Application and validation of an agro-meteorological model associated with high resolution satellite remote sensing

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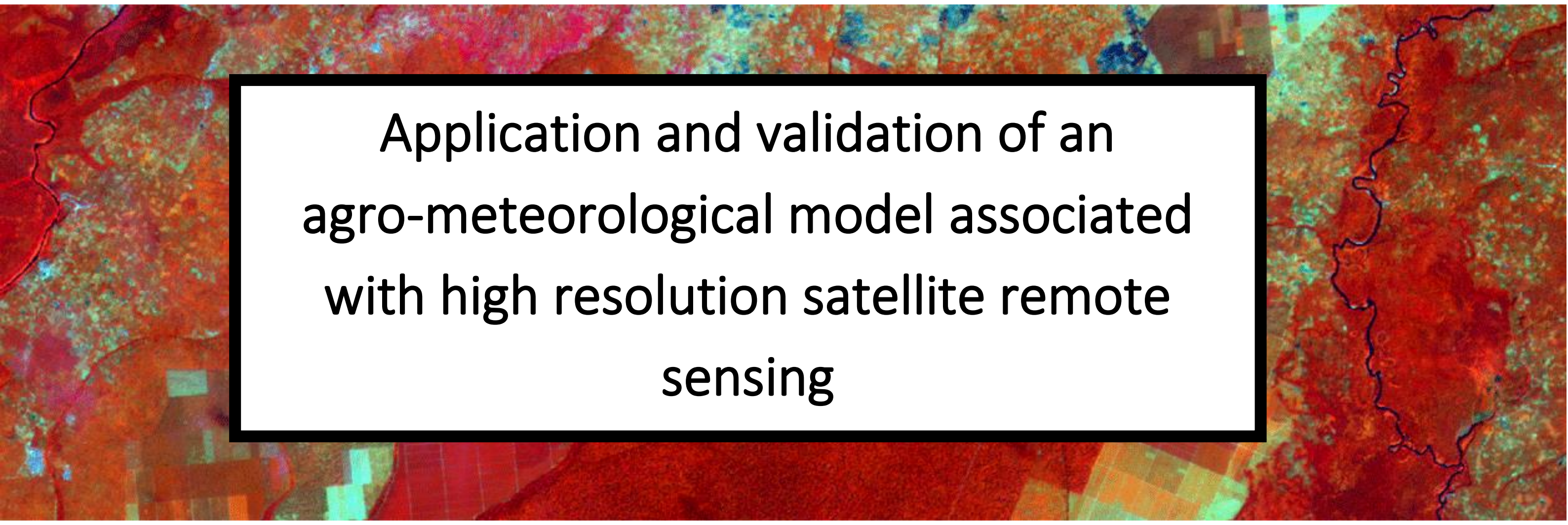

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ABSTRACT

Barely a month ago, the IPCC 2021 report made an alarming finding about current and future trends in the climate system. With a realistic estimate of the unprecedented rise in global climate, a whole number of direct and indirect consequences on our lives and habits are questionned. At the same time, the demand for food in the near future is announced as growing and exponential, to feed ever more living beings who share the world's resources. In such a context, between climate change and growing demand for food, it is necessary to fully understand the function of croplands and their impact on biogeochemical cycles. As cultivated land appears as part of the problem of GHG emissions but also as part of the solution through their high potential for sequestering carbon in the soil, interest in tools allowing the best management of these cultivated lands is growing. While it is common to estimate soil - atmosphere interactions on a very local scale, it is more difficult to reliably extend these estimates to a larger scale.

It is in this perspective that the SAFY-CO_2 model was developed, which, thanks to a limited amount of input data, estimates the net CO_2 flux components of plots as well as their biomass and yield. This simple agro-meteorological model uses high spatial and temporal resolution (HSTR) optical remote sensing data provided by Sentinel-2 to estimate these variables. Multi-temporal Green Leaf Area (GAI) maps derived from images from this satellite are used to calibrate light use efficiency and crop specific phenological parameters. Also, data measured in-situ or from the literature are used to run the model. In this study, the crop studied was maize based on a single year of measurement and on a single plot. The choice of such a crop is explained by the desire to extend the analysis of SAFY-CO_2 to major French and European crops, when winter wheat and sunflower have already been validated in previous studies. In particular, we will study here popcorn maize, following the desire of Nataïs company, the European popcorn leader, to apply this model on its plots in agroecology and in environmentally friendly practices.

The ability of the model to reproduce the variables was evaluated based on the mean square error (RMSE) and the correlation coefficient (R^2). The SAFY-CO_2 model is able to reproduce the GAI (RMSE = 0.28 $m^2.m^{-2}$ and R^2 = 0.96) as well as the production of biomass (RMSE = 80 $g.m^{-2}$ and R^2 = 0.99), which was relatively expected given that the study is carried out over a single crop year of measurements. Also, the components of the net CO_2 flux are well estimated by the model (RMSE of 1.56, 1.77 and 1.79 $gC.m^{-2}.d^{-1}$ for the GPP, R_{ECO}, NEE respectively and R^2 of 0.92, 0.39, 0.88 for GPP , R_{ECO}, NEE respectively). These results only reflect a first step in the SAFY-CO_2 chain process, and will be supplemented by more in-depth studies in the future.

RESUME (EN FRANÇAIS)

Il y a à peine un mois, le rapport du GIEC 2021 établissait un constat alarmant concernant les tendances actuelles et futures du système climatique. Avec une estimation réaliste de la hausse du climat global sans précédent, c'est tout un nombre de conséquences directes et indirectes sur nos vies et nos habitudes qui sont remises en cause. Parallèlement, la demande en nourriture dans les années à venir est annoncée comme croissante et exponentielle, pour nourrir toujours plus d'êtres vivants qui se partagent les ressources mondiales. Dans un tel contexte, entre changement climatique et demande croissante en nourriture, il est nécessaire de bien comprendre la fonction des cropland et de leur impact dans les cycles biogéochimiques. Comme les terres cultivées apparaissent comme part du problème des émissions de GHG mais aussi comme part de la solution à travers leur haut potentiel de séquestration du carbone dans les sols, l'intérêt porté à des outils permettant de gérer au mieux ces terres cultivées est grandissant. S'il est courant d'estimer des interactions sol – atmosphère à une échelle très locale, il est cependant plus difficile d'étendre ces estimations à une échelle plus étendue de manière fiable.

C'est dans cette perspective qu'a été développé le modèle SAFY-CO_2, qui grâce à une quantité limitée de données d'entrées, estime les flux nets des composantes du bilan de CO_2 des parcelles ainsi que leur biomasse et leur rendement. Ce modèle agro-météorologique simple utilise l'imagerie satellite à haute résolution fournie par Sentinel-2 pour estimer ces variables. Des cartes multi-temporelle de Green Leaf Area (GAI) dérivées des images de ce satellite sont utilisées pour calibrer l'efficience d'utilisation de la lumière et des paramètres phénologiques propres à chaque culture. Aussi, des données mesurées in-situ ou issues de la littérature sont utilisées pour faire tourner le modèle. Dans le cadre de cette étude, la culture étudiée a été le maïs sur la base d'une seule année de mesure et sur une seule parcelle. Le choix d'une telle culture s'explique par la volonté d'étendre l'analyse de SAFY-CO_2 aux grandes cultures françaises et européennes, quand le blé et le tournesol ont déjà été validés dans des études antérieures. Plus particulièrement, il a été question de maïs popcorn, suite à la volonté de l'entreprise Nataïs, leader du popcorn européen, d'appliquer ce modèle sur ses parcelles en agroécologie et en pratiques respectueuses de l'environnement.

La capacité du modèle à reproduire les variables a été évalué en fonction de l'erreur quadratique moyenne (RMSE) et du coefficient de corrélation (R^2). Le modèle SAFY-CO_2 est capable de reproduire le GAI (RMSE=0.28 $m^2.m^{-2}$ et R^2=0.96) ainsi que la production de biomasse (RMSE=80 $g.m^{-2}$ et R^2=0.99) de manière précise, ce qui était relativement attendu compte tenu que l'étude se fait sur une seule année culturale de mesures. Aussi, les composantes du flux net de CO_2 sont bien estimées par le modèle (RMSE de 1.56, 1.77 et 1.79 $gC.m^{-2}.j^{-1}$ pour la GPP, R_{ECO}, NEE respectivement et R^2 de 0.92, 0.39, 0.88 pour GPP, R_{ECO}, NEE respectivement). Ces résultats ne reflètent qu'une première étape dans le processus de la chaîne SAFY-CO_2, et seront dans l'avenir complétés par des études plus approfondies.

GLOSSARY

CESBIO : Centre d'Etudes Spatiales de la Biosphère

DAM : Dry Aboveground Biomass ($g.m^{-2}$)

GAI : Green Index Area ($m^2.m^{-2}$)

GPP : Gross Primary Production ($gC.m^2.d^{-1}$)

HI : Harvest Index

LAI : Leaf Index Area ($m^2.m^{-2}$)

NEE : Net Ecosystem Exchanges ($gC.m^2.d^{-1}$)

NECB : Net Ecosystem Carbon Budget ($gC.m^{-2}.d^{-1}$)

NEP : Net Ecosystem Production ($gC.m^2.d^{-1}$)

NPP : Net Primary Production ($gC.m^2.d^{-1}$)

R_a = Autotrophic respiration

R_{ECO} = Ecosystem respiration

SAFY-CO_2 : Simple Algorithm for Yield and CO_2 fluxes estimates

SLA = Specific leaf area ($m^2.g^{-1}$)

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I. INTRODUCTION

1.1. GENERAL CONTEXT

In a context of concern about the impact of agriculture on GHGs emissions, new techniques for monitoring agro-ecosystems are necessary and subject to scientific interest. Regarding their active participation in global warming and their impact on the modification of natural cycles (water, carbon, nitrogen, etc.), there is a need to manage greenhouse gases (GHG) emissions and store carbon (C) in the soil. National expertise 4 per 1000 aims to neutralize the annual increase in atmospheric carbon in the soil. This makes it more fertile by participating in larger amounts of organic matter (Pellerin et al. 2019). According to *Pique et al. (2020),* croplands are part of the problem but also part of the solution: they contribute to GHG emission but thanks to the soil ability to store carbon, they can also have a potential to mitigate climate change. Some methods in agriculture allow C to be stored in the soil. For example, reasoned practices that conserve and improve the qualities of the soil, and that use fewer inputs in their cropping systems as resonating surface tillage. Also, the introduction of intermediate covers between the main crop rotations to avoid bare soil and to enrich the soil by burying these covers. This last solution is assumed to be the most efficient to store C. To estimate these carbon budgets, different method are possible, and models using remote sensing data for agronomic issues are now developed. The use of such tools requires constant availability. However, the measurements considered depend on climatic factors, instrumented tools and visibility for the satellites (clouds). Thus, an approach combining the use of all these resources was developed in this project.

