



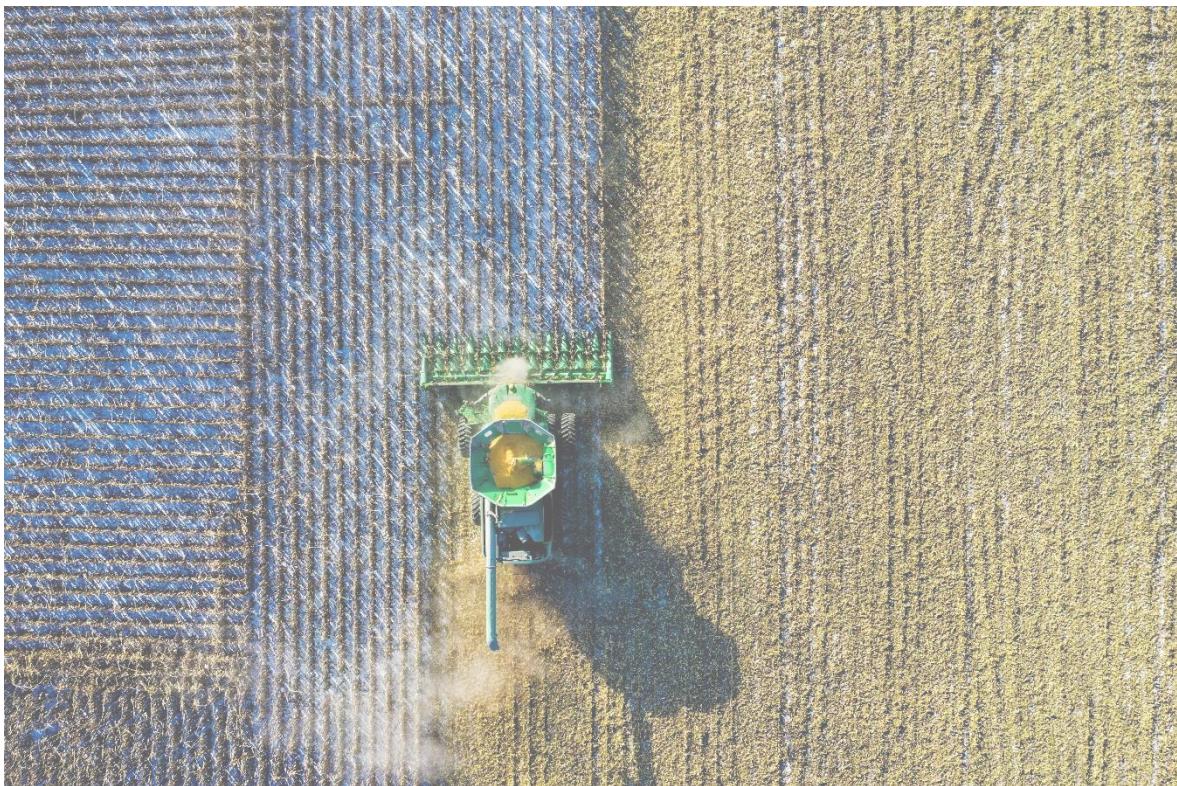
PROGRAMME OF
THE EUROPEAN UNION



Copernicus Land Monitoring Service – High Resolution Layer Vegetated Land Cover Characteristics

SPECIFIC CONTRACT NO 3506/R0-COPERNCA/EEA.60009
IMPLEMENTING FRAMEWORK SERVICE CONTRACT NO.
EEA/DIS/R0/21/013

D1.3 FEASIBILITY STUDY ON ADDING WINTER/SPRING CEREALS DISTINCTION TO THE CROPPING PATTERNS





Land Monitoring Service

Date: 2025-03-31

Doc. Version : 1.1

Content ID: D1.3 HRL winter/spring

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1 Executive Summary

Copernicus is the European Union's Earth Observation Programme. It offers information services based on satellite Earth observation and in situ (non-space) data. These information services are freely and openly accessible to its users through six thematic Copernicus services (Atmosphere Monitoring, Marine Environment Monitoring, Land Monitoring, Climate Change, Emergency Management and Security).

The **Copernicus Land Monitoring Service (CLMS)** provides geographical information on land cover and its changes, land use, vegetation state, water cycle and earth surface energy variables to a broad range of users in Europe and across the world in the field of environmental terrestrial applications.

CLMS is jointly implemented by the **European Environment Agency (EEA)** and the European Commission's **DG Joint Research Centre (JRC)**.

The **High-Resolution Layer (HRL)** vegetated land cover characteristics are a set of harmonised yearly maps dedicated to the thematic themes **Tree Cover & Forests**, **Grasslands** and **Croplands**. Those include a rich suite of raster products mapping the yearly status of those land cover types at a spatial resolution of 10 meters and change layers at 3-yearly interval and 20-meter resolution. HRL vegetated land cover characteristics extends the time-series of the existing HRL's Tree Cover & Forests and Grasslands and complements the CLMS portfolio with new layer dedicated to the mapping of crop types and agricultural practices such as mowing, harvest and cover crops.



The implemented **Crop Type (CTY)** distinguishes several types of cereals including Wheat, Barley and a class for Other Cereals but currently does not provide a distinction of strains into Winter or Spring cereals. This document provides result of a study which was conducted to investigate whether such a distinction could be implemented in future productions and / or updates of the HRL Croplands products.

2 Background of the document

2.1 Scope

This report presents a feasibility study on the integration of the HRL Crop Type (CTY) and Cropping Patterns products to differentiate cereal classes in the HRL CTY layer into winter and spring variants through an additional post-processing step. The motivation for this study stems from the need for Pan-European information on winter and spring cereals distribution, which is currently lacking in the HRL CTY product. The report details the proposed methodology, results, and provides recommendations and limitations regarding the feasibility and accuracy of this classification approach.

2.2 Content and structure

In more detail, the document is structured as follows:

- Chapter 3 outlines the selected methodology, detailing the approach used for distinguishing winter and spring cereals.
- Chapter 4 presents the validation results, evaluating the performance and accuracy of the proposed methodology.
- Chapter 5 discusses key recommendations and identifies limitations.
- Chapter 6 includes supplemental materials, offering additional data and supporting information.

3 Methodology

In this feasibility study, we adopted a post-processing approach to distinguish winter from spring cereals instead of separating winter/spring cereals in the CTY classification stage. This is mainly due to the underrepresentation of spring cereals, making it difficult to use as a separate class in CTY classification. Instead, we utilize the classification from the HRL CTY map and further subdivide the categories "1110-Barley," "1120-Wheat," and "1150-Other cereals" into winter and spring variants (Table 1)- resulting in a hierarchical approach.

Table 1: Crop types used to check the feasibility of splitting between winter/spring cereals.

CTY Code	Land Cover	Crop Group	Crop type	Season		
1110	Arable Crops	Cereals	Wheat	Winter Wheat		
				Spring Wheat		
1120			Barley	Winter Barley		
				Spring Barley		
1150			Other cereals	Other Winter Cereals		
				Other Spring Cereals		



To do this, we opted for a shallow decision tree approach. To do so, we used the *DecisionTreeClassifier* class from the *sklearn.tree* Python package. All default values were used, and the tree depth was set to 5. The main reasoning behind this value is to make the splitting structure as transparent as possible, allowing for easy interpretation and linking existing cropping systems to final decision tree nodes. A shallow decision tree ensures that the decision rules remain simple and interpretable, which is crucial in this feasibility study as it helps validate the approach against expert knowledge. Additionally, this approach mimics an expert-based ruling system while being computationally lightweight.

However, there is an inherent trade-off between interpretability and accuracy when choosing the depth of a decision tree. While increasing tree depth may improve classification accuracy by capturing more complex patterns, it also leads to more intricate decision rules, making it harder to understand and validate the model's behaviour. A deeper tree also risks overfitting to the training data, reducing its generalizability. Conversely, a shallow decision tree provides clear, easily interpretable rules but may sacrifice some accuracy by failing to capture finer distinctions.

To assess this trade-off, we will analyse the accuracy metrics (see 3.3.1) for different tree depths to determine the marginal gains of adding more layers. This analysis, detailed in the [Supplementary Materials](#), helps evaluate how much additional complexity is necessary to achieve an acceptable balance between accuracy and interpretability. Furthermore, using a shallow decision tree helps in understanding the complexity of algorithms required to construct a credible split, ensuring that the method remains adaptable for future refinements. We produced a separate decision tree per cereal type, and depending on a pixel's HRL CTY classification, a different classifier was used.

