Big Data to Enable Global Disruption of the Grapevine-powered Industries

D2.1 - Use Cases & Technical Requirements Specification

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EXECUTIVE SUMMARY

The deliverable D2.1, "Use Cases & Technical Requirements Specification", aims to give the outline, specify and present in detail the use cases that will be examined and undertaken during the project lifetime. It is a report documenting the use cases and the different scenarios and hypotheses that derive from them, which are directly linked and related to the BigDataGrapes pilots. More specifically, this deliverable provides the methodology that was followed by the project partners in order to define and categorize the use cases, the interpretation of the use cases with respect to their technical and infrastructural requirements, since each use case elicits to specific software requirements in terms of functionality, expected performance and required equipment.

The document is structured as follows. Chapter 1 serves as an introduction to the deliverable whereas Chapter 2 provides an overview of the use cases with details on the methodology which was followed in order to define them, their categorization and analysis as well as their importance on the domain. Each use case is separated in four sections: the scenario behind the use case, the real-life data problem to be addressed, the approach that is currently used to address the data problem, the scenario hypothesis, which practically presents a new approach to the data problem at hand thanks to the BigDataGrapes Project, the related data and their description, the technical requirements of the use case and the related pilot(s) that relate directly to the use case. Finally, Chapter 3 contains the conclusions regarding the use cases.

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1 INTRODUCTION

BigDataGrapes aims to explore realistic, applicable Big Data challenges in grapevine-powered industries, and as a result the early involvement of the relevant stakeholders in order to elaborate on the envisaged use cases has been defined as critical. The data problems of the targeted grapevine-powered industries require cross-sector technical solutions for the entire lifecycle of the Big Data Value Chain. While for some of the data problems entailed in the use cases there are established technologies and processes to be adopted, others require novel methodologies to ensure that the real-world demands posed by the industries are met. To this end, BigDataGrapes will produce a complete, integrated Big Data solution that responds to the different core challenges by adapting and extending existing standards and tools or, where necessary, advancing the state-of-the-art with outcomes of basic research in the relevant fields.

The driver for the project's developments is the Data Challenges faced by these industries, which have already been collected, refined and analyzed in the context of WP2, Grapevine-powered Industry Big Data Challenges (and will continue to do so) by solidifying the BigDataGrapes use cases, record and systematically analyze data assets, identify the pragmatic Big Data needs that need to be covered, and, ultimately, produce the architecture of the BigDataGrapes solution. WP2 in general aims to:

- Produce a concrete specification of the use cases where data challenges are of major significance for the relevant stakeholders;
- Elicit the technical requirements for serving these use cases, taking into account functional, operative and performance demands.

More specifically, the objectives of T2.1 "Use Cases and Requirements" are (i) the mapping of the various industry's data problems that exist within the domain, (ii) the elicitation of the technical requirements in order to address the data problem, and (iii) the definition of the hypotheses that need to be examined in order to pave the way for experimental testing.

The work of this task and its outcome, deliverable D2.1, is the main driver for the entire project since they directly linked to other activities covering a large spectrum of the project, namely activities related to WP8 and the BigDataGrapes pilots as well as to the technical WPs, which will make use of the data defined and used within the use cases and their instantiations, namely the BigDataGrapes pilots.

2 USE CASES

2.1 METHODOLOGY

The partners defined, identified and documented use cases mirroring the data challenges they face and their expectations and foreseen benefits from the application of the project's technological assets, in terms of operational, revenue and expansion gains. These are both technical and research problems that all partners would like to tackle, and they constitute the key point and are requested in the context of WP2. These requirements are expected to be based on both the partners experience as well as input from end-users.

The first step was to identify and map the different data problems that exist within the different domains. If the problem is important for the domain, then it is worth to further explore it as a use case. The second step was to examine whether there are data for a specific Use Case. In case of insufficient or no data at all, the intermediate step was to examine there would be enough time and equipment to generate the data in question. The third step was to examine if the use case is feasible and if there is the necessary experimentation space in order to carry out the related pilot(s) to verify and evaluate the use case.

2.2 USE CASES CATEGORIZATION

Four overarching (4) use cases and ten (10) relevant scenarios, in which the use cases are further divided, have been identified so far under WP2, "T2.1-Use Cases & Technical Requirements" (Table 1). Instantiations of these use cases are the pilots that have been defined in D8.1.

2.2.1 Use Case A - Earth Observation Data Anomaly Detection and Classification.

The purpose of this use case is to develop models that differentiate between Earth Observation data issues and anomalies. This is for triggering warnings to farmers and insurances concerning farm management practices or damage events. This use case is a cross-pilot use case since it is going to be addressed, tested and evaluated by all pilots.

2.2.2 Use Case B - Yield & Quality Prediction

The purpose of this use case is to leverage historical earth observation data combined with additional relevant information from the field to make educated guesses about yield and wine quality, based also on the expertise and know-how of the vine growers.

2.2.3 Use Case C - Farm Management

This use case would take care of optimizing the farm practices and of management. This would mean modelling climate, sunlight exposure, soil quality, slope and topography to predict the vine specific needs considering how different cultivation and vineyard management techniques affect grape quality and quantity.

2.2.4 Use Case D - Food protection

The purpose of this use case would be to predict the risk in food products in order to minimize the impact of food recalls and rejections in a supply chain. The use case will focus on how the risk prediction can be applied in the grapes and grapes-based products supply chain but also in other selected supply chains to validate the scalability of the approach.

