Climate Change Initiative Extension (CCI+) Phase 1
New Essential Climate Variables (NEW ECVS)
High Resolution Land Cover ECV (HR_LandCover_cci)

Algorithm Development Plan

(ADP)

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Changelog

Issue	Changes	Date
1.0	First version.	29/10/2019

Detailed Change Record

Issue	RID	Description of discrepancy	Sections	Change

Contents

1 Introduction

1.1 Executive summary

After one year of activity related to HR LC products generation a first processing chain has been implemented and tested over benchmark areas (see PVASR v1.0). As detailed in the same document, algorithmic and methodological choices have been made to select for the best performing ones and provide a first quality product output of the project. Comparison activities and foreseen improvements for future versions of the products are developed according to a plan as presented in this document.

1.2 Purpose and scope

This Algorithm Development Plan (ADP v1.0) provides the details on the expected evolutions to the current HR LC products available from processing Cycle 1 or pre-cursor studies. It includes planned developments to:

- The algorithms themselves.
- The necessary auxiliary data for best implementation of the algorithms.
- The training strategy and implementation.

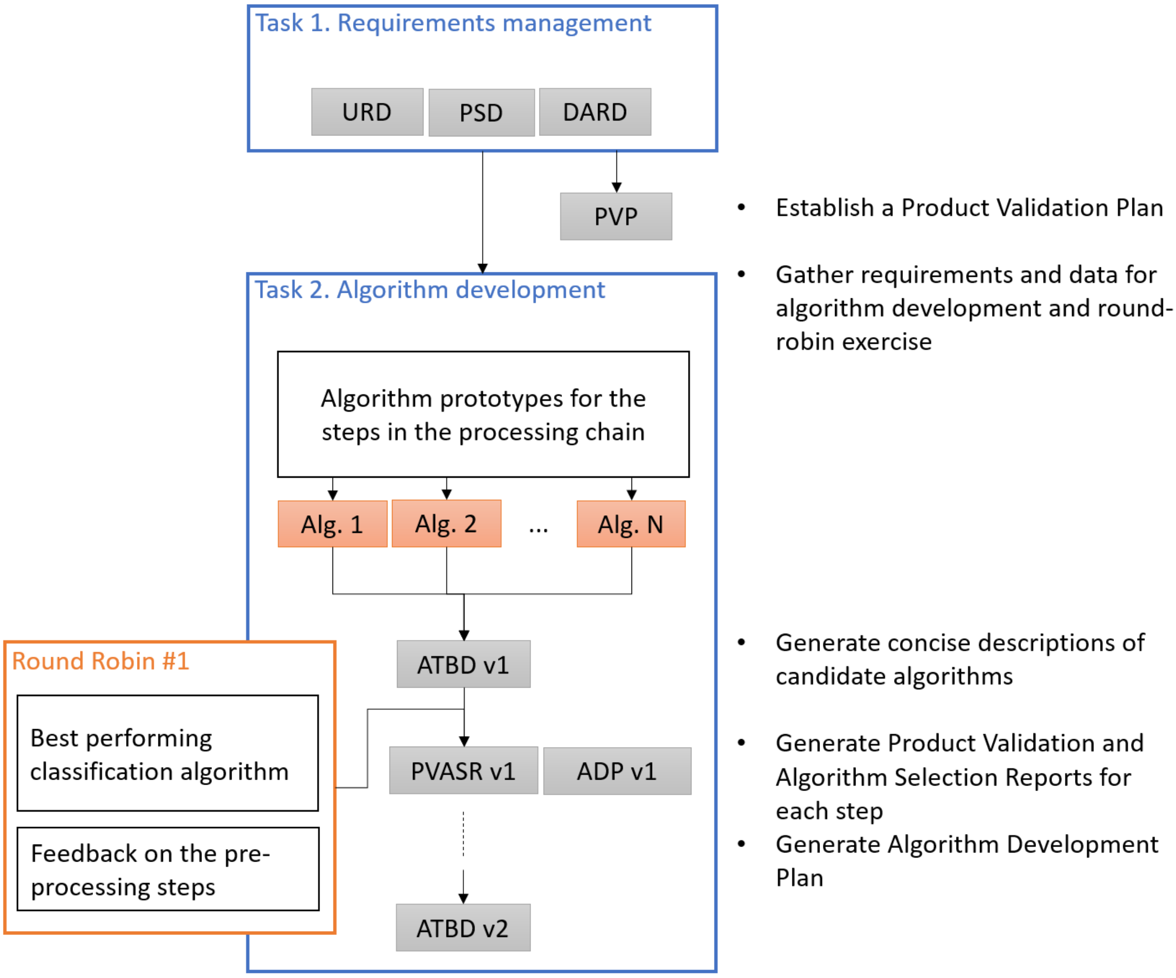

Figure 1. Concept of the ADP v1 in the workflow of Task 2 of the CCI+ HRLC project.

