SMART FARMING: A LOW-COST TECHNOLOGICAL DECISION SUPPORT SOLUTION FOR SUSTAINABLE PRECISION AGRICULTURE IN SME

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Abstract

Precision Farming (PF) solution implementated is one of the Earth Observation applications in the agricultural sector; uses satellite imagery to help farmers monitor and manage crops from seed to harvest. Some of the features of PF include identifying soil irrigation status, determining chlorophyll strength, monitoring plant diseases, and supporting farmers in evaluating and optimizing agricultural treatments. All services are provided in multi-channel mode using a Decision Support System (DSS) integrated into a WebGis. The satellite data is updated automatically con cadenza temporale programmabile.

INTRODUCTION

Around 37% of the planet's land is now used for agricultural purposes, with around 11% being used for cultivation and the rest of the land left for grazing. FAO estimates that in order to meet the growing demand for food, due to the expected increase in the world population, agricultural production will have to increase globally by 60% by 2050. On the other hand, land is being degraded by factors such as soil erosion, mineral depletion and drought (ESA Terra online 2000-2014), and the utilized agricultural area (UAA) is decreasing. In 2010 there was a UAA of 170 million hectares in 27. Compared to the 2003 data this shows a UAA decrease of approximately 2%. For example, in Italy since 1970 alone there has been a decline in UAA of 28% (5 million hectares of UAA lost, from 18 to 13 million hectares). This is a European challenge to improve crop production processes aimed at increasing yields while reducing environmental impacts (water consumption, pesticides, etc.). At the same time, in this difficult context, farmers must optimize the overall crop production process, by:

- Correlation of production techniques, harvests, and factors capable of positively influencing the harvest;
- Reducing expenses and related environmental impacts due to the use of pesticides, herbicides, fertilizers and, possibly increasing yields;

Precision Farming can definitely help farmers address the needs listed above. To date, some PF solutions have been developed envisaging rather expensive on-demand precision agriculture services, and their targeting is therefore oriented only towards large agricultural companies with high volumes of capital and which are accustomed to the use of of information. In the EU, large agricultural holdings represent only 20% of the UAA. At an Italian level, the percentage of large companies drops and is largely linked to northern Italy. In Campania there are a large variety of medium-small sized companies. From what has been illustrated, it is clear that there is a need for technological solutions that can be used not only by large companies but by the entire fabric of medium-small companies that represent a large untapped market opportunity. It is necessary to propose innovative solutions for the Precision Farming market that are aimed at producing services for small and medium-sized agricultural companies (which represent 80% of European UAA), to allow them to improve their production processes. The solution has to be;

- **economical**; the cost-effectiveness of the services that the solution aims to provide will also allow medium-small farms, as well as large ones, to optimize crop productivity and raise the quality of the agricultural product while respecting the environment.
- **sustainable**; the solution will be sustainable in terms of data availability, processed data (information), cost-effectiveness, ease of use and consultation, respect for the environment
- **automatic**; the observation data (maps) and the processed data (informative/thematic mappers) will be updateable according to two options: a) on demand depending on their availability, b) automatically whenever an update is available
- **constantly updated**: the updates of the maps and informative/thematic maps will take place on a weekly basis or alternatively timed with the availability of new satellite data.
- **easy to use**; ease of use represents one of the strengths of the solution. Access to information to improve agricultural management processes will be intuitive in order to allow the use of services even to users with low IT education. The interfaces will be ergonomic and assisted with online help and guided paths.
- **accessible** with multi-channel tools already widely available to end users (smart phones, tablets, etc.); The information will be available in a web-oriented manner and accessible through multi-channel systems (smart phones, tablets, desktops) certainly already available to end users (farmers, agricultural workers and farm managers). The data consumption of the multi-channel systems used will be limited as only the maps relating to the areas with the end users' fields will be periodically downloaded.

The application proposed with the project involves the integrated use of optical satellite images with L-band SAR images and satellite geolocation images (GPS and GALILEO), to obtain:

- a high-performance monitoring and support solution for the decision-making processes underlying agricultural activity, capable of operating 24 hours a day, even in the presence of adverse weather conditions
- An economical solution that can meet the needs not only of large agricultural companies but also of medium, small and micro-sized ones.

MATERIALS AND MODELS

COPERNICUS constellation

Copernicus, the EU Earth observation programme, will ensure regular observation and monitoring of Earth's subsystems, atmosphere, oceans and continental surfaces and provide reliable, validated and assured information to support a wide range of applications and decisions regarding the environment and safety.

The project uses data from Sentinel-2, A and B, i.e. optical satellites designed for multi-spectral observation; Sentinel-2 provides high-resolution optical imaging for ground services (e.g., images of vegetation, soil and water cover, inland waterways and coastal areas). In the project, Sentinel 2 A-B data is used for agricultural monitoring and development

The Sentinel-2 Mission offers an unprecedented combination of the following capabilities:

- systematic global coverage of the Earth's surface: from 56° South to 84° North, covering coastal waters and the Mediterranean;
- High revisit: every 5 days at the equator under the same viewing conditions with 2 satellites;

- high spatial resolution: 10m, 20m and 60m;
- Multi-spectral information with 13 bands in the visible, near-infrared and short-wave infrared part of the spectrum;
- Wide field of view: 290 km.

Data from Sentinel-2 is openly and freely available to all users with easy online access to ESA's "Copernicus Open Access Hub (https://scihub.copernicus.eu/") or "Copernicus Online Data Access" portal (https://www.copernicus.eu/en/access-data) from EUMETSAT, depending on the type of data

DISCUSSION

Multi-disciplinary approach

Precision agriculture, therefore, represents a topic of great interest both for the enormous economic implications it can have in terms of development and rationalization of the agricultural sector. Global political strategies on the development of precision agriculture mainly revolve around the concept of climate – Smart Agriculture, more properly called CSA (FAO 2015).

