Soubeyrand *et al.*
CABI Agriculture and Bioscience (2024) 5:72
https://doi.org/10.1186/s43170-024-00273-8

CABI Agriculture and Bioscience

REVIEW

Open Access

Building integrated plant health surveillance: a proactive research agenda for anticipating and mitigating disease and pest emergence

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Abstract
In an era marked by rapid global changes, the reinforcement and modernization of plant health surveillance systems have become imperative. Sixty-five scientists present here a research agenda for an enhanced and modernized plant health surveillance to anticipate and mitigate disease and pest emergence. Our approach integrates a wide range of scientific fields (from life, social, physical and engineering sciences) and identifies the key knowledge gaps, focusing on anticipation, risk assessment, early detection, and multi-actor collaboration. The research directions we propose are organized around four complementary thematic axes. The first axis is the anticipation of pest emergence, encompassing innovative forecasting, adaptive potential, and the effects of climatic and cropping system changes. The second axis addresses the use of versatile broad-spectrum surveillance tools, including molecular or imaging diagnostics supported by artificial intelligence, and monitoring generic matrices such as air and water. The third axis focuses on surveillance of known pests from new perspectives, i.e., using novel approaches to detect known species but also anticipating and detecting, within a species, the populations or genotypes that pose a higher risk. The fourth axis advocates the management of plant health as a commons through the establishment of multi-actor and cooperative surveillance systems for long-term data-driven alert systems and information dissemination. We stress the importance of integrating data and information from multiple sources through open science databases and metadata, alongside developing methods for interpolating and extrapolating incomplete data. Finally, we advocate an Integrated Health Surveillance approach in the One Health context, favoring tailored and versatile solutions to plant health problems and recognizing the interconnected risks to the health of plants, humans, animals and the environment, including food insecurity, pesticide residues, environmental pollution and alterations of ecosystem services.

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Keywords Biosecurity, Citizen science, Data integration, Data analysis, Decision-making, Epidemiology, Outbreak, Pathogen, Reservoirs, Spread

Introduction

Emerging and endemic pests or pathogens, here collectively referred to as pests* (see Table 1 for definitions of terms marked by an asterisk), are an inseparable component of plant health —in addition to symbioses and abiotic factors, for example. As such, they are the target of plant health surveillance strategies worldwide. Rooted in a long history paved with successes and failures, plant health surveillance for emerging or re-emerging pests (simply called "emerging pests" hereafter) currently needs both reinforcement and modernization. This is the central topic of this article. The need to improve plant health surveillance systems stems from a series of factors. Firstly, there is mounting

Table 1 Basic notions in plant health surveillance

Definitions	A pest is defined as any species, strain or biotype of pathogenic agents, animals or parasitic plants injurious to plants or plant products (EU legislation, Regulation 2016/2031)
	Plant pest emergence is the appearance or increased prevalence of a pest (hence including re-emergence) on cultivated or non-cultivated plants
	Global change encompasses climate change and various changes in trade, regulation, land use and agricultural practices
	A commons designates both (i) a tangible or intangible matter (e.g., a resource, a product) put in common between actors, and (ii) the social infrastructure, arrangement and processes settled for using and maintaining the common matter (Euler 2018)
Factors underlying pest emergence	Natural and human-mediated dispersal (air, surface water, trade in its local and global dimensions, hitchhiking, etc.)
	Genetic and ecological processes, and changes in the biotic environment (genetic variability of pests, pest adaptation, pathogen spillover, plant selection, reservoir hosts and environments, new plant species, biological community features, vectors, auxiliaries, competition, symbioses, etc.)
	Changes in the abiotic and social environment (climate, agricultural practices, regulation, land use and habitat continuity/fragmentation, etc.)
Main objectives of surveillance of emerging pests	Limiting the spread of emerging pests to reduce the cost of control and the risk of collapse of agricultural sectors
	Reducing the need for widespread harsh control measures impacting human and animal health as well as environmental quality, and push toward pesticide-free agriculture while meeting food demand
	Contributing to a better understanding of the ecology of emerging pests in a global context, and assessing the risks and available responses, including monitoring options, alert and control
	Improving information sharing to facilitate communication and collaboration between stakeholders, and effective decision-making
Main conventional actions for surveillance of emerging pests	Identification and categorization of pests that pose a risk of (re-)emerging from elsewhere or due to environmental changes and have the potential to cause significant damage according to multiple criteria (yield, economy, environment, etc.)
	Biosecurity measures (quarantine procedures, regulation of the movement of plant material, etc.) to reduce the risk of pest introduction and spread
	Early detection and rapid response systems to promote outbreak detection before pests become widespread and to enable control measures to be taken promptly
	Monitoring protocols of crops and surrounding environments grounded on visual inspections, genomic identification, etc
	Collaboration and communication between stakeholders (farmers, agricultural organizations, government agencies, etc.) to improve information sharing and increase the effectiveness of pest surveillance efforts
	Public awareness and education about the importance of plant health and the risks associated with pest emergence (including citizen science programs) to raise the level of concern and mobilize multiple sectors of the society

Definitions of key terms, main factors of pest emergence, and main objectives and actions for surveillance of emerging pests awareness of the need for more timely and cost-effective response to pest emergence* due to the increasing impact of global change* on pests (Brooks et al. 2022; Carvajal-Yepes et al. 2019; Chaloner et al. 2021; Garrett et al. 2022; Jeger et al. 2021; Morris et al. 2022; Ristaino et al. 2021; Silva et al. 2021; Trivellone et al. 2022). The rapid globalization of trade and climate change are introducing new dynamics in the spread of pests, which conventional surveillance systems are often unable to manage effectively. These systems may lack the agility to respond quickly to new threats that can emerge and spread across borders at unprecedented speed. For instance, there has been a significant increase in the number of emerging pest species, particularly insects, that had never been observed outside their home range and had never caused damage in their native areas (Schneider et al. 2022; Seebens et al. 2018). Therefore, grounding a surveillance system on quarantine lists, known invaders, or lists of species known as pests in other continents addresses only part of the problem, and research should explore the complementary, generally ignored, part. Secondly, for evident practical reasons, plant health surveillance has traditionally been directed toward detecting plants with visible symptoms or macro-pests. However, there are limitations to this approach, including the difficulty of detecting inconspicuous or unstable symptoms and pests, surveilling unknown and distant reservoir plants or inaccessible plants, and overcoming prohibitive surveillance costs. Thirdly, advances in technology and data analysis offer new opportunities to improve the efficiency and accuracy of surveillance, which traditional methods may not fully incorporate.

Crop failures or forest declines, due to emerging pests or changes in pest virulence, intensify the pressure on food security, the economy and major ecosystem services, which contributes to jeopardizing social stability and the well-being of human populations (Gullino et al. 2022; Singh et al. 2023). By helping to detect emerging pests at an early stage, surveillance can also be a means of reducing the need for harsh, area-wide control measures, which can have negative impacts on the environment and the sustainability of food systems (Cros et al. 2021; Fuller et al. 2020; Picard et al. 2019). Specifically, early detection and action in targeted areas limits the need to destroy large numbers of host plants or to use pesticides, antibiotics or other antimicrobials on a large scale. This reduces selective pressure and horizontal gene transfer, thereby reducing the risk of resistance in plant, animal and human pests (REX_Consortium 2013). Therefore, plant health surveillance has the potential to make a significant contribution to the goal of pesticide-free agriculture and its associated beneficial effects on human and animal health and environmental quality (Jacquet et al. 2022). Table 1 summarizes the main objectives of surveillance for emerging pests.

Many of the proposals for enhancing surveillance of plant health involve technologies that will intensify the creation and deployment of "information". By information we refer to (i) signals and data obtained from a multitude of new sensors, diverse sources of open massive data, and possibly derived from artificial intelligence (Garrett et al. 2022; Ristaino et al. 2021) and (ii) complementary knowledge from all involved disciplines. This wealth of information allows characterizing and anticipating potential health crises and acquiring new knowledge, which should contribute to decision-making to prevent or detect pest outbreaks early enough to control them more effectively. In turn, this ever-increasing wealth of information will render the decision-making process itself more complex, increasing the need for problem solving theory, decision theory, communication theory and systems thinking (Davila et al. 2021; Faure et al. 2023).

An obvious barrier to introducing upgraded surveillance systems is the risk of exhausting the necessarily limited resources that can be devoted to monitoring itself, as well as to related decision-making processes and public awareness. Implementing enhanced surveillance systems will require a variety of approaches that need to be evaluated for their efficiency (Jarrad et al. 2015), either alone or in combination. The design of multiple surveillance options and their evaluation will certainly be a matter for concerted research. As previously highlighted (Morris et al. 2022; Ristaino et al. 2021), such research will be inherently interdisciplinary to cover a wide range of scientific fields (biology, ecology and genetics of pests and the phytobiome, geography, economics, social sciences, data science, mathematics, etc.), risk factors (networks that can disseminate pests such as trade, the troposphere or surface water flow, weather and climate patterns, land use and soil properties, etc.), and technologies (sensors, sequencing, text mining, machine learning, database management, etc.). The aim of this research is to do more than just fill knowledge gaps. It will establish interdisciplinary interfaces for the development of tools that can handle massive and heterogeneous data and knowledge. These tools will facilitate knowledge inference, modeling and pattern recognition. Access to data, methods and results will have to be open in order to support worldwide collaboration, and trust by enabling verification. In addition, the research will aim to develop multi-stakeholder approaches that synergistically bring together different societal sectors and scientific disciplines (Morris et al. 2022). Finally, the research also has to promote thinking outside the box by questioning the assumptions associated with standard approaches to monitoring emergence.

