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Appel à projets Thématique Spécifique en Intelligence Artificielle (TSIA) – Edition 2025

Proposal Template

Acronym	JASMINA		
Project Title	Joint optimization of Action Sequence and MonItoring for plaNt Agriculture		
Total requested budget	699957.86€	**Duration**	4 years
Keywords	Crop Monitoring, Cultivation Strategy, Computer Vision, Sequential Decision Making under Uncertainty, Plant Biology, Phytotron, Drone		

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Partner (Institution / Department)	Last Name	First name	Current position	Role & responsibilities in the project (4 lines max)
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ISAE-SUPAERO	Dr. Gateau	Thibault	Associate Professor	Other member WP3 (+WP1) Farmbot & Drone experimentations
ISAE-SUPAERO	Dr. Chanel	Caroline	Professor	Other member WP3 Drone experimentations
INRIA	Dr. Maillard	Odalric-Ambrym	Researcher HDR	**PI Inria** WP2 (+WP3)
INRIA	Dr. Akrour	Riad	Researcher	Other member WP2 (+WP3) PhD thesis director WP2
Orius	Mr. Pluchon	Pierre-François	Head Scientist	**PI Orius** WP1 (+WP2) Phytotron experimentations
Orius	Mr. Oliver	Paul-Hector	Co-founder & CEO	Other member WP1 (+WP2)
Orius	Mr. Jay	Pierre	Co-founder & managing partner	Other member WP1 (+WP2)
Orius	Mr. Velociter	Jérôme	Co-founder & Software engineer	Other member WP1 (+WP2) Phytotron experimentations
Orius	Mr. Aubry	Bastien	Head of lab	Other member WP1 (+WP2) Phytotron experimentations
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Summary of the project in French (publishable non-confidential abstract, max. 1/2 page):

L'agriculture, notamment végétale, bénéficie déjà d'outils issus de l'IA. Le développement de ces approches est un atout précieux pour répondre aux nouveaux défis amenés par le changement climatique, la raréfaction des ressources ou encore les objectifs de développement durable. Ces défis demandent des capacités d'adaptation et de réactivité auxquels les progrès de la recherche en surveillance, notamment basée vision, peuvent contribuer pleinement. Minimiser l'usage des ressources et la production de déchets, tout en maximisant le rendement, fait appel à des capacités de prises de décision sur le long terme, multicritères et robustes, qui peuvent largement tirer parti des avancées de la recherche en décision séquentielle dans l'incertain. Ce projet se concentre donc sur le développement de méthodes et d'algorithmes d'IA pour raffiner le suivi de l'état des cultures et optimiser les décisions associées. Afin d'assurer leur généralité, les contextes considérés vont de la culture en milieu fermé et contrôlé à l'agriculture de pleins champs. Des campagnes de collectes de données et d'évaluation des outils développés permettront d'élaborer des bases de données d'entrainement et de validation, et d'analyser l'écart entre les modèles et la réalité. Les trois partenaires de ce projet, INRIA, l'ISAE-SUPAERO et Orius, proposent de bénéficier de la mesure de la composition chimique des cultures, et de données de cultures en extérieur avec l'utilisation de drones autonomes équipés de caméras. Les modèles de suivi et de prise de décision seront basés sur des variables d'état des cultures identifiées par la recherche en biologie végétale, favorisant l'explicabilité. Ce projet soulève les défis de gestion des échelles spatiales et temporelles (ex : culture en phytotron ou en plein champs), de robustesse du suivi (ex : aux conditions de prise de vue), et d'observabilité partielle (considérant l'erreur dans le suivi). Ce projet ambitionne de déployer des outils d'IA ouverts, développés à partir des connaissances de la biologie végétale et au profit de l'agriculture résiliente.

Summary of the project in English (publishable non-confidential abstract, max. 1/2 page):

Agriculture, particularly plant farming, already benefits from AI tools. The development of these approaches is an asset in addressing the new challenges posed by climate change, resource scarcity, and sustainable development goals. These challenges demand adaptability and responsiveness, to which advances in monitoring research, particularly vision-based, can fully contribute. Minimizing resource use and waste production, while maximizing yield, requires long-term, multi-criteria, and robust decision-making capabilities, which can greatly benefit from advances in sequential decision-making research in uncertain environments. This project therefore focuses on the development of AI methods and algorithms to refine crop status monitoring and optimize associated decisions. To ensure their generality, various contexts are considered, ranging from closed and controlled environment cultivation to open-field agriculture. Data collection and evaluation campaigns for the developed tools will result in training and validation datasets, and in the analysis of the gap between models and reality. The three partners in this project, INRIA, ISAE-SUPAERO, and Orius, propose to benefit from the measure the chemical composition of crops, and from crop data in outdoor environments with the use of autonomous drones equipped with cameras. The monitoring and decision-making models will be based on crop state variables identified by plant biology research, promoting explainability. This project raises numerous challenges, such as the management of spatial and temporal scales (e.g., cultivation in phytotrons or open fields), the robustness of monitoring (e.g., to shooting conditions), and partial observability (considering error in monitoring). This project aims to deploy open AI tools, developed from plant biology knowledge and for the benefit of resilient agriculture.