In Europe, agricultural areas cover 38% of the territory. The first European productions are represented by horticultural plants (13,6%), milk (13%) and cereals (11,4%) *(Ledroit, 2021, in touteleurope.eu).* In France, agriculture occupy 46% of the land *(from statistical data collected in 2018 by Agreste)* and the share of crops in the used agricultural area (UAA) is predominant in certain departments of the North and Southwest. Maize is originated from Central America, an came to Europe around the XVIth century. The diversity of maize varieties allows this crop to growth under various climates, and China is actually the second global producer. Since the XIX^{e} century, maize as the other plants, took benefits from the genetics and has a lot of hybrid varieties with higher yield, stronger resistance to disease and higher reliability due to their adaptations *(from the technical website www.arvalis.fr, 2021)*. We can distinguish three types of maize: forage maize, grain maize (sweat maize, popcorn maize..), and mixed maize. Maize represents 10% of the UAA in France. On a European scale, maize production is around 6 million of tons (from statistical data collected in 2019 by Agreste). This crop needs water during its development stages and its maturity because stresses can disturb its growth and final yield, and irrigated plot represents 40,6% of the total area of maize crop in France. Popcorn maize varieties are part of irrigated grain maize. In France, popcorn maize is mainly cultivated in Charente-Maritime and in the Gers on more than 9000 hectares each year, by around 400 producers. It represents 0.61% of the global maize crop *(from the technical website www.passioncereales.fr).*

Soil models or inventory approaches to estimate carbon budget, yield or biomass are existing. They require specific information, often very precise, about the soil dynamic (nutrients, water, organic matter...) or the plant dynamic (photosynthesis). Despite the intervention of precise, complex and numerous data, the models are always limited. For instance, these approaches offer inconclusive results in the application on a larger scale in time and space, due to their demand for information applicable to one year of culture only and specific to a study area. To extend these methods at larger scales, it would be necessary to know certain practices such as the crop type, the presence of intermediate cover or tillage, and the amendments applied to the crop. The contribution of remote sensing data into agronomic models is a way to improve these uncertainties by using another approach. The model studied here is defined as simple, since it uses a small number of non-complex equations, with the contribution of remote sensing data for monitoring the development of vegetation via simple indices (*i.e.* GAI or NDVI).

1.2. CONTEXT OF THE INTERNSHIP

This internship has to objective the parametrization of the model SAFY-CO_2 for the maize crop. Also, this internship is part of different projects. The first one is AgriCarbon-EO, a European program which has as main objective to encourage the progressive establishment of sustainable agriculture techniques, in order to reduce the impact of agriculture in the emission of GHG and to promote its usefulness in carbon sequestration. The SAFY-CO_2 model is involved in the third pillar of this project, which will make it possible to estimate carbon balances in crop rotation.

On a second hand, the data collected on the maize field were made possible by a farmer making popcorn maize for Nataïs, the European leader in popcorn. Nataïs is a private company based in the Gers department. For several years, Nataïs supported the implementation of conservative system and sustainable practices by a bonus for producers with its project “Naturellement Popcorn”. Today, they want to go further and pay the producers depending on their carbon footprint trough intermediate crops of legumes (faba bean, phacelia). By covering the soil during the critical season and being buried before the main crop sowing, intermediate cover crop is a great source of organic matter for the soil. It is in this context that Nataïs called on CESBIO to apply the model to popcorn maize. Today, SAFY-CO_2 has been validated on wheat (Pique et al., 2020a) and sunflower (Pique et al., 2020b). Ultimately, the objective is to extend the use of this model to crop rotations. It is in this context that the study and the integration of maize in the model was selected, regarding its culture in Europe.

1.3. AN AGRO-METEOROLOGICAL MODEL COUPLED WITH REMOTE SENSING DATA

Set up by scientific researchers from CESBIO (Toulouse) by using an agro-meteorological model combined to spatialized products, the SAFY-CO_2 model was developed with the aim of studying the main processes of development and growth of crops, in addition to the carbon budget components. SAFY-CO_2, for "Simple Algorithm for Yield and CO_2 fluxes estimates", allows to simulate different variables as the daily biomass production, the annual yield, the daily CO_2 fluxes or the annual carbon (C) budget of a given plot for a given crop over large areas thanks to the assimilation of Grean Area Index (GAI) times series derived from high resolution optical remote sensing data. It uses a low number of parameters in order to facilitate the spatialisation. SAFY-CO_2 may be run with only in-situ meteorological data and parameters derived from in-situ data or form the literature. The latter represents parameters extracted from the scientific literature. However, it can also use high spatial and temporal resolution (HSTR) GAI products derived from remote sensing data, to produce a timely and accurate picture of crop development, photosynthesis or net CO_2 fluxes (Pique et al., 2020). GAI time series provides important information on the phenology and status of the vegetation. These remote sensing data are provided by Sentinel-2 satellite. Sentinel 2 is an optical satellite with passive sensors that measures surface reflectance through spectral bands in the visible, near and infrared wavelengths. The combination of this simple model with remote sensing GAI products can improve the modelling and monitoring of agro-ecosystems at the regional scale. The approach adopted for SAFY-CO_2 is advantageous because of its low need for input data (Ta and Rg), and the fact that few or no external information on technical routes are needed . As a result, equations are reduced to a small number and rather simplified but allow for more than adequate results in the estimates requested. However, the use of remote sensing data can ask to concessions from the point of view of available images and may result in gaps.

The work realized in this internship is about parametrization of the SAFY-CO_2 model on the flux plot of popcorn maize first, and to apply the parametrization at a larger scale encompassing several departments in the Southwest of France. After presenting the materials and methods, we will look at the analysis of the results obtained through the various exercises carried out as part of this internship. Then, then, we will take a critical look at these results and try to make sense of them. Finally, we will conclude on the work carried out during the period.

II. MATERIAL

2.1. STUDY AREA

The study area is located in the Southwest of France, near to Toulouse. It covers the Haute-Garonne department as far as the Gers, where the head office of Nataïs is located and where biomass and yield measurements have been carried out. The climate of the region is defined as temperate, with an annual mean temperature about 13,8°C and an annual mean precipitation about 638,3 mm (measured by Météo-France at Toulouse-Blagnac between 1891 and 2010; see *http://www.infoclimat.fr/climatologie/index.php)*. Maize represents 12.95% of agricultural land in Occitanie and is the 4th largest crop in the region after soft wheat, sunflower and durum wheat (Agreste, 2019; see *https://draaf.occitanie.agriculture.gouv.fr/IMG/pdf/premiers_resultats_pkgc_2017_cle8ff4e6.pdf)*.

Figure 1. Left: Location of the study area in Southwestern France; **Right**: Location of the Pibrac's field and of the measurement station in 2020 (Source: Google Earth)

2.2. IN SITU DATA

The experimental plot encompasses an instrumented agricultural in Pibrac (***Fig. 1***). This micrometeorological measurement station is an independent flux site created for the project. It allows the measurement of air temperature, precipitations, net CO_2, latent and sensible heat fluxes. The Pibrac site has been instrumented since the 31th of October 2019 and was supposed to be monitored over 2 years. Following a proliferation of *Datura*, the tower had to be displaced in November 2020 on a plot near to the first one. The coordinates of the first tower are 43°38'26.40"N ; 1°16'1.78"E. The plot is 21.57 ha and it is managed based on conservation agriculture practices. There is no ploughing, cover crops are grown during fallow (green manure) and the biomass of the crop and of the cover crop is returned to the soil after harvest. During the cropping year 2019 – 2020, a cover crop of faba bean *(Vicia Faba)* was sown on Octobter 28th and crushed on April 1st. Popcorn maize was sown the same day and the harvest date was the 18th of September 2020 (***Table 1***). The variety used by the farmer is hybrid maize N8485B *(see https://www.zanggerpopcornhybrids.com/product-guide)*.

Table 1. Sowing and harvest dates of popcorn maize cultivated on Pibrac field and climatic variables during the cropping year.

Cropping year	Sowing	Harvest	Mean temperature [°C]
2020	1st of April	18th of September	13.8

Mineral and organic fertilizers were applied during the early stages of development in the form of solid potassium input, granulated urea and compost. Also, pesticides such as anti-slug and Coragen (insecticide) were applied to prevent corn borer and sesamy at the day of sowing. Weed killer were spread at the 2-3 and 6-7 leaf stages. The plot is equipped with a central pivot irrigation system which applies 25mm of water by periods of 6 days during the most critical growing season, around July and August. In total 200 mm of water were brought by irrigation (***Fig. 2***). According to the Köppen classification, the climate at this location is an oceanic climate (‘Cfb’).