The algorithms under development in the next processing cycles will be those selected from Consortium inter-comparison exercise as selected from internal benchmarking/development activities. The evolutions outlined in this document will be implemented in an end-to-end system to generate the first HRLandCover_cci climate data records on the next Cycle coming. It is also important to note that this document will be regularly updated on a yearly timely schedule, with possible intermediate notes possible in case significant achievements are obtained in between.

1.3 Reference documents

Ref.	Title, Issue/Rev, Date, ID
[RD1]	Product Validation and Algorithm Selection Report, v1.0, 29/10/2019, CCI_HRLC_Ph1-D2.1_PVASR_v1.0

1.4 Acronyms and abbreviations

ANN	Artificial Neural Network
biLSTM	Bitemporal the Long Short-Term Memory
BFAST	Breaks For Additive Seasonal and Trend
CCI	Climate Change Initiative
CD	Change Detection
COBYLA	Constrained optimization by linear approximation
CRF	Conditional Random Forest
DTW	Dynamic Time Warping
EM	Expectation Maximization
ESA	European Space Agency
GAN	Generative Adversarial Networks
GEE	Google Earth Engine
GLC	Global Land Cover
GLCNMO	Global Land Cover by National Mapping Organizations
HR	High Resolution
ICM	Iterated Conditional Mode
LandTrendr	Landsat-based detection of Trends in Disturbance and Recovery
LC	Land Cover
LSTM	Long Short Term Memory
ML	Maximum Likelihood
MRF	Markov Random Field
RF	Random Forest
RMSE	Root Mean Square Error
RR	Round Robin
RST	Rotation-scale-translation
SAR	Synthetic Aperture Radar
SITS	Satellite Image Time Series
SVM	Support Vector Machine
TS	Time Series

2 Algorithm development Plan for Optical Data

2.1 Current Status of Optical data classification

Figure 2 recalls the optical data processing chain for the prototype production of the HR LC map obtained by classifying the time series of Sentinel 2 data. The processing chain is based on three main steps: (1) the pre-processing of the optical data, (2) the training set production, and (3) the land-cover map production (see PVASR v1.0). According to the preliminary results obtained on the 4 study areas selected for the Round Robin (RR) phase, the team aims to investigate possible improvement for each step of the processing chain. In the following, details on the algorithm development plan are given.

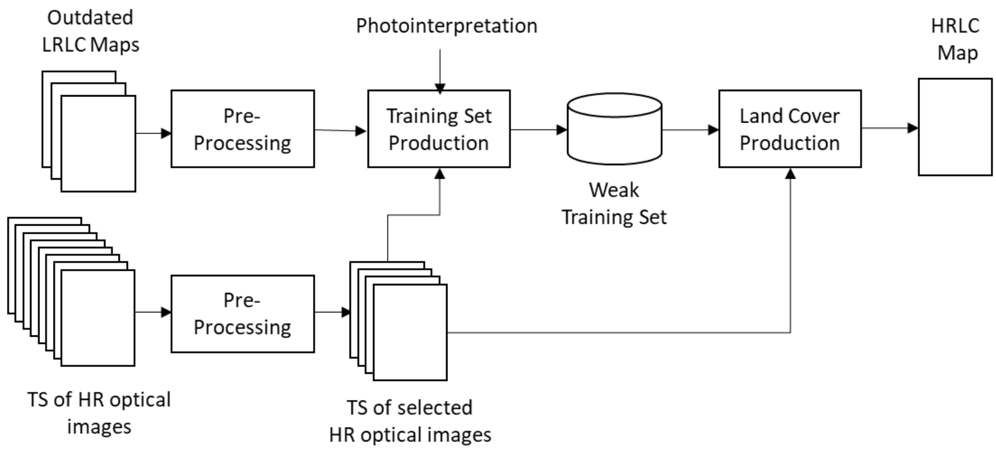

Figure 2. Workflows for optical data processing chain for the prototype production of the HR land-cover map obtained by classifying the time series of Sentinel 2 data.

2.2 Algorithm Development Plan for Optical Data classification

2.2.1 Optical Data Pre-processing improvement

2.2.1.1 Description

In the considered implementation of the processing chain, the atmospheric correction and cloud detection step are performed by using the specific tools provided by ESA, the Sen2Cor processor for Level 2A product generation in the Sentinel-2 toolbox.

2.2.1.2 Development plan

The team will investigate the possibility of using more sophisticated cloud detection algorithms to reduce the probability of having missed cloud detection. Moreover, the team will investigate the possibility of generating seasonal composite, i.e., to model the permanent LC classes a short time series of four optical images representative of the four seasons, if a cloud-free image is present in the season, that image is directly inserted in the Time Series, otherwise a seasonal composite will be generated by merging more cloudy images belonging to the same season.