The FAO program has three main objectives

- Sustainable increase in agricultural productivity and farmers' incomes
- Research into new forms of resilience of agricultural ecosystems, in order to adapt to climate change
- Reduction of greenhouse gases (where possible)

These 3 objectives are pursued by providing guidelines and to innovate global agricultural systems towards solutions compatible with the needs of food safety, environmental sustainability

Furthermore, these guidelines must be adapted to the specific characteristics of each nation and territory, without prejudice to the creation of cultural systems with low environmental impact and reduced costs, thanks to tools that automatically control the distribution of production factors (water, fertilizers, pesticides, etc.).

To date, some experiments that have proven to be very effective have been based on an approach purely aimed at the use of optical satellite images. Although this approach has proven to be very effective, especially for some types of cultures, it has limitations due to atmospheric variations. The impossibility of having information available during night passages or due to the presence of clouds, a condition which in some periods of the year can last for months, limiting and in some cases nullifying the benefits of cutting agriculture systems, requires new procedures and methods monitoring, processing and interpretation of not only optical data, but also SAR. Furthermore, there is the need to have economical solutions that can also be used by small-sized companies, as they represent the vast majority of agricultural companies in Italy.

Technological objective

To provide a solution to these problems, the application proposed with the project involves the integrated use of optical satellite images with L-BAND SAR images to obtain:

- • high-performance monitoring and support solution for the decision-making processes underlying agricultural activity, capable of operating 24 hours a day, even in the presence of adverse weather conditions

- An economical solution that can meet the needs not only of large agricultural companies but also of medium, small and micro-sized ones.

The proposed solution is composed of three cooperating units:

- L-BAND satellite image processing system
- SENTINEL 1A and 1B Optics Image Processing System
- Web oriented decision support system, based on:
    - or machine learning technology
    - or WebGIS
    - Interfaces in multi-channel and responsive technology

An innovation of the system consists of the introduction of automatisms for updating satellite maps (optical and radar), which allow the availability of new images (SAR and optical) to be periodically checked, downloaded, made available to the processing units to carry out the processing necessary to make them compliant in terms of format and information content with the needs of the DSS (Decision Support System). The latter, on the basis of the images received, carries out the appropriate superposition of the various maps developed and develops, on the basis of rules codified by experts in the agricultural sector, differentiated intervention plans for each territorial area examined.

Currently, the PF (Precision Farm) is based on the following main technological pillars:

- • Satellite images (optical and radar)
- • a geographic positioning system based on satellite constellations (such as the American Navstar GPS, the Russian Glonass, the European Galileo GSNN and the Chinese BeiDou-Compass);
- • a geographic information system (Gis);
- • many applications (sensors - remote and proximal - actuators for variable dosage, section control, guidance systems, artificial vision systems, systems for evaluating product quality, etc.);
- • systems for connectivity and interoperability (internet, ultra-broadband, LowRaWAN®, communication protocols, IoT, etc.).

The geographic positioning system is mainly used for two large groups of operations: machine navigation (Figure 2) and site-specific management of processes. Navigation takes on fundamental aspects in large companies, where the parallelism of contiguous passages and the absence of overlaps allows for notable operational efficiencies, but recent studies demonstrate that even in small companies, where surfaces are often irregular, satellite navigation allows you to implement the best route strategies, avoiding overlaps, unnecessary transits and limiting compaction.

The geographical positioning system not only serves to keep the adjacent passages parallel and to avoid overlaps, but also to guarantee the alignment between the tractor and the operator as in the example in the figure where the drift caused by the slope of the ground is automatically detected by the positioning of the tractor and the operator in communication with each other and instantly corrected by the guidance system

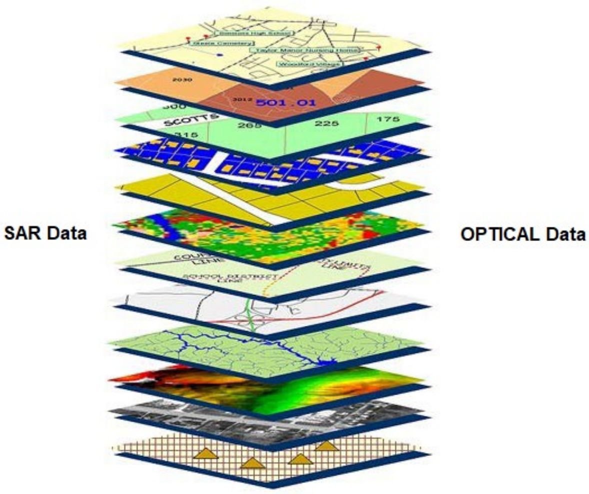
Fonte: Drummond & Etheridge

The site-specific management of treatments is a further (and very vast) application of satellite positioning systems which allows the areas of a plot characterized by wide variability to be specifically treated. For example, in a plot where the soil fertility characteristics have demonstrated high variability, the distribution of fertilizer will not be carried out uniformly over the entire plot, but by varying the dose according to needs. In this case the fertilizer spreader machine will receive the geographical instructions (prescription map) according to which to vary the doses to be distributed thanks to actuators specifically designed to distribute doses at a variable rate (Vrt). To implement this strategy, geographic information systems (GIS) are of primary importance.

The system monitors the work of the fertilizer spreader which, moving along the plot characterized by different fertility levels (colored areas), distributes variable doses of fertilizer, thus avoiding over or under doses.

Geographic information systems (GIS) serve to provide geo-referenced company maps. Simplifying a lot, we can say that they replace the paper maps present in every company and can report a very considerable amount of information that can be "stratified" between them, interconnected and historicized in order to represent an archive of useful indications for ongoing company management and for future ones.