1. Scientific and technical excellence, innovation and breakthrough in R&D

The JASMINA project aims to develop an integrated approach for non-destructive crop monitoring and optimization of production strategies. It proposes to take advantage of pre-trained models and foundation models for vision (e.g. SAM2 [1], YOLO [2]), as well as recent freely available datasets ([3], [4]), to improve vision-based plant cultivation monitoring. It also proposes the collection of its own data to extend training and validation scope: the resulting multimodal datasets will include comprehensive measurements in controlled cultivation environments, as well as measurements from outdoor crops, chemical composition analyses and multispectral images, enabling estimation of plant and environmental variables, and meeting the need for more meaningful quantitative measurements [5]. Leveraging plant state variables, sequential decision-making algorithms can utilize biological models, enabling physics-informed reinforcement learning [6] to overcome limitations in real-world data. Recent advancements in reinforcement learning, including breakthroughs in few-shot learning [7], pave the way for developing cultivation strategies in increasingly complex environments. This project aims to create simulators [8] for these crop optimization problems, providing a benchmark for evaluating proposed solutions, and develop reinforcement learning based paradigms to optimize plant cultivation decisions [9], [10]. In addition, by using the same state variables in the monitoring and decision-making processes developed in this project, partially observable sequential decision problems can be defined and solved, on the one hand by using the observations obtained as output from vision-based monitoring tools, and on the other by adapting the decision algorithms to this new source of information. Data collection sessions will serve as opportunities to assess the performance of the monitoring and decision-making tools, as well as to identify and deal with challenges related to cross-session generalization.

To ensure agriculture benefits from AI advancements, as highlighted in the literature [10], [11], it is crucial to foster stronger collaborations between computer science and plant biology research communities, as proposed in this project. Furthermore, with the aim of developing tools applicable to a wide range of contexts, experiments will extend from controlled environments to outdoor agriculture, using drone technology for field imaging. They will cover a diverse selection of plants, including field crops, medicinal plants, and vegetables, and will focus on processes with varying frequencies (e.g., feeding or harvesting). This challenge requires considering diverse scales of duration, decision frequency, and space. This notably allows for the study of distribution shift and transfer between indoor and conventional agriculture, which is underdeveloped in the literature, despite being essential for adapting the support allocated to crops. Datasets generated in controlled environments enable the refinement of plant models used, supporting monitoring and decision-making for both indoor and outdoor agriculture. Chemical analyses, in addition to a variety of environmental sensors and multispectral cameras, enable the compilation of valuable datasets that will collectively contribute to the development of more robust and general models, and foster the creation of foundation models for agriculture [12]. This research focuses on improving the generalizability and robustness of plant state variable estimators and associated decision making, tackling the inherent agricultural challenges of partial observability, uncertainty management, and multi-criteria optimization.

The central innovation of this project is the methodical exploitation of controlled environments to build robust AI models that can be transposed to less controlled systems. The fundamental and innovative hypothesis of this project is that fully controlled cultivation environments allow the establishment of precise quantitative relationships between environmental conditions, plant development, and production of biomass or compounds of interest, relationships that can then be adapted to less controlled contexts. This approach distinguishes itself from the state of the art through several major innovations:

1. Non-destructive prediction: Where current approaches are often limited to basic estimations (biomass, water stress), we will develop models capable of simultaneously estimating chemical composition, active

metabolic pathways, and potential yields, by combining computer vision and comprehensive environmental data.

2. Biological explainability: based on plant biology models, the state variables used will have biological significance, and the decision models will therefore be biologically explainable by construction, facilitating the analysis of cultivation strategies.

3. Inter-environment transfer modelling: Unlike current approaches that develop models specific to each environment, we will establish formal methods to transpose knowledge acquired in controlled environments to less controlled environments, systematically quantifying the simulation-reality gap.

4. Vertical monitoring-decision integration: Beyond existing segmented approaches, we will develop a unified architecture where the uncertainty of estimations is explicitly modelled and considered in decision algorithms, allowing robust management of the partial observability inherent to biological systems. The use of Orius phytotrons, offering a complete balance of plant-environment exchanges (evapotranspiration, gas exchange, photosynthesis, nutrient absorption), will provide data of unprecedented precision to calibrate the initial models. This approach aims to solve major scientific challenges: modelling complex biological systems from partial observations, domain adaptation for plant models, and multi-criteria optimization of cultivation strategies at different time scales (from daily control to multi-year planning including rotations and recycling).