2.2.2 Training Set Production

2.2.2.1 Description

Due to the missing availability of training data, existing thematic products available at global scale are considered to produce the training set. To extract samples able to represent the LC classes in the HRLC legend, three thematic products are considered: (1) the 2015 ESA CCI LC map available at 300m spatial resolution, (2) the 2015

Copernicus Global Land Cover (GLC) map produced at 100m spatial resolution, and (3) the Global Land Cover by National Mapping Organizations (GLCNMO) produced at 1 km spatial resolution.

2.2.2.2 Development Plan

As anticipated in the PVASR document, even though the existing thematic products represent a valid source of information, it is necessary to have ground reference data. Reference data will allow the implementation of more refined strategies to extract reliable samples from the considered thematic products. Moreover, reference data are needed to model complex classes which require reliable training samples (e.g., summer crops, winter crops) that cannot be extracted from the outdated coarse thematic products. Finally, there is the need of having ground reference data to model seasonal classes which are not included in the current training set.

2.2.3 Classification Algorithms

2.2.3.1 Description

Several well-known classifiers widely employed to generate LC maps are compared. To keep coherence with the classification methods used in the previous CCI MRLC project, the Maximum Likelihood Classifier (ML) and the Random Forest Classification Algorithms (RF) are considered. Moreover, the Support Vector Machine (SVM) classifier is considered given its effectiveness at high spatial resolution. Finally, the artificial neural network (ANN) is used due to its capability to deal with large feature space with high accuracy. Due to the missed availability of ground reference data, the selection of the best algorithm has been performed by qualitative analysis. Although in some area, the visual evaluation of the results is reliable, for some classes ground reference data are fundamental for the correct tuning of the classifier and the selection of the best algorithm. A quantitative evaluation will be performed as soon as ground reference data are available.

2.2.3.2 Development Plan

The team will investigate the use of deep learning technique such as the Long Short Term Memory (LSTM) or bitemporal Long Short Term Memory (biLSTM). These architectures extensively exploit the spectral information provided by the long time series Sentinel 2 images. Figure 3 and Figure 4 show some preliminary results obtained in Amazonia (tile 21KUQ). By exploiting a dense TS of 17 Sentinel 2 images, both the LSTM and biLSTM architectures achieve better classification results with respect to the SVM, which performed the best compared to the other standard machine learning techniques. While in the HRLC map generated by the SVM some build-up areas are detected in the permanent crops, these noisy pixels do not appear in the HR maps obtained by the deep classifiers. The importance of using such algorithms is highlighted in Figure 4, where both LSTM and biLSTM correctly classify the bare soil which is confused with permanent crops by the SVM. Please note that these preliminary results are obtained without ground reference data, which are necessary to train deep learning architecture. The team aim to further investigate the use of these system architectures by evaluating the trade-off between classification accuracy and computational effort.

