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Web-based spatial decision support system for precision agriculture: A tool for delineating dynamic management unit zones (MUZs)

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ABSTRACT

Precision agriculture (PA) is a farming management concept that aims to provide agronomic, economic, and environmental benefits. One of the fields of research in PA is the delineation of Management Unit Zones (MUZs). MUZs are the sub-division of fields featuring an inter-zonal variation delineated by agronomists for on-field PA operations. To develop MUZs, three factors typically need to be considered: input multi-dimensional data, procedures to process the information, and the optimal number of zones a field should be divided into. PA uses digital technologies to collect and analyze a large amount of data, outline MUZs, monitor crops, and carry out site-specific crop management. Web-based spatial decision support systems (WB-SDSS) can provide users with tools that ease the complex procedures for PA. The objective of this study is twofold: on the one hand, we developed a free and open source (FOSS) WB-SDSS to facilitate the implementation and use of such tools for delineating MUZs and monitoring crops; on the other, a MUZs outline procedure was developed based on Sentinel-2 and Planetscope time series data, and spatio-temporal dynamic clustering model using fuzzy c-means. Our study highlighted that the WB-SDSS might be a helpful solution for harmonizing data collected from different sources, easing the implementation and use of complex geospatial procedures for PA, and delineating MUZs. We tested the system on a particularly representative farm in the Emilia Romagna region (Northern Italy), with 512 hectares of durum wheat crops. Using the WB-SDSS, we quickly delineated homogeneous zones for 27 fields in the study area during the phenological cycle of durum wheat (November 2018-June 2019).

1. Introduction

Precision agriculture (PA) is an agricultural management strategy introduced in the mid-1980s, which not only attracted considerable interest but also started a revolution in resource management by addressing the following three key issues: a) agronomic, to improve the effectiveness of inputs concerning yield; b) economic, to increase productivity and competitiveness through more efficient practices; c) environmental, to reduce the ecological impact of agriculture by optimizing the use of inputs. Since 2019, the International Society of Precision Agriculture (ISPAG) has provided a widely accepted definition of PA, updated in 2021 and officially translated into 15 languages: '*Precision agriculture is a management strategy that takes account of temporal and spatial variability to improve the sustainability of agricultural production*' (www.ispag.org, last access 25 February 2024).

In PA, management unit zones (MUZs) are homogeneous areas or sub-regions within which the effects on the crop induced by spatio-temporal variability in climate, soil, and management are more or less uniform [1]. Outlining MUZs is crucial since it allows farmers and agronomists to execute site-specific management. Moreover, MUZs will enable the implementation of prescription maps constituting the reference base for applying agronomic inputs (e.g., fertilizers or seeding) using variable rate technology (VRT). The definition of these sub-regions starts from a multi-variety set of spatio-temporal data, including biotic and abiotic factors considered influential on crop yield. Among these data, we can mention photographic images of bare soil, remotely sensed radiometric images, geophysical sensors on the ground, and yield maps [2]. Using remotely sensed images during the different growth phases of

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crops assumes a strong correlation between them and yield data [3].

Crop yield prediction often uses multi-temporal Vegetation Indices (VI) derived from Earth Observation (EO). EO systems have been introduced in global projects over the last decade to track climate, atmosphere, land cover, land use, vegetation cycle, variables, and changes and to exchange data. It is worth noting that Copernicus, the Global Earth Observation System of Systems, and NASA's Earth Observation System are among the numerous initiatives on a global scale. The advancements in data collection methods also facilitated increased geospatial data acquisition capabilities. EO data can now be searched, acquired, and processed in technical infrastructures on an increasingly broad scale and with an increasing time series period.

Multispectral data acquisition requires appropriate geostatistical analyses to produce thematic maps visually describing the vegetative state of crops. To this end, a series of VI was developed to compare the crops' biomass measured in different wavelengths analytically. Normalized vegetation index (NDVI) and modified soil-adjusted vegetation index (MSAVI) are worth noting among the many VIs proposed by scholars in the last forty years. NDVI is recognized as directly related to the phenology and yield of wheat [4]. The MSAVI and its revision, MSAVI2, aim to resolve some of the shortcomings of NDVI for areas with a high degree of soil surface exposure [5].

The delineation of MUZs in both research and industrial sectors has primarily been accomplished using clustering approaches [6] or image processing-based segmentation algorithms [7]. Cluster analysis is based on the principle that similar individuals are grouped into discrete classes (i.e., clusters) established on the properties measured on each individual. There are several clustering procedures, but none is universally accepted to derive MUZs. However, many authors have used the well-known k-means and its fuzzy variant, the fuzzy c-means algorithm [8]. Many research studies have statically examined MUZ, assuming no dynamic changes during the growth period [9,10]. However, when it comes to fields and characteristics of plants that exhibit changing spatial patterns over time, some scholars have proposed that the delineation of MUZ should be dynamic, mainly due to variations in the thermal state of plants and their water requirements, changes in weather conditions and the nitrogen content of the soil after agronomic processes [11–15].

The rapid and intense transformation of information, both in data acquisition technologies and in the methods of access and sharing, offers new opportunities for the agricultural sector to improve production quality, agriculture's environmental sustainability, and effectiveness in using natural resources [16]. The new technologies developed for the agricultural sector, in conjunction with the rapid evolution of information communication technologies (ICT), geographic information systems (GIS), and geospatial technologies (GT), now offer enormous potential for the development and optimization of solutions supporting PA.

ICT and GT are now mandatory in implementing PA as they can manage the high amount of data, the intensity of knowledge, and the spatial and temporal aspects related to the management of agricultural practices. Although PA techniques and equipment are increasing, the adoption rate is slower than in the mid and late 1990s. Evidence shows that further expansion of PA is lagging [1,17] for educational and technological issues. Several authors [18–21] have examined the topics of technology requirements for PA diffusion arguing that: i) data management and decision-support systems should be tailored to farmers' individual requirements; ii) systems should have a simple graphical user interface (GUI); iii) data processing requires automated and user-friendly approaches; iv) users should be able to exercise complete control over processing and analytic functions whenever they choose; v) it should be possible to incorporate specialized knowledge (e.g., rule-based knowledge) allowing systems to be fine-tuned to local conditions while also considering user abilities, practices, and preferences; vi) information systems should be more connected and standardized, reducing the amount of money spent on technology and the need for technical support; vii) they are required integration and interoperability with various software packages (including simulation packages) and data sources (such as meteorological data and market data), both locally and remotely over the internet, using open standards, interfaces, and data protocols should be adopted, especially for legacy and distributed systems.

In addition, PA requires a large, heterogeneous, and continuous flow of multi-temporal data to be managed [22]. Data can be acquired by field sensors, optical and radar satellites, modern agricultural machinery equipped with data acquisition systems and GPS, institutional geoportals, smartphones with mobile applications, and web-based platforms. This large data flow must be harmonized [23] and interpreted to understand the causes of inter and intra-field variability to propose robust management PA practices. With the massive amount of data available, agronomists and farmers may find themselves at a loss when choosing agricultural management [24]. Platforms such as decision support systems (DSS) are required to aid them in making precise and evidence-based decisions. Even though DSSs are extremely useful in farm management, their use has been restricted due to several key issues [25]. First, farmers rarely have any expertise or knowledge of how to use DSS. They may find it challenging to complete desired tasks because the conventional GUI of DSSs is not always user-friendly. DSS developers may overlook end-user requirement analyses, resulting in DSS inputs and outputs incompatible with farmers' demands and decision-making processes.

