

# Article

# Carbon Benefits and Water Costs of Cover Crops by Assimilating Sentinel-2 and Landsat-8 Images in a Crop Model

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## Highlights

### What are the main findings?

- AgriCarbon-EO is able to reproduce the spatio-temporal variations of biomass, CO<sub>2</sub>, and water fluxes of winter cover crop at a decametric resolution.
- The spatial variability of the above-ground biomass of cover crops was high both within and between plots in the study area over the five years studied.
- Cover crops contribute to increase the carbon inputs into the soil while having limited impact on water availability for the following crop.

### What is the implication of the main finding?

- In South West France, cover crops represent a realistic option to increase soil organic carbon stocks under the current climatic conditions.
- The high spatial variability of cover crop development shows the importance of assimilating high resolution remote sensing data in a crop model to assess accurately their impact on soil carbon and water resources.



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## Abstract

The use of cover crops is one of the most effective practices for maintaining, or even improving, the carbon balance of agricultural soils, while offering various ecosystem benefits. However, replacing bare soil with cover crops can increase transpiration and potentially reduce the water available for subsequent cash crops. The study takes place in southwestern France where it is essential to strike a balance between carbon storage and water availability, and where agroecological practices are encouraged and water resources are limited and expected to diminish with climate change. In this study, estimates of cover crop biomass production, as well as of the components of the water and carbon cycles, are carried out using a hybrid approach, AgriCarbon-EO, combining modeling, remote sensing, and assimilation, with quantification of target variables and their uncertainties at decametric resolution. The SAFYE-CO<sub>2</sub> agrometeorological model used in AgriCarbon-EO is calibrated to represent cover crops development, and simulated variables are compared with CO<sub>2</sub> fluxes and evapotranspiration measured by eddy covariance (for NEE, R<sup>2</sup> = 0.57, RMSE = 0.97 gC·m<sup>-2</sup>; for ETR, R<sup>2</sup> = 0.42, RMSE = 0.87 mm), as well as to an extensive above-ground biomass dataset (R<sup>2</sup> = 0.71, RMSE = 93.3 g·m<sup>-2</sup>). Knowing the local performance of the approach, a large-scale, decametric-resolution modeling exercise was carried out to simulate winter cover crops in southwestern France, over five contrasting fallow periods. The significant variability in cover crop phenology and above-ground biomass was characterized, and estimates of the amount of humified carbon added to the soil by cover crops were quantified at the pixel level. With amounts ranging from 40 to 130 gC·m<sup>-2</sup>

for most of the considered pixels, these new SOC values show clear trends as a function of cumulative evapotranspiration. However, the impact of cover crops on soil water content appears to be minimal due to spring precipitation.

**Keywords:** crop modeling; carbon budget; water budget; remote sensing; cover crop; fallow period

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## 1. Introduction

Cover crops (CCs) are grown to provide a wide range of ecosystemic services [1]. Depending on variety, they can reduce soil erosion [2], structure the soil [3], provide resources to pollinators [4], while introducing additional carbon to the soil [5]. When species belonging to the Fabacea family such as faba beans (*Vicia faba* L.) are used, the cover crop can also provide an additional source of nitrogen to the field by releasing the nitrogen fixed through bacterial symbiosis during the mineralization of the crop residues [6,7]. In the perspective of climate mitigation, the implantation of winter CCs offers a scalable way to increase surface albedo [8,9] and soil organic carbon (SOC) stocks through increased biomass inputs to the soil, as they can be added in various crop rotations before the summer crops. This scalability is key, as the availability of exogenous carbon inputs like amendments is limited [10–12]. Aside from these benefits, the cover crop also induces additional transpiration but reduces evaporation (Evap). The total evapotranspiration (ETR) can thus be increased depending on the climatic context [13,14]. Additionally, the presence of CCs tends to decrease lateral water flow through the preferential flow induced by the presence of roots and thus fosters percolation. This induced reduction in Runoff allows for limiting soil surface erosion and the leaching of carbon and nutrients to surface water streams [15,16]. To assess the global role of CCs through carbon fixation and its local implications on the hydrological cycle, it is essential to put into perspective the dual effects of the CCs on the carbon and water budgets.

The existing literature mainly relies on direct measurements or simulated scenarios at field trials to determine the impact of CCs on the carbon and water cycles [17–19]. However, local measurements and modeling do not take into account the full scope of the spatial and interannual variability in production and phenology exhibited by CCs. Given their high levels of spatial and interannual variability of development [20,21], we argue that a diagnostic of the effects of CCs needs to represent crop developments and the biochemical fluxes it entails at high resolution. This variability can be linked among others to soil characteristics and the fact that CCs may not receive the care provided to cash crops (fertilization, herbicides/fungicides, soil work, and sub-optimal growth periods). To take into account this high-resolution variability in development and its impact on the carbon and water cycles, without explicitly knowing the causes, it is possible to use direct observations of the crop growth dynamics [22]. However, even for crop growth proxies, in situ measurements are still hard to come by at large scale and high resolution with high repetition [23,24].

To circumvent this limitation, remote sensing measurements are the most promising solution [25]. The global systematic high resolution and high repetitiveness of optical satellite observations provided by the Sentinel and Landsat missions are of particular interest to characterize crop growth dynamics at high resolution [26,27]. Those observations provide estimations of the reflectance of the surface that can be interpreted to provide biophysical characteristics. Among those variables, Green Leaf Area Index (GLAI) is a well-known biophysical variable that is related to key plant processes, such as photosynthesis

and transpiration and overall growth [28]. GLAI time series have been used to constrain crop models to correct simulations for local variations in leaf growth dynamics. It has been shown that this constraint significantly enhances the diagnostic capabilities of dynamic crop models in numerous studies such as in [29] or [30] and across a diverse array of applications as shown in [31].

In the highlighted studies, the spatial scaling of assimilation is presented as the factor that limits the broad use of data assimilation in crop models to perform agronomic analysis, but recent studies have overcome this issue [24,32]. High-resolution spatially explicit diagnostics also present the added benefit of matching the spatial scales of representativity of in situ measurements of CC biophysical variables such as Dry Above-ground bioMass (DAM) (e.g., [20,21]), but also in situ measurements representing field scales such as those provided by eddy covariance stations [33,34]. We argue that this evaluation against independent measurements combined with an effort to assess intrinsic uncertainties linked to the use of remote sensing guarantees a high level of transparency needed to guide local and regional decision-making regarding the deployment of CCs at large scales.

In the current context of climate change, the impact of agricultural practices identified as mitigation levers remains to be determined, particularly that associated with cover crops on soil carbon stocks and water flows, which remains poorly quantified at the local scale. Our objective is therefore to provide a framework for spatially diagnosing, at high resolution, the biogenic carbon and water flows associated with the introduction of cover crops, using a simple agronomic model. The AgriCarbon-EO processing chain, initially validated for wheat crops, was used to address this challenge [24]. This tool allows us to spatialize the SAFYE-CO<sub>2</sub> crop model constrained by GLAI time series at high resolution and regional scale while providing uncertainty estimates.

The tool is first calibrated and evaluated against CO<sub>2</sub> and water flux measurements by eddy covariance and in situ above-ground measurements of biomass for winter cover crops. After the assessment of the quality of the AgriCarbon-EO simulations, the methodology is applied at regional scale and high resolution to analyze the effects of those CCs on the addition of newly produced SOC and on components of the water cycle in southwestern France. This analysis includes both a regional simulation covering five intercropping periods and an assessment focused on a partner farm.

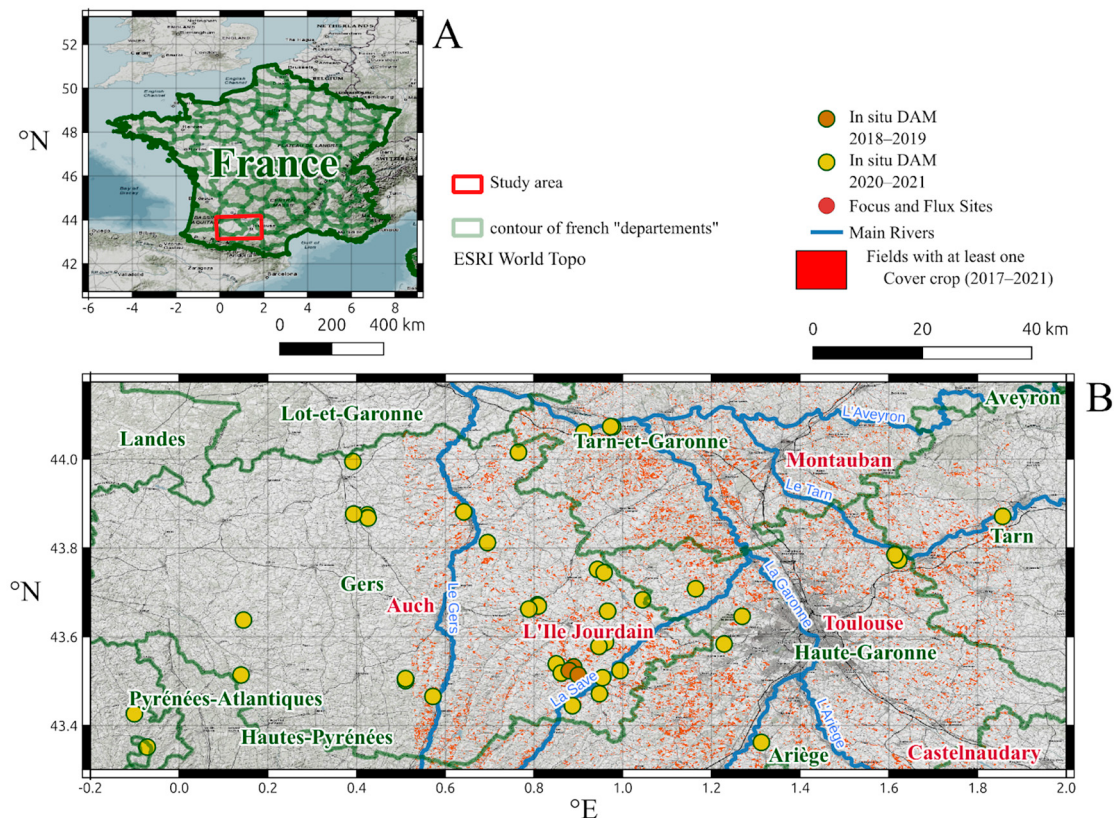
## 2. Materials and Methods

### 2.1. Study Area

The study area covers part of the Haute-Garonne and Gers departments in southwestern France (Figure 1). This area has been monitored since 2007 in the context of the Regional Spatial Observatory South-West (OSR SO, <https://osr.cesbio.cnrs.fr/>, accessed on 3 September 2025), which benefits from numerous field surveys and various experiments. With research activities mainly focused on monitoring and assessing natural and anthropogenic determinants of ecosystem functioning at a regional watershed scale and its landscape, this observatory is also part of the Pyrenees Garonne Regional Workshop Area (ZA PYGAR [35]), and it embeds one of the sites of the OZCAR Research Infrastructure on the Critical Zone [36] as well as two flux sites (FR-Aur and FR-Lam) of the Integrated Carbon Observation System (ICOS [37]).

The region has a hilly landscape, with shallow eroded clay soils on the hilltops, deeper clay and silt-loam soils on the slopes, and sandier and siltier soils in the river valleys. The study area is governed by a temperate climate with oceanic and Mediterranean influences, with annual rainfall and temperature close to 655 mm and 13 °C, respectively. The region is covered at more than 60% by farmland, most of which is used for seasonal crops. The main crops are winter cereals, sunflower, corn, and canola, which accounted for around

35, 17, 8, and 3% of agricultural surfaces, respectively (values derived from the analysis of land-use maps described in Section 2.3.3). Typical crop rotations are two-year rotations between winter wheat and sunflower, or corn monocultures. Longer crop rotations (over more than two agricultural seasons) integrating wheat, sunflower, canola, and soybean are also present. In this region, the winter fallow period extends from harvest of wheat or canola (late June to mid-July), or corn (October), to the seeding of the following summer crop, e.g., corn or sunflower (between April and May).



**Figure 1.** Location of the study site in southwestern France (area marked with a red rectangle (A)), as well as the network of fields studied (B). The two agricultural fields where the eddy covariance flux towers were installed are highlighted in red (AUR for Auradé, PIB for Pibrac), while the 49 fields where 185 cover crop biomass samples were collected are shown in orange and yellow, the difference depending on the measurement campaign considered (2018–2019 in orange, 2020–2021 in yellow).

The main motivations for cultivating cover crops (CCs) in this region lies in the mitigation of erosion risks linked to local topography and soil characteristics [38], which are well documented and explain the adoption of agroecological practices in the region [39]. Improving soil quality and increasing carbon, particularly in depleted areas such as clay soils, are also often cited [5,39]. Finally, there are also financial and regulatory factors that motivate the use of CCs; for example, the need to comply with the Nitrate Directive (91/676/EEC) and the increasing cost of nitrogen fertilizer. However, several constraints are often cited to justify limited adoption: the financial cost of their implementation (field management and seed cost), concerns about competition for water resources with subsequent commercial crops, and the risk of soil compaction in clay soils due to additional field operations or even herbicides required to terminate cover crops [39].

