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Collection of Methods for Data Analysis: from Signal Selection to Marker Detection

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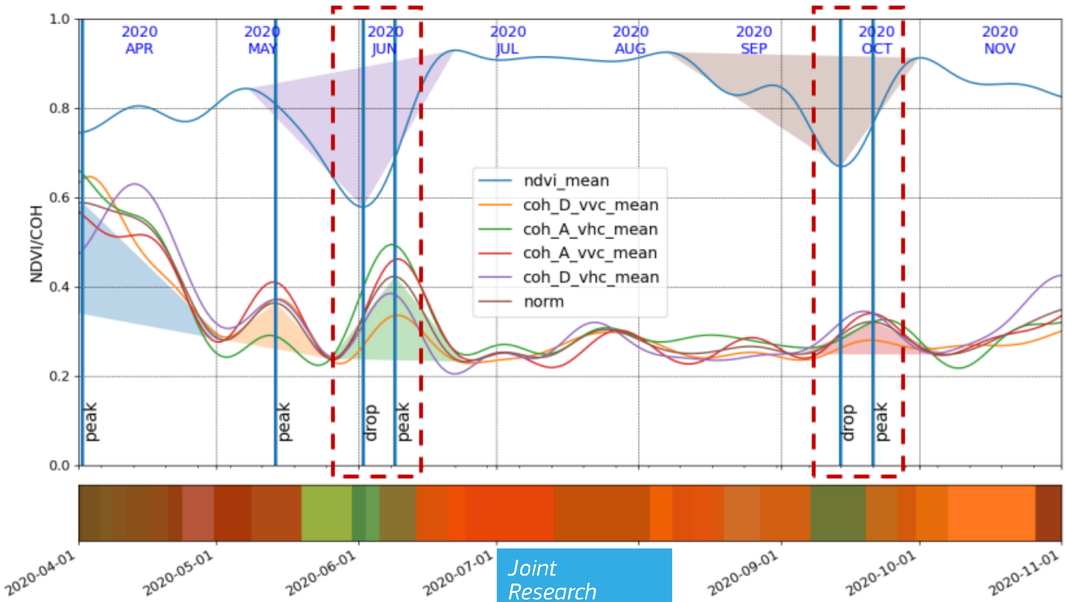

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Contents

Abstract

This technical report describes a collection of methods for data analysis in the context of Checks by Monitoring (CbM), that support the signal selection, development and implementation of marker detectors. CbM exploits the signals (i.e. time series of a physical variable) provided by Sentinel-1 and Sentinel-2 to detect markers corresponding to field behaviour, often indicative of specific activities. In such cases, a marker can be detected by a specific signal pattern reflecting that field activity. For instance, a drop in the Normalised Difference Vegetation Index (NDVI) can be associated to the removal of biomass corresponding, for instance, to a mowing activity. A reliable CbM system should consider several criteria for the selection of the most appropriate signals for marker/activity detection. These considerations include significance, repeatability and lack of correlation.

The first two chapters of the report analyse and discuss signal selection and algorithm development in the CbM context.
The third chapter of the report focuses on the implementation of a flexible data processing framework. Flexibility and configurability are key elements enabling the proper parametrization of makers and marker detectors. In this way, it is possible to adapt the detection process to the local conditions and practices. Flexibility and configurability are also needed to account for local natural disturbances that can bias the acquired signals.

The methods described form the core of a catalogue of best practices that could be considered for the design and implementation of a CbM system.

Acknowledgements

The authors wish to thanks the different Member States (MSs) for their support and contributions to the outreach and on-boarding activities. The contributions of DG AGRI colleagues from both C1 and H3 units are also acknowledged.

Authors

Zielinski R., Sedano F., Devos W. and Borio D.

1 Introduction

Since 2018, several Member States (MSs) and their Paying Agencies (PAs) have been progressively introduced Checks by Monitoring (CbM) to substitute the On The Spot Checks (OTSC). In the latter case, only a small sample of aid applications is checked. With CbM, which leverages the availability of free-of-charge satellite images from the Sentinels, almost all holdings can be monitored because Sentinel images and signals capture all parcels and provide timely information via specific makers that reflect field activities. A marker is a specific pattern occurring on a signal during a specific field activity that impacts on the field's condition. Such type of monitoring is not possible only in a limited number of cases, for instance for small parcels not containing even a single full Sentinel pixel.

The JRC has been supporting the development of CbM approaches and has conducted analyses on different CbM aspects including signal selection, marker behaviour, maker combining approaches and the final logic for assigning a decision to each Feature of Interest (FOI). These aspects have been analysed as part of different activities such the outreach, the on-boarding and the AGRI-support projects.

This report describes a collection of methods for data analysis developed in the context of the JRC CbM development activities. In particular, three main topics are tackled.

The first step in the design of a CbM system is the selection of the most appropriate signal(s) for marker detection. In this respect, several criteria were considered including significance, repeatability and minimise of correlation.

Significance denotes that a signal should behave differently in the absence and in the presence of a specific activity. This difference in behaviour should be statistically significant. For instance, a mowing activity should cause a drop in the Normalised Difference Vegetation Index (NDVI) computed from Sentinel-2 signals. This drop should be statistically different from other drops due to other phenomena (confounding factors) occurring in the absence of expected mowing or caused by an unrelated activity/event such as burning. Significance can be tested in a rigorous way using statistical tests.

Repeatability implies that the signal behaviour should be consistent in the presence of similar phenomena. For instance, a NDVI drop should consistently occur in the presence of mowing. It is clear that the duration and the depth of the drop can differ depending on the local practices (i.e. the way mowing is performed) and other phenomena (weather, natural disturbances, etc.). Despite this variability, a certain level of repeatability of the signal behaviour is required.

Finally, the absence of correlation refers to the joint use of two or more signals. While the adoption of several signals, possibly from different sensors, can significantly improve the reliability of a decision, the addition of a strongly correlated signal does not bring any additional or new information to the decision process. Indeed all relevant information was already present in the original pool of signals selected for CbM.

The next section of this document provides an overview of the signal selection process, better detailing the principles introduced above. The signal selection is dependent on the availability of reliable ground data that play a pivotal role in the process. The importance of ground truth data is thoroughly discussed in Section 2.

A further section develops these concepts and focuses on the tests of significance. The different elements of a test of significance are analysed and contextualized with respect to CbM. Examples based on real data are also provided.

After correctly identifying the signals, operational algorithms can be developed. The implementation of proof-of-concept CbM routines is indeed the focus of Section 3. For this, a processing framework to explore and analyse Sentinel-1 and Sentinel-2 data has been developed. This framework was designed using a set of integrated Python modules and Object Oriented Programming (OOP) to facilitate its potential extension with new modules and algorithms. This tool enables researchers to explicitly explore and model mechanistic relationships between land management practices and the variations in satellite signals over time.

The setup allows one to reduce the data volume from Sentinel satellites and transform it into manageable information. Indeed, the analysis is now based on information extracted from satellite bands for each homogeneous land management unit, replacing the usual pixel processing with object-based analysis. The framework also allows one to fully exploit the complementary nature of Sentinel-1 and Sentinel-2 observations.

The resulting processing architecture is built on four main modules: 1) import of band statistics, 2) data preprocessing, 3) identification of relevant changes in the signal time series (marker), 4) aggregation of markers from different sensors and association with land management practice, through the relevant bio-physical stages.

The different functional blocks and the operational algorithms are described in Section 3.

The code is open source and available with its documentation in https://github.com/ec-jrc/cbm.

2 Signal analyses towards core marker development

The following section describes signal analyses based on ground truth information in CbM. The methodology discusses aspects of the signal, signal descriptors and signal behaviour, including significance analyses, repeatability of signal behaviour and the signal correlation to be considered in the core marker development.

By following the described methodology a ranking of signals per given activity or land cover manifestation can be created. These analyses take into account signal behaviour strength and probability of expected behaviour together with information about potential correlation between pair of signals. Such approach launches the development process and introduces a local information into the process. The analyses including a proper scenario definition and understanding of the local practices allow for identification and selection of reliable markers for the automation process.

Ground truth data, are important for both: understanding the signal behaviour and quality control of the outcome, and should not be neglected in the development (Zielinski R., et al. 2022). During the CbM outreach 2021 activities, one out of 17 active participants had set up a dedicated ground observation set; only a handful were in the process of collecting it (one reported as completed). A majority considered it in the future task list (Devos et al. 2020). The existing datasets, e.g. OTSC/RFV, CwRS or geo-tagged photos captured during various controls, are not always fit-for-purpose. Either these data do not capture directly the framer's activities relevant for the need of signal analysis or they provide information in sub-optimal timing and limited frequency, such as once a year.

When available, the ground truth data with a specific date (or a period) of given farmer's activity facilitate correct understanding of land cover manifestations (or their change) and allow to link them with corresponding signal patterns. Such analyses allow the optimal selection of signals for an activity. There is already existing experience of well-designed and complete datasets with weekly ground observations collected to support of CbM development. In the design of a survey for CbM development or quality assessment, at least the following elements require careful planning: future functionalities (type of activity/event that needs to be confirmed), required observation frequency, type of information collected, spatial coverage, and sample size. Careful planning is crucial because the complete survey, which requires multiple ground observations, will only be available at the end the season. Missing or too scarcely collected data cannot be easily substituted or complemented. Fit-for-purpose ground observations provide more possibilities for data analyses and potentially will return the investment faster.

2.1 Specific challenge

Identification of an appropriate scenario is the first boundary condition of CbM (Devos et al. 2021). The scenario relies on the aid application to specify the land management declared for a parcel (FOI) and local context expressed by agricultural practices. The scenario consists of a sequence of stages (that could be understood as milestones in the farming process) resulting from farmer's activities, crop phenology or other potential events (including natural, like disasters). The stages are ordered in a sequence expected from a certain practice, e.g. mowing, growth of vegetation, second mowing etc. Their time setting (calendar year, growing season or consecutive years/seasons) and approximate timing is known and serves as guide in the process with no fixed dates nor deadlines.

In CbM, the scenario brings the local context into the process of image-based analyses through its knowledge on agricultural practices. Understanding which activities are likely to happen on the ground is fundamental to make correct design choices and is critical for real case implementations. The knowledge of local practice predicts reliable and correctly timed markers and enables to link a specific signal behaviour to particular bio-physical manifestations on the FOI.

CbM is strongly relying on automation. The operations rely on observations (markers) of satellite based signals. Markers are developed thanks to the established relationship between a physical phenomenon and the observable variation in remote sensing data. To link the two, knowledge of the physics behind the sensor and of the local practice is needed. The first is common remote sensing knowledge but the second will slightly vary from one territory to another. Markers offer factual evidence thus it is important to select the proper signal allowing for best detection of any land cover manifestation resulting from anticipated farmer's activities. So the analyses that translate the local practice into signal and select corresponding signal behaviour (marker) are central in the design of the system.

2.2 Ground truth observation

The ground truth data are necessary to embed local knowledge into the design process. These observations are meant to be collected on the ground, by observing known parcels/FOIs in regular time intervals that capture the desired phenomenon or traces of farmer's activities. In fact, farmers can also systematically provide ground information, captured according to a dedicated data collection protocol. The date of an activity and duration that its impact remains visible is the key information. Such information provides an accurate time stamp of an event observed on the ground enabling correct interpretation of signal behaviour. Ground observations allow understanding the potential and limitations of remotely sensed imagery in capturing these specific phenomena and provide the benchmark to assess the detection capabilities of different markers that might be considered in the CbM development process.

There are several approaches to organize the collection of information that supports signal analyses. First and most valuable is a dedicated survey where fit-to-purpose data are collected. The survey should be planned with caution, and the design process should include at least the following elements:

- Scope, including functionalities (type of activity/event that needs to be confirmed).
- Frequency of observations (i.e. weekly, monthly, etc.).
- Type of information to collect (i.e. crop, crop phonological status, activities type and day of observation).
- Survey extent, spatial coverage of data collection (i.e. specific region).
- Sample size (number of parcels/FOI to be observed).
- Duration (i.e. vegetative season, calendar year).

Careful planning is crucial because the complete survey results will only be available at the end the season. Missing or too scarcely collected data cannot be easily substituted or complemented.

Another potential ground data approach is to rely on existing field surveys, designed for another purpose, such as the OTSC and RFV. The advantages of using control data are obvious, not only from economical view point, but also in terms of quality of information available based on established protocols. The challenge lays in ensuring that information content, time frame and the frequency of observations with the needs of the signal analysis. It is also worth noticing that the existing survey data are characterised by a sample size and spatial distribution designed for another purpose, i.e. for control of farmer's applications. The local practice variability might be not captured, as the decision on sample selection was based on other priorities.

