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D2.1 EO Methodology for DIANA services

Wp2: Earth Observation data products and services

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Executive summary

The data products and services offered by DIANA will be based on a combination between EO data provided by various satellites as well as meteorological and complementary data derived from different data sources. In this way, it is possible to meet properly the data requirements of our users in terms of spatial, temporal and spectral resolution and by extending the operational capabilities of the platform offered.

Building upon the EO datasets provided by Copernicus (in particular from the satellites Sentinel-1 and Sentinel-2), this deliverable provides the methodologies and algorithms to achieve the EO products for following demand-driven services:

- Non-authorized water abstraction detection and monitoring
- Seasonal drought forecasting and monitoring
- Supporting the implementation and monitoring of the WFD.

The first service described in this deliverable explores the multi-temporal classification procedures based on spectral vegetation indexes (NDVI, NDWI and other Vegetation Index) and LAI: it includes the adaptions of existing algorithms of classification to obtain an operative process chain to map irrigated areas and to determine irrigation crop requirements and water abstractions. Other aspects are related to meteorological integration and other data source integration are briefly tackled.

In the second part, the Drought Monitoring and Forecasting Service are shown. The aim here is to estimate present and forthcoming possible drought conditions through a modelling framework that is a combination of hydrological modelling, real-time weather data and seasonal climate forecasts.

Finally, the third and last part of the document shows the key points of the services which DIANA aims to provide for supporting in implementation of Water Framework Directive.

<u>This document is left open for further updates based on new improvements and feedback that will be occurring during the development of the project.</u>

1 Non-authorized water abstraction detection and monitoring

1.1 Opportunities of using EO to detect irrigated areas and monitor water abstraction volume

Over-abstraction, or the abstraction of more water than is sustainably available, regularly triggers or increases water deficits in the EU. It is currently considered the second most common pressure on the ecological status of water bodies in the Union. The water restrictions or natural shortages it engenders are a potential cause of conflicts between competing uses and could have substantial socio-economic consequences.

In 2011, a quantitative target was set within the Roadmap for a Resource Efficient Europe1, recommending a water abstraction level below 20% of the available renewable water resources. In the 2012 Blueprint to Safeguard Europe's Water Resources2 document, the European Commission reinforced its commitment for better water management, in accordance to the 3rd Implementation Report on the WFD3 that assessed the 2009 River Basin Management Plans and the 2012 policy review of the Strategy on Water Scarcity and Droughts4. The Blueprint highlights the issue of non-authorised water abstraction and recalls the responsibility of Member States on law enforcement. Non-authorised abstraction consists in the abstraction of water without permits or beyond authorised amounts, either over a year, or during a restricted period of time where the use of water is rationed.

Earth Observation (EO), in particular European Union's Copernicus programme (ex-GMES5), was indicated in the Blueprint to Safeguard Europe's Water Resources as a promising approach to address quantitative issues related to water, through the detection of possible cases of non-authorised abstraction and as a complement to the often limited field data available. Copernicus is composed of three elements: (i) a space component with the development of the fleet of EU Sentinel satellites and with an access to data from other satellites, (ii) a service component

1 http://ec.europa.eu/environment/resource_efficiency/pdf/com2011_571.pdf
2 http://ec.europa.eu/environment/water/blueprint/index_en.htm
3 http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52012DC0670
4 http://ec.europa.eu/environment/water/quantity/pdf/non-paper.pdf
5 Global monitoring for environment and security services

including atmosphere, land, marine, emergency management, security and climate change services and (iii) an in situ component.

1.1.1 Introduction to the problem

The detection and the monitoring of non-authorised irrigation and abstractions are still challenging for water managers and water authority of EU member countries. In this context, there is practically very little reliable information available on the number and extent of non-authorised irrigations and/or abstractions from groundwater, in particular those from private wells. The qualification of irrigation as "non-authorised" implies having access to a database of individual users' water rights and spatial independent information to verify, by cross-checking, their compliance. Usually the monitoring and identification of irrigated areas are done by means of in-situ inspections and/or water meter records when available. Very often, when water meter are not installed or operating properly, irrigation volumes (and then irrigation fees) are estimated indirectly based on the declaration of crops that are cultivated (stated by farmers at start of irrigation season) and an average per-crop tabulated water requirement.

Typically, two kinds of "non-compliance" can be distinguished:

- irrigated areas which do not have the necessary water rights (non-authorized irrigation and/or abstractions of the first kind);
- irrigation water consumption which do not remain within the legally allowed or assigned water volume (non-authorized irrigation and/or abstractions of the second kind).

In the first case, all irrigated areas need to be identified and cross-checked with all available information/databases on irrigable areas (i.e. areas with a legal right to irrigate). Depending on national and/or regional legislation, the legal right to irrigate may be linked to the land, an abstraction point or a water source, either permanently or for limited periods of time (e.g. seasonal restrictions). In the second case, irrigation water consumption should be monitored and cross-checked with regulated allocation and/or hydrological planning data.

In both cases, geospatial legal reference data i.e. cadastral maps of water rights, allocation based on current hydrological plans) are always needed. This also applies to any other approach based on in-situ non-EO information. The availability of legal reference data is a key condition for the detection of non-authorized abstractions and is closely linked to the implementation of INSPIRE Directive and SEIS (Shared environmental Information system) principles.

Earth Observation (EO) can supply two key products to tackle both the above-mentioned kinds of "non-compliance" in support of the water authority in charge of monitoring. They are:

- maps of irrigated areas;
- maps of irrigation water consumption and abstracted volumes.

These products will empower users (i.e. water managers and public administration in charge of monitoring water rights) to:

- monitor irrigated areas and the abstracted volumes on a systematic basis;
- better target field inspections aimed at assessing compliance with legal water allocation;
- ensure the legitimacy of self-declared irrigation water abstractions.

1.1.2 EO for detection of irrigated areas

A powerful tool for discriminating irrigated crops and even natural vegetation types is to use the characteristic difference in their seasonal development or phenology. To this end, the analysis of time series of EO data provides information to follow the phenological development of crops and natural ecosystems. This is usually based on monitoring of seasonal pattern of changes in leaf area index (LAI) or Vegetation Indices such as NDVI (Normalized Differential Vegetation Index), NDWI (Normalized Differential Water Index), spectral reflectance, etc.

The detection of irrigated areas is, thus, accomplished by "multi-temporal analysis" of time series of above mentioned indices retrieved from EO and it is based on the assumption that in arid and semi-arid environment (like the Mediterranean Region), high trend of vegetation growth is compatible only with irrigation (Lockwood, Sarteel, Mudgaln, Osann, & Calera, 2014). More specifically, crop growing in hydrological deficit condition (rainfall is not sufficient to replace water losses by crop evapotranspiration) is compatible only with external irrigation supplies. The detection process is based on a digital classification procedure which aims to distinguish the different classes of irrigated crops based on the temporal pattern of their spectral response. The exact recognition of classes corresponding to irrigated crops requires the collection of groundtruth data in order to characterize "a priori" the crop phenology in a given area (and the corresponding temporal pattern of selected spectral indexes). Also, precipitation data are needed to verify the occurrence of hydrological deficit conditions.

The methodology briefly described here benefits from improved capabilities of recent satellite platforms such as Sentinel 2A-2B and Landsat 8; the sensors on-board of these three spatial platforms, operating as a multisensor constellation, provide much more spectral information, higher spatial resolution and shorter revisit time than in the past. In summary, the technical opportunities of using EO for irrigated areas mapping relay on: i) significance of irrigated areas response at NIR and SWIR wavelengths; ii) possibility of using novel Vis based on different spectral configurations; iii) high frequency of acquisition during a single growing season, hence increased accuracy also in presence of different growth stages. From the operative point of view, the usage of EO techniques is much more cost effective than field inspections and provides a territorial overview of irrigation fields.

The identification of plots that receive supplemental irrigation (i.e. less amount of water, but in a well-selected timeframe) usually implies more difficulties: under this practice plots show lower contrast compared to rainfed or irrigated plots of the same crop. Supplemental irrigation is usually used when water stress occurs, and is employed both in extensive herbaceous annual crops and woody crops. In this case, precipitations data is needed to distinguish irrigation (the vegetation index, reflecting the plant water status, does not differentiate between water coming from rainfall or irrigation). On the other hand, whilst the results are very accurate in the case of herbaceous crops, there are still other crops types where EO data interpretation is cumbersome, i.e. tree crops with sparse ground cover, like vine or olive orchards. In such cases, multiannual EO time series, ancillary data and cartographic information and very high resolution orthophotos should be used in order to correctly identify the plots where irrigation is applied.

The above mentioned process allows distinguishing:

- different categories of crops (e.g. wheat from corn), as illustrated in Figure 1;
- irrigated crops from non-irrigated crops within a same category of crops, , as illustrated for wheat in Figure 2. This process also allows the detection of intermediate irrigation magnitudes (e.g. high irrigation volumes vs. low irrigation volumes), as illustrated in Figure 3.

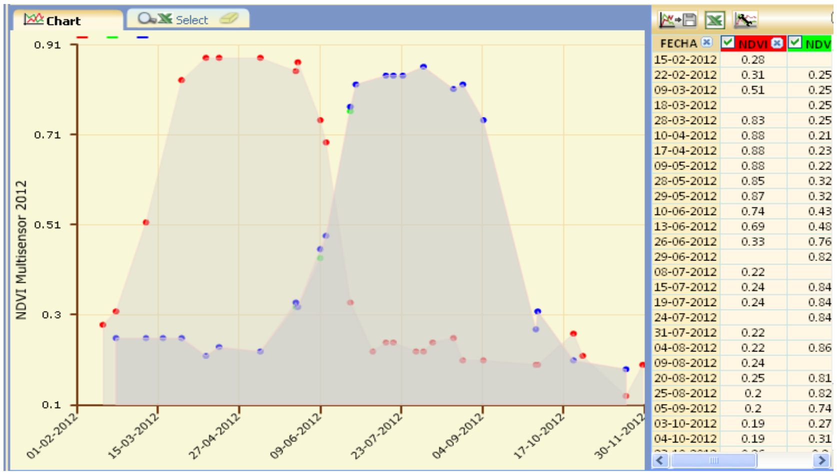

Figure 1 - Different temporal phenology patterns of wheat and corn both irrigated as described by NDVI

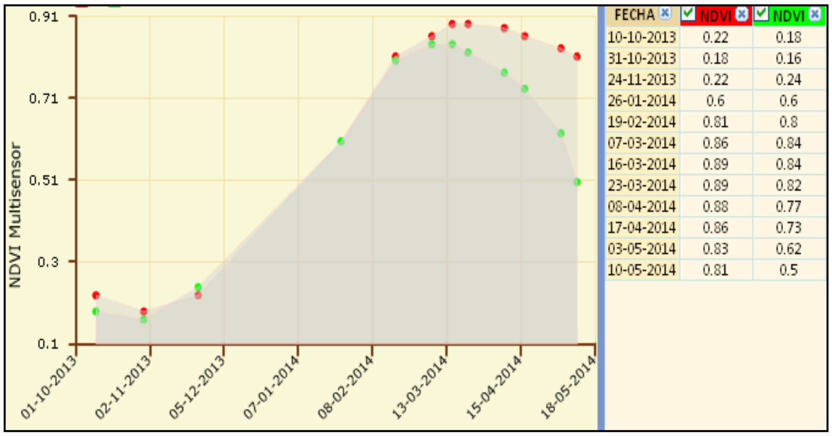

Figure 2 - Different NDVI magnitude patterns of irrigated and non-irrigated wheat

Note: Two parcels of wheat with the same sowing date and similar development at the beginning of the cycle (due to sufficient amount of rainfall) exhibit a different behaviour in the dry months as a consequence of no irrigation in one of them (green dots).

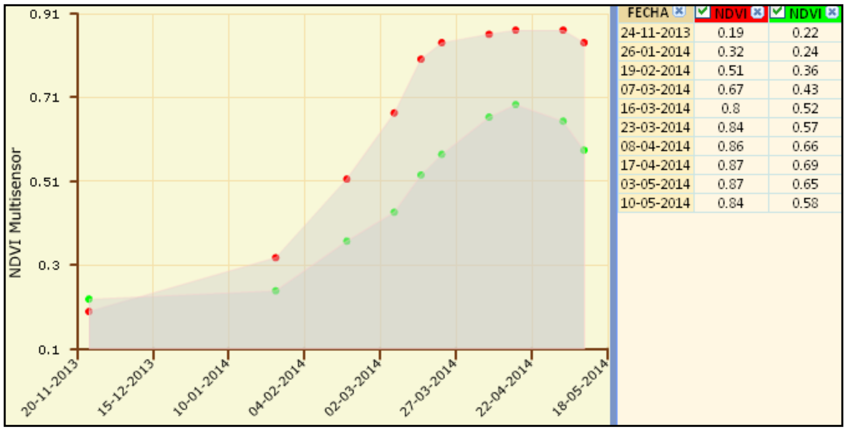

Figure 3 - Different NDVI's magnitude patterns of wheat with different levels of irrigation

Note: Two parcels of wheat under different water supply: fully irrigated (red) and not well irrigated due a failure of pumping (green). Sowing date is later in fall than in previous figure (leading to not enough rainfall during early phenology stage).

Finally, it is worth noting that:

- the whole procedure is not an automatic system because it requires a precise knowledge of crops and their phenology and needs further validation by an experienced operator;
- EO-derived information can represent a substantial tool to direct and guide field inspections (e.g. by providing targeted mission roadmaps for field technicians).

1.1.3 EO for detecting and monitoring abstraction

Several methods and experiences have demonstrated that EO are an effective tool to derive irrigation crop requirements maps (Calera, Campos, Osann, D'Urso, & Menenti, 2017) (Vuolo, D'Urso, De Michele, Bianchi, & Cutting, 2015). EO data enables water managers to estimate the water demand of crops located in the irrigated areas and to compare this with the authorized volume of abstracted water accordingly to the corresponding rights or hydrological plans.

EO is particularly relevant to monitor irrigation abstractions in agricultural areas with regular water shortages and high reliance on irrigation, and in areas with large parcels cultivated with summer crops. Irrigated areas and crop water requirements can be identified with great accuracy i.e. > 90% for herbaceous crops in optimal growing conditions. It may be less suitable in (sub-) humid areas (where irrigation remains often supplemental), where vegetation is mostly perennial and/or where mixed patterns of crops in small parcels (<1 ha) are predominant, as it requires further supporting from local data and/or more complex infrastructure (with additional costs and human resources requirements). EO is less suitable in areas with high presence of clouds, which can affect the frequency and timing at which images are acquired, although this latter issue has been greatly reduced since the launch of Sentinel 2B which allows a revisit time of 4-5 days in combination with the twin satellite Sentinel 2A.

The detection of non-authorised abstractions of the second type (volumes) requires mapping crop water consumption over time during the growing season. This can be accomplished by using the same time series of images used for the detection of irrigated areas, nonetheless requires further processing (Figure 5 and Figure 6).

The basis of irrigation water requirements calculations is:

- time series of reflectances and vegetation index (VI) maps can be converted into maps of basal crop coefficient, the basic input for the widely used FAO56 model on crop evapotranspiration calculations. The crop coefficient is analogous to a transpiration coefficient. The FAO56 approach is the most widely used and operationally mature method since the seventies to retrieve evapotranspiration from agricultural crops. The crop coefficient can be obtained directly from linear relationships with vegetation indices (Glenn et al. 2011) and/or from reflectance data and a series of intermediate relationships involving fAPAR or LAI. The degree of accuracy of both methods is similar (D'Urso et al. 2011). The VI-based basal crop coefficient approach is operationally mature and can use spectral data from all Interpolation of consecutive images is used to fill the gaps (e.g. due to cloud cover), and the product of basal crop coefficient and daily reference evapotranspiration from the agro-meteorological station subsequently provides daily crop water requirements on a pixel by pixel basis.
- remote sensing of evapotranspiration can also be obtained from surface temperature images by using additional techniques based on surface energy balance (Bastiaanssen et al. 1998). Given that of all operational high-resolution satellites only Landsat currently provides surface temperature (and with a revisit time of 16 days), and considering its thermal channel spatial resolution of 100 m pixel size, this procedure is complementary with the one previously described, and can provide an independent quality control in suitable areas. The upcoming Sentinel-3 will also provide a thermal band, albeit at the coarse pixel resolution of 1 km.
- EO-driven soil water balance, according to FAO56, enables to calculate irrigation water requirements on a pixel by pixel basis. Precipitation and soil hydraulic characteristics are required. Following FAO56 procedures it is possible to calculate irrigation water requirements under water stress situations, as is used either in controlled deficit irrigation or in the case of supplemental irrigation. Knowledge of the desired water stress degree is required, which needs local calibration. EO-based soil moisture data can be useful in some cases, which explores by using Sentinel-1, se Section 2.4.
- the calculation of abstracted volumes require the efficiency figures of both irrigation systems and irrigation distribution/storage.

Figure 4 and Figure 5 show the flux diagram of the whole process (including indications on the sources of uncertainty and accuracy).

