

GIS, Remote Sensing, and Forecasting Systems for Precision Agriculture Development

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Abstract. Precision Agriculture (PA) primarily aims to maximize productivity while reducing impacts on the environment. This is made possible thanks to the implementation of advanced land monitoring technologies, such as GIS (Geographic Information Systems), together with other data generators in all phases of agricultural operations, from cultivation to storage. With the aim of contributing to the evolution of this field of research, this article describes an integrated system capable of managing information on climatic variables coming from an innovative and experimental atmospheric simulator and on parameters indicating the state of vegetation obtained through Remote Sensing and UAV techniques. All this to collect all the necessary information in a GIS implemented for the automation of an agricultural vehicle and a drone equipped for fertilization. The innovation of the present research consists precisely in the atmospheric simulator which, exploiting the SPH model (Smooth Particles Hydrodynamic) for the interaction of the atmosphere particles, taking as input the DEM (Digital Elevation Model) of the area under study and the historical data of meteorological stations contained in it, returns as output a punctual distribution of some atmospheric variables fundamental for precision agriculture, such as rain and wind from which the three-dimensional trend can be obtained. These parameters, together with in loco sensors' data, are therefore fundamental for planning the action of both agricultural vehicles and drones and for making the production process more efficient. The operation of this system was tested on an area in the province of Reggio Calabria.

Keywords: Precision Agriculture · Atmospheric Simulator · atmospheric Variables · Smooth Particles Hydrodynamic · Digital Elevation Model · Geographic Information Systems

1 Introduction

Precision agriculture uses sophisticated technologies through which it is possible to optimize available resources, reduce consumption and maximize production by analyzing the data and information acquired through advanced tools and technologies [1, 2].

In the field of precision agriculture, resource management and agricultural vehicles automation are certainly two key aspects to increase productivity, accelerate agricultural operations (from production to storage) and reduce waste. In this sense, GIS can

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constitute a fundamental tool in precision agriculture, acting as a container for all that information useful for the management of production processes and more. Within the GIS, in fact, it is possible to manage data of different nature and it is possible to implement appropriate specific algorithms depending on the desired objectives [3–6].

In this context, the present work exploits GIS technology with a dual purpose: to optimize agricultural operations through the management of heterogeneous data and to automate an agricultural vehicle and a drone appropriately equipped to support production processes. The particularly innovative aspect of this article is the inclusion in the GIS of data coming from an innovative and experimental simulator prototype, which, taking as input the DEM (Digital Elevation Model) of the study area and the historical data of meteorological stations, through an SPH model (Smoothed Particles Hydrodynamics) which governs the interaction of particles, manages to provide a precise distribution of atmospheric variables such as precipitations and wind. In essence, the simulator replicates the dynamics of the Earth's atmosphere concerning weather patterns. It models the changes in the state of discrete atmospheric particles and illustrates how these particles interact with one another.

The parameters of the atmospheric simulator together with those of in loco sensors, appropriately analyzed by an open-source GIS implemented by the authors, will then be used to plan, and to visualize the route of an agricultural vehicle used for irrigation and a drone equipped for fertilization.

These data together with a series of on-site sensors, such as soil moisture sensor, leaf wetness sensor, pH sensor and temperature and humidity sensor, were analyzed and evaluated together with vegetation indices including the NDVI (Normalized Difference Vegetation Index), the LST (Land Surface Temperature) and the NDMI (Normalized Difference Moisture Index) calculated using World-View 3 and drone images [7, 8]. From the analysis and evaluation of these parameters, using geoprocessing and analysis tools of the GIS, the areas that needed irrigation and fertilization were evaluated. Subsequently, using an appropriate plugin, the route of the tractor and drone was calculated and subsequently transmitted through the Cannelloni software, written in C++ and capable of transferring CAN frame between two machines using UDP (User Datagram Protocol) or SCTP (Stream Control Transmission Protocol). In particular, data flows transmitted by the GIS also included information in relation to the irrigation and fertilization needs of the area [9, 10]. The integrated system was tested in an area situated in the south of Calabria (Italy).

The main and specific objectives of this paper are to analyze GIS technology in the field of precision agriculture, optimize the efficiency and accuracy of agricultural operations through automated agricultural vehicles and drones, and implement a comprehensive workflow that integrates the planning of agricultural vehicles and drones based on the analysis results. The proposed system could be useful for farmers and agricultural companies to optimize resource usage, reduce costs, and maximize production by improving operational efficiency and promoting sustainable agricultural practices while reducing environmental impact.

