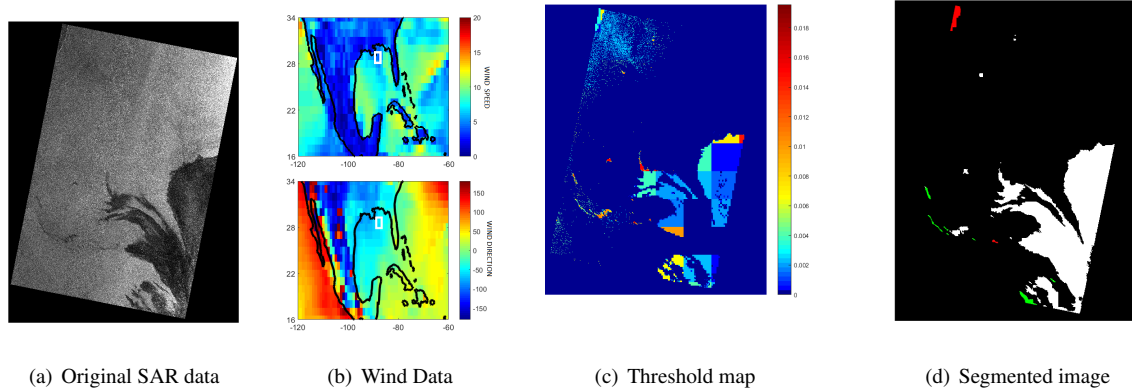


Fig. 1. Results of oil spill detection and classification

The proposed processing scheme is based on texture measurements and an adaptive thresholding algorithm to provide a segmented image that stand out the oil candidates clearly. PMR parameter, estimated following a multi-resolution philosophy, is considered to declare non-homogeneous areas that can include dark spots. The considered detector is based on a threshold fixed attending to the desired P_{FA} and GGD sea clutter model. As the detection performance is highly dependent on the wind conditions and the speckle noise, the P_{FA} requirements are proposed to be dependent on wind intensity and the non-homogeneous block size. In addition, a classifier of detected tail slicks is performed using contextual information (vessel-source pollution or wind direction).

The designed algorithm is evaluated with a SAR image acquired by TerraSAR-X over the Gulf of Mexico. The resulted segmented images confirm the suitability of the proposed technological solution that can be implemented in near-real-time constraints taking into account the inherent changing characteristics of the considered application.

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CLEAR-CUTS MAPPING USING LANDSAT NDVI TIME SERIES

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ABSTRACT

Detection of past forestry treatments is of great importance to know the current situation of forest stands. In this sense, Landsat program provides a good solution to detect disturbances in a spatially continuous way. The purpose of this study was to develop an automatic methodology for detecting clear-cut areas over the period 2000-2016 using all available Landsat images.

For each Landsat image Normalized Difference Vegetation Index (NDVI) was computed, having previously masked out those pixels classified as clouds or cloud shadows. For each year an annual mosaic of Landsat bands was generated, based on the highest NDVI value of the images collected in each year, as well as a set of annual statistics of the NDVI index (average, minimum and maximum).

Regarding clear-cuts mapping, two classes were defined: areas subject of clear-cutting operations and areas without clear-cuts over the study period. A whole set of band mosaics and NDVI statistics were included as predictor variables for clear-cutting detection in the VSURF algorithm. The most important variable was the difference in the average NDVI of the time period, taking into account this finding single decision trees were fitted using the R-package C-50. The decision tree fitted showed that difference in the average NDVI values close to 1450 were able to classified correctly 98% of the training points. Landsat time series poses a new opportunity to achieve a better understanding of forest dynamics.

1. INTRODUCTION

The recognition of forests in the fight against climate change has resulted in the adaptation of certain silvicultural treatments which contribute to the sustainability of forest resources. However, its successful implementation requires knowledge of past disturbances occurred in the forest stands as well as their current situation and status of health [1]. In this sense, the use of Landsat time series provides a good solution for change monitoring because for the same pixel there is information throughout a large time

period that allow us to know the dynamics of change [2].

The purpose of this study was to develop an automatic methodology to detect abrupt changes, such as clear-cuts, through a multi-temporal analysis over the study period 2000-2016 using all available Landsat Time Series data. The study focused on the Urbión Model Forest area located in the northern part of Spain, between the provinces of Burgos and Soria. This model is the largest forested area of the Iberian Peninsula where *Pinus pinaster* and *Pinus sylvestris* are the dominant species. Moreover, it is an area with a long tradition in its forest management due to the great number of important timber industries. Therefore, it is very important to count on a straightforward methodology for forestry interventions monitoring.

2. DATA

2.1. Landsat imagery

The study area was defined by the Landsat scene found in path/row 201/031. A total of 228 surface reflectance images from 2000 to 2016 with a cloud cover less than 80% were downloaded. Pixels classified as clouds, cloud shadows or non-data were masked out using the Fmask algorithm [3]. For our study purposes, we used bands 2 to 6 corresponding to blue (0.45 - 0.51 μ m), green (0.53 - 0.59 μ m), red (0.64 - 0.67 μ m), near infrared (NIR; 0.85 - 0.88 μ m), and the first shortwave IR bands (SWIR1, 1.57 - 1.65 μ m).

NDVI (Normalized Difference Vegetation Index) was computed for each cloud-free Landsat pixel as follows, where IRC is the infrared band and R the red band.

$$NDVI = \frac{IRC - R}{IRC + R}$$

Considering all the images of each year, the mean, minimum and maximum for NDVI index was calculated for each year. In addition an annual mosaic with the Landsat bands was generated based on the greenest available pixel (pixel with the maximum NDVI).

3. METHODS

3.1. Forest mask

A Landsat-based forest mask was created to exclude non-forested areas from the analysis using the *RandomForest* R package [4]. Two different years (2000 and 2016) were used to detect those pixels that had once been forest throughout the study period. Therefore, the annual mosaics of 2000 and 2016 and the vegetation index statistics computed for these years were used as predictor variables. VSURF variable selection procedure [5] was applied to eliminate irrelevant and redundant variables from the dataset. The most explanatory variables selected by the VSURF algorithm were the minimum and the average NDVI for both years, the maximum NDVI for 2016, the IRC and SWIR of both mosaics and the green spectral band for the year 2000.

3.2. Change classification

Two classes were defined for mapping clear-cuttings: areas subject of clear-cutting operations and areas without clear-cuts in the study period. Areas where clear-cutting were conducted showed a sharp decline in NDVI values that lasted for several years and subsequently these values tend to increase and approach the initial position. Taking into account this finding two different training datasets were created, one for the time period 2005-2010 and another for 2010 onwards. Regions of interest (training polygons) were defined in areas where we were confident to find the above-mentioned classes. To this end, changes detected were compared with available Google Earth images.

For each training polygon of each study period a set of bands of the annual mosaics and NDVI statistics were extracted (Table 1) based on the NDVI statistics initially calculated.

VSURF algorithm was applied for variable selection joining the two datasets created for each period. The

aim was to construct a simple regression model that included few predictor variables and was therefore easy to reproduce and understand on other circumstances. In addition, when few numbers of variables are enough to perform the classification, decision trees allow for a better understanding of the classifier than Random Forest. Therefore, decision trees adjustment was considered as an alternative for change classification purposes.

Table 1. Predictor variables included in the VSURF algorithm to be used for clear-cutting detection.

Predictor variables	Description
Landsat B1	Blue
Landsat B2	Green
Landsat B3	Red
Landsat B4	Near Infra-Red
Landsat B5	Shortwave Infra-Red
minabsNDVI	Minimum value from the minimum NDVI of the period
maxabsNDVI	Maximum value from the maximum NDVI of the period
minavgNDVI	Minimum value from the average NDVI of the period
maxavgNDVI	Maximum value from the average NDVI of the period
maxdifavgNDVI	Maximum difference in the average NDVI of the period $\text{maxavgNDVI} - \text{minavgNDVI}$
maxdifabsNDVI	Maximum difference between the maximum and minimum NDVI for the period $\text{maxabsNDVI} - \text{minabsNDVI}$

4. RESULTS

The most important variable to identify clear-cutting was the maximum difference in the average NDVI of the time period. Taking into account this finding decision trees adjustment was performed using C50 R package [6].

The decision trees showed that maxdifavgNDVI values close to 1450 were able to classified correctly

98% of the training points. In order to exclude misclassification errors the threshold established had to be consistent at least two years after the analyzed year, with the exception for the year 2015 and 2016 in which the two years verification was not possible. Once this threshold was found an automatic workflow was developed in R for annual clear-cuts detection (Figure 1).

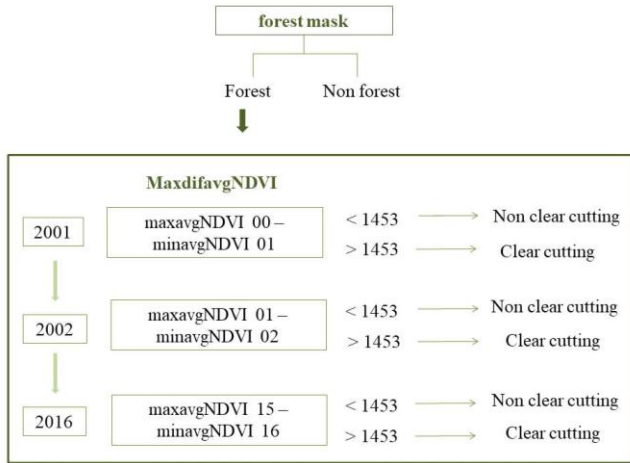


Figure 1. Clear-cutting detection workflow, *maxdifavgNDVI* refers to the maximum difference in the average NDVI for each year.

A clear-cut mapping with a 30 m resolution spatial was obtained identifying not only the clear-cut location, but also the year in which it was made (Figure 2). By knowing this year and the yield table, it is possible to determine the year in which forest treatments are recommended and the location of forest stands to be intervened in the future.

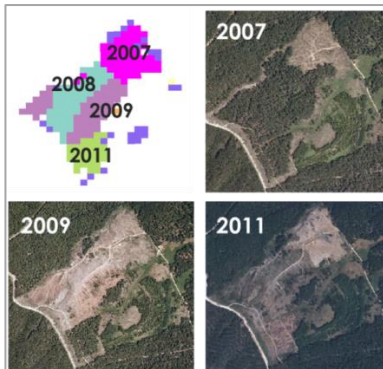


Figure 2. Some details of high resolution change classification mapping for the study area of Urbi6n Model Forest. High resolution images after the detected change are shown.

5. CONCLUSIONS

This study demonstrates the potential of Landsat images and decision trees for detecting clear-cuts, reaching satisfactory results. The methodology developed could be applied over other study areas almost directly and at a relatively low cost. For this reason, Landsat time series poses a new opportunity to achieve a better understanding of our forest management and dynamics. Moreover these finding have a significant importance from a management point of view in threatened areas concerning illegal clear-cuts where the approach described could be used as a monitoring system to track illegal logging. Finally, the availability of Sentinel-2 images could be an opportunity to create denser time series and to generate more detailed maps due to its better spatial resolution.

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CHLOROPHYLL ESTIMATION IN MEDITERRANEAN *QUERCUS ilex* TREE CANOPIES WITH HYPERSPECTRAL VEGETATION INDICES AT LEAF AND CROWN SCALES

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ABSTRACT

A number of studies have shown the potential of hyperspectral indices calculated from information derived by proximal and remote sensors to retrieve either leaf or canopy chlorophyll content. However, only few studies have addressed the multiscale estimation (leaf to crown) using concurrent datasets in a way that crown characteristics may be underlined. The aim of this work is to estimate chlorophyll leaf content and canopy content using data acquired in three sampling campaigns covering the main phenological phases of perennial *Quercus ilex* trees (spring, summer and winter). At a leaf level, reflectance (ρ) and transmittance (τ) factors were measured with a Li-Cor 1800-12 Integrating Sphere (Li-Cor, Lincoln, NE, USA) attached to an ASD FieldSpec® 3 spectroradiometer. At a crown level, an STS spectrometer (Ocean Optics, Dunedin, FL, USA) aboard an Unmanned Aerial Vehicle (UAV) was used to measure spectral response of tree crowns. Chlorophyll content at leaf level was determined using a SPAD-502 Leaf Chlorophyll Meter calibrated in the laboratory. Linear regression models were applied between chlorophyll measurements and spectral indices calculated from leaf and canopy spectra. The results showed that MCARI and TCARI spectral indices offer the best estimation at crown scale ($R > 0.6$) but only when current year leaves are used for leaf chlorophyll content determination.

Index Terms— Upscaling, chlorophyll, hyperspectral vegetation indices, UAV, leaf, canopy, *quercus ilex*

1. INTRODUCTION

Chlorophyll content (Chl) indicates plant health and photosynthetic capacity. Chlorophyll strongly absorbs radiation in the red (680 nm) and blue (445 nm) spectral regions. This information can be exploited by Remote Sensing to estimate vegetation Chl at different scales.

Spectral vegetation indices (SVI) are arithmetic combinations of spectral reflectance factors. At leaf level SVI (especially those including bands around 550 nm and 700

nm), strongly correlate with Chl [1,2]. However, less accurate empirical relationships are reported at canopy scale [3].

Some authors have improved Chl canopy level estimations by using radiative transfer models [3]. However, these models depend on several parameters and therefore demand extensive information to be used. Several authors have demonstrated that empirical methods based on the use of VIs can outperform the RTMs in the estimation of vegetation parameters.

The aim of this study is calibrating empirical SVI-based models to predict leaf and canopy Chl in *Quercus ilex* trees by using spectral information acquired at the two scales. Pearson correlation coefficient (r) identified the spectral bands most strongly related to. Then, hyperspectral SVI including such bands were selected as linear predictors of Chl.

2. STUDY SITE

The study site is located in Majadas de Tiétar (39°56'29" N, 5°46'24" W) in a typical Mediterranean tree-grass ecosystem called *dehesa*. It is integrated by two vegetation layers with different biophysical and phenological characteristics: a scattered tree layer, composed mainly by evergreen *Quercus ilex* trees covering approximately the 20% of the surface and a grass layer with a high biodiversity and dynamic annual phenology. The site is a well-established research station for ecosystem monitoring included in the FLUXNET global network (<https://fluxnet.fluxdata.org>).

3. MATERIALS AND METHODS

3.1. Input Data acquisition.

Biochemical and spectral variables were measured in three different campaigns (April, September 2017 and January 2018) which are representative of the main phenological phases of the *Quercus ilex* trees in our study site. At the leaf scale, twenty-four leaves per tree and leaf age (current and previous year leaves) were sampled in 6 different trees. For

each leaf, SPAD-502 Chlorophyll Meter (<http://www.konicaminolta.com>) provided pigment contents. Right after that, leaf ρ and τ factors were measured using a Li-Cor 1800 Integrating-Sphere device coupled to an ASD FieldSpec® 3 (www.asdi.com) spectroradiometer (400 to 2500 nm spectral range).

Canopy spectral measurements were carried out with an STS-VIS spectroradiometer (Ocean Optics, Inc.) onboard an Unmanned Aerial Vehicle (UAV). A twin ground-based sensor simultaneously measured down-welling irradiance. An UAV-borne RGB provided the STS field of view (FOV). Average distance between the UAV and the top of the tree crowns was 7 meters and mean STS FOV 50 cm diameter. Leaf Area Index (LAI) was additionally measured in each tree with a LAI 2200-C instrument (<https://www.licor.com/>); leaf age fractions (current and previous year leaves) were also visually estimated.

3.2. Data pre-processing.

Spectral information at both scales was limited to 400-900 nm spectral range for comparability purposes and anomalous values were filtered. 432 leaf ρ spectra were selected, half of them from previous leaves. Canopy-level STS acquisitions included a total of 108 spectra with an average of 6 spectra per tree/date. Average spectra were calculated for each tree and sampling date for further analysis.

Chl content ($\mu\text{g}/\text{cm}^2$) was calculated from the SPAD values using a calibration equation adjusted by [4]. Average tree chlorophyll values per tree were estimated by leaf age fraction weights. Total canopy Chl [5] was estimated by multiplying weighted leaf Chl by LAI.

3.3. Statistical analysis.

Correlations between Chl and original spectral bands at two scales were performed and Pearson coefficient (R) analyzed in order to determine the optimal bands to calculate hyperspectral indices to further estimate Chl content. Chl was estimated at leaf and canopy levels using Linear Regression Models (LRM) with hyperspectral vegetation indices as independent variables. Resample bootstrapping techniques were conducted to estimate coefficients and errors. To evaluate the goodness of the prediction model the determination coefficient (R^2) and the Relative Root Mean Square Error (RRMSE) were calculated. All these computations were implemented by R (R Core Team, 2017).

4. RESULTS

4.1. Temporal and spatial dynamics of Chl content.

Young *Quercus ilex* leaves emerge in spring with low Chl that increase during the first year with a pause during summer

due to water stress conditions [1]. Chl ranges are between $30\mu\text{g}/\text{cm}^2$ in current leaves and $80\mu\text{g}/\text{cm}^2$ in mature leaves. In spring, the leaves with the most different properties gather into the crown. Chl slightly decreases before the leaf fall. Chl presents a spatial (between trees) variability (standard deviation, $\sigma = 9\mu\text{g}/\text{cm}^2$), less important than the temporal one ($\sigma = 13\mu\text{g}/\text{cm}^2$).

4.2. Correlations and selection of hyperspectral vegetation indices.

Figure 1 shows the r values between current leaf Chl and leaf and canopy reflectance factors acquired with the STS (canopy) and ASD (leaf) sensors. The highest $|r|$ ($|r| > 0.6$) was obtained at 700 nm, with a second peak at 550 nm, which agrees with the literature [2]. Correlation was weaker for previous year leaves ($|r| < 0.4$) since they show narrower spatial and temporal variability and spectral properties can be modified by leaf deterioration, diseases and dirt [2]. Chlorophyll absorption regions did not show the largest correlations due to saturation of the optical signal with Chl. At a canopy level, the same pattern is observed but with lower correlations since structural and directional effects modify the reflectance factors. Hyperspectral VI's indices were calculated (see table 1) using bands within highest correlation wavelength regions.

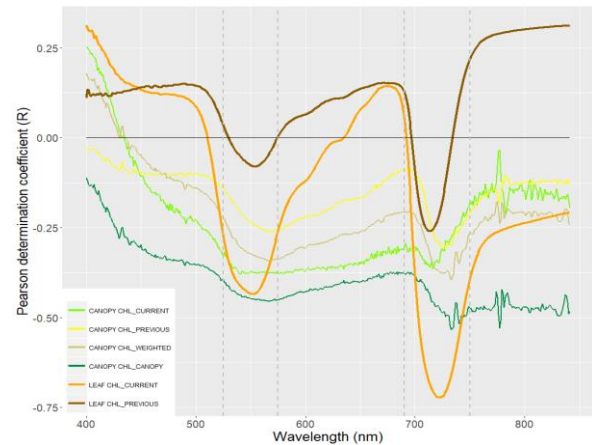


Figure 1. Leaf (orange) and canopy (yellow-green) level correlations between Chl and ASD and STS bands.

4.3. Chlorophyll estimation using Linear Regression Models.

Table 1 shows the coefficient of determination (r^2) and relative root mean square error (RRMSE, %) for the linear models fit with different SVI. Current year leaf level models achieved higher r^2 ($r^2 \geq 0.55$) and lower RRMSE than previous

		Previous leaves and ASD Spectra		Current leaves and ASD Spectra		Canopy and STS Spectra	
SVI's	Equations	R ²	RRMSE	R ²	RRMSE	R ²	RRMSE
Green NDVI	$(\rho_{750} - \rho_{550}) / (\rho_{750} + \rho_{550})$	0.02	13.76	0.16*	15.04	0.16*	18.26
Gitelson & Merzlyak	ρ_{750} / ρ_{550}	0.03	13.70	0.15*	15.08	0.02	19.78
RI – 3dB	ρ_{741} / ρ_{717}	0.20*	12.45	0.51*	11.37	-	-
ND705	$(\rho_{750} - \rho_{705}) / (\rho_{750} + \rho_{705})$	0.09*	13.21	0.28*	13.84	0.02	19.82
1/ρ ₇₀₀	1 / ρ ₇₀₀	0.02	13.76	0.18*	14.75	0.23*	17.57
Vog ₂	$(\rho_{724} - \rho_{747}) / (\rho_{715} + \rho_{720})$	0.24*	12.14	0.57*	10.70	-	-
MCARI	$(\rho_{700} - \rho_{670}) - 0.2 \cdot (\rho_{700} - \rho_{550}) \cdot (\rho_{700} / \rho_{670})$	0.16*	12.71	0.67*	9.45	0.15*	18.42
TCARI	$3 \cdot [(\rho_{700} - \rho_{670}) - 0.2 \cdot (\rho_{700} - \rho_{550}) \cdot (\rho_{700} / \rho_{670})]$	0.16*	12.71	0.67*	9.45	0.15*	18.42
RI – 2dB	ρ_{725} / ρ_{720}	0.15*	12.79	0.44*	12.23	0.03	19.75
B(log(1/ρ ₇₂₀))'	log (1 / ρ ₇₂₀)'	0.09*	13.25	0.57*	10.71	0.24*	17.41
Vog ₁	ρ_{740} / ρ_{720}	0.21*	12.33	0.55*	11.02	-	-
TCARI/OSAVI	Derived index	0.14*	12.86	0.57*	10.77	0.14*	18.48

Table 1. R² and RRMSE (%) obtained in the linear Regression Models between Leaf and Canopy Chl and VI's. * shows significance with (95% confidence). Bold font flags the best SVI's at performing.

year leaves ($r^2 \leq 0.24$). MCARI and TSAVI indices were the best predictors.

Canopy scale models performed similarly than previous year leaf models at leaf scale ($r^2 \leq 0.24$), but with higher errors. The indices 1/ ρ_{700} and $\log(1/\rho_{720})$ were in this case the best predictors. MCARI and TCARI did not outperform other indices despite of being designed to reduce influence of non-photosynthetic elements and background [6].

5. CONCLUSIONS

This work evidences the link between spectral information-SVI's and chlorophyll spatially and temporally except for previous leaves since their chlorophyll content does not change along the phenological year. Likewise, this study verifies the challenges of applying empirical models in evergreen species as they show less biophysical and spectral variation than the deciduous. This study also evidences that estimates are significantly more accurate at leaf scale (higher level of detail) than at canopy scale, which Chl estimates are comparable to previous year leaves at leaf level. Canopy chl through the upscaling procedure performed better than current leaf content at a canopy scale. However, advanced methods are necessary to assess Chl at a canopy level. Thus, future approaches shall include Radiative Transfer Models (RTM) to upscale leaf reflectance and improve the estimates.

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CROP-SPECIFIC PHENOMAPPING BY FUSING DENSE, HIGH-RESOLUTION LANDSAT AND SENTINEL TIME-SERIES: A CASE STUDY IN UKRAINE

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ABSTRACT

Accurate and timely agricultural monitoring is essential for operational tasks such as yield prediction and crop condition monitoring. Remotely sensed imagery allows for efficient and cost-effective analyses of large study-areas. The greater number of freely available satellite observations and frequent data acquisition provides an excellent opportunity to monitor changes in croplands. In this study, vegetation indices were used to derive phenometrics for cropland in Bila Tserkva district, Ukraine. A data fusion method was applied. Synthetic Landsat and Sentinel images were created from MODIS data to overcome radiometric and spatial differences between the sensors. Sentinel and Landsat data were then lined up into a mixed timeline together with their synthetically created counterparts to bridge data gaps caused by cloud-contamination. TIMESAT software was used to derive phenological parameters from these datasets. Results achieved from the mixed time-series kept their original resolution and allowed for differentiation of patterns on a field-level. The accuracy of the calculated seasonality variables was then compared with in-situ data. Results were mostly satisfying. Regressions for the creation of synthetic imagery showed R^2 outcomes between 0.4 and 0.7 for most pairings. Calculated phenology parameters mostly deviated by less than two weeks, for some datasets and crops by less than one week from in-situ information. Resulting maps kept the high resolution and detail of Landsat and Sentinel imagery for the gap filled time-series. The study demonstrated the potential of the proposed fusion method to overcome gaps in remotely sensed time-series; especially mixed Landsat time-series were able to achieve good overall results in timing as well as level of detail.

Index Terms—phenology, time series analysis, data fusion

1. INTRODUCTION

1.1 Remote sensing and vegetation

Remote sensing allows for efficient research of large areas in regard to many different parameters [1]–[3]. Characterization of vegetation has long been a staple of remote sensing

research [4]–[8]. For this paper, ESA’s new, high-resolution Sentinel 2A platform was used amongst others to analyze crop seasonality in Ukraine.

The objective of this paper is to present the potential of remote sensing methods as well as a mixed synthetic time-series approach to extract crop-specific phenological parameters, such as start and end of season. Sentinel 2A and Landsat 8 time-series were used in combination with synthetic imagery calculated from MODIS Terra data as gap-fillers for the year 2016.

1.2 State of Research

Kogan was one of the first to use remotely sensed imagery and vegetational indices to derive data for a remote analysis of vegetational parameters [4], [7]. The usage of VI-time-series to derive seasonal patterns is well researched, though most studies exclusively rely on coarse resolution sensors such as NOAA’s AVHRR [5], [6] or moderate resolution MODIS [5], [9]. Phenology derivation from Landsat 8 or Sentinel 2 data has been explored less. Wang et al. show preliminary results of a Landsat-Sentinel fusion which reveal positive outcomes regarding intercompatibility [10].

This study utilized TIMESAT software to extract phenological parameters [11]–[13]. Tests of Sentinel 2 phenology derivations using TIMESAT were performed on simulated data before Sentinel 2 launch [14]. Phenology derivation from Sentinel data is a comparatively new field of research at the time of this study.

Data fusion approaches for phenological analyses have recently gained more attention. Gao et al fused Landsat 5, 7, 8 and MODIS data to map phenology stages at field scale for Iowa, presenting a similar approach to this study [16].

2. STUDY AREA AND METHODS

1.2 Study area

Climatic conditions in Ukraine are viable for rainfed agriculture [16], [17]. In the Köppen-Geiger climate classification, most of the country falls under temperate and humid continental climate. Southern parts of the country fall within the warm and humid continental climate with the

southernmost parts reaching into subtropical climate zones [18].

Bila Tserkva Raion (second level administrative unit) represents the study area. Crop data were derived from a 2016 crop map provided by Space Research Institute, National Academy of Sciences of Ukraine and SSA Ukraine [19]–[21]. For Bila Tserkva, cropland covers almost two thirds of the raion.

1.2 Methods

Medium resolution MODIS (Moderate-resolution Imaging Spectroradiometer) data as well as high resolution Landsat 8 and Sentinel 2A data were used in this study [22]–[24]. For each of the satellites, data was downloaded from March to October of 2016.

Revisiting times differ by region for Sentinel 2A (Li and Roy 2017). For Bila Tserkva, overpasses varied between three and seven days. The availability of cloudfree observations varied highly amongst sensors. Landsat 8 and Sentinel 2A were at times heavily affected by cloudy conditions during the growing season. This lead to a manual assessment of most images. Also, cloudy conditions resulted in large data gaps for the earlier growing stages from April to June for both sensors. Twelve images remained for Landsat 8, 14 for Sentinel 2A. Atmospheric correction and cloud-masking were conducted [25] [26].

The agricultural fields for further analysis were picked manually after checking each image. For each field, a pixel which was not or mostly not affected by cloud-shadows during the time-series was chosen as a representative value for a field. Three of the four most important crops for Bila Tserkva raion were chosen: soy, maize and sunflowers.