3.1 In-Situ Data

To train (80%) and test (20%) the approach, we used in-situ data from the GeoSpatial Aid Application (GSAA) dataset (Table 2). GSAA data is comprised of georeferenced agricultural parcels. The parcels are declared by farmers and represented as polygons. The same data was used to train the crop type mapping. From each field polygon, the centroid point was used in further analysis.

Table 2: GSAA training data and years used in the training/testing of the winter/spring cereals split. Number of samples per crop in each dataset is provided by [Supplementary Table 1](#).

GSAA training locations crop type model					
Country Code	Country	2018	2019	2020	2021
AT	Austria	x	x	x	
BE	Belgium	x	x	x	x
DE	Germany				x
DK	Denmark		x		



EE	Estonia				x
FI	Finland			x	x
FR	France		x	x	
LV	Latvia	x			x
SE	Sweden				x
SI	Slovenia				x
SK	Slovakia				x

3.2 Features

As input features to the model, we used the HRL Cropping Pattern products that were already produced within the HRL-VLCC scope. From each point, we extracted information on Main Season Emergence (CPMCE), Main Season Duration (CPMCD), Main Season Harvest (CPMCH), and Locational information (Northing + Easting) derived from geographical coordinates. Data was extracted for the year in which each in-situ data point was taken.

3.3 Validation

3.3.1 Quantitative

The splitting algorithm was validated by using a randomly selected subset of 20% of the input data to construct confusion matrices and derive accuracy metrics from them. The training and testing subset were selected randomly per crop using the default *train_test_split* function from the sklearn python package- so without any stratification in terms of region or winter/spring class. Table 3 shows that both training and testing samples are clearly unbalanced with more winter points present than spring for all crops. This will likely result in lower accuracies for spring cereals than for winter cereals, but follows a probabilistic design and should, in principle, be a representation of the situation on the ground.

Table 3: Number of samples per crop type in training/testing subsets.

	Training Samples		Testing Samples	
	Winter	Spring	Winter	Spring
Wheat	2.309.442	166.145	518.147	28.372
Barley	726.681	426.736	159.027	81.995
Other Cereals	522.526	124.791	93.127	11.514



In this feasibility study, we used Overall Accuracy (OA) for general performance and Producers Accuracy (PA), Users' Accuracy (UA), and F1-score as class-dependent accuracy metrics (Eqs. 1-5).

		Predicted		
		Winter	Spring	
True		Winter	i_w, j_w	i_w, j_s
		Spring	i_s, j_w	i_s, j_s
		$\sum j_w$		$\sum j_s$
				$\sum i = \sum j$

Overall Accuracy

$$OA = \frac{\sum_x i_x, j_x}{\sum i} \quad \text{with } x = \{w, s\} \quad (1)$$

Producers Accuracy

$$PA_x = \frac{i_x, j_x}{\sum j_x} \quad \text{with } x = \{w, s\} \quad (2)$$

Users Accuracy

$$UA_x = \frac{i_x, j_x}{\sum i_x} \quad \text{with } x = \{w, s\} \quad (3)$$

F1-score

$$F1_x = 2 * \frac{PA_x \times UA_x}{PA_x + UA_x} \quad (4)$$

So that when combining (2), (3), and (4):

$$F1_x = 2 * \frac{(i_x, j_x)}{\sum i_x + \sum j_x} \quad (5)$$

3.3.2 Qualitative

To qualitatively assess the feasibility of producing an accurate winter/spring split in wheat, barley, and "other cereals" - we have compared our results to known information on the split

between winter and spring cereals. In particular, the USDA cropping calendar shows detailed information for wheat and barley at the level of the European Union (Figure 1). They estimate that 52% of barley production is by winter barley, and that the majority of wheat is winter wheat (96%).

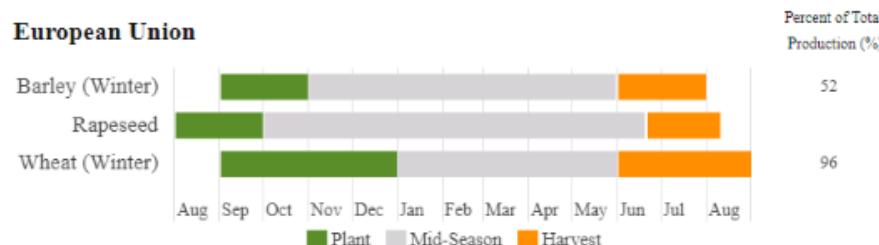


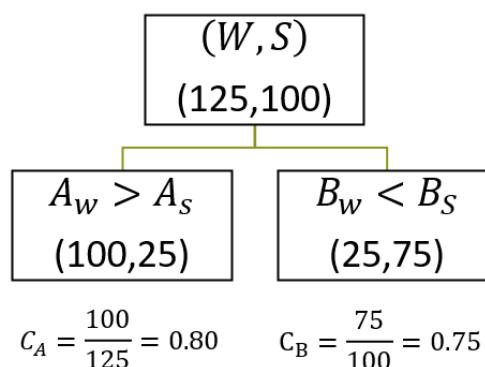
Figure 1: USDA Cropping calendar indicating the percentage of total production for winter and barley and winter wheat [1].

3.4 Confidence

To calculate the confidence of the classification, we integrate the confidence layers generated for emergence (CPMCECL), harvest (CPMCHCL), and duration (CPMCDCL) with the confidence provided by the decision-tree classifier itself.

During its training phase, the decision-tree classifier partitions data points into leaf nodes by iteratively identifying optimal splits based on input variable thresholds. This results in a defined number of points in each leaf node. The leaf nodes are classified as “winter” or “spring” based on majority voting. Consequently, each node has an intrinsic uncertainty that can be used to compute the confidence of its assigned class.

For example, in Figure 2, nodes A and B classify points as “winter” (w) or “spring” (s). Based on majority voting, node A is assigned “winter” and node B is assigned “spring”. The confidence (C) for each node is calculated as the proportion of correctly classified points. Since the training dataset is inherently imbalanced (see Table 3), it is also important to verify whether there are substantial differences in confidence between final “winter” and “spring” nodes.



$$C_A = \frac{100}{125} = 0.80 \quad C_B = \frac{75}{100} = 0.75$$

Figure 2: Schematic (simplified) representation of the decision-tree classification. A and B represent nodes classifying the points into winter (w) or spring (s). Following majority voting, the leaf nodes are assigned the class with the most data points, and confidence (C) can be calculated for each node.

As outlined in the CLMS Vegetated HRL ATBD [2], the confidence layers for emergence, harvest, and duration are quantified as the average deviation between the median estimate (q50) and the 10th (q10) and 90th (q90) percentiles (Figure 3, Eqs. 6-8).

$$fAPAR_{uncertainty\ q10} = fAPAR_{event\ q50} - fAPAR_{event\ q10} \quad (6)$$

$$fAPAR_{uncertainty\ q90} = fAPAR_{event\ q50} - fAPAR_{event\ q90} \quad (7)$$

$$\begin{aligned} days\ uncertainty_{event} \\ &= abs\left(\frac{fAPAR_{uncertainty\ q10}}{slope\ fAPAR_{event\ q50}}\right) \\ &\quad + abs\left(\frac{fAPAR_{uncertainty\ q90}}{slope\ fAPAR_{event\ q50}}\right) \end{aligned} \quad (8)$$

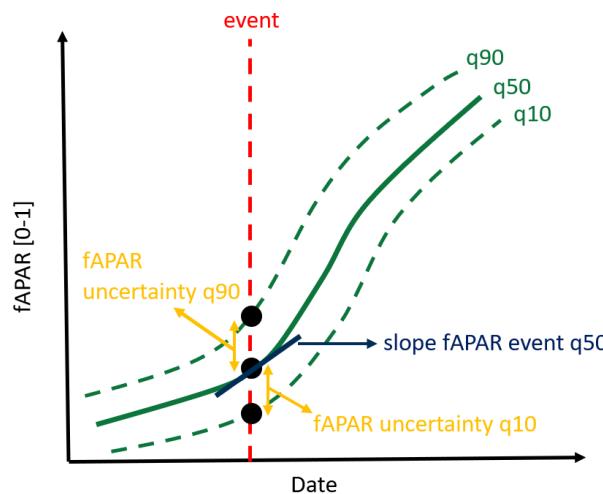


Figure 3: Schematic overview on the parameters used to calculate the uncertainty at an event date (i.e., emergence or harvest). Event date in this example is an emergence. Figure and Eqs. 6-8 sourced from ATBD [2].

To account for the impact of intrinsic uncertainties in the three confidence layers (emergence, harvest, duration) on the final classification uncertainty, we propose a combined approach. This involves running multiple classifications using the same decision-tree model, but with different combinations of q10, q50, and q90 as input values for each layer.