Table 1: Use Cases and Scenarios

Industry Users	Use Cases (Generic)	Use Case Scenarios	Used Tools
• Farmers, Table and wine grapes producers (Mezzacorona, San Leonardo)	A. Data Anomaly Detection & Classification	A. Earth Observation Data Anomaly Detection & Classification	SITI4FARMER
• Farmers, Table and wine grapes producers (Kontogiannis Familly, Palivou Estate, Fasoulis Nurseries, Zacharias Vineyards, farmers' associations in Peloponnese) • R&D experts working in universities doing research on Viticulture and Precision Agriculture (AUA) • R&D experts working in universities doing research on Viticulture (IFV, Institut Français de la Vigne et du Vin) • Farmers, Table and wine grapes producers (GCF Group (Grands Chais de France), Gérard Bertrand) • R&D experts working in companies that are developing products based on grapes (APIVITA)	B. Prediction	B1. Yield Prediction B2. Predicting Biological Efficacy B3. Crop Quality Prediction • for Optimizing Post Harvest Treatments of Table Grapes (B3-1) • for Optimizing Winemaking (B3-2)	SITI4FARMER
• Farmers, Table and wine grapes producers (Kontogiannis Familly, Palivou Estate, Fasoulis Nurseries,	C. Farm Management	C1. Optimization of Farm Practices in the Vineyard C2. Management Zones Delineation for Vineyards	SITI4FARMER

Zacharias Vineyards, farmers' associations) • R&D experts working in universities doing research on Viticulture and Precision Agriculture (AUA)			
• Buyers, QA & FS experts from companies that are selling or using grapes in their products (Conagra, Brüggen, AB Vasilopoulos) • Buyers, QA & FS experts from companies that are producing grapes, wines and/or raisins (e.g. Gallo Winery, Greek Grape Company) • Buyers, QA & FS experts from other food companies (e.g. Pepsico, Campbell, Chiquitta, Hershey) • R&D experts working in companies that are developing products based on grapes (Symbeeosis)	D. Food protection	D1. Supply Chain Risk Prediction Dashboard D2. Price Prediction Dashboard D3. Price & Fraud Correlation Dashboard D4. Marketing Automation Dashboard	FOODAKAI

2.3 USE CASES ANALYSIS

Each use case is separated in seven sections, namely (a) the scenario behind the use case, (b) the real-life data problem to be addressed, (c) the approach that is currently used to address the data problem, (d) the scenario hypothesis, which practically presents a new approach to the data problem at hand thanks to the BigDataGrapes Project, (e) the related data and their description, (f) the technical requirements of the use case and (g) the related pilot(s) related directly to the use case described in D8.1.

Depending on the experimentation feasibility with respect to the required availability of data, use cases have been further divided to two sets. The first one refers to use cases that will be piloted during the first project period. The second one refers to use cases that need preparatory actions to support the required data spectrum and will be planned for the second round of BigDataGrapes pilots.

The use case entitled (A) Data Anomaly Detection & Classification has one relevant scenario named "Earth Observation Data Anomaly Detection & Classification" (Table 2).

Table 2: Earth Observation Data Anomaly Detection and Classification Scenario

Use Case	(A) Data Anomaly Detection and Classification
Scenario	*Earth Observation Data Anomaly Detection and Classification*
Real-life Problem	In order to make efficient use of Earth Observation (EO) data for Farm Management applications it is crucial to be able to differentiate between data issues and anomalies. This is not a trivial thing. This is a prerequisite to be able to provide warnings to farmers about Management practices. Anomalies detection is possible through the detection of deviations between Expectation and Observation. Inputs that can support this are: Static Heterogeneity of the field (Management Zones) & Typical patterns of expected crop development for the observed environmental conditions; Classification of anomalies should be able to differentiate between Data errors (clouds, shadows, atmospheric disturbances) & Farm Management related issues (Pests, diseases, vegetation stress through missing water or fertilizer or weather related damage).
Current Approach	Mostly manual work

Scenario Hypothesis	• <u>HYP1</u>: We are able to detect anomalies in EO data with the support of Management Zones & Typical patterns of expected crop development
	• <u>GOALS1</u>:
	  ○ Find out if and how we can detect data anomalies in EO data. (what kind of data anomalies (e.g. clouds, cloud shadows, atmospheric disturbances (e.g. fire smoke), vegetation vitality decrease due to water stress, nutrient deficit, pest, disease, damage)?
	  ○ Which spatial resolution is necessary for which data anomaly?
	  ○ Which benefit do Farm Management Zones bring for this?
	  ○ Which benefit do we gain from the comparison of fields with expected patterns of crop development (e.g. by comparing fields with other (reference) fields in the area)
	• <u>HYP2</u>: We are able to classify detected anomalies into data issues and farm management related issues
	• <u>GOALS2</u>:
	  ○ Find out if and how we can classify anomalies into data issues & farm management related issues. (Understand what kind of farm management related issues are observable in EO data;
	  ○ Develop methods to differentiate between data anomalies and farm management related issues)
	• <u>Potential methods</u>:
	  ○ Time series analysis (e.g. outlier detection after curve smoothing); Data issues like clouds or shadows exhibit characteristic features (e.g. NDVI drops) in specific vegetation indexes and the multispectral images themselves while a decreased vegetation vitality shows other features
	  ○ Single Image analysis (e.g. analysis of spectral information or indices)
	  ○ Compare spatial patterns in images with expected patterns (Management Zones)
	  ○ Compare time series of fields with reference time series (e.g. by generating a reference curve through aggregating all similar fields in an area and searching for deviations)

Related Data/Description	Sentinel-2	Sentinel-2A/B MSI visible & NIR bands
	Landsat-8	LS-8 OLI visible & NIR bands
Technical Requirements	• Develop a data pre-processing component able to classify between EO data issues and anomalies. This component will rely on machine learning/deep learning libraries in order to perform the classification task. • Develop a data pre-processing component able to automatically send warning message to the specialist actors in response to certain events such that data anomaly detection.	
Related Pilot(s)	***Farm Management Pilot- ABACO***	

The use case under the generic name (B) Prediction has three (3) relevant scenarios named B1- Yield Prediction, B2- Predicting Biological Efficacy, B3- Crop Quality Prediction. More specifically, the third scenario is divided into two subcategories B3.1 Crop Quality Prediction for Optimizing Post Harvest Treatments of Table Grapes and B3.2 Crop Quality Prediction for Optimizing Winemaking (Tables 3,4,5,6).