To draw up a comprehensive research agenda dealing with the reinforcement and modernization of plant health surveillance for (re-)emerging pests, we convened 65 scientists mostly from the French National Institute for Agriculture, Food and the Environment (INRAE) (https://www.inrae.fr/en), as well as from Cirad (https://www.cirad.fr/en) and Anses (https://www.anses.fr/en), covering a wide range of scientific fields. Our goal was to identify priority research questions, approaches and emerging tools addressing the challenge of conceiving an enhanced plant health surveillance system. We deliberately looked beyond the social, economic, and political constraints of the present, thereby encouraging ourselves —and subsequently our readers— to rethink existing surveillance practices and bypass feasibility judgments. We have focused on the conceptual and technological advances in this area, and not on the detailed operational characteristics of the various approaches and tools (i.e., cost, spatial resolution, timeliness, accuracy, etc.). Indeed, many of the mentioned approaches/tools are still under development or in the early stages of application; thus, comprehensive data on cost-effectiveness or accuracy may not be available or would be largely speculative. By proceeding this way, we aimed to stimulate research interest in the concepts/approaches/tools mentioned in the manuscript, and to promote more in-depth exploration of their practical application and effectiveness in subsequent studies. The priority research questions, approaches and emerging tools were identified based on the expertise of the authors, the knowledge gaps they identified and the possibilities they could imagine if the knowledge gaps were closed (see Suppl. Table 1 for the list of topics the authors contributed to in this article). More specifically, we focused on research questions concerning the anticipation of emergence, early detection, risk assessment, rapid and efficient alert, operational approaches for monitoring the crops and the environment, as well as collaboration and communication between various stakeholders. In this article, we present the main outputs of this collective work after structuring them around four non-exclusive and complementary research axes (summarized in Fig. 1 and Suppl. Figures 1 and 2):

1. Anticipate pest emergence by building innovative forecasting capacity. This would include taking into

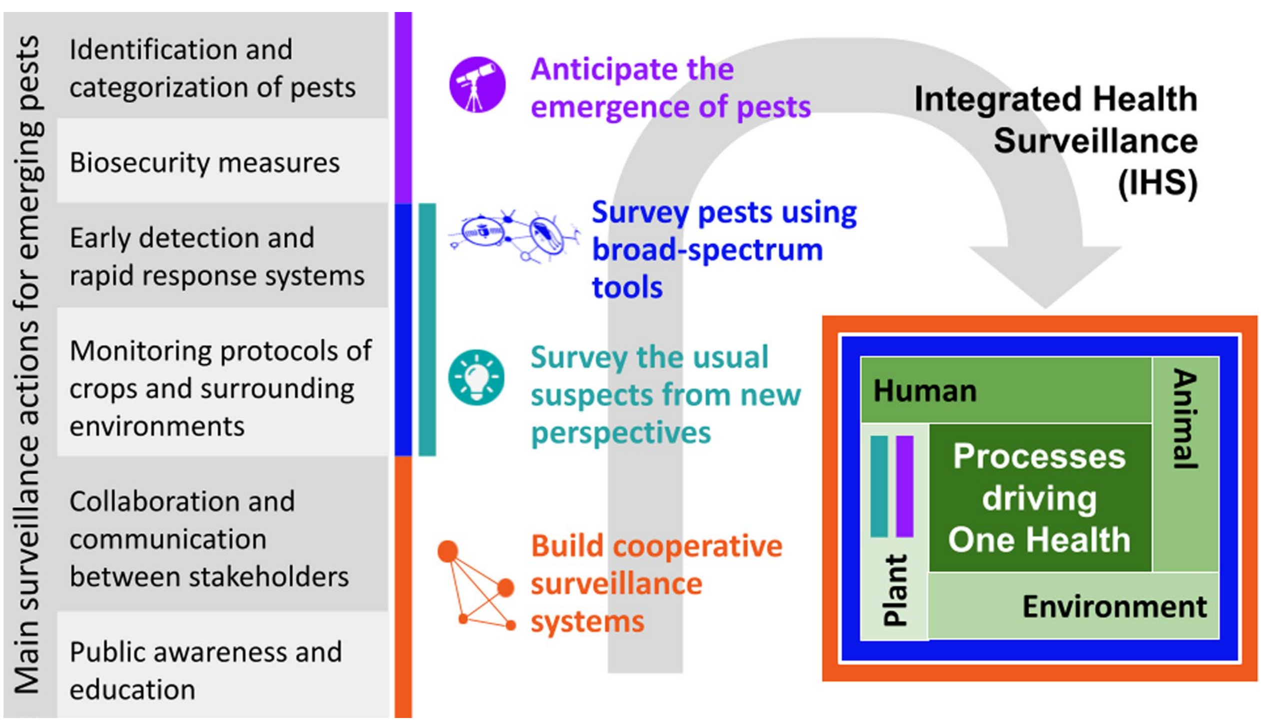

Fig. 1 Range of application of the four complementary research axes presented in the article (indicated with color bars) to the main surveillance actions for emerging pests in plant health (gray boxes on the left), and their contribution to Integrated Health Surveillance (IHS) and One Health components (green gradient boxes on the right). We indicated only the main range of application, but other relationships can exist. For instance, broad-spectrum tools may encompass threats over the different components of One Health, cooperative surveillance systems may include actors involved in the different components of One Health; both axes are thus transversal to human, animal, plant and environmental health. In contrast, research perspectives that we proposed regarding anticipation of pest emergence and surveillance of the usual suspects mostly concern plant health. However, from a methodological perspective the two latter axes may be relevant to the four components of One Health

account sub-species diversity and adaptive potential, making projections over longer time horizons including the effects of changes in climate and cropping systems, disentangling and quantifying connectivity between locations or environments, and improving the preparedness of stakeholders and affected areas.
2. Survey pests using broad-spectrum tools that are versatile enough to be mobilized for a wide range of organisms and by different types of stakeholders. These could include molecular or imaging diagnostics supported by artificial intelligence (AI), text mining, monitoring generic matrices such as air, water, and sentinel plants.
3. Investigate the usual suspects (i.e., those organisms already listed as quarantine or priority pests) from new perspectives and approaches, including approaches for improved diagnosis and characterization of pests.
4. Build long-term cooperative surveillance systems to enhance data-driven alert systems, further disseminate information to stakeholders and manage plant health as a commons* in a One Health perspective.

As depicted in Fig. 1, these four axes directly contribute to the main conventional actions for surveillance of emerging pests (listed in Table 1) but they cover a larger area than conventional surveillance. We indeed propose in this article to re-delineate surveillance such that it encompasses upstream to downstream components with respect to the emergence of a pest (adaptation studies, risk analysis, forecasting, horizon scanning, knowledge production, preparedness, multi-actor coordination, identification of sentinel matrices for data collection, monitoring, diagnostic, data analysis, information system, etc.). Including all these components in surveillance aims to develop a comprehensive vision of potential and actual emergence of pests and to anticipate their management. Another reason for re-delineating surveillance (i.e., pushing back its boundaries) is that the scope and diversity of plant health issues —due to the vast number of plant and pest species, along with the extensive variability in terms of trophic links, abiotic environment, spatial connectivity, temporal dynamics, practices, etc.— present a unique set of challenges, which remain uncovered by a restricted vision of surveillance. These complexities are inherent to the concept of One Health which offers valuable insights into the interconnectedness of health issues in ecosystems (beyond the simplistic notion that One Health would only concern zoonotic diseases). Nevertheless, embedding plant health surveillance into One Health does require substantial adaptation of the application of this concept to address the unique challenges associated with the diverse and dynamic nature of plant health issues globally. Recognizing these complexities, our manuscript advocates for an integrated approach to plant health surveillance that leverages interdisciplinary and multi-actor collaborations, anticipatory approaches, and advanced technologies.

Anticipating the emergence of pests

The widely mentioned axiom that "prevention is better than cure" may be applicable to the management of many –if not most– cases of pest (re-)emergence (Chhetri et al. 2021). In this section, we describe the methods that could be mobilized to anticipate pest outbreaks in a given region. The aim is to improve the ability to predict both the problematic pest species and the communities or species of hosts that would be particularly vulnerable to these threats, on a long-term horizon. It should be noted that the pests of interest here may already be present beyond the area of interest with or without explicit or official pest status, or may correspond to species that are not currently on our surveillance radar but are likely to become a problem in the future, in particular because of climate change that may favor (faster) completion of pest life cycles, thereby increasing their impact on plant hosts (see examples in IPPC Secretariat 2021). It is also important to emphasize that large-scale anticipation of emerging pests is a key element of integrated surveillance, as it helps to define what to monitor, where and when.

Profiling the pests of the future

By profiling their environmental, life-history traits and adaptive characteristics, potential emerging pests can be identified.

Environmental criterion

The risk of pest outbreaks in a given region can be predicted, and thus anticipated, by matching the environmental preferences of species that have been documented as problematic elsewhere and formalized in a knowledge base, with the environmental conditions in the region of interest. This approach, known as species distribution modeling (SDM; Zurell et al. 2020), involves the use of statistical models to relate the occurrence of the species of interest to large-scale environmental gradients in both native and invaded areas. The potential distribution of the species in the region of interest can then be projected under current environmental conditions, or under scenarios of climate, land use or cropping system changes (Bebber et al. 2013; Matzrafi et al. 2019). This approach can be extended to study the niche differentiation and hence agricultural risk for different populations or genotypes of the same species, to the extent that different genetic groups may be preferentially associated with different environmental conditions (Meynard et al.

2017). Importantly, the performance of SDM models is only as good as the quality of the data used to calibrate them: Occurrence data may not be of sufficient quality for some potentially problematic species to allow reliable predictions (e.g., few occurrences available, representing a small portion of the potential range, inaccurate locality or identification errors). This approach also relies on the assumption that environmental preferences are constant between the native and introduced ranges of pests, and are the main drivers of invasion risk. Interestingly, joint distribution models can incorporate species interactions and species traits into the modeling process (Caradima et al. 2019). However, compared to the simplest correlative SDMs that are more commonly used, this requires significantly more information regarding community composition and species properties, rather than just single species occurrences.

Adaptive criterion

It is the adaptive potential of species and populations that enables them to expand their range of favorable environmental conditions. Unfortunately, it is still difficult to integrate this crucial feature into the current inferential approaches, which are mainly based on environmental data. Early attempts to incorporate adaptation into SDMs combined mechanistic distribution models, which accounted for physiological constraints, with trait heritability estimates which took evolutionary capacity into account (Kearney et al. 2009). More recently, the use of genomic diversity data associated with environmental gradients has been advocated as a way to detect the genomic loci that drive local adaptation, and to predict the genetic composition that increases the fitness of a population in a given environment (Fitzpatrick and Keller 2015). In line with this idea, the level of (mal) adaptation of a population in a new environment can be assessed by the difference between its genetic composition and the optimal genetic composition in the new environment, a measure referred to as genomic offset (Fitzpatrick and Keller 2015). Genomic offsets are better predictors of population fitness than standard environmental distances because they implicitly weight environmental variables to account for their influence on fitness (Láruson et al. 2022; Rhoné et al. 2020). So far, this approach has mostly been applied to predict population vulnerability to expected future climate change (Bay et al. 2018; Tournebize et al. 2022), but it could also be used to predict the risk posed by population introductions to new areas, integrating various environmental variables (e.g., climate and host plant features). It should be emphasized that genomic offset approaches, like SDMs, are data intensive and therefore currently only applicable to a limited number of pest species.

Trait criterion

A trait-based framework can help to identify pests that are not on our surveillance radar at the moment, but are likely to become a problem in the future (Barwell et al. 2021). This framework relies on databases of species traits that include a large representation of both known or future pests and of species that do (or will) not have a significant impact on either natural or cultivated ecosystems. The definition of traits in this context is broad and may include life history traits as well as host, habitat and environmental preferences (Bossy et al. 2019). For example, the invasion success of a microbial pest (but also some insects such as aphids) could be predicted by life history traits such as dispersal modes, reproductive systems (sexual and asexual), morphological traits, optimal growth temperature or virulence factors (Philibert et al. 2011). Phylogenies can also be useful for the study of trait conservatism and the inference of missing values, taking into account evolutionary potential (Fournier et al. 2019). Furthermore, the importance of accounting for the environment when calculating the invasion fitness of pathogens has been demonstrated in ecological studies using adaptive dynamics (Papaïx et al. 2015). Interestingly, databases of species traits can also be used to identify species assemblies that are vulnerable to invasion. In particular, studying community composition along a gradient of vulnerability (quantified by exposure or disturbance metrics) should help to identify community traits (i.e., mean and variance of trait values) that increase risk, as well as the potentially damaging species that are more likely to succeed in these communities (Mouquet et al. 2012). However, large databases of relevant traits suitable for this type of modeling remain scarce, either to identify pest species not currently on our surveillance radar or to identify vulnerable communities.

