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Model-as-a-Service for Sustainable Viticulture: A Comprehensive Science-Driven Decision Support Platform

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Abstract

The scientific knowledge in viticulture produced by academic and research institutions is vast but often remains confined to those contexts. In an era of digital transformation and increasing connectivity, it is imperative to make this knowledge accessible to those who can benefit the most: agribusiness service providers and viticulture professionals. With this need in mind, this article proposes the development of a Model-as-a-Service (MaaS) platform designed to deliver consolidated scientific knowledge as consumable digital services. By integrating an operational Internet of Things (IoT) sensor network oriented to precision agriculture/viticulture – known as mySense – along with meteorological-based data sources, the platform offers grapevine-specific decision support by

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enabling the forecasting of irrigation requirements, tracking phenological stages, and predicting pest and disease outbreaks. The platform also supports climatic projections and remote sensing-based monitoring. Although still under development, several MaaS services are already implemented and available, as detailed in this article.

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1. Introduction

The Viticulture sector plays a relevant role in the global economy, where informed decision-making is crucial to improving productivity and grapevine resilience, and to ensuring that products meet both quantitative and qualitative standards. Traditionally, decision-making in this sector has relied on empirical knowledge and experiential intuition [1]. However, the ongoing digital transformation has introduced new paradigms, enabling the adoption of advanced, cost-effective, and sustainability-oriented approaches to support data-driven decision-making. These developments include the integration of agronomic expertise with digital technologies [2, 3], climatological modelling [4], widespread adoption of Internet of Things (IoT) [5], remote sensing [6–8], and the increasing availability of computational power and artificial intelligence (AI) [9]. Together, these innovations and approaches have improved the ability to monitor, predict, and manage important factors that influence crop health, yield and quality.

In precision viticulture, several are the tasks that contribute to data-driven sustainable practices [2]. One of them is irrigation monitoring, which consists in the accurate assessment of crop water requirements. A widely used metric is crop evapotranspiration (ET_c) [10], which derives from reference evapotranspiration (ET_0) that, in turn, represents the water lost from an optimally irrigated and actively growing reference crop covered with turfgrass [11]. Since crops differ in height, density, phenology, and drought tolerance, ET_0 is adjusted using crop coefficients (K_c) whose values vary throughout the growing season, reflecting changes in leaf area and transpiration rates. While the increase of temperatures further influence water uptake and relative humidity [12], effective grapevine irrigation management requires continuous monitoring of soil moisture and matric potential using sensors placed at various depths alongside the root zone. Irrigation should be initiated when soil moisture reaches a defined threshold, based on its own retention capacity and the crop's specific needs. The irrigation volume is determined by calculating the total available water (TAW), defined as the difference between the upper and lower thresholds for plant-available water [13].

Disease and pest detection is equally important for maintaining grapevine health in a cost-effective and environmentally responsible manner. Optimizing pesticide application through early detection promotes sustainable practices. Automated, continuous monitoring enables early warning and the containment of outbreaks. This can be strengthened by in-field sensors capable of detecting environmental changes and plant physiological responses, offering a robust tool for intelligent crop management [3]. For instance, the 3-10 rule (based on temperature, precipitation, and shoot length) is used to assess the risk of downy mildew [14], while powdery mildew detection relies on slightly different thresholds [15]. Pest monitoring, such as for the golden leafhopper, often employs simpler yet effective models based on growing degree-days (GDD), which estimate outbreak risk using species-specific thresholds [16].