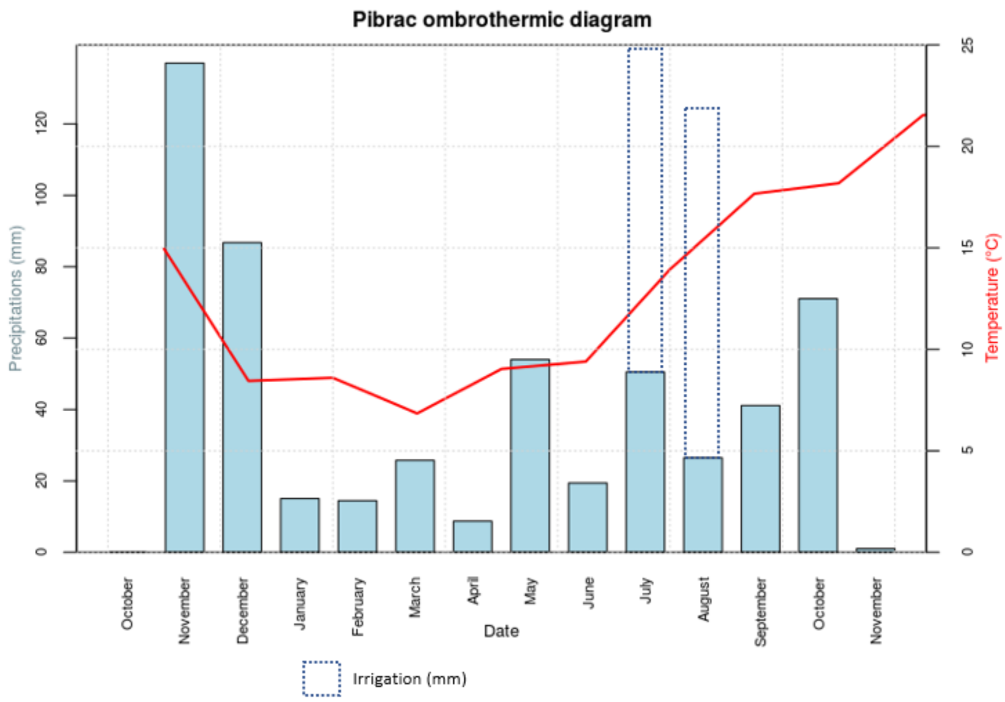


Figure 2: Ombrometric diagram of Pibrac with irrigation on the flux plot. The irrigation is in blue dotted line.

2.2.1. Eddy covariance setup and flux data processing

A mast equipped with an eddy-covariance (EC) system (Béziat et al., 2009) is located in the center of the plot to ensure that the fluxes measured are representative of the plot (distances between the mast and the limits of the plots are X and Y m in the two main wind directions, respectively NW and SE). The turbulent fluxes of CO_2, water vapour (evapotranspiration and latent heat), sensible heat and momentum were measured continuously at 20Hz. The EC system was placed at 4.5m above the soil in order to ensure a distance of 2m between the EC system and the crop at its maximum development. The EC system is composed a three-dimensional sonic anemometer (CSAT 3, Campbell Scientific Inc, Logan, UT, USA) and an open-path infrared gas analyser (LI7500, LiCor, Lincoln, NE, USA). The EdiRE software (Robert Clement, ©1999, University of Edinburgh, UK) was used to calculate the turbulent fluxes at 30 min intervals. Footprint analyzes are carried out from these data, which are checked beforehand. Finally, the fluxes obtained by EC are filtered to remove erroneous data corresponding to technical issues, inappropriate meteorological conditions, low spatial representativeness, and violation of EC theory and gapfilled according to the method presented in Béziat et al., 2009 ***(Fig.3)***.

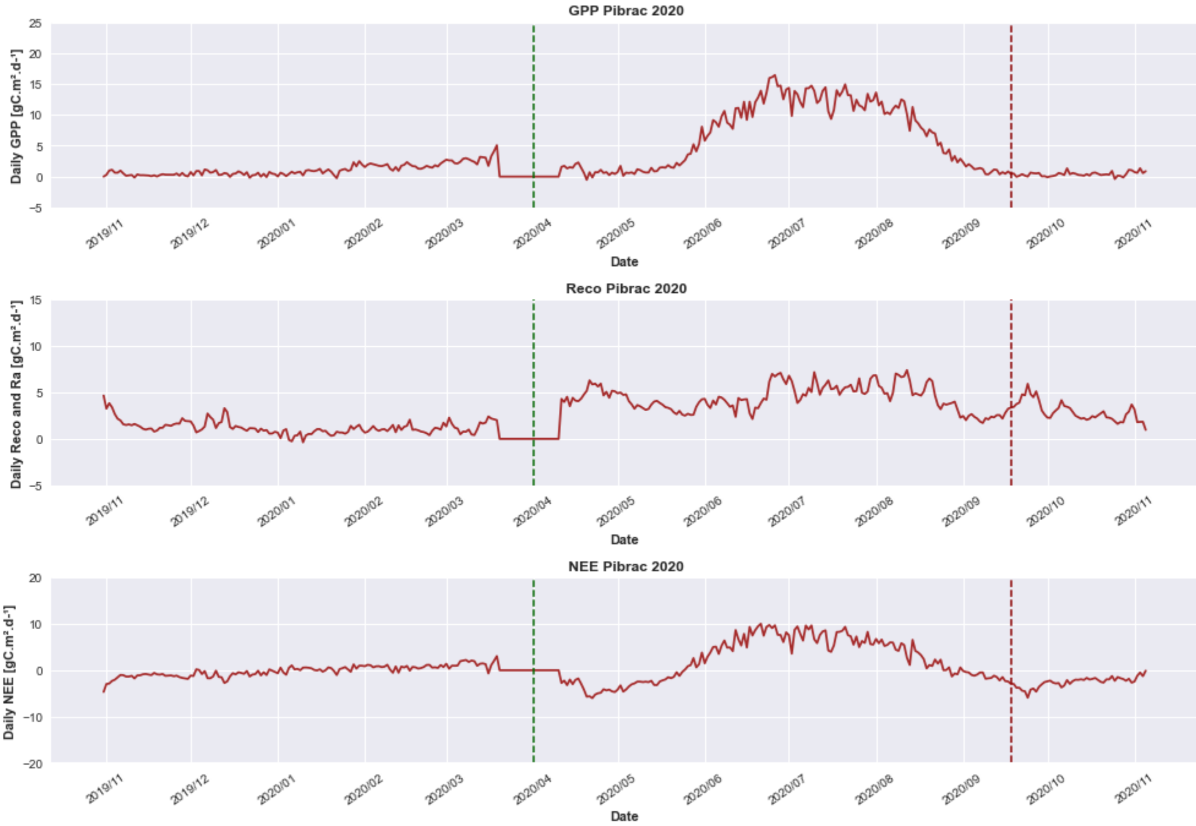


Figure 3: In-situ measurement of components of the net CO_2 fluxes: Gross Primary Production (top), Ecosystem Respiration (middle), Net Ecosystem Exchanges (bottom). The green dotted line represents the sowing of popcorn maize and the red dotted line its harvest.

2.2.2. METEOROLOGICAL DATA

SAFY-CO_2 requires input meteorological data of air temperature (Ta) and incoming global radiation (Rg). For the modelling exercices done at the Pibrac site, we use measured Ta (HMP45C-ET: Temperature and Relative Humidity Probe, see *www.campbellsci.fr)* at 1.6m and Rg (NR01 net radiometer, Hukseflux) at 6.5m on the EC mast location **(Table 1)**. Other variables measured by the micrometeorological station are, relative humidity, precipitation, atmospheric pressure, wind speed and direction, surface radiative temperature, albedo, soil temperature and soil moisture at 5, 10, 30 cm depth as well as soil heat flux (at 5 cm depth). For the spatialised modelling exercices, the SAFRAN meteorological data (Ta at 2m and Rg) provided by Météo-France (Durand et al., 1993) is used.

2.2.3. BIOMASS AND YIELD DATA

The crop development at the instrumented site is regularly monitored by collecting GAI observations and biomass samples. The sampling frequency is approximatively once a month, but it was disrupted in 2020 by the global Covid-19 pandemic and there are 4 biomass samples while those of GAI are only 2. Vegetation plants are collected according to the VALERI protocol *[http://w3.avignon.inra.fr/valeri/]* from five homogeneous square subplot inside the 4 Elementary Sampling Units (ESU) of 20x20m² ***(Fig. 4*).** The total sampling surface area is about 0.25m² per subplot. The fresh samples are weighed by distinguish three measurements which represent the fresh aboveground biomass: leaves, stems, senescent parts. They are also subject to a LiCor planimeter (LI3100, LiCor, 28 Lincoln, NE, USA) to define the GAI. They are then dried and stored, to be measured later. The exported carbon from the plot during harvest (C_{exp}) correspond to the difference between the carbon content in the aboveground biomass and the carbon content in crop residues. An average yield is often obtained by collecting farmer's data at several fields surrounding the instrumented site (Pique et al., 2020).

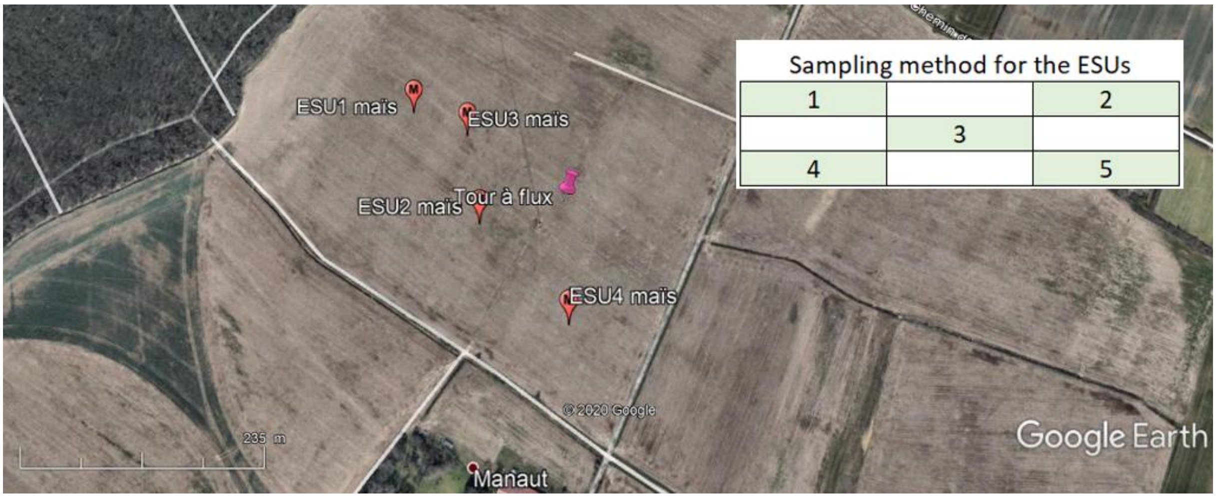


Figure 4: Location of the Elementary Sampling Units for biomass sampling and the sampling method.