Moreover, the existing DSS capabilities are restricted and task-specific. This means that only one point of view may be the focus of a DSS. As a result, farmers must manage their agricultural activities using many DSSs. In addition, current DSS may overlook essential elements such as climate change, soil spatial variability, and crop disease when advising. Most existing DSS for PA are desktop or web-based software without interoperable and standardization capabilities, which are difficult to maintain and upgrade since the data and system operations are fully integrated. It is also difficult to share data and achieve interoperability among various software programs because most of them are set up with custom web services. To overcome the barriers mentioned above, this research mainly aims to develop a web-based spatial decision support system (WB-SDSS) for delineating MUZs, thus simplifying both the system installation procedures and its use by agronomists and farmers. The WB-SDSS was developed with open-source software tools and source code and using open geospatial consortium (OGC) standards to achieve data and related web services interoperability on a global scale. The main objective of this study is to present a novel procedure implemented in WB-SDSS and based on the conjunction use of VIs and fuzzy c-means clustering for dynamically delineating MUZs. In the following sections, all steps that led to the development of the proposed WB-SDSS and all its components are explained in detail. Finally, the related MUZs delineation procedure was tested on a case study of 512 hectares of durum wheat fields falling in the municipality of Jolanda di Savoia (Ferrara Province, Northern Italy).

2. Materials and methods

2.1. Web-based spatial decision support system (WB-SDSS) architecture

The service-oriented architecture (SOA) paradigm was the foundation for developing the proposed WB-SDSS. In particular, software-independent, interoperable, discoverable, and reusable services constitute the multi-tier SOA architecture [26]. In a recent work, Yoon & Jeong [27] identified the main advantages of SOA. They can be summarized as follows: i) decoupling, the infrastructure and architecture are divided into various services, and the software can be freely coupled (or not dependent on each other); ii) flexibility, the architecture components can be developed in any language and platform (e.g., one can write the client-side in a dynamic language like Python, Ruby or Javascript and write performance-critical components in lower-level languages like C or Java); iii) simplicity, having components isolated in various services make it easy to test and debug them individually; iv) scalability, the presence of separate components makes it much easier to scale architectures (i.e., one can scale a particular component without affecting the others); v) reuseability, as the various components are built separately, it becomes much easier to reuse them later.

Based on these assumptions and previous research [22,28,29], we developed the proposed WB-SDSS as a three-tier SOA of distinct and independent modules of the software (Fig. 1). In particular, the three tiers are the following: data layer (A) where we store multi-temporal data; the service layer (B) that contains the business logic and enables service interoperability; and the presentation layer (C) that comprises the GUI for human interaction with the WB-SDSS.

The data layer is composed of five different repositories, each one dedicated to storing additional source data. In detail, the sensor data repository stores data from sensors installed directly in the field (e.g., soil moisture, electrical conductivity, etc.). The machine data repository is dedicated to storing data acquired in the field by agricultural machinery and can provide georeferenced information about yield and agronomic practices (e.g., fertilization, sowing, etc.). Meteorological data repository stores weather information such as temperature, precipitations, wind speed, and relative humidity. EO data repository deals with the storage of satellite-based multispectral images (i.e., Sentinel-2 and PlanetScope). Finally, the geospatial data repository stores all the geospatial data not included in the previous repositories (e.g., field boundaries, crops sown, management plans, etc.). The following subsection describes better all data acquired (§2.2).

Concerning the service layer, we implemented the following modules:

- Geo-Processing: allows for executing multi-temporal geospatial processing and algorithms for creating digital data from knowledge, such as MUZs delineation.
- Semantic: permits meta-dating systems to create and manage code lists, controlled vocabularies, and thesauri for a multilingual semantic enabling data description. We exploited the AGROVOC [30] multilingual thesaurus that covers concepts and terminology related to the food and agriculture organization of the United Nations (FAO) areas of interest.
- Authorization and authentication: allows users, data, and applications to be authenticated and authorized;
- Metadata: facilitates the meta-dating of data according to standard profiles, using the semantic module for data description and the conversion between metadata schemes.
- Catalogue: presents the collection and data index and relevant metadata, allowing unambiguous and exhaustive research of web services and data. The catalogue is exposed as an interoperable OGC catalogue service for the Web (CSW).
- Services: transforms data into interoperable web services. Taking advantage of existing OGC standards, we used web map service (WMS) to visualize all maps and data and web feature service (WFS) to share vector data such as fields and crop management plans, meteo-climatic data, and MUZs. We exploited the WFS transactional (WFS-T) capabilities to create and edit the above data and web coverage service (WCS) for sharing raster data such as NDVI and MSAVI2.

The presentation layer was devoted to implementing the GUI and was developed for user access based on Bootstrap and Leaflet frameworks. Bootstrap (https://getbootstrap.com – last access 07/12/2022) is an open-source front-end toolkit that quickly allows the development of websites and applications. Leaflet (https://leafletjs.com – last access 07/12/2023) is a JavaScript library for developing interactive geographic maps on the web. It supports most browsers and HTML5 and CSS3 standards. It allows the visualization and query of points, lines, areas, or data structures, such as GeoJSON files or OGC services, on a tile map.

The GUI allows users to access the maps and work with them (Fig. 2) based on numerous features, allowing for a high level of interactivity. First, the basic functionalities are available: the standard pan and zoom mapping, which includes identifying geospatial objects in the data layer; the editing capabilities that allow the drawing/editing/deleting of data (i.e., fields and related crops); the computation capabilities that enable geoprocessing and the execution of algorithms such as clustering algorithms. Thus, the GUI provides an interface mechanism for (a) loading, identifying, and selecting the data needed by the procedure; (b) elaborating the data by the chosen procedure; (c) making the result of the elaboration accessible to the users.

The technology platform on which we implemented the WB-SDSS was a private cloud managed by vCloud Director @VMware software (https://www.vmware.com/it/products/cloud-director.html - last access 07/12/2022). This software allows the creation of virtual data

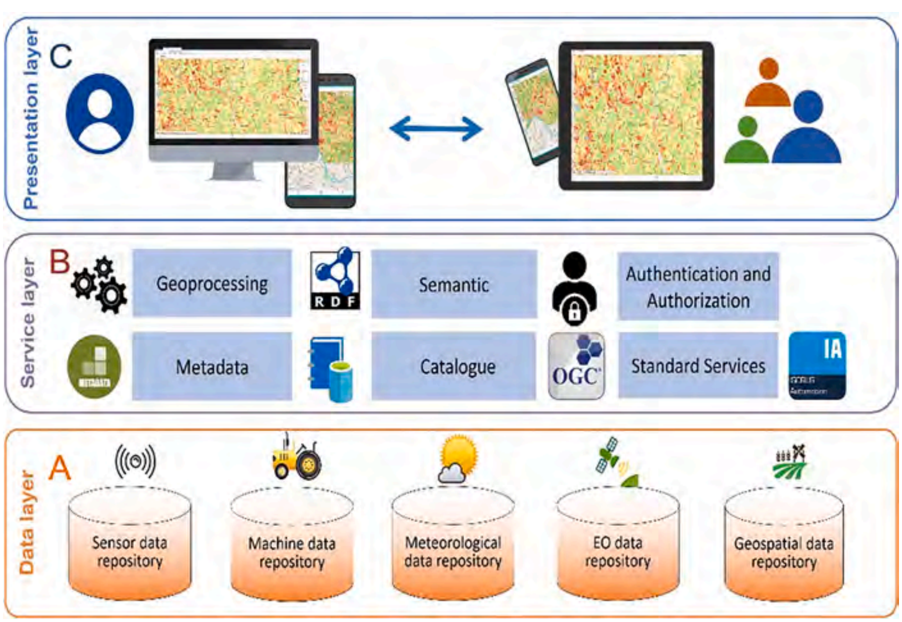

Fig. 1. Three-tier service-oriented architecture (SOA) and modules of the Web-Based Spatial Decision Support System (WB-SDSS) architecture: A) data layer, B) service layer, and C) presentation layer

