

A framework for mapping conservation agricultural fields using optical and radar time series imagery

Yue Zhou^{a,*}, Manon S. Ferdinand^a, Jelle van Wesemael^b, Klara Dvorakova^a,
Philippe V. Baret^a, Kristof Van Oost^a, Bas van Wesemael^a

^a Earth and Life Institute, Université catholique de Louvain, 1348 Louvain-la-Neuve, Belgium

^b Soil Capital, Rue du Buisson 19, 1360 Perwez, Belgium

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ABSTRACT

The importance of conservation agriculture (CA) is undeniable, both for improving soil health and offering a viable path towards achieving carbon neutrality. However, to date, survey statistics on the extent of conservation agriculture were based on farmer declarations or field inspections. This is a major impediment to the promotion or monitoring of conservation agriculture. Here, we collected the management practices of a total of 247 fields under conservation agriculture in the Walloon region of Belgium in 2020–2021, with the aim of developing a classification model for the prediction of conservation agriculture by combining remotely sensed data with census data. We identified seven variables in the model, linked to each of the three main principles of conservation agriculture (crop diversification, maximum soil cover and minimum mechanical soil disturbance). The number of different annual crops and cereals in the rotation was obtained from the agricultural census. For the extent of soil cover, the Google Earth Engine (GEE) platform was used to obtain a time series of optical remote sensing images (2015–2020, Sentinel-2, Landsat-7, Landsat-8) and precipitation data. We then analyzed the variation of spectral indices such as the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Tillage Index (NDTI) and constructed indicators to distinguish between bare soil and cover crop. For minimum mechanical soil disturbance, in addition to the above data, radar data (Sentinel-1) were also obtained from the GEE platform to establish a tillage practice model. Subsequently, the Random Forest (RF) classification method was used to construct a classification model distinguishing fields under conservation from those under conventional practices. The results of a ten-fold cross-validation showed a good overall accuracy of 92 %. The model was utilized to classify the farming systems in all croplands of the Hesbaye region of Belgium. The results show that 15.5 % (2875 fields) out of 18,516 cropland fields can be classified as conservation agriculture. These fields tend to adopt non-inversion tillage and have diverse crop rotations.

1. Introduction

Agricultural soils are suffering from increasing threats such as erosion, declining organic matter and biodiversity, pollution, sealing, compaction and salinization (Ferreira et al., 2022; Panagos et al., 2018; Foley et al., 2011). To address the challenges of soil degradation and promote sustainable agriculture, the Food and Agriculture Organization (FAO) advocates for the adoption of conservation agriculture (CA) as a set of widely adopted agricultural production systems that improve or maintain crop production while restoring degraded land and providing sustainable production systems. The FAO (fao.org/conservation-agriculture/) defines CA as a set of practices based on three main

principles: (1) crop species diversification; (2) maximum soil organic cover (including living mulch (cover crops, annual crops, temporary grasslands) and dead mulch (crop residues, decaying leaves, bark, manure)) and (3) minimal mechanical soil disturbance. Adopting these principles will have numerous benefits for soil health (Page et al., 2020; Cárcelos Rodríguez et al., 2022) such as increasing aggregate stability and soil quality (Castellanos-Navarrete et al., 2012; Sithole et al., 2019; Jat et al., 2019), reducing soil erosion (Petito et al., 2022), improving soil biological abundance and diversity (Ayuke et al., 2019; Giraldo-Perez et al., 2021), and increasing crop yields and farmers' incomes (Naab et al., 2017; Pradhan et al., 2018). However, current methods of distinguishing fields under CA from those under conventional

* Corresponding author.

E-mail addresses: yue.zhou@uclouvain.be, yuez9466@gmail.com (Y. Zhou).

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0034-4257/© 2025 Elsevier Inc. All rights reserved, including those for text and data mining, AI training, and similar technologies.

agriculture, or traditional agriculture (TA) are still limited to direct observation in the field in combination with farmers' interviews. This is labor-intensive and time-consuming, making it difficult for large-scale inventories of CA applications. Remote sensing techniques have proven to be an efficient and effective tool for generating various types of agricultural data (crop types, crop yields, management technique, critical soil properties such as soil organic carbon (SOC) content) (Griffiths et al., 2019; Sparks et al., 2022; Blickensdörfer et al., 2022; Evans and Shen, 2021; Zheng et al., 2014; Castaldi et al., 2019). However, predicting field management practices using remote sensing remains challenging, especially for CA, as it involves multiple principles that are difficult to quantify.

The important step forward in addressing this challenge is that remote sensing techniques can be used to effectively predict or assess each principle of CA separately. By integrating the indicators for all three principles, a comprehensive assessment of CA can be achieved. First, to measure species diversification, it is crucial to identify the crop planted each year. This typically requires field-scale agricultural census databases, such as the Land Parcel Information System (LPIS) used by Zhou et al. (2022a) for the Belgian region. However, such field-scale data are often scarce. An alternative approach is to use remote sensing data for crop type mapping (Johnson, 2019; Belgiu and Csillik, 2018). Since crop types determine the entire phenological cycle from seeding to harvest within a relatively short time (Blickensdörfer et al., 2022), the spectral trajectories of different phenological stages can be captured in detail using high-resolution, long-term remote sensing data (Preidl et al., 2020). Second, to identify winter cover crops not documented in agricultural census data, accurate differentiation of remote sensing signals from soil, main crops, and cover crops is essential (Zhou et al., 2022b). Current methodologies typically involve three sequential steps: (1) eliminating main crop signals through integration of phenological information with crop type maps; (2) removing bare soil periods using vegetation and soil index thresholds (Mzid et al., 2022; Dvorakova et al., 2023); and (3) identifying cover crops during potential growing seasons. For this final step, researchers commonly apply vegetation index thresholds when detectable plant growth signals appear within expected cover crop windows (Zhou et al., 2022a; KC et al., 2021). However, Zhou et al. (2022b) demonstrated that fixed thresholds lead to detection errors, while dynamic thresholds considered environment difference require additional modeling complexity. Alternatively, binary classification models trained on field data and remote sensing imagery (Seifert et al., 2018) can be employed, but demand extensive ground truth data collection. Finally, time-series of satellite imagery have been proven to be an effective tool for monitoring and evaluating tillage practices (Sonmez and Slater, 2016; Zhou et al., 2021; Liu et al., 2022). Inversion tillage (i.e. inverting topsoil layers, usually to a depth of 30 cm in Belgium) buries most of the crop residue in the soil, whereas non-inversion tillage retains most of the crop residue in the topsoil. This distinction in tillage practices can be detected through the differences in residue cover. The cellulose and lignin in crop residues and soil will exhibit distinctive absorption characteristics in the shortwave infrared (SWIR) range, particularly around 2100 and 2300 nm (Elvidge, 1990). The Cellulose Absorption Index (CAI) has been shown to accurately represent these features (Bai et al., 2021; Hively et al., 2021; Pancorbo et al., 2023), but it requires high spectral resolution in the SWIR range (centered at 2000, 2100, and 2200 nm; Nagler et al., 2000), which is not available on satellite platforms with moderate to high spatial resolution (20–30 m) and regular repeated global coverage such as Landsat and Sentinel (Dennison et al., 2023). As an alternative, broadband indices like the Normalized Difference Tillage Index (NDTI, van Deventer et al., 1997), have been adopted. However, while NDTI is useful, it can be affected by interference from green vegetation and moisture content (Lamb et al., 2022; Wang et al., 2013), which may introduce uncertainties into the assessment. Quemada et al. (2018) performed moisture correction on irrigated fields before using a tillage index for crop residue estimation. In addition, soil surface roughness can serve as

another indicator for detecting tillage, but its changes are more ephemeral, making it difficult to detect accurately with satellites passing every 5–10 days. Radar data has been proved for estimating bare soil surface roughness in many studies (Zribi and Dechambre, 2003; Baghdadli et al., 2002, 2018). Azzari et al. (2019) found that combining optical Landsat satellite data with radar-based Sentinel-1 data could improve classification accuracy for tillage practices in the North Central US Region.

Here, we integrate and improve existing methods to develop a classification model for CA. To achieve this, time series of optical data from Landsat-8, Landsat-7, Sentinel-2 and radar data from Sentinel-1 combined with environmental data are good sources of data support. In addition, the Google Earth Engine (GEE) platform can store large volumes of remote sensing data in a cloud environment, allowing us to save time in satellite data processing and enabling efficient, fast, easily replicable and scalable workflow.

The specific objectives can be summarized as follows:

1. To extract quantitative indicators from time series of optical and radar imagery, as well as agricultural census data, to estimate soil cover, tillage practices, and crop species diversity.
2. To develop a classification model to distinguish CA from TA using indicators constructed based on the three principles of CA.
3. To map the distribution of fields under CA in Hesbaye region of Belgium using the classification model.
4. To explore the contribution of covariates to the classification results of individual fields.

2. Method and materials

2.1. Study area

The study area is located in the southern part of Belgium, in the so-called Walloon region (Wallonia) (Fig. 1). Wallonia is a landlocked region covering a total area of 16,901 km². The altitude progressively increases from 100 m above sea level in the north-west to a maximum of 700 m in the south-east, leading to an increase in annual total precipitation from 800 to 1400 mm, and a decrease in the annual average temperature from 10 to 8 °C. Changes from deep sandy loam and silty soils to shallow silty and stony soils occur in the same direction, along with a shift from intensive arable agriculture to more extensive cattle grazing (Chartin et al., 2017; Goidts and van Wesemael, 2007).

Nine agro-geographical regions have been recognized in the Walloon territory (Fig. 1), which are classified based on the bio-physical conditions of the natural environment and similarity of agricultural systems (Source: <https://geoportail.wallonie.be/catalogue/3ec1510b-7e87-4f92-ab8a-22675249d84b.html>). Among them, the Hesbaye region, an intensive agricultural area with fertile silt loam soils, grows major crops such as cereals, sugar beet, potatoes and flax. Additionally, the Hesbaye region is entirely located within the Nitrate Vulnerable Zones (NVZ), as designated by the European Union's Nitrate Directive. This regulation mandates that farmers in the NVZ region are obliged to cover the soil with cover crops during the winter months to reduce nitrate leaching and protect water quality.

Field management data were collected across all Walloon regions, while the conservation agriculture mapping was done only in the Hesbaye region.