JASMINA will deliver a comprehensive suite of innovations forming a coherent value chain from fundamental research to practical agricultural applications:

1. - Advanced multi-scale monitoring using non-destructive vision and sensor fusion to assess plant physiology and track metabolic pathways, offering scalable solutions for both controlled and open-field environments. It enables the estimation of plant parameters traditionally requiring destructive methods, integrating visual, environmental, and biochemical data to monitor high-value compound synthesis.

2. Decision support frameworks providing optimized cultivation strategies and resource management through environment-specific algorithms and cross-environment prediction models. These systems offer multi-temporal decision-making, from daily management to seasonal planning, enhancing water, energy, and nutrient efficiency across various agricultural settings.

3. Implementation tools facilitating agricultural innovation through open datasets, benchmark frameworks, and standardized interfaces, enabling seamless integration and evaluation of monitoring and decision-making algorithms. A competition platform will foster community engagement and continuous improvement, driving advancements in agricultural technology.

A large body of research is developing the use of computer vision in agriculture, whether to estimate the quality of produce, soil and seeds, to limit the use of water, fertilizers or pesticides, or to monitor plant growth, health and yield [11]. Computer vision enables rapid, non-invasive acquisition of information with a low-cost sensor that can collect agricultural data over large areas using drone technology [13]. Numerous vegetation metrics, often based on different frequency bands, can be used to estimate stress, content and growth, using RGB, multi/hyperspectral or thermal cameras [11]. Work in computer vision for plant phenotyping also aims to measure important plant traits, through feature extraction, classification and segmentation of plants and their organs, enabling fine analysis of plant structure and development [5]. Recent open datasets, for example for plant segmentation [3] or disease detection [4], enable the use of deep learning algorithms for plant shape, structure and health estimation. Moreover, a growing number of drone image datasets labelled for agricultural use are being made freely available [14].

A critical gap in plant monitoring is the absence of comprehensive datasets linking plant imagery with detailed chemical composition, especially active ingredients. To address this, we will leverage Orius' established expertise in plant chemical analysis and growth control [15] to generate a novel dataset, enabling the development of robust chemical composition estimators and significantly expanding the scope of plant monitoring. By linking visual information to chemical composition in several contexts, this project contributes to work such as [16], which merges vegetation index values obtained from drone imagery with plant traits related to nitrogen and yield, and suggests working on other plant traits such as other nutrient deficiencies (e.g., potassium), or drought status. In our project, multispectral cameras will be used, in addition to RGB cameras, to guarantee complete datasets. Estimators will be trained to predict from RGB images, traits that are directly computable with spectral imagery (e.g. plant segmentation, water content) and thus enable data to be labelled. As multispectral imaging sensors are expensive, these estimators will help reduce the cost of agricultural monitoring tools. This project aims to leverage precise measurements in a controlled environment to refine models and estimations in other environments, thereby enabling the study of the transposition of mechanisms experienced in the laboratory to the open field.

Despite a sparse literature on the subject, reinforcement learning (RL) is a promising AI framework to support plant management [10]. RL with deep learning for sustainable agriculture is promoted in [9] suggesting the use of crop simulators to pre-train algorithms, the use of short-cycle plants for in-situ learning, and the training in a controlled environment with deployment in the field. Some models, simulation environments and algorithms [8], [17], [18] represent important efforts to optimize agricultural decisions and will greatly benefit our project.

As previously mentioned, JASMINA will establish a unified, biologically meaningful state representation for both plant monitoring and sequential decision-making. By integrating biological and physical parameters, such as compound concentrations and light exposure, we will enable the utilization of established biological models and achieve finer-grained state dynamics, for example, precise leaf area estimation to improve photosynthesis and evapotranspiration modelling. Aided by these biological models, we can address the sequential decision problem under uncertainty with tools inspired by the nascent physics informed reinforcement learning literature [19], that enriches through constraints and biases derived from physical laws, several aspects of reinforcement learning, such as the estimation of latent state variables [6] or the learning of transition dynamics [20]. While these physics priors can improve the sample efficiency and generalization capabilities of reinforcement learning, they are unlikely to perfectly model the real world. Yet, prior work in the physics informed reinforcement learning literature rarely studied the transfer from simulation to the real world, which will be one of the focuses of this project. Specifically, we will be interested in robust formulations of reinforcement learning, such as the adversarial setting of [21], where the learner faces an environment that selects worst case perturbations of its dynamics, which we have to carefully select in a way that is biologically plausible and sufficiently rich to improve sim-to-real transfer.

Despite the dynamical nature of agroecosystems, bandit optimization could be applied on well-targeted simplified subtasks as a starting point. In [22] (Nature Communications), the authors adapt the kernelized bandit strategy for sequential optimization introduced in [23] to optimize optical microscopy parameters over short experimental trajectories (60 trials) in increasingly complex setups. Though in a different applicative context, this demonstrates the feasibility of applying sample-efficient sequential techniques to real use case. This methodology was further extended into a full-fledged Python simulator for AI-assisted microscopy in [24] (Nature Communications), enabling seamless integration of bandit optimization techniques into biological imaging.