2 Materials and Methods

During experiments, were employed various systems, algorithms, and structured and integrated techniques (cited in greater depth in Fig. 1) to determine locations that best fit the various conceivable typologies of cultivations and to plan the itineraries of both self-driving tractors and UAVs. Thoroughly, we used: QGIS software (an open-source GIS), an innovational and developmental atmospheric simulator, satellite images, UAV images, in loco sensors, specific algorithms and protocols for data transmission.

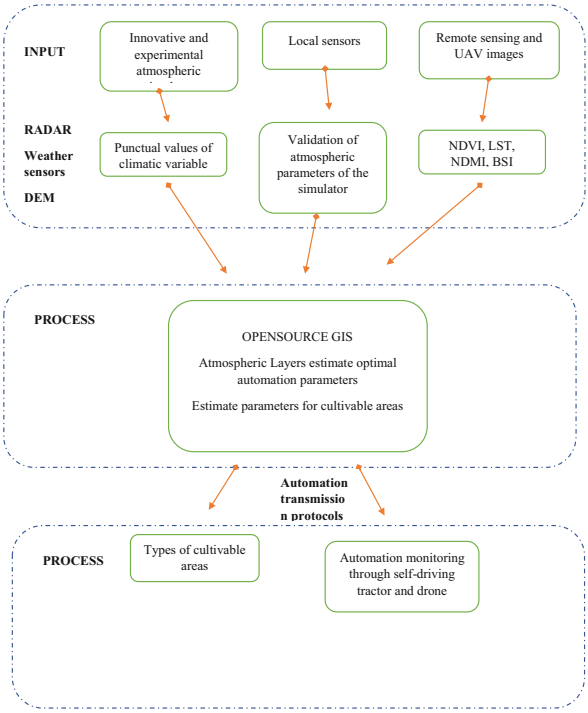

Fig. 1. A flowchart developed within the context of Precision Agriculture concept illustrates the methodological framework and the various integrated systems, algorithms, and methodologies designed to identify optimal areas for different types of crops and to strategize the most efficient routes for both autonomous tractors and UAVs.

First of all, the atmospheric simulator, which utilizes as input data the DEM (Digital elevation Model) territory, weather sensors data, radar data and large-scale weather models, is used for the production, as outputs, of the punctual measurements of typical meteorological variables such as: pressure, temperature, wind and precipitation; these values were then reprocessed to produce DEM layers of these variables. The previously meteorological variables are crucial for the so-called Precision Agriculture due to their direct influence on environmental conditions and consequently on crops. Precipitations are essential as they represent source of water for the plants; wind can influence plant development and can also spread diseases; information about imminent climatic changes

are supplied by atmospheric pressure, lastly, temperatures impact plant growth and maturation. The results confirmation was obtained combining different ground truth devices such as: local sensors (soil and leaf moisture sensors, pH sensors, wetness and temperature sensors, barometric pressure sensor) applying wireless sensor network nodes (WSNn). This network was assisted with the ZigBee protocol, an ATmega128L microcontroller, and a solar cell module with the purpose of transfer the collected sensor data to cloud server. With the application of data fusion methodology [11], was possible to combine satellite and UAV data and images obtaining significant indicators that can show the vegetation health and soil differences; these indices are:

- NDVI (Normalized Difference Vegetation Index).
- NDMI (Normalized Difference Moisture Index).
- LST (Land Surface Temperature).
- BSI (Bare Soil Index).

These indices have been chosen among the many available because they are the most significant, commonly used, and indicative for the analysis conducted. Through the combination and analysis of all this data in an open-source GIS, it was possible to evaluate the most suitable areas for cultivation and for the automation of tractors and drones.

In particular, the following materials and methods were used.

As regards satellite images, Sentinel-2, level 2A and WorldView-3 satellite images were used. From Sentinel-2 level 2A the processing involves a scenery classification and atmospheric correction related to a TOA (Top Of Atmosphere) level-1C orthophoto. The principal output from level 2A is an orthophoto BOA (Bottom Of atmosphere) corrected reflectance product.

WorldView-3 can acquire: panchromatic images at 31 cm, multispectral at 1.24 m, shortwave infrared images at 3,7 m and CAVIS (clouds, aerosols, vapors, ice and snow) at 30 m.