Accurate estimation of phenological stages is critical for optimizing vineyard management and improving profitability [17]. Phenological monitoring enables the identification of key growth stages such as budbreak, flowering, veraison, and maturation [18]. While temperature is the main driver of grapevine development, phenology is also influenced by cultivar characteristics, rootstock vigour, hormonal balance, pruning practices, nitrogen levels, water availability, and photoperiod. The most widely used model is based on GDD, which accumulates daily maximum and minimum temperatures relative to a base temperature (B_t) [19]. B_t values vary by phenological phase and environmental conditions. For example, Lopes et al. [18] propose $B_t = 3.5\text{ }^{\circ}\text{C}$ until budbreak and $10\text{ }^{\circ}\text{C}$ thereafter in their study involving 34 Portuguese cultivars (19 white and 15 red). Recently, machine learning models have been

introduced to improve phenological predictions by integrating field-specific data – such as training systems, cultivar characteristics, and multi-year phenological records – with local weather and remote sensing inputs, particularly land surface temperature (LST) from Sentinel-3 SLSTR sensors [20, 21].

From a broader spatial perspective, the integration of remote sensing data enables medium- to high-resolution and temporally consistent assessments of crop conditions across larger areas, surpassing the coverage of ground-based IoT sensors, providing data that allows for the estimation of plant health and yield potential [6]. Remote sensing platforms offer diverse data sources for evaluating crop parameters through different products [22]. For example, thermal infrared (TIR) imagery can assess water stress [23], while point clouds and digital elevation models help derive canopy geometry [24]. Hyperspectral data allows the detailed analysis of plant reflectance, and multispectral imagery supports the monitoring of vegetative vigor and biophysical changes [25, 26]. Among these platforms, earth observation (EO) satellites equipped with multispectral sensors are particularly suitable for large-scale vineyard monitoring [27]. Although freely available, EO data has lower spatial resolution than commercial satellites or unmanned aerial vehicles (UAVs), and its global coverage and frequent revisitation cycles makes it particularly suitable for cost-effective, multi-temporal analysis [28]. Vegetation indices derived from multispectral EO data enable spatial and temporal mapping of vineyard heterogeneity for assisting in the decision-making process in viticulture [29].

Another factor influencing viticulture is climate change, whose long-term effects may lead to geostrategic shifts in grapevine cultivation [30]. Therefore, the ability to predict these changes is highly relevant to the wine economy. The rising of average temperatures and altered precipitation patterns have profound implications for viticulture [31], and more specifically for grapevine phenology, grape composition, and ultimately, wine quality. In this context, agroclimatic indices, such as the Winkler Index and the Growing Season Average Temperature (GST) from April to October, among others [32], are essential for guiding varietal selection and vineyard management. The Winkler Index classifies wine-growing regions based on the accumulated GDD during the growing season, providing guidance on the suitability of grape varieties to specific thermal conditions. Similarly, GST contributes to the climatic compatibility for viticulture by evaluating temperature suitability during the growing season (variety-dependent). Employing such tools is critical for anticipating climate variability and ensuring the long-term sustainability and resilience of viticultural systems.

Despite the availability of platforms and sensors for data acquisition in viticulture, the resulting data volume often presents significant management challenges. Many existing solutions focus primarily on technical data collection and processing [33], using methods such as proximal sensing, image analysis, and computational modeling. However, they frequently do not deliver holistic, cross-platform solutions tailored for end-users. As a result, much of the potential value of this data remains untapped, particularly for viticulture professionals who require continuous, practical decision-support tools.

To address such a gap, this article documents an agnostic science-to-business (S2B) platform that consolidates scientific knowledge into a suite of responsive Model-as-a-Service (MaaS) endpoints (in Fig. 1).