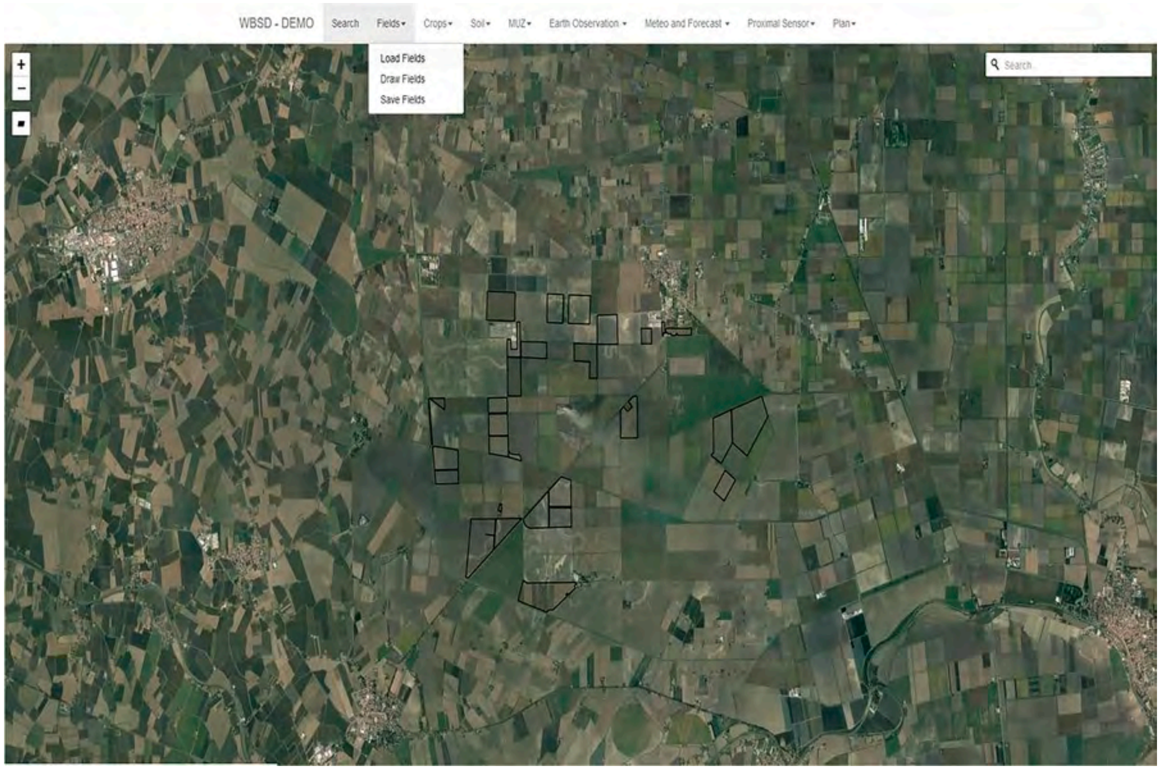

Fig. 2. Web-Based Spatial Decision Support System (WB-SDSS) interface showing the boundary fields superimposed on a satellite base map.

centers, and their use is simple and intuitive. It includes integrated services such as data protection, disaster recovery, data center backup systems, and multi-site data center management. The cloud environment permits the creation of virtual applications and their use simply and intuitively by a GUI. In the private cloud, we implemented several virtual machines based on the open-source operating system Ubuntu server to develop the previously described modules.

Since there is so much free and open source software for geospatial applications (FOSS4G) [31], we chose the one that supports multi-dimensional geospatial data, OGC standards compatibility, easy implementation, and presents a well-structured developer community support. Geospatial data (i.e., satellite imagery), sensor responses, agricultural equipment, meteorological, soil, farm, and crop information, and associated meta-data are stored and indexed using PostGIS (https://postgis.net/ - last access 07/12/2022), the spatial extender of the PostgreSQL object-relational database.

In our proposed WB-SDSS platform, we used the following software suites, all of them FOSS. Apache Jena (https://jena.apache.org – last access 07/12/2022) allows the enabling of the semantic web. EDI (http://edidemo.get-it.it – last access 07/12/2022) enables the editing of rich and standard metadata for resources. Apache Airflow (https://airflow.apache.org – last access 07/12/2022) programmatically schedules workflows enabling the execution of elaboration pipelines. GeonetWork OpenSource (https://geonetwork-opensource.org – last access 07/12/2022) simplifies the creation of a web catalog of resources, which also supports the CSW standard. GeoServer (https://geoserver.org – last access 07/12/2022) converts geospatial data into interoperable OGC web services (WMS, WFS, WCS). KeyCloak (https://www.keycloak.org – last access 07/12/2022) allows for authentication and authorization of users, data, and applications, also supporting OAUTH2 and Open-ID protocols.

The complete list of software, their related modules, and the URL of the source code are summarized in Table 1. It can be noticed that the architecture implementation was carried out through the docker system (https://docs.docker.com – last access 07/12/2022) and, in particular,

Table 1
Modules and corresponding software implemented in the proposed service oriented architecture (SOA). For each of them, we reported the source code URL.

Module	Software	FOSS Source Code URL
Data Archive	PostGIS	https://github.com/postgis/postgis
Geo-Processing	Apache Airflow	https://github.com/apache/airflow
Semantic	Apache Jena	https://github.com/apache/jena
Metadata	EDI	https://github.com/SP7-Ritmare/EDI-NG_client
Catalogue	GeoNetwork OpenSource	https://github.com/geonetwork
Services	Geoserver	https://github.com/geoserver
Authorization and authentication	Keycloak	https://github.com/keycloak/keycloak

docker-compose. The docker-compose tool eases the: a) implementation, b) future development; c) horizontal scalability, of the WB-SDSS.

We tested the proposed WB-SDSS platform on a farm located in the Jolanda di Savoia municipality, Emilia Romagna region (Northern Italy). The cropping plans are for 27 fields planted with durum wheat, sown in November 2018, harvested in June 2019, and for a total area of 512 hectares (Fig. 3).

We digitalized the data on crop management plans and field boundaries on the screen using the information provided by the farm concern.

2.2. Data acquisition

The multi-temporal data, collected from different sources and processed using geomatics techniques, are relative to fields' boundaries, crop management plans, soil properties, meteorological and climatic variables, and satellite data. The collected data allowed us to analyze the spatio-temporal variability intra- and inter-fields and test the WB-SDSS