A third data approach is using image based sources which provide singular observations acquired on the ground (geo-tagged photos), aerial oblique surveys and typical wall-2-wall aerial campaigns providing systematic orthophoto updates. Those data sources do not deliver direct solutions but require interpretation and data collection to derive the date of the activity and/or land cover status/change observations. Due to higher image resolution such datasets are particularly useful i.e. to distinguish between mowed/grazed grassland thanks to observable presence of animals/hay residuals, which are not detectable in Sentinel data. Another advantage of aerial acquisitions is in their coverage that may vary between a small region and part of the country but the data in any local area are collected at the same time. Usage of image-based data source to collect the ground truth observation might be complex and often it may not be possible to derive precisely the date of the activity, as the image acquisition times are not necessarily aligned with the farmer's activity calendar. Deriving information about the land cover manifestation at the time of image capture is more feasible than indicting an exact date of an activity.

The geotagged photos, similarly to other image-based sources, provide an information snapshot taken from at known position with limited field of view and a single direction (pointing). This approach can be advantageous when more photos from different positions and/or directions can be taken to provide more context and information. The images need to be further analysed to retrieve required observations and thanks to ground orientation are intuitive to interpret. For more information about geotagged photos (Sima et al. 2020).

The frequency of ground truth observations vs activity/land cover manifestation to report:

- Daily (or with multiple observations within a week): probably most suited for analyses of activities resulting in rapid change of land cover manifestation or short-lived phenomena, where the date of activity is crucial and should be precisely detected), field observations performed at every day of farmer's activity (or multiple times within a week), but very labour extensive and difficult to set up for larger sample collection covering all seasons. For an average crop scenario and corresponding number of farmer's activities of interest such frequent observations are not necessary.

- Weekly: an observation is collected once a week, where a person is present on the spot to note potentially the status of a crop and information about the farmer's activities recognised on the field in between the two dates of inspection. This setting most align with S1/S2 revisit times. Such data collection may cover the entire season/year, or just selected period of time (e.g. a specific vegetation growth stage, a farmer activity - crop harvest or post-harvest condition/treatment of the filed).
- Monthly, an observation is collected once a month, where an inspector notes potentially the status of a crop and information about the farmer's activities recognised on the field in between the two dates of inspection. Obviously, a day of activity that happened in between the inspections is not retrievable (a part of the ones performed at the inspection day), however the interpretation of the conditions on the ground might lead to conclusion whether a given activity happened in the period (e.g. sowing, mowing, harvest). The selection of such time interval might be linked to a specific crop/field status or information about persistence of certain phenomena.

Single time in the season, similar to RFVs or OTSC approach, where an inspector notes the status of a crop and information about the farmer's activities recognised on the field at the date of inspection or deduct about some past activities based on situation found on the ground. The single time visit approach gives good reliable data on observable phenomena, but has limitations in capturing the anticipated activity and does not provide accurate dates, unless the activity was shortly before or during the day of inspection. The existing controls data are good starting points in the process but fit-for-purpose ground observations, with detailed enough field observations, provide much more possibilities for data analyses and potentially will return the investment faster in reliable process automation.

2.3 Methodology

Here are some initial considerations when comparing multiple observations of the same activity recorded in different parcels/FOIs:

- In a weekly pattern of observations, where a person is present on the spot to record the status of a crop and information about the farmer's activities recognised on the field in between two consecutive dates of observation. The maximum delay between activities on the ground and its record by inspector may be 7 days.
- Sentinel (1 and 2) data operate on latitude based revisit cycles, i.e. the time between subsequent acquisitions depends on the geographical location. The use of optical sensor acquisitions is subject to further reduction due to presence of clouds and clouds' shadow, making availability of input data less predictable. In Europe, there are locations (e.g. Ireland) where during the May-August period only few valid acquisitions are left after the cloud filtering and therefore such signal may become unreliable in the context of the time series analysis.
- Some signals imply both radiometric and temporal aspects, e.g. The Sentinel-1 based coherence (COH6) signal, which expresses the difference calculated from a pair of consecutive acquisitions in a 6 days period. Therefore, in terms of time, observed single behaviour should be interpreted accordingly, and not as single date acquisition based signals.

2.3.1 Signal and signal data descriptor

In CbM, the signal is calculated using a statistical data descriptor that can be applied on different spatial feature primitives (polygons, image segments, image pixel clusters) on condition that they are representative for the FOI. The primitives are designed to represent a spatial extend of the phenomena within the FOI.

Assuming there is a parcel homogeneously used by farmer under a single practice, such parcel is described by the FOI boundary. A set of statistics is calculated from the corresponding satellite data pixels for valid acquisitions. The valid acquisition term refers to the result of a pre-selection of satellite data through defined protocols. For instance for the Sentinel 2, exclusion of acquisitions where presence of cloud or clouds shadows is detected as the presence of cloud or clouds shadow inside the parcel adversely influences the FOI statistics. This influence grows with proportion of unwanted (cloudy) to wanted (crop) pixels inside the parcel perimeter. Their presence leads to outlier data points in the time series, and may result in doubtful and erroneous interpretation For example, while looking for mowing activities on grassland, inclusion of cloud-shadowed pixels in the statistics results in a drop of the Sentinel 2 signal values, which might be wrongly interpreted as a mowing event.

The FOI is the initial spatial element in the processing and it refers to a surface of the Earth where specified practice is performed (Devos et al. 2021a). In practical terms, the surface corresponds to a plot, meadow or orchard (or a part of it) with a perimeter valid during the life circle of the practice (i.e. single growing season – cereal crop or multiple consecutive years – orchard/permanent pasture).

In order to facilitate time series analyses, values of image pixels (i.e. a single band) contained in the FOI perimeter are selected and compiled into a single value with help of the descriptive statistics which summarize a given data set, that can be either a representation of the entire population or a sample of a population (Mann P. S., 2018). The following calculation may results with measures of central tendency and measures of variability, including the mean, median, and mode, while measures of variability include standard deviation, variance, minimum and maximum variables, kurtosis, skewness and interquartile range (IQR).

The potential approaches for optimal data selection inside the FOI and the optimal pixel selection approach, as well as the validation procedure are described in a dedicated report (Milenov P., 2021).

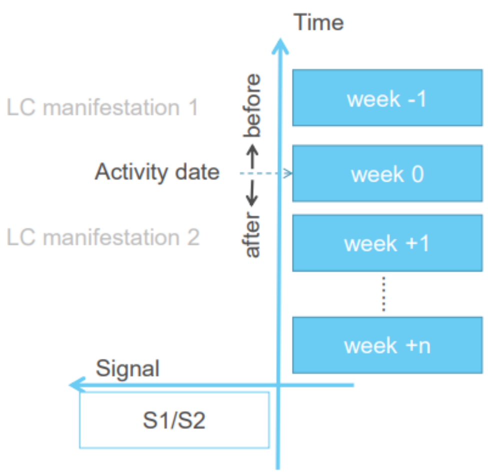
Most users so far make use of the mean value of the FOI pixels, without looking deeper into the subject. In the example below, several data descriptors were tested to find which of them have the greatest potential in the signal behaviour analyses. Every statistical data descriptor applied on the same data sample (a set of pixels values corresponding to a single FOI) gives a different response, which might be related in the analytical process to other physical property of the feature. As a result, each can be considered as a separate signal (i.e. max(NDVI), mean(NDVI), median(NDVI).

According to the investigation on descriptor selection (Zielinski R., et al. 2022), overall, the mean descriptor showed good performance, but the median provides more variability and thus could be considered as the prime descriptor. Still, it might be beneficial to consider additional descriptors during the data discovery and analyses especially for more complex cases of land cover manifestation.

2.3.2 Analysis of signal behaviour

The analyses of signal behaviour are fundamental to understand the relation between signal and land cover manifestations on the ground. Any evidence of significant change in the behaviour caused by the activity might support identification of monitorable stages, selection of most suitable signal to detect such activity/land cover manifestation stage or change and support the maker development process.

Figure 1. Data arrangement for ground truth analyses



Source: GTCAP

Assuming that the date available for an activity observed on group of FOIs sharing an activity, the multiple observations can be used in a single analyses flow using a certain data arrangement presented in Figure . The data are managed in a weekly manner, based on the ground truth data frequency. The *week 0* is the week when the activity took place in the field, *week -1* is a week preceding the activity and *week +1* is the week following the activity. The signals are arranged in the same pattern. For each activity a date and type of activity is prepared.

An observed activity, caused by anthropogenic or natural factor results in a land cover manifestation. The three principal signal responses are distinguished:

— Increase of the signal value observed after the activity date (i.e. case of mowing observed in Coh6 data- see example section below).

— Decrease of signal value observed after the activity date (i.e. case of mowing observed in the NDVI data – see example section below).

— No change, which might lead to a conclusion that a signal does not capture the given land cover manifestation (i.e. case of mowing observed on S1 - backscatter – see example section below).

For some activities where the entire land cover is converted rapidly (e.g. ploughing) the change of visual/physical state is immediately visible. In a case of mowing (topping, silage, hay) the observable change between before/after the activity performed might be visible in a few days (especially in optical data), when the grass residuals need time to dry out. In the mowing case, the visual effect grows proportionally with the amount of biomass cut, for example light topping activities might not be even detectable, whereas the first mowing in the season, with a maximised hay harvest, clearly stands out due to significant biomass reduction and increased proportion of soil contribution in the spectral response (after the activity). There are some activities (i.e. spraying) that are not easily observable due to limitation in the sensor spectral/spatial resolution or satellite revisit time.

The state of land cover manifestation or its observable change in the signal has a duration and an amplitude; both values are signal dependent and affected by local variability. Those properties can be estimated thanks to the analyses of signal with ground truth data.

Signal behaviour: example

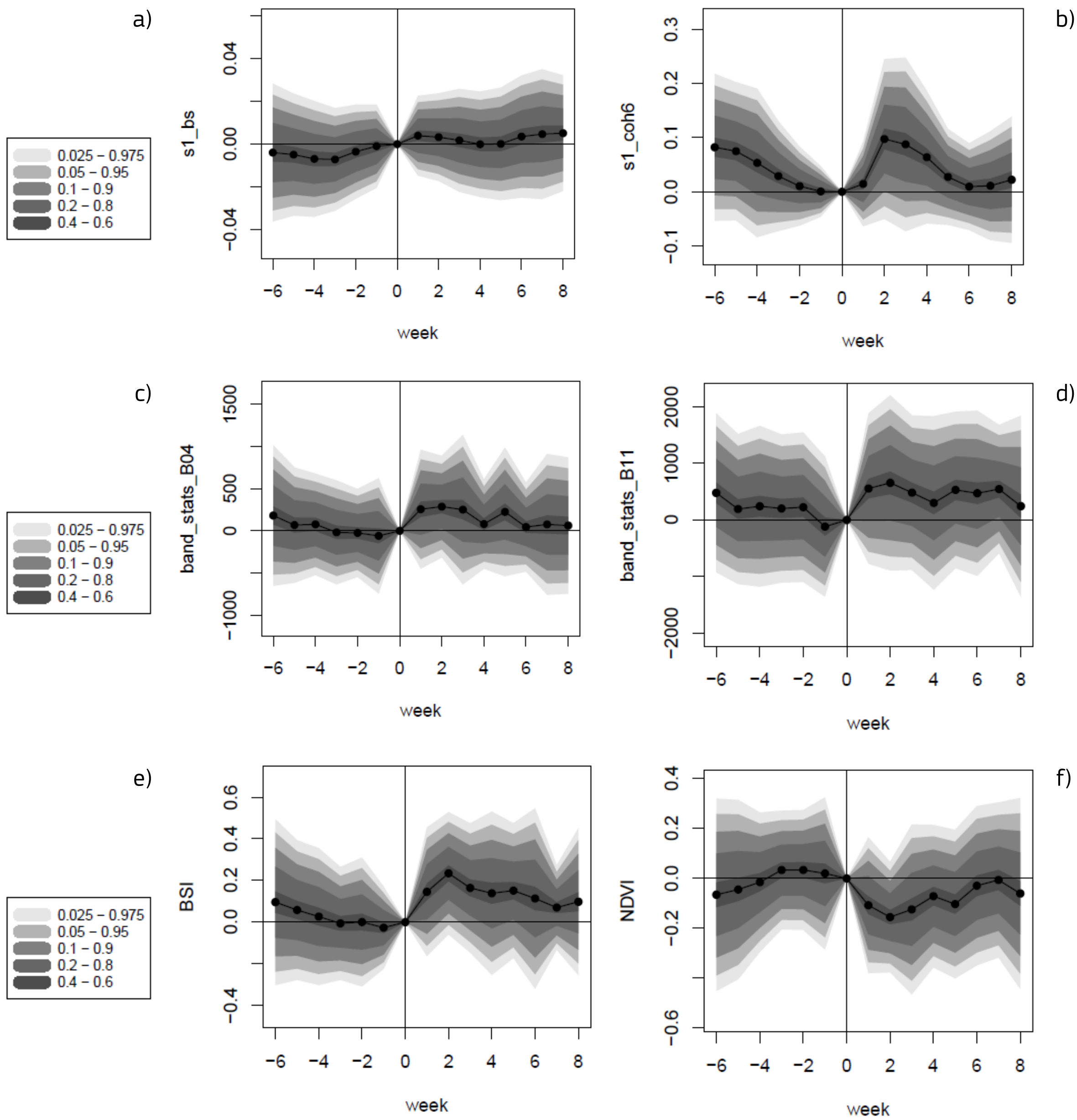
For a set of parcels/FOIs located in Latvia with known date of mowing activities a number of median signals were extracted from Sentinel data (

Figure), including: a) S1- backscatter, b) S1 – COH6, c) S2 – Red band (b4), d) S2 – Short wave infrared band (b11), e) S2- Bare Soil Index, and f) S2- Normalized Difference Vegetation Index. Note, the list of the signals presented is limited but adding new signals, is possible with a little effort.