The Normalized Difference Vegetation Index (NDVI) was used as an indicator of vegetational condition and therefore for derivation of seasonality parameters [4], [7]. A value of one shows highest possible biomass presence while lower values closer to zero show less vegetational activity [25]. NDVI was calculated from red and NIR bands according to the formula:

$$(1) \quad NDVI = (NIR - Red) / (NIR + Red) \text{ (Kogan 1987)}$$

All sensors differ in radiometric resolution to a certain extent. However, red bands have a certain degree of overlap as well as NIR bands (Table 1). Spatial resolution varied from 10 meters per Pixel for Sentinel 2A over 30 meters for Landsat 8 up to 250 meters for MODIS data [22]–[24]. Spatial resolution was sufficient for all sensors to cover fields in Bila Tserkva. Table 1 shows the exact thresholds for the study-relevant bands of each sensor.

	Red from...	...to	NIR from...	...to
MODIS	620nm	670nm	841nm	879nm
Sentinel 2A	650nm	680nm	767nm	900nm
Landsat 8	630nm	680nm	845nm	885nm

Table 1: 8 Comparing the bands of Sentinel 2, Landsat 8 and MODIS. The x-axis shows wave-lengths in nanometers. The bands are represented by the boxes with spatial resolution of the corresponding band (in meters) inside. Own diagram based on (ESA n.d., Barsi et al. 2014, MODIS Web 2018)

For a combined image use, these radiometric and spatial differences had to be kept in mind. The creation of synthetic Landsat and Sentinel imagery from MODIS data was therefore based on a linear regression approach. First, the relevant band values as well as NDVI were compared using a random point sampling inside the study area for sample images of Landsat and MODIS which were taken on the same day. NDVI was finally chosen as the regression basis for further calculations as NIR showed a lower accuracy which would add uncertainty to further calculations.

The fusion approach worked as follows: First, for each MODIS image, the closest usable Landsat (or Sentinel) image was selected, creating an image-pair for each eight-day period. The MODIS image was then resampled to Landsat (or Sentinel) resolution using nearest neighbor interpolation. Afterwards, for each pair, a linear NDVI-regression was applied using a random point-sampling. The regression results were then applied to the resampled MODIS-scene. This procedure was batch-applied to the data. Mixed time-series were created from synthetic and original imagery for Landsat and Sentinel to overcome data gaps.

TIMESAT software was used for the derivation of phenological parameters [11]–[13]. A green-up threshold of 0.4 for start and end of season was selected, considering that data from March to October does not include the lowest possible NDVI values for a complete season. Expert opinion from the Center of Remote Sensing of Land Surfaces (ZFL), Bonn, was also taken into account. Only start, end and peak time of season were considered for this study.

TIMESAT smoothing functions require data in equal time-intervals [12]. However, for the mixed time-series, a perfectly equal interval of images could not be achieved due to the use of multiple different scenes for Landsat images and unequal revisiting times for Sentinel images. Images were selected focusing on keeping the intervals as homogeneous as possible in addition to maintaining a sufficient share of original data. Resulting phenological parameters were mapped as raster images as well as extracted for each selected field and dataset. Time-series and crops were compared to another. Lastly, retrieved seasonality data was cross-checked with ground truth data provided by the State hydrometeorological Services, Ukraine, for each of the four datasets. The accuracy of seasonal estimation was compared for each dataset and crop.

3. RESULTS/DISCUSSION

The performance of the cloud-masks was good. The masking of cloud-shadows, though, was insufficient at times, which needed to be considered for later steps. fmask filters largely performed better in masking clouds and their shadows than the Sen2Cor flags did for Sentinel imagery [27]. Nonetheless, both time-series clearly show the rising of NDVI values during spring with a peak in summer and lowering values towards autumn.

Synthetic image creation was conducted next. Results were mostly good. For Landsat, images close to each other, about a week or less in difference, resulted in decent regressions where an R^2 of about 0.4 to 0.7 was achieved. For larger gaps between the images, correlation went down significantly. After review, some outliers for synthetic Sentinel may have been caused by remaining cloud-shadows on original Sentinel data. Other outliers may be caused by changes to the fields of crops not covered in this study in-between the time the pair-matched images were taken.

In general, patterns of seasonality are well visible. The difference between crop specific seasonal cycles was visibly identifiable in the NDVI values for both sets. All in all, every profile showed a reasonable NDVI signature.

Mapped phenology parameters

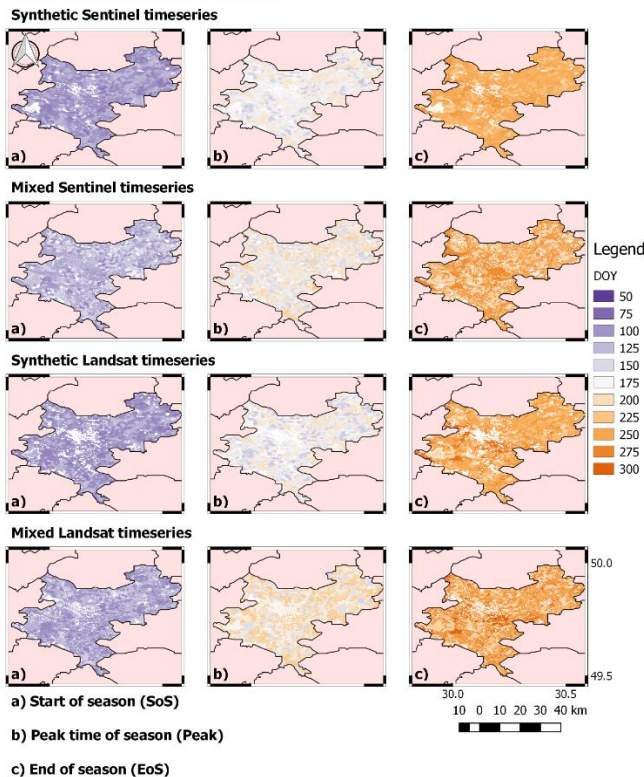


Figure 1: TIMESAT results for all four time-series.

Exported seasonality parameters from TIMESAT include start (SoS), end (EoS) and peak time of season. The pixel-values were converted to day of year (DOY). It should be mentioned that a specific pairing of vegetation indices with

certain growing stages is not optimally possible. Stages were linked with start and end of season using estimations of remote sensing capabilities. It is noticeable that the peak time was calculated later for both mixed time-series compared to the synthetic time-series. Start of season was calculated mostly between end of April and May with the mixed time-series showing a slightly later start as well. End of season was more even, showing a spread of roughly two weeks for most agricultural fields. All in all, results of the four time-series looked very alike in mapped form and showed similar patterns (Figure 1). All crops showed very similar starting dates. Soy and sunflower showed marginally earlier estimated start of season values than Maize. In total, Landsat time-series had a slightly higher value spread than Sentinel.

The mixed time-series retained their original resolution to a very high degree, closely resembling original Sentinel or Landsat data. Variations were clearly observable on field-level for the mixed Sentinel data. Visually, mixed Sentinel achieved the best results at intra-field level. Mixed Landsat phenometrics also show sharp field boundaries and some degree of intra-field variability.

Finally, metrics were compared with in-situ crop data provided by the State Hydrometeorological Services, Ukraine. Provided in-situ dates differed between crop types. The TIMESAT calculated seasonality parameters were taken as median values of the selected fields for each crop-type to minimize influence of possibly remaining outliers. Except for the mixed Sentinel time-series, the error margin for the metrics was around two weeks. With errors of up to 25 days, mixed Sentinel data was an outlier compared to the other timelines. Mixed Landsat data performed well on soy and sunflower. Out of the two metrics, start of season was closest to on-field data. End of season mostly took place later than the calculated metrics. Mixed Landsat time-series achieved the most accurate results for all metrics and crops. Results of the mixed Sentinel and Landsat series allowed for an intra-field-level assessment of seasonality parameters. Gap-filling with MODIS based data had very little impact on the outcome of phenological calculations.

6. CONCLUSION

The presented study aimed to perform a remotely sensed derivation of phenometrics as well as a data fusion approach of high-resolution data with MODIS cloud-free composites to create high-resolution phenomapping results which allow for a field-scale analysis of data. MODIS images were paired with the closest Landsat or Sentinel image to derive regressions to apply on MODIS data. The potential of simple synthetic gap filling and mixed timelines to use as time-series for TIMESAT phenology derivation was shown. Results of seasonal parameters for all three crops were mostly satisfactory. Results aligned with in-situ crop data and showed the general viability of the used methods.

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HIGH-RESOLUTION WORLDVIEW-2 DUNE SYSTEMS SPARSE VEGETATION MONITORING, BY MODELING LEAF OPTICAL PROPERTIES AND DIRECTIONAL REFLECTANCE OF THE VEGETATION

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ABSTRACT

Vegetation mapping is a priority element for the management of natural protected areas. In this context, very high-resolution satellite remote sensing data can be fundamental to provide accurate vegetation cartography at species level. Specifically, the analysis has been carried out using WorldView-2 (WV-2) imagery, which offers high spatial and spectral resolutions. In this paper, the SVM classification is properly applied to biophysical and structural vegetation indicators retrieved after an analysis of the most sensitive PROSAIL parameters to the WV-2 bands and applying the inversion of the model. The classification with these parameters have evidence robust results to discriminate different species with environmental interest. A field radiometer is used to characterize the different plant species and validate the results.

Index Terms—WorldView-2, PROSAIL, SVM

1. INTRODUCTION

The conservation of the environment is currently a key element due to the relevance natural ecosystems have for human development and well-being. The launch of new satellites, like WorldView satellites series with better performance and the progress in the processing techniques have allowed the application of remote sensing for the accurate generation of cartographic maps in natural protected areas. However, the spectral bands acquired by these sensors are influenced by different phenomena, resulting in a distortion of the representative reflectance of each element of the Earth's surface and, consequently, it is necessary to adapt advanced radiative models for the modeling of the reflectivity sensed by the satellite together with in-situ measurements. First, the elimination of the absorption-diffusion effect of the atmosphere, which alters the real reflectance of the land surface. This disturbance can be important in the 400-600 nm range, where the vegetation is less reflective due to chlorophyll absorption. Second, to

adapt the PROSAIL [1] model to the WorldView multispectral bands, which provides a bio-optical modeling of the behavior of the vegetation reflectance. An important aspect of the PROSAIL is the modeling of the high reflectivity dune soil that is below the plants, the low leaf density, makes fundamental a correct modeling capability of the mixture of reflectance with the soil. Finally, using these biophysical indicators, supervised classification can be applied to get the appropriate thematic map. Support vector machines (SVM) have evidence better results than traditional methods applied to the problem of classifying remote sensing data [2][3].

2. STUDY AREA AND DATA

The natural area to be studied, the dunes of Maspalomas (Gran Canaria, Spain), is a coastal dune ecosystem that cover an area of 403.9 hectares (ha). This is a protected area located at the southern part of the island of Gran Canaria Spain. Plant communities in Maspalomas are subject to variability that reveal changes and disturbances in the dune system of Maspalomas [4]. A total of 19 vegetal communities have been identified in the dunes field, although only non-herbaceous species and the most abundant were analyzed in this work (Figure 1).

Worldview-2 orthoready imagery was used in the study. The WV-2 satellite, launched by DigitalGlobe on October 8, 2009, was the first commercial satellite to have a very high spatial resolution sensor with 1 panchromatic and 8 multispectral bands. The image was acquired on June 4, 2015. In addition, a field campaign was performed simultaneously to the satellite pass with an ASD FieldSpec-3 field spectroradiometer to characterize the different plant species.

3. METHODOLOGY

Remote sensing images are subject to perturbances that need to be considered. The most representative disturbances to correct are due to the absorption and scattering of the

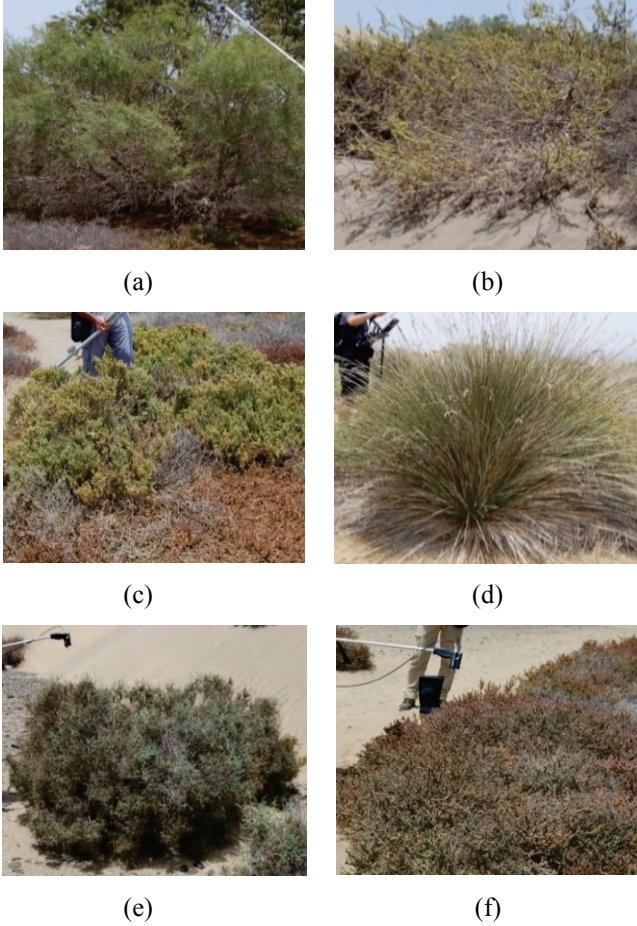


Figure 1. Plant species of Maspalomas analyzed: (a) *Tamarix canariensis*, (b) *Traganum moquinii*, (c) *Tetraena fontanesii*, (d) *Juncus acutus*, (e) *Suaeda mollis* and (f) *Launaea arborecens*.

atmosphere resulting in a distortion of the representative reflectance of each element of the Earth's surface. The 6S [5] radiative transfer model was adapted to WV-2 bands to transform the top of atmosphere radiance into ground reflectance removing the atmosphere effects.

Once images have been corrected, the PROSAIL model has been used to retrieve the vegetation biophysical and structural properties. This model combines the PROSPECT leaf optical properties model and SAIL canopy bidirectional reflectance model. The PROSPECT input variables are indicated in Table 1 and the output variables are the leaf directional-hemispherical reflectance and transmittance. In Table 2 the input variables for SAIL model to simulate the canopy reflectance are shown. This model treats the canopy as a layer diffusely reflecting and transmitting elements horizontally uniform [6].

Table 1. Input variables for PROSPECT model.

PROSPECT model	
Chlorophyll (a+b) content	C_{ab}
The carotenoid content	C_c
The anthocyanin content the equivalent water thickness	C_w
The dry matter content	C_m
Brown pigments content	C_{bp}
Leaf structure parameter	N

Table 2. Input variables for SAIL model.

SAIL model	
Hot spot parameter	S_L
Background reflectance (dry and wet)	ρ_{soil}
Leaf Area Index	LAI
Leaf inclination distribution function	$LIDF$
View zenith angle	θ_v
Sun zenith angle	θ_s
Ratio of diffuse to total incident radiation	$SKYL$

After a sensitivity analysis with the PROSAIL parameters considering the multispectral bands of the WV2 satellite, the model was adapted with the following configuration [7].

$$\rho_{wv-2} = PROSAIL_{WV-2}^{5nm}(C_{abc}, C_{bp}, LAI, \rho_{soil}, linAbu)_{bands\ 1-8}$$

where $PROSAIL_{WV-2}^{5nm}$ is the model configured to the WV-2 spectral filter bands with 5nm steps, C_{abc} includes the chlorophyll and carotenoid content, $linAbu$ the lineal abundance of the vegetation model and the rest of parameters are indicated in Tables 1 and 2. To get the optimal biophysical parameters in the inversion model Levenberg-Marquardt iterative algorithm has been used to minimize the error.

Finally, using these biophysical and structural indicators, supervised classification can be applied to get the appropriate thematic map. Support Vector Machine (SVM) has been applied to the classification problem because is more robust to the size and quality of the training dataset. SVM is based on statistical learning theory which has the aim of determining the location of decision boundaries that produce the optimal separation of classes and does not require assumption on their distribution. The concept of the kernel was introduced to extend the capability of the SVM to deal with nonlinear decision surfaces. To select the kernel and its parameters, a grid search strategy was applied using the classification accuracy as the measure of quality. The kernel selected was the Radial Basis Function due to its superior performance, in general. The two parameters to be optimized were C and γ , where C is a penalty parameter that controls the tradeoff between errors of the SVM on training data and margin maximization and γ is the width of the Radial Basis Function.

4. RESULTS

The SVM classification using the vegetation biophysical and structural indicators bands with the PROSAIL model shows properly results to identify and discriminate the most of vegetation species (Figure 2). Although some species like the *Tetraena fontanesii* was misclassified probably because of the small size with respect to the sensor resolution. The results were validated with in-situ observation and reference cartographic maps. As it is shown in Figure 3, the indicators estimated with the PROSAIL model inversion for each vegetation species present relevant differences.

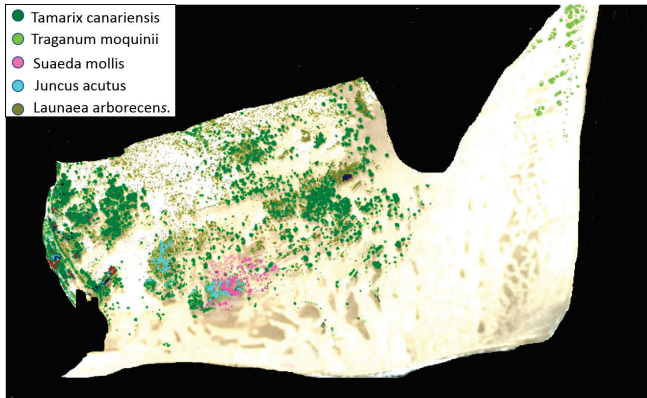
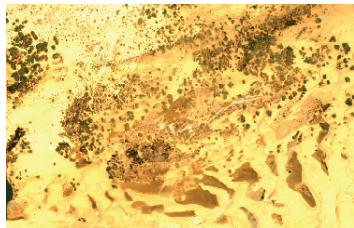
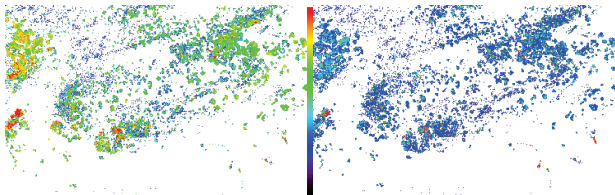


Figure 2. SVM classification results.



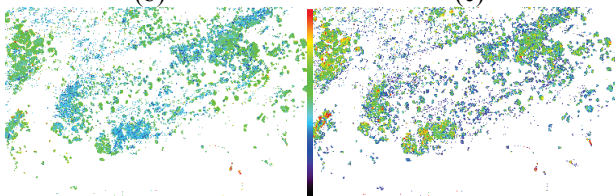
(a)



(b)



(c)



(d)



(e)

Figure 3. (a) RGB WV-2 image and Indicators estimated with the PROSAIL model inversion: (b) C_{abc} , (c) C_{bp} , (d) LAI and (e) ρ_{soil} .

5. CONCLUSIONS

This work performs the classification of vegetation species on a complex dunes ecosystem using biophysical and structural indicators estimated with the PROSAIL model. The WorldView-2 imagery was the source data and an adaption of the PROSAIL was carried out considering the parameters sensitivity for the WV-2 bands. SVM supervised classification was applied to get the appropriate thematic map achieving good results with high overall accuracy. To validate the results and characterize the spectral species response in-situ data measured with a spectroradiometer was used.

6. ACKNOWLEDGEMENTS

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NASA CYGNSS-REFLECTOMETER AND SMAP-RADIOMETER FUNCTIONAL CORRELATION OVER LAND SURFACES

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ABSTRACT

This work presents an assessment on the correlation between CyGNSS-derived Global Navigation Satellite Systems Reflectometry (GNSS-R) bistatic reflectivity Γ_{rl} and SMAP-derived brightness temperature T_B , over land surfaces. This parametric-study is performed as a function of Soil Moisture Content (SMC), vegetation opacity τ , and albedo ω . Several target areas are selected to evaluate potential differentiated geophysical effects on “active” (as many transmitters as navigation satellites are in view), and passive approaches. Although microwave radiometry has potentially a better sensitivity to SMC, the spatial resolution is poor ~ 40 km. On the other hand, GNSS-R bistatic coherent radar footprint is limited by half of the first Fresnel zone which provides about ~ 150 m of spatial resolution (depending on the geometry). The synergetic combination of both techniques could provide advantages with respect to active monostatic Synthetic Aperture Radar (SAR).

Index Terms— GNSS-R, multi-static radar, microwave radiometry, Soil Moisture Content (SMC), vegetation opacity, land, CyGNSS, SMAP

1. INTRODUCTION

Microwave remote sensing instruments operating at L-band have shown a good sensitivity to SMC. Higher-frequency (i.e. starting from C-band) radiometers, and scatterometers are significantly affected by vegetation cover, while optical sensors additionally suffer from weather conditions and clouds. It is well known that L-band radiometry provides higher sensitivity to SMC. On the other hand, L-band radiometers require large antennas to improve the associated spatial resolution. Different approaches for SMC determination from space have been implemented: a) ESA’s Soil Moisture Ocean Salinity (SMOS) mission [1] uses a ~ 8 m aperture deployable antenna and synthesis methods to achieve a ~ 50 km resolution; b) NASA’s Soil Moisture Active Passive (SMAP) mission uses a ~ 14 rev/min rotating 6 m real-aperture reflector antenna, providing ~ 40 km of resolution. An adequate performance $\sim [0.1,1]$ km for applications associated with hydrometeorology, hydrology, and agriculture is however

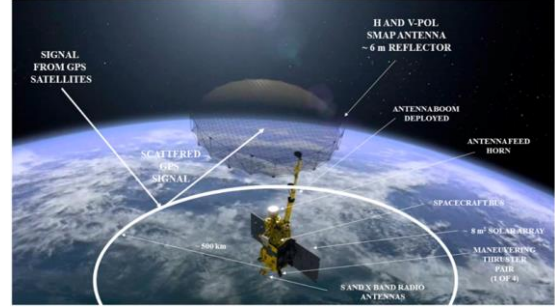


Fig.1 The Soil Moisture Active Passive (SMAP) mission was successfully launched on 31 January 2015 into a Sun-Synchronous Orbit (SSO) with a local time of ascending node (LTAN) of 06:00. The experiment set-up of the GNSS-R experiment on-board the SMAP mission is represented in this figure. Data processing was performed on-ground at NASA’s Jet Propulsion Laboratory [6].

not yet provided.

GNSS-R [2,3] multi-static radar (Fig. 1) measurements can potentially be used synergistically with radiometers as a means to improve the spatial resolution in a cost-effective way. GNSS-R uses navigation signals as signals of opportunity, so that the platform power requirements are reduced as compared to monostatic radar missions. Furthermore, GNSS-R techniques require relatively small antennas, and thus they can be affordable in constellations of small satellites. At present, there are three missions providing GNSS-R data from space: UK-TDS-1 [4], CyGNSS [5], and SMAP [6]. In this work, data from CyGNSS 8-microsatellites constellation are used together with SMAP radiometer data to evaluate the relationship between the bistatic reflectivity Γ_{rl} and the normalized first Stokes parameter ($T_1 / 2$), as a function of SMC, τ and ω

2. METHODOLOGY

2.1 CyGNSS AND SMAP DATA

CyGNSS’s high-priority mission objective is the study of tropical cyclones. Thus, the selected orbital configuration of each of these 8-GNSS-R receivers (operating at a frequency of 1.575 GHz) is an approximately circular Low Earth Orbit (LEO) with an inclination angle of 35°. Each single satellite has two ~ 14.7 dB-gain Left Hand Circular Polarization

(LHCP) antennas pointing to the Earth's surface with an inclination angle of 28° (antenna boresight). Here, the application of CyGNSS is extended to land surfaces studies using CyGNSS Level 1 Science Data Record [7-9]. Over land surfaces, the scattering is mostly coherent so that the spatial resolution is limited by approximately half of the first Fresnel zone i.e. ~ 150 m (depending on the geometry) [10].

SMAP's high-priority mission objective is to provide global (and thus, the operation from a Sun-Synchronous Orbit, with 6 a.m.-6 p.m. equatorial crossing times) SMC maps with a resolution of at least ~ 10 km, and with an accuracy of $0.04 \text{ cm}^3/\text{cm}^3$. This is achieved using the combination of active-passive information. SMAP's 36 dB-gain dual-polarization (Horizontal-H & Vertical-V) antenna reflector points to the Earth's surface with an incident angle of $\theta_{\text{inc}} \sim 40^\circ$. The approximately constant incident angle simplifies the data processing and enables accurate repeat pass for SMC estimation. Unfortunately, the radar High-Power Amplifier failed on 7th July 2015, leaving only the possibility to operate the receiver as a radiometer (operating at a frequency of 1.227 GHz). In this work, SMAP Level L3 SPL3SMP_E Version 1.0) [11,12] are used.

2.2 SYNERGISTIC USE OF CYGNSS AND SMAP

The selected temporal data-window corresponds to September-October 2017 (1 month). High SMC values and no ice/snow over the monitored surfaces are expected during the first weeks of autumn (North hemisphere) and spring (South hemisphere). The selected CyGNSS data are associated to $\theta_{\text{inc}} = [30,50]^\circ$, relatively close to those inside the SMAP's antenna beamwidth (half power = 2.5°) [12], so as to minimize the impact of θ_{inc} on Γ_{rl} , while providing enough sampling of the surface. GNSS-R sampling characteristics are non-homogeneous because they depend on the geometry. On the other hand, SMAP's antenna boresight rotates ~ 14 rev/min about Nadir, providing a ~ 1000 km wide-swath [12]. A 0.1° by 0.1° latitude/longitude grid is selected, and data are averaged using a moving window in steps of 0.1° . The associated spatial resolution is ~ 10 km at equatorial latitudes.

The reflectivity Γ_{rl} is estimated as the peak of the reflected $Y_{\text{r,Peak}}$ and the direct $Y_{\text{d,Peak}}$ power waveforms peaks, after compensation of the noise power floor and the antennas' gains as a function of the elevation angle:

$$\Gamma_{\text{rl}} = \frac{\langle |Y_{\text{r,Peak}}|^2 \rangle}{\langle |Y_{\text{d,Peak}}|^2 \rangle}, \quad (1)$$

where the subscript rl denotes the incident (r Right-HCP) and the scattered polarization (l Left-HCP). While CyGNSS uses a circular-polarized antenna, SMAP uses a linear polarization antenna (H & V).

The normalized first Stokes parameter $T_1 / 2$ is defined by:

$$T_1 / 2 = (T_{\text{BH}} + T_{\text{BV}}) / 2, \quad (2)$$

where T_{BH} and T_{BV} are the brightness temperature at horizontal and vertical polarization, respectively. $T_1 / 2$ provides a valuable measurement of the total incident brightness temperature at circular polarization.

Different target areas can be monitored belonging to a wide land-surface types variability: Sahara (Barren), Pampas (Cropland), US Midwest (Grassland), Murrumbidgee (Open Shrubland), Tanzania (Savanna), Northeast Region of Brazil (Woody Savanna), Amazon (Evergreen Broadleaf Forest). In this paper, the analysis is focused on China and Ethiopia. A more exhaustive study including further areas is in progress.