2.2. Field data

2.2.1. Data on fields under conservation agriculture

A preliminary list of farmers practicing CA was acquired involving twelve public and private institutions, eight farmer associations, two researchers from Belgian universities, and seventy farmers and/or agricultural entrepreneurs through the social network Facebook. We conducted semi-structured telephone interviews and cross-referencing

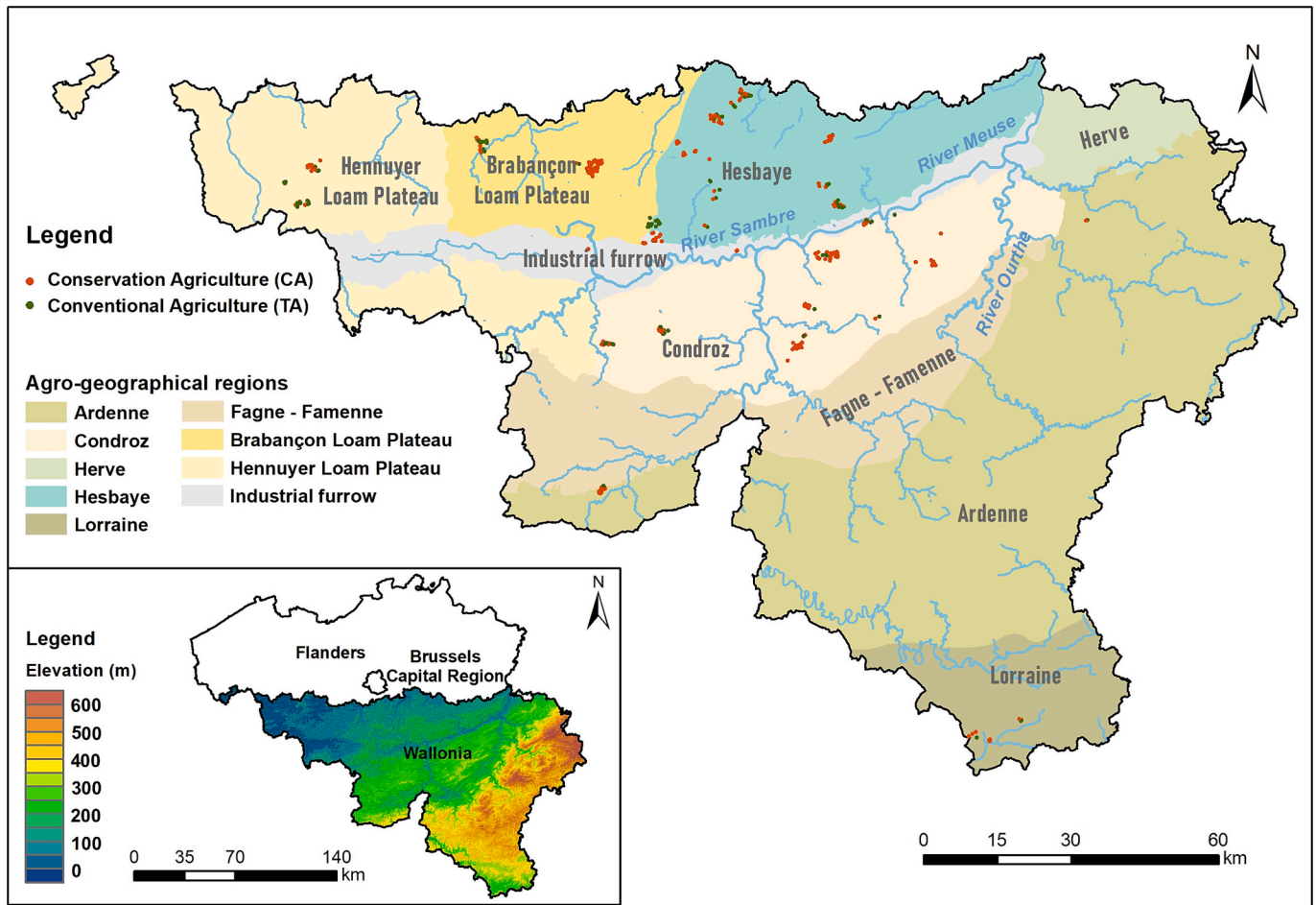


Fig. 1. Digital elevation model and agro-geographical regions of the Walloon region (Source: <https://geoportail.wallonie.be/>), along with the distribution of conservation and conventional fields. (Markers were dispersed for clearer visualization).

with these farmers to verify and gather the information on Wallonia's CA fields (Ferdinand and Baret, 2024). The years of implementation of CA practices and details on the tillage were two of the main questions asked during the interviews. At the end of the interviews, the respondents were requested to furnish a list of additional Walloon farmers who they knew to follow CA practices. This kind of "snowballing" strategy assisted us to obtain a more diverse source of data and more effectively target the next interviewees.

A total of 221 Wallonia farmers were contacted, and the farmers whose fields did not meet the CA criteria were removed from the database. The main prerequisites were: (1) at least five years of CA practice. (2) implementing conservation tillage, which included direct seeding (i.e. no-tillage, growing crops without any soil preparation), non-inversion tillage (a soil preparation practice involving fragmentation, mixing and burial, without horizon inversion) and occasional inversion tillage (horizon inversion with reduced tillage frequency or depth less than 15 cm) (Ferdinand and Baret, 2024). Given that some Walloon CA farmers face challenges in avoiding ploughing entirely due to factors like unfavorable weather and wet harvest conditions, occasional inversion tillage was included as part of conservation tillage practices (Ferdinand and Baret, 2024). Following the digitization of the interviews, information on each farmer covered the type of tillage/depth of tillage, direct seeding or not, as well as livestock presence or absence.

Between November 2021 and February 2022, 328 fields under CA practice were identified through semi-structured interviews with 28 farmers dispersed throughout eight of the nine agricultural regions (all but the Herve region, a hilly area predominantly composed of 98 % grasslands and orchards). These fields are mainly concentrated in the

Hesbaye, Brabant Loam Plateau and Hennuyer Loam Plateau area in the north of the Walloon region (Fig. 1). Among these, at least 47 fields were officially certified and received payments.

2.2.2. Data on fields under conventional agriculture

In the course of the semi-structured interviews, we also asked the farmers about the fields adjacent to their own fields. In particular, whether or not the surrounding fields were tilled at regular intervals and to a depth of more than 20 cm. If so, it indicated the use of inversion tillage, then we recorded these fields as TA fields. A total of 117 fields were obtained by this method. Furthermore, during the subsequent processing (see Section 2.4), due to the requirement for high density of time series data, the fields that did not meet the requirement were removed. We only focus on CA in croplands and therefore exclude all temporary and permanent grasslands. In the end, 247 fields under CA and 105 fields under TA were retained.

2.2.3. Agricultural census data

The annual crops and the field lay-out were collected from the website of the Walloon Region (<https://geoportail.wallonie.be/>), which offers free public access to basic geographic dataset and maps on the topography, administration, environment, transportation, and tourism. We have requested the data from the (LPIS) for the years 2015 to 2020, with each data file containing individual field boundaries and annual crop type for all fields for which subsidies under the Common Agricultural Policy (CAP) program are requested, stored as polygons. LPIS is a reference database of the agriculture parcels, identified and digitized from ortho-imagery (aerial or satellite photos) in the EU Member States

(Belgium, Denmark, France, Sweden, Luxembourg, Slovenia, Austria provide publicly accessible data, <https://eurodatacube.com/marketplace/data-products/lpis>). Based on farmer declarations, field verification, and remote sensing checks, crop information and field boundaries are updated annually. The data is used for cross-checking during administrative control procedures and serves as a basis for on-the-spot checks by the paying agencies to ensure accurate payment calculations.

The Hesbaye region contains 44,893 parcels of agricultural land, totaling 124,058 ha. First, we performed a preliminary screening, keeping only those fields with an area larger than 1 ha. Then, only those fields were kept that had not been recorded as temporary or permanent grassland within the previous six years. Finally, 18,740 cropland fields covering 98,289 ha were used for CA fields classification.

2.2.4. External validation dataset

Soil Capital© provided the external validation accuracy matrix based on our output maps of cover crop and tillage practice. Soil capital is an independent agronomy company founded in 2013, currently focused on developing a carbon payment program, which has already been implemented in Belgium, France, and the United Kingdom, in order to accelerate the transition to regenerative agriculture.

For the validation of the cover crop prediction model, Soil Capital randomly selected 108 fields with cover crops in the winter of 2019–2020 belonging to six farmers in the Hesbaye region. Winter wheat, potatoes, and sugar beet are the main crops at these farms. Soil Capital has a different classification for tillage practice compared to the CA & TA database (Sections 2.2.1 and 2.2.2). They distinguish between conventional and conservation tillage. We compared 64 overlapping fields between the two datasets. 13 non-inversion tillage fields in the CA data set are perfectly aligned with Soil Capital's conservation tillage fields. The remaining 50 occasional inversion or inversion fields in the CA & TA data set were also be matched and were displayed as conventional tillage in the Soil Capital database. Only one inversion field in the TA data set is shown as conservation tillage in the Soil Capital data set. Given this high match ratio, we perform external validation using Soil Capital's tillage data, that includes 114 fields with conservation tillage and 636 fields with conventional tillage.

2.3. Satellite data

The Google Earth Engine (GEE) platform was used to gather all remote sensing data, including Landsat-7, Landsat-8 and Sentinel-2 optical data, Sentinel-1 radar data and Global Satellite Mapping of Precipitation (GSMaP) products as auxiliary data.

2.3.1. Optical remote sensing dataset

Before uploading the croplands data to the GEE platform, we first removed a 15 m inwards buffer zone from the edges of the fields to remove mixed pixels with a signal from roads and/or adjacent fields. For the given field dataset, a defined time period (Jan 1st 2015 to Dec 31st 2020), and cloud threshold (less than 85 % cloud cover), three level-2 A atmospherically corrected datasets were initially acquired, obtaining the Landsat-7 surface reflectance (SR) dataset (199 scenes, Jan 1st 2015 to Dec 31st 2020), the Landsat-8 SR dataset (242 scenes, Jan 1st 2015 to Dec 31st 2020) and the Sentinel-2 SR dataset (645 scenes, Mar 28th, 2017 - Dec 31st, 2020). The multispectral instrument of Sentinel-2 acquires spectra in 13 bands with both high spatial resolution (10–60 m) and high temporal resolution (5-day revisit time). GEE only provides Sentinel-2 data since 2017, after the launch of Sentinel-2B. In the next step, a more rigorous cloud removal algorithm was carried out based on the image bands i.e. for Landsat 7 & 8 SR data we used a cloud mask function by excluding pixels flagged as cloud (Bit 3) and cloud shadow (Bit 5) in the pixel quality assurance (pixel_qa) band; for Sentinel-2 we combined a cloud mask function based on a bitmask band with cloud mask information (QA60) and a filter based on Cloud Score Index. (see for more details Zhou et al., 2022a). To address inter-sensor band

differences, we applied cross-sensor transformation coefficients (Claverie et al., 2016; Roy et al., 2016; Berra et al., 2024) to generate Harmonized Landsat and Sentinel data. All data were resampled to 30 m. Then the mean values of NDVI and NDTI (see Eqs. 1–2) were calculated in cloud computing for each individual field. Finally, the time series of these two indexes for the six-year time period were exported as csv. files (Ujaval, 2023).