In the analyses, the same activity type observed on different parcels are analysed together. The six different median signals are shown in

Figure with the mean response of observations and the corresponding variability ranges. For most of the signals, after the activity, a change of the signal behaviour is observed. The Sentinel-1 backscatter for mowing activity no significant change is noted, thus this signal has low potential for detecting this activity. The others have potential for further analyses as an increase of the signal is evident for four signals (S1-COH6, S2- bands 4 and 11 and Bare Soil Index), whereas significant decrease can be reported for the Normalized Difference Vegetation Index. The change is observable for 3-4 weeks after activity. The values (magnitudes) of signal changes are signal depended and reflect the sample population variability.

Figure 2. Examples of signal behaviour, centred for mowing activity, based on a set of grassland parcel located in Latvia. Sentinel signals presented: a) S1- backscatter, b) S1 – COH6, c) S2 – Red band (b4), d) S2 – Short wave infra-red band (b11), e) S2- Bare Soil Index, and f) S2- Normalized difference vegetation index.



Source: GTCAP

2.3.3 Test of significance

For signals arranged in a weekly manner, a statistical test can be used to verify whether the change between the week of the activity and the weeks before/after is actually significant. The T-test[1] is used to detect significant differences of the mean between two samples. In this case, we would see if the average change of signal value after the activity is significant. The null hypothesis is that the true difference is zero (any difference between the weeks is just by chance), whereas the alternative hypothesis is that the there is a true difference that is different from zero. We are looking at the values of the same parcels before and after an activity.

In a paired T-test, also often referred to as dependent T-test, a necessary assumption is that the difference between the weeks should be normally distributed. To test this assumption, it is possible to run a Shapiro Wilks[2] test of normality. However, the grater sample size (number of parcel or activities) will increase the significance for a similar change. Hence, it is easier to identify a significant change when a high number of samples is present. But whereas a significant change is a necessary requirement for our ability to detect changes, it does not tell how easy it is to detect activities in individual parcels/FOIs.

Statistical test of significance: example

In this example, a set of grasslands parcels located in Latvia, Czech Republic and Ireland together with the ground truth information (mowing activity dates) and two median signals are processed. Figure shows the points with estimated mean difference in signal values between week 0 and the weeks before and after. The blue line shows the 95% confidence intervals of the estimated differences. The grayscale of the dots reflects the level of significance of the estimated difference being different from week 0; the darker the colour the higher significance reported.

During mowing activity, a significant biomass reduction is triggered, therefore for signals highlighting the vegetation status, such as the NDVI, a reduction in value is expected after the activity date. Such a drop of value from the weeks before the activity to the weeks after for the NDVI index is notable in all datasets. In case of Ireland, the NDVI behaviour is different after the second week, comparing to others, but this probably reflects the difficulty of acquiring suitable (cloud free) S2 images. In case of the COH6 signal (Sentinal-1 based) similar behaviour is observed across the complete dataset. After the activity, the coherence values increases for up to 3-4 weeks.

Analyses of the same type of signals acquired at different locations result in similar results which confirms its stability and repeatability. However, the differences in the values or duration express the local variability captured in the FOIs.

Additional considerations with respect to the tests of significance are provided in Section 3.

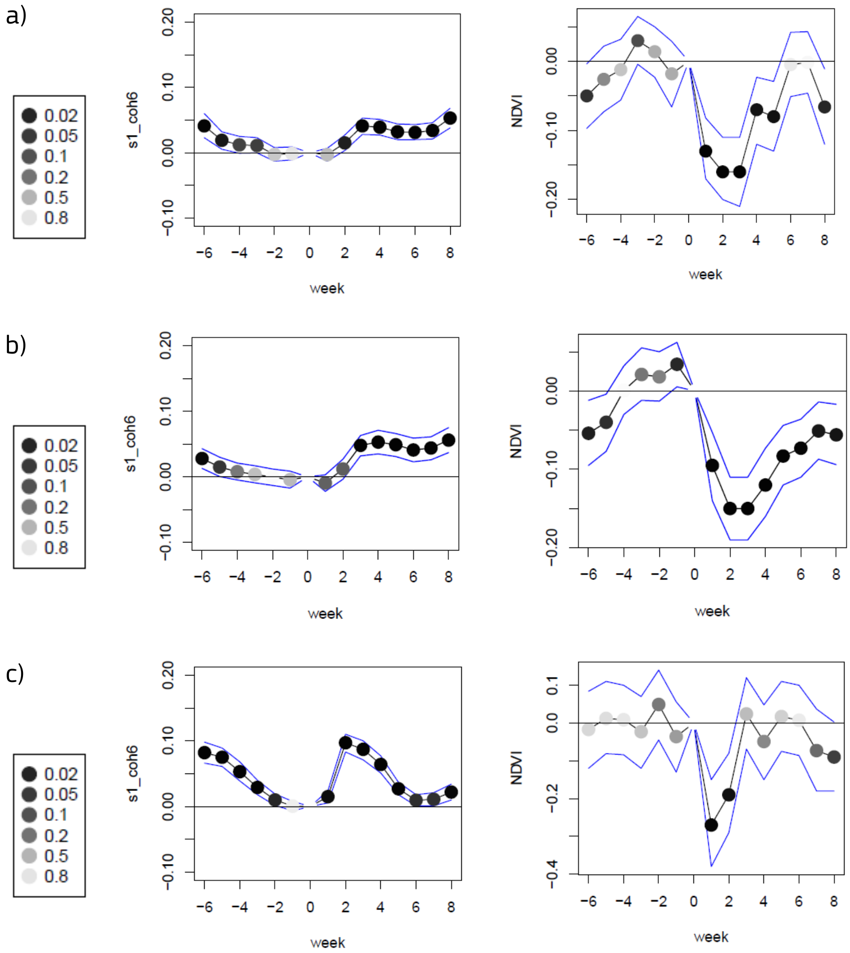
2.3.4 Repeatability of the signal behaviour

Similar activities observed on various parcels/FOIs, even in a single region, are not identical in terms of signal characteristics or properties, therefore those observations come with the range of variations. So, an important aspect of the signal behaviour is its repeatability, which can be assessed from further analyses of ground truth data provided by probability estimates. For each signal, we have estimated a mean and a standard deviation for the changes for each week, and then estimated the probabilities from these values. The assumption for this calculation is that the probability of the difference in a given week is greater/smaller than zero (greater: for increase of signal, smaller: for a decrease in signal after the activity). An observed high probability of signal shows stronger agreement with expected signal behaviour. Once high probability is observed in consecutive weeks, such signal is a good candidate to provide observation (marker) in the CbM context. The number of weeks, when the signal holds given land cover manifestation, are directly to the activity type and sensor characteristic used to acquire the signal.

The threshold used for marker detection should be adjusted accordingly, e.g. in a more advanced stage when predicted marker detection is concerned (i.e. % of single change, or specific threshold value).

([1]) https://en.wikipedia.org/wiki/Student%27s_t-test (accessed 06/30/2022)
([2]) https://en.wikipedia.org/wiki/Shapiro%E2%80%93Wilk_test (accessed 06/30/2022)

Figure 3. Statistical test of significance of two median signals for a set of grasslands parcels located in a) Latvia, b) Czech Republic, and c) Ireland



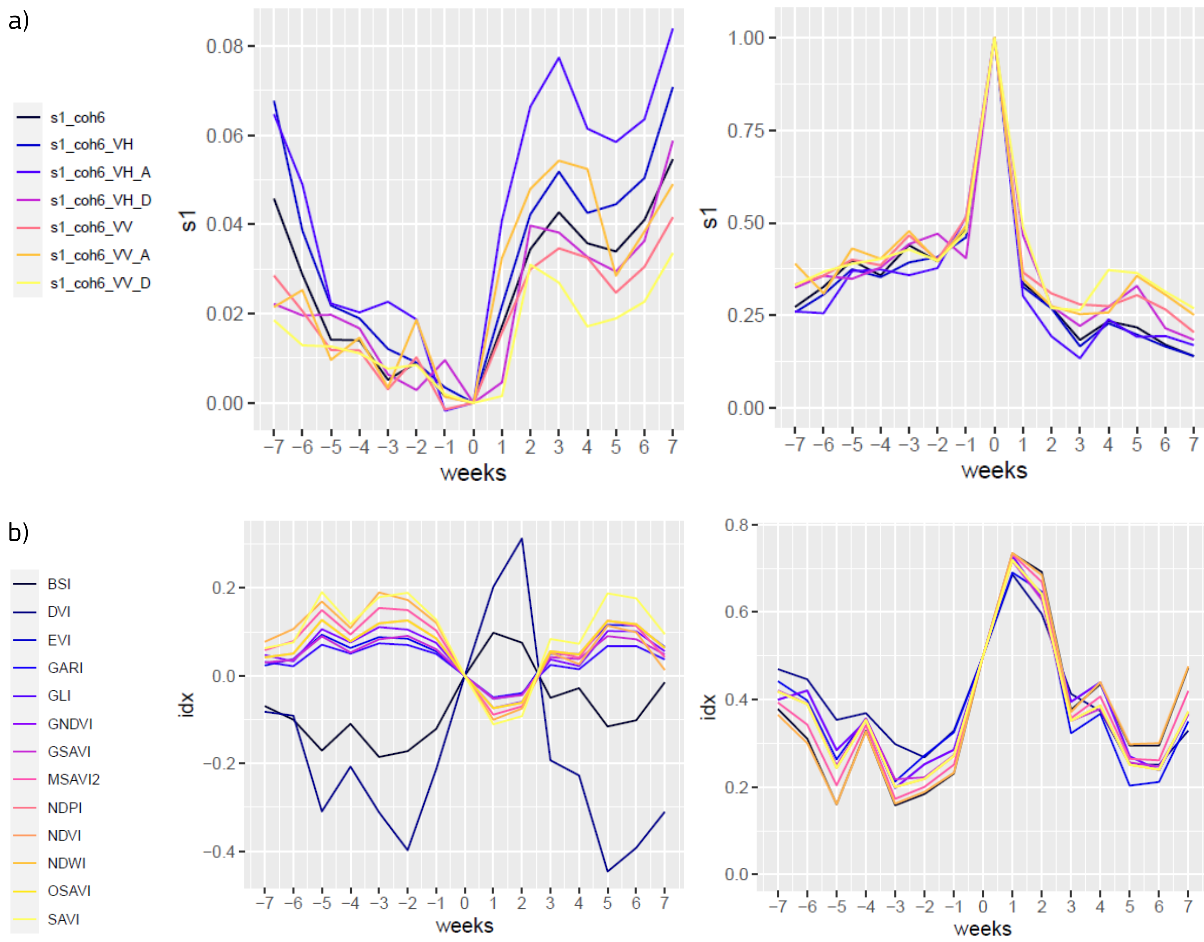
Source: GTCAP

Statistical probability analyses: example

Data from Latvia and Czech Republic, serve to illustrate the probability analyses. The datasets consist of parcels with permanent grasslands with mowing activities assigned (see Figure 4). For the first dataset, Sentinel-1 COH6 signals are used, whereas the second shows Sentinel-2 derived indexes.

Each curve in the left figure shows the difference between week 0 and the previous/following weeks for each S1/S2-signals (median value). The right figure shows the probability of the value changing in the opposite direction of what we would expect (increasing or decreasing) after the activity. This probability value should ideally be close to zero for any other week. For the S1-signals, we can see that the VH-polarization gives the lowest probabilities, indicating that these would be more performant than the VV-polarizations. For the S2-indexes in Czech Republic, NDVI seems to be the best index among presented.

Figure 4. Probability signal analyses for grasslands parcels located in a) Latvia and b) Czech Republic. On the left difference between week 0 and the previous/following weeks, on the right corresponding probabilities are presented.



Source: GTCAP

2.3.5 Correlations between signals

In the marker development process, the rule is that a marker derives from one signal, but that signal could source many markers. A phenomenon or land cover manifestation observed by multiple markers reinforces the performance reliability only if the information used for the extraction is not strongly correlated. In a case of strong correlation between the signals used to observe the same land cover manifestation state/change, the reliability reinforcement is minimal and the processing will be redundant.

