DEL 05 Progress report on larger scale application of the remote sensing approach

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Deliverable Proof – Reports resulting from the finalisation of a project task, work package, project stage, project as a whole - EIT-BP2021

Name of KIC project the report results from that contributed to/ resulted in the deliverable	210065 Carbon Farming: Experimenting Soil Carbon Sequestration Deployment in Farming Systems
Name of report	DEL 05 Progress report on larger scale application of the remote sensing approach
Summary/brief description of report	In this report we demonstrate the potential of remote sensing for 1) mapping cover crops and producing metrics associated to their development, 2) estimating cover crop biomass and the associated annual carbon storage effect based on remote sensing products assimilitation in the SAFYE-CO2 agronomical model (embeded in the AgriCarbon-EO processing chain). Then we describe our global approach for estimating and validating cropland carbon budgets over several years starting from the work done for future implementations of the coupled SAFYE-CO2/AMG models. Last we describe the soil sampling campaign that was conducted over the Nataïs case study, adapted from the procedure developed by Agricircle, that provided soil properties data for future applications of the coupled SAFYE-CO2/AMG modelling approach and validation of the spatialized C budget estimates.
Date of report	19/01/2021

Supporting Documents: Description of the soil sampling protocol provided by Agricircle

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Progress report on larger scale application of the remote sensing approach

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Centre d'Etudes Spatiales de la Biosphère (CESBIO)

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1. Introduction

In this document, we demonstrate first the potential of remote sensing for mapping cover crops at regional scale and producing accurate/high resolution estimates of the annual carbon budget components (CO_2 fluxes, biomass…) over more than 50 farms when assimilated in a crop model.

The cover crop mapping exercises concerned all crop plots in the studied region located in South West France that encompasses most of the Nataïs Farmer's network. The modelling exercises were done at high resolution (10) over a total of 153 plots belonging to farmers that produce maize popcorn for the Nataïs company. Most of them grow cover crops before the maize is seeded and Nataïs pays them for doing so. But this year, for the first time, Nataïs could pay 50 pilot farmers according to the biomass of cover crops they produced and buried in the soil for storing carbon thanks to the tools that were developed by INRAE/CESBIO.

Finally we present a new global approach for estimating cropland carbon budgets at the crop rotation scale and high resolution based on a combined smart soil sampling protocol developed by Agricircle and a coupled crop/soil modelling approach (AMG and SAFYE-CO2 models) taking benefit from the recent Sentinel 2 satellite missions.

2. Cover crop mapping

There is currently no comprehensive and reliable source of information on the presence and/or type of cover crops (CC) present or not present in agricultural plots in a territory for a given crop year. We therefore worked on the development of mapping methods based on the use of high-resolution satellite data that not only 1) identify the presence or absence of CC during the fallow period, but also 2) categorize them into winter catch crops (destroyed in December), multi-service winter cover crops (MSCC; that are grown till spring), summer CC and finally 3) to quantify their development intensity and heterogeneity at the parcel and intra-parcel level. These maps may subsequently be used to diagnose favourable conditions for the establishment of CC or to provide input to agro-meteorological models to quantify the effects of CC on carbon budgets.

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2.1 Methodology

A remote sensing processing chain based on the random forest approach was first tested to map cover crops over 2 Sentinel 2 tiles located around at west of Toulouse (see Figure 1) . To validate the results, field monitoring of the status of the plots during the fallow period was carried over 1600 plots between 2016 and 2018. Bare soil were very well detected (Fscore about 90%) and long winter CC were well detected also with a Fscore of 60% but the performances for fallows concerned by the summer CC and short winter CC where lower than 20% because of the strong intra-plot heterogeneity. Therefore a second approach based on the Kmeans using Sentinel 2 satellite images over 3 Sentinel tiles (Figure 1) covering about 30,000 km² was developed to map the plots at pixel scale in 4 classes during the fallow period (bare ground, summer cover crop/regrowth/weeds, winter catch crop, winter MSCC).

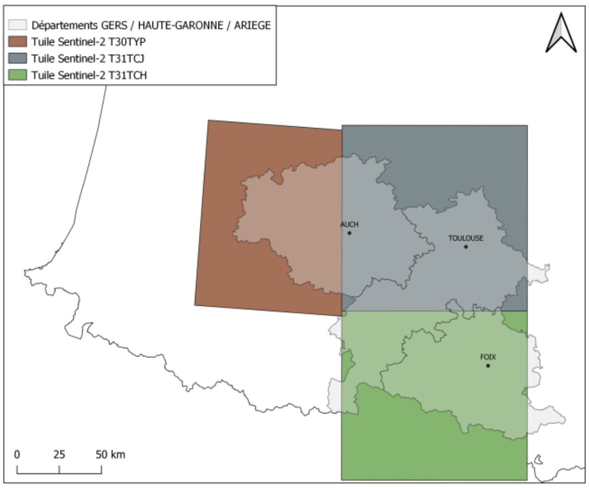
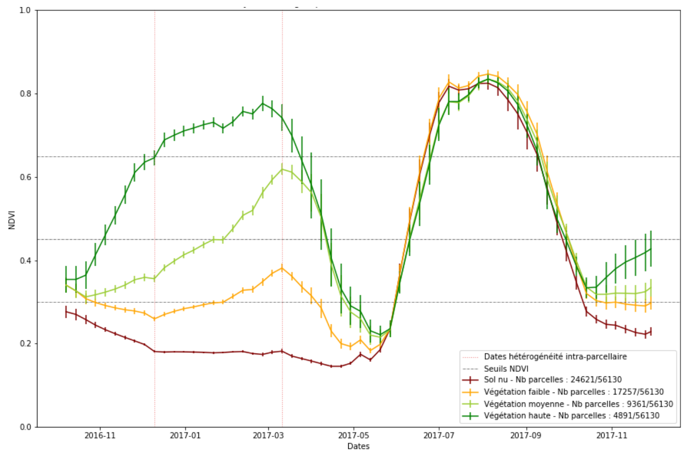


Figure 1: study area for crop fallow mapping at high resolution with corresponding Sentinel-2 tile numbers.

For each fallow type (EE, between two summer crops ; HE, between a winter and a summer crop) this mapping approach made it possible to distinguish the poorly, medium and well developed cover crops according to the methodology described in Figure 2. Finally, from these maps, an analysis of metrics (duration of soil coverage, percentage of land cover) was carried out.