JASMINA is a multidisciplinary research project uniting AI and plant biology experts to develop robust AI methods by integrating plant-specific knowledge into state and growth models, creating essential datasets and benchmarks for rigorous evaluation. These benchmarks will drive community engagement through competitions, fostering the development of open AI tools that accelerate scientific discovery in plant biology and agriculture. This project aims to significantly advance precision agriculture through several key deliverables. We will produce refined datasets and supervised learning algorithms, develop sophisticated plant models and reinforcement learning systems, create standardized benchmarks for comparative analysis, and innovate methodologies for integrating vision and decision-making. Rigorous validation across three distinct cultivation environments and plant species will demonstrate the project's practical impact and ensure its relevance to the community. By preventing losses and yield reductions (through monitoring), and optimizing production, resources and recycling over the long term (through decision support or automation), this project leads to economic and environmental opportunities. The associated knowledge creation is also an interesting social opportunity. Drone photography, as well as the use of other sensors, poses risks associated with personal privacy. Since the aim of this project is to make public the databases that will be collected, particular attention will be given to this issue.

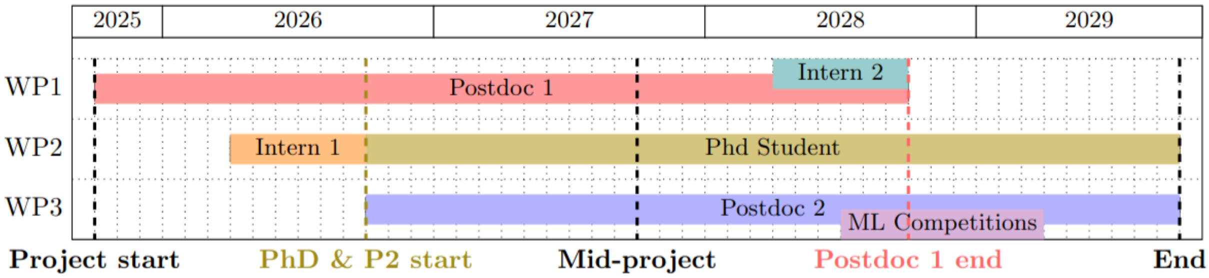

Figure 1: Gantt chart of the JASMINA project with the three work packages

2. Feasibility

Methods for monitoring plant growth, and for computing cultivation strategies, call on significantly different fields of AI. While sharing the same state variables, for estimating on the one hand, and for planning on the other, work on these two tasks will initially be developed in parallel. They will set benchmarks for both tasks, namely the estimation of state variables, and the computation of long-term optimized strategies based on these same state variables. The monitoring work will benefit from the latest state-of-the-art computer vision models, freely accessible databases, and data collected during experimental campaigns in this project. Strategy computation methods will take advantage of plant biology models, collected plant growth time series and effective planning and reinforcement learning algorithms. Following the launch of these two tasks, the combination of their contributions constitutes a third task. Optimizing strategies based on vision-based monitoring systems will focus on model estimation errors and uncertainty representation. In open field environment, it also includes the optimization of drone observation strategies. The project is thus divided into three work packages. The first (WP1), led by Orius, focuses on vision-based crop monitoring methods; the second (WP2), headed by INRIA, concentrates on cultivation strategy optimization; while the third (WP3), managed by ISAE SUPAERO, looks at the combination of the first two contributions, i.e. the perception-action loop. The schedule for these tasks and the associated recruitment are shown in Fig. 1.

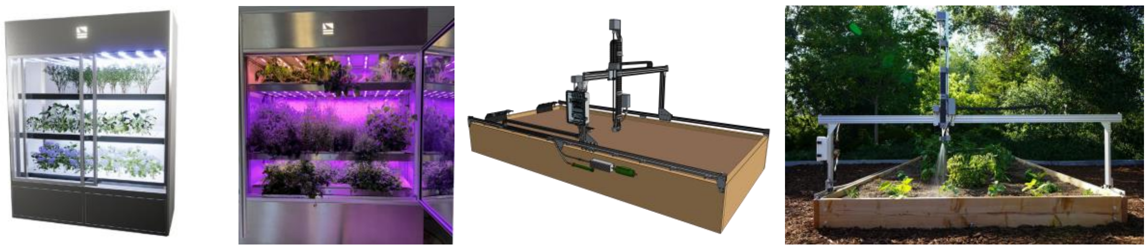

Figure 2: Biomebox phytotron, indoor fully controlled env. (left), and Farmbot, outdoor semi-controlled env. (right)

Three different cultivation contexts are considered: a controlled closed system (phytotron) equipped with cameras (Biomebox at Orius), a restricted outdoor area equipped with sensors and cameras

(Farmbot at ISAE-SUPAERO), see Fig.2, and a field with images taken by a drone (ISAE SUPAERO), see Fig. 3. To collect data, more than twenty cycles of phytotron cultivation are planned, accompanied by cycles of outdoor cultivation. Data collected in the early years is used to refine monitoring and decision models, while they later include real-world evaluations of optimized cultivation strategies.