3. EXPERIMENTAL CORRELATION FUNCTION

SMAP L-band radiometer measures the microwave emission in the form of the brightness temperature of the land surface, while CyGNSS L-band GNSS reflectometer measures the energy forward-scattered from the land surface after transmission of the navigation signals of opportunity. The functional relationship between these "active" and passive observations could be potentially used as a key-parameter for downscaling radiometer data, so as to increase the spatial resolution. Here, as preliminary results of this study, spaceborne data are analysed to improve our understanding on the geophysical relationship between Γ_{rl} and $T_1 / 2$. It is found the Pearson correlation coefficients are $r_{\text{China}} \sim -0.75$ and $r_{\text{Ethiopia}} \sim -0.78$ over target areas at China (Lat. = $[28,33]^\circ$, Lon. = $[105,116]^\circ$) and Ethiopia (Lat. = $[5,11]^\circ$, Lon. = $[28,37]^\circ$).

Figures 2a-f show the scatter plots of Γ_{rl} against $T_1 / 2$ measurements over China (Figs. 2a-c), and Ethiopia (Figs. 2d-f), as a function of SMC (Figs. 2a,d), τ (Figs. 2b,e) and ω (Figs. 2c,f). The range of Γ_{rl} is common in all the plots and the ranges of $T_1 / 2$, SMC, τ and ω have been adapted to each target area. This strategy is assumed to provide inter-comparable plots and at the same time, showing full variability. Both, SMC and τ gradients can be observed in both areas China and Ethiopia, from dry soils to wet soils. An inverse relationship is found between CyGNSS and SMAP passive observations with SMC, but also a clear influence of τ . Γ_{rl} values are higher when SMC increases (Fig. 2d), however τ attenuates the GNSS signals (Fig. 2b) for values higher than ~ 0.8 . The effect of albedo ω seems to be less important. Both dynamic ranges are wide; while Γ_{rl}

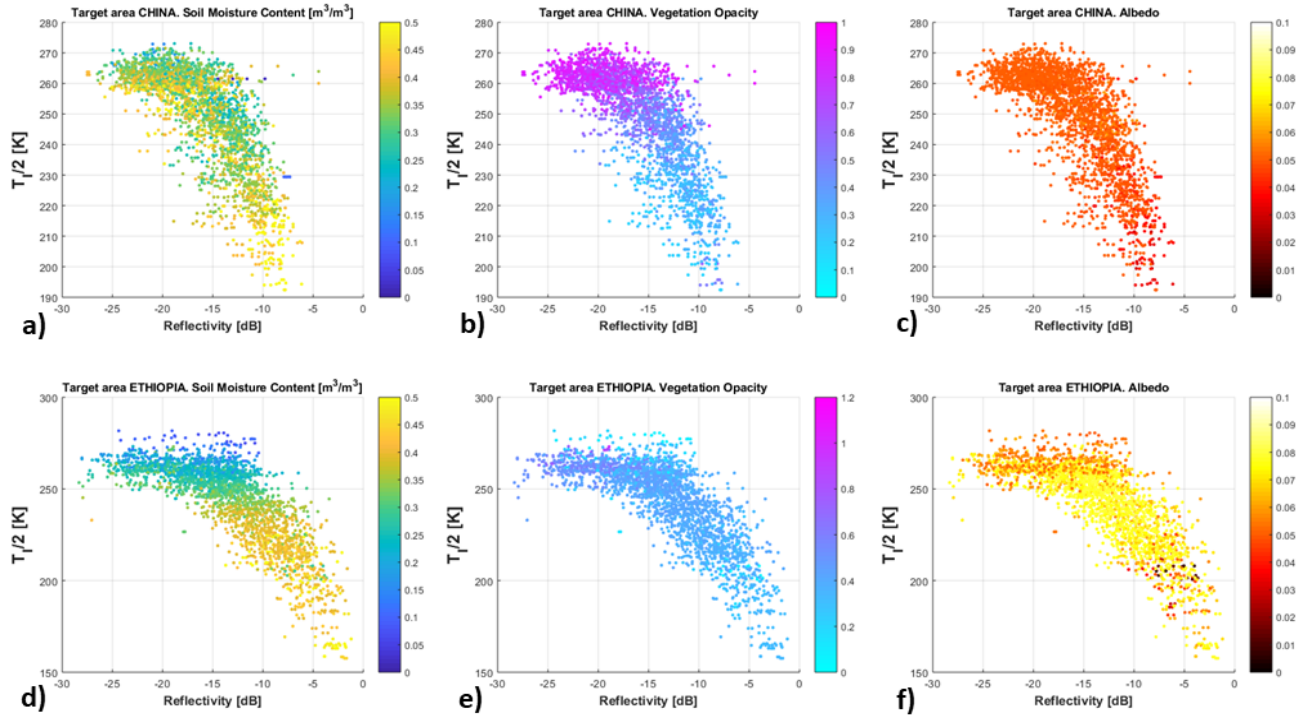


Fig. 2. Relationship between CyGNSS reflectivity Γ_r and SMAP microwave radiometry $T_r/2$ over target areas at China (a-c) and Ethiopia (d-f). Different geophysical parameters are used to evaluate this function: (a,d) Soil Moisture Content (SMC), (b,e) vegetation opacity τ , and (c,f) single scattering albedo ω .

peaks are up to -2 dB (Fig. 2d), possibly due to the effect of inland water bodies.

4. FIRST CONCLUSIONS

This preliminary analysis has shown a promising correlation between spaceborne GNSS-R and microwave radiometry, using data collected from CyGNSS and SMAP: $r_{\text{China}} \sim -0.75$ and $r_{\text{Ethiopia}} \sim -0.78$. This correlation is an indication that the bistatic reflectivity and the brightness temperature have sensitivity to the same geophysical parameters. The evaluation of this correlation over areas with different vegetation cover indicates a change on this functional relationship.

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THE FLEX MISSION AS EXAMPLE OF MULTIPLATFORM REMOTE SENSING: SCIENTIFIC OPPORTUNITIES AND IMPLEMENTATION CHALLENGES

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ABSTRACT

The concept of multiplatform remote sensing from space has gained more attention in the Earth observation sector as an alternative way to accomplish complex scientific objectives exploiting the synergies among different types of missions, following the recent successes of the A-Train set of missions and the formation consisting of EOS-Terra, Landsat-7, EO-1 and SAC-C. The next decade will see the development, launch and continued operation of several European operational missions (including the GMES-Sentinels, MetOp and Post-EPS), which shall provide long-term streams of EO data in a reliable way. These missions will provide a capacity for systematic, continuous and long-term Earth observation and monitoring and a stable baseline from which dedicated complementary satellite missions can be designed. The possibility of flying additional satellite missions in tandem with this baseline opens new opportunities to address novel areas of Earth science, which would be more expensive or even not have been possible previously. In particular, focused missions might take advantage of the synergetic EO opportunities offered to achieve new EO science objectives, which might be unachievable with single satellite measurements.

Such is the case for FLEX mission. Measuring vegetation fluorescence from space was already selected for assessment as one of the Earth Explorer 7 (EE7) mission and it was found that the mission would be relatively complex, since several instruments would have to be accommodated on a single big satellite to fulfill the mission objectives. FLEX was later proposed and selected for implementation in a lighter smart instrument configuration that is making use of the synergy with existing missions by flying in tandem with Sentinel-3. Disentangling the emitted and reflected light measured at the Top Of Atmosphere is a complex task relying on information collected over a large spectral range and therefore requiring costly and complex instrumentation. A partner mission, to flight with, reduces complexity and implementation cost by providing information on atmospheric characterization and land-surface description. Nevertheless, this not only represents an innovative way to addressing scientific questions, but also introduces technological challenges in the implementation and operations. Both opportunities and challenges will be presented in this paper performing a compared analysis

between the two mission architectures presented as proposed for EE7 (single platform) and EE8 (multiplatform) with the addition of final implementation decision of accommodation on an European quasi-recurrent small platform. Main implementation challenges foreseen due to this multiplatform remote sensing will be finally presented.

Index Terms— FLEX, Sentinel-3, multiplatform remote sensing.

1. INTRODUCTION

The Fluorescence EXplorer (FLEX) is an Earth observation mission endeavor by ESA, whose main objective is to perform quantitative measurements of the solar induced vegetation fluorescence with the goal of monitoring the vegetation photosynthetic activity.

Measuring vegetation fluorescence from space was already proposed in response to the ESA call for ideas for the 7th Earth Explorer mission. The suggested mission concept was then selected for assessment as one of the six Earth Explorer candidates to be studied within Phase 0. During the Phase 0 assessment of FLEX within the Earth Explorer 7 (EE7) core mission evaluation [1], it was found that the mission would be relatively complex, since several instruments would have to be accommodated on a single satellite to fulfill the mission objectives. FLEX was therefore proposed in a lighter smart instrument configuration that is making use of the synergy with existing missions by flying in tandem with Sentinel-3 [2]. ESA selected this new mission concept of FLEX for further (Phase A) feasibility study as one of the two candidates of the 8th Earth Explorer (EE8) opportunity mission and finally agreed for final implementation in a User Consultation Meeting in Krakow.

Analysis of the evolution of the mission configurations from the EE7 Phase 0 study to the EE8 Phase A-B1 study and further implementation serves as an interesting show case, where the formation flying leads to considerable savings, and where it facilitates the implementation of a core type mission (~500M€) within the budget constraints of an opportunity type mission (~180M€) without major drawbacks for the mission performance. Having this objective in mind, initial configuration of the five instruments of the EE7 configuration is presented together with comparison with the observations for EE8

configuration intrinsic to FLEX namely FLORIS (FLuOREscence Imaging Spectrometer) both High and Low resolution (FLORIS-HR and FLORIS-LR respectively) and those of the two ESA instruments onboard of Sentinel-3 namely, OLCI (Ocean and Land Colour Imager) and SLSTR (Sea and Land Surface Temperature Radiometer).

It is noted that the objective of this paper does not allow presenting and comparing the details of the fluorescence imagers, and of course, there is a strong evolution of FLORIS compared to Fluorescence Imaging Spectrometer (FIS) of the EE7 mission configuration. However, there has been no major change in the mission objective, which is primarily targeted at the measurement of vegetation fluorescence with an accuracy of about 10%. The biggest difference between the two configurations is the intended swath width of the instrument, which was initially assumed to be 390 km for FLEX EE7 and which has been reduced to 150 km for EE8 in order to simplify the instrument, and thereby to be able to design an instrument, which does not exceed the resource limitations of the mission and the foreseen resources of a small quasi-recurrent platform.

This paper reports about the mission evolution, and about the benefits and constraints of such light mission configuration flying in formation with Sentinel-3.

2. FLEX EE7 PHASE 0 CONFIGURATION

In the following, a brief overview of the objective and the requirements of the instrument as planned within the EE7 Phase 0 mission scenario are given. The ground sampling distance of all instruments was specified to be 300 m.

There was a core instrument FIS targeting specifically the measurement of vegetation fluorescence together with additional auxiliary instruments VIS, SWIR, TIR and ONI as presented in figure 1:

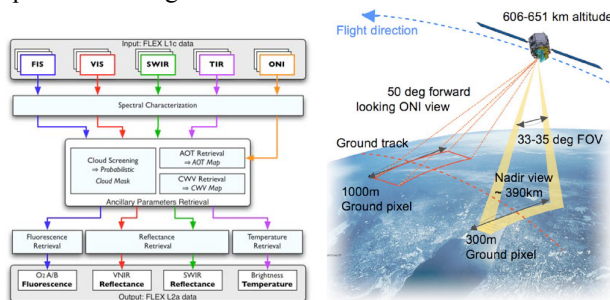


Figure 1: FLEX EE7 Phase 0 payload configuration and observational geometry

The required spectral bands for the FLEX mission within the EE7 Phase 0 study are shown in Figure 2. The figure presents also the transmission of the atmosphere in blue for the complete spectral range thereby illustrating the location of the bands, and a typical reflectance of vegetation in green and bare soil in brown. Finally, figure 1 also shows the observational geometry of all instrumentation.

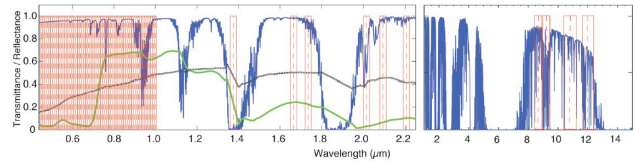


Figure 2: Spectral sampling coverage of the auxiliary instruments in FLEX EE7, from the visible to the thermal-infrared domain.

2.1. Fluorescence Imaging Spectrometer (FIS)

Objectives:

- Measure vegetation fluorescence in the O2A and O2B bands

Requirements:

- Two spectral bands of 20 nm around O2A and O2B
- Spectral resolution of 0.1 nm
- Spectral sampling distance 0.05 nm
- Spatial sampling distance 300 m
- SNR > 150 @ 761 nm

2.2 Visible/Near IR imaging Spectrometer (VIS)

Objectives:

- Provide atmospheric correction and cloud screening capabilities to be used with the main FIS instrument.
- Provide key information about total light absorbed (APAR) by plant chlorophyll, necessary for the normalization of fluorescence emission to compute fluorescence quantum efficiency (FQE).
- Provide key additional information about vegetation status (LAI, fCover).

Requirements:

- Imager spectrometer Spectral range 450 to 1000 nm
- 5 nm spectral resolution

2.3 Short wave IR imager (SWIR)

Objectives:

- Cloud screening (cirrus clouds)
- Estimation of plant water and dry matter content
- Separation of non-photosynthetic material from the green vegetation component and the fraction of soil background

Requirements:

- Radiometer with 6 bands
- Spectral range from 1375 nm to 2205 nm
- Spectral bandwidth 30 nm

2.4 Thermal IR imager (TIR)

Objectives:

- Measurement of canopy temperature

Requirements:

- Thermal imager with 4 bands
- Spectral range from 8.7 mm to 12.5 mm
- Band width 0.5 to 0.75 mm
- NEDT ~0.15 K

2.5 Off-Nadir Imager (ONI)

Objectives:

- Determination of Aerosol Optical Thickness (AOT)

Requirements:

- Radiometer with oblique view (50°)
- 3 bands at 450, 660 and 1665 nm
- Band width 20 to 30 nm
- Radiometric accuracy: 2K

3. FLEX EE8 PHASE A CONFIGURATION

In the EE8 configuration, objective was to reduce auxiliary instrumentation on FLEX satellite, obtaining this information from already flight capabilities. It was noticed that other EO missions, no matter whether atmosphere land or surface targeting, need to perform similar tasks, since they have to provide accurate context information. On the contrary, they limit the choice for the bands, the bandwidth, spectral resolution and related radiometric accuracies. Several other missions were traded-off, but Sentinel-3 instruments OLCI and SLSTR were found to provide the information initially coming from VIS, SWIR, TIR and ONI.

Sentinel-3 is targeting land and ocean and has therefore limited capabilities in correcting atmospheric effects, since it has not enough spectral resolution in the Oxygen absorption bands. But, on the other hand, because fluorescence is particularly prominent in the absorption bands, it is obvious that FLEX could provide this measurement by itself. FLEX may even in the future therefore generate information being useful for product optimization of Sentinel-3 in that respect.

In the comparison of both band configurations in Figure 4 it can be seen that there are some distinct differences. Since FLORIS has been configured to cover a spectral range between 500 nm and 780 nm, it provides all necessary functions, which were initially foreseen within VIS. FLORIS-LR and FLORIS-HR in combination provide the functions of both FIS and VIS. The remaining spectral range below 500 nm and above 780 nm is accomplished by the spectral bands of OLCI (865 nm, 885 nm, 900 nm, 940 nm and 1020 nm). These bands are particularly useful to model the aerosol absorption. Other bands for which an overlap between FLORIS and FIS exists can be used for cross calibration. This requires the approximation of OLCI bands by a composition of several hyperspectral channels of FLORIS. Therefore, for the visible part, sufficient information is expected for the retrieval, a dedicated and accurate atmospheric correction by FLORIS. Cross-calibration is possible, and due to the overlap and the same sampling distance, a good coregistration is possible.

For the SWIR instrument, SLSTR instead covers only three bands rather than six, so that the modeling of the reflectance of the ground is apparently becoming more difficult. Also the temperature modeling with only three bands in the thermal IR rather than four is expected to be more difficult, but the radiometric accuracy of the SLSTR thermal channels is 0.2 K, and therefore considered as adequate. It must

be noted also, that the spatial resolutions of the SLSTR bands are 500 m (SWIR) and 1 km (TIR). This was not considered as a major drawback since the heterogeneity of temperature is expected to be not so large.

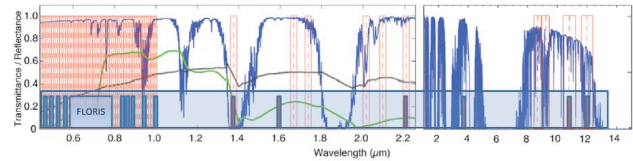


Figure 4: Comparison of the FLEX EE7 Phase 0 and FLEX EE8 Phase A-B1 study band configuration. OLCI bands in blue and SLSTR band in red.

4. FLEX EE8 FINAL IMPLEMENTATION CONFIGURATION

After initial phase-A configuration it was observed that possible European quasi-recurrent platforms were not out of usage for FLORIS instrument. Therefore a series of small accommodation studies were launch finding their advantage over customized platform for FLEX. Final implementation adopted after release of invitation to tender for implementation phase B2/C/D/E1 took advantage of the benefit of availability of European quasi-recurrent platforms able to accommodate payloads in the order to 150Kg mass range in order to reduce even further final implementation cost. FLEX mission was well in this recurrent platform flight domain with the criticality of orbit attitude on 800Km, as imposed by Sentinel-3, being on the limit of the domain and leading to care about propellant budget, due to high delta-V need for EOF deorbiting requirements.

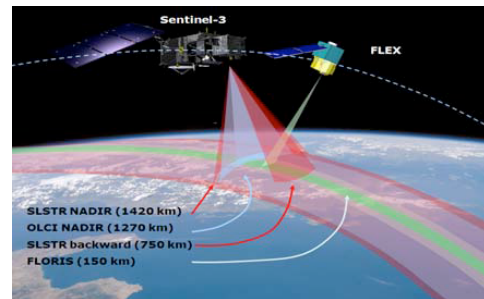


Figure 5: Observational geometry in FLEX EE8 final configuration.

5. IMPLEMENTATION CHALLENGES

While the main advantages and scientific opportunities emerged during the previous paragraphs, there is still some implementation challenges to face and respond to. These challenges can be grouped in:

5.1 Orbit adaptation

The first constraint flying in tandem with Sentinel-3 is coming from the imposed orbit of Sentinel-3 at ~815 km instead of 606 km. The loss of SNR for the instruments (scaling with 1/altitude) had to be compensated by correspondingly larger apertures of the involved

instruments. It was assumed that the Sentinel-3 instruments are designed accordingly. For FLORIS, compensation could be achieved by simpler optics (fewer elements), by less demanding spectral resolution and implementation of a smaller field of view. In fact the aperture sizes of FIS and FLORIS-HR are comparable (~90 mm). As a consequence, the sizes and mass of FIS and FLORIS are also similar. The advantage of flying with Sentinel-3 in tandem is that the total payload mass is reduced to below 150 kg for FLORIS, compared to the prospected ~300 kg in the FLEX EE7 mission study.

5.2 Time coregistration optimization

The second constraint comes from the need of a very timely co-registration of the observations made by both satellites in order to account for the dynamics of the scene. After analysis of typical cloud speeds, it was found that temporal co-registration was needed to be between 6s (goal) and 15s (threshold) corresponding to the movement of typical clouds by about 1 FLORIS pixel within that time frame. This requirement holds for OLCI and for SLSTR. However, the OLCI and SLSTR views on ground are not identical, since the SLSTR view is only near-nadir due to the conical scan configuration. There is a maximum difference of about 10 seconds or 66 km between OLCI and SLSTR, which means that pointing between OLCI and SLSTR would already give a temporal miss-registration of 5s for both instruments. FLORIS shall preferably point at nadir, pairing with OLCI camera 4, so that the remaining time frame for the control window is only 10s if the threshold shall be achieved. With a satellite velocity of 6.6 km/s, the maximum distance between FLEX and the midpoint between OLCI and SLSTR must not exceed 66 km. In fact there is a variation of the distance for SLSTR as a function of the across-track position as can be seen in Figure 6, which optimizes the differences for the complete OLCI swath.

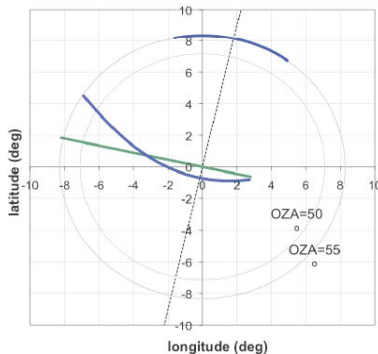


Figure 6: Sentinel-3 groundtrack: OLCI(green) SLSTR (blue).

5.3 Operations safety

Another consequence from the wish to point nadir for FLORIS is, that FLEX must fly ahead of Sentinel-3. As a prerequisite for the operations safety, it is always better to have a situation, where FLEX will drift away from Sentinel-3 in case it goes into safe mode.

This situation becomes reality if the ballistic coefficient (BC) of FLEX is smaller than the one of Sentinel-3. But this difference on BCs shall be limited such that the drift is very small, and in such case, the formation control is limited to the standard control maneuvers, which are carried out by Sentinel-3, and which are routinely followed by FLEX, preferable with a time gap.

5.4 Downlink Interference avoidance

Proximity of two satellites can also result in difficulties with respect to the downlinking of the data if the same or close ground stations shall be used. The separation angle between FLEX and Sentinel-3 must be maximized in order to minimize the degree of interference. As a consequence, the distance between Sentinel-3 and FLEX must be maximized while meeting the temporal co-registration requirement. Sentinel-3 uses the complete ITU allocated bandwidth, and it is using Svalbard as downlink station. With an avoidance angle of ~1° between the pointing of the antennas, it is expected that the data transmission efficiency increase with distance of the two satellites. Shorter distances will impose limitations on the data downlink rate. FLEX could therefore make only limited use of Svalbard and other alternatives are under study at the moment.

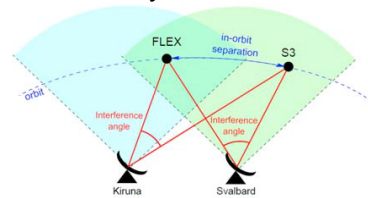


Figure 7: Observational geometry in FLEX EE8.

5. SUMMARY AND CONCLUSION

In this paper, Evolution of the FLEX mission from the Phase 0 of the Earth Explorer 7 stand alone configuration to the current implementation configuration was presented, where it flies in tandem with Sentinel-3 in a European quasi-recurrent small platform. It can be concluded that this configuration is very promising and is expected to provide a solid basis for multiplatform remote sensing where a broad set of instrument is need such is the case for fluorescence retrieval. FLEX serves therefore as a good example in which multiplatform leads to mission configuration capitalizing on the measurement provided by an existing satellite and leading to a well performing mission at much lower cost compared to the stand alone configuration.

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ATMOSPHERIC CORRECTION OF LANDSAT-8 VNIR BANDS USING DRONE IMAGERY AS REFLECTANCE REFERENCE

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ABSTRACT

Atmospheric correction of Landsat-8 (L8) imagery can be solved using physical (e.g. 6S LaSRC), image based (e.g. DOS) or reference values (e.g. PIA-MiraMon) approaches, among others. On the other hand, validation can be done with field spectroscopy measurements at the time of satellite overpass. However, the use of field measurements is constricted by space and time, since the area covered by a technician is typically less than 20 pixels within the satellite overpass ± 20 min. The hypothesis of this study is that imagery acquired with drone borne sensors and calibrated with field measurements can provide reflectance references of much more area, in a time closer to the satellite overpass (± 5 min) and including difficult to access land covers. To this end, we tested the use of drone-acquired multispectral data (MicaSense RedEdge camera) empirically fitted to the reflectance of field measurements (OceanOptics USB2000+ spectroradiometer) in order to take this data as reflectance reference to atmospherically correct visible and near infrared bands of almost simultaneously acquired L8 imagery. Results show a good correlation between the field measurements and the drone data ($R^2 > 0.94$). Atmospheric correction of satellite data was compared with test areas, showing a good agreement in visible bands ($RMSE_{vis} < 1.63\%$) and in NIR band ($RMSE_{nir} < 2.22\%$, not so good because of sensor response differences) and high consistence with LaSRC official product.

Index Terms— Field spectroradiometry, UAS, MicaSense RedEdge, Landsat-8, OLI, atmospheric correction.

1. INTRODUCTION

Satellite observations in the visible and near infrared (VNIR) spectral regions [400 nm – 900 nm] of the solar spectrum are affected by several atmospheric gases and aerosols, causing effects like scattering and absorption of solar radiation. The physical magnitude obtained after an atmospheric correction of remote sensing imagery in the VNIR is spectral surface reflectance ($\rho_{s\lambda}$) (dimensionless), that can be defined as the proportion of reflected radiant flux over the incident radiant flux in a given wavelength, being a key property to characterize main land cover types. A

typical VNIR satellite sensor measures spectral radiance ($L_{s\lambda}$) ($W \cdot m^{-2} \cdot sr^{-2} \cdot \mu m^{-1}$) including both the land surface reflected radiance -our main interest- and the atmospheric spectral radiance, $Latm_{\lambda}$ ($W \cdot m^{-2} \cdot sr^{-2} \cdot \mu m^{-1}$), composed by the upwelling spectral radiance and the reflection of the downwelling spectral radiance of the atmosphere. Atmospheric spectral Total Optical Depth, $\tau_{0\lambda}$ (dimensionless) weakens the downwelling solar irradiance, $E_{0\lambda}$ ($W \cdot m^{-2} \cdot \mu m^{-1}$) and the upwelling surface reflected radiance. Many modeling approaches have been developed to obtain atmospherically corrected surface reflectance data from multispectral imagery in the solar spectrum, as is the case of Landsat-8 (L8). These approaches can be summarized into 3 main groups: physically based [1], image based [2], and radiometric reference approaches [3]. Alternatively to these approaches, it is also possible to simply use a purely empirical line fitting using *in-situ* measurements by fitting satellite data to at-surface reflectance measured at the satellite overpass [4]; in that case linear regression is used instead of fitting the unknowns of a physical model. PIA-MiraMon radiometric reference approach uses pseudo-invariant areas, as MODIS pseudo invariant pixels, to fit the $Latm_{\lambda}$ and $\tau_{0\lambda}$ unknowns of the model [3] with results comparable to the official L8 atmospherically corrected product (LaSRC) [5]. In this work we experiment the use of the PIA-MiraMon approach using Unmanned Aerial System (UAS) data as reflectance references to obtain atmospheric unknowns.

Field spectroscopy measurement of surface reflectance at the satellite overpass is practically not affected by atmospheric effects and then it is a valuable source of information to assess the accuracy of atmospheric correction or even to support it [6]. Traditionally, *in-situ* measurements are carried out by operators with field spectroradiometers, but they have to face difficulties as accessing tree canopies or water surfaces, or the impossibility to take measurements in dangerous or restricted areas. Another important constriction of traditional field spectroradiometry is the covered area, since during the acceptable time of 20 minutes before and after the satellite overpass a skilled operator can scan up to the area equivalent to 20 L8 30 m pixels. To this end, imagery acquired with hyperspectral or multispectral sensors onboard UAS is expected to complement field data as the UAS platform can access those hardly accessible places and in a faster way than human operators.