Mean of the NDVI time series over 3 tiles for the EE type fallow period in 2016-2017



Fallow type	Bare soil	Poor development	Medium development	Strong development
EE	$d1_{NDVI \le 0.3}$ & $d2_{NDVI \le 0.3}$ Or $d1_{NDVI > 0.3}$ & $d2_{NDVI \le 0.3}$	$d1_{NDVI \le 0.3}$ & $d2_{0.3 < NDVI \le 0.45}$ Or $d1_{NDVI > 0.3}$ & $d2_{0.3 < NDVI \le 0.45}$	$d1_{NDVI \le 0.3}$ & $d2_{0.45 < NDVI \le 0.65}$ Or $d1_{NDVI > 0.3}$ & $d2_{0.45 < NDVI \le 0.65}$	$d1_{NDVI \le 0.3}$ & $d2_{NDVI > 0.65}$ Or $d1_{NDVI > 0.3}$ & $d2_{NDVI > 0.65}$
HE	$d1_{NDVI \le 0.3}$ & $d2_{NDVI \le 0.3}$	$d1_{NDVI > 0.3}$ & $d2_{NDVI \le 0.3}$	$d1_{NDVI \le 0.3}$ & $d2_{0.3 < NDVI \le 0.6}$ Or $d1_{NDVI > 0.3}$ & $d2_{0.3 < NDVI \le 0.6}$	$d1_{NDVI \le 0.3}$ & $d2_{NDVI > 0.6}$ Or $d1_{NDVI > 0.3}$ & $d2_{NDVI > 0.6}$

Figure 2: Examples of average NDVI profiles for classes of intensity of development of winter cover crops (and standard deviations) on the 3 Sentinel tiles and EE fallow type in 2016-2017 (the first cycles of NDVI increase/decrease correspond to the CC development while the second cycle corresponds to a summer crop) and methodology for mapping the intensity of development of cover crops based on vegetation index thresholds (NDVI).

2.2 Results

Our results show (Figure 3) strong spatial heterogeneities in the implementation and development of CC. It is striking, for example, to see that CC are much more widespread around Aire sur Adour than around Gimont.

Our results also show (Figure 4) that the percentage of plots of arable crops covered by CC varies from 0 to 100% depending on the municipality and that the geographical disparities are high.

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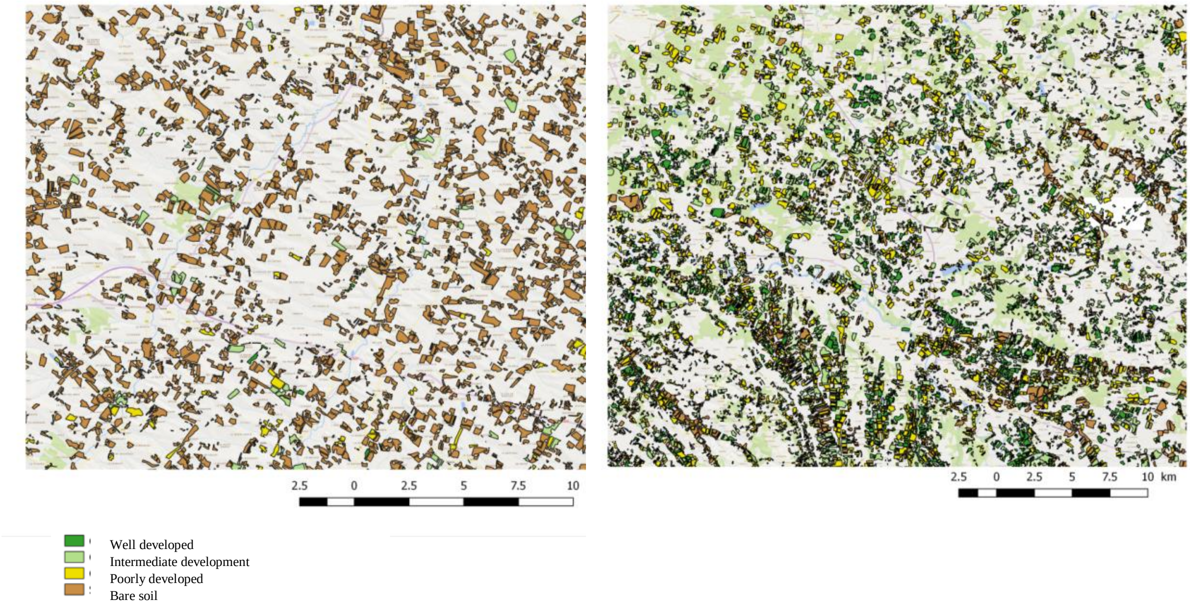


Figure 3: Examples of plot scale fallow mapping for 2016-2017 in 4 classes by the Kmeans method: bare soil, poorly, medium and well developed CC for long (HE) and short (EE) fallow periods that have been grouped into a single map. Around Gimont (left) and around Aire sur Adour (right).

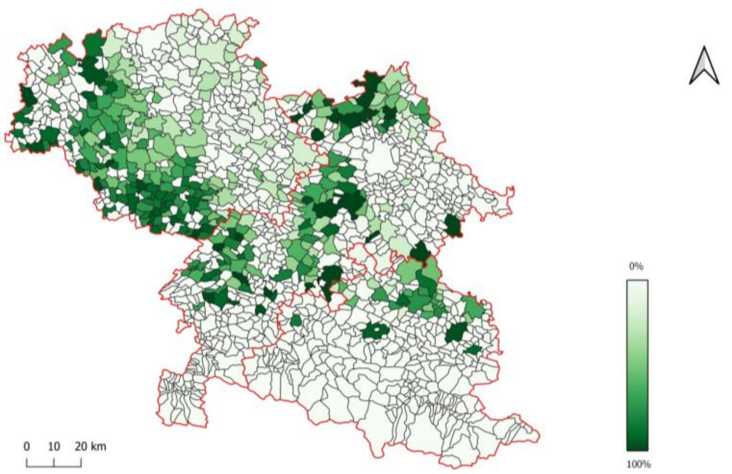


Figure 4: Mapping of the percentages of plots per municipality with CC during the winter-summer fallow period of 2017-2018 carried out using the Kmeans method for the 3 administrative regions (Arièges, Haute Garonne, Gers).

Then we analysed intra-plot heterogeneities during the winter fallow period. Our results show that for plots expected to be in bare soil, there are in fact in 2016-2017 and 2017-2018, respectively, 8% and 13% of the pixels on which vegetation developed for at least a few days during the fallow. Also, on average on the plots supposed to be bare soil there are only 51% of the surfaces (number of pixels) that remain totally bare soil. The average number of days with vegetation is for this category of 41,7 days ± 50.

For plots with strong CC development during HE fallow periods, there are actually only 70% of the pixels on which vegetation developed strongly and up to 22% of the pixels remained on bare ground during the entire fallow period. For this class, 6% of the surfaces remained in bare soil or were covered for less than 15 days by vegetation. The average soil cover time for this class was 106 days ± 46. These indicators of coverage time are very similar to those for the for the intermediate development CC class.