Concerning UAV images, a DJI Matrice 600 Pro was equipped with a Micasense Altum Camera to capture multispectral photos. This camera is suited to be used in agricultural environment because can collect crop's photos in visible and infrared wavelengths, simultaneously. The height of fly was about 30 m above the ground, obtaining so aerial GSD photo with a resolution of 5 cm.

Thanks to a range of sensors on board UAVs, real-time information may now be gathered in numerous application domains. Large volumes of data, including as photographs, are received by these flight objects; therefore, clever algorithms that can process and transform various data kinds into meaningful and succinct information must be introduced. The current approach to address this issue is the use of multiple sensor data fusions that can process data from high-resolution satellite imagery at frequent revisit times in addition to data from UAVs. So, UAVs are used to obtain periodic data, while the combination of satellites preserves a good spatial resolution in the observation area. UAVs and satellites data are not used in contemporary; the purpose is to merge these data through data fusion techniques, gathering so the images necessary to calculate the required agricultural indices, keeping in mind the pro and the cons deriving from UAVs and satellite data sources (cloud dependence, meteorological constraint, payload, data management).

This kind of data fusion strategy (spatial and spectral) wants to generate datasets with improved features, fusing one or more resolution from each source. This strategy, developed to tear out the characteristics of land and vegetation cover, at high resolution, is not often used in fields such as agriculture. This kind of data fusion offers several advantages such as: better spatial and temporal resolution, more customization possibility and more detailed and understandable information. Despite this, there are also some disadvantages: drone coverage is more limited compared to satellite, the costs are higher, the logistic is more complexed, and there are restrictions connected with the weather conditions. Specifically, the fusion spatial-spectral technique helps to increase the accuracy of land cover categorization and the spectral resolution of inexpensive UAV sensor data. When data are gathered over both space and time, they are analyzed using a spatiotemporal framework. It explains a phenomenon that occurred at a specific location and time. Some biophysical crop's indices, like leaf area index and chlorophyll content, can be obtained using the spatial-temporal fusion method, which also build a reliable prediction with fine spatial patterns. The image's spectral resolution consists in the frequency of the electromagnetic spectrum, observed by the satellite. Due to this spectral quality, is also possible to see various features as distinct entities. The temporal resolution of an image consists in the time required to return and to re-collect data for the same place. From the fusion spatial-temporal approach is possible to achieve information in multispectral satellite data with hyperspectral data from a UAV. The results acquired allow to obtain the required biophysical variables. Lastly, because of the structural features acquired from UAVs and the satellite-based spectrum characteristics gained from satellites, the satellite/UAV data fusion enhanced the model's performance when compared to data obtained separately from satellite or UAV.

Significant vegetation indices, derived through remote sensing techniques, serve as valuable tools for gathering information about vegetation characteristics. Optical sensors, including multispectral and hyperspectral systems, are utilized to collect this type of data. Key agricultural indices such as NDVI, NDMI, and BSI can be analyzed using this data. For this study, images were acquired from the Sentinel-2 satellite, which features a spatial resolution of around ten meters and revisits the same area every six days. Additionally, UAV images were captured concurrently, offering higher resolution and finer detail within canopy areas. Sentinel-2 Level 2A images were obtained on four different dates: June 16th, July 13th, August 17th, and September 14th. Furthermore, a WorldView-3 satellite image captured on November 17th, 2022, was included. WorldView-3 satellite images are recognized for their exceptional detail and precision, with a spatial resolution of approximately 30 cm per pixel. This allows for the identification of small objects on the Earth's surface.

The multispectral images were captured by DJI Matrice 600 Pro drone (SZ DJI Technology Co. Ltd., Shenzhen, China), equipped with a Micasense Altum Camera (AgEagle Aerial System Inc., Kansas, USA) which can capture images of crops in both visible and invisible spectra simultaneously, being so adapt for agricultural purpose. The drone's fly height was approximately 30 m above the ground, with an aerial GSD with a resolution of 5 cm.