These concerns are amplified in a context where water availability is becoming increasingly critical. Crop water needs are expected to increase by 13% to 28%, due to the growing demand for evaporative water in the coming years. At the same time, snow accumulation in the Pyrenees, a significant contributor to river discharge in spring and early summer,

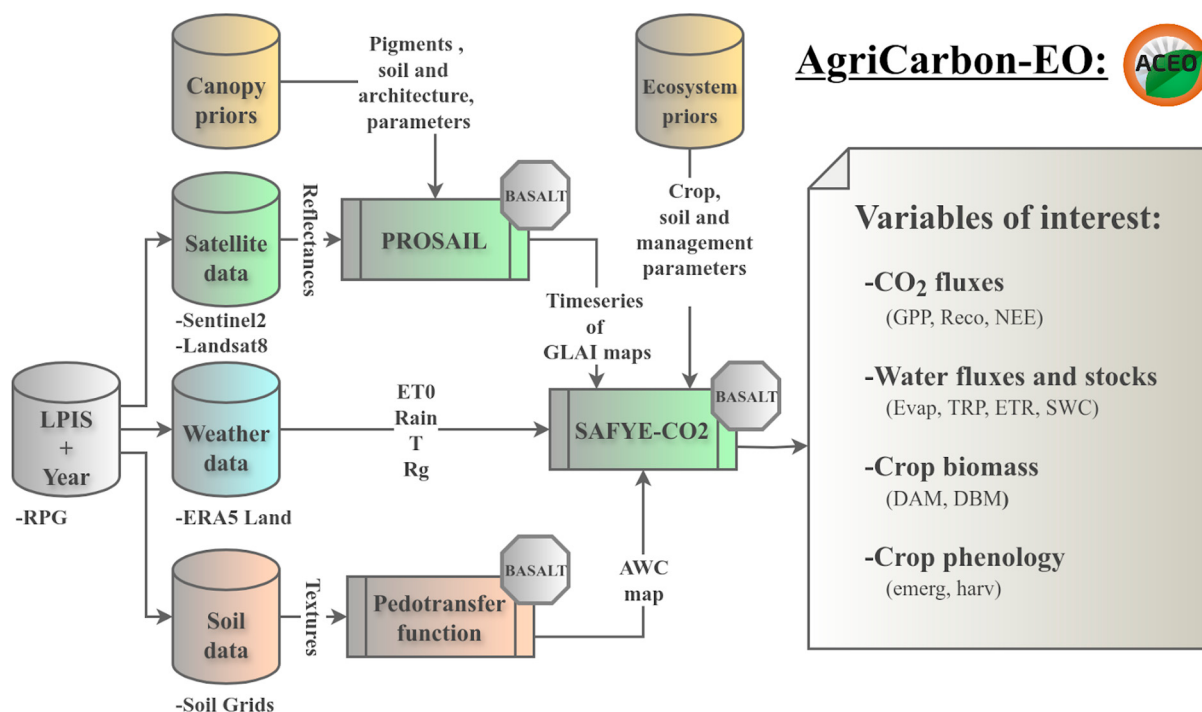
presents high uncertainty in terms of volume and melt dynamics, due to an expected concomitant increase in temperature and precipitation [40]. In addition to these climatic and agronomic concerns, population growth continues to put pressure on water resources, which may lead to trade-offs between personal water use and agricultural needs [41].

In this specific context, faba bean in mixture with phacelia was mainly adopted, as it grows quickly to stabilize the soil and produces a good amount of biomass compared to other annual Fabaceae [42]. In addition, the mix of species adds resilience to the cover crop in the event of disease or adverse climatic events or pests. Like other Fabaceae, faba bean fixes atmospheric nitrogen through the action of its ectomycorrhizal symbioses, reducing fertilizer requirements for the following crop [7].

## 2.2. Main Features of the Processing Chain

AgriCarbon-EO is an end-to-end processing chain that simulates multiple relevant variables to crop development, including yield, total biomass, biomass inputs to the soil (e.g., crop residues or cover crops), CO<sub>2</sub> fluxes, and water fluxes, on a daily timescale and over large territories. These different variables can be combined to assess carbon and water balances at various timescales (e.g., daily up to cropping year). This tool is specifically designed to assimilate biophysical variables, derived from native high-resolution optical remote sensing data using a radiative transfer model (PROSAIL [43,44]) into a parsimonious agronomic model: SAFYE-CO<sub>2</sub> [33,34].

This tool has been described in detail and evaluated for winter wheat in [24]. In the present study, the processing steps implemented in AgriCarbon-EO (Figure 2), namely the gathering of meteorological and satellite data, the inversion of GLAI maps from satellite images using the PROSAIL model, and the assimilation of GLAI time series into the SAFYE-CO<sub>2</sub> crop model, are used to estimate components of the carbon and water balances of CCs.



**Figure 2.** Simplified synopsis of the AgriCarbon-EO processing chain used for carbon and water budget components and biomass estimations in this study (see [24] for the detailed model and processing chain descriptions).

All models used in the processing chain rely on BASALT (BAYesian normalized importance SAMpling via Look-up Table generation) to perform numerical uncertainty

propagation and data assimilation. BASALT is a naive Bayesian method that relies on the generation of Look-up Tables (LUT), where each line of the tables is weighed given its relative likelihood computed through a comparison with an observable. This methodology ensures computational efficiency through a minimal number of model simulations and the uncertainty propagation through probabilistic weighting of LUTs, which allows providing a posterior estimate.

In practice, a unique prior distribution is used for the pedotransfer function and PROSAIL, while a site-specific prior distribution, forced by fixed local meteorological conditions for each ERA5 grid cell, is used for SAFYE-CO<sub>2</sub>. These priors are sampled and used to run the models for each parameter combination. The next step is to calculate the likelihood of each combination given the available relevant observables: reflectances in the case of PROSAIL, soil textures for the pedotransfer function, and time series of GLAI and AWC<sub>max</sub> for SAFYE-CO<sub>2</sub>. The raw weighted ensembles or statistics representing these ensembles can then be used to describe the surface state, given the observables and constraints provided by the models. This posterior state can then be represented using normal distributions ( $\mu$ ,  $\sigma$ ) or weighted ensembles.

The data or thematic maps required to run the processing chain are first presented (Section 2.3), followed by the variables of interest used during the calibration phase and for statistical performance evaluation (Section 2.4). Section 2.5 focuses on three methodological points specific to the present study: the determination of the available water content, the calibration strategy used to retrieve the prior values of cover crop phenological and light-use efficiency parameters, and the relationship implemented to estimate the quantity of SOC produced by the decomposition of the simulated cover crop biomass. The biophysical variables obtained by AgriCarbon-EO are first confronted with in situ ground data, in order to derive a series of results illustrating the quality of the simulations (Section 3.1). Secondly, simulations performed during five consecutive fallow periods (i.e., the periods between the years 2016–2017, 2017–2018, 2018–2019, 2019–2020, and 2020–2021) are analyzed at regional scale (Sections 3.2.1 and 3.2.2) as well as at farm and field spatial scales (Section 3.2.3). As the winter fallow periods overlap two years, the results presented in the following sections will be associated with the year in which the cover crop is destroyed (e.g., 2017 for the 2016–2017 fallow period).

### 2.3. Spatial Input Data for AgriCarbon-EO

#### 2.3.1. Climatic Data

The climate variables used to force the agrometeorological model are global incident radiation, temperature at 2 m, precipitation, and potential evapotranspiration. These data are provided by ERA5-Land [45] and are automatically downloaded from the ECMWF web portal (accessed on 3 September 2025). The data are provided at a spatial resolution of 0.1° (i.e., around 9 km in the study area), at a half-hourly time step and on a global scale. To be used by SAFYE-CO<sub>2</sub> the data are aggregated on a daily time scale, by computing the mean temperature and summing the other variables.

There is significant variation in weather conditions between the winter cover crop seasons from 2017 to 2021. In terms of winter temperatures, the winters of 2016–2017 and 2017–2018 experienced significant cold spells in January and February, respectively, which were absent in the other three years, which were generally milder. In terms of global solar radiation, the last two years have fewer low peaks, which can be explained by less cloud cover. In these years, ET<sub>0</sub> is higher in spring, which coincides with spring temperatures above the average for the five years studied. Finally, an average of 500 mm of precipitation is observed for the period from September to May, with significant regional variation. The years 2019–2020 and 2020–2021 tend to be the wettest among the simulated years.

### 2.3.2. Optical Satellite Images

The series of optical satellite images used to characterize the fallow periods are acquired from 2016 to 2021 by three satellites belonging to two satellite missions, Landsat and Sentinel, respectively, managed and funded by the United States Geological Survey (USGS) and the National Aeronautics and Space Administration (NASA), and by the European Space Agency (ESA).

Landsat-8 was launched in February 2013. It carries two kinds of instruments that operate in spectral bands ranging from visible to thermal wavelengths. The multispectral sensors, delivering images in spectral bands ranging from visible to mid-infrared (from 0.43 to 2.35  $\mu\text{m}$ ), provide products with a spatial resolution of 30 m, in 8 bands, and a revisit of 16 days.

Launched two years apart in June 2015 and in March 2017, the Sentinel-2A and Sentinel-2B satellites carry a multispectral imager that provides images in thirteen spectral bands ranging from the visible to the short-wavelength infrared (from 0.44 to 2.19  $\mu\text{m}$ ). The images are characterized by a spatial resolution of 10, 20, or 60 m depending on the considered wavelength, with a 5-day revisit (when considering the 2 satellites).

All images are automatically downloaded from the web THEIA portal (<https://www.theia-land.fr/>, accessed on 3 September 2025). Whatever the satellite, the reflectance data are derived from the observed luminescence, using the MAJA processing chain of the Thematic Center for Continental Surfaces (THEIA), which aims to correct atmospheric effects, and detect clouds as well as their shadows [46].

### 2.3.3. Land Cover Map

The SAFYE-CO<sub>2</sub> model requires knowledge of land-use. When applied to cash crops, previous studies [24,33,34] have relied on the Registre Parcellaire Graphique (RPG), maps produced by the Institut Geographique National for the Agence de Service de Paiement (French Paying Agency) in charge of paying the subsidies to the farmers in the context of the EU Common Agricultural Policy (CAP) in France (IGN., 2020 <https://geoservices.ign.fr/rpg>, accessed on 3 September 2025). The RPG provides information on the field contours and the main cash crop each year. The RPG does not contain exhaustive and accurate data on cover crops, therefore the information on their presence or not in a field during the fallow period was derived as follows. The fields whose crop rotation can accommodate winter cover crops are identified using the RPG. Fields having a winter or summer crop followed by a summer crop have a fallow period long enough to host potentially a cover crop. Among the concerned fields, only the ones with a maximum Normalized Difference Vegetation Index (NDVI) greater than 0.4 during the fallow period between the 1st of January and the 15th on at least 70% of their surface were considered as cover crops. This filtering procedure aims at filtering out spontaneous regrowths and weed growth that are expected to be heterogeneous, as well as cover crops that show poor development and have a limited impact on water and carbon balances. Cover crops that were destroyed before the end of December in our study area were not considered. Finally, the simulations were carried out on fields larger than 5 hectares, to eliminate fields with a shape conducive to edge effects and with a low number of pixels after erosion.

### 2.3.4. Soil Property Maps

Soil texture is needed to calculate the hydrological soil properties that constrain the water reservoirs and therefore the water fluxes in SAFYE-CO<sub>2</sub>. The procedure implemented to calculate the available water content is described in Section 2.5.1. Soil properties were extracted from the Soil Grids database [47], which represents soil texture in terms of volume percentages of clay, sand, and silt, as well as other soil characteristics such as carbon content

for layers 0–5 cm, 5–15 cm, 15–30 cm, 30–60 cm, 60–100 cm, and 100–200 cm, with a lateral resolution of 250 m. It should be noted that these 250 m products do not allow for the full extent of soil variability in situ over 10 m to be represented, particularly given the hilly terrain.

#### 2.4. *In Situ* Data Used for Calibration and Statistical Performance Evaluation

##### 2.4.1. Daily Flux Measurements on Two Experimental Fields

The eddy covariance flux towers were installed near the center of two agricultural fields, located in the villages of Auradé (AUR, 43.54966°N–1.10612°E) and Pibrac (PIB, 43.64022°N–1.26675°E) (Figure 1). The Auradé field exhibits a cereal–sunflower–cereal–rapeseed rotation, and the Pibrac site a popcorn–maize–wheat rotation. For both fields, the cover crop is sown during the winter after a winter cereal crop and before the subsequent summer crop. Auradé is rainfed and located between the higher end of the alluvial terrasses of the Garonne River (dominated by the silty–sandy boulbene soil with low organic content and unstable structure, typical of southwestern France) and the coteaux that exhibit a hilly landscape with heavy clay soils. The Pibrac site is irrigated and situated on straight boulbene soils of the alluvial terrasses of the Garonne.

The eddy covariance method allows continuous measurement of turbulent fluxes of CO<sub>2</sub>, water (ETR and latent heat), sensible heat, and momentum [48,49]. Our setup included an open-path fast infrared gas analyzer (LI-7500, LI-COR, Lincoln, NE, USA) and a 3D sonic anemometer (CSAT3, Campbell Scientific, Logan, UT, USA) mounted on a mast. Evapotranspiration and net CO<sub>2</sub> fluxes were computed using the EdiRe software from the University of Edinburgh [50]. Quality controls and quality checks of the data, filtering, as well as gapfilling were performed following the methodology recommended by the CarboEurope-IP project and described in [49]. The NEE (net ecosystem CO<sub>2</sub> exchange) was partitioned to estimate gross primary productivity (GPP) and ecosystem respiration (R<sub>ECO</sub>) by using the algorithms proposed by [51] and adapted for croplands by [49]. Among the flux measurements collected under different surface conditions, cover crops were being planted at the Auradé and Pibrac sites during the 2019–2020 fallow period.

##### 2.4.2. Biomass Data Collected on a Network of Fields

Biomass data were collected during two field campaigns carried out during the winter fallow periods of 2018–2019 and 2020–2021 (Figure 1). The first campaign focused on a single farm with significant experience of cover crop cultivation, located on hillsides, and geared towards sustainable popcorn production. To achieve this objective, cover crops are systematically planted after winter wheat and before irrigated popcorn in a two-year rotation. Reduced tillage practices are used to minimize soil disturbance. This farm is involved in various programs (e.g., naturellement popcorn, <https://www.popcorn.fr/en/news/naturellement-popcorn-consortium/>, accessed on 3 September 2025) as a pilot site for demonstrating and testing protocols for estimating cover crop productivity and soil organic matter dynamics. Measurements were located on 4 fields, where the sown species were faba bean and phacelia. The second campaign covered a larger number of fields (45), with more diversified specific compositions, with mainly pure cover crops of faba bean, a few associations of faba bean with phacelia or oats, and a single field with crimson clover. The fields all have the same crop rotation as before and similar management. However, soil types can vary considerably between fields depending on their distance from the rivers that carved out the Gascony hillsides. Fields closer to the riverbeds tend to have silty soils due to alluvial deposits, while fields further out on the uplands have heavier, clay-rich soils. In the end, measurements were collected at 167 geo-referenced measuring locations, using the Elementary Sampling Units (ESU) protocol [33]. In the ESU protocol,

above-ground vegetation (cover crops and weeds) is sampled at five placets (of  $1 \times 1$  m) located at the corners and center of a  $10 \times 10$  m square (i.e., the resolution of a Sentinel-2 pixel). The fresh above-ground mass of the five samples is measured in the field, and one of the samples is brought back to the laboratory and dried in an oven to determine the dry above-ground mass (DAM) and the relative humidity. This relative humidity value is then applied to the other in situ measurements (placets) of the ESU to calculate the mean cover crop DAM as well as its standard deviation. The in situ biomass data used here for validation is therefore the sum of the DAM of all CCs and of the weeds. Mean DAM values range from 100 to  $500 \text{ g}\cdot\text{m}^{-2}$  and from 15 to  $750 \text{ g}\cdot\text{m}^{-2}$  for the 2018–2019 and 2020–2021 campaigns, with a mean biomass at the end of the growing season of  $340 \text{ g}\cdot\text{m}^{-2}$  for both datasets. A relative error ranging from 15 to 20% was observed when the five replicates of the ESU are considered.