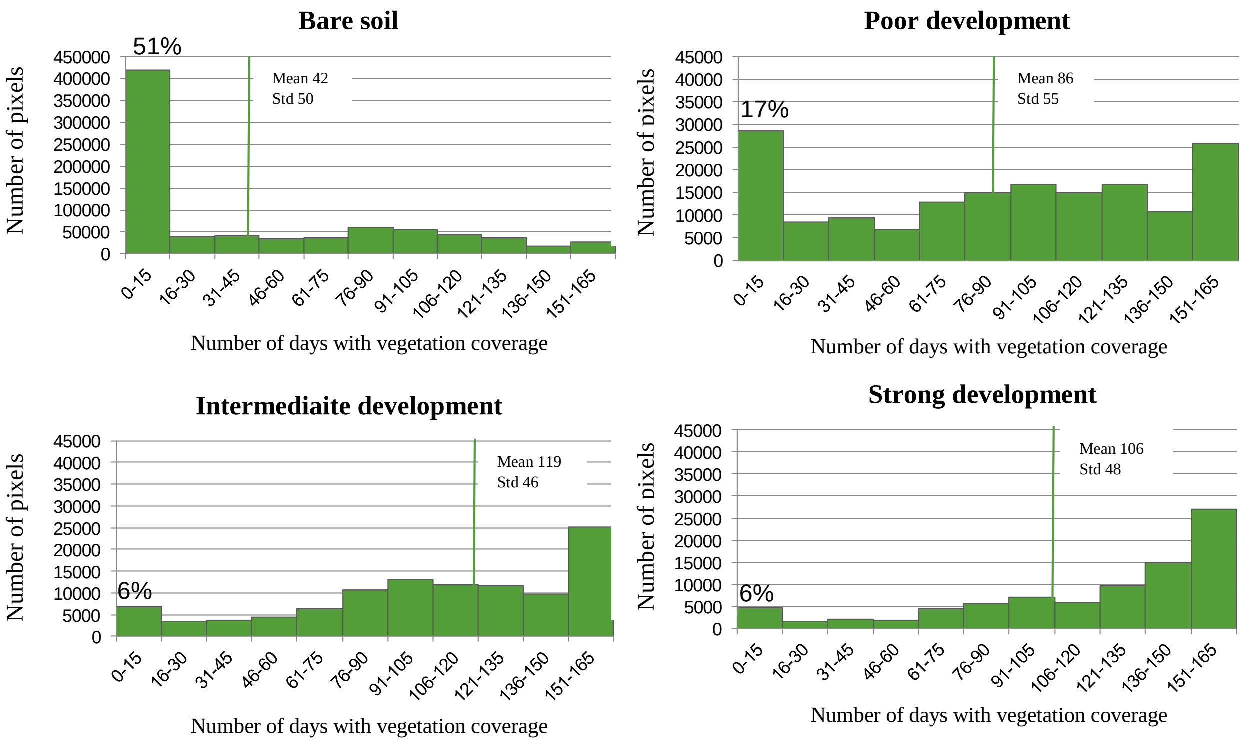


Figure 5: Percentage of area that represent the classes of soil coverage for each class of CC development for the 2017-2018 fallow and for the 31TCJ tile covering mainly the Haute Garonne region.

Those results highlight the importance of analysing cover crop development at high resolution when assessing their effect on soil organic carbon storage.

3. Estimates of the cover crop biomass and of the annual components of the C budget at popcorn maize plots with SAFYE-CO2

3.1 Methodology

In this study, we quantify the components of the carbon budget at high resolution and we analyse the effect of cover crops on soil organic carbon storage.

Computations are based on the newly developed end to end AgriCarbon-EO processing chain that encompasses the SAFYE-CO2 model and utilizes the PROSAIL radiative tranfer model. The AgriCarbon-EO processing chain (see Figure 6) allows to calculate the components of the carbon budgets (yield, biomass, CO_2 fluxes) at plot scale or at 10-20m resolution by assimilating Sentinel 2 satellite reflectance data into physically based parsimonious models. The assimilation scheme is based on a Bayesian approach which provides dynamic maps of biogeophysical variables (Green Area Index, GAI; Fraction Cover, Fcover) with their associated uncertainties. Uncertainties are essential when determining the carbon budgets as they can impact negatively the bonus paid to the farmers for storing additional C with the cover crops. The biogeophysical variables are derived from the Sentinel-2 surface reflectance by inverting the PROSAIL model (Jacquemoud et al. 2009). These are then assimilated (as well as their uncertainties) into the SAFYE_CO2 model (Pique et al. 2020 a and 2020 b) to determine the components of the carbon budgets at pixel scale for each plot (and their associated uncertainties).

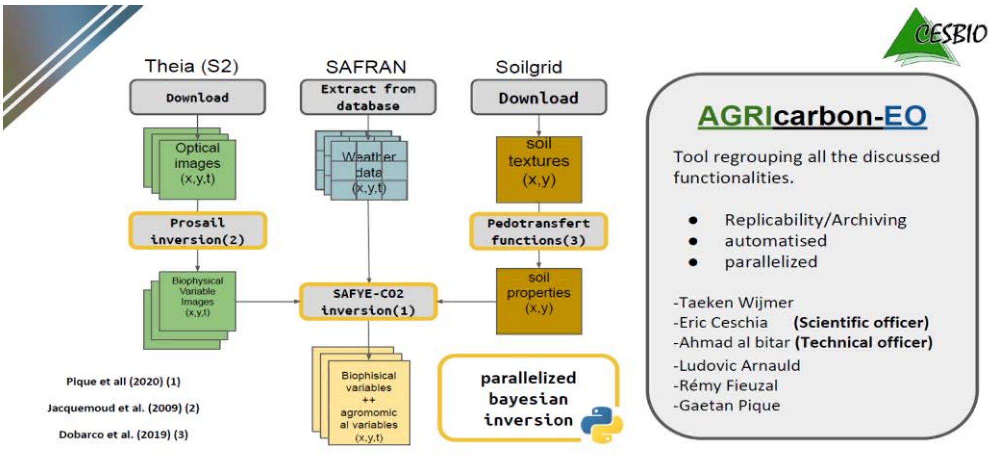


Figure 6: Schematic representation of the AgriCarbon-EO processing chain

The daily time steps SAFYE-CO2 model (see Figure 6) simulates the temporal evolutions of vegetation variables (GAI, biomass and yield) and of the CO_2 (photosynthesis, plant and soil respiration) and water (evapotranspiration) fluxes using climate input variables (precipitations, air temperature and global incoming radiation). The parameters of the model are either fixed (extracted from literature or from in-situ measurements) or variable and calibrated based on the comparison between GAI observed by satellite and GAI simulated by the model. The parameters (fixed and calibrated) are crop specific and fully detailed in Pique et al. (2020a) Pique et al. (2020b) and in Pique (2021) for winter wheat, sunflower and maize respectively. The parametrisation for cover crops is generic and are presented in Pique et al. (2020a). Concerning the calibrated parameters, on each simulated field/pixel and for each vegetation cycle independently, the values of the 8 calibrated parameters (relative to phenology and light use efficiency) are determined by minimizing the quadratic difference between the simulated and satellite derived GAI through a Bayesian approach and the use of lookup tables. This step allows the model to reproduce all types of vegetation developments observed by satellites (cash crops and cover crops) on the considered fields and to calculate the uncertainties associated to each simulated variable.

In SAFY-CO2, the photosynthesis (GPP) is estimated as a function of the incoming global radiation (Rg), the climatic efficiency (εc), the fraction of incoming radiation (APAR) absorbed by the plant (fAPAR), a temperature stress function (fT), the effective efficiency of the conversion of absorbed radiation to fixed CO2 through plant photosynthesis (fELUE), and a multiplicative coefficient (sR10), which takes into account the decline in canopy photosynthetic capacity during the senescence phase (see Pique et al. 2020a). The total biomass production (NPP) is then derived from the difference between the GPP and the plant respiration (Ra), which was separated into two components: maintenance respiration (Rm) and growth respiration (Rgr) (McCree, 1974). Then, the total NPP is divided into root (NPPr) and aboveground (NPPa) components, estimated by considering a root-to-shoot ratio (RtS) in accordance with the method proposed by Baret et al., (1992).

