RÉPUBLIQUE FRANÇAISE
Liberté Égalité Fraternité

FRANCE 2030 — PROGRAMME DE RECHERCHE AGROÉCOLOGIE ET NUMÉRIQUE

anr INRAE Inria

PEPR d'une Stratégie Nationale
Appel à Projets
2023

PEPR Agroécologie & numérique

Document présentation projet

AgroEcoReco

Acronym / Acronyme	**AgroEcoReco**
Title of the project in French / Titre du projet en français	Compagnon de recommandation numérique pour l'aide à l'expérimentation de pratiques agroécologiques
Title of the projet in English / Titre du projet en anglais	Digital Recommendation Companions to assist experimentation of agroecological practices.
Keywords / Mots-clefs (min 5-max 10)	Apprentissage par renforcement, Systèmes de recommandation, Bandits manchots, Expérimentation de terrain, Données séquentielles, Plateforme numérique, Sciences des données, Science participative, Fermes pilotes, Savoirs locaux.
Axis (a project may be positionned in several axes) / **Axes** (un projet peut se positionner dans plusieurs axes)	☐ Axis 1: Shaping a socio-ecosystem conducive to responsible research and innovation ☐ Axis 2: Characterising genetic resources to assess their potential for agroecology ☐ Axis 3: Designing new generations of agricultural equipment ☒ Axis 4: Developing digital tools and methods for agriculture data processing and modelling, for agricultural equipment, and for decision support
Leading Institution / Établissement coordinateur	INRIA
Scientific Coordinator / Responsable du projet	**Last Name, First Name, Position / Prénom, Nom, Qualité** Maillard Odalric-Ambrym, Senior Researcher (CR, HDR) **Email / Courriel** **Téléphone** odalric.maillard@INRIA.fr 0359577811
Project Duration / Durée du projet (de 36 à 60 mois)	60 mois
Requested Funding / Aide totale demandée	2 698 554 € **Full Cost / Coût complet** 6 228 756 €

Partner Institutions / Liste des établissements du consortium :

Higher Education and Research Institutions / Établissements d'enseignement supérieur et de recherche	**Activity / Secteur(s) d'activité**
Université de Montpellier	EPSCP

Research Organisations / Organismes de recherche	**Activity / Secteur(s) d'activité**
INRIA	Recherche en sciences du numérique
INRAE	Recherche en agriculture, alimentation et environnement
CIRAD	Recherche-développement en autres sciences physiques et naturelles
ARMEFLHOR	Institut technique agricole basé à La Réunion spécialisé dans les filières fruitières, légumières et horticoles

Other Partners (eligible for funding) / Autres partenaires (éligibles à l'aide d'Etat)	Activity / Secteur(s) d'activité
CNA (Centre National d'Agroécologie)	Agroécologie (expertise, réseaux d'agriculteurs innovants, diffusion)

Other Partners / Autres partenaires	Activity / Secteur(s) d'activité
LRI Agro (Madagascar)	Recherche en Agronomie

List of Research Units / Liste des unités de recherche impliquées :

Research Units / Unités de recherche	Institution / Établissement de tutelle
SCOOL (202023603Y)	INRIA
MIAT (198717966P)	INRAE
MISTEA (198217965K)	INRAE
IMAG (200311827X)	Université de Montpellier
AÏDA (201421281A)	CIRAD
RECYCLAGE&RISQUE (200718430G)	CIRAD

Abstract in English (non-confidential – maximum 4000 characters spaces included)

In the recent years the transformative power of Machine Learning (ML) has been demonstrated worldwide across a multitude of sectors, from healthcare to marketing and finance, from transportation to entertainment. This success is largely attributed to ML's ability to extract meaningful insights from vast amounts of data, enabling unprecedented levels of efficiency, accuracy, and personalization. In parallel, the world is witnessing a paradigm shift in agriculture, transitioning from traditional practices towards agroecology. This shift is driven by the urgent need to address the pressing challenges of climate change, biodiversity loss, and food security. Agroecology, with its focus on sustainable and resilient farming systems, offers a promising solution. However, the adoption of agroecological practices is hindered by the complexity and diversity of these systems, as well as the lack of comprehensive, high-quality data to guide decision-making personalized to each context. While the transformative power of ML may potentially revolutionize agroecology by providing robust, data-driven tools to support and massify the design and evaluation of agroecological practices, it is blocked by several challenges.

The overarching scientific challenge addressed by AgroEcoReco is to enable the use of Digital Experimentation Companions (DEC) to assist the massification of FAIR experimental data in agroecology and the efficient identification and adoption of beneficial agroecological practices. The central question is “how to act” on a given agrosystem, personalized to its specific environmental, crop, and farmer context, to maximize a diversity of agroecological indicators. Given that agroecological dynamics are not fully modeled and agroecological variables are not easily measured, there is inherent uncertainty in both the modeling and measurement process. Decision-making under uncertainty, traditionally formalized under the Reinforcement Learning (RL) framework in ML, provides novel perspective towards addressing this challenge. Our global scientific vision is to establish a lasting interdisciplinary connection between world experts in the design of AI algorithms for decision making under uncertainty, world experts in the design of agroecological knowledge, and leading stakeholders in the diffusion of agroecological practices across agronomists and farmers. The key approach is to exploit the similarities between the learning process of a human practitioner acting on an agrosystem and that of a reinforcement learning agent acting in a digital environment, leveraging the promising performances of RL in increasingly many domains. Central to this approach is the design of a digital platform that embeds the full decision-making pipeline, interconnecting the design of sequential learning algorithms and their mathematical analysis with the acquisition of experimental data and advice to farmers tailored to their territorial context.

Overall, AgroEcoReco aims to bridge the gap between agroecology and digital technologies by developing innovative experimentation and recommendation algorithms tailored to the diversity of agroecological practices and performance criteria. The AgroEcoReco project proposes a multi-disciplinary consortium that covers the entire decision-making chain, gathering experts from the core design of sequential learning algorithms and their mathematical analysis all the way to the acquisition of experimental data and advice to farmers, covering diverse types of agriculture in different climates. A key component of the coherence of this diversity of expertise is to focus the project's endeavors on the collective design of a Digital Experimentation Companion platform that aggregates the skills of all partners. The intended impact is to foster massive, collaborative field experimentation to disrupt traditional knowledge production in agroecology.

Résumé du projet en français (non confidentiel – 4000 caractères maximum, espaces inclus)

Ces dernières années, le pouvoir de transformation de l'apprentissage automatique a été démontré dans le monde entier dans une multitude de secteurs, de la santé au marketing et à la finance, du transport au divertissement. Ce succès est largement attribué à la capacité de l'apprentissage automatique à extraire des informations utiles à partir de grandes quantités de données, ce qui permet d'atteindre des niveaux d'efficacité, de précision et de personnalisation sans précédent. Parallèlement, le monde assiste à un changement de paradigme dans l'agriculture, passant des pratiques conventionnelles à l'agroécologie. Ce changement est motivé par la nécessité urgente de relever les défis globaux tel que le changement climatique, la perte de biodiversité et la sécurité alimentaire. L'agroécologie offre une solution prometteuse en mettant l'accent sur des systèmes agricoles durables et résiliants. Toutefois, l'adoption de pratiques agroécologiques est entravée par la complexité et la diversité des agrosystèmes et par le manque de données complètes et de qualité pour guider la prise de décision. Si le pouvoir de transformation des méthodes d'apprentissage peut potentiellement révolutionner l'agroécologie en fournissant des outils robustes pour soutenir et massifier la conception et l'évaluation des pratiques agroécologiques, elles se heurtent à plusieurs obstacles.

AgroEcoReco relève un défi scientifique majeur : utiliser des Compagnons d'Expérimentation Numérique pour faciliter la massification des données expérimentales FAIR et l'adoption de bonnes pratiques agroecologiques. La question centrale est de savoir « comment agir » sur un agrosystème spécifique pour maximiser divers indicateurs agroécologiques. Face à l'incertitude inhérente à la modélisation et à la mesure de la dynamique agroécologique, l'apprentissage par renforcement (RL), qui formalise traditionnellement la prise de décision sous incertitude en apprentissage automatique, offre une nouvelle perspective. Notre vision ici est de créer une connexion durable entre les experts en IA, en agroécologie et les pionniers de la diffusion de pratiques agroécologiques. Pour cela, l'approche clé est d'exploiter les similitudes entre l'apprentissage d'un praticien humain et celui d'un agent RL, tout en s'appuyant sur les performances prometteuses du RL dans de nombreux domaines.

Globalement, AgroEcoReco vise à combler le fossé entre l'agroécologie et les technologies numériques en développant des algorithmes innovants pour l'expérimentation et la recommandation, adaptés à la diversité des pratiques agroécologiques et des critères de performance. Le projet AgroEcoReco propose un consortium multidisciplinaire qui couvre l'ensemble de la chaîne de décision, rassemblant des experts allant de la conception d'algorithmes d'apprentissage séquentiel et leur analyse mathématique jusqu'à l'acquisition de données expérimentales et le conseil aux agriculteurs, couvrant divers contextes agricoles sous différents climats. Un élément clé de la cohérence de cette diversité d'expertise est de concentrer les efforts du projet sur la conception collective d'une plateforme d'expérimentation numérique qui regroupe les compétences de tous les partenaires. L'impact attendu est de favoriser l'expérimentation massive et collaborative sur le terrain afin de bouleverser la production traditionnelle de connaissances en agroécologie.

Table of Contents

1. Context, objectives and previous achievements **1**
1.1 Context, objectives and innovative features of the project 1
1.2 Main previous achievements 4

2. Detailed description of the project / Description détaillée du projet **5**
2.1 Project outline, scientific strategy 5
2.2 Scientific and technical description of the project 6
2.3 Planning, KPI and milestones 8
2.4 Risk management 14

3. Project organisation and management **16**
3.1 Project manager 16
3.2 Organization of the partnership 16
3.3 Stakeholder involvement 17
3.4 Management framework 18
3.5 Institutional strategy 18
3.6 Data management / Stratégie en matière de données 19
3.7 Ethical framework / Cadre éthique 19

4. Expected outcomes and impact / Impact et retombées du projet **19**

5. Funding justification / Justification des moyens demandé **20**

6. Références bibliographiques citées **21**

7. CV of the project leader / CV du responsable du projet **28**

1. Context, objectives and previous achievements

1.1 Context, objectives and innovative features of the project

Scientific context: In response to the escalating global challenges of food security [23], water scarcity [79], and biodiversity collapse [75], there is an urgent need to transform agriculture. Agroecology [4, 54, 59], a sustainable alternative to conventional agriculture, has emerged as a promising solution. It emphasizes natural processes over synthetic inputs and fossil fuels, integrating the evolving relationships within agricultural systems at various levels. This holistic approach combines ecological and social principles to develop sustainable food systems, addressing food security along with water, soil, and environmental protection under context-specific constraints. However, the complexity of agroecology requires a more intricate representation to account for diverse variables, processes, and objectives [61]. The high number of influential factors, available practices, and diversity of objectives creates a combinatorial explosion, posing an unprecedented experimental challenge to quantify the context-specific benefit of each practice.

To support the development of new practices and assess their performances at the cropping system level and beyond, agronomy research has traditionally relied on the development of crop models [48, 53] and various types of information systems [5, 100, 56]. Yet, the challenge of developing crop models capable of tackling the complex interactions in agroecological systems across a wide range of cropping situations has resulted in a gap in meeting the urgent need for support in designing new cropping systems within the agroecological transition framework. Moreover, few crop models concretely integrate aspects linked to the crop management plans, which are mostly considered as fixed, making them less relevant given that farmers are subject to numerous hazards [108]. Each farmer has unique constraints and objectives that guide their choice of practices best suited to their situation.

Machine Learning (ML) has started to assist agriculture in yield-prediction and identification tasks using massive sensor and image data analysis [73, 15]. The emergence of new machine learning or reinforcement learning methods presents enormous potential to address the urgent need for new recommendation tools to accelerate the search for new agroecological systems [52, 72]. Agronomists have recently initiated On-Farm Experimentation initiatives [68], involving practitioners to experiment beyond the limited, controlled context of lab-farms, and massify experimentation to identify best practices, personalized to each individual and context. However, assisting a diverse group of practitioners to collectively test and identify best-personalized practices in a real-world context comes with significant machine learning and statistical challenges.

Next, the diversity inherent in agroecological practices presents significant obstacles in managing the resulting data, particularly in terms of knowledge accumulation and distribution. The scientific pursuit to integrate digital sciences into agroecology experimentation is multifaceted: (i) Establishing a database capable of housing extensive and valuable experimental data that can be processed by algorithms. This data should encompass the wide range of variables and practices inherent in agroecology, all the while adhering to the FAIR principles [112]. (ii) Creating an active user community that consistently updates the database with new experimental data and direct user feedback. (iii) Continual improvement of research through the use of collected data to enhance both models and learning algorithms, which subsequently refines these digital aids in a beneficial cycle. The objective extends beyond mere optimization; it aims to revolutionize data acquisition, drawing parallels with Waze's impact on mobility and Pl@ntNet's influence on botany. Indeed, while mere optimization of existing methodologies often yields incremental improvements while preserving the status quo, transformation has the potential to usher in innovative strategies with considerable advantages.

Research questions: The research aims to address the following key questions: 1) How can we adhere to principles when dealing with predominantly heterogeneous experimental data, often collected via traditional methods, to ensure reproducibility, explicability, interpretability, and interoperability of practices? 2) How can we collaboratively design a tool that is beneficial to both practitioners and researchers, promotes mass collaborative experimentation, encourages a participatory and open science approach, and attracts more digital science researchers to agroecology? 3) How can we train and design decision-making algorithms to handle the complexity of statistical agroecosystem experimentation and adapt to local management practices?

Project objectives and contribution to agroecological transition: To address these questions, we propose a systematic approach that involves assembling a comprehensive consortium of partners, ranging from algorithm designers to agronomists and farmer associations. This consortium will continually exchange ideas on a set of collectively defined tasks, ensuring continuous alignment of terminology and cross-pollination of ideas.

Specifically, we aim to create software supporting Digital Experimentation Companions (DEC) that is interoperable with machine learning and reinforcement learning algorithms and agrosystem models and data. The recorded experimental data from various contexts should be made interoperable with digital algorithms, and the algorithms and models should be extended to realistic experimental conditions. We plan to monitor a diverse set of case studies to provide concrete examples for co-designing the DEC interface and format. Our consortium covers data from hundreds of farms in both temperate and tropical regions, involving various types of agriculture and experiments designed by both researchers and farmers. This diversity will enable us to analyze real constraints of practitioner adoption in a unique way. Our ultimate goal is to gradually form a user community based on various case studies, adhering to the highest standards of open science and open source, providing novel tools to the research community, and actively studying obstacles to user appropriation.

State of the art and scientific positioning:

i. Lack of FAIR agrodatabases and interoperable tools. The FAIR principles, commonly applied in machine learning, ensure that algorithms can interact directly with data. However, in the agricultural domain, especially for on-farm experimentation, data collection is often recorded on paper or Excel-like documents, still unfortunately lacking interoperability and homogeneity. Efforts like the Kobotoolbox [69] project have attempted to address this issue, but substantial effort is still needed to ensure interoperability with learning algorithms and visualization tools. The academic nature of the AgroEcoReco consortium enables the promotion of open-data, open-source, and open-science principles, fostering trust from data providers. Successful transformative data platforms like e-Bird, i-Naturalist, and Pl@ntNet demonstrate the efficacy of such principles. Besides, available machine learning procedures in agronomy today are often specific and lack interoperability. The introduction of transformative platforms like Gym [22] in reinforcement learning and Autograd in deep learning revolutionized their respective fields, enabling interoperability, reproducibility, and accelerated progress. Projects like Waze in the mobility sector transformed data acquisition, connecting user requests with state-of-the-art algorithms, thus streamlining the process from theory results to end-users. AgroEcoReco follows this line of thought, aiming to transfer the success of such approaches to agroecology.

ii. Success of Reinforcement Learning (RL) algorithms in real-world problems. Machine Learning (ML) started to assist agriculture [73, 15] in yield-prediction and identification tasks using massive sensor and image data analysis [24, 10]. To answer the decision making task, the core numerical contributions of this project revolve around the theme of sequential decision making under uncertainty, which broadly drives learning in recommendation systems. The sub-field of Machine Learning (ML) that studies sequential decision making under uncertainty is called Reinforcement Learning (RL). RL algorithms aim to sequentially learn from the experience and to optimize the total error conceived in the process. Thus, RL is the ML paradigm that resembles the vision of 'general' AI. In RL [95], a learning *agent* sequentially interacts with an *environment* by taking a sequence of *actions*, and subsequently observing a sequence of *rewards* and changes in her *states*. Her goal is to compute a sequence of actions that yields as much reward as possible given a time limit. In other words, the agent aims to discover an optimal *policy*, i.e. an optimal mapping between her state and corresponding feasible actions leading to maximal accumulation of rewards. Two principal formulations of RL are Bandits [70] and Markov Decision Process (MDPs) [82]. Depending on the information available for a problem and its complexity, we leverage both formulations in AgroEcoReco.