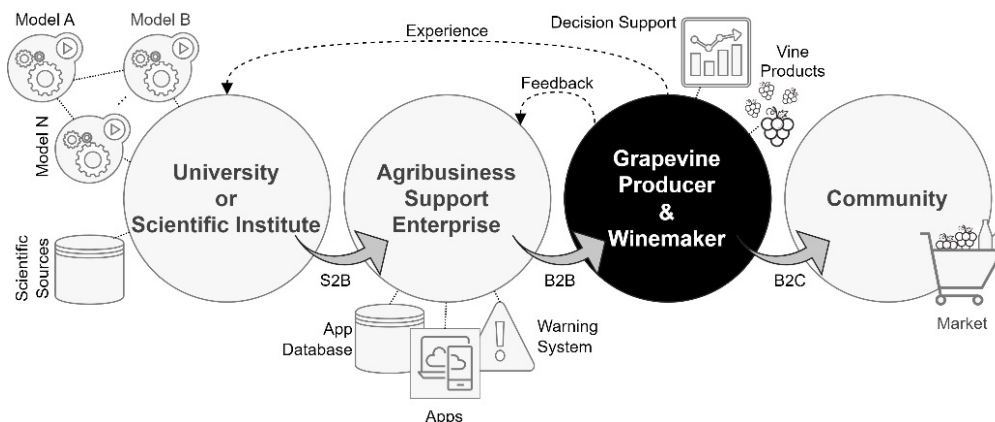


Fig. 1. Integration of science in the agribusiness chain, with a strategy centered in the quality of the grapevine producer/winemaker outcomes.

MaaS platform resorts to data from diverse sources to provide decision support across key viticultural domains, including irrigation management, phenological forecasting, pest and disease monitoring, climate variability assessment, and remote sensing monitoring. Designed for integration by agribusiness service providers operating under business-to-business (B2B) models, the platform enables the delivery of value-added services to viticulture professionals. By transforming complex data into accessible, actionable insights, the platform promotes sustainable vineyard productivity, ultimately strengthening the business-to-consumer (B2C) segment.

In terms of organization, the remainder of this paper is structured as follows: Section 2 contextualizes the proposed platform, detailing its architecture and the main services envisioned for future implementation. Section 3 presents the current state of development, illustrating functional examples of service invocation. Finally, Section 4 concludes the paper by summarizing the key contributions and outlining the main conclusions and directions for future work.

2. Model-as-a-Service (MaaS) proposal for viticulture: integrating IoT data with scientific expertise

This section introduces the proposed MaaS concept, presenting an integrated architecture that combines multi-source-derived data with scientific domain expertise for decision-making support across key areas of vineyard management, including irrigation, phenology, pest and disease forecasting, climatology, and remote sensing.

2.1. General MaaS architecture

The MaaS architecture (Fig. 2) follows a service-oriented design, built around a multi-thematic model layer that integrates key viticulture services such as irrigation, phenology, climatology, pest and disease monitoring and aerial imagery analysis. A single endpoint manages both input and output interactions with the MaaS. Input requests are validated and checked for errors before being routed to the appropriate service within the model layer. In the end and based on the model layer computations, a structured decision-support message is set up and returned as output.

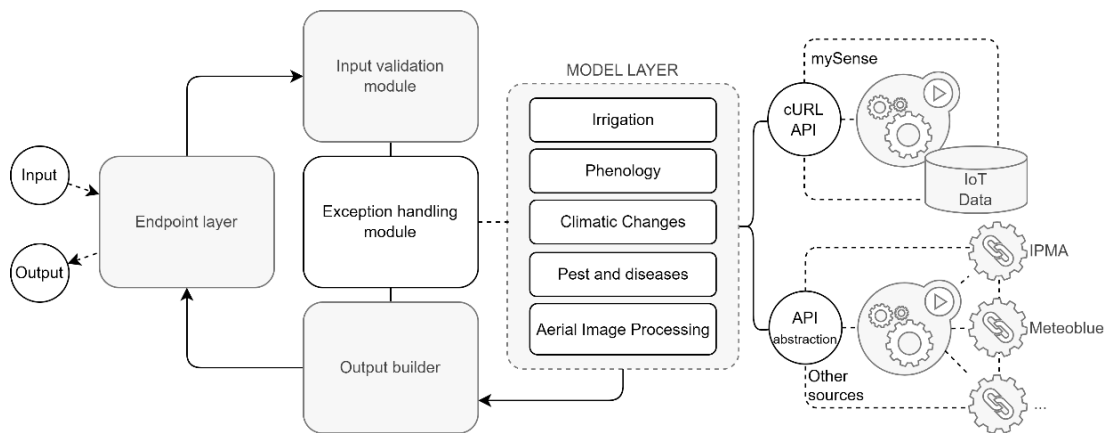


Fig. 2. Conceptual architecture of the proposed MaaS system for viticulture decision support.