## 2.5. Modeling Point Specific to This Study

### 2.5.1. Determination of the Available Water Content

To retrieve the available water content (AWC) maps, a simple Bayesian approach (BASALT [24]) was adopted. In practice, the clay and sand fractions were sampled 5000 times uniformly between 0 and 1, and the AWC was calculated for each sample using the pedotransfer functions adapted to the French context by [52]. These texture AWC pairs represent a prior distribution. The relative likelihood of each sample was calculated given the Soil Grids texture probability density functions. To derive the texture probability density function, the standard deviation of the Soil Grids products was approximated based on the provided quantiles. The final products of this procedure are maps of the mean and standard deviation of the AWC given the texture values provided by Soil Grids. This information is assimilated in SAFYE-CO<sub>2</sub> by adding a normal noise of 0.05 to the field capacity values centered around 0.25, and by calculating likelihoods based on GLAI and AWC instead of GLAI alone.

### 2.5.2. Calibration Strategy for the Agrometeorological Model

The calibration of the model for winter CCs was carried out at the Auradé site, which was seeded with faba bean CC. This was performed by assimilating NEE and GLAI using the BASALT method and broad priors. The posterior distribution of phenological parameters obtained from this calibration step is then site-specific. The a posteriori values have been relaxed for phenological parameters to encompass regional variability and allow reproduction of the different dynamics observed at emergence or leaf allocation over the region. The relaxed posterior values were used to run the simulations presented in Section 3. The quality of the simulation with the broadened parameter priors was assessed on Auradé and independently validated on Pibrac sites (Section 3.1.1).

### 2.5.3. Estimation of Soil Carbon Stock Changes Caused by Cover Crop

Based on estimates of the dry biomass before the destruction of the cover crop ( $\text{DAM}_{\text{harv}}$ ) and the dry biomass below-ground ( $\text{DBM}_{\text{harv}}$ ), the amount of C returned to the soil as biomass and the soil organic carbon stock change (dSOC) caused by the cover crops can be determined, taking into account the carbon content of the biomass and the humification coefficients of the above- and below-ground vegetation, as follows:

$$\text{dSOC} = C_{\text{cont}} \times (\text{DBM}_{\text{harv}} \times \text{hum}_{\text{root}} + \text{DAM}_{\text{harv}} \times \text{hum}_{\text{crop}}), \quad (1)$$

where  $C_{\text{cont}}$  is the carbon content of the dry biomass (fixed at 45%) and  $\text{hum}_{\text{crop}}$  and  $\text{hum}_{\text{root}}$  are the humification coefficients of the above- and below-ground parts of the crop and are, respectively, equal to 0.384 and 0.4. These humification coefficients represent the fraction

of the carbon contained in the biomass that is stabilized as SOC. Those coefficients are provided by the [53] dataset produced as part of the SOLÉBIOM project.

The work presented here focuses on variations in soil organic carbon stock following CC destruction. This newly produced SOC will then be mineralized (at a slower rate than biomass) and will decrease significantly over a period of 5 to 10 years. To capture the dynamic nature of SOC on multi-year time scales, specific soil models such as AMG [54], RothC [55], or Century [56] are required, but are outside the scope of this study.

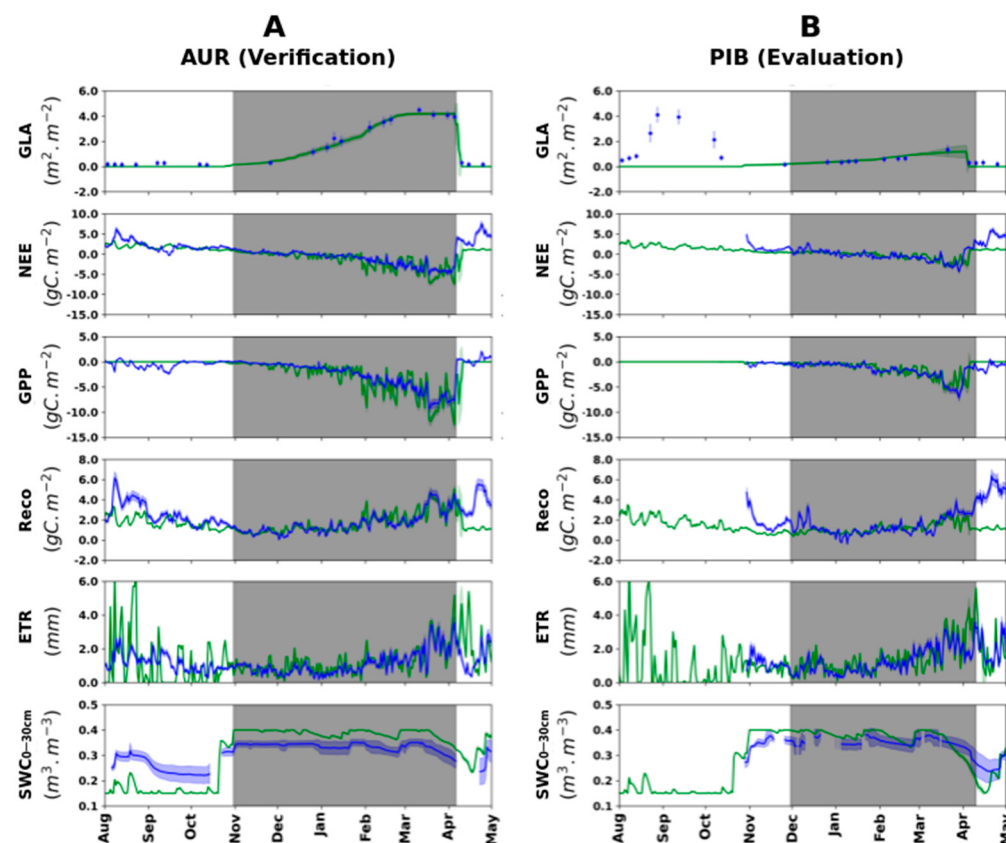
### 3. Results

#### 3.1. Characterization of the Modeling Approach's Performance

The model evaluation was divided into two distinct exercises, one on the flux tower sites and the other on the two cover crop biomass campaigns (Figure 1).

##### 3.1.1. Assessment of the Model for the GLAI, and for the Components the Net CO<sub>2</sub> Fluxes and Water Budgets

Daily values of GLAI, CO<sub>2</sub> flux components (NEE, GPP and RECO), and water cycle components (ETR, SWC<sub>0–30cm</sub>) estimated by the model are compared with those observed during the 2019–2020 fallow period at the AUR and PIB flux sites (Figure 3).



**Figure 3.** Temporal evolutions of the in situ or satellite-derived measurements (in blue) and modeled (in green) GLAI, NEE, GPP, RECO, ETR, and SWC<sub>0–30 cm</sub> for the two flux tower sites of Auradé (A) and Pibrac (B) (AUR and PIB, respectively). The graphs focus on the fallow period, with gray areas indicating the presence of a cover crop. The results from the AUR site correspond to a verification of the parameterization, and those from the PIB site to an independent evaluation of the proposed approach.

In this analysis, two periods are distinguished, namely the fallow period (between the two cash crops, integrating bare soil conditions and the presence of vegetation) and a focus

on the cover crop (period in dark gray on Figure 3). A summary of statistical fitting criteria distinguishing both periods is presented in Table 1. It is important to stress that the results presented for AUR are a verification of the a priori (obtained by calibration against GLAI, NEE, and ETR) and applied in the case where only GLAI is available. The results obtained on the PIB site correspond to an independent model evaluation.

**Table 1.** Summary of statistical performances (i.e., coefficient of determination,  $R^2$ , root mean square error, RMSE, and bias) for the different simulated variables at the 2 study sites during the 2019/2020 cover crop and whole fallow period (NR stands for not relevant).

| Sites | Variables             | Cover Crop Period |      |       | Fallow Period |      |       |
|-------|-----------------------|-------------------|------|-------|---------------|------|-------|
|       |                       | $R^2$             | RMSE | Bias  | $R^2$         | RMSE | Bias  |
| AUR   | GLA                   | 0.98              | 0.21 | 0.01  | 0.99          | 0.03 | NR    |
|       | NEE                   | 0.66              | 1.19 | −0.33 | 0.63          | 1.51 | −0.63 |
|       | GPP                   | 0.78              | 1.45 | −0.39 | 0.79          | 1.26 | −0.12 |
|       | Reco                  | 0.75              | 0.53 | 0.06  | 0.24          | 1.12 | −0.5  |
|       | ETR                   | 0.76              | 0.4  | 0.1   | 0.26          | 1.15 | 0.2   |
|       | SWC <sub>0–30cm</sub> | 0.81              | 0.01 | 0.05  | 0.74          | 0.06 | 0.01  |
| PIB   | GLA                   | 0.76              | 0.16 | 0.01  | 0.69          | NR   | NR    |
|       | NEE                   | 0.42              | 1.04 | 0.01  | 0.57          | 0.97 | −0.55 |
|       | GPP                   | 0.56              | 1.09 | 0.21  | 0.58          | 0.87 | 0.32  |
|       | Reco                  | 0.27              | 0.73 | −19   | 0.1           | 1.38 | 0.87  |
|       | ETR                   | 0.54              | 0.63 | 0.16  | 0.42          | 0.87 | 0.1   |
|       | SWC <sub>0–30cm</sub> | 0.58              | 0.03 | 0.0   | 0.82          | 0.04 | 0.01  |

The dynamics of the simulated variables are well reproduced overall, particularly when cover crop is present (as highlighted by the values of the various statistical criteria, Table 1). The assimilation process enables good reproduction of the canopy development phase till the destruction, as shown by the performance associated with GLAI simulations, with the  $R^2$  of 0.98 at the Auradé site and 0.76 at the Pibrac site, which is reasonably good considering the low intensity of cover crop development. Overall, the model reproduced well these contrasting levels of vegetation development.

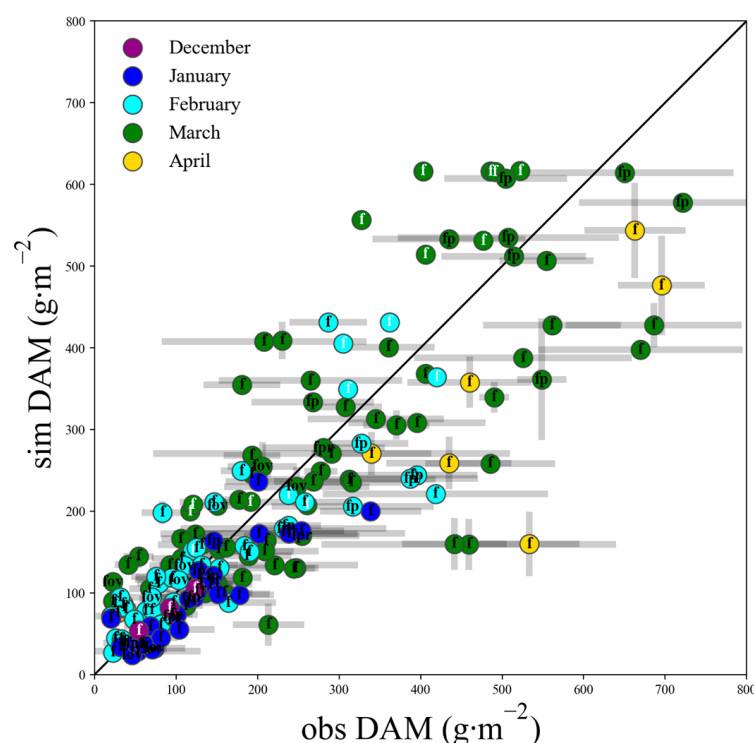
NEE is well reproduced during the period when vegetation is present (RMSE lower than  $1.19 \text{ gC} \cdot \text{m}^{-2}$ ) but errors are greater when the fallow period is considered (maximum RMSE of  $1.51 \text{ gC} \cdot \text{m}^{-2}$ ). This difference is explained by a poorer representation of ecosystem respiration during periods of bare soil, in particular after the destruction of the cover crop. The higher error levels observed during those periods before the cover crop emergence may be associated with the increase in respiration due to the humification of the previous crop and cover crop residues that are not explicitly represented in the SAFYE-CO<sub>2</sub> soil respiration module. This systematic underestimation of soil respiration causes an overestimation of the SOC-related and climatic benefits in a diagnosis that would rely on these simulations of about  $90 \text{ gC} \cdot \text{m}^{-2}$  given the observed bias over a five-month period. This is the reason why a humification coefficient was introduced to calculate their effect on SOC stock changes induced by the decomposition cover crop (see Section 2.5.3). Finally, the development of spontaneous regrowth and weeds at AUR before the cover crop also causes additional dispersion in the results.

The evapotranspiration dynamics observed when the cover crop is present are well reproduced, as evidenced by the error levels of 0.40 and 0.63 mm for the AUR and PIB sites. The ability of the model to reproduce evaporation before and after the cover crop is more contrasted. The choice of a single formalism to represent “bare soil” periods may present limitations, when crop residues cover the soil or when weeds/spontaneous regrowth develop.

Finally, the topsoil water content dynamic is quite well reproduced, except before the cover crop emergence at the AUR site. The poor representation of surface water content can be explained by the low ETR levels simulated during the initial bare soil period and by the presence of spontaneous regrowths and weeds. Furthermore, a discrepancy between the ERA5-Land land-rain product and in situ precipitation could induce a systematic bias during the whole cover crop period.

### 3.1.2. Assessment of the Spatio-Temporal Representativity of Cover Crop Biomass Simulations

The above-ground biomass (DAM) estimates simulated by the model over the 2018–2019 and 2020–2021 fallow periods are compared with in situ data collected on various fields (Figure 4).



