Chapter 9
Management Information Systems and Emerging Technologies

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Abstract The following chapter addresses the principles of farm management information systems, i.e., computational, communication, and algorithmic subsystems, that integrate sensing, actuation, data management and analysis, knowledge of horticultural practices, and decision-making to automate the operation and management of modern orchards and vineyards. Topics include types of data and information, infrastructures, architectures, standardization, data ownership and sharing, and decision support system technologies.

9.1 Introduction

9.1.1 Farm Management Information Systems for Crop Production

During the last few years, rapid technological developments have introduced radical changes in the working environment in the agricultural sector. The level of complexity for farming enterprises has gradually increased in recent decades. Agriculture has entered a new data-driven era, in which access to accurate and timely information is of vital importance. Simple production units have evolved into agricultural businesses with multifunctional service sectors (Fountas et al., 2015a). Thus, modern farms can survive financially and be sustainable only when well managed (Husemann & Novkovic, 2014). However, farm management is a challenging and time-consuming task (Paraforos et al., 2017), with farm operations and activities often not being properly logged systematically and analytically (Fountas et al., 2015a).

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Farmers need an effective way to manage large volumes of information and technological tools to help them make optimal and sustainable decisions year-round (Paraforos et al., 2016). Farm management information systems (FMISs) are systems that support the collection, processing, and storage of data in a form that allows for the accurate scheduling and execution of farming operations (Fountas et al., 2015a; Sørensen et al., 2010) or provide farmers with valuable information to support decision-making. Figure 9.1 shows a commercial FMIS application for crop production, extensively used in vineyards, called SITI4farmer. ABACO's precision

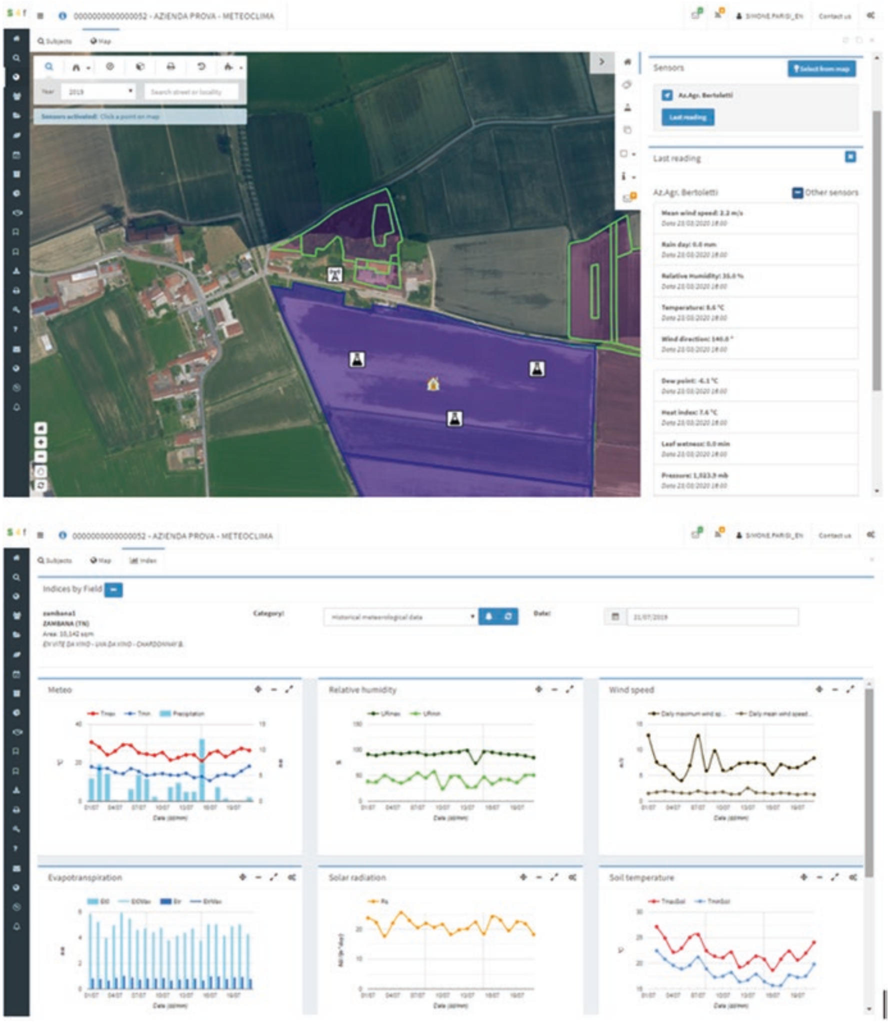

Fig. 9.1 Weather stations' latest readings and historical weather data are stored in the SITI4farmer, ABACO's precision farming tool. SITI4farmer is an example of a crop management platform and a decision support system, widely used in viticulture

farming tool collects sensor-based data, such as weather and soil, satellite data, and other historical data. It provides the user with easy-to-understand visualizations of this information.

Several FMIS structures and software architectures have been presented, while a constantly increasing number of commercial solutions are available on the market, such as 365FarmNet, AgriWebb, Agworld, FarmLogs, and FarmWorks (Ampatzidis et al., 2016; Nikkilä et al., 2010; Paraforos et al., 2017).

9.1.1.1 Historical Overview

The first agricultural FMISs were developed in the 1970s and focused on record-keeping and operations planning. In contrast, more complex record-keeping platforms with integrated decision support tools covering irrigation, pest management, and fertilizer applications appeared during the next decade. It was not until the late 2000s that precision agriculture (PA) as a concept emerged and introduced the consideration of agricultural fields as heterogeneous entities that required selective treatment instead of homogenous entities that are treated equally (Aubert et al., 2012). For this reason, new information systems focused on accurate farming operations were required (Cardín-Pedrosa & Alvarez-López, 2012). For the first time, farmers obtained the ability to generate large amounts of data using sensors and satellite systems (Tozer, 2009). As a result, efficient data management became a top priority, and sophisticated information systems using the newly introduced concept of "field variability" became necessary.