This project is co-funded by the European Union

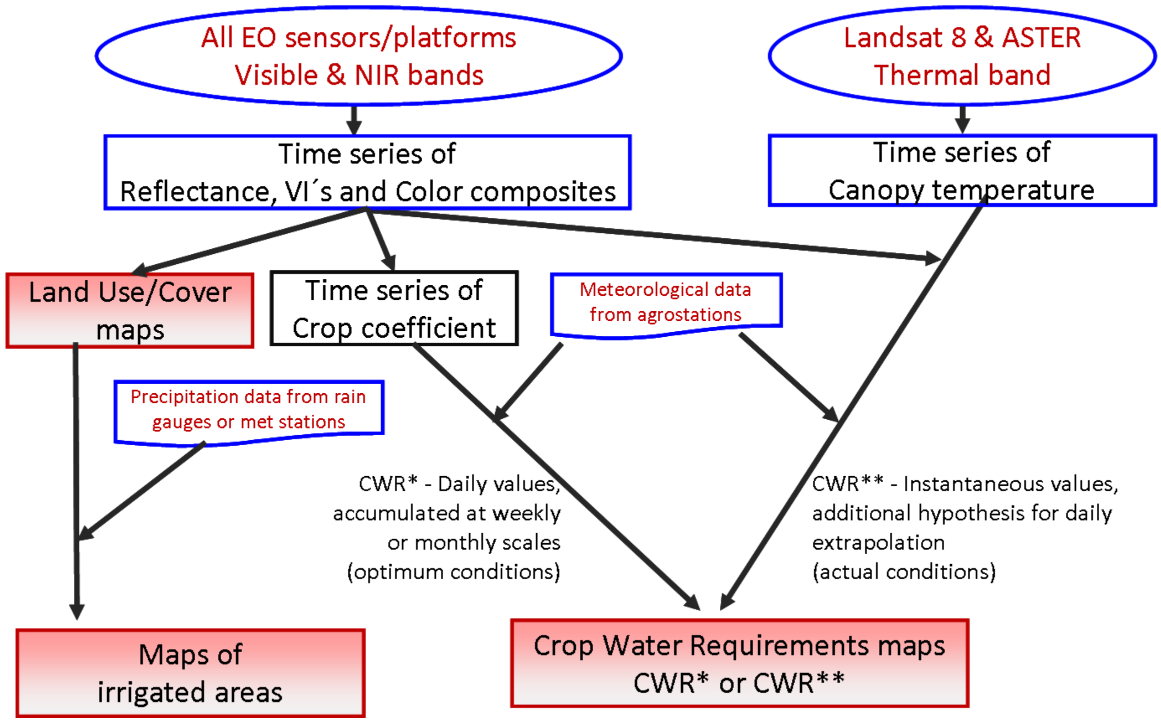

Figure 4 - Overview of steps in using EO for detecting non-authorised abstractions

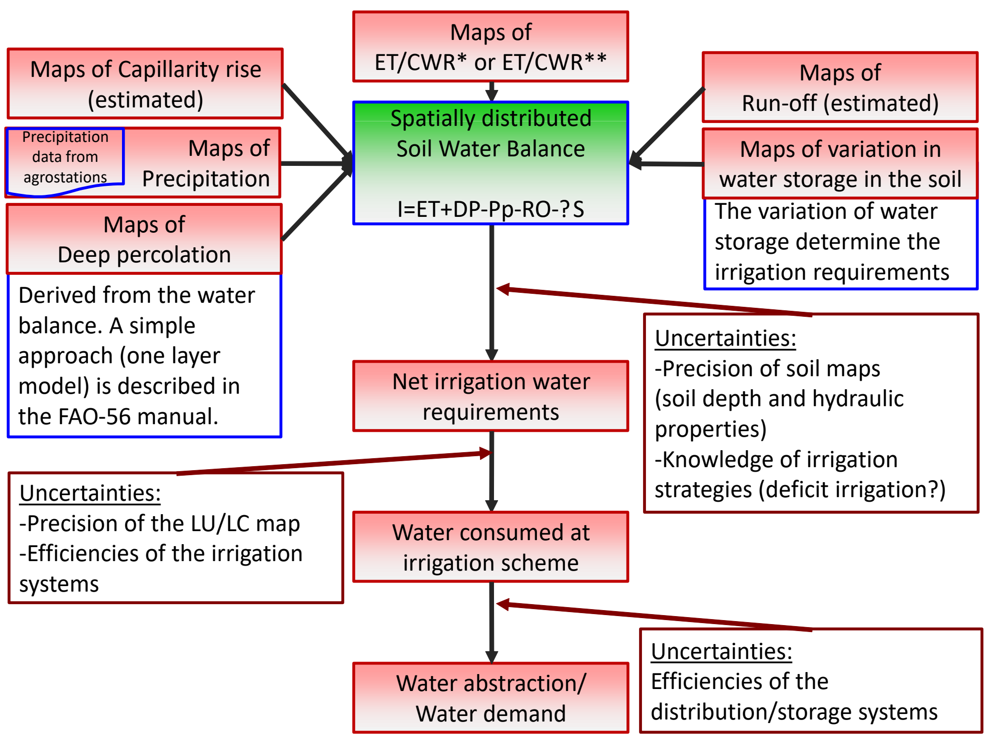

Figure 5 - Overview of processing steps from crop water requirements (CWR) to water abstraction

As described, Irrigation Water Requirement is an output of the soil water balance, where estimates of evapotranspiration rely on the time series of multispectral images. Soil water balance is the basis of water accounting, http://wateraccounting.org/. Even so, it is worth noting that the described EO-based procedure provides estimates of water abstractions and not real figures, because it is not a physical measurement of applied water, then it is not intended to replace individual metering of abstraction points. But the EO-based procedure to obtain IWR is being used routinely to advise farmers about how much water to apply (Calera et al., 2017). Therefore we can expect reasonably the IWR so obtained represent the behaviour of farmer driven by the maximum benefit. It provides a complete territorial view of abstractions and therefore is a powerful tool that can guide inspections to areas where it is more likely infringements to occur.

1.1.4 Opportunity from active remote sensing

During the past decade, several radar sensors have been deployed in space. Though none was designed specifically for irrigation mapping, several investigations have demonstrated that the data may provide useful information about the characteristics of irrigated landscapes. Firstly, the radar data can be acquired as frequently as possible without atmospheric interference and solar angle variations. Secondly, depending on the wavelength, the radar backscatter signal carries information about the moisture status of vegetated landscapes.

Theory

Backscatter may decrease or increase when vegetation grows, depending on whether the attenuation of the soil contribution is more important than the enhanced contribution from the vegetation canopy or vice versa. An increase in surface roughness (as determined by vegetation growth) and soil moisture content determines a more pronounced backscattering.

- Attenuation of the soil contribution is dominant at low incidence angles
- Canopy scattering dominates at higher incidence angles
- There is a cross-over angle at which both effects balance each other (minimal vegetation influence)

Therefore, backscatter values must be normalized to a reference angle of 40° for each acquisition geometry.

Sentinel 1 data can be downloaded from the ESA-Scihub in the following configuration modes:

1) **S1 GRD IW format** (ground range detected, interferometric wave mode) acquired on descending orbits at an incidence angle between 230 and 400 (VV-VH polarization);
2) **S1 SLC IW format** (single look complex data which contain phase information) on descending orbits (depending on topography – local incidence angle) in order to find dominant scattering mechanism and to obtain coherence information

The GRD dual pol data require further processing for soil moisture retrieval like:

1. Orbit correction
2. Thermal noise removal
3. Multi-looking with 2 in range and 0.5 in azimuth
4. Co-registration time series using a master sample as input
5. Advanced multi-channel filtering (reduce noise while maintaining a high spatial resolution which enclosed: i) despiking and respiking; ii) structural spatial filtering with 13 x13 pixel window using temporal average image to select structure windows to use and iii) combined multi-channel filtering for VV and VH polarization [Wegmuller]
6. Geocoding/Radiometric calibration, normalization and slope correction;
7. Change detection method based on image ratio method.

Drawback for Sentinel 1 data: only one backscatter measurement at one incidence angle per *image acquisition -> no seasonal varying slope parameter.*

Limitation:

1. From temporal perspective, seasonal vegetation signal in C band time series much weaker than soil moisture signal -> Seasonal vegetation effects are neglected in first approximation.
2. When using HH polarization, better penetration of vegetation than in VV polarized backscatter.

Advantage: Benefiting from the dense time series of SAR S1 images, we can suppose that the backscatter change between two subsequent acquisitions is mainly related to the temporal change of soil moisture. Thus, vegetation biomass or crop canopy or surface roughness, which also affect the radar response, are considered constant [Balenzano et al., 2012].

Image time series will be investigated assuming a linear correlation between SAR backscatter and relative SM between estimated dry and wet references of a given soil. This methodology originally developed and operationally implemented using scatterometer data could be applied on S1 data in order to calibrate the model and accurately compute dry and wet references [Wagner et al., 1999]. Thus, a relative soil moisture index can be retrieved.

$$m_s(t) = \frac{\sigma^0(\theta,t) - \sigma^0_{dry}(\theta,t)}{\sigma^0_{wet}(\theta,t) - \sigma^0_{dry}(\theta,t)} \qquad \textit{eq. 2.1}$$

where: σ^0_{dry} is historically lowest backscatter and σ^0_{wet} is historically highest backscatter.

2 Diana methodologies to detect irrigated areas

2.1 Overall Approach

The basic assumption of the proposed methodology is that, under conditions of hydrological deficit as in semi-arid environments, high crop growth trends are compatible only with external irrigation supplies. Based on this assumption, the detection of the irrigated areas can be conducted independently of the actual cultivated crops. Practically, this means that a detailed knowledge of the spatial distribution of the different crops is not required. Rather, it is enough to take into account the timing of some indices able to represent the vegetative vigor, such as NDVI, NDWI, LAI.

The classification process based on temporal pattern recognition exploits the captured differences from the canopy on the above-mentioned indices to assign each pixel (or object) to an irrigated/not irrigated class. These classes need to be defined on the basis of field work and "a-priori" knowledge about the crop phenology in a given area. This crop classification is the basis for identifying irrigated areas and the point in time when this irrigation happens.

From an operational point of view, the procedure consists of the following stages:

- **Choice of data and preliminary processing**; in this phase, the types of sensors most suitable for the study are chosen based on the requirements in terms of spatial, temporal and spectral resolution;
- **Production of multi-time series of vegetation index NDVI map**s (bat also the Normalised Difference Wetness Index (NDWI) has also been suggested in similar studies, as it is sensitive to vegetation moisture content) (Gao, 1996); at this stage, a spectral index map NDVI is produced for each of the acquisitions; subsequently, a temporal stack (layer stack) is created;
- **Manual masking of areas not of interest**, typically urban, mountain and wetlands such as rivers, lakes and water basins;
- **Unsupervised classification** (clustering) applied to time series of NDVI index maps.
- **Automatic extraction of temporal NDVI index pattern**;
- **Labelling of vegetative areas**, identification of classes of vegetation categories that, given the water deficit conditions, show NDVI pattern compatible only with irrigation;

- **Supervised classification**: this is done using such training pixels of irrigated areas identified via the multi-time classification of NDVI index combined with on field inspection and ground trues; this phase is aimed at improving the accuracy of the unsupervised classification;
- **Mapping of irrigated areas** along with possible integration with other GIS data.

In summary, the time series maps of NDVI index collects all the information needed, pixel-by - pixel, parcel-to-parcel, to establish whether or not a given area is irrigated. However, the solution to the problem of identification requires a single map for the whole irrigation season. Ideally, this would include a binary information (irrigated/non-irrigated) in which regions are divided into classes (irrigated herbaceous crops, irrigated tree crops and not irrigated areas with associated their accuracy).

2.2 EO Technical requirements

2.2.1 Spatial resolution requirements

Researches has shown that the finer the spatial resolution, the greater the accuracy of irrigated area class designations (Thenkabailc, Biradar, & Noojipady, 2007). This simple statement would always pick the sensor with the best spatial resolution available. In general, to map accurately irrigated areas, the spatial resolution of the sensor must be equal to or less than the size of the fields of interest.

From the operational point of view, the choice of the most appropriate spatial resolution depends by the smallest cartographic unit. In technical practice, it is common to refer to what is stated in the Table 1- Using Sentinel-2 data (10 m best spatial resolution) it can be assumed that the minimum mapping area is half hectare, and by excluding elongated shape plots with at least one dimension less than five times the pixel size of available satellite data.

Scale denominator	Minimum mapping object dimension (m)	Pixel dimension on the ground (m)
250.000	250	125
100.000	100	50
50.000	50	25
25.000	25	12,5
10.000	10	5

Table 1 - Scale Denominator, Minimum mapping object dimension and pixel dimension on the ground

2.2.2 Spectral data Requirements

The selection of spectral bands or indices (Tab.3.2) which contain the maximum amount of irrigation-related information is a significant challenge. While the analysis of EO data for detecting vegetated areas in agricultural lands is quite straightforward, the distinction between irrigated and non-irrigated crops is more difficult (Ozdogan, Yang, Allez, & Cervantes, 2010). A further complication may arise when only supplemental irrigation is usually applied because these crops exhibit less contrast against rainfed or irrigated plots. There is a wide consensus that NDVI is a valuable information for monitoring vegetation and irrigated lands. Particularly, in arid and semi-arid areas, which are under hydrologic deficit (Agnew & Anderson, 1992), characterized by single irrigation period and simple land cover types, the pattern of NDVI associated with irrigation is a well-defined feature. However, difficult cases for distinguishing irrigated from not irrigated crops occur in location where the corresponding growing seasons overlap. To overcome this shortage, other authors (Zarco-Tejada & Miller, 2002) have shown that the chlorophyll index suggested by Gitelson (A. Gitelson, Kaufman, & Merzlyak, 1996) is correlated with vegetation stress and hence it may allow for distinguishing irrigated from not irrigated crops. The Normalised Difference Wetness Index (NDWI) has also been suggested in similar studies, as it is sensitive to vegetation moisture content. This spectral index is based on the increased absorption of shortwave-infrared from leaf moisture. NDWI is a measure of liquid water molecules in vegetation canopies that interacted with the incoming solar radiation. It is less sensitive to atmospheric scattering effects than NDVI. NDWI increases as leaf layer increases, indicating NDWI is sensitive to the total amounts of liquid water in the stacked leaves (Gao, 1996).

Index	Formula	References
NDVI (Normalized Difference VI)	*(NIR-RED)/(NIR+RED)*	https://dx.doi.org/10.1080/01431160500168686
NDWI (Normalised Difference Wetness Index I)	*(NIR-SWIR)/(NIR+SWIR)*	(Gao, 1996)
CI $_{\text{red-edge}}$	$\left(\frac{R_{783}}{R_{705}}\right) - 1$ *(for Sentinel-2)*	(A. A. Gitelson, Gritz †, & Merzlyak, 2003)

Table 2 - Spectral vegetation indices for irrigated area mapping

2.2.3 Temporal data Requirements

To determine the optimal period of image acquisitions and the minimum temporal resolution, “a priori” knowledge about the main cultivated crop and their crop calendar (seeding, harvesting, development) is required. Another issue related to temporal resolution is the clouds presence: with short revisit time it is possible to replace cloudy acquisitions with the next cloud free. The problem of persistent clouds of humid regions is still challenging.

Typically, the temporal resolution required for irrigation detection purpose is to have a fairly cloud-free image (<10% cloud) every 1-2 weeks from about 2 weeks before the start of the growing season until its end.

Temporal resolution of Sentinel-2 A&B and Landsat-8 satellites:

The European Space Agency’s Copernicus programme has expanded on March 7th, 2017 with the launch of Sentinel-2B, which alongside Sentinel-2A will provide 5-day revisit period.

The Landsat 8 satellite (launched February 11, 2013) images the entire Earth every 16 days in an 8-day offset from Landsat 7.

2.3 Pre-processing of EO data

2.3.1 Inter-calibration and Atmospheric correction

Evaluation of crop development based on data from different satellites needs to take into account factors that may affect the sensor's response, such as calibration differences, between different sensors, variability of atmospheric conditions, and different viewing and illumination angles due to acquisition geometry.

To reduce the errors caused by these factors, it is needed to adopt procedures for the radiometric and atmospheric correction of EO data, even in the simple case of time-series of vegetation index (Duggin and Robinove 1990); it has been documented these corrections are especially relevant when the aim is to assess and evaluate the NDVI variations between acquisitions of different epochs (Song, Woodcock, and Seto 2001).

2.3.2 Clouds masking and gap filling

There are many ways on how to get cloud free images of Sentinel-2 and Lansat-8. All techniques are based on two steps: cloud masking and gap filling.

In the following, an overview on possible technologies that can be used for cloud masking is given.

FMASK

FMask is a very popular method that was developed by Zhu and Woodcock for Landsat-8. Since Sentinel-2 uses other bands (i.e. no thermal infrared but) the method had to be revised and is currently available here. Generally speaking, FMask results for Sentinel-2 are not as good as for Landsat (mainly due to the missing thermal band). The algorithm is implemented in Python and can be executed via the command line.

SEN2COR

Sen2Cor is a processor for cloud-free Sentinel-2 Level 2A products. It performs the atmospheric-terrain and cirrus correction of Top-Of- Atmosphere Level 1C input data. Sen2Cor returns three cloud probability classes: High, medium and low. The satellite image can then be masked with a custom user combination of these three classes. Sen2Cor can be downloaded from http://step.esa.int/main/third-party-plugins-2/sen2cor/. It is executed via command line or can also be integrated into a desktop application via SNAP. Another very useful website concerning Sen2Cor is the official user forum with designated trouble shooting sections. Many users have reported bugs while using Sen2Cor which are currently being worked on. Sen2Cor is a good cloud masking alternative but there are still many unresolved issues (over-/underestimation, bugs with water pixels.)

MAJA

The MAJA processor (MACCS ATCOR Joint Algorithm, say "maja") is a processor for cloud detection and atmospheric correction, specifically designed to process time series of optical images at high resolution, acquired under quasi constant viewing angles. It allows for the processing of time series of LANDSAT or Sentinel-2 images. Since 2016, it has been progressively including methods taken from DLR’s ATCOR processor. It is now the object of a collaboration between CNES, DLR and CESBIO, and benefits from ESA funding.

Its main feature is to use the multi-temporal information contained in time series to detect the clouds and their shadows, and to estimate the aerosol optical thickness and correct the atmospheric effects (taking into account the adjacency effect and the illumination variations due to topography). To process time series, an example of a scheduler able to launch MAJA is available here: https://github.com/olivierhagolle/Start_maja.

The **gap filling procedure** is generally applied to the vegetation indices. There are several methods to fill data from time-series of vegetation indices or surface reflectance values, grouped into four major classes (Table 2):

1. **slope methods**, including the best index slope extraction technique (BISE);
2. **filter-based methods**, including the Savitzky-Golay filter technique and its variants, and the mean value iteration filter;
3. **function fitting methods**, such as the Asymmetric Gaussian fitting and the harmonic analysis of time series (HANTS);
4. **smoothing techniques**, i.e. the Whittaker smoother.

Comparisons of these techniques have been carried out in several case-studies, by using different indicators of performance. Each method has its own advantages and drawbacks. New techniques have been proposed in recent years, and in many cases there is not a rigorous comparative analysis with other techniques. Almost all comparisons have been based on one sensor.

Besides the choice of the algorithm, it is important in the context of DIANA to consider which tools are available for performing these analyses. For this reason, within the categories given in Table 2, partners of DIANA project (Ariespace and Agrisat Iberia) have successfully applied the Best-Index slope extraction technique and Whittaker smoother in the context of H2020 FATIMA project. These methods can be implemented in Matlab and in the open-source package R.

Category	Method	Description
Slope Interpol.	Best-Index slope extraction technique	Compares the current term value with the previous and the next term within a predefined sliding window, and replaces these values with the mean value of the previous and the next values if the percentage difference is greater than a predefined threshold (20%).
Filter based	Savitzky-Golay and its variants	Local polynomial fitting of the upper envelope of data series, based on two parameters: the length of the temporal window used and the order of the polynomial. As proposed by Chen et al. (2004), the values of these parameters have to be optimized for each case to get the best match between observations and reconstructed values. In newer variants, the temporal window may be asymmetric and variable in length.
	Mean value iteration	Iteratively compares each date with the average of the dates before and after it, replacing the date with this average if the difference is above a certain threshold. The maximum difference date value will be removed in an iteration process. Iteration will stop when all differences are less than the threshold.
Function fitting	Asymmetric Gaussian fitting	Fits local, nonlinear functions at intervals around the local maxima and minima, then merges these into a global function describing the full NDVI time series.
	Fast Fourier and Harmonic analysis (HANTS)	Time series are decomposed into sum of sinusoidal functions; once derived phase and amplitudes, these parameters are used for reconstructing and analyzing the data set.
Smoothing	Whittaker smoother	Based on "penalized" least squares regression, it fits a discrete series to discrete data and penalizes the roughness of the smooth curve. In this way, it balances the reliability of the data and roughness of the fitted data.

Table 3 - Summary of gap filling methods considered in the present study

2.4 Production of Time-series of vegetation indices

The signals from an EO satellite sensor can be converted into reflectance and vegetation indices (VI) by combining the various spectral bands. Particularly, as reported in Allen et al. 1998, the Normalized Difference Vegetation Index (NDVI) is linearly related to the basal crop coefficient. (defined as the ratio of the unstressed crop transpiration to the reference evapotranspiration). Therefore, the phenological curves can also be expressed in terms of NDVI vs. time. Other indices useful for classification purpose are already described in Table 2. For irrigation detection some authors (Gao, 1996) have explored the usefulness of SWIR bands. A particular mention deserves the Leaf Area Index which is one of the most powerful parameter related to the crop development. The Leaf Area Index (LAI), defined as the total one-sided area of green leaf area per unit ground surface area, is used to derive agronomical indicators for various crop management purposes. For instance, LAI maps are used in agro-meteorological models to derive the crop water requirements, as implemented in the irrigation advisory service Irrisat (Vuolo et al., 2015), to monitor the nitrogen status and to apply fertilizer with variable rates (e.g., FarmSat, Fatima), and finally as input in crop models. On a larger scale, LAI and other biophysical variables are used for example for yield predictions at administrative level. A general overview of remote sensing contributions to agriculture is given in (Atzberger, 2013).

