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A framework to integrate innovations in invasion science for proactive management

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ABSTRACT

Invasive alien species (IAS) are a rising threat to biodiversity, national security, and regional economies, with impacts in the hundreds of billions of U.S. dollars annually. Proactive or predictive approaches guided by scientific knowledge are essential to keeping pace with growing impacts of invasions under climate change. Although the rapid development of diverse technologies and approaches has produced tools with the potential to greatly accelerate invasion research and management, innovation has far outpaced implementation and coordination. Technological and methodological syntheses are urgently needed to close the growing implementation gap and facilitate interdisciplinary collaboration and synergy among evolving disciplines. A broad review is necessary to demonstrate the utility and relevance of work in diverse fields to generate actionable science for the ongoing invasion crisis. Here, we review such advances in relevant fields including remote sensing, epidemiology, big data analytics, environmental DNA (eDNA) sampling, genomics, and others, and present a generalized framework for distilling existing and emerging data into products for proactive IAS research and management. This integrated workflow provides a pathway for scientists and practitioners in diverse disciplines to contribute to applied invasion biology in a coordinated, synergistic, and scalable manner.

Key words: IAS, invasive species, nuisance species, remote sensing, bioinformatics, infectious disease ecology, big data analytics, species distribution modeling, environmental DNA, genetics

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CONTENTS

I INTRODUCTION

Invasive alien species (IAS) are both a major driver and consequence of anthropogenic global change with serious impacts on biodiversity, ecosystem functioning, human health, and economic sustainability (Bellard, Cassey & Blackburn, 2016; Mollot, Pantel & Romanuk, 2017; IPBES, 2019). IAS management and environmental damages cost tens to hundreds of billions of U.S. dollars in individual countries per year (Bradshaw *et al.*, 2016; Diagne *et al.*, 2021). The ecological–economic crisis of biological invasions has been recognised as a priority in international environmental initiatives including the United Nations Sustainable Development Goals (SDGs; target 14.8), previously the Aichi Biodiversity Targets, (Targets 9 and 13) and now the post-2020 Global Biodiversity Framework (Target 6; Essl *et al.*, 2020; van Rees *et al.*, 2021).

Biological invasions show no sign of slowing across time (Seebens *et al.*, 2017), and the severity and spatial footprint of IAS impacts will increase where ongoing landscape and climate change favour invasive over native taxa (Jourdan *et al.*, 2018). IAS management is highly time sensitive; once a population becomes established in a locale, the costs and feasibility of eradication or management often become prohibitive. This understanding has led to the prevailing paradigm of Early Detection and Rapid Response (EDRR; Reaser *et al.*, 2020a) which calls for widespread and coordinated monitoring and collaboration among institutions. Since widespread and frequent monitoring can be difficult to achieve with limited resources, the EDRR paradigm has resulted in an emphasis on proactive approaches in the research and management of IAS. Spatial prioritization or predictive modelling are considered an extremely helpful workflow for operationalizing this paradigm (Ricciardi *et al.*, 2017). Specifically, ecological modelling and forecasting of the environmental niches and potential spread of IAS can facilitate risk assessment, spatial prioritization at early stages of invasion, and management triage (i.e. ranking sites for management) (Carlson *et al.*, 2019; Robinson *et al.*, 2020).

An idealized research and management workflow for generating spatially explicit, actionable predictions can be concisely summarized in six parts (Fig. 1). First, at the decision-maker level, (1) problem IAS are identified and research and management practices are delineated. Next, (2) researchers and practitioners at multiple organizational levels collect and collate spatially explicit information on focal taxa occurrences and (3) relevant environmental characteristics. These data are ideally (4) shared and managed broadly for accessibility and use at multiple jurisdictional scales, and (5) analysed using various forms of ecological modelling and simulation. (6) Researchers and practitioners collaborate with stakeholders and decision-makers to co-produce management and implementation actions from these data, or use these to identify new problems or project

