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Technical guidance on the decision to go for substitution of OTSC by monitoring

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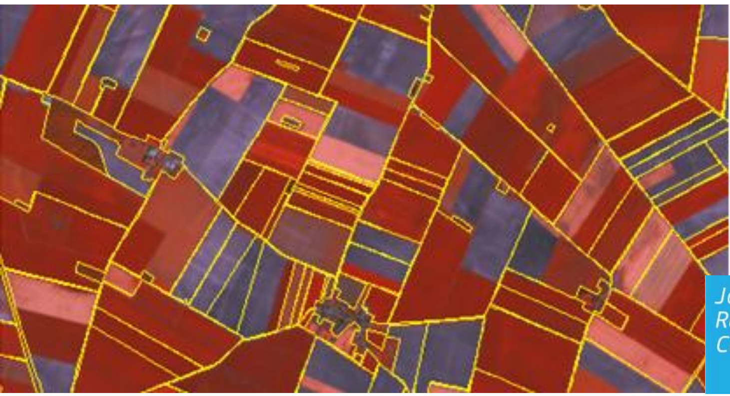

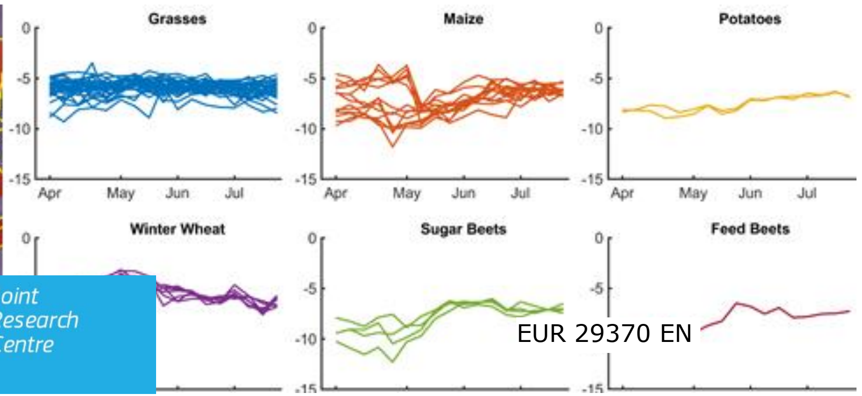

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Contents

Abstract

This document describes the main pre-requisites and conditions that have to be addressed by a given EU Member State in order to implement on operational basis the CAP monitoring as a substitute of the OTS Controls. It further provides guidance on how the MS Administrations could check the fulfilment of these pre-conditions and how to interpret the outcomes of these checks.

The main considerations for implementing monitoring are: (1) the conformity of specific elements of the Integrated Administrative and Control System (LPIS, GSAA, cross-checks, retroactive-recovery system) to ensure the correctness of the "area component" of the farmer declarations; and (2) specificity of the agricultural landscape of the region subject to monitoring, in terms of land management structure (land fragmentation/land change dynamics) and cropping/agronomic practices.

The first component can largely be verified through the annual LPIS Quality Assessment, while the second relies on analysis of the crop/land use recognition using machine learning and EO data provided by Copernicus Sentinels, as well as on assessment of the relevance of the small parcels on the processing of the farm dossier.

This document constitutes the Commission's proposal of common practices and includes comments from: DG AGRI D3, DG AGRI H3, DK, BE-FL, MT, ES, CZ and HU. The feedback received during the series of technical meetings on the CTS for monitoring made in 2018, is also taken into account.

Declaration: the document provides details of the current status of the thinking process and should be viewed as provisional. There are gaps in some areas and further elaboration will be added following discussions with the main stakeholders and practitioners involved in the processing and management of aid application process of 'checks by monitoring'.

1 LPIS and GSAA data pre-requisites

1.1 Background

The effective and efficient performance of the monitoring of agricultural parcels declared by farmers depends on three main assumptions:

- The eligible area declared within the agricultural parcel for a particular payment scheme is truthful, as confirmed by the administrative checks;
- The agricultural land cover or eligible non-agricultural land cover associated to the declared land use is truthful, as confirmed by the administrative checks;
- The graphical outline (spatial extent) of the declared agricultural parcel corresponds with the true land use "exerted" on the ground. Said otherwise, there is either (1) a one-to-one spatial match between the declared agricultural parcel and its actual "footprint" present on the field; or (2) the declared agricultural parcel correctly reflects a portion of larger homogeneous unit of management.

The role of these three pre-requisites in the monitoring is essential for the correct handling and automated processing of farmer applications:

1. Ensuring the area component in advance would allow the monitoring to focus on what it is efficient at – tracing the agricultural activity (or absence thereof) declared by the farmer within the eligible area declared. Although it can detect anomalies in relation to the correctness of the eligible area, the spatial resolution of imagery currently available for the monitoring is not sufficient for precise verification of the eligible area in line with the established Community standards.
2. The land use/crop declared by the farmer is constrained by the land cover present on the ground. The definition of the correct scenario for each agricultural parcel and the associated markers largely depends on the type of land cover. If the true land cover is correctly provided by the input reference data (LPIS), then the follow up of the relevant scenario and the interpretation of the associated markers will provide meaningful outcomes. Certainly, monitoring would be able to verify the correctness of the land cover too. However the systematic application of this verification would require additional time, which will render the system less efficient with respect to the processing of the farmer applications and the possible "early warning" messages.
3. The correspondence between the agricultural parcel and its "footprint" present on the ground would ensure that any outcomes generated by the markers as part of the relevant scenario, reflect the land behaviour associated to one and only one unit of management, defined as feature of interest (FOI). We would expect that in the majority of the cases, the "footprint" would encompass areas occupied by a single crop or single crop group. However, there would be cases where such 1:1 cardinality might not be present; for example, parcels under horticulture cultivation may have different crops within same agricultural parcel and may vary during the season especially in intensive farming areas. The degree of homogeneity of the crop or agricultural activity within the agricultural parcel would strongly influence the adopted approach – namely, extent of the FOI and the type of applicable markers that need to be selected within a given scenario.

The Integrated Administration and Control System (IACS) provides the necessary components to ensure the above-mentioned pre-requisites. These components are namely: (1) the Land Parcel Identification System (LPIS), (2) the Geo-Spatial Aid Application (GSAA), and the (3) system for administrative cross-checks.

LPIS can provide a stable, up-to-date and truthful spatial reference for the correct localization of the agricultural parcel by providing a "tessellation" of the territory on non-overlapping and uniquely defined units of management (reference parcels) in which agricultural activity can occur. In this context, "truthful" means that it reflects the reality of the agricultural management in the given territory, while "stable" means persistent over time. Moreover, LPIS should provide for each specific scheme/measure the value for the maximum eligible area possible to declare within a given reference parcel, as well as the spatial extent and type of agricultural and eligible non-agricultural land cover within. All this information is verified and validated by the LPIS custodian. The stringent and regular LPIS update cycle would also support effective retroactive recovery.

The GSAA provides the interface for the farmer to prepare and submit a correct declaration in an electronic form. It acts as a single entry point for all spatial and alphanumeric data associated with the farmer declaration: spatial extent of the agricultural parcel, crop/land use, specific practices and commitments relevant to particular schemes. It can also provide the communication channel for all further farmer inputs related to the update of his/her declaration, and (if found appropriate) for the provision of supplementary evidence. GSAA also assists the farmer during the declaration process by providing for consultation all necessary reference geospatial information in GIS-enabled environment such as: LPIS, orthoimagery, previously declared agricultural parcels, relevant third-party layers (cadaster, NATURA 2000, ANC, etc..). In such case the farmer can define graphically and describe the thematic content of the correspondent agricultural parcels, taking into account the conditions and constraints outlined by the validated reference data. In the ideal case it will result in agricultural parcels fulfilling all three pre-requisites given above.

Finally, the subsequent administrative cross-checks will confirm and "validate" all initial data provided by the farmer by carrying out spatial intersection of the digitized area declared with the identification system of agricultural parcels, which in addition would prevent duplicate claims on the same area.