2.5 Multitemporal classification

The detection of irrigated areas (defined as the identification of their location and their areal extent) requires land-use/land-cover maps that allow distinguishing irrigated from non-irrigated crops. This is accomplished by a supervised “multi-temporal classification” based on a time series of VIs. The classification process based on temporal pattern recognition exploits the captured differences from the canopy on the VI to assign each pixel to a vegetation class. These classes need to be defined based on field work and knowledge about the crop phenology in a given area.

2.5.1 Pixel based classification vs. Object based Classification

For the classification of satellite data, two basic methods are to be distinguished: the pixel-based and the object-based method. In the case of the pixel-based method, each individual image pixel is analysed and classified according to its spectral features. Object-based methods assume that a pixel is very likely to belong to the same class as its neighbouring pixel. In a first step, the image space is segmented into homogeneous objects consisting of similar pixels. These objects are then also grouped in classes of the same semantic significance. For classification, however, apart from the spectral features, additional features such as shape, size, texture and neighbourhood relations of the objects are available (Koch et al., 2003).

2.5.2 Classification and recognition of NDVI temporal patterns of irrigated crop

Two basic categories exist in current classification methods, supervised and unsupervised.

Unsupervised clustering classification method is often used for studies in which the location and characteristics of specific classes are unknown. Unsupervised classification uses clustering to identify ‘‘natural’’ groupings of pixels with similar NDVI properties. In this case, the clusters correspond to locations with similar annual sequences in green-up, maximum, and senescence of green biomass. Several clustering algorithms exist, generally they are a variation of the k-means. In the context of DIANA, it will be adopted an iterative statistical clustering algorithm that defines clusters or groups of NDVI values with similar properties.

Supervised classification clusters pixels in a data set into classes corresponding to user-defined training classes. Several supervised classification algorithms are available for image classification.

From “ancient” minimum distance classification method to most recent application of machine learning.

In the context of new classification algorithm based on machine learning, the Random Forests (RF) classification (Breiman, 2001) is one of most popular. It is an ensemble learning classification tree algorithm, which became very common for remote sensing data classification in the past few years. One main advantage of RF is that the construction of each tree is based on a bootstrap sample of the same size as the input data set (sampling with replacement). The generated trees are applied only to the not drawn samples (out-of-bag data, OOB) and the majority votes of the different trees are used to calculate the model accuracy. Additional benefits of RF are the random selection of split candidates, the robustness of the output with respect to the input variables (distribution of variables, number of variables, multi-collinearity of variables) and the provision of importance information for each variable. The latter characteristic of RF permits the user to rank and select features. Several studies reported that a reduced/optimized feature set further improved the mapping accuracy.

2.5.3 Accuracy

In remote sensing, estimates of precision are an important technique for assessing and comparing classification results. There are various methods of determining this precision, which have already been derived and extensively discussed in the literature. Banko (1998), Congalton (1991), Rosenfield et al. (1982), Hudson and Ramm (1987) and van Genderen et al. (1978) give a good overview of the various measures, the general methodology as well as the establishment of an error matrix and the topic of training areas (samples).

In the present study, the mathematical derivation of the individual measures will not be shown and readers are referred to the literature mentioned above. For quality assessment (estimates of precision), the overall accuracy and the user's and producer's accuracy are calculated. The representation takes the form of a conventional error matrix. This matrix lists the reference data (ground truth) in the columns and the classified training areas in the rows. The diagonal of this matrix shows the correct classified objects.

A user's and producer's accuracy basic measure is the overall accuracy, which can be calculated from the ratio of the number of correctly classified samples (sum of the diagonal values in the error matrix) to the total reference data. This measure is easy to calculate and enables the quality to be estimated across a number of classes. Quality estimates for individual classes are, however, also possible.

The user's and producer's accuracy (Congalton, 1991) is suitable for this purpose. The producer's accuracy is calculated from the correctly classified number of objects in a class divided by the number of reference objects in this class. This is a measure of how well the respective class was identified. It includes the so called error of omission. This corresponds to the reference objects that belong to the class under consideration but were not recognized by the classification model.

The user's accuracy can be derived from the correctly classified objects of a class divided by the total number of all the objects assigned to this class. This permits a statement to be made on the reliability of the classification for the class under consideration, since it also includes in the measure of quality those objects that do not belong to the class under consideration but which are identified as such objects by the classification model. These objects correspond to the error of commission.

3 Estimation of Abstracted Volumes from groundwater, Irrigation Water Requirement and Crop Water Requirement based on Earth Observation (EO) data

One of the major outputs of the Diana Project is the development of tools based on E.O. to estimate the irrigation water requirements and, by means of it, the abstracted volume from groundwater.

Currently, in operative context, the abstracted volumes are usually monitored:

1. Directly, through in-situ metering (i.e. flow meters in the case of groundwater wells (electricity used for pumping can sometimes be used as proxy), a variety of counters in the case of surface water release from dams, reservoirs, channel networks or individual pumping devices); Or
2. Indirectly, through the record of operation hours and channel delivery flow, in areas with irrigation channels; or

By calculating a water balance, taking into account soil water storage and depletion (and eventually capillary rise), evapotranspiration and precipitation, as indicated by standard procedures of FAO- paper 56 (Allen et al. 1998).

Technically speaking, it's worth to note that the problem of estimation of water abstraction from groundwater to irrigate the crops and the irrigation water withdrawal from collective irrigation networks are conceptually similar. Both aim to replace the water consumed during all the development stages of the crop. In the hypothesis that each farmer withdraws an irrigation water volume not less than the irrigation water requirement of crops, the estimation of water abstraction can be achieved by the calculation of Net Irrigation Water Requirement (NIWR) of crop. In the literature, the definition for NIWR is:

NIWR: *Net Irrigation Water Requirement* is the water that must be supplied by irrigation to satisfy evapotranspiration, leaching, and miscellaneous water supply that is not provided by water stored in the soil and precipitation that enters the soil (Jensen, Burman, & Allen, 1990). It is expressed in millimetres per year or in m3/ha per year (1 mm = 10 m3/ha). Generally, NIWR can be calculate as follow:

$$NIWR = (ET_C + W_l + W_m) - (P_e + \Delta W_s) \qquad \textit{eq. 3.1}$$

where ETC (mm) is the crop evapotranspiration under standard conditions (i.e. crops in optimal agronomic conditions and soil water supply); P_e is effective precipitation available for the crop, ΔWs is the variation of soil water storage (volume per unit area or depth) taking into account percolation and capillary rise, W_l is the water required for leaching, Wm is the miscellaneous requirement (germination, frost protection and so on). To obtain the actual quantity of water to be applied, an efficiency coefficient has to be applied to take into account losses of irrigation distribution system.

From the operational point of view, in the eq 4.1 the most important terms are ETC and P_e. Considering a long-medium period, such as the duration of a typical irrigation season (3-6 months), the miscellaneous losses, leaching and soil water content variation tend to be negligible (while for irrigation scheduling the estimation of the variation in soil water content becomes a notable terms). With these assumptions in mind, it is clear that the most important terms is the so-called Crop Water Requirement defined as follow.

$$CWR = ET_C - P_e \qquad \textit{eq. 3.2}$$

which is the standard approach proposed by (Allen, Pereira, Raes, & Smith, 1998) and adapted to E.O. data as described below.

Effective precipitation. Several formulations have been proposed to estimate P_e, in which the effective precipitation depending on canopy development described by means of the Leaf Area Index LAI, and the fractional vegetation cover f_{cover}, accordingly to (Braden, 1985).

Crop evapotranspiration. Crop evapotranspiration under standard conditions, denoted as ET_C, is the evapotranspiration from disease-free, well-fertilized crops, grown in large fields, under optimum soil water conditions, and achieving full production under the given climatic conditions. The Penman-Monteith equation was implemented in the standard procedure for estimating of ET_C, commonly known as the FAO-56 method. This procedure can be adapted to Earth Observation (E.O.) data for the operational assessment of crop water requirements. It is generally made by using the following procedures:

3. the approach based on the crop coefficient concept Kc, establishing a direct correspondence between Kc and reflectance measurements;
4. the direct calculation, “one-step” approach, based on the application of the Penman-Monteith equation with appropriate values of canopy variable such as crop height, surface albedo and Leaf Area Index (LAI).

Surface energy balance algorithms like SEBAL or METRIC (Allen et al., 2011), requiring thermal observations, which are only available from Landsat at spatial resolution of 100 m.

Considering the technical constraints of the third approach outlined above, the first two approaches will be adopted in DIANA. Following a short description of them will be provided. For detailed description see: D’Urso et al., 2010; Vuolo, D’Urso, De Michele, Bianchi & Cutting, 2015.

3.1 Kc-NDVI approach

In the original P-M equation, this condition implies a minimum for the leaf resistance, which can be considered as a constant for most crops. Experimentally determined ratios of ET_C/ET_0 called crop coefficients (Kc), are used to relate ET_C to ET_0 (where ET_0 is the reference evapotranspiration as defined in FAO 56),

$$ET_C = Kc\ ET_0 \qquad \textit{eq. 3.3}$$

Moreover, the crop coefficient approach, as proposed by (Neira, Álvarez, Cuesta, & Cancela, 2005) and adopted within the FAO procedure, splits Kc into two separate coefficients, one for crop transpiration (Kcb, basal crop coefficient) and one for soil evaporation (Ke), which describes the evaporation component of ET:

$$ET_C = (K_{cb}+K_e)\ ET_0 \qquad \textit{eq. 3.4}$$

where K_{cb} “spectral” basal crop coefficient [0.15 – 1.15], NDVI, calculated from surface reflectance bands. The soil evaporation needs to be accounted for the estimation of Kc. As is known, K_e, is related with bare soil fraction, and is strongly dependent on the wetting state of bare soil fraction, because the evaporative power of soil changes strongly if the soil is wetted or if the soil is dry. Irrigation system (gravity, sprinkler, drip, etc) and irrigation frequency, coupled with type and stage of crop, are the factors that determine the time of different bare soil wetting states. An approach for crops that in their maximum crop development fully cover the soil, like wheat, corn, barley, and so on, can be stated as:

$$Kc = 1.15\ NDVI + 0.17 \qquad \textit{eq. 3.5}$$

where: Kc is the "spectral" crop coefficient.

3.2 ETp direct calculation, based on the application of the Penman-Monteith equation

In direct calculation, ETp can be estimated by the Penman Monteith equation, explicitly written in terms of albedo α, Leaf Area Index (LAI) and meteorological data:

$$ET_p = \frac{86400}{\lambda}\left[\frac{\Delta\left[\left((1-\alpha)R_s - R_{nl}\right) - \left(1-0.4e^{-0.5LAI}\right)\right] + \frac{\rho c_p (e_s - e_a)}{r_a}}{\Delta + \gamma\left(1 + r_{c,min}/r_a\right)}\right] \qquad \textit{eq. 3.6}$$

Where: λ is the latent heat of vaporization [MJ kg^{-1}], Δ is the slope of saturation vapor pressure curve at air temperature T [kPa $°C^{-1}$], R_s is the incoming solar radiation [MJ m^{-2} day^{-1}], R_{nl} is the net outgoing longwave radiation [MJ m^{-2} day^{-1}], c_p is the specific heat at constant pressure [MJ kg^{-1} $°C^{-1}$], ρ the mean air density at constant pressure [kg m^{-3}], ($e_s - e_a$) is the vapor pressure deficit [kPa], γ is the psychrometric constant [kPa $°C^{-1}$].

In direct calculation of the Penman-Monteith equation can be estimate the maximum fluxes of evaporation from soil (E) and transpiration from plant leaves (T) once provided with the canopy parameters related with the surface properties ; essentially the surface and canopy resistances (rs and rc respectively) and the net radiation (Rn). These parameters are, in turn, related to three parameters derived from E.O. data: namely, the leaf area index (LAI), the crop height (hc), and the surface albedo (r). The variable rc is inversely related to the active LAI and, in turn, dependent on the maximum resistance of a single leaf.

3.3 Accuracy in evaluation of ETC by EO approaches

The literature is abundant in E.O.-based ET models or model-variants and validations of these models in different environments, surfaces and managements. Every model has strong scientific bases and are well calibrated for ET assessment at particular temporal and spatial scales. The experiences carried out within the DEMETER, PLEIADES and SIRIUS project have confirmed that E.O. is a mature technology ready to be transferred to operational applications in irrigation management. Several papers have demonstrate the accuracy of the methods mentioned above (Rubio et al., 2006). Comparison between different methods and in field measurements are shown, for example, in Rubio et al., 2006; D'Urso et al., 2010. The figure below shows some results from D'Urso et al., 2010.

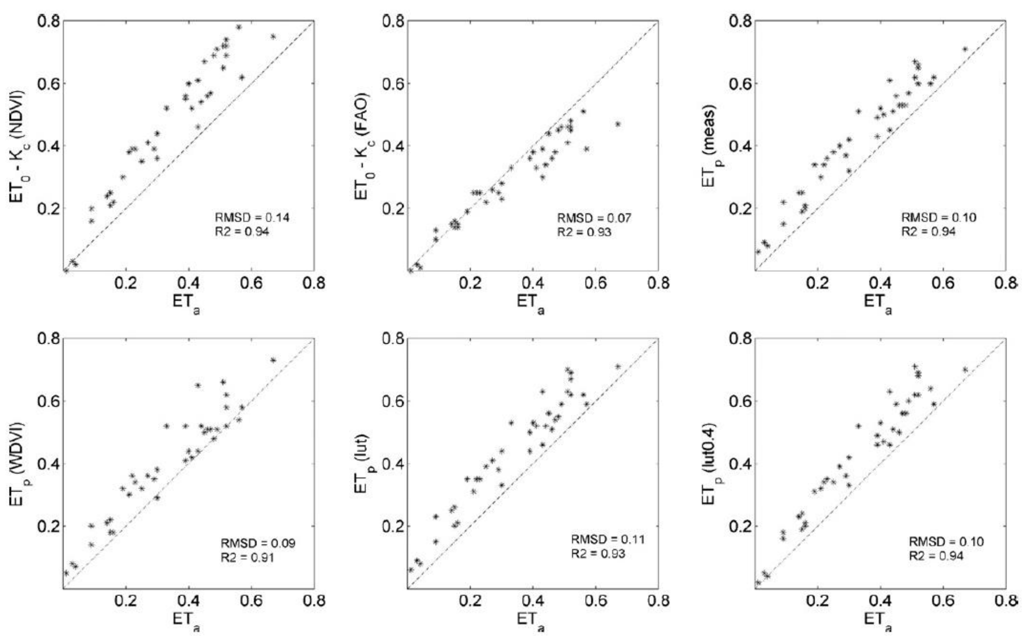

Figure 6 - Actual (ETa) versus crop evapotranspiration (ET_C) of irrigated maize (mmh−1), from 12 to 25 July 2007, commercial farm farm, Sardinia. ET_C values were estimated using the FAO methodologies with six different approaches to retrieve canopy parameters such as LAI, r or Kc-coefficient (D'Urso et al., 2010).

3.4 Assessment of uncertainties and mitigation strategies

Earth Observation presents a range of technical assets in contrast to field observation alone. It can provide detailed maps of irrigated areas and estimate the level of water consumption in large geographical areas (e.g. watershed scale), where field measurements provide only point values of evapotranspiration (ET) for a specific location and fail to provide the ET on a broader regional scale. Images can be obtained, e.g. on a weekly basis, depending on the resolution required. Several comparative analyses show that Earth Observation systems have good accuracy relative to field measurement techniques of crop water requirements (Neira et al., 2005) (Castaño, Sanz, & Gómez-Alday, 2010) (Vuolo et al., 2015) and water abstractions. In the Italian Pilot area of Sannio Alifano, during the IRRISAT project implementation, for example, the overall difference between the EO based estimation vs. flowmeter measurements was only 9% over 150 days for an area of about 3.000 ha. Similar comparisons were carried out in other areas, thus confirming that E.O.-based crop water requirements provide a satisfactory estimation of water abstractions for irrigation.

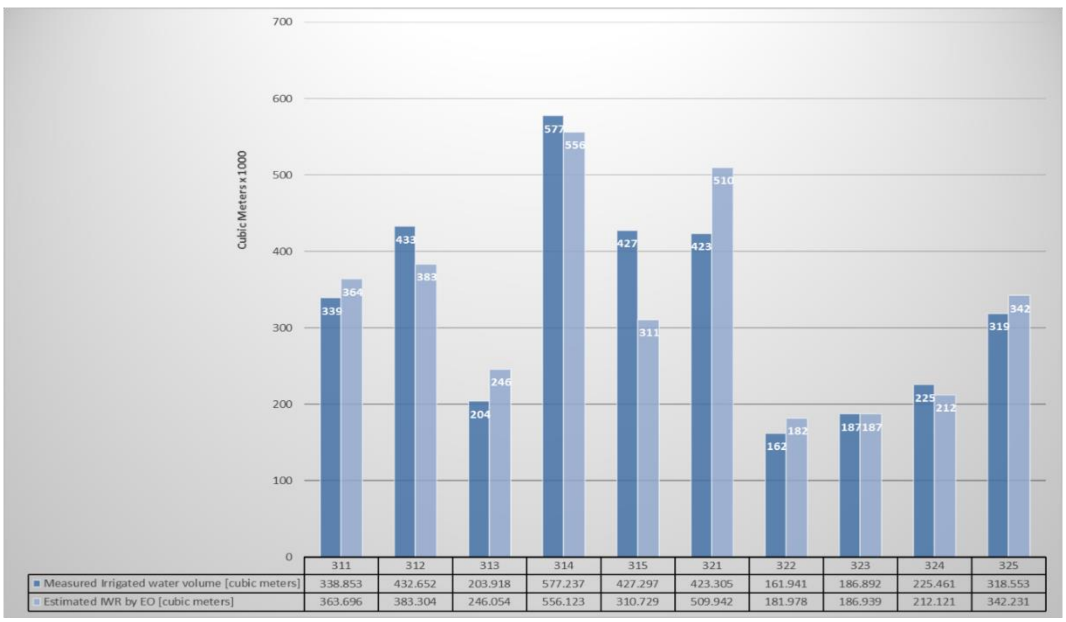

Figure 7 - Measured Irrigation water withdrawal (dark blue) versus estimated by EO (light blue) for 10 districts in the Pilot Area of Sannio Alifano during Irrisat Project implementation (year 2012).

However, as any estimation procedure, EO based techniques have their own uncertainty. The main uncertainties, which affect the estimation of irrigation water abstractions and withdrawals, are:

1. The accuracy of the procedure to classify irrigated areas: overestimation or underestimation of irrigated areas leads to an error in the estimation of irrigation water requirements at district level, by considering not irrigated plots (commission error) or by neglecting irrigated plots (omission error);
2. The calculation of irrigation water requirement from EO involves several steps, each of which is associated with further uncertainties (i.e. precipitation and soil data, efficiencies

   of irrigation system). These uncertainties remain in the same order of magnitude as for fieldwork. Uncertainty of EO-derived crop water requirements is around 5-10%.
3. The difficult to monitor water consumption with a sufficient resolution on small-cultivated parcels with mixed patterns of crops (about 1ha or less).
4. The presence of clouds can also affect the frequency and timing at which images are produced.