9.1.1.2 FMIS for Precision Agriculture

PA refers to information technologies and electronic communications and the implementation of more accurate Global Positioning Systems (GPS) that enable farmers to collect large amounts of data to use effectively for site-specific crop management (Aubert et al., 2012). Sensor arrays provide constant streams of data on soil properties such as moisture, temperature, humidity, and crop growth parameters information derived mainly from crop spectral reflectance. These data can help understand field variability and allow appropriate management practices to be implemented accordingly (Matese et al., 2009). This has created the need to design and develop dedicated FMISs to cope with the increased amount of data generated by applying PA in field production (Fountas et al., 2015b). Similarly, digital agriculture is a broader term that refers to digital sensor-derived data to support farm management decisions (Keogh & Henry, 2016).

9.1.1.3 FMIS Adoption and Profitability

FMIS development and adoption are strongly related to system profitability, with benefits extending to the value of improved decision-making. However, this is often difficult to quantify, as the benefits of using an FMIS could depend on the user's level of satisfaction. Younger farmers without farming experience can benefit from using an FMIS, which automatically generates documentation data and reduces the required task time while providing better management.

Agricultural management software mainly includes production planning, process integration, performance management, quality and environmental resource management, and sales order and contract management. Moreover, field operations management, best practices and predictions, finance, machinery management, traceability, and quality assurance are additional functions or services that many commercial FMISs offer to farm managers. An analysis of commercial software solutions revealed that current FMISs mostly target everyday farm office tasks related to financial management and reporting, particularly those related to sales, inventory, and field operations management (Fountas et al., 2015a).

9.1.2 Applications for Tree Fruit Orchards and Vineyards

Tree fruit orchard and vineyard products are considered specialty crops of high value since they require a significant amount of labor at various stages. Despite being characterized by high production costs, they have emerged as a fast-growing agribusiness segment. Increasing importance is directed toward detailed traceability systems for the product's origin and especially for the treatments used in production (Tsiropoulos & Fountas, 2015).

Fruit production is a demanding sector where trees have high fertilizer and irrigation needs, which should be carefully planned and applied. Optimal pest management, irrigation scheduling, and harvest timing are strongly related to the final quality of the yield (Tamirat & Pedersen, 2019). Furthermore, the timing of harvest is critical to the quality of the yield. For this reason, selective harvesting based on the ripeness level of the fruit in different zones of the orchard is often used. Finally, during critical periods when farming tasks should be planned and executed with utmost accuracy, farm machinery should constantly operate at optimal rates (Tsiropoulos & Fountas, 2015).

9.1.2.1 Pest Control Information Systems

Pest control and applying plant protection products (PPPs) are one of the most critical factors in crop production due to the severe consequences for human health and the environment from irresponsible practices. Agrochemicals directly impact the quality of yields and the market-selling price of the products. Excessive PPP use financially burdens the farmers and results in high residues of hazardous chemicals on the products that subsequently enter the food chain. FMIS can determine periods when disease outbreaks are more likely to occur and help growers apply the exact amount of PPP needed, avoiding overapplication. These systems can comply with legal regulations and agricultural production standards to ensure food safety and environmental protection (Fountas et al., 2015b). Modern spraying machinery for orchards stores spray data for each spray application to automatically produce the farm calendar that records all plant protection product treatments and provides full product traceability (Berger & Laurent, 2019).

9.1.2.2 Irrigation Management Information Systems

Irrigation is a crucial factor in crop growth and product quality. Despite how simple it may appear, irrigation planning and management is an extremely complicated procedure that requires enormous amounts of real-time data and utmost accuracy and timeliness to achieve optimal results. Soil water content and water availability for the plants depend on several parameters, including soil, climate, and topography. When rainfall is insufficient to meet crop water needs at critical growth stages, water stress can cause major losses in fruit orchards. Several projects, such as USERPA (USability of Environmentally sound and Reliable technologies in Precision Agriculture), propose holistic precision agriculture solutions for tree orchards and vineyards, with the focus being directed on irrigation and harvest management to increase the quality characteristics of fruits by optimizing input use while preserving environmental sustainability.

9.1.2.3 Harvest Management Information Systems

Harvesting is an extremely challenging procedure due to the short time window in which fruit is at optimum ripeness for picking. Fruit harvested prematurely or beyond optimal time can potentially affect how desirable the product is to consumers (Chauvin et al., 2009). Accurate and timely collection of data is driving harvest-related decisions on the farm. A harvest management information system that allows access to real-time harvest data was developed in California, USA, in 2016. This integrated system could automatically generate yield maps that provide farmers with data on the productivity of their farms and allow them to investigate factors related to potential spatial yield variability (Ampatzidis et al., 2016).

9.2 Big Data in the Emerging Technologies

Big Data is a hot research topic that has attracted much attention from the scientific community. Although there is extensive literature on the benefits that can be reaped from the exploitation of Big Data, no consensus exists about what a typical definition of the term is. As for existing definition attempts are concerned, it can be observed that these have focused on a wide spectrum of issues and aspects, ranging from Big Data sources, characteristics, and types to technical requirements and the potential impact of Big Data analysis on the socioeconomic level.