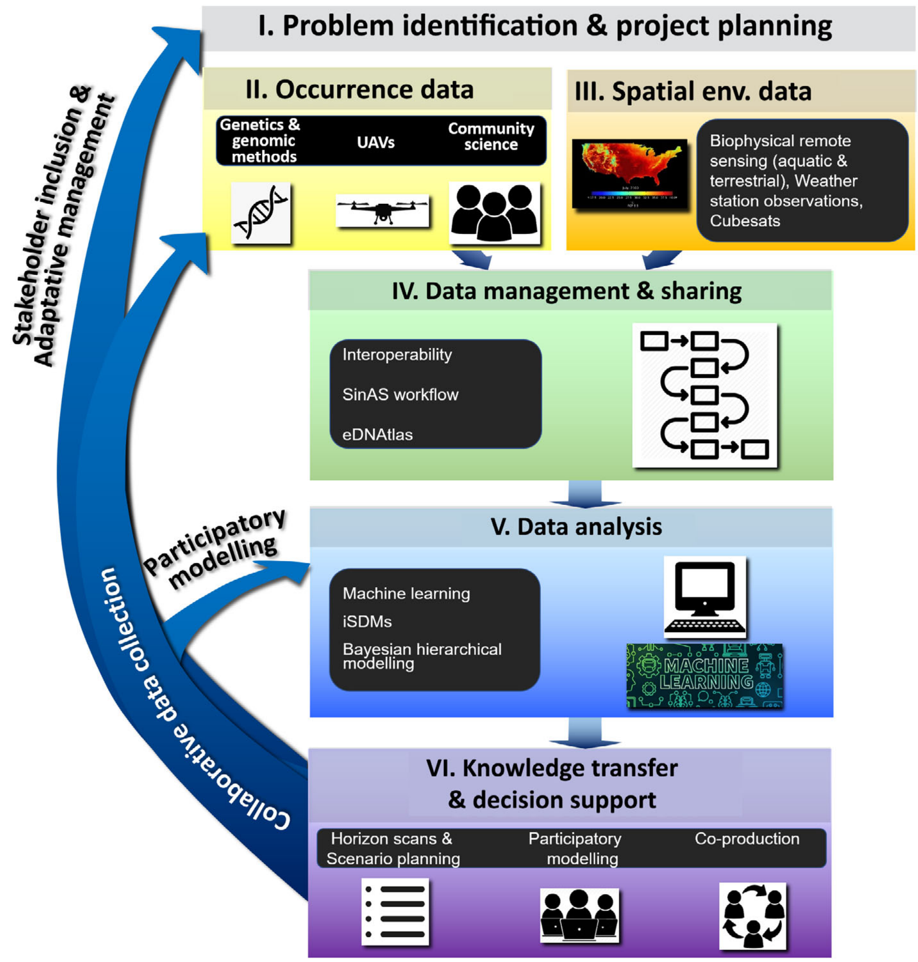

Fig. 1. A framework for conducting actionable, spatially explicit research on invasive alien species (IAS) occurrences and spread to guide management and decision-making. The framework consists of an initial problem identification and project planning step (I), which will be unique to each management scenario, and a generalized workflow (II–VI) which is used as the organizational basis for this review. The workflow can be applied wherever occurrence and spatial environmental data (Steps II and III) are available. Such data can be drawn from existing databases, or added to them to contribute to future or larger-scale research and management (Step IV), and analysed according to project needs to generate relevant inferences of IAS spread or occurrence across space and time (Step V). In the final step (VI), study findings are made accessible and relevant to stakeholders, managers, and decision-makers. Interactions with these data users should ideally feed back into the entire workflow (II–VI), as well as the first stage of the framework. eDNA, environmental DNA; iSDM, IAS spatial distribution model; SinAS, standardising and integrating alien species data; UAV, unmanned aerial vehicle.

priorities, starting the workflow again (Fig. 1). Importantly, this is not the only way that invasion science is or should be carried out, but one example of an especially efficient and powerful approach that makes use of rapidly growing methods and technologies that are becoming more widely available (Ricciardi *et al.*, 2017; Martinez *et al.*, 2020; Robinson *et al.*, 2020).