Finally, the net daily CO_2 flux (NEE) is calculated as the difference between the NPP and the carbon losses due to soil respiration (Rh). Rh is calculated using a Q_{10} first-order exponential equation depending on soil temperature (Delogu, 2013). For a detailled description of the SAFY-CO2 model, see DEL-15 “Report on an operational processing chain”.

Note that SAFY-CO2 automatically detects the presence of cover crops and calculates their biomass incorporated in the soil at destruction. By comparing simulations with and without accounting for the presence of cover crops, their effects on the net annual CO_2 fluxes and on the change in soil organic carbon content can be quantified. Note that SAFY-CO2 does not allow to simulate the carbon budget on plots with agroforestry and that the simple formalisms representing the soil process are well adapted to annual CO_2 flux/C budgets estimates but not to medium/long term SOC stocks monitoring. For this purpose it was decided to couple SAFYE-CO2 with the soil AMG model see section 4.2.

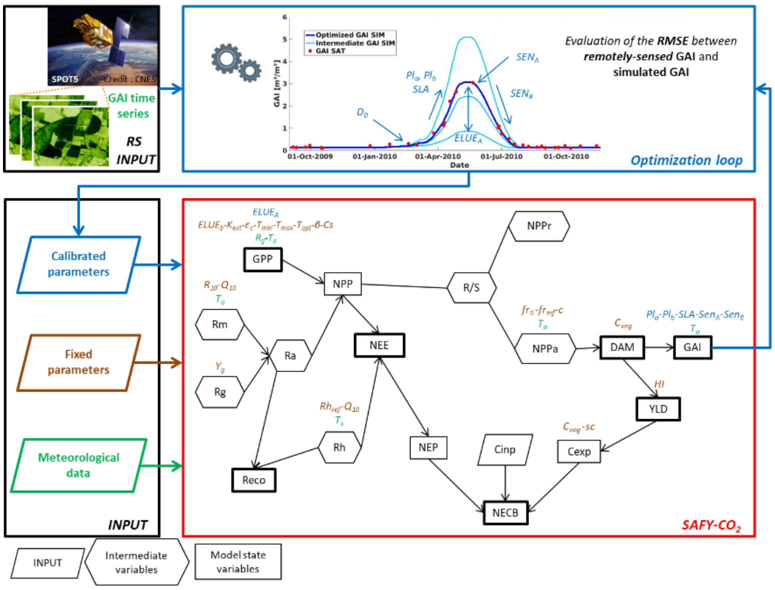


Figure 7: Schematic representation of the assimilation procedure of high resolution satellite optical images for the calibration of the agro-meteorological model SAFY-CO2, which estimates the crop biomass and the components of the net annual CO2 fluxes (GPP for photosynthesis; RECO for ecosystem respiration, i.e. the sum of plant and soil respiration; NEE for the net ecosystem exchange that is the sum of GPP and RECO) to derive the carbon budgets (NECB) over a cropping season.

Simulations were done for two Sentinel 2 tiles (T30TYP and T31TCJ, see Figure 8) for the cropping year 2018-2019, covering in total 153 plots belonging to farmers producing popcorn maize for the Nataïs company and therefore covering most of the Nataïs network. The ability of the model to simulate photosynthesis (GPP), ecosystem respiration (Reco) and the daily net CO2 fluxes (NEE) was evaluated against 2 years of in situ flux measurements acquired at a plot located in Pibrac. This plot is equipped with and eddy-covariance setup similar to the one described in Béziat et al. (2009). Data were process with tha same procedure as the one described in that study.

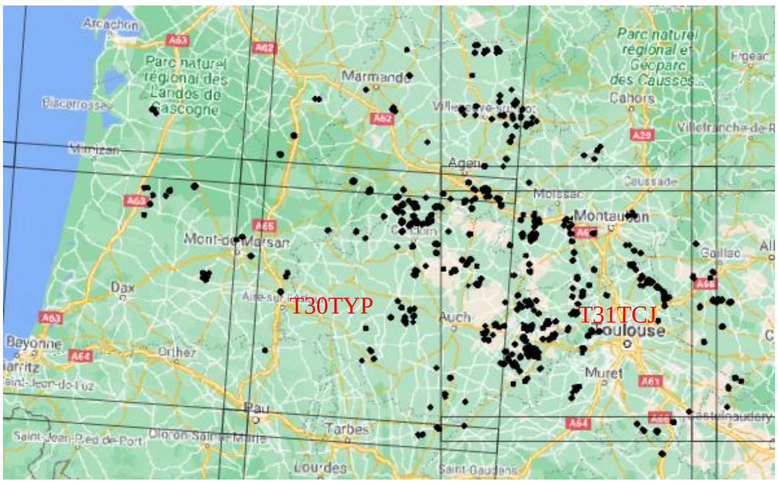


Figure 8: Map of the plots belonging to the Nataïs network of producers. The code of the tiles concerned by the simulations are noted in red.

3.2 Results

3.1.1 Performance of the model to simulate the CO_2 fluxes

SAFY-CO2 reproduced with a good accuracy the dry above ground biomass (DAM), the photosynthesis (GPP) and the net daily CO2 fluxes (NEE) dynamics measured at the Pibrac plot that belong to one of the farmers producing maize for Nataïs.