**Figure 4.** Comparison between the measured and the simulated cover crop biomass. Measurement months are differentiated by the color of the points. Points with f concern faba beans biomass measurements; p, phacelia; and fp a mix of both. Points with white text were measured during the 2018–2019 fallow and with black text during the 2020–2021 fallow period. The gray bars correspond to an error of 1 sigma for each point.

The modeling approach shows overall good performance, characterized by a coefficient of determination of 0.71, and an error level below the variability observed in the measurements. RMSE values are  $93.9 \text{ g} \cdot \text{m}^{-2}$ , compared with standard deviations of in situ biomass of  $154.2 \text{ g} \cdot \text{m}^{-2}$  (Table 2).

These statistical indicators are derived at different periods of the vegetative cycle, showing good levels of relatively stable performance. Thus, for maximum biomass values observed at the end of the cycle, close to destruction, the  $R^2$  levels are 0.61 and 0.78 for the months of March and April, and as previous, the RMSE values are lower than the standard deviations of the measurements. The same applies for estimates made on lower biomass levels, observed at earlier stages of vegetation development during January and February ( $R^2$  levels are 0.77 and 0.71, respectively).

**Table 2.** Summary of statistical performances (i.e., coefficient of determination,  $R^2$ , root mean square error, RMSE, and bias) obtained from the comparison between measured and the simulated cover crop biomass.

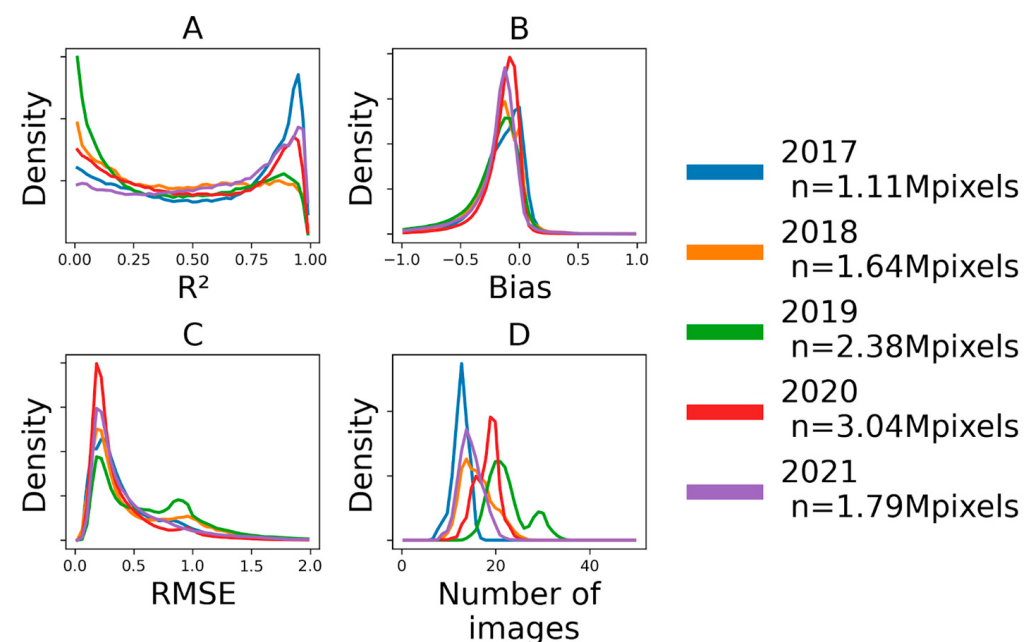
| Months   | nb  | Mean   | Std    | $R^2$ | RMSE   | Bias  |
|----------|-----|--------|--------|-------|--------|-------|
| December | 3   | 80.23  | 21.10  | 0.99  | 12.08  | 9.71  |
| January  | 28  | 94.27  | 58.01  | 0.77  | 45.28  | 28.40 |
| February | 48  | 155.07 | 105.31 | 0.71  | 63.90  | 1.16  |
| March    | 78  | 283.80 | 162.85 | 0.61  | 110.99 | 8.00  |
| April    | 10  | 239.73 | 164.02 | 0.78  | 160.73 | 85.67 |
| Total    | 167 | 208.73 | 154.17 | 0.71  | 93.93  | 14.14 |

### 3.2. Landscape-Scale Simulation for 2017–2021 Period

After characterizing the model's performance based on various observations relating to biomass, carbon, and water budgets, simulations were carried out on the Sentinel-2 tile of interest during five consecutive fallow periods (between 2017 and 2021). First results present the model's ability to reproduce the spatio-temporal development of cover crops. Then, the results of biomass estimates, dSOC, ETR, and soil water content are presented and analyzed.

#### 3.2.1. Ability of the Model to Reproduce High-Resolution Crop Spatio-Temporal Development Variability at Regional Scale

The quality of GLAI assimilation in the modeling approach is characterized by the statistical criteria presented in Figure 5, for five fallow periods between October 1st and April 15th of the following year.



**Figure 5.** Distribution of the statistics between simulated GLAI values and those derived from optical satellite images at pixel scale (i.e., coefficient of determination (A),  $R^2$ , bias (B), and root mean square error (C), RMSE), with the number of images (D) for the 2017–2021 period.

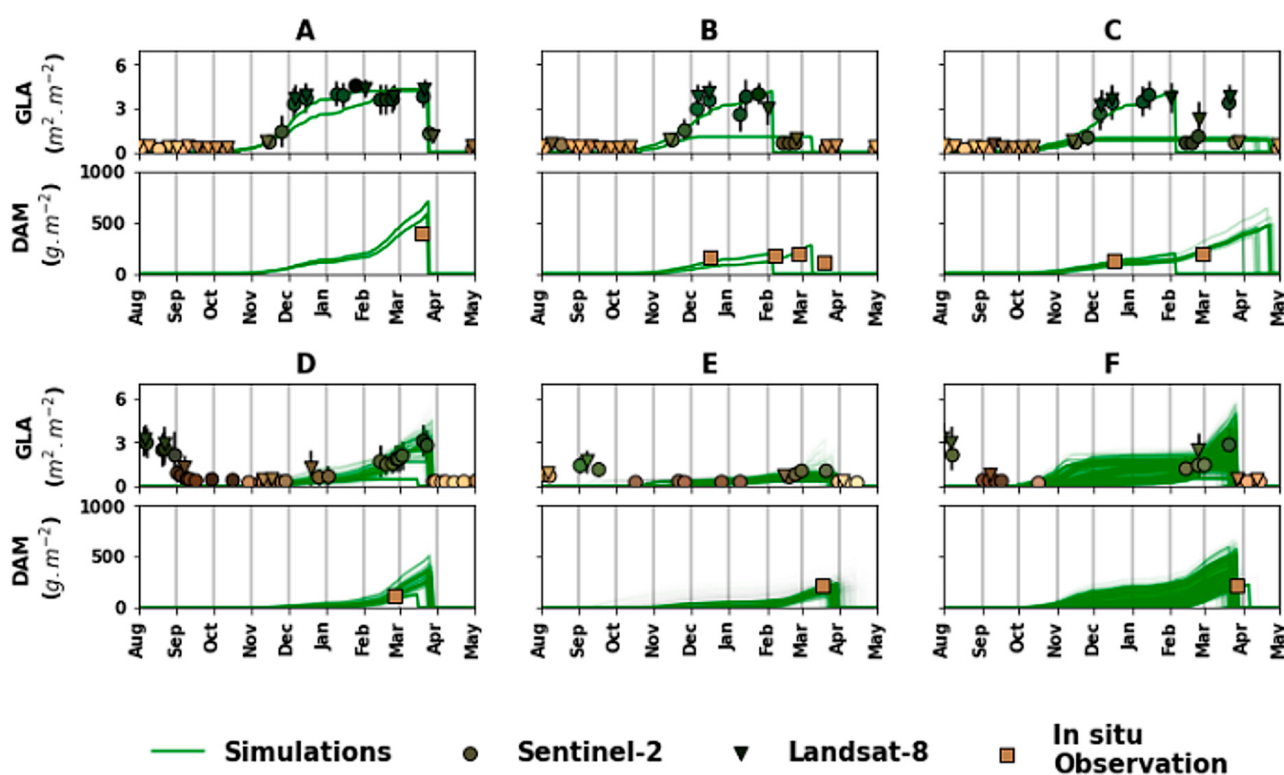
Regarding bias and RMSE values, overall performance is very acceptable and relatively stable for the studied years, despite the variable number of available images, with median values ranging from 13 to 22 images for the years 2017 and 2019, respectively. Mean biases are slightly negative, with a narrow distribution, with median values around  $-0.14 \text{ m}^2 \cdot \text{m}^{-2}$ .

In terms of RMSE, the year 2017 stands out slightly from the other studied years. This translates into a higher error, with a median value of  $0.56 \text{ m}^2 \cdot \text{m}^{-2}$ , compared to the other years that are characterized by median RMSEs varying between  $0.29$  and  $0.36 \text{ m}^2 \cdot \text{m}^{-2}$ .

Analysis of the agreement between GLAI observations and simulations (Figure 5) shows that bias and RMSE values are generally low. The low  $R^2$  values, in the context of low bias and low RMSE, can be explained by the fact that areas with low vegetation development have low GLAI variability to explain.

A significant proportion of the bias and error is observed during bare soil periods and can be explained by the fact that PROSAIL's Bayesian inversion method is never 100% certain that the soil is bare. Therefore, the mean of the inverted GLAIs is always greater than  $0 \text{ m}^2 \cdot \text{m}^{-2}$ . The model, on the other hand, simulates GLAIs strictly equal to  $0 \text{ m}^2 \cdot \text{m}^{-2}$  during bare soil periods.

Figure 6 illustrates the diversity of cover crop growth as observed during the fallow periods for several locations where DAM validation data are available.



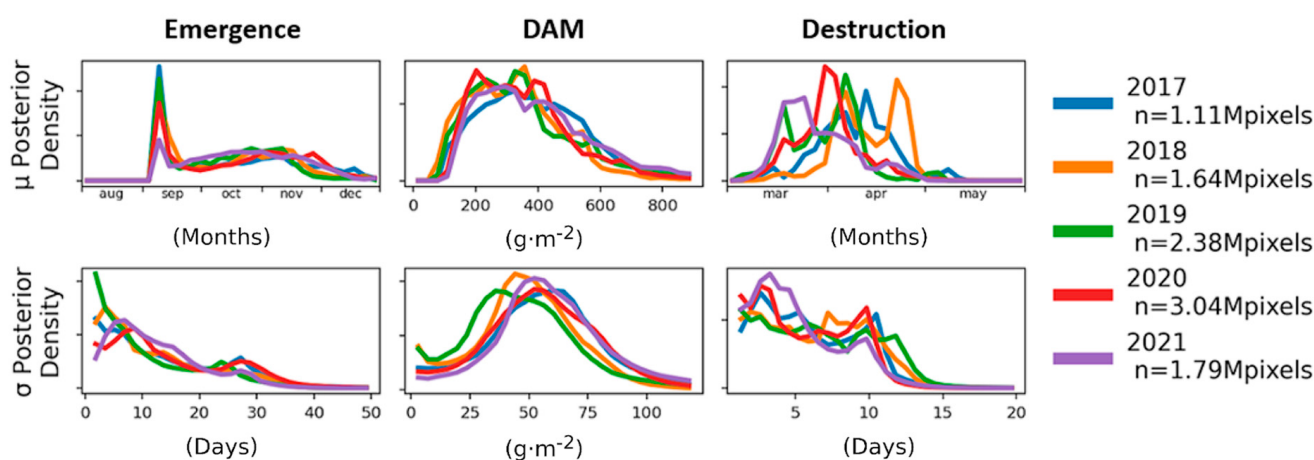
**Figure 6.** Examples of temporal evolutions of the satellite-derived (circles for Sentinel-2 observations and triangles for Landsat-8, the colors correspond to a RGB color composite from the RGB reflectance observed by satellite) and estimated (green lines) GLAI and DAM during the fallow period. In situ DAM measurements are represented by brown squares. The examples illustrate: (A) a long, well-developed CC, (B) early CC death, (C) severe damage followed by CC recovery and growth, (D,E) low CC development, and (F) a small number of satellite images during the CC growth period.

The case presented in Figure 6A corresponds to a long, well-developed cover crop. The growth phase is clearly visible, with GLAI values increasing until they reach a maximum close to  $4 \text{ m}^2 \cdot \text{m}^{-2}$ , until the vegetation is destroyed. In some cases, disease can affect the CC, resulting in early vegetation death (Figure 6B), or severe damages followed by a plant recovery and growth (Figure 6C). Vegetation development is more limited in Figure 6D, with a cover crop that emerged late and was destroyed during the growth phase. The cover crop development is even lower in Figure 6E.

In these examples, image acquisitions are numerous and regular. The model reproduces the different vegetation states observed by the optical satellites, with a greater dispersion of solutions when canopy development levels are low (cases D and E). The events observed in case C (i.e., canopy mortality followed by renewed growth) lead to solutions that are split between a short cycle with high leaf area index values, and a long cycle associated with a low level of vegetation development. Finally, in Figure 6F, only a small number of satellite images were available. The dispersion between solutions is therefore significant, with the inversion approach not being able to differentiate different growth dynamics given the lack of relevant information.