Big Data is generated, intentionally or unintentionally, by interactions and transactions digitally performed in our everyday personal and professional lives and ubiquitous sensor-based devices (George et al., 2014). Continuously increasing capacities of tools and infrastructures for collecting, logging, and transmitting data are the main reasons for data abundance, yet big volumes of produced data along with divergence in data types (i.e., structured, semi-structured, and unstructured data) and the increasing rates of data generation keep pushing demands for storage and process-related affordances (De Mauro et al., 2016; George et al., 2014).

To make sense of this overwhelming amount of data, it is often broken down and characterized into the following dimensions, often referred to as "Vs." The "Vs" of Big Data constitute concise and comprehensive summarizations of distinctive characteristics of Big Data and, by focusing upon its key properties, serve excellently as a basis for a Big Data management discussion. Starting with Volume, Velocity, and Variety, the Big Data property list has been extended to further include Veracity and Value, Volatility and Validity (Khan et al., 2014), and Vulnerability, Variability, and Visualization (Firican, 2017). It is the big volume and high rates at which Big Data is made available, the wide range of available types and formats, trustworthiness of the sources of Big Data, potential inconsistencies in the data, and its lifespan along with security and privacy issues that pose challenges for Big Data management at various levels.

The digital revolution is transforming agriculture, and the advent of new technologies increases the amount of data collected. The term agricultural Big Data refers to the variety and volume of data collected either directly in the field or from other sources. Chi et al. (2016) support the "Vs" approach by defining data in terms of volume, velocity, variety, and veracity:

- Volume: refers to the size of data collected for analysis.
- Velocity: measuring the flow of data and the time frame when it is useful and relevant.
- Variety: reflecting the frequent lack of structure or design to the data.
- Veracity: reflecting the quality, reliability, accuracy, and credibility of the data (Chi et al., 2016).

Although the "Vs" can describe big agricultural data, their analysis does not have to satisfy all dimensions (Rodriguez et al., 2017). Terms of big agricultural data are more about the combination of technology and advanced analytics than just the volume of data that creates a new way of processing information in a more useful and timely manner (Coble et al., 2018).

The following sections present information on capturing agricultural data and tools to perform data management and data analytics, including machine learning techniques. However, since the data revolution hasn't reached every agricultural sector yet and Big Data and AI are not yet specific to orchards and vineyards, the following description is general to all horticultural systems, including orchards and vineyards.

9.2.1 Sensing and Monitoring

The digital revolution transforms agriculture by using modern machinery, computerized tools, and emerging information and communication technologies (ICTs) to improve decision-making and productivity. The evolution and revolution in agricultural Big Data come from the expansion of small agricultural data. Growers can collect data about their operations by spreading several cutting-edge techniques and technologies. Vast amounts of agricultural data and many datasets are collected from GPS and remote sensing to artificial intelligence and machine learning, robotics, and the Internet of Things (IoT). Agricultural data originate from various sources, including:

- Farmers' fields utilize ground sensors, such as weather stations and soil sensors.
- Handheld crop sensors or tractor-mounted sensors.
- Data from aerial sensors, namely, unmanned aerial vehicles, airplanes, and satellites.
- Governmental and third-party organizations gather spatial and temporal historical data or distribute it via online repositories and web services.
- Real-time farm data via online web services and crowdsourcing-based techniques from mobile phones.

Challenges Related to Big Data in Horticulture

The basis for enhanced and effective decision-making is the availability of timely, high-quality data. The demand for large volumes of data and the lack of significance of limited amounts of data create challenges in developing Big Data applications in the agriculture sector, especially in orchards and vineyards. In addition, the sources mentioned above are mostly heterogeneous. The data are represented in different types and formats and differ in volume and velocity and in the way they are updated and governed (Kamilaris et al., 2017).

Most agricultural data sources are fragmented, difficult, and time-consuming to use. At the individual farm level, many digital agriculture applications are not true Big Data applications. Therefore, data errors may be a critical limiting factor in the utility of farm management information systems. Data errors can arise from multiple sources, including low-quality data and errors associated with poor data analytics and processing. This suggests that the full potential of such data and information is not being completely utilized. Integrating a variety of data into a coherent management information system is expected to remedy this situation (Fountas et al., 2015a).

A range of indicators suggests that the availability of farm-level sensors and other precision agriculture technologies, such as mapping and tracking technologies, have already changed the management of many farming systems. Effective collection, storage, sharing, and use of data can support farming decisions toward increased yield and quality of agricultural products and decreased use of inputs, thus increasing profitability and sustainability of farming. However, technical and governance barriers to collecting, storing, and transferring data hinder farmers' transition to digital agriculture. Various management systems, database network structures, and software architectures have already been proposed to improve functionality.

9.2.2 Data Management

Data utilization and decision-making about the application of targeted crop management and harvesting methods are at the core of precision agriculture, which is defined as "a holistic and environmentally friendly farming strategy in which practitioners can vary cultivation and input methods to match varying soil types and cross conditions in a field" (Srinivasan, 2006) to increase "the number of (correct) decisions per unit area of land per unit time with associated net benefits" (McBratney et al., 2005). However, the continuous evolution of digital devices' and infrastructures' capacities to capture and stream data of various formats and types at ever-increasing rates has led to a shift from precision agriculture to smart farming, a novel paradigm of data-driven holistic farm management (Pivoto et al., 2018; Vermesan & Friess, 2016). Smart farming does not rely exclusively on data collected in the field but rather views farm management decisions and operations from a broader perspective of context- and situation-awareness (Wolfert et al., 2017), which can be developed through systematic processes of sourcing, integrating, processing, and analyzing agricultural Big Data.