The principal innovation of this study is the utilization of an atmospheric simulator [12] which, combining DEM, radar and sensor data, supplies climatic information related

to territory orography. This study describes the operation of an atmospheric simulator capable to produce high-detail weather fields outputs in a delimited area. The simulator can produce outputs for several atmospheric variables (i.e., wind, temperature, humidity, etc.) for a cubic cell of 50 m, even with few inputs. The microphysics of the simulator's atmosphere is regulated by laws governing the interaction of a number of particles with which the atmosphere has been discretized. The latter, indeed, comprises a collection of particles housed at the core of a cube (cells). Each particle encapsulates a distinct amount of gas, water, and humidity, determining its mass exchanges and interactions with other particles and the surrounding environment These particles experience a force derived from their energy state, interactions with other particles, or contact with surfaces. Basically, the simulator reproduces the conduct if Earth's atmosphere in relation to weather trends and describes the changes of the particles, whit which atmosphere was discretized, and the interaction whit each other. The simulator includes two solvers, called L1 and L2, which work simultaneously and face task at higher level. These solvers convert vertical exchange and troposphere processes into a particle model [13] of the atmosphere. Solver L1 performs several tasks, such as: attributing both physical and chemical properties to the particles, applying, in relation to their energy state, force to the particles, designing the particles and environmental objects initial condition, partitioning the 3D environment into macro-cluster, and offering individually identifiable forecast field for each. In Solver L1 we can also input real time data and hypothetical values. Solver L2, which is a Newtonian simulator utilizes the features of the SPH (smoothed particle hydrodynamic) software library (developed by Nvidia and technology is called "Nvidia PhysX"), which is developed to reliably simulate fluids or gasses down to a few hundred meters. This Solver, introduces the forces assigned to the particle by the previous solver and starts, using SPH fluid rules (based on PhysX) the dynamic development. For example, when cells locally overlap at time t, repulsive forces are activated based on specified parameters (viscosity, friction, mass, partial compressibility). In a 3D setting, this mechanism delineates wind patterns, encompassing intricate turbulence characterization and confined pressure fluctuations. This approach excels particularly in topographically intricate regions, such as the Apennines, where controlling sudden altitude changes using traditional Numerical Weather Prediction (NWP) methods proves challenging. The initialization process of SolverL2 entails assessing an ASCII DEM representing the orographic layout of the simulation area. Particles are uniformly distributed within the environment and evolve until they reach a state of stability. Following the processing of initial conditions derived from sensor or radar data, Solver L1 directs the allocation of forces, velocities, and positions within specific spatial volumes to Solver L2. Subsequently, after adhering to these directives for a predetermined duration, L2 progresses. Upon the completion of the evolution, Solver L1 is informed of the updated state of the particles, encompassing their position, velocity, density, and alterations from the initial state. Then, using the attributes provided by L2, Solver L1 correlates particle properties with atmospheric state-related attributes such as temperature and humidity. The pattern detector, a component of L1, forms groupings with consistent atmospheric features, including cloud cover, precipitation, humidity, mean temperature, and pressure, based on the information supplied by Solver L2. The results identified as clusters represent the output generated by the simulator.

The study used five types of sensors to assess key parameters: soil moisture sensor, leaf moisture sensors, pH sensor, humidity and temperature sensors, and a barometric sensor. In today's era of modern technology and the advent of precision agriculture, these advanced sensors enable farmers to optimize crop yields while minimizing the consumption of essential resources such as fertilizer, water, and agrochemicals. With the deployment of these new and more efficient sensors at ground level, farmers can obtain detailed insights into crop growth, leading to resource conservation and reduced environmental impact, [14–17]. The modern agricultural is based on several chemical and physical analysis and this is achievable considering sensors and IoT networks. According to this idea, the use of sensors in agriculture is mainly used to evaluate characteristics in soil, plants water and air. A sensor is a transducer developed to convert a physical quantity into another, often an electrical signal. This one must satisfy the requirements like operates at microscale. About the communication of the local sensors, WSNs [18–23] communicate through their radio modules. Two or more modules are directly connected if they can send and receive data from each other. The final outcome is a network that is capable of transmitting and receiving data, collecting a lot of data in the process. The advantage of WSNs is represented by the wireless connection. Nowadays, WSNs are a viable solution to improve quality and quantity in agricultural. The primary components of a sensor node are its sensing, storage, processing, and communication capabilities. A number of sensors that support this WSN are included, including an ATmega128L microcontroller, temperature, humidity, rain, leaf wetness, and ZigBee protocol [24, 25]. Intelligent IoT-based agriculture relies heavily on communication protocols that can be used over short or long distances for smart farming. For short-range applications, wireless technologies such as Wi-Fi and ZigBee are utilized in agriculture; for long-range applications, mobile communication networks, Bluetooth, long-range wireless area networks (LoRaWAN), and LPWAN protocols are employed. Regarding microcontrollers, the most used in agriculture, due to its ability to support multi-level data aggregation, low complexity, storage capabilities, energy management and flash memory, is ATmega128L nodes. Conventionally, batteries, which are limited in size and capacity, affect the lifespan of WSNs. Actual solutions consist in a combination of ultra-low-power nodes and energy harvesting techniques, making so a WSNs perpetually operative. Moreover, there are two special nodes-called sink-that will be added when there will be the necessity to communicate with an external network. This node transfers all information to the cloud platform. The low-power ZigBee wireless protocol is adopted from all sensors, sink and actuator nodes. Finally, the data gained from sensor and governed by actuators are subsequently sent by gateway to cloud computing and will be processed and stored. The aim of the gateway is to collect information and pass it to the cloud server [26–37].