1.2 Quality of the LPIS

In order to be successful, the monitoring requires a spatial reference system (LPIS) of appropriate quality. The LPIS quality can roughly be defined as the ability of the system to fulfil two explicit LPIS functions:

1. the provision of unambiguous and stable reference for the localisation of all declared agricultural parcels by farmers, the control measurements of the inspectors and the CAP-relevant spatial data provided by other stakeholders,

   and

2. the correct quantification of all agricultural and eligible area (per payment scheme) available to the farmer for his/her declarations and for the administrative cross-checks by the paying agency.

The correct fulfilment of these functions is a key pre-condition for effective and efficient checks by monitoring.

The LPIS Quality Assurance (LPIS QA) provides the technical framework for planned and systematic demonstration of the LPIS quality, through the annual quality assessment. Article 40a(2) of Regulation (EU) 2018/746 explicitly requires those competent authorities in the EU MSs that decide to carry out checks by monitoring to prove the quality of the identification system for agricultural parcels as assessed in accordance with LPIS QA (Article 6 of Regulation (EU) No 640/2014). Table 1 provides a comprehensive list of the quality elements of the LPIS QA with their relevance in the context of monitoring, as well as their interdependency.

Table 1. List of the quality elements of the LPIS QA and their importance in the context of the monitoring.

Quality Element	Relevance to the monitoring	Relevance of its conformity in the monitoring context
First conformance class		
QE1a and QE1b: correct quantification of the maximum eligible area for the whole system	This quality element provides an information on the area correctness for the entire LPIS. The monitoring is based on the fact that the LPIS in combination with effective GSAA is able to guarantee an error rate with respect to the quantification of the maximum eligible area below the materiality threshold of 2%. If the LPIS shows systematic bias with respect to area correctness (overestimation or underestimation) beyond these 2%, the whole credibility of the monitoring with respect to the correctness of EU Fund expenditures will be compromised.	Mandatory
QE2a: proportion of reference parcels with incorrect maximum eligible area recorded or "contaminated" with ineligible features	This quality element provides information on the correctness of the "eligible area component" at the level of the individual reference parcel and on its "purity", as representation of the unit of management. It assesses whether the proportion of reference parcels with incorrect eligible area or contaminated with ineligible features is significant enough to create notable negative impact on monitoring.	Mandatory
QE2c: proportion of reference parcels with incorrect agricultural land cover area (AL, PC, PG) recorded	This quality element provides information on the correctness of the "agricultural land cover" at the level of the reference parcel, as representation of the unit of management. It assesses whether the proportion of reference parcels with incorrect agricultural land cover is significant enough to create notable negative impact on monitoring.	Mandatory
QE3: occurrence of reference parcels with critical defects	This quality element provides information on the extent to which the reference parcel represents correctly the unit of management. It assesses whether the proportion of reference parcels with incorrect design is	Mandatory

	significant enough to create notable negative impact on monitoring.	
Second conformance class		
QE4: categorization of non-conformities found within reference parcels	This quality element is correlated with the results of QE2a, QE2c and QE3, as it provides information on the causes of non-conformities, found in the first conformance class. Yet, it provides more "insight" information on the possible reasons for the non-conformities found, which individual magnitude might have specific impact on the performance of monitoring.	Recommended
QE5: ratio of declared area in relation to the maximum eligible area inside the reference parcels	This quality element is only partly derived from the quality elements of the first conformance class, as it relies on a data input, external to the ETS (the declared area of the farmer). Although without particular threshold, this quality element is essential to understand the cardinality between agricultural parcel and reference parcel, and to assess the level of convergence of the LPIS towards the unit of management - a key concept in monitoring.	Recommended
QE6: proportion of reference parcels which have been subject to change, accumulated over the years	This quality element is partly derived from the quality elements of the first conformance class, but it also relies on the cumulative results for this quality element from previous years. It provides indications for the up-to-datedness of the LPIS, which is critical factor to ensure the correctness of the area component, taken for granted in the monitoring workflow. A LPIS which is systematically lagging in picking up the annual changes affecting the eligible area and agricultural land cover cannot ensure an effective monitoring of the farmer applications (AP-based monitoring), as well as efficient recovery of undue payments.	Recommended

As evident from the table above, achieving conformity with respect to the quality elements of the first conformance class is mandatory, for effective and efficient checks by monitoring. However, it is recommended to strive for achieving conformity also with respect to the quality elements from the second conformance class. Certainly, the conformance must be ensured not only prior to the implementation of monitoring, but as to enable full operation of monitoring in the longer term, also in the subsequent annual cycles.

Even if the ETS assessment report reveals that the given LPIS implementation is conforming to the expectations set in the LPIS QA Framework (scores of the quality elements are found below the correspondent thresholds), EU MSs are encouraged to evaluate further the results achieved. It would help them to understand better the impact of the LPIS quality on the performance of the different components of the monitoring and to identify eventual pitfalls. Such evaluation might comprise, for example:

- Analysis of the abundance and nature of the reference parcels that were found as not measurable (size, land cover);
- Assessment of the histogram of the reference parcels found as area non-conforming (standard deviations, outliers);
- Assessment of the correlation between the nature of the non-conformity found and the cause for non-conformity assigned.

An LPIS that meets the quality requirement laid down in the LPIS QA, would ensure that nearly any agricultural parcel located within a given reference parcel (or the part of it within the same agricultural land cover) will have the correct eligible area and appropriate agricultural land cover corresponding to the given scenario.

1.3 Effective recovery of undue payments, GSAA and cross-checks

In addition to the quality of the LPIS, the competent authority in a MS/region must demonstrate that the operational procedures related to the recovery of undue payments, the full GSAA implementation and the administrative cross-checks (Articles 7, 17 and 29 of Regulation (EU) No 809/2014 respectively) are effective.

In the ideal case, the GSAA in combination with LPIS and third-party thematic data, should enable the farmer to determine the spatial extent of his/her agricultural parcel as present on the ground. For many current LPIS implementations and IACS setups, this is not always possible, due to different reasons as for example:

1. The reference parcel (due to adopted reference parcel type) does not match the agricultural parcel or farmer block, but represents a bigger/smaller unit. Since several agricultural parcels or farmers blocks can be present within the reference parcel or vice versa, it might be difficult for the farmer to outline correctly the extent of the individual agricultural parcel. As the farmer cannot rely on the validated reference data, he/she needs to use reference orthoimagery, which might not depict the actual situation on the ground, especially if not acquired in the same year.
2. Due to national specificities and local rules, the limits of the agricultural parcels might be further constrained by cadastral or other administrative boundaries, which are virtual and not physical by nature.

Furthermore, even if the farmer outlines correctly the extent of the agricultural parcel at the time of the declaration, he/she might decide to change (or "swap") the location and type of land use of the parcel within the declared (BPS/SAPS) eligible area of the farm, without an obligation to notify the administration. These cases would be handled by the concept of Feature of Interest (FOI), explained in the further sections.

In order to understand the possible cardinalities between the agriculture parcel and the reference parcel, and the role of the other relevant "layers", the EU MS should perform a more comprehensive analysis of the LPIS design and the interaction of the different datasets in the GSAA and administrative cross-check.

The tool for such analysis is already available in the form of the TG IXIT, a key component of the LPIS Model Test Suite (MTS), part of the LPIS quality assurance framework.

TG IXIT can be regarded as a structured set of questions on the design/assembly of the LPIS reference parcel and related components such as landscape features (subject to retention) and maximum eligible area. They are grouped into so-called qualifiers, which correspond to/reflect specific requirements set in the EU regulation in relation to the LPIS and to the GSAA. The combination of choices made for these qualifiers by an EU MS can reveal the level of complexity of the given LPIS implementation and can provide a proxy for the correspondence between the declared agriculture parcels and the unit of management represented by the LPIS reference parcels.

More specifically, IXIT can provide important information and indications on:

- the qualities of a reference parcel in GSAA terms, (provide/confirm the true extent of his/her agricultural parcels and the correct value for the maximum eligible area per scheme),
- the individual particularities of the LPIS concept applied,
- the ability of the given LPIS implementation to process and integrate correctly the information from third-parties for the purpose of the GSAA.