A GIS cartographic system allows you to connect "stratified" company information that helps to understand the phenomena that underlie variability (production, phytosanitary, physical-chemical, etc.) and to seek improvement strategies



Fonte: Omnia Precision Agronomy, 2018 (modified)

PF applications are one of the most diversified and expanding technological sectors today. In an attempt to provide a first classification of these applications, the European Parliament (2014) published a study (available on the site listed in the bibliography) which reports a repertoire of technologies and applications present in European countries, their level of development (experimental or commercial) and the main critical issues. Another study carried out in the United States (Miller et al., 2017) reports a survey carried out at company level where the main applications already in use, their diffusion and the main critical issues are highlighted. Finally, the European Agency for Global Navigation Satellite Systems (Gsa, 2017) also reports the market data of the main commercial systems for PF. From these works, albeit with due precautions given the speed with which the sector evolves, we can list the main applications for PF currently widespread in the field of open-field herbaceous crops: i) semi-automatic driving, ii) the applications at variable rates (fertilization, treatments, sowing), iii) production mapping, iv) section control and v) soil sampling. Finally, the last technological pillar of the PF concerns systems for connectivity and interoperability as there is a need not only to acquire data, but also (above all) to manage it. This aspect concerns both the machines (which must be able to receive, send, generate, process and exchange data through common protocols) and the company (which must exchange data with the machines, technical and commercial partners, etc.) . This makes it necessary to spread the GSM signal and the presence of ultra-broadband (Bul) even in rural areas. Where this has not yet happened (such as in the larger agricultural areas of Australia and Canada, where the competitiveness handicap with the areas covered by the signal is evident) there have already been individual initiatives by individual farmers who, while waiting that the internet reaches even the most isolated places, they have organized themselves with wi-fi radio links, autonomous laying (and at their own expense) of optical fiber or the use of satellite connections, even if very expensive, in order to have access to information

Social objective

SMART FARMING's main objective is to create and launch on the market an innovative Precision Farming service aimed at medium and small-sized companies (average size starts with 8 hectares), addressing a clear user need, which allows the market to be strengthened emerging commercial applications of EO services in agriculture, which is estimated to be worth around €43 million in 2018. The project will provide technologically advanced services to increase the productivity of the national agricultural sector, increase the quality and authenticity of agricultural products, improve land use and environmental quality.

SMART FARMING provides a unique Precision Farming service, which can represent a disruptive innovation in the use of space technologies in the agricultural sector, targeting small farms (80% of European UAA) with a cost-effective and easy-to-use solution. By opening PF to small farmers, SMART FARMING has the potential to become a game-changer in an agricultural sector that is still characterized by the lack of use of new IT spaces and technologies. The SMART FARMING solution is based on:

- The combined use of GIS and remote sensing, for the development of a Webgis platform relating to a geographical database.
- A system for indexing and searching historical data,
- A database with crop vigor maps, thematic maps, vegetation state maps, green leaf maps

- Use of SAR data test SAOCOM 1A and -1B, and (PALSAR / ALOS) 2
- The use of Sentinel 2 and Landsat 8 evidence data as basic information for the creation of thematic maps
- A web and mobile app to allow direct access to SMART FARMING services by workers when operating in the field;
- All kinds of different output definition

Easiness of use

Ease of use remains one of the priorities of the SMART FARMING project, as its objective is to be a tool for optimizing agricultural processes also for farm managers and operators who may have low IT education. In practice the farmer can carry out the following actions:

- log in using your login details (email and password)
- define the areas of interest of your fields (online editing or set the address, or kml, KMZ, pdf, upload JPEG) which are thus associated with your authentication profile
- start a 60-day free trial
- request the update on a monthly / 10 day / week basis of a series of different maps for each field included in the defined areas (map in WebGIS, or in kml, KMZ, pdf, SHP) by customizing your access profile with areas of delimitation, different class levels (5th and 9th class) and each class with quantity of hectares. This operation is assisted with visual tools and in practice is very simple and intuitive. It should be noted that the series of maps downloaded automatically will not only relate to the observation data but also to the results of a series of processing (quantity of chlorophyll, etc..) and therefore it is correct to speak of information maps rather than data maps.
- create a calendar with all the data for each month that allows you to verify the evolution of the management process of your fields, also in light of the actions carried out at each consultation step.
- download an app for consulting and monitoring the state of the fields, to be used during the processing phase for precision actions aimed at obtaining economic savings (pesticide reduction, water reduction, etc..) and at the same time improving the quality of products and the state of health of the environment.
- create an alert to receive email notifications of the availability of new maps to download. The update can be requested on demand or completely automated.

The consultation platform will have the following characteristics

- • site in Italian and English, to guarantee easy export both nationally and internationally of the model tested in Campania companies, to promote new efficiency in the agricultural field at reduced costs and high quality of products made in Campania thanks to reduced use of chemicals and greater attention to land exploitation and environmental protection. This marketing action induced by the project is particularly important in light of the scandals that have involved the land of fires in Campania and damaged the Made in Italy products of the entire region and not just those originating from a limited area of Caserta.
- • The platform must be clear and easy to use even for users with little familiarity with info-telematic means. They must be able to use their mobile phones or tablets to use the platform and improve the production efficiency of their company with low, sustainable costs and amply repaid by the significant increase in productivity
- • Integration of the platform into a WebGIS for consultation, easy to use and multi-channel oriented (smart phone, tablet, desktop) and adaptive with respect to the various types of consultation tools (sensitive)

- • The platform will allow the use of multiple output formats (data maps and information maps) (SHP, raster, pdf, kml) in order to guarantee the widest usability depending on the various levels of computerization of the end users (farmers and company managers agricultural)

Adopted Technologies

L-band SAR data processing

One of the main objectives of the project is to analyze the potential use of L-band radar data for soil moisture estimation over agricultural areas under dense vegetation conditions.