In this approach, we simulate the emergence, harvest, and duration layers by considering three different quantiles. Each quantile represents a different scenario – q10 for a lower-bound estimate, q50 for the median (which is also the provided value for CPMCE, CPMCH, and CPMCD), and q90 for an upper-bound estimate. By running the decision tree for each combination of these quantiles, we generate multiple classification outcomes- each linked to a certain probability of occurrence.

The weight of each model run is determined by the probability density of each combination of quantiles. For a normal distribution, the probability density function (PDF) is given by:

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \quad (9)$$

For quantiles q10, q50, and q90, the z-scores can be calculated by:



$$z(q) = \frac{x_q - \mu}{\sigma} \quad (10)$$

So that for a standard normal distribution ($\mu = 0$ and $\sigma = 1$):

$$z(q10) = -1.28, \quad z(q50) = 0, \quad z(q90) = 1.28$$

And the PDF values for these quantiles are:

$$f(q10) \approx 0.18, \quad f(q50) \approx 0.40 \quad f(q90) \approx 0.18$$

These values represent the relative likelihood of values clustering near these quantiles. Due to the symmetry of the standard normal distribution, q10 and q90 have identical PDF values.

The weights (W) for each model run (r) are calculated as the product of the PDFs of the corresponding quantiles used for emergence (q_E), harvest (q_H), and duration (q_D):

$$w_r = f(q_{E,R}) \times f(q_{H,R}) \times f(q_{D,R}) \quad (11)$$

The weights are normalized to ensure their sum equals 1:

$$W_r = \frac{w_r}{\sum_m^M w_m}, \quad \text{so that } \sum_r^R W_r = 1 \quad (12)$$

The symmetry of the standard normal distribution reduces the number of unique weights required for combinations of q10, q50, and q90. Table 4 provides the calculated weights for each combination.

Table 4: Number of different model runs and calculated weights for each combination of quantiles. For a detailed list of all combinations, see [Supplementary Table 5](#).

Combination	Number of Different Model Runs	w_r	W_r
0 x q50	8	0.005	0.013
1 x q50	12	0.012	0.029
2 x q50	6	0.028	0.066
3 x q50	1	0.063	0.151
\sum	27	0.420	1.000

Using these weights, the confidence for the final classification is computed as a weighted average of the confidences from all model runs, per pixel and per crop type.

$$C_x = \sum_r^R W_r C_{r,x} \quad (13)$$

As this is done posterior to the CTY classification, it does not explicitly consider CTY confidence.



$$C_x = \sum_r^R W_r C_{r,x}$$

4 Results

4.1 Wheat

All leaf nodes from the Wheat decision tree classifier are the result of a combination of both locational arguments and input variables from the cropping patterns products (Figure 4). All input variables are represented in the decision tree classifier and most leaf nodes have a high confidence (more info in [Supplementary Material](#)). The independent validation also shows that the classifier results in quite accurate results (Table 5). This is true for the overall classification (OA = 0.98), and for class-specific metrics. Accuracy of Spring Wheat is visibly lower than for Winter Wheat- which is likely caused by the imbalance in training points between winter/spring wheat. Still, the accuracy of spring wheat (minority class) is quite high, indicating that it might not be necessary to account for this imbalance in further developments. For Spring Wheat, UA values are higher than PA values, which might imply an underestimation. This should be considered when the area of spring wheat is calculated.

Table 5: Accuracy Metrics for the Wheat classifier. Values were calculated using the 20% subset. Confusion Matrix can be found in [Supplementary Material](#).

Wheat Accuracy			
	PA	UA	F1
Spring Wheat	0.77	0.88	0.82
Winter Wheat	0.99	0.99	0.99

Overall Accuracy (OA) = 0.98

Wheat

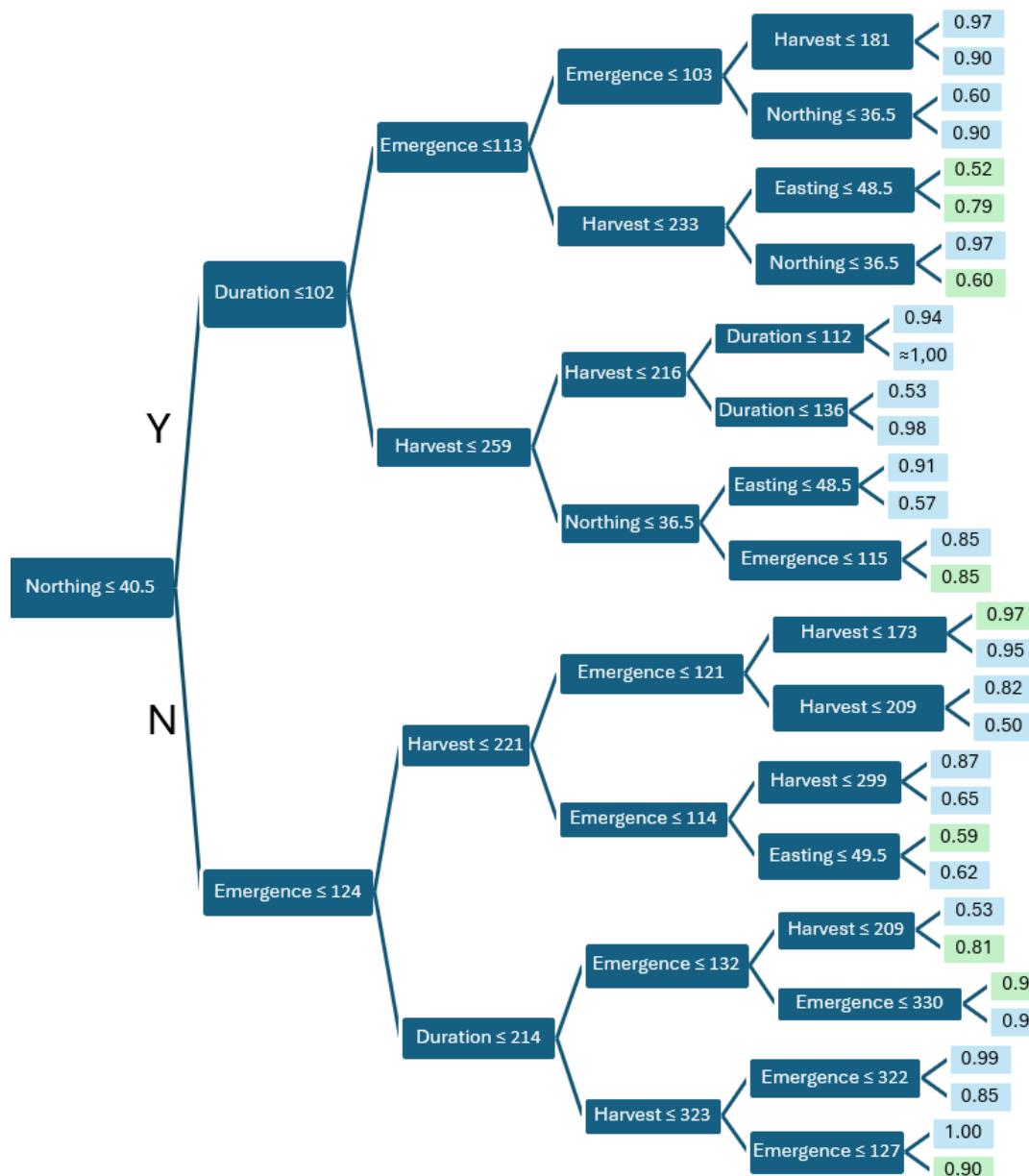


Figure 4: Decision Tree Classifier for Wheat, assigned classes are indicated by blue for winter wheat, and by green for spring wheat. Values indicate the confidence of the assigned class. Emergence and Harvest are given in DOY, duration in number of days, and Northing/Easting are provided in coordinates following LAEA projection (EPSG 3035). A geographical delineation of these thresholds is provided by [Supplementary Figure 1](#).

4.2 Barley

For Barley, all nodes are the result of a combination of both locational arguments and crop pattern input variables (Figure 5). Compared to wheat, more nodes indicate a spring season, which is also reflected by the larger relative share of spring points in the training sample. Consequently, the difference in accuracy values between spring and winter barley is less apparent (Table 6). Overall Accuracy is high ($OA = 0.93$) and class-specific accuracies are also high. As UA for Spring Barley is slightly higher than PA and vice-versa for Winter Barley, there is likely to be a slight underestimation of spring barley and overestimation of winter barley. This should be considered when deriving area estimates. Information on the leaf nodes confidence for barley can be consulted in the [Supplementary Material](#).