Origin, spread and arrival of pests

Targeted surveillance and control measures can be implemented by identifying the geographic origin and the potential pathways responsible for the introduction of pests into new areas. Pests are introduced and spread by a variety of means (airborne particles, animal vectors, movement of goods and people, etc.). Rather than relying solely on epidemiological parameters, examining the connectivity of transport and trade hubs provides a fuller understanding of the spread of pests. Recent advances in data integration have made it possible to simulate the dynamics of pest spread in a realistic manner. For example, the continental spread pathways of the airborne wheat stem rust (*Puccinia graminis* f. sp. *tritici*) were studied using Lagrangian simulations of air mass movement (Meyer et al. 2017). This framework has been adapted into a real-time early warning system for rapid disease outbreak response by policymakers (Allen-Sader et al. 2019). Combining such connectivity models with species distribution models (see "Environmental criterion" section) may be a promising way to prioritize surveillance to the most connected suitable environments for a pest. The main aim of such approaches is not to pursue the goal of accurately pinpointing the exact entry pathway for any pest, but to leverage connectivity data for a probabilistic assessment of entry risk. Scientists are also using genetic polymorphisms to track pest invasion routes (Estoup and Guillemaud 2010). This involves the reconstruction of the geographical pathways and demographic features that were taken up by individuals from a set of sampled invading and native populations. With the development of genome-wide genetic markers and new statistical methods, it is possible to unravel the recent history of populations with an unprecedented level of precision (Gautier et al. 2022). The combination of genomic and transport/connectivity data might reinforce hypotheses about pathways by which emerging pests arrived, and subsequently enhance our ability to probabilistically assess possible pathways for future emerging pests. Moreover, the combination of genomic data with environmental and phenotypic data (including properties of agronomic interest such as virulence spectrum against resistance genes already deployed or resistance to available plant protection products) can also improve risk assessment of a genotyped target pest population by taking into account its expected fitness in a new environment (see "Adaptive criterion" section). Conversely, the latter approach could be used to more accurately identify the most likely source area(s) of the invasive population(s), including regions from which no genotyped population sample is available.

Anticipating regulation capacity and emergence risk from microbiomes

The advances of metagenomics and metabarcoding approaches have shed a new light on the plethora of microorganisms associated with plants (in, on and near their tissues) or living in close interactions with plant pests. Hence, plant health is increasingly recognized as resulting not solely from the absence of pests, but as the result of a complex web of interactions between plants and their associated macro- and microorganisms, i.e., the phytobiome. It is often observed that denser or more complex interactions among species of the phytobiome generally contribute to biotic regulation, including pest regulation; and plant health may equally rely on direct competition within the phytobiome and the intrinsic plant immunity (Vannier et al. 2019). Transposed to pest surveillance, this paradigm opens up the possibility of monitoring the quantity and quality of species interactions to infer and anticipate the regulatory capacity of the plant environment from the composition and structure of the phytobiome: this surveillance process is referred to as next-generation biomonitoring (Bohan et al. 2017). For example, using AI, the suppressiveness of soils was assessed solely from the nature of the bacterial communities in soil (Zhang et al. 2022); and root microbiota were shown to stimulate or prime the plant immune system by enhancing plant defenses against a broad spectrum of pathogens (Vannier et al. 2019). Nevertheless, we need to further identify indicators of functional diversity and phylogenetic signals that can be used as predictors of the capacity of microbiomes to foster plant health.

Another discovery of microbiota studies is that diseases, even when caused by an identified primary agent, are the result of interactions between a (generally small) subset of the taxa composing the phytobiome (Bass et al. 2019). This subset (possibly including prokaryotes, eukaryotes, and viruses) is the pathobiome (Vayssier-Taussat et al. 2014), and can be identified, e.g., with network-based community ecology approaches (Jakuschkin et al. 2016). Monitoring all species in the pathobiome and investigating its functioning is a promising approach for accelerating the detection of emerging pests and the identification of conditions under which pests emerge. For instance, the risk of the citrus greening disease has been predicted based on the bacterial flora of citrus plants (Liu et al. 2023), and Doonan et al. (2020) has shown how pathogenicity can emerge from interactions among the pathobiome involved in acute oak decline.

From a general perspective, a versatile approach to anticipating potentially emerging diseases could be to monitor the key functions of disease-related processes in relation with the structure and function of the neutral and beneficial microbiome rather than targeting single species of the pathobiome.

Anticipating the impact of changes in cropping systems on plant health

Changes in agricultural and forestry practices motivated by environmental concerns provide contrasting effects on pest emergence and spread (Petit et al. 2020). The resulting new balances may be beneficial (e.g., reduced fertilization may limit disease development; Lekberg et al. 2021) or detrimental (e.g., reduced tillage may benefit pests previously considered secondary; Kerdraon et al. 2019). Similarly, while organic farming can promote natural pest regulation (Muneret et al. 2018), pesticide reduction is also associated with the re-emergence of certain endemic pathogens (e.g., grape black rot in vineyards; Pirrello et al. 2019). Introducing disease-tolerant plants may increase risks for sensitive varieties (Doropoulos and Roff 2022). These plants can silently harbor pathogens, acting as disease reservoirs and posing a threat to nearby susceptible crops, leading to unexpected disease outbreaks. The mobilization of innovative methods could address the uncertainty associated with these complex feedback loops. For example, plant diversification is recognized as a global solution to limit (re-)emergence at the scale of the whole agroecosystem (Vialatte et al. 2021). However, plants can act as (i) reservoirs of previously insignificant pests (e.g., stem rust caused by *Puccinia graminis* alternating on barberry; Saunders et al. 2019), (ii) reservoirs of vectors of (re-)emerging pathogens, (iii) means of pest introduction, or (iv) natural traps for pests. The practical implementation of solutions based on plant diversification will hence require reactivating epidemiological knowledge in order to ensure effective prophylaxis against various pests, and this for different types of crop diversification (Précigout et al. 2020). The transitional period we are entering requires improved knowledge of the diversity and biogeography of pests to activate relevant regulations based on phytosanitary standards with the goal of limiting their introduction, while addressing the complex issue of derogatory regulation (e.g., neonicotinoids in sugar beet; Ristaino et al. 2021). Finally, in the face of changes in cropping systems (e.g., new regulations on pesticide use, irrigation, fertilization, etc.), adaptive evolutionary changes in pests should be anticipated (Précigout et al. 2020).

Toward an integrated biosecurity risk framework

Focusing on anticipation, the previous subsections explore research axes that extend surveillance upstream to the emergence of a pest. Here we highlight how these axes can contribute to an integrated biosecurity risk assessment, aiming to provide key information for establishing monitoring programs, implementing preventive measures and improving the preparedness of authorities (Probert et al. 2020; Jarrad et al. 2015; see also Text box 1 for a broader vision of preparedness). Pre-impact risk assessment consists of assessing the risk of introduction, establishment and spread of pests before they arrive. The pre-impact ranking of species is based on a wide range of species-level characteristics (see "Profiling the pests of the future" section) and available information on potential pathways of introduction and spread (see "Origin, spread and arrival of pests" section). It relies on methods such as consensus horizon scanning (Roy et al. 2019) and multi-criteria analysis (European_Food_Safety_Authority et al. 2022). Once high-risk species have been identified, species distribution models provide an additional level of information by indicating environmentally suitable areas as a function of current or future climate conditions (see "Environmental criterion" section). This pre-impact risk, combined with an estimate of the economic or ecological harm that might result if the species became established (i.e., the post-impact risk), defines the integrated risk, and indicates where monitoring must be concentrated. Such a pre-emptive risk assessment may not be fully feasible for some potential pests, mainly due to data and knowledge limitations. However, even subtle information can be useful, for example to allocate monitoring effort more efficiently than without any information. It can also help to identify knowledge and data gaps that need to be filled in order to iterate the analysis and ultimately carry out an integrated risk assessment. Although not covered in the previous sections, post-impact risk assessment should not be neglected. Based on knowledge of established biological invaders, it provides a better understanding of invasion success, pathways and management strategies. By identifying gaps in prevention and management strategies, post-impact analyses can also help prevent multiple reintroductions and improve preparedness. Finally, integrated risk assessment over longer time horizons, including under different scenarios of climate, land use and cropping system changes, would be improved by more systematic considerations of the adaptive capacity of potential pests (see "Adaptive criterion" section).

Text box 1: At the crossroads of anticipation and cooperation

Text box 1.1: Developing resilience and preparedness of territories

The overall resilience and preparedness of geographic areas in the face of emerging plant pests can be based on two broad strategies: (i) the promotion of landscape diversity at all scales, and (ii) the establishment of an effective and extended pest surveillance strategy that decreases the detection time of new pests, maximizes the responsiveness for efficient prevention or eradication of detected introductions, and even reduces the risk of pest introduction (e.g., the assessment of pest origins and pathways discussed in "Origin, spread and arrival of pests" section could lead to pest control at origin or during transport, depending on feasibility, thereby reducing pest arrival). Increasing crop diversity at the individual farmer level is both a strategy of bet-hedging (spreading the risk of potential epidemics across multiple crops) and of effective agro-ecological crop protection that reduces pest spread in the advent of an outbreak. The application of the same idea at the landscape scale (Picard et al. 2019), in addition to its use as a mean for managing pest-resistant varieties (Rimbaud et al. 2021), can extend benefits beyond a single farm, but requires coordination of stakeholders toward a common goal (Kneeshaw et al. 2021). Other coordination issues arise in the definition of a surveillance strategy and the implementation of a surveillance network. For this reason, and for reasons of efficiency (optimal allocation of resources, large-scale view of spatio-temporal pest detection patterns), state-level administration of pest surveillance is often required. The funding of surveillance is also a key challenge, which may need state intervention as well as the involvement of non-agricultural actors providing human and economic resources, especially when a pest is not yet present. Indeed, farmers may only be willing to pay for surveillance and crop loss compensation schemes if they expect high crop losses, and are highly confident in the effectiveness of the surveillance/eradication strategy and the return on investment.

Text box 1.2: Continuously updating the focus of awareness

In order to achieve a high level of vigilance in the face of emerging situations, awareness-raising and training on plant health issues is required for both the agricultural community and the general public. It prepares individuals for circumstances that require a rapid response and enables collective problem solving (e.g., to prevent the introduction of regulated organisms or to contain/eradicate them once they have been introduced). Awareness and training initiatives should be developed in the long term and in an anticipated manner, because emergency responses are usually not conducive to their implementation. For example, in the early stages of the COVID-19 pandemic, public health emergency measures such as ensuring health service availability took precedence over health literacy development (Paakkari and Okan 2020). It is therefore essential to develop information systems, tools, services and visuals that enable individuals to understand current and future health issues (Soubeyrand et al. 2020), to adopt practices that prevent pests from spreading, and to be able to detect them. Many such tools already exist. These include pest maps, real-time web maps, smartphone applications, media campaigns, educational signs in public spaces such as national parks, and notices at borders. There is a need for greater dissemination of these elements throughout society, which may be achieved in part through improved formats taking advantage of the new possibilities of information technology (IT).