2.3. SATELLITE DATA AND PRODUCTS

2.3.1. MULTI-TEMPORAL SATELLITE OPTICAL DATA

This study uses HSTR satellite products derived from the Sentinel-2 satellites (*www.esa.int*). The Sentinel-2 mission is part of the Copernicus European program, and is based on the constellation (ie. two or more satellites) of two identical satellite on the same orbit: Sentinel-2A (S2A) and Sentinel-2B (S2B). They have the same Multi Spectral Imager captor (MSI) and allow a revisit time reduced to 5 days, for a spatial resolution of about 10m. This makes it possible to obtain 13 spectral band in the visible and mid infrared, especially used to observe land and vegetation **(Fig. 5).**

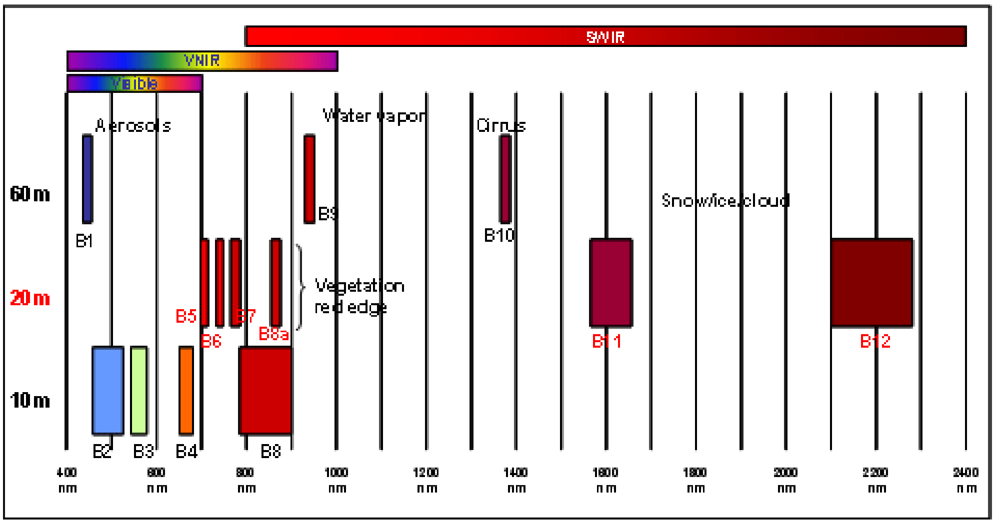


Figure 5: Spectral bands of Sentinel-2 (Source: CESBIO)

As all optical satellites, the Sentinel-2 satellites are very sensitive to clouds and atmospheric conditions (water vapour, aerosols). The Sentinel images are processed with the MAJA processing chain (Baetens et al., 2019) for geometric and radiometric corrections, detection of clouds and of their shadow. To calibrate some of the model parameters, remote sensing image at some key dates are needed. In the case of popcorn maize, the critical periods are around March-April during the development of the first leaves of the crop, which depend on the sum of the degree day, and the availability of satellite data during this period can be restrictive about weather conditions. Another critical period is in summer because it is the maturation stage where the plant has a strong need for water, and where this resource is becoming scarcer. With satellite images, it is possible to observe the states of development and senescence (yellowing of the leaves), because the images in summer are rather available due to the general absence of clouds, but may be biased depending on the years. Figure 7 shows that during the key phases of maize development, clear (cloudless) images may be missing.

2.3.2. FROM IMAGE REFLECTANCE TO GAI ESTIMATES

The GAI time series are derived from the reflectances measured from the Sentinel 2 satellites. For this, the BV-NNET tool for Biophysical Variables Neural NETwork (Baret et al., 2007) is used. Globally, it is a trained artificial neural network (ANN) which uses the outputs of a radiative transfer model. There may be a margin of error in estimating the GAI during the significant growth phases (dense foliage) because the BV-NNET procedure does not consider the aggregation of the leaves (Claverie et al., 2012). This "effective GAI" may tend to an underestimation of the "true GAI" during these periods. Finally, the GAI estimates are averaged regarding the different pixels obtained on the studied plot, with an application of an offset of 10 m to avoid edge effects and to consider only the GAI of the studied crop (Pique et al., 2020). The figure 7 shows the product from satellite data when modelized.

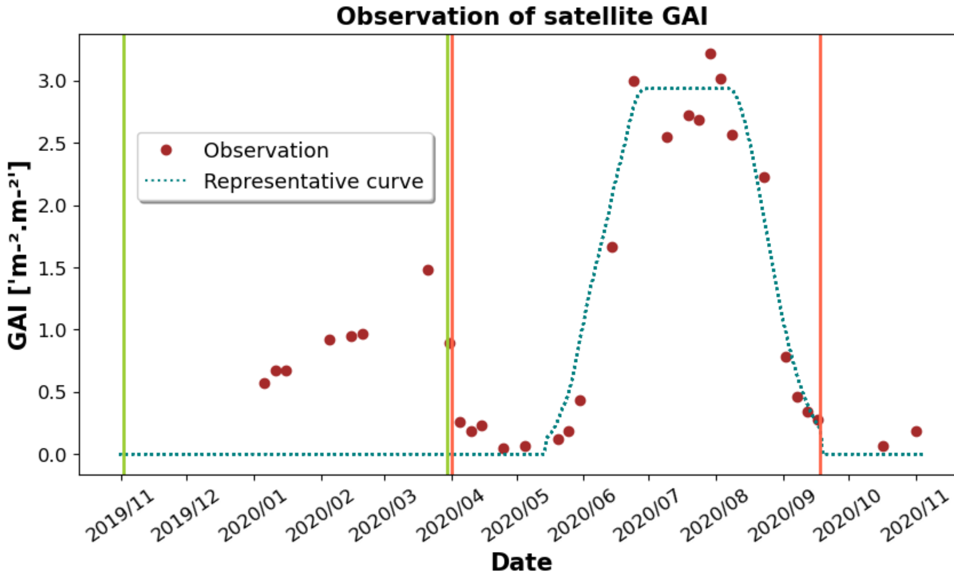


Figure 7: Time course of GAI derived from satellite images (red dots) and estimated using the agro-meteorological model (blue dotted curve on a plot cultivated with an intermediate crop (faba bean) and a main crop (popcorn maize). The period between the green axis represents the intermediate cover crop. The period between the orange axis represents the studied period with popcorn maize as main crop.

III. METHODS

3.1. THE SAFY-CO_2 MODEL

SAFY-CO_2 model ***(Fig.8)*** is defined by its users as a "daily time step crop model that simulates the temporal evolution of green area index (GAI), dry aboveground biomass (DAM) final grain yield (YLD), CO_2 fluxes and C budget by considering two climatic input data: incoming radiation (Rg) and mean air temperature at 2m (Ta)" (*Pique et al., 2020*). The model is characterized by simple formalisms, based on a limited number of equations and parameters (calibrated or fixed), from which the variables of interest are derived. For the simulation of the plant processes, two types of parameters are found: fixed and calibrated. The fixed parameters are taken from the literature or from in-situ data. The calibrated ones are related to the crop phenology (Pl_a,Pl_b, Sen_a, Sen_b, SLA and D_o) that can be observed by remote sensing or to the light use efficiency ($ELUE_a$) of the plant. $ELUE_a$ allows to calculate the amount of light (PAR) absorbed converted in photosynthesis (GPP). It is related to the intensity of development of the vegetation. This approach is based on the light use efficiency model proposed by Monteith and Moss (1977), which define the light use efficiency of a plant canopy as the ratio of net primary productivity (NPP) to absorbed photosynthetically active radiation (APAR). Under LUE, there is an implicit hypothesis which determine the ratio PT / R_a as constant over the seasons. However, in SAFY-CO_2 LUE relates the amount of light to photosynthesis and not to biomass. With this approach, LUE may be constant over a year but is not within a season. SAFY-CO_2 is using the Monteith approach, but it bypasses it in order to get values of 1) photosynthesis, 2) respiration, 3) biomass as the difference between photosynthesis and autotrophic respiration.

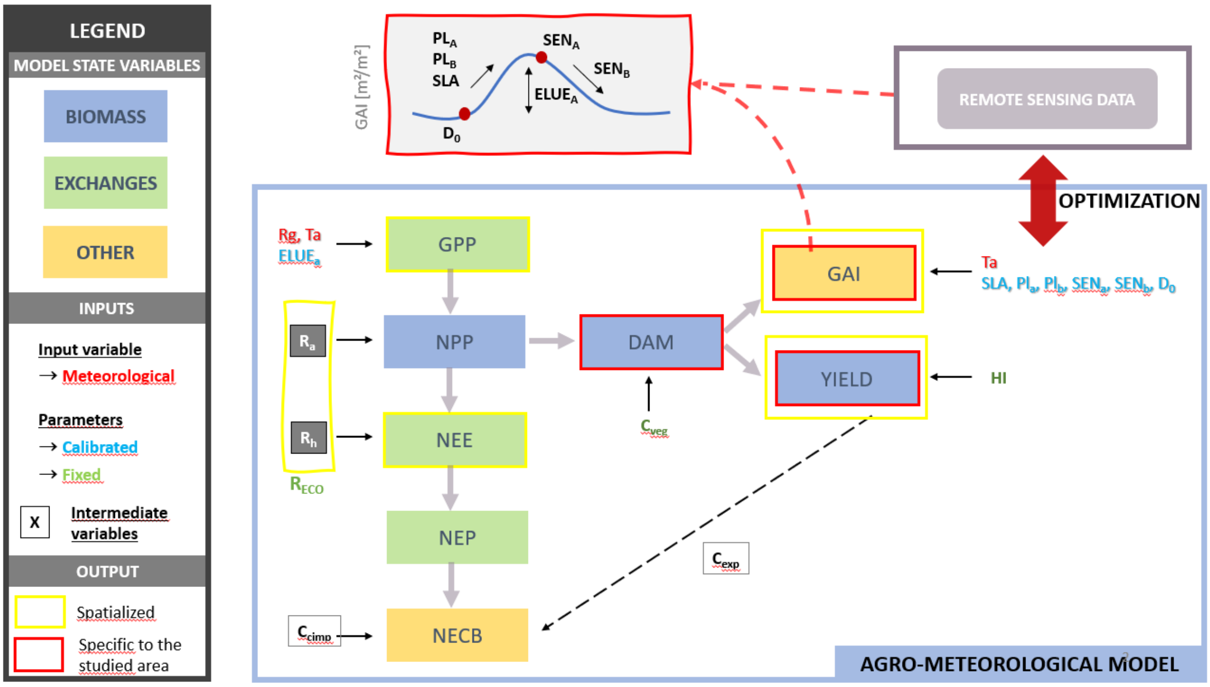


Figure 8: Scheme of the SAFY-CO2 model

The GPP [eq. 1], defined as the amount of CO_2 absorbed by the plants. It is calculated as a function of the incoming radiation (Rg), the climatic efficiency (ε_c) wich is the share of useful solar energy converted by the plant cover for photosynthesis, the fraction of absorbed photosynthetically active radiation of the plant (APAR), a temperature stress function (f_T), the effective efficiency of the conversion of absorbed radiation to fixed CO_2 through plant photosynthesis (fELUE), and of a multiplicative coefficient which represents the decline in canopy photosynthesis capacity during senescence (sR10).