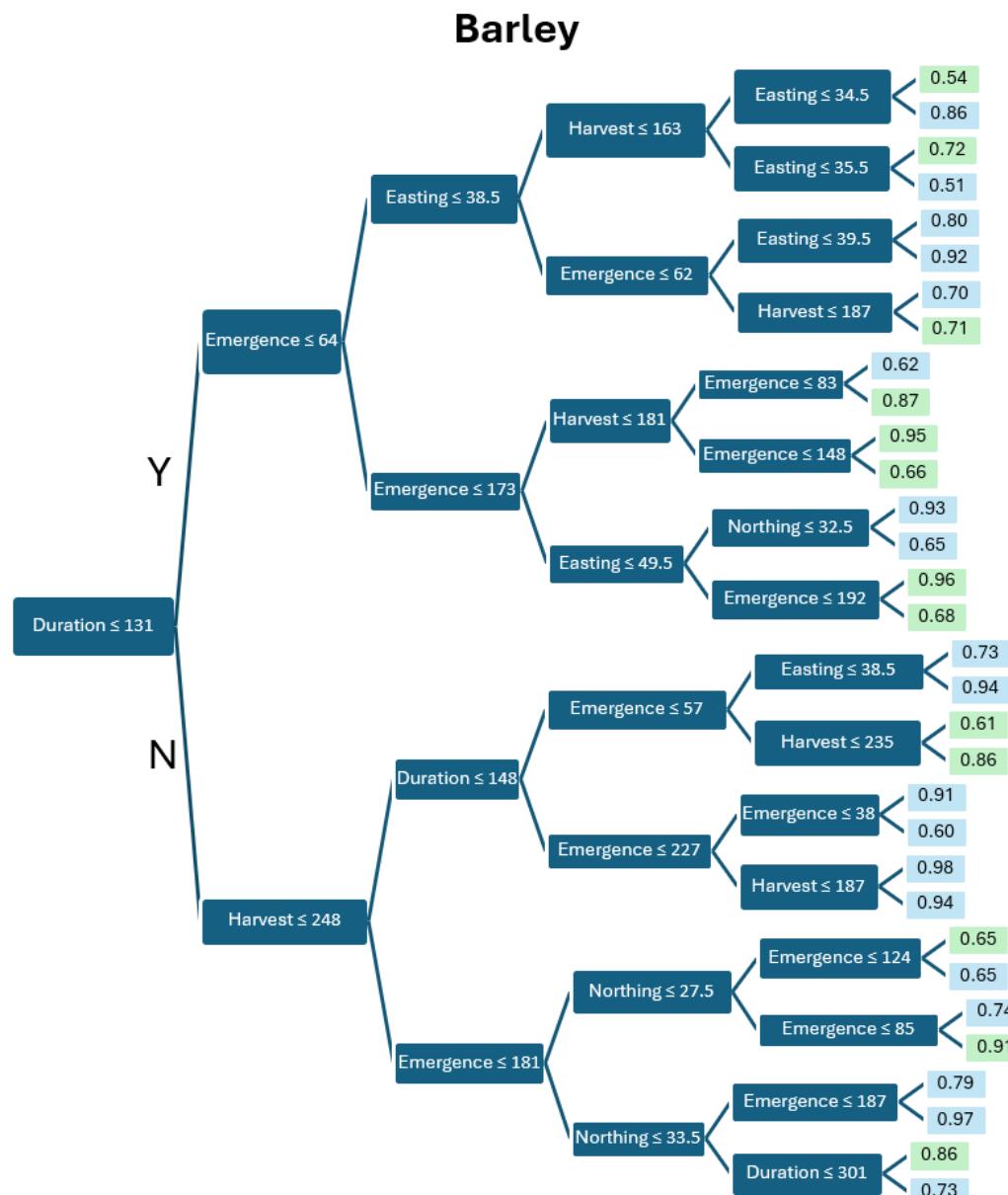


Figure 5: Decision Tree Classifier for Barley, assigned classes are indicated by blue for winter barley, and by green for spring barley. Values indicate the confidence of the assigned class. Emergence and Harvest are given in DOY, duration in number of days, and Northing/Easting are provided in coordinates following LAEA projection (EPSG 3035). A geographical delineation of these thresholds is provided by [Supplementary Figure 2](#).



Table 6: Accuracy Metrics for the Barley classifier. Values were calculated using the 20% subset. Confusion matrix can be found in [Supplementary Material](#).

Barley Accuracy			
	PA	UA	F1
Spring Barley	0.89	0.93	0.91
Winter Barley	0.96	0.94	0.95

Overall Accuracy (OA) = 0.93

4.3 Other Cereals

For other cereals, the decision tree classifier looks strikingly different than for wheat or barley (Figure 6). While the classifiers for wheat and barley included a combination of both location and cropping pattern in almost every node, the classifier for “other cereals” almost exclusively uses cropping pattern variables and only one locational argument. Looking to the accuracy of the classification, this does not mean that there is a sharp drop in accuracy as overall accuracy is high (OA = 0.97), and class-specific accuracy values are also high (Table 7).

It is assumed that this is caused by the fact that the “Other Cereals” class is a heterogeneous class of different cereal types. The “other cereals” class includes a range of cereals, each of which have different growing conditions at different locations, making it difficult for the classifier. Information on the leaf nodes confidence for other cereals can be consulted in the [Supplementary Material](#).

Other Cereals

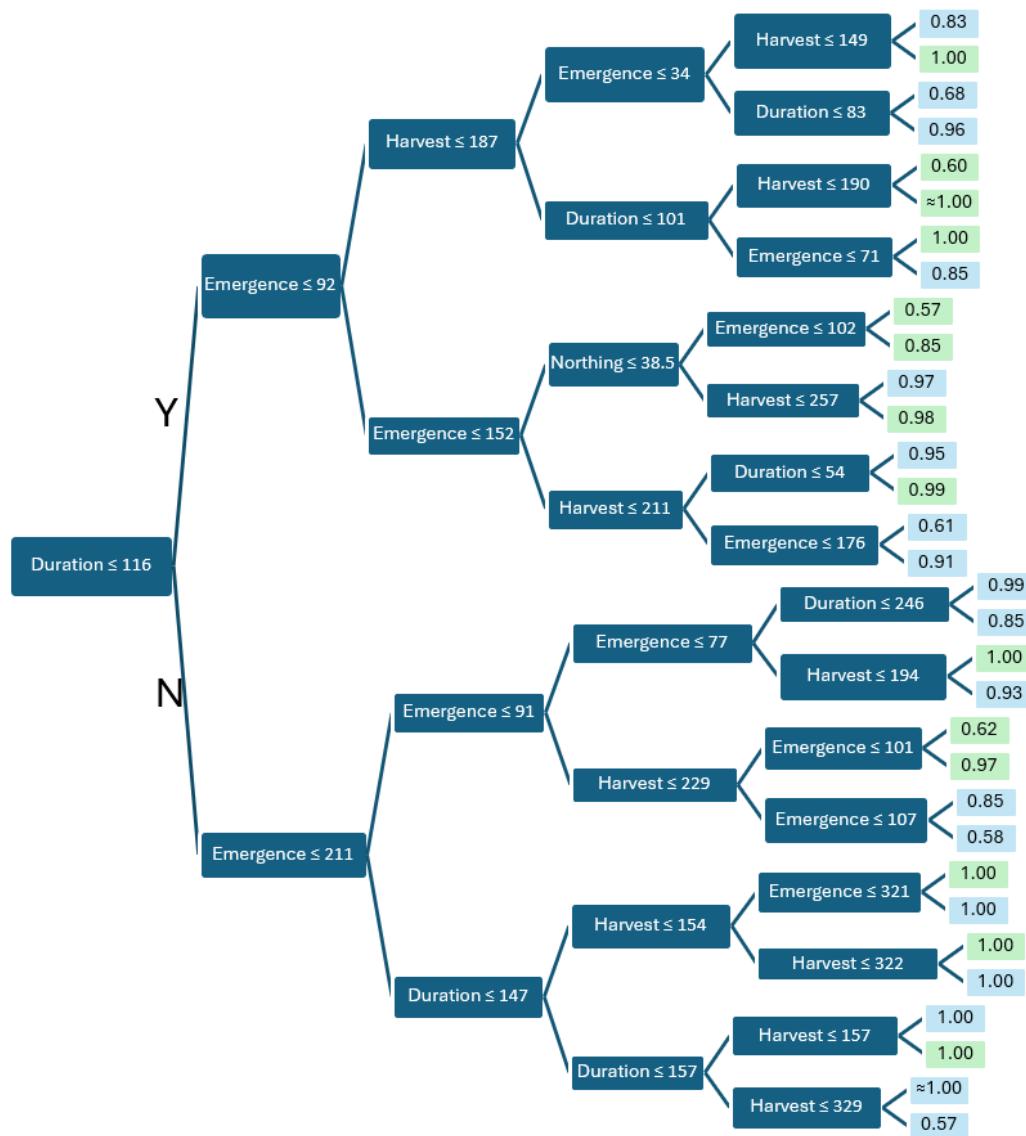


Figure 6: Decision Tree Classifier for Other Cereals, assigned classes are indicated by blue for other winter cereals, and by green for other spring cereals. Values indicate the confidence of the assigned class. Emergence and Harvest are given in DOY, duration in number of days, and Northing/Easting are provided in coordinates following LAEA projection (EPSG 3035). A geographical delineation of these thresholds is provided by [Supplementary Figure 3](#).