For example, for an EU MS that has LPIS implementation ready and 'fit for purpose' (ideal case of agricultural parcel), one would expect the following outcomes from IXIT:

1. The unit of land representing agricultural area can be directly provided/located by the farmer in an unambiguous way at the level of the single crop/management practice;
2. The RP can be created through delineation or confirmation on the basis of the information provided by a geospatial aid application. Validation of the RP by the MS Administration would be always required;
3. The maximum eligible area is directly derived from this delineation and immediately confirmed by the reference information in the GSAA.

In relation to the procedures that form part of the administrative cross-checks, particular attention should be paid to ensure correctness (in terms of precisions, consistency and robustness) of the spatial handling and interaction of the declared agricultural parcels in between and with the reference parcels from the LPIS.

2 Guidelines and parameters for optimal machine learning use

In order to understand the degree of suitability of the agricultural landscape of a given country/region for CAP monitoring, it is recommended (but still optional) to perform an assessment of the land use/crop recognition capability over the agricultural area using machine-learning techniques. The assumption is then that, if a high accuracy of recognition is achieved for a given land use/crop, then there would be a high probability for its detection in the monitoring process, though the relevant scenarios and markers defined (as explained in the Second discussion document on the introduction of monitoring to substitute OTSC (Devos et.al., 2018)). Initially, the assessment could focus on the main land uses/crops present in the area of interest and the expected target accuracy (discrimination ability) could be set as 95%.

The results from machine-learning on those land uses/crops depicted with high accuracy could be then used in the following year to "train" the scenarios and "instantiate" the relevant marker parameters. In the following paragraphs of this chapter, a full example of assessment of the crop recognition for an entire country using machine learning is given. The two kay datasets required are: (1) the declared agricultural parcels (declared area and declared crops), represented by the vector dataset; and (2) the Sentinel-1 data, represented by the raster dataset.

As machine learning technique for land use/crop recognition, the Commission (DG JRC) has chosen Tensorflow[1] based on its growing reputation as a versatile open source toolkit for a wide range of machine learning problems. Nevertheless, results reported in this document are likely to be reproducible in other (python based) open source machine learning libraries (theano[2], scikit-learn[3], etc.).

Tensorflow is installed by building from source[4], which optimizes the use of specific hardware acceleration features of the platform. The tflearn module[5] is required as ancillary library to run the deep neural network for training and testing. Tensorflow runs are launched either from a command line or as a batch procedure.

The exported feature vector set is further prepared by removing parcel attributes that should not be used in the training and testing phase (e.g. area, perimeter, crop name, etc.). The set has to be split into a training and testing samples. For large sets (> 100000 records), a random selection of 20% of the overall set is recommended. This step is repeated 5 times to produce 5 distinct training sets with their complementary test sets. We illustrate results using a subset of 114477 parcels of the 2017 Danish open access parcel set (DK2017), for which 10 classes are defined.

For information, the single Tensorflow run for the DK2017 record set required less than 5 minutes of processing time (100 epochs, 8 core Intel Xeon E3-1505M v6 @ 3.00 GHz, with 64 GB RAM and Quadro M2200 GPU)[6]. Training accuracy levels off beyond 80 epochs, and does not significantly increase with higher numbers of epochs.

A (current) drawback in machine learning is the need for consistently sampled, gap-free feature vectors that feed into the learning framework of the method (typically a neural network). Feature vectors are the records that are extracted for each "feature", which is typically a declared parcel. The elements of the record are the individual values in the time series, usually in time order, and often "reduced" to a single value, usually the arithmetic

[1] https://www.tensorflow.org/

[2] https://github.com/Theano

[3] http://scikit-learn.org/stable/

[4] https://www.tensorflow.org/install/install_sources

[5] http://tflearn.org/

mean and/or the standard deviation, for all pixels that are included in the feature. “Consistently sampled” does not necessarily mean that a regular, equal interval sampling is required, but whatever sampling approach is chosen, it needs to be applied, consistently, for all features. In practice, a regular equal interval sampling is preferred.

It is relatively straightforward to extract such series for the entire (national or regional) territory for Sentinel-1, for instance, as weekly averages. Due to cloud cover, this is less straightforward for Sentinel-2, for which data composition and gap filling methods are needed to create consistent, gap-free time series. However, the application of the machine learning is adaptable with respect to the type of feature data (e.g. S1 polarization bands or S2 multi-spectral bands) that is fed into it, as long as they have no missing data. The manner in which the time series are extracted from the Sentinel data stacks is not relevant, e.g. either from discrete stand-alone download-process-storage solutions or cloud-hosted solutions.

The procedure to create the Sentinel-1 feature vector set currently relies on the use of Google Earth Engine (GEE[7]), as it is the only "Big Data" repository that provides access to geocoded, calibrated S1 backscattering coefficients at the full 10m resolution, and for arbitrary selections. The GEE team downloads Interferometric Wide mode (IW) GRD images from the Copernicus Sentinel hub[8] and runs these through the open source SNAP Sentinel-1 toolbox[9] using a standard recipe, to convert to geocoded, calibrated backscattering intensity imagery, which is then added to the catalogue (with approximately a 1 day delay after publication on the Copernicus Sentinel Hub). With the recent deployment of the Copernicus DIAS instances, effort will be made so that a European data access and processing capacity will be available in the course of 2019, facilitating analogous workflows, for instance, with the use of the open source sen4agri for Sentinel-2.

Using standard functions in GEE, weekly images are stacked for a predefined period (e.g. 1 April - 1 August) for both VV and VH polarizations (Figure 1 and 2). The parcel sets are imported as a table asset into GEE. For each parcel outline, this stack can be reduced to a mean temporal signature (by week). Optionally, parcels are buffered with an internal boundary of 10m, to avoid including edge pixels. The complete set of signatures can then be exported to a CSV formatted table, retaining the original and calculated feature attributes for each parcel (e.g. including a unique ID and crop code, crop name, area, perimeter, etc.).

[7] https://earthengine.google.com/

[8] https://scihub.copernicus.eu/dhus/#/home

[9] https://github.com/senbox-org/s1tbx

Figure 1. Example of weekly country-wide composite for Denmark, for the weeks starting on 6 May, 27 May and 17 June 2017 (VV polarization).