Table 3: Quality/Yield management/prediction Scenario

Use Case	(B) Prediction
Scenario	*B1- Quality/Yield management/ prediction*
Real-life Problem	Ever since the first adoptions of precision viticulture, the need for accurate yield predictions has become obvious. Yield estimations can help the growers optimize variable rate applications, the timing of harvest operations, as well as storage and shipping of their production. However, the difficulty of sampling and the lack of efficient methodologies become obstacles that greatly limit the growth and development of the sector.
Current Approach	The traditional method used by table and wine grapes growers for predicting yield is based on weight measurement of bunches, an inefficient and time-consuming operation, which also fails to provide accurate estimations. More sophisticated yield prediction models have been developed based on data of temporal soil and weather patterns; however, the accuracy is still not adequate. Proximal and satellite data that can be converted into vegetation indices demonstrate high correlation to yield, but the number of factors that can affect the indices' values is far too great to be considered a reliable stand-alone data source. The knowledge of spatial patterns within a field is critical to select homogenous zones with site-specific input to better understand and predict the impact of weather, soil and landscape characteristics on spatial and temporal patterns of crop yields to enhance resource use efficiency at field level.
Scenario Hypothesis	Ever since the first adoptions of precision viticulture, the need of accurate yield predictions has become obvious. Yield estimations can help the growers optimize variable rate applications, the timing of harvest operations, as well as storage and shipping of their production. However, the difficulty of sampling and the lack of efficient methodologies become obstacles that greatly limit the growth and development of the sector. The traditional method used by table and wine grapes growers for predicting yield is based on weight measurement of bunches, an inefficient and time-consuming operation, which also fails to provide accurate estimations. More sophisticated yield prediction models have been developed based on data of

	temporal soil and weather patterns; however, the accuracy is still not adequate. Proximal and satellite data that can be converted into vegetation indices demonstrate high correlation to yield, but the number of factors that can affect the indices' values is far too great to be considered a reliable stand-alone data source. The knowledge of spatial patterns within a field is critical to select homogenous zones with site-specific input to better understand and predict the impact of weather, soil and landscape characteristics on spatial and temporal patterns of crop yields to enhance resource use efficiency at field level.	
Related Data/Description	Sentinel-2	Sentinel-2A/B MSI visible & NIR bands
	Landsat-8	LS-8 OLI visible & NIR bands
	Canopy sensing	Canopy sensing and vegetation indices data
	Yield data	Historical yield data
	Drone imagery	Aerial images
	IoT stationary data	Soil moisture data, meteorological data
	Crop calendar	Records of crop growth stages and agricultural operations, yield and quality, soil analysis
	Eca sensing	Georeferenced soil electrical conductivity data
	Topographic data and elevation maps	Spatial data (boundaries and elevation data)
	Grape and berry mechanical properties	Lab analysis data
	Phenolic composition data	Lab analysis data
Technical Requirements	Develop a data analytics component able to support management decisions concerning the yield and quality of grape production (under different quality criteria).	
Related Pilot(s)	***Table and Wine Grapes Pilot- AUA***	

Table 4: Predicting Biological Efficacy Scenario

Use Case	(B) Prediction
Scenario	*B2- Predicting Biological Efficacy*
Real-life Problem	There is a need in extracting the most out of pharmaceutical plants for both economic and environmental reasons. A real challenge is to add high value to by-products. Wine making produces a lot of by-products that may have a significant biological value if there are adequate data concerning farm management. These data can lead to decisions concerning the processing of by-products in order to produce high added value active ingredients for cosmetics and food supplements. The real-life challenge applies to both farmers and companies. Farmers during the wine making process produce valuable high-quality by-products that may be used in other industries. Nevertheless, a farmer using the state of the art doesn't exploit all the significant parameters and data that play an important role to the final quality and value of its products. The challenge is to be able to exploit data from diverse sources in order to predict some key quality

<table>
<tr><td></td><td colspan="2">parameters of the products and by-products that will eventually find an application in the industry.
Potential buyers or companies on the other hand, perform market research and evaluations in order to choose suppliers of raw materials. Nevertheless, using the state of the art there is no efficient and economical way of knowing which one best suit a specific need, except trial and error by sampling and performing lab measurements on every raw material. Linking data such as the location of a domain, the weather conditions in the area or the cultivation methods can lead to conclusions regarding the most suitable supplier and raw material for a specific product with a specific biological function.
The goal of the pilot is to prove the correlation between data from the field and the quality of extracts developed from vine materials.</td></tr>
<tr><td>Current Approach</td><td colspan="2">Standard approach involves processing of by-products (e.g. grape seed) according to the availability of the material.</td></tr>
<tr><td>Scenario Hypothesis</td><td colspan="2">The main purpose is to find how we can link crop location and weather conditions to the biological quality of the products. A company can then choose a list of suppliers for a specific need, just by evaluating crop location and weather conditions and thereby reaching conclusions regarding biological activity of by-products. A farmer on the other hand, can perform decision making by evaluating location and weather conditions on his field and thereby reaching conclusions regarding biological activity of its products. The farmer will then be able to make decisions on the commercialization of the by-products.
This scenario hypothesis is aiming to create a predictive model that will correlate parameters concerning weather conditions and parameters linked with biological efficacy. The appropriate algorithms will be created that will use existing datasets and explore the relationship between them. Datasets concerning weather conditions will work as independent variables, while the datasets concerning biological efficacy will work as the dependent variables. A number of potential correlations will be generated (regression models?) between them. Once the correlations are generated, the selection process of the ideal correlation will focus on minimum complexity and error.
This scenario hypothesis has the potential for increased scalability using additional weather and spatial data by choosing larger territories as points of interest.
Our goal is to develop a decision support system (DSS) that nurtures users' trust. To achieve this goal, the system must be transparent, meaning it must be able to clearly communicate the prediction model with users and show differing effects of input variables on the model's output. Research had suggested that visual tools are the most efficient for these tasks.</td></tr>
<tr><td rowspan="6">Related Data/Description</td><td>Vine leaf extract var. 1</td><td>Extraction using water soluble solvents</td></tr>
<tr><td>Vine leaf extract var.1</td><td>Extraction using water soluble solvents</td></tr>
<tr><td>Vine leaf extract var. 2</td><td>Extraction using water soluble solvents</td></tr>
<tr><td>Vine leaf extract var.2</td><td>Extraction using water soluble solvents</td></tr>
<tr><td>Sentinel-2</td><td>Sentinel-2A/B MSI visible & NIR bands</td></tr>
<tr><td>Landsat-8</td><td>LS-8 OLI visible & NIR bands</td></tr>
<tr><td>Technical Requirements</td><td colspan="2">Develop a data analytics component able to support decision making</td></tr>
</table>