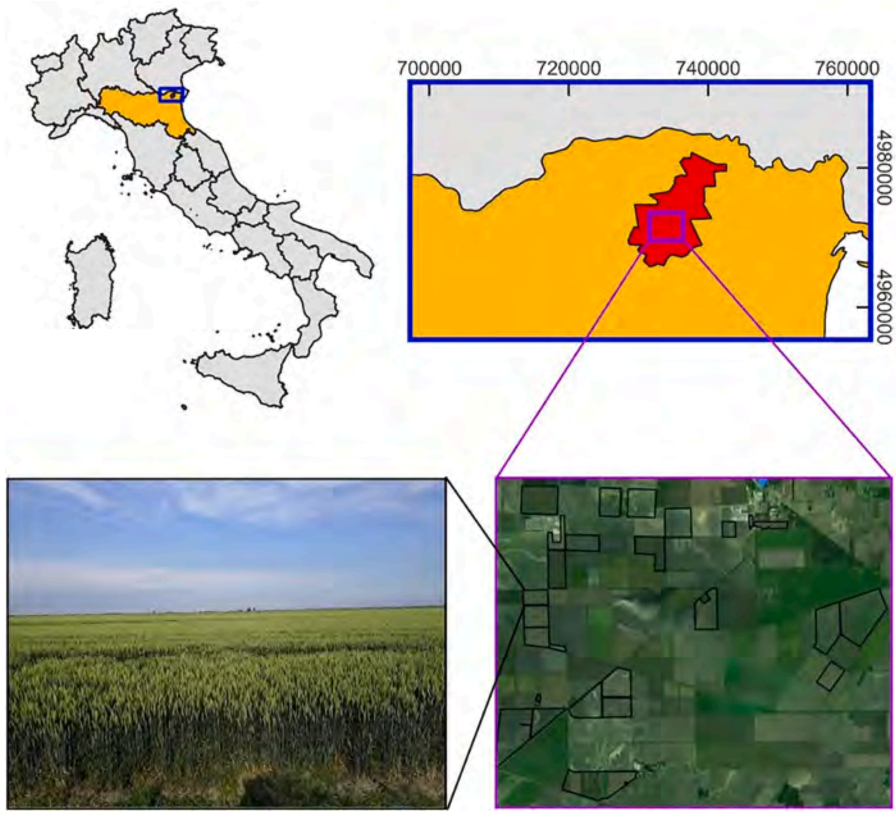

Fig. 3. Localization of the study area. Italy is on the upper left corner, with Emilia Romagna region in orange and Jolanda di Savoia municipality in red (upper right corner, coordinates in WGS 84 UTM32N, EPSG: 32632). The details of the fields with durum wheat cultivar are on the bottom part of the figure.

interoperability. All data acquisition procedures are entirely automated within the WB-SDSS, and field boundaries, as well as crop plans can be entered directly via the GUI. Table 2 shows the complete data types, file formats, and sources list.

We collected the soil data from SoilGrids (SG). SG is a global digital soil mapping system that uses global soil profile information and artificial intelligence to model the spatial distribution of soil chemical and physical properties globally [32]. SG generates and makes soil maps available for free, using machine learning at 250 m of spatial resolution and six standard depths (i.e., intervals). Soil data are shared by WMS, WCS, and Web-based distributed authoring and versioning (WebDAV) standards. The soil chemical and physical properties available in SG are summarised in Table 3, while the six standard depths are listed in Table 4. We exploited the WCS to acquire soil data and use it as input to processing pipelines for our research aims.

After the acquisition phase of the soil data, we harmonized them in one raster for each soil parameter and conventional unit (Table 3). We developed the entire processing pipeline for soil parameters acquisition and harmonization using geospatial libraries in Python scripting language.

Once we acquired soil data, we collected multi-temporal satellite data from the Copernicus open-access hub and Planet. The first one, developed as part of the European public programme Copernicus, provides complete access to Sentinel constellations data via an interactive GUI or API. The second one has been set up by a private company that provides access to various satellite constellations (i.e., PlanetScope, RapidEye, and SkySat) via interactive GUI or the RESTful interface. The Sentinel-2 (S2) multispectral sensor collects 12 bands with a ground sample distance (GSD) between 10 m and 60 m with a revisiting time of 2-3 days for the European countries. The PlanetScope (PS) sensor

Table 2
Datatypes, file format, and source of the data collected.

Data Type	File Format	Source
Field Boundaries	Shapefile	Digitalization
Crop management plans	Shapefile	Digitalization
Soil Chemical properties	GeoTIFF	SoilGrid WCS
Soil physical properties	GeoTIFF	SoilGrid WCS
Meteo-Climatic	JSON	MeteoBlu API
Sentinel-2 images	GeoTIFF	Sentinel open-access hub
PlanetScope images	GeoTIFF	Planet API

Table 3
SoilGrids soil parameters, mapping unit, conversion factor, and conventional units

Description	Mapping units	Conversion factor	Conventional units
Bulk density of the fine earth fraction	cg/cm^3	100	kg/dm^3
Cation Exchange Capacity of the soil	mmol(c)/kg	10	cmol(c)/kg
Volumetric fraction of coarse fragments (> 2 mm)	cm^3/dm^3 (vol‰)	10	$cm^3/100cm^3$ (vol%)
The proportion of clay particles (< 0.002 mm) in the fine earth fraction	g/kg	10	g/100g (%)
Total nitrogen (N)	cg/kg	100	g/kg
Soil pH	pHx10	10	pH
The proportion of sand particles (> 0.05 mm) in the fine earth fraction	g/kg	10	g/100g (%)
The proportion of silt particles (≥ 0.002 mm and ≤ 0.05 mm) in the fine earth fraction	g/kg	10	g/100g (%)
Soil organic carbon content in the fine earth fraction	dg/kg	10	g/kg
Organic carbon density	hg/dm^3	10	kg/dm^3
Organic carbon stocks	t/ha	10	kg/m^2

Table 4
SoilGrids standard depths corresponding to the six intervals of soil parameters.

Depth	Interval I	Interval II	Interval III	Interval IV	Interval V	Interval VI
Top depth [cm]	0	5	15	30	60	100
Bottom depth [cm]	5	15	30	60	100	200

collects four bands with a revisit time of one day and a GSD resampled to 3 m from the original 3.7-4 m (depending on the off-nadir angle at the time of acquisition). S2 data are free, while PS data are available after the payment of a commercial subscription. We implemented the two data acquisition pipeline both to allow WB-SDSS users to choose which satellite data to process VIs from and to enable possible future developments of further models, e.g., the comparison of MUZs obtained from the two distinct satellite data and the delineation of MUZs obtained by data fusion techniques. Actually, the accuracy of the VI is consistent between Sentinel-2 and PlanetScope [33]. A complete list of satellite platforms, revisiting times, bandwidths covered, and GSDs are shown in Table 5. For both sources, we collected data via API customized in our WB-SDSS.

After acquiring the multi-temporal satellite data, we acquired multi-temporal Meteo Climatic Data from the MeteoBlue services (https://www.meteoblue.com - last access 07/12/2022). MeteoBlue is a private company that collects, processes, and shares worldwide meteorological, forecast, and historical data through FTP, API, and email. We exploited the API to download the historical data for every analyzed field in the JSON file format for our research. The list of meteorological data parameters and the measuring unit acquired are shown in Table 6.

2.3. Management Unit Zones (MUZs) delineation

The procedure to delineate the MUZs can be summarised in the following steps: a) acquisition, storage in a multi-dimensional Data Cube, and correction of multi-temporal S2 and PS satellite data; b) time series processing of NDVI and MSAVI2 indices; c) masking of NDVI and MSAVI2 time series for each field boundary; d) storage of masked data e) processing of the maximum value composite (MVC) and f) fuzzy c-means clustering of the MVC for each field.

Table 5
Main characteristics of the used satellite data: revisiting time [days], band, bandwidth, and ground sample distance (GSD) [m].

Satellite	Revisiting time [days]	Band	Bandwidth [nm]	ground sample distance (GSD) [m]
Sentinel-2 (S2)	2-3	1 - Coastal aerosol 2 - Blue 3 - Green 4 - Red 5 - Vegetation Red Edge 6 - Vegetation Red Edge 7 - Vegetation Red Edge 8 - NIR 8A - Vegetation Red Edge 9 - Water vapor 10 - SWIR - Cirrus 11 - SWIR 12 - SWIR	421–457 439–535 537–582 646–685 694–714 731–749 768–796 767–908 848–881 931–958 1.338–1.414 1.539–1.681 2.072–2.312	60 10 10 10 20 20 20 10 20 60 60 20 20
PlanetScope (PS)	1	1 – Blue 2 - Green 3 – Red 4 - NIR	455–515 500–590 590–670 780–860	3.7 3.7 3.7 3.7

Table 6
Meteorological data parameters provided by MeteoBlue and acquired in the JSON file format through the implemented API.