Nowadays, FMIS has increased in sophistication through the development and integration of new technologies and advances in hardware and software capabilities of mobile phones. Web- and app-based applications enable real-time data recording and automated data transfer (Fountas et al., 2015a; Nikkilä et al., 2010; Peets et al., 2012). Cloud-based FMIS improves operational planning and optimizes the work performed in the fields (Ampatzidis et al., 2016; Kaloxylos et al., 2014). Cloud platforms and cloud computing improve flexibility and accessibility, reduce infrastructure, and streamline processes while offering possibilities for large-scale storing, preprocessing, analysis, and data visualization (Barrett et al., 2014; Nativi et al., 2015). In many cases, computational capacity, both in terms of speed and volume, allows to conduct novel analysis on large volumes of data and use it for actionable decision-making previously not possible (Coble et al., 2018).

Various technologies directly linked to smart farming can be used for data collection and transmission to processing and storage. However, technology requirements for (agricultural) Big Data exploitation and management go far beyond the capacities of a single machine. Therefore, to take full advantage of agricultural Big Data and smart farming necessitates the deployment of systems and services on top of technologies that can handle the complexities of Big Data. One such technology is Apache Hadoop (https://hadoop.apache.org/), a state-of-the-art distributed framework consisting, among others, of three core components, including (i) HDFS (i.e., Hadoop Distributed File System) for handling data storage, (ii) YARN for resource management and optimization, and (iii) MapReduce for workload distribution across multiple nodes of commodity hardware.

Another typical example of cutting-edge Big Data technology is Apache Spark (https://spark.apache. org/), a "fast and general-purpose cluster computing platform" designed mainly for the execution of computations in memory. Apache Spark can also run applications on disk more efficiently than MapReduce and accommodate real-time processing of large sets of streamed data. It can easily be integrated with other tools in the Hadoop ecosystem and thus exploited in various architectures while accessing via custom APIs in widely adopted programming languages, such as Java, Python, Ruby, and SQL.

Other storage solutions for Big Data, tailored to different data structures, are provided by NoSQL databases which have gained momentum against traditional relational database management systems (RDBMSs) in recent years. According to Tiwari (2011), "NoSQL is used today as an umbrella term for all databases and data stores that don't follow the popular and well-established RDBMS principles and often refer to large datasets accessed and manipulated at web-scale" (Tiwari, 2011). There are several different NoSQL data store types, each of which adopts a specific data model (e.g., key-value pairs, column-based, document-based, and graph data models) to best accommodate the particularities of the data structures they have been designed for. Scalability, efficiency, flexibility, high access rates to data, and availability of a range of data models targeting different storage needs are some of the NoSQL data store system advantages over traditional RDBMSs (Nayak et al., 2013).

Another concept that is highly relevant to the need for efficient Big Data storage infrastructures is that of data lakes. Data lakes can be conceptualized as repositories containing large collections of loosely annotated data ingested from various sources (Hai et al., 2016). The key idea behind data lakes is to create collections of various types of data available to be integrated on-demand and utilized to create actionable insights and value. Apart from data extraction and ingestion, it is also necessary to extract metadata from data sources to efficiently support data reasoning, query processing, and data quality management (Hai et al., 2016).

Increased demands for Big Data storage and processing coupled with the high costs for in-premise hosting/maintenance of hardware and difficulties in setting up and configuring Big Data tools have led to a market for cloud-based processing and storage services. Cloud computing platform providers, such as Amazon AWS, Cloudera, and MapR, offer on-demand access to storage and integrated suites of analytics tools under Platform-as-a-Service (PaaS) and/or Infrastructure-as-a-Service (IaaS) schemes, tailored to a range of individual and corporate needs. With access to easily configurable solutions, users can design and execute resource-intensive tasks without worrying about parameterization and workload optimization.

9.2.3 Big Data Analytics

Big Data analytics is the complex process of examining large and diverse amounts of data to uncover information such as hidden patterns, correlations, market trends, and various other insights that can help organizations make informed decisions. Data analysis is categorized into five different stages:

1. **Identification of required data types**: *Find what you want to analyze and determine the questions you want to ask.* Having the solution to a problem in mind, Big Data analytics is a means to an end. Therefore, the solution process needs to commence by identifying what data needs to be collected to gain data-driven insights. The discussion about required data is not confined to formats and types but involves data sources that should be accounted for.
2. **Data acquisition/collection**: *Collect data and determine which is best to use. Having answered the question about the data that should be collected, the following step is to proceed to the actual data collection.* Many issues should be considered as part of this step. For example, data may have to be extracted from multiple databases and stored in a central repository. In this case, setting up ETL (i.e., extract-transform-load) processes is necessary. Other scenarios may involve real-time or near real-time processing. Streaming technologies or systems for temporary data storage are, in such cases, issues to be considered. When it comes to large raw data streams, we may also have to encounter data relevance issues. This means that not all data is important. Thus, filtering out irrelevant data is critical for optimal resource utilization. Yet, filters need to be carefully selected to avoid discarding useful information.
3. **Data preprocessing**: *Identify anomalies and correct duplicates, missing entries, or inconsistent data. Put in place standards to ensure data entry is consistent, but also expect that you will need to do regular maintenance over time.* Data cannot be provided as input to analytics algorithms in its raw form because we need to integrate and aggregate data available in different formats. Apart from that, there may also be errors and inconsistencies. Format conversion and data cleaning are core to this step. Data anonymization is also an issue to consider when the data includes sensitive personal details.

4. **Analyze**: *Several data analysis methods can be considered depending on the problem.* In this context, a discussion of different kinds of Big Data analytics is applicable. An outline of the different types of data analytics is provided below:
   - Descriptive analytics focus on answering questions about who, where, what, when, and how many.
   - Diagnostic analytics is concerned with responding to queries about why something happened.
   - Predictive analytics investigates and identifies trends in relationships between variables, determines the degree of relationships' correlation, and hypothesizes causality.
   - Prescriptive analytics focuses on investigating future scenarios and attempts to give answers to what-if questions and subsequently propose courses of relevant actions. Machine learning models based on Big Data play a significant role in this endeavor as they allow the prediction of outcomes considering a range of variables.
5. **Interpretation of data analysis results**: Once you have the data and understand it, what can you do with it? The final step is about making decisions and taking action regarding problem-solving. To successively do so, developing an understanding of analysis outcomes is necessary. Results' reports and visualizations have the potential to facilitate data-driven insights and, thus, inform problem-solving actions.