### 3.2.2. Regional Variability in the Timing of Cover Crop and Biomass Production

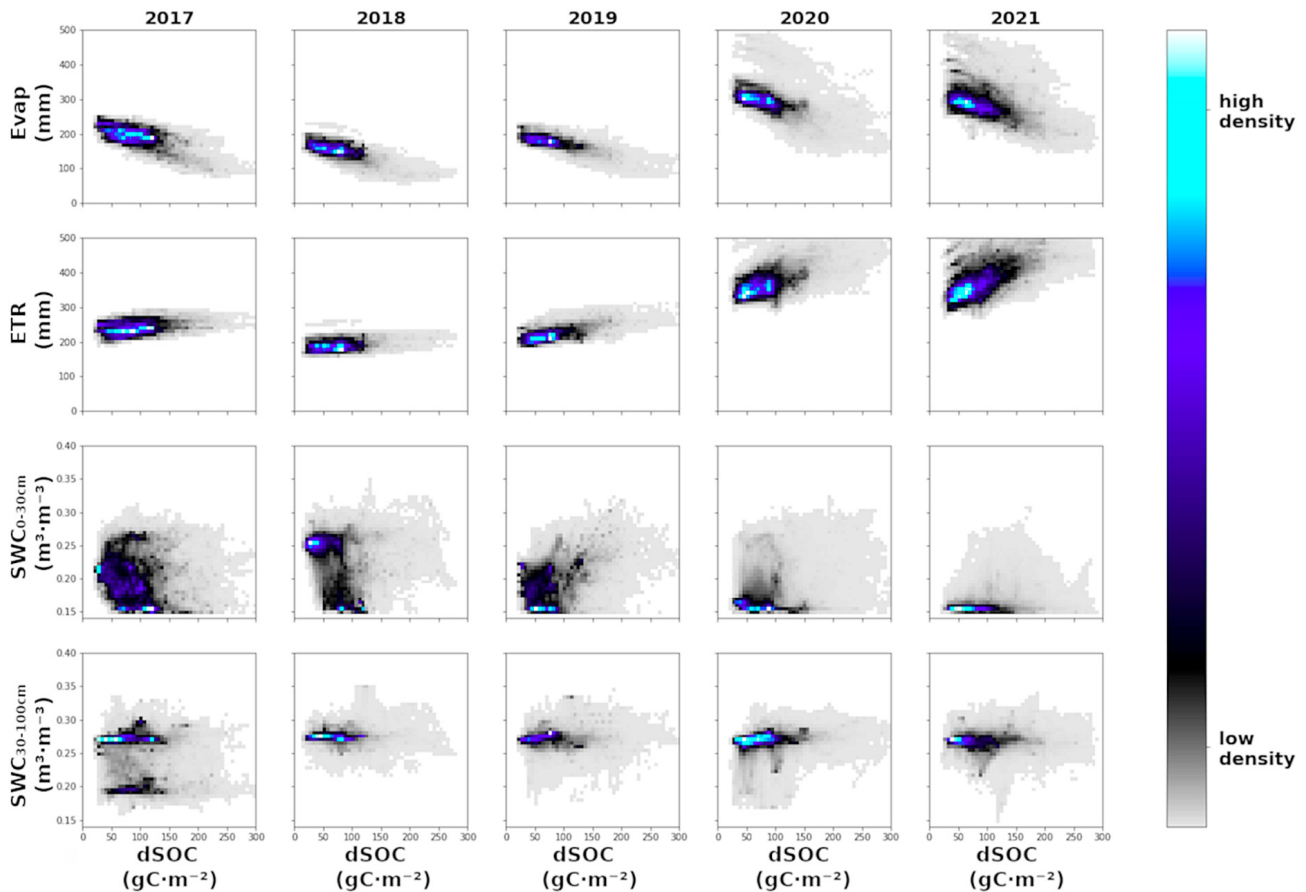
The implementation of the model gives access to a set of variables of interest such as emergence or destruction dates, as well as the amount of cover crop biomass before destruction (Figure 7).



**Figure 7.** Distribution of mean values and standard deviations for the dates of vegetation emergence and destruction, as well as biomass levels of cover crops prior to destruction, estimated using the modeling approach for the five fallow periods.

Cover crop emergence can be observed as early as September, in 30 to 40% of the fields (depending on the considered year). In other fields, the date of emergence is spread out from October to December. The uncertainty of this metric reaches its maximum at around 5 days, and can extend up to 35 days, when few images are available during the emergence period. In contrast to emergence, the dates of destruction observed within the tile are much more contrasted depending on the studied years. For example, cover crops are already destroyed on 50 to 70% of the fields in early April in years 2019, 2020, and 2021, whereas less than 30% of the cover crop fields were destroyed in this period in years 2017 and 2018. This difference is related to climatic conditions, which influence the timing of management practices, and particularly the possibility to enter the fields with tractors, depending on soil water content (e.g., they are a significant risk of soil compaction and getting stuck when entering the field while soil humidity is high). Since the destruction takes place during a period when cloud cover is less significant, we observe lower temporal uncertainties for the date of destruction, mostly less than fifteen days. At the scale of the satellite tile, the biomass estimates before destruction ( $DAM_{harv}$ ) are close, with median values ranging from 320 to 375  $g \cdot m^{-2}$  depending on the considered year. Uncertainties relating to this variable are centered around 50  $g \cdot m^{-2}$ . It should be noted that this uncertainty value generally correlates well with biomass production, and that the average values of the coefficients of variation (i.e., ratio between standard deviation and mean) are approximately 10 to 15%

On the fields where cover crops are grown, the values of organic carbon returned to the soil vary between 0 and  $300 \text{ gC}\cdot\text{m}^{-2}$  (Figure 8). However, the majority of pixels have values within a narrower range, i.e., 80% of pixels have values of carbon returned to the soil between 40 and  $130 \text{ gC}\cdot\text{m}^{-2}$  (with a median value close to  $77 \text{ gC}\cdot\text{m}^{-2}$ ) whatever the year considered.



**Figure 8.** Bivariate plots of the mean posterior distribution of different variables relate to water budget (i.e., daily accumulated evaporation and evapotranspiration, Evap and ETR, as well as soil moisture of top and deep soil layers) and soil organic carbon stock changes (dSOC) induced by the decomposition of cover crop biomass. The average posteriors are derived from the pixel wise simulations of the fallow periods from 2017 to 2021.

A joint analysis of the soil organic carbon stock changes following CC destruction and soil moisture at the date of destruction shows no notable trend. Soil water content at the cover crop destruction for the deep soil layer (30 to 100 cm) are generally similar between the studied years, as shown by the median values close to  $0.27 \text{ m}^3\cdot\text{m}^{-3}$ . Soil water content at the surface (0 to 30 cm) is more contrasted between years and spatially. The ranges of values observed for the years 2020 and 2021 are similar (with median close to  $0.16 \text{ m}^3\cdot\text{m}^{-3}$ ) and reflect drier conditions than those observed in the other 3 years (median values between 0.19 and  $0.23 \text{ m}^3\cdot\text{m}^{-3}$ ) that show greater variability. These significant differences are related to differences in climatic conditions, which result in contrasting evaporative demands, as evidenced by the evaporation and evapotranspiration values simulated during the fallow periods. Cumulative daily evapotranspiration reaches maximum values between 260 and 310 mm in the years 2017 to 2019, while these values are the lower limits for the years 2020 and 2021. The scatterplots between dSOC and cumulative Evap or ETR show opposite trends, more or less pronounced depending on the considered years. With Pearson correlations between  $-0.46$  and  $-0.71$  between dSOC and evaporation, and

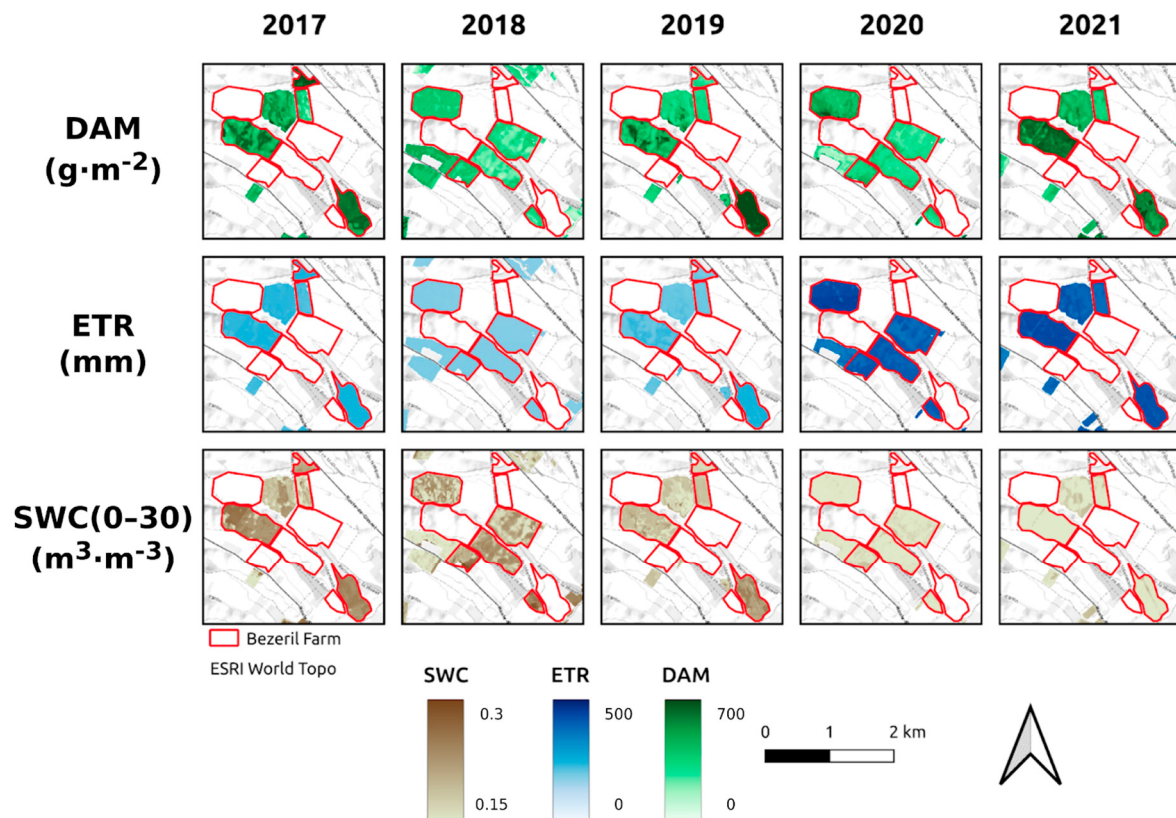
slopes between  $-0.34$  and  $-0.46$  mm per  $\text{gC}\cdot\text{m}^{-2}$  (for years 2019 and 2021), the observed trends reflect a limitation of evaporation because of the cover crop development. For a median value of carbon returned to the soil of  $77 \text{ gC}\cdot\text{m}^{-2}$ , this limitation of evaporation represents quantities of water of 26.2 mm and 35.2 mm (for years 2019 and 2021). Considering ETR (evaporation + transpiration), trends become positive with slopes between 0.11 and 0.28 mm per  $\text{gC}\cdot\text{m}^{-2}$  for years 2017 to 2019, and more pronounced slopes of 0.51 and 0.70 mm per  $\text{gC}\cdot\text{m}^{-2}$ , for 2020 and 2021, respectively. These positive trends can be explained by the link between transpiration and biomass production: CCs with higher GLAI dynamics photosynthesize more and are associated with higher cumulated transpiration and higher levels of biomass production. As before, for a median value of carbon returned to the soil of  $77 \text{ gC}\cdot\text{m}^{-2}$ , the quantities of water consumed range from 8.5 mm to 53.9 mm (for years 2017 and 2021, respectively).

Throughout the study area, according to Soil Grids products, the values of the differences between wilting point and field capacity vary between 0.03 and  $0.2 \text{ m}^3\cdot\text{m}^{-3}$ . Based on these values, the amount of water that can be contained in the surface 30 cm soil layer varies between 9 and 60 mm. In terms of precipitation, during the two months when cover crops are destroyed and summer crops are sown (i.e., April and May), cumulative precipitation averages 135 mm. This amount of precipitation is sufficient to fill the surface reservoir. Cover crops have no direct effect on surface water levels in May and almost no effect at the end of April. However, the conclusions may change with the evolution or combination of different factors: (i) if rainfall patterns change, (ii) if more productive and more transpiring CCs are grown, and/or (iii) if destruction of CCs occurs too late (reducing the gap with the main crop).

### 3.2.3. A Case Study at Farm Scale

In Figure 9, simulations of the fields from a farm that grows winter CCs every second year between winter wheat and maize are shown. DAMs of cover crops were measured at this farm during the two field campaigns. At this scale, the interannual variability of simulated DAM values when CCs are destroyed during the five fallow periods is clearly observable, with contrasting values, in contrast to the previous analysis carried out at the tile scale (Figure 7). In Figure 9, the years 2018 and 2020 show lower values of DAM than the other years, with mean above-ground biomass values of 318 and  $369 \text{ g}\cdot\text{m}^{-2}$  respectively, compared to more than  $480 \text{ g}\cdot\text{m}^{-2}$  for the other years. On the other hand, for a given year, the simulated DAM shows significant variability at farm scale and at intra-field scale. For example, in 2019, the three fields on the farm growing CCs have mean DAMs ranging from 331 to  $758 \text{ g}\cdot\text{m}^{-2}$ . The coefficients of variation for these same fields range from 12 to 22%, reflecting areas of high and low vegetation development.

On the same fields, the simulated daily evapotranspiration values are cumulated for each fallow period from 2017 to 2021 (Figure 8). The trends observed within these fields are like those previously observed for all the fields at the scale of the studied tile. The years 2017 to 2019 show lower cumulated ETR (mean values close to 211 mm) than those simulated in the years 2020 and 2021 (mean values close to 415 mm). This difference can be explained by climate variability, which results in higher evaporative demand for years 2020 and 2021. Regarding topsoil water content at the end of the fallow period, drier levels are observed in years of high evaporative demand, with lowest average values of  $0.15 \text{ m}^3\cdot\text{m}^{-3}$  for 2020 and 2021. In other years, the mean values of soil water content of the top layer are close to  $0.20 \text{ m}^3\cdot\text{m}^{-3}$ . The generally wetter conditions reveal more contrasting intra-field patterns (with maximal values of mean coefficients of variation of 14% for 2018), linked to soil properties and topography.



**Figure 9.** Maps of dry above-ground biomass estimated before the destruction of cover crops from 2017 to 2021, together with estimations of cumulative evapotranspiration during the fallow periods, and soil water content of the topsoil layer (0–30 cm) at the end of the fallow period.

## 4. Discussion

### 4.1. Performance Comparison with the Existing Literature

In this study, we simulated long winter cover crops in southwestern France over approximately 10 million pixels with a resolution of 10 m over five years. In this exercise, we observed significant variability between years, between fields, and even within fields. Most of the phenological diversity observed using satellite-based GLAI is well represented, as shown in Figure 5, which indicates that most pixels have an RMSE of less than  $0.5 \text{ m}^2 \text{ m}^{-2}$ . The simulations of  $\text{CO}_2$  and water flows are quite accurate during the plant growth period, but the bare soil period is less well represented, as the humification of cover crop biomass is not taken into account in the simple soil respiration formalism used in SAFYE- $\text{CO}_2$ . Finally, the spatial and temporal variability of cover crop biomass was well reproduced, with a high  $R^2$  greater than 0.6 and an RMSE between 12 and  $160 \text{ g} \cdot \text{m}^{-2}$  depending on the month. It should be noted that the validation datasets mainly contain faba beans, grown during two intercropping periods. This leads us to compare the present work with the simulation performance obtained through other modeling exercises for faba beans.