Parameter	Measuring units
Date	day
Max Temperature	°C
Min Temperature	°C
Mean Temperature	°C
Accumulated Precipitation	mm
Max Windspeed	ms^{-1}
Min Windspeed	ms^{-1}
Mean Windspeed	ms^{-1}
Max Relative humidity	%
Min Relative humidity	%
Mean Relative humidity	%

We used two pipelines for the satellite constellations, different for S2 and PS, to download the data and elaborate the NDVI and MSAVI2 (Fig. 4). The pipeline for S2 exploits the Copernicus API Hub to download Level 2A (L2A) data. L2A products provide the bottom of atmosphere (BOA) reflectance projected to a cartographic projection. The PS pipeline uses the Planet API to download Level 3B (L3B) data from PS Satellites. L3B data provide top-of-atmosphere (TOA) radiance projected to a cartographic projection. After downloading PS L3B data, we applied atmospheric and radiometric corrections using the parameters supplied by PS XML metadata. Once the satellite data have been downloaded and corrected, the pipeline calculates the VIs mentioned above and the relative time series for both satellite sources and, in the end, stores them.

The entire pipeline of acquisition, correction, processing, and storage of satellite data and VIs was implemented via Python programming language in the geoprocessing service layer of the proposed WB-SDSS platform.

After obtaining NDVI and MSAVI2 indices, we masked each field's NDVI and MSAVI2 time series. We archived all masked data to be shown on the platform (Fig. 5). Masking was carried out for all the images within each field having a cloud cover of 5% or less; the other images of the time series were not considered.

To identify the inter- and intra-field variability, first, we processed the MVC for each field. It should be noted that agronomic operations (sowing, fertilization, defense) were implemented following the same practices in all fields on which the MVC calculation was carried out. Also, the WB-SDSS can store maps of the agronomic operations implemented, such as variable rate fertilization, and then take them into account in the production of MUZs. The MVC is a well-known procedure that minimizes the influences of atmospheric aerosols and clouds on the VIs time series. The MVC procedure examines a series of multi-temporal satellite data (compositing period) and, analyzing each value on a pixel-by-pixel basis, maintains only the highest value for each pixel location [34]. After all, the pixels were evaluated. The procedure creates a new image, the MVC image. We exploited the GUI to perform the MVC multi-temporal analysis of the MSAVI2. We entered the sowing date as the starting date of the analysis and the harvest date as the ending one, thus encompassing the entire phenological cycle of the analyzed crop. The GUI allows the user to calculate and visualize the MVC from S2 or PS data. The WB-SDSS processes and shows the MVC map results for the phenological cycle of durum wheat, highlighting inter-field and intra-field variability (Fig. 6).

After elaborating and storing the MVC results, we applied a clustering procedure to delineate the MUZ for each field. One of the main issues facing PA is the evaluation of different algorithms for delineating MUZ. Clustering techniques may be a basis for delineating zones, but it

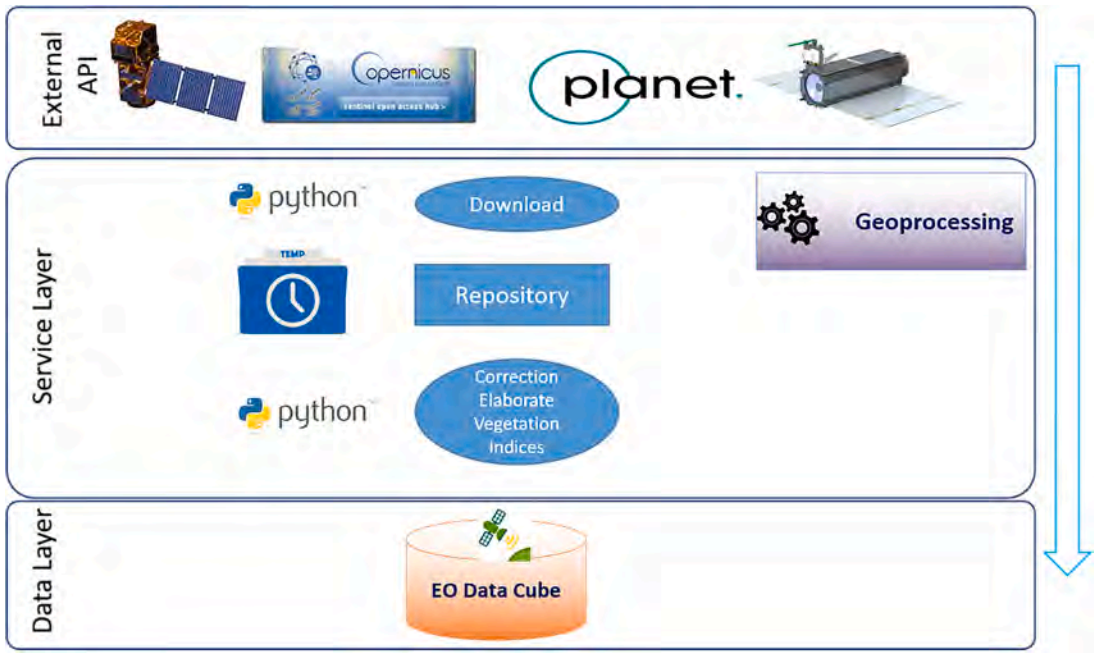

Fig. 4. Workflow of pipelines for the satellite data's acquisition, correction, processing, and storage.

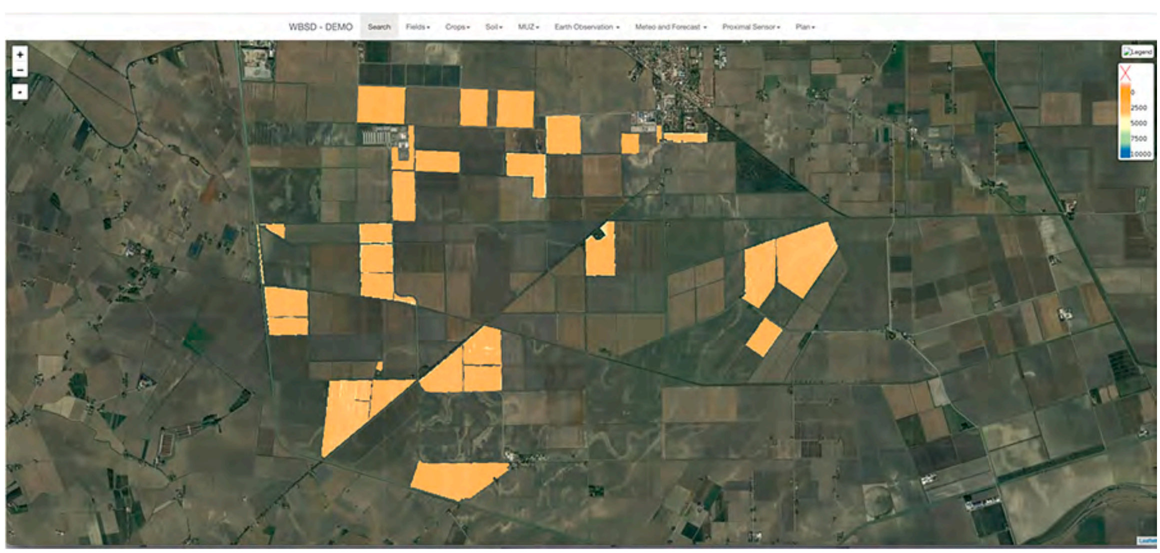

Fig. 5. The normalized difference vegetation index (NDVI) index was calculated for the selected 27 fields of the study area, starting from Sentinel-2 (S2) data acquired on 18 February 2019 and superimposed on a satellite base map.

can be argued that no widely accepted methods exist. Cluster analysis is an explorative method that characterizes data in various combinations of numerous variables in discrete classes. It is separated into two main categories: non-hierarchical and hierarchical. The most significant non-hierarchical clustering is the k-means, where multi-dimensional information is characterized into k classes [35].