The scientific discourse on Big Data goes hand in hand with the extraction of value. As Gandomi and Haider (2015) characteristically point out, "the potential value of Big Data is only unlocked when leveraged to drive decision making." Yet, to "enable evidence-based decision making, there is a need for efficient processes to turn high volumes of fast-moving and diverse data into meaningful insights" (Gandomi & Haider, 2015). This is the exact point at which Big Data analytics comes into play. Exactly like in the case of Big Data, there are several definitions of Big Data analytics found in the literature. A brief review of this reveals that the term focuses on applying fit-for-purpose analysis methods and tools tailored to the particular characteristics and properties of Big Data. Starting from the need to solve a problem, the intention is to acquire actionable insights and knowledge to support decision-making and arrive at a problem solution. However, the extraction of knowledge from Big Data is not a one-step process. It involves multiple interconnected steps needed to be executed, most of the time, in an iterative fashion until outcomes are reached. This chain of Big Data analysis-related tasks is illustrated in a straightforward manner in a definition, according to which (Big) data analytics is "the process of extracting, transforming, loading, modeling, and drawing conclusions from data for decision-making."

It is important to investigate how existing Big Data analytics methods fit with agricultural Big Data and the knowledge needs they are collected for. According to Coble et al. (2018), machine learning, artificial neural networks (ANNs), decision trees, and clustering are some methods and tools that can be exploited for agricultural Big Data analysis purposes. For example, by utilizing available weather data, machine learning can be exploited for building weather forecasting models aiming to support decision-making by farmers. Other machine learning applications are linked to crop disease protection and crop yield prediction and selection. Clustering methods (e.g., K-nearest neighbors), decision trees, and ANN models can also facilitate crop yield prediction and selection. Irrigation-related models (built upon rainfall and water level predictions) and price prediction models (based on crop production outputs, input cost changes, market demand and supply, market price trends, wages, and costs of cultivation, transportation, and marketing) can also be built with the help of ANNs. Kamilaris et al. (2017) contribute to the discussion on the potential use of Big Data analytics in agriculture by linking specific sectors to agricultural Big Data sources and Big Data analytics (Kamilaris et al., 2017). Machine learning methods and tools, such as clustering, decision trees, support vector machines, logistic regression, and artificial neural networks, are prominent with applications in weather and climate change, land use, weed control, animal research, crops and soils, and food security and availability. Analytics tailored to geospatial data is core to the sectors of remote sensing, food security and availability, and weather and climate change. In addition to the above, interesting use cases for advanced image recognition and processing concerning weed control, remote sensing, and land use-related applications can be found.

9.2.4 Machine Learning

Machine learning (ML) is a branch of computer science, an application of artificial intelligence, which gives computers the ability to learn without being explicitly programmed. It can be used to construct various mathematical algorithms to exploit the potential value of Big Data, which makes learning possible.

Machine learning is comprised of a two-step process. The first process involves the machine "learning" the input data, and in the second process, the machine translates and analyzes both the input and output data. This leads to the creation of machine algorithms that then construct a system model to predict future values.

9.2.4.1 Types of Machine Learning Algorithms

There are three types of machine learning algorithms:

1. **Supervised learning (SL)**: When input and output variables are provided, learning becomes supervised. In this type of ML, the algorithm uses various training examples, and the machine analyzes the inputs and corresponding outputs. More widely used SL algorithms include artificial neural networks, decision trees, K-means clustering, support vector machines, and Bayesian networks. SL is further divided into two subparts, regression and classification, as explained below.

Regression: The output data can be continuous (i.e., in the range of 0–5000) or percentage-wise. Let's take the example of predicting downy mildew disease in vineyards and approaching this as a simple regression problem. Based on the agronomic knowledge, humidity is a parameter that escalates the downy mildew presence and expansion. Thus, using regression analysis, we can correlate the severity of disease presence to the air humidity measurements. Data from previous years will provide humidity measurements (x) and disease presence (y). So, a function $y = f(x)$ will be established considering a specific regression order that shows how accurately we fit the regression to our reference data x, y. Based on the relevance of the new input humidity measurements (xi) and the regression order, we can predict the severity of the disease (yi).

Classification: The output data is in discrete form, i.e., 0, 1, 2, but it should not be a fraction. Using the example of apple scab disease, we assign images of healthy leaves to class 0 and images of infested leaves to class 1, when using cameras to detect the problematic areas (Fig. 9.2). The classifier in this example is the k-nearest neighbor (k-NN). Each image is accompanied by a set of features, in most cases (i) color features, (ii) shape features, and (iii) texture features. Considering that apple scab appears as visible color anomalies on leaves, we expect major differences in color features during the classification process.

Consequently, in the training phase, we defined a set of features associated with healthy apple leaves (class 0) and apple scab leaves (class 1). So, in every new apple image of an unknown class, the features are calculated, and this observation will be placed on the feature map. We consider a 2D feature plane with a y-axis for color features and an x-axis for shape features. Depending on the k-nearest features ($k = 1$ in the example), the new observation is assigned either in class 0 or 1, **based on its proximity to the already known classes (d_{min})**.