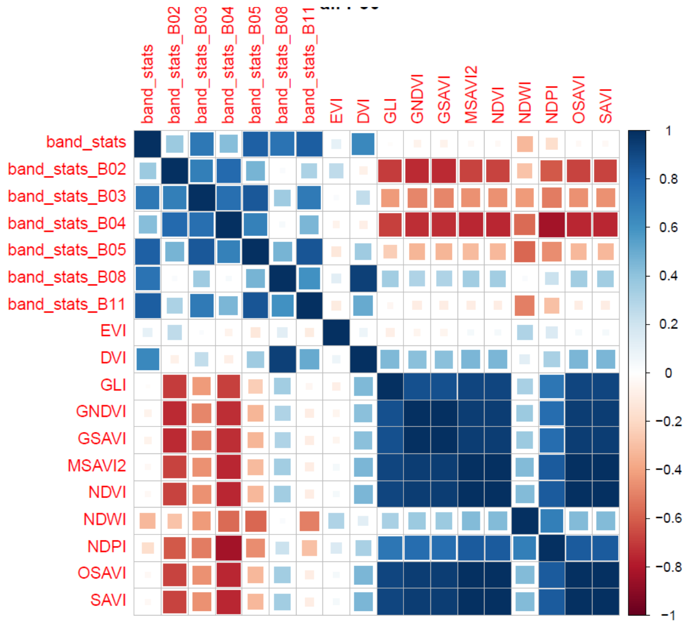
The use of signals from many independent sensors is advisable (see Section 3) to take advantage of different sensors characteristics and properties. Utilisation of image data captured by different sensors might secure the automated process from weather dependencies and limitations of passive sensors and result in higher repeatability of observations (markers).

For every single sensor, there are many candidate patterns in signals and derivatives to explore. Once signals with repeatable post-activity behaviour are identified, they can be further analysed to check their correlation (pairwise). The lower the correlation, the higher the potential of adding new information to the detection process.

Signal correlation analyses example:

For a set of grasslands parcels located in Ireland, 18 Sentinel-2 based median signals are derived. The signal selection includes simple image bands and their derivatives (image indexes). The correlation coefficient[3] calculation between two signals are performed at the parcel level using the temporal subset (15 weeks around the mowing activity date available for each parcel), then averaged to a single value and arranged graphically (see Figure). The values of correlation coefficients are by definition between −1 and 1. Correlations equal to +1 or −1 correspond to signals that imply a linear relationship between them, with all data points lying on a line. Essentially, these two signals have the same information content. A value of zero implies that there is no correlation between the signals, and any respective markers would have complementary information.

Figure 5. Sentinel-2 based signals correlations. High correlation values (1 or -1) indicate similar content. Value of close to zero (marked in white or pale blue and pale red) implies that there is little to no correlation between the signals



Source: GTCAP

For the mowing activity in this dataset, there are noticeable strong positive correlations between image bands and the image indexes marked in blue colour. Negative correlations are found i.e. for the B02 (Blue)/B04 (Red) image bands with most of the indexes marked in red. Thanks to signal correlation analyses, selection of potential signals that introduce added value to the development of markers to detect an activity is possible.

This approach is applicable to a greater number of signals (i.e. derived from Sentinel 1 and 2) and performed for any activities/land cover manifestation of the interest. For more details, please consult (Zielinski R., et al. 2022).

2.4 Practical recommendations

To design a check by monitoring implementation that will be performant and effective, the following points could be considered:

— Understand the local practice starting from a single activity or land cover manifestation (or its change) and describe it from the field phenomena perspective. Identify the ones that are potentially observable in satellite data and may provide evidence that the farmer completed the required activities.

(3) https://en.wikipedia.org/wiki/Pearson_correlation_coefficient (accessed 29/06/2022)

— Ground truth data are needed to optimise the monitoring results performance and reliability.
— Plan and collect the ground truth data that are relevant for the analyses type (or question to be answered). According to the budget plan, consider defining: scope and type of information needed to be collected, the frequency of observations, sample size, spatial coverage of data collection and duration of the survey to assure data fit-to-purpose.
— In signal analyses, for each question to investigate select appropriate analysis and statistical method.
— Make sure that the analyses are performed at least with devaluate level of statistical rigor, including sample size. Test the result of the analyses against the logic of expected characteristic from the practice.
— Document relevant components of the practice and analyses.

3 Testing Markers with Ground Data

In the previous section, a general overview of the different principles guiding the selection of signals for CbM has been provided. These principles includes repeatability, significance and (lack of) correlation. This section further elaborates on the concept of significance and describes the inclusion of statistical tests as preliminary analysis for signal selection. The recommendations derived aim to contribute to a more efficient and robust design of CbM systems.

3.1 Context

As of 2021, several PAs have announced their intentions to carry out CbM in some of their payment schemes. The practices and activities under monitoring are mostly related to Basic Payment Scheme (BPS) and Voluntary Coupled Support (VCS) schemes. More schemes will follow. These additional schemes are likely to include more complex management practices that come with more challenging technical problems.

This section covers the analyses during the signal selection phase of a monitoring design. These analyses provide a robust and statistically sound approach to ensure that the information content of the selected signals is suitable for monitoring any applicable land management activity.

As discussed above1, the evaluation of the information content of an individual signal, ensures that information redundancy between signals is minimal and that the selected signals provide unique information content.

This section expands the concepts introduced in Section 0 and provides brief explanations and a checklist of the main elements for testing significance of a selected signal.

3.2 Rationale of using tests of significance

The usefulness of a signal for detecting and monitoring a specific land management practice implies that the signal can be uniquely linked to that specific land management (e.g. changes in the signal can be exclusively attributed to a specific land management activity).

The overall assumption is that there is a clear difference between the signal before the land management practice takes place (pre activity signal) and the signal after the land management practice took place (post activity signal). However, this initial condition may not be sufficient to ensure that a signal can unambiguously detect a practice. Additionally, the information content of the signal should also verify that:

1. The variations between pre and post activity signals are significantly different in parcels implementing the land management practice of interest and those not implementing it.
2. The variations between pre and post activity signals in parcels implementing the land management practice are significantly different from signal variations registered during the rest of the crop cycle.

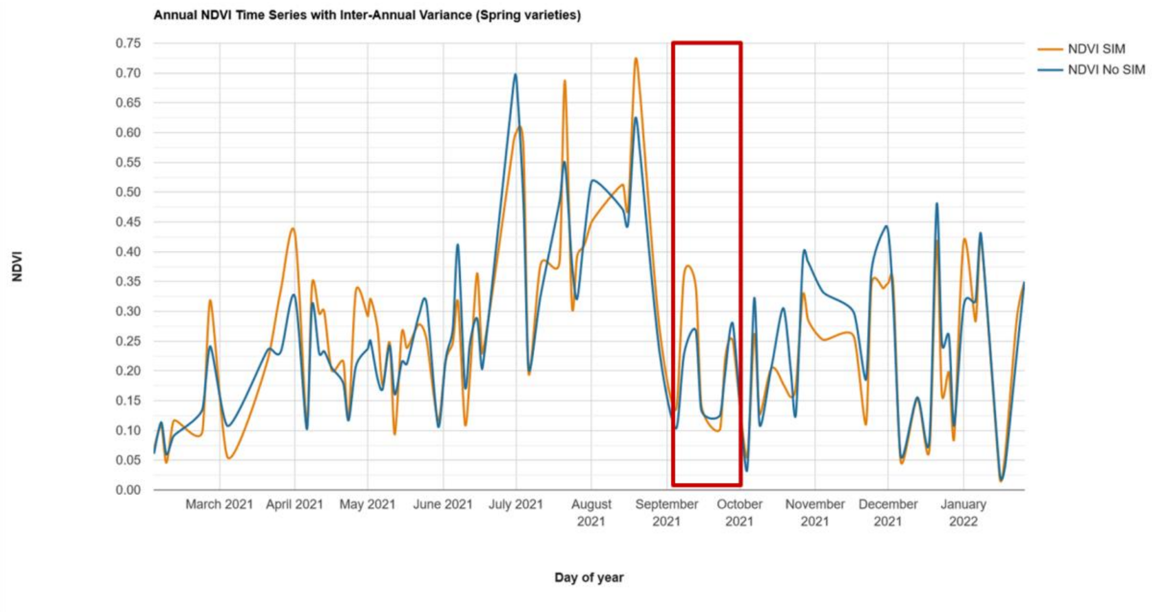
Both conditions can be tested applying specific tests of significance.

If a signal has the relevant information content, the implementation of a land management activity should be observable from that signal. These signal variations, commonly associated with specific temporal windows, will be captured in a series of markers.

Condition 1 implies that, for a signal to be selected to monitor a practice it should have statistically robust evidence that markers are only present, or are significantly distinct, in parcels subject to the practice. Figure shows the NDVI signals for two subpopulations of parcels. One of them (orange line) undergoes a generic land management practice while the other one (blue line) does not. This practice normally takes place around September (red box). In this specific case, a similar signal behaviour (marker) can be observed for both types of parcels. Source: GTCAP

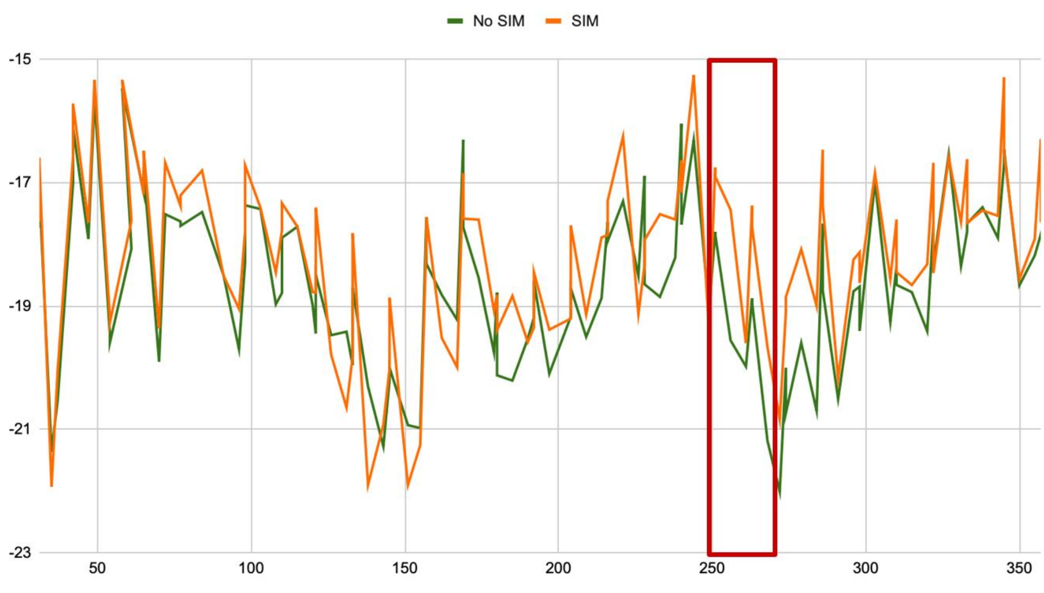
Figure describes a similar case with a Sentinel 1 backscattering signal. A test of significance would evaluate if these differences were significant enough to identify the land management practice of interest.

Figure 6. NDVI signals from Sentinel 2 satellite (10 m spatial resolution) for parcels cultivated with spring crops implementing a certain scheme (Orange line) and not implementing the scheme (Blue line). The red box represents the post activity period.



Source: GTCAP

Figure 7. Backscatter coefficient (ɣ) signals from Sentinel 1 satellite (VH polarization, 10 m spatial resolution) for parcels cultivated with spring crops implementing a certain scheme (Orange line) and not implementing the scheme (Green line). The red box represents the post activity period.



Source: GTCAP

As mentioned above, if a signal has the relevant information content, the occurrence of a land management activity should be reflected in that signal and subsequently be captured in a marker. Yet, the fact that there are signal variations during the period in which the practice takes place does not imply that all those variations are caused by the practice.

Meeting Condition 2 implies that those variations are significantly different from other signal variations taking place during other periods of the year. Figure 8 shows signal variations during the period when the activity is implemented. Yet, similar variations occur at some other periods of the year (green boxes). A test of significance should determine if differences during the period when the practice is expected are significantly different from differences occurring at other periods during the year.

Figure 8. NDVI signals from Sentinel 2 satellite (10 m spatial resolution) for parcels cultivated with spring crops implementing a certain scheme (Orange line) and not implementing the scheme (Blue line). The red boxes represent the post activity period and the green boxes represent other periods during the year in which the signal could be evaluated.

Source: GTCAP

3.3 Tests of Significance

Tests of significance are methods of statistical inference used to support or reject hypotheses based on sample data. Once sample data has been gathered through an observational study or experiment, statistical inference allows assessing evidence in favour of some claim about the population from which the sample has been drawn (http://www.stat.yale.edu/Courses/1997-98/101/sigtest.htm)

A test of significance is a formal procedure for comparing observed data with a claim (e.g. hypothesis), the truth of which is being assessed. The claim is a statement about a parameter, like the population proportion or the population mean. The results of a significance test are expressed in terms of a probability that measures how well the data and the claim agree (https://www.westga.edu/academics/research/vrc/assets/docs/tests_of_significance_notes.pdf).

The implementation of a test of significance guarantees a consistent and statistically sound approach for signal and image selection, avoiding the inclusion of irrelevant information and/or spurious conclusions.