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (1)$$

$$NBR2 = \frac{SWIR1 - SWIR2}{SWIR1 + SWIR2} \quad (2)$$

Where NIR, RED, SWIR1, SWIR2 represent the near infrared red band, red band, first shortwave infrared band and second shortwave infrared band respectively.

2.3.2. Sentinel-1 radar dataset

The Sentinel-1 constellation collects data from dual-polarization C-band Synthetic Aperture Radar (SAR) sensors operating at 5.405GHz. Clouds have no effect on imaging because of microwave spectrum characteristics. The GEE cloud platform provides Sentinel-1 Ground Range Detection (GRD) scenes, processing them using the Sentinel-1 Toolbox to produce calibrated, orthogonally corrected products. These GRD images were acquired in interferometric wide-swath (IW) mapping mode, with a spatial resolution of 10 m and a temporal resolution of 6 to 12 days.

After limiting the time period (Jan 1st 2015 to Dec 31st 2020), we obtained 4095 scenes in total of the backscatter coefficient at single Vertical-Vertical (VV) and Vertical-Horizontal (VH) polarization modes. We exported the time series data of VV and VH bands as csv. Files for each field.

From 2015 to 2020, the average available images per field in the optical remote sensing dataset and radar dataset were 295 and 495 scenes respectively.

2.3.3. Precipitation data

For precipitation, we used the GSMaP (Okamoto et al., 2005), which is accessible on the GEE platform. This data product was created in Japan for the Global Precipitation Measurement (GPM) mission (Skofronick-Jackson et al., 2017). It provides global hourly rainfall rates at a resolution of 0.1×0.1 degrees, with data available since March 2014. We compiled daily precipitation data for each field from the hourly data on the GEE cloud platform.

2.4. Defining indicators for the three principles of CA

In order to more accurately quantitatively identify and characterize the three fundamental criteria of CA, seven variables were created (Table 1), i.e., one to four indicators for each principle.

2.4.1. Crop species diversification

Based on the agricultural census (Section 2.2.3), two indicators of crop diversity were calculated. **Indicator 1**: number of different annual crops in six years; **Indicator 2**: cereal abundance in rotation represents the frequency of cereal crops in the rotation, without considering the specific cereal species. (eqs. 3–4).

Indicator 1 Number of different annual crops

$$= \text{Count}(\text{unique}(\text{crop code})), \quad (3)$$

$$\text{Indicator 2 Cereal abundance} = \sum_{i=1}^n \text{Cereal or not}_i, \quad (4)$$

Where i represents the year i of the total n years (here, $n = 6$).

Table 1

The seven variables for quantifying principles of conservation agriculture.

	Name	Data requirements	Range	Unit
Indicator 1	Number of different annual crops	Census database	1–6	number
Indicator 2	Cereal abundance	Census database	0–6	number
Indicator 3	Number of the cover crops	Census & Satellite	0–5	number
Indicator 4	Duration of the cover crops	Census & Satellite	0 ~ .	days
Indicator 5	Bare soil period	Census & Satellite	0 ~ .	days
Indicator 6	Fallow period	Census & Satellite	0 ~ .	days
Indicator 7	Tillage practice	Census & Satellite & Tillage info	inversion or non-inversion tillage	/

2.4.2. Length of the cover crop growing season and periods of bare soil or fallow

We define the period between the harvest date of the previous year's annual crop and the seeding date of the next year's crop (as declared in the agricultural census) as *inter*. During this *inter* period, the field can be classified into three states: under cover crops (field that is growing cover crops), bare (field without vegetation), and fallow (field without cover crops but not bare, usually characterized by the presence of crop residues, regrowth of previous annual crops, and weeds). To determine the field status and duration, data on time series NDVI, NDTI, and precipitation, as well as annual crop types and seeding and harvest dates from 2015 to 2020, are required.

Information on the phenology of multiple annual crops (e.g. seeding,

emergence, flower, maturity, harvest) is available on the website of the German National Meteorological Service (<https://www.dwd.de/>), recorded on a yearly basis by region. Data on the phenology of different crops is obtained through a network of phenological observers who are assigned fixed observation areas and record key growth stages from seeding to harvest. Observers submit their observations for data recording, which undergoes quality control to ensure accuracy. The Rheinland-Pfalz region of Germany, which borders Belgium at the same latitude, served as the primary reference for the seeding and harvest date. Additionally, farming and agriculture websites were used to gather information on the seeding and harvest dates for the remaining crops (Table A.1).

Since NDTI values are significantly higher in moist soils compared to dry ones (Dvorakova et al., 2023), we introduced precipitation data into our calculations to eliminate the problem of elevated NDTI due to precipitation. In addition, cover crops frequently do not completely overlap with *inter*. Therefore, the growing seasons obtained from automatic NDVI splitting (phenofit package, Kong et al., 2022; Kong, 2023) was utilized to assess the presence or absence of cover crops and to calculate the length of the cover crop growing season. Alternatively, an *inter* may have a single cover crop, or a combination of cover crop & bare soil or cover crop & fallow. Based on the NDVI and NDTI values we determined whether soil was left bare or in fallow. We then computed the total cover crop duration as well as bare soil and fallow duration over the entire observation period.

The specific steps of this procedure are listed as follows, along with a general workflow (Fig. 2) and an example shown in Fig. A.1. For details on parameter selection, see Appendix B.

Step 1: Identify the *inter* period. Confirm the start (*Start*) and end (*End*) date, as well as the duration (*Days*) of each *inter*, via the harvest date (same as *Start*) of the previous crop and the seeding date (same as *End*) of the next crop. Ignore this *inter* if the duration is shorter than 30 days. If not, proceed to step 2.

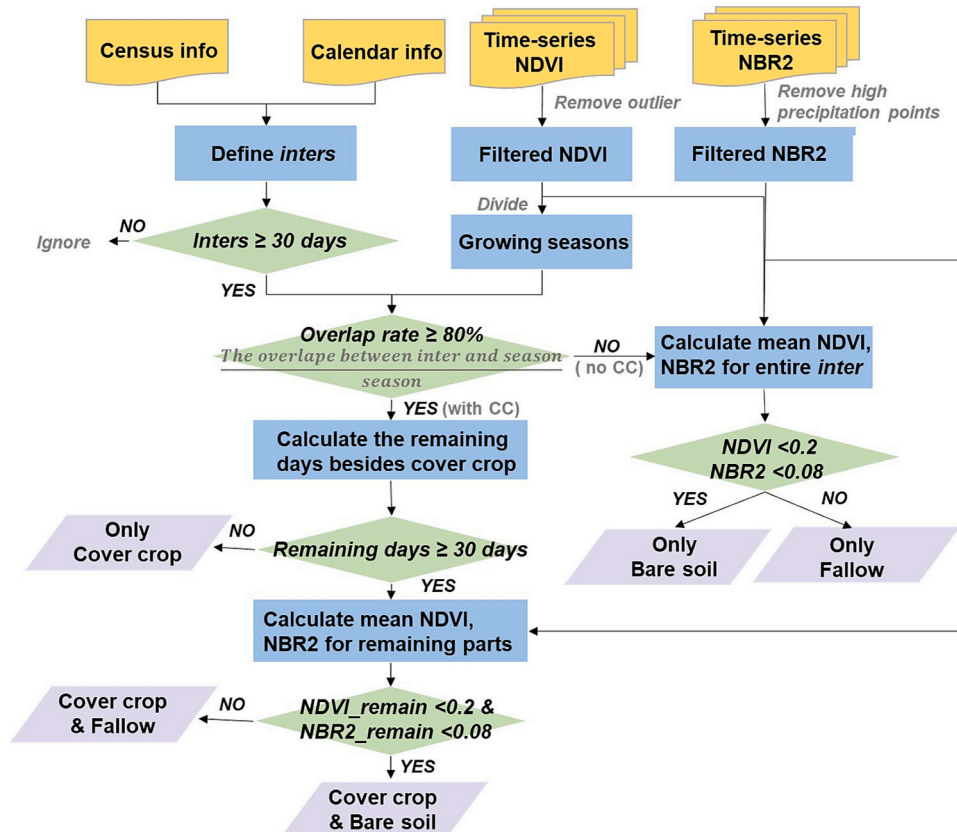


Fig. 2. Flowchart for identifying inter period field cover status. (CC: Cover crop).

Step 2: Preprocessing remote sensing data. The outlier points were removed using the phenofit package (Kong, 2023), followed by the calculation of the mean NDVI ($NDVI_{mean}$) within the *inter*. The NDTI points were filtered using the precipitation data, the total rainfall over the preceding five days (*Prec*) of each NDTI data point acquisition time was calculated and the data point was removed if *Prec* is greater than 2.5 mm, then the mean NDTI value ($NDTI_{mean}$) was calculated.

Step 3: Define the growing seasons based on NDVI curves. The seasons are automatically divided by the phenofit package based on NDVI time series data (Kong et al., 2022). We ensure that it is a complete growing season of an annual crop or cover crop, rather than the spontaneous regrowth of the previous annual crop or weed, by conditioning that the NDVI peak is 0.6 or more for each season. For detailed parameter settings, please refer to the code in the data availability section.

Step 4: Determine whether a cover crop is present. Compare the *inter* with all seasons and compare the *inter* period with the growing seasons and calculate the duration of their overlap (e.g. the overlapping part in Fig. A.1 Field A Step 4). An overlap rate (overlapping/growing season) greater than 80 % indicates strong crop emergence during the *inter*, and we identify it as a cover crop, moving on to step 6. Go to step 5 if there is no cover crop.

Step 5: Provided cover crops are absent, if $NDVI_{mean} < 0.2$ (Barben et al., 2024) and $NDTI_{mean} < 0.08$ (Broeg et al., 2024), the soil remains bare during this period, set *inter* as the duration of the bare soil. Otherwise, soil is fallow, set *inter* as the fallow period.

Step 6: If a cover crop is detected, we firstly calculate the length of the remaining period without cover crop (*Remain*) in the *inter*. If *Remain* is less than 30, we consider that only cover crops exist in that interval, record the number (one *inter* exists once), the duration, and the start and end dates of cover crop, the fallow period and bare soil is set to 0; if *Remain* is greater than 30, proceed to Step 7.

Step 7: Provided cover crops are present, if $NDVI_{mean} < 0.2$ and $NDTI_{mean} < 0.08$, the soil state during this period consists of cover crops and bare soil, set *Remain* as the duration of the bare soil. Otherwise, the soil state is under cover crop and fallow, set *Remain* as the fallow period.