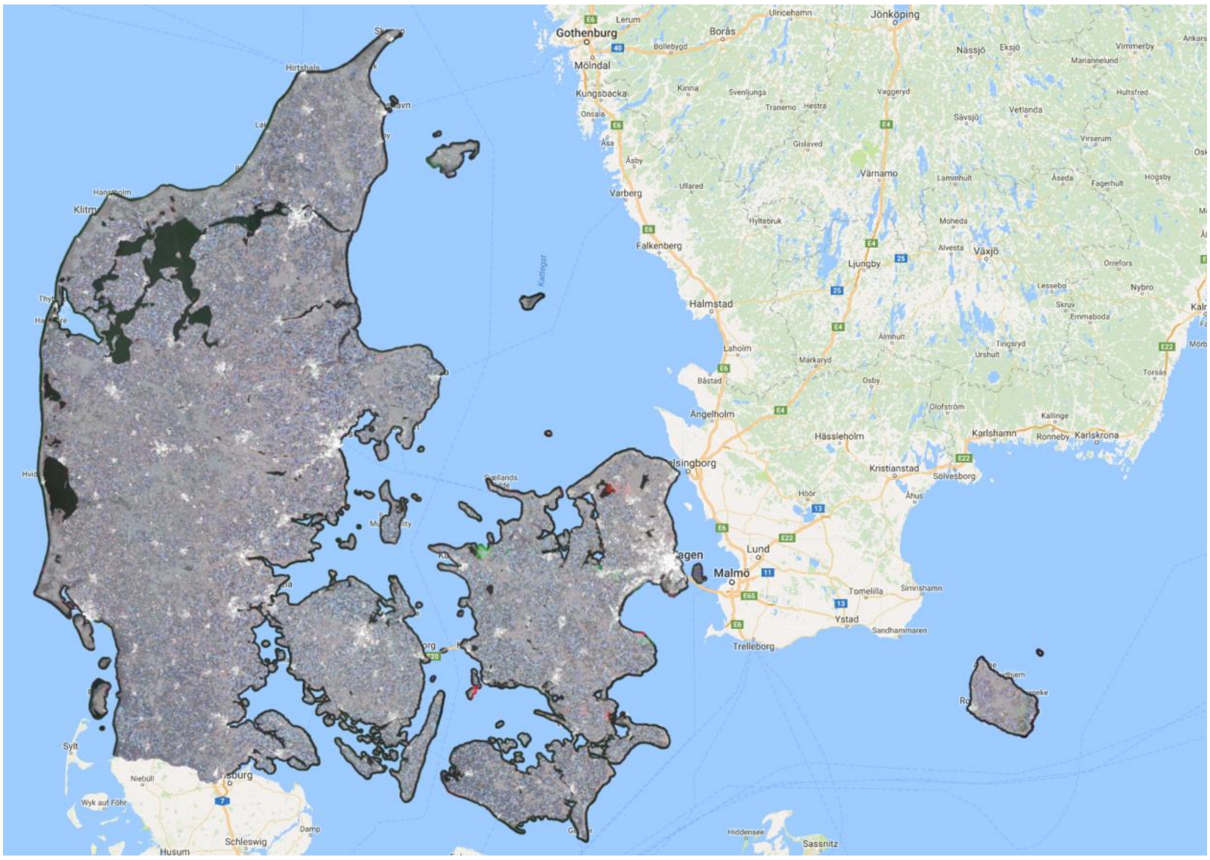


Figure 2. A full resolution zoom of Figure 1 into an area West of Otterup (DK) for the weeks starting on 6 May, 27 May and 17 June 2017 (VV polarization left, VH polarization right).

It is not yet entirely clear whether a full country approach is preferable over a segmented approach, e.g. for agro-environmental areas that have similar cropping parameters. One would assume that the latter would provide some opportunities to fine tune crop class composition and training set selection. On the other hand, the dimensions of the extracted data sets do not restrict the application of machine learning techniques to smaller than country-wide application.

The technical tests in this document focus on the comparison of declared parcel labels with those predicted by a trained deep neural network. There are many variations possible, though: e.g. approaches that may try to separate the more heterogeneous classes (e.g. grassland); compare distinct crop development by phenological progress and/or agronomical relevant factors (e.g. soil type); etc. The tools are rather generic and leave it up to the practitioner to device the test set-up and working hypothesis.

Based on the analysis of parcel statistics for the full set, those crop codes for which the summed area coverage of the correspondent parcels is larger than 95% of the total area of the full set are selected. Optionally, it can be decided at this stage to eliminate small parcels (e.g. < 0.3 ha) or parcels with odd shapes to exclude noisy samples. These codes are then grouped, based on the crop category and crop name, into crop classes. Separation in crop classes is partially based on the expectation that these classes have distinct temporal signatures. For instance, silage Maize and corn Maize will be grouped in one class in first instance. They may be dealt with separately in additional machine learning runs, especially if such discrimination is relevant for a particular aid scheme/measure or type of operation.

Note that a number of parameter settings have been fixed in the reported tests as discussed above. These are summarized in Table 2, together with some remarks on what effect on overall accuracy (*OA*) would be expected from changing of the parameters.

Table 2. Parameter settings used in the reported tests and expected effects of changing those parameters on overall accuracy.

Parameter setting	**Value**	**Expected effect on overall accuracy if changed**
Time step for S1 sampling	7 days	Shorter time step will introduce more noise in the time series, longer time steps risk missing characteristic sharp transition phases of particular crop classes. For Northern latitudes (> 52 N), 5 days would likely still work. *OA* would drop if > 10 days.
Period of S1 selection	1 April - 1 August	This captures the main part of growing season of both winter, summer crops and grassland (at mid - high latitudes). This can easily be adapted to the prevalent season start and duration, where appropriate. Including extended parts of the "off-season" risks including temporal phenomena (pre-sowing, post-harvest) that are not necessarily representative for all parcels in a crop class, and thus decrease *OA*.
Summed area covered by the parcel declared with the crop codes (types) selected	95% of the area of the full parcel set	If increased, a much larger set of, relatively minor crop types need to be included. Most of these would mostly contribute to omission and commission, i.e. decreasing *OA*.
Composition of crop categories	Main crop categories	Several crop codes are lumped together, e.g. seed potatoes and consumption potatoes in POT, while these may have a distinct seasonal profile. Separation in distinct classes would be feasible, as

Parameter setting	Value	Expected effect on overall accuracy if changed
		long as a sufficient number of samples of each are available into the training set. OA would likely be lower, if more distinct classes would need to be separated. Separate Tensorflow runs on the distinct classes only, would be an alternative.
Training set size	20% of the full set of parcels	This primarily affects the rate at which the to-be-separated crop classes are represented for training the model, and, the speed of the training. A lower set size risks under-representation of minor classes, and likely decrease *OA*. A higher number requires fewer epochs to train, which is overall somewhat faster.
Probability threshold	max(probN)	The predicted class is assigned on the basis of the maximum probability. This could be thresholded, for instance, by requiring the maximum to be > 0.50. This is likely to increase *OA* somewhat, but only by excluding inconclusive cases. This may be desired in particular tests, i.e. selecting "pure" representatives of a particular class.
Prediction threshold	majority	A mismatch is tagged if the majority of predicted labels is different from the parcel label. This could be made stricter (e.g. none of the predicted labels can be different) or less strict (at least one must match), with similar effects as the probability threshold, i.e. higher/lower pseudo-*OA* by excluding/including inconclusive cases.

3 Interpretation/reporting of machine learning results

Based on the analysis of the results from the machine learning, and considering the availability of the LPIS/GSAA pre-requisites, the EU MS Administration would be able to estimate the expected performance of the monitoring system, if implemented. Machine learning will also continue to play essential role in the operational monitoring, since it would allow for yearly fine-tuning and improvement of the marker parameters, as well as for structural assessment of the difficult/complex cases, requiring an implementation approach that is more specific.

Tensorflow results (extracts) are output as presented in Table 3.

Table 3. Results from Tensor flow.

id	klass	prob 0	prob 1	prob 2	prob 3	prob 4	prob 5	prob 6	prob 7	prob 8	prob 9
a4	0	98.39	0.04	0.00	0.19	0.00	0.03	0.01	0.77	0.54	0.01
3b	7	0.03	98.18	0.85	0.00	0.38	0.00	0.00	0.43	0.03	0.12
1d	7	0.02	0.01	0.00	0.01	0.00	0.00	0.00	99.25	0.51	0.20
06	3	1.58	0.04	0.00	93.77	0.00	0.10	0.00	3.69	0.80	0.01

For each parcel (id), which has class label in column 'klass' ('class' is a reserved word in python/pandas), 10 probabilities are estimated by the trained model, i.e. one for each crop class. The first parcel (a4) has the highest value for prob0, i.e. predicted class (0), thus matching and conforming its input klass label (0). On the contrary, for the second entry there is a significant mismatch between the input klass label 7 and the predicted higher class 1). For the third parcel, the predicted label and input label are matching, and so on.

A single confusion matrix can now be created for each run, by accumulating the counts of each matching case (on the matrix diagonal elements) and each mismatch on the relevant off-diagonal element. Assignment is based simply on the maximum probability across the row for each parcel. Overall accuracy is then the sum of the diagonal counts divided by the total count of all confusion matrix elements. Off-diagonal elements can be inspected to understand likeliness that particular class pairs are confused (omission and commission). An example confusion matrix for a single run is given in Table 4 below.

Table 4. Confusion matrix from TensorFlow run. Overall Accuracy: 93.46%.