RL has recently been successfully deployed in real-time systems. With the increasing computational resources and new theoretical findings, RL has been successfully deployed in games, like Go, Chess, Minecraft etc., where it has performed at per or better than human experts. Also, Recommender systems [84, 85, 86], and contextual RL [71, 66, 1, 110, 42, 57, 62, 93] have upscaled the possibility to collect feedback and efficiently learn recommendations for a large group of users at an unprecedented world scale. In all these success stories of RL, a common thing is availability of data, immediateness of feedback, and ease of experimentation with computer systems and gamers. Access to data, feedback to decisions, and experimentation ensures availability of enough data to explore different decisions and measuring their utilities accurately.

iii. Challenges of RL for agroecology. Agroecology brings a fresh bouquet of challenges for RL algorithms as the experimentations are often labour and financially-intensive, and a feedback of a decision arrives after a crop cycle. Additionally, unlike the existing applications on computer games and systems, the agroecological decisions directly impact humans and have to be understandable to humans to be correctly executed. This brings a facet of challenging questions in each of the RL setups. There has been numerous workshops in international ML, AI and Computer Science venues, such as AI for Agriculture and Food systems at AAAI'22 and AAAI'23, IEEE workshops ((a), (b), (c) (d)). Though RL has been a popular method in these workshops and some competitions are regularly organized,there are a bunch of **challenges** that yet to be resolved before applying RL to real farms:

1. **RL with the time of intervention as a decision.** MDPs are ubiquitous in RL but do not model well decision over times such as when to observe or to intervene [36, 35, 41], which is often an important decision in agriculture.

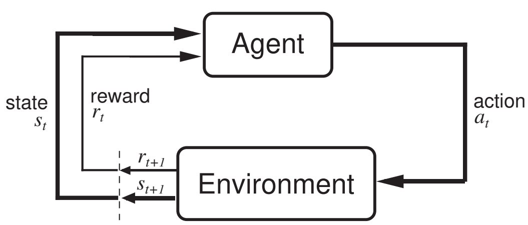
2. **Contextual RL with data frugality.** In agricultural decision making, feedback of decisions are obtained after long delays, and thus, often ML and RL methods rely on crop simulators instead of real-world data.

3. **RL with robust learning and planning.** Agroecological systems encounter dynamic risks due to natural events, specific geographic contexts which pose specific opportunities and challenges to extend the field of RL to take risk-averse decisions, but see [67, 16, 13, 46, 44, 2].

4. **RL with transferability and generalizability.** Since agricultural decisions vary from geographic and social contexts but share the similar structure of information and decisions across places, it is of utmost importance to transfer and generalize knowledge of an RL algorithm to a new environment [8, 87, 114, 45].

5. **Explainable and interpretable RL.** In order strategies to be adopted by farmers, it of utmost importance that stakeholders are able explain the decisions recommended by RL [39].

6. **Multi-agent and social RL.** Farmers and stakeholders are social agents and it is of utmost importance to take decision in socio-ecological systems [98, 43].



iv. Crop simulation models [63, 60, 21, 65] are computational tools that mimic crop growth in response to environmental conditions and management practices, typically using daily time step routines [78]. They are powerful complements to field experiments, providing valuable data to support discussions with farmers, advisors, and policymakers. A main strength of these models is that they can model the effects of several abiotic stresses (e.g. water, nitrogren, temperature) and their interactions on crop performance. However, the transition to agroecology introduces greater complexity that current crop models struggle to handle. For instance, they are unable to correctly simulate a range of agroecological practices or their effects on cropping system performances. Crop models primarily developed for sole crops fail to capture all processes influencing crop mixture performance [48]. They also typically do not represent multiple biotic stresses, limiting their use in simulating low-input or organic cropping systems. One approach to represent plant-pest/weed interactions is to combine crop models with pest/weed models or use individual-based models [77]. However, these models require many parameters, extensive data collection, and high computational costs, making it challenging to scale their use from plant to field level [34]. Despite these limitations, reinforcement learning techniques used for agricultural practice recommendations may leverage the strengths of crop models to replicate well-represented processes. These models can be expanded to simulate real-world conditions, offering potential solutions to the challenges faced by crop modeling in agroecology [52].

Main hypothesis and justification of scientific choices: Our project prioritizes experimentation within the reinforcement learning framework over all potential agrosystem interactions, as it aligns with hypothesis testing and evaluation. We opt for concrete use-cases over a generic, overly abstract interface, ensuring our digital tool is diverse enough for easy adoption by experiment designers. We consider a wide range of agricultural practices, anticipating the contribution of additional data from enthusiastic researchers or farmers during the project. Rather than tackling all associated challenges, we focus on a subset of tasks that form a functional pipeline between reinforcement learning research, agroecology research, and practitioners. This approach ensures our project's focus on key experimentation tasks without being overly restrictive.

1.2 Main previous achievements

We detail hereafter the main achievements and results of the partners of the AgroEcoReco consortium that support the research hypothesis and scientific choices of the project. They together highlight the strength of the consortium both in publishing in top venue of their respective field and conducting interdisciplinary research.
Some of the main previous achievements of **INRIA (SCOOL)** can be found in the CV of the PI, showing the leading expertise in RL. Recently, the PhD of R. Gautron with **CIRAD (AÏDA)** provided a key survey of Reinforcement Learning for agrosystems [52] and the first result demonstrating actual benefit of bandit-inspired RL techniques on an agronomic task using simulator DSSAT [50]. This major step towards supporting beneficial application of RL in agrosystems, was done following a series of major fundamental contributions adapting bandit theory to non-parametric [13, 14] and risk-averse [12, 91] setting within INRIA-Japan associate team RELIANT. We further developed strategies for corrupted distributions [2], which is important when dealing with real data, being not perfectly modeled, and established a new state-of-the-art in learning of dynamical systems (Markov decision processes) [80, 89], relevant for system experimentation in agronomy. Within the PhD of P. Saux, we extended mathematical statistics techniques of concentration inequalities [25], and demonstrated interdisciplinarity aiming at applying RL in medical domain with an output publication in Lancet, [90]. Also, the team actively investigates trustworthy ML and how to deploy trustworthy ML techniques with RL. This has led to the ANR JCJC project REPUBLIC (D. Basu), inter-European CHIST-ERA project on Causally Explainable RL (CausalXRL), and also participation in PEPR AI project FOUNDRY (D. Basu and O.-A. Maillard). Besides, the team has developed the Gym-DSSAT (PhD of R. Gautron) adaptation of DSSAT simulator to RL setup, as well as FarmGym, a gamified agronomy simulator for RL, and WeG@rden (alpha-version), a data acquisition platform for farmers and gardeners within project SR4SG. **INRAE (MISTEA)** and **University of Potsdam** developed and analyzed sequential algorithms on active learning for complex decisions direclty related to challenges 1 and 2 —see also [88, 81]. In particular, the work of Pr. Carpentier bridging the gaps between active learning and statistical theory [37] will serve as a stepping stone for challenge 1. **INRAE (MIAT)** and **U.Montpellier (IMAG)** develop promising research on interacting planning agents through planning, reinforcement learning and game theory realted to challenges 5 and 6 through the ANR-DFG project CHIP-GT and ANR project HSMM INCA. In particular they co-supervise the PhD thesis of O. Rossini (2022-2025) on “Reinforcement Learning for the control of Piecewise Deterministic Markov Processes” [3, 28, 29, 30, 31, 102]. In the past, IMAG members proved their ability to design efficient numerical procedures to solve control problems for stochastic processes and solve applied problems in the field of reliability [26, 104], at the core of challenge 2.

On the agronomical side, **CIRAD AÏDA** has a long history of multidisciplinary research in the field of agroecology applied to annual crops in tropical contexts for family farming and at different spatial scales. In recent years, it has entered into a partnership with **INRIA** through the supervision of PhD thesis by R. Gautron earlier mentioned. The project will also benefit from previous important realizations of **AÏDA**. First, AEGIS (AgroEcological Global Information System) [100] is an opensource and public information system developed by AÏDA to improve data management practices and create quality data repositories dedicated to experimentation and cropping system modelling. CIRAD provides free and open access to KoboToolbox platform [69], a user-friendly data collection platform deployed on CIRAD servers, akin to Excel, with automatic synchronization to databases, enabling FAIR database management. Since 2023, AÏDA has incorporated a multisimulation platform from LIMA, which enables the creation and simulation of large-scale virtual experimental designs through the integration of common crop models (STICS, DSSAT), incorporating automatic file generation from a shared database schema and spatial mapping for model outputs. The **CIRAD Recycling and Risk research unit** has led major projects involving territorial foresight approaches and, in that occasion, has developed the simulation model UPUTUC [109] for territorial residue management, now integrated into the simulation model MAELIA [97] at the territory scale. Their experience in simulation model will be instrumental for the success of RL models. The **Laboratoire des RadioIsotopes (LRI AGRO)** within university of Antanarivo has a long expertise in soil science and agroecological for enhancing rice production in Madagascar (soil mapping, soil spectroscopy, on-farm rice fertilization experimentation) [6, 107]. It has developed with scientific partnership the main national soil property database called "VALSOL-Madagascar" with geolocalized soil property data [107] and will led for soil fertility maps (with RADAMA project cf. T4.5) directly relevant to WP4. This and the ability of **LRI** to conduct new on-farm experiments will allow the use of Digital Experimentation Companions.

The technical institute **ARMEFLHOR** gather farmers who works to find better ways of producing fruits and vegetables in Reunion Island (Indian Ocean). Its purpose is to conduct applied research activities, such as agronomical experimentations and prototyping, as part of a global approach carried out throughout the entire value chainc̃itemango,cottineau. In particular, in the DEPHY ST0P project, **ARMEFLHOR** evaluated three multi-species cropping systems that have been co-designed in collaboration with 3 groups of the different stakeholders, namely growers, experimenters, agricultural advisors and researchers [55]. The french association **Centre National d'agro-ecologie (CNA)** gathers many stakeholders (Triple performance, Neya, Ver de Terre production, etc.). **CNA**'s active role in disseminating information and communicating with farmers and agricultural sector stakeholders sets it apart. Its member Ver de Terre Production, leads in the free diffusion of agroecological knowledge among French farmers through a YouTube Channel. With over 1000 educational videos on agroecology, 12 million views, and 86k followers, it stands as a testament to CNA's outreach efforts. Additionally, the Triple Performance (agronomic, environmental, and economic) web platform, another initiative by CNA, offers a collaborative digital tool for farm-level social, economic, and environmental assessment and knowledge sharing. This innovative approach, featuring open-source architecture, free content under a creative commons license, and entirely free access and use, has generated 5k available pages and 40k monthly readings.

2. Detailed description of the project / Description détaillée du projet

2.1 Project outline, scientific strategy

Scientific challenge and vision: The overall scientific challenge addressed by AgroEcoReco is to enable the use of Digital Experimentation Companions (DEC) to assist the massification of FAIR experimental data in agroecology and the efficient identification and adoption of beneficial agroecological practices. The central question is "how to act" on a given agrosystem, personalized to its specific environmental, crop and farmer context, in order to maximize a diversity of agroecological indicators. Since agroecological dynamics are not all modeled and agroecological variables are not all easily measured, there is uncertainty, both in the modeling and measurement process. In machine learning, decision-making under uncertainty is naturally formalized under the Reinforcement Learning (RL) framework. To address this challenge, our global scientific vision is to establish a tight and perennial interdisciplinary connection between world experts in the design of AI algorithms for decision making under uncertainty, world experts in the design of agroecological methods and leading pioneers in the diffusion of agroecological practices. The key approach is to exploit the similarities between the learning process of a human practitioner acting on an agrosystem and that of a reinforcement learning agent acting in a digital environment [52], to leverage the promising performances of RL in increasingly many domains. Central to this approach is the design of a digital platform embedding the full decision-making pipeline from the design of sequential learning algorithms and their mathematical analysis to the acquisition of experimental data and advice to farmers tailored to their territorial context.

Contribution to Agroecology transition: AgroEcoReco directly contributes to a systemic approach to the agroecological transition using digital science at several levels. Indeed this innovative approach requires to disrupt the way knowledge is produced in agroecology in many ways: First, by promoting FAIR principles regarding experimental data acquisition, which is only emergent in the agronomy community [9], and crucial for large scale aggregation of data required by machine learning algorithms. The consortium will actively address this key bottleneck by homogeneizing the integration, into FAIR database, of agroecological data collected by our partners representative of a diverse type of agriculture and experimentation contexts. Then, by mobilizing digital algorithms such as from reinforcement learning to assist experimentation and optimization of practices, which also requires dedicating effort on advancing methodology. Hence, the data collection and design of decision-support tool both incorporate digital innovation and agroecology. Last, by directly contributing to the root of experimentation methodology: to factorial experiments [113, 38], closely related to the multi-armed bandit framework in RL, to system experiments [58], more related to POMDP (partially-observed Markov decision process) framework, and to on-farm experimentation [99, 68], akin to recommender system framework, in which farmers collective specify the trial program and may also become a direct evaluator and producer of practices. Further, we will pay special attention not to restrict to academic knowledge only but also actively incorporate non-academic farmer knowledge, thanks e.g. to the

TriplePerformance collaborative wiki initiative from CNA.

Organization of research efforts: Overall, the expertise of our consortium, gathering French research institutes or universities, international universities, stakeholder associations or agriculture technical institutes, covers the requirement for implementing the entire decision-making chain: RL methodology and models (INRIA, INRAE), software development (INRIA, CIRAD, CNA), plant models (CIRAD), soil prediction (LRI Agro), agronomists experiments in lab farms (CIRAD, ARMEFLHOR) and farms (ARMEFLHOR), farmer experiments (LRI Agro, ARMEFLHOR, CNA), farmer knowledge retrieval and diffusion (CNA).

Diversity of expertise: The diversity of expertise aligns with the ambition, as the objective requires consolidating the feedback loop connecting actual fields, data acquisition, analysis, models, algorithms, and practitioners. However, the diversity of expertise of the multi-disciplinary consortium, starting with different methodology and vocabulary, must be handled with care: Its coherence will be reinforced throughout the project by co-supervision of PhD students between partners, homogenization tasks, scientific meetings, sharing of data and software, on top of supervision by an interdisciplinary program and scientific committee.

2.2 Scientific and technical description of the project

SCIENTIFIC OBJECTIVES AND WORKPLAN

Our overall objective is four-fold: [A] Generate agro-ecological knowledge from field feedback: In contrast to "top-down" methods where practices are first developed in the lab and then transferred to the field, each farmer or experimenter becomes an evaluator and producer of practices, establishing an interaction loop between hypothesis generation and testing under real conditions, with the aim of tailoring practices to each crop context. [B] Assist the massification of collaborative experimentation, by promoting participatory open science approach and principles to guarantee the reproducibility of results, as well as the explainability, interpretability, and interoperability of practices. [C] Facilitate the learning and implementation of statistical experimentation by practitioners, by designing digital companions (recommendation systems, contextual bandits) adapted to the local management of agroecological processes, incorporating research in sequential learning. [D] Contribute to the design of companion algorithms by the ML research community (sequential and automatic learning) to overcome the challenge of bridging the "sim-to-real gap" in the experimental science context of agroecology.

INTERMEDIATE OBJECTIVES AND EXPECTED RESULTS

We detail hereafter the main scientific and technological objectives that will be pursued towards the development of digital experimental companion for agroecology within the AgroEcoReco project.