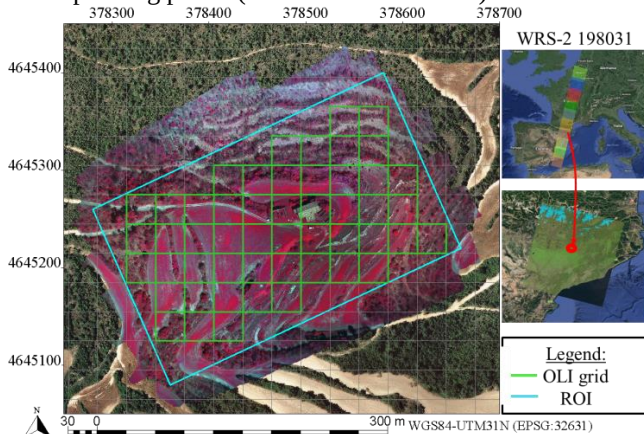
Nevertheless, UAS imagery has to be accurately processed to be trustable. A possible approach is the comparison, through reference panels, of UAS-acquired imagery + field spectroscopy data, for example using band-by-band linear relationship between *in-situ* field measurements and UAS sensor data [7,8]. MicaSense RedEdge (MS) imagery and Sentinel-2 satellite imagery were compared in [9], concluding that there is a good correlation between derived vegetation indices. In 2015, [10] presented a critique to field spectroradiometry and advanced the impact of the introduction of new technologies as UAS, particularly in supporting empirical calibration and validation of satellite observations; OPTIMISE [11] is another similar initiative.

The objective of this paper is to use the multispectral information acquired with a MS sensor onboard a UAS as radiometric reference to atmospherically correct L8 imagery with the PIA-MiraMon algorithm. The hypothesis is that UAS acquired imagery can be used as a reference to correct Landsat-like images in single dates, similarly as MODIS invariant pixels are used as references to correct Landsat-like time-series in [3]. Validation is performed calculating the RMSE between the atmospherically corrected L8 image (using the UAS data) and the atmospherically corrected L8 official product (LaSRC), both in test areas and comparing the full satellite scene.

2. STUDY AREA

The experiment took place on 21st of April 2018 at Can Gelabert farm (Catalonia) located at the NE of the Iberian Peninsula. The flight was planned at 80 m height above ground level, with a side overlap of 70 % and a front overlap of 80 %, resulting in 265 photograms and a 6 cm pixel size of 6 cm. Flight time was between 10:31:52 UTC and 10:41:42 UTC under excellent illumination conditions. The Region of Interest (ROI) is centered at 1° 32' 1.4" E - 41° 56' 59.3" N and is representative of different land covers (crops, forests, a pond and a built-up area). ROI covered 5.26 ha, and include 51 OLI 30 m pixels (Figure 1).

Figure 1: Study area covered with the drone and Landsat-8 corresponding pixels (WRS-2 198031 scene).

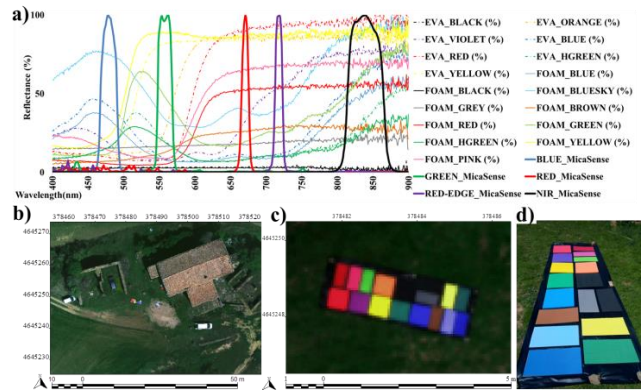


3. MATERIALS

Materials comprehend 3 geographical scales: a) ground reflectance measurements, b) UAS data and c) satellite data.

a) Ground reflectance measurements were carried out with a hand-held OceanOptics USB2000+ spectroradiometer with a 50 μ m diameter optical fiber of 25° Field Of View and operated with SpectraSuite software [12]. A Spectralon reference panel was used to measure the incoming irradiance, and the reflectance of 17 rectangular ethylene-vinyl acetate (EVA) foam panels of different colors was measured. The optical fiber head was in nadir position at 20 cm over the reference panel surface (8.87 cm circular footprint). Once the reference was taken, individual target reflectance was read averaging 100 readings to obtain a robust measurement. The 1 nm spectral resolution signature was analyzed and integrated within the MS Relative Spectral Response Function (RSRF) (Figure 2).

Figure 2: a) Spectral signatures of targets and MS RedEdge bands. b) Target location in drone imagery. c) Zoom to targets in UAS image. d) Targets photograph.

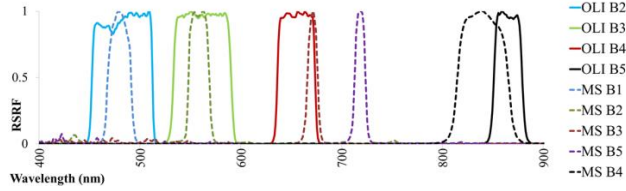


b) UAS data was acquired with a MS multispectral sensor, onboard a DJI-S1000 vertical take-off and landing platform (8-rotor HTR multicopter). The drone is 81 cm wide, with a 9 kg maximum take-off weight, a top speed of 9.7 m/s (35 km/h) and 15-minute flight autonomy when carrying the instrument. The MS sensor is sensible in 5 solar spectrum bands, that following the typical RSRF provided by the manufacturer [13] has a bandpass Full Width at Half Maximum (FWHM) of 468 nm - 491 nm (blue, #1), 548 nm - 568 nm (green, #2), 666 nm - 676 nm (red, #3), 712 nm - 723 nm (red-edge, #5) and 814 nm - 865 nm (near infrared, #4) (figure 3). Radiometric resolution is 12 bits.

c) Satellite data was acquired with the Operational Land Imager (OLI), onboard L8 (16 days revisit period), which overpassed the study area at 10:36:43 UTC. Through the USGS website [14] we downloaded the L8 198031 scene official products L1T (Level1T: precision terrain-corrected at 30 m spatial resolution, TOA radiances) and L2A (Level2A: geometry as L1T but surface reflectance atmospherically corrected through LaSRC algorithm [1]).

L1T image was corrected using PIA-MiraMon algorithm and UAS imagery, while LaSRC product was used to test the radiometric consistency. OLI sensor has 9 spectral bands, from which 4 bands match the UAS sensor. Matching bands FWHM is 452 nm - 512 nm (blue, #2), 533 nm - 590 nm (green, #3), 636 nm - 673 nm (red, #4), and 851 nm - 879 nm (near infrared, #5) (Figure 3).

Figure 3: Relative Spectral Response Function of OLI VNIR bands and MicaSense RedEdge bands.



4. METHODS

UAS data was geometrically and radiometrically processed. Indirect georeferencing [15] was carried out using 7 Ground Control Points measured with post-processed DGPS. Once georeferenced, individual photograms were calibrated through the sensor panel altogether with EXIF information [16], and the orthomosaic was generated with Agisoft Photoscan. UAS orthomosaic was correlated with the 17 reflectance targets, and the lineal function applied (empirical line correction).

OLI 30 m grid was vectorized in polygons, where internal statistics of 6 cm drone imagery pixels were calculated, considering the median reflectance value as the synthetic MS reflectance reference. 80 % cells were used as reference to fit the $Latm\lambda$ and $\tau_{0\lambda}$ unknowns of the PIA-MiraMon model [3]; finally, the full L8 L1T scene was atmospherically corrected (Eq.1); the remaining 20 % of the resampled pixels were used to validate the results.

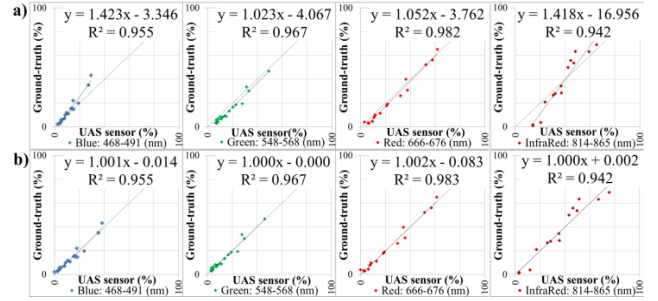
$$\rho_{S\lambda} = \pi (L_{S\lambda} - Latm_{\lambda}) d^2 / [\cos(\theta) E_{0\lambda} \tau_{1\lambda} \tau_{2\lambda}] \quad (1)$$

Where $\rho_{S\lambda}$ is the surface reflectance (the subscript λ , when present, means spectral); $L_{S\lambda}$ is the satellite at-sensor radiance; $Latm_{\lambda}$ is the atmospheric path radiance; $E_{0\lambda}$ is the exoatmospheric solar irradiance; d is the Sun-Earth distance corrector; θ is the angle between the Sun vector and the terrain normal; $\tau_{1\lambda}$ $\tau_{2\lambda}$ are the downwelling and upwelling transmittances, depending on Sun Zenith Angle and View Zenith Angle, respectively, but both depending on the Total Optical Depth ($\tau_{0\lambda}$).

5. RESULTS

UAS-acquired data showed an acceptable fitting to ground-truth measurements, except for the NIR band, which presented a high coefficient of determination ($R^2_{nir} > 0.942$) but an unacceptable bias (-16.956 %). VIS bands showed a higher R^2 ($R^2_{blue} > 0.955$; $R^2_{green} > 0.967$; $R^2_{red} > 0.983$) and low bias (Figure 4).

Figure 4: Correlation of field spectroscopy reflectance measurements and MS values: a) Before the empirical line correction. b) After empirical line correction.



Drone data (6 cm) was resampled to 51 OLI grid pixels (30 m). Band-by-band reflectance RMSE was below 1.63 % in VIS bands and below 2.22 % in the NIR band. When calculating the RMSE between test areas and LaSRC atmospheric correction, the value is higher than with PIA-MiraMon correction. The RMSE in the whole scene comparing LaSRC and PIA-MiraMon was higher, especially in the blue (3.53 %) and NIR bands (3.42 %) (Table 1).

Table 1: Band RMSE of L8 data atmospherically corrected using UAS references (PIA) and the official product (LaSRC), within test areas and full 198031 WRS-2 scene.

	BLUE	GREEN	RED	NIR
RMSE Test-PIA	0.61	0.54	1.63	2.22
RMSE Test-LaSRC	2.23	1.43	2.87	3.13
RMSE LaSRC-PIA (full 198031 scene)	3.53	2.71	2.20	3.42

6. DISCUSSION

Photogrammetric software reflectance calibration using a characterized panel and EXIF information obtained good fitting with *in-situ* measurements ($R^2 > 0.94$), but even better fittings were obtained in a posterior correction using multiple reflectance targets characterized with field spectroscopy measurements. As expected, in test areas, PIA-MiraMon RMSE were lower than for LaSRC, since in PIA-MiraMon the atmospheric parameters ($Latm_{\lambda}$, $\tau_{0\lambda}$) were obtained from *in-situ* references. Consequently, using UAS references improved local accuracy in atmospheric correction. When comparing LaSRC and PIA-MiraMon atmospheric correction in the full scene, the consistency between both methods was acceptable considering that PIA-MiraMon only used references in a small area, although in blue band differences increased because is the spectral region most sensible to atmospheric scattering.

L8 OLI sensor spectral configuration and MS sensor spectral configuration overlap in 4 spectral bands, but not with the same RSRF and FWHM, a source of error when comparing corresponding data. The RSRF mismatching is remarkable in the NIR band, where the reflectance inaccuracy was higher both in LaSRC and PIA-MiraMon.

The number of OLI (30 m) sampled pixels with the drone was 51 and the time needed was only 10 minutes although the area was larger than that coverable by a specialized operator in that time; moreover, included tree canopies, a house roof, a pond and difficult to access places.

7. CONCLUSIONS

Atmospheric correction of L8 VNIR bands was achieved using multispectral reflectance references acquired with a drone in synergy with field spectroscopy measurements and PIA-MiraMon algorithm. Results were evaluated with RMSE using test areas, with accuracies up to 1.63 % in visible bands and 2.22 % in the NIR band. The main source of error was the band mismatching between drone and satellite sensors RSRF. Locally, PIA-MiraMon accuracy improved LaSRC, but, as expected, differences increased until the 3.5 % in the full scene.

Field spectroradiometry measurement remains as the ground-truth source due to the proximity of the sensor to the surface, the intensity of scans and the control of the measurements and instrument features. Thus, UAS-acquired data can benefit from traditional field spectroscopy and, moreover, this synergy can provide valuable surface reflectance reference data.

Atmospheric correction of Landsat-like images using drone imagery as reflectance references offers good results, being especially useful for the surrounding area of the drone flight, as in protected areas. This contribution opens the door to the usage of sparse drone flights together to the collection of ground-truth references to atmospherically correct satellite images or to validate atmospheric corrections results, especially if using remote sensors with similar spectral configuration.

8. ACKNOWLEDGEMENTS

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DRONE HYPERSPECTRAL SYSTEM FOR MONITORING COASTAL BATHING WATER QUALITY

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ABSTRACT

The bathing water quality is an essential issue because of the consequences for the public health of the coastline users that make an extensive recreational use of it, even more in tourist areas. Overpopulation of coastlines generates large volumes of wastewater that must be treated as a prior step to its discharge into the coastal outfalls. In order to carry out a control of the wastewater treatment and discharge process, it is necessary to monitor the discharge points through a systematic and costly in-situ sampling analyzed in laboratory for the detection of bacterial pathogens. This requirement of bathing water monitoring made clear thanks to the European directive 2006/7/CE of February 15, 2006. This complex and slow procedure does not allow obtaining early alerts of the presence of pathogens because the biological bacterial analysis method require a minimum of three days. We propose, the use of a hyperspectral camera aboard a drone in order to monitor the bathing water by using the Radiative Transfer Model (RTM) to obtain indicators of the presence of bacterial pathogens. In this way, this paper presents the first preliminary results of our study.

Index Terms— Water quality, bacterial pathogens, early alert, Drone, hyperspectral images, RTM.

1. INTRODUCTION

Nowadays, advances in the field of hyperspectral remote sensing, UAV and faster computer systems, makes possible the monitoring of study areas in a more synoptic and optimized way than using in-situ methods. In parallel, there is a need from public administrations to generate early alerts of bacterial pathogens presence in bathing waters. The boom of airborne remote sensing thanks to drones together with the miniaturization of the hyperspectral optical sensors, providing very high spectral and spatial resolution, allows the development of new methods for monitoring of biologically areas such as coastlines with a moderate costs. Obtaining the water spectrum in a large number of bands allows the implementation of the Radiative Transfer Modeling [1], where the absorption and backscattering processes of pure water and elements in solution and suspension can be inferred. In this manner, parameters related with water quality such as suspended matter (turbidity), phytoplankton and dissolved matter (also known

as CDOM) can be characterized. In the same way, within the framework of this work, we are obtaining the spectral characterization of the coliform bacteria (*Escherichia Coli* and the *Enterococcus Intestinally*) [2]. By the inversion of this updated model, which includes the bacterial characterization, it will be possible to obtain the water quality as well as the coliform bacteria indicator. In this manner, the generation of coliform bacteria concentration maps is achieved. This image processing only requires a few hours so early alerts can be obtained improving and accompanying the current methodology. In any case, the use of in situ sampling is necessary for validation.

2. METHODOLOGY

2.1. Hyperspectral Data

UAV hyperspectral remote sensing provides a high spatial and spectral resolution imagery used as systematic and synoptic framework for advanced monitoring of the earth's surface. In this way, the last decade, the use of UAV hyperspectral remote sensing for land and marine projects has grow significantly. In this context, a monitoring of the bathing waters of the Canary Islands coast is being carried out. In order to achieve this work, a RESONON Pika-L hyperspectral camera is employed, which can be used in both cases: in laboratories using a Benchtop Hyperspectral Imaging Systems or mounted in a DJI Matrice 600 Hexacopter Aerial Drone, to get the best image quality on the airborne platform, a DJI Ronin MX gimbal was used.

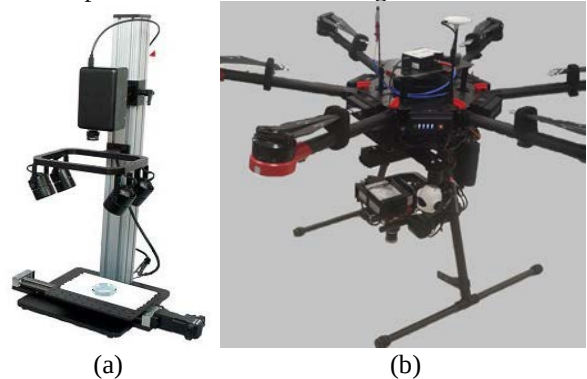


Figure 1. Hyperspectral System: (a) Benchtop Imaging and (b) Matrice 600 Drone with Hyperspectral flight system (gimbal, flight computer, IMU-GPS and Irradiance sensor).

The following table shows the Pika-L system specifications:

Table 1. Hyperspectral Pika L sensor specifications.

Spectral Range	400 - 1000 nm
Spectral Resolution	2.1 nm
Spectral Channels	281
Spectral Pixels	561
Spatial Channels	900
Max Frame Rate	249 fps
Signal-to-Noise Ratio (peak)	368 (2x bin)-520 (4x bin)
Bit Depth	12
Focal Length (nm)	17
FOV (deg), IFIV (mrad)	17.6, 0.88
Weight	0.6 kg
Dimensions (cm)	10.0 x 12.5 x 5.3

The first test flight was in Las Eras, on the island of Tenerife. There is a small beach with confined water near a submarine outfall. The mosaic of 10 Ha was generated by multiple hypercubes of 300 spectral bands with a spatial resolution of 10 cm x 10 cm.

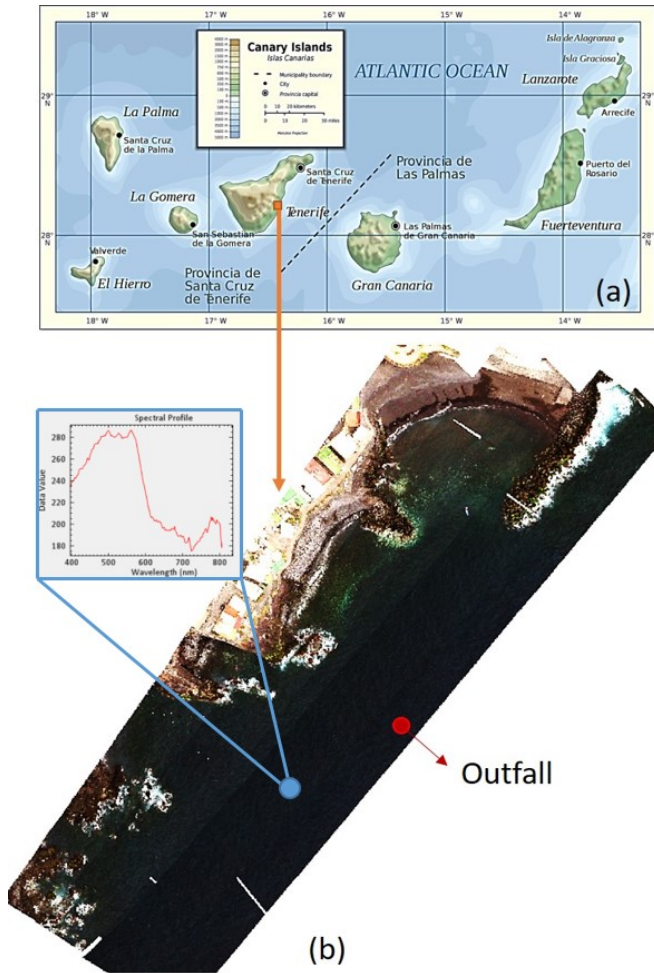


Figure 2. Area of study: (a) geographic location and (b) Pika L hyperspectral image mosaic (color composite) of Las Eras.

2.2. Pre-processing for water environment

A critical step for high resolution remote sensing monitoring of marine spaces is the pre-processing. It involves radiance quantification, atmospheric correction, and sunglint removal.

A fundamental advantage of the use of airborne sensors with respect to satellites is that the atmospheric correction can be carried out directly by obtaining the irradiance that reaches the earth's surface. This avoids the use of complex atmospheric models that require the atmospheric state data that are not usually available. Thanks to the usage of the irradiance sensor, we are able to obtain accurate surface reflectivity [3]. In addition, sunglint introduces a reflectivity contribution coming from the water surface that does not provide any information about the properties of the water. Therefore, it is taken as a source of noise and its removal is necessary. In our work, we have used a physical and image processing based algorithm for sunglint removal [4].

2.3. Bathing water quality

The radiative transfer modeling of the water is necessary to take into account the exponential attenuation of the light due to absorption and back-scattering. These parameters varies with the wavelength, depending on the inherent properties of the water and in shallow depths according to the bottom albedo. The equation proposed by Lee et al [1] is used to model the reflectivity r_{rs}^m due to the reflectance of the deep water $r_{rs,\infty}$ and the seabed albedo ρ_{alb} :

$$r_{rs}^m(\lambda) \approx r_{rs,\infty}(\lambda) \left(1 - e^{-\left[\frac{1}{\mu_s^{sw}} + \frac{D_u^c}{\mu_v^{sw}} \right] k_d z} \right) + \frac{\rho_{alb}(\lambda)}{\pi} e^{-\left[\frac{1}{\mu_s^{sw}} + \frac{D_u^b}{\mu_v^{sw}} \right] k_d z}$$

where μ_s^{sw} and μ_v^{sw} correspond to the conditions of the sun and satellite viewing geometry, k_d is the diffuse attenuation coefficient which depends on the Inherent Optical Properties (IOPs). z is the coastal bottom depth. D_u^c and D_u^b are light diffusion factors for the two ascending light sources (water column and bottom albedo). Finally, the absorption and backscatter parameters or IOPs affect both the deep-water reflectivity and the diffuse attenuation coefficient.

After obtaining the IOPs it is possible to quantify the presence of dissolved matter, suspended matter and phytoplankton, being used as indicators of water quality. By using these parameters, it is possible to obtain an indicator of the presence of possible wastewater from submarine outfalls where pathogenic bacteria may appear. In turn, in a direct way, it is possible to characterize in the laboratory the attenuation and back-scattering of water with high bacterial content, where the absorption and back-scattering of different bacterial concentration is measured. Finally, this new parameter can be introduced in the model to detect the bacterial presence.

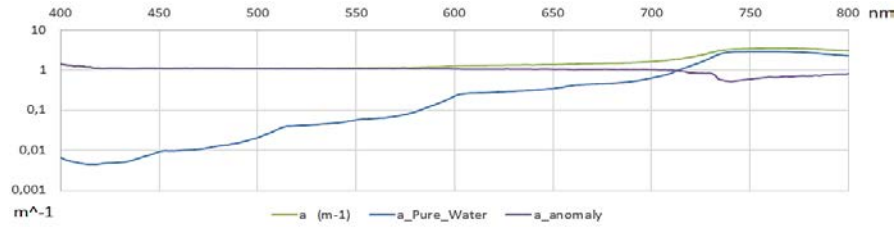


Figure 3. Attenuation of a high concentration of E. Coli: total absorption as a function of depth (Green curve), attenuation of pure water (blue), and anomaly with respect to the absorption of pure water (purple), due to the presence of bacteria.

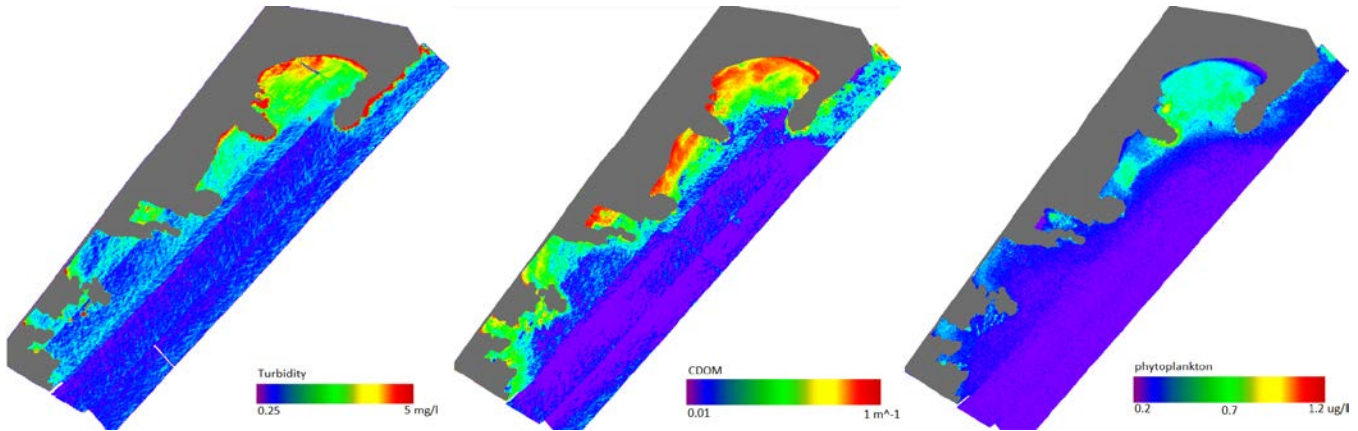


Figure 4. Water quality parameters obtained in the area of study (Las Eras): (a) Turbidity, (b) CDOM and (c) Phytoplankton.

3. RESULTS

3.1. Characterization of bacterial solution

Currently we are starting the spectral characterization of bacterial cultures. Figure 3 shows an example of the attenuation generated by a high dissolution of E. Coli. As we can see, the attenuation ($a_{anomaly}$) is quite flat with a small descending slope according to the wavelength; this is due to the lack of pigments of the coliform bacteria. Once the spectrum is characterized, the dry residue of the mass of bacteria in the solution will be obtained, thus, by measuring multiple levels of the solution, it will be possible to obtain a bacterial absorption as a function of its dissolution in water.

3.2. Water quality maps

After Radiative Transfer Model execution, it is possible to obtain maps with water quality parameters, which are shown in Figure 4. For this, it was necessary to calculate the bathymetry and the albedo from the coastal bottom. As can see, the concentrations of the water quality parameters are very low, increasing slightly near the coast. In the same way, there are no increases in these parameters near the submarine outfall, which indicates that the discharge of wastewater was minimal at that time.

These results were validated by taking three in-situ data after the drone's pass (outside the breakwater, on the beach and near the outfall), providing results similar to those obtained by the model.

4. CONCLUSIONS

The hyperspectral systems on board drone allow the monitoring of coastal bathing waters with great spatial and spectral detail. Thanks to the RTM, it is possible to obtain water quality parameters that indicate possible wastewater discharges in the outfall, providing early pollution alerts. In turn, the characterization of the spectra of the pathogenic bacteria (in preliminary study) will generate a new modelable parameter in the RTM model, which will provide us with maps of bacterial concentration.

5. ACKNOWLEDGEMENTS

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MULTI-INDEX IMAGE DIFFERENCING METHOD FOR FLOOD WATER DETECTION

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ABSTRACT

This study presents a remote sensing methodology to detect floods with a change detection approach based on image differencing of several water-related indexes. The proposed methodology is expected to integrate the strengths of each individual index and considers the agreement level among outputs obtained by different indexes as an indicator of overall uncertainty.