From technical point of view, these shortcomings will be tackled by the adoption of mitigation procedures. In the development of DIANA project, an assessment to evaluate the magnitude of uncertainties will be performed. The following table describe for each source of uncertainty the mitigation procedure and the related accuracy assessment.

n.	Source of uncertainty	Expected Magnitude	Mitigation	Accuracy Assesment
1	Classification of irrigated areas is affected by commission and/or omission errors	Accuracy in semiarid areas reaches typically over 90%, which is comparable to field work accuracy. Distinguishing non-irrigated areas from irrigated areas - especially in years with a rainy spring as well as areas with perennial crops - can be difficult.	Use additional information; increase the global accuracy by using the capacity of time series of images and by relying on a multiannual perspective.	An error matrix will be produced to evaluate the overall accuracy of the classification.
2	Calculation of irrigation water requirement from EO involves several steps	These uncertainties remain in the same order of magnitude as for fieldwork. Uncertainty of EO-derived crop water requirements is around 5-10%	Collect as accurate data as possible and ensure transparency about the degree of uncertainty	Comparison with flow meters' measurements of representative sample of irrigated plots or whole districts.
3	Low resolution of EO images to monitor small	It depends on the pilot area average field size	Use higher resolution images	Assessment of detection of small parcels in well-known

	plots			area.
4	Presence of clouds	Low, with the advent of Sentinel-2b this risk are greatly reduced.	Use the full virtual constellation of available Earth Observation satellites; gap filling procedure to replace clouds.	Assessment of minimum number of cloud free images.

Table 4 - Estimation of irrigation water requirement and water abstraction from EO - Source of uncertainty, magnitude, mitigation procedures and the related accuracy assessment.

3.4.1 Mitigation actions in practice

It is worth explaining in more details some of proposed mitigation actions.

1. *Increase the global accuracy by using the capacity of time series of images and by relying on a multiannual perspective.*

The mapping of irrigated lands with remote sensing is strongly affected by the timing of image acquisition and the number of images used (Pax-Lenney & Woodcock, 1997). For example, with a single or few satellite acquisitions, errors come from the difficulty in distinguishing barren field and temporarily fallow, immature crops with low density cover and not irrigated poor crops, etc. Alternatively, if scene were observed in multiple dates, certain characteristics trends become evident. This is more evident for tree crops, which have annual, or pluriannual phenological patterns. Another important benefit of multi-date (time-series) acquisitions is the capability to clearly define the peak period of crops. For these reasons, long-time series of satellite images improve the global accuracy of non-irrigated area classification, leading the reduction the classification errors.

In practice in the context of DIANA project, the global accuracy will be increased by using the capacity of time series of images and by relying on a multiannual perspective, which provides an expert system of classification layers (e.g. containing previous successful classifications of perennial crops and winter crops). Detection of new irrigated areas by using this updated frame can be done through the overlay of annual irrigated maps (Lockwood, Sarteel, Mudgaln, Osann, & Calera, 2014).

Furthermore, another mitigation procedure involves the availability of historical data and information on land-use, crop rotations and management (like typical seeding and harvesting date) and, finally, field inspections. Based on these supplementary information, additional supervised classification procedures will lead to achieve the expected global accuracy.

2. *Collect as accurate data as possible and ensure transparency about the degree of uncertainty.*

Earth Observation methodologies to estimate crop water requirements have a long-time application and they have already demonstrated their capabilities and robustness as effective tool (Rubio et al., 2006; Jochum & Calera, 2006; Bastiaanssen, Molden, & Makin, 2000). Of course, uncertainties can still come with input dataset itself. For example, ancillary data, like meteorological data used in crop water consumption calculations. To reduce it, different models and source of data will be used and each one of these will be provided with a “transparent” assessment of their accuracy.

3. *Improve spatial resolution of images*

The monitoring of CRW of small plots needs higher spatial resolution. Based on “a priori” knowledge of plot size, commercial satellites with higher resolution will be used in combination with “free of charge” acquisitions. Also for this issue, multi-temporal data availability has also proved to be very useful in identifying the best time for higher resolution acquisition (generally corresponding with crop development peak). With this strategy, two goals will be achieved: improvement of segmentation accuracy in plot detection (with the help of higher spatial resolution data) and reduction of cost acquisitions (acquiring only one or few images during the peak of crop development).

4. *Gap Filling and Cloud free images*

The presence of clouds can also affect the frequency and timing at which images are produced. The use of multi-sensor time series can help to overcome this issue, as well as the use of Sentinel-2 data (10m resolution, 5 days revisiting period with 2 satellites).

4 Example of concrete implementation: Italian Pilot area: Sannio Alifano Consorzio (province of Caserta, Campania Region) for year 2016

The methodology described above was applied to map the irrigated area of Sannio Alifano Consorzio, located in Southern Italy, encompassing an irrigable surface of about 19,000 hectares divided in two districts: Sannio Alifano and Valle Telesina. This region is shown in Figure 8. The study area is characterized by irrigated agriculture in the period from May to September, with main crops grown corn, alfalfa, fruit trees and vegetables. The average size of each plot is about 2 hectares. An important source of knowledge for this study has been the irrigation information system used by the Consorzio Sannio Alifano. In 2013, the Consorzio set up a geographic information system (GIS) to streamline irrigation management. The system, designed by the academic spin off company Ariespace srl., which is consulted and updated via web, allowed the Consorzio to generate single irrigation plot mapping referred to land parcels, irrigation districts, distribution networks, etc. and also integrates information supplied by the farmers about the type of cultivated crops, the time of planting and harvesting, the irrigation techniques etc.

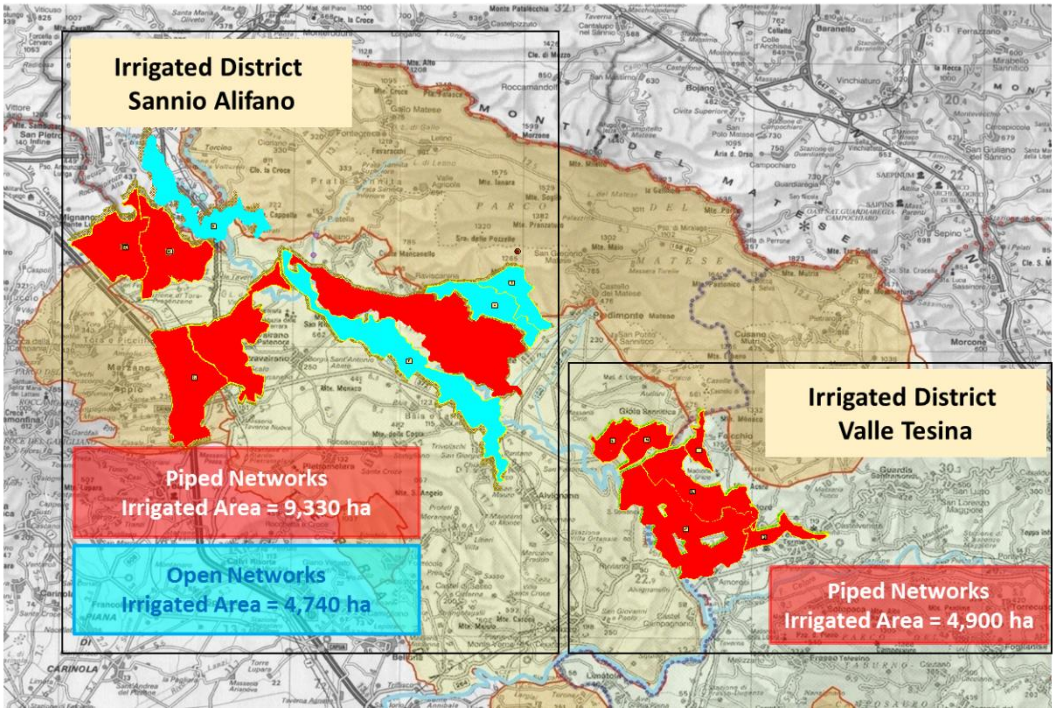

Figure 8 - Italian Pilot Area of Sannio Alifano Consorzio. It is divided in two irrigation districts: Sannio Alifano and Valle Telesina

4.1 Material and Method

The proposed methodology is founded on the assumption that the hydrologic deficit typical of semi-arid environments, as for the Mediterranean basin, only detectable crops are those irrigated. In order to follow the phenological development of crops in the irrigated season, the considered approach is based on the use of a time series of the multispectral satellite images, opportunely processed in a semi-automatic workflow. In details, the Irrigated Areas (IA) detection process consists in different steps shown in the Figure 9. Each step is detailed in the following subsection.

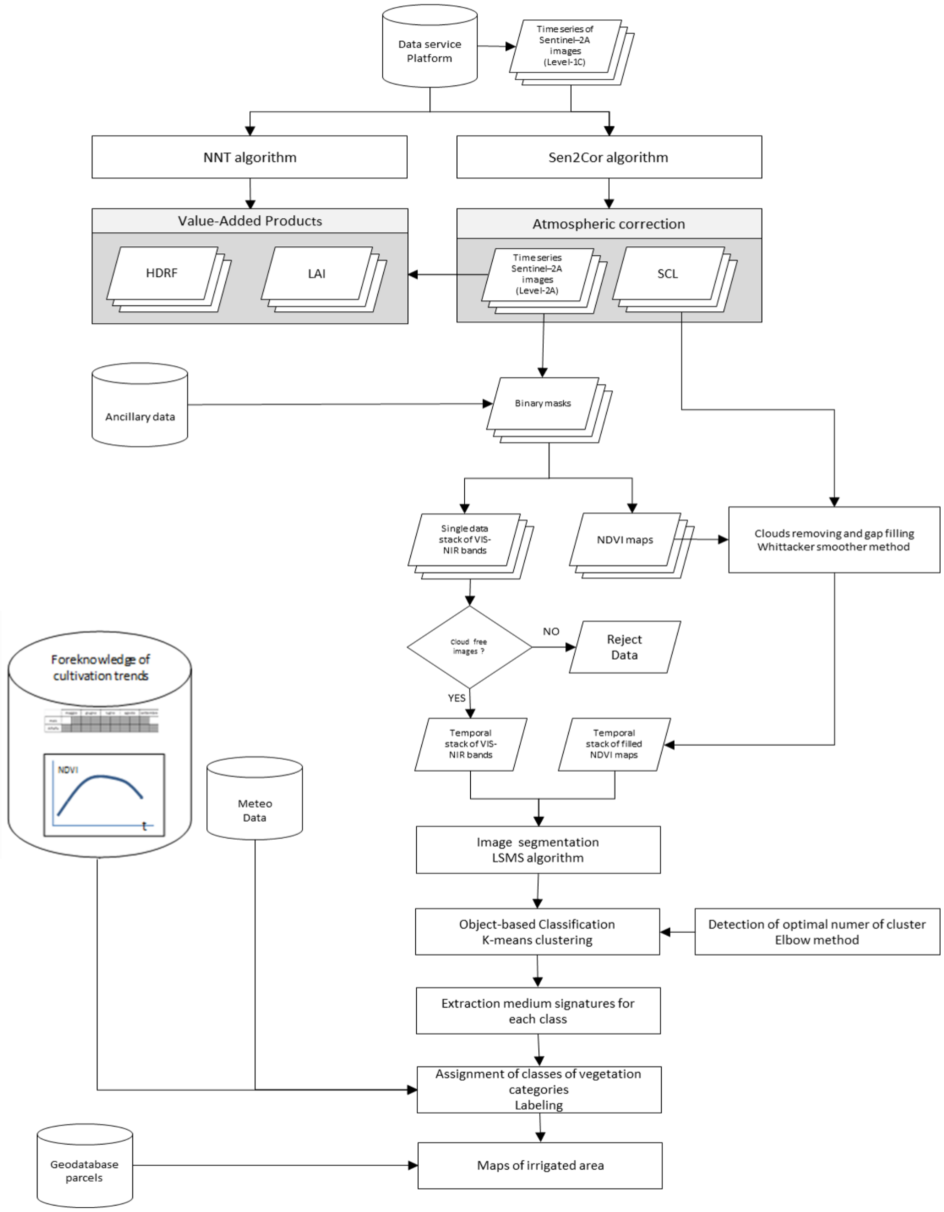

Figure 9 - Flowchart of the Irrigated areas detection process

4.2 Earth Observation data

This application is based on the utilization of data from the Multispectral Instrument (MSI) on board of the Sentinel 2A & 2B platforms, with a swath width of 290km, permits to acquire 13 spectral bands (443 -2190 nm) with a radiometric resolution of 12 bit and a spatial resolution of 10 m, 20 and 60 m (ESA Earth Online).

Acronym	Spectral Band	Center Wavelenght (nm)	Band width (nm)	Spatial resolution (m)
B1	AEROSOL	443	20	60
B2	BLUE	490	65	10
B3	GREEN	560	35	10
B4	RED	665	30	10
B5	RED EDGE 1	705	15	20
B6	RED EDGE 2	740	15	20
B7	RED EDGE 3	783	20	20
B8	NIR	843	115	10
B8a	NIR NARROW	865	20	20
B9	WATER VAPOUR	945	20	60
B10	CIRRUS	1380	30	60
B11	SWIR 1	1610	90	20
B12	SWIR 2	2190	180	20

Table 5 - Spatial Resolution bands specifications of Multi Spectral Instrument (MSI) on board of Sentinel-2.

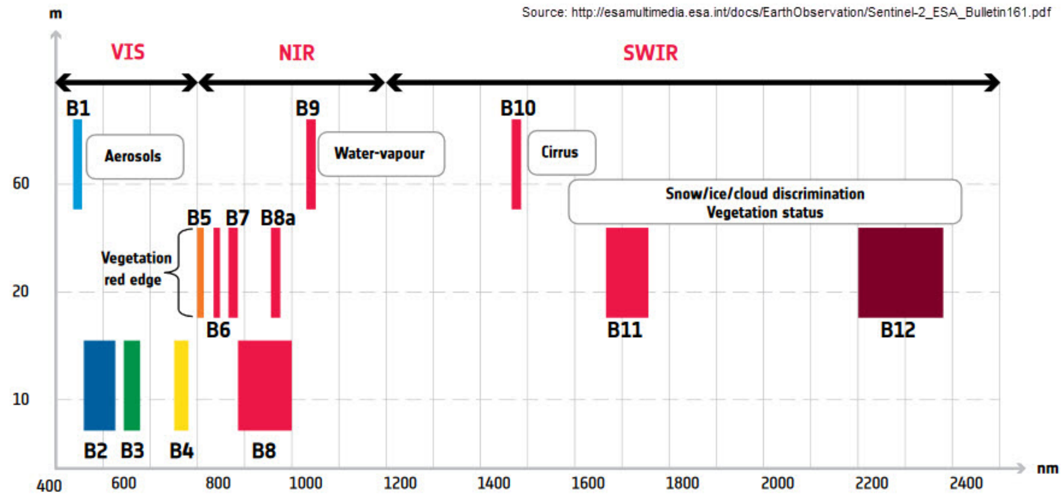

Figure 10 - Spatial Resolution versus wavelength: Sentinel-2 span of 13 spectral bands, from visible and near infrared to the shorthwave infrared at different spatial resolutions ranging from 10 to 60 m on the ground.

To perform the irrigated areas detection a time series of S2A is selected. In details, considering a cloud cover less than 20%, eighteen images captured for the year 2016 are chosen (Table 6).

Title	Granule	Acquisition Time (yyyy-mm-dd)
T33	TVF	20160107
		20160124
		20160206
		20160506
		20160625
		20160702
		20160712
		20160722
		20160725
		20160804
		20160814
		20160903
		20160920
		20160930
		20161030
		20161112
		20161129
		20161209

Table 6 - S2A images used in the irrigated areas detection process

4.3 Atmospheric correction

For the EO applications, based on the multitemporal approach (i.e. change detection, land surface phenology, land cover classification, etc.) an atmospheric correction is one of the most important steps, with aim to convert the original digital data, generally in Digital Number (DN), into the specific physical magnitudes (Caselles & Lopez Garcia, 1989). In other words, the surface reflectance for each considered input data is required.

In this application, to obtain the atmospherically corrected images a Data Service Platform is used. Implemented by the University of Natural Resources and Life Science in Boku (Austria) (Vuolo et al., 2016), this platform permits to access to individual S2 granules (extends 100 x 100 km2 - UTM/WGS84 projection). The available data are derived from the conversion of S2 Level-1C images (ToA-Top of Atmosphere reflectance) into Level-2A products (BoA – Bottom of Atmosphere reflectance), performed using the Sen2Cor processor. Sen2Cor is implemented by the ESA as a third-party plugin for the Sentinel-2 toolbox and it can be runs in the ESA Sentinel Application Platform (SNAP) or directly from the command line. In addition, other output layers are available such as Scene Classification (SCL), Aerosol Optical Thickness (AOT), Water Vapor (WV) and different Quality Indicators (QI) (ESA Sentinel Online).

Furthermore, the Boku's data service platform, available at this web page (https://s2.boku.eodc.eu/), offers other products as Leaf Area Index map (LAI) and Hemispherical-Directional Reflectance Factor (HDRF) using a specific neural network (NNT) algorithm developed by INRA (Baret et al., 2006).

4.4 Clouds removing and gap filling

As reported in the previous subparagraph, in this application each candidate images are selected considering a cloud coverage less than the 20 % of the full scene. Nevertheless, with aim to achieve a correct interpolation for the time-series of vegetation indices or surface reflectance values, the clouds removing and gap filling technique is executed.

In details, to remove the clouds and relative shadows from each considered scene the Whittaker smoother is used (Eilers, 2003). This smoothing method adjusts a discrete series to discrete data and penalizes the roughness of the smooth curve. In other words, this method based on "penalized" least squares regression, improves the reliability of the data and roughness of the fitted data (Atkinson, Jeganathan, Dash, & Atzberger, 2012).

In this study, the Whittaker smoother is executed using the MODIS Package (Mattiuzzi, 2017), implemented in R software (R-Project). Developed to process the Moderate Resolution Imaging Spectroradiometer data (MODIS), the smoother is adjusted on the S2 data. Particularly, the time series filtering is performed on the NDVI maps (described in detail in the next subsection), where considering for each scene the specific SCL mask, the cloud and shadow cloud pixels are replaced.

4.5 Time series of NDVI maps

In this phase, a NDVI map is obtained for each image of the time-series. Obviously, the NDVI maps are computed following the classical formula introduced by Rouse et al., (1973). In details, the specific S2 bands used in this computation are B08 (NIR) and B04 (Red), both characterized by a spatial resolution of 10 meters (Table 5).

Subsequently, a binary mask is applied for each NDVI maps, with the aim to delete those areas not interest in the irrigated crops detection process, as urban, mountain, wetlands, rivers, lakes and water basins.

Finally, after the cloud removing and gap filling process (described in the previous subsection), to analyze the crop phenology and to detect the irrigated areas a temporal stack layer of the NDVI maps is generated.