Figure 3: Multi-spectral sensor Parrot Sequoia (left) used in each cultivation context, and Parrot Bluegrass drone (right)

WP1: "Vision-based crop monitoring method" Orius and ISAE-SUPAERO

Leader and participants: P-F. Pluchon, P-H. Oliver, P. Jay, J. Velociter, B. Aubry, N. Fouere Klein, J. Vaillant (Orius), N. Drougard (ISAE-SUPAERO), T. Gateau (ISAE-SUPAERO)

Supported by a post-doctorate position and an internship (at Orius), this work package starts at the very beginning of the project for three years. It benefits from the latest datasets and models freely accessible, particularly for computer vision, to develop plant production monitoring, based on sensors and cameras. It focuses on the estimation of plant state variables present in biological models (and shared with other WPs), including chemical concentrations. This work package will set up several openly accessible datasets for each context (Biomebox phytotron, Farmbot and open field), monitoring methods and predictive algorithms along with associated benchmarks, enabling comparison of the performance of crop parameter estimation algorithms. It will also focus on producing solutions enabling different timescales, since limited-size systems enjoy near-continuous monitoring, while open-field production allows only occasional snapshots.

While Orius leads this WP, ISAE-SUPAERO is involved in terms of computer vision, deep learning and drone technology, and INRIA will provide valuable advice on open-field farming. Building on state-of-the-art computer vision models, this work package aims to estimate critical plant measurements (biomass production, chemical composition, metabolic activity) without destructive sampling. This will be accomplished through correlation of visual data with actual measurements from sacrificed plants at various growth stages. The plant development monitoring system will benefit from the combination of visual data and environmental sensors data and will aim to detect early signs of stress, disease, and growth anomalies before they significantly impact yield or quality. Finally, controlled-to-field transposition models will be developed by leveraging the precision of indoor cultivation environments to establish mathematical relationships between controlled and less controlled environments, enabling prediction of field outcomes based on controlled experimentation.

This work package combines experimental cultivation and model development, using a structured experimental design to establish cross-environment correlations and validate monitoring techniques across cultivation scales and types. It will progress through four interconnected stages:

1. Feature extraction models: Developing context invariant computer vision algorithms to identify and quantify key visual markers from RGB and multispectral imagery;

2. Composition estimation models: Creating robust computer vision models correlating visual features and plant chemical/biological properties, based on ground-truth destructive testing;

3. Environmental response models: Building predictive frameworks for plant responses to environmental parameter variations with multi-modal data fusion and plant metabolic pathway mapping;

4. Cross-environment transposition models with uncertainty quantification: Developing domain adaptation techniques to apply indoor-trained models to less controlled environments.

A rigorous model development methodology will be employed starting with model training on indoor data with high-precision ground truth, and progressive validation through controlled parameter variation. Uncertainty on the model reliability will be quantified and systematic testing across environments with unified measurement solutions will validate transposition.

WP2: "Cultivation strategy optimization" INRIA and Orius

Leader and participants: O-A. Maillard, R. Akrour (INRIA), P-F Pluchon, P-H Oliver, P Jay, J Velociter, B Aubry (Orius)

Supported by a Ph.D. thesis (at INRIA), this work package starts six months after the beginning of the project and runs until the end. It includes a literature study in plant production modelling, and develops planning models and simulators for the optimization of cultivation strategies taking into account all the criteria involved, such as resources (e.g., energy) and waste production. It shares the same crop and environmental state variables as the work package on vision-based cultivation monitoring (WP1) for explainability purposes, and with a view to combine the contributions of these two work packages (WP3). Data collection campaigns will be used to adjust and validate the models, and to study the simulation-to-reality gap. Although managed by INRIA, this work package will benefit from Orius' expertise in plant biology models and controlled experiments, as well as ISAE-SUPAERO for the use of the Farmbot. This work package will enable the implementation of planning models, simulators and optimization criteria for each of the three usage contexts. Algorithms for computing cultivation strategies will be compared on this basis, providing new benchmarks, and the most promising approaches will be deployed in the real world for assessing their performances in practice.

Beyond traditional optimization techniques, this WP will explore the application of bandit optimization strategies. Inspired by successful implementations in other domains, such as the work of [22] on optimizing optical microscopy parameters, we will adapt kernelized bandit strategies for efficient sequential optimization of cultivation parameters. This approach is particularly relevant for contexts with limited experimental trajectories or when rapid adaptation to changing conditions is crucial. We will investigate how bandit algorithms can be applied to specific subtasks within the cultivation strategy, providing a computationally efficient starting point for optimizing parameters such as irrigation schedules or fertilizer application rates, potentially drawing parallels with applications in resource-constrained environments such as those described in [8] focusing on agriculture usecase in Mali.