Radar images acquired using the Phased Synthetic Aperture Radar/Advanced Ground Satellite (PALSAR/ALOS)-2 sensor are used over vast air characterized by densely vegetated crops to perform:

• simultaneous soil measurements of soil moisture,

• Soil roughness and were also recorded

• recording of the leaf area index (LAI).

The sensitivity of PALSAR observations to variations in soil moisture has been reported by several authors and is confirmed in the present study, even in the case of very dense crops.

The radar signals are simulated using five different radar backscattering models (physical and semi-empirical), on bare ground and on areas with various types of plant cover (wheat, vines and tomatoes). When the semi-empirical water cloud model (WCM) is parameterized as a function of LAI, to account for the contribution of vegetation to the backscattered signal, it can provide relatively accurate estimates of soil moisture in grape and tomato fields, but has some limitations when applied to wheat fields. The observed limitations highlight the need to expand the analysis beyond LAI by including additional vegetation parameters in order to account for the diffusion of the backscattered radar signal volume in the L-band for accurate estimation of soil moisture.

Accurate knowledge of soil moisture is important for the evaluation of numerous processes, such as evapotranspiration, infiltration and runoff, and for modeling the soil-vegetation-atmosphere interface [1-5]. In an agricultural context, soil moisture measurements can contribute to water resource management

[6,7]. Although soil moisture has long been measured through the use of local field measurements, this technique can become impractical and very expensive when large surface areas need to be measured and/or long-term monitoring is required. Over the last 30 years, various algorithms based on the use of optical and radar remote sensing observations have been proposed for soil moisture estimation [8-11]. Currently, various global soil moisture products are available on an operational basis. These are based on microwave radiometric measurements (e.g. SMOS: Soil Moisture and Ocean Salinity, AMSR-E: Advanced Microwave Scanning Radiometer for EOS, SMAP: Active and Passive Soil Moisture Moisture) and/or measurements dispersive (e.g. ASCAT: Advanced SCATterometer) and have a spatial resolution between 10 and 40 km [12–16]. Since farms are small in size (~ ha), these global soil moisture products alone are of little use for assessing soil moisture at the scale of individual fields.

Optical/thermal aperture radar (SAR) sensors can generate high spatial resolution (less than 30 m) images, which can be processed to provide meaningful information for agricultural businesses. On the other hand, optical and thermal sensors have reduced sensitivity to soil beneath plant biomass and are unable to penetrate clouds, thus limiting their relevance for studying tropical agriculture [17]. High-resolution SAR data have been used in numerous studies for soil moisture estimation [18-23], and several new satellites have been launched in the last decade, with SAR payloads operating in the C- and , RADARSAT-1,2, TerraSAR-X, COSMO-SKYMED, RISAT-1 and the Sentinel-1 constellation). The recent availability of these data has led to the development of new algorithms, such as multi-temporal [18], neural networks [19,20], cumulative density function (CDF) transformation [21], and detection algorithms of changes [22] and allowed the direct inversion of physical or empirical models [23].

In the case of a bare ground surface, the backscattered radar signal is influenced by the dielectric constant of the first few centimeters of the upper surface layer and the roughness of the ground. In practice, the penetration depth of the radar signal varies between 1 cm in the X band and 5 cm in the L band, in case of high soil humidity [10,24]. The dielectric constant of the soil depends on its humidity and consistency and on the frequency band used by the radar sensor [25]. Numerous studies have quantified the backscattering of the radar signal as a function of soil humidity and roughness [26]. The backscatter coefficient was found to have relatively high sensitivity to soil moisture at lower incidence angles (20° – 35°) [27,28]. In this context, various radar backscattering models (physical, semi-empirical and empirical) have been developed in an attempt to improve the scientific understanding of the relationship between the backscatter coefficient and the parameters used to characterize the ground. The most used models are the integral equation model (IEM) proposed by Fung et al. [29] and the Advanced Integrated Equation Model (AIEM) [30], both of which can be applied to a wide range of soil roughness conditions. Semi-empirical models have been proposed, such as those by Oh [31], Dubois [32] and Baghdadi [33], which have the advantage of providing simple analytical relationships between the backscattered radar signal and the physical parameters of the ground.

When the surface is covered with vegetation, the backscattered radar signal depends not only on the ground, but also on the characteristics of the vegetation. Several studies have been proposed, based on solving the radiative transfer equation, to account for the contribution to the radar backscatter coefficient produced by vegetation cover [34,35]. A semi-empirical approach, known as the water cloud model [35], has been widely used in the literature due to its simplicity. This model considers the total backscattered radar signal as the sum of contributions from vegetation cover, together with a second soil-related contributor, which is attenuated by vegetation cover. Attenuation produced by vegetation was estimated using crop-related physical variables such as biomass, vegetation water content, crop height and leaf area index (LAI) [36–38], and through the use of satellite observations of optical indices such as the normalized difference vegetation index (NDVI) [39].

These studies have led to a better understanding of radar scattering over agricultural surfaces in the C- and 1 [20,22,40,41].