Related Pilot(s)	***Natural Cosmetics Pilot- Symbeeosis***

Table 5: Crop Quality Prediction for Optimizing Post Harvest Treatments of Table Grapes Scenario

<table>
<tr><th>Use Case</th><th colspan="2">(B) Prediction</th></tr>
<tr><td>Scenario</td><td colspan="2">B3.1- Crop Quality Prediction for Optimizing Post Harvest Treatments of Table Grapes</td></tr>
<tr><td>Real-life Problem</td><td colspan="2">Vineyards demonstrate high levels of variability of both yield and quality of the production. Selective harvesting is an example of targeted management, in which split picking of fruit at harvest is performed according to different yield and quality parameters of management zones within the field. Strategies such as selective picking may be highly profitable for grape growers; however, predictions of high accuracy are a requirement for this approach to be effective. A tool that can provide highly accurate information on crop quality can help the growers to optimize harvest, storage and processing of table grapes.</td></tr>
<tr><td>Current Approach</td><td colspan="2">Currently, there is limited use of crop quality prediction in the table grapes industry by using few parameters like sugar content and berry diameter. These parameters are usually used for determining only the time of harvest on the field using berry refractometers and calipers while these measurements are conducted only on specific plants and as a result there is no information on table grapes quality for the whole field.</td></tr>
<tr><td>Scenario Hypothesis</td><td colspan="2">The table grapes growers are in need of a system that will help them optimize the timing of table grapes harvest and storage based on data from multiple sources. They will also receive production data and assure them whether the production covers the specific standards that are set by the supermarkets. A powerful system that allows growers to efficiently plan the harvest and storage of their table grapes will greatly benefit them and increase the overall production quality of the sector.</td></tr>
<tr><td rowspan="11">Related Data/Description</td><td>IoT stationary data</td><td>Soil moisture data, meteorological data</td></tr>
<tr><td>Canopy sensing</td><td>Canopy sensing and vegetation indices data</td></tr>
<tr><td>Yield data</td><td>Historical yield data</td></tr>
<tr><td>Drone imagery</td><td>Aerial images</td></tr>
<tr><td>Crop Calendar</td><td>Records of crop growth stages and agricultural operations, yield and quality, soil analysis</td></tr>
<tr><td>Eca sensing</td><td>Georeferenced soil electrical conductivity data</td></tr>
<tr><td>Topographic data and elevation maps</td><td>Spatial data (boundaries and elevation data)</td></tr>
<tr><td>Grape and berry mechanical properties</td><td>Lab analysis data</td></tr>
<tr><td>Sentinel-2</td><td>Sentinel-2A/B MSI visible & NIR bands</td></tr>
<tr><td>Landsat-8</td><td>LS-8 OLI visible & NIR bands</td></tr>
<tr><td>Phenolic composition data</td><td>Lab analysis data</td></tr>
<tr><td>Technical Requirements</td><td colspan="2">Develop a data analytics component able to support crop quality prediction</td></tr>
<tr><td>Related Pilot</td><td colspan="2">Table and Wine Grapes Pilot- AUA</td></tr>
</table>

Table 6: Crop Quality Prediction for Optimizing Winemaking Scenario

<table>
<tr><th>Use Case</th><th colspan="2">(B) Prediction</th></tr>
<tr><td>Scenario</td><td colspan="2">B3.2- Crop Quality Prediction for Optimizing Winemaking</td></tr>
<tr><td>Real-life Problem</td><td colspan="2">Wine making needs knowledge on grape quality at harvest. Different sugar content in wine grapes can produce wine with different characteristics. Moreover, some quality parameters like the concentration of nitrogen in wine grapes can affect the vinification process. As a result, wine makers have no idea on the quality of the wine grapes that they buy from the wine grape growers and adapt their vinification process accordingly while growers cannot obtain higher selling prices for their products due to better quality.
Moreover, during wine making process, the effects of each step on the final wine quality are well known. The quality of wine is mainly due to human actions after harvest.
The main current purpose is to understand how to improve grapes quality to make a good wine and which parameters drive grapes quality.</td></tr>
<tr><td>Current Approach</td><td colspan="2">Currently, there is limited use of crop quality prediction in wine grapes industry by using few parameters like sugar content and titratable acidity. These parameters are usually used for determining only the time of harvest on the field using berry refractometers or by collecting berry samples from few plants that take some time for providing the results. Thus, there is limited information on wine grape quality for the whole field.</td></tr>
<tr><td>Scenario Hypothesis</td><td colspan="2">The main purpose is to know the variables that have an effect on quality at harvest and then on the final product (wine).
• <u>Goals:</u>
  o To identify the relevant leverage (vintage, yield) on a quality measurement (polyphenol content, aromas for example) to optimize wine making.
  o To link quality parameters with environmental data
• <u>Hypothesis</u>: Which parameters (environment, genetic, …) have the main impact on grapes quality to optimize winemaking? to optimize alcoholic fermentation (fermentation strategy)? How to obtain a satisfying grapes quality at harvest to make a good wine and have a satisfying alcoholic fermentation / aroma composition?
  o Understand what is going to influence alcoholic fermentation / aroma production for a variety of vine (year of production, environment) to be able to have an optimized fermentation and winemaking strategy.
  o Maybe we need to work separately in function of the type of wine (red, white, rosé)
  o Start from quality parameters and see which data (inputs) impact them.</td></tr>
<tr><td rowspan="4">Related Data/ Description</td><td>Genetic Data</td><td>Genetic profile, Morphological description, origin, etc.</td></tr>
<tr><td>Soil / Plot characteristics [Plot management]</td><td>soil type, treatments, borders</td></tr>
<tr><td>Harvest information [Plot management]</td><td>weight, date</td></tr>
<tr><td>Climatic data</td><td>Rainfall, temperature, radiation etc.</td></tr>
</table>