Finally, we can obtain the number of cover crop per *inter*, as well as the duration of cover crop, fallow, and bare soil. In total, six years were used and the values within the five *inters* were summed to produce the following four indicators: **Indicator 3**: Number of the cover crops; **Indicator 4**: Duration of the cover crops; **Indicator 5**: Bare soil period; **Indicator 6**: Fallow period (eq.5–8).

Indicator 3 Number of the cover crops

$$= \sum_{j=1}^k \text{cover crop presence or absence}_j (\text{Presence (1)}/\text{Absence (0)}), \quad (5)$$

$$\text{Indicator 4 Duration of the cover crops} = \sum_{j=1}^k \text{Days of cover crop}_j, \quad (6)$$

$$\text{Indicator 5 Bare soil period} = \sum_{j=1}^k \text{Days of bare soil}_j, \quad (7)$$

$$\text{Indicator 6 Fallow period} = \sum_{j=1}^k \text{Days of fallow}_j, \quad (8)$$

Where *j* represents the period *j* of the total *k inters* (in this study, *k* = 5).

2.4.3. Tillage practices

In order to quantify the principles of mechanical soil disturbance for Hesbaye region, we utilized data on tillage practices combined with remote sensing data to develop a tillage model. The tillage model was designed to accommodate three scenarios (Short Interval, No Cover

Crops, With Cover Crops) for the *inter* periods and modeled them separately.

We binarized the tillage practice data of all fields (247 CA fields and 105 TA fields) and recorded them as non-inversion tillage and inversion tillage, which served as dependent variable of the model. The non-inversion tillage dataset comes from the CA fields where they implement non-inversion tillage and no till; the inversion tillage dataset combines the occasional inversion tillage fields under CA and the inversion tillage fields under TA. The mean/minimum values of NDTI, NDVI, VV and VH within each *inter*, and the cover crop/bare soil duration ratio were used as independent variables of the model.

The specific steps are listed below, along with a general workflow (Fig. 3) and an example shown in Fig. A.2.

- (1) Short Interval (*inter* < 30 days): The interval between two annual crops is short (less than 30 days). This often occurs when the next year's crop is a winter crop, and we omit this situation and categorize this tillage practice as "NA". Ploughing may occur within this interval, but the time frame between two main crops is very short, with farmers typically completing soil preparation and planting within a few days (e.g. in maize-winter cereal and potato-winter cereal rotations). Hence it is not possible to obtain sufficient information within such a short period from satellite imagery.
- (2) No Cover Crops (*inter* ≥ 30 days): In the absence of cover crops, build a model (Model I) using the mean/minimum values of NDTI, NDVI, VV and VH backscatter.
- (3) With Cover Crops (*inter* ≥ 30 days): In the presence of cover crops, use the proportion of cover crop/bare soil duration for the entire interval (i.e., the ratio of the period occupied by cover crops or bare soil within the *inter* period. The start and end dates for cover crops and bare soil were derived from the field status identification results in Section 2.4.2), as well as the mean/minimum values of NDTI, NDVI, VV and VH in the remaining period to build a model (Model II).

Each *inter* of the field is considered independently, analyzed under the corresponding scenario to obtain the predictions. Finally, we analyzed and predicted tillage practices of five different *inters* over six years for each field. The overall tillage practice of the field is defined as **Indicator 7: Tillage practice** (eq. 9). It is worth noting that the multi-year tillage practice was judged to be inversion as long as inversion tillage occurred at least once during the six-year period.

$$\text{Indicator 7 Tillage practice} = \text{inversion or non-inversion tillage}, \quad (9)$$

2.5. Model development and evaluation

2.5.1. Statistical analysis

To assess the significance of the differences between the constructed indicator values under CA and TA, we employed the Wilcoxon rank sum test. This is a non-parametric test that serves as an alternative to the independent two-sample *t*-test, when the data do not conform to a normal distribution. This procedure was implemented using *rstatix* and *ggsignif* R package.

2.5.2. Covariates decorrelation and recursive feature elimination

De-correlation analysis can be used to reduce redundant information. Only covariates with correlation coefficients less than 0.85 with all other covariates were kept (Poggio et al., 2021), and the first covariate was removed from the set of covariates that exceeded this threshold.

Recursive feature elimination (RFE, Guyon et al., 2002) is an effective method for simplifying the structure of machine learning models, reducing dependencies and collinearity while retaining model accuracy. It is simplified by recursively eliminating features from the training dataset to select an optimal set of features. Also, RFE is frequently

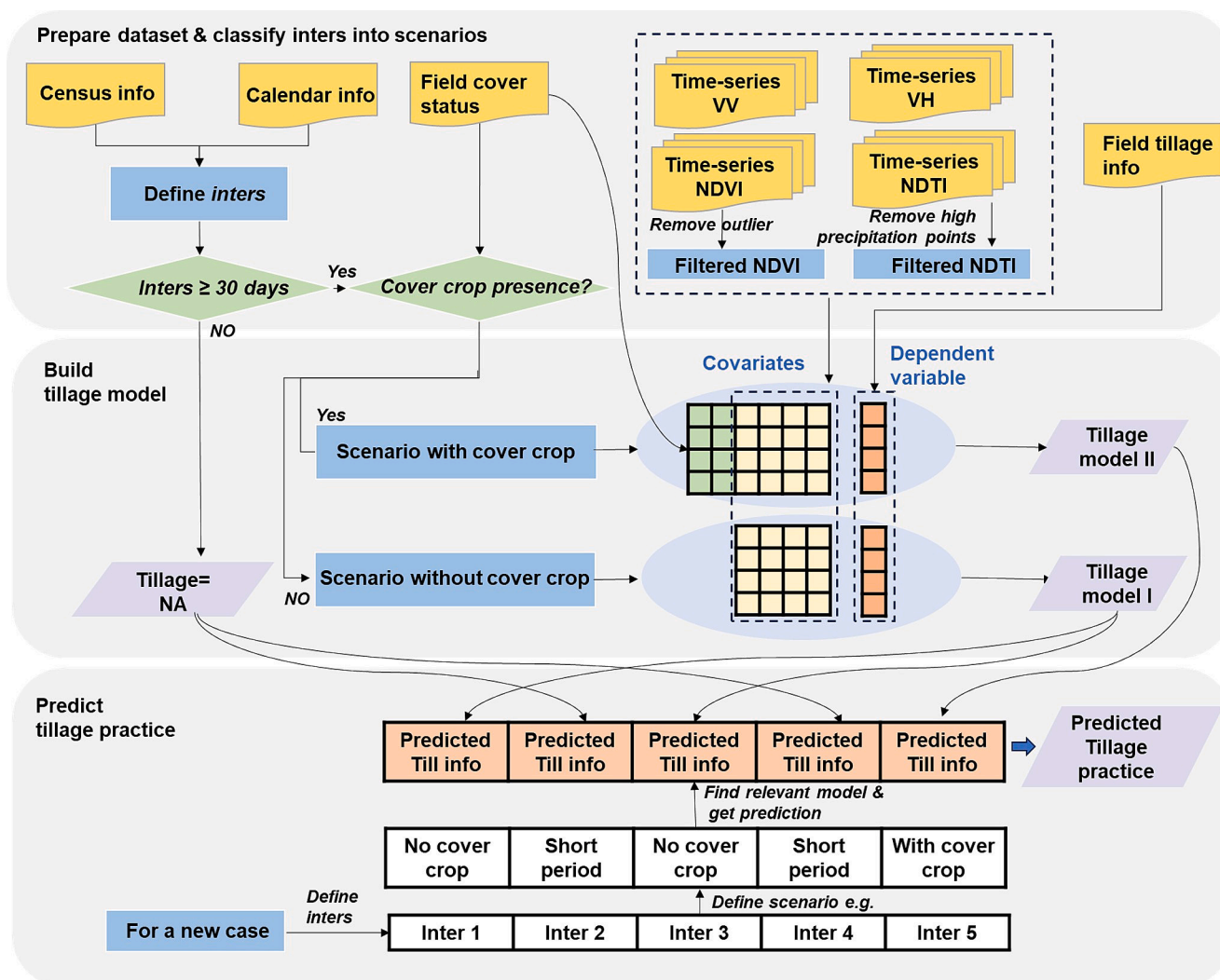


Fig. 3. Flowchart for predicting tillage practice.

utilized in spatial mapping exercises with random forest models (Kuhn and Johnson, 2019; Poggio et al., 2021). The algorithm first fits the model using the entire set of covariates, then evaluates its performance by cross validation while computing the importance score of the covariates. The least important covariates are then removed from the pool, the model is fitted and evaluated again per loop. The process is repeated until the number of covariates reaches the specified number. The optimal subset of covariates after this backward selection is used to train the final model. The implementation of RFE in R can be realized with the *caret* R package.

2.5.3. Classification model and accuracy evaluation

We chose to use Random Forest as the classification model, which is an ensemble classifier made up of numerous individual decision trees (Breiman, 2001). The implementation of random forest in R can be realized with the *randomForest* R package. To evaluate the performance of classification, we generated a confusion matrix (Table A.2) based on the results of 10-fold cross-validation, from which we calculated the overall accuracy (OA), producer's accuracy (PA), user's accuracy (UA) and Kappa coefficient (Eqs. A.1–A.4). The OA refers to the probability that the classification for each unknown point is consistent with the measured class of that point, assesses the overall performance of correctly classified. The PA illustrates how accurately the producer (or classifier) identifies objects of a specific class on the ground, and is associated with errors of omission (i.e. when actual members of a class

are left out of that class). While the UA describes how correct the user (or analyst) is in interpreting the results, and relates to errors of commission (i.e., when objects are incorrectly included in a class). Kappa coefficient characterizes the agreement between the predicted and measured classification maps.

3. Results

3.1. Species diversification

The number of cereals and the number of different crop types are significantly different under TA and CA (Fig. 4). According to the standard raised by FAO (fao.org/conservation-agriculture/), CA fields should involve at least three different annual crops. In our database, most CA fields (81 %) have at least four different annual crops over six years. The mean and standard deviation values for the indicators can be found in Table A.3.

3.2. Accuracy for identifying cover crops and soil cover

After comparing our classified cover crop maps with the observed data from Soil Capital, a confusion matrix was obtained with an overall accuracy of 86 % (Table 3). For the cover crops, there is a certain probability (26 %) of omission error from the producer's perspective. Further analysis revealed that omission errors primarily occurred when:

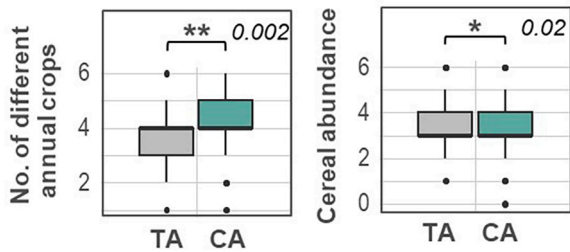


Fig. 4. Grouped boxplots with significance notation under Wilcoxon test, comparing the levels of two indicators related with species diversification under two farming system in Walloon region during 2015–2020. (ns: not statistically significant ($P > 0.05$), *: $P \leq 0.05$; **: $P \leq 0.01$; ***: $P \leq 0.001$). (Here: CA: Conservation Agriculture; TA: Conventional Agriculture). The numbers in each subplot indicate P value of Wilcoxon test.