Table 7: Accuracy Metrics for the Other Cereals classifier. Values were calculated using the 20% subset. Confusion Matrix can be found in [Supplementary Material](#).

Other Cereals Accuracy

	PA	UA	F1
Other Spring Cereals	0.87	0.82	0.84
Other Winter Cereals	0.98	0.98	0.98

Overall Accuracy (OA) = 0.97

4.4 Qualitative Validation

Results from the “triple q50 run” (Table 4) show consistent spatial patterns over time (Figure 7). We used this run for qualitative validation as this is the run that uses all values provided by the cropping patterns layers as produced for HRL. It is expected that the results of this run will be very similar to the final outcome and allows us to make a qualitative comparison without having to run the entire confidence scheme.

For *barley*, spring barley is more observed in Northern and Eastern Europe, while the Southern and Western parts of Europe are more dominated by winter barley. Spain has a higher share of spring barley than other Southern European countries. The estimated share of winter barley increases between 2017-2021 from 0.56 to 0.67. Compared to the production share estimated by the USDA cropping calendar (Figure 1) [1], the estimates made here are slightly higher—particularly at later years. It is unclear whether this is a bias or because USDA indicates share of production, while Table 8 provides an indication of area.

For *other cereals*, other winter cereals seem to dominate according to our classification. Order of magnitude is consistent over time (ranging between 0.78-0.86). Slightly higher shares of other spring cereals are predicted over Central Europe (e.g., Poland) or Turkey.

For *wheat*, the picture is even more leaning towards winter wheat. Our classification estimates that between 95-98% of the wheat extent is cultivated during winter. Exceptions are predicted in Scandinavia (notably Finland). The order of magnitude of our predictions is very much in line with those of the USDA cropping calendar for production.

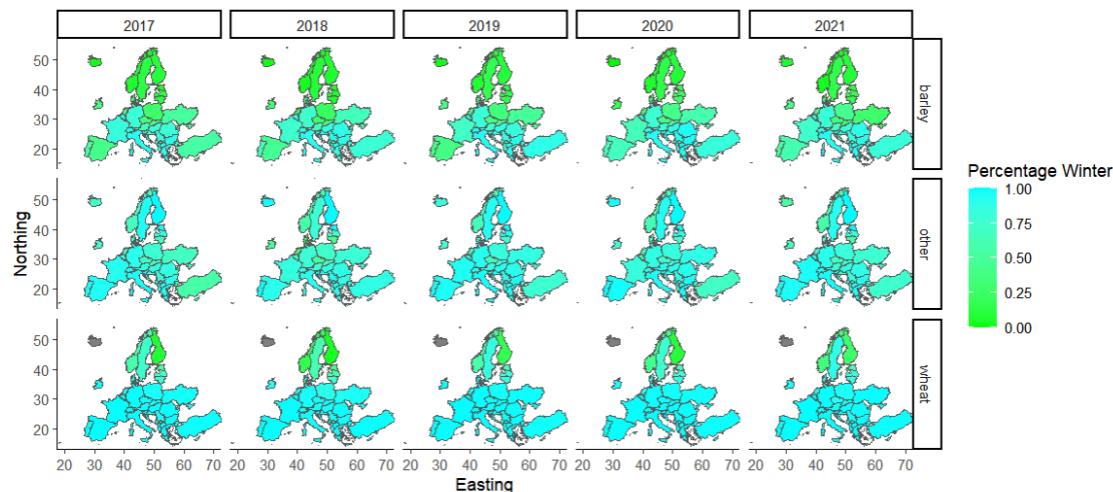


Figure 7: Share of winter cereals per crop (rows) and per year (columns). Percentages are calculated by considering the results of the triple q50 run.

**Table 8: European share of winter cereals per crop (rows) and per year (columns). Shares are calculated by considering the results of the triple q50 run.**

	Share of Winter Cereals				
	2017	2018	2019	2020	2021
Barley	0.56	0.60	0.61	0.66	0.67
Other	0.83	0.78	0.86	0.85	0.86
Wheat	0.97	0.95	0.98	0.97	0.97

5 Recommendations

5.1 Feasibility

Based on the above feasibility study, we believe it is feasible to produce a product that splits winter from spring cereals in a credible manner at a European scale. The amount of in-situ data points on spring cereals is too limited to be included in training of the CTY model, but the proposed approach would make it possible in post-processing.

In a similar fashion to other cropping pattern data products, the calculation of a confidence layer is also feasible. As the proposed algorithm builds on information from the CTY and cropping pattern detection algorithms, it is well aligned with existing products.

The proposed classifier is a decision-tree classifier. This is far from the most performative classifier but has the advantage of being understandable and transparent. In this way, the processing is not a black box as would be the case for other, more performative algorithms. This way, it created a ruling system by determining optimal thresholds rather than being expert-based. Even though the algorithm is not too complex, it achieves high accuracy.

Figure 8Figure 9 present the results of the proposed approach for a selected region within a single LAEA tile in Spain, along with the corresponding confidence levels. We propose integrating the winter and spring cereals classification, along with associated confidence levels, as an additional layer within the HRL Croplands portfolio. This approach preserves the original HRL CTY layer without further subdivision.

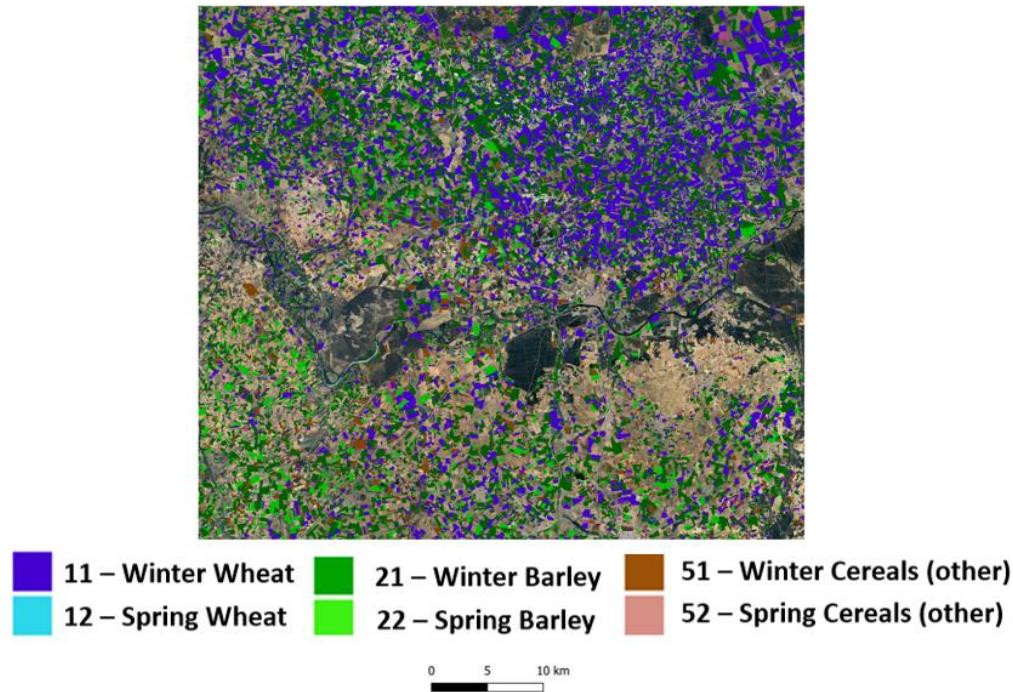


Figure 8: Example of a season cropping pattern layer. (Results are from the triple q50 run). Results are shown for a part of LAEA tile E30N21.