$$GPP = R_g * \varepsilon_c * fAPAR * f_T * fELUE * sR10 \quad \text{[eq. 1]}$$

The calculation of sR10 requires the computation a corrective factor (Cs) for senescence based on in-situ data, which represents the difference between the true phenological status of the crop and the one detected by satellite observation. Senescence represents the degeneration of plant cells, which can lead to the degradation of one or several of its organs. In the case of maize, for example, the current senescence may be observed in the form of yellowing of the leaves which dry and then fall. sR10 is equal to 1 from sowing to senescence beginning, and then equal to GAI_{n-1}/GAI_{max} * Cs (with n-1 = the previous day). Also, fELUE, is calculated based on $ELUE_a$ which is a calibrated parameter through other fixed or meteorological parameters as shown in eq. 2:

$$fELUE = ELUE_a * \exp(^{ELUE_b * R_{df} / R_g}) \text{ [eq. 2]}$$

$ELUE_b$ is an important factor which will represent the diffuse and direct radiation. The ratio $Ra_{direct}/Ra_{diffuse}$ have a large incidence on photosynthesis, since the efficiency of using light in a plant is more efficient in $RA_{diffuse}$, which will then have a lower value. Once calibrated, $ELUE_a$ will allow to simulate the correct amplitude of the GAI curve.

From this, the net primary production (NPP) defined as the amount of biomass (or CO_2) produced by a plant per unit of area and time (*WAD, 2019*) may be estimated by subtracting the autotrophic respiration (R_a) to the GPP [eq. 3]. Ra can be calculated as the sum of maintenance respiration (R_m) and growth respiration (R_{gr}). The maintenance respiration [eq. 3.1] is calculated as a function of the standing biomass of the previous day (NPP_{n-1}), a maintenance respiration coefficient ($m_{R)}$ defined as the fraction of R_m per NPP unit and obtained from the literature. A multiplicative coefficient (sR10) depending on a constant maintenance respiration parameter (Q_{10}) and the maintenance respiration at a temperature reference of 10°C (R_{10}) obtained from the literature is also part of the function. R_{gr} represents the respiration during the growth of the crop, and is calculated [eq. 3.2] using a constant parameter from the literature for the growth conversion efficiency (Y_g) and is also depending on the difference of GPP minus R_m. This relation is taken from the Amthor (1989) method improved by Choudhury (2000) (Pique et al., 2020).

$$NPP = GPP - R_a \qquad \text{[eq. 3]}$$

$$R_m = NPP * m_R * sR10 \qquad \text{[eq. 3.1]}$$

$$R_{gr} = (1 - Y_g) * (GPP - R_m) \text{ [eq. 3.2]}$$

Finally, NPP can be divided into two parts: NPP_{root} and NPP_{aerial}. NPP_{aerial} is then used to compute the DAM [eq. 4], defined as the ratio between NPP_{aerial} and C_{veg} , where C_{veg} represents the plant carbon content (i.e the amount of C/amount of dry biomass).

$$DAM = NPP_a/C_{veg} \quad [eq.\ 4]$$

After the biomass computing, it is possible to estimate the green area index (GAI) and the yield (YLD). The GAI represents the ratio of green area (leaf and steam) to the area of ground (AHDB, 2018). It gives information on the status (phenology, intensity of development,) of the vegetation and often reflects the effect of the stresses on the plant development. It provides information that can be linked to the NPP based on information concerning biomass allocation. It is also a driving factor in regional and global models about biosphere/atmosphere (BA) exchanges of CO_2 *(Bréda, 2008).* Here, its estimation is based on the GAI of the day before and the positive or negative change on day *n* [eq. 5]. ΔGAI^+ is a function of the daily DAM production and of two calibrated parameters: the leaf partitioning (Pl) function and the specific leaf area parameter (SLA). SLA is a physiological characteristic defined as ratio between leaf area per plant and aboveground weight per plant in $m^2.g^{-1}$. It is related to the dynamic of the biomass and may be affected by the stage of N application *(Amanullah, 2007).* Because it refers to the leaf thickness, it will play a role in the light interception *(Kumar et al., 2012).* Pl is also an important parameter for plant growth because it corresponds to the function of biomass allocation to leaves. It depends on two parameters which describe the dynamics of allocation during growth. According to Potter et al. (1977), $Pl_{(A\ and\ B)}$ is the share/partitioning of photosynthesis according to the distribution of leaves, which tends to increase during growth. Negative ΔGAI only can be found during the senescence phase (at least in the model) and is depending on 2 senescence parameters: SEN_a and SEN_b. *Pique et al. (2020)* explained that GAI was decreasing with senescence. This decrease is estimated from the day of plant emergence (D_0) detected by remote sensing. From that day on, the model uses degree-day data to determine the senescence of the culture from the sum temperature for senescence (SEN_a) and the rate of senescence (SEN_b). Leaf production and senescence are depending on a growing degree-day approach in this model. Finally, the yield (YLD) [eq. 6] is calculated from the total aboveground biomass production at the end of the vegetative period (DAM_{max}) and a constant harvest index (HI).

$$\Delta GAI = GAI + \Delta GAI^+ - \Delta GAI^- \quad [eq.\ 5]$$

$$Yield = DAM_{max} * HI \quad [eq.\ 6]$$

Once Rh, Ra and GPP have been estimated, the model calculates the net ecosystem exchange (NEE) [eq. 7] to obtain the net exchange of C as CO_2 between the ecosystem and the atmosphere per unit of ground area *(Pique et al., 2020).* The soil CO_2 fluxes are represented by the heterotrophic respiration calculated as a simple function of the temperature based on fixed parameters from the literature [eq. 8]. (R_h) is the product of a reference respiration at 0°C (R_{ref} = a) and a first-order exponential equation where $Q10=exp^{b*10}$. Q10 has to be adapted to the soil type and the climate *(Pique et al. 2020).* In SAFY-CO_2, there is no water module. Therefore, only the temperature of the soil (T_s) is taken into account to estimate R_h. The ecosystem respiration (R_{ECO}) [eq. 9] is the sum of R_a and R_h.

$$\mathrm{NEE} = \mathrm{NPP} - R_h \qquad \text{[Eq. 7]}$$

=NPP - carbon losses due to heterotrophic respiration (R_h)

$$R_h = a * \exp^{b*Ts} \text{ [Eq. 8]}$$

$$R_{ECO} = R_a + R_h \qquad \text{[Eq. 9]}$$

The annual net ecosystem carbon budget (NECB) represents the gain or loss of carbon in a given ecosystem over a crop year. It can be calculated by considering three terms [eq. 10]. The annual sum (considering a cropping year) of the daily NEEs simulated by the model (NEP) and two additional terms: the amount of carbon imported in the field as organic amendments (C_{imp}) and the amount of C exported at harvest (C_{exp}). If NEP is positive, it means that the cumulated soil and autotrophic respiration is higher than the cumulated photosynthesis, so the field has lost CO_2 towards the atmosphere *(Pique et al., 2020)*. If NEP is negative, then it is the opposite. C_{imp} is provided by the farmers because it represents the organic fertilizer they chose to apply. C_{exp} is represented by the grain exported from the field, i.e the yield, but also by the straw exported. The model only calculates the grain yield. As far as straw is concerned, the information comes only from the farmers because their fate (export or not) is not an information that we can obtain by remote sensing.

$$\mathrm{NECB} = \mathrm{NEP} + C_{exp} + C_{imp} \qquad \text{[Eq. 10]}$$

3.2. MODEL PARAMETRIZATION

3.2.1. BIBLIOGRAPHY OF THE PARAMETERS

At this stage of the modelling, many parameters have already been researched and studied. However, some crop-specific parameters remained to be studied in the literature when in-situ measurements are not available. The respiration parameters Q_{10}, R_{10} and Y_g are intervening in the equations of growth and maintenance respiration. In the literature, the distinction between R_m and R_g is sometimes very thin, as well as some subtleties in the nomenclature of these terms which may vary from one article to another. However, this step is important because it is necessary to keep a realistic look when modelling, to not exceed extreme values imposed by the literature. **Table 2** shows the values retained for respiration parameters before calibration, thanks to their relevance and consistency with our study.

Table 2
List of SAFY-CO_2 model parameters for growth and maintenance respiration for maize.

Description	Notation	Unit	Value	Method	Source
Maintenance respiration parameter	Q10	-	2	Literature	Amthor (2000)
Reference respiration at 10°C	R10	g_c/g_{DM}	0.0015	Literature	Yang et al. (2004) Penning De Vries et al. (1989)
Growth conversion efficiency	Yg	-	0.70	Literature	Ruget (1981)

3.2.2. Root-to-Shoot

SAFY-CO_2 is applied on many crops over many different areas. The idea is to develop a powerful and versatile tool that adapts to the different needs offered by each case. It is with this in mind that the different equations representing reality were chosen, sometimes to the detriment of certain components. The "root:shoot" (RtS) is not integrated in SAFY-CO_2, because the bias was to opt for the fraction of biomass allocated to the roots *(parameter called 'PRT_R')*. The root equation is different for all plants but is similar in terms of curve tendency. The idea is to have an only equation and to optimize on the curve. However, previous studies on maize (*M. Battudes, 2017 ; G. Piques, 2020)* showed that an equation proposed by Amos and Walters (2006) allowed to follow satisfactorily the RtS for the case of maize (Eq.11) compared to in-situ measurement ($R^2 = 0.94$) (E. Burrel, 2018).

$$\mathrm{RtS} = 0.15 + 0.53 * \exp^{-0.03*\mathrm{DAE}} \quad \text{[Eq. 11]}$$

with DAE 'day after emergence'

The growth rate of roots and shoots during the vegetation cycle are strongly linked, since the roots have the fundamental role of taking nutrients and water to the soil, to determine the production and tolerance of the plant. The Root:Shoot Ratio which is specific to every plant in its own conditions, translate the importance of plant integrity. Maize – e.g. popcorn maize – is a C4 plant which requires a higher water use efficiency in comparison to C3 plants, and will responds stronger to atmospheric CO_2 if the water in the soil is limiting (L. Bláha, 2019). Regarding the importance of this ratio in our situation, we decided to add this formula in the model for the specific case of maize in the context of this internship, to reach the optimal results.