Fuzzy c-means is an extension of the k-means clustering that represents uncertainties related to class boundaries and membership [8]. Different authors have demonstrated the usefulness of k-means and fuzzy c-means clustering techniques for MUZs delineation. Researchers also used different approaches in terms of data proxies. On the one hand, we can find experiences based on soil properties and yield monitoring. For example, Ping et al. [36] used k-means cluster analysis of yield and soil properties to delineate MUZs in irrigated cotton fields, while Molin & Castro [37] applied fuzzy c-means on a soybean-corn rotation system with wheat or black oat as a cover crop to delineate management zones.

On the other hand, other approaches are based on using remotely sensed imagery and VIs to delineate MUZs. In this direction, the work of Li et al. [8], which delineated MUZs using fuzzy c-means coupling NDVI and yield data in cotton fields, is significant. Kyaw et al. [38] found reliable the use of NDVI and apparent soil electrical conductivity in delineating MUZs for pH-induced iron chlorosis in maize and soybean. In particular, these authors used the management zone analyst software [39], which performs fuzzy c-means clustering. Termin et al. [15] delineated dynamic MUZs for nitrogen fertilization in a citrus orchard exploiting fuzzy c-means clustering. Fontanet et al. [14] delineated dynamic MUZs for irrigation exploiting NDVI time series. Nutini et al. [40] delineated MUZ using Sentinel-2 imagery and fuzzy c-means clustering to define site-specific fertilization strategies implemented with VRT. In any case, all the authors just mentioned, outlined MUZs on

Fig. 6. The maximum value composite (MVC) was calculated for 27 fields, starting from Sentinel-2 (S2) MSAVI2 index, superimposed on a satellite base map. The MVC is calculated in the period of the phenological cycle of durum wheat, middle autumn – early summer (November 2018-June 2019). The legend in the upper right of the figure shows the values of MSAVI2, reclassified into five classes.

relatively limited number of fields, ranging from one to six, and a small areas, ranging from two to thirty hectares. Our proposed procedure exploits the fuzzy c-means algorithm on MVC, this is the novelty compared to the approaches of other authors. It can be synthesized in the following steps. First, the data pre-processing was performed, returning an array with standardized values. For many machine learning estimators, standardization of datasets is a common requirement because they could misbehave if the individual characteristics do not look like standard, normally distributed data [41]. Obtaining the standardized values, the Fuzzy c-means algorithm returns an array classified according to the chosen number of clusters. The algorithm clusters the multi-dimensional data by assigning each point to a membership in each cluster center from 0 % to 100 %. We exploited the SciKit-Fuzzy Python framework (https://pythonhosted.org/scikit-fuzzy/overview.html - last access 10 January 2023) to implement the SOA service layer procedure. Once obtained the array, it is classified according to the number of clusters chosen. The results are archived both in GeoTIFF and vector format in the data layer of the architecture described in Section 2.1.

Fig. 7 summarizes the workflow implemented to obtain the MUZs.

We elaborated the MUZ, choosing by the GUI the number of zones

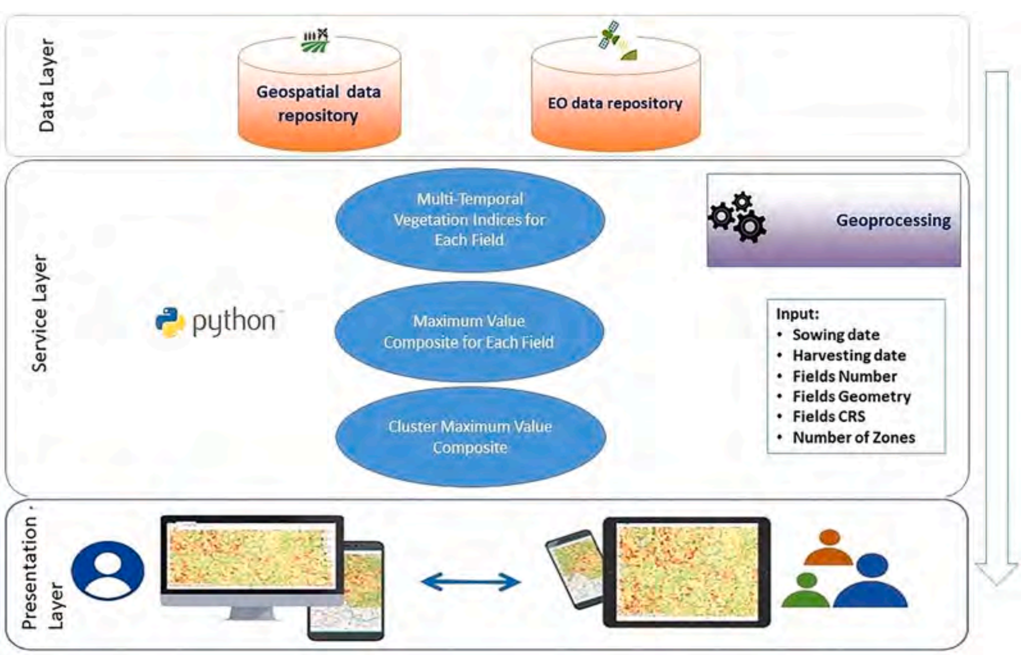

Fig. 7. Management unit zones (MUZs) workflow implemented in the proposed Service Oriented Architecture (SOA).

into which we want to subdivide the field (Fig. 8).

Some of the data obtained were used for the MUZs delineation procedure, while others were not, such as soil and weather data. These latter data can currently be used in the WB-SDSS for monitoring operations and are ready for easy use in future models.

3. Results

In the present research, we developed a WB-SDSS architecturally based on the concept of SOA and composed of three layers (data, service, presentation) within which the different modules are developed: data archive, semantics, metadata, catalog, services, geo-processing, authentication and authorization, and front-end. The obtained platform is scalable and, as described in the materials and methods section, wholly based on FOSS. More in-depth, the implementation was carried out by developing a horizontally scalable container system that can be further improved and adapted to different crops and geographical contexts. This way, significant improvement was obtained in terms of: a) flexibility and scalability; b) resource efficiency; c) rapid deployment; d) reliability and isolation; e) agile development and deployment. Concerning flexibility and scalability, the container architecture allows an application to be divided into isolated components called containers, which can be deployed and managed independently. This makes it possible to scale horizontally, increasing or decreasing the number of containers according to workload requirements. Scalability is particularly advantageous when rapid expansion or reduction of computing resources is required, allowing adaptation to fluctuations in demand without interruptions or slowdowns in application execution.

Regarding resource efficiency, using containers makes efficient use of available hardware resources. Containers share the kernel of the host operating system and can be started and terminated quickly, maximizing resource utilization and reducing waste. In addition, isolation between containers prevents resource conflicts, allowing different applications or services to run in the same environment without mutual interference. Regarding rapid and consistent deployment, due to the portable nature of containers, the application can be easily deployed across different platforms and environments, ensuring consistency in configuration and execution. Concerning reliability and isolation, separation between containers ensures that one container does not affect the operation of the others. This improves the resilience of the architecture since error or failure in one container will not propagate to other containers or the entire application. Furthermore, the use of container images ensures that the execution environment is reproducible, allowing for consistent and predictable results. Concerning agile development and deployment, the container architecture favors a modular approach to application development, allowing functionality to be separated into different containers. This simplifies application lifecycle management, allowing specific components to be updated and deployed without affecting the rest of the application. In addition, using container images makes creating consistent development and testing environments easy, improving efficiency and collaboration among development team members.