3.3.1 Elements of a test of significance

Box model. Every test of significance requires a box model. The box model defines the population (e.g. parcels in a certain territory) and a sample extracted from the population (e.g. parcels extracted from the population).

Null and alternative hypotheses. The null hypothesis is that an observed difference is just the result of chance variation. The alternative hypothesis is that an observed difference is real. The null hypothesis must always be formulated as a statement about the box model.

Test statistics. A test statistic is a number calculated from a statistical test of a hypothesis. It is used to measure the difference between data and what is expected on the null hypothesis.

Significance levels. Observed significance level is the chance of getting a test statistic as extreme as or more extreme than the observed one. The chances are computed on the basis that the null hypothesis is right. The smaller this chance, the stronger the evidence against the null. The test aims to answer the question of whether an observed difference is real or just a chance variation.

3.4 Important elements for implementing of a test of significance in a CbM context.

This chapter lists some of the key elements to be considered in the design of a significant test within the CbM context.

Signal preselection. A first preselection of the signals should be done on the basis of the prior knowledge about the behaviour of the signal and its expected manifestation of the activity on the ground. Only signals with a likely connection between signal and land surface state should be evaluated with a test of significance.

Defining the population. The population should include all parcels that could potentially implement the CbM scheme under analysis. For instance, when evaluating the presence/absence of a catch crop, the population will comprise all the parcels that could cultivate the catch crop between successive plantings of the main crop.

Defining the sample. The selection of the sample dataset must follow well-established sampling standards (see Section 2.2). For instance, the sample should be randomly extracted from the population and it should be representative of the variation in environmental factors (e.g. latitude, elevation, soil type, etc.) and agricultural contexts (e.g. common management practices) within the territory. Both subsamples (parcels implementing and not implementing the land practice) should be represented and their size should be large enough to extract statistically robust evidence.

Parcel data extraction. Signal descriptive statistics are to be extracted at parcel level for all the parcels in the sample. While median and mean have been widely used as descriptive statistics, the use of other statistics (e.g. percentiles, standard deviation) could be relevant in specific cases.

If available, a cloud mask can be applied to identify and remove cloud and cloud shadow presence. Yet, no cloud mask is perfect and undetected clouds and cloud shadows can introduce noise in the signal. Signal smoothing can potentially remove some of this noise. However, this operation could also remove relevant signal variations. If implemented, the smoothing method and its settings should be selected to minimize the potential loss of meaningful signal information.

Choosing a test of significance. There are several alternative methods for tests of significance (e.g. Fisher's Z-Test, Student's t-test, X_2-Test, F-Test). Moreover one-side tests and two-sided tests can also be implemented. While Z-test and Student's t-test are common options, other alternatives should be considered depending on the problem at hand. Each test has its own assumptions and its corresponding limitations and advantages. The specific characteristics of each test and its suitability for each specific case should be considered before the selection.

Population and Sample data collection. The population and sample datasets should be consistent and correspond to the same agricultural season. The population dataset should come from the original geospatial aid application dataset in the territory. Parcels in the sample dataset should be compiled once there is certainty that the field operations related to the land management practice of interest are completed, to ensure that parcels implementing and not implementing the practice are not mislabelled.

If the Sample dataset is built based on visual interpretation of high and very high resolution optical remote sensing data, the image acquisition window should be after the last expected date of the land management practice of interest, according to known crop calendars. Equally, if the information is collected on field inspections, these inspections should also be carried out at the end of the expected period when the practice takes place. If the footprint (mark) of land management practice under study is short-lived, several image acquisitions or field visits could be required to ensure a complete and consistent sample dataset.

Temporal window for targeted manifestation stages. The test of significance will evaluate variations in the satellite signal at specific periods during the year. A temporal window must be established to evaluate the variations between pre and post activity signals in parcels implementing or not the land management practice of interest.

This temporal window constraints the dates from which signal values will be extracted. The definition of the window should be based on expert-knowledge (e.g. crop calendars) regarding the likely period when the practice takes place. A precise definition of the temporal window is key for a precise analysis of the signals. Signal statistics will be calculated for the temporal window, and application of filters over a long temporal window comes with the risk of smoothing the signal statistics (e.g. mean, median) extracted at parcel level removing key temporal variations. Short temporal windows may miss the activity in some parcels. A similar logic should be considered when running a test of significance to analyse the pre and post activity signal variations against variations during the rest of the crop cycle. The length of the temporal windows (bins) at various stages of the crop cycle should be carefully selected.

All these elements have to be properly selected and used for evaluation of the significance of specific signal behaviours.

4 Using Multiple Signals for Reliable Marker Detection

Marker detection involves the analysis of signals derived from the Sentinels. Examples of such signals are the NDVI, computed using the RED and NIR bands from Sentinel-2 and the Backscattering (BS) and COH6 from Sentinel-1. A marker is a registration of a specific signal pattern likely caused by a field activity. For instance, a mowing activity is expected to cause a drop in the observed NDVI that is picked up by the detection algorithm. The same field activity can trigger different markers on signals from different sensors. In this respect, multiple signals can be jointly processed for a more reliable marker and activity detection.

This section provides a summary of the work performed toward the development of a flexible framework able to exploit several signals from different sensors for a more reliable marker detection.

4.1 Background and purpose

The GTCAP team has supported DG AGRI in the context of audits and this support involved participation to audit missions and desktop analyses based on the CbM paradigm. With the COVID restrictions and the impossibility to perform field activities, CbM approaches and Sentinel derived information became more relevant, providing a complementary (and sometime an alternative) way to collect evidence.

In this process, large populations of parcels were checked to verify that either mowing or grazing were performed at least once over the season. The screening of such large parcel populations motivated the initial development of a signal and marker processing framework able to effectively and efficiently exploit Sentinel-1/2 signals.

A prototype version of the code exploited Sentinel-1 COH6 and Sentinel-2 NDVI for a first screening of about 30000 parcels. It already allowed to identify inconclusive cases that were then further inspected using National aerial orthophotos.

The analysis of these parcels highlighted the need for a flexible framework easily adaptable to the different local conditions. In particular, while only mowing and grazing conditions were expected, parcels covered by trees or flooded for several months were found. These conditions were causing unexpected signal patterns that were not properly handled by the prototype and led towards the development of the multi-signal detection approach discussed in the following sections.

4.2 Main components

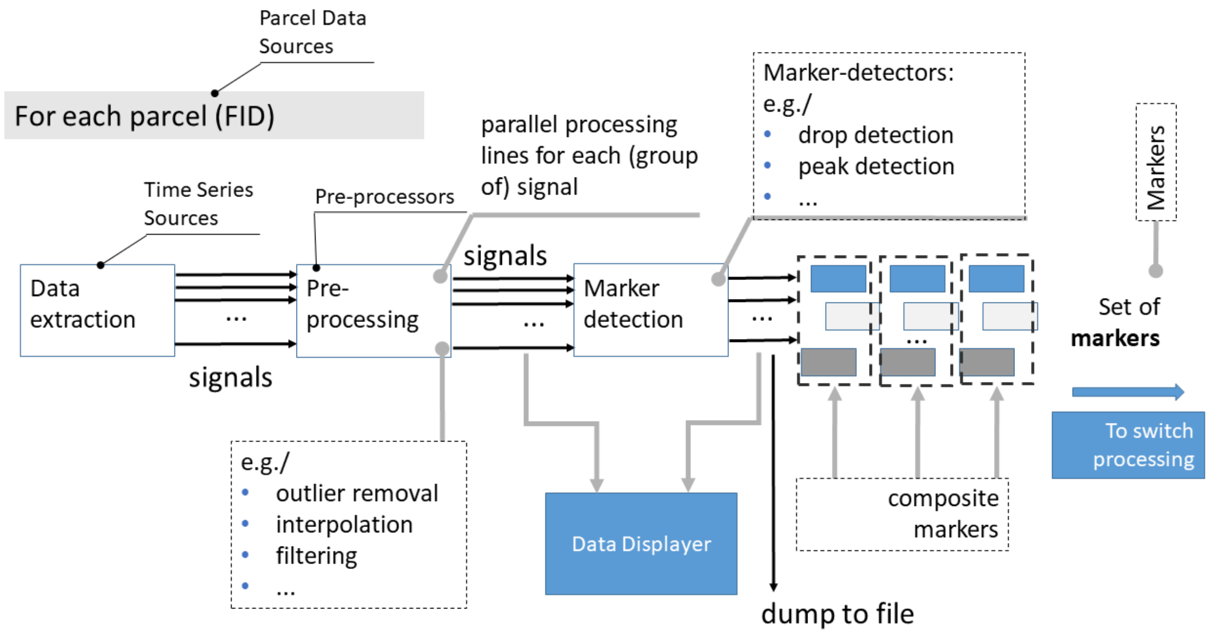
In order to develop a processing framework that is able to accommodate the flexibility needs discussed above, to use several signals and to implement different processing strategies, the OOP paradigm was adopted. Under this paradigm, several independent software objects interact to implement the desired processing objective. Objects derived from the same base class can be interchanged and the processing framework can be easily extended implementing new derived classes[4]. A high-degree of flexibility was achieved using object factories that create the desired processing chain at run-time following the parameters provided in an external configuration file. A factory is an object designed to create other objects: it is a specific design pattern used in OOP to achieve a high-level of flexibility with the possibility to support several processing configurations.

The main components forming the processing framework developed are depicted in Figure 1 along with their interactions. The framework processes signals, i.e. functions of time, which are obtained from Sentinel-1/2 data for each parcel. At this stage, the spatial information is no longer processed after time signals are obtained through summary statistics computed on a geometry for each parcel.

For each Sentinel-2 band, mean, median, standard deviation, minimum, maximum and first and third quartile were computed at parcel level. These statistical values form the amplitude of the signals at the input of the processing framework. The objects responsible for providing the input signals have been denoted as Time Series Sources (TSS) and can use different approaches such as loading data from a Comma-Separated Values (CSV) file, though calls to **RE**presentational **S**tate **T**ransfer (RESTFul) Application Program Interface (API) or using a query to a database.

([4]) A base class or superclass does not have any parent and does not inherit properties or methods from any other class. A derived class is a child class derived from a parent. For instance, a base class can represent geometric objects with area and perimeter as properties. A square is a class derived from the “geometric object” class and inherits its properties.

Figure 1. Main components of the framework developed for signal processing and marker detection.



Source: GTCAP

The TSS provides raw signals that may be affected by noise and artefacts for example caused by clouds or shadows. In addition, derived signals such as Vegetation Indexes (VIs) may need to be computed. This is the role of the pre-processors which also implement different signal enhancement operations such as:

— **Filtering and smoothing**: to reduce the impact of noise and other high-frequency components not corresponding to any underlying phenomenon or activity.

— **Resampling and interpolation** to obtain uniformly sampled signals which allow simplified operations and the use of a common time scale between signals.

— **Time series combining** for the computation of derived signals such as VIs from different Sentinel-2 band data.

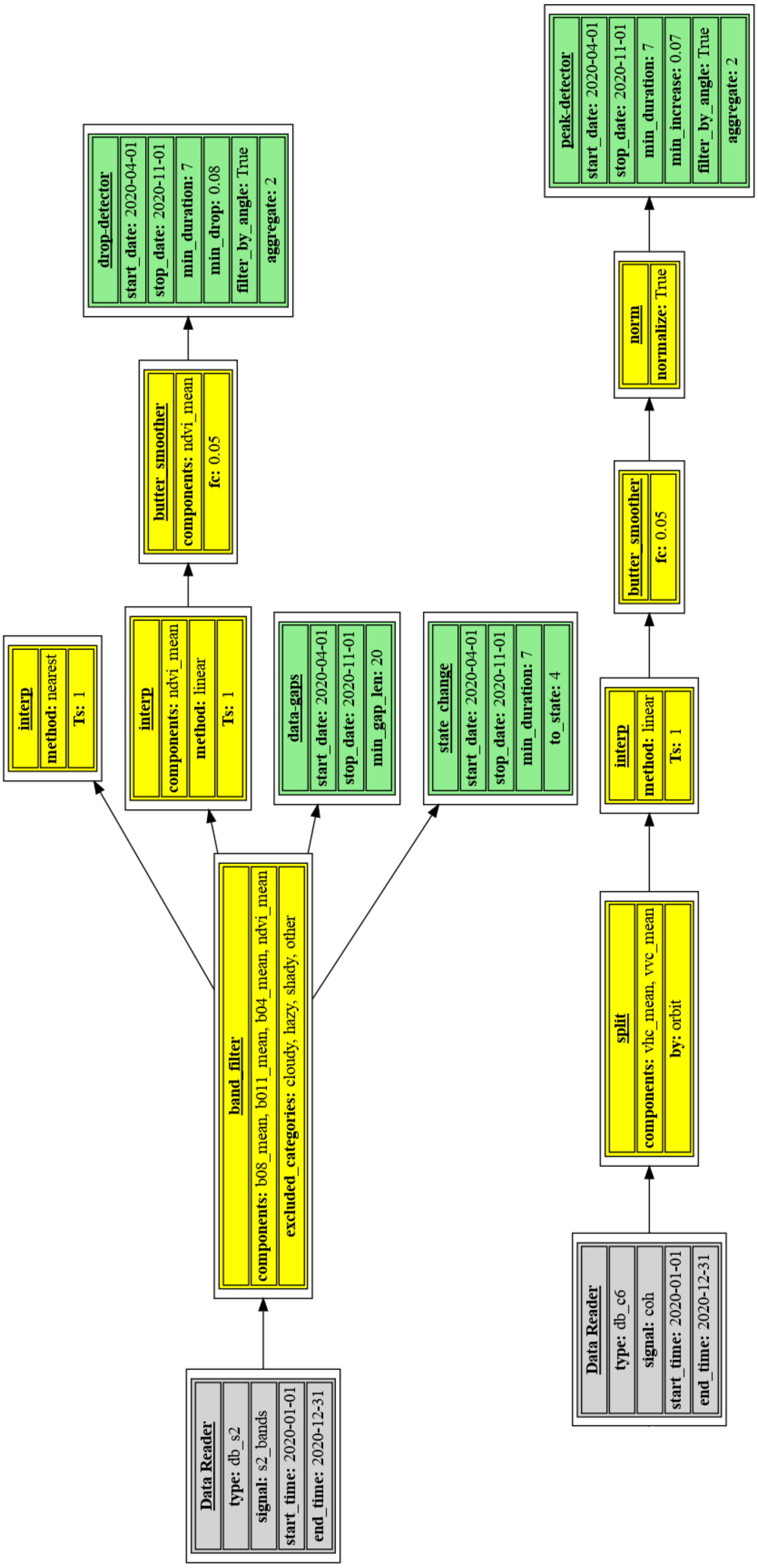
Pre-processors return new signals and can be combined in series. Different parallel processing lines, made of chains of pre-processors, can be created to implement different processing strategies on different signals. In the database each signal is stored table with amplitude and date columns.