The analysis of data frequency distribution is used to obtain thresholds to implement data slicing and production of thematic maps. By considering different magnitudes of change, the proposed method is expected to be sensitive to detect different types of flood-related changes, including the detection of recent tracks of water presence. This is particularly interesting for those situations whenever it is impossible to obtain cloud-free satellite images immediately after a flood event, which is often the case given the limitations of optical sensors.

The methodology has been applied to a fluvial flood event occurred in the surrounding of a natural lagoon in the Aveiro region (Portugal). Landsat 7 ETM+ and Landsat 8 OLI surface reflectance products were used as inputs. Sentinel 1 GRD data was used for comparison purposes. Results indicate an overall consistency, which allows us to expect the proposed method is replicable for other events and areas.

1. INTRODUCTION

Floods are amongst the most important weather-driven hazards, being capable of inducing multiple damages, including economic losses and threatening of human lives. Floods may result from heavy or persistent rainfall, flooding by waterbodies, water table rise, snowmelt, or being originated from artificial sources [1]

The definition flood, e.g. “temporary covering by water of land not normally covered by water” [2], conceptually implies occurrence of a certain type of change over time.

Digital change detection techniques based on remote sensing imagery are capable of providing both long-term and short-term solutions [3]. Bi-temporal change detection analysis include several methods capable of dealing with short-term phenomena, such as floods.

Univariate image differencing is the most widely applied amongst bi-temporal algorithms. It consists in subtracting spectral or transformed data (e.g. by means of water-related indexes), producing positive and negative values, depending on the type of change [3]. In theoretical and ideal conditions, no-change areas should result in zero values, however, in real conditions, this is not the case as effect of spatial and spectral co-registration errors, as well as natural time-dependent changes. One or more thresholds may be required to define two or more classes of change (density-slicing), which may provide hints about amounts and types of change. However, by quantifying absolute differences, this method is unable to specify directly the type of change.

The main objective of this study is to provide a satellite remote sensing method to detect floods, integrating several water-related indexes in a change detection method. The method was developed to be applied to multispectral satellite data acquired from Landsat (LS) series.

2. METHODOLOGY

In Figure1, we illustrate the proposed methodology for flood areas detection, based on combining several Water-related Indexes (Wrl) in a change detection approach. We considered the following Wrl: the Normalized Difference Water Index (NDWI) [4]; the Modified Normalized Difference Water Index (MNDWI) [5]; the Automated Water Extraction Index (AWEI) (including ‘shadow’ and ‘no shadow’ versions) [6]; and the Tasseled Cap Wetness (TCW) [7].

The methodology assumes that a certain area could have experienced a flood event within a certain time period.

For flooded areas, Wrl variation develops between the epochs $t1$ and $t2$ (respectively prior and after the given flood event).

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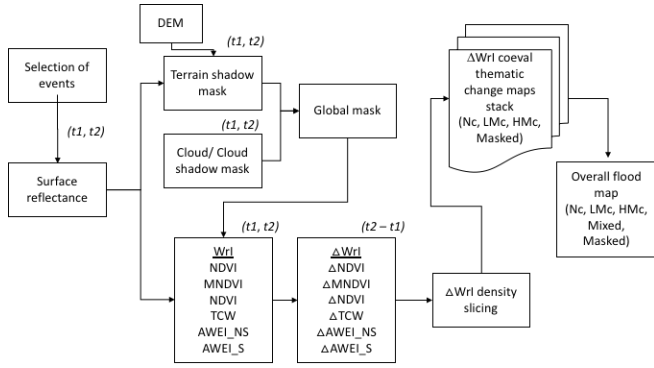


Figure 1 - Methodological scheme

In theory, for change detection methods based on image differencing, no-change areas (Nc) are represented by zero digital values. Assuming the time span ($t_2 - t_1$) is reasonably short, Nc has to be the majority of the pixel image distribution corresponding to the modal range of the frequency distribution. In contrast, digital values different to zero represent change areas and they tend to be located toward both tails of the frequency distribution. If Wri differencing (ΔWri) is applied we expect to locate flooded areas changes in only one of the tails, either positive for NDWI, MNDWI, TCW, AWEI, or negative for NDVI (in respect to the Wri here considered). The higher the distance from the modal ΔWri value, the higher the magnitude of change, corresponding to a complete change of state from dry to flooded surface. If flooding causes only such kind of changes, this results in an ideal bi-modal distribution where the discrimination between Nc and flooded areas is unambiguous. In practice, flooding may involve areas characterized by different initial conditions (land cover, substrate properties, surface roughness and wetness, and their spatial distribution in respect to pixel size) along with different flooding conditions (water thickness and suspended materials, water surface roughness), which implies a continuous distribution of ΔWri values between the Nc and change end-members.

Moreover, when analyzing the frequency distribution one should also take into consideration the effect of spatial and spectral misregistration between input t_1 and t_2 imagery, those changes resulting from phenomena other than flooding and effective sensitivity of Wri to detect surface water. The main consequence of these conditions is that the real distribution of Nc is represented by a bell-shaped range of ΔWri values located around zero.

Given the above considerations and the fact that image differencing doesn't allow to discriminate among the types of change, but only change signal and intensity, we assume to classify flooded area into the categories Low-Magnitude change (LMc) and High-Magnitude change (HMc) as a function of the ΔWri value. This assumption requires for the definition of two thresholds, between Nc-LMc (TL) and LMc-HMc (TH) which are then used to apply density slicing to the multitemporal imagery. These thresholds could be

defined either by using ground truth information or analyzing the frequency distribution of data, the latter approach being a key point of the proposed method, allowing us to perform semi-automatic remote sensing procedures to extract flooded area from satellite imagery. We assume that these thresholds correspond to sudden variation of ΔWri frequency. In the first case, the first order derivative of the function is a useful tool to define the thresholds which correspond to change of sign of the derivative function. In the other cases, the first derivative continuously gets closer to zero without reaching it, therefore we choose the ΔWri where the second order derivative function reaches a local maximum. In practice, for a given scene differencing, the distribution of ΔWri may follow both conditions, around either TL or TH.

Depending on the availability of cloud-free optical satellite images, surface reflectance is used to determine each Wri for t_1 and t_2 (additional preprocessing steps may be required, e.g. geometric and radiometric calibrations, as well as cloud/shadow masking). After performing the ΔWri calculation, by density slicing based on TL and TH, we obtain a stack of six different coeval thematic change maps.

These different thematic maps represent changes caused by flooding according to each Wri specific sensitivity. Hence, the overall flood map integrating the information from each individual Wri is obtained by picking the absolute majority among the frequency of the classes Nc, LMc, HMc. Whenever the absolute majority does not occur, pixels are classified as 'Mixed'. This means that the overall flood map directly provides an indication of pixel uncertainty, in which 'Mixed' pixels have more uncertainty than those attributed to classes Nc, LMc, HMc.

HMc should correspond to a complete change of state from dry lands to water surface. LMc is expected to represent pixels changing from dry to wet/saturated surfaces, as well as wet/saturated to water surfaces. Moreover, depending on the duration of the time span ($t_2 - t_1$), LMc may also correspond to those flooded areas that underwent drying/drainage processes after the flooding event. This is particularly interesting for those situations whenever it is impossible to obtain cloud-free satellite images immediately after a flood event, which is often the case given the limitations of optical sensors. Finally, the Nc areas will include permanent water bodies, continuously wet/saturated surfaces, as well as any other kind of permanently dry surfaces.

3. RESULTS

Herein, we provide results of the application of the proposed methodology to a flood event occurred in the Aveiro Region, located on the NW part of continental Portugal. All image processing tasks were performed with GRASS GIS (v7.2.2) and map compositions with QGIS (v2.18.15).

According to meteorological databases, a maximum of 128.9 mm of daily precipitation were registered in the study area for 2016/02/13, corresponding a precipitation event with a return period of 16.4 years.

For t_1 , we considered the LS 8 OLI from 2016/02/05 and for t_2 the LS 7 ETM+ from 2016/02/29 (SLC-off) (Level-2 products obtained from <https://earthexplorer.usgs.gov>). Cloud/Cloud shadow masks were extracted from the 'pixel_qa' band of each scene. Terrain shadows were extracted from shaded relief maps, using the SRTM 1 arc sec DEM and azimuth and elevation (found in LS metadata). After determining each WrI (for t_1 and t_2) and the corresponding ΔWrI (t_2-t_1), we proceeded to the extraction of thresholds according to the proposed methodology. Figure 2, illustrates every ΔWrI coeval thematic map, along with the overall flood map. Moreover, considering the lack of ground truth data, for comparison purposes, we have also included water masks obtained from Sentinel-1A (S1A) GRD images from 2016/02/18 and 2016/03/01 (extracted from visual inspection of Sigma0 VV (dB) histograms).

4. DISCUSSION

In the present study, we were able to extract thresholds for every ΔWrI using the histogram frequency analysis. However, we found this task to be more straightforward for normalized indexes (i.e. NDWI, MNDWI and NDVI), when compared to non-normalized indexes (i.e. TCW and both versions of AWEI). For non-normalized WrI , smoothing of data (by means of mobile averages) was required to interpret first and second order derivatives of ΔWrI . Considering the overall flood map, we verify a low occurrence of 'Mixed' pixels, which is an indicator of overall coherence between the different ΔWrI coeval thematic maps, meaning low uncertainty.

Despite the temporal proximity between t_2 (LS7 from 2016/02/29) and S1A (2016/03/01) scenes, the agreement between flooded areas (i.e. LMc + HMc) and the S1A water mask is only 37%. Regarding the S1A scene closer to the event (2016/02/18), the agreement is higher, 47%. This confirms the sensitivity of the proposed method in detecting recent tracks of water from flood events, in particular for LMc. The overall low agreement levels could be related to the unavailability of S1A scenes obtained during the flood event (or immediately after). Besides, it could also mean that the proposed method is overestimation flooded areas, or S1A could be underestimating them by not detecting wet/saturated areas which take place in the following days after the flood event.

5. CONCLUSION

The proposed methodology demonstrated capability of extracting flooded areas from optical satellite imagery obtained several days after a heavy precipitation event. The combination of multiple water-related index differencing resulted in overall coherence, suggesting low uncertainty. The overall flood map is consistent with water masks extracted from Sentinel-1A (S1A) scenes obtained several days after the event. However, low agreement levels suggest

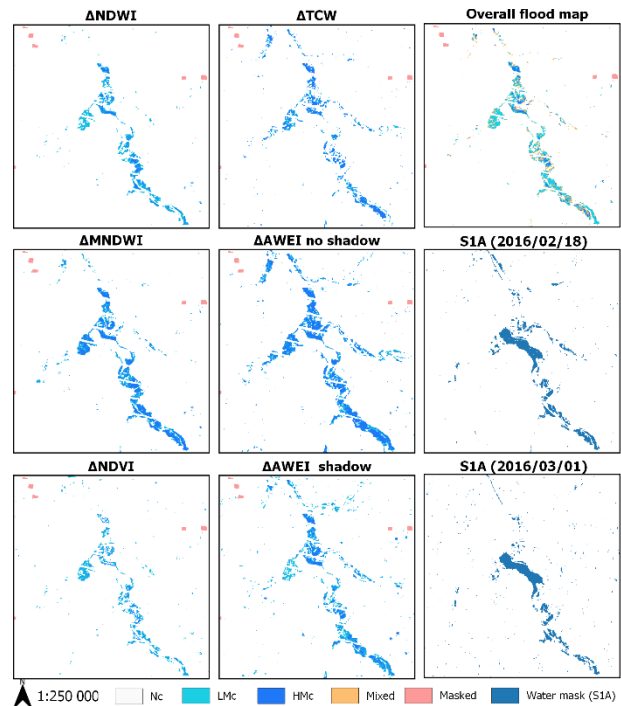


Figure 2 - ΔWrI coeval classifications and overall flood map for 2016/02/13; Water masks obtained from S1A scenes, from 2016/02/18 and 2016/03/01.

either overestimation of flooded areas, or underestimation by S1A water masks. The proposed method is expected to be replicable for other events and study areas.

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IMPROVING FOREST CARBON MAPS: MODELING APPROACHES FROM HIGH-RESOLUTION TO NATIONAL SCALE

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ABSTRACT

Forest carbon estimation is crucial to manage Mediterranean ecosystem, very sensitive to climate change effects. Many modeling procedures have been tested; however, most of them cover small areas with high accuracy but hardly updated or extent areas with large uncertainties. In this study we integrated nationwide bio-geophysical remote sensing products with aboveground forest carbon estimations obtained from high-precision LiDAR data at regional scale. We used Quantile Regression Forest (QRF) to spatially predict carbon and their associated uncertainty. The model produced robust performance (R^2 0.69 and RMSE 24.45 kg/ha) with NDVI and LAI as environmental drivers, in combination with terrain variables. External, independent dataset of predicted carbon map showed a statistically-robust model (R^2 0.70 and RMSE 25.38 kg/ha), confirming its applicability at national scale.

Index Terms- Aboveground carbon, LiDAR, Copernicus products, Quantile Regression Forest, Uncertainty.

1. INTRODUCTION

Since Iberian Mediterranean ecosystems are very sensitive to climate change effects, they require adaptive management for assessment, monitoring and management of organic carbon in ecosystems, essential to achieve global change commitments at national level. However, such maps are difficult to produce and the uncertainties are often large [7]. Light detection and ranging (LiDAR) technology has been extensively used in forestry practices including biomass mapping, due to its high-sensitivity to structural attributes and high-precision ability of measure stand parameters, including vegetation carbon density [3]. LiDAR data, in combination with a random forest algorithm, find a substantial accuracy in biomass estimation [1]. However, despite technological advancement, the high cost of LiDAR data presents much longer repeat cycles compared to satellite data and complicates its continuous spatial acquisition, being inoperative at national scale studies. In addition, different studies integrated optical satellite data into spatio-temporal estimation of forest biomass. Since 2014, the PROBA-V land monitoring satellite mission of the

European Space Agency is providing imagery for filling the gap between SPOT-VGT and the Sentinel-3 mission. It presents a spectral and radiometric performance identical or better than SPOT-VGT and a spatial resolution of 300 m in VNIR bands.

This study aims to develop a methodological approach to improve a nationwide aboveground carbon map derived from satellite high-resolution data. We compared the performance of a remote sensing-based generic model integrating bio-geophysical remote sensing products with aboveground forest carbon estimations obtained from LiDAR data at regional scale.

2. MATERIALS AND METHODS

2.1. Study area

The study area, Southeastern Iberian Peninsula (Region of Murcia), is a Mediterranean region with warm temperatures and scarce rainfall, very threatened by global change. Climate diversity is related to a diverse orography with mountains, high plateaus and badlands. The lithology is represented by Calcisols, Leptosols, Regosols and Flvisols, mainly. The land uses are basically cultivated areas and forest areas (45% of land uses).

Most of the wooded area is composed of pine forest, being *Pinus halepensis* Mill the main specie (90% approx.) mixed with *P.nigra* and *P.pinaster*, and oak forest (*Quercus ilex*) in a lesser extent. The shrubland area covers 60% of the forest area in the Region of Murcia.

2.2. Estimation of aboveground forest carbon

We used public LiDAR data (0.5 pulse/m²) from 2016 Spanish National Plan (<http://pnoa.ign.es/>). For tree cover, LiDAR statistics were correlated with stand variables using a plot-level technique. To estimate aboveground biomass we applied specific conversion factors (source: AFIB-CTFC) related to wood density for each species. For shrubland biomass modeling we used a generic allometric equation from Montero *et al.* [5]. Grassland was excluded from the estimation due to LiDAR inaccuracy in this cover type. The regression models applied to the total area produced a continuous high-resolution map (25 m) for each forest cover: pine, oak and shrubland. After calculating the carbon stock by applying carbon sequestration factors [8], we resampled the carbon map to 300 m moderate resolution.

The function was implanted by bilinear method and parameters of Copernicus remote sensing vegetation products (Resample package in R). We used this LiDAR carbon map as the aboveground forest carbon benchmark.

2.3. Vegetation and topographic variables

To model from high-resolution carbon map to national scale, we generated a stack based on 38 environmental predictor variables: dynamic and statics. The dynamic variables refer to 300 m resolution vegetation products of Copernicus Global Land Service (CGLS): NDVI, LAI, FAPAR and FCOVER (<https://land.copernicus.eu/global/themes/vegetation>). The products dates were selected according to LiDAR flight dates and vegetation phenology (3 images per month: May and October 2016). The statics variables were 14 topographic parameters derived from a 25 m digital elevation model (DEM), available from the Geographic Information National Centre (Spain), using the Terrain Analyst functions included in SAGA GIS software. Previously to the terrain parameters computation, we aggregated pixel raster to a coarser resolution, 300 m pixel size, by the same method used for the LiDAR carbon map.

2.4. Spatial predictive model and associated uncertainty of aboveground forest carbon

The input data frame for carbon predictive model was obtained by selecting a systematic sampling (40,000 data) from the 300m LiDAR carbon map. Covariate data in data frame were extracted from the environmental variable stack at the same location as target data. To select the best correlated predictor variables we used VSURF package (R software) and variance inflation factor (VIF) to identify statistical redundancy.

The predicted model was performed based on machine learning techniques using quantile regression forest (qrf), a generalization of random forest used to estimate an accurate approximation of the full conditional distribution of the response variable [4]. Therefore, the qrf infers conditional quantiles to build predicted intervals, as surrogate of uncertainty associated with the response variable for each pixel value. To perform predicted and uncertainty maps we used quantregForest (QRF) package [4] in R software.

Out-of-bag predictions were used to evaluate the quality of the conditional quantile approximations. We computed 2 maps at 300 m resolution: predicted values of aboveground forest carbon and their associated uncertainty. In order to predict the relationship between carbon estimated values and their associated uncertainty, we performed a regression model with aboveground forest carbon data and their corresponding relative uncertainty.

An independent validation of the predicted aboveground carbon map was performed base on a 3,000 point random sampled from the 300 m LiDAR carbon map.

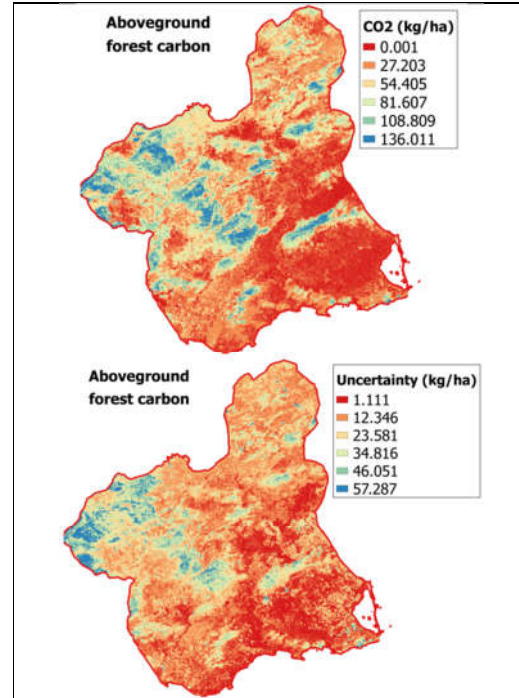


Fig. 1. Maps of predicted values (top) and associated uncertainty estimated by qrf method (qrf= “quantregForest” R package). The display has been stretched by cumulative pixel count cut method (default range 2%-98%).

3. RESULTS

The maximum values of aboveground forest carbon corresponded to tree cover in middle and northwest of the study area. The minimum values were associated to shrubland covers. As expected, aboveground forest carbon in the study area showed a decreased in mean values the coarser the pixel resolution: 35.47 kg/ha (59.82 sd) and 32.07 kg/ha (44.86 sd) at 25 m and 300 m respectively.

According to the variable selection procedure of VSURF R package, the environmental drivers of the spatial variability of forest carbon at 300 m spatial resolution were associated to vegetation indices: NDVI (2016/10/11 and 2016/05/21) and LAI (2016/10/10); and terrain variables: DEM, relative slope position and channel network base level (related to high, slope and soil moisture respectively).

Accuracy of carbon estimation model were based on determination coefficient (R^2) and root mean square error (RMSE), being 0.69 and 24.45 kg/ha respectively. Resulting carbon map (Figure 1) showed predicted mean value lower than baseline one: 20.66 kg/ha (34.70 sd). Considering the associated uncertainty of predicted values, the results revealed a mean value of 18.77 kg/ha (13.31 sd). External validation tested a good fitting of predictive model since it presented a reasonable R^2 and similar RMSE than predictive model (0.70 and 25.38 respectively).

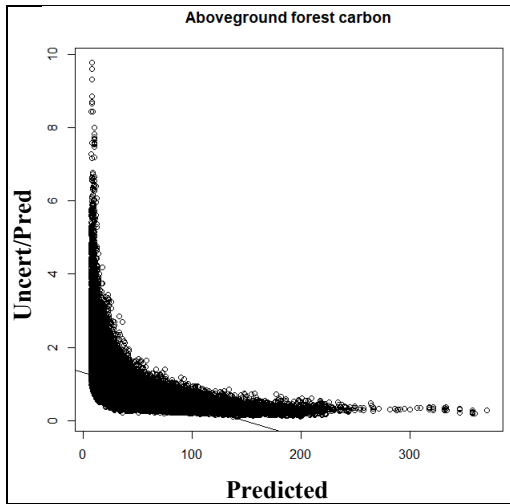


Fig.2. Plot relationship between predicted values of aboveground forest carbon and the associated relative uncertainty

The relationship between the predicted values and their associated uncertainty (Figure 2) showed high values of uncertainty with low values of aboveground forest carbon.

4. DISCUSSION AND CONCLUSIONS

Remote sensing imagery has increasingly been employed in combination with field plot data and synthetic dataset [1] to estimate aboveground carbon stocks across heterogeneous forested landscapes around the world [2]. Widely established this close relationship between vegetation characteristics described by satellite data (dynamics, distribution, structure) and biomass, remote sensing data are used in many studies to calculate biomass estimates, showing a high correlation mainly with NDVI [6]. This vegetation index, closely linked to the FAPAR, gives an indication on the current greenness of the vegetation. Its spectral reflectance measured in the near infrared and red wavebands respectively, makes it extensively used for ecosystems monitoring. More physical canopy variables are related to LAI which quantifies the density of the vegetation. Satellite-derived value corresponds to the total green LAI of all the canopy layers, including the understory which may represent a very significant contribution, particularly for forests. LAI is recognized as an Essential Climate Variable (ECV) by the Global Climate Observing System (GCOS). In this sense, our results were consistent according to the better correlated environmental drivers of spatial variability of forest carbon: NDVI and LAI in spring and autumn.

The results of uncertainty of the predicted map showed that the aboveground carbon values can be estimated with good reliability from information about topography and remote sensing vegetation indices from CGLS. Lower relative uncertainty was found in areas with higher carbon values, linked to tree forest cover. Tree species presented best fitted and most accurate biomass models since they

were estimated using plot-level techniques. However, the predictive map showed highest relative uncertainty related to low carbon values. These areas correspond to sclerophyllous shrubland and grassland covers characterized by scattered and low canopy cover which carbon estimation may be associated with the accuracy of the general allometric equation obtained from literature.

The test of the predicted carbon map in an external, independent dataset showed a statistically-robust model. Therefore, vegetation products of CGLS are a feasible and cost-effective approach for monitoring and easily updating aboveground carbon evolution. Main advantages of this methodology are the high temporal availability of images (every 10 days) and their moderate spatial resolution (300 m), which make it applicable for regional, even national, land use planning and management.

5. ACKNOWLEDGE

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Extended Random Jumps: A New Spatial-Spectral Classification Algorithm for Hyperspectral Remote Sensing Images

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ABSTRACT

Extended random jumps (ERJ) basically combines extended random walks (ERW) and watershed segmentation algorithms in a special way with a spectral classifier. In ERW only the intensity gradient between adjacent points is taken into consideration and the integration between ERW and watershed is performed by calculating the intensity gradient between all points in the same segment which is obtained by the watershed segmentation method. Support vector machine (SVM) can be utilized as a spectral classifier and the probabilities extracted from the SVM result can be used directly or after applying some modifications to fit the data in a better way. ERW and watershed segmentation algorithms have different way to integrate the spatial information and combining them together in ERJ can improve the classification results in hyperspectral image classification.

Index Terms — Spectral-spatial classification; extended random walkers; extended random jumps; watershed; hyperspectral image classification

1. INTRODUCTION

Hyperspectral images (HSI) are widely used in remote sensing applications due to their capability to collect detailed information about the imaging area. This information stored in high dimensional spectral feature space which is considered as the main advantage of HSI. From machine learning perspective this advantage causes a lot burdens to deal with. Curse of dimensionality is one of the main problems one comes across when dealing with HSI because modeling in high dimensional feature space with relatively small number of training samples with respect to dimension is a vital task. Moreover, theoretical the increment in the feature space is expected to lead a better discriminating ability which means better classification accuracy, but in some practical cases the increment of feature space may adversely affect the classification accuracy and this negative effect is Hughes phenomenon [1]. Another problem worth to mention is existence of the limited number of training samples compared to the number of feature space. The conventional classification methods used for multispectral images may fail to support satisfactory results and overcome the above-mentioned difficulties [2]. In the literature SVM is reported as a robust spectral classification algorithm on hyperspectral images [3]. One of the new powerful approaches is to combine both spatial and the spectral information to improve the classification accuracy. This way, we can obtain better results especially for misclassified samples in homogenous areas. In this paper, more spatial information was included with proposed method ERJ by combining ERW and watershed segmentation in a spatial way.

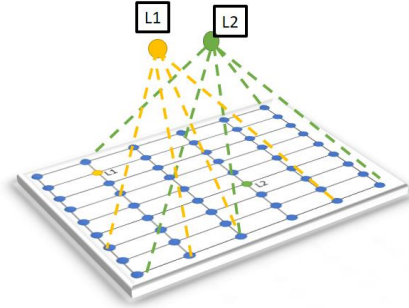


Fig. 1 ERW graph representation.

2. PRELIMINARIES

A. Extended Random Walker

ERW [4] is an extension of the powerful segmentation method random walks (RW) [5]. RW is semi-automated algorithm where the user must define a seed in each separated region. ERW turns the semi-automated segmentation algorithm into classification algorithm by combining a spectral classifier with the RW algorithm. Before talking about the integration between the spectral and the spatial algorithm, ERW deals with the image as a weighted graph made up vertices and edges. The edges have a value called weight and the weight represents the different in intensities between adjacent points/pixels [4]. Different weight functions can be used e.g. a simple weight function $\omega(e_{ij}) = e^{-\beta(v_i - v_j)^2}$, where β is a free parameter related to the image and the quantization, v_i and v_j are the intensities in the vertices i and j , respectively.

The integration between the spectral and the spatial classification is performed by having extra nodes (points) added to the graph. These nodes represent the classes in the image and

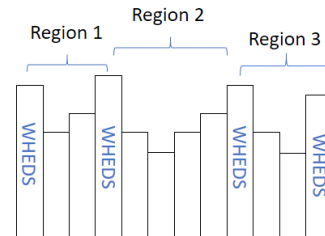


Fig. 2 Watershed algorithm in 1D feature space.

each point is connected to all vertices in the original graph. Fig. 1 shows the new graph obtained in ERW.