Many of the computations carried out in the MaaS services rely on external data sources such as mySense for in-situ observations and meteorological data from the Portuguese Institute for Sea and Atmosphere, I. P. (IPMA, IP) and Meteoblue.

The platform offers three service tiers: (i) basic – freely accessible; (ii) intermediate – requires API key authentication for medium-complexity services; and (iii) advanced – also requires authentication and provides more complex computations and customizable outputs. Integrating entities can manage end-user access to non-free tiers, enabling monetization based on service complexity and predictive performance.

2.2. Data sources

Currently, the MaaS platform integrates data from public and institutional sources: IPMA [34], the Portugal's official meteorological agency, providing weather forecasting and environmental monitoring for both general public and commercial sectors; Meteoblue [35], a Swiss-based provider of high-resolution weather forecasts and climate data, offering localized insights for agriculture; mySense [5, 36], an IoT platform developed at the University of Trás-os-Montes and Alto Douro, designed for precision agriculture, managing wireless sensor networks that monitor parameters such as air temperature and humidity, soil-related parameters and remote sensing data (RGB, multispectral, hyperspectral, TIR). Registered users of mySense can access their data through Web-based dashboards, enabling real-time field monitoring and critical agroclimatic event analysis.

MaaS also supports the ingestion of custom full-year datasets composed by key meteorological parameters (e.g., air temperature, relative humidity, precipitation, leaf wetness sensor readings). This allows users to integrate data from their own sensors, enabling precision decision support, particularly valuable for irrigation management, phenological modelling, and pest/disease risk assessment.

2.3. Irrigation management support

The irrigation-related services that will be made available by the MaaS platform are detailed in Table 1, covering basic, intermediate, and advanced levels, according to the type of prediction provided and the complexity of the underlying models.

Table 1. Specification of MaaS's basic, intermediate and advanced irrigation services.

Level	Input fields	Model description	Outputs
Basic.	Phenological stage; Geographic coordinates; Date (optional, current by default).	Uses public IPMA data to estimate crop evapotranspiration based on phenological stage. Calculates daily water needs [12].	Daily water needs in mm.
Intermediate.	Soil water tension (kPa); Soil water content (mm); Date (optional, current by default); Phenological stage (optional).	Resorts to soil moisture and soil water tension data to assess irrigation thresholds and generate the corresponding irrigation recommendations [13, 37].	Available soil water for the plant (mm); Irrigation recommendation with the corresponding amount of water (mm).
Advanced.	Soil Water Tension (kPa) Soil Water Content (mm) Acquisition date (optional, current by default); Phenological stage (optional)	Combines sensor data with 5-day weather forecasts (via Meteoblue) to adjust irrigation recommendations based on predicted precipitation and extreme weather events [13, 37].	Available soil water for the plant (mm). Irrigation recommendation with the amount of water (mm) under normal and extreme weather conditions.

2.4. Phenology estimation

The MaaS platform phenology-related services planned for integration are presented in Table 2, spanning basic, intermediate, and advanced levels, depending on the scope of the prediction and the complexity of underlying models.

Table 2. Specification of MaaS's basic, intermediate and advanced phenology prediction/estimation services.