4.6 Multi-time classification

4.6.1 Object-based Classification

According to (Garcia-Pedrero, Gonzalo-Martin, Fonseca-Luengo, & Lillo-Saavedra, 2015), to deliver agricultural services based on EO data, a correct delineation of agricultural parcels is a fundament requirement and the high-resolution satellite images and machine-learning algorithms play a key role for these purposes. Hence, in this work to detect the irrigated areas, the image segmentation process is applied, with aim to detect and delineate each individual parcel located in the study area. The object detection is performed, using the Large Scale Mean Shift (LSMS) algorithm, available as package in the Orfeo – ToolBox (OTB) software (Orfeo-Toolbox). Implemented by (Michel, Youssefi, & Grizonnet, 2015), this image segmentation workflow is based on different steps.

As input data, a temporal stack of S2 bands is used, choosing only fully cloud-free data. Particularly, the bands involved in this step are B03, B04 and B08 (Table 5), merged to create a temporal stack of NDVI maps in the final steps of the LSMS workflow.

The final output of this elaboration step is a vector file, containing the polygons of the segmented image, with element attributes consisting of the mean and variance NDVI values for each date of the time series considered (Orfeo-ToolBox).

4.6.2 Classification and recognition of irrigated crop temporal patterns

The NDVI mean and variance values, extracted from each NDVI map included in the temporal series, are used to perform an unsupervised classification based on the multi-temporal approach. In other words, the classification process is performed at object-based level and the chosen clustering method is the K-means (Hartigan & Wong, 1979), executed using the K-Means Clustering package available into R software (R Stats Package).

To determine the optimal number of cluster the Elbow method is performed (RPubs) (Kodinariya & Makwana, 2013). Opportunely adjusted for the K-means clustering, this R code plotting the within cluster sum of squares and the number of clusters and permits to find the appropriate number of clusters, located theoretically in correspondence of the “bend or knee” of the curve (Figure 11). In our case, following this approach, the optimal number of cluster is fixed at 70, while 100 is the maximum number of classes and iterations.

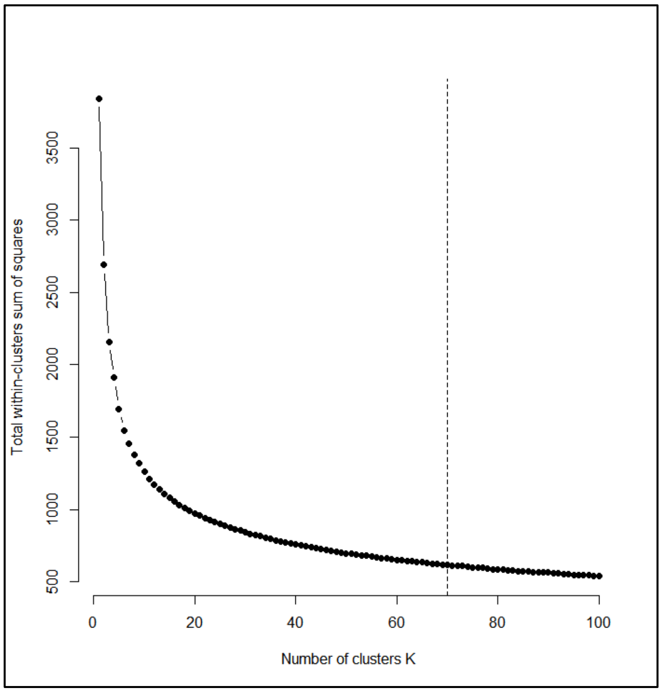

Figure 11 - Elbow method plot

In the subsequent step, each K-means class is analyzed, with the aim to associate the similar clusters into the potentially irrigated or not irrigated classes. This association is performed using the rainfall data and the crop phenology curves obtained plotting, for each class, the NDVI mean and variance temporal trends (Figure 12) (see Annex I).

In details, considering also ground truth and others a priori knowledge the 70 K-means clusters are labeled in four classes, reported in the following table.

Recoded classes	K-means classes
Class A, not irrigated areas, low NDVI trend during the irrigation season (bare soil, uncultivated land, etc.)	2,8,10,13,16,25,33,34,38,46,49,57,66,68
Class B, irrigated areas, high NDVI trend during the irrigation season (Corn, Alfa alfa)	1,3,4,5,7,9,12,15,17,19,20,23,24,26,27,28,30, 31,32,35,36,39,41,42,48,50,51,52,55,56,60,61,62,65,67,69,70
Class C, irrigated permanent crop, with a high and constant NDVI trend beyond the irrigation season (orchards and vineyards)	6,11,14,18,21,22,29,37,40,43,44,45,47,53,54, 59,63,64
Class D, natural areas characterized by a high aboveground biomass, high NDVI trend with values close to 1 (woody and riparian areas)	

Table 7 - Recoding of the K-means classes

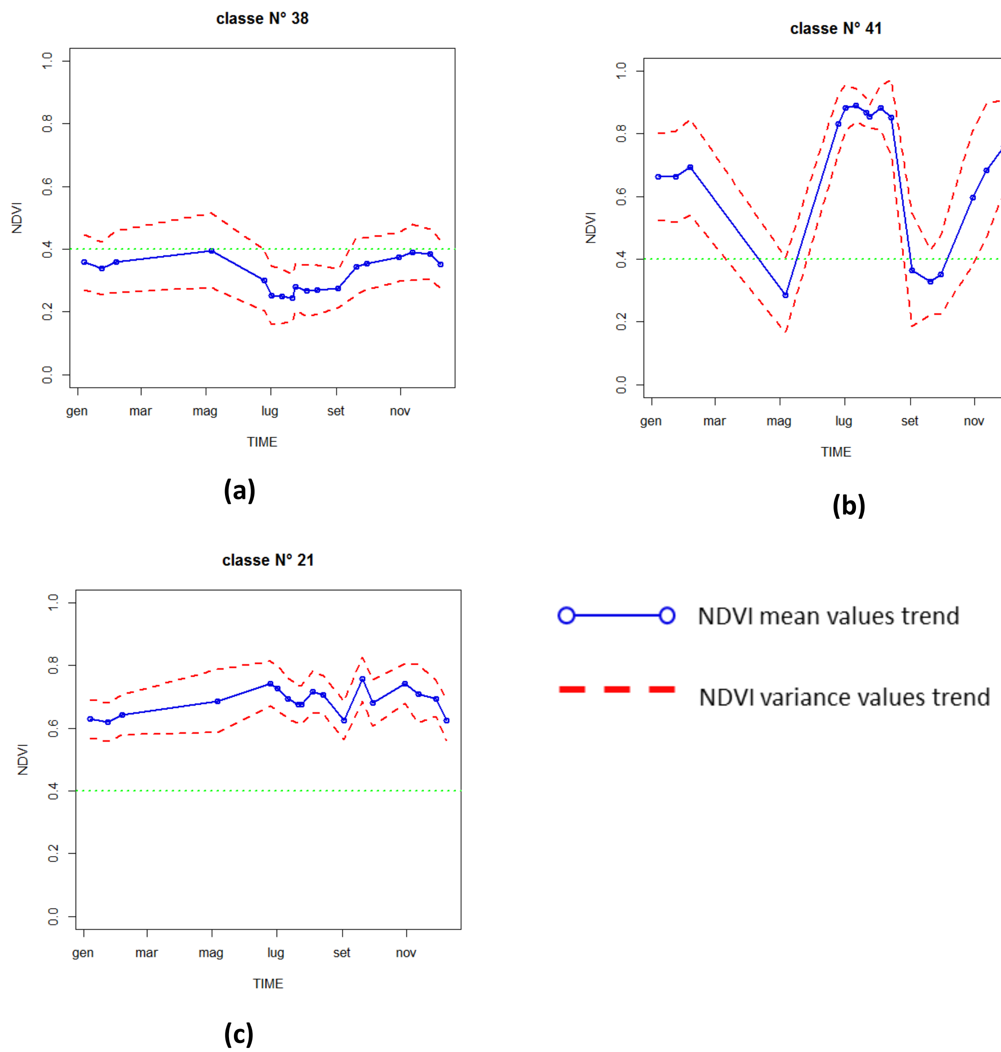

Figure 12 - Examples of the multi-time NDVI index curves: a) not irrigated area, b) irrigated areas, c) irrigated permanent crop area.

4.7 Result and Discussion

4.7.1 Irrigated map for season 2016

The methodology implemented was applied to map the irrigated area for each district served by Consorzio Sannio Alifano (Figure 13). The results show that for irrigation season 2016, the total irrigated area is 14,020 hectares, with 42% of permanent crops (mainly vineyards and hazelnuts) and by 37% of herbaceous crops (mainly corn and alfalfa). In addition, with the aim to achieve a clearer overview and a more accurate quantitative analysis of the results, for each considered district the class surface in hectares was estimated. The results show that the Piana di Telese Piana Alifana Bassa e Piana di Riardo-Pietravairano- Pietramelara districts are characterized by an irrigated area over 1000 hectares, both for herbaceous and permanent crops (Figure 14).

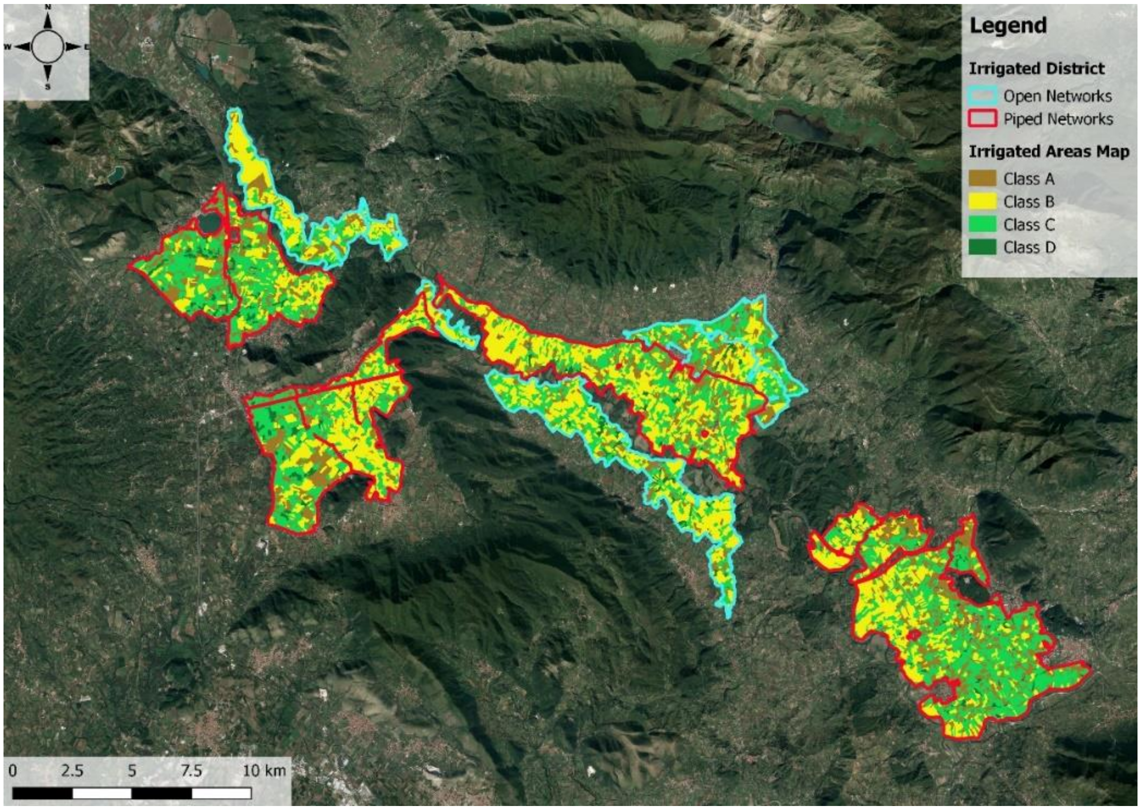

Figure 13 - Irrigated areas map obtained by the proposed methodology

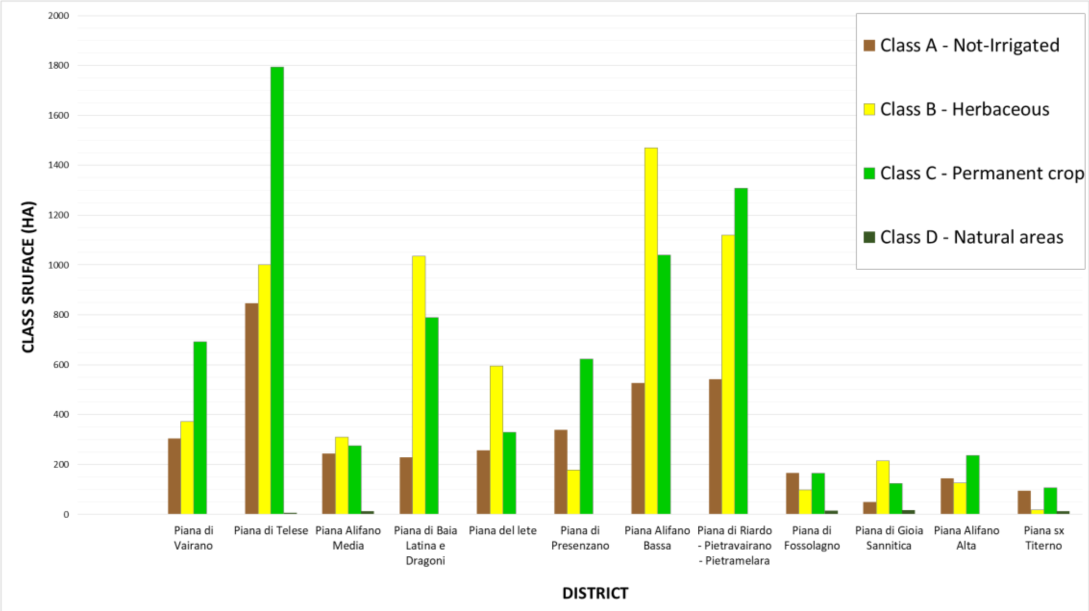

Figure 14 - Class surface in hectares for each district of the Sannio Alifano consorzio

4.7.2 Accuracy

To estimate the thematic accuracy of the classification an error matrix is computed (Table 8). Considering opportune accuracy measures - Producer's Accuracy (PA), User's Accuracy (UA) and Overall Accuracy (OA) (Story & Congalton, 1986) (Congalton & Green, 2009) to perform the accuracy assessment of the irrigated areas 100 random sampling points are used. These test sites are visually interpreted using the crop development, S2A colour composites and Google Earth. As can be seen from Table 5.5, the OA of the detection process was 75%. The results of the accuracy assessment show high values of the PA and UA for the Not-irrigated and Herbaceous class. For the Permanent crop class similar results was achieved, but a lower UA was recorded 59%.

	Reference data				
Classification data	Classes	Not irrigated	Herbaceous	Permanent crop	Total per class in the map
	Not irrigated	22	4	3	29
	Herbaceous	4	33	0	37
	Permanent crop	5	9	20	34
	Total per truth class	31	46	23	100

Table 8 - Error matrix

Accuracy measures (%)	Not-irrigated	Herbaceous	Permanent crop
PA	71	72	87
UA	76	89	59
OA	75		

Table 9 - Thematic accuracy of the irrigated areas classification

4.7.3 Gross Irrigation Water Requirements from EO data

The estimation of abstracted volumes from groundwater, irrigation water requirement and crop water requirement based on EO data was performed using the approach described in the Section 4. In addition to this, an efficiency coefficient of 0.8 is applied to the estimated crop water requirements to take into account in a lumped way of all water losses occurring in the distribution network of irrigation canals and pipelines. We call this Gross Irrigation Water Requirement (GIWR).

To quantify the goodness of this methodology, a comparison of the water volume applied and GIWR estimated from EO data was performed considering 24 farms. The information was provided, by the Consorzio Staff, in terms of cadastral coordinates - Municipality, Sheet and Parcel - and identity of land owners. The results of this investigation are plotted in the Figure 5.8. In this phase, considering also the classification results, it was possible compare the irrigated area declared by the farmers and those estimated from EO data. An example is reported in the Figure 16.

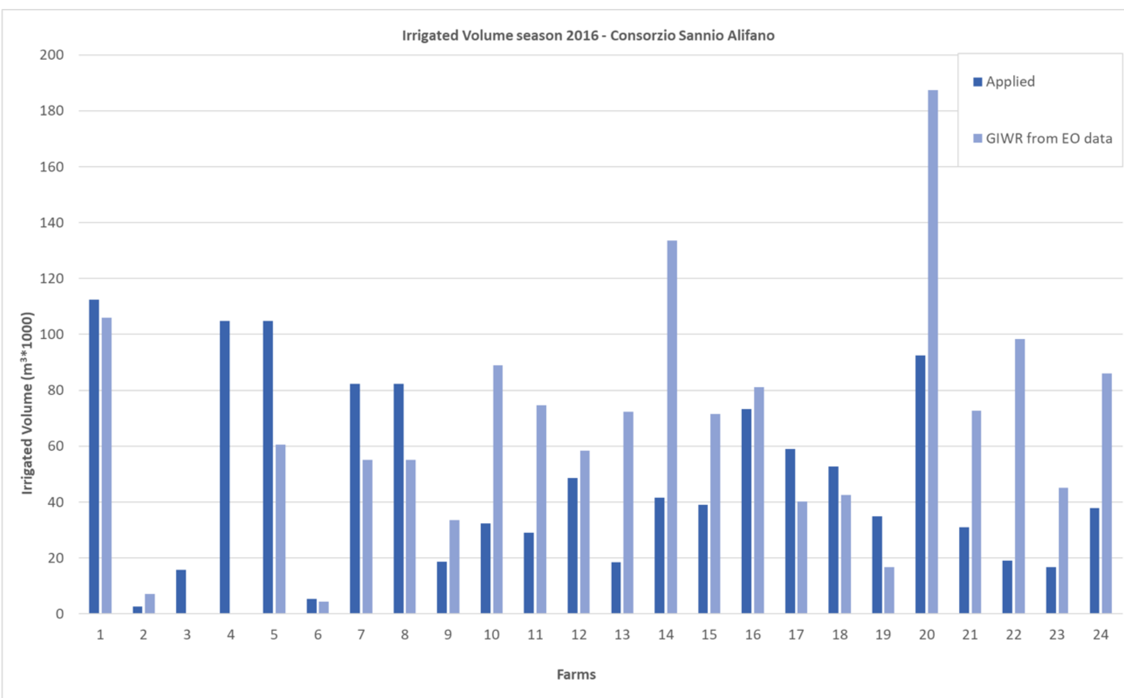

Figure 15 - Comparison of the water volume applied and GIWR estimated from EO data at Farm-Scale

Farm 1			
Irrigated Area (Declared) [ha]	Irrigated Area (EO) [ha]	Irrigation Volume Applied m^3	GIWR (EO) m^3
17.32	27.69	112.000	106.000

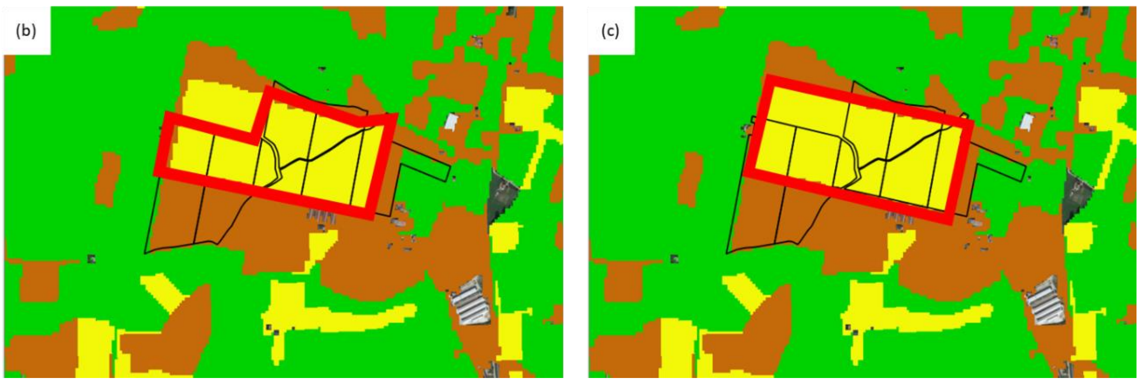

Figure 16 - Mismatch between the irrigated area declared and those estimated from EO data*: a) Cadastral parcel (b) Declared irrigated area (boundered in red) c) Irrigated area estimated from EO data (boundered in red)*

4.8 Further developments

Further lines of investigation could be examined to test and extend the results achieved by the proposed approach. Firstly, for the irrigation season 2017, also the imagery acquired by the S2B could be used, with aim to obtain a more dense NDVI temporal series. In fact, considering both S2 sensors, an increase of the temporal resolution is obtained, with only 2-3 days between the two acquisitions. In this way, can be achieved more details about the phonological crop trends during the irrigation season. In addition, is increased the availability of cloud-free images.