A brief mathematical exposition of the ERW algorithm can be found as follows. (1) represents the energy function for the new aspatial part added to the original graph.

$$E_{Total}^s = E_{Spatial}^s + \gamma E_{Aspatial}^s \quad (1)$$

Where γ is a free parameter to control the contribution of the spatial and aspatial energy terms.

$$\left(L + \gamma \sum_{r=1}^k \Lambda^r \right) x^s = \gamma \lambda^s \quad (2)$$

$$\left(L_u + \gamma \sum_{r=1}^k \Lambda_u^r \right) x_u^s = \gamma \lambda_u^s - B f^s \quad (3)$$

(2) and (3) are the solution of ERW with or without using seeds, respectively. L is the Laplacian matrix representing the graph and L_u is only for the unlabeled samples. Λ^r and Λ_u^r are diagonal matrixes where the values of λ^s and λ_u^s on the diagonal and the rest of the elements are zero.

B. Watershed on Hyperspectral Images

Watershed is a 2D segmentation algorithm based on mathematical morphology was first introduced by Beucher and Lantuejoul [6]. This algorithm separates the original image into small regions by selecting watershed pixels (WHEDs). Watershed is applied on the gradient of the image, where WHEDs are the high gradient values and these WHEDs divide the original space into smaller region where each region has its own local minimum value. The integration between the spectral and spatial information in watershed can be performed by applying majority voting for the result obtained from spectral classifier in each region. Fig. 2 demonstrates how watersheds work in 1D feature space.

Different solutions of watershed on HSI were introduced in [7]. In this paper Principle Component Analysis (PCA) [8] is applied on HSI. Then edge detection and image filtering are performed on the first and the second principle components. The gradient of each component is calculated, and watershed segmentation is applied on the 2D average of two gradient maps.

3. EXTENDED RANDOM JUMPS

In ERJ more spatial information are extracted and exploit to enhance the spatial-spectral-classification of HSI. The extra spatial information is obtained by combining two different spatial algorithms together. In this case we integrated ERW and watershed algorithms together as each one of them functioning in different way which might help to include even more spatial information. In ERW [4] only the relation between the adjacent pixels is taken into consideration, but here we called the algorithm extended random jumps, because not only the relation between first degree neighbors is taken into consideration, but also the relation between all the samples in the same region. Regions in this approach are formed by the watershed algorithm. Fig. 3 demonstrates the new graph used in ERJ.

To apply ERJ a parallel spatial space is created; in this parallel space the weight between the samples in the same region excluded the neighboring (adjacent) samples and the

degree of each vertex according to the new parallel space. The probability can be calculated in the parallel spatial space to minimize the following energy function:

$$E_{Parallel\ Spatial}^n(p_n) = p_n^T PL p_n \quad (4)$$

where PL is the new Laplacian for the parallel space:

$$PL_{ij} = \begin{cases} d_i, & \text{if } i = j \\ -\omega(e_{ij}), & \text{if } i, j \in R_k \text{ and } i, j \text{ are not adjacent pixels} \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

The degree and the weight in the new Laplacian matrix are the same as the degree and the weight in RW and ERW. R_k is the region obtained from the segmentation algorithm. There are three spaces namely spatial, parallel spatial and aspatial, all need to be added together to obtain the final energy function. One free parameter to control the impact of the parallel spatial space in the result, as we have γ to control the spectral part, a new variable σ is defined to control the new space as follow:

$$E^n(pp_n) = E_{spatial}^n + \gamma E_{aspatial}^n + \sigma E_{parallel\ spatial}^n \quad (6)$$

In (6), the new energy function can be minimized as it is done by the ERW algorithm and the solution of the minimization results is the following linear equations:

$$\left(L + \sigma PL + \gamma \sum_{r=1}^k \Lambda^r \right) x^s = \gamma \lambda^s \quad (7)$$

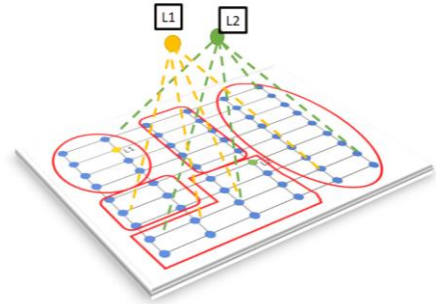


Fig. 3 Extended random jumps algorithm

$$\left(L_u + \sigma PL_u + \gamma \sum_{r=1}^k \Lambda_u^r \right) x_u^s = \gamma \lambda_u^s - B f^s \quad (8)$$

(7) is used to solve the probabilities in case of having no seeds, (8) to solve the probabilities while having seeds in the image.

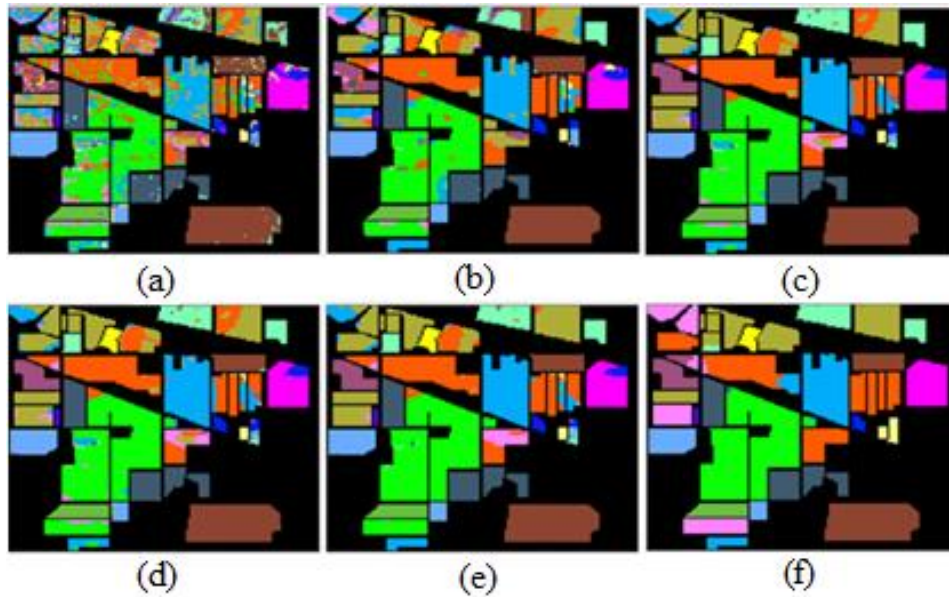


Fig. 4 Classification results on Indian Pines for (a) RBF-SVM (b) Watershed, (c) ERW without seeds (d) ERW with seeds, (e) ERJ without seeds, (f) ERJ with seeds

4. EXPERIMENTAL RESULTS

ERJ were applied on the Indian Pines Dataset which contains 16 classes and the results were compared by the results obtained from the baseline algorithms. In the experiment randomly selected samples were used as training samples and these samples were used as seeds as well. The total number of training samples is 128 as of 8 samples for each class. Table I tabulates the overall accuracy (OA), average accuracy (AA) and Kappa (κ) coefficient. In this study RBF-SVM were used as a pixelwise spectral classifier. Free parameters $\gamma = 0.1$ and $\sigma = 0.09$ were chosen for ERJ without seed and $\gamma = 0.01$ and $\sigma = 0.009$ were chosen, for ERJ with seeds after some trials. . Classification results are depicted in Fig.4. Classification results for RBF-SVM, watershed, ERW- without seeds, ERW with seeds, ERJ without seeds and ERJ with seeds are depicted in Fig. 4 (a), (b), (c), (d), (e) and (f), respectively.

Table I Classification results

Methods	Classification results			
	OA	AA	κ	Fig.4
RBF-SVM	64.19 %	73.03%	0.5971	(a)
Watershed	72.86 %	74.63%	0.7463	(b)
ERW without seeds	76.05 %	85.24 %	0.7292	(c)
ERW with seeds	86.76 %	92.94 %	0.8508	(d)
ERJ without seeds	77.47 %	86.03 %	0.7452	(e)
ERJ with seeds	88.53 %	93.92 %	0.8706	(f)

5. CONCLUSION

Exploiting extra spatial information in proposed ERJ algorithm improves the classification performance of the HSI. As seen in Table I we obtained 1.42% performance increment in proposed

ERJ over ERW when training samples were not used as seeds (see Fig.4 (c) and (e) for ERW without seeds and ERJ without seeds, respectively) and 1.77% performance improvement was obtained in ERJ over ERW when training samples were used as seeds (see Fig.4 (d) and (f) for ERW with seeds and ERJ with seeds, respectively). As a result of visual inspection on ERJ results less noisy like decisions seen in the results of proposed ERJ algorithm. ERJ is an efficient solution of HSI spatial-spectral classification tasks and provides desirable performance.

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Exploring NDVI Data Continuity between Landsat 8 OLI and Sentinel-2A MSI in a Temperate Forest District

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ABSTRACT

Determining NDVI data continuity of Sentinel-2A MSI and Landsat 8 OLI with three or five days visiting time have a significant contribution in long-term time series of forest monitoring [1]. Current study tried to examine the NDVI data continuity between Sentinel-2A and Landsat 8 OLI at the maximum growing season in the Çamlıyayla forest district, Turkey. Landsat 8 OLI L1TP, Landsat 8 OLI level L1T, and Sentinel-2A level L1C were acquired. Pearson correlation coefficient, boxplots, cross calibration, and regression statistical analysis were used to determine the consistency between two NDVI data sets. NDVI maps were generated after implementing necessary preprocessing operations on images including different atmospheric methods DOS1, and Sen2Cor, and geo-shift corrections. Results showed correlation coefficient was approximately greater than 0.8 which reveals good consistency between two data set. Highest correlation coefficient between Landsat 8 OLI NDVI and Sentinel-2A NDVI obtained 0.89 ($\rho < 0.0$) by DOS atmospheric correction approach. Findings imply that Landsat 8 OLI NDVI is almost consistent with Sentinel-2A NDVI data. Finally, Landsat 8 OLI NDVI and Sentinel-2A NDVI can be used as a complementary data that was one of the ESA mission aims [2–5] and it can be considered as a valuable data source for consistently doing time series forest monitoring. In further investigation, other vegetation indices continuity for other forest types and different tree species types is recommended.

Keywords: NDVI, Geo-shift, Çamlıyayla Forest District, Landsat 8 OLI, Sentinel2A

1. INTRODUCTION

Determining consistency and continuity of derived NDVI from Sentinel2A MSI (Multi Spectral Instrument) and Landsat 8 OLI (Operational Land Imager) have a significant contribution for conducting the Earth's surface monitoring studies [1], [6], [7]. Moreover, these data are freely accessible particularly Landsat images for more than 45 years. Additionally, certainly producing such combined data which have consistency will provide an extraordinary opportunity with 3 or 5 days visiting time and medium-spatial resolution for forest scientists to investigate effective forest cover change monitoring and specially monitoring forest vegetation phenology[1]. The number of conducted that have investigated the NDVI data consistency is nearly rare. However, data continuity of various satellite data such as Landsat images and SPOT images with Sentinel data have been conducted [8]. Current study tried to examine the NDVI continuity and

consistency between Sentinel2A and Landsat 8 OLI at the maximum growing season (July) in the Çamlıyayla forest district in Turkey.

2. METHODS

2-1. STUDY AREA

The study area is located on the shore side of the Mediterranean Region Adana Division, Eastern Karaisalı, Pozantı from the north, and Mersin Forest Operations Directorate from the West between 34° 21' 49"- 35° 06' 24" East Longitudes and 36° 43' 44" - 37° 25' 25" North Latitudes and it is belong to Tarsus Forest Management Directorate. It is located in the climate zone of the Mediterranean region (Fig.1).

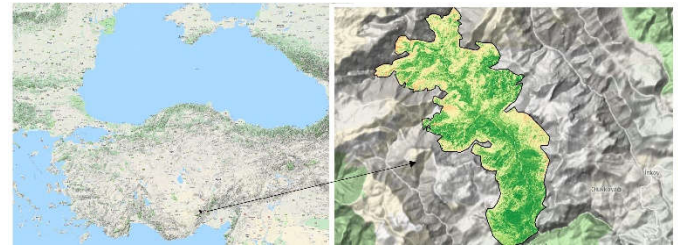


Figure 1. The study area location in Turkey

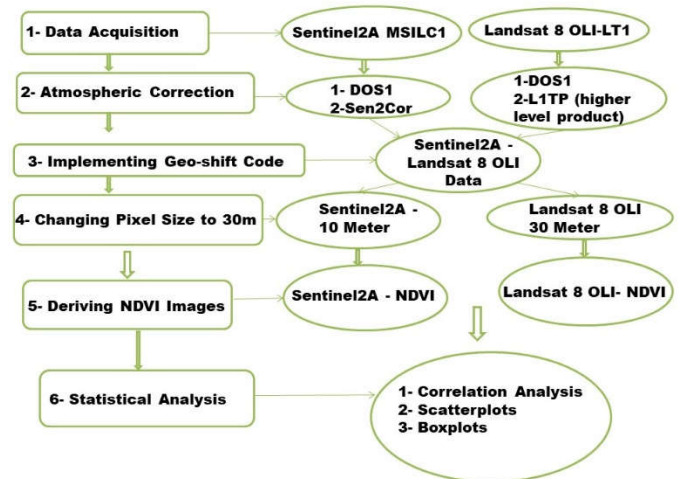


Figure 2. Methodology Framework

2-2. MATERIALS AND DATA ANALYSIS

Data sets include Landsat 8 OLI L1TP (higher level product) (10 July 2016), Landsat 8 OLI level L1T (10 July 2016, 26 July 2016), and Sentinel 2A level L1C (top of atmosphere reflectance) (14 July 2016). NDVI layer maps were produced

after implementing necessary preprocessing operations on images consist different atmospheric methods (Dark Object Subtraction1 (DOS1), Sen2Cor, and geo-shift corrections. To perform further analysis, the subset of the research area is generated for all images. It should be mentioned that intervening time between two used satellite image data is 4 and 12 days: Sentinel 2A time leaps with two Landsat data sets. However, geo-registration between images is significantly reduced by operating geo-shift process on images. In our study, it was used Pearson correlation coefficient, boxplots, and regression statistical analysis to determine the consistency between two NDVI data sets (Fig.2). All statistical analyses and image processing operations were conducted with R statistical software and various Quantum GIS plugins, respectively.

3. RESULTS

The comparison and cross calibration analysis results by scatter plots is indicated in Fig.3. Result exhibit that images that had the similar atmospheric correction (DOS1) displayed highest correlation coefficient close to 0.89. However, images acquisition time were different. The cross calibration between Landsat 8 OLI L1TP (higher level product) and Sentinel 2A level L1C (top of atmosphere reflectance) had lower correlation coefficient approximately 0.79. Moreover, Sentinel 2A images that were done atmospheric correction by Sen2Cor showed moderate correlation equal to 0.82 with Landsat 8 OLI L1TP (higher level product). Exploring boxplots range values displayed that all mean NDVI range values were almost similar in most obtained results (Fig.3).

4. DISCUSSION

The present study tried to explore the NDVI data continuity between Sentinel2A and Landsat 8OLI in a temperate forest. Results showed correlation coefficient was approximately greater than to 0.8 approximately 0.89 which reveals good consistency between two data set which is in agreement with conducted researches [1], [8]. Moreover, examining and investigating the boxplots indicate the NDVI range varies and almost similar in both sensors approximately in observed results. Interestingly, the higher the correlation coefficient was, the NDVI range values were similar in two data sets. The highest correlation coefficient between Landsat OLI NDVI and Sentinel2A NDVI is obtained close to 0.89 by DOS atmospheric correction approach. Even though, in most conducted investigations tried to use images with similar acquisition time specially on the same day which correlation coefficient were close to 1 [1], [7]. It has been emphasized that the time leaps are one of the factors that impacts on the results [1]. However, we observed there is no any difference in achieved correlation coefficient when there are 12 days' time leaps. Although, it should be taken into account impacts of environmental condition, images acquisition time, sun azimuth, and etc. on the results in further investigations.

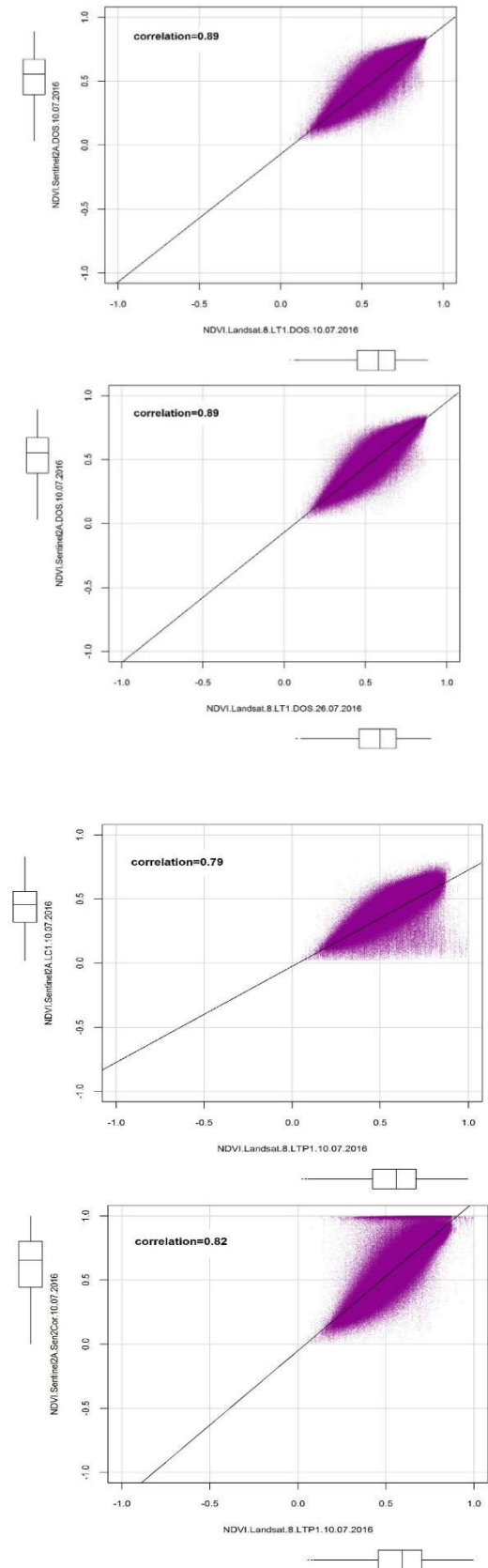


Figure 3. Scatterplots of the Normalized Difference Vegetation Index (NDVI) derived from Landsat 8 OLI and Sentinel 2A and Pearson's correlation coefficient

4. CONCLUSION

Research finding implies that Landsat OLI 8 NDVI and Sentinel2A NDVI is almost consistent and had good compatibility in the Çamlıyayla forest district. We recommend that it is necessary to implement similar preprocessing process on images and introducing suitable atmospheric correction techniques that could reduce uncertainties in the long-term land monitoring studies. Implementing geo-shift R code could be the best way to reduce the errors caused by applying the geo-registration and resampling on the images to match NDVI data to each other which is pointed out mainly an issue in recently conducted researches. Finally, it can be expressed that Landsat OLI 8 NDVI and Sentinel2A NDVI can be used as a complementary data that was the one of the ESA mission aims and considering them as a valuable data source for consistently forest monitoring (such as forest phenology, biodiversity, forest health, climate change). In addition, further investigating continuity studies should be implemented in other forest types and other available vegetation indexes such

as Enhanced Vegetation Indices (EVI), Normalized Difference Water Index (NDWI), and etc. is recommended.

Abbreviations

MSI	Multi-Spectral Instrument
NDVI	Normalized Difference Vegetation Index
OLI	Operational Land Imager
DOS1	Dark Object Subtraction1
L8 OLI L1TP	Landsat 8 OLI higher level product
L8 OLI L1T	Landsat 8 OLI Level 1 product generation system (LPGS)
Sentinel 2A Level-1C	TOA reflectance (top of atmosphere reflectance)

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WIND SPEED ESTIMATION ENHANCEMENT USING SAR DESPECKLING FROM C-BAND SENTINEL-1 IMAGES

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ABSTRACT

Sea surface wind speed plays an essential role for the investigation of several oceanic applications. This parameter can be estimated through Synthetic Aperture Radar (SAR) images using Geophysical Model Functions (GMFs) approaches i.e. CMOD.5 empirical method. However, SAR data suffer from an inherent dilemma called Speckle Noise that complicates the visual interpretation of the image and causes a bad estimation of parameters. In order to mitigate the adverse effects of this multiplicative noise, several approaches have been proposed especially SAR filtering approach. This paper deals with adapting speckle noise reduction while applying SAR despeckling process for wind speed retrieval. It aims estimate wind speed using CMOD.5 empirical method from SAR images in VV-polarization. This will be done, in a first step, without the filtering process and then, by adding two mainly used filters in the scientific community: Lee filter and NL-SAR filter. In fact, all published works in this field, do not address SAR despeckling process for wind speed estimation. After referring to the Advanced Scatterometer (ASCAT) Data measurements used for validation, numerical results on Sentinel-1 data showed that the the filtering step's adoption allows an accurate estimation of wind speed. Thus, Speckle noise reduction stage is essential for a better wind speed estimation.

Index Terms— Synthetic aperture radar (SAR), Speckle noise, Sea wind speed retrieval, CMOD.5, ASCAT Data.

1. INTRODUCTION

Seas and oceans are a central part in the climate balance of our planet. Their observation by modern methods such as sensors embedded on satellites is fully integrated in our daily life [1]-[2]. Furthermore, the use of active sensors emitting microwaves seems perfectly natural to provide global measurements of sea surface from space [1]. Synthetic Aperture Radar (SAR) is defined as a microwave imaging active system which has cloud-penetrating capabilities [2] and is particularly useful for wind vector estimation since it provides stable operations in most meteorological conditions and revisit mode periods. On Indeed, Sea Surface Wind plays a

crucial role for the studies of several oceanic applications for instance: oil slick observation, sea mapping and ship detection. For that, the estimation of this parameter seems to be important. Actually, wind speed can be estimated thanks to the use of various methods such as numeric weather models, In-Situ Measurements and SAR data technique [3] from which several methods are used to retrieve wind speed including Electromagnetic (EM) Methods and Empirical (EP) Methods, i.e. CMOD.4 [4], CMOD.5 [5], and CMOD.5N [6]. It is noted that CMOD.5 and CMOD.5N are widely used because of their accuracy for most wind regimes [5]-[6]. Meanwhile, Speckle Noise is a fundamental characteristic of SAR imagery which is defined as the grainy Salt-and-pepper caused by the interaction of out-of-phase waves with a target [7]. In fact, this phenomenon decreases the utility of satellite images since it reduces the ability to detect ground targets, obscures the recognition of spatial patterns [8]. Consequently, it not only complicates visual interpretation of the image, but also causes bad estimation of the parameters [8]. To our knowledge, there is no research that focuses on reducing the bad effects of speckle noise for a better wind speed estimation. For this purpose, we will discuss the accuracy of wind speed retrieval after speckle noise reduction.

The rest of the paper is organized as following: In section 2, we will describe wind speed retrieval process and the filtering approaches applied for this purpose. Then, in section 3, we will define the acquired Sentinel-1 images used in this paper. Section 4 illustrates wind speed estimation experimental results. Finally, this paper summarizes the conclusions and perspectives discussed in this study.

2. METHODOLOGY

In this section, we present the process used for estimating sea wind speed from Sentinel-1 images. In addition to that, we illustrate the SAR despeckling approaches that are evaluated during the filtering step.

2.1. Wind Speed Retrieval Process

The main objective of this paper is to demonstrate whether we proceed with the Speckle Noise Reduction step during wind

speed retrieval process or we will neglect the filtering part and focus only on estimating wind speed from noisy SAR data. Thus, the process is detailed in the organigram depicted in Fig. 1 which illustrates the adopted Methodology.

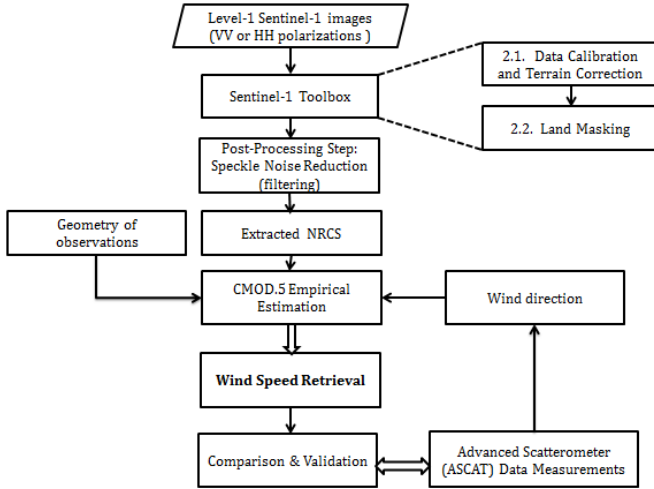


Fig. 1: Diagram of Wind Speed Retrieval from Level-1 Sentinel-1 images

2.2. Description of used filters

In order to evaluate SAR despeckling effect on wind speed estimation process, we propose to work with two main family of approaches: the spatial-based approach illustrated by Lee filter [9] and the non-local approach figured by the NL-SAR filter [10]. These widely known filters are described as following:

- *Lee Filter* [9]: a spatial approach that adapts the additive noise to the multiplicative noise by introducing a linear approximation to transform Speckle Noise expression to the sum of the signal and an additive noise independent of the signal. For this filter, we focus on using a 7×7 window size, a number of looks L equal to 1 with only one iteration.
- *NL-SAR Filter* [10]: a general method that evaluates non-local neighbourhoods based on multi-channel comparison of patches for denoising different types of SAR images. NL-SAR filter supports single and multi-look images and it shows interesting results for resolution preservation. The equivalent number of looks used L in this approach is equal to 1, with a 7×7 patch size and 21×21 window search size.

3. ACQUIRED DATA

The data used in this paper is provided by C-Band Sentinel-1 Satellite over the study region of Brazil country and partic-

ularly São Paulo City Coastline (Port of Santos) located between $(-46.47^\circ, -46.94^\circ)$ longitude and $(-24.39^\circ, -22.66^\circ)$ latitude. Moreover, this SAR image is acquired a Stripmap (SM) acquisition mode, in Jun, the 11th, 2017 from 21:43:33 UTC to 21:44:02 UTC as a Single-Look Complex (SLC) Product in dual polarization VV&VH that we will only focus on VV-polarization as sketched in Fig. 2.

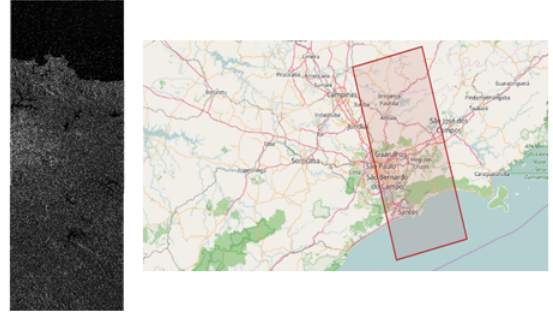


Fig. 2: S1A – SM – SLC – Intensity – pol – VV – 20170611T214333UTC – 20170611T214402UTC.