The data collected by sensors and drones are subsequently processed, analyzed in a cloud data repository through a communication link. The real time data transferring to the cloud platform is achievable by the common communications protocols between sensors/UAVs and operators. Generally, drones for agricultural use have a flight height under 120 m and use a Wi-Fi with a range between 3 of 7 km, if drone is equipped with a large transmitting antenna. Instead, the use of 4G network link mitigate the distance related problem, so the drone is allowed to fly several kilometers away from the operator. The 5G mobile network is suited to support low-flying drone communications

and improve the safety and security of drone operations, hence extending the range of UAVs. Furthermore, the use of 5G networks allows the reception of several kinds of data in real time and in a faster and seamlessly way, compared to the previously mobile network. Drones do not need to have very powerful processors because 5G technology makes it possible to send all data to the cloud for quicker processing. The actual cellular technologies are essential in IoT devices development. The actual LTE (long-term evolution) capabilities have given rise to a new IoT system protocol the NB-IoT (narrow-band-IoT), which can use the same device, share the LTE frequency band without causing coexistence issues, and connect to the LTE main network with ease. NB-IoT characteristics are: large coverage area, longer battery life (up to almost 10 years), great network size (up to 52000 devices/channel/cell) and low-cost devices. Due to their low power consumption, NB-IoT technologies like LoRa (long-range radio) will soon be the dominant method of delivering agricultural data over vast distances. Using a point-to-point Zigbee network can extend the communication range up to 100 m in an outdoor environment; Zigbee's range could also been elongated using a specific distributed and mesh network typology. Furthermore, UAVs can also function as a mobile router node that can enlarge the communication range of the smart farm. Drones can transmit the acquired data from sensors to a master nodes, using a multi-hop [38–43]. The GIS processed all this data, estimating the ideal automation parameters and those associated with cultivable areas. In detail, the following algorithms were employed to determine the cultivable areas: Spatial data analysis algorithms (especially buffering, intersection, overlay, clustering analysis) are usable to recognize areas of interests, estimating the nearness of the different data sources (sensors, climatic and DEM) and performing comparative tests among distinct areas. Raster analysis algorithms to tear out information from raster data (i.e., DEM and NDVI) by calculating terrain data and distinguishing slope or elevated area that are more suitable for specific crops. Supervised classification algorithms, like Random Forest (RF), Support vector machine (SVM) and Neural network, to classify image, to find crop typology and to construct a forecast model. These algorithms can be installed and utilized within the QGIS environment as extra extensions or plugins. About the algorithms used suited for tractor automation, in QGIS are present several tools and algorithms able to perform tracking analysis and planning, the software also admits the exploit of additional plugins and the incorporation of other libraries and instruments which provides better features related to route optimization. In detail, the plugins used to achieve this advanced tracking analysis in QGIS were "NAI (Network Analysis Library)" and "PgRouting." These instrument offers, evaluating several variables such as: speed limits, obstacles, and particular option, to calculate the optimal itinerary. The output variables used to determine the cultivable fields are: crop classification map, crop suitability evaluation, evaluation of environmental characteristic, evaluation report and tabular output data. The map related to the cultures was obtained using supervised and unsupervised algorithms and allows to allocate the most suitable crop for each portion of the study area. Combining the various type of data [44–48] (Climatic, sensor, DEM and NDVI) was created a crop appropriateness evaluation and an analysis of the environmental characteristics of the study area [49–52]. In the evaluation report were presents several information such as: indices of crop fitness, characteristics of the prevailing crops and of the environment of the study area and other knowledge to

determine the cultivation of the area. Furthermore, in addition to maps and reports, data were also provided in tabular form, giving more detailed information.