	GRA	MAI	POT	WWH	SBT	WBA	WOR	SCE	WCE	VEG
GRA	31416	141	82	328	3	36	9	467	86	28
MAI	136	3790	63	15	5	6	0	132	43	16
POT	34	124	516	3	124	20	0	43	1	41
WWH	191	9	10	19472	3	52	11	238	39	5
SBT	18	14	38	4	685	1	0	53	10	16
WBA	34	2	5	71	0	4363	6	20	20	1
WOR	12	0	0	12	0	16	5346	31	1	3

	GRA	MAI	POT	WWH	SBT	WBA	WOR	SCE	WCE	VEG
SCE	507	148	44	248	19	23	12	15871	184	108
WCE	323	49	10	167	4	20	3	857	3319	14
VEG	14	33	81	1	22	0	1	122	14	812

The counts in this confusion matrix are the number of parcels assigned to each matrix element. The overall accuracy for each of the 5 runs ranges between 93.1% and 93.6%. Expressing the confusion matrix counts by area in each parcel will lead to an increase of several percent in overall accuracy, reflecting the fact that the larger parcels contribute more to correctly classified, while smaller parcels are more often counted on the off-diagonal elements. The overall accuracy is an overestimate, because it excludes 5% of parcels in the crop groups.

Each parcel is selected once to be part of the 20% training set, and classified 4 times for those cases when the parcel is in the complementary 80% testing set. For each parcel, the join of the individual runs can be generated, as in the example shown in Table 5, i.e. for each unique parcel ID the 4 predicted majority labels can be compared to the parcel label.

Table 5. Majority labels cf. parcel labels.

id	klass	pred0	pred1	pred2	pred3	pred4	majarg	majcount
76	0	0	0	-1	0	0	0	4
b0	3	3	3	-1	3	3	3	4
78	8	-1	8	8	8	8	8	4
89	3	3	-1	3	3	3	3	4
ea	8	-1	7	7	7	7	7	4

The -1 value is for the run in which the parcel was selected as training sample (thus, no predicted label available). The obtained total number of parcels for which the majority of predicted labels is not the same as the parcel label is 7542 (out of the 114477 from DK2017), i.e. 6.5%, which is more or less the same as the 1 - *OA* (6.9% - 6.4%) achieved for each individual run. This shows that the method is very robust.

One can note that for 4456 parcels (out of the 7542 predicted with different label than the one declared), all 4 predicted labels are identical and contradict the declared label. For further processing of the dataset, these parcels could be reallocated to their respective identified 'correct' crop class.

The tabular result can now be categorized to prioritize follow-up activities. From the confusion matrix it can be determined which cases of omission and commission are likely to have relevant impact on compliance in the context of the farmer dossier with respect to particular scheme (e.g. preservation of permanent grassland as part of greening measures). Also, in case small and oddly shaped parcels were not excluded from the feature vector data set, the results' size and shape attributes distribution can be analysed to understand whether noise factors play an important role. Re-runs with fine-tuned parameter settings (accounting for the regional/local specificities) may help in eliminating or better specifying outlier categories. Outliers can be analysed in the context of the farmer dossier, e.g. to highlight whether they are spatially clustered and how they impact the dossier for a given scheme (e.g. crop diversification). The combination of these analysis results helps in defining possible follow-up approach, such as: the selection and use of Sentinel-2 imagery; the generation of specific time series for analysis; the use of longer/shorter time series analysis; or as later resort a field visit. In order to reduce the follow-up activities at minimum, the development of efficient tools to process the outliers in order to confirm or reject them within the automated monitoring process, could be a next focus.

The overall accuracy of 93.4% produced for the DK2017 data, being close to the desired target accuracy of 95% (discrimination ability), is an excellent result, considering that the machine-learning was run without particular fine-tuning, and only using Sentinel-1. Note that the same order of accuracy has also been obtained with NL2017 and BEVL2017 data, using exactly the same workflow but with different crop class compositions. To note also in the DK2017 data set, the encouraging high accuracies amongst the distinct cereal categories, as this is considered a major challenge in conventional crop classification approaches.

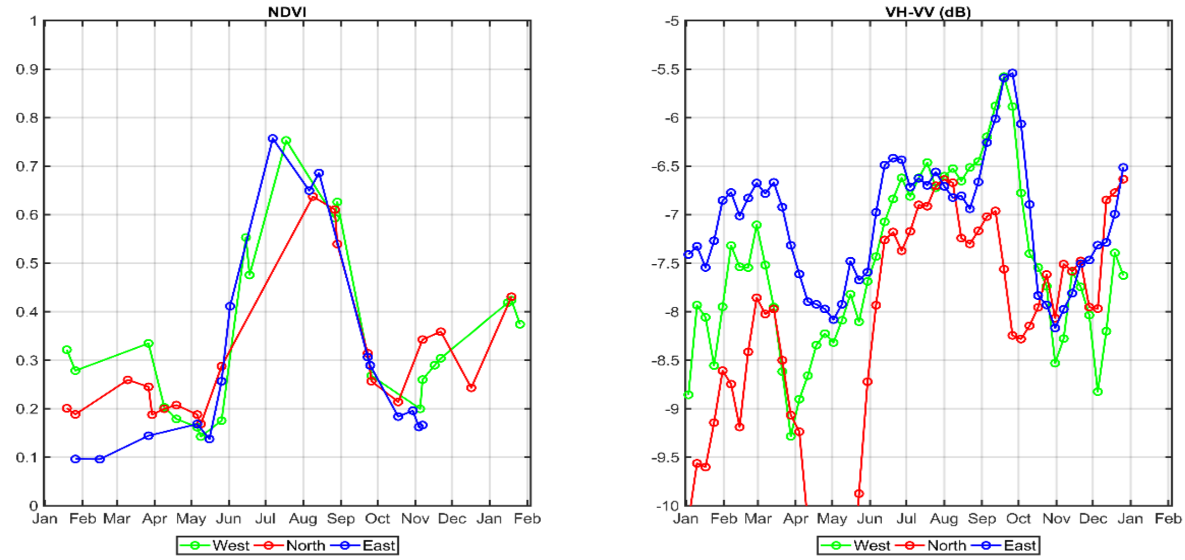
4 Analysis of optimal "classes" towards scenarios / targeted discrimination

4.1 Visual Interpretation of temporal profiles

Once high accuracy crop classification/recognition is obtained using the machine learning models, the next step, in this preparatory process towards operational monitoring, is to: (1) define the possible scenarios,; (2) define the sequence of expected markers and their instantiation with the relevant signal types..

It is important then to establish the expected sequence of farming activities needed for each crop. Such list is not only crop-dependent but might also be refined at regional-(or even farm) level. It is thus recommended to consider homogeneous sub-regions (depending on, e.g., the climate, the meteorological conditions, the altitude, the agro-economic conditions…). For example Figure 3 presents average temporal series of sets of 20 parcels of potatoes selected in 3 different geographical zones in 2017. On NDVI profiles, no significant distinction can be made. However, in the case of VH minus VV (in dB) profiles, one can see that the North zone (sandy zone) exhibits a distinctive than the other two (loamy areas).

Figure 3. Comparison of the average temporal profiles of potato fields from three different sub-regions and for both NDVI (left) and VH-VV (right).



A phase of mutual learning between knowledge on crop cycles/crop phenology and classification results has to be undertaken in order to adjust the sequence of activities. For instance:

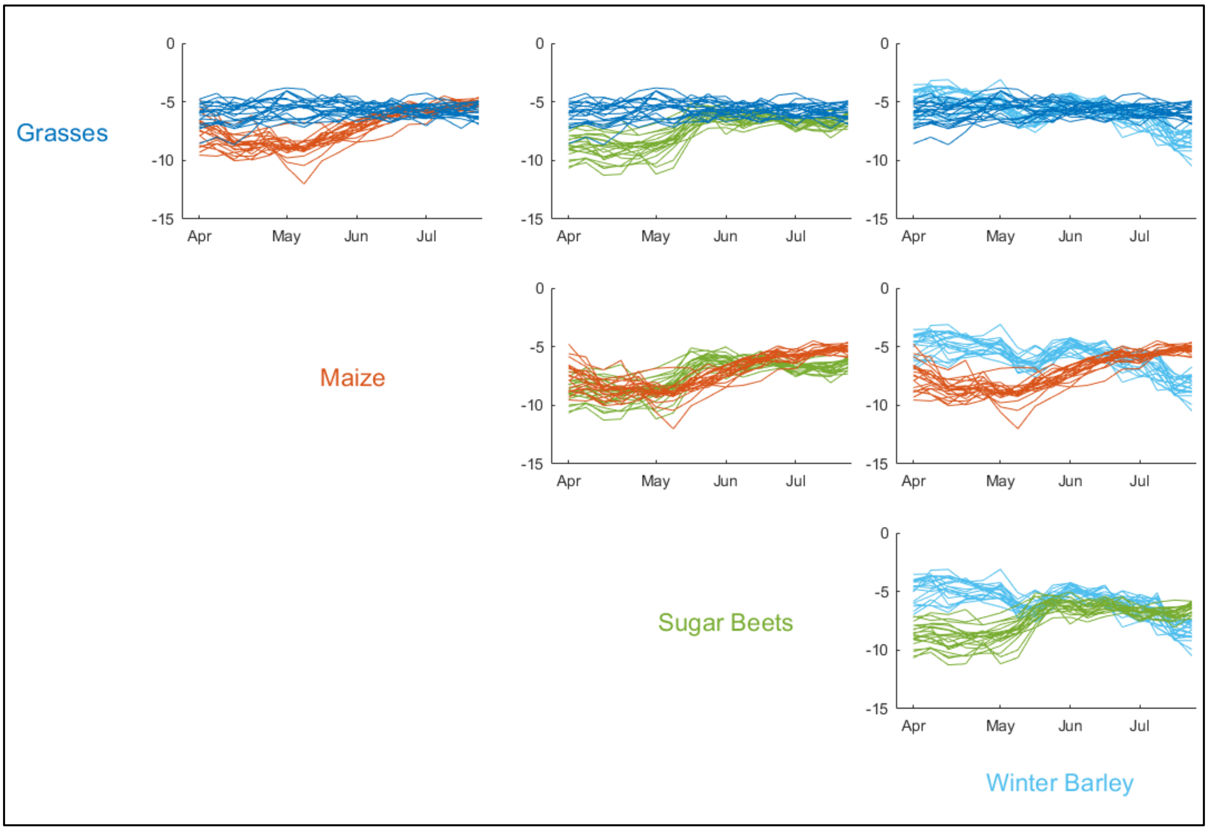
- Profiles will help to define the expected calendar for each of the crops. The crop calendar is directly describing the period over which the crop is expected to be present on the field. Hence, it exactly determines the period over which one should focus. For winter crops, there might be a need to look back to October of the previous year in order to observe the full crop calendar.
- With the sequence of expected events, one can better interpret the temporal profiles behind the feature vectors that were fed in the machine learning classification and focus on the most relevant of their characteristics.
- For each of the expected events, one must assess whether it can be seen/detected using Sentinel or equivalent remotely sensed images. It is counter-productive to try to impose the detection of a physical phenomenon

that is not manifested by any of the data at hand (both radar and optical). For instance, there are no chances to detect the pesticide and fertilizer sprays using Sentinel data.

To help deriving information from the different "optimal classes", one can first select a sample (e.g. 20 parcels) for each of the classes and graphically superimpose their temporal profiles. Like this, one can better spot the patterns for the specific class.

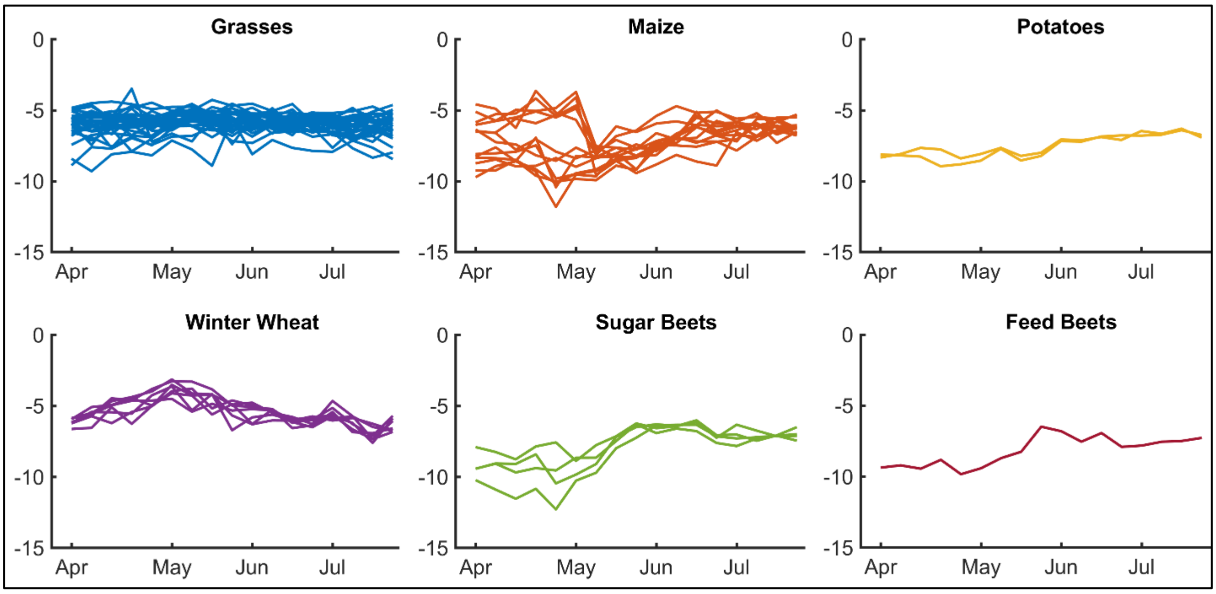
In addition, superimposing the temporal profiles of two different classes can also help to understand what really differentiate these two classes. The Figure 4 provides examples of a pairwise comparison of 4 classes using the difference of polarization VH-VV (in dB) over the April-July period. The grassland (dark blue) clearly shows a steady flat trend over the period compared to the other crops. The winter barley (light blue) presents a high amount of vegetation already in April with an early decrease (by end of June). Comparatively, the maize (orange) and the sugar beets (green) both present a low level in April-beginning of May (when parcels are ploughed and sown). Differences appears after for these latter two crops. The sugar beet is characterised by a fast growth followed by a long plateau phase. For maize, we observe a regular growth over May to August.

Figure 4. Comparison of the temporal profiles of VR-VV for four different classes. Each class is represented by 20 parcels (no restriction of sub-regions).



Obviously, many options can be envisaged in order to identify pertinent information. For instance, Figure 5 presents the temporal profiles of the parcels corresponding to a same holding and grouped by classes. One can see the coherence of the profiles for each of the classes (certainly reflecting the fact that parcels are in equal soil and weather conditions). However, for maize fields, one can observe two different patterns probably due to two different practices i.e. Maize preceded by a winter cover and Maize sown on a soil left bare for a while.

Figure 5. Comparison of the temporal profiles of VR-VV for the parcels of a single holding.



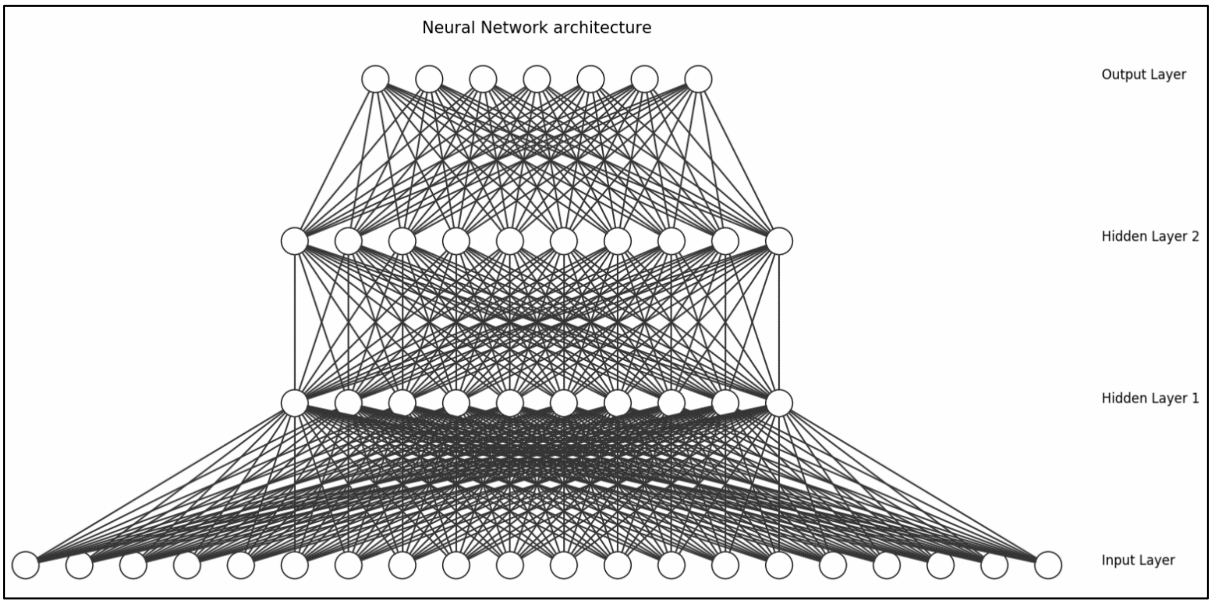
4.2 Analysis of the classification model