In this context, although L-band radars are particularly effective in terms of their ability to penetrate vegetation cover, for estimating underlying soil parameters, relatively small volumes of remotely sensed data have been produced in this frequency band. In practice, recent L-band measurements transmitted into space are limited to those provided by two JAXA missions: (PALSAR/ALOS) [42] and PALSAR/ALOS-2 [43], to SMAP measurements recorded over a short period in 2015 [44] and scatterometer data provided by the Aquarius Sea Surface Salinity mission. The L-band is particularly suitable for observations in tropical areas characterized by dense vegetation cover and the frequent presence of dense clouds, which can lead to strong attenuation even in C-band radar data [45]. Various studies have analyzed the potential of airborne or space-dispersed L-band radars for observing agricultural surfaces, as well as for estimating land cover and vegetation properties [46-50]. Numerous studies have proposed the use of polarimetric measurements of SAR in air to analyze soil moisture [51–63] and have demonstrated the potential of L-band data for high-precision retrieval of soil moisture. These studies applied polarimetric decomposition models to the analysis of different types of plant cover (corn, soybean, wheat, etc.). Jagduber et al. [51] reported an accuracy of 6-8 vol% using a multi-angle polarimetric decomposition, applied to a variety of crop types, Wang et al. [59] tested various polarimetric decompositions for soil moisture recovery over different areas characterized by vegetation cover, with a root mean square error (RMSE) of 6–11 vol%. Using Aquarius data, Liu et al. [63] proposed a method for global estimation of soil moisture. Using the water cloud model, they achieved an accuracy of 6% by volume, comparing Aquarius humidity estimates to passive microwave radiometer products. In the case of future L-band remote sensing missions such as ISRO/NASA NISAR [64], further advances in understanding radar signals are needed, in order to progress towards the development of more operational algorithms,

Ten L-band SAR images (wavelength ~ 24 cm in free space) acquired by Phased Synthetic Aperture Radar (PALSAR), the main payload of ALOS-2 (Advanced Land Observing Satellite), were analyzed for this study. These images were recorded in dual polarization mode, with HH (horizontal-horizontal) and HV (horizontal-vertical) polarizations with a pixel size of 6 x 6 m. SAR images were initially multi-reviewed to reduce speckle, using NEST software [69]. We considered two looks in the azimuthal direction and one in the distance direction. The images were then radiometrically calibrated to derive the backscatter coefficients σ0. Since NEST cannot perform automatic georeferencing of ALOS-2 imagery, this step is performed using control points retrieved from a Sentinel-2 optical image of the site. All images were georeferenced and overlaid, with a root mean quadrant (RMS) checkpoint error of approximately one pixel. The average backscattering coefficient (linear scale) was calculated from each calibrated SAR image by averaging the σ0 values for all pixels corresponding to the reference plots of interest.

The study of the effectiveness of satellite measurements is validated with ground measurements carried out with specific instruments::

- **Soil moisture measurements**; Soil moisture measurements were performed using a portable theta probe (SM-300, Delta-T Devices, Ltd, Cambridge, UK), which measures the average value of soil moisture to a depth of 5 cm
- **Leaf area index measurements**: Leaf area index (LAI) is defined as the total one-sided area of leaf tissue per unit of soil surface area, and is therefore a dimensionless quantity that characterizes the plant cover of an ecosystem. During ground campaigns, LAI is derived using the LAI-2200C plant canopy analyzer.
- **Roughness measurements**: Roughness measurements are only relevant for a limited number of reference fields, with bare soils or highly dispersed vegetation cover. Roughness measurements are obtained with a needle profiler, 150 cm long and a sampling interval of 2 cm between needles.

Metodologies

Model of backscattering

The project involves testing different models used to simulate PALSAR data in HH and HV polarizations on bare terrain and vegetated fields.

1 . Water Cloud Model (WCM)

The water cloud model was used to model the radar signal backscattered from covered surfaces. With an angle of incidence equal to θ, the backscatter coefficient in this model [35] is given by the following expression

$$\sigma^0 = \sigma^0_{canopy} + \sigma^0_{canopy+soil} + \tau^2\sigma^0_{soil}$$

Where:

- τ2 is the two-way vegetation transmissivity
- σ^0_{canopy} represents the scattering produced by vegetation,
- $\sigma^0_{canopy+soil}$ is related to multiple scattering effects, and $\tau^2\sigma^0_{soil}$

represents the dispersion of the soil attenuated by the vegetal cover. The second term, which is generally neglected in cases of dispersal resulting from annual vegetation cover, is used to explain double-bounce dispersal. This term is generally overlooked in studies dealing with low levels of vegetation cover, even in the L-band [49,53,63], and is known to be particularly low at high incidence angles [10,11].

Equation (1) can then be simplified to [33]:

$$\sigma^0 = \sigma^0_{canopy} + \tau^2\sigma^0_{soil}$$

where $\tau^2 = exp(-2\ B\ V1\ sec\theta)$; and $\sigma^0_{canopy} = A\ V2\ cos\theta\left(1-\tau^2\right)$, and V1 e V2 they are parameters relating to vegetation

A and B are parameters that depend on the characteristics of the vegetation canopy. This formulation provides a first-order solution to the radiative transfer equation through a weak medium, in which multiple scattering is neglected. Parameters A and B are estimated empirically, using ground truth measurements and radar signals measured on vegetation covers. The most commonly used vegetation descriptors, which are mainly derived from optical data, include the satellite indices LAI and NDVI, which provide an accurate representation of the influence of vegetation on the total backscattering coefficient in the C band [20,24].

2. Soil Backscattering Models

To retrieve soil moisture, we need to combine the water cloud model with a backscattering, bare soil model to estimate the value of σ^0_{soil} defined in the previous equation.

(a) Dubois Model

Dubois et al. [32] proposed a semi-empirical model that estimates the co-polarized backscatter coefficient on bare ground, as a function of dielectric constant, incidence angle, RMS height and wavelength. In the present study, we only consider HH polarization

$$\sigma_{HH} = 10^{-2.75}\left(\frac{cos^{1.5}\theta}{sin^{5}\theta}\right)10^{0.028\varepsilon tan\theta}\lambda^{0.7}(ks\ sin\theta)^{1.4}$$

where k is the wavenumber, defined as 2π, λ is the wavelength of the radar signal, ε is the dielectric constant of the ground, and θ is the angle of incidence. The validity domain of the model is defined as: ks ≤ 2.5; mv <0.35 cm3 / cm3; and θ> 30◦.