Implementation of Generic Digital Companion Experiment toolkit: this piece of software will be developed as a layer (or plugin), compatible with existing initiatives of the consoritum (e.g. AEGIS, TriplePerformance), and possibly a few others during the project, selected with care regarding open-source compliance. At a high level, the tool connects a catalog of protocols describing activities (observation, intervention, evaluation), a catalog of plant models (from LIMA platform) to simulate the evolution of agroecological variables and a database of sequential interactions of users, in order to enable the execution of RL algorithms. These algorithms output specific recommendations of actions to be performed on a well-specified experimentation, expressed in a generic format. Hence the software will perform the interface between these components. We separate the task of building the core interface and the specific integration with existing user platforms. Special attention will be given to providing an experimentation description format able to encompass all experiments considered within the scope of the project.

Increased knowledge of agroecological practices: the digital collection of Agroecology Protocols and Knowledge used in the project will integrate practices continually enriched in the collaborative wiki Triple Performance (CNA), together with the ones described in other sources, such as Aegis (CIRAD) or the FAO. The project will contribute to better visibility and unification of such sources, thanks to the addition of systematic context-dependent feedback from users experimenting with such protocols.

Collecting sequential on-field experimental data: To complement classical agroecological databases, the goal is to massify the collection of a sequence of observation/intervention/evaluation follow-up, grouped by experiments ad-context The data will be primarily recorded using existing tools (e.g. Kobotoolbox, WeG@rden) and interface developed during the project, to ensure proper usage by digital experimentation companion. The database will gather sequential data from various type of experiments, including Factorial experiments, System experiments with researchers, and On-farm experiments and Pilot farms studies with farmers.

Imperfect models enriched with field data: Models have been developed over the years by agronomists regarding the development of certain plants under certain conditions. While existing models do not capture most of the interactions considered in an agroecology context (e.g. plant association, insects, etc.), they enable RL agents to understand the basics of plant dynamics. After an initial training phase using such a model, it is then natural to enrich the training of the RL agent (fine-tuning) with complementary field data corresponding to unmodeled behaviors. Interfacing plant models and a recommender toolkit is required to enable such possibility.

Enhanced RL algorithms for realistic experimental conditions (group-sequential, non-parametric, risk-averse, etc.): bandits and RL algorithms are often formalized for simplified abstraction of realistic situations. Field conditions are much more challenging than the idealized bandit or POMDP framework. Taking strategies from traditional RL environments to gamified agrosystems, to realistic models, then to imperfect models enriched with real data, will stimulate the research of more efficient and robust strategies while paving the way towards solving the sim-to-real RL grand challenge. We will explore the key fundamental challenges that come from such challenges, and maintain all algorithms resulting from this study in an open-source library toolkit maintained in INRIA Scool.

Experimental validation of companions in diverse contexts: We consider a selected set of experiments spanning a diversity of agroecology use cases in various user contexts (research, transfer, farming). In each case, a key milestone is the formal definition of the experiment in the framework of sequential decision-making prior to the study. This includes precise definition of time frame, actions, context, rewards and policies, including explicit and implicit user-constraints (tool availability, skills, etc), in a computer-friendly format.

Understanding human appropriation of digital tools: Transverse to the project is the understanding of appropriation of digital tools from various human users (farmers, students, researchers, etc). This involves setting up polls of users focusing on barriers to the appropriation of experimentation companions, study and modeling of the compliance of such users, and strategies to improve user engagement and appropriation of the co-designed tool.

Growing a community of users and connection with other initiatives: Within the project, a rich community of users is expected to emerge, thanks to co-construction of the Digital Experimentation Companion with various stakeholders on a variety of experimentation types (including factorial, system, and on-farm), and strengthened by the unique diffusion ability of CNA (Youtube channel, community Wiki). Further, our academic, open-source, open-science approach will provide trust from end-users faciliting its diffusion.

SCIENTIFIC COHERENCE AND JUSTIFICATION OF METHODOLOGICAL CHOICES

AgroEcoReco gives primary focus to machine learning for decision making (Bandits, Reinforcement Learning, Recommender systems), as it formalizes decision-making plus is naturally associated to (adaptive) exeprimental design, which received less attention from an agroecology perspective than other machine learning paradigms (e.g. supervised learning) in the recent years. Importantly, this does not mean we exclude using other machine learning methods such as prediction, classification or regression methods that are complementary to RL techniques (for instance to predict possible trajectories of the agrosystem in response to a specific strategy). They are essential to process raw data into valuation information useful to the decision making algorithm. For instance, LRI Agro has combined computer vision and regression techniques to predict soil fertility, which provides key contextual information. Besides, time series techniques help predict trajectory evolution of a system. We give focus to decision making as we expect to design -rather than simply use- novel decision making algorithms within the scope of the project, while mostly use, rather than design, machine learning techniques from supervised or unsupervised learning.

We choose to incorporate data from a diversity of agriculture and diversity of experimental setup to demonstrate interoperability of our tool and methodology with many experimental approaches, and to facilitate adoption by both researchers in farmers. This contrasts with approaches solely providing a generic but too abstract or specific but too narrow tool. We choose to gather partners with highly complementary expertise spreading theory, models, data and knowledge to ensure we get an appropriate balance maximizing the transformative potential of our approach.

RELATION TO OTHER PROJECTS AND NATIONAL STRATEGY

Within PEPR Agroecologie et Numérique, Project Pl@ntAgroEco combines AI research on computer vision with application in botany, co-built with and association federating a large community of citizens and experts. Likewise, AgroEcoReco focuses on AI research on sequential decision-making with applications in agroecology, co-built with researchers and stakeholder association federating a large community of citizen farmers. Hence, both projects aim to consider large databases with user inputs connected to AI models. OAM (INRIA) is involved at 5% in Pl@ntAgroEco. However, the projects differ significantly: Pl@ntAgroEco uses a computer vision AI (supervised learning), which is different from a decision-making AI (reinforcement learning); gathered data consist of labeled images, versus time series for AgroEcoReco; Pl@ntAgroEco does not focus on agricultural practices nor crop system scale. Partners of AgroEcoReco also participate in projects from other PEPRs (e.g. PEPR IA (FOUNDRY), PEPR FairCarboN).

The project will directly fit the digital pillar of the national acceleration strategy SADEA, by advancing AI for decision making and optimization of policy efficiency. Our Digital Experimentation Companion will help improve agroecological knowledge directly linked to the great challenge "Biocontrôle et biostimulants".

2.3 Planning, KPI and milestones

WP1 DEVELOPING A DIGITAL EXPERIMENTATION COMPANION (DEC) PLATFORM	M1:M42
Leader & participants : **O-A Maillard (INRIA)** & CIRAD, CNA	
T1.1 Backend interface between data, models and algorithms	M3:42
Leader & participants: **O-A Maillard (INRIA)** & INRIA, CIRAD, CNA, LRI Funding: 30m Eng (INRIA), 45k€ Equip. Develop the software backend of the DEC platform, that connects a library of protocols describing practices and activities (e.g. TP wiki, Smartis), a catalogue of crop models (e.g. Dssat, Mosicas, Stics), and a database of on-field sequential interactions of users (experiments), to enable the execution of RL algorithms using gymnasium interface. The task also requires setting up the corresponding server. **Deliverables and/or milestones** D1.1.a - Generic DEC description format for experiment data and metadata (M12) M1.1.a - Full experimentation pipeline compatible with gymnasium interface. (M18) D1.1.b - Core interface (version 1) demonstrator and initial server deployment (M21) M1.1.b - Interface compatible with specific protocols from CNA & CIRAD, and experiment databases. (M27) D1.1.c - Core interface (version 2) release and stable server deployment (M40)	
T1.2 Interoperability with realistic and gamified agronomic models and data platforms	M27:M36
Leader & participants: **O-A Maillard (INRIA)** & INRIA, CIRAD Funding: 6m Eng (INRIA) (i) Making the DEC platform backend interoperable with two simulators, e.g. gymnasium version of the realistic DSSAT model [51], and of gamified agroecological model farmgym [105]. (ii) Making the DEC platform interoperable with data acquisition platforms such as kobotoolbox [69], to prepare for fine-tuning of RL algorithm task T3.1 **Deliverables and/or milestones** D1.2.a - DEC interoperability with gym-dssat and farmgym (M30) D1.2.b – DEC interoperability with aegis, smartis and kobotoolbox (M33)	
T1.3 Adaptation of crop simulation models to the reinforcement learning framework	M3:M24
Leader & participants: **C. Midingoyi (CIRAD AÏDA)** & INRIA, CIRAD Funding: 18m Postdoc (CIRAD) Agronomic plant models are often not adapted to the sequential interaction requirement of the reinforcement learning platform. In [52], we turned DSSAT model into gym-dssat, compatible with RL standard interface. This required a PhD and links with HPC [49]. Such efforts simplify integrating alternative models from LIMA (e.g. Mosicas and Stics) more adapted to our study, for a postdoc experienced with applied RL. A related task that requires experience with agronomics models is to calibrate and possibly improve existing models based on acquired experimental data. **Deliverables and/or milestones** M1.3.a - DEC integration of plant models relevant to the project (mosicas, stics, etc) (M12) D1.3.a - Academic publication regarding simulation of RL algorithms on agrosystem models (M18) M1.3.b - Experimentation data incorporated into existing models (M21)	

T1.4 Frontend user-friendly interface, visualization and integration with user platforms M22:M36
Leader & participants: **O-A Mailllard (INRIA)** & INRIA, CIRAD, INRAE, LRI Funding: 12m Eng. (INRIA)
The core DEC platform will be firstly available to computer scientists. To further broaden usage of the tool, we will build on WeG@rden (INRIA) software to make it interoperable with open-source platforms used to interact with farmers at CNA (in T2.2), and open-science project kotobotoolbox used by CIRAD (T4.3-4), and RADAMA project from LRI (T4.5). Further, we will develop user-friendly data management and visualization tools extending the platform, to help support project case studies, and provide a front-end user interface to simplify usage by practitioners.
Deliverables and/or milestones
D1.4.a - DEC frontend (version 1) interface and basic visualization. (M25)
M1.4a - User test of user interface. (M27)
D1.4.b - DEC integration with partner softwares (M31)
D1.4.c - DEC frontend (version 2) and final visualization (M33)

KPI: Release of the DEC toolkit.

WP2 ENFORCING FAIR DATA AND KNOWLEDGE MANAGEMENT OF CASE STUDIES M1:M45

Leader & participants : **L Fontaine (CNA)** & all project partners

T2.1 Collaborative farmer knowledge-base enriched with farmer feedback M6:M42
Leader & participants: **B. Gorge (CNA)** & INRIA Funding: 4m Eng (CNA).
Develop interoperability of the collaborative wiki TriplePerformance (TP) and related database with the DEC toolkit develop in WP1, possibly using Kobotoolbox. The objective is to ensure proper usage of data collection by the DEC.
Deliverables and/or milestones
D2.1.a – List of relevant protocols data registered in TP (observations, practices and impact indicators) (M9)
D2.1.b – Report on potential automatic synchronization of knowledgebase with DEC database (M18)
D2.1.c – Automating synchronization of the knowledge-base with a FAIR database with Eng (M40)
D2.1.c – Enhancing interoperability of the data produced by TP and by the DEC with Eng (M40)

T2.2 Documenting innovative practices in diverse cropping systems M1:M42
Leader & participants: **V. Levavasseur (CNA)** & CNA, INRIA, CIRAD Funding: 12m Eng (CNA)
(i) Documenting practices of 300 (pilot) farms representing diverse agriculture (mixed crop-livestock, agroforestry, market-gardening) covering all mainland France: success stories, evaluation of practices and farmer interviews.
(ii) Study of knowledge transferability to 300 neighbouring (transfer) farms.
(iii) Incorporation of survey results in human-oriented knowledge-base (T2.1) and agrosystem trajectories in algorithm-oriented FAIR database (T2.3, T2.4), updated on a regular basis.
Deliverables and/or milestones
D2.2.a – List of pilot and transfer farms together with their agroecological management (M12)
D2.2.b – Technical publications regarding documentation (M24)
D2.2.b – Technical publications regarding transfer (M42)

T2.3 FAIR Database management from previous and on-going lab experiments M1:60
Leader & participants: **S Auzoux (CIRAD AÏDA)** & all project partners Funding: 18m PostDoc(CIRAD)
Capitalize past data generated in previous and current partner experiments, and develop tools for structuring and matching data in a FAIR compliant way [20] to facilitate their reuse for analysis, modeling and deploying machine learning and reinforcement learning algorithms. The challenge of this task is to homogenise, qualify, automate the cleaning and structuring of the data [111], in accordance with T1.1. We will also integrate the novel data of T4.3-5.
Deliverables and/or milestones
D2.3.a - Inventory of available data of project partners and description of new data (M18)
D2.3.b - Experiment Variables dictionary with controlled vocabularies to annotate and exchange data (M18)
D2.3.c - Database Fairness Tool (M42)
D2.3.d - Academic publication (M60)

KPI: Integration and reuse of data and knowledge in the DEC

WP3 ENHANCED ALGORITHMS FOR REALISTIC EXPERIMENTAL CONDITIONS M1:M48

Leader & participants : **N. Verzelen (INRAE Mistea)** & CIRAD, INRIA, U. Montpellier, U. Postdam

T3.1 Training ML and RL algorithms on agronomic models, and fine tuning with sampled data M2:M48
Leader & participants: **M. Christina (CIRAD Aïda)** & INRIA Funding: PhD (CIRAD Aïda)
(i) Adapt machine (ML) and reinforcement learning (RL) algorithms to support contextualization of agricultural plots
(ii) Complete missing data in existing dataset (e.g. water stress from satellite images) and calibrate crop models
(ii) Adapt reinforcement-learning methods to improve crop management plans (application on weed management practices) by pre-training RL algorithms on a well-established sugarcane crop model [101] and fine-tuning them on field databases including different agroecological practices in sugarcane cropping systems [94].

Deliverables and/or milestones
M3.1.a – ML algorithms predicting weed infestation risk under agroecological practice (e.g. crop association) (M18)
D3.1.a – Academic publication (M24)
M3.1.b – RL algorithms suited to crop models and leveraging field data (M30)
D3.1.b – Academic publication and Addition to DEC software library (M36)
D3.1.c – PhD Manuscript (M45), Advisors: K. Naudin (CIRAD) & OA Maillard (INRIA)

T3.2 Contextual bandits for factorial (group-sequential) experiments M2:M48
Leader & participants: **N. Verzelen (INRAE Mistea)** & INRIA, U. Potsdam Funding: PhD (INRAE Mistea)
Design reliable and mathematically grounded sequential experimental schemes built upon modern machine learning and high-dimensional statistical theory. The main activity is the design of group-sequential testing procedures to improve quality of decisions drawn from agro-ecology trials with scarce and complex data. We will bring together latest developments in high-dimensional unsupervised learning with contextual active learning theory. This setting is particularly relevant to deal with complex decisions such as choices of crop varieties in mixed cropping fields.

Deliverables and/or milestones
D3.2.a – Academic publication (M20)
D3.2.b – Test on available mixed cropping data (M32)
D3.2.c – Academic publication and Addition to DEC software library (M36)
D3.2.d – PhD manuscript (M45), Advisors: N. Verzelen (INRAE), OA Maillard (INRIA) & A Carpentier (U. Postdam)

T3.3 Timing decisions for RL in autonomous system M2:M48
Leader & participants: **B. de Saporta (U. Montpellier IMAG)** & INRIA Funding: PhD (U. Montpellier IMAG)
To tackle the key challenge of deciding when to act in an autonomous system, we will design and study algorithms for controlling non stationary stochastic dynamical hybrid systems (with both discrete and continuous-valued components with interdependent dynamics) while learning unknown parameters. It will bring together the modelling power of hybrid processes (Piecewise deterministic Markov processes) with the latest developments in reinforcement learning for discrete space models, and be implementated on relevant case studies (to be selected)

Deliverables and/or milestones
D3.3.a – Academic publication regarding mathematical setting and control policies in simplified use-cases (M24)
D3.3.b – Academic publication regarding more complex/realistic models and Addition to DEC software library (M36)
D3.3.c – PhD manuscript (M45), Advisors: B. de Saporta (IMAG) & OA Maillard (INRIA).

KPI: Journals and conference publications. Integration of algorithms to DEC.