To test the capabilities of the WB-SDD in the implemented case study, we acquired the following data for the study area: 27 fields boundaries and crop management plans, 11 chemical and physical soil properties for 6 depth intervals, 10 meteorological properties, with a daily time interval from November 2018 to June 2019, 26 Sentinel-2 and 40-PlanetScope images from November 2018 to June 2019. All acquired data derive from heterogeneous sources and formats. Therefore, in an operational context, the first step deals with harmonizing and storing all acquired data in the SOA data layer [23]. Also, by exploiting semantic and AGROVOC thesaurus, we semantically enriched the data, such as in other previous work of our research team [23,42]. The semantic enrichment allowed us to improve the machine-readability of the data while at the same time addressing the issue of language and unclear concepts, which are an obstacle to interoperability across datasets. Exploiting the metadata editing capabilities of the WB-DSS, described in Section 2.1, we meta-dated every dataset, adding information on the source, quality, and accuracy of the data.

As the first procedural step in delineating MUZs, we processed the satellite data to obtain NDVI and MSAVI2 time series for each field investigated. Then, the NDVI and MSAVI2 were masked by field

Fig. 8. An example of mapping 3 Management unit zones (MUZs), delineated for one field by the Fuzzy c-means algorithm on Maximum Value Composite (MVC) data superimposed on a satellite base map.

boundaries and produced for each time series. This procedure allows for the analysis of inter- and intra-field variability and the variation of VI indices throughout the phenological cycle. Once we obtained the time series of VIs for each field, we applied the MVC procedure, with the phenological cycle's composition period, to identify intra-field and inter-field variability for all the analyzed fields. Also as demonstrated by different authors in annual crops, biomass, yield, and vegetation indices are closely linked, so by exploiting the MVC technique we obtained the maturity phenological stage for each pixel of fields [43–46]. After elaborating on MVC for all fields, we delineated the dynamic MUZs through the implemented fuzzy c-means clustering. Several authors [12,14,15] have established that in PA, the delineation of MUZs should be dynamic, and the spatio-temporal variations in crop growth have to be taken into account.

As described in Section 2, in our proposed WB-SDSS, we implemented a specific GUI section that allows the user to execute the MUZs delineation by simply choosing the desired number of clusters. Fig. 9 shows the obtained MUZs for the 27 field boundaries of the study area, categorized into three classes.

Also, the GUI is the system component through which the user can view and analyze the data. The functions identified and implemented in the WB-SDSS GUI are currently the following:

- Uploading and editing field boundaries, crop plans, and soil data.
- Visualization and consultation of data with essential functions such as pan, zoom, identify, and other advanced operations such as spatial queries.
- Multi-temporal and multi-platform satellite query (PS and S2) and visualization of the different VIs (NDVI and MSAVI2).
- Querying and visualization of meteorological and soil data.
- Accessing all data stored in the database through GIS software using OGC standards.
- Downloading of geospatial data.
- Processing of MUZs according to the previously described methodology.

The user can quickly load and draw on the map the field boundary and recall, through a spatial query, information related to a particular field; he can also check meteorological, pedological, and satellite data. In addition to the functions of visualization (pan, zoom), interrogation, and location search, it is also possible to recall processing operations for MUZs. Thus, the application provides a tool for data analysis and querying by researchers, agronomists, and farm managers, thus becoming the gateway to the vast wealth of information collected and processed during the research activity to share and efficiently use the knowledge acquired.

The WB-SDSS can offer several advantages, including:

- Remote access: being web-based, the system can be accessed anywhere, anytime, and from any device connected to the internet, allowing farmers to use it conveniently without having to physically move.
- Easy access to data: the system integrates data from a variety of sources, such as satellite maps, terrain data, cultivation information, weather conditions, and so on, allowing rapid, near real-time access to the information needed to make informed decisions.
- Cost reduction: a web-based system can reduce the costs associated with purchasing and updating expensive data processing software and maintaining specialized hardware. Also, it allows the use of shared computing resources and potentially reduces the need for skilled personnel.
- Automation: a decision support system can automate much time- and resource-intensive processes, such as delimiting homogeneous zones, collecting and analyzing data, estimating yields, and so on, thus saving time and effort.
- Precision and accuracy: the use of advanced algorithms and data analysis techniques allows for more precise and accurate delimitation maps of homogeneous zones than traditional methods, enabling farmers to take more targeted and customized management measures based on the specific conditions of each area.
- Data sharing: the exploitation of OGC standards enables the interoperable sharing of data, globally.

In a nutshell, WB-SDSS can improve the efficacy of precision agriculture, increase productivity, reduce costs, and improve the sustainability of agriculture.

4. Discussion

Previous studies [1,17–21] have highlighted the weaknesses in

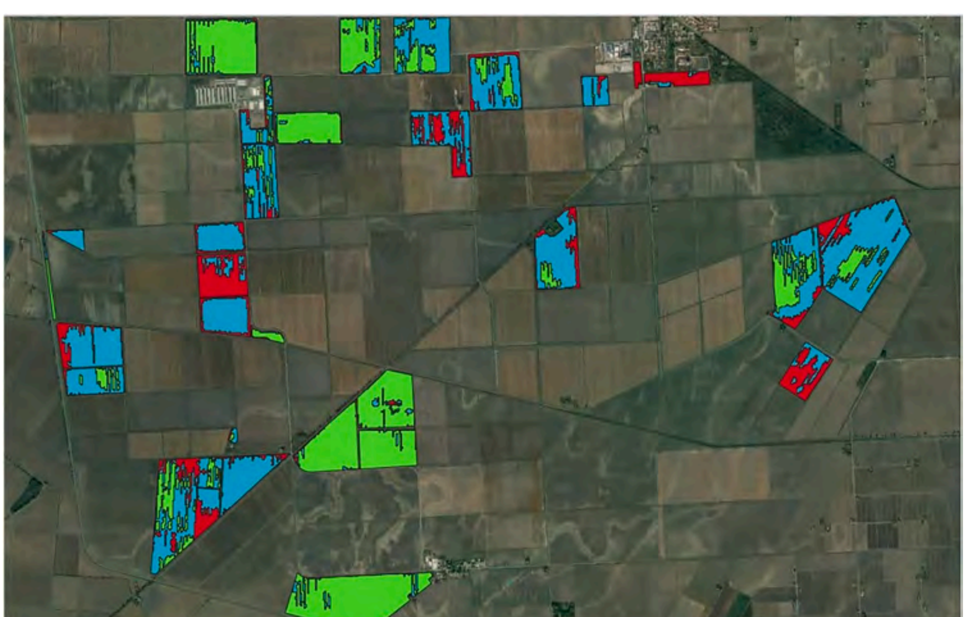

Fig. 9. A map showing how the obtained management unit zones (MUZs) for the 27 fields of the study area are categorized into three classes.

adopting PA and MUZs delineation, mainly for educational and technological issues. In detail about these specific issues: a) Castillo-Villamor et al. [47] developed a system for the detection of in-field anomalies using both Sentinel-2 and PlanetScope imagery and FOSS software; b) Granell et al. [48] developed a Conceptual Architecture and Service-Oriented Implementation of a Regional Geoportal for Rice Monitoring; anyway the proposed architecture lacks standard and interoperable OGC web service for data sharing; c) Lin et al. [49] developed a Web Platform for Water and Soil Monitoring and Assessments in Agricultural Areas exploiting, also, OGC web service. The Author also highlights the benefit of ICT systems, which drastically increase the amount and accessibility of spatio-temporal data by integrating heterogeneous data types; d) Nutini et al. [40] developed operational site-specific fertilization in rice cropping systems; e) Terribile et al. [29] developed a free and open source WB-SDSS for land management and soil conservation. In this research, we developed a free and open-source WB-SDD that enables heterogeneous data integration, easy dynamic MUZs delineation, data sharing by international OGC standards, and easy implementation and usage of the system. Also, Spatial Decision Support Systems (SDSSs) have been created to address a wide range of issues [29], as recent literature on the topic has remarked. These aspects include a) implementing a system to ensure the sustainability of agriculture in a pilot study conducted in Tanzania [50]; b) developing a web service to explore geospatial cropland data in the United States [51]; c) providing support for fertilization practices for farmers in northeastern China [52].