(b) Baghdadi Model

Baghdadi et al. [33] proposed a modified version of the Dubois model, which is generalized to include the effects of cross-polarization and low incidence angles:

$$\sigma_{HH} = 10^{-1.287}(cos\theta)^{1.227}10^{0.009\ cotan(\theta)\ mv}(ks)^{0.86\ sin(\theta)}$$

$$\sigma_{HV} = 10^{-2.325}(cos\theta)^{-0.01}10^{0.011\ cotan(\theta)\ mv}(ks)^{0.44\ sin(\theta)}$$

where θ is expressed in radians and mv is in vol.%.

3, Statistical Parameters

In the present study, statistical analyzes are applied, using two quality measures: Pearson correlation and RMSE (root mean square error).

The Pearson correlation is defined by

$$R = \frac{\sum_{i=1}^{N}(x_i-\overline{x})(y_i-\overline{y})}{\sqrt{\sum_{i=1}^{N}(x_i-\overline{x})^2}\sqrt{\sum_{i=1}^{N}(y_i-\overline{y})^2}}$$

where xi and yi are individual samples taken at points indexed with the variable i, N is the number of samples, x is the mean of the samples xi, and y is the mean of the samples yi.

RMSE (root mean square error)

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i-O_i)^2}$$

where N is the number of data samples, Pi is the predicted value of sample i, and Oi is the measured value of sample i.

The data is checked to ensure that it follows a normal distribution and for its meaning before any analysis. Simulated soil moisture (SM) values were compared with in situ measurements and the validity of each simulation was assessed using RMSE.

Optical data elaboration

COPERNICUS constellation

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- High revisit: every 5 days at the equator under the same viewing conditions with 2 satellites;
- high spatial resolution: 10m, 20m and 60m;
- Multi-spectral information with 13 bands in the visible, near-infrared and short-wave infrared part of the spectrum;
- Wide field of view: 290 km.

Data from Sentinel-2 is openly and freely available to all users with easy online access to ESA's “Copernicus Open Access Hub (https://scihub.copernicus.eu/”) or “Copernicus Online Data Access” portal (https://www.copernicus.eu/en/access-data) from EUMETSAT, depending on the type of data

Metodologies

The revolutionary innovation behind the SMART FARMING project is the new approach. The farmer, agronomist and field technician need real-time information. SMART FARMING in a 3-click process interface can directly produce the map in the right format for the farmer. The heart of the system is the "set of algorithms" developed by IPTSAT in collaboration with CREA, the Italian national council for agricultural research, the most important research center in the agricultural sector in Italy. The algorithm is derived from a combination of four existing indices, which allows the simultaneous production of 4 types of maps, i.e.

- Vigor Map,
- Chlorophyll & Fertilizer Map,
- Biomass Map,
- Hydro & Water Thick Map.

This represents one of the biggest innovations of the project and a clear market barrier for potential competitors, as there are no similar algorithms on the market capable of working simultaneously on 4 types of maps.

This feature makes the SMART FARMING solution faster than currently used solutions and capable of satisfying multiple requests at the same time. Furthermore, the innovative algorithm requires fewer computing resources, reducing costs related to the operational activities of the services.

The combination of the four algorithms:

- A modified NDVI index (normalized difference vegetation index) which outputs a VIGOR MAP
- A modified NAOC index (normalized area above the reflectance curve) which outputs a HYDRO MAP

- A modified MCARI 2 index (modified chlorophyll absorption ratio) - which outputs a CHLOROPHYL MAP
- A modified MTVI 2 index (modified transformed vegetation index) which provides as output a BIOMASS MAP.

Below is a description of the changes that have been made, also explaining the best effects that the algorithm will have:

A modified NDVI index - which outputs a VIGOR MAP: a generic normalized difference vegetation index (NDVI) has been specifically adapted to the Sentinel 2 bands, following specific interest in the context of agricultural remote sensing applications for Monitor 4 bands of “Sentinel 2” in the visible edge, infrared and red (B4 665 nm RED and B8 NIR 842 nm).

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

A modified NAOC which outputs a HYDRO MAP: also in this case the NAOC index has been specifically adapted to the Sentinel 2 bands:

$$\mathrm{NAOC} = 1 - \frac{\int_a^b \mathrm{R} \cdot d\lambda}{\mathrm{R_b}(\mathrm{b} - \mathrm{a})}$$

(λ is the wavelength, Rb is the maximum far-red reflectance, corresponding to the reflectance at wavelength b, and a and b are the integration limits surrounding the chlorophyll absorption centered at 70670 nm). The results were in close agreement with those calculated from the in situ analysis. Both NDVI and NAOC open up opportunities to deploy into Sentinel 2 data processing operations chains to deliver high-level products such as green LAI and canopy chlorophyll.