Once the signals have been properly pre-processed, marker detection can be performed. This task is carried out by the marker detectors.

4.3 A possible methodology for mowing detection

The framework developed was used for mowing detection. In particular, the processing strategy depicted in Figure was adopted.

Figure 10. Graphical representation of the processing strategy adopted for mowing detection. Grey boxes represent TSSs and provide the input signals. Yellow boxes are the pre-processors whereas green boxes represent the different marker detectors.



Source: GTCAP

Two processing lines can be clearly seen in the figure. The upper describes the processing adopted for Sentinel-2 data whereas the lower specifies the operations performed on the Sentinel-1 COH6.

Data have been obtained through two TSS (indicated as Data Readers in the figure) directly interfaced with a database providing the different signals. In this case, also the NDVI is provided by the Sentinel-2 TSS.

Sentinel-2 optical data are at first passed through the band filter pre-processor described in Section 4.3.1. In this case, the pre-processor selects and uses four vegetation relevant bands and indexes: the RED (B04), the NIR (B08), the SWIR (B11) and the NDVI. The band filter removes invalid observations corresponding to cloudy/shady/hazy conditions. It returns stretched RED, NIR and SWIR values (mainly for plotting/displaying purposes), raw NDVI observations and a list of classes corresponding to the different conditions estimated from the RED, NIR and SWIR values. Indeed the band filter performs classification using the RED, NIR and SWIR bands and assign to each observation date a class corresponding to one of different conditions such as cloudy/shady/hazy. Depending on the user settings, observations related to different conditions can be removed.

Raw NDVI observations are passed to a data gap detector to record data gaps longer than a specified duration (default set to 20 days). NDVI is also interpolated and smoothed in order to obtain a signal regularly sampled. Smoothing is used to reduce noise and can be controlled through a cut-off frequency as better discussed in Section 4.3.3. Finally, drop detection is performed on this filtered signal.

The classes corresponding to the different states are then used for state change detection. This approach is better discussed in Sections 4.3.1 and 0.

COH6 has been adopted for its ability to detect mowing/grazing events (Tamm et al., 2016, De Vroey et al., 2021). In particular, (Tamm et al., 2016) showed that after a mowing event, a higher COH6 should be observed: when the grass canopy is removed, the surface becomes more firm over time leading to a higher coherence. This fact was confirmed by De Vroey et al. (2021) who experimented different approaches to detect mowing events through the sudden increase of COH6. In comparison to optical data, COH6 is not affected by cloud cover and provides a more predictable data flow. On the other side, COH6 is quite noisy and its increase can be caused by several confounding factors unrelated to a mowing event (Tamm et al., 2016, De Vroey et al., 2021).

According to the methodology depicted in the bottom part of Figure , the COH6, which is obtained in a tabulated form, is split according to the polarization and orbit direction. In this way, the four combinations detailed in Section 0 are obtained. These combinations are resampled, interpolated and smoothed and put back together. The norm of these 4 components is computed and a single signal value is found. This signal is the input of a peak detector which has been implemented to identify peaks corresponding to a potential mowing activity.

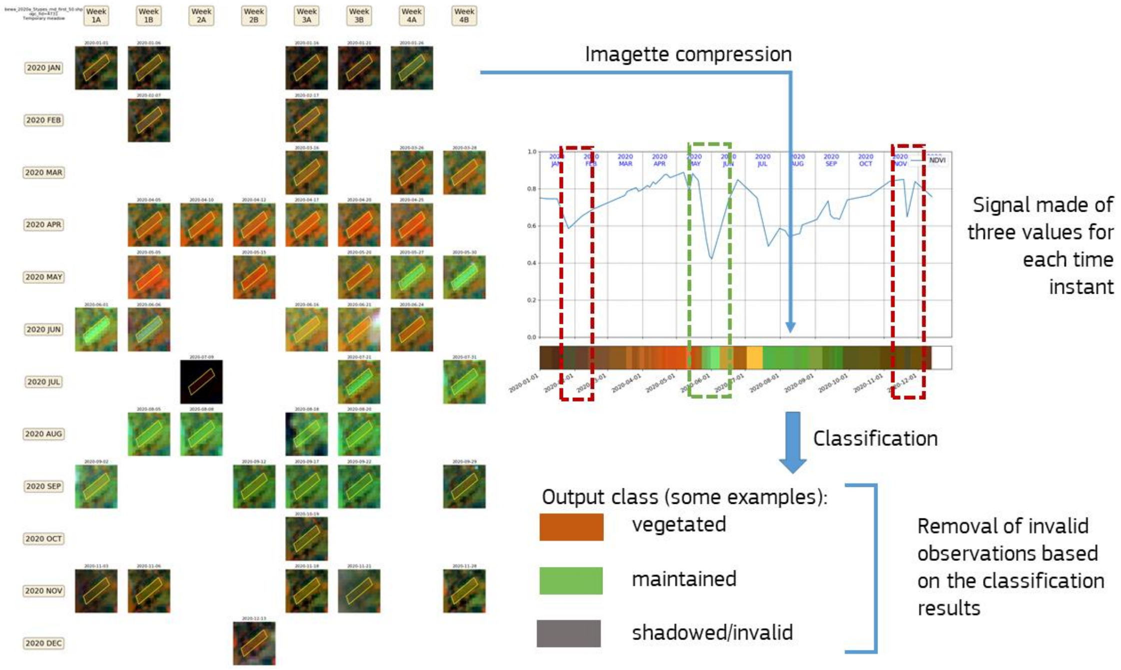
The different markers (NDVI-drops, COH6-peaks, state changes and data gaps) are combined according to the decision logic discussed in 4.5 which is used to assign a final state (red, green, yellow) to each parcel analysed.

The different elements forming the processing chain depicted in Figure are better discussed in the following sections.

4.3.1 Band filter

Up to 3 bands of Sentinel 2 optical data can be combined to generate false colour composites. A false colour composite made of NIR (B08), SWIR (B11) and RED (B04) has been considered in this work and used to build the so called **band filter** pre-processor. The working principle of this pre-processor is shown in Figure: NIR (B08), SWIR (B11) and RED (B04) are considered together and used to form a false colour composite, which can be plotted as function of time as a colour bar. This approach is equivalent to compressing image chips obtained using these components into a single observation, assigning it the mean colour observed on the parcel under analysis at a specific date. Each colour corresponds to a different vegetation class including, vegetated (orange/light brown colours), maintained (green) and invalid/shadowed (dark colours).

Figure 11. Working principle of the band filter pre-processor: NIR, SWIR and RED components are considered together as a false colour composite. A class is assigned to each colour and observations are filtered out on the basis of the associated class.



Source: GTCAP

Box1. Classes and classes

In this document, the term "class" has been used with different meaning. In particular, it has been adopted in two general contexts:

— In **OOP**: a class is a user-defined data type that is used as template to create objects with specific attributes and methods.

— In **statistics** and classification: a class is one of the possible outputs of the classification process. For each date with a vector of observations, a class is assigned.

Additional classes have been considered, including hazy and cloudy observations he band filter implements a simple K-Nearest Neighbors (KNN) classifier (Bishop, 2006) which is used to assign a class to each colour obtained from the three bands. Observations are then filtered on the basis of the classification results.

For instance, consider the NDVI curve shown in the middle of Figure: two drops in NDVI have been highlighted using red dashed boxes. While an NDVI drop is expected as the result of a mowing/grazing activity, the colour seen in the bottom bar obtained does not suggest a maintained state. Indeed the dark colours coinciding with such drops indicate observations hampered by natural disturbance (clouds, snow or other) that should be excluded from processing. This operation is performed by the band filter that uses the assigned classes to remove invalid observations.

The band filter is highly configurable and allows one to select the observation classes that should be filtered. This pre-processor returns:

— The three band signals stretched in order to obtain the desired colour composite.

— The filtered observations

— The classes assigned to the different colours.

A colour is coded through a triplet of three 8 bit unsigned integers, one for the red, green and blue band, and thus the band values can be stretched to cover the full [0-255] range. This operation is performed using a stretching function which can be modified by the user. The stretched signals can be useful for generating summary plots including a colour bar similar to the one shown in Figure. Stretching is a widely used image enhancement technique.

The filtered observations are the main output of the pre-processor which are passed to the next processing objects implementing the subsequent operations.

In addition, the classes associated to the different colours can target the detection of specific markers. A **state change detector** has been implemented: it finds markers corresponding to a state change, for instance from a vegetated to a maintained state. This detector is schematically represented in the middle of Figure .

4.3.2 Interpolation

After removing invalid observations, the signals obtained take values on irregularly spaced time instant. In order to obtain a regularly sampled signal, resampling and interpolation are adopted.

This operation is performed by the corresponding pre-processor that implements resampling and different interpolation methods including nearest neighbour and linear interpolation.

The type of interpolation strongly depends on the input signal and on the type of application considered. Linear interpolation has been found suitable for signal assuming continuous values, such as reflectance or vegetation indexes. The use of a smoother can then reduce the impact of artefacts for example at the nodes where signal amplitudes are available. Nearest neighbour interpolation is more suitable for signal assuming discrete values such as the signal describing the classes (states) assigned by the band filter described in the previous section. Nearest neighbour interpolation preserves the discrete nature of the signal.

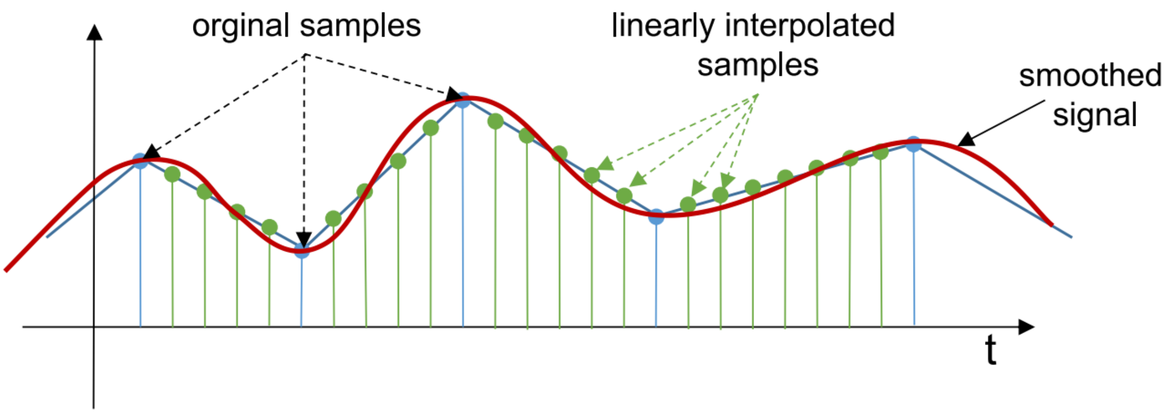
4.3.3 Butterworth smoother

After interpolation, smoothing can reduce the unwanted effect of high-frequency phenomena not corresponding to real activities. Smoothing is implemented using a simple Butterworth Liner Time-Invariant (LTI) filter (Oppenheim et al., 1998). Filtering is performed both forward and backward in time in order to avoid the introduction of delays on the time series. The adoption of a Butterworth smoother was originally motivated by the need of smoothing COH6, which is affected by high frequency noise. Its use was however found beneficial also for the NDVI that should reflect the same activities influencing the COH6 signal.