Furthermore, different classification techniques will be tested to improve the detection of the irrigated areas (i.e. Random Forest), considering also the more information provided by the field inspections in the Sannio Alifano pilot areas.

5 Seasonal drought forecasting and monitoring

5.1 Drought Monitoring and Seasonal Forecasting System - Methodology

The Drought Monitoring and Forecasting System aims to estimate present and future drought conditions through a modelling framework that is the combination of hydrological modelling, real-time weather data and seasonal climate forecasts. The system is consisted by the following three parts:

In the first part, a historic, multi-decadal reconstruction of the terrestrial water cycle is obtained by forcing the NOAH-MP land surface model, using the MERRA[6] reanalysis atmospheric dataset, to produce the soil moisture and precipitation climatology against which current and predicted conditions is compared. In the second part, the real-time monitoring system based on the NOAH-MP land surface model coupled with a channel-reservoir flow module using the coupler of the WRF-Hydro[7] system, is forced by the atmospheric analysis fields that are produced by the atmospheric data assimilation system (LAPS[8]), in order to track present drought conditions. Finally, in the third part, bias-corrected and downscaled seasonal forecasting data from the CFSv2[9] climate model are used to force the NOAH-MP land surface model, to produce seasonal hydrological predictions and derived drought maps and other hydrological products out to six months.

5.2 Data Requirements and Data Sources

The drought monitoring, and seasonal drought forecasting system is using various meteorological data (observations, satellite derived products, reanalysis, forecasts etc.) to drive the WRF-Hydro modelling system to produce the hydrological data assimilation and seasonal prediction, and complementary data for the definition of the characteristics of the simulation domains of the models. Besides the data products described below, the system is also flexible enough to incorporate other sources of data including output from other models and prediction systems.

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[6] https://gmao.gsfc.nasa.gov/reanalysis/MERRA/

[7] https://www.ral.ucar.edu/projects/wrf_hydro

[8] Jiang, Hongli, et al. "Real-time applications of the variational version of the local analysis and prediction system (vLAPS)." Bulletin of the American Meteorological Society 96.12 (2015): 2045-2057.

[9] https://gmao.gsfc.nasa.gov/reanalysis/MERRA/

The data used by the system are collected from the following sources:

MADIS Meteorological Data: The Meteorological Assimilation Data Ingest System (MADIS) is a meteorological database and data delivery system that provides atmospheric observations covering the globe. The observations are derived from multiple official and unofficial sources, including metar messages from surface weather stations, radiances and atmospheric profiles from satellites, airborne observations, station radiosondes and ocean meteorological parameters from ships and buoys. After the collection of the observations, the MADIS system decodes the ingested observations, perform a three-stage quality control and encodes all the data in a common format (CF-compliant netcdf). MADIS data set is continuously updated with a varied frequency from 1hour to 2days according to the requested atmospheric variable. The dataset concerning the meteorological information from surface weather stations is free to use both for commercial and noncommercial purpose, and it is available for downloading upon request through web[10] or ftp[11] server. The drought monitoring system is downloading operationally the MADIS data every hour in order to provide the vLAPS data assimilation system with weather observations from surface stations.

GFS Weather Forecasting Data: The Global Forecast System (GFS) data is a global atmospheric dataset containing atmospheric information (analysis and forecast fields) produced by the global numerical weather prediction system GFS. GFS model runs operationally 4 times per day under the administration of National Center of Environmental Predictions (NCEP)/ National Oceanic and Atmospheric Administration and produces forecasts for 16 days ahead. GFS dataset covers the globe with a spatial resolution of 27Km for the first 8 days and with a spatial resolution of 75Km for the last 8 days. NCEP/NOAA provides the data free of charge for commercial and noncommercial use through NCEP public ftp[12] server. The GFS data are downloaded operationally every 6 hours and used by the vLAPS data assimilation system to define the background forecast error.

CFS Seasonal Forecasting Data: The Climate Forecast System (CFS) data is a global seasonal forecasting dataset containing atmospheric and oceanic forecast fields produced by the global

10 https://madis-data.ncep.noaa.gov/madisPublic1/data/

11 https://madis-data.ncep.noaa.gov/

12 ftp://ftpprd.ncep.noaa.gov/pub/data/nccf/com/gfs/

numerical climate model CFSv2. The CFSv2 is a climate model representing the global seasonal interaction between Earth's oceans, land and atmosphere, and incorporates all the latest scientific advancements in data assimilation and climate simulation methodologies (Saha et al., 2012). CFS model runs operationally 4 time per day under the administration of NCEP/Climate Prediction Center producing seasonal forecasts for the next 9 months. CFS dataset covers the globe with an approximately spatial resolution of 56Km and is available free of charge for commercial and noncommercial use through NCEP public ftp[13] servers. CFS forecasts are downloaded every 6 hours including the analysis fields and all the forecast surface fields from "now" until the next 6 months.

MERRA Reanalysis Data: Modern Era Retrospective Analysis for Research and Applications is a global reanalysis dataset containing atmospheric and hydrological fields produced by the Godard Earth Observing System (GEOS) atmospheric model and data assimilation system (DAS) (Rienecker et al., 2011). MERRA dataset focus on the satellite era from 1979 to present and covers the globe with an approximately resolution of 60km. The dataset is free to use both for commercial and non-commercial purposes, and it is available for downloading through a web[14] server.

CMORPH Precipitation Data: The CMORPH Precipitation data are produced by using the Climate Prediction Center morphing technique (Al, Joyce, Janowiak, Arkin, & Xie, 2004). This technique uses precipitation estimates that have been derived from low orbiter satellite microwaves observations exclusively, and whose features are transported via spatial propagation information that is obtained from geostationary IR satellites. The data is available free of charge for commercial and non-commercial purposes from the Climate Prediction Center.

The EU-Digital Elevation Model: The EU-DEM is a 3D raster dataset with spatial horizontal resolution of 30m available from the European Environment Agency. The dataset based on SRTM and ASTER-GDEM data fused by a weighted averaging approach and is used for the definition of topography and channel routing of the WRF-Hydro simulation domains.

[13] ftp://ftpprd.ncep.noaa.gov/pub/data/nccf/com/cfs/

[14] http://disc.sci.gsfc.nasa.gov/uui/search/"MERRA"

European Soil Database: The European Soil Database is a gridded soil database containing a large number of soil related parameters on a spatial resolution of 1x1km. The data if used for the definition of the soil hydraulic properties of the WRF-Hydro simulation domains.

5.3 Atmospheric Data Assimilation System

The atmospheric data assimilation system is based on the variational Local Analysis and Prediction System (vLAPS). The vLAPS is a variational atmospheric data assimilation and forecast system designed from NOAA to support situational awareness and nowcasting applications of high impact weather events (Albers, McGinley, Birkenheuer, & Smart, 1996) and it is used operationally by many national meteorological services and private weather companies across the world (Albers et al., 1996).

The system is using the GFS analysis and near to analysis forecast data and is assimilating surface observational data (MADIS) and satellite retrievals for the precipitation estimates (CMORPH). vLAPS is operating by using one coarse outer domain and four high resolution nested domains (Figure 17). The coarse domain is covering most of the Europe and parts of Middle East and North Africa on a horizontal grid increment of 9Km and 48 vertical levels. The other four domains are covering the pilot areas in Spain, Italy and Romania on a horizontal grid increment of 3Km and 48 vertical levels, as well. The system runs every hour and the data assimilation products are available with 1.5 hours latency. The produced atmospheric fields of the data assimilation system are used by the drought system to define the current drought conditions and for the initialization of seasonal drought forecast.

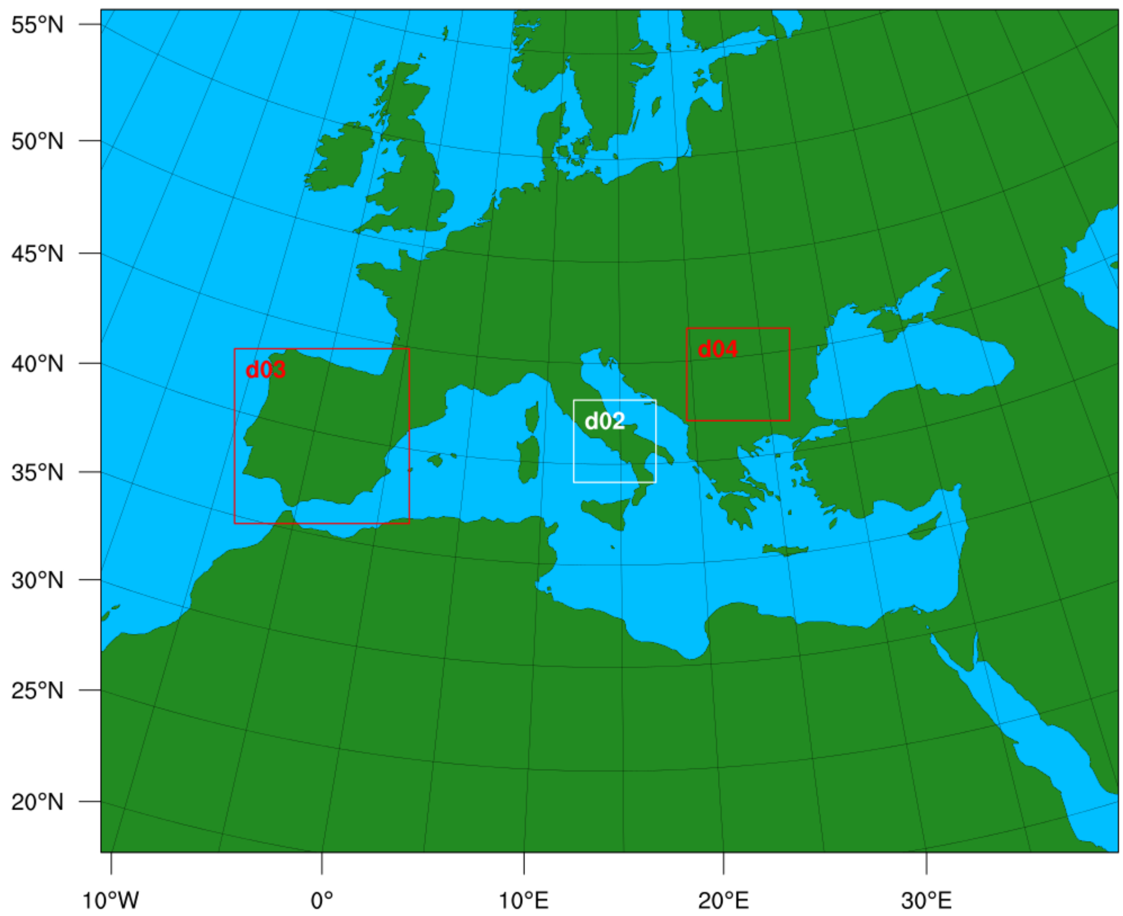

Figure 17 – Data Assimilation Integration Domains

5.4 Seasonal Climate Forecasts

The seasonal forecast system is based on climate forecasts from the NCEP Climate Forecast System, version 2, which is the second-generation system from the CFSv1 and is a fully coupled land–ocean–atmosphere dynamical seasonal prediction system. The CFSv2 consists of the NCEP Global Forecast System, the Geophysical Fluid Dynamics Laboratory Modular Ocean Model version 5.0 coupled with a two-layer sea ice model, and the four layer Noah land surface model. CFSv2 is operating every day by utilizing the forecast cycles of 00, 06, 12 and 18UTC and produce all the needed data by the WRF-Hydro to perform the hydrologic simulation. The CFSv2 seasonal forecasts before used by the WRF-Hydro system are bias corrected and downscaled using a Bayesian merging method (Luo et al. 2007, 2008) to 9x9Km 6-hours resolution.

5.5 WRF-Hydro

The WRF-Hydro modelling system version 3.0 is the heart of the drought monitoring and seasonal forecasting system. It contains several components of distributed hydrologic processes and channel flow, and is designed to enable improved simulation of land surface hydrology and energy states and fluxes at a fairly high spatial resolution (typically 1 km or less) using a variety of physics-based and conceptual approaches. The WRF-Hydro in the framework of the drought monitoring and seasonal forecasting system is using the NOAH-MP land surface model coupled with the VIC hydrological model for channel routing and ground water flow.

WRF-Hydro uses as input data the atmospheric fields of incoming shortwave and longwave radiation (W/m), specific humidity (kg/kg), air temperature (K), surface pressure (Pa), near surface wind components (m/s) and liquid precipitation rate (mm/s). Based on these input data, the system produces as output data surface heat fluxes, ground heat flux, ground surface and/or canopy skin temperature, surface evaporation components (soil evaporation, transpiration, canopy water evaporation, snow sublimation and ponded water evaporation), soil moisture, soil temperature, deep soil drainage, surface runoff, canopy moisture content, snow depth, snow liquid water equivalent, stream channel inflow, channel flow rate and channel flow depth.

Model simulation domains is covering most of Europe and parts of the Northern Africa and Middle East with a grid resolution of 9X9Km, while the pilot areas are covered with a higher resolution grid of 250mX250m on a river basin scale. To define the surface boundary conditions for the land surface model, the land cover map based on CORINE land use/cover database is used along with vegetation data derived from MODIS TERRA, and soil type and texture based on the European Soil Database[15]. To initialize the NOAH-MP model and to avoid imbalances between the hydrological fields, for the reconstruction of the 30-years' terrestrial water cycle climatology, the model have been forced with 38 years' MERRA data, using the first 8 years for model spin-up.

15 http://esdac.jrc.ec.europa.eu/content/european-soil-database-v20-vector-and-attribute-data

This project is co-funded by the European Union

5.6 Drought Indices

The system uses a set of different drought indices to identify the occurrence and the type of a drought event, as well as to estimate the severity of the event. The drought indices that are used by the system are the following:

Standardized Precipitation Index (SPI): Drought events are indicated when the results of SPI, for whichever timescale is being investigated, become continuously negative and reach a value of −1. The drought event is considered to be ongoing until SPI reaches a value of 0. The ability of SPI to be calculated at various timescales allows for multiple applications. Depending on the drought impact in question, SPI values for 3 months or less might be useful for basic drought monitoring, values for 6 months or less for monitoring agricultural impacts and values for 12 months or longer for hydrological impacts.

Standardized Precipitation Evapotranspiration Index (SPEI): SPEI uses the basis of SPI but includes a temperature component, allowing the index to account for the effect of temperature on drought development through a basic water balance calculation. SPEI has an intensity scale in which both positive and negative values are calculated, identifying wet and dry events. It can be calculated for time steps of as little as 1 month up to 48 months or more. Monthly updates allow it to be used operationally, and the longer the time series of data available, the more robust the results will be. With the same versatility as that of SPI, SPEI can be used to identify and monitor conditions associated with a variety of drought impacts.

Palmer Drought Severity Index (PDSI): Calculated using monthly temperature and precipitation data along with information on the water-holding capacity of soils. It takes into account moisture received (precipitation) as well as moisture stored in the soil, accounting for the potential loss of moisture due to temperature influences. Developed mainly as a way to identify droughts affecting agriculture, it has also been used for identifying and monitoring droughts associated with other types of impacts.

Effective Drought Index (EDI): Uses daily precipitation data to develop and compute several parameters: effective precipitation (EP), daily mean EP, deviation of EP (DEP) and the standardized value of DEP. These parameters can identify the onset and end of water deficit periods. Using the input parameters, EDI calculations can be performed for any location in the world in which the results are standardized for comparison, giving a clear definition of the onset, end and duration of drought. A good index for operational monitoring of both meteorological and agricultural drought situations because calculations are updated daily.

Crop Specific Drought Index (CSDI): By calculating a basic soil water balance, it takes into account the impact of drought, but identifies when the drought stress occurred within the development of the crop and what the overall impact to the final yield will be. PDSI and CMI can identify drought conditions affecting a crop, but do not indicate the likely impact on yields.

Soil Moisture Deficit Index (SMDI): A weekly soil moisture product calculated at four different soil depths, including the total soil column, at 0.61, 1.23 and 1.83 m, and can be used as an indicator of short-term drought, especially using the results from the 0.61 m layer.

Evapotranspiration Deficit Index (ETDI): A weekly product that is helpful for identifying water stress for crops. ETDI is calculated along with the Soil Moisture Deficit Index (SMDI), in which a water stress ratio is calculated that compares actual evapotranspiration with reference crop evapotranspiration. The water stress ratio is then compared with the median calculated over a long-term period. ETDI is very useful for identifying and monitoring short-term drought affecting agriculture.

The reason that the system uses too many drought indices is twofold, from the one hand we need different indices to identify different types of drought and on the other each index has different performance in each area.

6 Support for the implementation and monitoring of the WFD

6.1 Water Framework Directive: General aspects

The Water Framework Directive (WFD) is one of the most significant pieces of EU environmental legislation to date and considers, for the first time, the management of water within the context of the natural river basin as opposed to within traditional political and administrative boundaries.

The Directive establishes a framework for the protection of all water bodies (surface, transitional, coastal and underground) as it is described in its first article, in order for Member States to prevent further deterioration and improve the status of their waters and protect them by ensuring pollution reduction and control from all sources such as agriculture, industrial activity and urban areas impact in order to achieve “good status” objectives for water bodies throughout the EU. More specifically, the main objectives of WFD include:

- Prevent further deterioration and protect and enhance status of aquatic ecosystems.
- Promote sustainable, balanced and equitable water use based on long term protection of available water resources.
- Enhance the improvement of aquatic environment through the implementation of specific measures for the reduction of emissions of toxic substances.
- Ensure the progressive reduction of pollution of groundwater and prevent its further pollution.
- Mitigate the effects of extreme flood and drought events.

The EU Water Framework Directive covers a number of different steps for achieving “good status” of water bodies. Member States have been required to implement these different steps in order to accomplish WFD’s main objectives. The required steps include:

- River Basin characterization (typology and reference conditions, water body delineation, pressures and impacts assessment using DPSIR methodology for risk assessment)
- Registration of protected areas
- Establishment of programmes for the monitoring of water status of surface water bodies, ground water bodies and protected areas.

- Establishment of River Basin Management Plans for each river basin district that must be reviewed and reissued every 6 years.
- Implementation of the necessary measures within integrated programmes of measures.
- Implementation of pricing policies and encouragement of sustainable water management.