2. **Unsupervised learning (UL)**: Here, we provide data whose input is known but whose output is unknown. Techniques such as clustering, which groups data into

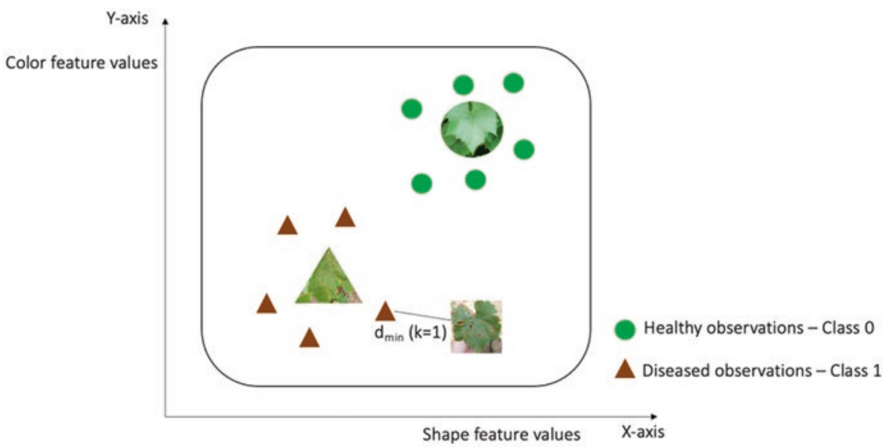

Fig. 9.2 k-nearest neighbor classification example

separate classes, are popular in this analysis. More widely used UL algorithms are self-organizing map (SOM), partial-based, hierarchical, K-means, COBWEB, and density-based spatial clustering. Applications using UL detect anomalies that do not fit any group or segmented datasets by some shared attributes. For example, DBSCAN is a clustering method that employs density and topology information to segment vegetation pixels from bare soil pixels in many agriculture vision applications.

3. **Reinforcement learning (RL)**: This is a special type of machine learning that focuses on learning through penalties and rewards. It is mostly implemented in video games and robotics. The learning process for RL is based on the principle of feedback. The idea is that every action impacts the system, which is then reported back to the algorithm, modifying its behavior. Exposing the fundamental concept of this method used in orchard and vineyard farming, many agriculture robots learn from mistakes such as colliding with obstacles or failing to pick fruit through penalty scores. At the same time, they figure out the shortest path to bypass obstacles or grab a fruit with the minimum number of motions through rewarding optimum practices.

All the methods mentioned above constitute different approaches to increasing the intelligence of a computing system. Another term often used in the artificial intelligence world is deep learning (DL). DL is a subset of machine learning and refers to the computer software technique that mimics the network of neurons in a brain. Deep learning co-exists with the learning methods listed above but offers great advantages in feature extraction and prediction accuracy.

9.2.4.2 Application Domains

ML provides a powerful and flexible framework for data-driven decision-making and the incorporation of expert knowledge into the system. These are some of the key characteristics of the ML techniques that make them widely used in many domains and highly applicable to precision agriculture (Chlingaryan et al., 2018).

Covering a large portion of ML applications in agriculture, a recent study indicated (i) crop management, including applications for yield prediction, disease and weed detection, crop quality, and species recognition; (ii) water management; and (iii) soil management as the most important categories in the farm management cycle (Liakos et al., 2018). The following section will showcase ML applications covering the categories that play a crucial role in the orchard and vineyard production cycle.

For yield prediction purposes, a study on coffee trees employed 42 color features in digital images and supervised learning methods to count the fruits on the branches and provide information on the maturity stage and weight in each measurement (Ramos et al., 2017). Another approach focusing on yield prediction in apples with unsupervised learning offered promising results by considering the driving factors affecting yields, such as soil texture (clay and sand content), soil electrical conductivity (EC), and potassium (K), phosphorus (P), organic matter (OM), calcium (Ca), and zinc (Zn) content (Papageorgiou et al., 2013). In grapevines, a 3D imaging technique combined with ML managed to estimate the yield accurately before ripening with 98% accuracy and 96% during ripening (Dey et al., 2012).

As far as disease detection is concerned, ML has found fertile ground in many applications related to detecting diseased leaves and fruits accurately. Color cameras provide useful color, shape, and textural information that allow the ML classifiers to decide if the content of an image belongs to the healthy or diseased class. But what happens when the visible spectrum cannot reveal evidence of disease? Multispectral, hyperspectral, and thermal cameras provide more sophisticated information on the crop reflectance, allowing the effective detection of diseases even at the presymptomatic stage when disease stress is not visible to the naked eye. Such research concepts are tested in diseased crops, including citrus (Sankaran & Ehsani, 2013), banana, lemon, and mango (Arivazhagan et al., 2013), and downy mildew and black rot diseases in grapevines (Waghmare et al., 2016). However, the unstructured field environment challenges the field deployment of such computer vision techniques. Fruit occlusion and poor lighting conditions are the major problems that vision-based systems are suffering.

Crop quality is another application domain of ML that facilitates the accurate crop status assessment. For example, unsupervised learning techniques utilized soil data (e.g., electric conductivity) and NDVI measurements to estimate grape quality and effectively delineate into separate farm management zones (Tagarakis et al., 2013). In pear orchards, hyperspectral imaging and supervised learning techniques were used to discriminate deciduous-calyx pears (high quality) from persistent-calyx pears (low quality) (Hu et al., 2017).

Regarding water management in orchards and vineyards, several studies have been conducted to estimate daily, weekly, and monthly evapotranspiration. This is a complex process that requires sufficient water resource management and the effective design of irrigation systems. ML techniques are ideal tools for understanding patterns and sequences of meteorological data; thus, two studies used temperature records from 1961 to 2014 (Feng et al., 2017) and 1951 to 2010 (Mehdizadeh et al., 2017) to estimate evapotranspiration. Finally daily dew point temperature is an important element for identifying expected weather phenomena, so a relevant study employed ML techniques to estimate daily dew temperature, having two local weather stations as a source of input data (Mohammadi et al., 2015).