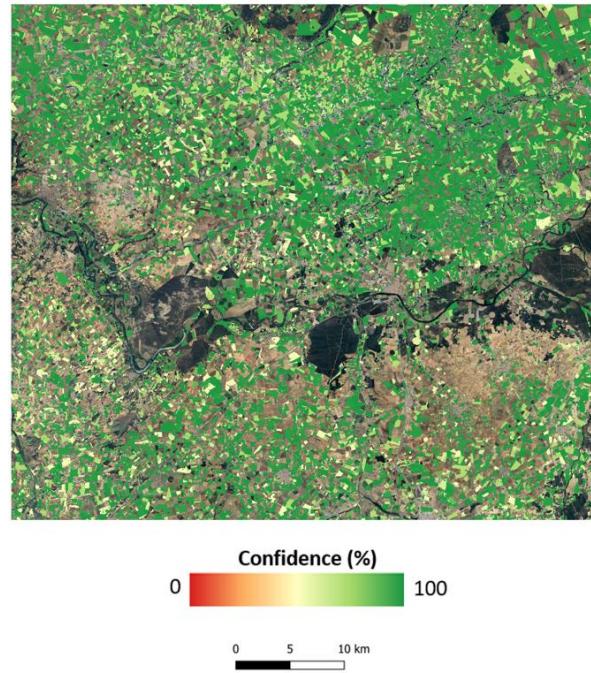


Figure 9: Example of a confidence layer for the season cropping pattern layer. Results are shown for a part of LAEA tile E30N21.



5.2 Limitations

- The models were trained and validated using the available information on winter/spring cereals existing within the LPIS/GSAA database. This means that the consecutive quantitative accuracy assessment also only includes data points from the countries that were included in the initial training (see Table 2). It is unclear whether the same accuracy can be achieved for countries/regions not included in the initial dataset. This is particularly true for Southern or Eastern European countries where reference data were virtually absent.
- Because of strong seasonal differences and vastly different crop management practices, overseas areas are not considered in this analysis.
- Since a separate classifier is developed for each crop type based on the initial crop type classification, the results are highly dependent on the accuracy, constraints, and limitations of the original classification, including factors such as the minimum mapping unit.
- Currently, the algorithm operates only for pixels with recorded emergence (CPMCE), harvest (CPMCH), and duration (CPMCD) values. However, some pixels are flagged due to high uncertainty or field boundary issues, resulting in cases where a crop type is assigned, but no additional cropping pattern information is available. Consequently, estimating the season (winter/spring) is not feasible for these pixels (more info in Cropping Patterns section in ATBD [1]). This limitation is consistent with other cropping pattern products, where similar flagging values could be applied.

6 References

- [1] United States Department of Agriculture, Foreign Agricultural Service. (n.d.). Crop Calendar – Europe. International Production Assessment Division (IPAD). Retrieved March 1, 2025, from https://ipad.fas.usda.gov/rssiws/al/crop_calendar/europe.aspx
- [2] CLMS Vegetated HRL ATBD (2024). HRL Algorithm Technical Basis Document.

7 Supplementary Materials

7.1 Detailed Samples

Supplementary Table 1: Number of samples per dataset.

Dataset	Wheat		Barley		Other Cereals		Total
	Winter	Spring	Winter	Spring	Winter	Spring	
AT-2018	138.828	2.847	52.989	30.733	69.661	21.593	316.651
AT-2019	132.366	2.213	55.991	23.832	71.823	20.354	306.579



AT- 2020	129.945	2.278	57.109	20.613	69.123	19.735	298.803
BE- 2018	29.734	384	8.465	669	370	379	40.001
BE- 2019	31.577	365	9.296	506	451	309	42.504
BE- 2020	28.978	471	8.779	937	433	384	39.982
BE- 2021	31.052	546	7.721	737	488	250	40.794
DE- 2021	146.827	2.665	78.683	12.317	85.624	10.421	336.537
DK- 2019	68.119	2.671	13.649	87.925	27.486	11.147	210.997
EE- 2021	13.726	5.525	2.245	10.737	533	195	32.961
FI- 2020	6.436	52.201	148	0	5.762	1.381	65.928
FI- 2021	14.111	46.470	330	0	5.646	1.104	67.661
FR- 2019	1.006.541	6.616	290.910	115.953	139.940	19.366	1.579.326
FR- 2020	846.941	16.669	257.208	166.960	121.496	26.277	1.435.101
LV- 2019	44.329	22.422	611	16.312	1.315	212	85.201
LV- 2021	45.767	19.298	1.409	11.770	1.132	117	79.493
SE- 2021	56.888	9.382	3.755	0	6.701	567	77.293



SI- 2021	27.901	1.228	28.599	1.924	8.342	1.820	69.814
SK- 2021	24.211	4.028	4.017	10.600	21	0	42.877
Total	2.823.827	198.279	881.914	512.525	616.347	135.611	5.168.503

7.2 Confusion Matrices

7.2.1 Wheat

Supplementary Table 2: Confusion Matrix with absolute numbers for the Wheat classifier.

Wheat		Observed		
		Spring	Winter	\sum
Predicted	Spring	24.870	7.264	32.134
	Winter	3.502	510.883	514.385
	\sum	28.372	518.147	546.519

7.2.2 Barley

Supplementary Table 3: Confusion Matrix with absolute numbers for the Barley classifier.

Barley		Observed		
		Spring	Winter	\sum
Predicted	Spring	76.049	9.740	85.789
	Winter	5.946	149.287	155.233
	\sum	81.995	159.027	241.022



7.2.3 Other Cereals

Supplementary Table 4: Confusion Matrix with absolute numbers for the Other Cereals classifier.

Other Cereals		Observed		
		Spring	Winter	\sum
Predicted	Spring	9.392	1.428	10.820
	Winter	2.122	91.699	93.821
	\sum	11.514	93.127	104.641



7.3

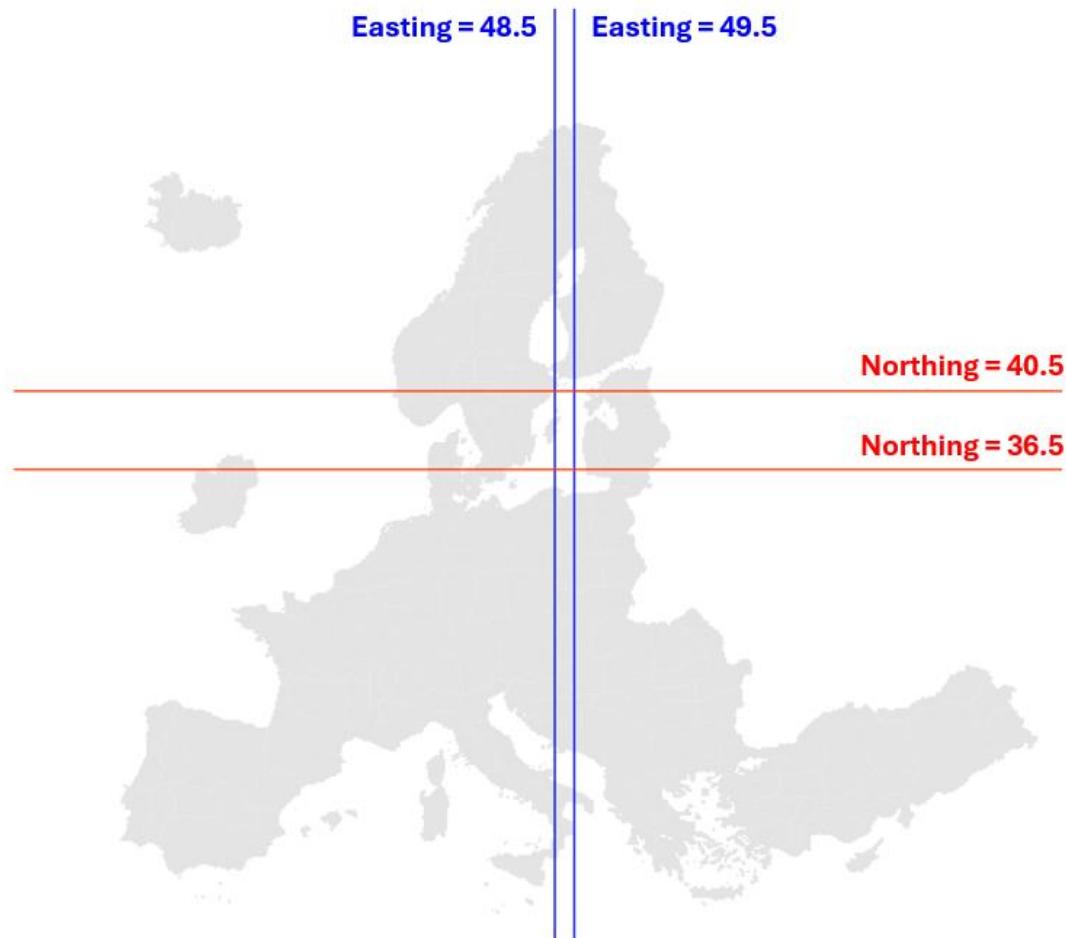
7.4 Model Combinations

Supplementary Table 5: Derived weights for each combination of emergence, duration, and harvest quantiles. Note that many combinations have equal weights because of similar probability of occurrence.