WP4 EXPERIMENTAL VALIDATION OF DIGITAL EXPERIMENTATION COMPANION (DEC) M1:M59

Leader & participants: **S. Auzoux (UR Aïda, CIRAD)** & LRI, Armeflhor, INRIA, INRAE

T4.1 Specification of experiments (states, actions, rewards) M1:M12
Leader & participants: **B. Heuclin (CIRAD)** & ARMEFLHOR, CIRAD, LRI, INRAE, INRIA
(i) Describe the reference terminology for experiments, used by DEC to learn about cropping practices (with T1.1).
(ii) For each case study, describe initial conditions and scope of the experiments on which the DEC will be working.
(iii) For each case study, specify all RL-related quantities (context, state variable, actions, rewards, etc).
(iv) Based on collected experimental data and expert knowledge, collectively define the reward functions to help DEC improve its decision-making process.
Deliverables and/or milestones
D4.1.a – Specification of terminology, experimental conditions and scope for each case study (M12)
D4.1.b – Specification of state variables, actions and reward functions for each case study (M12)

T4.2 Transfer of algorithms across diverse and multimodal experimental contexts M13:40
Leader & participants: **D. Basu (INRIA Scool)** & CIRAD, LRI, ARMEFLHOR Funding: 18m Postdoc (INRIA)
Address how much can we transfer a bandit algorithm across multiple environments (e.g. growing a crop under different soil and weather conditions) and multiple contexts (e.g. multiple agricultural practices followed by farmers at different places).
Deliverables and/or milestones
D4.2.a – Defining limits of transferability of standard bandit and RL algorithms across diverse environments (M18)
D4.2.b – Designing bandit and RL algorithms optimal across multiple context distributions (M24)
D4.2.c – Designing bandit and RL algorithms effective across multiple environments with multimodal data (M36)

T4.3 Follow-up of system experiments and companion co-development in La Réunion M10:M51
Leader & participants: **T. Nurbel (ARMEFLHOR)** & CIRAD Funding: 36m VSC Eng & 12m Eng (Armeflhor)
In tropical context, this companion tool will use historical data to overcome technical obstacles and will be improved throughout the project (via T1.4) with the acquisition of new data from agroecological experiments and the usage feedback of agricultural experimenters:
(i) Synthesis and sharing of historical experimental data from factorial experiments regarding alternative cultivation methods to pesticides (e.g. biocontrol, mechanization, prophylaxisin comparison with controls and highlighting ecosystem services, made interoperable with DEC via T4.1, T1.1
(ii) Exploiting system experiment data from controlled observatories to propose alternative collection tools and trial methods to expert experimenters, and evaluate/improve their usage under real production conditions.
(iii) Testing practical application of the DEC through one experimental trial in a selected agroecological system.
Deliverables and/or milestones
D4.3.a – Data from controlled observatories and factorial experiments made available to DEC (M15)
D4.3.b – Feedback and agronomic assessment of scenarios by experimenters (48)

T4.4 Follow-up of factorial experiments and companion co-development in La Réunion M33:M59
Leader & participants: **A. Ripoche (CIRAD AÏDA)** & INRIA, CIRAD Funding: 18m Postdoc (CIRAD), 35k€ Xp
Evaluate the learning methods and recommendations tools (weed regulation and water use optimization) developed in WP3.1 in sugarcane experiments and assess the ability of the DEC to guide plans satisfying the user's objectives.
(i) Setting up sugarcane experiments in controlled and farmers' conditions to compare management plans suggested by the DEC based on reinforcement learning (T3.1).
(ii) Setting up similar sugarcane experiment to compare water management plan using water stress index observed or provided by recommendation tool.
(iii) Technical workshop and surveys to get user's feedback on the tools and plans resulting from the use of DEC compared to their usual practices or other initiatives (e.g. serious game in development by CIRAD partner eRcane), in relation to WP5.
Deliverables and/or milestones
M4.4.a – Experimental datasets of sugarcane cropping systems implemented in the project database of T2.3 (M48)
D4.4.a – Multicriteria assessment of the cropping system performances considering both weed and water management plans and ease of adoption by practitioners (M56)
D4.4.b – Academic publication on the comparison of plans guided by DEC (M59)

T4.5 Follow-up of on-farms experiments and companion co-development in Madagascar M1:M37
Leader & participants: **N. Ramifehiarivo (LRI Agro)** & INRIA Funding: 52k€ external
Within project RADAMA ("**R**évolutionner l'**A**griculture en utilisant les **D**onnées **A**gropédologiques et le NTIC à **MA**dagascar"), LRI Agro aims to transform rice agriculture in Madagascar by combining an accurate spatial soil fertility and fertilization information tool they developed (ML, computer vision) and RL algorithms for decision support fit on personalized soil fertility information plus researcher and farmer's knowledge.
(i) LRI makes available soil database, fertilization maps and practices co-selected with farmers to be tested.
(ii) AgroEcoReco makes DEC (via T1.4) available as an application for farmers (beyond researchers).
(iii) Trial of personalized decision support on on-farm experiment involving 200 farms are performed DEC.
Deliverables and/or milestones
D4.5.a – Soil fertility database (C-N-P-K content) collected from 100 farmers' plots plus soil fertility maps build from ML algorithms, integrated into DEC data base (with WP2) (M8).
D4.5.b – Specification of rice fertilization practices to be tested co-developed with farmers, reflecting local and scientific knowledge based on local conditions and soil fertility level.(M12)
M4.5.a – Rice yield information obtained from 100 farmers' plots (M20). DEC
D4.5.c – Technical publication on DEC efficiency through on-field experimentation and farmer feedback loops (M37)

KPI: Agronomic, environmental and socio-economic performance indicators for and of DEC recommendations.

WP5 HUMAN APPROPRIATION OF AGROECOLOGICAL PRACTICES & DIGITAL EXPERIMENTATION COMPANIONS M1:M59

Leader & participants : **R. Sabbadin (INRAE MIAT)**, CIRAD, CNA, & INRIA

T5.1 Agent-based simulations to model the adoption of agroecological practices M3:M48
Leader & participants: **J.-C. Soulié (CIRAD, Recycling and Risks)** & INRAE Funding: PhD (INRAE MIAT)
This task will involve modeling agents' behaviors, as well as their propensity to change the way they are willing to carry out agronomical practices. The simulations will be compared with the various observations (WP4). This task will enable us to make advances in the field of change capacity modeling, as well as their adoption in multi-agent systems. (i) Design of a conceptual model describing the different types of agents involved in the simulation and their possible behaviors and interactions. (ii) Design of a conceptual model to represent practices and an agent's ability to adopt these practices (for T5.2) (iii) Validation of these models by simulation.
Deliverables and/or milestones:
D5.1.a - State of the art in the representation of agents' capacity to adopt agroecological practices (M18)
D5.1.b - Creation of a methodological framework to represent this propensity through multi-agent behavior (M24)
D5.1.c - Report validation results from multi-agent learning simulations in the agroecological context (M36)
D5.1.d - PhD manuscript (M48), Advisors: R. Sabbadin (INRAE MIAT) & JC Soulié (CIRAD)

T5.2 Multi-Agent Social Reinforcement Learning to model the impact of digital tools on the adoption of agroecological practices M3:M48
Leader & participants: **M. Vinyals (INRAE MIAT)** & CIRAD Funding: PhD (INRAE MIAT)
This task will enrich the initial agent model (of T5.1) with RL capabilities, defining agents capable of dynamically adjusting their practices leveraging their own experience as well as the experiences shared by peers through digital platforms. (i) Design of social RL algorithms for automatic learning within the architecture proposed in Task 5.1. (ii) Validation of these algorithms to validate (by simulation) based on the decision-making performance of social learners (e.g. using digital tools).(iii) Analyze empirically the social-learners behavior in case studies of WP4
Deliverables and/or milestones:
D5.2.a - Computational social learning agent-based architecture (M18)
D5.2.b - Social reinforcement learning algorithms (M24)
D5.2.c - Report validation results from multi-agent learning simulations in the agroecological context (M36)
D5.2.d - PhD manuscript (M45), Advisor: M. Vinyals (INRAE MIAT)

T5.3 Adapting companion decisions with non-compliant agents and preferential feedback M1:M26
Leader & participants: **D. Basu (INRIA Scool)** & INRAE Funding: PostDoc 18 month (INRIA Scool)
In practice, the users (farmers) can be non-compliant, i.e. they might not implement the recommendation exactly, or at all. Also, users might have personal preferences over different decisions, and favour the recommendations aligned with their preferences. These challenges call for: (i) understanding how much we can adapt to different types of non-compliant users, (ii) designing RL algorithms that can adapt to and robust to non-compliant users, (iii) designing RL algorithms that can adapt to distributions of preferences of users.
Deliverables and/or milestones:
D5.3.a – Adaptation of different types of non-compliant feedback for learning (M9)
D5.3.b – Learning to adapt to different ranges of preferences of users (M15)
D5.3.c – Robust recommendations and learning algorithms for non-compliant users with different preferences (M21)

T5.4 Explainability and interpretability of companion decisions M15:M60
Leader & participants: **D. Basu (INRIA Scool)** Funding: PhD (INRIA Scool)
Explainability is one of the four pillars of trustworthy AI. As agricultural recommendations have social impact and implementing them involve diverse human intermediaries (e.g. farmers, scientists etc.), explainability [64, 96, 76] and interpretability [11, 92, 40] are fundamental requirements here. Building on the recent advance on eXplainable AI, we aim (a) to develop interpretable bandit and reinforcement learning methods for agricultural recommendations for developers, and (b) to derive accurate but comprehensive explanations of agricultural recommendations to explicate the decisions to the farmers and the agricultural scientists.
Deliverables and/or milestones:
D5.4.a – Explainable algorithms for recommendation and learning (M56)
D5.4.b – Causal explanation of decision making under different contexts and personalization (M39)
D5.4.c – Robust recommendations and learning algorithms across environments (M27)
D5.4.d – PhD manuscript (M60), Advisors: D. Basu (INRIA) & OA Maillard (INRIA)

T5.5 Growing a community of users and connection with other initiatives M3:M60
Leader & participants: **V. Levavasseur (CNA)** & CIRAD, INRIA Funding: 2m Eng (CNA), 10k Communication
(i) Communication supports towards other initiatives, researchers and farmers inside and beyond AgroEcoReco project. (ii) Production of videos for CNA Youtube platform Ver de Terre (VdT), and community animation around CNA wiki Ver de Terre (TP). (iii) Communication supports regarding results of the project.
Deliverables and/or milestones:
D5.5.a - Communication supports v1 (M12)
D5.5.b - Communication supports v2 (M48)
M5.5.a - Reaching 200k views on TP, and 300k views on novel videos produced on VdT (M60)

KPI: Socially compliant algorithms, Explainable and Trustworthy AI, Socioeconomic dissemination of research.

WP6 PROJECT MANAGEMENT AND EXPLOITATION M1:M66

Leader & participants : **O-A. Maillard (INRIA)** & INRIA head office

T6.1 Scientific and Technical coordination M1:60
Leader & participants: **O-A Maillard (INRIA)** & and project partners Funding: 12m Project manager (1/3, INRIA)
(i) Project coordination, progress monitoring and internal communication
(ii) General meetings and workshops organization
(iii) AgroEcoReco boards and committees (Bureau, Technical and Scientific Committee, Steering Committee)
(iv) Interactions with steering of the PEPR (report indicators, mid-term evaluation, participation to conferences)
Deliverables and/or milestones: (PM hired at 33%, shared with other INRIA projects)
M6.1.a - Project coordination tools setup (M2)
M6.1.b - Kick-off meeting organized (M3)
M6.1.c–f - General meetings organized (M12, M24, M38, M52)

T6.2 Financial and administrative management	M1:60
Leader & participants: **S. Dalmas (INRIA head office)** & INRIA Scool (i) Consortium agreement specifying the modalities of valorization and intellectual property, distribution of tasks, resources and deliverables, regime of publication, dissemination of results and governance of the project. (ii) Financial management of the aid granted by the ANR and the repayments to the partners (iii) Final and intermediate reporting (periodicity, form to be defined in the granting agreement with ANR). **Deliverables and/or milestones:** D6.2.a - Consortium agreement (M10) M6.2.a - Intermediate reports - not yet known D6.2.b - Final report on all the results obtained (M60)	
T6.3 Data management plan and software management plan	M1:60
Leader & participants: **S. Auzoux (CIRAD AÏDA)** & INRIA Scool, project partners (i) A Data Management Plan (DMP) [83] to describe how the AgroEcoReco project will make all existing or new data compliant with FAIR practices [112] (see also section 3.6). (ii) A Software Management plan (SMP) [74] to help implement good software development and code management practices in the AgroEcoReco project (see also section 3.6). **Deliverables and/or milestones:** D6.3.a - A first version of the DMP and SMP (M6) D6.3.b - A second version of the DMP and SMP (M36) D6.3.c – A final version of the DMP and SMP at end project +6M (M66)	
KPI: Indicators defined by the global PEPR, intermediate and final reports	

2.4 Risk management

Description	P	I	WPs	Proposed Risk-Mitigation Measures
Project Execution Risks – Partner Related				
Project schedule is partly not appropriate	L	M	All	The steering committee (SC) will continuously monitor the performed work according to the project plan. Corrective actions will be performed under Tasks T6.1-3. If needed, they will adapt the plan with the PO.
Underestimated partner resources	L	M	All	The PC will investigate ways to ensure completion of planned work: (i) reallocating resources among the partners, (ii) committing further internal partner resources in project tasks; (iii) re-planning work inside tasks.
Project milestones or deliverables are delayed	M	M	All	Detailed analysis of both global and lower Task implementation levels will ensure early identification of delay-inducing situations on milestones or deliverables, and appropriate correction of work plan.
Project Execution Risks – Planning issues				
One or more partners leaving the consortium	L	H	All	Given the previous involvement of all consortium partners in national and international projects, this possibility is considered to be very unlikely. The PC would decide whether the uncovered project activities can be carried out by other partners or if new partner recruitment is necessary.
Overspending by one or more partners	L	M	All	Management report T6.2 will detect such situation early. Actions will be considered by the PC, such as mobilizing more experienced or better skilled resources from partner, capable of working more efficiently. Ad-hoc recovery plan could also be put in place.
Project Execution Risks – Consortium collaboration issues				

Unsatisfactory tasks interaction within and amongst WPs	L	H	All	Regular synchronisation of the work amongst WPs, performed in the scope of project management activities, will limit such eventualities or identify them timely. PC together with the WP leaders will analyse problem occurrence jointly.
Agreement amongst partners difficult to be achieved	L	M	All	The collaboration spirit in the consortium targets to achieve consensus among all partners on open issues, and the PC will work in this direction. To avoid too long consensus making processes, management procedures for decision-making and conflict resolution will be applied.
Many stakeholders acting on their own goals	M	M	All	Stakeholders' participation is of crucial importance to implement and accept the innovation. WP leaders will monitor stakeholder involvement, alignment and agreement on ambitions, scope and plans.
Technical risks				
Specifications too high level or missing requirements	M	M	All	Some necessary time is needed to fully specify certain tasks. Proactive meetings and working groups, with interdisciplinary perspective will be formed to ensure adequate specification.
A case study is not executed due to extreme climate hazard	M	M	4	By diversifying these studies across multiple regions, we reduce the risk of data loss as it's unlikely for a major event to occur in all areas simultaneously. Potential logistical issues, such as manpower shortages or equipment failure, are also considered. Both risks will be addressed in our digital experimentation toolkit
External stakeholders validate human appropriation	M	M	5	Human feedback introduces risk in tasks. We'll use simulators, existing interaction models, and preferred literature explanations to start research, integrating new data over time
Learning hypothesis mismatch experimental conditions	L	M	3	We will mitigate this risk with regular meetings with other partners to assess the relevance of the proposed solutions and challenges to tackle.
Case study hindered by resource shortage/delay.	L	M	4	Chosen case studies address real-life challenges. If a study can't be executed, the issue will be urgently raised with partner management. If no alternative is found within the consortium, a replacement study and possibly partners will be considered.
External project risks				
Low coordination with other relevant projects and initiatives	L	M	6	The consortium has included in T6.11 the liaison with relevant activities with emphasis on relevant projects and existing initiatives, to ensure that the proper links exist with the different Working Groups and the rest of the PEPR pilot projects, to build consensus on future systems with different perspectives applied in various environments.
Snowball effects in case of delays due to unforeseen factors	H	M	All	In case of a new pandemic, consortium will employ all means for remote collaboration, therefore, the work in closed offices and workspaces will be reduced to the minimum possible degree. For the cases that face-to-face meetings are unavoidable, the participants will take all the necessary healthcare precautions and conform with the necessary protocols.
Emergence of superior standards and technologies	M	M	All	Given the leading status of partner in RL development, this is unlikely. Research trends will be monitored, and collaborations with relevant projects will be established. Technical choices will be updated considering latest advances to prevent obsolescence.