Smoothing can be controlled through the cut-off frequency of the Butterworth smoother: all signal components above the cut-off frequency will be removed. This parameter should be carefully selected since a too small cut-off frequency will remove relevant signal components. A too-large cut-off frequency will retain significant noise and high-frequency components. This selection can be performed by studying the frequency spectrum of a large set of signal carrying useful information. From the spectral content of such signals, the cut-off frequency can be determined.

The combined effect of resampling, interpolation and smoothing is illustrated in Figure .

Figure 12. Effect of resampling, interpolation and smoothing.



Source: GTCAP

4.3.4 Data splitter

The time series, such as the COH6, are provided in tabulated form. Each column corresponds to a different attribute such as the polarization or the orbit direction, either ascending or descending. The data splitter pre-processor splits a time series according to a specific attribute. For instance, it is used to separate COH6 data according to the orbit direction. After this block, four time series are obtained from the COH6:

— **Vertical transmitting, Horizontal receiving, Ascending orbit (VH-A)**: obtained by considering a vertical polarization in transmission, a horizontal polarization in reception and an ascending orbit.

— **Vertical transmitting, Horizontal receiving, Descending orbit (VH-D)**: obtained by considering a vertical polarization in transmission, a horizontal polarization in reception and a descending orbit.

— **Vertical transmitting, Vertical receiving, Ascending orbit (VV-A)**: obtained by considering a vertical polarization in transmission, a vertical polarization in reception and an ascending orbit.

— **Vertical transmitting, Vertical receiving, Descending orbit (VV-D):** obtained by considering a vertical polarization in transmission, a vertical polarization in reception and a descending orbit.

Depending on the satellite incidence angle and other factors, only a subset of these components may increase after a mowing event. Note that previous work (Taravat et al., 2019) concluded that "it seems infeasible to determine a single wavelength or polarization that is best suited to detect cutting events". While additional analysis is required to support this conclusion, the processing still considers all the four COH6 components obtained at the output of the data splitter.

4.3.5 Norm

After data splitting, the four COH6 components are resampled, interpolated and smoothed using the pre-processing blocks discussed above. At every date, these smoothed components form a four dimensional vector: in order to detect an increase of COH6, a summary function of these four components was required. The summary function should have the following properties:

— It should be symmetric in its arguments. In particular, any permutation the four components should lead to the same output value,

— When three of its arguments are kept constant, the summary function should increase/decrease as the fourth argument increases/decreases.

Potential candidates for this summary function, $f_s(\cdot)$, are the p-norms for the vector composed by the four COH6 components. In the following, the Euclidean norm, i.e. for p = 2, has been adopted:

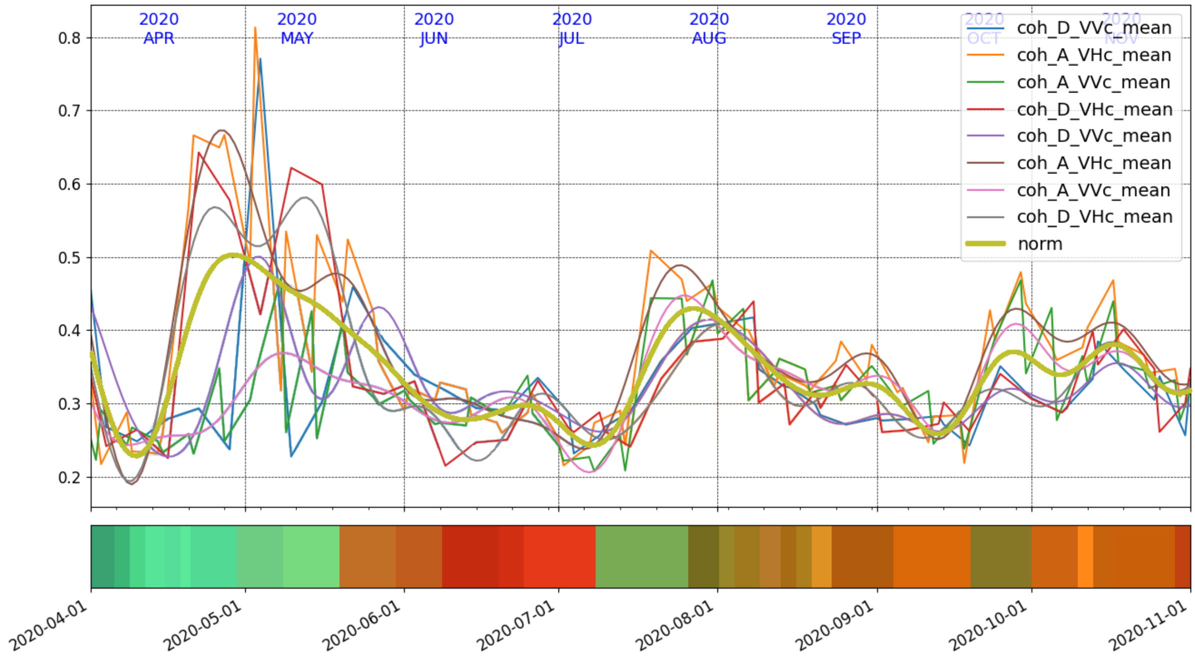
$$co_s[n] = \sqrt{co_{VH-A}^2[n] + co_{VH-D}^2[n] + co_{VV-A}^2[n] + co_{VV-D}^2[n].} \qquad (1)$$

Where the terms under square root are the four COH6 components and n is the time index.

The norm (1) is computed by the norm pre-processor which also includes the possibility to introduce a normalization term. COH6 signal amplitudes range from 0 to 1: in this way the output of (1) is always lower than or equal to 2 (the square root of 1 + 1 + 1+ 1). This value is obtained when all the four components are equal to 1. A normalization by a factor 2 can thus be introduced in order to guarantee that also the COH6 norm is always between 0 and 1. The resulting values represent a new time series and therefore a new signal.

An example showing the different processing stages of the COH6 signals is provided in Figure 2: the four COH6 components are first resampled and linearly interpolated. High-frequency noise is reduced through smoothing. Finally, the normalized norm of the four components is computed and used for marker detection. The figure also provides the false colour composite obtained using the NIR, SWIR and RED bands. Green colours corresponding to a removal to biomass are observed in correspondence of the COH6 peaks.

Figure 2. Example showing the different processing stages of the COH6 signals. Resampled and linearly interpolated curves are affected by high-frequency noise that is reduced through smoothing. Bottom bar: false colour composite obtained using the NIR, SWIR and RED bands.



Source: GTCAP

4.4 Marker detection

After pre-processing, signals can be used for marker detection. As already mentioned a marker is the observation of a specific pattern occurring on a signal and a marker detector is an algorithm designed to detect and record such pattern.

For the mowing case the following marker detectors were implemented:

— **Drop detector**: it searches for the local maxima and minima of a signal and determines patterns defined by the sequence of a local maximum, a minimum and a second maximum. It is used to detect a mowing activity on the NDVI signal. While actual mowing occurs between the NVDI maximum and subsequent minimum, the second part of the marker, identified by the minimum and the second maximum, provides evidence for the grass regrowth phase.

— **Peak detector**: it is similar to the drop detectors but it searches for patterns defined by a sequence a local minimum, a maximum and a second minimum. It is used to detect peaks on the COH6 norm and also in this case the corresponding marker includes the regrowth phase.

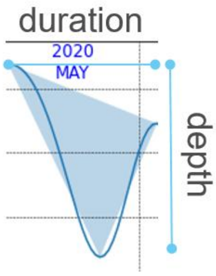
— **Change state detector**: this detector has been specifically designed for the signals indicating the classes assigned to the NIR, SWIR and RED colour composite by the band filter. It is used to detect a change from an arbitrary class to the “managed class” which is identified by greenish colours in the colour composite.

— **Data gap detector**: this is not a maker detector is a strict sense since the pattern identified does not correspond to any field activity. The construct is used to record data gaps on the raw NDVI signal, i.e. the signal obtained before resampling and interpolation. A data gap is defined by a minimum time interval between two consecutive samples. If two valid samples are too far apart in time, a data gap is recorded. A data gap is used to flag as unreliable the information provided by the NDVI on the corresponding time interval.

Each marker is characterized by a set of **local parameters** which defined the **marker parametrization**. For instance, a signal drop is characterized by a duration, defined as the temporal distance between its local maxima, and a depth, defined as the difference between the amplitudes of the largest maximum and the central minimum.

An example of NDVI drop is provided in Figure 3. The marker is represented as a triangle. The case also illustrates its duration and depth.

Figure 3. Example of drop identified on the smoothed NDVI. The marker is depicted as a triangle: its depth and duration are also indicated.



Source: GTCAP

Marker parametrization plays an important role in marker detection. For instance, only drops with a minimum/maximum duration should be detected. Indeed some minimum time is required to allow the grass to regrow and excessively short marker durations may indicate that a false positive was detected. For instance a narrow drop in NDVI can be due to shady observations. Similarly, an excessively large duration may indicate that an activity different from mowing occurred. Also the depth of the drop should be bounded from below to avoid to record a random fluctuation of the signal as a marker. The marker parametrization can be set at the level of the marker detectors which can be configured to identify only signal pattern matching specific parametrizations.

From the experiments conducted, a minimum drop depth around 0.15 should be considered for the NDVI. This value, however, needs to be adjusted to the local conditions and better determined through the analysis of large datasets selecting the best compromise in terms of false alarm and missed detection probabilities.

4.5 Marker aggregation, switch processing and decision logic

The result of marker detection is a sequence of markers, obtained from the set of signals. In the mowing case, we obtain drop markers from the smoothed NDVI, peak markers from the COH6 norm, data gaps from the raw NDVI and state/class changes from the NIR, SWIR and RED composite.

The makers in these sequences can be either combined or directly enter the so called switch processing (Devos et al. 2021a). Such marker combinations allow deterministic elements of the business logic to be directly encoded in the time series processing.

In the above framework, several options are provided to combine markers from different signals into new, more reliable makers.

For instance, it is possible to concatenate markers into a single decision. Alternatively a marker can be used to confirm another one. We use this option for the NDVI drops and avoid false positives caused by residual cloudy or shady observations that slipped through the pre-processing such as cloud masking.. A valid NDVI drop, i.e. caused by a mowing activity, should occur only when a state change to managed conditions occurs. Thus, state changes from the NIR, SWIR and RED composite are used to confirm NDVI drops.

A second option is to aggregate different marker patterns in a single new marker. This is done by considering COH6 and NDVI markers at the same time: when mowing is performed, an NDVI drop and a COH6 peak should be simultaneously observed. Here the term “simultaneously” has to be carefully interpreted. The COH6 is a differential quantity and is computed considering measurements occurring in a 6 day time interval. Thus, a delay of the COH6 peak is expected with respect to the NDVI drop.

By combining NDVI drops and COH6 peaks, a new marker (denoted as peak-drop) is found. Unlike with concatenations, an aggregated marker will not be detected if either drop or peak is missing.

After aggregating markers, it is finally possible to define the remaining decision logic: in the experiment performed we decided to declare a parcel “mowed/grazed” (green) if at least one peak-drop marker was detected during the season. Otherwise, the parcel was declared inconclusive (yellow) for further processing. This decision logic corresponds to a simple switch deciding between the green and yellow states depending on the presence/absence of the peak-drop marker.

Note that this simple decision logic was used as an example for demonstration purposes: more complex decision logics should be adopted for a real CbM system.

The same processing described above can be implemented using the original markers and more complex switches. For instance, a parcel can be declared green if a peak in COH6 is found at the same time of drop in NDVI.

4.6 Sample results

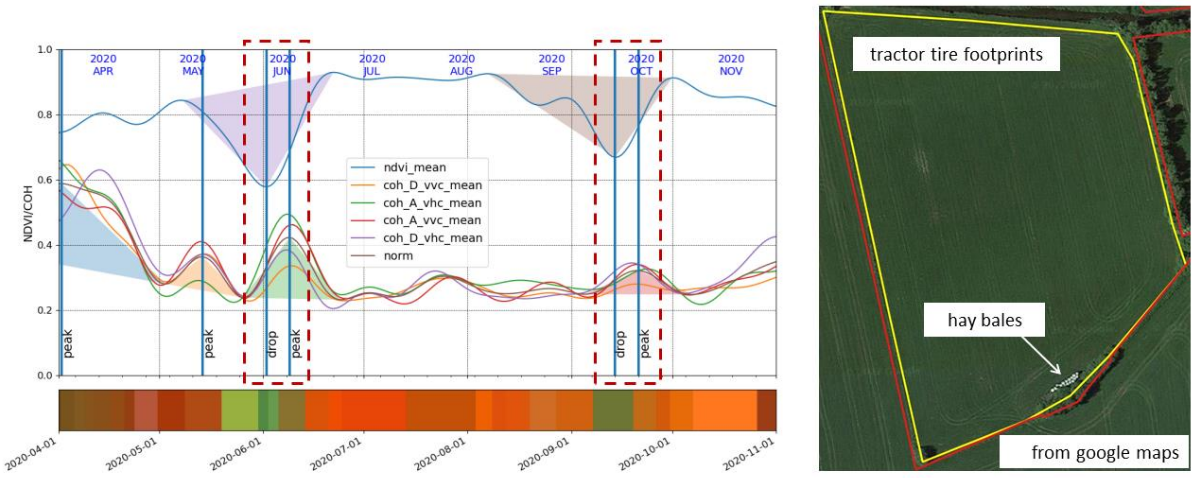
The methodology for mowing detection described above has been applied to the signals extracted in the context of the Outreach project and used to detect markers on whole parcel populations submitted by the MSs.