Emergence	Duration	Harvest	w_r	W_r
Q10	Q10	Q10	0.005	0.013
Q10	Q10	Q50	0.012	0.029
Q10	Q10	Q90	0.005	0.013
Q10	Q50	Q10	0.012	0.029
Q10	Q50	Q50	0.028	0.066
Q10	Q50	Q90	0.012	0.029
Q10	Q90	Q10	0.005	0.013
Q10	Q90	Q50	0.012	0.029
Q10	Q90	Q90	0.005	0.013
Q50	Q10	Q10	0.012	0.029
Q50	Q10	Q50	0.028	0.066
Q50	Q10	Q90	0.012	0.029
Q50	Q50	Q10	0.028	0.066
Q50	Q50	Q50	0.063	0.151
Q50	Q50	Q90	0.028	0.066
Q50	Q90	Q10	0.012	0.029
Q50	Q90	Q50	0.028	0.066
Q50	Q90	Q90	0.012	0.029
Q90	Q10	Q10	0.005	0.013
Q90	Q10	Q50	0.012	0.029
Q90	Q10	Q90	0.005	0.013
Q90	Q50	Q10	0.012	0.029
Q90	Q50	Q50	0.028	0.066
Q90	Q50	Q90	0.012	0.029
Q90	Q90	Q10	0.005	0.013
Q90	Q90	Q50	0.012	0.029
Q90	Q90	Q90	0.005	0.013

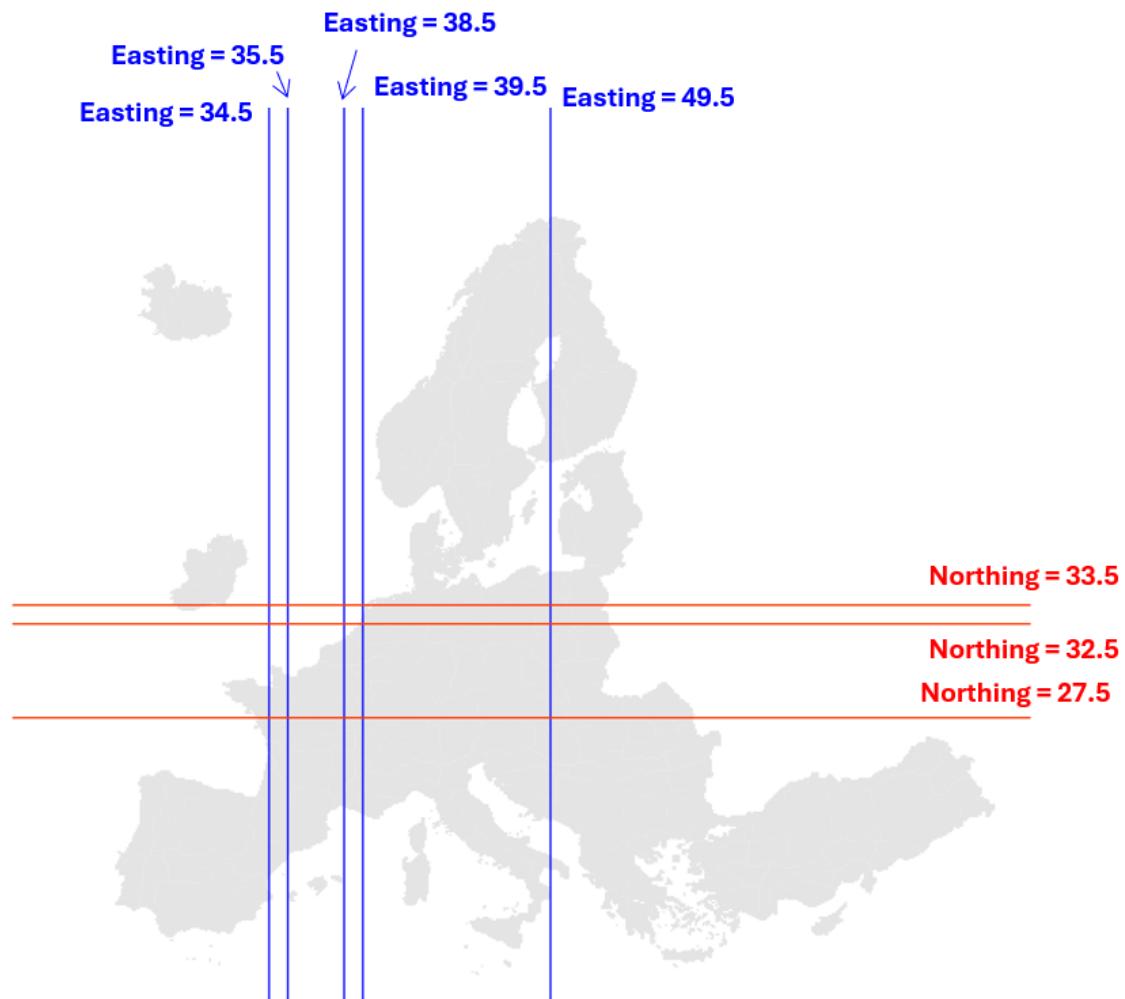
7.5 Location Thresholds

7.5.1 Wheat



Supplementary Figure 1: Map showing the thresholds defined by the decision tree classifier for Wheat. Values represent coordinates in the LAEA coordinate reference system (EPSG:3035).

7.5.2 Barley



Supplementary Figure 2: Map showing the thresholds defined by the decision tree classifier for Barley. Values represent coordinates in the LAEA coordinate reference system (EPSG:3035).

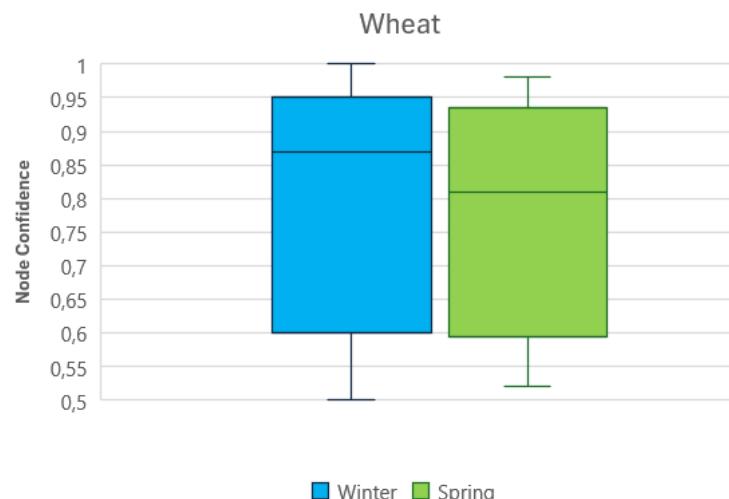
7.5.3 Other Cereals



Supplementary Figure 3: Map showing the thresholds defined by the decision tree classifier for Other Cereals. Values represent coordinates in the LAEA coordinate reference system (EPSG:3035).