Level	Input fields	Model description	Output fields
Basic.	Geographic coordinates; Grapevine variety;	Uses public sensor data to calculate GDD up to a given date, to estimate current phenological stage [18].	Current phenological stage (among Buddbreak,

	Date (optional, current by default); Budbreak initiation date (optional).	Also provides 5-day GDD forecasting using Meteoblue data via mySense.	Flowering, Veraison, or Maturation);
Intermediate.	Grapevine variety; Date of budbreak initiation (optional); Custom sensors GDD – observed; Custom sensors GDD – predicted.	Uses private sensors data are used to calculate GDD and estimate phenological stages [18], including a 5-day forecast based on custom data sources/services.	GDD (°C) until the next predicted phenological stage; Phenological stage forecast for the next 5 days (after date of request).
Advanced.	Geographic coordinates; Grapevine variety, rootstock and training system; Phenological, land surface temperature, and climate data of the last 5 years; Annual update of the phenological stage records; Date (optional, current by default); Custom weather sensors (optional). 5 years of data provided by custom sensors (optional).	Uses machine learning models trained on parcel-specific data such as training system, cultivar, and historical phenological records, combined with local meteorological data and land surface temperature derived from remote sensing [20, 21].	Current phenological stage; Phenological stage forecast for the next 5 days (after provided date).

2.5. Pests and diseases outbreak risk assessment

The services for monitoring and predicting relevant grapevine pests and diseases, including *Lobesia brotana*, downy mildew and powdery mildew are presented in Table 3, Table 4, and Table 5, respectively.

Table 3. Specification of MaaS's basic, intermediate and advanced grape moth (*Lobesia botrana*) activity prediction services.

Level	Input fields	Model description	Output fields
Basic.	Geographic coordinates; Date (optional, current by default).	Uses public sensors for calculating observed (mySense) and predicted (Meteoblue) to calculate GDD and estimate grape moth flights [16].	Observed GDD-based outbreak of the 1 st generation of grape moth (start and peak). GDD-based outbreak forecast at a 5-day range regarding the 1 st generation of grape moth (beginning and peak).
Intermediate.	Geographic coordinates; Date (optional, current by default).	Same as basic, but extended to all four generations of grape moth [16].	Observed GDD-based outbreak of four generations of grape moth (beginning and peak per generation). GDD-based outbreak forecast at a 5-day range regarding the 4 generations of grape moth (beginning and peak per generation).
Advanced.	Image from a grape moth delta trap; Model confidence level (0-1, default = 0.5).	Applies a deep learning model (e.g. YOLOv8) to detect and count insects [38].	Insect counting; Bounding-boxes of detected insects.

Table 4. Specification of MaaS's basic, intermediate and advanced downy mildew prediction services.

Level	Input fields	Model description	Output fields
Basic.	Geographic coordinates; Shoot length (default: true when ≥ 10 cm);	Applies the “3-10” rule using public sensor data (temperature, precipitation, shoot length) [14].	Infection risk level (low, medium, high).

	Date (optional, current by default).		
Intermediate.	Geographic coordinates; Shoot length (default: true when ≥ 10 cm); Date (optional, current by default).	Extends the infection risk forecast for 5 days, using Meteoblue data [14].	Current and 5-day forecasted infection risk.
Advanced.	Shoot length (default: true when ≥ 10 cm); Custom sensors – observed data; Custom sensors – predicted data.	Applies the “3-10” rule using custom sensor data, including relative humidity[14].	

Table 5. Specification of MaaS’s basic, intermediate and advanced powdery mildew prediction services.

Level	Input fields	Model description	Output fields
Basic.	Geographic coordinates; Shoot length; Date (optional, current by default).	Uses public sensor data (temperature, precipitation, shoot length) to assess infection risk [15].	Infection probability (low, medium, high).
Intermediate.	Geographic coordinates; Shoot length ; Date (optional, current by default).	Adds 5-day infection risk forecast using Meteoblue data.[15]	Current and 5-day forecasted infection risk.
Advanced.	Shoot length; Custom sensors – observed data; Custom sensors – predicted data.	Uses custom sensor data including relative humidity to assess infection risk.[15]	

Most pest and disease services rely on GDD (°C), agroclimatic- and phenology-driven rules. The counting of potentially harmful insects is performed using deep learning approaches.