	Laboratory analysis on must, grape and wine [Grape and berry mechanical and chemical properties] [Qualitative and quantitative characteristics of must]	Sugar content, alcohol, pH etc.
	Alcoholic fermentation monitoring - online data [Winemaking activities]	Co2 flow rate, fermentation kinetic…
	Winemaking activities	Steps of winemaking, Bioconversion of sugar into ethanol and CO2, Monitoring of alcoholic fermentation and sugar content, yeast characteristics etc.
	Sensory analysis	Expert panel of tasters' sensory analysis (wine bitterness, astringency, phenol content, aroma etc.)
	Sentinel-2	Sentinel-2A/B MSI visible & NIR bands
	Landsat-8	LS-8 OLI visible & NIR bands
Technical Requirements	Develop a data analytics component able to support selling price decisions.	
Related Pilot	***Wine Making Pilot- INRA***	

The use case by the name (C) Farm Management, has two (2) scenarios C1- Optimization of Farm Practices in the Vineyard and C2- Management Zones Delineation for Vineyards (Table 7, 8).

Table 7: Optimization of Farm Practices in the Vineyard Scenario

Use Cases	(C) Farm Management
Scenario	*C1- Optimization of Farm Practices in the Vineyard*
Real-life Problem	Management Practices as irrigation, fertilization and phytochemicals are regularly over or underestimated with respect to the real plant needs. Especially in case of overestimation in quantities there is a negative countereffect towards the plants.
Current Approach	Currently, cropping, irrigation levels, fertilization, spraying and pruning can only be adjusted at the vineyard block level and do not account for individual vine requirements.
Scenario Hypothesis	For the last campaign 2018, in the two Italian vineyards pilots we will perform a data analysis crossing mid and high-resolution multispectral satellite data and best practices data from the farmer. The hypothesis and relative goals are the following: • <u>**HYP 1**</u>: The fertilization or phytochems spraying actions can be supported by satellite data. • <u>**GOAL 1**</u>: Before and after the management actions are there detectable differences in satellite data? Is an increasing of the plant health detectable afterwards? (e.g. increases in certain vegetation indexes or changes in patterns on the field (homogenization?)) • <u>**Goal 2**</u>: Are the actions justified by a real evident problem in the vineyard? (is an anomaly (see above) detectable before the event?)

	• **Goal 3:** Do the satellite data provide a benefit to the farmer when he has to decide on fertilization? Additional for the next campaign (2019) • **HYP 2**: There are interaction effects between weather, management practices and vegetation/fruit qualities that we are able to detect (what kind of effects? Methods: Machine Learning?) • **Goal 4**: Develop a model to predict where and when a fertilization is required • **Goal 5**: Provide a real Decision Support System to the farmer to improve grape quality and quantity.	
Related Data/Description	SENTEK DRILL & DROP TRISCAN	Soil moisture and temperature profiler from 10 cm to 60 cm deep
	Rain gauge Metos weather station	Rain gauge to measure precipitations occurred in a certain period
	Air temperature/humidity Metos weather station	measurements of air temperature/humidity
	IR Temperature Metos weather station	measurements of leaf / bunches IR temperatures
	Leaf moisture sensor	measurement of minutes in which leaf is humid
	Soil profile	soil data survey on texture and chemical properties
	Sentinel-2	Sentinel-2A/B MSI visible & NIR bands
	Landsat-8	LS-8 OLI visible & NIR bands
Technical Requirements	Develop a data analytics component able to support management decisions regarding the quality of the wine production.	
Related Pilot(s)	***Table and Wine Grapes Pilot- AUA, Farm Management Pilot- ABACO***	

Table 8: Management Zones Delineation for Vineyards Scenario

Use Cases	(C) Farm Management
Scenario	*C2- Management Zones Delineation for Vineyards*
Real-life Problem	Delineation of management zones has provided many advantages to the table and wine grape growers by decreasing their input costs and increasing their production value due to selective harvesting. Management zones represent subfield regions within a field with homogeneous characteristics and allow for site-specific management. Nevertheless, the determination of subfield areas is difficult due to the complex factors that can affect crop yield. The optimum number of zones to use when dividing a field may vary from year to year and are mainly functions of the following multivariate spatial and temporal attributes: yield maps, soil and topographic properties, electrical conductivity data, remote sensing, vegetation indices and weather data. Current methodologies for the delineation of management zones includes the following: 1) the use of principal component analysis (PCA) to summarize and aggregate the selected datasets, 2) the Management Zone Analyst (MZA) software using a fuzzy c-means unsupervised clustering algorithm that assigns field information into like classes or potential management zones, and 3) using multivariate geostatistical analysis, a method based on the coefficient of variation (CV) of each data.