Table 3
Confusion matrix of cover crop (CC) classification.

		Reference Data			User's accuracy
		No CC	CC	Totals	
Classified Data	No CC	56	13	69	81 %
	CC	2	37	39	95 %
	Totals	58	50	108	
Producer's accuracy		96 %	74 %	Overall: 86 %	

(1) root crops (e.g., potato, sugar beet) were planted outside typical windows due to their planting sensitivity to spring soil conditions, disrupting cover crop window detection; and (2) undefined crop types in census database which lacked growth pattern references. Nevertheless, from the user's perspective, the accuracy for the cover crops classification was 95 %, which is extremely trustworthy.

We then created box plots for the indicators related with cover crop and soil cover (Fig. 5) under the two farming systems and calculated the significance of the differences. Significant differences under conventional and conservation agriculture were found in the length of bare soil and cover crops. The mean and standard deviation values for the indicators can be found in Table A.3.

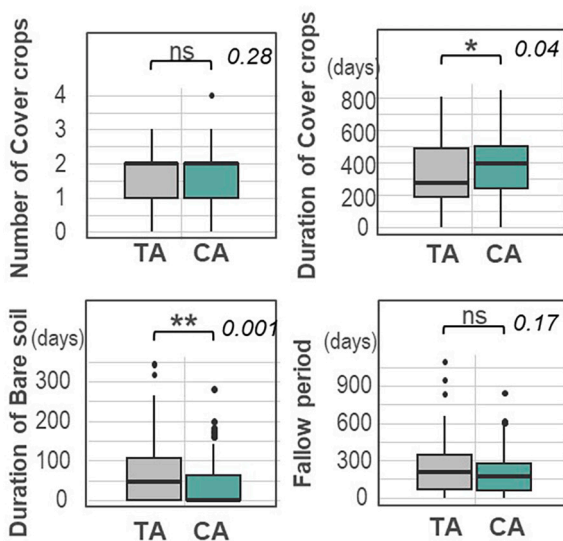


Fig. 5. Grouped boxplots with significance notation under Wilcoxon test, comparing the levels of 4 indicators related with soil cover under two farming system in Walloon region during 2015–2020. (ns: not statistically significant ($P > 0.05$), *: $P \leq 0.05$; **: $P \leq 0.01$; ***: $P \leq 0.001$). (Here: CA: Conservation Agriculture; TA: Conventional Agriculture). The numbers in each subplot indicate P value of Wilcoxon test.

3.3. A model of non-inversion/inversion tillage practice prediction

The main explanatory variables for the tillage model are NDTI and backscatter coefficient, as shown by the importance of the covariates in model I and II (Fig. 6). In addition, the proportion of cover crop duration in the entire interval is also critical, and we found a statistically significant difference in this index between fields using non-inversion tillage and those using inversion tillage (Fig. A.3).

The tillage model has an overall accuracy of 66 % compared to the dataset from the interviews for 10-fold cross-validation and 76 % compared to the external validation dataset of Soil Capital (Table 4). To identify inversion tillage, our user's accuracy (87 %) and producer's accuracy (85 %) were good based on external validation, but many of the non-inversion tillage fields were wrongly classified as inversion tillage. This overestimation of inversion tillage results from our conservative multi-year classification criteria, where fields with ≥ 1 inversion tillage event within the 5-year window were categorized as inversion. While this strict approach minimizes false negatives in inversion tillage detection (ensuring high monitoring reliability), it inevitably increases false positives for non-inversion tillage in single-year external validation.

3.4. Covariates selection and model accuracy for conservation agriculture field classification model

Ultimately, the data available for model development consisted of 247 fields in CA versus 105 fields in TA. The seven indicators (Eqs. 3–9) include number of different annual crops, cereal abundance, number of cover crops, duration of the cover crop, bare soil period, fallow period, and tillage practice (outputs from the tillage model). Strong correlations between two covariates were found between number of cover crops and duration of the cover crop (0.93, Fig. A.4). We simply need to keep one of the covariates in every pair to have sufficient information. As a result, the number of cover crops was removed.

The recursive feature elimination results demonstrate that the best precision is obtained when four covariates are taken into account (Fig. 7A) and they were ranked in order of importance (Fig. 7B) as follows: Tillage practice, number of different annual crops, period of fallow and bare soil. The confusion matrix and model accuracy for the classification model obtained from 10-fold cross-validation are shown in Table 5. Random Forest, as an ensemble machine learning strategy, produces an acceptable classification accuracy with overall accuracy of 92 %. For identifying CA fields, user's accuracy was 94 % and producer's accuracy was 95 %.

3.5. Classification map for conservation agriculture

Finally, we applied the random forest model to predict and categorize 18,516 cropland fields in the Hesbaye region into conventional or conservation systems (Fig. 8). The model predicts that 15.5 % of these fields (2875) were designated for CA, and 84.5 % (15,641) were classified as TA. CA covers 148.2 km² and TA 830.7 km² of the Hesbaye croplands, with average field sizes of 5.1 ha for conservation and 5.3 ha for TA. Meanwhile, we zoomed in on two typical areas (Fig. 8). CA is practiced on a larger portion of the cropland in region B1, whereas region B2 is dominated by TA. Comparing the grading of the two most important variables for the classification model (tillage practice and the number of crop types) between the two regions, it can be noted that CA fields tend to more frequently adopt non-inversion tillage and grow more diversified crops.

4. Discussion

4.1. Track management practices with time-series imagery

Time-series of optical satellite imagery have proven effective for

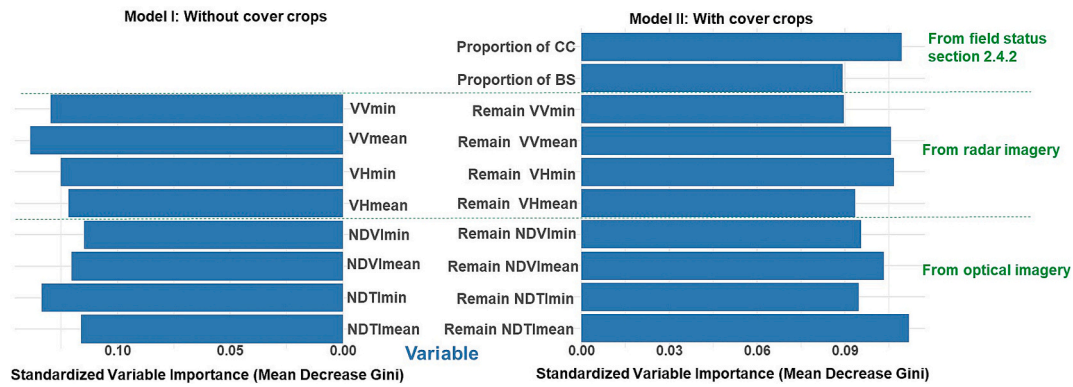


Fig. 6. Random Forest standardized feature importance of covariates in predicting tillage practices under Model I: Without cover crops and Model II: With cover crops (CC: Cover crop; BS: Bare soil).

Table 4

Confusion matrix of non-inversion/inversion tillage model.

10-fold cross-validation		Reference data			User's accuracy
		Non-inversion	Inversion	Totals	
Classified data	Non-inversion	112	34	146	78 %
	Inversion	83	114	197	58 %
	Totals	195	148	343	
Producer's accuracy		57 %	78 %		Overall: 66 %
External validation		Reference data			User's accuracy
		Non-inversion	Inversion	Totals	
Classified data	Non-inversion	34	97	131	26 %
	Inversion	80	539	619	87 %
	Totals	114	636	750	
Producer's accuracy		30 %	85 %		Overall: 76 %

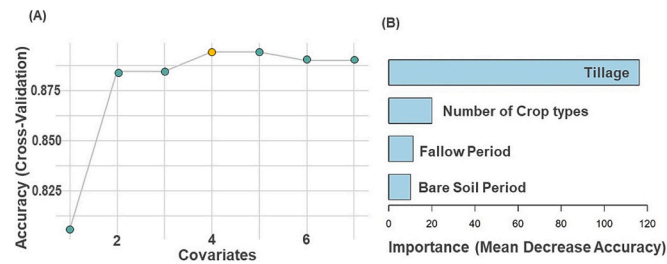


Fig. 7. (A) Model accuracy evolution for different number of covariates under recursive feature elimination and (B) Random Forest feature importance of covariates.

Table 5

Confusion matrix of Conservation Agriculture field classification model.

		Reference data			User's accuracy
		Conventional	Conservation	Totals	
Classified data	Conventional	91	13	104	88 %
	Conservation	14	224	238	94 %
	Totals	105	237	342	
Producer's accuracy		87 %	95 %		Overall: 92 % Kappa:0.82

identifying surface conditions (Laamrani et al., 2020; KC et al., 2021). The phenology of crops changes during the year, which is particularly evident in optical images. Prior to applying either threshold-based or modeling approaches for cover crop identification, the potential growing period must be determined to filter relevant satellite imagery for processing. Existing studies typically specify a fixed potential growing period: October to April (KC et al., 2021), November to May (Laamrani et al., 2020), December–January and March–April (Thieme et al., 2020), or October–December (Barnes et al., 2021). Within these windows, researchers have employed either fixed vegetation index thresholds (KC et al., 2021; Thieme et al., 2020), dynamic thresholds adjusted annually (Zhou et al., 2022b), or machine learning classifiers (Seifert et al., 2018; Barnes et al., 2021). In contrast, our cover crop classification model offers several novel aspects: (1) **Automatic potential window and Growing Season Detection**: By integrating main crop calendars, our model automatically identifies cover crop windows in between the main crops, adapting to different harvest dates in complex European rotations. In addition, unlike binary classification models (Seifert et al., 2018; Barnes et al., 2021) that simply detect presence or absence, our approach also generates precise start/end dates and duration data. While our model adapts to regional crop calendars, non-standard sowing practices (due to weather variability or farm management decisions) caused cover crop misclassification. Future work could integrate real-time planting reports or satellite phenology to mitigate this problem (Sun et al., 2022). (2) **Reduced Dependence on vegetation index Thresholds**: Instead of requiring a single fixed or dynamic vegetation index threshold (KC et al., 2021; Zhou et al., 2022b), our algorithm analyzes long-term NDVI curve shape, achieving spatiotemporal self-adaptation detection. (3) **Multi-Year Analysis**: Our model simultaneously evaluates multiple years to determine cover crop frequency (Fig. A.5), rather than analyzing each year independently (Zhou et al., 2022b), which significantly reduces processing time. This provides more comprehensive assessment of cover crop implementation patterns while respecting rotation constraints (e.g., cover crops cannot be planted during the growing seasons of winter cereals). A timeframe aligned with the crop rotation cycle offers a more representative proxy for crop cover and biomass input into the soil.