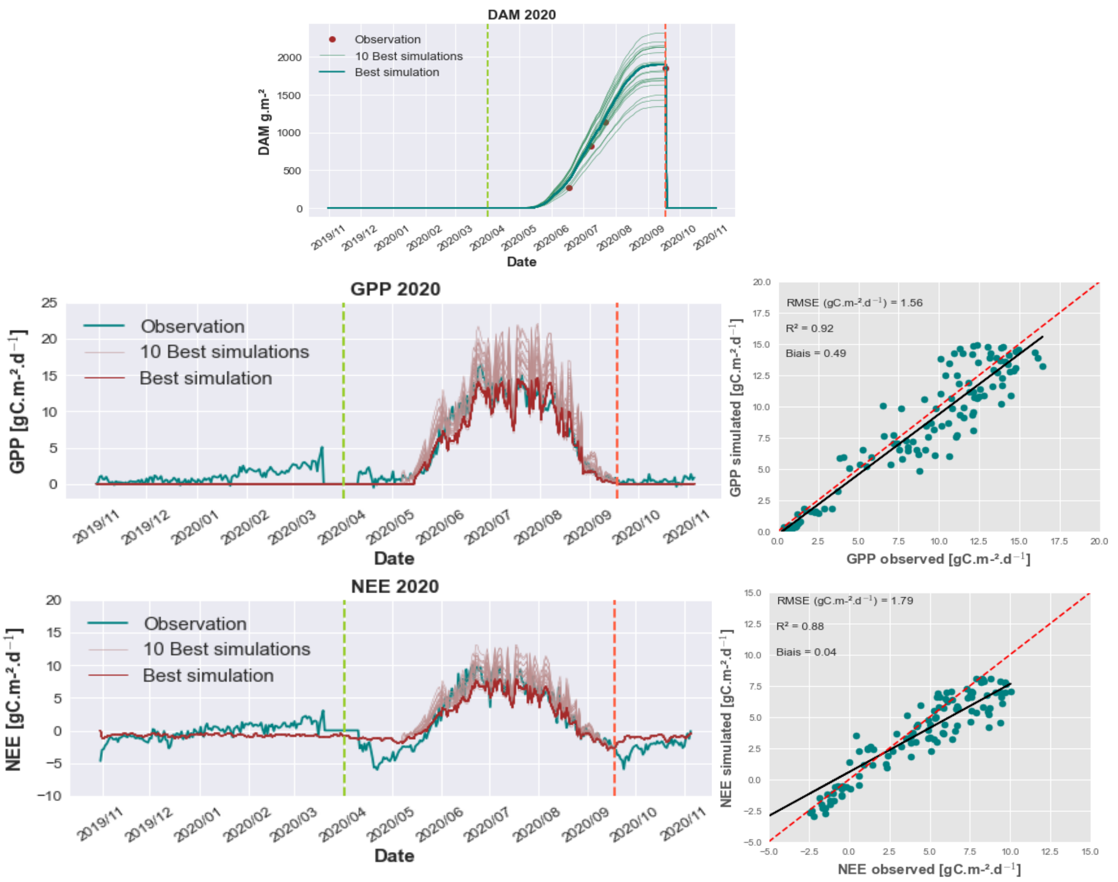


Figure 9: Comparison of the measurements and simulations with SAFY-CO2 of the DAM, GPP and NEE at the Pibrac site in 2020. Positive values correspond to net CO_2 fixation. Negative values correspond to net CO_2 losses.

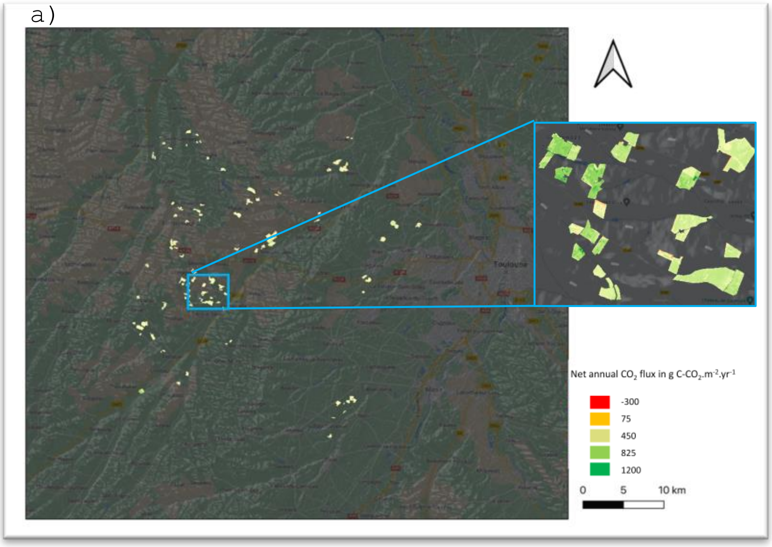
3.1.2 Effect of the cover crops on the net annual CO_2 fluxes

Simulations of CO_2 fluxes and cover crop/maize biomass were done daily at 10m resolution for 153 plots belonging to farmers producing maize for the Nataïs company. For each plot, on which cover crops were grown or not, simulations were then aggregated for the cropping year in order to calculate the net annual CO_2 flux (NEP) as shown in Figure 10. Uncertainties on the NEE estimates were estimated at pixel level as shown in Figure 11.

For each pixel, simulation were done twice in fact: by considering the presence of the cover crops and their effect on NEP when they were grown before maize (Figure 10a), and by ignoring their presence and their effect on NEP (Figure 10b). The difference between the two scenarii allows to quantify for each pixel the effect of cover crops (when grown before maïze) on the net annual CO_2 fluxes (Figure 12).

Figure 10 shows a high inter and intra plot spatial variability in the net annual CO_2 fluxes. Part of this spatial variability is caused by differences in pedoclimatic conditions affecting the soil processes, the development of maize and of cover crops. However, when comparing Figures 10a and 10b, it is clear that the spatial variability in the simulations of NEP for the case without cover crops (i.e. bare soil followed by maize, Figure 10b) is less pronounced than when considering the effect of cover crops on NEP (Figure 10a). This observation is confirmed by Figure 12 that shows the differences in NEP between the two scenarii, i.e. the effect of cover crops on NEP. Plots/pixels with differences in NEP close to zero had no cover crop grown (either they were not seeded or they did not grow). Plot/pixels showing high values were concerned by strong cover crop developments. Also form those figure, it is clear that cover crops allow fixing more CO_2 when they are grown before maize.

a)



b)

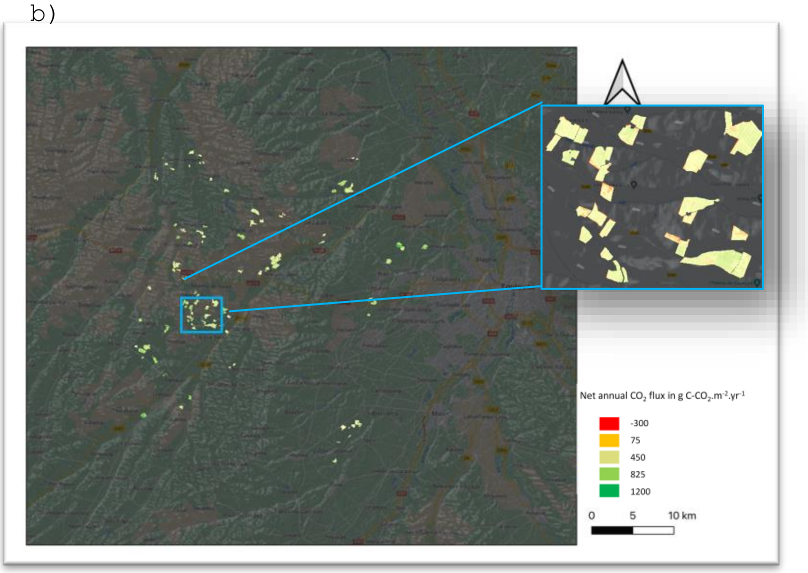


Figure 10: Simulations of the net annual CO_2 fluxes (NEP in g C-CO_2.m^{-2}.yr^{-1}) at plots growing popcorn maize in 2019 having or not cover crops grown before maize on top (a) and simulations done on the same plots but ignoring the presence of cover crops and their effect on the NEP on the bottom (b). Positive values correspond to net CO_2 fixation.

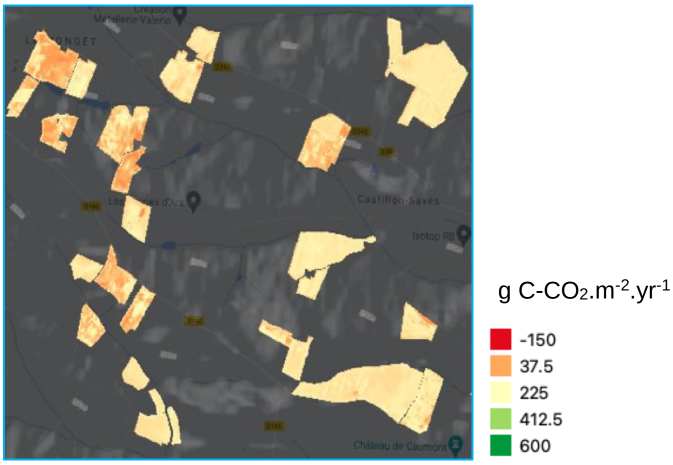


Figure 11: Map showing the uncertainties of the net annual CO_2 fluxes (NEP) at plots growing popcorn maize in 2019 having or not cover crops grown before maize. Positive values correspond to net CO_2 fixation.