A modified MCARI 2 - which outputs a CHLOROPHYL MAP: A modified MCARI 2 - which outputs a CHLOROPHYL MAP: The general idea behind these modifications was to make the MCARI index less sensitive to chlorophyll effects, more sensitive to green LAI variations, and more resistant to soil and soil effects. of the atmosphere to have more standardized data. For this reason, MCARI has been modified as follows: the suppression of the ratio (R700 / R670) in order to reduce the sensitivity to the effects of chlorophyll and the integration of a near-infrared wavelength to increase the sensitivity to LAI changes. Consequently, Eq. of MCARI was simplified and a variant of MCARI was obtained and denoted MCARI1. It is worded as**;**

$$\mathrm{MCARI1} = 1.2[2.5(R_{800} - R_{670}) - 1.3(R_{800} - R_{550})]$$

A modified MTVI 2 - which outputs a BIOMASS MAP: regarding TVI, the transformation is based on the fact that increasing the chlorophyll concentration causes a red shift of the red edge reflections, introducing changes in the reflectance at 750 nm which represents the beginning of the infrared shoulder. To make TVI suitable for LAI (leaf area index) estimates, the 750 nm wavelength was replaced by the 800 nm wavelength, whose reflectance is affected by changes in leaf and canopy structures and is insensitive to changes in pigment level. This means that the area information will not be affected by the change in pigment level, but only by the change in size. By applying a scaling factor, a modified TVI (denoted MTVI1) was defined based on:

$$\mathrm{MTVI1} = 1.2[1.2(R_{800} - R_{550}) - 2.5(R_{670} - R_{550})]$$

To reduce the effects of soil contamination, a soil adjustment factor was incorporated, using the concept developed by Huete (1988). This term was optimized with the constraint of preserving sensitivity to LAI and resistance to the influence of chlorophyll. As a result, improved versions of MCARI and TVI were formulated as:

$$\mathrm{MCARI2} = \frac{1.5[2.5(R_{800} - R_{670}) - 1.3(R_{800} - R_{550})]}{\sqrt{(2R_{800}+1)^2 - (6R_{800} - 5\sqrt{R_{670}}) - 0.5}} \qquad \mathrm{MTVI2} = \frac{1.5[1.2(R_{800} - R_{550}) - 2.5(R_{670} - R_{550})]}{\sqrt{(2R_{800}+1)^2 - (6R_{800} - 5\sqrt{R_{670}}) - 0.5}}$$

The four algorithms are able to work simultaneously, simultaneously providing the 4 maps below:

I. **Vigor map:** vigor maps are based on the NDVI (Normalized Difference Index) and show differences in plant vigor; this allows us to evaluate their vegetative health, highlighting possible critical problems due to lack of nutrition, presence of parasitic infections or hydro-stress. The early diagnosis of these insurrections allows targeted, effective and cost-saving intervention, with greater harvest efficiency. It allows you to detect problems that arise in the observed area, before they are visible to the naked eye.

II. **Chlorophyll and fertilizer map:** the chlorophyll map is a qualitative map based on the MCARI2 index, strongly correlated with the concentration of chlorophyll in plants. Crop yields depend on an adequate supply of nitrogen (N), therefore knowledge of this component state represents an important factor for agricultural management. The chlorophyll map shows the nutritional needs of plantations, allowing corrective interventions to improve crop management. The Chlorophyll Map service includes the fertilizer map. It is a quantitative map based on a correlation abacus derived from the relationships between vegetation indices and relevant field data. It allows you to manage the optimal supply of fertilizers. This possibility is a key factor for precision agriculture. In fact, nitrogen-based fertilizers represent a significant cost for many crops such as corn, rice and wheat. The fertilizer map improves targeted fertilization, adapting the supply to the soil fertility at each point of the parcel, as detected by the VRT technique through the ISOBUS standard (for agricultural device communication protocol).

III. **Biomass map:** the biomass map is a quantitative map based on a cross-reference vegetation index (MTVI 2) which allows the energy potential of plant biomass to be assessed and therefore to support the management and use of the agro-forestry biomass produced for nutrition.

IV. **Hydro & Water Thick Map:** the Hydro Map is a qualitative map based on multiple vegetation indices (NAOC, LAI and NDWI) and which allows you to analyze the water stress of plants, allowing you to limit the damage caused by the lack of water in the soil, whether temporary or extensive. The hydroelectric map is essential for correct technical-economic planning of agricultural resources. It can help both to understand in which area different cultures can find the best environmental conditions in terms of natural water supply, and to optimize procedures and tools for irrigation activities in the field.

RESULTS

Decision Support System

The Decision Support system in SMART FARMING aims to make available to public administrations or private organizations that operate on their behalf, a series of easy-to-use and consult functions to better manage the activities of:

- Planning of agricultural water use operations
- Planning of fertilizer use
- Planning of use of pesticides

The complexity of the problems to be treated requires a multidisciplinary approach based on multi-criteria techniques. Multi-criteria techniques were developed to help decision makers explore and solve problems that experience “competition between multiple and conflicting objectives”

To support the various analysis, prediction and simulation processes, MCE (Multi Criterial Evaluation) techniques have been integrated into an SDSS by creating a Multi Criterial SDSS (MC-SDSS)

The use of an expert system, i.e. a system capable of simulating the behavior of an expert on specific topics, also through the use of inferential rules, has been integrated with an MC-SDSS, to obtain an MC-ESDSS (Multi Criterial Expert Spatial Decision Support System). Decisions are supported by the processing of both SAR data and optical data.

The types of data processed, for the operational purposes of the Decision Support System, are the following:

SAR images in L band

- simultaneous soil measurements of soil moisture,
- Soil roughness and were also recorded
- recording of the leaf area index (LAI).

Optical Images

Optical images are used to:

I. Measurement of vigor: of cultures
II. Measuring the amount of chlorophyll and fertilizers:
III. Biomass measurement:
IV. Measurement of fin water stress (lack of water)

The prototype is published on the Microsoft Azure platform. Azure is the cloud platform created by Microsoft to enable organizations to create, deploy and manage services and solutions that previously required investments and installations in on-premises services and infrastructure.

Using cloud-based services means being able to promptly size the resources you need with total flexibility and scalability. An A3 virtual machine was configured (4 cores, 7GB RAM, 120 GB Hard Disk). The machine is installed with the Linux Ubuntu 64 bit operating system, an operating system designed to provide an enterprise-class platform for professional uses.