3. Project organisation and management

3.1 Project manager

Odalric-Ambrym Maillard (INRIA Senior Researcher) is an established researcher in the field of bandit and reinforcement learning, with a strong background in reinforcement learning theory and mathematical statistics. He received the AFIA prize 2012 (Association Française pour l'Intelligence Artificielle) for the best French Ph.D. thesis in Artificial Intelligence. He has been working for more than 10 years on the design of state-of-the-art sequential decision making algorithms with provable learning guarantees, with a strong focus in the last 4 years on interdisciplinary research with agroecology and medecine. In 2022, independent researchers named an algorithm after him [17].
In terms of **management**, he has been PI of ANR JCJC Badass (2016-2020) on RL theory, PI of Action exploratoire INRIA SR4SG (2020-2023) initiating RL for agriculture research (including softwares Farm-Gym, WeG@rden), PI of Associate team France-Japan RELIANT (2022-2024), gathering 8 researchers from 4 institutes on bandits for small data, co-PI of INRIA-INRAE project 3RSDM (2022-2025) with R. Sabbadin (partner INRAE), co-PI of U. Montpellier project RLRL 2021 with B. De Saporta (partner U. Montpellier), co-PI of Chaire of AI "Apprenf" 2020-2024 on RL theory. He is further involved in ANR PRC Bip-up, PEPR Agroécologie et Numérique Pl@ntAgroEco and PEPR AI Foundry, and was involved in FP7 program COMPLACS, ERC program SUpReL. He as **supervised** 13 PhD (3 ongoing), 2 postdocs, 3 engineers, 17 masters. His students E. Leurent received two national Ph.D. prize, M. Asadi received the ACML best student paper award [7], P. Saux published in the Lancet (medecine journal) [90].
He has been **teaching** at Ecole Polytechnique 2019-2023, Master Ai-ViC, 48h/y and Executive master 2020-2023 (6h/y) Ecole Centrale Supélec 2021-2022 Master 2 mention IA (24h/y), Ecole Centrale Lille 2017-2018 Master 2 DaD (18h/y), Reinforcement Learning Summer School 2019 (5h, 300 students).

3.2 Organization of the partnership

CONSORTIUM SKILLS AND QUALITY

This project brings together unique complementary research teams at the crossroad of AI and agroecology. **INRIA Scool** is internationally renowned for its key contributions in the design of *reinforcement learning (RL)* and *sequential decision making algorithms*, as well as statistical methods for their analysis. On top of this strong fundamental backbone, the team initiated 3-4 years ago key collaborations in medicine and healthcare on the one hand (continued with ANR Bip-up), and agronomy and agroecology on the other hand. They lead progress on responsible and trustworthy AI (ANR Republic, CHIST-ERA project CausalXRL, and PEPR IA (FOUNDRY)) link with WP5. Complementary to the latter, the statistics and machine learning teams of **INRAE Mistea** and **U. Potsdam** are recognized for their expertise in *high-dimensional statistics and unsupervised learning* (ANR/DFG programl ASCAI, Emmy Noether fellowship and von Kaven prize of Pr. Carpentier) and their implications in interdisciplinary projects in agronomy with stakeholders (e.g. COEX project). This allows them to bridge the gaps between active learning and statistical theory [37, 88]–see WP3. Within **UM/IMAG**, Pr. de Saporta brings specific *probabilistic and statistical expertise for piece-wise deterministic markov process* (modeling, simulation, inference, numerical resolution, hiden variables [26, 27, 33, 103, 104, 18, 19, 32], which are central for controlling the behaviour of strategies for in RL –see WP3. Within the scidyn team of **INRAE MIAT**, among others, Pr. Sabaddin, Dr. Vynials, Pr. Taillandier bring their recognized expertise on *modeling and optimization of the behavior of agents in agriculture, using mathematical/AI or economics models* and is currently co-leading ANR-DFG project CHIP-GT and ANR HSMM INCA on this topic. This field of AI is instrumental in the human appropriation of RL and AI methods. It is at the core of WP5.

In addition, research institutes for development **CIRAD**, **LRI Agro**, and the agriculture technical institute **ARMEFLHOR** bring their expertise in agroecological research in tropical systems and in the development of agricultural practice recommendation tools, particularly for the case studies of WP3 and WP4. **CIRAD AÏDA and Recycling & Risk** coordinate numerous projects in agroecology on various topics ranging from agroecological transition (CANALLS) to the design of innovative cropping systems in terms of herbicide reduction and livestock effluent management (CapTerre, FAIR SAHEL). The agricultural technical institute **ARMEFLHOR** in La Reunion is certified by Digiferme since 2022. It develops innovations and technical itineraries based on agroecology principles, including varietal selection, biocontrol, biodiversity, and ecosystem services. Its involvement with local farmers, its experimental station, and its network of 18 experimental farms will allowsto test and develop digital technology collectively with farmers. **LRI Agro** is the lead in soil science studies in Madagascar (soil mapping, spectroscopy, on-farm rice fertilization experimentation) and will bring both its skills in soil fertility database and in on-farme experimentation.

Concerning citizen science, networking, and community management activities, the project will rely on three main players' stakeholder associations: **CNA**, **TP**, and **VdT**. **CNA** brings farmer expertise in agroecology, thanks to a collaborative wiki Triple Performance (TP) that documents agroecological practices and management (40K views per month). It provides documentation of farm practices by collecting on-farm data and the realization of "farm portraits" or testimonies from farmers on specific practices. Finally, dissemination is ensured by a YouTube channel of Ver de Terre (VdT) Production with 86K views and nearly 1000 videos.

COMPLEMENTARITY AND VALUE OF PARTNERS

Thanks to the actions initiated by the PI over the last few years, some key links have been developed between partners, via e.g. the PhD of R. Gautron (CIRAD-INRIA), project 3RSDM (INRIA-INRAE), RLRL (INRIA-IMAG) or RADAMA (LRI-INRIA). Further, Cirad and CNA know each other well, and Cirad and Armeflhor have a long history of collaboration in La Reunion. INRAE MIAT and IMAG, are also involved in common projects. These links ensure scientific fluidity of the project, and minimize collaboration risks amongst partners.

TRANSVERSALITY BETWEEN AI AND AGROECOLOGY

The transversality between agroecology and digital sciences is apparent in the organization of the project. One of the strength of the project is indeed the co-conception of the digital tool in close collaboration between research in AI, in agroecology, and practicioners in link with a large community of farmers. This approach is similar to the early development of Pl@ntNet with Association Telabotanica. In AgroEcoReco, we work via the CNA with associations Triple Performance and Ver De Terre production. This enables a real co-conception of the digital experimentation companion to ensure the tool is indeed used, while forming an initial community of users.

STEERING AND SCIENTIFIC COMMITTEE

In addition to the project manager who will lead WP1 and 6, four key persons will compose the steering committee
WP2: **Laurence Fontaine** (CNA), senior research engineer in agroecology, is the research director of CNA. Agronomist, she is a specialist in organic agriculture and design of innovative cultivation systems.
WP3: **Nicolas Verzelen** (INRAE MISTEA), research scientist at INRAE, leader of the scientific team "probability and statistics" within MISTEA, expert in high-dimensional statistics and unsupervised learning.
WP4: **Sandrine Auzoux** (CIRAD), senior research engineer in data science, scientific data referent for the PERSYST (Performance of tropical production and processing systems) department at CIRAD, expert in semantic integration and databases from agro-ecology experiments
WP5: **Régis Sabbadin** (INRAE MIAT), senior research scientist at INRAE, leader of SCIDYN team within MIAT, expert on game theory and RL for agriculture and ecosystem management.
The Scientific Committee (SC) will include researchers both inside and outside the partner units, to form a diverse and complementary set of advice. This includes e.g. Krishna Naudin (CIRAD), Jean-Noël Aubertot (INRAE), Romain Gautron (CIAT), to cite a few. The SC will further choose, at each main project meeting, two experts external to the project to be invited in order to provide outside evaluation and guidance to the project execution.

3.3 Stakeholder involvement

Active involvement of the stakeholders from the beginning of the process will guarantee that the developed solutions align with user needs. The AgroEcoReco partnership will follow a bi-directional approach, combining researcher and stakeholders' perspectives. Likewise, we consider a co-creation approach, exemplified in, e.g. WP4, where the DEC is built together with real-use case studies. Further, in contrast to "top-down" methods where practices are first developed in the lab and then transferred to the field, we promote the approach where each practitioner becomes an evaluator and producer of practices, establishing an interaction loop between hypothesis generation and testing under real conditions, with the aim of tailoring practices to each crop context. We put special attention to user appropriation of such companion tools, dedicating a full package WP5 to this topic.

3.4 Management framework

Organization between partners and management: The Steering committee consists of the PI and all WP leader, and will ensure the scientific and technical coordination of the project. They will gather physically 3-4 times the first year and 1-2 times a year after that, besides more informal virtual meetings once a month. The Scientific committee will provide a complementary view. Regular meetings will be organized as well as impromptu meetings as required. They will organize a scientific AgroEcoReco day, with scientific presentations, once a year, and will choose external experts to be invited at these meetings. This day will help monitor progress, prepare reports, facilitate scientific discussion and encourage communication. A larger coordination group (personal experienced in research management and related administrative, logistical, financial, quality management, legal, information dissemination and technical aspects) will coordinate the daily operational management.
Shared resources, valorization and IIP strategy: Special attention will be given to sharing of data from different partners, enabling access especially to PhD students and postdocs, as well as access to relevant server infrastructure. The publications will be monitored by the scientific committee to enforce compliance with the IIP plan.
Relation to PEPR management framework: Regular links will be established with the overall steering of the PEPR Agroécologie et Numérique, especially regarding contribution to the list of indicators measuring its scientific and societal impact, and participation to specific events/conferences organized by the PEPR.

3.5 Institutional strategy

The PEPR Agroecology et Numérique is jointly coordinated by **INRIA** and **INRAE**. As AgroEcoReco is coordinated by INRIA and involves INRAE as one of its main partners, it naturally aligns with the institutional strategy. In particular, both institutes have produced a joint white paper on the agroecology transition and digital technologies in which they underline the potential of RL[1]. As for INRAE, in its strategic orientation document for 2030, INRAE targets 5 priority scientific priorities (SP), two of them being clearly in line with the objective of the present PEPR and our project: Facilitating transitions by mobilizing data sciences and digital technologies (SP5) and Accelerating agroecological and food transitions while answering socioeconomic challenges (SP2). Other French academic partners are at the forefront of PEPR's priorities. The **I-Site Montpellier Université d'Excellence** focuses, in particular, on promoting innovative agriculture to contribute to food security and environmental sustainability. As such, this I-site is France's main research cluster in agronomy and agro-ecological transition. Agroecology is one of **CIRAD**'s 6 priority themes[2]. As CIRAD is committed to broadening the 'agroecological transition' beyond Metropolitan France, it broadens the project's scope and impact. **University of Potsdam** , which acts as an external collaborator of the project, has set research priorities in AI. In Madagascar, **LRI Agro** sets research priorities on soil which is at the core of agro-ecology transition. In particular, it uses and produces scientific tools and proofed results co-constructed with stakeholders (scientists, decision-makers, farmers) to develop agronomy in Madagascar. **Centre National d'agroécologie** (CNA) is a French association gathering many stakeholders (Triple performance, Ver de Terre production,. . .). AgroEcoReco fits the CNA strategy as it is aligned with the ambition of automatizing the data collection and recording behind the TriplePerformance wiki. Also, as the objective of CNA is to amplify agroecology through the demonstration of farm performances with digital tools, AgroEcoReco should participate in enhancing it. Finally, **Armeflhor** is an agricultural technical institute of la Réunion. Its strategy on agroecology and digital innovation is best illustrated by its adhesion to the national network of Digifermes (r) and its participation in the national program shared among technical agricultural institutes on digital agriculture. In summary, AgroEcoReco is at the core of the priorities of the different partners of the project, whether it be French research institutes or universities, international universities, stakeholder associations, or agriculture technical institutes. In light of that, all the partner institutions are committed to the strategy and the material, financial, and human resources. Besides, their long-term strategic directions will ease possible follow-up of the project at a wider scale (e.g., H2020 project).

[1] https://www.INRIA.fr/sites/default/files/2022-02/white-paper-agriculture-digital-technology-2022_INRIA_BD.pdf
[2] https://www.cirad.fr/nos-activites-notre-impact/thematiques-de-recherche

3.6 Data management / Stratégie en matière de données

AgroEcoReco will mobilize, capitalize, make accessible and reusable a large quantity and diversity of data from experiments, agroecological farms, surveys and simulation results. One of the challenges of the project is to develop a strategy based on the FAIR principles (Findable, Accessible, Interoperable, Reusable) for managing the heterogeneity of these data. They concern accessibility and use by and for humans, but also by and for machines. Firstly, this will involve identifying and centralising existing and new data in a FAIR database, taking care not to lose any information when integrating the data. Data Fairisation tools will be developed that can mobilise AI algorithms to help detect anomalies, merge and clean data automatically (Task 2.3). Then, it will be necessary to ensure the interoperability of the various platforms used by the partners, to ensure the sharing, exchange, dissemination and re-use of data and that the data formats are standardised to ensure compatibility (Task 1.2).
A data management plan (DMP) describing the data management policy adopted for all existing data or data generated by the project (WP1-WP5), will be drafted using the ANR's DMP model available on the OPIDoR DMP portal (`https://dmp.opidor.fr`). The main elements of this DMP will include the inventory of existing data and data produced during the project, associated documentation and metadata, ethical aspects and intellectual property rights, as well as tools and methods for storing, preserving, sharing and re-using data.
In line with the National Plan for Open Science and the recommendations of the Committee for Open Science (CoSO), the data generated by the AgroEcoReco project will be distributed in open access, published in the form of Data Paper and deposited in institutional repositories (e.g. `https://entrepot.recherche.data.gouv.fr/dataverse/INRIA`) compatible with the ResearchDataGouv platform.
The project will develop the DEC, produce catalogs of practices and sequential learning algorithms, integrate simulators for the pre-training of RL agents. A Software Management Plan (SMP) will be designed to help implement software development best practices to ensure the quality and reproductibility of the digital companion toolkit and guarantee that it is accessible, deployed and maintained after the end of the project. As for the data and in connection with open science, the source codes and technical innovations developed within the framework of AgroEcoReco will be shared with open access on the consortium's software forges (e.g. `https://gitlab.INRIA.fr/`).

3.7 Ethical framework / Cadre éthique

The ethical committee of each partner (e.g. Comité opérationnel d'évaluation des risques légaux et éthiques (COERLE) at INRIA, Comité d'éthique des projets de recherche at INRAE) will be consulted regularly to ensure the project fully abide by the highest EU ethical standards for Responsible Innovation & Research, both in definition and actual implementation of ethical rules, in all aspects regarding GDPR, software licensing, and data production. Special care will be given to discuss impacts on agricultural world and society. To ensure this, members of the ethical committees will be invited to the general project meetings to anticipate and discuss each issue.

4. Expected outcomes and impact / Impact et retombées du projet

Transformative impact: The project's success will have a transformative impact on the agroecological transition by facilitating massive, collaborative experimentation in diverse fields. It will promote the co-creation of knowledge, enabling agricultural practices to be tailored to the specific local contexts of farms and practitioners. The introduction of digital companions will guide practitioners in statistical learning and the implementation of experiments, reinforcing the dissemination of good agroecological practices. These advances will contribute to the creation of an active and committed community stimulating interdisciplinary research and innovation in the field of digital agroecology, nurturing positive synergies aiming at the global agroecological transition.
Scientific impact: Success in the AgroEcoReco project is expected to answer a bouquet of methodological challenges, significantly improving the efficiency and applicability of AI agents, while unveiling sound methodological techniques to bridge the sim-to-real gap, both generically regarding experimental sciences and specifically tailored to the agroecology context. The project will directly expand the knowledge on agroecology practices and models. Above all, it will nurture key scientific links between leading institutes in advancing the fields of AI and AgroEcology.