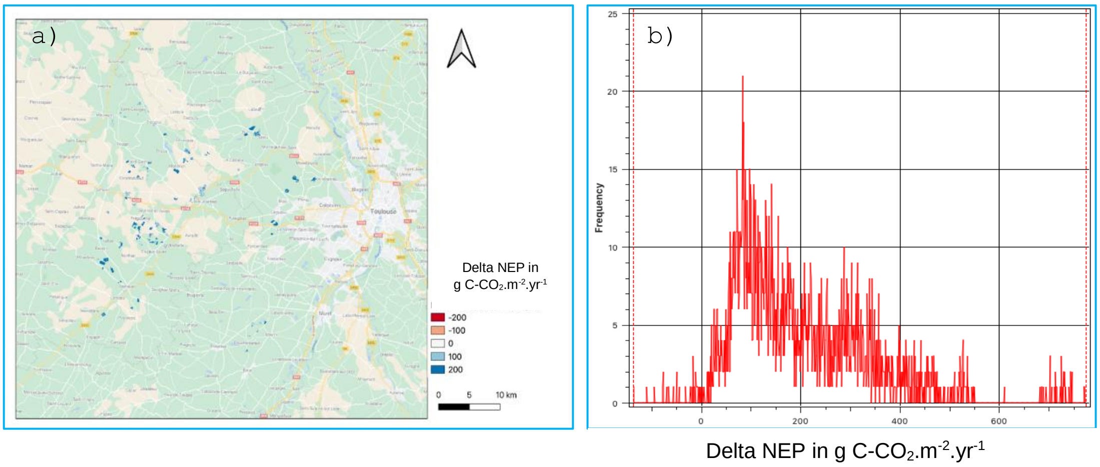


Figure 12: On the left (a), map of the differences between the two scenario of simulation (accounting or ignoring the presence of cover crops grown before popcorn maize). On the right (b), distribution in frequencies of the differences in NEP between the two scenarii of simulations for all the pixels simulated in this exercise. Positive values mean additional net CO_2 fixation with the cover crops.

Figure 12b shows the distribution in frequencies of the difference between the two scenarii of simulation. Those results show that except for a very small number of pixels, cover crops allowed fixing more CO_2. The few negative values can be explained by differences in reference values when building the Look Up Table prior to the calibration process, as the set of solutions for a given leaf area index (LAI) temporal profile in a given climatic grid cell will differ between the two scenarii. It means that for a given pixel, considering or not the presence of cover crops, the set of parameters for calibrating the model so that it matches the LAI dynamic will differ causing some uncertainty in the calculation of the difference in NEP between the two scenarii. Yet, for most of the pixels, cover crop allow fixing close to 100 g C-CO_2 m^{-2} yr^{-1} (with maxima up to 700 g C-CO_2 m^{-2} yr^{-1}) which is lowest on average than what was estimated on average by Poeplau & Don (2015), Kaye & Quemada (2017) and Pellerin et al. (2019) but in the range of the results found in their studies. It should be noted that in most of those studies, the results that are reported concern field trials in experimental farms with good homogeneous soil conditions and a lot of efforts for producing strong biomass which tends to overestimate the cover crop production.

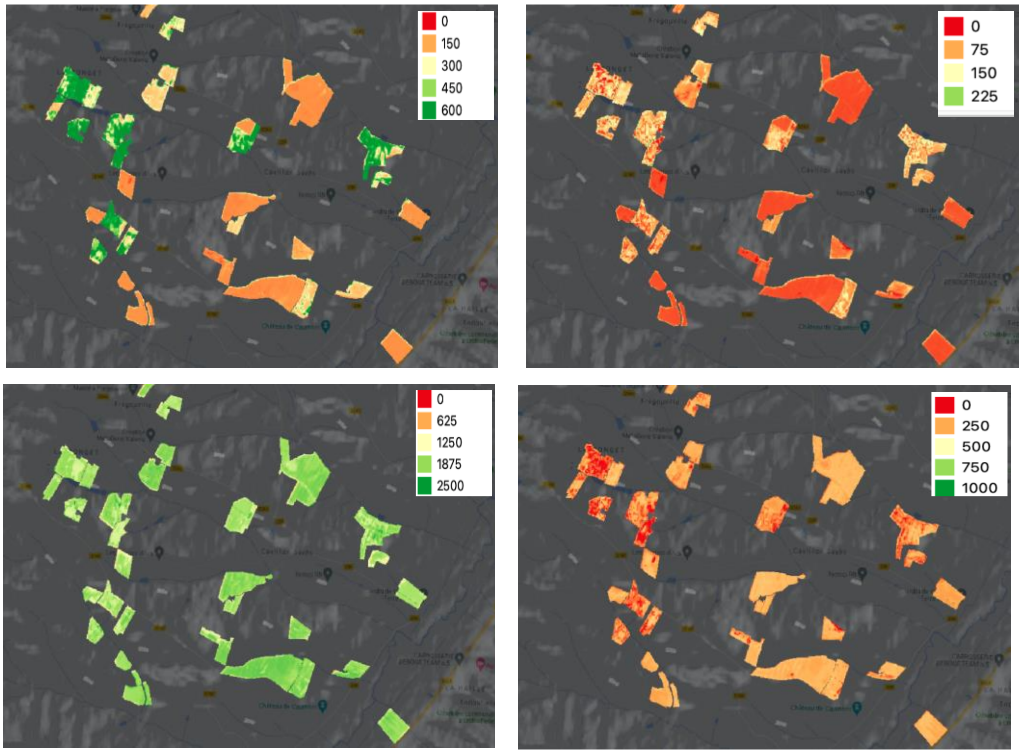


Figure 13: On the top left, 10m resolution map of the cover crop aboveground biomass (in gC.m-2) before destruction in a subset of the area of study and on the top right, associated uncertainties. On the bottom left, 10m resolution map of the maize final aboveground biomass (in gC.m-2) in a subset of the area of study and on the bottom right, associated uncertainties

4. A coherent spatialised approach for estimating and validating cropland carbon budgets

In this section, we present first a coherent approach for estimating cropland carbon budgets at the crop rotation scale and high resolution based on a combined smart soil sampling protocol developed by Agricircle and a coupled crop/soil modelling approach (AMG and SAFYE-CO2 models) taking benefit from the recent Sentinel 2 satellite missions. Then we present some specific elements of this approach

4.1 Description of the approach

In the previous sections as well as in the last year's report "200328 – D05 Report on the comparison of 3 carbon monitoring methods and on the implementation of the method (French case)" we demonstrated the importance of taking into account the high spatial variability in crop and cover crop biomass production for estimating accurate net annual CO_2 fluxes, and subsequently the cropland C budgets, as well as their spatial variability. This is essential as, at some point, the modelled carbon budgets estimates needs to be validated against localised in-situ soil measurements meaning that the spatial resolution of the C budget estimates and of the soil sampling must match.