For what concern the automation of the tractor, the output variables are:

- Real-time GPS coordinates,
- Operating routes: for increasing the efficiency of the operation,
- Speed regulation: to guarantee a safe and effective drive,
- Actuator control: to guarantee a smooth and accurate drive, in relation to the routes,
- Monitoring of ground state: to adjust the tractor's drive, take real-time choices and guarantee an optimal use of resources,
- Alert systems: to alarm operator/user in case of emergency,
- Performance monitoring.

3 Case Study

The research's study area is located in the municipality of Reggio Calabria (Calabria, South Italy), as shown in Fig. 2. The black circle shows the application area of the simulator, while the application of the entire methodology was focused in a zone near the Fiumara of Armo, always in Reggio Calabria, with an extent of 35 hectares. Several reasons lead to choose this area, in particular: it is a virgin area with no cultivation and little populated, so the GIS was allowed to detect the most indicated area for cultivation, the morphology is suitable for the simulator use, it is a small area and so it is possible to apply the entire proposed system.

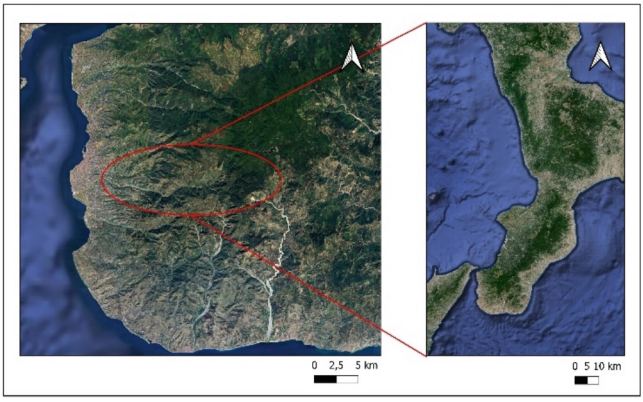

Fig. 2. Study area for the experimentation of the entire system. The area is located in the province of Reggio Calabria, south of Italy, is highlighted with a black line. The Image was extrapolated from QGIS, Google Satellite base map. (Color figure online)

4 Results

To pinpoint the regions more susceptible to adverse climatic events, we employed interpolation techniques to generate the three-dimensional map illustrated in Figs. 3 and 4. The occurrence of climatic events may vary depending on seasons and specific weather

conditions. Achieving precise predictions for adverse climatic events necessitates the utilization of local meteorological data. Consequently, we conducted an analysis of data obtained from local weather stations in Calabria, which were instrumental in the initialization phase of the simulator. The findings from this analysis indicate that, fundamentally, the most impacted areas in Calabria are those situated along the coast and in mountainous terrain.

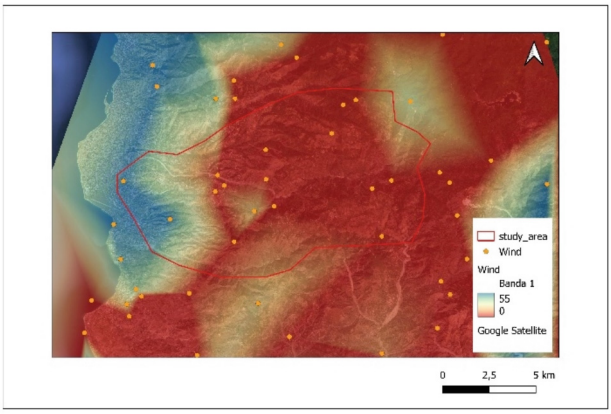

Fig. 3. GIS environment: three-dimensional distribution of wind values analyzed the Atmospheric Simulator values.

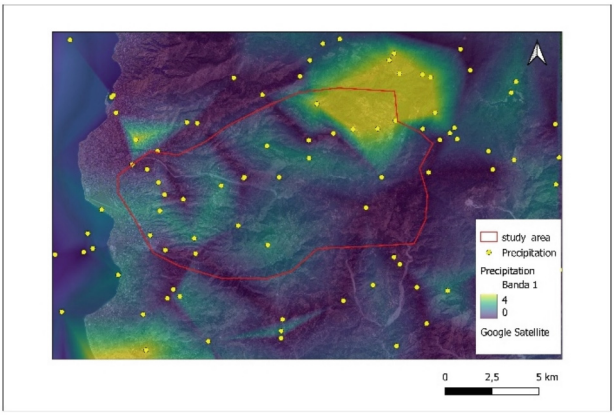

Fig. 4. GIS environment: three-dimensional distribution of precipitation values analyzed the Atmospheric Simulator values.