Finally, soil properties such as soil drying, condition, temperature, and moisture content are pivotal elements of the production cycle, while the mechanisms and processes are difficult to be determined. ML has proven to be a promising tool in identifying the soil status since soil measurements are generally time-consuming and expensive for mapping the soil properties in large-scale vineyards and orchards. One notable study managed to estimate the daily soil temperature at six different soil depths of 5, 10, 20, 30, 50, and 100 cm (Nahvi et al., 2016), while another research used ML techniques to predict soil moisture only from the force data derived from tillage machines and the working speed (Johann et al., 2016).

9.3 Decision-Making and Intervention

In data-driven agriculture, high-quality data is the most valuable currency in the sector. Producers need an enormous amount of information to enable efficient planning and decision-making throughout the entire growing season. Nutrient deficiencies, water stress, and disease occurrence can be effectively managed during the growing season (Usha & Singh, 2013). These problems can be solved with constant data sources that provide valuable information on crop health and stress, nutrient requirements, and infestation threat levels. However, the challenging aspect of the agricultural sector is that data loses value the later it becomes available. Decisions such as disease control or inputs application require utmost accuracy in their timing, with a miss of a few days resulting in major losses in the final yield. Therefore, agricultural decision-makers at all levels need an increasing amount of information to better understand the possible outcomes of their decisions and to assist them in developing plans and policies that meet their goals.

Many decision support systems (DSS) have been developed, and farmers have shown great interest in limiting uncertainty in decision-making (Stone & Hochman, 2004). However, DSS-related "problem of implementation" remains in many cases because of the "lack of sustained use in a way that influences practice" (McCown, 2012). Factors that may influence the implementation of a DSS in agriculture include profitability, user-friendly design, the time requirement for DSS usage, credibility, adaptation of the DSS to the farm situation, information update, and level of knowledge of the user (Kerr, 2004).

Even though most of the technical problems related to DSS (farmer's access and connectivity issues) have been solved during the past few years (Rossi et al., 2014), the following restrictions remain and could be the next challenge for the future developers of agricultural DSS: (a) they often fail to see crop production holistically, and most DSS is problem-specific; (b) they have poor quality because of insufficient validation; (c) they could be more user-friendly; (d) they are time-consuming, because of delays in data processing or complex input requirements; (e) information is sometimes delivered to users asynchronously related to decision-making timing and the need for action; (f) there is a need for constant maintenance and updates; (g) they have low capacity of modification and customization; and (h) they often describe a result as the optimal solution which is discouraging to the farmer who usually wants to take part in the decision-making process.

9.3.1 Agricultural Decision Support Systems (DSS)

Agri-information systems can be defined as a system for collecting, processing, storing, and disseminating data in the form needed to carry out a farm's operations and functions or providing farmers with valuable information to support decision-making and farm management. Agricultural decision support systems (DSS) are computing systems that help decision-makers leverage field data and agronomical models to solve problems and develop carefully planned strategies to meet their production targets. Sophisticated DSS aims to improve the performance of agricultural production units by analyzing enormous volumes of information and translating it into complex decisions that often cannot be made by human means.

Spatial DSS (SDSS) are computer-based systems designed to solve complex problems related to multiple parameters that demonstrate spatial variability. Typically, an SDSS consists of a geo-informatic system (GIS) and a DSS. Geospatial cyber-infrastructure (GCI) is the most current version of a DSS, using data resources, network protocols, computing platforms, and computational services. They support functionalities such as data acquisition, storage, management, and integration of both static (e.g., pedology, geology) and dynamic data (e.g., daily climate), data visualization, and on-the-fly computer applications (such as those enabling simulation modeling for the determination of water stress), all potentially accessible via the web (Terribile et al., 2017).

In general terms, most DSS used in agriculture have similar basic architecture:

- Collection, organization, and integration of several types of information required for producing a crop or describing complex multifactorial processes in agricultural units. Data is entered either from the farmer, via the web, which provides site-specific information, for each field decision unit, or obtained automatically (often in real time) by sensors positioned on the farm. In general, these data may include cropping and plant parameters (dimensions, growth stage, reflection of light in certain frequencies), field data (altitude, sun exposure), soil data (dynamics, temperature, water, nitrogen, salinity, carbon balance), climate data (temperature, humidity, rainfall, direction and strength of wind), and farm management practices (irrigation, fertilization, pest control).
- All this information is then analyzed and processed, usually by a server, as part of a web infrastructure in most cases that provides output to the farmer to support his field management. The processing and interpretation of the data are facilitated through crop models, classified as either empirical/statistical or dynamic. Empirical models usually exploit the statistical relationship between all parameters mentioned above; they are computationally demanding (e.g., regressions) and are widely accepted (Terribile et al., 2017). However, they have various weak points, such as the high level of calibration required (when applied to a new environment). Most importantly, they do not address the nonlinear relationships between plant and environmental factors. On the other hand, dynamic models attempt to solve the nonlinear relationships and allow for greater generalization of crop growth processes and, consequently, a better adaptation to new environments and an overall much better performance. Generally, dynamic models simulate plant growth development daily and consider site features at specific locations (Terribile et al., 2017).
- After processing and interpretation, depending on the type of the DSS, it may recommend the most appropriate action or action choices. Depending on the type and specificity of the DSS, these suggestions could concern (a) planting dates based on soil and weather conditions; (b) harvest dates based on maturity, along with soil and weather conditions; (c) daily irrigation based on daily values or soil

water depletion; (d) fertilizer additions, based on read-in values or automatic conditions; (e) application of residues and other organic materials (plant, animal); (f) prevention steps if disease risk is detected; and (g) both daily operational and long-range farm-related strategic decisions.