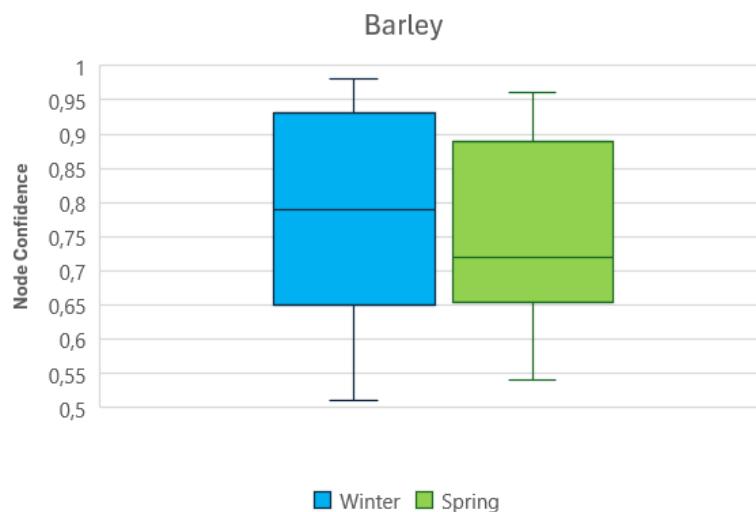
7.6 Node Confidence

7.6.1 Wheat



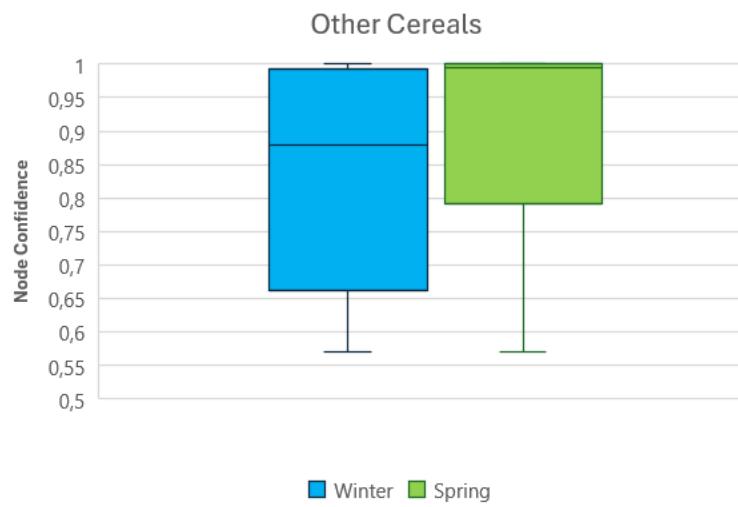
Supplementary Figure 4: Boxplots indicating the node confidence of winter and spring wheat.

7.6.2 Barley



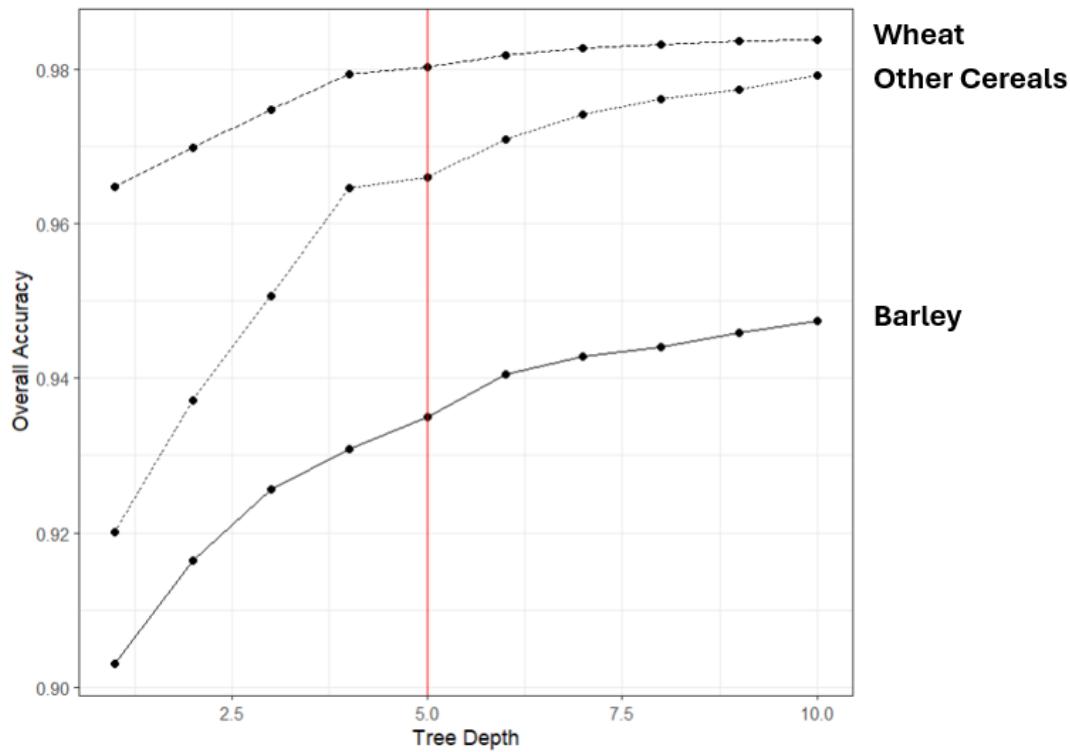
Supplementary Figure 5: Boxplots indicating the node confidence of winter and spring barley

7.6.3 Other Cereals

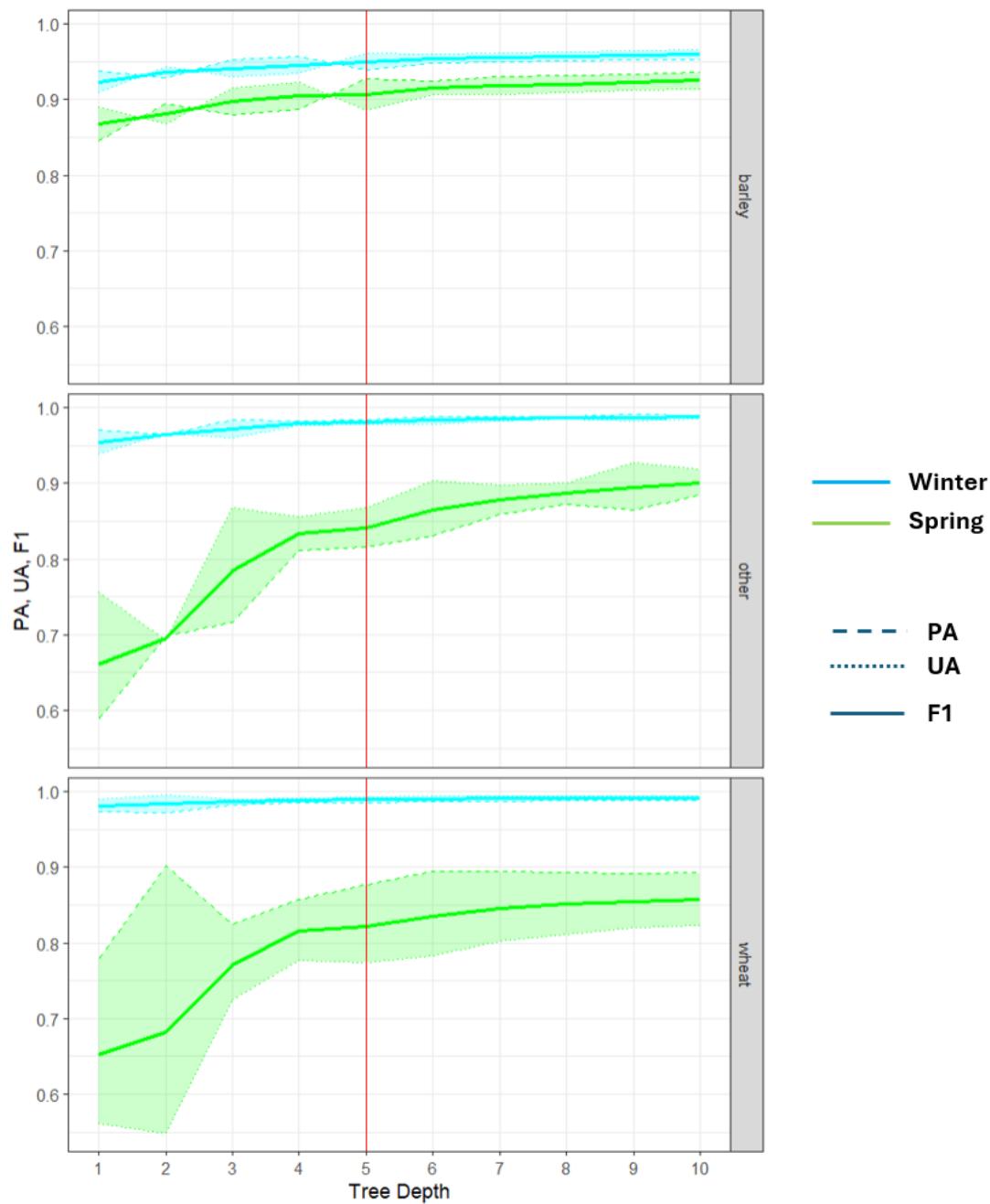


Supplementary Figure 6: Boxplots indicating the node confidence of other winter and spring cereals.

7.7 Tree Depth Analysis



Supplementary Figure 7: Overall Accuracy gained for different tree depths. Values were calculated using the same testing subset. Red line indicates the final tree depth of 5.



Supplementary Figure 8: Class-Specific accuracy values gained for different tree depths.
Values were calculated with the same testing subset. Red line indicates the final tree depth of 5.