As regards the calculation of the different indices used, Fig. 5 shows an elaboration with "Raster Calculator" function in QGIS to obtain a crucial index, the NDVI (valuable for assessing vegetation richness) starting with multispectral images by drone. Figure 6 illustrates, instead, the application of a data fusion technique between UAV and satellite images, showcasing the calculation of NDVI using a Very High-Resolution (VHR)

image. Data fusion techniques allows for the integration of diverse data sources, such as satellite data and Unmanned Aerial Vehicle (UAV) images, to gather comprehensive information about an area and its cultivation needs.

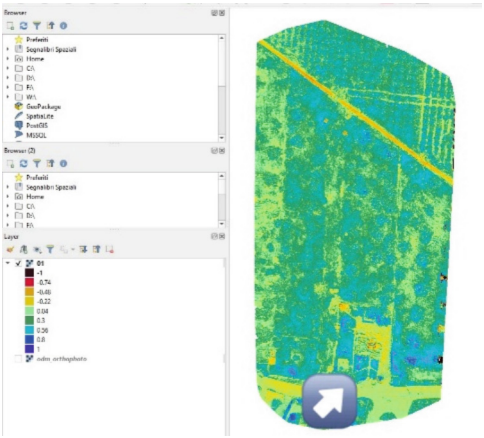

Fig. 5. GIS environment: NDVI calculation through "Raster Calculator" starting from multispectral images.

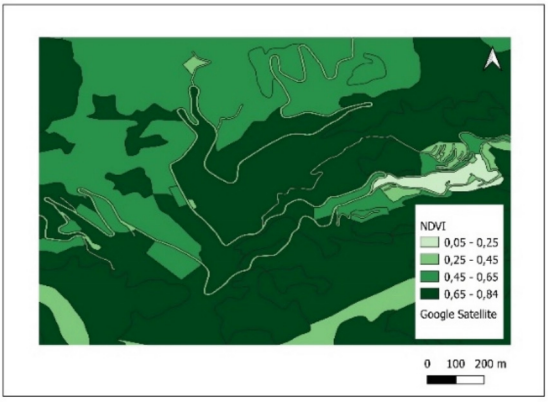

Fig. 6. GIS environment: application of data fusion technique between UAV and VHR image for the calculation of NDVI.

Upon aggregating data from various sources, open-source Geographic Information System (GIS) tools facilitated the identification of different cultivation areas based on climate parameters, sensor values, and indices derived from satellite and Unmanned Aerial Vehicle (UAV) images (including wind, soil type, soil moisture, NDVI, etc.). These areas, denoted by distinct capital letters (A, B, C, D, etc.), were categorized and grouped for ease of analysis according to parameters pertinent to specific crop types. In particular, the available dataset enabled the identification of three exclusive classes (A, B,

and C) in the study area, each represented by a distinct color. Class A (orange): designated for cultivation areas suitable for crops that do not require continuous irrigation. Class B (green): allocated for cultivation areas suitable for crops that necessitate continuous irrigation. Class C (yellow): earmarked for cultivation areas suitable for trees. Figure 7 visually depicts the distinct typologies of cultivation in these three categories.

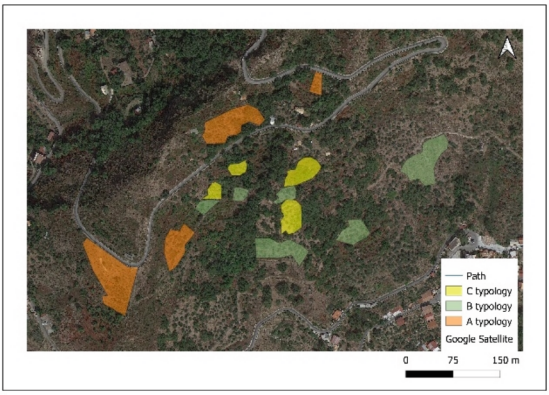

Fig. 7. GIS environment: representation of the three different typologies (A, B, C).