	While these approaches address the complexity of delineating management zones, they do not imply linear, cost-effective and practical usage when more than two variables are introduced to the models. Spatiotemporal modelling, compared to static input, is a challenging task since it includes input dynamics as part of the problem. Additionally, there is insufficient information regarding efficient algorithms that combine further data layers over different spatial scales, in order to define the management zones based on more variables.	
Current Approach	Delineation of management zones has provided many advantages to the wine grape growers by decreasing their input costs and increasing their production value due to selective harvesting. Delineation of management zones is done using satellite/drone imagery and/or soil measurements (soil type, nutrient concentration, terrain elevation). The ultimate goal is to achieve maximum differentiation among classes (zones) and minimum differentiation within each class. This enables for delineating management zones for different operations such as fertilizer application, pruning, spraying, irrigation and selective harvesting in order to reduce the infield variation or take benefit from it. However, the delineation of management zones is affected by numerous factors, such as the agricultural operations, demonstrating in-field temporal variability and resulting in suboptimal management strategies.	
Scenario Hypothesis	This scenario hypothesis is aiming to create a dynamic tool to delineate management zones. Algorithms will be developed (WP4) to address upcoming important developments of big data, smart farming and open source satellite data. They will aim at extending the existing methodologies using a dynamic multivariate approach and adopting algorithm designs for solving problems that address aspects of the spatiotemporal domain. The proposed method for the delineation of management zones is the use of algorithms that will convert a high dimensional input signal into a simpler low dimensional discrete signal, such that the distance and proximity relationships and topology are preserved. The algorithms will generate a number of options for delineating management zones, taking into consideration two or more variables. Once the options are generated using specific data spectrums, the selection process of the ideal option will focus primarily on the minimum dimensionality, lowest cost and minimum complexity criteria. Those options that are being characterized, as multidimensional, costly and/or complex will be eliminated from the final selection process of the optimal management zones delineation for a specific field and data spectrum. The selection process will depend on the following rules: (1) the number of management zones in which the field is divided should be feasible and dependent on the field size (2) use variable weighting factors by ranking variables according to their importance 3) supports resource optimization (e.g. for irrigation, fertilization). In addition to the above stated rules, factors such as the existing topography, as well as the minimum actuation from current status, including the complexity of equipment reinstallations and the distance from current state, should be taken into consideration for the final selection of the ideal management zones delineation. This scenario hypothesis has the potential for increased scalability using additional spatial and temporal data.	
Related Data/Description	Eca sensing	Georeferenced soil electrical conductivity data

	Topographic data and elevation maps	Spatial data (boundaries and elevation data)
	Yield data	Historical yield data
	Canopy sensing	Canopy sensing and vegetation indices data
	IoT stationary data	Soil moisture data, meteorological data
	Drone imagery	Aerial images
	Crop calendar	Records of crop growth stages and agricultural operations, yield and quality, soil analysis
	Grape and berry mechanical properties	Lab analysis data
	Phenolic composition data	Lab analysis data
	Sentinel-2	Sentinel-2A/B MSI visible & NIR bands
	Landsat-8	LS-8 OLI visible & NIR bands
Technical Requirements	Develop a data analytics component able to support management decisions concerning the delineation of management zones.	
Related Pilot(s)	***Table and Wine Grapes Pilot- AUA, Farm Management Pilot- ABACO***	

The use case by the name (D) Food protection Use Case, has two (4) scenarios D1- Supply Chain Risk Prediction Dashboard, D2- Price Prediction Dashboard, D-3 Price & Fraud Correlation Dashboard and D-4 Marketing Automation Dashboard (Table 7, 8,9,10).

Use Cases	(D) Food Protection Use Case
Scenario	*D1- Supply Chain Risk Prediction Dashboard*
Real-life Problem	Risk assessment is a very critical part of a food safety system in order to prevent food safety incidents in the supply chain. Today, Quality Assurance and Safety Experts that are working in food companies are using risk estimation approaches that are based on static data such as literature and guidelines published by National Authorities. Such risk estimation approaches are not taking into account the emerging and increasing risks of the global supply chain and cannot predict the risk. This results in several serious food safety incidents that may impact public health, can cause large financial loss for a food company and can damage company's brand. Specifically, for the case of grapes and wines, pesticides residues are very critical factors that the wine producers need to take into consideration to ensure the compliance of their products with the target markets.
Current Approach	Risk approaches for agricultural and food products are mainly based on static information, such as literature and guidelines published by National Authorities and laboratory testing. Relying on static information and guidelines may result in outdated risk estimation. In addition to this, using laboratory testing needs time and a large investment by the companies.
Scenario Hypothesis	Risk module that will provide the estimation and prediction of the risk for a specific raw material, ingredients and product recipe. The module will use product specific models to predict the risk. Moreover, the model will integrate the processing steps followed during the production. Alerts will be sent every time that an increasing and emerging risk will be predicted.

	More specifically, the Food Safety/ Quality departments of wine producers test samples from different batches and production stages against various toxicological factors. One of the main lab tests that they perform (and one of the most expensive in terms of frequency and cost) is the chemical residues test. The main parameter affecting this indicator regards pesticide residues are occurring through the cultivation/ production process. Some of the pesticide residues are being metabolized during maceration, while others remain in the grapemust and thus to the final product (wine). The most important phase that the QA and Food Safety team takes critical decisions is the "blending phase". During this phase the final blends of wines that will be bottled are selected according to quality parameters, sensory parameters and compliance parameters. Especially for the compliance part, the Toxicology/ Food Safety team is responsible for evaluating whether the selected blend is compliant with the regulatory threshold set by the laws of each target market. For this reason, lab analysts need to perform different variations of the blends in order to select which blend is the most appropriate in terms of regulatory compliance. The main problem is that analysts are testing against regulatory thresholds on pesticide residues (MLRs) according to the target market regulations. The blends are carefully selected to match sensory and quality criteria and then are tested towards MLRs. In the case that the blend is not compliant, it is decided to change its end market destination. As this extensive testing is expensive and takes a lot of time to test against different MRLs and quality parameters, the people working in the QA and FS departments could use the power of data stemming from the production (vineyard level) – such as spraying logs- and corelate them with enological practices in the winery and get a MRLs compliance profile for each batch of wine.	
Related Data/Description	Food recalls	Food recalls data published by the national authorities and international systems
	Border rejections	Border rejections (import refusals) data published by official sources
	Spraying logs	Data about the spraying that the producer has applied on the vineyard level.
	Surveillance studies data	Data from surveillance studies that are conducted by Authorities
	Lab testing data	Results of the lab testing that the companies and authorities perform to identify hazards in raw materials, ingredients and products.
Technical Requirements	Development of a risk module that will provide the estimation and prediction of the risk for a specific raw material, ingredients and product recipe. The module will use models to predict the risk for a specific product and will take the processing steps followed during the production. We will focus on the wine making industry case the risk prediction model will take into consideration the different productions steps starting from the cultivation and ending up at the blending phase.	
Related Pilot(s)	***Food Protection Pilot- AGROKNOW- Natural Cosmetics Pilot- Symbeeosis***	