2.6. Climatology

To anticipate variety-specific adaptations and potential geostrategic shifts in cultivation and to support viticultural long-term decision-making, the MaaS platform incorporates climatic data services based on historical and projected climate data. These services are built upon a robust dataset derived from 9 Global Circulation Models (GCMs), downscaled to 30 arc-sec resolution using the CHELSA approach [39]. The downscaling process uses bias-adjusted climate projections from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP3b) [40] and the Coupled Model Intercomparison Project Phase 6 simulations (CMIP6) [41].

The output data is the downscaled daily minimum (Tasmin), mean (Tas), maximum (Tasmax) temperature and precipitation (Pr). A total of four scenarios are included: the historical (1981-2014) and three Shared Socio-Economic Pathways regarding a future period (2015-2100) – SSP1-2.6, SSP3-7.0, and SSP5-8.5. From this, the daily data output processed for each scenario targeted a 9-member GCM-based ensemble mean, considering 20-year intervals: 1981-2000, 2021-2040, 2041-2060, 2061-2080, 2081-2100. Such output has been achieved using Climate Data Operators (CDO) and consolidated into Network Common Data Form (NetCDF) files serving as repository archives. Fig. 3 provides a visual overview of two relevant indices: Winkler and GST. Both are particularly useful for long-term planning of viticulture exploration, especially when the data analysis is combined with multiple bioclimatic indices and considering certain thresholds [42] across different scenarios.

The NetCDF archives have been incorporated by the MaaS platform, from which the several associated services leverage (Table 6). Basic service supply climate normals of bioclimatic indices related to viticulture: Mean Annual Temperature; GST; Growing Season Precipitation; Annual Precipitation; Cool Night Index; Dryness Index; Huglin Heliothermal Index; Hydrothermal Index of Branas; Selianinov Hydrothermic Index; Winkler and De Martonne Index; and Tropical Nights and Extreme Summer Days [32, 42–45]. The intermediate level incorporates additional ensembles of monthly averages of Tasmin, Tas, Tasmax and monthly Pr, while the advanced level provides the same ensembles but at a daily scale.

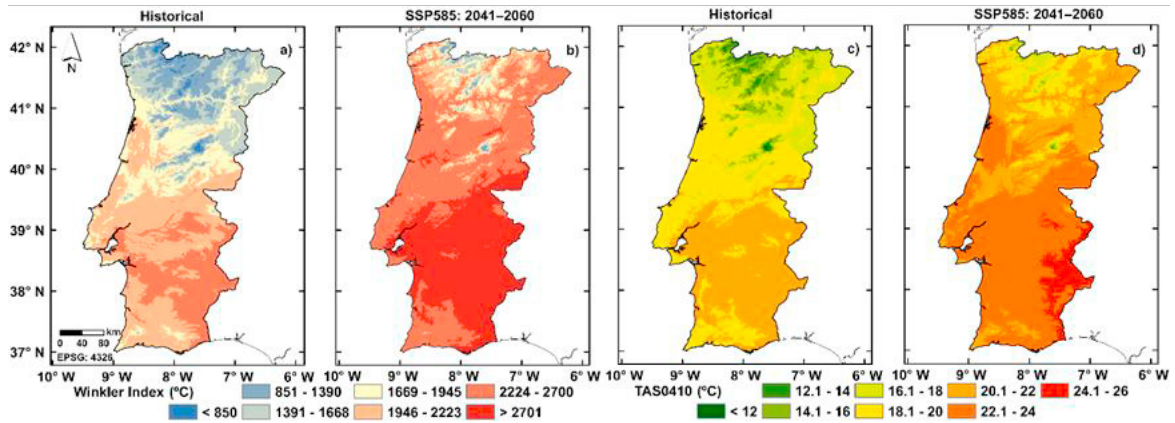


Fig. 3. Climate normals of bioclimatic indices for the historical period (1981-2000) and future projections (2041-2060) under the SSP585 scenario: for Winkler index (a-b) and growing season average temperature (c-d).