Ultimately, leveraging the methodology and algorithms detailed in paragraph 2, the Geographic Information System (GIS) facilitated the determination of routes for a drone tasked with monitoring existing crops and an automated tractor responsible for fertilization and irrigation. In Fig. 8, the drone's path within an existing crop is depicted by a blue line. It exemplifies the application of the methodology in selecting different cultivation typologies within a confined section of the study area.

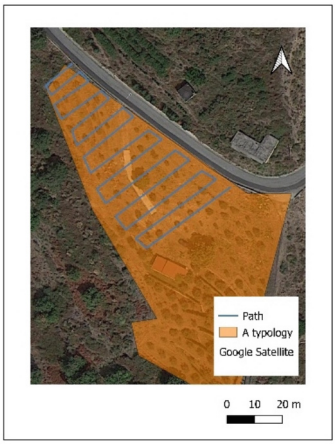

Fig. 8. GIS environment: drone's path highlighted with a blue line.

5 Discussion

The goal of this work's research was to test and experiment with an automated integration system for crop control and optimization. An experimental atmospheric simulator, UAV and satellite imagery, data from local sensors, data transmission methods, and an open-source GIS are all integrated into the process. The goal of the study was to categorize various farming practices and determine the best paths for a drone and an automated tractor to follow to track crop health and growth. A particular region in the province of Reggio Calabria was selected for the research because it was deemed suitable for the application of the many technologies discussed. In contrast to similar methodologies, this study presents various advantages and drawbacks. One significant strength is the comprehensive integration of multiple technologies, facilitating a holistic approach to Precision Agriculture. Our research enables precise optimization of fertilization and irrigation, offering deep insights into crop conditions. However, Precision Agriculture, encompassing our tested approach, also faces several challenges. The effectiveness of Precision Agriculture, including our proposed technique, depends on access to accurate and up-to-date data, as well as the necessary expertise for interpreting and effectively using the gathered data. Widespread adoption may also be hampered by the initial setup costs and the requirement for trained staff to run and maintain the system. Despite these inherent limitations of Precision Agriculture, this investigation provides insightful details about the sector's potential. To oversee crop well-being and refine irrigation techniques, it is exceedingly beneficial to amalgamate diverse technologies and data origins. It's evident that the authors prioritized the methodology over the results, retaining the option to scrutinize the data more deeply using various methods for the segmentation of the cultivable regions. Drones equipped with integrated technology hold promise for executing a range of functions, such as dispersing natural insecticides or fertilizers. These technologies encompass more intricate sensors. Indeed, industrial fertilizer manufacturing facilities still commonly employ evaporation and crystallization techniques.

This research progresses Precision Agriculture by showcasing the assimilation of various tools and approaches. The benefits of employing such integrated systems for precision agriculture outweigh the disadvantages, which necessitate attention. The findings underscore the significance of employing state-of-the-art technologies to streamline agricultural practices and pave the way for future advancements in more productive and environmentally sustainable farming techniques.

6 Conclusion

The advantages of the suggested and innovative system are obvious in terms of time savings, human resources, and productivity. Indeed, the automatization of some basic agricultural activities that are normally performed by people, saves time and money. Moreover, the possibility of evaluating different types of data on the condition of the soil and the health of the crops can increase productivity and quality and preserve a very precious resource, water, which is instead managed according to the weather variables provided by the simulator, which, with little input data, enables an evaluation of weather conditions. Furthermore, self-driving tractors already have a significant impact

on the agricultural industry, despite they are still recent technologies. With rapid improvements in technology, it seems probable that self-driving tractors will become increasingly common in the future, further changing the way farming is done.

This study applied different technologies to a particular region in the province of Reggio Calabria by taking advantage of the orographic and morphological features of the area. This illustrates how such approaches can be tailored to particular agricultural environments with the right planning and execution, optimizing the results. The primary goals of this research should be to expedite and optimize data processing and data transmission protocols; additionally, to validate and deploy these integrated systems on a large scale, as well as to potentially experiment with more productive and efficient algorithms. To facilitate the implementation of these innovative solutions that address the needs of various crops, environmental conditions, and farmer requirements, cooperation among research institutions, agricultural organizations, and farmers will be essential. The ultimate objective is to develop a sustainable farming strategy that benefits farmers, minimizes the impact on the environment, and makes effective use of the resources that are already available.

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