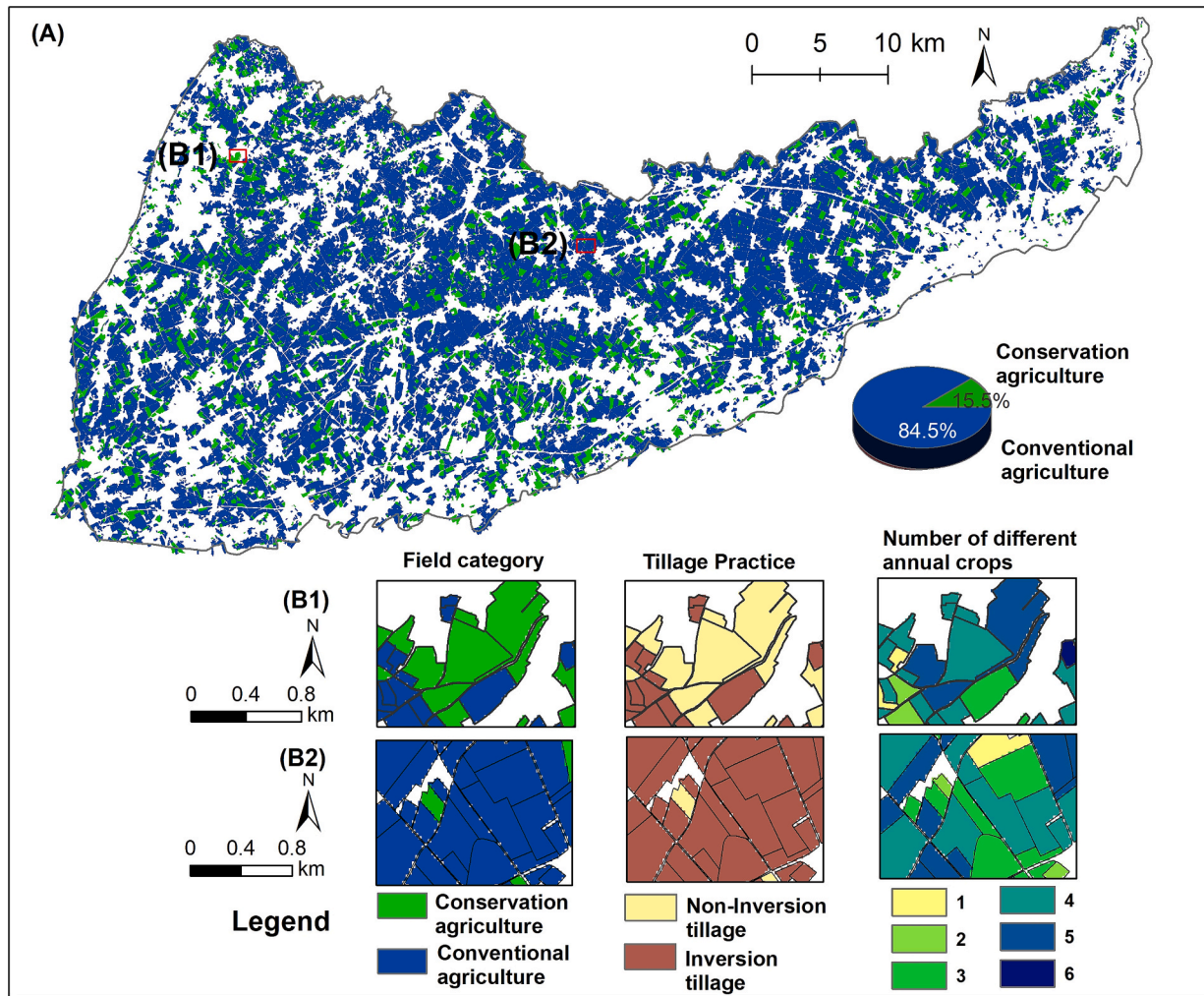


Fig. 8. Classified map (A) and enlarged views in representative regions are presented in (B1) and (B2), with the two most important indicators, tillage practice and the number of main crops reported in the agricultural census (for the period 2015–2020), only croplands are mapped leaving grassland, forest and built up areas in white (see Fig. 1 for the location of the Hesbaye region).

Overall, we achieved a better user's accuracy of 95 % for cover crop at a fine resolution (30 m), and our automated processing workflow allows for simultaneous calculating duration of bare soil or fallow. It is worth noting that wet conditions darken soil and crop cover, making it difficult to distinguish between them (Sharma et al., 2020; Dvorakova et al., 2023). We included precipitation data to limit the effect of soil moisture when distinguishing between bare soil or fallow, but irrigation factors are difficult to characterize. Filtering NDTI values will limit available data, but this strict filtering enhances analysis accuracy by reducing moisture-related errors; we need to consider that this trade-off is the best option. It should be noted that for removing the influence of moisture using precipitation limitation, as well as setting threshold parameters for bare soil classification, a more effective approach would involve using a calibrated dataset for continuous parameter adjustment. In addition, we use the definition of “fallow” because so far, we can't distinguish between crop residues, regrowth of previous crops, or weeds. To address this issue and reduce the interference of green vegetation on residue determination, future work will include implementing an NDVI threshold to restrict analysis to fields with low-vegetation cover (e.g., $NDVI < 0.3$ as suggested by Lamb et al., 2022; Hively et al., 2018) or by analyzing trends in the NDVI and NDTI curves over time.

Differences in the spectral reflectance of crop residues can be used to characterize tillage. In addition, radar images can penetrate clouds and capture data in adverse weather conditions, making them useful for

monitoring tillage practices (Kontgis et al., 2017). However, because the time between tillage and seeding and crop emergence is typically brief and their timing varies significantly depending on field conditions and crop rotations, large-scale detection remains challenging. As a result, most current large-scale studies on tillage detection focus only on fields growing one or two crop types, or on farming systems with specific tillage schedules. For example, Azzari et al. (2019) examined tillage practices across 5866 fields using Sentinel-1 imagery (2005–2016), although the study was limited to fields with soybean. Similarly, Zhou et al. (2021) utilized Sentinel-2 data to analyze 2830 farms in India, with prior knowledge that all fields would be planted with winter wheat in the following season. Both Sharma et al. (2020) and Zheng et al. (2012) focused on U.S. fields with only two crop types (soybeans and corn). These approaches benefit from a simple agricultural system, which makes it easy to identify fixed analysis windows and subsequent application of tillage indices or radar data. This is particularly effective in regions with large fields and homogeneous management practices, like the United States and Latin America (Zhou et al., 2021; Azzari et al., 2019).

Our contributions to tillage identification are twofold. (1) based on field-scale crop rotation patterns and calendar information, the potential field-specific tillage window is established, varying annually to accommodate different crops such as winter cereals and summer crops e.g. potatoes and sugar beet. (2) We integrate multiple proven data sources

including tillage indices (Lamb et al., 2022), precipitation data (Quemada et al., 2018), and radar data (Azzari et al., 2019), while also incorporating field status information derived from our cover crop identification procedure. The approach distinguishes fields into three distinct cover status scenarios, i.e. short intervals, with cover crops, and no cover crops. For each scenario, we perform separate tillage analysis and prediction. This integrated framework reduces interference from green vegetation and soil moisture in tillage prediction, while maintaining detection accuracy across a diverse European agricultural landscape.

The model shows that NDTI and VV/VH backscatter coefficients were important variables (Fig. 6). This is consistent with most papers stating that the tillage index NDTI is the most effective indicator for broadband satellites (Zheng et al., 2014; Dennison et al., 2023; Lamb et al., 2022), and that the backscatter coefficient enables detecting tillage-induced changes in soil roughness (Satalino et al., 2018).

Farmers sometimes complete ploughing, soil preparation and seeding in a very short time before planting winter crops (e.g. maize-winter cereal rotations and potato-winter cereal rotations). Due to high cloud cover and other factors, it can be challenging to simulate tillage practices using remote sensing data with a temporal resolution of 5–10 days; therefore, we omitted the “short intervals.” Our tillage model cannot distinguish each tillage operation in situations of “short intervals”; however, it can distinguish a rotation where tillage is used every 3–5 years. One potential approach is to extend the analysis period of “short intervals” to include the time from seeding the next crop to its emergence. However, this interval is highly influenced by climatic factors, which necessitates a more refined crop model (e.g. SAFYE-CO2; Pique et al., 2020) based on climate conditions to simulate the phenological calendar.

While our tillage model’s conservative nature leads to underestimation of non-inversion tillage, this design is well-suited for monitoring in carbon farming schemes. Although the model’s overall accuracy (76 %) based on external validation is moderate, it achieves good user’s accuracy (87 %; Table 4) for inversion tillage detection. This high user’s accuracy for inversion tillage ensures reliable identification of non-compliant practices. Farmers should then be allowed to contest misclassification, whereas missing actual inversion tillage events would compromise the trust in the carbon farming program. These characteristics will improve a strict adherence to conservation farming or carbon farming schemes for which refraining from tillage is a condition. In addition, the predicted tillage map (Fig. A.6) show 89.9 % of the fields adopted inversion tillage at least once in the past five years, and 66.8 % of the tillage occurred before planting sugar beet and potato. This is because farmers prefer tillage practices before seeding root crops to improve soil aeration for the regular development of the tubers (Djaman et al., 2022). However, there are a few studies show that no-till produced similar yield and quality compared to conventional tillage (Keshavarz Afshar et al., 2019; Holmstrom and Carter, 2000).

Our cover crop identification model and tillage model can be easily applied to other countries and regions using our shared code (see Data Availability). However, it should be noted that field-collected tillage information is essential for calibrating the tillage model.

4.2. Current status for classifying conservation agriculture

For their comprehensive review, Ahmed et al. (2024) selected 68 articles on CA and grouped them into five categories of conservation practices: cover crop (15), crop residues (26), crop rotation (9), mulching (4) and tillage practices (14). They noticed that these studies focused on a single facet of conservation practices at the time. We attempted to classify CA and TA fields by constructing quantitative indicators for three recognized criteria of CA, i.e. crop diversity, maximum soil cover and minimum soil disturbance. Overall, we analyzed data over a six-year period from 2015 to 2020. Combining data from the LPIS with time-series of optical and radar imagery and precipitation data, we

obtained a classification model with an overall accuracy of 92 %. To date, there is no standard for classification accuracy for CA fields. Thomlinson et al. (1999) set an overall accuracy target of 85 % for land use patterns, with no subcategories falling below 70 % accuracy. Our model successfully achieved this target.