Table 6. Specification of MaaS's basic, intermediate and advanced SSP-based long-term climatic evolution.

Level	Input fields	Model description	Output fields
Basic.	Scenario.	9-member ensemble means of bioclimatic indices are extracted from a preprocessed NetCDF file.	JSON and GeoTIFF files of the selected bioclimatic indices, for the respective locations, periods and scenarios.
	Bioclimatic indices.		
Intermediate.	Coordinates.	9-member ensemble means of monthly Tasmin, Tas, Tasmx and Pr are extracted from a preprocessed NetCDF file.	
	Period.		
Advanced.	Scenario.	9-member ensemble means of daily Tasmin, Tas, Tasmx and Pr are extracted from a preprocessed NetCDF file.	
	Bioclimatic indices.		

2.7. Remote sensing data processing

The remote sensing services are currently based on multispectral data provided by the Copernicus Sentinel-2 programme. These services use Level-2A products, which include orthorectified and atmospherically corrected surface reflectance data. The main input is a polygon representing the vineyard plot to be analyzed. Table 7 details the three levels of complexity planned for this set of services. Depending on the service level, different vegetation indices can be requested, including: Normalized Difference Vegetation Index (NDVI) to assess vegetation vigour using red and near-infrared bands; Enhanced Vegetation Index (EVI), which enhances the vegetation signal in dense canopies and is responsive to structural variations; Nitrogen Reflectance Index (NRI), for estimation of leaf nitrogen content; Normalized Difference Red Edge (NDRE), sensitive to chlorophyll content changes; and Normalized Difference Moisture Index (NDMI), to evaluate soil and plant moisture.

The continuous data acquisition enables the multi-temporal analysis of vineyard conditions, enabling to monitor spatial and temporal variability. From user interface perspective, the provided data can be used as an interactive map interface for visualizing georeferenced imagery and dynamic charts for tracking values change over time.

Table 7. Specification of MaaS's basic, intermediate and advanced aerial image processing-based decision support services.

Level	Input fields	Model description	Output fields
Basic.	Coordinates polygon	Computes the NDVI [46] using Sentinel-2 imagery of the most recent period from the last 60 days with a cloud cover below 30%.	NDVI geotiff; Summary statistics (min, max, mean, std) in CSV format.

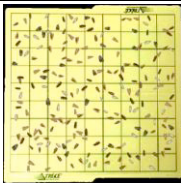
Intermediate.	Coordinates polygon; Number of classes (3 to 5).	Generates NDVI-based vigour maps [46] with 3 to 5 classes for prescription mapping.	Reclassified NDVI map with intuitive vigour levels.
Advanced.	Coordinates polygon; Vegetation indices to compute; Acquisition interval.	Computes multiple indices and colour composites for each acquisition period within the specified interval.	Vegetation index maps; True/false-colour composites; Associated statistics and band composites.

3. MaaS current development status

Among the services previously specified for the MaaS platform, a significant number are already implemented using FastAPI framework [47], offering robust decision support tools for viticulture. These include basic services such as irrigation and phenology forecasting, pest and disease risk prediction (grapevine moth, downy mildew, and powdery mildew), long-term climate forecasting (across SSP scenarios, time periods, and indices by geographic reference), and NDVI maps for vineyard plots. Intermediate services extend these capabilities through rule-based irrigation models using custom sensor data (e.g., soil water tension and water content), improved phenology forecasting with user-provided observations, and multi-generation pest modelling. Furthermore, advanced services provide high-resolution disease prediction using custom data inputs and automated pest monitoring through image-based moth counting from delta traps.

Preliminary testing has been conducted for several of these services. Table 8 summarizes selected examples, including input parameters and representative outputs, which include: basic irrigation prediction; basic phenology forecast; advanced pest and disease outbreak estimation; basic geographical point-wise climatic projection with 1 km² of spatial resolution; and basic remote sensing data processing. For the endpoints requiring a location, Quinta do Bomfim (41.189950, -7.538871) and vineyard plots on the University of Trás-os-Montes and Alto Douro campus (41.288381, -7.739318) were considered.