The framework for delivering the Directive is through River Basin Management Planning. RBMPs will integrate a great lot of the implementation activity of the WFD and represent the principle mechanism for meeting the WFD's objectives. The contents of these plans include among others the Environmental Objectives that have been set to achieve the purpose of the Directive of protecting all Water Bodies, analysis of pressures and impacts of the economic activities and the proposed measures that should be taken in order to achieve WFD's objectives.

One of the innovative elements the Directive 2000/60 introduced is that for the first time in EU environmental policy, a legal text (Directive) proposes economic principles and economic tools as key measures to achieve specific environmental objectives. The Directive is trying to balance between social, environmental and economic value of water.

One of the main tools that WFD introduces is the cost recovery of water services, including the environmental and resource cost, in accordance with the polluter-pays principle. In this context, Member states are required to price water in a way that ensures the full cost recovery and provides adequate incentives to use it efficiently, through the following tasks:

- Determination of water services providers, users and polluters
- Estimation of total cost of water services (financial, environmental and resource cost)
- Identification of cost recovery mechanism and cost allocation to the users
- Estimation of the level of cost recovery.

Earth observation is considered one of the most cost-effective methods for providing the **spatial and temporal environmental data that are necessary for fulfilling the requirements of effective monitoring and implementation of the WFD**. In recent years, earth observation techniques are being incorporated in the implementation procedures of WFD more often, as Earth Observation provides access to a wide range of water monitoring parameters from different satellite data sources.

Earth observation techniques are more often implemented as a complement to in-situ estimations in the stage of water bodies' classification and more specifically during water quality monitoring (surveillance, operational, investigative monitoring), providing data regarding biological, physicochemical and hydro-morphological quality elements (i.e. Chlorophyll-a, algal blooms, turbidity, water extent, hydro-morphological changes etc) (Malve et al. 2016; Chen et al. 2004). Additionally, land-use changes and particularly crop change detection as part of pressure analysis constitutes one of the most common application fields for earth observation approach.

6.2 Agricultural Activity and WFD

Agricultural activity remains a key source of non-point pollution in EU that exerts significant pressures mostly on surface water and groundwater, as well as on groundwater dependent terrestrial ecosystems such as wetlands. Main pressures that are generated by agricultural activity are water abstraction for irrigation purposes, fertilizers and pesticides application, hydro-morphological modifications for reclamation for agricultural land in riparian and wetland areas, the alteration and status of the riparian areas etc.

Agriculture is a significant water user in Europe. Ineffective water management in agricultural sector may have negative impacts on both quantity and quality of related water bodies. Over-abstraction of water constitutes one of the most common pressures that put many surface and ground water bodies at risk, especially in areas where drought events occur. Also, over-abstraction of water and more specifically the importance of non-authorized abstractions, which remain out of record and may play a substantial role in over-abstraction, were highlighted in the Blueprint to Safeguard Europe's Water Resources (Communication COM/2012/673) as significant pressures impeding the achievement of Water Framework Directive's (WFD) good status objectives.

The significance of the above-mentioned pressure is reflected on the important impacts that are generated on quality and quantity of related water bodies. These impacts include change of groundwater levels, water quality deterioration, groundwater salinization, reduction of the flow of rivers and springs, indirect impacts on biodiversity, increase of desertification risk in some areas, modification of dependent aquatic or terrestrial ecosystems, habitat loss, hydro-morphological modifications etc.

Pressures from agriculture can be mitigated or prevented through an appropriate programme of spatiotemporal distributed measures based on precise data in order to be more effective. These measures could include targeted application of best management practices based on spatial and temporal information, crops allocation etc.

Member states dealing with non-authorized abstractions face the problem of lack of data and tools that could enable them to manage these unsustainable practices. Data such as crop spatial distribution, volume of abstracted water etc. are not usually available; as a result, it is not feasible to develop specific measures for addressing the related pressures.

Earth Observation (EO) was identified in the Blueprint to Safeguard Europe's Water Resources as a promising approach to address quantitative issues related to water, through the detection of possible cases of non-authorised abstraction and as a complement to the often-limited field data available.

6.3 Support of WFD

6.3.1 Recycling the data produced from the DIANA Services

In the frame of **The Detection of Non-Authorised Water Abstractions** and **Drought Monitoring and Seasonal Forecasting** services of DIANA project, a huge amount of high spatial and temporal resolution data on river basin scale will be produced. The data produced are among others the detection of non-authorised irrigation, the total abstraction volume for irrigation, seasonal drought forecasting and monitoring, maps of Potential Evapotranspiration, maps of Crop Evapotranspiration, maps of Precipitation. These data products could be a potential data source to support the implementation of the WFD and more specifically on the following areas:

- Analysis of Pressures and Impacts (IMPRESS Analysis)
- Monitoring Programmes for surface and ground water bodies
- Programme of Measures through the process of river basin management plans
- Recovery of costs for water services through water pricing

The above-mentioned areas constitute the main stages of the implementation process of WFD. The produced data will contribute to the improvement of the methodologies of these areas and in turn to the achievement of the WFD's environmental objectives.

6.4 Areas of WFD to which produced data contribute

6.4.1 IMPRESS analysis

The "risk assessment" which is a process in the context of the implementation of WFD includes the methodology of analysing pressures and their impacts using the Driver, Pressure, State, Impact, Response (DPSIR) framework. This analysis which is required in the design of monitoring programmes and helps developing the programme of measures should be repeated in a six-year cycle in the context of implementing the River Basin Management Plans (RBMP).

As it has already been mentioned, water abstraction for irrigation is considered to be one of the major pressures that exert impact on both surface and ground water bodies. More specifically, over-exploitation contributes to surface water desiccation, especially of non-perennial rivers (Skoulikidis et al. 2016), through lowering of the groundwater table. Additionally, to the significant lowering of the groundwater tables, drying out of springs, degradation of wells and boreholes, and salt-water intrusion are among the main impacts that water abstraction cause (Skoulikidis et al. 2016). Nevertheless, illegal water abstraction may account for a high percentage of the total water abstraction, but it is not included in water consumption calculations. So, the detection of illegal water abstraction that takes place in the context of the project DIANA will result to a more accurate and integrated identification of water abstraction pressure.

Additionally, abstracted volume for irrigation can be used as a quantitative indicator for pressure. This indicator compared against computed recharge for each groundwater body would result in groundwater abstraction risk assessment. A spatiotemporal differential pressure will be assessed by using of high spatial and temporal resolution data produced by **the Detection of Non-Authorised Water Abstractions** service of the project. In addition, produced data such as precipitation maps, maps of Potential Evapotranspiration, maps of Crop Evapotranspiration and soil moisture maps could be used in groundwater recharge calculations depending on the computational method. Finally, the integration of the data into a geographical information system contributes to the regional differentiated quantification of water abstraction pressure.

The produced data could be further used by models simulating point and diffuse pollution and calculating water balances in order to estimate the impact of economic activities on surface and ground water bodies in river basin scale. The accuracy of the input data to these models is one of the crucial factors that affect the quality of produced data. Usually, regarding the irrigation volume data and potential evapotranspiration, modelers have no accurate data for their simulation. Data produced by the first service of the project will fill this gap. Moreover, the accuracy of the simulation results depends a lot on validation data used. The high resolution produced data by **the Detection of Non-Authorised Water Abstractions** service can be used for models validation. Use and apply of groundwater – surface water models for calculating water balances in river basin scale is also proposed by Guidance Document N^{o} 34 (Water Balances Guidance).

6.4.2 Monitoring Programme

The monitoring programmes must provide the information necessary to assess whether the Directive's environmental objectives will be achieved. Monitoring actions include surveillance and operational monitoring for both surface and ground water bodies and investigative monitoring only for surface water bodies. Regarding ground water bodies, monitoring requirements should include chemical status and quantitative assessment of all the groundwater bodies being at risk. Quantitative assessment is crucial as groundwater hydrological alterations affect hydromorphological quality elements (i.e. flow regimes of rivers, water level of groundwater dependent wetlands etc.) which in turn affect water quality of aquatic ecosystems and related habitats.

Establishment of a complementary representative sampling network and suitable sampling frequencies taking into account the continuous, updated, temporally and spatially distributed produced data of abstracted volume for irrigation will contribute to the classification of all water bodies.

Moreover, after researchers had recognized that environmental flow is a key measure for restoring and managing river ecosystems (Acreman and Ferguson, 2009), the WFD proposes that ecological flows (that is the "amount of water required for the aquatic ecosystem to continue to thrive and provide the services we rely upon") may be applied in the next cycle of river basin management plans (RBMPs). These flows comprise a measure towards good surface water status and good quantitative groundwater status which should be estimated and applied for water bodies which failed to reach “good ecological status” due to hydrological alterations (Theodoropoulos and Skoulikidis, 2015). The assessment and application of environmental flows follow a specific framework with specific steps, proposed by WFD. Monitoring abstracted water for irrigation that is produced data by **the Detection of Non-Authorised Water Abstractions** service, is a key parameter in two of the abovementioned steps; identification of water bodies at hydrological risk and monitoring the current hydrological state.

6.4.3 Programme of measures

The whole process of river basin management planning includes the preparation of programmes of measures at basin level for achieving the environmental objectives of the Water Framework Directive cost-effectively. Programs of Measures should cover the gap between the current situation and the good status. The spatiotemporal distribution of water abstraction pressure would contribute to a more accurate and spatiotemporal targeted measures.

More specifically, proposed measures aiming at mitigating the impacts from water abstraction pressure may include crop pattern allocation, best agricultural practices, definition of water abstraction limits, controls of the abstraction of surface and ground water etc. The produced data in the context of the project DIANA will enhance the effectiveness of the proposed measures promoting sustainable water use, as they can influence the place and the time of the activity which apply best.

Additionally, the continuous updated monitoring of water abstraction volume will contribute to the evaluation of the implementation of proposed measures. In particular, the detection of illegal abstractions and the estimation of total water abstraction volume could indicate if the proposed water abstraction limits are being met, the proposed crop allocation is applied etc.

6.4.4 Water pricing and recovery costs of water services

In the frame of the implementation of WFD, Member States are required to price water in a way that ensures full cost recovery and provides adequate incentives for a better use of available resources and shifting to less polluting input and practices. For every water use, such as agricultural, the total cost, including environmental and resource cost, should be estimated. According to Wateco guidance (2002) environmental cost represents *the costs of damage that water uses impose on the environment and ecosystems and those who use the environment* and resource costs are defined *as the costs of foregone opportunities which other uses suffer due to the depletion of the resource beyond its natural rate of recharge or recovery*. Resource costs concerns only groundwater bodies when the amount of annual pumping exceeds the average annual enrichment.

A significant amount of groundwater abstraction and surface water abstraction -but to a lesser extent- takes place without being registered or monitored. So, the challenge of water pricing in agriculture is that non-authorised water abstraction is not estimated in total water consumption by authorities in charge. To address the problem of including non-authorised water abstraction to the total water consumption estimations and thereby resource cost estimation, a form of extraction control or an efficient monitoring system has been proposed (Bogaert et al. 2012; Lockwood, 2014). In this context, the detection of irrigated areas, including the non-authorized irrigated areas, highlights the regions with the highest water demand that have to bear the cost of using the resource.

Additionally, the pressure of water abstraction for irrigation is more intense during summer or drought events. Furthermore, there is a great variability of agricultural conditions and characteristics such as probability of drought across basins. For these reasons, the estimation of environmental and resource costs should be differentiated temporally and spatially. The spatiotemporal resolution of the produced data from the two services of the project (detection of irrigated areas, water abstraction volume for irrigation, seasonal drought forecasting and monitoring) could contribute to a more effective determination of service users and polluters and accurate estimation of resource costs.

6.4.5 Advantages of produced data recycling

Use of all the above-mentioned data that were produced using Earth Observation techniques, for supporting the WFD, provides many advantages on both the implementation procedures and the produced results. First of all, the high spatial and temporal resolution of the data contributes to the more accurate identification of water abstraction pressure and its quantification. The spatial and temporal distributed pressure will result to a most accurate, continuous and long-term monitoring program, providing spatially and temporally denser information and improved frequency of data. As a result, a more targeted spatially and temporally programme of measures could be established.

By monitoring these data, stakeholders that are in charge of water management, inspections and implementation of WFD would ensure the reliability of self-declarations on water abstractions, optimize field inspections to ensure compliance with legal water allocation and could validate a volume-based system for water pricing. Additionally, comparing with data produced by the **Drought Monitoring and Seasonal Forecasting** service, it would be feasible to ensure compliance with seasonal water restrictions in case of drought management.

Lastly, as WFD is a European framework there is a need of consistent and comparable results, which will be obtained during all stages of the implementation of the Directive, by all European countries and regions. Use of earth observation techniques in the context of the implementation of WFD, would provide these advantages and could be a crucial factor for a successful implementation of the Directive.

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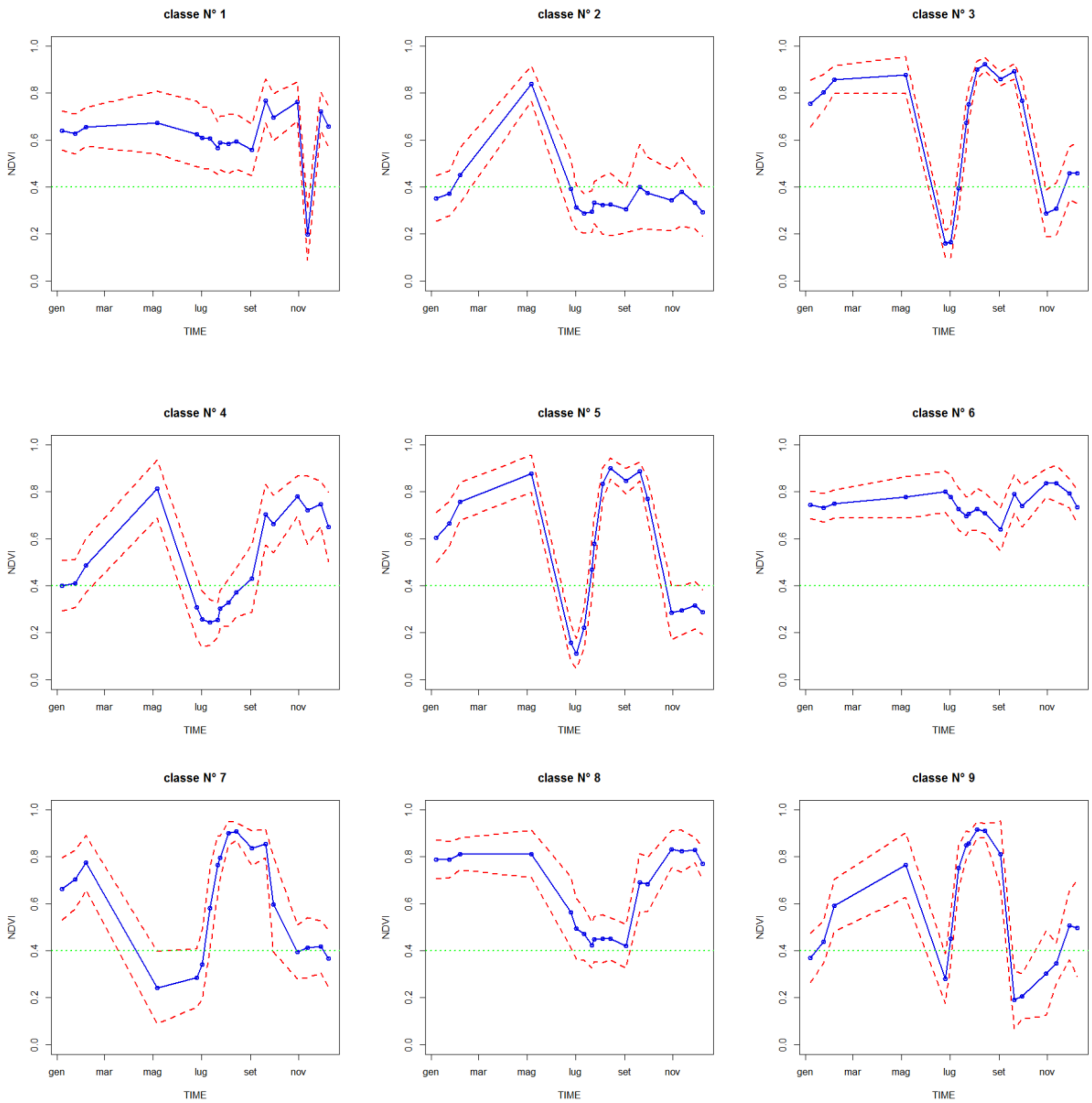
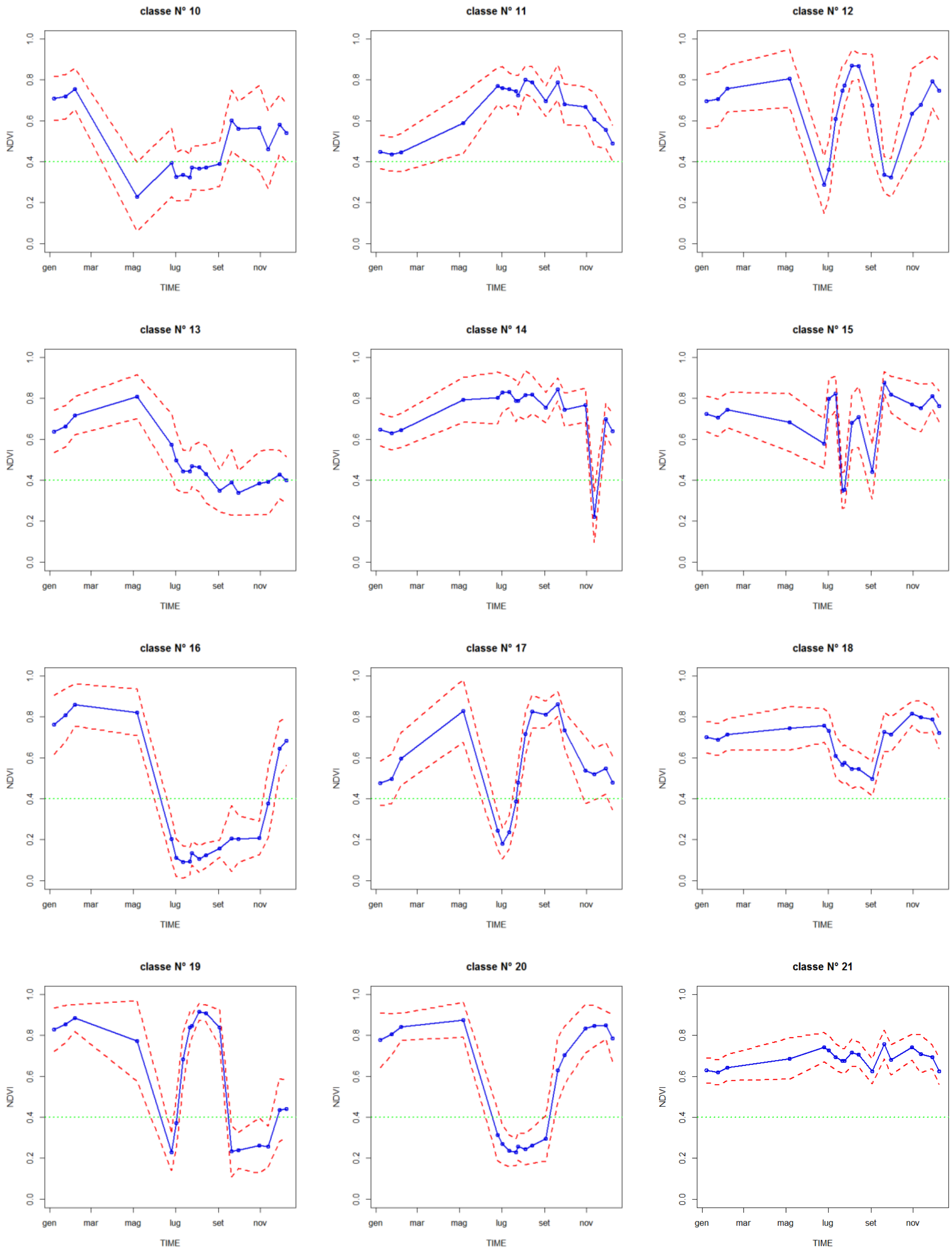
7 Annexes