Use Cases	**(D)** Food Protection Use Case
Scenario	*D2- Price Prediction Dashboard*

<table>
<tr><td>Real-life Problem</td><td colspan="2">Changes and fluctuations in raw materials' prices is an important parameter to be considered when performing a food fraud vulnerability assessment. A significant increase of a raw material's/ingredients's price can be highly correlated with an adulteration of the raw material/ingredient.</td></tr>
<tr><td>Current Approach</td><td colspan="2">Quality Assurance and Food Safety Experts working in the food industry are following agricultural commodities' price that is announced by trading and financial organizations. They rely only on seasonality and their experience in price variations. They are also reading professional websites that are publishing articles regarding the agricultural products variations.</td></tr>
<tr><td>Scenario Hypothesis</td><td colspan="2">Using the local and global pricing data and by applying machine learning and deep learning algorithms we can predict prices for specific agricultural commodities and specific raw materials.

We will collect and monitor the prices of agricultural commodities at both global and national levels, providing information that could be utilized by food manufacturers when evaluating food fraud risks in their facilities.</td></tr>
<tr><td rowspan="5">Related Data/Description</td><td>Greek market price data</td><td>Daily pricing data for agricultural products published by the Central Market of Athens</td></tr>
<tr><td>EU Observatories</td><td>Monthly, quarterly and annual price data for agricultural products.</td></tr>
<tr><td>UK Office for National Statistics</td><td>Monthly, quarterly and annual price data for agricultural products.</td></tr>
<tr><td>Food and Agricultural of United Nations</td><td>The Food and Agriculture Organization of the United Nations publishes every month an index measuring the international price changes of food commodities.</td></tr>
<tr><td>Eurostat</td><td>Monthly pricing data for agricultural products</td></tr>
<tr><td>Technical Requirements</td><td colspan="2">Algorithms that will predict agricultural products' prices based on historical pricing data</td></tr>
<tr><td>Related Pilot(s)</td><td colspan="2">Food Protection Pilot- AGROKNOW</td></tr>
</table>

Use Cases	**(D)** Food Protection Use Case
Scenario	*D3- Price & Fraud Correlation Dashboard*
Real-life Problem	Fraudulent food can result in illegal profit and it can cause serious health issues. During the last 15 years very important fraud issues like the horse meat scandal and the melamine in milk powder has greatly affected the food industry and the public health. Fraud and adulteration are relatively new issues that concern the people working in the QA and FS departments of the food companies. Food fraud includes issues like economical motivated adulteration, false marketing claims, food authenticity and certificates issues (absence, illegal).
Current Approach	The food fraud vulnerability assessment done by the food companies is based on static information such as literature, regulation, case studies and guidelines published by Authorities and Certification bodies.
Scenario Hypothesis	Parameters like the agricultural product prices, the socio-economical stability of a country, laboratory testing results and frequency of incidents in the supply chain as well as their correlation, can provide a robust framework for a fraud

	vulnerability assessment. The continuous collection and analysis of datasets for these parameters can enable the prediction of food risk in a supply chain.	
Related Data/Description	Country risk	Monthly country risk index that is published by Organisation for Economic Co-operation and Development
	Country Corruption	Corruption index that is published by Transparency International for each country.
	Price data	Pricing data for agricultural products that can be collected from National Authorities and International Ogranizations.
	Food fraud recalls	Data about food fraud incidents that are published by National Authorities and International Organizations.
	Fraud and adulteration Surveillance data	Surveillance studies that are conducted by Official Authorities and include results for the adulteration of specific products.
Technical Requirements	A new module will be developed and integrated in the FOODAKAI product. Food fraud module will provide a dashboard that will focus on the main parameters that affect the vulnerability of products, ingredients and raw materials (price index, corruption index, country risk index). The dashboard will be adapted to customers' supply chain by taking into consideration the suppliers and the incoming raw materials.	
Related Pilot(s)	***Food Protection Pilot- AGROKNOW***	

Use Cases	**(D)** Food Protection Use Case
Scenario	*D4- Marketing Automation Dashboard*
Real-life Problem	The deployment of content-based marketing activities require time and need a lot of effort. Agroknow is using a lead generation approach that is based on reports that are using data available in Agroknow's Big Data Platform. The people that are downloading a marketing content are manually classified to a category and a sequence of follow up emails are sent to the leads aiming at converting them to trials and eventually to purchase the digital services.
Current Approach	Today all the statistics and trends for food safety and fraud that are included in a report is manually created by a food safety domain expert. The average time for the creation of the report for a product category is 2 weeks. Leads are classified to predefined categories by a sales expert and all the personalized follow up emails are developed and sent manually. The process is labor intensive and time consuming.
Scenario Hypothesis	Report is developed automatically following a specific template and by retrieving relevant data from Data platform. The report will be reviewed and post edited by the domain expert and the final version will be published as web page that can be accessible by any device. People that opt in to read the report are automatically classified in a category and a specific workflow with personalized follow up emails are activated for each category. Analytics are collected in each step and provide useful insights to marketing people. Integration of the process with the CRM that the company is using will be

	implemented. All the process is monitored and controlled by a marketing automation dashboard.	
Related Data/Description	Food safety incidents	Food safety incidents available in Agroknow's Data Platform.
	Fraud incidents	Food fraud incidents available in Agroknow's data platform
	CRM data	Profile data about the potential customers.
	Analytics data	Analytics data from email and landing pages.
Technical Requirements	Development of an automated process that will include components for personalized content creation and for marketing nurturing.	
Related Pilot(s)	***Food Protection Pilot- AGROKNOW***	