Societal impact: By addressing challenges of experimental sciences with little data and real-life constraints, providing open-sources codes and algorithmic platform targeting high reproducibility standards for digital experimentation companions in agroecology, AgroEcoReco is expected to get significant echos both in machine learning and agriculture communities, giving visibility and possibly assisting thousands researchers and practitioners on the long run. Enabling agroecologists to understand agrosystems more efficiently and collectively will directly help address societal hazards such as e.g. food security, biodiversity collapse, etc, hence will benefit society at large.
Industrial and territorial impact: By contributing to significantly closing the sim-to-real gap in such a challenging application area as agriculture, AgroEcoReco will open reinforcement learning to significantly more applications, including for the industry. By targeting personalized recommendations, and considering territorial context, especially in case-studies (in La Réunion, Madagascar, and several regions in mainland France), together with local stakeholders, the impact of the project will be directly integrated into the considered territories.

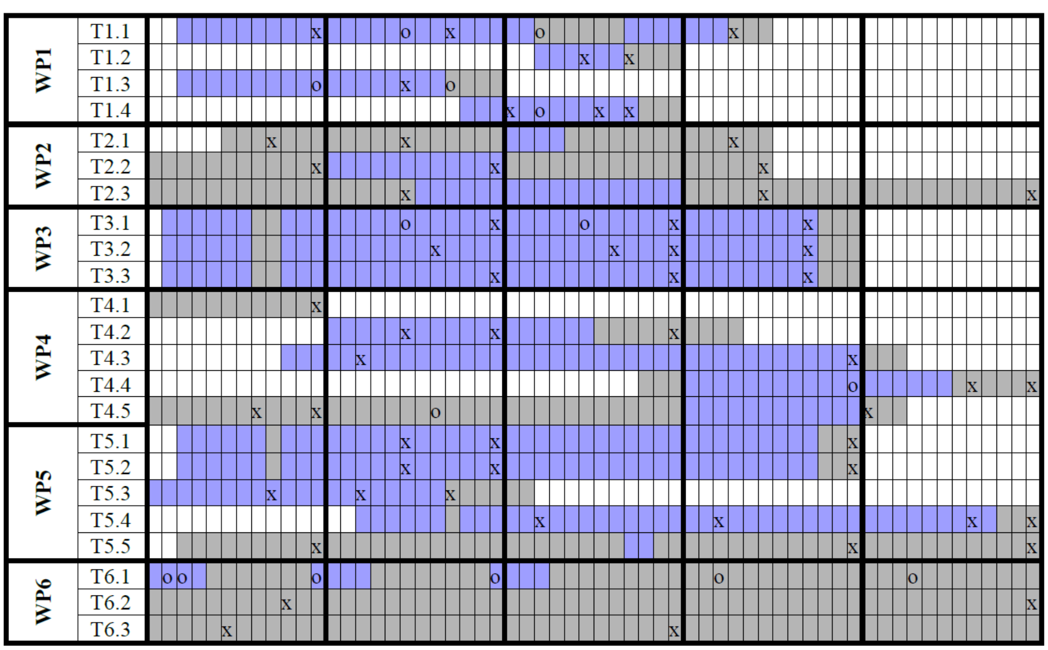
5. Funding justification / Justification des moyens demandé

The document "Annexe financière" details the funding of each partner. We have indicated tasks each time it is relevant, especially regarding involvement of researchers from each institute and hiring of human resource. Altogether, the project mobilizes about 36 researchers from all partners.

The funding requested to the ANR covers hiring of PhD (plus interns), Postdoc and Engineers for the project, on top of which we add specific funding dedicated to a server hosting the `DEC` (45k€ in total), to conduct one project specific experimental trial (35k€ for T4.4), to hire a project manager (54k€, 12m on 3 years, shared with other PEPR INRIA projects) to help reduce the management and reporting work load, and communication supports (10k€) that are essential to the valorization of the project beyond the partners and especially to farmer stakeholders. In complement, the missions are budgeted considering on average one 2.8k€ mission per 6 human month involvement in the project (excluding engineers), to cover international conferences and internal project missions. We finally balanced the budget according to effective involvement of each partner in the project.

Amongst our partners, LRI Agro is the only one not eligible to funding, being a foreign institution. LRI Agro will complement funding from International fundation for Science (IFS), "Bourse du Gouvernement Français" from Madagascar and other opportunities relevant to fund their RADAMA project.

GANTT DIAGRAM OF THE PROJECT
(x indicate Deliverables, o indicate Milestones, blue shade indicate expected non-permanent effort)



6. Références bibliographiques citées

[1] Yasin Abbasi-Yadkori, Dávid Pál, and Csaba Szepesvári. Improved algorithms for linear stochastic bandits. In *Advances in Neural Information Processing Systems*, pages 2312–2320, 2011.

[2] Shubhada Agrawal, Mathieu, Timothée, Basu, Debabrota, and Maillard, Odalric-Ambrym. Crimed: Lower and upper bounds on regret for bandits with unbounded stochastic corruption. In *International Conference on Algorithmic Learning Theory*, pages 74–124. PMLR, 2024.

[3] Cleynen Alice, de Saporta, Benoîte, Orlane Rossini, and Sabbadin, Régis. Un exemple d'optimisation de traitement médical avec modèle incertain. In *54es Journée de la Statistique de la SFdS*, 2023.

[4] Miguel A Altieri. Agroecology: the science of sustainable agriculture. boulder. *Westview Press. Part Three Dev. Clim. Rights*, 238:12052–12057, 1995.

[5] Estelle Ancelet, Nicolas Munier-Jolain, and Ophélie Jolys. Agrosyst, le système d'information au coeur du plan ecophyto de réduction d'usage des pesticides. In *Colloque" Données, Agriculture, Environnement... Innovation", Agreenium-IAVFF*, page np, 2015.

[6] Bruce Haja Andrianary, Yasuhiro Tsujimoto, Hobimiarantsoa Rakotonindrina, Aung Zaw Oo, Michel Rabenarivo, Nandrianina Ramifehiarivo, and Herintsitohaina Razakamanarivo. Phosphorus application affects lowland rice yields by changing phenological development and cold stress degrees in the central highlands of madagascar. *Field Crops Research*, 271:108256, 2021.

[7] Mahsa Asadi, Mohammad Sadegh Talebi, Hippolyte Bourel, and Maillard, Odalric-Ambrym. Model-based reinforcement learning exploiting state-action equivalence. In *Asian Conference on Machine Learning*, pages 204–219. PMLR, 2019.

[8] Christopher G Atkeson and Juan Carlos Santamaria. A comparison of direct and model-based reinforcement learning. In *Proceedings of international conference on robotics and automation*, volume 4, pages 3557–3564. IEEE, 1997.

[9] Samar Attaher, Layal Atassi, Khaled El-Shamaa, Mina Devkota Wasti, and Vinay Nangia. In-person training report on: Agronomic data collection and management tools for better agricultural research. 2023.

[10] Fatih Bal and Fatih Kayaalp. Review of machine learning and deep learning models in agriculture. *International Advanced Researches and Engineering Journal*, 5(2):309–323, 2021.

[11] Osbert Bastani, Yewen Pu, and Armando Solar-Lezama. Verifiable reinforcement learning via policy extraction. In S. Bengio, H. Wallach, H. Larochelle, K. Grauman, N. Cesa-Bianchi, and R. Garnett, editors, *Advances in Neural Information Processing Systems*. Curran Associates, Inc., 2018.

[12] Dorian Baudry, Romain Gautron, Emilie Kaufmann, and Maillard, Odalric-Ambrym. Optimal thompson sampling strategies for support-aware cvar bandits. In *International Conference on Machine Learning*, pages 716–726. PMLR, 2021.

[13] Dorian Baudry, Emilie Kaufmann, and Maillard, Odalric-Ambrym. Sub-sampling for efficient non-parametric bandit exploration. *Advances in Neural Information Processing Systems*, 33:5468–5478, 2020.

[14] Dorian Baudry, Kazuya Suzuki, and Junya Honda. A general recipe for the analysis of randomized multi-armed bandit algorithms. *arxiv:2303.06058*, 2023. Under review.

[15] Lefteris Benos, Aristotelis C Tagarakis, Georgios Dolias, Remigio Berruto, Dimitrios Kateris, and Dionysis Bochtis. Machine learning in agriculture: A comprehensive updated review. *Sensors*, 21(11):3758, 2021.

[16] Felix Berkenkamp. *Safe exploration in reinforcement learning: Theory and applications in robotics*. PhD thesis, ETH Zurich, 2019.

[17] Jie Bian and Kwang-Sung Jun. Maillard sampling: Boltzmann exploration done optimally. In *International Conference on Artificial Intelligence and Statistics*, pages 54–72. PMLR, 2022.

[18] Ibrahim Bouzalmat, de Saporta, Benoîte, and Solym Manou-Abi. Estimating parameters of continuous-time multi-chain hidden markov models for infectious diseases. arXiv:2403.18875, 2024.

[19] Ibrahim Bouzalmat, de Saporta, Benoîte, and Solym Manou-Abi. Parameter estimation for a hidden linear birth and death process with immigration. arXiv:2303.00531, 2024.

[20] L Catherine Brinson, Laura M Bartolo, Ben Blaiszik, David Elbert, Ian Foster, Alejandro Strachan, and Peter W Voorhees. Community action on fair data will fuel a revolution in materials research. *MRS bulletin*, 49(1):12–16, 2024.

[21] Nadine Brisson, Christian Gary, Eric Justes, Romain Roche, Bruno Mary, Dominique Ripoche, Daniel Zimmer, Jorge Sierra, Patrick Bertuzzi, Philippe Burger, et al. An overview of the crop model stics. *European Journal of agronomy*, 18(3-4):309–332, 2003.

[22] Greg Brockman, Vicki Cheung, Ludwig Pettersson, Jonas Schneider, John Schulman, Jie Tang, and Wojciech Zaremba. Openai gym. *arXiv preprint arXiv:1606.01540*, 2016.

[23] Jelle Bruinsma. *World agriculture: towards 2015/2030: an FAO perspective*. Routledge, 2017.

[24] Mang Tik Chiu, Xingqian Xu, Kai Wang, Jennifer Hobbs, Naira Hovakimyan, Thomas S Huang, and Honghui Shi. The 1st agriculture-vision challenge: Methods and results. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops*, pages 48–49, 2020.

[25] Sayak Ray Chowdhury, Patrick Saux, Maillard, Odalric-Ambrym, and Aditya Gopalan. Bregman deviations of generic exponential families. In *The Thirty Sixth Annual Conference on Learning Theory*, pages 394–449. PMLR, 2023.

[26] Alice Cleynen and de Saporta, Benoîte. Change-point detection for piecewise deterministic markov processes. *Automatica J. IFAC*, 797:234–247, 2018. arXiv:1709.09467, hal-01596670.

[27] Alice Cleynen and de Saporta, Benoîte. Numerical method to solve impulse control problems for partially observed piecewise deterministic markov processes. arXiv:2112.09408, hal-03833408, 2023.

[28] Alice Cleynen, de Saporta, Benoîte, Orlane Le Quellennec, and Sabbadin, Régis. Un exemple d'optimisation de traitement médical avec modèle incertain. In *54e Journées de statistique de la SFdS, Brussels, Belgium*, 2023.

[29] Alice Cleynen, de Saporta, Benoîte, Orlane Rossini, and Sabbadin, Régis. An example of medical treatment optimization under model uncertainty. In *Applied Probability Society Conference*, 2023.

[30] Alice Cleynen, de Saporta, Benoîte, Orlane Rossini, and Sabbadin, Régis. Contrôle dynamique stochastique: une approche à base de modèles semi-markov. In *10èmes Rencontres des Jeunes Statistien. ne. s*, 2024.

[31] Alice Cleynen, de Saporta, Benoîte, Orlane Rossini, Sabbadin, Régis, and Vinyals, Meritxell. Deep reinforcement learning for controlled piecewise deterministic markov process in cancer treatment follow-up. In *55e Journées de statistique de la SFdS, Bordeaux, France*, 2024.

[32] Alice Cleynen, de Saporta, Benoîte, and Amélie Vernay. Sojourn time estimation in partially observed pdmps — application to myeloma modeling. In *55e Journées de statistique de la SFdS, Bordeaux, France*, 2024.

[33] Bertrand Cloez, de Saporta, Benoîte, and Tristan Roget. Long-time behavior and Darwinian optimality for an asymmetric size-structured branching process. *J. Math. Biol.*, 83(6-7):Paper No. 69, 30, 2021. hal-02902640.

[34] N. Colbach, F. Colas, S. Cordeau, T. Maillot, W. Queyrel, J. Villerd, and D. Moreau. The florsys crop-weed canopy model, a tool to investigate and promote agroecological weed management. *Field Crops Research*, 261, 2021.

[35] Oswaldo LV Costa and François Dufour. Stability and ergodicity of piecewise deterministic markov processes. *SIAM Journal on Control and Optimization*, 47(2):1053–1077, 2008.

[36] Mark HA Davis. Piecewise-deterministic markov processes: A general class of non-diffusion stochastic models. *Journal of the Royal Statistical Society: Series B (Methodological)*, 46(3):353–376, 1984.

[37] Rianne De Heide, James Cheshire, Pierre Ménard, and Carpentier, Alexandra. Bandits with many optimal arms. *Advances in Neural Information Processing Systems*, 34:22457–22469, 2021.

[38] Magno De Oliveira, Valéria MM Lima, Shizue Melissa A Yamashita, Paula Santos Alves, and Augustus CaeserFranke Portella. Experimental planning factorial: a brief review. *International Journal of Advanced Engineering Research and Science*, 5(6):264164, 2018.

[39] Quentin Delfosse, Sebastian Sztwiertnia, Wolfgang Stammer, Mark Rothermel, and Kristian Kersting. Interpretable concept bottlenecks to align reinforcement learning agents. *arXiv*, 2024.

[40] Lauro Langosco di Langosco, Jack Koch, Lee D. Sharkey, Jacob Pfau, and David Krueger. Goal misgeneralization in deep reinforcement learning. In *International Conference on Machine Learning ICML*, 2022.

[41] François Dufour, de Saporta, Benoîte, and Huilong Zhang. *Numerical methods for simulation and optimization of piecewise deterministic Markov processes: application to reliability*. John Wiley & Sons, 2015.

[42] Audrey Durand, Maillard, Odalric-Ambrym, and Joelle Pineau. Streaming kernel regression with provably adaptive mean, variance, and regularization. *The Journal of Machine Learning Research*, 19(1):650–683, 2018.

[43] Hannes Eriksson, Basu, Debabrota, Mina Alibeigi, and Christos Dimitrakakis. Risk-sensitive bayesian games for multi-agent reinforcement learning under policy uncertainty. In *OptLearnMAS@ AAMAS*, 2022.

[44] Hannes Eriksson, Basu, Debabrota, Mina Alibeigi, and Christos Dimitrakakis. Sentinel: taming uncertainty with ensemble based distributional reinforcement learning. In *Uncertainty in Artificial Intelligence*, pages 631–640. PMLR, 2022.

[45] Hannes Eriksson, Basu, Debabrota, Tommy Tram, Mina Alibeigi, and Christos Dimitrakakis. Reinforcement learning in the wild with maximum likelihood-based model transfer. *International Conference on Autonomous Agents and Multi-Agent Systems (AAMAS)*, 2024.

[46] Yannis Flet-Berliac and Basu, Debabrota. SAAC: Safe Reinforcement Learning as an Adversarial Game of Actor-Critics. In *RLDM 2022-The Multi-disciplinary Conference on Reinforcement Learning and Decision Making*, 2022.

[47] Aurélien Garivier and Olivier Cappé. The kl-ucb algorithm for bounded stochastic bandits and beyond. In *Proceedings of the 24th annual conference on learning theory*, pages 359–376. JMLR Workshop and Conference Proceedings, 2011.

[48] Noemie Gaudio, Abraham J. Escobar-Gutierrez, Pierre Casadebaig, Jochem B. Evers, Frederic Gerard, Gaetan Louarn, Nathalie Colbach, Sebastian Munz, Marie Launay, Helene Marrou, Romain Barillot, Philippe Hinsinger, Jacques-Eric Bergez, Didier Combes, Jean-Louis Durand, Ela Frak, Loic Pages, Christophe Pradal, Sebastien Saint-Jean, Wopke Van der Werf, and Eric Justes. Current knowledge and future research opportunities for modeling annual crop mixtures. a review. 39(2):20. Num Pages: 20 Place: Paris Publisher: Springer France Web of Science ID: WOS:000460728100002.