4. EXPERIMENTAL RESULTS

This section aims to mention either we should proceed with the post-processing step (SAR despeckling) or not for wind speed estimation process and evaluate the accuracy of the obtained results using a comparison with ASCAT data measurements. For that, Fig. 3 illustrates wind speed estimation of a selected patch, derived from the acquired data described previously (size: 6000×3000), for the noisy image (affected with Speckle) and filtered images using Lee and NL-SAR filters. As for Fig. 4, it shows the ASCAT data measurements obtained for the Brazilian Coastline in the same date (almost the same time) of the acquired Sentinel-1 image. By analyzing these figures, it is clear that we obtain a bad estimation of wind speed for the noisy image. However, while proceeding with Lee filter and NL-SAR filter, we reach wind speed results which are quite similar to those given by the ASCAT measurements. In fact, wind speed values are between 5 and 10 knots near the coastline of the SAR image. Nevertheless, these values decrease and become between 2 and 5 knots as we go far from the coastline. Besides, we must mention that NL-SAR filter performs better than Lee filter in terms of Speckle noise reduction and good resolution preservation. Thus, we conclude that speckle noise reduction stage is essential for a better wind speed estimation.

5. CONCLUSIONS

This paper focused on the ability of applying SAR despeckling for a good wind speed estimation from SAR images

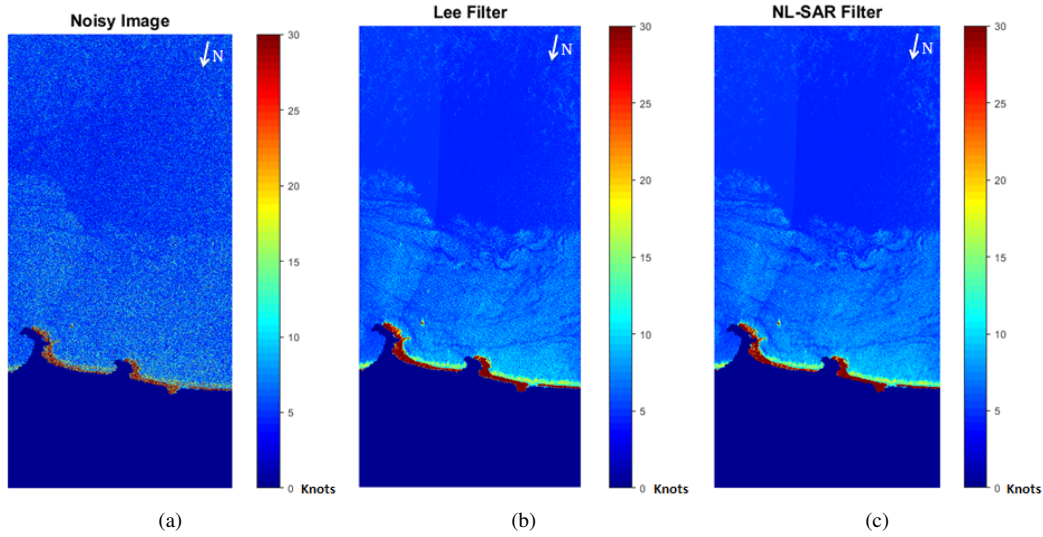


Fig. 3: Wind Speed Estimation from VV-pol Brazil Sentinel-1 image: (a) Noisy SAR image, (b) filtered Image with Lee, (c) filtered Image with NL-SAR. The size of the selected Patch is 6000×3000 (Wind direction is estimated as $\phi = 90^\circ$).

in VV-pol using CMOD.5 Empirical approach. Concerning SAR data in HH-pol, we discover interesting results that we hope to publish in another paper. In further research, we plan to generate an algorithm for the processing stage (Radiometric Calibration and Land Masking) in order to avoid working with the Sentinel-1 Toolbox. Furthermore, we think of substituting CMOD.5 Empirical Method by Electromagnetic approaches such as SPM process for the sake of comparing wind speed estimation using both EM and EP approaches.

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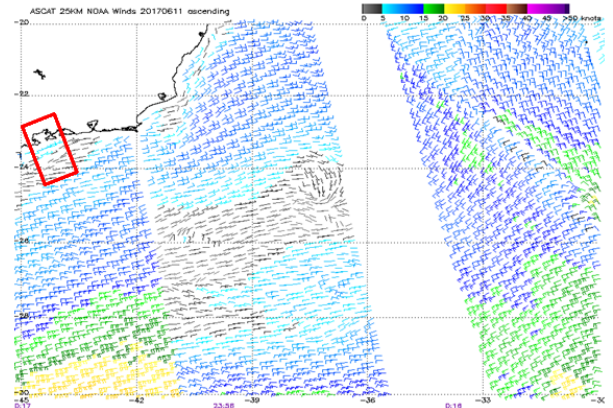


Fig. 4: ASCAT Data Measurements of the Brazilian Coastline

HYDROLOGICAL MULTITEMPORAL STUDY OF THE MOUNTAIN REGION IN THE STATE OF RIO OF JANEIRO (BRAZIL) THROUGH SATELLITE DATA AND IN-SITU DATA.

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KEY WORDS: Remote Sensing, Landsat-8, Landsat 4 & 5, Sentinel-2, Classification, Soil and vegetation index,

ABSTRACT:

This project is based on a multitemporal hydrological study of the Mountain Region in the state of Rio de Janeiro (Brazil) through satellite data (Landsat 4 & 5, Landsat-8 and Sentinel-2) and in situ data. Using this technology and digital processing tools of remote sensing as Supervised and Unsupervised classification, vegetation and soil index, we will obtain a correlation between different physical soil variables in two temporary ranges (2010-2011 and 2016-2018). From the result we will analyse and discuss the significant soil and environmental changes in the Mountain Region. In addition, the project follows a very recent area though we will soften the devastating effects of tropical rains which annually affect the Brazilian state of Rio de Janeiro. The communities more vulnerable suffer climatic risks as floods and landslides due to construction features and location.

1. INTRODUCTION

The hydrological study includes the central mountain region in the state of Rio of Janeiro (Brazil). Last years, the area has been affected by the Amazonian rains which have caused severe floods and landslides. This paper aims to establish a line of study extrapolated to other areas of the Brazil which have also suffered the consequences of tropical rains (Vásquez et al, 2015; Marchamalo et al, 2014; Rejas et al, 2012).

Through satellite images from Landsat-8 and Sentinel-2 to current time range (2016-2018) and images from Landsat-4 & 5 to old temporary range (2010-2011) and the data obtained during the in situ campaigns in 2017-2018 , we intend to establish a correlation between both soil and vegetation data that allow raise the possible technical measures to avoid the catastrophic consequences due to these climatic phenomena.

The project consists of a first step more theoretical and a second more practical where we have introduced the geographical information system (GIS) and remote sensing tools completed with the field work. In the first step, we have investigated and compiled information about event extreme weather that affected the fluminense mountain region during the last twenty years.

On the other hand, in the second part of the study we have recollected in situ data to carry out several correlation analyses and a validation phase.

2. STUDY CASES AND DATA SETS

The study is located in the Brazilian state of Rio of Janeiro and is focused in the Mountain Region (Teresópolis, Nova Friburgo and Guapimirim).



Figure 1: Location of region of study in the state of Rio of Janeiro (Brazil)

We have used six reflectance scenes of sensors. Two reflectance scenes of Landsat 4 & 5 sensor to the 2010-2011 temporary range (*July 12nd 2011 and March 3rd 2010*) , two scenes of Landsat-8 and two scenes of Sentinel-2 to the 2016-2018 current temporary range (*August 29th 2017 and January 31st 2016*). All of them were acquired in the two different

Brazilian seasons (rainy and dry season) in the same temporary ranges: 2010-2011 and 2016-2018.

We selected 2010-2011 range because in January of 2011 occurred the greatest climate catastrophe in the history of Brazil and took place in this region, the Mountain Region in Rio of Janeiro (Vásquez et al, 2015;Mendoza et al, 2008).

We adquired all the images from the *Earth Explorer* that consists on a search, discovery and ordering online tool, created by the United States Geological Survey (USGS).

Sentinel-2 is a mission released by European Space Agency (ESA) through Copernicus Programme and presents data from 13 spectral bands of VNIR and SWIR. Landsat-8 presents two new sensors OLI (with 9 spectral bands) and TIRS (with two spectral bands) (Marchamalo et al, 2014).



Figure 2: Real colour combination RGB 321 of August 29th 2017 (Sentinel-2) and July 12nd 2011 (Landsat 4 & 5) scenes.

3. DIGITAL PROCESSING AND METHODOLOGY

The methodology used for the study is:

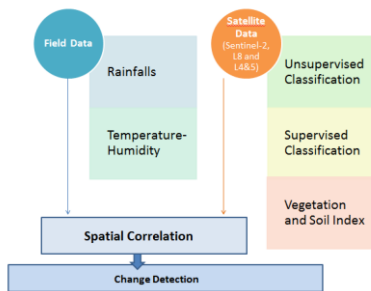


Figure 3: Methodology

3.1. Image Classification

For this analyse we have used the unsupervised digital classification and supervised digital classification tools to identify the different categories surfaces and its temporary evolution.

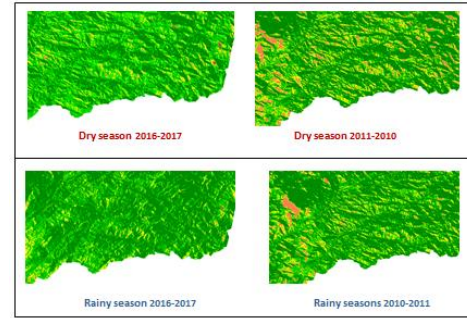


Figure 4: Result of Unsupervised classification of Landsat scenes.

The algorithm classifier in the unsupervised classification does not need any more information that the own scene and some parameters that limit the number of classes. Based in previous experiences, this method is used when we do not know the soil characteristics of the area since the surface spectral characteristics are not defined clearly in the image. We have done the same process for all the images through K-Means algorithm with ten classes and five interactions (Rejas et al, 2012); Richards et al,1986; Chang et al,2007).

On the other hand, in the Supervised Classification we have already known the identity and location of some type of elements (Region of Interest) due to field work. The algorithm used is based on the method of the spectral angle which has already used in previous analyses (Rejas et al, 2012).

$$\theta(x, y) = \cos^{-1} \left(\frac{\sum_{i=1}^n x_i y_i}{(\sum_{i=1}^n x_i^2)^{1/2} * (\sum_{i=1}^n y_i^2)^{1/2}} \right) \quad (1)$$

First of all, we have established seven classes and three macro classes (Vegetation, Soil and Water) to define all types of region interest in the analysed area.

Macro-class	Macro-class ID (MC)	Class	Class ID (C)
Vegetation	1	High vegetation	1
Vegetation	1	Less dense vegetation	2
Vegetation	1	Plain vegetation	3
Soil	2	Urban soil	4
Soil	2	Nake soil	5
Water	3	Water	6
Non-classified	0	Non-classified pixels	-

Table 1: Definition of Macro-classes and classes in the supervised classification

The green and yellow colours represent the vegetation macroclass, pink and brown colours are the soli macroclass and water is reflected with the blue colour.

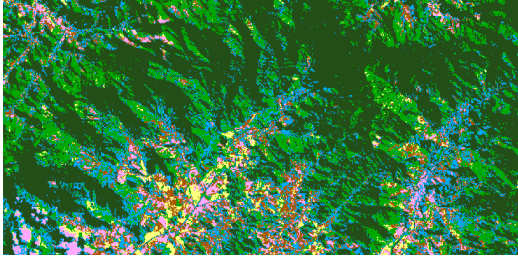


Figure 5: Colour map of the central area of the Supervised-classification of dry season, August 29th 2017.

From the colour Unsupervised Classification map, we observed that the majority macroclass in all the scenes is the vegetation with average values of 1.710,82 km² (31, 7%) of high vegetation, 700 km² (12,9%) of less dense vegetation and 146 km² (2,7%) of plain vegetation. With the Supervised Classification the average values are inferior to the previous unsupervised classification obtained, with 25% (class 1), 9,7% (class 2) and 1,5% (class 3).

To verify the veracity of classifications is necessary calculate the *Confusion Matrix*. This is a estimation of accuracy which is used as quantitative method and needs a reference image with area real data. Using this method we analyse the number of pixels that were bad-classified and what kind of classes are similar (Chandger et al, 1986; Hollinger et al, 2005).

The Kappa Coefficient calculated by the Confusion Matrix for all the images were between values of 0,75 and 0,95. So it is an indicator of a good supervised classification.

Image	Method	Kappa coefficient
Landsat-8 (29-08-2017)	Supervised classification Spectral angle	0,95736
Landsat-8 (31-01-2016)	Supervised classification Spectral angle	0,8507
Landsat 4&5 (12-07-2011)	Supervised classification Spectral angle	0,8320
Landsat 4&5 (06-05-2010)	Supervised classification Spectral angle	0,7950
Sentinel-2 (29-08-2017)	Supervised classification Spectral angle	0,8340
Sentinel-2 (31-01-2016)	Supervised classification Spectral angle	0,8067

Table 2: Kappa coefficient of all classified scenes.

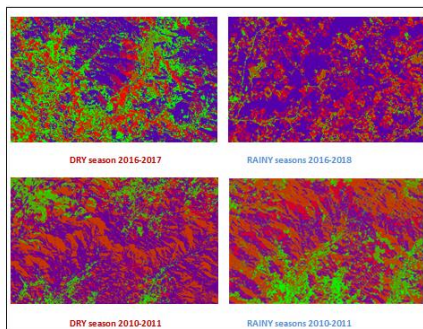


Figure 6: Colour maps of the Confusion Matrix in different images.

3.2. Index Classification

Vegetation indeces and soil have been calculated for the set of images. These image transformations were carried out with the intention of assess the influence of vegetation cover in the subsequent image analysis and estimate the land cover changes during the temporary range (Rejas et al, 2012).

The Brightness Index algorithm (BI) consists on the brightness average in all of the satellite images. So, this index is sensitive to the brightness of the ground which shows a high correlation between the humidity and the presence of salt in the Earth's surface. The result is giving by the expression:

$$BI = (R^2 + G^2)^{1/2} / 2 \quad (2)$$

Where R is the spectral resolution in the red band (B3) and G is the spectral resolution in the green band (B2).

The Soil Ajusted Vegetation Index (SAVI) minimizes the effect of the reflectance of the soil through *the L factor*. This factor is constant to adjust the correlation vegetation-soil to the reality and its normal value is about 0,5. The SAVI is obtained by the formula:

$$SAVI = \frac{\rho_{NIR} - \rho_R}{(\rho_{NIR} + \rho_R) + L} * (1 + L) \quad (3)$$

Where ρ_{NIR} is the reflectance of the near-infrared band and ρ_R is the reflectance of the red band.

The Normalized Difference Vegetation Index (NDVI) has been the most used index in remote sensing in the last twenty years. It is calculated as the difference in reflectance between the near-infrared band and red band and the sum of these bands. NDVI is an indicator of the greenery of the biomass and takes values from -1 to 1.

$$NDVI = \frac{\rho_{NIR} - \rho_R}{(\rho_{NIR} + \rho_R)} \quad (4)$$

All of this digital processing has been contrasted with the field data obtained during the visits to the region of interest (Teresópolis and Nova Friburgo). We visited the most significant points where stronger landslides occurred in January 2011. We took essential soil data to the hydrological study as moisture, temperature, precipitation, etc. Furthermore, visiting the area we discovered the different types of land cover and, for this reason, the digital processing of supervised classification was more precise due to the knowledge of the region.

4. DISCUSSION AND COMPARATIVE ANALYSIS

The multitemporal analysis of the evolution of the land cover and the water is a key piece to understand the conditions in the past and in the future. The main objective consists on determining and analysing those important changes over a period of eight-ten years that modify the environment in the Mountain Region of Rio of Janeiro state. Comparing the different soil classification calculated, the vegetation and soil index obtained (NDVI, SAVI, BI) and field data we can observe the area changes over the eight years.

From the results, we observed that the majority vegetation percentage corresponds to high vegetation in all of index calculated, BI (0,05-0,1), SAVI (-0,3-0,1) and NDVI(-0,3-0).

It has been established a clear relationship between vegetation changes and two Brazilian seasons (dry and rainy season). NDVI and SAVI show an increase in high-mountain vegetation (nascent or less dense vegetation) after the rainy months (January, February and March). The main reason of this effect is the relationship between heavy rains and poor land cover on the slopes of the mountains which causes landslides since the ground is not able to absorb all of rainwater.

The results of digital supervised classification also shows a temporary evolution in the types of regions of interest. In the 2010-2011 temporary range the percentage of naked soil in Teresópolis and Nova Friburgo was 58,4 km² (1,08%) approximately the double that in the successive years, 22,7 km² (0,41%).

From the analysis of correlation soil data we have observed a growth of the urban soil and sub-mountain vegetation (more dense) in both cities.

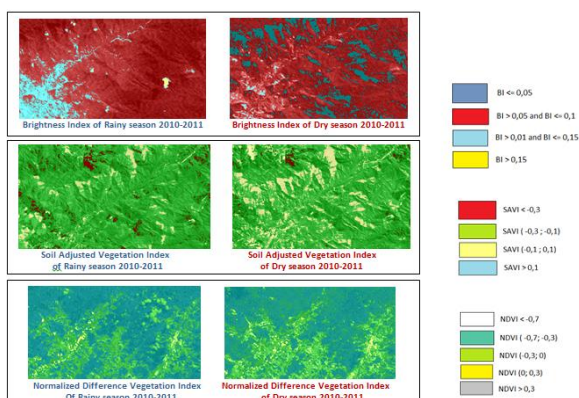


Figure 7: BI map, SAVI map and NDVI map of different scenes.

5. CONCLUSIONS

The characteristics of high resolution data, both spatial and spectral, and field data for vegetation and soil covers in the Mountain Region of Rio of Janeiro (Brazil)

have been studied by different spatial data (L4&5, L8 and Sentinel-2). This paper evaluates the land changes in two temporary scenes, 2010-2011 and 2016-2018, for Teresópolis and Nova Friburgo (state of Rio of Janeiro).

There is a decrease in the percentage of naked soil from 1,08% to 0,41% in the central area of the Mountain Region from 2010 to the present. In addition, the index results show an increase of high mountain vegetation after rainy season in both temporary ranges.

Sentinel-2 (Copernicus) gets improved results since it presents best spatial characteristics (resolution and reflectivity).

The technical and results of our study follow a current research-line that is necessary for the purpose of the detection, prevention and investigation of the climate changes that our planet is experiencing.

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HIGH RESOLUTION BATHYMETRY OF LITTORAL ZONES BASED ON VERY HIGH RESOLUTION WORLDVIEW-2 IMAGES

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ABSTRACT

Very high-resolution remote sensing imagery of coastal areas provides valuable information, where the highest biodiversity of the planet accumulates. With the great improvements in spatial resolution obtained in recent years for the satellite WorldView-2 (WV2), we have available very high-resolution images with a sub-metric panchromatic band and multispectral bands below two meters resolution. Its eight multispectral bands allow obtaining a greater spectral information of the complex coastal environments, allowing more complex algorithms for coastal monitoring. These new features allow the detection of the coastal seabed with sufficient resolution for bathymetric and benthic studies. This research, in the frame of the ARTEMISat-2 project, has developed algorithms based on Radiative Transfer Modeling of the seawater (RTM) to obtain high-resolution bathymetries using WorldView-2 images.

Index Terms— WorldView-2, RTM, bathymetry.

1. INTRODUCTION

The use of multispectral imagery from satellites such as MODIS, Sentinel-2, Landsat-8 and others has allowed the development of multiple marine applications such as the estimation of chlorophyll, suspended matter, dissolved matter contents in seawater. Due to the particular characteristics of water absorption, it is necessary to use spectral bands between 400-700 nm for the correct study of the vertical water column and the coastal seabed. For this purpose, the use of multiple spectral bands with reduced bandwidths is desirable. In this aspect, the WorldView-2 and later WorldView-3 satellites provide eight multispectral bands in the VIS-NIR spectra. The first six bands are in the adequate range for the coastal waters study, greatly improving the four bands RGB-NIR of the regular high-resolution satellites.

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The atmospheric correction is an essential step to obtain the reflectivity in coastal areas. Due to the low reflectivity of the water, thus it is critical to make an adequate correction. To this end, an atmospheric correction model (Second Simulation of a Satellite Signal in the Solar Spectrum: 6S) [1] has been used. Bathymetry computation requires the execution of a Radiative Transfer Model (RTM) [2] that jointly calculates all the elements involved in the reflectivity of coastal water. These elements are the water quality parameters (content of chlorophyll, dissolved and sustained materials), bathymetry and coastal albedo. Estimating water depths and seabed albedo using RTM model has yielded good results by considering the physical absorption-backscattering water phenomena. In this way, the seabed reflectivity contribution depends on the bathymetry and the bottom albedo, which is disturbed by the effects of the water. In this work, an efficient multispectral physics-based model has been developed for obtaining high-resolution bathymetry maps. The results of the bathymetry maps based on WorldView-2 images have been evaluated in this study by comparison with bathymetric data obtained by sonar.

2. VERY HIGH RESOLUTION WV2 PRE-PROCESSING

This work is based on Ortho Ready Standard WV2 imagery. WV2 with 11-bit of radiometric resolution have nine multispectral bands: coastal, blue, green, yellow, red, red edge, NIR1 and NIR2. In the Ortho Ready product, the image resolution is resampled to 2.0 m x 2.0 m, providing a nominal swath of 16.4 km. The area of study is Canary Islands coast, off the northwest African coast, as we can see in the Figure 1. We can see a location in Corralejo area (Fuerteventura Island) and another location in Maspalomas area (Gran Canaria Island).

In the preprocessing step, the 6S atmospheric correction model and a sunglint removal algorithm was implemented. The 6S model was configured with the correct parameters of geometrical atmospheric conditions, aerosol model and concentration, spectral bands and ground reflectance for the corresponding areas of study.

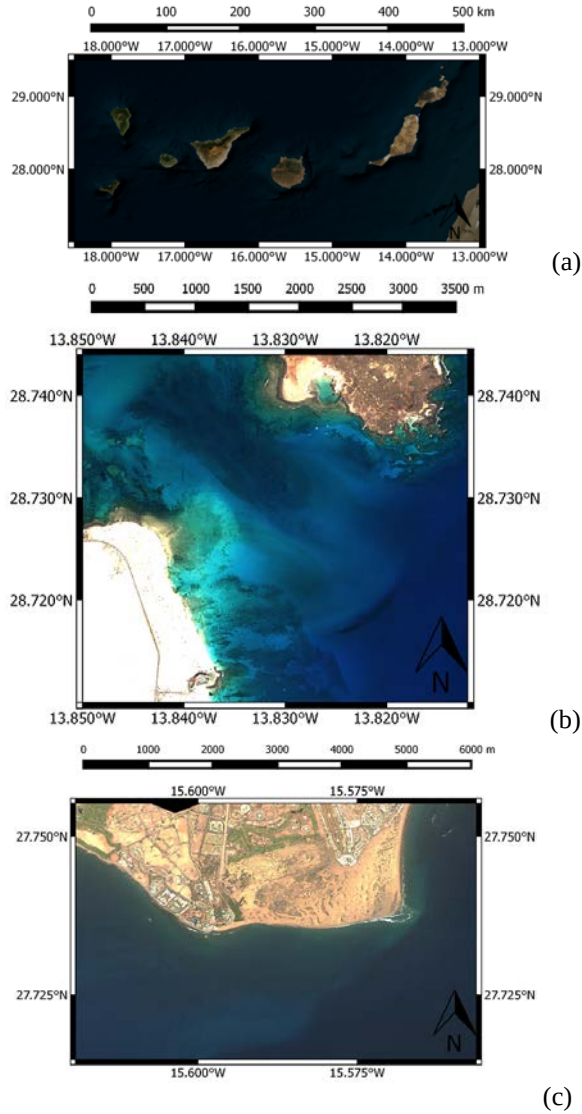


Figure 1. Area of study location: (a) Canary Islands, (b) WV2 image Corralejo (Fuerteventura Island), (c) WV2 image Maspalomas (Gran Canaria Island).

The specular reflection of solar radiation on water surface is a serious confounding source of noise for remote sensing in shallow water environments. For this reason, we used a combined physical principles and image processing techniques method to remove the sunglint of the image [3].

3. HIGH RESOLUTION WV2 BATHYMETRY MAPPING

After atmospheric and deglinting correction of the coastal areas, a radiative transfer modeling for remote bathymetry mapping of shallow water can be executed. This efficient multispectral physics-based algorithm is capable of solving through optimization the coastal seawater model. In this way, the RTM calculates the bathymetry within a multivariable problem where the albedo of the coastal

bottom and the inherent properties of the water or IOPs are also found [2]. The equation of the model can be expressed by,

$$r_{rs}^m \approx r_{rs}^{dp} \left(1 - e^{-\left[\frac{1}{\cos(\theta_s)} + \frac{D_u^c}{\cos(\theta_v)} \right] k_d z} \right) + \frac{\rho}{\pi} e^{-\left[\frac{1}{\cos(\theta_s)} + \frac{D_u^b}{\cos(\theta_v)} \right] k_d z}$$

Where r_{rs}^m is the modeled subsurface reflectivity, r_{rs}^{dp} is the subsurface deep water reflectivity, ρ is the seafloor albedo, θ_s is the subsurface solar zenith angle, θ_v is the subsurface view angle, D_u^c and D_u^b are the optical path-elongation factor for the water column and the coastal bottom, K_d is the diffuse attenuation and Z is the depth.

The coastal bottom albedo is generated by a linear mixing model, being the sum of the reflectivity of green algae, sand and dark sediment by their abundances,

$$\rho = (\rho_{algae} * A_{algae}) + (\rho_{sand} * A_{sand}) + (\rho_{sediment} * A_{sediment})$$

For the implementation of the gradient optimization algorithm, Levenberg-Marquardt (LMA) method was used for solving the nonlinear equations. The use of the six first bands in the VIS range increases the spectral information, allowing more precise bathymetry calculation. The initialization of the Z parameter has been performed using the ratio algorithm [4].

$$MIN_{optimization} = \sum_{ch_1}^{ch_6} \{r_{rs}^m(ch) - r_{rs}(ch)\}^2$$

4. RESULTS

Figure 2 shows the results of the preprocessing step for an example of the study of Maspalomas, in very high wave conditions, where it can be noted the great elimination of specular solar brightness, being able to observe the coastal bottom details.

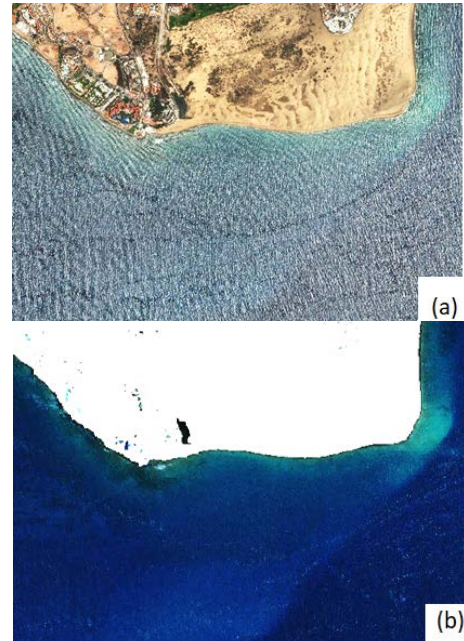


Figure 2. Atmospheric correction and deglinting for a Maspalomas area: (a) original image and (b) corrected one.