In this perspective, a first soil campaign was performed over 20 plots (at 30 locations corresponding to approx. 250 samples in total) in winter 2020 based on the methodology developed by Agricircle that allows a good accounting of the soil properties spatial variability for estimating accurate initial SOC stocks. Another soil sampling campaign will be conducted at the same sampling points in 5 years to validate the modelled C budget estimates.
Also, for proper estimates of cropland C budget at this time frame (i.e. more than one cropping year), the simple and empirical formalisms representing soil CO_2 emissions associated to SOC mineralisation in SAFYE-CO2 had to be replaced by a well established soil model representing the dynamics of the SOC pools. For this reason, we recoded the AMG model in python and we coupled it with SAFYE-CO2. For a comparison of AMG and SAFYE-CO2 at a farm level, please refer to last year's report "200328 – D05 Report on the comparison of 3 carbon monitoring methods and on the implementation of the method (French case)".

Note that the winter 2020 soil campaign will be used also to provide pixel specific soil properties data as input in the AMG model for accurate C budgets estimates as it was shown by Pique et al. (2020b) that soil products such as Global Soil Map (90m resolution) or SoilGrids (250 m resolution) are not accurate enough (in terms of texture, SOC, soil depth…) for this king of exercise.

In the following sections, we will therefore present first the AMG model recoded in python that will be evaluated against its original version, then we will present the soil campaign that was conducted during the winter 2020 in the perspective of initialising the AMG model (python version) coupled to SAFYE-CO2 and for future validations of the cropland carbon budget estimates at 20 plots belonging to farmers producing maize popcorn for Nataïs.

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4.2 Recoding of AMG and evaluation of the new version

The original version of AMG was coded in Fortran. In the perspective of coupling it to SAFYE-CO2 in the AgriCarbon-EO processing chain, it was recoded in Python. Then, we compared the results of the two versions of the code on a case study. The Figure 14 shows that the two version provide exactly the same results.

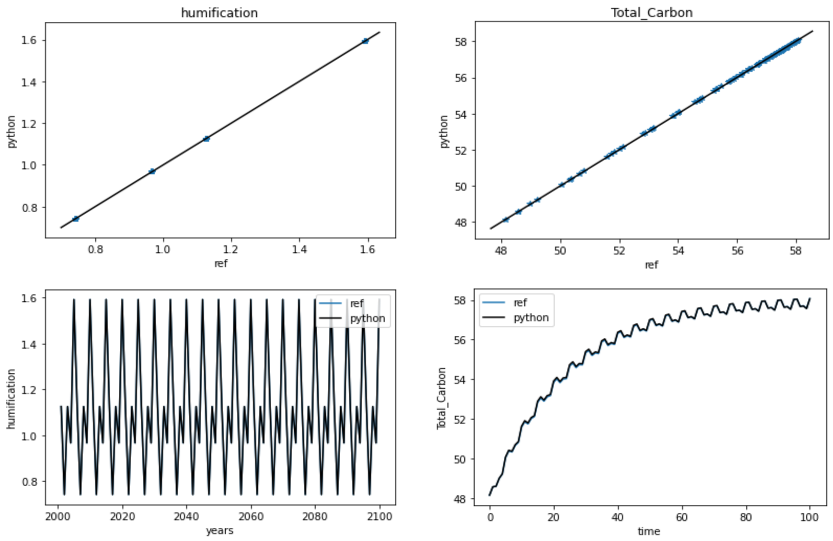

Figure 14: Comparison of the results of simulation for a case study with the original version of AMG and with the version recoded in python

Unfortunately, in spite of those good results, we couldn't go further and do some coupled SAFYE-CO2/AMG modelling exercises as we are waiting for the AMG Consortium Comitee to provide us a specific testing procedure that we will have to follow before they validate our version of the model.

Once this is done, we will be able to finalise the coupling of SAFYE-CO2 with AMG and to propagate the uncertainties from the Sentinel 2 data till the AMG outputs for quantifying the uncertainties on the high resolution C budgets estimates.

4.3 Soil campaign

Compared to the version provided by Agricircle (see attached document), the soil sampling protocol had to be adapted to account for the effect of topography on SOC content and stocks. Indeed all soil experts form INRAE and Agrotransfer involved in this project, as well as local soil experts, considered that topography was an essential parameter to account for when addressing SOC stocks spatial variability in this area of study. Indeed, topography causes lateral transfers of SOC in the soil and influence soil depth (and subsequently SOC stocks).

The method for locating soil samples is based on the stratified random procedure proposed by Minasny and McBratney, 2006 (i.e., Latin hypercube sampling), that allows to select and located a limited number samples while replicating the distribution of ancillary data. This method offers the advantage of being able to take into account different types of information, namely: the index derived from satellite images produced by Agricircle, the heterogeneity of the topography (thanks to different indicators derived from a digital elevation model, such as altitude or slope), as well as the number of years with cover crops. As an example, Figure 15 presents the distributions of three variables used to locate the samples (i.e., the index produced by Agricircle, the altitude and the number of years with cover crops). Whatever the considered variable, the original distributions (extracted on all the plots considered in the study) and those relative to the selected points are comparable.