Surveying for pests using broad-spectrum tools

For high risk pests, conventional surveillance (see Table 1) usually deploys means of detection that are highly pest-specific. With a substantial and almost constant increase in the number of pest species introduced, this strategy is expected to reach its limits in terms of cost and effectiveness. The development of broad-spectrum tools could contribute to overcoming these limitations. The approaches described below are in this vein and are expected to improve or complement existing non-pest-specific surveillance approaches (e.g., generalist baits and lures, site inspections, industry vigilance, monitoring of decline symptoms and general surveillance by the public).

AI-enhanced molecular or image-based diagnostics

With progress in DNA/RNA library preparation, long- and short-read sequencing, and AI, we can now expect progress toward versatile and rapid detection systems for plant pests that can be applied in the laboratory, or even in the field, across a wide range of organisms. For some microorganisms (viruses, bacteria, fungi and fungal-like pathogens) such high-throughput molecular approaches have had marked success and are gradually nearing broad application in diagnostic laboratories (Johnson et al. 2023; Kutnjak et al. 2021). Overall, an important limitation for these approaches (beyond the funding issue) is the availability of appropriate skills in both the academic sector and among plant protection operators. Another issue is the lack of complete and accurate sets of molecular markers for all species and, in particular, of sequence databases validated by taxonomists or pathologists for the identification of organisms (Rasplus et al. 2023). Indeed, existing molecular tools perform poorly on novel/undocumented species as they rely on matches to known pests. Identifying new emerging organisms is further made difficult because molecular signature libraries for endemic organisms are often non-existent. Progress in our ability to sequence DNA from museum collections could contribute to improving sequence databases for some groups of arthropods (Burrell et al. 2015), provided that identification of the museum specimens is accurate. This could also help to document insect pest-parasitoid associations leading to insights for biocontrol. However, determining the identity of the massive numbers of samples needed to develop databases of adequate size —of contemporary and museum specimens— will require automation.

Automated image classification, in particular for symptomatic plants, has largely benefited from the development of deep learning algorithms based on convolutional neural networks (Redford et al. 2023). This approach however often requires large sets of specimens for training and validation. Research could focus on the optimization of AI-based approaches to balance the trade-offs between imprecision from a training set of insufficient size, validation samples and the curse of overprecision (overfitting) caused by an excess of samples. These problems could be at least partially overcome by domain generalization, such as transfer learning or data augmentation (Lee et al. 2020; Wang et al. 2023). Active learning could also reduce annotation effort by identifying samples that are worthy of labeling (Atighehchian et al. 2020). Because methods based on neural networks can handle and combine different types of data, including molecular and image-based data, they are expected to become more common in pest surveillance in the coming years.

Prospecting a wide range of data sources for anomalies

Monitoring generic disease-associated phenotypes like dieback or decline symptoms of plants, rather than monitoring specific pests, plays a crucial role in the general surveillance of plant health. Various approaches have been adopted for this purpose, including visual inspections, citizen science data, and remote sensing (Baker et al. 2019; Chan et al. 2021; Goodwin et al. 2021). This generalist surveillance can be likened to syndromic surveillance in human and animal health (Henning 2004; May et al. 2009). The COVID-19 pandemic has demonstrated the proliferation of opportunities to detect health-related anomalies, including the discovery of indicators from analyses of seemingly unrelated data sources such as consumer reviews of popular products or images of hospital parking lots (Beauchamp 2022; Hennin 2022). Likewise, indirect measurements could be used for monitoring plant health. The challenge lies in developing real-time data and analysis systems that signal alerts proactively rather than retrospectively. Numerous opportunities can be explored in this regard, such as detecting anomalies in the sales of plant and phytosanitary products, analyzing plant-related posts on social media, and even exploring innovative possibilities such as monitoring volatiles or sounds emitted by stands of plants (Khait et al. 2023). Other possibilities are mentioned in "Alternative surveillance approaches based on data mines" section.

Horizon scanning in the age of big data, AI and open science

Continuous, active, and comprehensive monitoring of health and scientific knowledge is necessary for broad-spectrum surveillance (Morris et al. 2022). Currently, these approaches are mostly manual and focus on a specific subject. However, keeping knowledge in a field up to date is more challenging than ever. Knowledge is evolving rapidly, is obtained from sources and processes that are more or less reliable, and essential signals can be drowned out by a high degree of information redundancy over an increasing diversity of subjects making it beyond human capacities to keep abreast. At the same time, public policies on surveillance require short-term risk anticipation and identification of weak signals. There has been some progress toward development of systems that will provide the necessary reactivity.

In this context, event-based surveillance (EBS) systems (O'Shea 2017) can be used to monitor and detect plant health threats. EBS tools (e.g., MedIsys/EMM to produce EFSA newsletters, PestAlert, ESV Platform pipeline to produce international health monitoring bulletins, ProMed, PADI-web; see Suppl. Table 2 for details) monitor textual data (online news, publications, etc.) and other unofficial sources, with the primary aim to provide timely information to users on disease outbreaks occurring worldwide. These systems can integrate other structured and accessible data. These data are limited to a few targeted databases (e.g., EPPO Global Database, CABI Digital Library, FLOW, World Auchenorrhyncha Database, e-phytia; see Suppl. Table 2 for details), which are non-exhaustive and updated manually at variable time intervals. Further progress is needed to address the significant questions of the relevance of extracted information in the context of the very rapid evolution of expert knowledge and to meet the dual need for data interoperability (i.e., FAIR principles; Wilkinson et al. 2016) and knowledge synthesis at a given time. An interdisciplinary approach combining biology, natural language processing (Jiang et al. 2023), and knowledge representation (Bossy et al. 2019) promises to achieve the ambition of collecting, structuring, and sharing the knowledge of a targeted domain in an unbiased, massive and automated manner. In addition, the formalization of knowledge would make it possible to cross-reference information of all kinds (e.g., genetic, ecological, geographic) and origins (e.g., citizen, scientific, professional data). Moreover, this paradigm shift would enable the detection of inconsistencies between observations and knowledge (novelty or noise?) and identify and explain new morsels of knowledge to be validated. Predictive capabilities of the AI framework will generate novel hypotheses and out-of-the-box biological scenarios. However, this path will require the removal of many conceptual and methodological barriers in the three above-mentioned scientific fields or at their interface.

Monitoring generic substrates to develop multi-pest surveillance

Generic substrates, including natural environments (e.g., air, water and soil) and human-mediated dissemination pathways (e.g., transportation and commercial exchange routes), can provide critical information on disease risk when they indicate connections of specific environments where disease outbreaks can occur or when they can be sentinels for the actual presence of pests at a broader scale (Crowl et al. 2008). Therefore, they should be considered as targets of surveillance. Developing such generic surveillance would require monitoring the substrates that can spread pests, such as air and water, as well as trade and transportation routes that may inadvertently disseminate pests. Such substrates are challenging to monitor since they are spatially vast and often dynamic. Therefore, appropriate surveillance strategies must be designed to optimize the available monitoring resources in order to achieve a specific surveillance objective. These strategies should provide meaningful criteria for the selection of sampling sites based on the probability of detection and the representativeness of the site with respect to the environments that they connect (i.e., their degree of connectedness). At regional and continental scales, this requires elucidating the network of possible transportation/dissemination pathways. For freshwater environments, this can be achieved quite straightforwardly, since the natural division of the landscape into waterways may provide an intuitive set of sentinel sites (Bailey et al. 2020). The atmospheric dissemination network is more challenging since air mass movements are less easily observable and change constantly, although great progress has been made in the last decades to describe and characterize this substrate (Radici et al. 2022; Richard et al. 2023; Schmale and Ross 2015). Human-mediated dissemination networks, including transportation and trade (via roads, railways, airlines, shipments), are increasingly recognized as major drivers of pest emergence (Chapman et al. 2017; Hulme 2009; Seebens et al. 2017; Sikes et al. 2018). Whereas these networks can be described in terms of topology, challenges remain in the design of appropriate monitoring strategies due to the ever-increasing volume of transport and traded goods, as well as tradeoffs with industry and national security. In addition to assessing the intensity of environmental connectedness provided by different substrates, we will need generic pipelines to identify relevant samples in these substrates. Biomonitoring of environmental DNA (eDNA) offers the possibility of sampling pests in all substrates with a common suite of methods and identification pipelines (Bohan et al. 2017; Cordier et al. 2021); see also Text box 2 envisioning broad-spectrum biomonitoring of viromes from sentinel insects.

Sentinel plants

Sentinel plants are defined as plants grown near high-risk sites that are inspected at regular intervals for signs and symptoms of pests (Eschen et al. 2019). In addition to their inherent sensitivity to certain pests, their power as “phytosensors” can be altered by wounding, or with semiochemicals to render them attractive to a given target pest species. Inspections of sentinel plants represent one of several surveillance activities, after inspections during border controls, that can be carried out to detect recently introduced non-native pests soon after their arrival, increasing chances of eradication and control.

However, the detection of alien pests prior to their arrival is even more important from a preventive perspective and, in the context of plant material trade, is the object of various approaches including a standard from the European Plant Protection Organization (EPPO 2020). Ex-patria sentinel plantations (Eschen et al. 2019) consist of plants from an importing region introduced in an exporting region and surveyed for colonization by pests from the exporting region. Such sentinel plantations may involve the planting of pest-free seeds or seedlings of different plant species, with the possibility to adjust the plants’ genetic diversity and the number of individuals (Roques et al. 2015). They may also correspond to collections of plants from the region of importation in botanical gardens of the exporting region, which may present mature individuals representing a fixed genetic diversity and few individuals (Kirichenko and Kenis 2016). These approaches are complementary because young plants are likely to show only damage to foliage and roots whilst older individuals in botanical gardens may reveal damage on other plant parts (e.g., trunk and branches of trees; Roques et al. 2017). Identification of novel associations between hosts from the importing region and pests from the exporting region provide information about the potential impact of introducing these pests into the importing region. However, subsequent tests under quarantine conditions are essential to confirm the pest potential for the importing region. Experiments carried out in China and Russia have already shown the interest of such sentinel plantations to identify pests potentially harmful for tree species native to Europe (Roques et al. 2015; Vettraino et al. 2015) or North America (Ernstsons et al. 2022). Their generalization to herbaceous plants seems possible.

A second approach corresponds to sentinel nurseries (or in-patria plantings; Eschen et al. 2019). These are plantings of species in their native range, either in nurseries or in open fields, but without phytosanitary treatments. Surveys and identification of native-to-native pest–host associations in these plantations provide information on the likelihood of transportation of the harmful organisms with traded plants. For example, the huge damage noted on Chinese *Buxus* in the sentinel nurseries would have provided warnings about the possible introduction of the box tree moth prior to its arrival in Europe (Eschen et al. 2019).

Interoperability of surveillance systems of health and biodiversity

Given the great heterogeneity of monitoring targets and tools described in previous sections, we envision three key challenges to consider in making surveillance systems effective at large scales and fit to different purposes.