Popular crop models such as APSIM, STICS, and Aquacrop are parametrized to be able to simulate faba bean cash crops. Regarding DAM, Aquacrop, STICS, and APSIM have been evaluated for faba beans in different contexts. Aquacrop was evaluated in southeastern Australia by [57] and by [58] in Tunisia. These studies obtained  $R^2$  of 0.95 and 0.52, and RMSE of 260 and  $140 \text{ g} \cdot \text{m}^{-2}$ , respectively. In [59], STICS was calibrated for faba beans in southwestern France using data collected during field experiments. The evaluation found  $R^2$  of 0.77 and an RMSE of  $140 \text{ g} \cdot \text{m}^{-2}$ . Finally, APSIM obtained scores of  $R^2$  of 0.57 and 0.28, RMSE of 440 and  $793 \text{ g} \cdot \text{m}^{-2}$ , and bias of 163 and  $729 \text{ g} \cdot \text{m}^{-2}$  when faba bean was used as a cash crop and as a cover crop, respectively [60]. All those studies were

performed at sites going from Sweden to Spain, which illustrates the ability of faba beans to adapt to large pedoclimatic conditions and for contrasted uses. In our study, the DAM values retrieved with AgriCarbon-EO have  $R^2$  and biases, respectively, in the high and low ends of the range observed in the literature.

Regarding the evaluation of models to simulate ETR and  $\text{CO}_2$  fluxes for faba beans, no relevant literature was found. When we expand the search perimeter to the Fabaceae, most of the studies relate to soybean. To study this crop, the [61] study has coupled the CMS CROPGROW crop model to the ECOSMOS ecosystem model and the resulting model was evaluated against data collected at an Ameriflux site in Nebraska. This study obtained average RMSEs of 1.68, 2.22, 1.24  $\text{gC}\cdot\text{m}^{-2}$  and 0.89 mm for NEE, GPP, Reco, and ETR, respectively. Those values are in line with the ones obtained in our study but may not be comparable due to contrasting management.

When comparing the results of AgriCarbon-EO to the previously mentioned studies, it is necessary to keep in mind that those studies benefit from detailed field management data and descriptions of the crop varieties. Despite this handicap, AgriCarbon-EO allows retrieving the variables with comparable accuracy by relying on the high-resolution phenological information provided through the assimilation of satellite data.

The results may thus be more comparable to studies based on remote sensing, such as [62–64]. Those studies have comparable performances, but the study by [20] may be the best comparison to the current study in terms of agronomic context. This study demonstrates among others the use of the Random Forest method for predicting cover crop DAM at the end of the cropping cycle based on a series of Sentinel-2 images.  $R^2$  of 0.75 and RMSE of 73  $\text{g}\cdot\text{m}^{-2}$  were obtained. Those scores are slightly better than those obtained here but may need to be tested on multiple years to demonstrate robustness. Wang et al. 2023 inverts the scope radiative transfer, energy budget, and plant physiology model with a machine learning correction with aerial hyperspectral data as a constraint to obtain similar results to [20] for cereal rye ( $R^2 = 0.71$ , RMSE = 50  $\text{g}\cdot\text{m}^{-2}$ ). These approaches are limited to mono temporal information mainly for biomass while our approach allows us to assess other key components of the carbon and water cycles at a daily frequency. The ability of the AgriCarbon-EO processing chain to analyze multiple physical variables and the possibility to physically and agronomically interpret modeling errors demonstrates the usefulness of this approach, even when compared to high-performing machine learning methods focused on single variables. The possibility of assimilating biophysical variables provided by machine learning methods, such as those deployed in [20] or other ones provided by the inversion of physical models as in [64], may also be considered to further improve AgriCarbon-EO's performance.

#### 4.2. Limits Related to the AgriCarbon-EO Processing Chain

For both  $\text{CO}_2$  and water fluxes, the main biases are observed during bare soil periods.

The current formalism of SAFYE- $\text{CO}_2$  soil respiration is provided by [65]. This approach was chosen for its simplicity, which facilitates its implementation, even if this comes at the expense of some physical and biological accuracy. This model represents base mineralization as a function of temperature and soil moisture, and it has no dependencies, either on the input of organic matter to the soil, or on the initial soil organic carbon stocks. This leads to a systematic underestimation of soil respiration, which accounts for approximately 0.5–0.6  $\text{g}\cdot\text{m}^{-2}$  in the presented model evaluations. Over a five-month period of bare soil, this bias represents a cumulative bias of up to 90  $\text{gC}\cdot\text{m}^{-2}$ .

More complex formalisms or models could be used to dynamically represent the respiration resulting from litter and amendment decomposition. However, such models require more input data (e.g., management data on organic amendment and accurate soil

measurements). This information is often only available for tightly monitored fields/farms (e.g., long-term soil experiments at ICOS sites) and is currently far from systematically available, especially at high resolution. The systematic availability of these variables and the implementation of a more detailed soil model would most likely allow for a better representation of soil respiration, through the integration of humification in the first instance, but also of secondary processes such as the priming effect [66,67]. However, the systematic gathering of such information would depend on the mandatory reporting of agricultural practices, which may not be feasible or accepted, and/or remote sensing techniques capable of detecting changes, in order to obtain information on actual carbon inputs. Work based on satellite images shows that it is possible to derive a range of information, on the presence of crop residues or on tillage [68,69], which could be integrated into the proposed modeling approach. Nevertheless, in order to implement such approaches, a considerable leap forward is needed in terms of the accuracy of soil carbon mapping [70]. Although it does not provide a comprehensive framework for spatial modeling of soil carbon, this work proposes a methodology for accurately estimating soil carbon inputs from cover crops. This information is a key step toward modeling soil carbon in agricultural systems transitioning to agroecological and soil conservation practices.

With regard to modeling water stocks and flows, it should be noted that the current use of the simple FAO methodology limits the applicability of this processing chain to soils that are not too sandy. Furthermore, this formalism does not take into account hydraulic conductivity and matrix pressure, which can be influenced by soil type and texture. These limitations may exclude certain regions from being simulated and may also limit the physical realism of the simulated water stocks and flows.

In several monitored fields of this study, anthracnose symptoms were observed. These led to partial or total premature death of the vegetation that were more or less well captured by the model (illustrated, for example, in Figure 6B,C). In fields where phacelia and faba beans were sown together, it was possible to observe a strong recovery of vegetation after the partial or total death of the faba beans, which corresponded to the growth of phacelia, which became dominant. It would be possible to adapt existing mechanistic but complex formalisms [71,72], or to consider several vegetation cycles during fallow periods. However, such modifications could lead to over-fitting during the assimilation process, as the noise on GLAI provided by the PROSAIL inversion could be modeled as disease.

The limitations described above can all be resolved by integrating more processes, forcing data, or assimilating parameters and variables. However, in the context of a methodology aimed at systematic spatial modeling, parsimony is essential. The controlled complexity of the approach limits the intake of uncertain and sometimes contradictory information, ensuring robustness and facilitating technical deployment. Therefore, if new formalisms were to be integrated into this approach, it would be necessary to rigorously evaluate the additional performance and verify access to relevant input data and its quality in order to maintain the ability to perform large-scale spatialization, by considering several criteria: the question of performance gain, the number of added parameters to take into account a new process, and above all the possibility of informing them, particularly at the considered spatial scales (i.e., simulations on decametric pixels of one or more satellite tiles).

#### *4.3. Limits Related to the Use of the Remote Sensing Data*

The proposed modeling approach requires a mask indicating the location of fields with cover crops. In the present study, this mask is derived from satellite images and information from the RPG, with a focus on long winter cover crops. Nevertheless, there are different types of cover crops, with short (e.g., catch crops) and long winter cover crops

or summer cover crops, and various destruction methods [73]. Precise mapping of fields with these types of CCs constitutes a specific field of research. It is the subject of ongoing research, and relies on methods based on optical and/or radar remote sensing data [74–76]. In addition, discussions are underway on the systematic inclusion of cover crops in CAP declarations by farmers, which could replace satellite image-derived classifications for a posteriori estimates and diagnoses.

Cover crop development can be very heterogeneous (as illustrated in Figure 5). In the case of poor vegetation development, it may be difficult to differentiate between the estimated biomass corresponding to a short cycle, and that resulting from the assimilation of noisy GLAI values. In such cases, it would be advisable to propose GLAI behavior filtering, or to define a minimum limit for biomass estimation, to limit “false positive” errors.

Due to cloud cover, one year of flux measurements could not be used in this study, nor could some biomass samples. During fallow periods, cloud cover can be either total, preventing the implementation of the proposed approach, or partial, affecting the results as in Figure 6F. In this case, the consequences for the estimation of the target variables will differ according to the period without images. For example, an absence of images in the weeks prior to destruction can be highly detrimental to the estimation of biomass quantity. Indeed, during this period, climatic conditions offer vegetation good growth conditions, as shown by the flux measurements, particularly those of GPP before destruction (Figure 3). In this context, an alternative would be to assimilate biophysical variables derived from SAR data (for example, those acquired by Sentinel-1), which would provide complementary information, allowing for better constraint of the simulations. Various studies have demonstrated the potential of these data for monitoring crop-related biophysical variables [77–80] as well as their added value for assimilation into crop models [81–85]. However, the behaviors observed on crops often show crop-specific dynamics. It remains to be demonstrated that generic SAR information can be used to constrain a simulation in the context of cover crops, given the architectural differences between species and the agricultural practices implemented (sowing method, single species, or mixture, etc.).

## 5. Conclusions

This study shows that the AgriCarbon-EO processing chain is a valuable tool for assessing cover crop production, as well as their impact on critical components of the water and carbon budgets during the fallow periods. The validation of this approach, through a regional assessment based on measurements taken by flow towers and the collection of biomass samples during two intensive field campaigns, provides benchmark performance levels for a framework for implementing intermediate cover crops. These results are promising, but need to be supplemented with more comprehensive datasets, representing a greater diversity in terms of climates, soils, and CC varieties, in order to ensure their transferability at the European level. Modeling exercises have enabled the establishment of new parameterization for long cover crops in southwestern France, allowing for accurate representation of CO<sub>2</sub> and water fluxes during the crop growth phase, as well as the spatial and temporal variability of biomass production for datasets with the aforementioned limitations, while accurately representing regional phenological variability at high resolution.

Spatial simulations were used to characterize the phenology of cover crops and above-ground biomass across nearly 10 million pixels with a resolution of 10 m over five contrasting years. Median biomass values ranged from 320 to 375 g·m<sup>-2</sup>, with significant variability detectable only through remote sensing observations. Annual gains in soil organic carbon from cover crop decomposition were estimated using an approach based on humification coefficients, as dynamic simulations of soil respiration during CC litter decomposition were

deemed too unreliable. This method provided amounts of newly formed SOC ranging from 40 to 130 gC·m<sup>-2</sup> for most pixels related to CC cultivation. When analyzing the link between this neoformed SOC derived from CC biomass and cumulative evapotranspiration, clear trends were found, but the impact of cover crops on soil water content appears to be minimal due to rain events during the spring.

This calibration and evaluation of the SAFYE-CO<sub>2</sub> model and AgriCarbon-EO processing chain adds long winter cover crops to the list of crops that can be represented, but needs to be evaluated in a wider range of soil and climate contexts. This step is an essential prerequisite for conducting further studies to assess the local effects of adding cover crops to multi-year crop rotations, in order to evaluate their medium- and long-term agroecological impacts using a broader range of indicators.

**Code Availability:** This section discusses the availability of the code. AgriCarbon-EO is implemented in Python 3. AgriCarbon-EO requires the PROSAILv5 Python package and the SAFYE-CO<sub>2</sub> v2.0.5 Python implementation. AgriCarbon-EO v1.0.1 is available free of charge for research and evaluation purposes (non-commercial) upon signature of a license agreement with the Toulouse Technology Transfer (TTT) office of Université Toulouse 3. For this, the user contacts the TTT at “contact@toulouse-tech-transfer.com”, providing contact information, affiliation, and objective of use. Upon validation of the license, the code is provided by the team at CESBIO. SAFYE-CO<sub>2</sub> v2.0.5 is provided with AgriCarbon-EO v1.0.1 by this same procedure. Note that for this paper, and in compliance with the journal requirements, an anonymous procedure was put in place to grant access to the reviewers. PROSAIL: Python Bindings v2.0.3 for PROSAIL5 is hosted at <https://github.com/jgomezdans/prosail> (accessed on 15 December 2023) and archived under <https://doi.org/10.5281/zenodo.2574925> (accessed on 15 December 2023) by José Gómez-Dans.

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**Data Availability Statement:** Links to the data used in the study are provided below. Remote sensing data for Sentinel-2 and Landsat-8 using MAJA processing are downloaded from THEIA at <https://www.theia-land.fr/en/homepage-en/> (accessed on 3 September 2025). The Sentinel-2 level 2A and Landsat-8 L2A data are distributed under the ETALAB V2.0 open license. Land cover datasets are available at <https://geoservices.ign.fr/rpg> (accessed on 3 September 2025). Era5Land data are made available by ECMWF on the climate data store: <https://cds.climate.copernicus.eu/> (accessed on 3 September 2025). Validation datasets are available on the SIE website at <https://sie.cesbio.omp.eu/> (accessed on 3 September 2025). Eddy covariance datasets are freely made available on request; Accessing the cover crop biomass data requires a data-sharing agreement.

