PhD School on Agriculture, Environment and Bioenergy

(http://sites.unimi.it/dottorato_aab/)

(XL cycle, 2024-27)

Project draft

1. Field of interest

Agronomy (AGRI-02/A) - Agronomia e coltivazioni erbacee)

2. Project title

Combining remote sensing and cropping system simulation models towards efficient monitor, report and verify protocols for crop productivity and net agroecosystem carbon balance

3. Tutor

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4. Relevance of the topic and state of the art

In developed and industrialised countries, geo-information products can be used to provide farmers with decision-supporting spatial information of crop traits and development, able to highlight among-fields and within-field crop variability, as a fundamental tool to support site-specific management (i.e. precision farming; Hank et al., 2019), to provide timely and accurate estimation of crop yield before harvest (Jin et al., 2018), to assess the SOC sequestration potential based on more accurate estimation of net agroecosystems carbon balance. However, the use of remote sensing is limited to the retrieval of few crop traits, not sufficient to provide precise and accurate estimation of crop and soil status. Conversely, crop simulation model (CSMs) are considered key instruments to face these challenges. CSMs are computer-based tools that manage data from different sources and represent mathematically dynamic interactions between crop management, crop growth and the environmental factors within soil-crop-atmosphere systems (Wallach et al., 2018), allowing to predict the effect agro-management decisions of a range on a range of crop and soil related variables. However, CSMs have some limits when used out of experimental conditions and with the aim to support the real-time monitoring of crop development and status on a spatial scale. Thus, the developing of effective approaches for coupling CSMs and remote sensing (RS) in the last decades has raised the interest of many scholars as a chance to provide high-resolution and real-time quantitative estimations of interest variables related to the agroecosystem status on a spatial scale. The application of data assimilation (DA) techniques can reduce uncertainties in CSMs by assimilating external observations of crop variables into the model. On the other end, DA can help to better exploit RS observations to make accurate prediction on several spatial scale (Jindo et al., 2023). Since, there is some criticism of the application of CSMs and RS due to their complex structures, which are often too complicated for end users such as farmers, policymakers and extension officers, some research experience has highlighted the need of assessing the potential of metamodels in combination with DA with the aim of emulating the outputs of complex models with greater accuracy. In recent years, machine learning (ML) has been proposed as a solution to develop metamodels for assess agro-environmental variables useful to support decision making (Hoffman et al., 2020; Saha et al., 2021). Their application in agriculture is recent and experinces are still limited (e.g. Feng et al., 2019; Shahhosseini et al., 2021), and mostly related to large-scale assessments. However, coupling data assimilation of CSMs and

RS within ML based metamodels has the potential to further increase the explanatory ability of spatiotemporal variability of field conditions that, otherwise, cannot be completely accounted by simulation models. Therefore, the objective of this project is to evaluate the potential of integrating CSMs-RS into a metamodeling approach to predict crop growth and development, and the net agroecosystems carbon budget a field level, in relation to pedoclimatic conditions and soil/crop management.

5. Layout of the project (draft)

5.1. Materials & Methods

The project will be carried out through four different activities:

1) Development of a conceptual framework: i) design of the DA approach based on the review of existing approaches and the selection of benchmarks; ii) design of the metamodeling approach; iii) design of experimental trials.
2) Data collection and pre-processing: i) collection of experimental data related to model input from RS and ground measurement of available experiments, ii) acquisition of ad-hoc ground measurements for data assimilation, iii) data quality assessment, scaling and building of harmonised datasets;
3) ~~Simulations with~~ Simulations: i) Calibration of ~~of a mechanistic cropping systems simulation model (~~CSM, ii) RS data assimilation, iii) simulation of training scenario: A) pure CSM simulation; B) RS assimilation simulation
4) ~~.~~ Metamodeling: development of parametric and MLA based metamodels from pure CSM and RS assimilation simulation
5) Assessing the prediction potential and stability of metamodels and RS data assimilation
6) Analysis of results: i) comparison of modelling approaches with a set of metrics and generation of knowledge from remote sensed multispectral data ii) mapping and interpreting spatio-temporal patterns of crop growth, aboveground biomass production and net agroecosystem carbon balance.

5.2. Schedule and major steps (3 years)

The research will be articulated in the following activities and tasks.

Activity	Task	Year 1	Year 2	Year 3
Development of a conceptual framework:	Literature review and framework design	X		
Data collection and pre-processing	Dataset development	X		
Simulations	Crop model adjustment and parametrization RS data assimilation	X	X	
Metamodeling	development of parametric and MLA based		X	
	Data assimilation of metamodels		X	X
Analysis of the results	comparison of modelling approaches		X	
	mapping and interpreting spatio-temporal patterns			X
Thesis and article writing			X	X

6. Available funds

Remote-C - Scaling soil C sequestration in croplands with operational remote sensing-based MRV tools 71.129,00

7. Literature

Hank, T.B., Berger, K., Bach, H., Clevers, J.G.P.W., Gitelson, A., Zarco-Tejada, P., Mauser, W., 2019. Spaceborne Imaging Spectroscopy for Sustainable Agriculture: Contributions and Challenges, Surveys in Geophysics. Springer Netherlands. https://doi.org/10.1007/s10712-018-9492-0

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Jindo, K., Kozan, O., de Wit, A. (2023). Data Assimilation of Remote Sensing Data into a Crop Growth Model. In: Cammarano, D., van Evert, F.K., Kempenaar, C. (eds) Precision Agriculture: Modelling. Progress in Precision Agriculture. Springer, Cham. https://doi.org/10.1007/978-3-031-15258-0_8

Saha, D., Basso, B., Robertson, G.P., 2021. Machine learning improves predictions of agricultural nitrous oxide (N_2O) emissions from intensively managed cropping systems. Environmental Research Letters 16, 024004. https://doi.org/10.1088/1748-9326/abd2f3

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