The first challenge is institutional and economic (Meynard et al. 2020). Data gathering, sharing and early analysis are key to the success of early detection of outbreaks or shifts in ecosystem health. Transboundary practices and policies can hinder monitoring and management, which need to cover national and transnational strategies, sometimes spanning distinct governmental and non-governmental organizations. The political will and associated funding are fundamental in this context, given our global economies. For example, developing in the Global South tools that allow enhanced surveillance, early detection and management before a sanitary crisis arises is key to sustainable food security and human well-being worldwide (Sánchez Herrera et al. 2024).

The second challenge is technological, and is commonly associated with the issue of big data (Farley et al. 2018; Wüest et al. 2020) and with interoperability of data of very different sources and types as stressed by the semantic web community (Jonquet et al. 2018). This integration requires informatics systems to share common reporting standards, and analysis tools accessible to users with a large range of expertise. Taxonomic and technical expertise should be geared to act efficiently on key check-and-balance points along the surveillance chain. The monitoring and analysis systems also need to be fully replicable, to be able to update risk assessments continuously with incoming meteorological, epidemiological or other information. Moreover, the system needs to deal with heterogeneous data quality, depending on the data source (e.g., citizen science vs expert monitoring) and detection system (e.g., eDNA surveillance vs remote sensing). Data analysis should therefore incorporate enough flexibility to use datasets that are heterogeneous in terms of quality and nature and provide uncertainty estimates.

The third challenge is to clearly define which facets of crop health we want to analyze and then identify effective quantitative indicators that provide information related to crop health. Some aspects of crop health related to the presence of a pest or to the level of crop damage are quite straightforward to monitor. However, other aspects are much more difficult to tackle: lag effects between pest presence and crop damage, crop resistance to pest, effective natural pest control, impact on harvest quality, etc. Defining crop health and linking system property to tractable indicators need both disciplinary research to identify relevant indicators, but also interaction between disciplines (e.g., ecologists, biologists, physicists) to match what is technologically possible to what is ecologically sound (Cheruvelil and Soranno 2018). Pests are part of an ecological network of multiple interactions that influence their dynamics (Hassell et al. 2021) and some hidden or non-intuitive interactions may be important in the observed dynamics (Vasseur et al. 2013). Moreover, taking into account the complexity of crop health requires a shift from segmented research to system-wide research, to understand the separate and interactive effects of pests in relation to production methods on both crop production quantity and quality, and their impact on the environment.

Text box 2: Monitoring viromes in insects for emergence anticipation and surveillance

"Anticipating the emergence of pests" section envisions, in particular, the anticipation of regulation capacity and emergence risks from microbiomes. "Surveying for pests using broad-spectrum tools and Surveying the usual suspects from new perspectives" sections deal with diverse biotic and abiotic matrices that may be used to monitor pests from broad-spectrum and specific viewpoints. At the crossroads of these topics, monitoring the viromes of non-vector "sentinel insects" appears as a promising avenue for anticipation and surveillance. Sentinel insects may be phytophagous or pollinator insects visiting crops, reservoirs, and any pest habitat in the landscape, or may be predators (e.g., of vectors, of phytophagous insects, of predators). The metagenomics analysis of such sentinel insects makes it possible to detect emerging viruses and variants (and possibly other pests) in plants, vectors, polyphagous insects, regulator insects, etc. Several examples illustrate the potential of this approach: A study used phytophagous insect pests to monitor virus abundance and diversity in crops, and showed that trophic accumulation results in a higher diversity of plant viruses in insect pests compared to host plants (François et al. 2021). Honeybees were used to detect avocado viroids within 100 m of the sampled hives (Roberts et al. 2023). The gut content of carnivores was exploited for the molecular detection of plant viruses ingested by their herbivorous prays (Rosario et al. 2013). Opportunistic omnivorous ants were used as natural and efficient samplers of a tropical forest patch for the detection of virus sequences initially attached to different faunal and floral compartments of the patch and finally contained in the ants' digestive tracts (Fritz et al. 2023). These examples illustrate how metagenomics applied to sentinel insects can be used for surveillance purposes.

Nevertheless, three key questions remain: (i) Which insects are relevant sentinels for identifying and quantifying all the relevant viruses in a given environment? (ii) How to sample these insects in the landscape and over time (either for anticipating regulation capacity and emergence risks, or for early detection)? (iii) How to reduce uncertainties about the eventual host plant species in the landscape that were carrying the pathogens detected in the sentinel insects? The answers to these questions are obviously dependent on the specific environment and trophic chains at stake, and necessitate further multidisciplinary research.

Surveying the usual suspects from new perspectives

Novel strategies could be employed to better detect pests of concern that are often the objects of plant health surveillance, what we refer to here as the usual suspects. Such approaches remain challenged by the need to scale up, adapt and make data interoperable in phytosanitary surveillance systems.

Novel ways to detect known pest species

Multiple new sources of information can be used for more effective detection and monitoring of plant pest species, both in crops and reservoirs.

Surveillance through insect-related volatiles

Traps baited with pheromones or kairomones (allelochemicals that are favorable to the organism that receives the signal) have been used since the 70 s, thereby allowing the optimization of control measures in time and space. The exponential increase in the introduction of non-native insects into other continents includes more and more species that had not yet been found outside their native range (Seebens et al. 2018), and thus are not included in the quarantine lists. Since these species are unexpected, their detection at entry points cannot rely on traps baited with specific attractants. However, the deployment of traps baited with broad-spectrum semiochemical lures could be an early detection tool. For example, a cocktail of 10 cerambycid pheromones has been tested successfully as a generic attractant for the simultaneous detection of multiple taxa of non-native long-horned beetles (Roques et al. 2023), and is now routinely used in baited traps for early detection in French ports. The addition of plant volatiles also enhanced the trapping scope for detection of bark beetle invaders. However, the definition of generic baits for other insect groups remains highly challenging. The detection of odors emitted by insects (pheromones) or by the plants they feed on (herbivory-induced plant volatiles) may soon offer alternatives to olfactory traps for real-time in-field performance. Valuable progress in the coming years is expected from the development of the nanochemistry toolbox and supramolecular chemistry, and from the use of biosensors in which olfactory proteins selectively bind specific odorants and are coupled to sensitive transducers (Bohbot and Vernick 2020; Ivaskovic et al. 2021).

Surveillance by vectors

Using insect vectors as sampling agents in crops and surrounding habitats could help to scale-up early warning and long-term monitoring of vector-borne pathogens (see Text box 2 for pathogen monitoring from non-vector insects viewed as sentinels). The specific detection of a target pest in its vectors has already been reported in areas supposedly free of pathogens based on plant surveillance (Farigoule et al. 2022; Rosario et al. 2015). High-throughput screening methods may be used on known vector-pathogen pairs. While the enrichment of viral particles from pools of vectors (vector-enabled metagenomics; Ng et al. 2011) has proven feasible, costs of such genome skimming approaches are still prohibitive for surveillance of multiple pathogens over large geographical and temporal scales. Indeed, pathogens might not be detected due to competition between target and non-target nucleic acids during the sequencing process. Moreover, reference databases for assigning genomic fragments to any target species or strain are far from being readily available. The development of protocols to target multiple genomic regions of the most damaging pathogens to European agriculture in vector communities (e.g., using amplicon sequencing or RNA probes to capture new variants) would be helpful both to discover unknown vectors and for the early detection of pathogens.

Surveillance by automated imaging

Recent technological advances allow, or will soon allow, image capture of the field at a wide range of spatial and temporal scales and resolutions, from remote sensing or drone images, handheld sensors (e.g., smartphones), to real-time image capture by automated laser sensors. In particular, in the area of plant health, many published studies have shown, at least at the proof-of-concept level, the potential of optical sensors and computer vision methods for in situ automated detection of specific disease symptoms and insect pests, including vectors of plant pathogens (Mahlein et al. 2018; Nansen and Elliott 2016; Oerke 2020). A desirable feature of automated imaging is its capacity to detect some diseases even when plants are presymptomatic or asymptomatic (Galvan et al. 2023; Hornero et al. 2021; Oerke 2020). However, some challenges should be addressed for a broader use of image-based phenotyping and a more efficient surveillance of (re-)emerging pests affecting agrosystems and forests (Luo et al. 2023). First, there is a need to work with pathologists, entomologists and field experts to build and share large annotated datasets on targeted diseases or insect pests to use state-of-the-art machine learning models that solve classical problems in computer vision (e.g., identification, object detection, segmentation) with the best performance (Chai et al. 2021). In this process, domain generalization approaches may overcome the lack of ground-truth knowledge (see "AI-enhanced molecular or image-based diagnostics" section). Another challenge is to define and acquire the best signals (e.g., wavelengths) to improve detection of target organisms. This hardware development is particularly important to provide future optical sensors dedicated to surveillance of disease symptoms and insect pests (Mohammad-Razdari et al. 2022).

Discovery and surveillance of reservoirs

Pests are often not restricted to their main cultivated host plant(s). They can infect weeds within the cropped field, wild plants in surrounding ecosystems or ornamental plants on nearby private properties (Yazdkhasti et al. 2021). Their life cycle can be complex, with different stages in various substrates such as air, water, soil or plant products (Morris et al. 2022). Often underestimated, non-cultivated plants and alternative substrates can play a crucial role in the dynamics of epidemics as shelters for pathogens or insects (pests or vectors). Thus, these reservoirs should be integrated into disease surveillance strategies and risk assessment. However, identifying them can be challenging for many reasons. For example, infected plants may be asymptomatic, their abundance can vary in agroecosystems, and the insect vectors are not always known or may be highly diverse. Consequently, reservoir discovery may involve extensive sampling from fields or biorepositories, followed by conventional or advanced pest detection methods, which may be ubiquitous (see "Monitoring generic substrates to develop multi-pest surveillance and Sentinel plants" sections) or more specific (see "Diagnostics with dogs, Monitoring the evolution of emerging pest populations and Monitoring resistance to plant protection products" sections; Brooks et al. 2022). The use of insect vectors collected from the environment (see "Surveillance by vectors" section) can help identify potential reservoir plants (Inaba et al. 2023). After pest detection, integrated research is required to decipher their ecological cycles in agroecosystems, identify the drivers of virulence, and quantify spillover potential at the field and landscape levels (see "Fine-tuning surveillance below the species level" section; Morris et al. 2022; Papaïx et al. 2015; Power and Mitchell 2004). Once characterized, reservoirs need to be monitored using approaches that may differ from those used for standardized and referenced field crops (see "Surveillance by automated imaging, Controlled-cost surveillance approaches, Controlled-cost surveillance approaches, Alternative surveillance approaches based on data mines, Facilitating the integration of data from multiple sources and Interpolation and extrapolation of information" sections).