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## References

- Rivière, C.; Béthinger, A.; Bergez, J.-E. The Effects of Cover Crops on Multiple Environmental Sustainability Indicators—A Review. *Agronomy* **2022**, *12*, 2011. [\[CrossRef\]](#)
- Du, X.; Jian, J.; Du, C.; Stewart, R.D. Conservation Management Decreases Surface Runoff and Soil Erosion. *Int. Soil Water Conserv. Res.* **2022**, *10*, 188–196. [\[CrossRef\]](#)
- Blanco-Canqui, H.; Ruis, S.J. Cover Crop Impacts on Soil Physical Properties: A Review. *Soil Sci. Soc. Am. J.* **2020**, *84*, 1527–1576. [\[CrossRef\]](#)
- Beyer, N.; Gabriel, D.; Kirsch, F.; Schulz-Kesting, K.; Dauber, J.; Westphal, C. Functional Groups of Wild Bees Respond Differently to Faba Bean *Vicia faba* L. Cultivation at Landscape Scale. *J. Appl. Ecol.* **2020**, *57*, 2499–2508. [\[CrossRef\]](#)
- Poeplau, C.; Don, A. Carbon Sequestration in Agricultural Soils via Cultivation of Cover Crops—A Meta-Analysis. *Agric. Ecosyst. Environ.* **2015**, *200*, 33–41. [\[CrossRef\]](#)
- Jean-Baptiste, B. Recherches Chimiques Sur La Vegetation, Entreprises Dans Le but d’examiner Si Les Plantes Prennent de l’azote à l’atmosphère. *Ann. Chim. Phys.* **1838**, *67*, 5–54.
- Köpke, U.; Nemecek, T. Ecological Services of Faba Bean. *Field Crops Res.* **2010**, *115*, 217–233. [\[CrossRef\]](#)
- Carrer, D.; Pique, G.; Ferlicoq, M.; Ceamanos, X.; Ceschia, E. What Is the Potential of Cropland Albedo Management in the Fight against Global Warming? A Case Study Based on the Use of Cover Crops. *Environ. Res. Lett.* **2018**, *13*, 044030. [\[CrossRef\]](#)
- Lugato, E.; Cescatti, A.; Jones, A.; Ceccherini, G.; Duveiller, G. Maximising Climate Mitigation Potential by Carbon and Radiative Agricultural Land Management with Cover Crops. *Environ. Res. Lett.* **2020**, *15*, 094075. [\[CrossRef\]](#)
- Bolinder, M.A.; Crotty, F.; Elsen, A.; Frac, M.; Kismányoky, T.; Lipiec, J.; Tits, M.; Tóth, Z.; Kätterer, T. The Effect of Crop Residues, Cover Crops, Manures and Nitrogen Fertilization on Soil Organic Carbon Changes in Agroecosystems: A Synthesis of Reviews. *Mitig. Adapt. Strateg. Glob. Change* **2020**, *25*, 929–952. [\[CrossRef\]](#)
- Minasny, B.; Arrouays, D.; Cardinael, R.; Chabbi, A.; Farrell, M.; Henry, B.; Koutika, L.-S.; Ladha, J.K.; McBratney, A.B.; Padarian, J.; et al. Current NPP Cannot Predict Future Soil Organic Carbon Sequestration Potential. Comment on “Photosynthetic Limits on Carbon Sequestration in Croplands.”. *Geoderma* **2022**, *424*, 115975. [\[CrossRef\]](#)
- Soussana, J.-F.; Lutfalla, S.; Ehrhardt, F.; Rosenstock, T.; Lamanna, C.; Havlík, P.; Richards, M.; Wollenberg, E.; Chotte, J.-L.; Torquebiau, E.; et al. Matching Policy and Science: Rationale for the ‘4 per 1000-Soils for Food Security and Climate’ Initiative. *Soil Tillage Res.* **2019**, *188*, 3–15. [\[CrossRef\]](#)
- Selzer, T.; Schubert, S. Water Dynamics of Cover Crops: No Evidence for Relevant Water Input through Occult Precipitation. *J. Agron. Crop Sci.* **2023**, *209*, 422–437. [\[CrossRef\]](#)
- Nordblom, T.; Gurusinghe, S.; Erbacher, A.; Weston, L.A. Opportunities and Challenges for Cover Cropping in Sustainable Agriculture Systems in Southern Australia. *Agriculture* **2023**, *13*, 688. [\[CrossRef\]](#)
- Hanrahan, B.R.; King, K.W.; Duncan, E.W.; Shedeckar, V.S. Cover Crops Differentially Influenced Nitrogen and Phosphorus Loss in Tile Drainage and Surface Runoff from Agricultural Fields in Ohio, USA. *J. Environ. Manag.* **2021**, *293*, 112910. [\[CrossRef\]](#)
- Muñoz-Ventura, A.; Christianson, R.D.; Bhattarai, R.; Christianson, L.E. Runoff and Drainage Trade-Offs from Cover Crops Exposed to Freeze–Thaw Events. *Agrosyst. Geosci. Environ.* **2022**, *5*, e20324. [\[CrossRef\]](#)
- Baker, J.M.; Griffis, T.J. Examining Strategies to Improve the Carbon Balance of Corn/Soybean Agriculture Using Eddy Covariance and Mass Balance Techniques. *Agric. For. Meteorol.* **2005**, *128*, 163–177. [\[CrossRef\]](#)
- Sanz-Cobena, A.; García-Marco, S.; Quemada, M.; Gabriel, J.L.; Almendros, P.; Vallejo, A. Do Cover Crops Enhance N<sub>2</sub>O, CO<sub>2</sub> or CH<sub>4</sub> Emissions from Soil in Mediterranean Arable Systems? *Sci. Total Environ.* **2014**, *466–467*, 164–174. [\[CrossRef\]](#)
- Tribouillois, H.; Constantin, J.; Casal, L.; Villerd, J.; Therond, O. Introducing and Expanding Cover Crops at the Watershed Scale: Impact on Water Flows. *Agric. Ecosyst. Environ.* **2022**, *337*, 108050. [\[CrossRef\]](#)
- Do Nascimento Bendini, H.; Fieuzal, R.; Carrere, P.; Clenet, H.; Galvani, A.; Allies, A.; Ceschia, É. Estimating Winter Cover Crop Biomass in France Using Optical Sentinel-2 Dense Image Time Series and Machine Learning. *Remote Sens.* **2024**, *16*, 834. [\[CrossRef\]](#)
- Breunig, F.M.; Dalagnol, R.; Galvão, L.S.; da Conceição Bispo, P.; Liu, Q.; Berra, E.F.; Gaida, W.; Liesenberg, V.; Sampaio, T.V.M. Monitoring Cover Crop Biomass in Southern Brazil Using Combined PlanetScope and Sentinel-1 SAR Data. *Remote Sens.* **2024**, *16*, 2686. [\[CrossRef\]](#)
- Huang, J.; Gómez-Dans, J.L.; Huang, H.; Ma, H.; Wu, Q.; Lewis, P.E.; Liang, S.; Chen, Z.; Xue, J.-H.; Wu, Y.; et al. Assimilation of Remote Sensing into Crop Growth Models: Current Status and Perspectives. *Agric. For. Meteorol.* **2019**, *276–277*, 107609. [\[CrossRef\]](#)
- Batjes, N.H.; Ceschia, E.; Heuvelink, G.B.M.; Demenois, J.; Le Maire, G.; Cardinael, R.; Arias-Navarro, C.; van Egmond, F.M. *International Review of Current Mrv Initiatives for Soil Carbon Stock Change Assessment and Associated Methodologies*; ISRIC: Wageningen, The Netherlands, 2023.

24. Wijmer, T.; Al Bitar, A.; Arnaud, L.; Fieuzal, R.; Ceschia, E. AgriCarbon-EO v1.0.1: Large-Scale and High-Resolution Simulation of Carbon Fluxes by Assimilation of Sentinel-2 and Landsat-8 Reflectances Using a Bayesian Approach. *Geosci. Model Dev.* **2024**, *17*, 997–1021. [\[CrossRef\]](#)
25. Karthikeyan, L.; Chawla, I.; Mishra, A.K. A Review of Remote Sensing Applications in Agriculture for Food Security: Crop Growth and Yield, Irrigation, and Crop Losses. *J. Hydrol.* **2020**, *586*, 124905. [\[CrossRef\]](#)
26. Segarra, J.; Buchaillet, M.L.; Araus, J.L.; Kefauver, S.C. Remote Sensing for Precision Agriculture: Sentinel-2 Improved Features and Applications. *Agronomy* **2020**, *10*, 641. [\[CrossRef\]](#)
27. Misra, G.; Cawkwell, F.; Wingler, A. Status of Phenological Research Using Sentinel-2 Data: A Review. *Remote Sens.* **2020**, *12*, 2760. [\[CrossRef\]](#)
28. Fang, H.; Baret, F.; Plummer, S.; Schaepman-Strub, G. An Overview of Global Leaf Area Index (LAI): Methods, Products, Validation, and Applications. *Rev. Geophys.* **2019**, *57*, 739–799. [\[CrossRef\]](#)
29. Upreti, D.; Pignatti, S.; Pascucci, S.; Tolomio, M.; Huang, W.; Casa, R. Bayesian Calibration of the Aquacrop-OS Model for Durum Wheat by Assimilation of Canopy Cover Retrieved from VENμS Satellite Data. *Remote Sens.* **2020**, *12*, 2666. [\[CrossRef\]](#)
30. Battude, M.; Al Bitar, A.; Brut, A.; Tallec, T.; Huc, M.; Cros, J.; Weber, J.-J.; Lhuissier, L.; Simonneaux, V.; Demarez, V. Modeling Water Needs and Total Irrigation Depths of Maize Crop in the South West of France Using High Spatial and Temporal Resolution Satellite Imagery. *Agric. Water Manag.* **2017**, *189*, 123–136. [\[CrossRef\]](#)
31. Wang, J.; Wang, Y.; Qi, Z. Remote Sensing Data Assimilation in Crop Growth Modeling from an Agricultural Perspective: New Insights on Challenges and Prospects. *Agronomy* **2024**, *14*, 1920. [\[CrossRef\]](#)
32. Kang, Y.; Özdoğan, M. Field-Level Crop Yield Mapping with Landsat Using a Hierarchical Data Assimilation Approach. *Remote Sens. Environ.* **2019**, *228*, 144–163. [\[CrossRef\]](#)
33. Pique, G.; Fieuzal, R.; Al Bitar, A.; Veloso, A.; Tallec, T.; Brut, A.; Ferlicoq, M.; Zawilski, B.; Dejoux, J.-F.; Gibrin, H.; et al. Estimation of Daily CO<sub>2</sub> Fluxes and of the Components of the Carbon Budget for Winter Wheat by the Assimilation of Sentinel 2-like Remote Sensing Data into a Crop Model. *Geoderma* **2020**, *376*, 114428. [\[CrossRef\]](#)
34. Pique, G.; Fieuzal, R.; Debaeke, P.; Al Bitar, A.; Tallec, T.; Ceschia, E. Combining High-Resolution Remote Sensing Products with a Crop Model to Estimate Carbon and Water Budget Components: Application to Sunflower. *Remote Sens.* **2020**, *12*, 2967. [\[CrossRef\]](#)
35. Ouin, A.; Andrieu, E.; Vialatte, A.; Balent, G.; Barbaro, L.; Blanco, J.; Ceschia, E.; Clement, F.; Fauvel, M.; Gallai, N.; et al. Chapter Two—Building a Shared Vision of the Future for Multifunctional Agricultural Landscapes. Lessons from a Long Term Socio-Ecological Research Site in South-Western France. In *Advances in Ecological Research*; Bohan, D.A., Dumbrell, A.J., Vanbergen, A.J., Eds.; The Future of Agricultural Landscapes, Part III; Academic Press: Cambridge, MA, USA, 2021; Volume 65, pp. 57–106.
36. Gaillardet, J.; Braud, I.; Hankard, F.; Anquetin, S.; Bour, O.; Dorfliger, N.; de Dreuz, J.R.; Galle, S.; Galy, C.; Gogo, S.; et al. OZCAR: The French Network of Critical Zone Observatories. *Vadose Zone J.* **2018**, *17*, 180067. [\[CrossRef\]](#)
37. Franz, D.; Acosta, M.; Altimir, N.; Arriga, N.; Arrouays, D.; Aubinet, M.; Aurela, M.; Ayres, E.; López-Ballesteros, A.; Barbaste, M.; et al. Towards Long-Term Standardised Carbon and Greenhouse Gas Observations for Monitoring Europe’s Terrestrial Ecosystems: A Review. *Int. Agrophysics* **2018**, *32*, 439–455. [\[CrossRef\]](#)
38. Blanco-Canqui, H.; Shaver, T.M.; Lindquist, J.L.; Shapiro, C.A.; Elmore, R.W.; Francis, C.A.; Hergert, G.W. Cover Crops and Ecosystem Services: Insights from Studies in Temperate Soils. *Agron. J.* **2015**, *107*, 2449–2474. [\[CrossRef\]](#)
39. Prosperi, P.; Terres, J.M.; Doublet, S.; Pointereau, P. Conservation Agriculture Effects and Policy Support to Mitigate Soil Degradation in Midi-Pyrénées (France). *Land Degrad. Dev.* **2011**, *22*, 70–83. [\[CrossRef\]](#)
40. Bonsoms, J.; López-Moreno, J.I.; Alonso-González, E. Snow Sensitivity to Temperature and Precipitation Change during Compound Cold–Hot and Wet–Dry Seasons in the Pyrenees. *Cryosphere* **2023**, *17*, 1307–1326. [\[CrossRef\]](#)
41. Lhuissier, L.; Lamblin, V.; Sauquet, E.; Arama, Y.; Goulard, F.; Strosser, P. Retour Sur l’étude Prospective Garonne 2050. *La Houille Blanche* **2016**, *102*, 30–35. [\[CrossRef\]](#)
42. Brasier, K.; Zaragoza, I.; Knecht, J.; Munster, R.; Coulter, H.; Potter, A.; Enke, E.; Fox, A.; Mosqueda, E.; Zakeri, H. Potential of Faba Bean (*Vicia faba* L.) for Dual-Purpose Vegetable Production and Cover Cropping. *HortScience* **2023**, *58*, 23–31. [\[CrossRef\]](#)
43. Jacquemoud, S.; Baret, F.; Andrieu, B.; Danson, F.M.; Jaggard, K. Extraction of Vegetation Biophysical Parameters by Inversion of the PROSPECT + SAIL Models on Sugar Beet Canopy Reflectance Data. Application to TM and AVIRIS Sensors. *Remote Sens. Environ.* **1995**, *52*, 163–172. [\[CrossRef\]](#)
44. Wang, J.; Lopez-Lozano, R.; Weiss, M.; Buis, S.; Li, W.; Liu, S.; Baret, F.; Zhang, J. Crop Specific Inversion of PROSAIL to Retrieve Green Area Index (GAI) from Several Decametric Satellites Using a Bayesian Framework. *Remote Sens. Environ.* **2022**, *278*, 113085. [\[CrossRef\]](#)
45. Muñoz-Sabater, J.; Dutra, E.; Agustí-Panareda, A.; Albergel, C.; Arduini, G.; Balsamo, G.; Boussetta, S.; Choulga, M.; Harrigan, S.; Hersbach, H.; et al. ERA5-Land: A State-of-the-Art Global Reanalysis Dataset for Land Applications. *Earth Syst. Sci. Data* **2021**, *13*, 4349–4383. [\[CrossRef\]](#)