<u>Details on sonftware and technologies adopted:</u>

Spring; Spring is an open source framework for developing enterprise applications using Java. The framework provides numerous modules, each of which provides a range of services to facilitate application development. For example Spring MVC for the development of web applications using the MVC pattern, Spring Data for communication with databases, Spring Security for managing security and authentication procedures.

PostGis; PostGIS adds geographic object support to PostgreSQL. PostGIS makes the PostgreSQL server spatial through the use of geographic coordinates, allowing it to be used as a backend in GIS (Geographic Information Systems), as ESRI's SDE or Oracle's Spatial extension also do. PostGIS is OGC standard and follows the 'Simple Features Specification for SQL'. It was developed by Refractions Research as an open source spatial database project. It is released under the GNU General Public License.

GeoServer; GeoServer is an Open Source GeoSpatial server written in Java, following common Java Enterprise practices, for the management, dissemination and analysis of geospatial data. GeoServer allows you to distribute, manipulate and analyze data using the most popular OGC standards (WMS, WFS, WCS, WPS), without forgetting specific extensions for transparent interaction with clients such as Google Earth and commercial software in general, nor the now widespread approaches based on REST and GeoJSON protocols for the simplified distribution of simple vector data.

OpenLayers; OpenLayers is an Open Source JavaScript library for displaying interactive maps in web browsers. OpenLayers offers an API to programmers to access various sources of cartographic information on the Internet such as: Web Map Service, commercial maps (Google Maps, Bing, Yahoo), Web Feature Service, various vector formats, maps from the OpenStreetMap project , etc.

Bootstrap; Bootstrap can rightly be considered the king of frameworks for the development of Web interfaces and the de facto standard as a starting point in areas such as the creation of pre-packaged HTML templates and themes for the main CMS, especially from a responsive perspective.

In the following figure. the functional diagram of the SMAR FARMING 4.0 solution is shown. a) shows the technological elements that make up the MC-SEDSS while b) shows the logical infrastructure of the MC-SDSS and the data flows between all the components of the architecture.

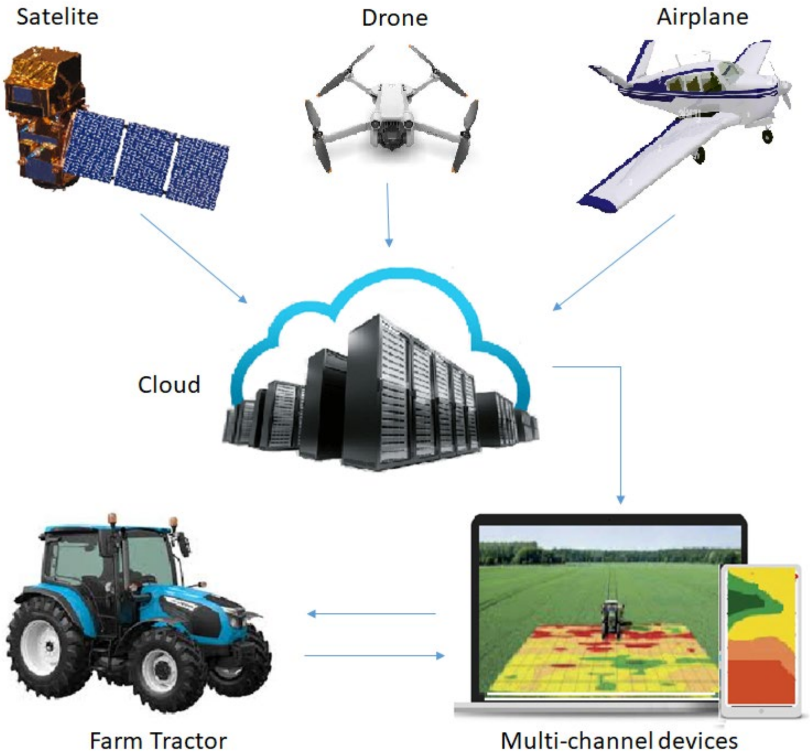

Figure x -Functional diagram of the DSS

The processing unit of the solution consists of four main components:

- the database with Postgis geographic extensions
- the webgis Geoserver geographic services server

- a software layer that provides services for geoscientific analyzes (Saga gis + Matlab)
- the Spring web application for the presentation of content in a responsive perspective

The system with the type of architecture being implemented allows:

- the one hand to integrate heterogeneous spatial and non-spatial data and georeference them on GIS maps
- the other hand to manage and provide answers to end user queries ((farmers, agronomists, etc..)

Elements of innovativeness compared to other similar proposals

- Combined and integrated use of L-band SAR sensor data with optical sensor data
- possibility of 24/7 monitoring, regardless of climatic conditions,
- use of free data Sentinel 2 A and B of the Copernicus constellation,
- use SAOCOM 1A and -1B data, and (PALSAR / ALOS) 2,
- possibility of low-cost service to have updates available on a weekly (or other) basis,
- automatic updating of raw data (observation maps) and processed data (informative/thematic maps) based on the availability of new satellite data,
- Easy use of the platform for consultation, planning and operational support of activities (decision support),
- provision of the service on multi-channel technology with the possibility of using it with your own snart phone. tablet, desktop and be supported in various operational activities to increase company productivity,
- improvement of product quality,
- better use of the territory,
- reduction of environmental impact.

CONCLUSIONS

The solution introduced represents a valid example of integrated use of technologies and scientific methods for sustainable management of Precision Farming projects for SMEs.

Optical and SAR (L-band) satellite imagery is used to help farmers monitor and manage crops from seed to harvest. SMART FARMING includes identifying soil irrigation status, determining chlorophyll strength, monitoring plant diseases, and supporting farmers in evaluating and optimizing agricultural treatments. We have implemented a DSS integrated with a WebGis to provide at low cost various services for the PF to SME, guaranteeing an automatic periodic update of satellite.

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