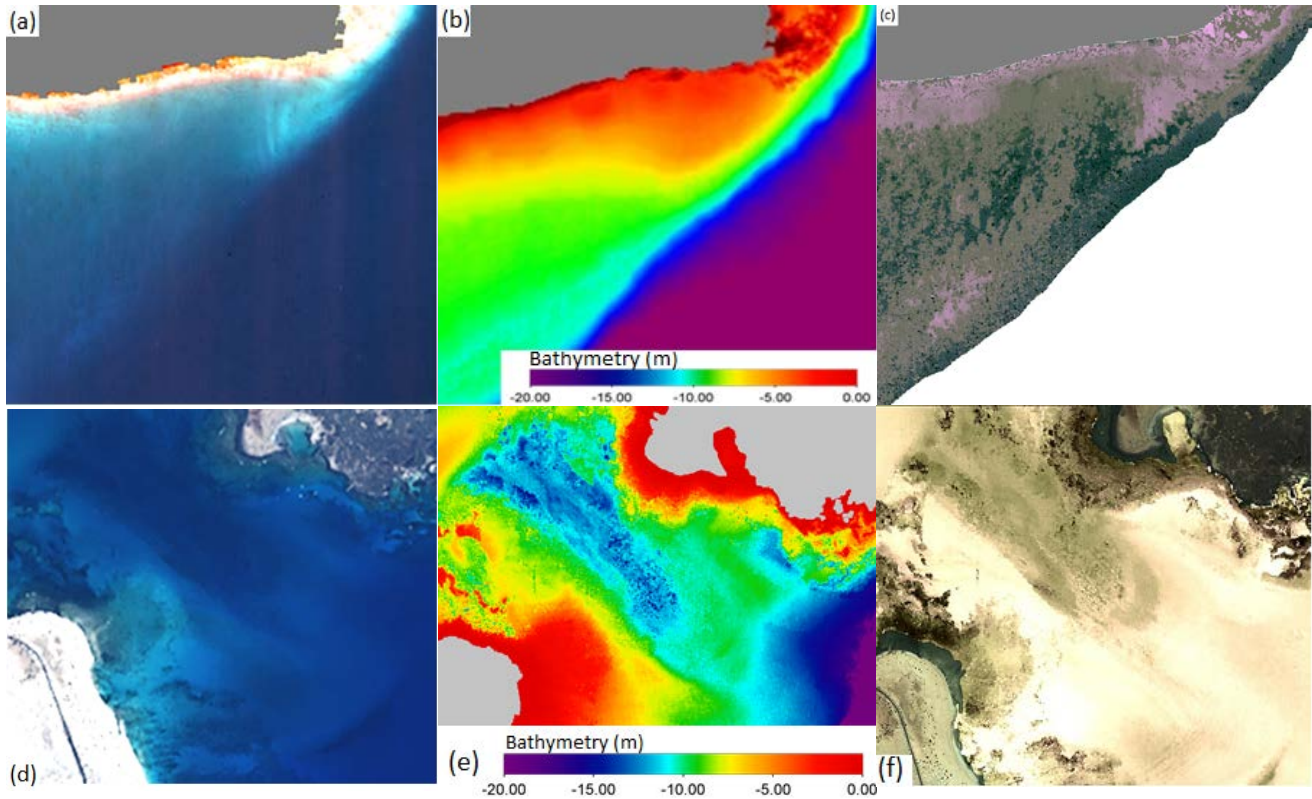


Figure 3. WorldView-2 images of areas of interest: (a) RGB composition of Maspalomas coast (Gran Canaria), (b) high resolution bathymetry of Maspalomas, (c) seabed albedo of Maspalomas, (d) RGB composition of Corralejo coast (Fuerteventura), (e) high resolution bathymetry of Corralejo, (f) seabed albedo of Corralejo.

After the execution of the radiative transfer model adapted to the WV2 bands we obtain the results of the bathymetry, see Figure 3. RMSEs less than the resolution of the pixel (2 meters) are obtained, comparing them with the bathymetry obtained by a sonar. In turn, the correlation between sonar bathymetry data and those obtained by remote sensing images reach a high level of correlation with R^2 above 0.9.

5. CONCLUSIONS

Monitoring changes in the coastal areas is fundamental for its conservation being the remote sensing data an important tool in understanding our environment. This work has confirmed the application of very high-resolution imagery to obtain bathymetry maps for shallow water areas. To obtain these results an efficient multispectral physics-based model was implemented, where it was necessary to solve a multivariable problem where both the bathymetry, the albedo of the coastal bottom and the inherent properties of water came into play. The results obtained provide errors close to the spatial resolution of the pixel (less than 2 meters), were the results have been validated with sonar data providing a good accuracy.

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Differential Tomography Model to deal with Temporal Decorrelation of Volumetric Media

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Abstract

Differential synthetic aperture radar tomography (TomoSAR) has been proven to be effective in characterizing the bi-dimensional spatial-temporal backscattering from the distributed volumetric media. The purpose of this paper is to investigate the effectiveness of differential SAR tomography under the presence of temporal decorrelation. Under the assumptions of short and long terms decorrelation (due f.i. to motion caused by winds, or to dielectric changes caused by temporal changes of the scattering properties, or to sudden decorrelation induced by rain, snow and deforestation), differential SAR tomography using model-based Capon focusing technique is evaluated for volumetric media characterization and sub-canopy ground monitoring. The analysis is performed by simulating the temporal decorrelation with different terms and including the dependence on the vertical structure of volumetric media. This is a very important aspect to be taken into account for the assessment of different sources of decorrelation in forest reality. Moreover, the experiment is extended to the P-band data set relative to the forest site of Remningstorp, Sweden, acquired by German Aerospace Center’s E-SAR airborne system in the framework of the European Space Agency (ESA) campaign BioSAR.

1 Introduction

In the context of modelling of volumetric media by means of synthetic aperture radar (SAR), different approaches have been proposed to characterize each separated scatterer using scattering polarimetry [1, 2]. Such models use multi-baseline (MB) acquisition to reconstruct the vertical reflectivity profile of forest associated with each scattering mechanism by means of SAR tomography (TomoSAR) [3]. Under some specific hypotheses [1, 2], the MB polarimetric covariance matrix is decomposed into the contributions from each scattering mechanism, which makes it possible to identify and characterize the under-foliage ground and the forest.

In case of repeat-pass MB acquisition, particularly for the spaceborne sensors, usually long-time intervals between acquisitions causes some physical changes to happen in the scatterers, and as a consequence the coherence drops quickly over the acquisition time. This turns to be a limiting factor for an accurate separation of canopy and ground in the elevation direction. Moreover, elevation focusing for partially coherent or moving scatterers leads to blurring effects. Generally, decorrelation can occur in the scatterers over the short or long interferometric time intervals. The decorrelation introduced on a short temporal scale is typically related to weather conditions and wind or temperature transitions, while the decorrelation occurring on longer time intervals is for instance due to natural vegetation growth. In addition, some anthropogenic reasons like irrigation and deforestation can be taken into account as other sources of

decorrelation [4]. In particular in case of spaceborne data of forested area, as it has been recognized by ESA and NASA-JPL, temporal decorrelation is a major problem to the applications of SAR tomography [5]. The signal received from the scatterers in MB acquisition, under the presence of temporal decorrelation, has a spatial-temporal spectrum that can affect the results of TomoSAR focusing [6]. In this context, multi-dimensional focusing or differential SAR tomography is a break-through and unified framework to decouple interference coming from noise and the signal components. Differential SAR tomography allows spectral analysis in a bi-dimensional space-time domain and producing of velocity-elevation signature of the scatterers. Typically, this technique integrates the TomoSAR concept with the concept of differential interferometry without exploiting any *a priori* assumption on the received spatial-temporal. This capability has been exploited in number of studies to avoid misinterpretation in tomographic processing and decompose a signal from a scatterer with temporal decorrelation or identify non-uniform motion of the scatterers [6, 7].

Here, to get a flavor, we assess differential SAR tomography with presence of temporal decorrelation to well identify and characterize the under-foliage ground and the forest’s canopy. We evaluate the method using simulated and quad-polarimetric P-band data acquired by E-SAR airborne system in the framework of BioSAR’s campaign.

2 Temporal decorrelation

Vegetation scenarios are usually affected by the temporal decorrelation due to the leaves falling or their motion and their natural growth. Each source of temporal decorrelation can induce different effects on the backscattering. Hence, temporal decorrelation can be considered as an ensemble of different terms and components. Generally, depending on the interferometric time interval of the SAR data, decorrelation sources can be decomposed into different terms. Temporal decorrelation induced by the motion of scatterers, for instance leaves and branches gesture by the winds, which is usually describe as a short-term decorrelation. Moreover, dependence of this term of decorrelation to the vertical direction of forest is inevitable. In [4], it has been proven that at zero spatial baseline, the decorrelation caused by random motion can be modeled as:

$$\gamma_s = \exp \left[-\frac{1}{2} \left(\frac{4\pi}{\lambda} \sigma_r(s) \right)^2 \right] \quad (1)$$

$$\sigma_r^2(s) = \sigma_g^2 + (\sigma_v^2 - \sigma_g^2) \frac{s - s_g}{h_r}$$

where s indicates the interferometric height, σ_g and σ_v are the motion standard deviation of the scatterers at the ground level s_g and at reference height h_r , respectively. From (1), the decorrelation by motion is always real valued, which changes only the backscattering amplitude.

Moreover, temporal changes of the scattering properties due to the natural growth, falling leaves and weather condition, is usually the case of long term decorrelation. By referring to [8], this term can be described using the following exponential model:

$$\gamma_t = \exp \left[-\frac{t}{\tau_r(s)} \right], \quad \tau_r(s) = \tau_g + (\tau_v - \tau_g) \frac{s - s_g}{h_r} \quad (2)$$

where t is time span of SAR acquisitions. τ_g and τ_v are the characteristic time at ground and canopy level. Here we consider that characteristic time changing along the vertical decorrelation. Accordingly, the general temporal decorrelation can be interpreted by taking into account the above-mentioned terms.

Typically, TomoSAR focusing process relies on the fact that the scene stays coherent, while this condition usually cannot be met in repeat-pass MB over the forested area. As it is well known for conventional azimuth focusing, partially coherent scatterers lead to blurring effects. In the TomoSAR case, decorrelation can impair focusing and leads defocusing and some distortions and blurring's. Hence, in order to avoid misinterpretation of TomoSAR results, decorrelation effect has to be recognized and compensated in the acquired MB time series data set. To this aim, simple adaptive beam forming technique is taken into account that is robust to the temporal decorrelation.

3 Differential SAR tomography

At a general case, the received complex signal g_n , at the n^{th} acquisition by SAR system operating at wavelength λ , range distance r , and in a given range-azimuth pixel (r, x) , after azimuth and range focusing and proper phase compensation is given by [3]:

$$g_n = \iint_{s, v} \gamma(s, v) e^{i \frac{4\pi}{\lambda r} b_n s + i \frac{4\pi}{\lambda} t_n v} ds dv \quad (3)$$

where $\gamma(s, v)$ is the complex reflectivity function in the spatial-elevation domain, Δs and Δv describe the range of possible heights and velocities, and b_n and t_n are the orthogonal baseline and acquisition time, respectively. In (3), the signal at the spatio-temporal bidimensional array is the sample of the Fourier transform (FT) of the reflectivity function, with the spatial (w_s) and temporal (w_t) frequencies being:

$$w_s = \frac{2s}{\lambda r}, \quad w_t = \frac{2v}{\lambda} \quad (4)$$

From reconstruction of the function γ in (3), differential tomography can thus jointly resolve multiple scatterer in the elevation-velocity plane. Beside the simple Fourier processing, non-parametric adaptive Capon filter can be employed to improve the resolution and decrease the peak of sidelobe level with respect to the FT technique. The intensity distribution by Capon is given by: [9]

$$P_c(w_s, w_t) = \frac{1}{\mathbf{a}^\dagger(w_s, w_t) \mathbf{R}^{-1} \mathbf{a}(w_s, w_t)} \quad (5)$$

Moreover, it is possible to adapt distributed source model to include the distribution along the spatial and temporal frequency [10]. In this regard, the popular Capon estimator can be generalized to deal with continuous spatial-temporal spectral components. Here, in order to take into account the temporal frequency bandwidth from temporal decorrelation, the generalization is extended only to the temporal frequency domain. The resulting generalized Capon estimator can be represented by:

$$P_{GC}(w_s, w_t, \Delta w_t) = \frac{1}{\lambda_{\max} \{ \mathbf{R}^{-1} \mathbf{H}(w_s, w_t, \Delta w_t) \}} \quad (6)$$

where $\mathbf{H}$ is called the covariance matrix model, and here we consider a general exponential model of decorrelation correspond to (1) and (2) in the definition of $\mathbf{H}$. Accordingly, the highest peaks in the model fitting in (6) can estimate the height location of the dominant scatterers with w_t and Δw_t as temporal frequency and its bandwidth.

4 Experimental Results

4.1 Simulated data experiments

In order to analyze and evaluate the decorrelation effects due to different terms, realistic simulations have to be performed. To this aim, a MB stack with zero temporal baselines in controlled conditions related to a forest area are produced using PolSARproSIM [11]. The forest height is 18 meters and acquisition parameters and patterns are the same as in [1]. Then, the 3D complex image $\gamma(r, x, s)$ is generated by focusing using TomoSAR concept [3]. The availability of $\gamma(r, x, s)$, allows imposing decorrelation with dependence to the vertical direction of forest. The covariance matrix of MB dataset at height of s , affected by temporal decorrelation can be represented by:

$$C(r, x, s)_{pq} = |\gamma(r, x, s)| \exp\left(-\frac{1}{2} \left(\frac{4\pi}{\lambda} \sigma_r(s)\right)^2\right) \exp\left(-\frac{|t_q - t_p|}{\tau_r(s)}\right) \quad (8)$$

where p and q denote the corresponding entity of the covariance matrix. Accordingly, $\gamma(r, x, s, t_n)$ that represents the complex scatterer at coordinate (r, x, s) and time t_n can be obtained by multiplying a random complex vector and the square root of the above covariance matrix. Hence, simulated complex SAR data that account for temporal decorrelation can be computed by projection of the all contributions of scatterers lying in the considered azimuth-range resolution cell at different heights.

Here, mild temporal effect is simulated and the average velocity of the ensemble scatterer is zero. In ideal case and without the decorrelation effect the superimposed vertical profiles from 15 selected forest pixels are reported in Fig. 1, where the profiles obtained by Capon and multi-signal classification (Music) techniques [9]. The presence of dominant peaks corresponding to the canopy and ground locations are evident from both reconstruction techniques, where, as expected, result by Music (Fig. 1b) shows more effective super-resolution capabilities. However, as it has been reported in [6], and in comparison, with Capon, Music is strongly affected by the second term of temporal decorrelation effects. Here, we analyzed the capability of these techniques when both terms of decorrelation are presented simultaneity. In Fig. 2, the reconstructed profiles under presence of decorrelation are shown. Two peaks still are visible in Capon profiles however (Fig. 2a), the resolution is slightly reduced. In contrast, the decorrelation has strong effect on the results of Music (Fig. 2b) and resolution is worsened (the ground and canopy cannot be distinguished). Hence, it can be declared that Capon is more robust technique to Music, and accordingly, generalization of Capon can be more constructive technique to the generalized music one. In the following we reported

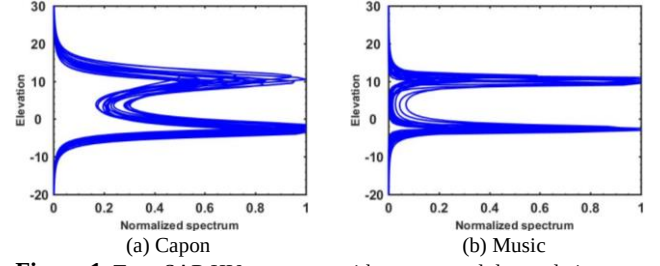


Figure 1. TomoSAR HV spectra without temporal decorrelation.

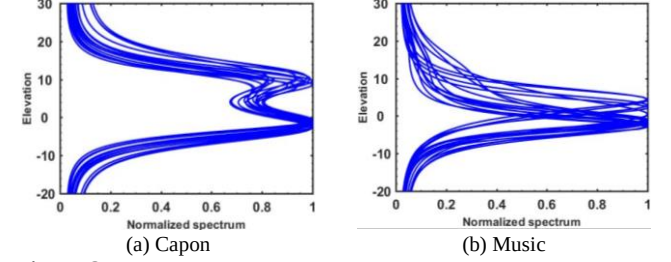


Figure 2. TomoSAR HV spectra with temporal decorrelation.

the results of differential tomography by generalized Capon.

A typical implementation of differential tomography using classical (5) and generalized (6) Capon in the presence of mild decorrelation is shown in Fig. 3. Intensive blurring and defocusing effect can be observed in the result by classical Capon, in which ground and canopy are hardly distinguishable, while two peaks are clearly visible with generalized capon focusing and the result is more similar to the original data without decorrelation effect.

We extended our analysis to evaluate the efficiency of generalized Capon in identification of different scattering mechanisms using the fully polarimetric MB data set. To do this, two different decomposition techniques 1) sum of Kronecker product (SKP) [2], and 2) three-component technique [1], have been employed. SKP decomposes the estimated fully polarimetric covariance matrix to the contributions of

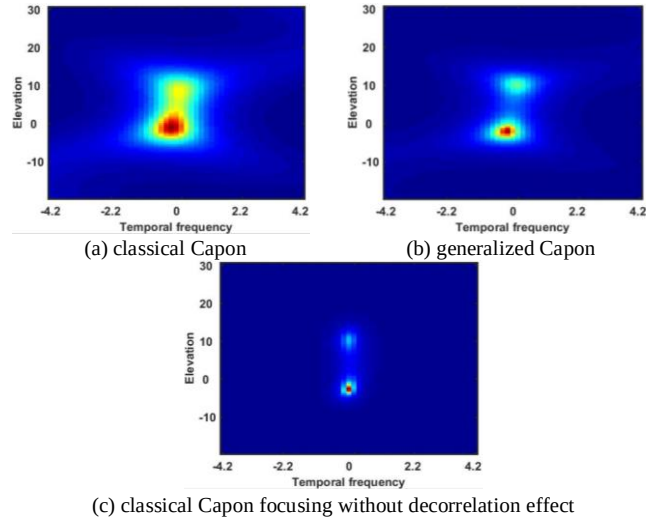


Figure 3. Differential TomoSAR images in HV polarization, (a) and (b) with and (c) without presence of temporal decorrelation.

ground-only and canopy-only covariance matrices, while three-component approach is able to compute the surface, double-bounce and volumetric scattering contributions. After the decomposition of polarimetric MB covariance matrix with presence of temporal decorrelation, differential tomography is applied to the obtained covariance matrices and the results are reported in Figs. 4 and 5. The average velocity for canopy and ground are zero and therefore it is expected to have focused images around zero temporal frequency. Although, canopy-only, surface and volumetric scattering are well focused with classical capon, however, the ground-only and double-bounce

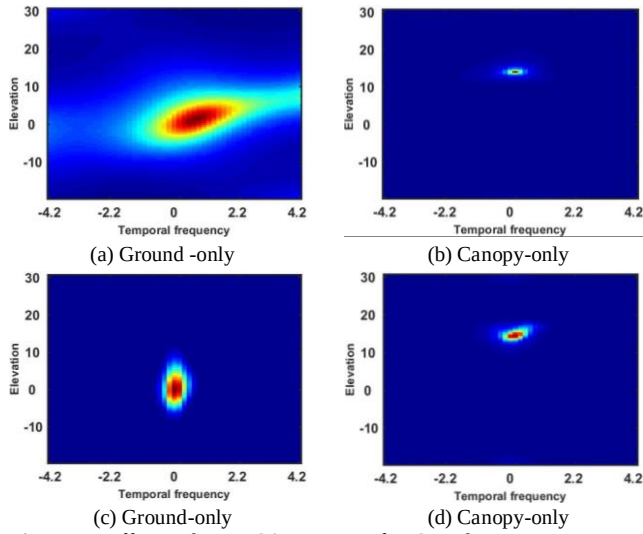


Figure 4. Differential TomoSAR images after SKP decomposition. Upper and lower images are Capon and generalized Capon based focusing

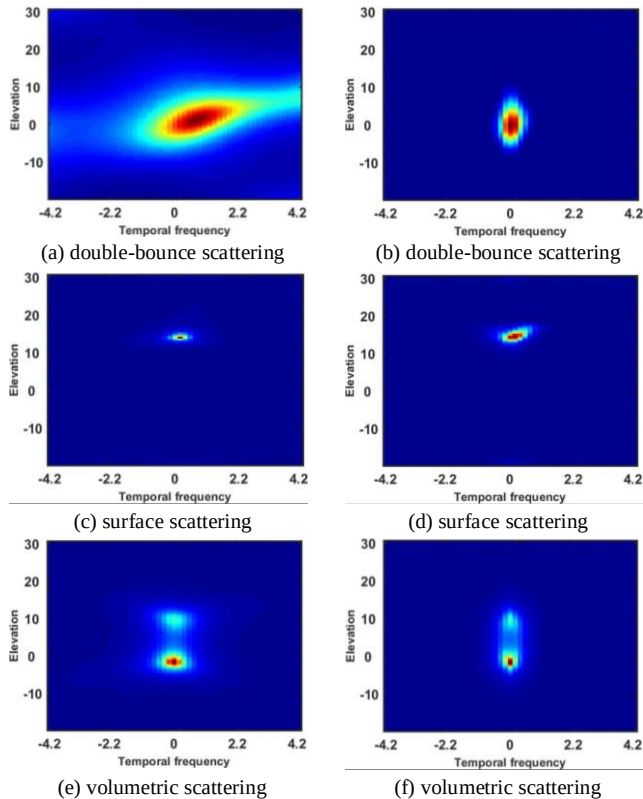


Figure 5. Differential TomoSAR images after three-component decomposition. Left and right images are Capon and generalized Capon based focusing.

(Figs. 2a and 3a) are strongly affected with the temporal effect and unacceptable results are obtained, while this problem is addressed using generalized focusing technique.

4.2 Read data experiments

The experiment on real data has been performed using 9 P-band fully polarimetric SAR images of the forest site of Remningstorp, Sweden, acquired by German Aerospace Center's E-SAR airborne system from March to May 2007, in the framework of the European Space Agency (ESA) campaign BioSAR 2007. The overall baseline is 80 m corresponding to elevation Rayleigh resolution of 19m. The time span is 2 months and temporal frequency Fourier resolution is thus 0.5 phase cycles per month. The preliminary results of differential tomography from HV polarimetric covariance matrix using classical capon together with the generalized capon are shown in Figs. 6. It is expected that result from HV polarization be more affected by canopy contributions, and this clearly is in agreement with the differential TomoSAR image obtained by generalized Capon (Fig. 6b). Moreover, the results of differential tomography from the decomposed fully polarimetric covariance matrix are presented in Figs. 7 and 8. In analogous to the simulated case, TomoSAR images of ground-only and double bounce (Figs. 7a and 8a) by classical Capon based reconstruction are highly affected by side-lobes.

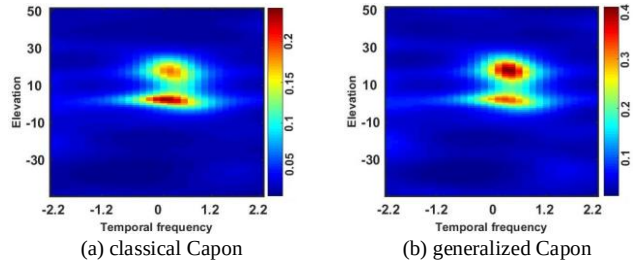


Figure 6. Differential TomoSAR images in HV polarization (Real data set).

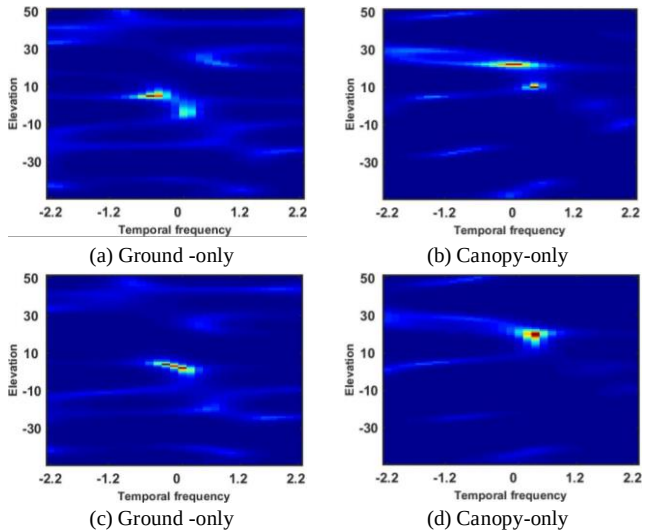


Figure 7. Differential TomoSAR images after SKP decomposition. Upper and lower images are Capon and generalized Capon based focusing (Real data set).

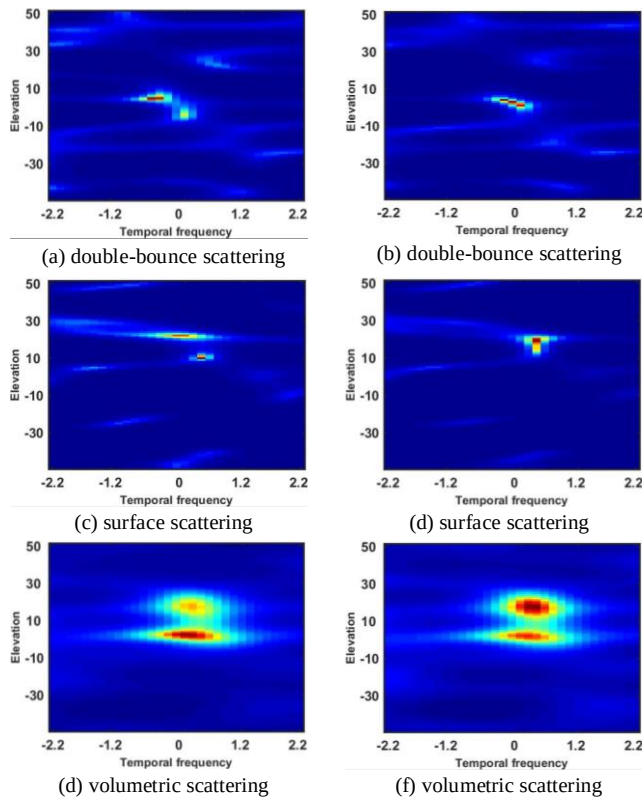


Figure 8. Differential TomoSAR images after three-component decomposition. Left and right images are Capon and generalized Capon based focusing (Real data set).

Such a destructive effect even can be observed in the reconstructed images from the canopy-only and odd-bounce scattering covariance matrices. However, from the results it can be seen that generalized Capon is more robust to the destructive effects and is able to reconstruct differential TomoSAR images while side-lobe effectively suppressed.

5 Conclusion

In this paper, temporal decorrelation as the one of the main important problem of multi-dimensional SAR image focusing has been assessed in the proposed framework of robust differential SAR tomography. It has been shown that the classical Capon based focusing is less affected by temporal decorrelation compared to the super-resolution Music technique. Hence, here a robust model-based Capon focusing approach was proposed and assessed under the presence of different terms of decorrelation. In the considered framework and by exploiting a 5D function in the domain of $(w_s, w_t, \Delta w_t)$, it is possible to deal with the decorrelation. The efficiency of the technique in dealing with decorrelation in single polarimetric MB SAR image and together with fully polarimetric MB data was investigated. Results showed the efficiency of proposed differential SAR tomography in the focusing of ground and canopy or separated scattering mechanisms.

The introduced temporal decorrelation-robust tomography technique is need to be assessed with more data and strong effect of decorrelation. In particular, our future activity will regard extensive experiment with our real data and strong decorrelation using simulated case.

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