[49] Romain Gautron. *Apprentissage par renforcement pour l'aide à la conduite des cultures des petits agriculteurs des pays du Sud vers la maîtrise des risques.* PhD thesis, Montpellier SupAgro, 2022.

[50] Romain Gautron, Dorian Baudry, Myriam Adam, Gatien N Falconnier, Gerrit Hoogenboom, Brian King, and Marc Corbeels. A new adaptive identification strategy of best crop management with farmers. *Field Crops Research*, 307:109249, 2024.

[51] Romain Gautron, Emilio J. Padrón, Philippe Preux, Julien Bigot, Maillard, Odalric-Ambrym, and David Emukpere. gym-DSSAT: a crop model turned into a Reinforcement Learning environment. Research Report RR-9460, Inria Lille, July 2022.

[52] Romain Gautron, Maillard, Odalric-Ambrym, Philippe Preux, Marc Corbeels, and Sabbadin, Regis. Reinforcement learning for crop management support: Review, prospects and challenges. 200:107182. Num Pages: 14 Place: London Publisher: Elsevier Sci Ltd Web of Science ID: WOS:000930567200001.

[53] Yohanne Larissa Gavasso-Rita, Simon Michael Papalexiou, Yanping Li, Amin Elshorbagy, Zhenhua Li, and Corinne Schuster-Wallace. Crop models and their use in assessing crop production and food security: A review. Num Pages: 31 Place: Hoboken Publisher: Wiley Web of Science ID: WOS:001068469300001.

[54] Stephen R Gliessman. *Agroecology: the ecology of sustainable food systems*. CRC press, 2014.

[55] R. Graindorge, J. Delaunay, Joël Huat, A. Lefèvre, Marlène Marquier, and Luc Vanhuffel. Dephy expe st0p project: for the transition of current horticultural systems to agroecological systems without chemical uses in a tropical area. *Acta Horticulturae*, pages 91–98, 12 2022.

[56] Laurence Guichard, R. Ballot, J. Halska, E. Lambert, J.M. Meynard, S. Minette, M.S. Petit, R. Reau, and V. Soulignac. AgroPEPS, un outil web collaboratif de gestion des connaissances pour produire, echanger, pratiquer, s'informer sur les systèmes de culture durables. 43:83–94. Publisher: INRAE.

[57] Assaf Hallak, Dotan Di Castro, and Shie Mannor. Contextual markov decision processes. *arXiv preprint arXiv:1502.02259*, 2015.

[58] Morgane Havard, Aude Alaphilippe, Violaine Deytieux, Vianney Estrogues, Baptiste Labeyrie, David Lafond, Jean Marc Meynard, Marie Sophie Petit, Daniel Plénet, Sébastien Picault, et al. Guide de l'expérimentateur système: concevoir, conduire et valoriser une expérimentation système pour les cultures assolées et pérennes. 2017.

[59] Laurent Hazard, Claude Monteil, Duru Michel, Laurent Bedoussac, Eric Justes, and Jean-Pierre Theau. Agroécologie. *Dictionnaire d'agroécologie*, 2016.

[60] Gerrit Hoogenboom, Cheryl H Porter, Kenneth J Boote, Vakhtang Shelia, Paul W Wilkens, Upendra Singh, Jeffrey W White, Senthold Asseng, Jon I Lizaso, L Patricia Moreno, et al. The dssat crop modeling ecosystem. In *Advances in crop modelling for a sustainable agriculture*, pages 173–216. Burleigh Dodds Science Publishing, 2019.

[61] Marie-Helene Jeuffroy, Pierre Casadebaig, Philippe Debaeke, Chantal Loyce, and Jean-Marc Meynard. Agronomic model uses to predict cultivar performance in various environments and cropping systems. a review. 34(1):121–137. Num Pages: 17 Place: Paris Publisher: Springer France Web of Science ID: WOS:000332417500007.

[62] Nan Jiang, Akshay Krishnamurthy, Alekh Agarwal, John Langford, and Robert E Schapire. Contextual decision processes with low bellman rank are pac-learnable. In *International Conference on Machine Learning*, pages 1704–1713. PMLR, 2017.

[63] James W Jones, Gerrit Hoogenboom, Cheryl H Porter, Ken J Boote, William D Batchelor, LA Hunt, Paul W Wilkens, Upendra Singh, Arjan J Gijsman, and Joe T Ritchie. The dssat cropping system model. *European journal of agronomy*, 18(3-4):235–265, 2003.

[64] Subbarao Kambhampati, Sarath Sreedharan, Mudit Verma, Yantian Zha, and L. Guan. Symbols as a lingua franca for bridging human-ai chasm for explainable and advisable ai systems. In *AAAI Conference on Artificial Intelligence*, 2021.

[65] Brian A Keating, Peter S Carberry, Graeme L Hammer, Mervyn E Probert, Michael J Robertson, Dean Holzworth, Neil I Huth, John NG Hargreaves, Holger Meinke, Zvi Hochman, et al. An overview of apsim, a model designed for farming systems simulation. *European journal of agronomy*, 18(3-4):267–288, 2003.

[66] Andreas Krause and Cheng Ong. Contextual gaussian process bandit optimization. *Advances in neural information processing systems*, 24, 2011.

[67] Prashanth L.A. and Michael Fu. Risk-sensitive reinforcement learning: A constrained optimization viewpoint. *arXiv preprint arXiv:1810.09126*, 2018.

[68] Myrtille Lacoste, Simon Cook, Matthew McNee, Danielle Gale, Julie Ingram, Véronique Bellon-Maurel, Tom MacMillan, Roger Sylvester-Bradley, Daniel Kindred, Rob Bramley, et al. On-farm experimentation to transform global agriculture. *Nature Food*, 3(1):11–18, 2022.

[69] MC Lakshminarasimhappa. Web-based and smart mobile app for data collection: Kobo toolbox/kobo collect. *Journal of Indian Library Association*, 57(2):72–79, 2022.

[70] Tor Lattimore and Csaba Szepesvári. *Bandit algorithms*. Cambridge University Press, 2020.

[71] Lihong Li, Wei Chu, John Langford, and Robert E Schapire. A contextual-bandit approach to personalized news article recommendation. In *Proceedings of the 19th international conference on World wide web*, pages 661–670, 2010.

[72] Konstantinos G. Liakos, Patrizia Busato, Dimitrios Moshou, Simon Pearson, and Dionysis Bochtis. Machine learning in agriculture: A review. 18(8):2674. Num Pages: 29 Place: Basel Publisher: MDPI Web of Science ID: WOS:000445712400274.

[73] Konstantinos G Liakos, Patrizia Busato, Dimitrios Moshou, Simon Pearson, and Dionysis Bochtis. Machine learning in agriculture: A review. *Sensors*, 18(8):2674, 2018.

[74] Carlos Martinez-Ortiz, Paula Martinez Lavanchy, Laurents Sesink, Brett G. Olivier, James Meakin, Maaike de Jong, and Maria Cruz. Practical guide to software management plans, January 2023.

[75] Chase D Mendenhall, Daniel S Karp, Christoph FJ Meyer, Elizabeth A Hadly, and Gretchen C Daily. Predicting biodiversity change and averting collapse in agricultural landscapes. *Nature*, 509(7499):213–217, 2014.

[76] Stephanie Milani, Nicholay Topin, Manuela Veloso, and Fei Fang. Explainable reinforcement learning: A survey and comparative review. *ACM Computing Surveys*, 2023.

[77] N.M. Munier-Jolain, S.H.M. Guyot, and N. Colbach. A 3d model for light interception in heterogeneous crop: Weed canopies: Model structure and evaluation. *Ecological Modelling*, 250:101–110, 2013.

[78] Christoph Müller, Joshua Elliott, David Kelly, Almut Arneth, Juraj Balkovic, Philippe Ciais, Delphine Deryng, Christian Folberth, Steven Hoek, Roberto C. Izaurralde, Curtis D. Jones, Nikolay Khabarov, Peter Lawrence, Wenfeng Liu, Stefan Olin, Thomas A. M. Pugh, Ashwan Reddy, Cynthia Rosenzweig, Alex C. Ruane, Gen Sakurai, Erwin Schmid, Rastislav Skalsky, Xuhui Wang, Allard de Wit, and Hong Yang. The global gridded crop model intercomparison phase 1 simulation dataset. 6(1):50. Publisher: Nature Publishing Group.

[79] World Water Assessment Programme (United Nations) and UN-Water. *Water in a changing world*. Earthscan, 2009.

[80] Fabien Pesquerel and Maillard, Odalric-Ambrym. IMED-RL: Regret optimal learning of ergodic Markov decision processes. In *NeurIPS 2022 - Thirty-sixth Conference on Neural Information Processing Systems*, Thirty-sixth Conference on Neural Information Processing Systems, New-Orleans, United States, Nov 2022.

[81] Emmanuel Pilliat, Carpentier, Alexandra, and Verzelen, Nicolas. Optimal permutation estimation in crowdsourcing problems. *The Annals of Statistics*, 51(3):935–961, 2023.

[82] Martin L Puterman. *Markov decision processes: discrete stochastic dynamic programming*. John Wiley & Sons, 2014.

[83] Nathalie Reymonet, Magalie Moysan, Aurore Cartier, and Renaud Délémontez. Réaliser un plan de gestion de données «fair»: modèle. 2018.

[84] Francesco Ricci, Lior Rokach, and Bracha Shapira. Introduction to recommender systems handbook. In *Recommender systems handbook*, pages 1–35. Springer, 2011.

[85] Francesco Ricci, Lior Rokach, and Bracha Shapira. Recommender systems: introduction and challenges. In *Recommender systems handbook*, pages 1–34. Springer, 2015.

[86] Francesco Ricci, Lior Rokach, and Bracha Shapira. Recommender systems: Techniques, applications, and challenges. *Recommender Systems Handbook*, pages 1–35, 2022.

[87] Andrei A Rusu, Sergio Gomez Colmenarejo, Caglar Gulcehre, Guillaume Desjardins, James Kirkpatrick, Razvan Pascanu, Volodymyr Mnih, Koray Kavukcuoglu, and Raia Hadsell. Policy distillation. *arXiv preprint arXiv:1511.06295*, 2015.

[88] El Mehdi Saad, Verzelen, Nicolas, and Carpentier, Alexandra. Active ranking of experts based on their performances in many tasks. In *International Conference on Machine Learning*, pages 29490–29513. PMLR, 2023.

[89] Hassan Saber, Fabien Pesquerel, Maillard, Odalric-Ambrym, and Mohammad Sadegh Talebi. Logarithmic regret in communicating mdps: Leveraging known dynamics with bandits. In *Asian Conference on Machine Learning*, pages 1167–1182. PMLR, 2024.

[90] Patrick Saux, Pierre Bauvin, Violeta Raverdy, Julien Teigny, Hélène Verkindt, Tomy Soumphonphakdy, Maxence Debert, Anne Jacobs, Daan Jacobs, Valerie Monpellier, et al. Development and validation of an interpretable machine learning-based calculator for predicting 5-year weight trajectories after bariatric surgery: a multinational retrospective cohort sophia study. *The Lancet Digital Health*, 5(10):e692–e702, 2023.

[91] Patrick Saux and Maillard, Odalric-Ambrym. Risk-aware linear bandits with convex loss. In *International Conference on Artificial Intelligence and Statistics*, pages 7723–7754. PMLR, 2023.

[92] Andrew Silva, Matthew Gombolay, Taylor Killian, Ivan Jimenez, and Sung-Hyun Son. Optimization methods for interpretable differentiable decision trees applied to reinforcement learning. In Silvia Chiappa and Roberto Calandra, editors, *Proceedings of the Twenty Third International Conference on Artificial Intelligence and Statistics*. PMLR, 2020.

[93] Shagun Sodhani, Franziska Meier, Joelle Pineau, and Amy Zhang. Block contextual mdps for continual learning. In *Learning for Dynamics and Control Conference*, pages 608–623. PMLR, 2022.

[94] Mathilde Soule, Alizé Mansuy, Julien Chetty, Auzoux, Sandrine, Pauline Viaud, Marion Schwartz, Ripoche, Aude, Heuclin, Benjamin, and Christina, Mathias. Effect of crop management and climatic factors on weed control in sugarcane intercropping systems. 306:13 p.

[95] Richard S Sutton and Andrew G Barto. *Reinforcement learning: An introduction*. MIT press, 2018.

[96] Stefano Teso, Öznur Alkan, Wolfgang Stammer, and Elizabeth Daly. Leveraging explanations in interactive machine learning: An overview. *Frontiers in Artificial Intelligence*, 2023.

[97] Olivier Therond, C Sibertin-Blanc, Romain Lardy, Benoit Gaudou, M Balestrat, Y Hong, T Louail, D Panzoli, J.-M. Sanchez-Perez, and S Sauvage. Integrated modelling of social-ecological systems: The MAELIA high-resolution multi-agent platform to deal with water scarcity problems. In *D. Ames, N. Quinn, A. Rizzoli (Eds.), International Environmental Modelling and Software Society (IEMSs); 7th Intl. Congress on Env. Modelling and Software, San Diego, CA, USA. San Diego, CA, USA*, 2014.

[98] Olivier Therond, Christophe Sibertin-Blanc, Romain Lardy, Benoit Gaudou, Maud Balestrat, Yi Hong, Thomas Louail, Van Bai Nguyen, David Panzoli, José-Miguel Sanchez-Perez, et al. Integrated modelling of social-ecological systems: The maelia high-resolution multi-agent platform to deal with water scarcity problems. 2014.

[99] Quentin Toffolini and Marie-Hélène Jeuffroy. On-farm experimentation practices and associated farmer-researcher relationships: a systematic literature review. *Agronomy for Sustainable Development*, 42(6):114, 2022.

[100] Auzoux, Sandrine, Eric Scopel, Christina, Mathias, Christophe Poser, and Soulié, Jean-Christophe. AEGIS, an extended information system to support agroecological transition for sugarcane industries. In *Proceedings of the XXX International Society of Sugar Cane Technologists Congress. ISSCT. Tucuman : ISSCT, 186-192. ISBN 978-616-92761-0-4*.

[101] Christina, Mathias, M.R. Jones, Antoine Versini, Mézino, Mickaël, Le Mezo, Lionel, Auzoux, Sandrine, Soulie, Jean-Christophe, Christophe Poser, and Edward Gérardeaux. Impact of climate variability and extreme rainfall events on sugarcane yield gap in a tropical island. 274:11 p.

[102] de Saporta, Benoîte, Alice Cleynen, Orlane Rossini, Sabbadin, Régis, Amélie Vernay, and Aymar Thierry d'Argenlieu. Stochastic control for medical treatment optimization. In *Journées de lancement de la fédération OcciMath*, 2024.

[103] de Saporta, Benoîte, Alice Cleynen, Sabbadin, Régis, and Aymar Thierry d'Argenlieu. Medical follow-up optimization: A monte-carlo planning strategy. arXiv:2401.03972, 2024.

[104] de Saporta, Benoîte, François Dufour, and Huilong Zhang. *Numerical methods for simulation and optimization of piecewise deterministic Markov processes: application to reliability*. Mathematics and statistics series. Wiley-ISTE, 2015. hal-01249897.

[105] Maillard, Odalric-Ambrym, Timothée Mathieu, and Basu, Debabrota. Farm-gym: A modular reinforcement learning platform for stochastic agronomic games. In *Artificial Intelligence for Agriculture and Food Systems (AIAFS)*, Wahington DC, United States, February 2023.

[106] Maillard, Odalric-Ambrym, Rémi Munos, and Gilles Stoltz. A finite-time analysis of multi-armed bandits problems with kullback-leibler divergences. In *Proceedings of the 24th annual Conference On Learning Theory*, pages 497–514. JMLR Workshop and Conference Proceedings, 2011.

[107] Ramifehiarivo, Nandrianina, Michel Brossard, Clovis Grinand, Andry Andriamananjara, Tantely Razafimbelo, Andriambolantsoa Rasolohery, Hery Razafimahatratra, Frédérique Seyler, Ntsoa Ranaivoson, Michel Rabenarivo, et al. Mapping soil organic carbon on a national scale: Towards an improved and updated map of madagascar. *Geoderma Regional*, 9:29–38, 2017.