Diagnostics with dogs

Dogs possess remarkable olfactory and memory skills that have been employed empirically over millennia to detect and localize a broad range of scents, but only in recent decades to detect diseases (Juge et al. 2022). The use of sniffer dogs, particularly in the fields of medical diagnostics and conservation biology, has expanded rapidly in recent years. In particular, dogs have demonstrated a great ability to detect human, animal and plant pathogens (Gottwald et al. 2020; Jendrny et al. 2021) and a number of threatened and invasive species, including invertebrates (Grimm-Seyfarth et al. 2021). This rapidly growing field opens up invaluable opportunities for plant health, with respect to the monitoring of pest species of concern. Wider use of sniffer dogs would allow low-tech, real-time and mobile detection in various environments (crops and their environment, cargo zones, etc.), with a sensitivity that would allow earlier detection than with traditional molecular or image-based techniques (Gottwald et al. 2020). However, for optimal deployment of canine olfactory detection, it is necessary to better understand the olfactory capabilities of detection dogs and the factors that influence their performance, particularly in real-world conditions. Moreover, to ensure high-quality reproducible results and large-scale deployment (for numerous pests, with numerous dogs), it is crucial to establish standardized training designs and performance assessments that meet the rigorous validation standards employed in laboratory detection methods (Juge et al. 2022), noticing that dog training is generally pest-specific.

Fine-tuning surveillance below the species level

Anticipating and targeting pest monitoring and control often requires the identification, within pest species, of particular populations that pose an elevated risk. The subsequent paragraphs highlight the main situations in which surveillance is conducted at an infraspecific level. They collectively cover four necessary steps to monitor populations of concern: (i) defining which population may be of concern, (ii) identifying in which environments they are likely to emerge, (iii) developing specific diagnostic tools that are sensitive enough for early detection, and (iv) implementing monitoring actions in relevant environments.

Monitoring the evolution of emerging pest populations

The worldwide experience with COVID-19 and its causative agent (SARS-CoV-2) has reemphasized the need to monitor the causative agent of a disease at the level of the genotype (Dorp et al. 2020). Beyond the viral perspective, this requirement may apply to populations of all pest groups. Different genotypes from the same species may differ substantially in their transmission, colonization and aggressiveness on individual hosts. These life history traits shape pest dynamics and determine major agronomic features such as host range, and damage on resistant and tolerant cultivars as well as resistance to pesticides (Latorre et al. 2023). Besides monitoring individual genotypes, it is also important to characterize coinfections, as they tend to generate new genotypes with enhanced virulence potential through genomic recombination (Bhat et al. 2022), alter population dynamics (Susi et al. 2015), and impact crop damage (Bellah et al. 2023). Whatever the nature of the (re-)emerging organism —virus, bacterium, fungus, oomycete, nematode or arthropod— monitoring the evolution of pest populations typically involves a large number of samples that are characterized using molecular genotyping or whole genome sequencing. The present diversity of high-throughput sequencing technologies provides exciting opportunities to obtain low-cost and rapid in-field genomic data to track pathogen genotypes (Radhakrishnan et al. 2019). Together with adequate bioinformatics tools and population genomics concepts, this approach is used to monitor ongoing epidemics and reveal the origin of specific genotypes (Campos et al. 2021; Jombart et al. 2014). Estimating the divergence date from closely related genetic groups and retracing routes of introduction or invasion is essential for developing a knowledge-based disease management response. For instance, the demonstration that the two dominant groups of *Xylella fastidiosa* in southeastern France, including Corsica, diverged from their American relatives about 50 and 30 years ago and established in southeastern France before being introduced in Corsica (Dupas et al. 2023) suggests that the current eradication strategy in mainland France has a very low chance of success.

Risk of establishment and adaptive potential

Genetic polymorphism data obtained from the whole genomes of a sample of recently captured individuals of a given pest species can enable two types of inference, provided there is a reference database containing similar data from a large number of populations sampled in the native and invasive range of that pest. First, it is possible to determine the most likely genetic origin of these individuals, which corresponds to the most likely source population(s) in the database (see "Origin, spread and arrival of pests and Monitoring the evolution of emerging pest populations" sections). The risk of establishment and spread can be considered particularly high if the captured individuals belong to an "invasive bridgehead" population (i.e., a particular invasive population that acts as a source for many other large-scale invasions in distant areas; Estoup and Guillemaud 2010). Second, one can estimate the expected fitness of the captured individuals relative to the sampled region features, which is a key component of the risk of establishment and spread of the sampled propagule in the area where it is captured (see "Adaptive criterion" section). Indeed, the difference between the actual genetic composition and the optimal genetic composition in the new environment, a measure called genomic offset, can be used to assess the adaptive potential of an emerging population in a new environment (Bay et al. 2018; Láruson et al. 2022; Rhoné et al. 2020).

Preparedness for the monitoring of future genotypes of concern

Experimental evolution (EE), either in the laboratory or in mesocosms, using selection pressures imposed by the experimenter (biocides, plant immunity, abiotic stresses, etc.) could be another approach for defining in advance which variants are of concern. EE could be representative of a real-world emergence, as shown for viruses (Hajimorad et al. 2011) or nematodes (Castagnone-Sereno et al. 1994) overcoming plant resistance factors, or for wheat blast resistance to a fungicide (Latorre et al. 2023). However, EE often lacks exhaustiveness and representativeness. The phenomena to target could include resistance-breaking, resistance to plant protection products (PPPs), resistance to physical stresses or increased persistence in the environment, host jump risks, phenotypic reversion of attenuated cross-protection agents, etc. Specific diagnostic tools could rely on phenotyping (usually costly and labor intensive and almost impossible to implement on a very large scale) or genotyping (increasingly affordable given the development of high throughput sequencing). However, genetic-based diagnostic tools may be hampered by uncertainty in the phenotype-to-genotype mapping or by the diversity of genetic events (mutations, recombination, hybridization) to target. For example, resistance-breaking pest genotypes can show a tremendous diversity (Daverdin et al. 2012) of structural variations (mutations, deletions, insertions, inversion, translocation, duplication), which may require resorting to a phenotypic diagnostic.

Monitoring resistance to plant protection products

Pest genotypes that are resistant to PPPs are a major concern, because PPPs exert strong selective pressures on pests, which thus generally evolve resistance to PPPs. In addition, the current decrease in the diversity of modes of action of the available chemical substances (at least in Europe; Marchand 2023) will likely lead to overusing the remaining ones and thus increasing the selective pressure and the associated probability of pest resistance. When the genetic determinants underlying resistance are known and simple (which is often the case of target-site resistance mechanisms), high throughput molecular detection methods can be developed for surveillance in the field. However, resistance to some synthetic PPPs has complex genetic bases (e.g., non-target site resistance, behavioral resistance) and their study requires biotests or challenging field monitoring techniques. This issue is more acute for biocontrol agents, against which pests can also evolve resistance (Bardin et al. 2015; Leftwich et al. 2016; Tomasetto et al. 2017). The development of fast and accurate methods for monitoring such resistances requires more knowledge about the genetic architecture and evolutionary potential of the traits involved (Green et al. 2020). An additional challenge for the surveillance of resistance is the huge diversity of resistances that may evolve. This diversity originates from the combination of the diversity of PPPs causing selective pressures and of the number of plant pest species with their genetic peculiarities. It is therefore necessary to prioritize resistance surveillance based on measurable criteria such as the level of selective pressure, the ability of pests to adapt, and the economic impact on the crop.

Building cooperative surveillance systems

Here we emphasize the need for inclusive and collective approaches as well as timely and cohesive information flow between stakeholders with the goal of targeting optimal surveillance of pest emergence and preventing breakdown of cooperation and misalignment of effort. Developing such cooperative systems should allow increasingly decentralized and data-intensive monitoring of invasive organisms that could benefit from a multitude of opportunities, in particular low-tech solutions and frugal innovation as well as sources of data not initially dedicated to surveillance purposes, which may prove to be advantageous in a cost–benefit balance. Seizing these opportunities, however, requires (i) bringing together different disciplines supported by research infrastructures (Cardon and Barbier 2017); (ii) organizational prerequisites including a polycentric system of governance and adaptive capabilities for the surveillance of emergence risks and biosecurity issues (Cook et al. 2010), and (iii) technical resources such as versatile integration, interpolation and extrapolation methods to cope with heterogeneous data.

Plant health as a commons

While crop production relies on many actions undertaken by individuals at the farm scale, surveillance and pest control need to be handled at larger scales (Regev et al. 1976). Surveillance strategies limited to administrative boundaries result in suboptimal pest control (Radici et al. 2023; Thompson et al. 2016), highlighting the need for decision-making at broader socio-ecological scales. Therefore, pest surveillance is a collective action that implies the coordination of stakeholders (farmers, cooperatives, plant health companies, extension services, etc.) and is often the subject of social dilemmas (Bagavathiannan et al. 2019). A large international survey of 250 pest surveillance systems led to the identification of three types of systems with different assets (R4P_network 2021): (i) private systems, which exhibit superior funding capabilities and operate across a majority of agricultural regions; (ii) academic systems, which focus on a limited range of pests and pathogens, but are proficient at detecting emergences and largely benefit from scientific knowledge and analytical capacity; (iii) governmental systems, which favor information dissemination and encompass a diverse range of actors involved in pest surveillance. The survey highlighted that even if a surveillance system can be improved by combining the complementarities of private, scientific and governmental actors, a comprehensive collaboration among them (and the associated benefits on surveillance effectiveness) is rare. Every actor has capabilities, resources and information that can contribute to improving plant health surveillance. Efficient and resilient surveillance requires every actor to share their piece of the puzzle and to contribute to the social infrastructure that produces information about pests and plant health. From this point of view, plant health surveillance is indeed a "commons" (Ostrom 2015) that requires "commoning" (Euler 2018) among different actors and territories.

Further enhancement of pest surveillance systems requires: (i) strong participation of stakeholders and large-scale coordination, and (ii) organizational innovations adapted to the ecology of pests and based on shared agency and the capabilities of the actors. This differs from structural compartmentalization induced by the Taylorian division (Kanigel 2005) of agri-production activities and administrative boundaries of agency. Thus, we need to develop pest surveillance as a commons (Ostrom 2015). Firstly, pest surveillance should not solely be the concern of public authorities, academics, or plant health companies. To this end, raising public awareness (see Text box 1.2) is crucial to encourage broader stakeholder participation (Brown et al. 2020). Secondly, the reconfigured surveillance systems should be inclusive, facilitate surveillance tasks at the individual level, and promote collective actions. The following paragraphs present perspectives in these directions.

Information dissemination for inclusive surveillance

The impacts of emerging pests can be limited if timely information is available to the relevant stakeholders and if these stakeholders are organized into relevant networks for pest surveillance and control. This not only involves the top-down dissemination of information from central actors and public administration but also the upstream flow of information from farmers, value-chain actors, and intermediaries, who are directly connected to fields, greenhouses, farm environments, natural and urban areas (Sherman et al. 2019). The effectiveness of information systems for pest surveillance and control relies on the cohesion among these actors, the equitable distribution of information about the existence of threats and the severity of their emergence, the relevance of indicators communicated to the different actors (considering their roles, responsibilities and analytical capacities), and the availability of means and tools for surveillance and control. Information dissemination is crucial because poorly-informed actors struggle to make decisions and to promptly respond to critical situations. Accuracy of actionable knowledge is also essential to promote collective action and avoid potential breakdown of cooperation. A fragmented distribution of information leads to asymmetries, which erode trust and can result in non-cooperative actions (Dasgupta 1988). However, it is important to consider that the circulation of information depends on knowledgeable actors who operate within their professional jurisdictions, commitments, strategies, and privacy. Consequently, differences in the perception and utilization of information for setting up measures or triggering actions may lead to informational feedback (Mory 1992) that may challenge the consistency of the information system over time. Such differences can obscure the accountability of pest emergence, create disparities in the assessment of priorities for plant health, and even result in misalignment in mobilization efforts. The surveillance of emergence is thus an excellent context in which to study the role of information flow and informational feedback in the (sub)optimal state of surveillance. Such studies may be carried out in the framework of empirical research grounded on collection and analysis of data characterizing the socio-economic sector of interest (Glavee-Geo et al. 2022) or in the framework of companion modeling and serious games (Étienne 2013; Jouan et al. 2021).