From a Reinforcement Learning (RL) perspective, we will investigate transfer learning and continual learning techniques [25], [26] to improve the adaptability and scalability of our cultivation strategies. The initial approach will involve training RL agents in simulated environments, leveraging the plant models and simulators developed within this WP, and then transferring these learned policies to real world settings. This addresses the challenge of data scarcity and reduces the need for extensive in situ training. To overcome domain shifts between simulation and reality, we will explore techniques such as domain randomization and fine-tuning of the RL policies using real-world data. We will also address the challenge of continually adapting to new conditions and plant varieties through continual learning, where the RL agent learns new tasks without forgetting previously acquired knowledge. Algorithms for computing cultivation strategies will be compared based on the criteria defined for each context, establishing new benchmarks for performance evaluation. The most promising approaches, incorporating elements of bandit optimization and transfer/continual RL, will be deployed in real-world settings to assess their practical performance and robustness. This iterative process of simulation, real-world deployment, and refinement will drive the development of effective and adaptable cultivation strategies.

WP3: "Assembling monitoring and decision-making components" ISAE-SUPAERO and INRIA
Leader and participants: N. Drougard (ISAE), C. Chanel (ISAE), T. Gateau (ISAE), R. Akrour (INRIA), O-A. Maillard (INRIA)
A postdoc position starting one year after the beginning of the project and running until the end will focus on this work package dedicated to the combination of vision-based monitoring with sequential decision-making, for the latter to benefit from a better estimate of the state of crops and their environment. It involves analysing and modelling the conditional distributions of the plant monitoring estimator and implementing solvers that tackle associated complexity to compute robust policies for plant growth supervision. Thanks to the state variables shared by crop monitoring solutions (WP1) and decision models (WP2), the focus of this work package lies in the formal definition and implementation of partially observable sequential decision-making models, including the uncertainty linked to observations coming from vision-based monitoring, and the adaptation of simulators and sequential decision-making solvers. Note that not only the estimators developed in WP1, but also the quantification of the uncertainty associated with them, are necessary for the complete definition of such partially observable models. Due to model imprecision, a risk-averse approach can be used to obtain robust policies. These considerations may call upon various models of uncertainty, depending on its nature. Finally, the partial observability of the system state significantly increases the complexity of the problem, which must nevertheless be dealt with by the proposed solvers. Optimization criteria will be defined for each study context, and the strategies resulting from the optimization of these criteria, taking advantage of the initial data collection campaigns, will be deployed for validation under real-world conditions.

This work will produce models and simulators in this new setting of observation availability trough vision-based monitoring, as well as different approaches on plant cultivation strategy computation that can be compared on the basis of the developed simulators and criteria, providing the last benchmark of JASMINA. Although managed by ISAE-SUPAERO, this work package benefits directly from the work of the first two work packages managed by Orius and INRIA (WP1 & WP2).

While WP1 focuses on drone vision, WP2 bases its strategies solely on other available information and sensors. Therefore, a particular effort will be placed on drone observation strategies within this work package. Since drone usage is limited in duration and frequency, the drone must adjust its image capture policy based on the estimated state of the crop and its environment, focusing for example on certain areas or specific plants that would be prioritized at this decision stage, considering the long-term optimization of the strategy. Close-up shots allow for finer estimations of crop state but require more time than a distant shot, which will provide less precise estimations, this conditional estimator precision being taken into account by the sequential decision-making problem.

Finally, this work package will organize a Machine Learning competition during the second part of the project, which will unite and engage the research and engineering community around the challenges of this project, supplement the benchmarks in a participatory manner, and provide visibility to the results.

Each work package is supported by the recruitment of a new project member by one of the partners: a post-doc recruited by Orius for WP1, a PhD student recruited by INRIA for WP2, and a post-doc recruited by ISAE-SUPAERO for WP3. An internship is planned just before the thesis (WP2), and another will support the post-docs in the completion of benchmarks for their WPs (WP1, WP3) and in setting up the competition. In addition to weekly team meetings, monthly progress meetings will be held for each work package, and at least one physical event bringing together all partners is planned each year.

The experiments are carried out by the Orius team with the fully controlled indoor environment (Biomebox phytotron), and the ISAE-SUPAERO team, with the semi-controlled outdoor environment (Farmbot) and the drone shooting campaigns in open field environment. All WPs are involved in these three types of experimentation, to validate monitoring or strategies, except WP2, which does not include a drone shooting campaign, as it does not consider vision-based monitoring tools. While the fully controlled indoor environment (Biomebox, Orius) benefits from a complete environmental instrumentation to measure all exchanges between plants and environment (evapotranspiration, gas exchange, photosynthesis, nutrient uptake), the semi-controlled environment (Farmbot) only benefits from a programmable position soil moisture sensor and camera, as well as water management. The drone campaigns use the "Parrot Bluegrass" drone, equipped with the "Parrot Sequoia" multispectral sensor, as will the Biomebox phytotron and Farmbot.