Contrasting with our predicted CA adoption rate of 15.5 %, The European CA Federation (ECAf; <https://ecaf.org/>) calculates a significantly lower conservation agriculture adoption rate for Belgium at only 0.03 %. One reason for this discrepancy may be that ECAf’s data is outdated and lacks recent updates. On the other hand, our CA adoption rate may be overestimated, as our initial data collection lacked field audits. Additionally, our CA field predictions are based on a set of indicators created within our model, rather than on FAO’s strict CA definition, which requires all three CA principles to be fully met. These discrepancies align with global challenges in CA estimation, where various definitions and data transparency affect reported rates (Ferdinand, 2024). Nevertheless, the indicators established in our study are clearly different under two farming system, with CA fields overall scoring better on the indicators (Fig. 8).

Moreover, there is an ambitious aspiration to develop regenerative agriculture (Tittone et al., 2022) focusing on restoration and rebuilding of the soil health and planet’s ecosystems and helping to meet the objectives of the EU Soil Strategy for 2030 (Rehberger et al., 2023; European Commission, 2021). There are five principles of regenerative agriculture policy, in addition to the three principles that overlap with CA, the other two principles that were not discussed here include minimizing the use of chemical inputs and integrating livestock. There are currently some studies that use hyperspectral drones or aerial photographs to identify livestock species and count animals on a small scale (Ocholla et al., 2024). However, using satellite data to detect livestock or chemical inputs on a larger scale remains challenging. A feasible solution is to convert administrative-level statistical data into pixel-scale distribution using spatial models or based on crop distribution. (Liu et al., 2024; Shen et al., 2022).

4.3. Potential applications and limitations of our work

Some data products which can be used as input data for soil carbon models are generated simultaneously (downloadable in Data availability). For instance, the RothC model (Coleman and Jenkinson, 2014) utilizes the degree of soil cover (bare or vegetated). Integrating these data into soil carbon models enables credible and robust simulations of soil organic carbon dynamics, and supports the development of Monitoring, Reporting, and Verification (MRV) platform (COWI, 2021) to ultimately validate the effectiveness of soil carbon sequestration as a strategy for greenhouse gas removal. One major limitation of this paper is this study relies on high quality and high-frequency remote sensing data covering the length of a crop rotation (3–5 years). Bad weather conditions such as cloud cover will cause data loss, affecting the final forecast. Although not perfect, remote sensing remains the most realistic option for studying crop rotations, detecting management practices over large areas. Future research could incorporate additional available satellite data (such as Sentinel-3 and Landsat-9) or upcoming hyperspectral data (e.g., from the Copernicus Hyperspectral Imaging Mission (CHIME) and Surface Biology and Geology (SBG)), which would greatly help address the limitations of the current study.

Furthermore, this study is based on phenological data from the Rheinland-Pfalz region of Germany, which may not accurately represent the conditions in Wallonia due to differences in soil types and climate. Additionally, the statistical nature of the phenological data does not account for variations in the start and end dates for the same crop across different fields and years. While these discrepancies may have a limited impact on cover crop identification, they can affect the identification of tillage practices, which are sensitive to narrow temporal windows. Future work should consider integrating local phenological data to improve the accuracy of agricultural assessments in the study region.

5. Conclusion

By combining long-term series of optical and radar satellite data with precipitation data, and using machine learning methods, a conservation agricultural fields classification model in the Walloon region of Belgium was successfully established (overall accuracy of 92 %). The input indicators of this model cover the three principles of CA. The model can distinguish fields under conservation agricultural land and associated management practices for large areas. The adoption rate of conservation agriculture in the Hesbaye region is 15.5 %, and the dominant management practice that determines the predicted results is the tillage practice. However, tillage followed by seeding in one or two days and management practices such as application of fertilizers and other chemical input remain beyond our current ability to model through remote sensing.

CRedit authorship contribution statement

Yue Zhou: Writing – original draft, Visualization, Software, Methodology, Conceptualization. **Manon S. Ferdinand:** Writing – review & editing, Validation, Investigation, Data curation. **Jelle van Wesemael:**

Writing – review & editing, Validation, Data curation. **Klara Dvorakova:** Software, Methodology. **Philippe V. Baret:** Writing – review & editing, Data curation. **Kristof Van Oost:** Writing – review & editing, Conceptualization. **Bas van Wesemael:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Tables and figures

Table A.1

Crop calendar of main crop types in Hesbaye region (The frequency during 2015–2020, data source: <https://geoportail.wallonie.be/>). (*represent start from previous year).

Crop type	Frequency	Seeding(mm/dd)	harvest(mm/dd)	Type	Source of date
Winter wheat	38.4 %	10/01*	07/30	Winter	dwd.de
Sugar beet	13.6 %	04/15	10/25	Summer	getmeteoattract.com
Potato	11.3 %	04/15	09/20	Summer	dwd.de
Maize silage	6.7 %	05/01	09/25	Summer	dwd.de
Winter barley	6.0 %	10/01*	07/15	Winter	dwd.de
Flax	4.2 %	04/01	08/10	Summer	agro-v.com
Peas	3.6 %	05/01	08/20	Summer	almanac.com
chicory	3.0 %	03/15	10/31	Summer	growveg.com
Maize grain	1.8 %	05/01	11/05	Summer	dwd.de
Winter rapeseed	1.5 %	8/13*	07/20	Winter	dwd.de

Table A.2

Composition of the confusion matrix (NN represents the number of fields considered conventional by both measured and predicted data, CC represents the number of fields considered conservation by both measured and predicted data, CN represents the number of fields that are measured as conservation but predicted as conventional, NC represents the number of fields that are measured as conventional but predicted as conservation.)

$$\text{Overall Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}} = \frac{NN + CC}{NN + CC + CN + NC} \quad (\text{A.1})$$

$$\text{Producer's accuracy} = \frac{\text{Number of correctly predictions of a class}}{\text{Total number of observations of that class}} = \frac{NN}{NN + NC} \text{ OR } \frac{CC}{CN + CC} \quad (\text{A.2})$$

$$\text{User's accuracy} = \frac{\text{Number of correctly predictions of a class}}{\text{Total number of predictions of that class}} = \frac{NN}{NN + CN} \text{ OR } \frac{CC}{NC + CC} \quad (\text{A.3})$$

$$\text{Kappa} = \frac{\text{Observed agreement} - \text{chance agreement}}{1 - \text{chance agreement}} = \frac{\left(\frac{NN + CC}{NN + CC + CN + NC} \right) - \left(\frac{NN + NC}{NN + CC + CN + NC} \times \frac{NN + CN}{NN + CC + CN + NC} + \frac{NC + CC}{NN + CC + CN + NC} \times \frac{CN + CC}{NN + CC + CN + NC} \right)}{1 - \left(\frac{NN + NC}{NN + CC + CN + NC} \times \frac{NN + CN}{NN + CC + CN + NC} + \frac{NC + CC}{NN + CC + CN + NC} \times \frac{CN + CC}{NN + CC + CN + NC} \right)} \quad (\text{A.4})$$

		Reference data		
		Conventional	Conservation	Total
Classified data	Conventional	NN	CN	NN + CN
	Conservation	NC	CC	NC + CC
	Total	NN + NC	CN + CC	

Table A.3

Mean and standard deviation (SD) values of six indicators under two farming system in Walloon region during 2015–2020.

		Conventional agriculture		Conservation agriculture	
No. of different annual crops	Mean	3.8		4.2	
	SD	0.9		0.9	
Cereal abundance	Mean	3.7		3.4	
	SD	1.2		1.1	
Number of cover crops	Mean	1.6		1.6	
	SD	0.8		0.9	
Duration of cover crops	Mean	326		372	
	SD	208		210	
Duration of bare soil	Mean	67		35	
	SD	84		51	
Duration of fallow	Mean	236		188	
	SD	221		157	

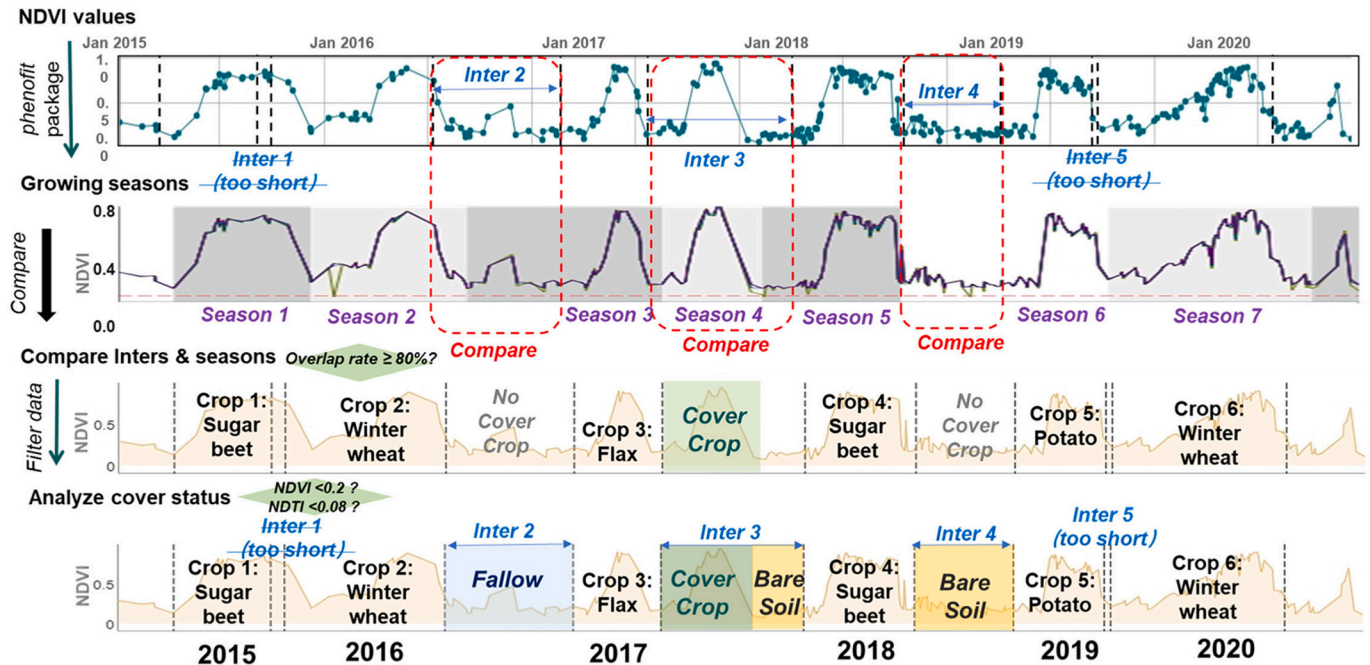
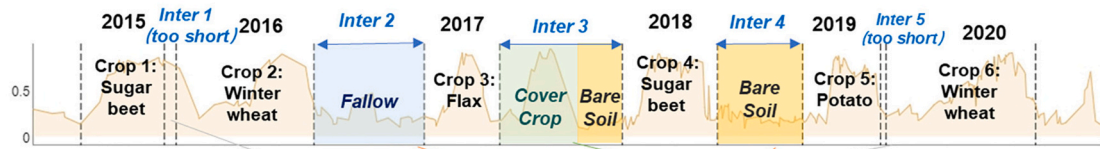


Fig. A.1. Example of identifying cover crops and bare soil based on long-term series NDVI and NDTI values during 2015 to 2020. This field was fallow between the two annual crops from 2016 to 2017 (Inter2) and consisted of a cover crop and bare soil between the two annual crops from 2017 to 2018 (Inter3), while the next year (inter4) was bare soil.