7.1 Annex I: Multi-time NDVI index curves – Sannio Alifano Case Study 2016

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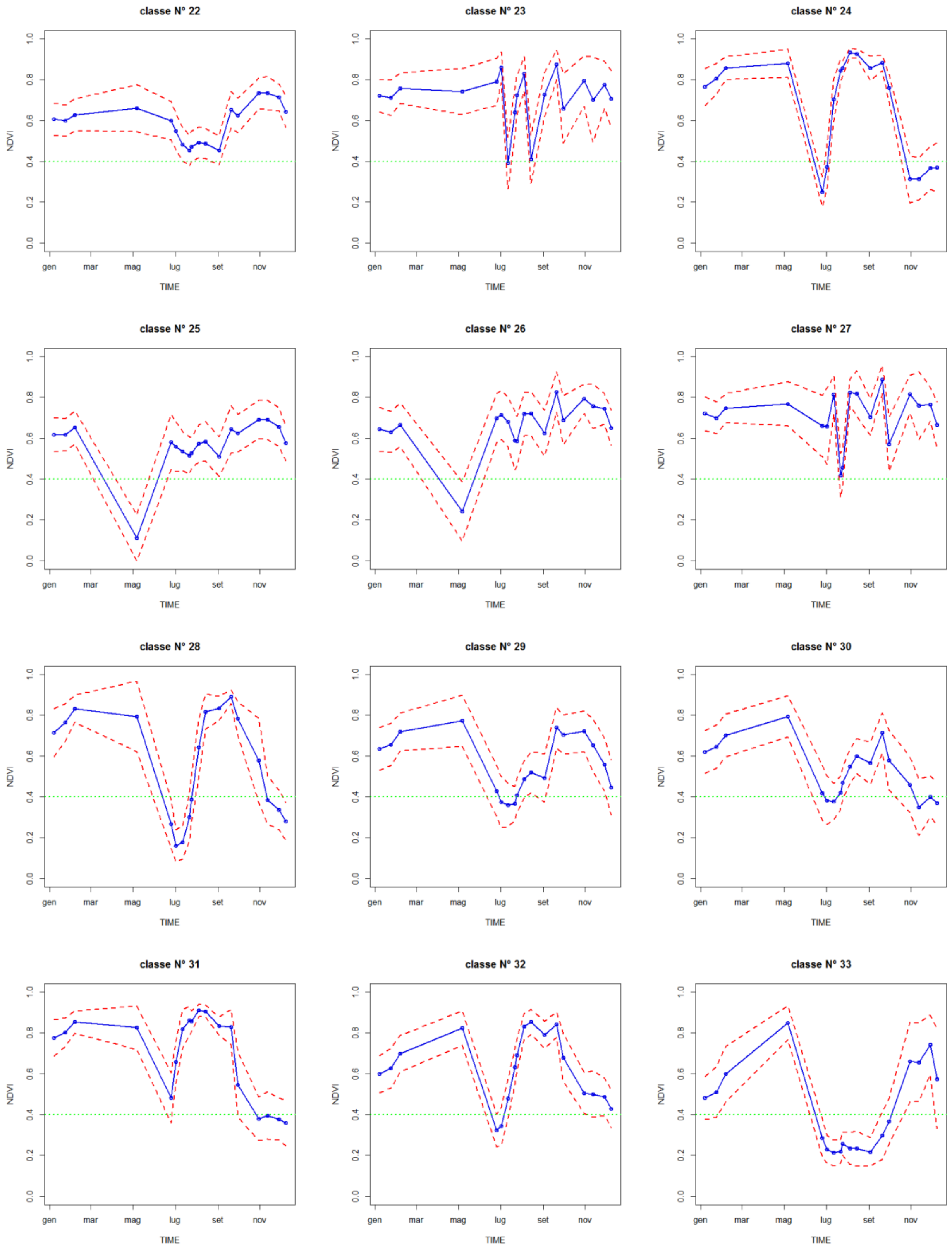
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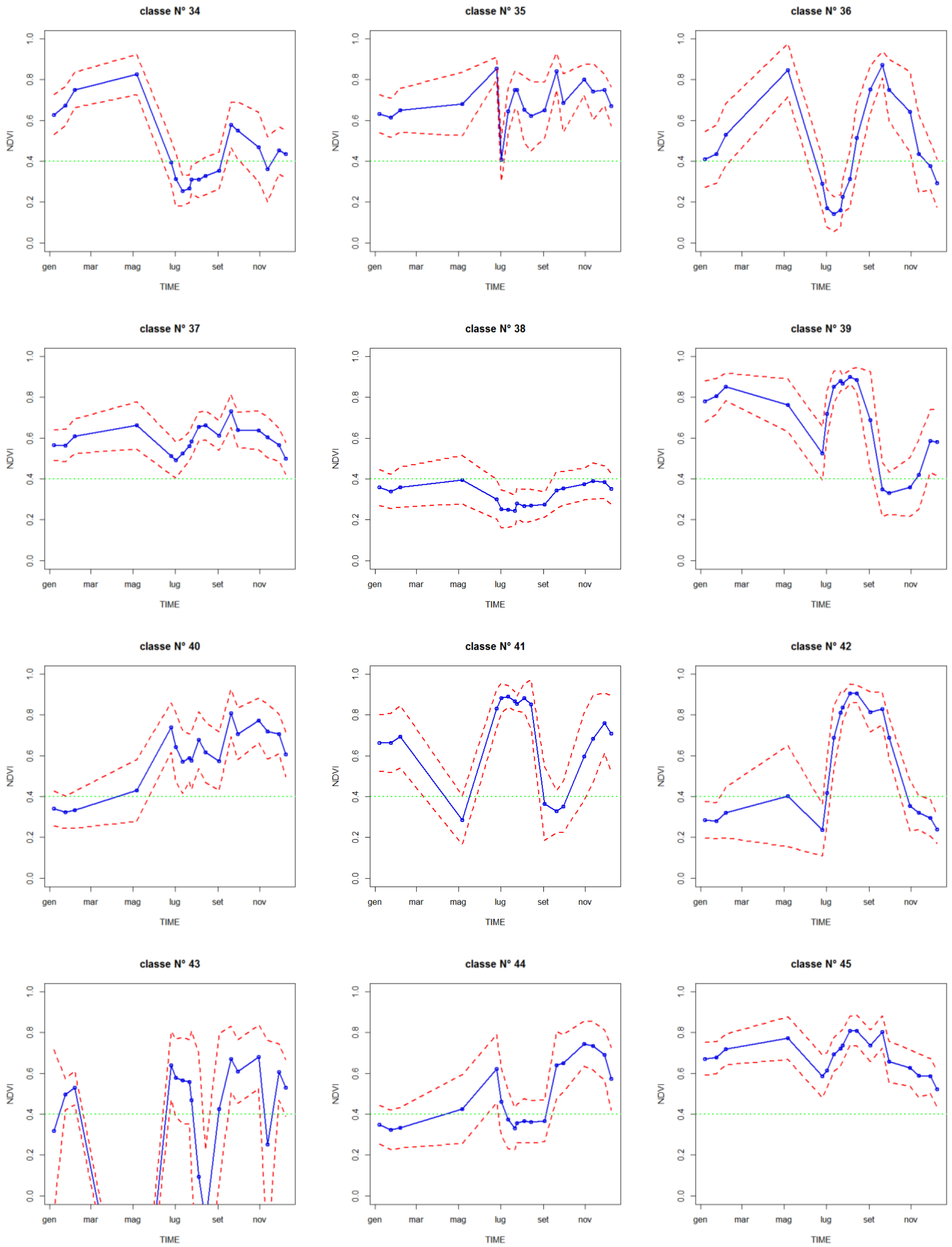
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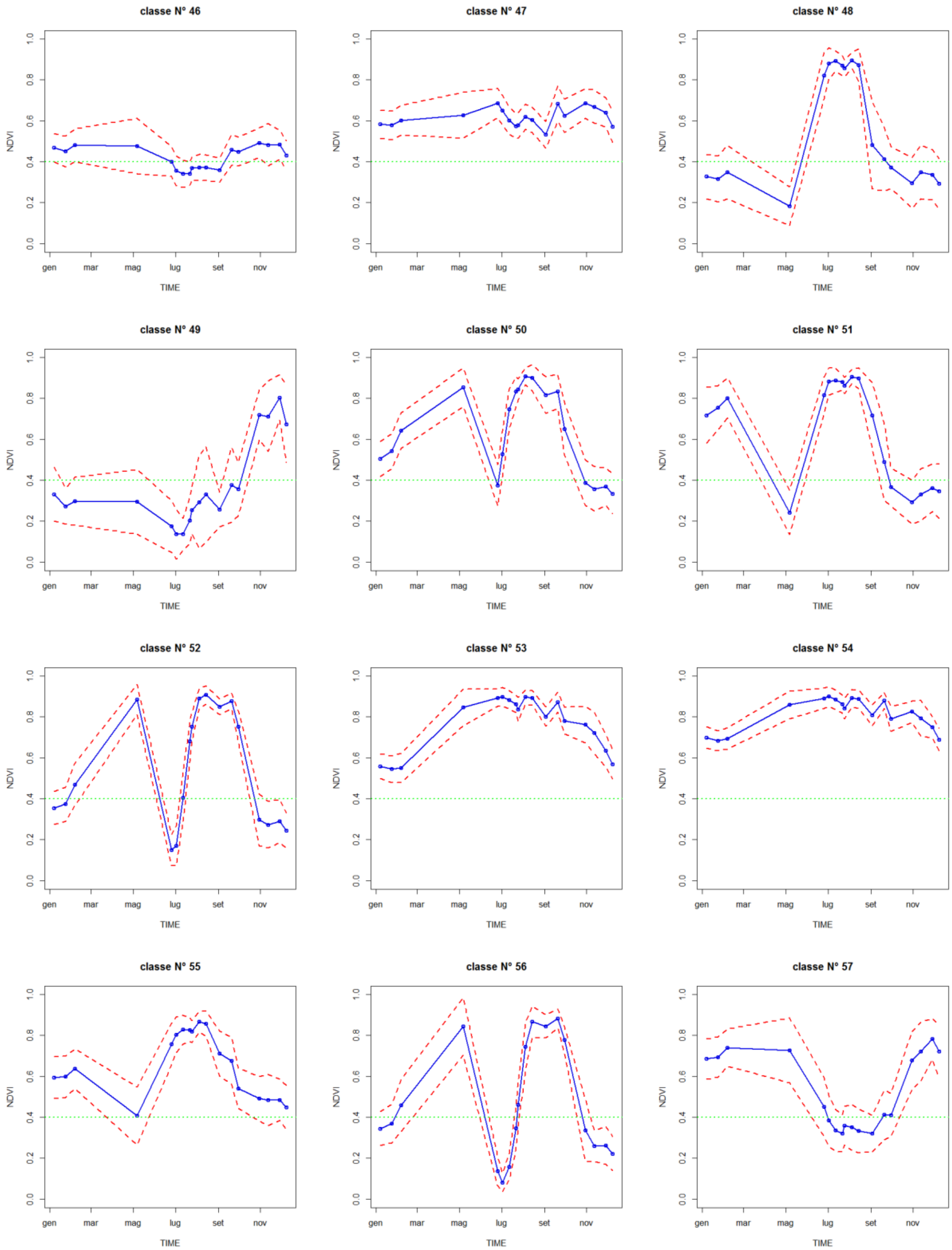
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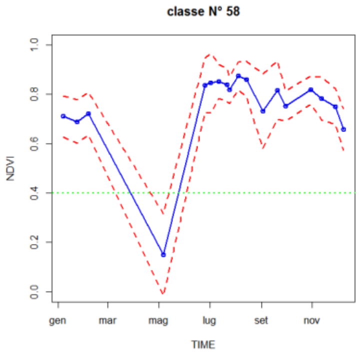
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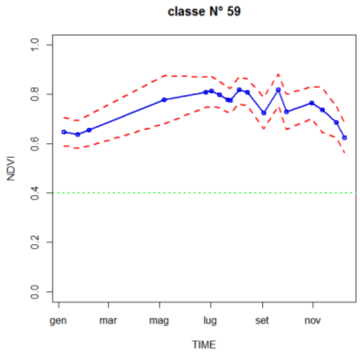
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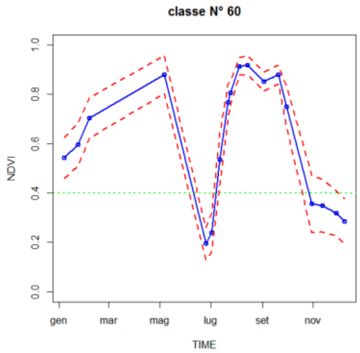
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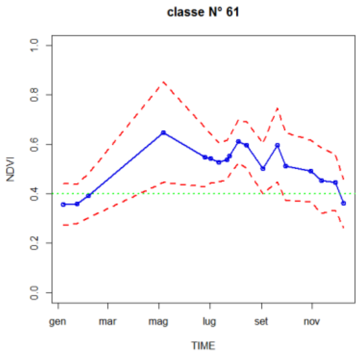
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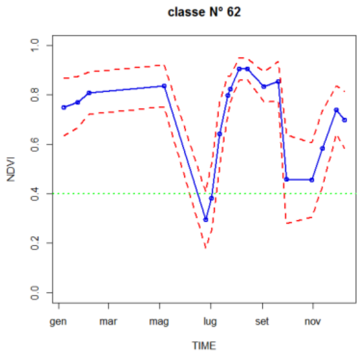
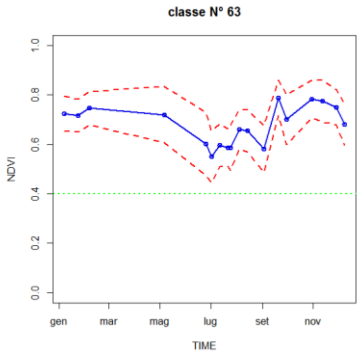
gen mar mag lug set nov
TIME


classe N° 62
NDVI
0.0 0.2 0.4 0.6 0.8 1.0
gen mar mag lug set nov
TIME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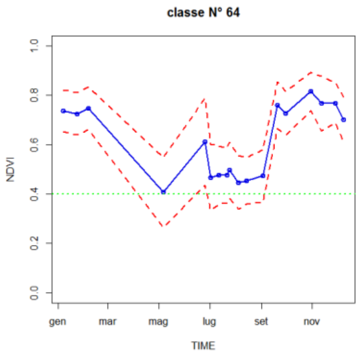
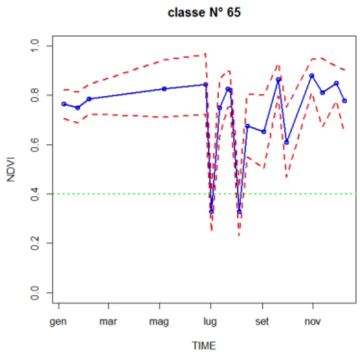
NDVI
0.0 0.2 0.4 0.6 0.8 1.0
gen mar mag lug set nov
TIME


classe N° 64
NDVI
0.0 0.2 0.4 0.6 0.8 1.0
gen mar mag lug set nov
TIME


classe N° 65
NDVI
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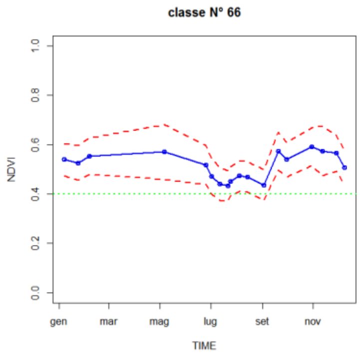
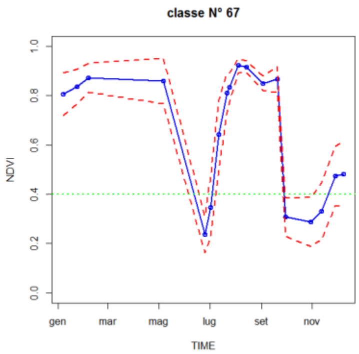
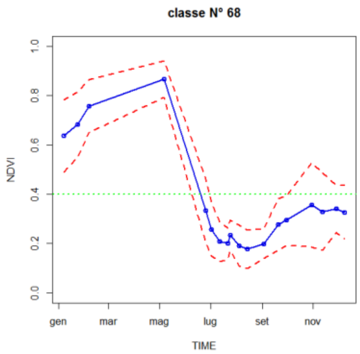
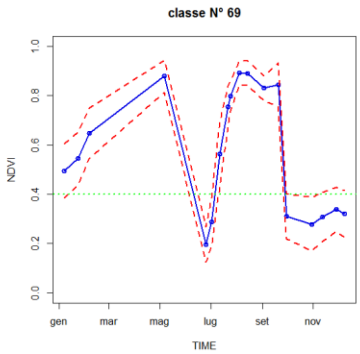
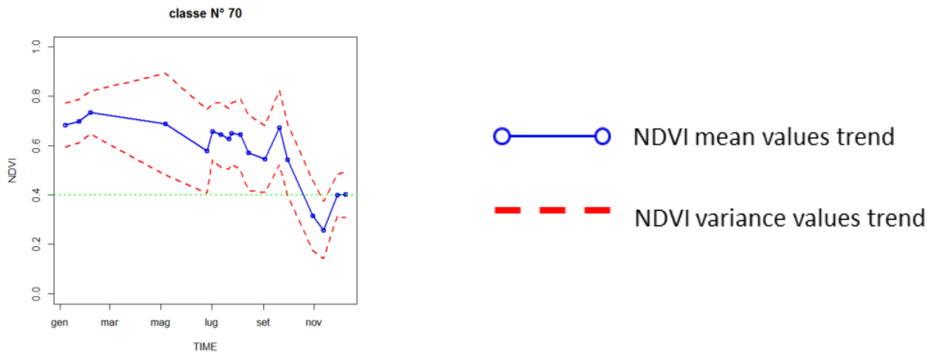
gen mar mag lug set nov
TIME


classe N° 66
NDVI
0.0 0.2 0.4 0.6 0.8 1.0
gen mar mag lug set nov
TIME


classe N° 67
NDVI
0.0 0.2 0.4 0.6 0.8 1.0
gen mar mag lug set nov
TIME


classe N° 68
NDVI
0.0 0.2 0.4 0.6 0.8 1.0
gen mar mag lug set nov
TIME


classe N° 69
NDVI
0.0 0.2 0.4 0.6 0.8 1.0
gen mar mag lug set nov
TIME


classe N° 70
NDVI
0.0
0.2
0.4
0.6
0.8
1.0
gen
mar
mag
lug
set
nov
TIME
NDVI mean values trend
NDVI variance values trend