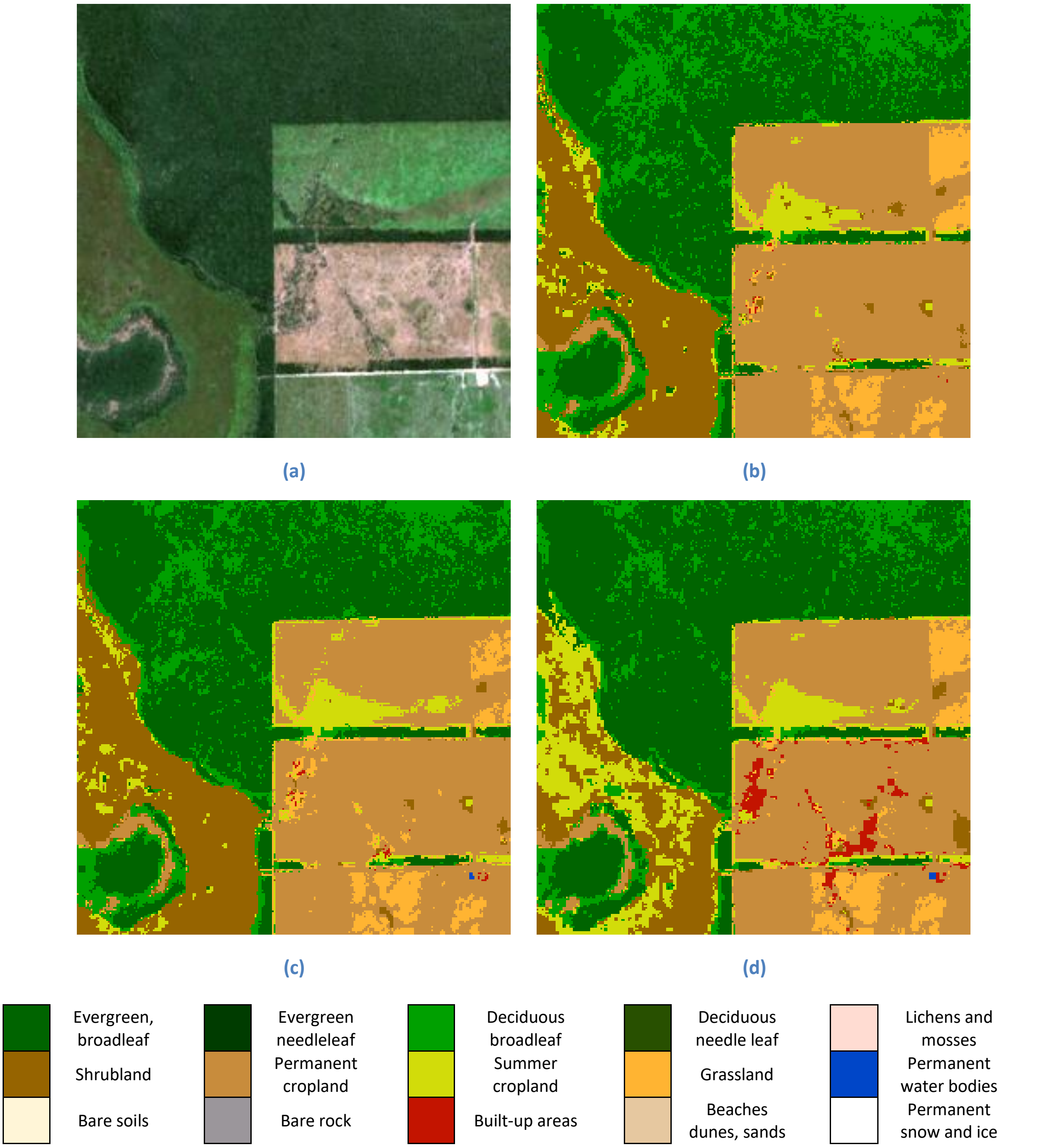

Figure 3. Visual comparison of: (a) the true color composition of Sentinel 2 image acquired on the 4th April 2018; (b) LC map obtained by using a LSTM characterized by three layers, (c) LC map obtained by using a biLSTM characterized by two layers, and (d) LC map obtained by SVM. The study area is located in Amazonia (Tile 21KUQ).