Resource wise, it was possible to process a set of about 18K parcels in about 6 hours using a PC with an i7 processor and 16 GByte of RAM. This processing time included the generation of summary graphs with the processed signals and markers. Extreme cases with either an excessive number of markers or with no markers where then manually analysed. Three parcels from the set are discussed in detail. To understand what went on those parcel, orthophotos from public databases such as Google Satellite were also consulted.

4.6.1 Parcel with ideal signal behaviour

The first example relates to a parcel characterized by signals with an ideal behaviour, i.e. showing the patterns ideally expected in correspondence of a mowing activity.

Figure 4. a) Summary graph with the signals used for mowing detection: parcel with signals showing an ideal behaviour. b) Corresponding parcel orthophoto from Google Satellite.



a) b)

Source: GTCAP

Part a) of Figure 4 provides a summary of the processed signals and markers. The algorithms identified two aggregated markers corresponding to a simultaneous drop in NDVI and peak in COH6. The colour bar in the bottom of Figure 4 a) represents the false colour composites made of the NIR, SWIR and RED bands. Greenish colours corresponding to a managed (mowed) state are found in correspondence of the drop-peak marker further strengthening the detection results. While the COH6 is affected by oscillations not due to a real mowing activities, false peaks can be excluded on the basis of the information provided by the other signals.

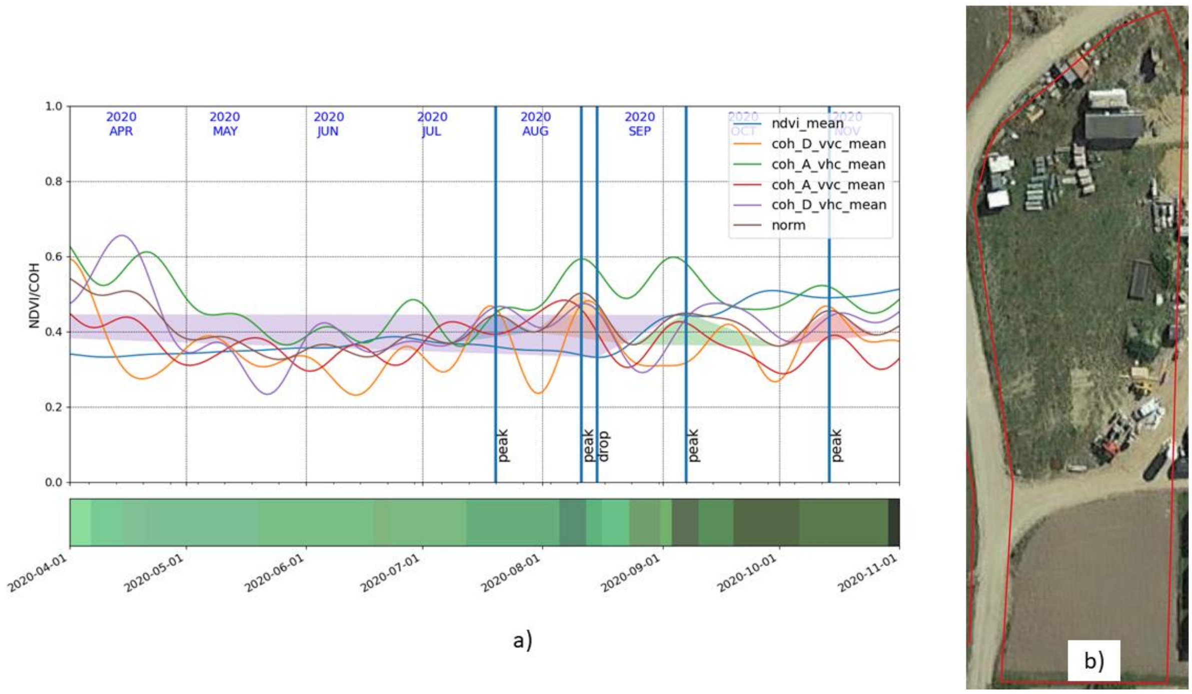
This parcel has been classified as green, i.e. mowing activity has been detected at least once during the season. The correctness of this decision is confirmed by the corresponding orthophoto shown in part b) of Figure 4: hay bales and tractor tire footprints can be clearly seen. These are clear evidence that mowing was actually performed.

Generating summary graphs for the neighbouring parcels allows comparison between peers: in this case, close-by parcels showed similar signal patterns. Crosschecking information from neighbouring parcels can be useful to solve residual doubts on the final decision.

4.6.2 Parcel with anomalous signal behaviour

A parcel with signals showing an anomalous behaviour is considered in Figure : in this case, the NDVI drops to very low values (lower than 0.6) and a passage from a vegetated (orange/brown colours in the bottom bar) to a maintained state (greenish colours) is never observed. The coherence is affected by several oscillation due other phenomena than a mowing activity. When checking the associated orthophotos from 2020, a land use/cover change was observed. While a drop is found in the NDVI, the associated marker has a very large duration and can be excluded with a proper parametrization. Also, the lack of a state change in the NIR, SWIR, RED bar allows the algorithm to exclude (not confirm) the NDVI drop.

Figure 16. a) Summary graph with the signals used for mowing detection: parcel with signals clearly showing an anomalous behaviour. b) Corresponding parcel orthophoto from Google Satellite.



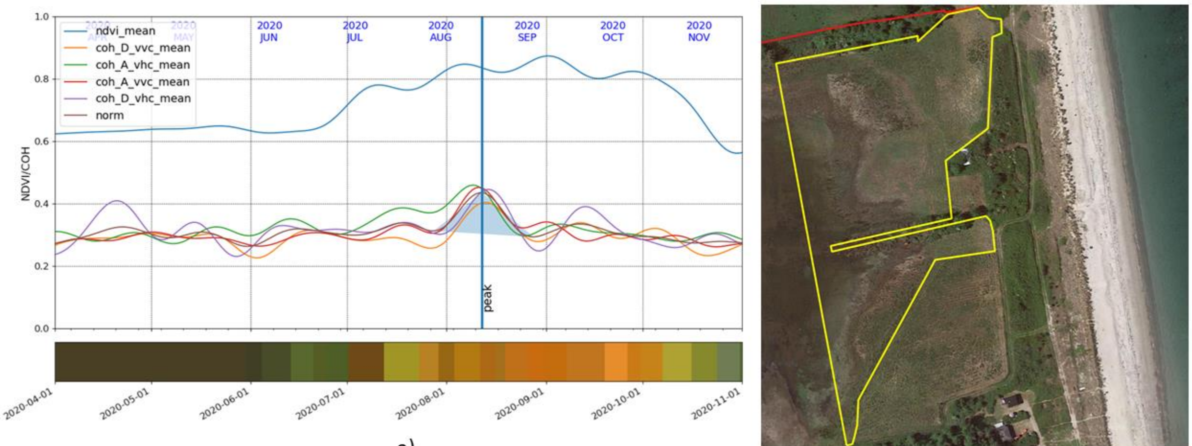
Source: GTCAP

The case analysed in Figure should be flagged as inconclusive and considered for further analysis. The use of several signals and markers would allow for a more reliable conclusion on the activities performed on the parcel.

4.6.3 Parcel with undecided signal behaviour

While the previous two examples were clear cases where mowing was detected and not detected, there are more complex conditions where the signal/maker behaviour does not lead to clear conclusions. This is the case of the parcel considered in Figure 5, which is located close to the sea and probably flooded for several months.

Figure 5. a) Summary graph with the signals used for mowing detection: parcel with signals difficult to interpret. b) Corresponding parcel orthophoto from Google Satellite.



a) b)

Source: GTCAP

In particular, the flat behaviour observed from April to July in the NDVI curve and the associated colours in the NIR, SWIR and RED bar are difficult to interpret. This case shows the importance of properly characterizing the signals used for marker detection under the different scenarios and for different local conditions. At the same time, the signals in Figure 5 are strongly influenced by local natural disturbances that should be properly accounted for.

4.7 Recommendations and Best Practices

The current framework is available as open source at https://github.com/ec-jrc/cbm. It complies with the standard technical best practices including

- Adoption of an open source model involving the use of freely available software libraries and components. This approach reduces the development burden through code sharing.
- Adoption of OOP for modular design respecting standard code and naming conventions.
- Flexibility and configurability by a modular design and the adoption of standard design patterns such as object factories.
- Possibility of automatic versus manual processing paths, including the option for the generation of summary graphs and outputs facilitating result interpretation and debugging.
- Algorithms that have gone through the appropriate validation methods.
- Documentation of all components.
- When designing a processing framework CbM implementation, based on either this framework or another that adheres to the above best practices, MS could.
- Select the most appropriate signals and scan for candidate markers (see Section 2 and **Error! Reference source not found.**).
- Identify (and document) the deterministic elements of the signal/marker/decision logic for the local conditions (ground truth – Section **Error! Reference source not found.**).
- Characterize the performance in terms of conclusive/inconclusive outcomes, trough the adoption of proper validation methods, including the comparison with ground truth and the manual screening of automatic detection output (e.g. the 3 parcels discussed above).

4.8 Conclusions and future developments

This section described a flexible framework for the processing of several signals and markers using Sentinel-1 and Sentinel-2 signals. Flexibly and configurability are key elements for implementing an effective CbM system that has to be properly parametrized taking into account the different scenarios, local conditions and local natural disturbances. While it was built around the particular case of mowing detection, the framework itself is flexible and can be easily configured for other information challenges. The framework proposed demonstrates how to fully exploit the complementary nature of Sentinel-1 and Sentinel-2 observations. It is constantly under development and new features are frequently added. The code is open source and available with its documentation in https://github.com/ec-jrc/cbm.

5 Conclusions

The design and development of a CbM system require several steps going from signal selection to the final decision logic, which relies on the outcome of several marker detection processes. The GTCAP team has actively developed the various CbM system components in collaboration with MSs. This activity has produced a proof of concept and a framework for a systematic analysis of several signals, potentially suitable for both the design of markers/marker detectors and the implementation of a processing chain.

This technical report provides a summary of the R&D activities and the lessons learned in the CbM context. In particular, it has been shown that signal selection involves several criteria including:

— **Significance**: the signal variations observed before and after an activity should be different in parcels implementing the land management practice of interest and those not implementing it. Moreover, the signal variations in parcels implementing the land management practice of interest should be significantly different from signal variations registered during the rest of the crop cycle.

— **Repeatability**: while observations come with a range of variations influenced by local conditions, a good candidate signal for CbM should reveal a consistent pattern when a specific activity occurs. For instance a NDVI drop should consistently occur in the presence of a mowing activity.

— **Absence of correlation**: multiple signals, possibly from different sensors, have the potential to improve detection performance. However, strongly correlated observations add little information and cause redundant processing. Only uncorrelated signals should be considered in the process design.

— These concepts have been analysed and illustrated by practical examples. These emphasize the importance of ground truth data for assessing significance, repeatability and correlation.

After proper signal selection, a CbM processing framework will operationalize the results of the previous analyses. The development of such framework has highlighted the need for flexibility and for the possibility to properly parametrize markers and marker detectors: while a certain level of consistency (repeatability) is expected, marker detectors, triggered by tell-tale signal patterns, have to be fine-tuned for the local conditions. A proper marker parametrization allows one to account for the local specificities and improve the detection process.

Flexibility and configurability also allow one to manage local natural disturbances that can disrupt the acquired signals.

The framework developed achieves flexibility through a modular architecture based on the OOP paradigm and provides the user with the possibility to configure most marker parameters through an external option file.

Finally, the framework developed demonstrates the joint use of Sentinel-1 and Sentinel-2 signals for a more reliable detection of mowing activities.

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List of abbreviations and definitions

API	Application Program Interface
BPS	Basic Payment Scheme
BS	Backscattering
CbM	Checks by Monitoring
CSV	Comma-Separated Values
FOI	Feature Of Interest
GTCAP	GeoData Technologies for Common Agriculture Policy
IQR	Interquartile Range
KNN	K-Nearest Neighbors
LTI	Linear Time-Invariant
MS	Member State
NDVI	Normalised Difference Vegetation Index
OOP	Object Orient Programming
OTSC	On-The-Spot Checks
PA	Paying Agency
QA	Quality Assurance
REST	Representational State Transfer
RFV	Rapid Field Visit
TSS	Time Series Sources
VCS	Voluntary Coupled Support
VI	Vegetation Index

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