Apart from a visual interpretation of the temporal profiles, one can also try to analyse the data used by the classification model. However, this task may be difficult depending on the complexity of the model ("black box" interpretation problem).

Some models use few parameters (e.g. the multinomial logistic regression model) and are thus easier to interpret. There can be as many parameters as input variables, each contributing to the final classification. Sorting the parameters by decreasing order can already give an idea of the most important input variables to use. Moreover, such statistical models generally allow testing the significance of the parameters, which in turn can be translated in "contribute or do not contribute to the classification". On the other hand, such models are relatively rigid and are less effective than other non-parametric (non a priori knowledge) approaches.

Artificial neural networks (ANN) are a family of models that are increasingly used in different contexts. The TensorFlow tool from Google is precisely using ANN. The structure of an ANN tends to be rapidly complex as it depends on the number of layers and the number of neurons in each of the layers (see Figure 6 as illustration for an ANN with 20 inputs, 7 classes and two layers of 10 neurons each). Potentially, all neurons are communicating between two consecutive layers. It is thus problematical to evaluate the actual contribution of each of the initial input variables to the output (final) layer (i.e. the layer that provides the probability of the different classes).

Figure 6. Illustration of the complexity of an ANN with 20 inputs, 2 hidden layers with 10 neurons each and an output layer with 7 outputs.



Nevertheless, several approaches exit for highlighting the main contributors within this complex structure.

Neural Interpretation Diagram (NID) provides a visual interpretation of the connection weights by changing the width of the corresponding lines (the larger weights represented with a thicker line).

Sensitivity analysis can also be applied. It consists of adding random noises to the model inputs and observing how the estimated weights change. Stable weights (i.e. less sensitive to noise) are then considered as the main contributors of the model.

More sophisticated approaches exist. Garson (1991) proposed a method that aims at weighting the contribution of each of the inputs on the outputs by combining all the inner hidden layers. This method has been implemented in the R software:

(https://www.rdocumentation.org/packages/NeuralNetTools/versions/1.5.1/topics/garson).

Olden and Jackson (2002) are using a randomization procedure in order to test which of the input contributions is significant. Similarly to Garson's algorithm, the contribution of each of inputs is first evaluated and stored. Then, the outputs are randomly permutated and the ANN is retrained on the permutated outputs and the contributions are evaluated and stored. This three-steps procedure is iterated several times. The original contributions are then compared to the randomized contributions. If the original contribution is significantly different from "the randomized contributions" (i.e. it is not contained in the 95% probability interval), then the contributions is considered to be significant.

5 Consumer/producer error analysis

The Commission proposes one simple expectation on the reliability (quality) of the automated system, as the backbone of the monitoring process, based on the statistical widespread concepts of the type I (α) and type II (β) errors:

1. type I error [α] is the rejection of a true null hypothesis (a "false positive" or false RED finding for a particular GSAA parcel/FOI), the α expectation is set at 5%,
2. type II error [β] is the failure to reject a false null hypothesis (a "false negative" finding or false GREEN for a particular GSAA parcel/FOI), the β expectation will be set at the later point when having more information on performance of the monitoring systems. Whilst in principle this value should be set at 5%, in absence of historical data and as to ensure the practicability of the monitoring procedure in the initial phase, the initial value for β can be set in the range of 10-20%.

Type I (α) and type II (β) errors express the robustness of the standalone automated procedure with respect to the appropriateness of the defined compliance and non-compliance markers and the performance of the "detection engine". As concepts, type I and type II errors, seem analogous to the user (UA) and producer (PA) components of the Overall Accuracy, used to validate the results from machine-learning, before being used as an input for the marker parameters. Yet, the presented error concept could, under the principles laid down above, be used also in the operational phase of the monitoring to express the tolerable error with respect to the final verdict for the farm application (including any follow up and assessment on the effect on payment).

In such context, GREEN would be interpreted as "the farmer is confirmed to be compliant and RED being "the farmer is confirmed to be non-compliant".

A type I error would occur when an applicant with correct declaration is classified by the automation system as non-compliant. In such cases, applicants will most likely and rightly not agree with the verdict and react or launch appeal procedures. The expectation of α 5% means that less than 1 out of 20 non-compliant farmers should have a cause to appeal.

A type II error occurs when an applicant who in reality is not (completely) compliant passes through the automation and hence receives (a part of the) subsidies he is not entitled to. An expectation of β of e.g. 20% means that only 1 out 5 non-compliant applicants can slip through the automation system undetected. It is unlikely that this will trigger reaction or appeals from his part, but there remains the following year where the applicant faces the same odds.

The feasibility of achieving these expectations over a reasonable amount of time for a given system and landscape can reliably be derived from validating the machine learning results with the corresponding field observations. As monitoring is an approach that is believed to be improving at every campaign year (better markers and scenario parameters), the phrase "over a reasonable amount of time" was added to indicate this is not an absolute starting criterion. Field observations would need to be collected also on regular basis to act as representative ground truth for the performance/tuning of the monitoring as part of the quality management of the monitoring system[10]. Relevant "ground truth" could be collected also from voluntary farmer input or from the system monitoring processes (LPIS upkeep).

[10] See Section 3.4 of "Second discussion document on the introduction of monitoring to substitute OTSC: rules for processing applications in 2018-2019"

Here is an example of analysis between the TensorFlow classification results on selected set of GSAA parcels and the “ground truth” from OTSC on the corresponding parcels in a given member state:

Table 6. Example of consumer/producer error analysis.

All classes regrouped		Field visits		
		Crop confirmed	Problem found	TOTAL
TensorFlow	Crop confirmed	3593	6	3599
	Problem found	216	41	257
	TOTAL	3809	47	3856

The type I error is computed as 216/3809≈5.7%.

The type II error is computed as 6/47≈12.8%.

These results are computed on all the classes. The same analysis can be performed at class level (i.e. crops) in order to identify for which scenarios there might be a higher need for yellow flags and/or warnings.

6 Assessment of the impact of small parcels on the monitoring: an example of crop diversification

6.1 General remarks

One of the major concerns of the EU Member State towards the operational implementation of checks by monitoring is the perceived limitation of the monitoring approach with respect to the small parcels. This, according to the MS Administration, would create an "avalanche" of field visits needed to provide conclusions on the conformity of these small parcels.

The problem with the small parcels should be always put in the context of their relevance to conclude on the payment of the given farmer dossier. In many cases, small parcels will have either marginal or no impact on the final conclusion for the payment. The number of the parcels requiring such conclusion would depend on the size and structure of the farm and the applicable scheme. The following example illustrates a possible approach to assess the impact of small parcels in the context of greening (crop diversification - CD). It could be extended towards other schemes/requirements, i.e. EFA, BPS etc.