3.2.3. Modelling

The exercises that were realized during this internship covered different phases. A first exercise consisted in doing a sensitivity analysis of the model by using in-situ temperature, radiation and precipitation. The objective is to test the sensitivity of the model for simulating 5 variables of interest: GPP, R_{ECO}, NEE, DAM and LAI with SAFY-CO_2. Because we had only 2 data for LAI, we did not consider this variable for this exercise. This exercise allowed to understand the functioning of the model and the effect of each parameter on the variables of interest, as well as a sensitivity analysis of the calibrated parameters and a first optimization on the flux site data. The optimization process is presented in the next part.

When the 2 previous step become satisfying, it is possible to apply the model with GAI derived from remote sensing:

1) On the flux site and to compare the model outputs with in-situ data (CO_2 fluxes, DAM),

2) On targeted plots, where biomass sampling campaigns have been carried out on specific locations,

3) On targeted plots at pixel scale, for comparison of the model with yield maps obtained from combined harvester.

At the beginning of the internship, we emit the possibility to realize these 3 exercises if the modelling progressed correctly without too many obstacles. However, the steps for getting started with the model and calibrating the parameters took more time than expected and we had to revise our objectives downwards, which will be presented in the "Results" section.

3.3. MODEL OPTIMIZATION AND VALIDATION

An optimization is needed to verify the realistic aspect of the adjusted boundaries of phenological parameters applied to the model by using minimization and comparison processes. A sensitivity analysis allows to define parameter bounds to be then calibrated. The model may simulate the output variables with only meteorological data (R_g, T_a), soil and plant parameters. However, with this low number of parameters and without a proper calibration process, the estimates obtained would be probably wrong. Six phenological parameters (Pl_A, Pl_B, SEN_A, SEN_B, SLA, D_0) and the parameter A of the light-use efficiency ($ELUE_A$) were optimized first. Realistic values of these parameters were taken from the literature, in particular from previous studies carried out on maize in earlier versions of SAFY-CO_2 (Claverie et. al, 2012 ; Battude et. al, 2017, Pique et. al, 2020). We have established ranges for each parameter, with minimum and maximum bounds which limit the model, and searched for an optimal mean value to inform on the model. For the optimization, the cost function is based on the minimization of the RMSE between the satellite GAI and the model GAI. In our case, we used the RMSE as a statistical tool instead of likelihood because we do not beneficiate from uncertainties. I used the numerical optimization method, by testing a large number of solutions and keeping the best one. To find these solutions, I used a simple exploration. A simple exploration is based on a multivariate simple sample according to the mean, the standard deviation, the minimum and the maximum of each parameter or variable, and on an evaluation of these simulations to find the optimal RMSE values. More simply, I ran a LUT on the model, which was doing 2000 or 5000 simulations at a time, and selected the 20 or even 50 best simulations. For these LUTs, the parameters of interest were bounded. A centered average was informed, and a standard deviation (std) was granted according to the scale of the values of the parameters, in order to allow a certain plasticity to the model. On the selected best simulations, the values of the parameters, the graphical and statistical data were recorded. When these steps are done, a last step allows to validate the quality of the simplified version model with the optimal set of parameters. It is then a question of comparing the other variables (biomass and fluxes) between the observations and the estimates. The validation allows to conclude to a good combination of the parameter values on in-situ data as well as on satellite data.

IV. RESULTS

4.1. SENSITIVITY ANALYSIS, OPTIMIZATION AND CALIBRATION

The sensitivity analysis, carried out before the modelling exercises, first allowed me to familiarize myself with the Python 3.0 environment, and to handle the phenological parameters. This step is necessary to understand the graphical analysis, and to understand how the parameters behave between them or in isolation on the target variables, at what stage, and at what level of sensitivity. This analysis has been realized on each variable (to remind: GLA, GPP, R_{ECO}, NEE), for each of the six phenological parameters. The procedure consisted of fixing all the phenological parameters first, and then applying a range of +/- 5% to +/- 50% for one parameter only. Considering cumulative GPP, Figure 9 shows as an example what this sensitivity analysis looked like. We can observe that the phenological parameters do not all react the same, some are very sensitive (PLa, PLb), and others are less (SENb). However, it should be kept in mind that these parameters do not intervene at the same time (*cf. curve in **Fig.8***).

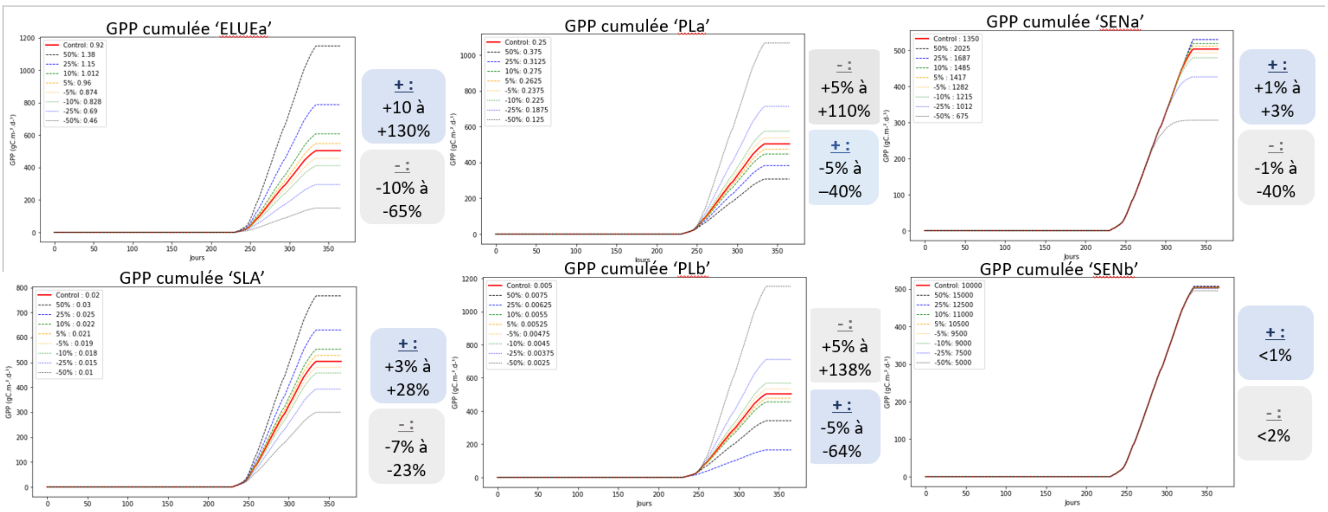


Figure 9: Sensitivity analysis of the six phenological parameters applied to the cumulative GPP target variable in the SAFY-CO_2 model. The vertical axis represents the values of GPP [gC.m-².d-¹] and the horizontal axis the time evolution in days.

The optimization of parameter bounds carried out on in-situ measurements of flux and DAM, since the LAI collected only included 2 values (as said previously). It was therefore a question of manipulating the parameters in order to make the model simulations stick with the observations of our in-situ data, while remaining within the imposed and defined limits. Thanks to the optimization method expressed in the previous section, I tried to ensure that the values of the parameters were centered (neither stuck to a maximum limit, nor to a minimum limit) for each of the studied variables (cf. example in ***Appendix***). The value of the phenological parameters to be considered for the following sections are presented in **Table 4**. We can read the means and their standard deviations, which constitute an interval of values that the parameters can take during the calibration process.

Table 4. Value of the calibrated parameters for maize

PARAMETER	UNIT	MEAN	STD	BOUNDS
EMERGENCE	Day of the year	115	10	[97 - 135]
$ELUE_A$	$gC.MJ^{-1}$	1.4	0.2	[1.04 – 1.7]
SLA	$m^2.g^{-1}$	0.018	0.005	[0.001 – 0.04]
PL_A	-	0.33	0.05	[0.01 – 0.5]
PL_B	-	0.0023	0.0005	[0.00001 – 0.01]
SEN_A	°C	1050	50	[800 – 1600]
SEN_B	$°C.day^{-1}$	4750	50	[1000 – 30000]

4.2. GAI AND DAM ESTIMATES

The results presented here take into account the parameters presented previously, and are based on RMSE values obtained during the calibration phase on the GAI satellite of the flux site. It means that on a LUT of 5000 simulations, the 20 best are represented graphically in order to observe their trend and how they organize themselves around the best one (***Fig. 10, 11 and 12***). The statistical performance of the best only is taken into account. The LUT analyzed here was carried out considering the best solution (ie statistical performance) between the satellite and simulated LAI, while ensuring that the other variables were efficient too.

Figure 10 shows temporal evolution and statistical indicators of GAI and DAM measured (red dots) between popcorn maize sowing and harvest. On figure 10a. GAI (top left) start to increase one month after the sowing date, at the emergence. The growing phase represents the development of the plants, with the growth of the green aerial parts of corn. The plateau of GAI around 3 $m^2.m^{-2}$ between early July and August, indicates the flowering period. Finally, the senescence phase begins when the sum of the degree days reaches around 2000-5000 °C, during this it is the period and the maturation of the grains occur and the leaves and stem dry. The biomass (top right) grows and does not reach a plateau until around the beginning of September with a value of around 1950 $g.m^2$, then drops suddenly: it is the harvest. We can observe on this figure that the best simulation (curve in bold) is centred when compared to the 10 bests simulations. This indicates a good variability of the calibrated parameters, which remain in values close to the means despite their variability (std) and do not stick to the minimum and maximum limits. Also, despite the 4 biomass observations, the estimation curve seems to start at the same time as the GAI observations: overall (see figure 10b), the model is able to reproduce both the GAI and the biomass dynamics with root mean square error (RMSE) of 0.28 $m^2.m^{-2}$ while the determination coefficient (R^2) is 0.96. These results are very satisfying regarding the estimations of the model during the main crop period and confirm the ability of the model to simulate the biomass as seen in previous studies (Duchemin et al., 2015 ; Fieuzal et al., 2011 ; Hadria et al., 2010, Pique et al. a&b, 2020).