9.3.2 Types of Agricultural DSS

9.3.2.1 Irrigation DSS

Regulated deficit irrigation (RDI) is a strategy in which water is saved by reducing or completely restricting irrigation at certain crop growth stages to control the growth of shoots. This technique has been widely used for many decades to increase the quality of fruit yields; however, its application in drought-sensitive orchards carries the risk of imposing too much water stress. For this reason, DSS is often used when such practices are adopted to ensure that no critical mistakes occur when accuracy matters the most. Marsal and Stöckle (2012) carried out an experimental pilot to test the efficiency of CropSyst in a pear orchard where an RDI program was applied. The model performed exceptionally well, especially for the period after applying deficit irrigation (Marsal & Stöckle, 2012). In 2012, Peets et al. described the development and validation process of a GIS-based SDSS for precision irrigation management of tree crops. Their system combined crop growth data generated by various field sensors under environmental conditions and irrigation regimes in orchards with abiotic soil, elevation, and climatic data to construct a site-specific orchard irrigation DSS.

9.3.2.2 Fertilization DSS

Excessive use of fertilizers has both environmental and economic impacts. The farmer spends money without improving his yield, and increased concentrations of nutrients in the soil often cause phytotoxicity, which leads to yield decrease and quality degradation. On the other end, the under-application of fertilizers does not allow the crops to reach their maximum productivity since available nutrients are not sufficient for their needs. Both cases result in low nitrogen use efficiency.

Fertilization DSS is based on agricultural models after vigorous tests on a large number of fertilization experiments for each crop type. Therefore, the ability to estimate the optimal application rates and dosages for each fertilizer application is essential for efficient farm management (Papadopoulos et al., 2011). Figure 9.3 shows a commercial application of a crop management platform and a decision support system with the proposed variable rate fertilization that can be visualized.

Fig. 9.3 A pH soil map of a vineyard (top image) and a "Precision Farming Project" suggesting variable rate fertilization of the field (bottom image), as suggested by ABACO's SITI4farmer DSS

9.3.2.3 Pest Management DSS

The pest control methods and timing require deep knowledge of pests and the mechanisms that affect their spreading, setting pest DSS as an essential part of pest management programs. Advanced integrated pest management (IPM) programs require complex tactical decisions for planning and execution. Agrochemicals are often applied when there is no actual infestation and when the farmer decides when to spray. Therefore, knowledge derived from field data is needed to enable accurate decisions on pest management.

9.3.3 Examples of DSS in Agriculture

Many new technologies have been developed for or adapted to agricultural use in the last 30 years. The most recent information systems that support agriculture decisions allow the segregation of minor differences, both objective and statistically significant. Existing tools are even now designed to better manage crop adaptation between different parcels, focusing on the variability within the parcel. Many of these processing systems have been initialized in the framework of research projects, but they are often transformed into commercial services offered to single farms.

DSSAT (Decision Support System for Agrotechnology Transfer) is a software application program for simulating crop models which incorporates models for 42 different crops, in constant development, since its beginning as a research program. It has a modular structure with multiple components, including soil, crop, water, weather, soil-plant-atmosphere competition, management, pest control module, etc.

Many DSS have been developed especially for vineyard management, research, and commercial purposes. Vite.net is a research project in Italy developed for the sustainable management of vineyards and is intended for the vineyard manager (Rossi et al., 2014). The DSS consists of two main parts: (i) an integrated system for real-time monitoring of vineyard components (air, soil, plants, pests, and diseases) and (ii) a web-based tool that analyzes these data by using advanced modeling techniques and then provides up-to-date information for managing the vineyard in the form of alerts and decision supports. GeoVit (Terribile et al., 2017), developed as a GCI, may provide an important web-based operational tool for high-quality viticulture as it better connects the farm and landscape levels. It supports the acquisition, management, and processing of static and dynamic data, data visualization, and computer applications to perform simulation modeling, all potentially accessible via the web. The NAV (Network Avanzato per il Vigneto – Advanced Vineyard Network) system is a wireless sensor network (WSN) designed and developed for remote real-time monitoring and collecting micro-meteorological parameters in a vineyard. VineSens is a hardware and software platform for supporting pest management decision-making. Using a WSN and epidemiological models can predict and prevent diseases, most usually faced by vine growers, such as downy mildew. In commercial services, several companies offer solutions for monitoring and managing vineyards, combining hardware and software with most of them provided and supported through web-based platforms, such as VintiOS, a precision viticulture software, supporting vine growers and oenologists on the grapevine production and quality.

9.4 Discussion and Conclusions

This chapter presented an overview of farm management information system (FMIS) principles that integrate sensing, data management and analysis, and decision-making to automate the operation and management of modern orchards and vineyards. It investigated how existing emerging technologies, such as Big Data analytics methods and machine learning, fit with agricultural Big Data for tree fruit orchards and vineyards and the knowledge needs for which they are collected.

Farmers need an effective way to manage large volumes of information and technological tools to assist them in making year-round optimal and sustainable decisions. The integration of a variety of data into a coherent management information system is the solution. Farm management information systems support the collection, processing, and storage of data in a form that enables accurate scheduling and execution of farming operations or provides farmers with valuable information to support decision-making. The availability of farm-level sensors and other precision agriculture technologies has changed the management of many farming systems. Nowadays, FMIS has increased in sophistication through the development and integration of new technologies and advances in hardware and software capabilities of mobile phones. Web- and app-based applications enable real-time data recording and automated data transfer. Several technologies directly linked to smart farming can also be used for data transmission, processing, and storage.

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