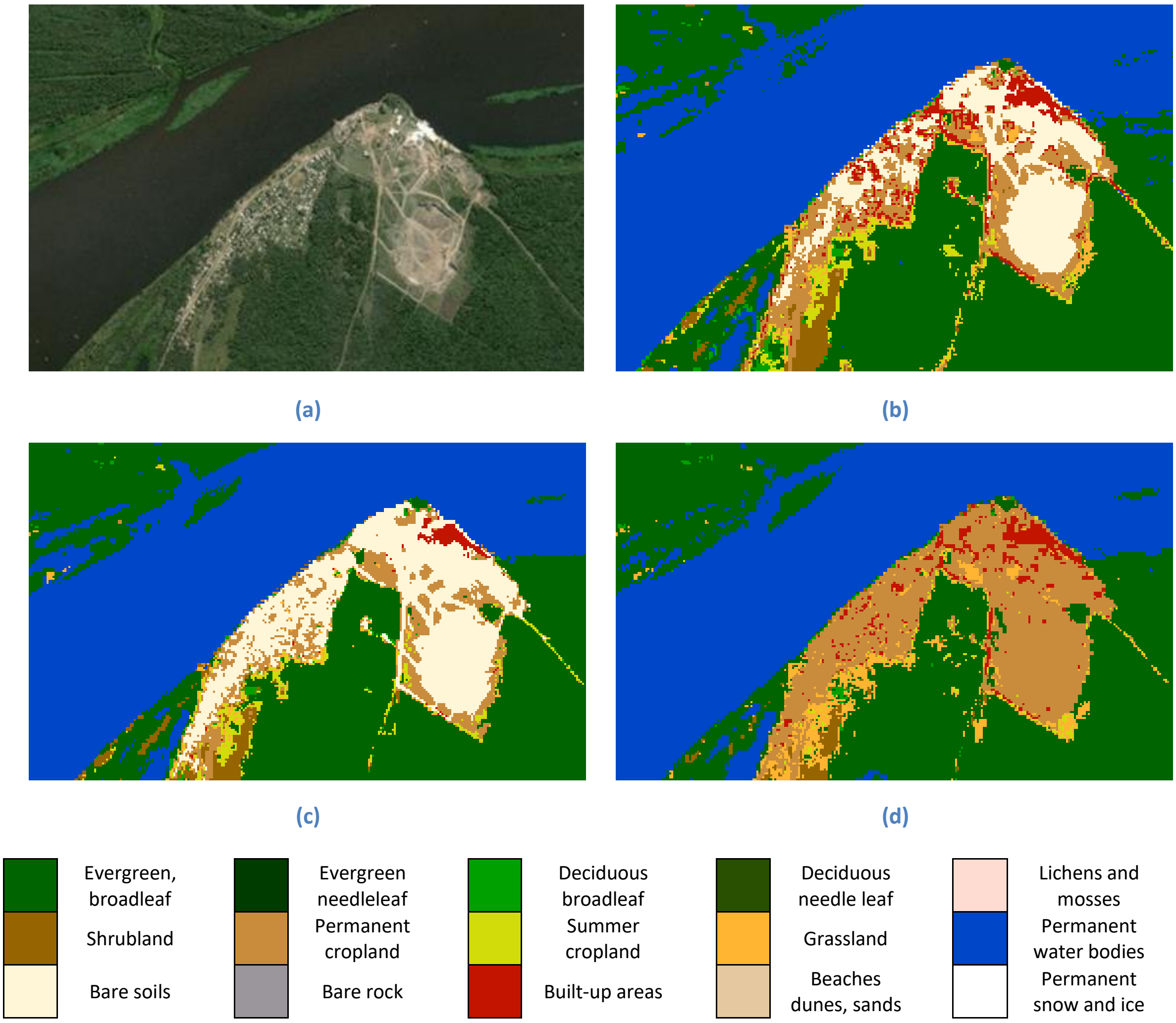

Figure 4. Visual comparison of the: (a) HR optical image used for photo-interpretation; (b) LC map obtained by using a LSTM characterized by three layers, (c) LC map obtained by using a biLSTM characterized by two layers, and (d) LC map obtained by SVM. The study area is located in Amazonia (Tile 21KUQ).

3 Algorithm development Plan for SAR Data

3.1 Current Status of SAR data classification

In the CCI+ HRLC initiative, performance of candidate algorithms for Synthetic Aperture Radar (SAR) data classification has been assessed and compared. The main purpose was to identify the best promising methods to be implement in the SAR image processing chain in Figure 5.

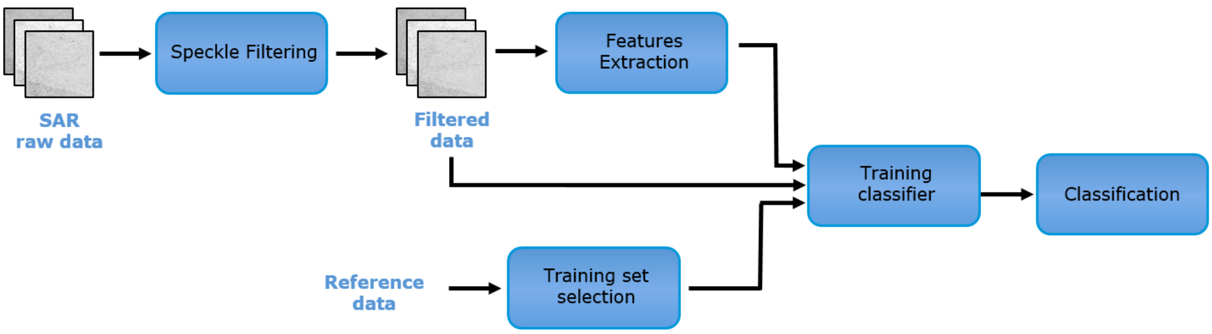

Figure 5. Block diagram for SAR data of the land cover map production procedure.

The algorithms chosen for each step of chain in Figure 5 were:

- *Training set Selection*
    - Random extraction from a set of reference data
- *Speckle Filtering*
    - Multitemporal despeckling filter [1]
- *Feature Extraction*
    - Single band analysis:
        - *Mean filter*
        - *Median filter*.
        - *Lee filter*.
        - *Minimum (maximum)*.
    - Dual band analysis:
        - *Ratio*, VV/VH;
        - *Sum*, VV+VH;
        - *Mean*, (VV+VH)/2;
        - *Difference*, VV-VH.
- *Classification*
    - RF classifier

These algorithms are the ones which will continue to be improved over the course of the processing cycles. The full descriptions are provided in [2].