Also, DAM (bottom right) is well estimated by the model with very satisfying performances if we compare it with the recent study of Pique et al. (2020) about winter wheat, which has similar but less good performances. However, these performances are based on 8 years of evaluation and not 1, with very contrasting climatic years. RMSE is equal to 3.2% and R^2 is close to one, not equal as indicated by the graph which commits an abuse of rounding of values

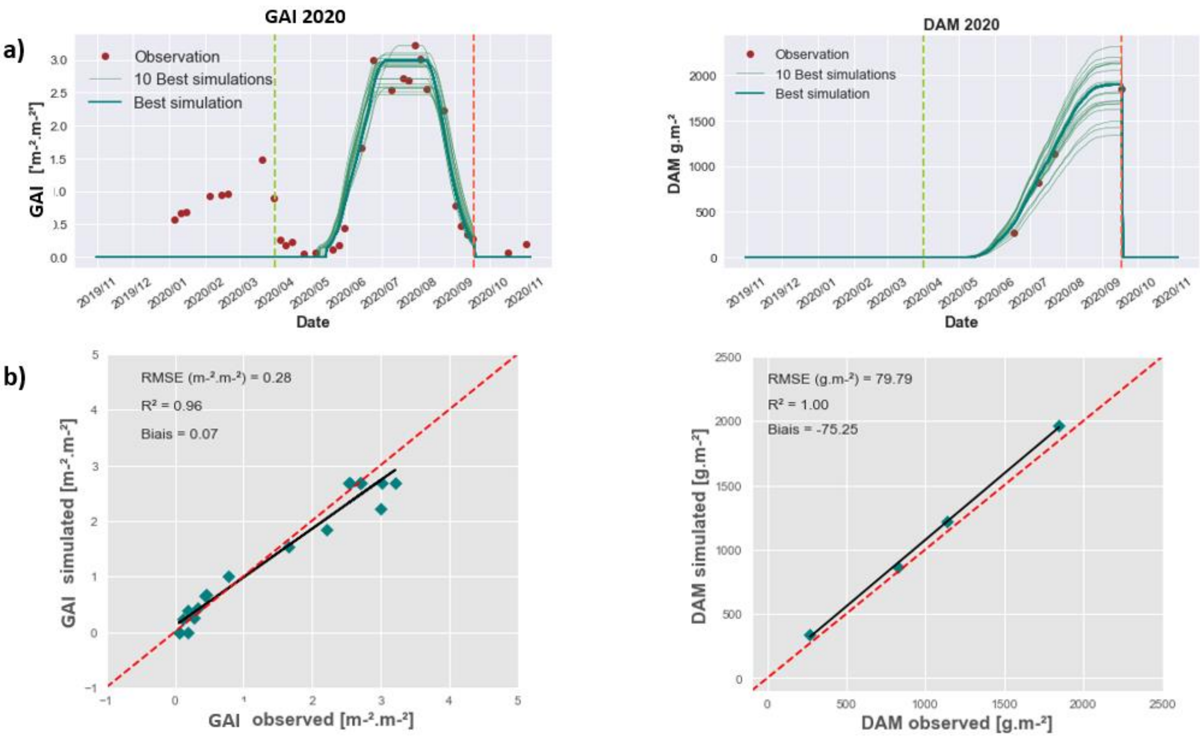


Figure 10: a) Graph representing the 10 best simulations on a LUT of 5000 simulations, with optimization on the GAI. The observation points on the GAI are taken from satellite images inside the contours of the flux plot during the cropping year 2019-2020: this period correspond to cover crop development followed by the popcorn maize. The DAM observations were collected on site for the cropping period only. The period between the two vertical dashed lines on figure a) and c) correspond to sowing of the maize in green and harvest in red, Scatter-plots **b)** show statistical comparisons between the observed and estimated GAI and DAM variables during the maize cropping period.

4.3. NET CO_2 FLUXES: GPP, R_{ECO}, NEE

The components of net CO_2 fluxes simulated by SAFY-CO_2: GPP, R_{ECO} and NEE, are compared to the flux data collected at the Pibrac's site (***Fig. 12***). This section resumes the performance of these estimations, based on the analysis of errors (RMSE) and correlation (R^2) during the crop development (between growth and senescence) only ***(Fig. 11)***. The cover crop and the post-harvest periods are not considered in the statistical analysis of the variables.

In general, the fluxes are rather well simulated for the three variables studied. If we observe the curves of the graphs in Figure 11, we notice that the variability of the 20 best simulations covers the observation. If we focus on the NEE (top) and GPP (middle), the best simulation tends to be slightly underestimated, but the set of results covers the observation given fairly well with an overestimation, in going through simulations close to reality. Only the period between sowing and observable emergence, which occurs at the beginning of May, is not well covered by the simulations. On the statistical performance side, the GPP is well estimated during the cropping year in term of error and correlation with an RMSE of 1.56 $gC.m^{-2}.d^{-1}$ and a powerful R^2 of 0.92. For the NEE, these statistics are slightly worse but still very correct, with values of 1.79 $gC.m^{-2}.d^{-1}$ for the RMSE and a R^2 about 0.88. It is important to contextualize these results, which are the result of only one year of measurement, without taking into account post-harvest events. For the same situation (from sowing to harvest only), the study about winter wheat by Pique et al. (2020) indicates performances from 0.90 to 2.79 $gC.m^{-2}.d^{-1}$ for RMSE and between 0.86 and 0.96 for the R^2. This shows that despite good results, the model is able to obtain very satisfactory results with data over a higher number of years and under different conditions. The model has an adaptability that we can only observe little here.

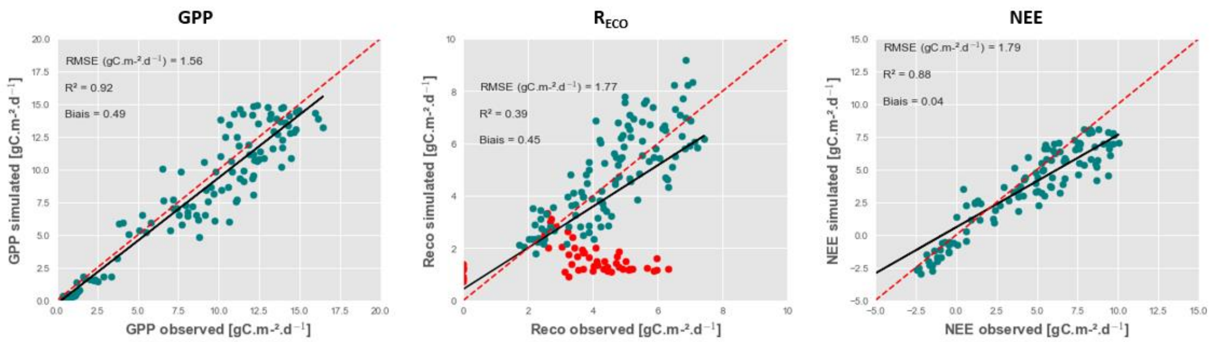


Figure 11: Scatter plot of the comparison between observed and simulated components of net CO_2 fluxes (GPP, R_{ECO} and NEE) during the crop period. The red dots represent the priming effect period.

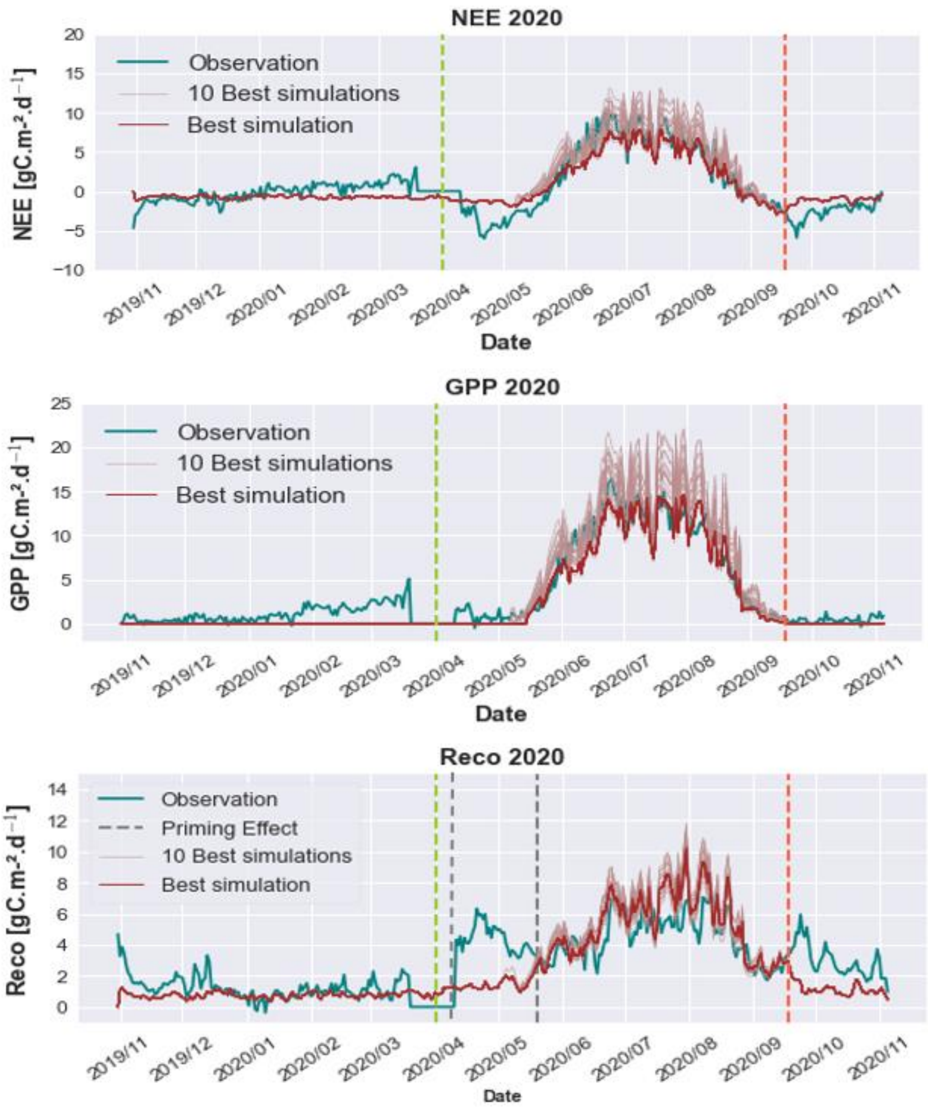


Figure 12: Temporal evolution of measured (blue) or estimated (red or pink) GPP, R_{ECO} and NEE during the crop development of popcorn maize in 2020. The vertical dashed lines (green and orange) represent the crop development period as in Figure 5. The grey vertical dashed line represents the priming effect on R_{ECO}.