Food production and its sustainability represent a major global challenge for the future. FAO recommends using digital technologies for this purpose, in view of the achievement of the “Zero Hunger Goal” of the United Nations Agenda 2030. The PA, which by its nature is strictly linked to ICT, can represent a solution to address the challenges and objectives mentioned above. With each passing year, new generations of EO satellites deliver increasingly large volumes of data with such extensive global coverage that data limitations are no longer a problem for many applications. New data applications have been dispatched through comprehensive research and development activities that provide a great potential to significantly affect the major critical environmental, economic, and social issues at any level, local to global. Such applications emphasize EO’s importance, although providing proper links between data, applications, and users is challenging.

Despite modern machine and research infrastructures, much archived EO satellite data are underutilized. It is difficult for advanced economies to overcome this problem, and it is even more challenging for developing countries that are interested in using EO satellite data. In many economies, if they are considered the conventional local processing and data sharing methods (e.g., scene-based file uploading), overcoming this “scaling” problem is not technically feasible or financially affordable. Depending on data planning, handling, storage, and analysis difficulties, they remain significant obstacles in managing these data at different spatial and temporal scales. Indeed, just as the technology for satellite EO has significantly improved, so has ICT. New computing infrastructures, technologies, and data architectures, such as the ‘Data Cube,’ will solve the data processing and analysis problems emerging from the massive rise in free and open data volumes. Such a solution has tremendous potential to streamline the delivery and management of data for providers while reducing technological obstacles to consumers’ maximum potential to leverage the data.

The PA studies the inter and intra-field space-time variability to propose concrete agronomic management strategies that reduce inputs and increase yields to view environmental sustainability. The delineation of MUZs is a critical approach that makes it possible, among other benefits, to reduce the cost of production while reducing the environmental impact of agricultural activities.

The system we implemented could be expanded through a WebAPP application for pocket devices and reach the operators in the field by providing complementary tools and support to the operational and monitoring strategies. The WebApp would allow users to enter georeferenced information related to a single plant, row, or area and store it in the system.

Developing a shared knowledge environment that can support advanced research for economic and environmental sustainability is a concept that seems very simple to apply in contexts where the actors involved operate in the same sector. Implementing shared routes and establishing an infrastructure that utilizes the potential of integrating ICT with geospatial sciences is challenging in practice. This integration will combine gathered data and information, leading to new frameworks of knowledge that can effectively mitigate the environmental impact of agriculture. These criticalities do not relate only to the search for appropriate technological solutions to create the connection between data and devices. They can also involve actors in the development processes of diversified applications or cross-cutting services.

5. Conclusions

This work aimed to present a detailed overview of the architecture and design of a novel WB-SDSS solution for delineating dynamic MUZs. The proposed infrastructure has proven to be efficient in harmonizing different data (i.e., satellite imagery, VIs, meteorological data, and soil data) in a web-based, user-friendly environment, overcoming the issues related to installing several software. Moreover, the adopted standards made the proposed solution interoperable with third-party applications providing complementary tools. The results presented here could be the basis for developing a cyber-infrastructure for PA data management and the dynamic MUZs delineation. It is assumed that MUZs can be used to implement VRA applications (irrigation, fertilization, etc.), which leads to more efficient crop management.

In future work, the following efforts are needed to improve the frameworks of knowledge and information flows:

a) Technical and semantic interoperability.

Considering the wide range of data formats managed, we can affirm that we reached satisfactory levels of technical data interoperability. However, to facilitate the semantic understanding of the data in multidisciplinary working groups, many efforts should still be made to overcome those difficulties related to using different languages that characterize the different research disciplines and the different professional and productive sectors. The development of the FAO AGROVOC thesaurus has made an essential contribution in this direction. This thesaurus can be a standard reference for all PA and farm management systems for all software applications to understand the data and obtain semantic interoperability.

b) Data management and modeling.

Data management and processing require the adoption of computer tools much more complex than traditional spreadsheets or personal databases. Moreover, understanding the relationships between different environmental variables is not only a problem of integrating data formats. Adopting new methodologies of analysis requires data modeling consistent with the main objectives of the research. For example, implementing relational databases and data modeling tools can help better manage and explore multiscale and multi-temporal data for developing new site-specific analysis methodologies. In this direction, using open-source databases allows many users to use a common platform to query the system, extract the data they are interested in, and enable further handling and processing of the database at no cost. To solve these critical issues, the best investment is in increasing human resources skills, encouraging advanced training of technical and scientific personnel, and contributing simultaneously to preparing new professionals needed to transfer innovation in the agricultural sector and beyond.

c) Data information flow.

Data flow is one of the main bottlenecks for the experimentation and operational adoption of products and results from adopting new technologies and advanced research in agriculture. The data flow is often limited to the transmission between the acquisition system and the related management software (e.g., between meteorological sensors and field sensor management software) and, at most, in very advanced cases, with the same integration into the farm management software. The use of interoperable web services with internationally recognized standards for accessing and distributing spatial data is a solution adopted today to receive, visualize and distribute real-time data via the web. The availability of standard web services, such as those of OGC standards, helps this process. In any case, developing and disseminating specific standards for PA, already addressed in international research, for interoperability in agriculture and mechanical engineering is necessary.

d) Research perspectives in PA.

The research needs funds to be carried out to reach developments and results that show the experiments' real operational impact. Also, this work has required resources, at least in the realization of the application part, to be tested and evaluated regarding the technical and methodological choices adopted in implementing a distributed service. The criticality of the stages of research progress is due to the often-uncertain prospects of continuity of investigations, especially in research paths so long and complex, and that requires, among other things, extensive use of technology. A fundamental role for higher investment in research and development is undoubtedly that of the agricultural sector's development and innovation policies. Moreover, the European directives and new European agricultural policy on research and the environmental sustainability of agriculture can undoubtedly give hope for innovative paths to follow.

In a period of a financial crisis, such as the one that Europe, particularly Italy, is going through, it is hoped that we will begin to invest in research and innovation as a driving force for a resumption of economic growth. Furthermore, this is also in the perspective of creating new development models for better environmental sustainability of agriculture.

CRediT authorship contribution statement

Simone Lanucara: Writing – review & editing, Software, Methodology, Conceptualization, Data curation, Formal analysis, Investigation, Validation, Visualization, Writing – original draft. **Salvatore Praticò:** Visualization, Writing – original draft, Writing – review & editing. **Giovanni Pioggia:** Supervision, Writing – review & editing. **Salvatore Di Fazio:** Writing – review & editing. **Giuseppe Modica:** Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Methodology, Conceptualization, Data curation, Formal analysis, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Ethics Statement

Not applicable: This manuscript does not include human or animal research.

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