Three plant models representing different cultivation archetypes will be studied: a field crop model (wheat) allowing indoor/outdoor comparison, a medicinal/aromatic plant (chamomile) for indoor greenhouse comparison, and a model vegetable crop (mizuna) for comparison with small-scale systems like Farmbot. Thus, these experiments will generate comprehensive datasets across three distinct cultivation contexts and three distinct plant types. The focus of the experiments will evolve as the project progresses: in the early years, it will be to collect data for learning and evaluating (vision and decision) models, and in the later years to deploy and evaluate the calculated strategies. So, the first experiments focus on cultivation baselines with regular environment parameters, and then with environment parameter manipulation and response characterization. Follows an emphasis on cross-environment testing and stress, response profiling, and finally on a unified model and plant response comparison across systems.

During the project, two Biomebox phytotrons will run three-month growth cycles for three years of effective cultivation time. In this way, the project experiments can be spread over the resulting 24 cycles (8 per plant type) distributed over the two Biomebox phytotrons. Considering the other three growing contexts (apart from open fields for unsuitable plants), the project involves some 60

different experimental conditions. Regarding open-field experiments, at least 12 full days of drone imagery are planned during the project, i.e. a minimum of 3 full days per year. In the early years of the project, these will be several sessions separated by time (to collect baseline growth trajectories), and in the later years consecutive days (to evaluate the computed strategies), for example to observe the effect of a water or fertilizer management strategy. Note that these experiments require a team to deploy the drone system, and fields with access authorization. This also implies the provision of compensation for any collaborating farmers.

To promote recruitment we have made provision for long-term contracts and salaries of experienced postdocs. The project may also encounter difficulties in finding suitable crop fields for experimentation, or in obtaining a farmer's agreement to equip her/his field for drone imaging sessions. The project would then be restricted to observing the cultivation of other plants, with monitoring and decision tasks potentially different from those planned, such as fruit counting. Finally, statistically significant improvements with computed strategies deployed in the real world are not guaranteed. Models should only be made progressively more complex, so as to retain an understanding of the decisions deployed. In all cases, following deployment, the datasets produced will be available for further study.

3. Partnership (consortium or team)

The consortium is composed of three partners: INRIA Centre at the University of Lille, ISAE-SUPAERO (University of Toulouse), and the company Orius (Escalquens, greater Toulouse area.) The INRIA researchers taking part in the project are part of the "School" team (team.inria.fr/scool), which specializes in Sequential Decision Making under Uncertainty. In particular, they are working on (Deep)

Reinforcement Learning [27], implementing simulators [28], and applying their work to the field of agriculture and agro-ecology [8], [10], [17]. On the ISAE-SUPAERO (www.isae-supaero.fr) side, the participating researchers are part of the "Decision and Control" and "Space Systems Design" teams in the "Aerospace Vehicle Design and Control" department, and specialize in Machine Learning, Planning under Uncertainty [29] and Reinforcement Learning applied in particular to UAVs [30] and robots [31]. This project proposes to develop tools for monitoring and controlling plant growth, similar to the tools developed by the ISAE-SUPAERO's researchers for monitoring [32] and adapting [33], [34] the interaction of human operators with their systems. The Orius company (www.orius.co) develops advanced plant production systems for sustainable production of ingredients, nutraceuticals and food, from industrial applications to space exploration. Founded in 2021, Orius combines expertise in biological systems and environmental control technologies to create next-generation cultivation systems based on state-of-the-art indoor farming techniques. Orius tackles complex challenges in biological production, from space food systems [15] to high-value chemical compounds for health and beauty sectors. Orius' approach integrates cutting-edge engineering with deep biological understanding to create reliable and resource-efficient solutions.

Beyond conventional plant production, Orius possesses unique expertise in manipulating biosynthetic pathways and metabolic mechanisms in plants. Their approach focuses not simply on biomass yield, but on maximizing valuable compound production per square meter per year while minimizing resource inputs (energy, labor, water). This is achieved through their deep understanding of the environmental triggers and conditions that stimulate specific metabolic pathways in plants. Orius is actively working with CNES (French space agency) on developing cutting-edge deployable production systems to feed astronauts, where extreme constraints in terms of resources (mass, energy, water) drive innovation in cultivation efficiency. Rather than focusing exclusively on indoor production, Orius aims to transpose high-performance models to more energy-efficient and resource-frugal systems, developing supply chains based on existing production tools (conventional farmers) while offering them new perspectives (increased crop value, climate-adaptive cultivation methods).