3 CONCLUSIONS

This deliverable, the "Use Cases & Technical Requirements Specification", belongs to WP2, which aims to identify and solidify the BigDataGrapes use cases, record and systematically analyse data assets, identify the pragmatic Big Data needs that have to be covered, and, ultimately, produce the architecture of the BigDataGrapes solution.

As identified through this report, all use cases describe different data challenges and data problems of the various aspects of the domain, which will be addressed and evaluated through the instantiations of the Use Cases, the BigDataGrapes pilots.

The project's Use Cases and Technical Requirements presented in this report is the basic driver to an efficient definition and evaluation of the use cases, their scenarios and hypotheses of the project and it is aligned with the project vision and objectives. Moreover, it is directly linked with other activities of the project, namely the BigDataGrapes pilots as well as the technical WPs.

4 REFERENCES

Anastasiou, E., Tsiropoulos, Z., Balafoutis, T., Fountas, S., Templalexis, C., Lentzou, D., & Xanthopoulos, G. (2017). Spatiotemporal stability of management zones in a table grapes vineyard in Greece. Advances in Animal Biosciences, 8(2), 510-514.

Arnó Satorra, J., Martínez Casasnovas, J. A., Ribes Dasi, M., & Rosell Polo, J. R. (2009). Precision viticulture. Research topics, challenges and opportunities in site-specific vineyard management. Spanish Journal of Agricultural Research, 7(4), 779-790.

Arnó, J., Rosell, J. R., Blanco, R., Ramos, M. C., & Martínez-Casasnovas, J. A. (2012). Spatial variability in grape yield and quality influenced by soil and crop nutrition characteristics. Precision Agriculture, 13(3), 393-410.

Battilani, P., Pietri, A., & Logrieco, A. (2004). Risk assessment and management in practice: ochratoxin in grapes and wine. Mycotoxins in food, 244.

Brown, M. E., Pinzon, J. E., Didan, K., Morisette, J. T., & Tucker, C. J. (2006). Evaluation of the consistency of long-term NDVI time series derived from AVHRR, SPOT-vegetation, SeaWiFS, MODIS, and Landsat ETM+ sensors. IEEE Transactions on Geoscience and Remote Sensing, 44(7), 1787-1793.

Cunha, C. R., Peres, E., Morais, R., Oliveira, A. A., Matos, S. G., Fernandes, M. A., ... & Reis, M. J. C. S. (2010). The use of mobile devices with multi-tag technologies for an overall contextualized vineyard management. Computers and Electronics in Agriculture, 73(2), 154-164.

Dunn, G. M., & Martin, S. R. (2004). Yield prediction from digital image analysis: A technique with potential for vineyard assessments prior to harvest. Australian Journal of Grape and Wine Research, 10(3), 196-198.

EFSA (European Food Safety Authority) (2017). Peer review report to the conclusion regarding the peer review of the pesticide risk assessment of the active substance trifloxystrobin. EFSA Journal 2017, 15(10):4989, 29 pp. https://doi.org/10.2903/j.efsa.2017.4989

Kitchen, N. R., Sudduth, K. A., Myers, D. B., Drummond, S. T., & Hong, S. Y. (2005). Delineating productivity zones on claypan soil fields using apparent soil electrical conductivity. Computers and Electronics in Agriculture, 46(1-3), 285-308.

Lamb, D. W., Weedon, M. M., & Bramley, R. G. V. (2004). Using remote sensing to predict grape phenolics and colour at harvest in a Cabernet Sauvignon vineyard: Timing observations against vine phenology and optimising image resolution. Australian Journal of Grape and Wine Research, 10(1), 46-54.

Morice, C. P., Kennedy, J. J., Rayner, N. A., & Jones, P. D. (2012). Quantifying uncertainties in global and regional temperature change using an ensemble of observational estimates: The HadCRUT4 data set. Journal of Geophysical Research: Atmospheres, 117(D8).

Nuske, S., Achar, S., Bates, T., Narasimhan, S., & Singh, S. (2011). Yield estimation in vineyards by visual grape detection. In Intelligent Robots and Systems (IROS), 2011 IEEE/RSJ International Conference on (pp. 2352-2358). IEEE.

Pedersen, S. M., & Lind, K. M. (2017). Precision Agriculture–From Mapping to Site-Specific Application. In Precision Agriculture: Technology and Economic Perspectives (pp. 1-20). Springer, Cham.

Poulsen, M. E., Hansen, H. K., Sloth, J. J., Christensen, H. B., & Andersen, J. H. (2007). Survey of pesticide residues in table grapes: determination of processing factors, intake and risk assessment. Food additives and contaminants, 24(8), 886-895.

Somma, S., Perrone, G., & Logrieco, A. F. (2012). Diversity of black Aspergini and mycotoxin risks in grape, wine and dried vine fruits. Phytopathologia Mediterranea, 131-147.

Tan, P., Steinbach, M., Kumar, V., Potter, C., Klooster, S., & Torregrosa, A. (2001). Finding spatio-temporal patterns in earth science data. In KDD 2001 Workshop on Temporal Data Mining (Vol. 19).

Vitalif, M., Guidotti, M., Giovinazzo, R., & Cedronet, O. (1998). Determination of pesticide residues in wine by SPME and GC/MS for consumer risk assessment. Food Additives & Contaminants, 15(3), 280-287.