46. Rouquié, B.; Hagolle, O.; Bréon, F.-M.; Boucher, O.; Desjardins, C.; Rémy, S. Using Copernicus Atmosphere Monitoring Service Products to Constrain the Aerosol Type in the Atmospheric Correction Processor MAJA. *Remote Sens.* **2017**, *9*, 1230. [\[CrossRef\]](#)
47. Poggio, L.; de Sousa, L.M.; Batjes, N.H.; Heuvelink, G.B.M.; Kempen, B.; Ribeiro, E.; Rossiter, D. SoilGrids 2.0: Producing Soil Information for the Globe with Quantified Spatial Uncertainty. *Soil* **2021**, *7*, 217–240. [\[CrossRef\]](#)
48. Baldocchi, D.D. Assessing the Eddy Covariance Technique for Evaluating Carbon Dioxide Exchange Rates of Ecosystems: Past, Present and Future. *Glob. Change Biol.* **2003**, *9*, 479–492. [\[CrossRef\]](#)
49. Béziat, P. Effets Des Conditions Environnementales et Des Pratiques Culturelles Sur Les Flux de Carbone et d'eau Dans Les Agrosystèmes. Ph.D. Thesis, Université Toulouse III-Paul Sabatier, Toulouse, France, 2009.
50. Clement, R. *EdiRe Data Software*; The University of Edinburgh: Edinburgh, Scotland, 1999.
51. Reichstein, M.; Falge, E.; Baldocchi, D.; Papale, D.; Aubinet, M.; Berbigier, P.; Bernhofer, C.; Buchmann, N.; Gilmanov, T.; Granier, A.; et al. On the Separation of Net Ecosystem Exchange into Assimilation and Ecosystem Respiration: Review and Improved Algorithm. *Glob. Change Biol.* **2005**, *11*, 1424–1439. [\[CrossRef\]](#)
52. Román Dobarco, M.; Bourennane, H.; Arrouays, D.; Saby, N.P.A.; Cousin, I.; Martin, M.P. Uncertainty Assessment of GlobalSoilMap Soil Available Water Capacity Products: A French Case Study. *Geoderma* **2019**, *344*, 14–30. [\[CrossRef\]](#)
53. Clivot, H.; Duparque, A.; Ferchaud, F.; Lagrange, H.; Levavasseur, F.; Levert, M.; Marsac, S.; Mary, B.; Mouny, J.-C.; Piquemal, B.; et al. *AMGv2 Parameters*; 2023. Available online: <https://entrepot.recherche.data.gouv.fr/dataset.xhtml?persistentId=doi:10.57745/MEQQIX> (accessed on 3 September 2025).
54. Clivot, H.; Mouny, J.-C.; Duparque, A.; Dinh, J.-L.; Denoroy, P.; Houot, S.; Vertès, F.; Trochard, R.; Bouthier, A.; Sagot, S.; et al. Modeling Soil Organic Carbon Evolution in Long-Term Arable Experiments with AMG Model. *Environ. Model. Softw.* **2019**, *118*, 99–113. [\[CrossRef\]](#)
55. Coleman, K.; Jenkinson, D.S. RothC-26.3—A Model for the Turnover of Carbon in Soil. In *Evaluation of Soil Organic Matter Models*; Powlson, D.S., Smith, P., Smith, J.U., Eds.; Springer: Berlin/Heidelberg, Germany, 1996; pp. 237–246.
56. Kelly, R.H.; Parton, W.J.; Crocker, G.J.; Graced, P.R.; Klir, J.; Körschens, M.; Poulton, P.R.; Richter, D.D. Simulating Trends in Soil Organic Carbon in Long-Term Experiments Using the Century Model. *Geoderma* **1997**, *81*, 75–90. [\[CrossRef\]](#)
57. Zeleke, K.T. AquaCrop Calibration and Validation for Faba Bean (*Vicia faba* L.) under Different Agronomic Managements. *Agronomy* **2019**, *9*, 320. [\[CrossRef\]](#)
58. Dhoubi, M.; Zitouna-Chebbi, R.; Prévot, L.; Molénat, J.; Mekki, I.; Jacob, F. Multicriteria Evaluation of the AquaCrop Crop Model in a Hilly Rainfed Mediterranean Agrosystem. *Agric. Water Manag.* **2022**, *273*, 107912. [\[CrossRef\]](#)
59. Falconnier, G.N.; Journet, E.-P.; Bedoussac, L.; Vermue, A.; Chlébowski, F.; Beaudoin, N.; Justes, E. Calibration and Evaluation of the STICS Soil-Crop Model for Faba Bean to Explain Variability in Yield and N<sub>2</sub> Fixation. *Eur. J. Agron.* **2019**, *104*, 63–77. [\[CrossRef\]](#)
60. Berghuijs, H.N.C.; Weih, M.; van der Werf, W.; Karley, A.J.; Adam, E.; Villegas-Fernández, Á.M.; Kjaer, L.P.; Newton, A.C.; Scherber, C.; Tavoletti, S.; et al. Calibrating and Testing APSIM for Wheat-Faba Bean Pure Cultures and Intercrops across Europe. *Field Crops Res.* **2021**, *264*, 108088. [\[CrossRef\]](#)
61. Dias, H.B.; Cuadra, S.V.; Boote, K.J.; Lamparelli, R.A.C.; Figueiredo, G.K.D.A.; Suyker, A.E.; Magalhães, P.S.G.; Hoogenboom, G. Coupling the CSM-CROPGRO-Soybean Crop Model with the ECOSMOS Ecosystem Model—An Evaluation with Data from an AmeriFlux Site. *Agric. For. Meteorol.* **2023**, *342*, 109697. [\[CrossRef\]](#)
62. Raimondi, G.; Maucieri, C.; Borin, M.; Pancorbo, J.L.; Cabrera, M.; Quemada, M. Satellite Imagery and Modeling Contribute Understanding Cover Crop Effect on Nitrogen Dynamics and Water Availability. *Agron. Sustain. Dev.* **2023**, *43*, 66. [\[CrossRef\]](#)
63. Ye, L.; Guan, K.; Qin, Z.; Wang, S.; Zhou, W.; Peng, B.; Grant, R.; Tang, J.; Hu, T.; Jin, Z.; et al. Improved Quantification of Cover Crop Biomass and Ecosystem Services through Remote Sensing-Based Model–Data Fusion. *Environ. Res. Lett.* **2023**, *18*, 094018. [\[CrossRef\]](#)
64. Wang, S.; Guan, K.; Zhang, C.; Jiang, C.; Zhou, Q.; Li, K.; Qin, Z.; Ainsworth, E.A.; He, J.; Wu, J.; et al. Airborne Hyperspectral Imaging of Cover Crops through Radiative Transfer Process-Guided Machine Learning. *Remote Sens. Environ.* **2023**, *285*, 113386. [\[CrossRef\]](#)
65. Delogu, E.; Le Dantec, V.; Mordelet, P.; Ceschia, E.; Aubinet, M.; Buysse, P.; Pattey, E. Improved Methodology to Quantify the Temperature Sensitivity of the Soil Heterotrophic Respiration in Croplands. *Geoderma* **2017**, *296*, 18–29. [\[CrossRef\]](#)
66. Löhnis, F. Nitrogen Availability of Green Manures. *Soil Sci.* **1926**, *22*, 253. [\[CrossRef\]](#)
67. Kuzyakov, Y.; Friedel, J.K.; Stahr, K. Review of Mechanisms and Quantification of Priming Effects. *Soil Biol. Biochem.* **2000**, *32*, 1485–1498. [\[CrossRef\]](#)
68. Zheng, B.; Campbell, J.B.; Serbin, G.; Galbraith, J.M. Remote Sensing of Crop Residue and Tillage Practices: Present Capabilities and Future Prospects. *Soil Tillage Res.* **2014**, *138*, 26–34. [\[CrossRef\]](#)
69. Bégué, A.; Arvor, D.; Bellon, B.; Betbeder, J.; De Abelleira, D.; P. D. Ferraz, R.; Lebourgeois, V.; Lelong, C.; Simões, M.; R. Verón, S. Remote Sensing and Cropping Practices: A Review. *Remote Sens.* **2018**, *10*, 99. [\[CrossRef\]](#)

70. Huang, H.; Yang, L.; Zhang, L.; Pu, Y.; Yang, C.; Wu, Q.; Cai, Y.; Shen, F.; Zhou, C. A Review on Digital Mapping of Soil Carbon in Cropland: Progress, Challenge, and Prospect. *Environ. Res. Lett.* **2022**, *17*, 123004. [\[CrossRef\]](#)
71. Caubel, J.; Launay, M.; Ripoché, D.; Gouache, D.; Buis, S.; Huard, F.; Huber, L.; Brun, F.; Bancal, M.O. Climate Change Effects on Leaf Rust of Wheat: Implementing a Coupled Crop-Disease Model in a French Regional Application. *Eur. J. Agron.* **2017**, *90*, 53–66. [\[CrossRef\]](#)
72. Caubel, J.; Launay, M.; Lannou, C.; Brisson, N. Generic Response Functions to Simulate Climate-Based Processes in Models for the Development of Airborne Fungal Crop Pathogens. *Ecol. Model.* **2012**, *242*, 92–104. [\[CrossRef\]](#)
73. Justes, E.; Beaudoin, N.; Bertuzzi, P.; Charles, R.; Constantin, J.; Durr, C.; Hermon, C.; Joannon, A.; Bas, C.L.; Mary, B.; et al. Réduire Les Fuites de Nitrate Au Moyen de Cultures Intermédiaires: Conséquences Sur Les Bilans d’eau et d’azote, Autres Services Écosystémiques. Ph.D. Thesis, Ministère de l’Ecologie, du Développement Durable et de l’Energie, Paris, France, 2012.
74. Fendrich, A.N.; Matthews, F.; Van Eynde, E.; Carozzi, M.; Li, Z.; d’Andrimont, R.; Lugato, E.; Martin, P.; Ciais, P.; Panagos, P. From Regional to Parcel Scale: A High-Resolution Map of Cover Crops across Europe Combining Satellite Data with Statistical Surveys. *Sci. Total Environ.* **2023**, *873*, 162300. [\[CrossRef\]](#)
75. Nowak, B.; Michaud, A.; Marliac, G. Soil-Climate Factors Have a Greater Influence on the Presence of Winter Cover Crops than Regulatory Constraints in France. *Agron. Sustain. Dev.* **2022**, *42*, 28. [\[CrossRef\]](#)
76. Jain, K.; John, R.; Torbick, N.; Kolluru, V.; Saraf, S.; Chandel, A.; Henebry, G.M.; Jarchow, M. Monitoring the Spatial Distribution of Cover Crops and Tillage Practices Using Machine Learning and Environmental Drivers across Eastern South Dakota. *Environ. Manag.* **2024**, *74*, 742–756. [\[CrossRef\]](#)
77. Fieuzal, R.; Baup, F.; Marais-Sicre, C. Monitoring Wheat and Rapeseed by Using Synchronous Optical and Radar Satellite Data—From Temporal Signatures to Crop Parameters Estimation. *EARSeL Adv. Remote Sens.* **2013**, *2*, 162–180. [\[CrossRef\]](#)
78. Fieuzal, R.; Baup, F. Estimation of Leaf Area Index and Crop Height of Sunflowers Using Multi-Temporal Optical and SAR Satellite Data. *Int. J. Remote Sens.* **2016**, *37*, 2780–2809. [\[CrossRef\]](#)
79. Baup, F.; Villa, L.; Fieuzal, R.; Ameline, M. Sensitivity of X-Band ( $\Sigma^\circ$ ,  $\gamma$ ) and Optical (NDVI) Satellite Data to Corn Biophysical Parameters. *EARSeL Adv. Remote Sens.* **2016**, *5*, 103–117. [\[CrossRef\]](#)
80. Allies, A.; Roumigué, A.; Dejoux, J.-F.; Fieuzal, R.; Jacquin, A.; Veloso, A.; Champolivier, L.; Baup, F. Evaluation of Multiorbital SAR and Multisensor Optical Data for Empirical Estimation of Rapeseed Biophysical Parameters. *IEEE J. Sel. Top. Appl. Earth Observ. Remote Sens.* **2021**, *14*, 7268–7283. [\[CrossRef\]](#)
81. Fieuzal, R.; Marais Sicre, C.; Baup, F. Estimation of Sunflower Yield Using a Simplified Agrometeorological Model Controlled by Optical and SAR Satellite Data. *IEEE J. Sel. Top. Appl. Earth Observ. Remote Sens.* **2017**, *10*, 5412–5422. [\[CrossRef\]](#)
82. Baup, F.; Ameline, M.; Fieuzal, R.; Frappart, F.; Corgne, S.; Berthoumieu, J.-F. Temporal Evolution of Corn Mass Production Based on Agro-Meteorological Modelling Controlled by Satellite Optical and SAR Images. *Remote Sens.* **2019**, *11*, 1978. [\[CrossRef\]](#)
83. Allies, A.; Roumigué, A.; Fieuzal, R.; Dejoux, J.-F.; Jacquin, A.; Veloso, A.; Champolivier, L.; Baup, F. Assimilation of Multisensor Optical and Multiorbital SAR Satellite Data in a Simplified Agrometeorological Model for Rapeseed Crops Monitoring. *IEEE J. Sel. Top. Appl. Earth Observ. Remote Sens.* **2022**, *15*, 1123–1138. [\[CrossRef\]](#)
84. Ameline, M.; Fieuzal, R.; Betbeder, J.; Berthoumieu, J.-F.; Baup, F. Estimation of Corn Yield by Assimilating SAR and Optical Time Series Into a Simplified Agro-Meteorological Model: From Diagnostic to Forecast. *IEEE J. Sel. Top. Appl. Earth Observ. Remote Sens.* **2018**, *11*, 4747–4760. [\[CrossRef\]](#)
85. Betbeder, J.; Fieuzal, R.; Baup, F. Assimilation of LAI and Dry Biomass Data From Optical and SAR Images Into an Agro-Meteorological Model to Estimate Soybean Yield. *IEEE J. Sel. Top. Appl. Earth Observ. Remote Sens.* **2016**, *9*, 2540–2553. [\[CrossRef\]](#)

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