Table 8. Preliminary tests made to some of the most relevant implemented MaaS services.

Service/Level	Input Example	Response
Irrigation prediction (Intermediate)	soil_water_tension_kPa = 37 soil_water_content_percent = 20 ref_swc_with_min_swt = 25 min_tension_rule = 15 max_tension_rule = 40	{ "quantity": 40, "unit": "mm", "warning_level": 0 }
Phenology prediction (Basic)	vine_variety = Touriga Nacional lat = 41.285627 lon = -7.737961	{ "observed": { "degree_day": 532.15, "date": "2025-04-26", "phenological_stage": "Sprouting", "dd_until_next_phen_stage": 335, "next_phen_stage": "Blooming"}, "next_5days": { "degree_day": 569.4, "date": "2025-05-01", "phenological_stage": "Sprouting", "dd_until_next_phen_stage": 298, "next_phen_stage": "Blooming"} }
Pests and diseases outbreak risk assessment – grape moth counting (Advanced)	 (Insect trap image)	{ "counting": 201, "xyxy_boxes": { "item": [[295, 139, 312, 154], ...] }

Geographical point-based long-term climatic predictions (Basic)	lat = 41.189950 lon = -7.538871 period = 2041_2070 SSP = Intermediate	<pre> { "Viticulture_Winkler_Index": { "coords": [41.28736058600005, -7.720972911300005], "values": 2042.0638427734375, "long_name": "...", "units": "gdd_(°C)/year" }, "Viticulture_Huglin_Index": { "coords": [41.28736058600005, -7.720972911300005], "values": 2527.6328125, "long_name": "Huglin_Index_(HI)", "units": "°C/Year" } } </pre>
Aerial imagery processing – NDVI (Basic)	<pre> geo_polygon = [[-7.540409, 41.189339], ..., [-7.539411, 41.189835], ..., [-7.540409, 41.189339]] </pre>	 (TIFF file loaded into https://app.geotiff.io/)

Next section draws this paper conclusions and proposes future lines to be explored regarding the refinement and completion of MaaS.

4. Conclusions and future work

This article introduced a science-driven digital MaaS platform designed to support sustainable viticulture by transforming agro-environmental models into structured, accessible digital services. Implemented over FastAPI framework, the platform delivers decision support tools across key viticultural domains for irrigation needs estimation, phenology prediction, pest and disease outbreak forecast, long-term climate projections, and remote sensing vegetation indices. These services are organized into three access tiers: basic (freely available), intermediate, and advanced (both managed through API keys by agribusiness service providers). While the basic services presented are fully implemented, intermediate and advanced levels are still under development.

To complete the service portfolio, future efforts will focus on implementing the remaining functionalities with increased model precision and context-awareness. This includes integrating custom data sources (e.g., user-managed sensors and location-specific datasets), applying machine learning techniques to improve predictive capabilities and extending disease modelling to include secondary infections. An additional goal is to enhance climate services by incorporating agroclimatic indices, thereby broadening the assessment of sustainability in grapevine cultivation. In parallel, improvements to remote sensing services will be pursued by incorporating additional satellite catalogues (e.g., Harmonized Landsat–Sentinel), improving temporal resolution via sensor fusion (e.g., Landsat OLI and Sentinel-2 MSI), and exploring multi-temporal Interferometric Synthetic Aperture Radar (InSAR) for structural monitoring in sloped vineyards. UAV-based imaging with alternative sensors will also be considered to support finer-scale biophysical assessments on vine-populated environments. These developments, together with an extensive field validation, aim to consolidate MaaS as a robust, scalable, and science-based platform for data-driven decision-making in viticulture, supporting the sustainability and competitiveness of the wine sector.

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