Transition to decentralized and data-intensive monitoring

The present technological and societal context provides the opportunity to build more collaborative and ambitious surveillance systems. We can indeed leverage in this aim recent developments in high-throughput sequencing as well as computer vision for automated detection and classification (see "AI-enhanced molecular or image-based diagnostics" section), predictive models for pest spread, and the permeation of environmental concerns throughout society (Chai et al. 2021; Cordier et al. 2021; Ryan et al. 2018; Viboud et al. 2018). Surveillance of (potentially) emerging organisms is generally pest-specific, affected by delays between sampling and data analysis, and limited in terms of monitored sites (except in exceptional cases, such as *Xylella fastidiosa* in Europe). However, e-DNA is widely used by researchers for biodiversity assessments without a focus on pests. Moreover, participatory observatories (possibly exploiting smartphone geolocation and camera) are proliferating, for biodiversity surveys but also for early detection and monitoring of pests (Epanchin-Niell et al. 2021; Hester and Cacho 2017; Redford et al. 2023). These trends and the easy-to-use diagnostic tools and detection approaches presented in "Surveying for pests using broad-spectrum tools and Surveying the usual suspects from new perspectives" sections could be used to develop decentralized and data-intensive monitoring of invasive organisms integrating the contribution of a wide variety of stakeholders. This perspective will require (i) truly collaborative surveillance systems with closer links and knowledge transfer between communities of stakeholders, (ii) some numeric solutions for importing, annotating and storing data, and the ability to share and merge disparate data, (iii) some modeling and analysis tools (taking into account different notification rates for different pests), the implementation of these tools in reliable automated pipelines to process and analyze data in real time, and (iv) cost–benefit analyses to determine which components of surveillance strategies are most relevant (Caley et al. 2020).

Controlled-cost surveillance approaches

Low-tech solutions and frugal innovation, which refer to affordable, easy-to-use, sustainable methods or tools for monitoring the spread of pathogens, were first formalized for the management of human diseases (Miesler et al. 2020). They can be used in resource-limited situations where advanced technology and data collection systems may not be feasible, and are hence especially inclusive and prone to be adopted in large stakeholder communities. They can be envisioned as human-centered alternatives to the common practice of promoting cutting-edge and expensive technologies (Sarkar and Mateus 2022). Nevertheless, low-tech solutions can be deftly combined with modern technologies, such as mobile apps, remote sensing and AI to provide more accurate and timely information on the emergence of plant diseases or vectors. Such tools and methods include well-designed pest recognition cards, easy-to-use trapping systems, simple kits for pathogen detection in fields (Donoso and Valenzuela 2018), which can all be used by farmers, agricultural groups, advisors or distributors. Sentinel plants surveyed by botanical gardens or repositories (see "Sentinel plants" section) or the use of dogs for detecting specific diseases (see "Diagnostics with dogs" section) can also be considered as low-tech opportunities. They can be linked to structured initiatives to promote collective monitoring of pests and potential reservoirs, or to build local agricultural initiatives such as sharing agricultural equipment, farmers' workshops or FabLabs to facilitate the transfer of skills and knowledge (Angeli Aguiton et al. 2022). Professional training combined with efficient and simple reporting systems are crucial for the success of such settings that should be strategically deployed in risk areas or entry points of pests. Irrespective of the surveillance approach envisaged, the spatial optimization of surveillance locations can be developed to minimize either the expected cost of mitigating outbreaks or the expected time to first detection, taking into account the constraint of surveillance costs (Yemshanov et al. 2019).

Alternative surveillance approaches based on data mines

Standard surveillance systems for emerging pests conducted by governmental organizations and agricultural sectors can be complemented by alternative approaches. This can allow for increased observation effort and coverage at lower costs that are shared or even supported by other socioeconomic sectors. These alternative approaches reviewed by Ristaino et al. (2021) can, for example, rely on scientific observations (Hily et al. 2020), citizen science data, and more generally, citizen-generated data through crowdsourcing (Brown et al. 2020; Streito et al. 2023), information from scientific literature, media, social networks, governmental and non-governmental organizations (European_Food_Safety_Authority et al. 2021), imagery from virtual navigation services enabling visualization of surroundings along transportation routes (e.g., Google Street View; Rousselet et al. 2013), signals transmitted by ground-based radars (Lukach et al. 2022), and satellite data (Oerke 2020). Each type of data can be independently utilized to provide complementary information to relevant stakeholders. However, the next step is to integrate these data within a coherent statistical framework that appropriately weights each type of data. This requires, first and foremost, the organizational and technical prerequisites discussed in "Facilitating the integration of data from multiple sources" section. It then necessitates analytical tools to establish the link between each type of observation and the signal of interest, measure the information content they provide, assess associated uncertainties and biases, determine their spatial and temporal coverage (which may require downscaling or upscaling), unravel dependencies between observations, and correct the weighting of observations that provide partially redundant information. Achieving this integration while assessing the cost of each type of observation can help in streamlining the alternative surveillance approaches that are employed and, potentially, reducing sampling effort in standard systems or enabling more efficient deployment of such effort across time and space (i.e., developing risk-based surveillance using alternative approaches). However, this requires some form of sustainability for alternative approaches: long-term accessibility, consistency in the type of information provided, and timely alerts if these features change.

Facilitating the integration of data from multiple sources

The proposals mentioned in "Alternative surveillance approaches based on data mines" section involve integrating data ranging from those about the pests themselves to the biotic and abiotic characteristics of the environment. Such data are collected at various spatiotemporal scales and for different purposes. As such, they are not only heterogeneous in their nature but also in their quantity, representativeness, precision and reliability for surveillance. With the rise of advanced technologies in diverse areas such as genomics, remote sensors, robotics and AI (Garrett et al. 2022), plant health surveillance is now also challenged –like public health– by a lack of metadata, i.e., the structured information about the data such as spatial, temporal and taxonomic coverage, methods and protocols (Rasmussen and Goodman 2019). Metadata are indeed critical to determine the relevance of the data, to define how they can be combined for analysis, and to enhance interoperability using semantic vocabularies as defined in structured metadata languages for data indexation (Jonquet et al. 2018). In the absence of data standardization (see https://rdamsc.bath.ac.uk for examples of standards), automatic tools for alignment of data and semantic references contribute to unifying the representation of heterogeneous data, for example by entity-linking methods and alignment standards (e.g., SSSOM *A Simple Standard for Sharing Ontological Mappings*; Matentzoglu et al. 2022). Sharing and opening surveillance systems (from the cooperative perspective suggested above) would require open-science databases as a commons (Ostrom 2015), dedicated IT infrastructure and curators to facilitate data integration, exploration and queries. Such open platforms will need to address issues related to data security and privacy, and to reach agreements between various partners who may have different objectives (Weisberg et al. 2021). Some of the challenges underlying cooperative systems could be reduced by identifying common monitoring objectives. Common targets can be environmental ensembles, such as environmental networks connected by surface water or air (Aguayo et al. 2021), or areas forming coherent agro-ecological and socio-economic units, where the diverse actors share inherently interdependent concerns (e.g., biodiversity, urbanization, environmental resources, agricultural production, local industry and employment).

Interpolation and extrapolation of information

Even if we tend toward decentralized and data-intensive monitoring, data generally covers time and space in a very patchy and non-uniform manner. Moreover, the monitored points or areas are usually representative of only a subset of possible environmental conditions and human interventions. Interpolating (and even extrapolating) the signal of interest (e.g., disease level, regulation score, probability of exceeding a threshold) in time and space based on raw observations is crucial for providing information tailored to each stakeholder, whether they require localized information (e.g., concerning a farm distant from surveillance points) or aggregated information (e.g., on the health status of a territory). Approaches such as smoothing, kriging, autoregressive modeling, and machine learning (Martinetti and Soubeyrand 2019; Ver Hoef et al. 2018), which rely on spatiotemporal proximity and (possibly) on covariates associated with observations, enable this interpolation while providing measures of uncertainty. The spatiotemporal distribution of uncertainty can moreover be used to adapt sampling with the aim of optimally reducing areas of high uncertainty (Brus 2019). One of the current challenges is to simultaneously (i) identify the variables with high predictive power that should be prioritized among the large number of variables characterizing environmental conditions and human interventions, (ii) incorporate a dynamic or even mechanistic component into the interpolation process, and (iii) explicitly model the relationship between the signal of interest and the observations, which may have different natures if they are obtained from different observation means. This perspective could rely on the hybridization of the mechanistic-statistical approach (Papaïx et al. 2022) and machine learning (Bi et al. 2019). More generally, AI coupled with mechanistic approaches has the benefit of identifying unsuspected relationships between different biological and environmental phenomena, leading to more realistic representations of biological systems. This is one intended application for AI in understanding animal health (Ezanno et al. 2021), which should extend to plant health.

Discussion

Information is the key to (plant) health management

Plant health surveillance systems are the road maps for the operators who assure health protection (Langmuir 1971). By dissecting the relationship between surveillance and health protection, an essential and generic link arises: "information". The production, dissemination, utilization and asymmetries of information are central topics in economics (Stiglitz 2000), including in economics of the agricultural sector. When provided to stakeholders, information generated from surveillance contributes to decision-making about possible monitoring measures for protecting health, as well as other actions including planning and evaluation of health programs and formulation of research hypotheses (German et al. 2001). The term "information" is not simply reciprocally associated with surveillance. As previously pointed out (Hoinville et al. 2013), some activities that do not directly correspond to surveillance actions also provide useful information. For example, an intervention for controlling a disease outbreak provides information about the likely local reduction of disease inoculum. Research and risk assessment activities, which are largely the subject of this article, are additional means of generating information that could improve stakeholder awareness, preparedness and resilience to phytosanitary issues (see Text box 1.1). In order to achieve optimal efficiency, all the activities that provide information to stakeholders should ideally be combined to lead to a level of risk reduction that maximizes social welfare (Hoinville et al. 2013). Paradoxically, this plethora of information from multiple sources could lead key actors to a state of cognitive hypervigilance. Hypervigilance is a state of heightened awareness and sensitivity to potential threats from the surroundings and can lead to high levels of anxiety (Richards et al. 2014). From an evolutionary point of view, it is thought to be the result of a bias in the processing of information aimed at improving the chances of survival (Richards et al. 2014). In plant health surveillance, hypervigilance can be a source of anxiety for key actors, leading to unnecessarily broad and stringent regulations that disorganize and overwhelm the surveillance and response system.