[108] Ripoche, Aude, Jean-Pierre Rellier, Roger Martin-Clouaire, Nakié Paré, and Christian Gary. Modelling adaptive management of intercropping in vineyards to satisfy agronomic and environmental performances udner mediterranean climate. *Environmental Modelling and Software*, 26:1467–1480, 2011.

[109] Soulié, Jean-Christophe and Tom Wassenaar. Simulating regional organic waste flow management. *Environmental Modelling and Software*, In prep, 2024.

[110] Michal Valko, Nathan Korda, Rémi Munos, Ilias Flaounas, and Nello Cristianini. Finite-time analysis of kernelised contextual bandits. In *Uncertainty in Artificial Intelligence*, 2013.

[111] Jeffrey W. White, L.A. Hunt, Kenneth J. Boote, James W. Jones, Jawoo Koo, Soonho Kim, Cheryl H. Porter, Paul W. Wilkens, and Gerrit Hoogenboom. Integrated description of agricultural field experiments and production: The icasa version 2.0 data standards. *Computers and Electronics in Agriculture*, 96:1–12, 2013.

[112] Mark D Wilkinson, Michel Dumontier, IJsbrand Jan Aalbersberg, Gabrielle Appleton, Myles Axton, Arie Baak, Niklas Blomberg, Jan-Willem Boiten, Luiz Bonino da Silva Santos, Philip E Bourne, et al. The fair guiding principles for scientific data management and stewardship. *Scientific data*, 3(1):1–9, 2016.

[113] Frank Yates. The design and analysis of factorial experiments. 1937.

[114] Zhuangdi Zhu, Kaixiang Lin, Anil K Jain, and Jiayu Zhou. Transfer learning in deep reinforcement learning: A survey. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2023.

7. CV of the project leader / CV du responsable du projet

Personal details/Identité					
Gender/Genre	M				
Name and first name/Nom et prénom	MAILLARD Odalric-Ambrym				
Country/Pays	France				
Current position/Poste actuel					
Function/Titre	Senior Research Scientist (Chargé de recherche, HDR)				
French public organisation(s)/Organisme(s) public(s) français					
Code RNSR/ RNSR code	Organisation/ Organisme	Laboratory/ Laboratoire	Unit code/ Code unité	Postcode/ Code postal	Town/ Ville
202023603Y	INRIA	Centre Inria de l'Université de Lille	Scool	59650	Villeneuve d'Ascq

Other activities/Autres activités

(Services, committement in scientific events, scientific editing, scientific reviewing activities/Responsabilité scientifique, engagement dans des manifestations scientifiques, activités d'évaluation ou d'expertise scientifique, d'édition scientifique)

REVIEWING ACTIVITIES

International conferences (55 PC) and journals (+50 reviews): Algorithmic Learning Theory, Bernoulli Journal, Artificial Intelligence and Statistics, The Annals of Statistics, Conference On Learning Theory, European Conference on Machine Learning, European Workshop on Reinforcement Learning, International Conference on Machine Learning, Journal of Machine Learning Research, Machine Learning Journal, Neural Information Processing Systems, IEEE Transactions on Automatic Controls, IEEE Transactions on Information Theory, Theoretical Computer Science. I have been meta-reviewer/senior-reviewer for Artificial Intelligence and Statistics, Conference On Learning Theory, International Conference on Machine Learning. I am **editor** of the Journal of Machine Learning Research. I also reviewed for the French ANR (Agence Nationale de la Recherche) and Hungarian Scientific Research Fund (OTKA). Since 2019 (Habilitation), I regularly participate in Ph.D. juries.

MEMBERSHIPS OF SCIENTIFIC SOCIETIES: SSFAM

INSTITUTIONAL ACTIVITIES

INRIA CR hiring commitee: 2018/2019/2020. INRAE CR MathNum hiring commitee: 2021.
INRIA Comission Emploi Recherche (CER): 2020/2021/2022. Université de Lille McF hiring committee 2023.

ORGANISATION OF SCIENTIFIC MEETINGS

2020-2022: all planned workshops and meetings were canceled due to Covid.
2019 - Co-organization of Reinforcement Learning Summer School `https://rlss.INRIA.fr`.
2018 - PI of "ANR BADASS Lecture Series", hosting P. Grünwald, at INRIA Lille – Nord europe.
2017 - PI of Workshop "Sequential Structured Statistical Learning" at Institut des Hautes Études Scientifiques.
2014 - PI of NIPS Workshop "From Bad models to Good policies"

GRAND PUBLIC COMMUNICATION

2024/04 - Speaker at Table Ronde "DigitAgora" on AI and Agroecology
2024/02 - Speaker at Inria showroom to high-school and BEP students from Lycée Horticole on AI and Agroecology.
2023/11 - Speaker at Table Ronde "Decision making in an uncertain environment" to all master students of graduate programs from Université de Lille
2023/02 - Interview for INRIA regarding AI for agroecology
2020/10 - Fête de la science "Et si demain jardiner devenait une expérience de vie massivement collaborative ?"

SCIENTIFIC COMMUNICATION

I am regularly invited to give presentations. More details here Link.

Pedagogical and administrative responsability/Responsabilités pédagogiques et administratives

TEACHING ACTIVITIES

I have been teaching **Statistical Reinforcement Learning** in several M.Sc over the last few years:
École Polytechnique, 2019-2023 (5y) Master 2 "Artificial Intelligence & Advanced Visual Computing (Ai-ViC)" (48h, ∼20 students) and 2020-2022 (3y) Executive Master Data-Science (3h, ∼50 students)
École Centrale Supélec, 2021/2022, Master 2 Mention IA (24h, ∼70 students) and **École Centrale de Lille**, 2017/2018, Master 2 "Données, Apprentissage, Décision (DAD)" (18h, ∼40 students)
I also taught **Bandits** in the **Reinforcement Learning Summer School (RLSS)**, 01-12 July 2019, https://rlss.INRIA.fr/, (5h, ∼300 students)

SUPERVISION OF GRADUATE STUDENTS AND POSTDOCTORAL FELLOWS

I have supervised the following smart people:
Tuan Dam (Postdoc, 2022-2023, Chaire IA), Timothée Mathieu (Postdoc, 2021-2023, INRIA),
Mohammad Sadegh Talebi (Postdoc, 2018-2020, ANR), Hernán Carvajal (Engineer, 2021-2023, INRIA).
I continue this list with the Ph.D. students I have advised since my habilitation (2019):
S. Vashishtha (100%, 2022-2025, Chaire IA fellow) F. Fabre (33%, 2021-2024, U. Reunion & CIRAD)
F. Pesquerel (100%, 2020-2023, ENS fellow) P. Saux (50%, 2020-2023, ENS fellow)
D. Baudry (50%, 2019-2022, INRIA fellow) R. Ouhamma (50%, 2019-2023, Ecole Polytechnique fellow)
H. Saber (100%, 2019-2022, INRIA fellow) E. Leurent (50%, 2017-2020, CIFRE Renault; 2 PhD awards)
Before my habilitation, I also co-supervised [a] S. Akhtar (2017, ANR) R. Alami (2016-2020, CIFRE Orange Labs) R. Allesiardo (2015-2017, CIFRE Orange Labs) N. Galichet (2016, Université Orsay).
I have advised 18 Master internships since 2015, among which M. Asadi (ACML 2019 Best student paper award).
Also, foreign Ph.D. Students regularly get in touch to visit and work with me for a few months during their Ph.D. Below is a list of recent visiting students:

- Chuan-Zheng Lee, Stanford University, Stanford fellow, May-August 2019.
- Arun Verma, IIT Bombay, Raman-Charpak fellow, June-Nov 2019.
- Ramakrishnan K, IISc Bangalore, Raman-Charpak fellow, May-July 2022.
- Shubhada Agrawal, TIFR Bombay, funded by INRIA Scool, March-May 2022.

Likewise, young researchers get in touch to visit me, e.g. recent visits of J. Komiyama (2019, Research Associate, University of Tokyo), A. Mehrabian (2019, Postdoctoral Researcher, McGill University).

[a] in French, doctoral school officially recognizes supervision only after habilitation.

Previous positions/Postes antérieurs

Function/Titre

Start date/ Début	End date/ Fin	Town/ Ville	Organisation/ Etablissement	Function/ Fonction
2011	2013	Leoben, Austria	Montanuniversität	Postdoctoral fellow
2013	2014	Haifa, Israël	EECS, Technion	Postdoctoral fellow
2014	2015	Haifa, Israël	EECS, Technion	Senior Researcher
2015	2016	Orsay, France	INRIA Saclay - Île de France	Chargé de Recherche (CR2)
2016	2019	Lille, France	INRIA SequeL - Nord Europe	Chargé de Recherche (CRCN)

Career interruption(s)/Interruption(s) de carrière

None, but COVID years (2020-2022) hindered research activities.

Education/Formation supérieure

2019 Habilitation, Sciences Mathématiques, Université de Lille, France.

2011 **Ph.D.** "*Sequential Learning: Bandits, Statistics and Reinforcement.*", Université Lille 1, France, Advisors: Rémi Munos (INRIA, Lille) & Philippe Berthet (IMT, Université de Toulouse)

2008 Diploma from École Normale Supérieure de Cachan, selectively given for outstanding cursus.

2008 M.Sc research in Comput. Sci.: "Master Vision et Apprentissage", ENS Cachan, France (rank 1).

2007 M.Sc research in Mathematics: "Théorie Statistique", Université Rennes 1, France (rank 1).

Awards, grants/Prix, distinctions, bourses

PRINCIPAL INVESTIGATOR I have been PI of several national and international projects:
Reliant "Real-life bandits", INRIA-Japan Associate Team, CoPI J.Honda (U. Kyoto), 2022-2024, 30k.
RLRL"Real-Life Reinforcement Learning", CoPI B. De Saporta (U. Montpellier), 2021, 20k.
AppRenf "Apprentissage par Renforcement", Chaire of IA, CoPI P.Preux (U. Lille), 2021-2024, 500k.
3RSDM "Three risk-proof sequential decision making", INRIA-INRAE project, co-PI R. Sabbadin (INRAE MIAT), 2020, 4k. **SR4SG** "Sequential Recommendation for Sustainable Gardening", INRIA A-Ex., 2019-2023, 200k.
BADASS "Bandits against non-Stationarity and Structure", ANR JCJC, 2016-2020, 180k.
"Contextual MABs with hidden structure", IFCAM, CoPI A. Gopalan (IISc Bangalore), 2016, 7k.
PROMO , PEPS JCJC - INS2I, CoPI R. Bardenet (CNRS, Lille), 2015, 7k.
"Outil générique de prévision/contrôle de flux hydrauliques", INRIA-Carnot, Prolog, 2015, 50k.
Programme Invité Digiteo (Invitation of A. Gopalan for 3 weeks), 2015, 4k.

FELLOWSHIPS I secured the following fellowships:
2016-2020. Recipient of INRIA "Prime d'encadrement doctoral et de recherche" (PEDR).
2013-2014. Postdoctoral fellowship FP7 European Project SUpReL, Israel.
2011-2013. Postdoctoral fellowship FP7 European Project CompLacs, Austria.
2008-2011. Ph.D. fellowship from ENS Cachan (selective application, rank 1), France.

PRIZES AND NOTABLE FACTS
2012 Recipient of 1st national Ph.D. prize from AFIA (Link).
2022 Independent researchers name an algorithm after me (Link).

OTHER
2015 Part of the 200 "promising young researchers" internationally selected to attend the 3rd Heidelberg Laureate Forum and meet Abel, Fields and Turing laureates.

Scientific productions/Productions scientifiques

5 publications/ 5 publications	What is the major contribution of this publication /Quel est l'apport majeur de cette publication ?
1] Odalric-Ambrym Maillard, Boundary crossing probabilities for general exponential families. *Mathematical Methods of Statistics*, 27(1):1–31, 2018.	Following this publication, that solves a 30-year old problem as a tribute to the work of T.L. Lai, I was invited as plenary opening speaker at the 20th IBIS (Information-Based Induction Sciences) conference, Sapporo and also at the RIKEN institute (Tokyo). This also sowed seeds for the INRIA-Japan associate team RELIANT, which I am now co-heading with J. Honda from Kyoto University.
2] Edouard Leurent, Denis Efimov, and Odalric-Ambrym Maillard, Robust-adaptive control of linear systems: beyond quadratic costs. in *34th Conference on Neural Information Processing Systems* (NeurIPS), 2020. Oral, 1% acceptance rate	This is a collaboration with the INRIA Valse team specialized in Control, and Renault. E. Leurent, whom I co-supervised with D. Efimov, received two national prizes for his PhD thesis about Safe Reinforcement Learning for Autonomous Driving.

3] Sayak Ray Chowdhury, Aditya Gopalan, and Odalric-Ambrym Maillard. Reinforcement learning in parametric mdps with exponential families. In *International Conference on Artificial Intelligence and Statistics* (AI&STATS), pages 1855–1863. PMLR, 2021.	This is a collaboration with A. Gopalan from IISc Bangalore and his student, after I visited IISc Bangalore for a few weeks. This fundamental article explores parametric MDPs from a statistical and geometrical perspective. It introduces novel sharp confidence intervals obtained by a novel proof technique, and introduces the notion of bilinear parametric MDPs, that encompasses a wide of range of models. I have known Aditya since my postdoc in 2014, and we regularly discuss.
4] Olivier Cappé, Aurélien Garivier, Odalric-Ambrym Maillard, Rémi Munos and Gilles Stoltz. Kullback–leibler upper confidence bounds for optimal sequential allocation. *The Annals of Statistics*, 41(3):1516–1541, 2013.	This paper comes from the fusion of [106] that I did during my PhD with R. Munos (PhD advisor) and G. Stoltz, and [47]. It was decided to use alphabetical order. This is the first paper providing finite-time optimality regret bounds for the KL-UCB strategy, introduced in 1987. Following this paper, many optimaity regret bounds were derived for other bandit strategies.
5] Fabien Pesquerel and Odalric-Ambrym Maillard. IMED-RL: Regret optimal learning of ergodic Markov decision processes. In *NeurIPS 2022 - Thirty-sixth Conference on Neural Information Processing Systems*, Thirty-sixth Conference on Neural Information Processing Systems, New-Orleans, United States, November 2022.	In this work, done with my student, we obtained the first provably exact optimal (as opposed to order optimal) learning algorithm for regret minimization in MDPs. This strategy, inspired from multi-armed bandits, further displays striking performance largely outperforming the state-of-the-art, while being computationally cheap.
Data set, software, source code, data paper, etc./ Jeux de données, codes sources, logiciels, data paper, etc.	Brief description/Description succincte
1] Romain Gautron, Emilio J. Padrón, Philippe Preux, Julien Bigot, Odalric-Ambrym Maillard, Gerrit Hoogenboom and Julien Teigny. Learning crop management by reinforcement: gym-DSSAT. In *AIAFS 2023 - 2nd AAAI Workshop on AI for Agriculture and Food Systems*, Washington DC, United States, February 2023	Software paper, presenting Gym-DSSAT, the adaptation of 30y-old expert agronomy simulator DSSAT (written in Fortran) to the gymnasium reinforcement learning interface, hence enabling benchmarking of RL strategies. R. Gautron was the lead developer for this project.
2] Odalric-Ambrym Maillard, Timothée Mathieu and Debabrota Basu. Farm-gym: A modular reinforcement learning platform for stochastic agronomic games. In *AIAFS 2023 - 2nd AAAI Workshop on AI for Agriculture and Food Systems*, Washington DC, United States, February 2023.	Software paper, presenting Farm-Gym, a python simulator for gamified agronomy game. This is a fast running simulator, enable to capture interactions between many agronomic entities, hence complement gym-dssat. I was the lead developer for this project.
3] WeG@rden `https://scool.gitlabpages.INRIA.fr/wegarden/website/`	This is a software being developed with my engineer H. Carvajal (until May 2024) initially hired on SR4SG project. It is intended to provide a data-acquisition platform for agronomic experiments, compatible with format required by reinforcement learning algorithms, and oriented towards researchers in agronomy. This is under development.
4] Average-reward-reinforcement-learning `https://gitlab.INRIA.fr/omaillar/average-reward-reinforcement-learning`	This is an open source library of multi-armed bandits and reinforcement learning algorithms, that I developed over the years for reproducibility purpose. It is fully compatible with the gymnasium interface.
5]	
Valorisation/Valorization	
Patent, création of a start-up, prototype, audiovisual production, artistic creation etc./Brevet, création d'entreprise, prototype, production audiovisuelle, création artistique etc.	