3.2 Algorithm Development plan for SAR classification

3.2.1 Feature extraction improvement

SAR data have long been used in several classes management, for instance water, snow and vegetation [3]. To the best of our knowledge, according to a preliminary analysis of state-of-the-art of literature, the feature extraction improvement could be achieved in implementing a pre-defined subset of features for different sub-sets of classes, as made for urban area extraction [4]. A brief list is reported in the following table:

Table 1. Brief list of features for different sub-sets of classes

Class	Feature(s)
Water [5]	Average backscatter, minimum backscatter of time series, standard deviation of backscatter
Snow [6]	σ^0VV band; backscattering ratio
Crop [7]	Occurrence variance; co-occurrence contrast
Deciduous vegetation [8]	Temporal signature
Evergreen vegetation [9]	Polarimetric features; σ^0VH band
Soil [10]	Polarimetric features

3.2.2 Classification

Satellite images are precious sources of information required for various investigations since they provide spatial and temporal information about the nature of the surface of the earth and feature therein. The purpose is to improve the classification step in order to optimize the classes recognition. At present, only a subset of the whole HR legend is covered, which are listed in Figure 6.

Value	Label	Color
0	No data	
1	Evergreen broadleaf tree	
2	Evergreen needleleaf tree	
3	Deciduous broadleaf tree	
4	Deciduous needleleaf tree	
5	Shrubland	
6	Permanent cropland	
7	Annual summer cropland	
8	Grassland	
9	Lichens and mosses	
10	Permanent water bodies	
11	Permanent snow and ice	
12	Beaches dunes and sands	
13	Bare soils	
14	Bare rock	
15	Built-up areas	

Figure 6. Subset of HR Land cover classes derived from MR Land cover one and used for Sentinel-1 classification

To improve classification performance, further approaches might be tested being able to extract a global land cover map with a high-level of information in recognizing natural resources, and low uncertainties and inconsistencies simultaneously. A possible alternative may be the use of unsupervised classification inside the areas that have been recognized as belonging to one of the more general classes in the current legend.

4 Algorithm development plan for Multi-Sensor Geolocation

4.1 Image Registration using Affine or Higher-Order Transformations

4.1.1 Current Status

The focus so far has been on rotation-scale-translation (RST) transforms, which are a special case of affine transformation. The multi-sensor geolocation methods developed within the Round Robin will be updated with the usage of fully general affine transforms or higher-order transformations (e.g., shear transformation and polynomial transformation).

4.1.2 Development plan

The usage of these more general transformations will be explored. It will be particularly interesting with respect to the cases where the acquisitions correspond to mountainous regions. The different acquisition geometry of optical and SAR sensors usually has a stronger impact on the generation of the related images. In such cases, the usage of higher-order transformations will be important to match the two different types of image. Additionally, it could be interesting to also explore the usage of spatially non-uniform transformation (e.g., spline transformation and deformable fields).

4.2 Image Registration using Improved Optimization Methods

4.2.1 Current Status

As anticipated in the PVASR document, the Constrained optimization by linear approximation (COBYLA) optimization method will be integrated with the possibility of optimizing the “initial search radius” parameter within the optimization strategy and better explore the search space. Moreover, global optimization methods will be explored, with focus on the accuracy versus time trade-off.

4.2.2 Development Plan

As anticipated in the PVASR document, the COBYLA optimization method will be integrated with the possibility of optimizing the "initial search radius" parameter according to the behaviour of the registration metric. This way, the method will be able to more exhaustively explore the search space and will more successfully converge to a solution characterized by smaller registration mean square error. An example is the case of pairs of images characterized by large spatial deformation, where simpler conjugate-gradient-like methods (like Powell's algorithm) failed to converge to a satisfactory result.

Moreover, the usage of global optimization methods will be explored. Examples are given by simulated annealing and genetic algorithms. Usually, such methods perform better than simpler gradient descent-like methods, yet requiring longer time to converge. This drawback will be analysed with particular interest due to the large datasets to register for the CCI+ HRLC product. The advantage of using a global optimization method with respect to the achievable accuracy will be compared to the required overhead in terms of computation time.

4.3 Image Registration using Other Metrics

4.3.1 Current Status

New implementations of mutual information (e.g., Parzen window estimation) will be investigated. Moreover, additional metrics will be experimented within the context of the next Round Robin.

4.3.2 Development Plan

In the PVASR, multi-sensor geolocation has been designed and developed in the case of cross-correlation and mutual information as similarity metrics. It has been proven that mutual information is more reliable and effective in a multi-sensor scenario, where the cross-correlation is not able to deal with the different statistics of the input imagery. Therefore, focusing on mutual information, different implementations and approximations of such metric will be taken into account (e.g., Parzen window estimation, Parzen window applied to a random selection of sample to reduce the computation time, etc.). Moreover, the possible usage of other similarity metrics will be studied in the context of the future Round Robin.

4.4 Image Registration using Generative Adversarial Networks

4.4.1 Current Status

The usage of generative adversarial networks for multi-sensor registration will be explored. Generative Adversarial Networks (GANs) will be used, in a domain adaptation sense, to transform optical images into SAR-like images or, similarly, to transform SAR images into optical-like images. Then, conventional single-sensor registration methods will be used.