Improving information effectiveness

Information is useful, but its effectiveness (qualitative and quantitative usefulness, and economic benefit) also matters. Surveillance efforts can multiply along the many dimensions presented in this article, and integrate the produced data to improve the level and quality of information while reducing the biases inherent to any single surveillance approach. However, the surveillance system as a whole has to be economically and technically sustainable. Its cost has to be balanced with costs and benefits of crop production, control measures and environmental externalities. Moreover, the sources of data as well as the human resources and tools for collecting, analyzing, interpreting and disseminating data must be available and functional over medium to long terms. Ideally, methods/tools/technologies contributing to the surveillance system have to be timely, representative of the area and the period, accurate, repeatable and cost-effective. These criteria can be the basis on which new approaches must be assessed before they are included in any plant health surveillance system. It is worth stressing, however, that what does not seem feasible one day may be feasible later (with technical innovation, cost reduction, new requirements, etc.) and hence deserves to be explored in research programs. Moreover, some approaches might not meet the criteria mentioned above when they are considered alone but could be complementary and hence valuable in a multimodal surveillance system. For example, one could envisage to couple a low-accuracy but cheap participatory monitoring approach with high spatiotemporal-coverage, and a high-accuracy but expensive diagnostic tool that can only be applied at a few locations and times, thanks to a statistical method that leverages data from the participatory monitoring by calibrating them with diagnostic data. Therefore, when designing a multimodal surveillance system, cost–benefit analyses (Hanley and Roberts 2019) need to be carried out to identify the combination of surveillance approaches that will lead to effective information. Cost–benefit analyses, which might be implemented in the future in empirical pilot studies at territory scales, should not only be performed for comparing multimodal surveillance approaches, but also for assessing the added value of surveillance as a component contributing to preventive pest management, allowing the development of a more sustainable agriculture in general and the reduction of pesticide use in particular (Cros et al. 2021; Fuller et al. 2020; Picard et al. 2019). Cooperative surveillance approaches based on both opportunistic data and stakeholder communities much larger than the farmer community is a way to reduce the burden of surveillance/prevention on the farmers and, hence, make it more acceptable the adoption of pest management practices with potentially reduced effects on the pests but significantly reduced negative impact on the environment. Therefore, surveillance must be considered as a full-fledged component of agriculture and included in the calculation of costs, benefits and externalities of the agricultural system. We conjecture that this calculation, when considering the potential emergence of pests, may lead to a choice of surveillance approaches that (i) allow the detection of weak signals enabling early preventive or limited curative actions (see "Surveying for pests using broad-spectrum tools and Surveying the usual suspects from new perspectives" sections), and (ii) make it possible to characterize the conditions that avoid the need for curative action (see "Anticipating the emergence of pests" section); see Morales et al. (2021) regarding preventive versus curative pest management. Finally, it is important to emphasize that the path from innovation to implementation also includes the challenges of integrating new surveillance technologies within the stringent regulatory frameworks of international trade.

Towards a better understanding of the factors involved in pest emergence

Beyond their primary objectives of better anticipating and monitoring pest (re-)emergence, the research directions outlined in this article and summarized in Suppl. Figure 2 can provide insights into (re-)emergence factors and their interactions. In turn, a better understanding of the role of the factors contributing to emergence is crucial for the development of effective prevention and mitigation strategies (Corredor-Moreno and Saunders 2020). Further thinking could therefore focus on the relevance of the proposed research directions to elucidating and quantifying the contributions of emergence drivers (Bebber 2015; Corredor-Moreno and Saunders 2020; MacLeod et al. 2010). Here we propose a classification of pest emergence factors into three main categories (Table 1): (i) natural and human-mediated dispersal (air, surface water, trade in its local and global dimensions, hitchhiking, etc.), (ii) genetic and ecological processes and changes in the biotic environment (genetic variability of pests, pest adaptation, pathogen spillover, plant selection, reservoir hosts and environments, introduction of new plant species, biological community features, biological vectors, auxiliaries, competition, symbioses, etc.), and (iii) changes in the abiotic and social environment (climate change, changes in agricultural practices, regulation, land-use and habitat continuity/fragmentation, etc.). Such a categorization can help to identify research gaps in the analysis of the factors of (re-)emergence, and the new avenues of research highlighted in this article that can contribute to filling these gaps.

Relevant scales for the anticipation and monitoring of pest outbreaks

Pest emergence is inherently a multiscale process —from brief local outbreaks to long-lasting pandemics— with local and global drivers. We point out that we have not specified the relevant scales for the anticipation and monitoring of pest outbreaks in this article. Determining the relevant spatial and temporal scales of surveillance data is still a major challenge (Glennon et al. 2021). Models can be part of the solution to this challenge (Lloyd-Smith et al. 2015), particularly multiscale models (Picault et al. 2019). The international dimension of surveillance has long been recognized as a crucial aspect contributing to the management of transboundary pests (Domenech et al. 2006). Several research directions outlined in this article contribute to this dimension, such as horizon scanning or epidemiological intelligence, exploiting new capabilities in artificial intelligence applied to texts (Morris et al. 2022), and the design of worldwide cooperative surveillance networks based on new descriptions of connectivity at a global scale (Radici et al. 2023). National and international organizations in charge of alert systems should be able to update their processes in a timely manner, taking into account such new trends with high potential and benefiting from new technologies or new concepts (Kreuze et al. 2023). Finally, a permanent interface between the research community and alert system organizations seems essential to promote the rapid integration of innovation into surveillance and, reciprocally, of surveillance data into research projects.

Putting plant health in the One Health context

At the interface of human, plant, animal and environmental health, we face a wide spectrum of risks, further highlighting the need for a comprehensive and interdisciplinary approach. These risks include food scarcity, environmental contamination, and pesticide toxicity. Damage to plant health can result in a loss of food production, potentially leading to malnutrition or famine. Plant health issues can facilitate the transmission of general pathogens such as *Salmonella enterica* responsible for enteric infections, or in acute or chronic poisoning of consumers by mycotoxins (ergot, fusariosis, etc.; Andrivon et al. 2022; Brandl 2006). Pesticides in agriculture can affect both producers and consumers through residue exposure, having important health implications (Andrivon et al. 2022). Furthermore, the interplay between plant pests and control measures affects ecosystems, disrupting ecological functioning. In response to these multifaceted risks, we advocate a comprehensive One Health approach of plant health and its surveillance, with a clearer integration of human, animal, plant and environmental aspects. This widens the scope of plant health surveillance, shifting to epidemiological indicators highlighting future risks rather than present dangers. This approach will facilitate the transformation of agricultural practices towards those that both maintain plant health and avoid or mitigate risk in human health, animal health and the environment, thereby promoting agroecology and organic farming. To improve global health, we need to build bridges between monitoring systems for plant, animal and human health as well as for environmental quality (Hulme 2020). This means developing information flows that are useful for decision-making and action (Soubeyrand et al. 2020), and increasing cooperation in terms of structures, methods and shared data (epidemiological, molecular, etc.). Regarding the latter point, the ideal of unrestricted data sharing will be challenged by legitimate concerns and constraints related to intellectual property, cultural sensitivities, privacy, and potential economic impacts. While these obstacles need to be considered, we remain convinced that wider access to data adequately anonymized (as advocated for instance within the European Union) is essential to significantly improve global biosecurity efforts by enabling more effective and timely responses to emerging threats. In any case, open, interoperable and regularly updated catalogs of data from heterogeneous sources are needed to take account of the necessarily heterogeneous nature of the data considered in such cooperation (Morris et al. 2022). Considering plant health in an upgraded One Health approach will allow for a better understanding and management of plant health problems without the hegemony of one-size-fits-all approaches.

Conclusion and perspectives: advocating Integrated Health Surveillance (IHS)

Plant health is the roughly visible result of processes in a complex system (Ladyman et al. 2013) with boundaries extending much further than conventionally thought. Plant health is indeed entangled with numerous biotic and abiotic processes, among which some are well known (those classically included in the famous disease triangle linking the host, the pest and the environment, including human actions) and others that need to be disentangled or decrypted (typically, some processes related to One Health or involving large trophic communities and regulation networks at all scales). The research directions envisioned in this article are options that can contribute to enhanced surveillance and that can unravel from different angles the complex system driving plant health. However, how many and which options should be adopted in which situation and how they should be combined remain open questions. A major challenging perspective in that respect is to identify the "game changer approaches" in terms of information efficiency, i.e., the combinations of approaches that can significantly outperform or fundamentally change current surveillance systems for single or multiple, specified or unknown pest(s), while complying with the stringent regulatory frameworks governing international trade. Addressing this challenge is beyond the scope of this article. We can state, however, that it at least requires specifying criteria that measure surveillance efficiency and performing the cost–benefit analyses discussed above (see "Improving information effectiveness" section). In addition, fully addressing this challenge, in the present era of global change, necessitates considering not only incremental but also radical innovation (Dosi 1982). The risk and uncertainty associated with radical innovation may require governmental intervention, especially in the presence of generally non-commodity aspects such as environmental health in agro-ecological systems (Dosi 1982), but also "dynamic capabilities" of economic actors to transform their organization towards agility (Teece et al. 2016) as pointed out in "Relevant scales for the anticipation and monitoring of pest outbreaks" section. By (i) cultivating this adaptive positioning with respect to innovation and research, (ii) favoring anticipation in pest emergence, (iii) considering both broad-spectrum and specific surveillance approaches, (iv) assessing these approaches within a cost–benefit framework, (v) promoting fully collaborative surveillance systems, and (vi) setting plant health in the One Health context from an interdisciplinary perspective, we advocate for Integrated Health Surveillance (IHS), where the health of plants, the environment, animals and humans are considered in an inclusive and collaborative manner that integrates a multitude of actors and technological approaches.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s43170-024-00273-8.

Supplementary material 1: Figure 1. Representation of research directions for enhanced surveillance.

Supplementary material 2: Figure 2. Summary of research directions and approaches for enhanced surveillance.

Supplementary material 3: Table 1. List of topics the authors contributed to in the article.

Supplementary material 4: Table 2. Examples of event-based surveillance (EBS) systems to monitor and detect plant health threats and databases integrated into EBS systems.

Acknowledgements
We thank the INRAE executive board for prompting the reflection presented in this article and encouraging the Plant Health and Environment division to make it multidisciplinary beyond its typical scientific scope.

Author contributions
Conceptualization: SS, AE, GT, CEM. Methodology: SS, AE, GT, CEM. Writing—original draft: all authors. Writing—review & editing: all authors. Visualization: SS, AE, NS, GT, CEM. Supervision: SS.

Funding
This review and prospective reflection was supported by the BEYOND project (Grant ANR-20- PCPA-0002), the SEPIM project (FranceAgriMer Grant 3890396), the CLIMESCA project (CLIMESCA: FranceAgriMer Grant 22001641), the CoAct2 project (FranceAgriMer Grant 220001455), the INITIATE project (Grant from the SuMCrop program of INRAE), and the AgroStat project (Grant from the French National Scientific Program PEPR MathsVives).

Availability of data and materials
Not applicable.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare that they have no competing interests.

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Received: 8 January 2024 Accepted: 23 July 2024
Published online: 17 August 2024

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