Similarly as indicated in the general approach of the Technical Guideline for the On-the-Spot checks of Crop Diversification (DS-CDP-2015-08), it might not be necessary to check all the parcels by monitoring in order to reach a conclusion on the compliance of a holding with respect to CD. However, while the focus of that technical guidance was on the potential optimisation of the selection of the parcels subject to the CD OTS check, here the focus is on the parcels that are suboptimal (e.g. too small) for conclusive analysis using the Sentinel data. A methodology for assessing the impact of the small parcels in the context of the operational implementation of checks by monitoring is presented in the following sections.

6.2 Methodology

Assuming that the CD requirements for each holding were already established, the methodology is based on the additional assumption that the small parcels are hidden (or unseen so that no conclusive information can be derived for them from the Sentinel data) and thus any discrepancy with the declaration can be assumed. Then, the core of the methodology is to apply the simple principle of "worst case scenario" (WCS) on these "hidden" parcels, i.e. "which small parcel configuration would lead to the worst situation in the context of CD for this specific holding?" In that sense, the approach can be seen as "what could be the conditions of the small parcels that would bring a compliant CD holding to non-compliance?"

One must pay particular attention to the conditions for CD exemptions. Following the WCS, the CD exemption of a holding might be impacted by the small parcels but it does not mean that the holding will have to respect some CD requirements. For instance, a holding that is exempted because it has less than 10ha of arable land (AL) might also be exempted because it has more than 75% of "grasses" on the AL. The WCS must also take these particularities into account.

There are four main potential situations where (some of) the small parcels might have a significant impact on the conclusion on CD at holding level:

- All the small non-AL parcels could actually be used for arable crops (Situation 1; threshold on Total Arable Land (TAL))
- All the small 'grasses' parcels might not actually be 'grasses' (Situation 2; percentage of 'grasses' on TAL or on Total Eligible Area - TEA)

- All the small parcels (both AL and non-AL) could be used for the main crop (Situation 3; 75% threshold on the main crop for arable land)
- All the small parcels (both AL and non-AL) could be used for one of the two main crops (Situation 4; 95% threshold on the two main crops for arable land)

These different potential situations are not mutually exclusive, i.e. more than one potential situation could take place in the same holding.

For each of these potential situations, a potential impact on the area is then computed by comparing the result of the new hypothetical assignation of the small parcels with the corresponding threshold.

6.3 Examples

6.3.1 No CD with potential influence on TAL less than 10ha

Table 7. Summary of a holding declaration (situation 2).

Holding	Crops	Number of parcels	Area of parcels [ha]	Number of small parcels	Area of small parcels [ha]
AL	Zea	2	9.9625	0	0
PG	Permanent grass	3	6.4563	1	0.0470
TOTAL	**-**	**5**	**16.4188**	**1**	**0.0470**

The declared total arable land is 9.9625ha.

In the worst case scenario all the small permanent grasslands are actually arable crops and the TAL would be = 9.9625ha + 0.0470ha = 10.0095ha. In such case the area of arable land is larger than 10h and the holding should not be exempted from crop diversification.

6.3.2 CD2 with potential influence on the 75% limit for the main crop

Table 8. Summary of a holding declaration (situation 1).

Holding	Crops	Number of parcels	Area of parcels [ha]	Number of small parcels	Area of small parcels [ha]
AL	Triticum_winter	3	9.6611	0	0
	Beta	1	2.0057	0	0
	Hordeum_winter	1	1.3442	0	0
PG	Permanent grass	4	0.6817	4	0.6817
TOTAL	**-**	**9**	**13.6927**	**4**	**0.6817**

The declared share of the main crop is 9.6611ha/(9.6611ha + 2.0057ha + 1.3442ha) = 74.25%.

In the worst case scenario all the small permanent grasslands are actually arable crop (Triticum_winter). In such case the share of the main crop would be (9.6611ha + 0.6817ha)/(9.6611ha + 0.6817ha + 2.0057ha + 1.3442ha) = 75.53% and thus is too large to comply with the requirement of the main crop to stay below 75% of the TEA.

The impacting (CD rules violating) area can be computed as (75.53% - 75%)*(9.6611ha + 2.0057ha + 1.3442ha) = 0.0689ha. In order to conclude on the holding compliance with the 75% limit of the main crop on arable land, the land use (arable land or grassland) need to be confirmed on this 0.0689ha.

6.4 Generic method of small parcels "sifting"

Section 6.3 outlines an example of impact analysis of the small parcels on the conclusion for crop diversification at a holding under checks by monitoring. Based on this example, some generic steps for such parcel "sifting" analysis, can be drafted. The following logic should be applied:

1. Quantify/locate all the parcels of area below a certain threshold (e.g. <0.5ha or less). Other parcels traits suspected suboptimal for monitoring with Sentinel data for a given scenario may also be considered here, e.g. elongation and width.
2. Per scheme, operate the steps below.
    a. Identify, from GSAA, adjacent parcels, declared with the same land cover/land use, and aggregate into a larger unit (FOI) (see details in section 4.3 of the Second discussion document on the introduction of monitoring to substitute OTSC).
    b. Identify and eliminate parcels
        i. either irrelevant to the conclusion on the payment at holding level
        ii. or belonging to a holding that is exempted from a given scheme e.g. as shown in the crop diversification example in section 6.3.
    c. Assess whether the parcel can be checked through a multi-annual procedure (e.g. permanent crops and permanent grasslands) and process through the LPIS update cycle.
3. Analyse how many parcels will be eliminated by applying the financial thresholds (50Eur and 250Eur) at the holding level (see details in section 3.2 of the Second discussion document on the introduction of monitoring to substitute OTSC).

For the remaining small parcels, alternative check methods should be prepared, e.g.:

- Feasibility studies for the use of HHR data depending on markers and parcel geometry (size/shape) could be performed to procure such data.
- Targeted input from the farmer (e.g. geotagged photos or seed labels) should be carefully set up to timely provide the required check data. This requires careful design of the information request timeline and communication channels.

At the end of this sifting process, one should be able to estimate the remaining number of small parcels, that would, in worst cases, need a check in the field. If the estimated number of small parcels that could require a field visit turns up to be substantially higher than the average number of parcels checked in field during On-The-Spot Checks, the scheme concerned should probably not be a priority to start monitoring.

7 Final remarks

The present technical guidance focusses on the main points that EU MS administration should assess and address in the preparatory phase toward implementation of monitoring as a substitute of the OTSC. These points concern (1) the pre-requisites that ensure the correctness of the "eligible area" component (LPIS, GSAA) and (2) the specificities of the agricultural landscape with respect to parcels size, agronomic conditions and related region-specific farming activities.

The document lists the key methods and tools for assessing the readiness of the LPIS/GSAA systems for the implementation of checks by monitoring. It further gives certain guidelines with respect to the use of novel technologies, such as machine learning, to evaluate the capabilities of the automated systems to discriminate the crop/land use types at country/region level.

It provides a real case computation in the context of the monitoring workflow and interpretes the achieved results and related accuracies. A draft methodology for impact assessment of the small parcels on the checks by monitoring is illustrated on the crop diversification example.

Acknowledging raised concerns on the Sentinel based checks by monitoring, this document guides the EU MS Administration towards addressing the possible bottlenecks, through the implementation of sound and pragmatic solutions.

8 References

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9 List of abbreviations and definitions

AL	Arable land
ANC	Area with natural constraints
ANN	Artificial neural network
AP	Agricultural parcel
BPS	Basic payment scheme
CAP	Common Agricultural Policy
CD	Crop diversification
EFA	Ecological focus area
ESPG	Environmentally Sensitive Permanent Grassland
FOI	Feature of interest
GEE	Google Earth Engine
GSAA	Geospatial aid application
IACS	Integrated Administration and Control System
IXIT	Implementation extra information for testing
IW	Interferometric Wide mode
LPIS	Land Parcel Identification System
LPIS QA	LPIS Quality Assurance
MTS	Model Test Suite
NDVI	Normalised difference vegetation index
NID	Neural Interpretation Diagram
OA	Overall accuracy
OTSC	On the spot check
PC	Permanent crop
PG	Permanent grassland
RP	Reference parcel
SFS	Small farmer scheme
TAL	Total arable land

TEA	Total eligible area
VCS	Voluntary couple scheme
WCS	Worse case scenario
YFS	Young farmer scheme

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