4.4.2 Development Plan

The Round Robin dataset will be used to train a generative adversarial network able to transform optical to SAR images or SAR to optical images. The resulting image pairs will be registered using conventional image registration methods, also developed for single-sensor scenarios. The focus will be put on computation time requirements, due to the large scale of the HRLC product.

5 Algorithm development plan for Decision Fusion

5.1 Automatic Hyper-parameter Optimization

5.1.1 Current Status

The opportunity to automatically optimize the hyper-parameters of the decision fusion algorithms will be analysed by developing and experimentally testing techniques based on Bayesian and mean square error (RMSE) concepts.

5.1.2 Development plan

Both the non-contextual consensus-theoretic and the contextual Markovian methods that have been developed for decision fusion exhibit internal hyper-parameters, which mostly play the role of weight coefficients that tune the relative relevance of the individual information sources. On one hand, the opportunity to set them in a manual / semi-empirical way represents a valuable degree of freedom that can be exploited to best fit the requirements of the climate community. This comment is especially relevant for the hyper-parameters of the Markov random field (MRF) models, which tune the spatial regularity of the output map. On the other hand, we shall also investigate the automatic optimization of these hyper-parameters to favour the full automation of the processing chain. For this purpose, techniques based on the expectation-maximization (EM) algorithm (and rooted in Bayesian estimation theory) and on the mean-square-error criterion will be developed and tested.

5.2 Edge-preserving contrast-sensitive contextual models

5.2.1 Current Status

A contrast-sensitive conditional random field (CRF) model will be integrated in the Markovian formulation of the decision fusion processing chain to favour edge-preserving behaviour in addition to spatial regularization.

5.2.2 Development plan

The Markovian formulation developed so far has formalized spatial-contextual information by making use of the well-known Potts MRF model, which favours spatial smoothness, possibly implying a degradation in edges and small-scale spatial details. While this model acts as a natural baseline with regard to MRF models for image classification, more advanced probabilistic graphical models aimed jointly at favouring spatial regularity within homogeneous image regions and at preserving edges will be developed and tested. In this framework, contrast-sensitive CRFs will be considered. They incorporate both the random field of class labels and that of the satellite observations in the spatial-contextual energy contributions in order to capture local contrast in the satellite data and adaptively tune the impact of spatial regularization across edges or in a neighbourhood of small details.

5.3 Markovian energy minimization through graph-theoretic methods

5.3.1 Current Status

The opportunity to integrate last-generation energy minimization methods in the Markovian fusion process will be addressed. Special care will be given to the accuracy-vs-time trade-off.

5.3.2 Development plan

As compared to the iterated conditional mode (ICM) algorithm that is currently integrated in the MRF formulation of the decision fusion process, recent methods based on graph theory (graph cuts or belief propagation) may generally improve classification accuracy thanks to their capability to attain global or near-global energy minima. However, these methods typically imply longer execution times and remarkably larger memory requirements. Accordingly, the opportunity to incorporate one of them into the HRLC processing chain will be considered, methodologically and/or experimentally, devoting special attention to the evaluation of the expected advantage in accuracy as compared to the expected increase in time and memory requirements.

5.4 Decision Fusion through Deep Learning

5.4.1 Current Status

Similar to the case of multi-sensor geolocation, the possible added value of deep neural networks will be investigated in the case of decision fusion as well. Indeed, the adversarial architecture that is envisaged for the registration case implicitly addresses a type of multi-sensor fusion *per se*. Hence, the opportunity of an integrated network relating both tasks will be considered.

5.4.2 Development plan

Deep neural networks bear the potential of a remarkable improvement in the accuracy of the HRLC product, generally at the cost of more intense requirements in terms of training data, memory, and parallelization. The adversarial deep network that has been mentioned above with regard to multi-sensor geolocation intrinsically addresses a type of multi-sensor fusion as well. Hence, the opportunity of an integrated network that jointly addresses registration and fusion will be considered, methodologically and/or experimentally. The aforementioned architecture, as compared to deep nets for classification (semantic segmentation), bears the advantage of being trained using only the optical and SAR data and without requiring ground truth about the class labels (from the viewpoint of the classification task, it is unsupervised). The opportunity of incorporating this processing approach into the HRLC chain will be discussed in light of the trade-off between the accuracy and the memory, time, and parallelization requirements.

6 Algorithm development plan for Multitemporal Change Detection and Trend Analysis

Being the multitemporal change detection and trend analysis the last step of the CCI+ processing chain, during the first year the main focus has been to study and compare the performance of different state of the art algorithms. The main goal of this was to understand the limitations and advantages of the state of the art methods in the context of HRLC data.