Regarding the R_{ECO} performances, we can observe a global overestimation of the dynamics (***Fig. 12***) during the cropping period. The RMSE is equal to 1.77 $gC.m^{-2}.d^{-1}$ while the R^2 is equal to 0.39, which is not really satisfying if we compare with the R^2 obtained on the two other flux variables. If we focus on the beginning of the cycle, we notice a period that is poorly reproduced by the model in the graphs (***Fig. 12)*** and in the scatter plots (***Fig. 11***). This concerns the effect of heterotrophic respiration of the preceding cover, which is called the 'priming effect' and which will be more fully discussed in the next section. Indeed, the model seems too simplistic to correctly reproduce heterotrophic soil respiration and its other processes. However, the modelling of R_{ECO} remains satisfactory and correctly reproduces autotrophic respiration, when we know that this can represents 80% of R_{ECO} (Béziat, 2009) and considering a calibration on the LAI and not on a flux.

V. DISCUSSION

5.1. THE SAFY-CO_2 APPROACH: ADVANTAGES AND DISADVANTAGES

In this study, our objective was to parameterize the SAFY-CO_2 model for popcorn maize, since its potential was already analyzed in previous studies (Pique et al., 2020). The main advantages of a model like SAFY-CO_2 are the low need for input data, whether in-situ, from the literature or calibrated, as well as the simplistic aspect of the approach. Also, it requires little or no external information (mainly imported carbon, straws). With the growing availability of satellite data for the benefit of agronomic research, among other things, the future of such models looks promising.

On the limitations side, we can first mention the uncertainty of remote sensing observations. Climatic conditions are not always favorable to obtaining usable images, even in crucial periods for the development of crops. This was not the case in 2020 on our study plot, but large periods can sometimes be unusable. Also, we have mentioned it a few times in this report, but to go to the end of the model procedure, it is necessary to know the fate of the straws (buried, exported ...) or the organic fertilization, in order to correctly estimate the NECB. These informations may be limiting to estimate the C budget.

5.2. DATA IMPROVEMENTS

The collected data depend on the instrumental setup (flow, rain, temperature, radiation, etc.), or on the protocols for non-continuous vegetation measurements (LAI, biomass). In May 2020, the raingauge malfunctioned and stopped working for a approximatively 30 days (we do not know exactly). The data collected was thus erroneous and equal to 0 every day. It was therefore necessary to gapfill the data with the ones from Météo-France on the Blagnac's site, located 15 km from Pibrac, for the rain in May. Despite the accuracy of the data provided by Météo-France *(www.infoclimat.fr)*, there is probably a difference, large or not, between these and those specific to Pibrac, which constitutes a certain bias in the input data. If this information does not directly impact the operation of SAFY-CO_2, this could be the case if we were to add a 'water' module to it. Also, LAI and biomass data on the experimental plot were scarce in 2020, which is mainly due to the Covid-19 pandemic and the difficulty of circulating during this period. The person in charge of the collect did not have the required authorizations to visit the plot regularly, which directly impacted the availability of these data. In addition, beyond this lack of data to constitute reliable observations, the model and its estimates are based in the case of maize on a single cropping year. Previous studies on wheat or sunflower (Pique et al., 2020) are based on data from more years (eg 8 cropping years for winter wheat), which makes it possible to validate the model on different conditions (heavy rains, drought, etc.) and make it more robust. However, there are still two years of measurements left on the Pibrac site with popcorn maize, which will make future studies more efficient and complete. Finally, as part of this internship, we did not consider any regrowth or weeds that could interfere with the results, as it has been done in the study of Pique et. al (2020). In plots in agroecology or tending towards practices more respectful of the environment, it will, in the long term, be not negligible to consider these data.

5.3. PRIMING EFFECT

If we focus on R_{ECO} represented in Figure 5 (temporal evolution) and 6 (scatter plot), we can observe the evidence of a period that the model cannot reproduce around the emergence period of the crop. These high values of R_{ECO} at the start of the maize growing phase are not caused by the popcorn maize development, but by the burying of the faba bean. Indeed, the increase in R_{ECO} is caused by an increase in heterotrophic respiration called "priming effect". It is caused by the mineralisation of the cover crop incorporated in the soil before maize was sown. In other words, this is the increased soil respiration (microbes) when fresh organic matter is buried, here following the destruction and burying of the intermediate crop of fabba bean. Due to this effect, the statistical performances of R_{ECO} are not very satisfying, as the model doesn't simulate those effects. If we reduce the period of comparison by excluding this priming effect, R_{ECO} performances about errors and correlation are better : RMSE is equal to 1.64 $gC.m^{-2}.d^{-1}$ and R^2 to 0.64 in this case, against 1.77 $gC.m^{-2}.d^{-1}$ and 0.39 respectively by including the priming effect into the statistical indicators. In the future, this type of process should be taken into account in the model.

5.4. PERSPECTIVES

In this study about popcorn maize, the planned exercises went beyond the estimation of biomass. Due to lack of time but also due to the particular situation we are currently experiencing (pandemic, teleworking), I had to revise downwards the exercises performed. This gives way to several perspectives for the work undertaken, such as the extension of the study to a spatialized biomass campaign over a larger area. The rest would be a harvest campaign with several farmers to check if the model reproduces the yield ('YLD') well, which would make it possible to estimate the net ecosystem carbon balance (NECB). To hope for such a final result, it will be necessary to consider extending in-situ data to imported and exported carbon (landfill, straw, amendment).

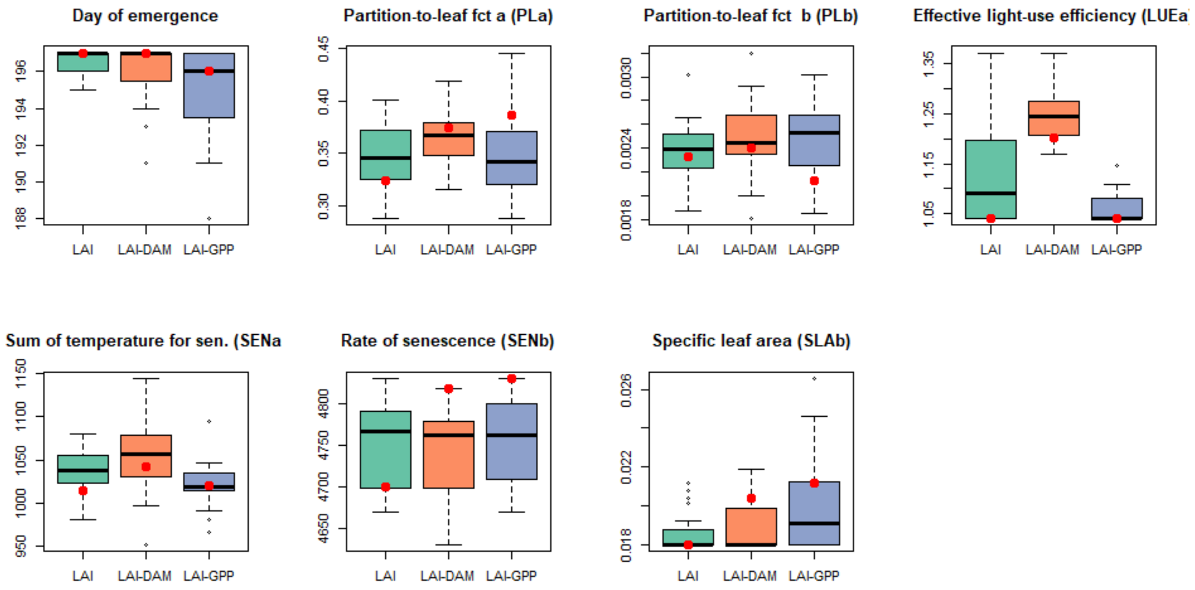
Another perspective is directly linked to Nataïs expectations, since it would involve simulating intermediate crop. Indeed, at this stage, the model does not take into account the intermediate crop nor their potential effects on the main crop (priming effect, regrowth, soil enrichment, etc.). This is a possible prospect, since it would ensure the continuous improvement of the model, as well as its robustness in the estimates.

Finally, it would be possible to insert the "water" module to integrate maize (or popcorn maize) in SAFYE-CO_2, and then make the estimates more efficient. The water requirement has a huge influence on the maize crop, since the critical stages in irrigation are when water is scarce, i.e. in summer.

VI. CONCLUSION

In this study, we initiated the combined use of a simple crop model and temporal remote sensing data to estimate maize crop production. Through a dense step of parameterization of the model with its optimization and calibration, we obtained satisfactory results on maize. SAFY-CO_2 was validated at local scale for maize crop. Despite differences in size and therefore in final biomass with "classic" maize, popcorn maize shows strong similarities in the development cycle and phenological stages observable from space. Thus, the results obtained with this study case can be retained and applied on a global scale. With the aim of extending SAFY-CO_2 modelling to major field crops, this study on popcorn maize demonstrates the potential of such an approach to estimate C budget and biomass. The high-resolution remote sensing data assimilated in a simple crop model may claim good results in terms of estimating components of cropland annual carbon budget, here with net CO_2 flux components. The high temporal frequency of Sentinel-2 is required to calibrate six phenological parameters of this model, which are then used to simulate biomass, vegetation index (GAI) and net CO_2 fluxes. This approach is based on a low demand for input data, but can sometimes be limited when we are interested in the processes linked between intermediate cover and main crops, in particular with regard to soil respiration. In future studies with biomass or yield data, or a larger spatial campaign, it will be possible and conceivable to extend the application of this model to a regional or even more global scale, with greater robustness. Also, new soil and climatic conditions will be appreciated for the flux plot analysis.

APPENDIX



Appendix A.

Example of an analysis of the value of the parameters with an optimization on the RMSE of the simple LAI (left), or multivariate with LAI-DAM (middle) or LAI-GPP (right).

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