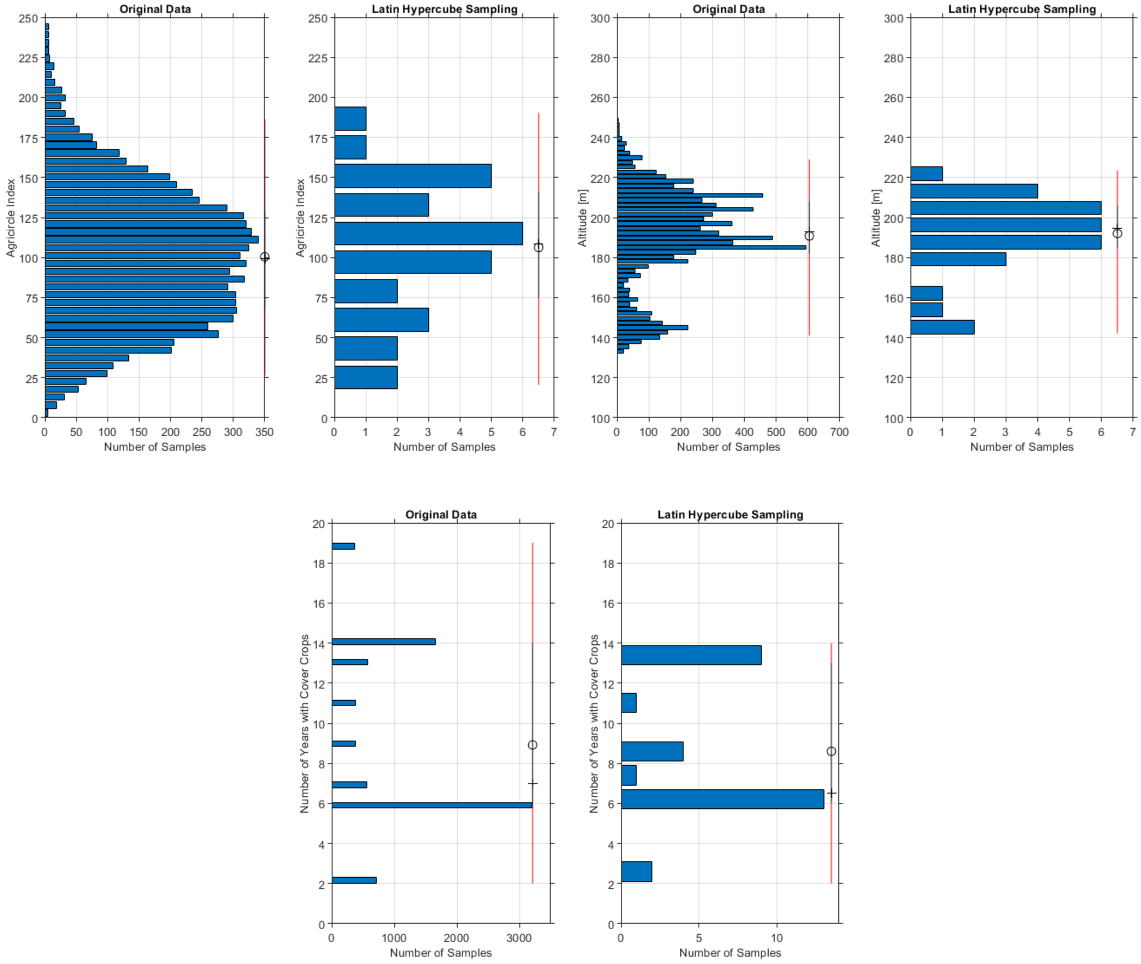

Figure 15: Histograms of original data and selected samples (using Latin hypercube sampling procedure) for Agricircle index (top), altitude (middle), and number of years with cover crops (bottom).

We selected 20 plots belonging to farmers producing popcorn maize for Nataïs located 30 km max. from the Villeneuve farm (Bézéril) where the Nataïs headquarters are located. This area of study covers hilly areas and valleys representative of the Nataïs farmer's network (see Figure 16). For some plots presenting high spatial variability in soil properties, several sampling zones were sampled (30 in total).

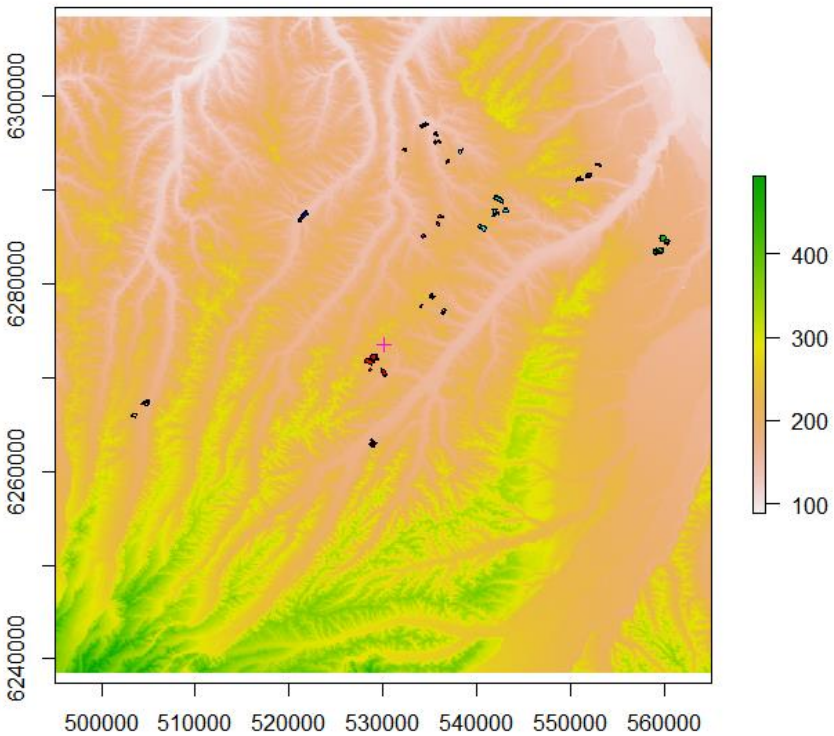

Figure 16: Location of the selected plots superimposed on a digital elevation model. The Villeneuve farm is located by the pink cross.

On each selected sampling zone, 5 cm diameter cores were sampled at two horizons (0-30 and 30-60 cm depths) for quantifying soil bulk density and soil properties (e.g., texture, SOC content) (Figure 17). Soil bulk density is essential for quantifying SOC stocks.

Also, for a better representativity of the soil properties in the area of 10 x 10m (corresponding to a Sentinel 2 pixel) centred around the 5 cm core samples, 12 cores of 2cm diameters were collected (Figure 17). Each 2 cm core sample was divided according to the 0-30, 30-60 and 60-90 cm horizons. Finally, the 12 2 cm core samples for each horizon were pooled and analysed. It represented in total close to 210 soil analyses.

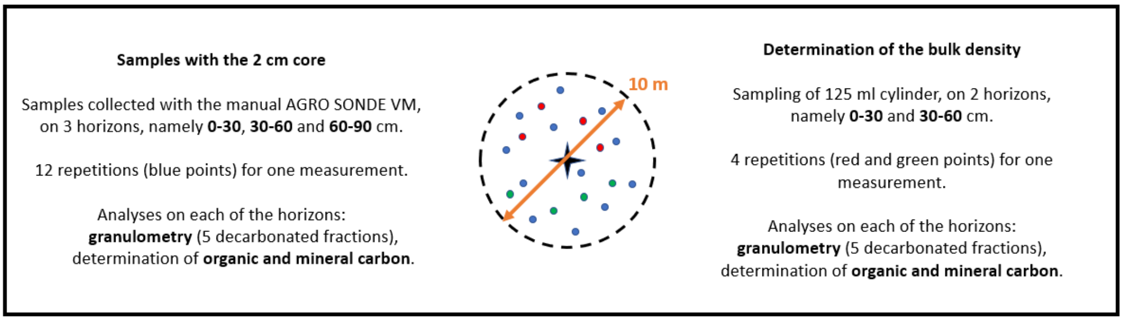

Figure 17: Description of the two protocols used to collect the soil samples.

Conclusion

In this report we demonstrate the potential of remote sensing for mapping cover crops and producing metrics associated to their development. We also showed that the assimilation of LAI time series derived from high resolution remote sensing satellites in a crop model (SAFYE-CO2) provides good estimates of the CO_2 fluxes and biomass production of crops and cover crops. Additionnaly, the development of the AgriCarbon-EO processing chain integrating SAFYE-CO2 allowed to quantify at high resolution and over a large network of farmers the annual carbon storage effect of cover crops and the C budget components at a daily/annual time step with their uncertainties. Also, we concluded that the coupling of SAFYE-CO2 and AMG in AgriCarbon-EO is very promising as it will allow the quantification of high resolution corpland carbon budget estimates at crop rotation scale. Finally, the soil sampling methodology implemented in this project will allow accurate validations of the C budget estimates with AgriCarbon-EO.

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