Step1: Define *inters* & Add results from section 2.4.2
-- the information of cover crop / bare soil / fallow



Step2: Classify each *inter* into different scenarios, and build relevant tillage model

Scenario	Short Interval (<30 d)	No Cover Crops	With Cover Crops
Independent variables	NA (often occurs when next crop is a winter crop)	mean/min values of NBR2, NDVI, VV and VH backscatter	proportion of CC/BS mean/min values of NBR2, NDVI, VV and VH backscatter
Dependent variable		inversion/non-inversion	inversion/non-inversion
Output	NA	Model I	Model II

Step3: Predict tillage practices with tillage models for each inter and determine the multi-year tillage practices

Field	Inter 1 Predicted Tillage	Inter 2 Predicted Tillage	Inter 3 Predicted Tillage	Inter 4 Predicted Tillage	Inter 5 Predicted Tillage	multi-year Predicted Tillage
1	NA	inversion	NA	inversion	inversion	inversion
2						
...						

Fig. A.2. Workflow for building tillage models and predicting non-inversion/inversion tillage practice under three scenarios.

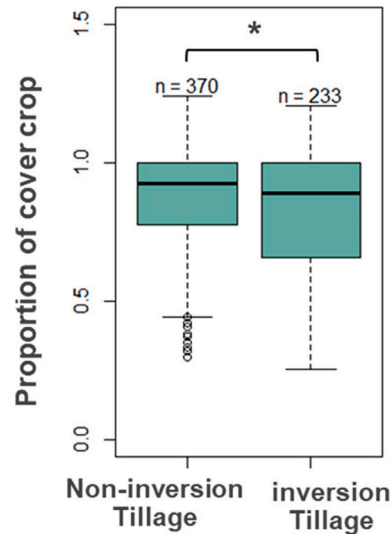


Fig. A.3. Boxplot of proportion of cover crop duration in the entire interval under inversion and non-inversion tillage (*: $P \leq 0.05$, significance notation under Wilcoxon test).

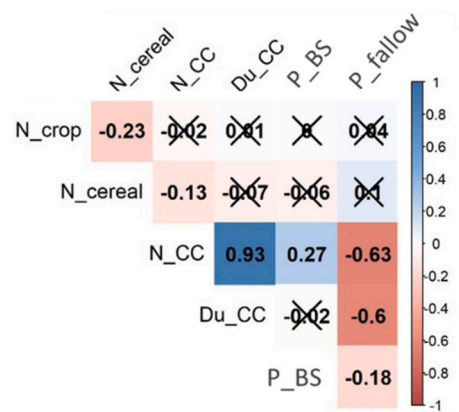


Fig. A.4. Correlation plot between 7 continuous covariates, where a cross denotes the relationship is not significant (Here: N_crop: number of different annual crops; N_cereal: number of cereals; N_CC: number of cover crops; Du_CC: duration of the cover crop; P_BS: bare soil period; P_fallow: fallow period).

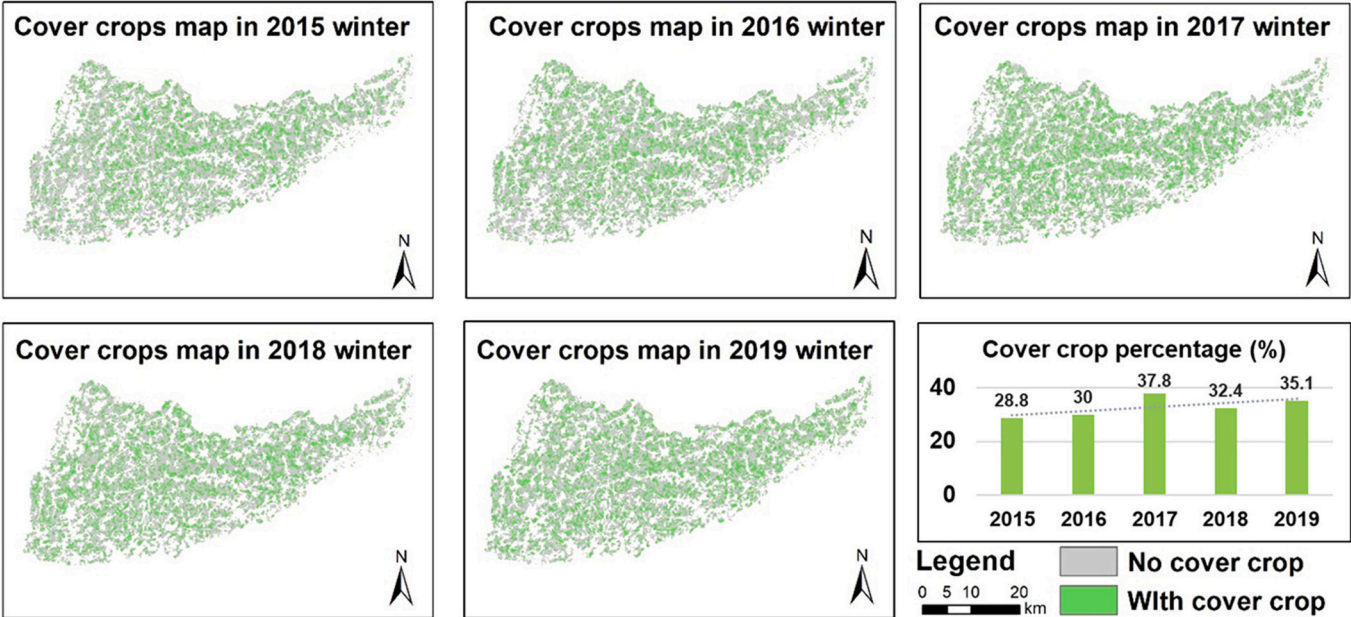


Fig. A.5. Cover crops maps during 2015–2020 in the Hesbaye region. Note that the “No cover crop” category includes both winter cash crops (which account for approximately 50 % according to LPIS data) and fields where no main or cover crops were planted.

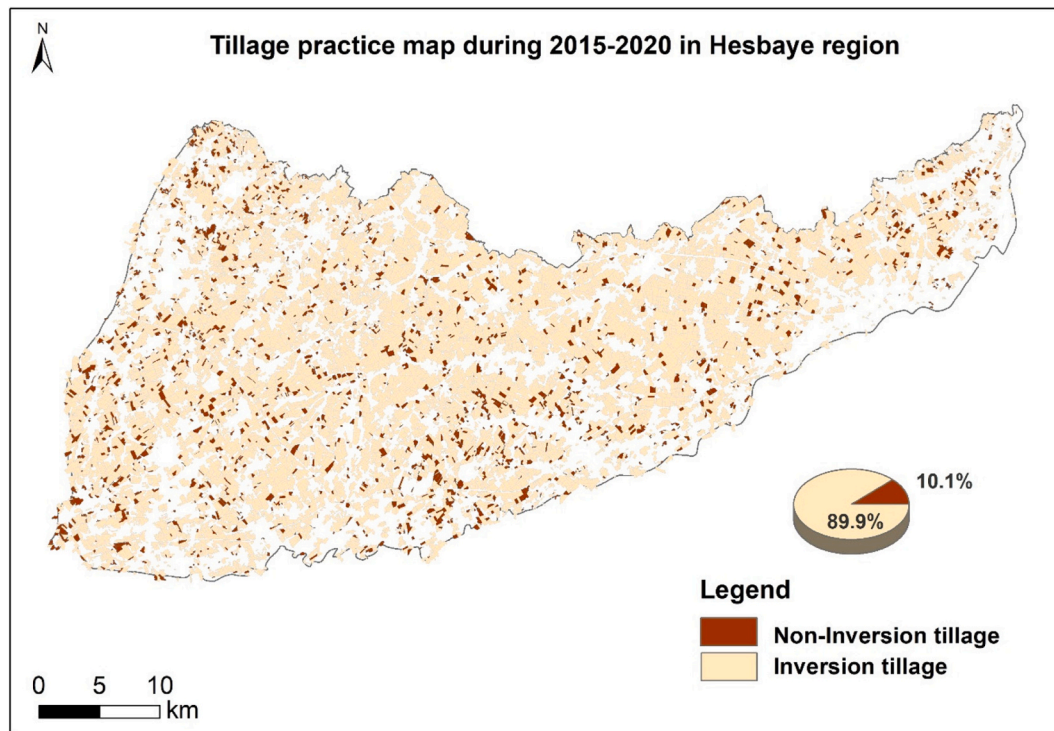


Fig. A.6. Tillage practice map during 2015–2020 in Hesbaye region.

Appendix B. Details on parameter selection

- **30 days:** We chose a one-month threshold, because our remote sensing observations have an interval of 5 to 10 days, and cloud cover can further reduce data availability. Periods shorter than 30 days often result in insufficient data, preventing meaningful time-series analysis. This is supported by our response to Question 28, where the flowchart shows that short periods frequently lack any usable data points or have only one. Thus, a 30-day minimum ensures sufficient data for analysis.
- **Precipitation of 2.5 mm within 5 days:** The five-day window aligns with the revisit time of Sentinel-2. The choice of the 2.5 mm threshold was based on an analysis of all periods, where we added the corresponding NDVI, NDTI, and cumulative precipitation data for each time point. We observed that for periods showing abnormal increases in NDTI, 2.5 mm was the minimum precipitation value frequently associated with such events. Therefore, we selected 2.5 mm as the threshold.
- **NDVI peak of 0.6:** “High NDVI values (approximately 0.6 to 0.9) correspond to dense vegetation such as that found in temperate and tropical forests or crops at their peak growth stage” (<https://www.usgs.gov/special-topics/remote-sensing-phenology/science/ndvi-foundation-remote-sensing-phenology>)
- **NDVI_{mean} < 0.2 and NDTI_{mean} < 0.08:** These values were chosen based on the literatures, and we also tested different thresholds with visual Interpretation.

Data availability

We provided the source codes and five cover crop maps during 2015–2020 at field scale via the link: <https://doi.org/10.5281/zenodo.10370700>.

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