Naturally, the Orius team provides expertise in plant biology and plant cultivation in controlled environments, while INRIA and ISAE-SUPAERO provide expertise in artificial intelligence, including supervised learning and reinforcement learning. It reflects the multidisciplinary aspect of JASMINA which works for sustainable agriculture using plant biology & AI. In practice, indoor experiments will be managed by Orius, and outdoor experiments by ISAE-SUPAERO with the help of the Farmbot and the drone, and precious advice from INRIA about conventional agriculture. Orius and ISAE-SUPAERO already collaborate on space and regenerative life support systems. PhD theses founded by CNES, ISAE and ORIUS already planned.

4. Exploitation and dissemination plan

Robust monitoring of meaningful state variables and sequential decision-marking with different time and space scales or criteria are relevant tasks to optimize in the agricultural sector as shown for instance by Hectar's ecosystem (en.hectar.co). Transposition from indoor to conventional agriculture is also an important need for the agricultural industry, seeking for yield maximisation and minimal resource use. This innovation chain creates significant value by enabling data-driven precision agriculture across scales, from high-value indoor production to extensive field crops. It bridges the gap between controlled experimental conditions and practical field implementation, allowing for:

- Reduced development times for optimized cultivation protocols
- Lower resource consumption through targeted interventions
- Enhanced crop resilience through early stress detection

- More efficient production of high-value compounds

The technology value chain extends from fundamental data collection and algorithm development to practical implementation tools, ultimately providing farmers and agricultural enterprises with robust, explainable AI-based systems for sustainable and resilient cultivation. The genericity of the different developed solutions is ensured by the three cultivation contexts and the three plant types. This project will create open access datasets, code and benchmark for each work package, and a Machine Learning competition will be organised around the related challenges (as already organised by the members of ISAE-SUPAERO for passive Brain Computer Interfaces [35]). Publications in Artificial Intelligence and Computer Vision conferences (AAAI, UAI, NeurIPS, ICML, CVPR, ECCV, WACV, etc.), in journals on Computer Science for Agriculture (Computers and Electronics in Agriculture, Artificial Intelligence in Agriculture, Information processing in agriculture, etc.), as well as in open-acces journals, will follow the development of these datasets, methods, and algorithms to share the project's progress. The contributions will be used to illustrate courses and practical work for Master's level students at ISAE-SUPAERO. Before sharing the results, the intellectual property aspects will be defined by a consortium agreement. Results and new intellectual property rights (IPR) resulting from this project and the protection of the knowledge will be engaged through the administrations each partner depends on according to national rules on IPR and to the participation effort in case of discoveries involving several partners.

5. Financial tables: Summary of costs & efforts

INRIA: Staff expenses cover salary for PhD scholarship (36 months) and one master internship grants (124.2k€). Instruments and material costs (1.5k€) cover one laptop for the PhD. Overheads/Other costs include travel expenses for the project implementation, for national and international conferences (16K€).

ISAE-SUPAERO: Staff expenses cover salary for one post-doc (36 months, 198k€) and one master traineeship grants (3.9k€). Instruments and material costs cover one laptop for the Post-doc (2,1K€), two Sequoia Sensors (8K€), the Parrot Bluegrass drone (5K€), as well as replacement equipment for the experimental facilities and scientific computer hardware (15K€). Services and IPR cover publication costs (3K€), Machine Learning Competition (8K€), the use of a high performance calculator on CALMIP facilities (4K€) and compensating farmers (1K€). Overheads/Other costs include travel expenses for the project implementation, experimentation and coordination (14K€), travel expenses for international conferences (12,5K€). Involvement in the project is 35% for the coordinator (N. Drougard), 25% for T. Gateau and 10% for C. Chanel.

Orius: In addition to hiring the WP1 post-doc (36 months, 180K€), Orius plans to hire a laboratory technician (53.6K€). Its budget then corresponds to the use of the two phytotrons (28K€) and chemical analyses (10K€). Overheads include the use of its premises (30K€), management costs (45K€) and IT equipment (6K€).

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(FINANCIAL TABLE FOR PARTNERS)

Name and organisation	Salaries –Staff (euro)						Instruments and equipements (euro)	Services and Intellectual property rights (euro)	Other costs (euro)	**Total (euro)**
	Permanent position		Non permanent position with funding requested		Non permanent position without funding requested					
	Cost (euro)	Person month	Cost (euro)	Person month	Cost (euro)	Person month				
French partner 1 : ISAE-SUPAERO	310 071 €	34	201 900€	42			30 100€	16 000€	26 600€	584671€
French partner 2 : SCOOL INRIA	59 400€	7.2	124 200€	42			1 500€		16 000€	201 100€
French partner 3 : Orius	153 667€	26	233 667€	50			28 000€	10 000€		425 334€

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