6.1 Current status of multitemporal change detection and trend analysis

The multitemporal change detection and trend analysis takes as input the multi-sensor geolocated Satellite Image Time Series (SITS) coming from both optical and SAR sensors, as well as the 5 year regional HRLC maps at 30m spatial resolution. This data is then analysed in two main stages: 1) abrupt/permanent changes and trend detection and 2) inter-annual Change Detection (CD). At the moment, the time series (TS) analysis has been performed only at pixel level and considering the data available in the Google Earth Engine (GEE) platform. Because of the TS step being the last one, analysis has been performed only for optical data during the first year, but similar assumptions are expected to hold for SAR case.

6.1.1 Abrupt/permanent changes and trend detection

In this case, two algorithms (out of 8 different ones) have been chosen to be further analysed:

- Landsat-based detection of Trends in Disturbance and Recovery (LandTrendr) [11]–[13];
- Breaks For Additive Seasonal and Trend (BFAST) [14], [15].

LandTrendr takes a SITS from a single pixel (spectral or higher level information), and goes through a process to identify breakpoints separating periods of durable change or stability in spectral trajectory, and records the year that changes occurred. In order to detect this information, LandTrendr uses as input a representative value for each year, coming only from information of 3 months. This becomes a strong limitation, since there is no guarantee to detect a change happening in a particular year if it has happened in different months from the selected ones. Another limitation is related to the type of data and trend that it can analyse, being this only optical one.

BFAST, on the other hand, is based on the aggregation of different models that approximate the trend of the considered SITS, then using a Bayesian model to weigh the individual models. It allows to identify change points both in the seasonal trend and the long lasting trend. In order to detect the change points, it requires a continuous and uniform SITS. This increases the probability of detecting different types of changes over the year. But introduces a problem related to the generation of a continuous and uniform SITS. It can work with any type of trend, but no information is available as per the use in SAR data.

For both algorithms, test were performed only at single pixel level, for the period 1990-2018. Since one of the biggest problems of the TS analysis part is the collection of ground truth for validation, advantage was taken from two papers with reference information in Australia [16] and Bolivia [17]. Both cases work in detection of changes in forest/vegetation.

6.1.2 Inter-annual CD

For the inter-annual CD, a method based on Dynamic Time Warping (DTW) distance computation has been developed. Similar to the trend analysis, this method has been applied only at pixel level. In this case, the study area is located in the historical zoom of the Africa area and the images considered come from Landsat sensor. All the information has been obtained from GEE.

The proposed DTW is multi-dimensional and hierarchical and other than the information of Land Cover (LC) classes, it does not require further information from the user. It has three main steps:

1. TS reconstruction: makes use of a non-parametric regressor in order to build a continuous and regular SITS for different normalized indices. Similar to the trend analysis part, this step suffers from the lack of a proper TS reconstruction that can account for variance in the LC classes.
2. LC training: this step is meant to derive the prototype trends of different LC classes that will be further used to detect if a change has occurred and what type of change has occurred. To do the training, it makes use of a DTW similarity measure in a hierarchical architecture and multi-dimensional manner. It also requires the selection of training samples that need to be pure and if possible in a large quantity per class. This is of course a critical step that sums up to the high computational requirements, since it cannot work in parallel.
3. LC classification and CD: given the availability of trend prototypes for different classes along the year, it applies a time division strategy and a multi-dimensional DTW similarity measure in order to first classify the new coming samples and then determine (by a stability strategy) if there has been a change and what time of change it is. In this case, limitations are related to computational time and the strong dependence to the two previous steps.

6.2 Development plan

6.2.1 Abrupt/permanent changes and trend detection

Among the analysis done in the first year, our conclusion is that algorithms like BFAST are the ones to be considered for further analysis. Nevertheless, the encountered limitations regarding the building of a regular and continuous SITS will have to be faced. Based on previous experiences from the team, a non-parametric regressor will be considered for this task [18], [19]. But a detailed study will be carried out in order to be able to generate continuous information, even when considering different types of land covers (this since state-of-the-art methods generally work only for vegetation-based land covers).

Another problem that will be studied is the integration of both optical and SAR data. In this case, the use of non-parametric regressor will be considered [19], where correlation among optical and SAR will be partially modelled.

This will only be done in cases where too many cloudy images are present in the SITS, which basically penalizes the capacity of any regressor to predict the missing information.

Finally, the study must be extended to image level (instead of pixel one only).

6.2.2 Inter-annual CD

During the second year, the team will focus the attention on improving the different problems identified for the proposed DTW based method. This means, focusing on improving the TS reconstruction method, by combining the efforts with what learnt from the trend analysis part. Another important improvement will be regarding the selection of pure training samples for the LC training phase of the method. In this regard, classification maps obtained from the decision fusion step will be exploited, allowing not only to know information about the purity of the samples, but also to select a larger amount of training samples. A further focus will be on the design of strategies for the parallelization of different steps, as well as to add further control points to guarantee a more reliable result.

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