This workflow integrates several fast-moving fields (e.g. ecological and evolutionary modelling, invasion biology, structured decision-making) punctuated by frequent advances in theory, applications, analytical techniques, and computing applications. In the last decade, the simultaneous and rapid maturation of diverse technologies and practical approaches has generated a surfeit of potentially revolutionary tools that could – in synergy – improve predictive modelling and proactive management of IAS. However, this rapid innovation has outpaced implementation and coordination (Iacona *et al.*, 2019; Lahoz-Monfort *et al.*, 2019; Martinez *et al.*, 2020). Substantial advances have been made in conceptual tools and technologies that have great promise for predicting and reducing spread risk, including approaches to horizon scanning (Roy, Peyton & Booy, 2020), novel methods for occurrence data acquisition (Larson *et al.*, 2020), spatially explicit environmental data (Dauwalter *et al.*, 2017; Randin *et al.*, 2020), and facilitating knowledge transfer and co-production (Shackleton *et al.*, 2019a; see Section VI), but these tools are rarely applied in concert.

There have been repeated calls in the biological invasion literature for integrated frameworks that outline and organize the roles of new technologies in invasion research and management (Dehnen-Schmutz *et al.*, 2018; Martinez *et al.*, 2020; Wilson *et al.*, 2020). Clarification on how different technologies and forms of knowledge can be applied to improve invasion forecasting and spatial risk assessment for IAS spread would be especially valuable for guiding resource investment for biosurveillance and management interventions (Latombe *et al.*, 2017; Robinson *et al.*, 2020). Although several publications have highlighted the utility of individual technologies to invasion biology, none has demonstrated the potential synergies between important, relevant disciplines or technologies in an actionable workflow. Such a framework should clarify the relationships between new technologies, insights from the field of human–computer interactions (Preece, 2016), and on-the-ground conservation applications, and illustrate where the work of natural resources managers and researchers from diverse fields fit into an idealized workflow.

In this review, we survey technological and methodological innovations across diverse fields (including remote sensing, genomics, and big data analytics) and highlight their applications and contributions to an idealized workflow for predictive IAS management. This applied analytical pipeline focuses on supporting decision-making through spatial risk analyses, based on similar frameworks in the epidemiology of emerging pathogens (Fig. 1; Chown *et al.*, 2015; Machado *et al.*, 2019; Hamelin & Roe, 2020; Kress, Mazet & Hebert, 2020). Ideally, it represents a generalizable workflow for collecting and integrating diverse environmental and organismal data on IAS occurrences, analysing these to generate estimates of spatiotemporal spread risk, and informing management decisions and conservation interventions. It also highlights how diverse disciplines can be brought to bear on pressing issues in IAS research and clarifies their relevance to managers and decision-makers. Our overarching goal is to provide a broad introduction to the newest practices and concepts in invasion science and provide a pathway for their synthesis for a proactive, applied approach to research and management to address the biological invasion crisis. Throughout this review, we will highlight examples that represent the successful implementation of various steps in this workflow for context and clarity, making special reference to which step is represented.

We organize our review around a workflow for proactive IAS research and management through spatial prioritization: (1) Problem identification and project planning; (2) Occurrence data; (3) Spatial environmental data; (4) Data management and sharing; (5) Data analysis; and (6) Knowledge transfer and decision support. Notably, our review does not cover the first decision-making step in this framework in which IAS problems are identified and initial projects are planned. Although our section on decision support emphasizes how information can be made actionable to inform this process, this review focuses on steps 2–6, and is especially directed towards scientists, practitioners, and decision-makers engaged in step 1. We focus on those steps in the workflow that are closely tied to recent innovations in the science and technology of invasion science in the hope of highlighting how these new developments can be leveraged in project planning and implementation.

In the first section, we introduce the importance of IAS occurrence data for surveillance and monitoring, then review state-of-the-art and emerging detection methods. Section II focuses on the utility of spatial environmental data to contextualize IAS occurrences and covers exciting developments in remote sensing and earth systems modelling for invasion research. In the following section on databases and data management, we explain the necessity for large-scale databases of these foundational data types, concerns for their collation and management, and current initiatives for centralization and sharing. Next, we cover the range of analytical approaches by which such data can be used to generate spatial estimates of risk, highlighting the particular difficulties and considerations involved with modelling IAS distributions and strategies to address them. Finally, we explore how such analyses can be converted into useful and informative products for stakeholders, decision-makers, and managers, and how to enhance IAS research through knowledge co-production.

Our aim is to encourage the coordinated use and uptake of helpful technologies and approaches in proactive IAS management and research, and to highlight fruitful areas for interdisciplinary collaboration and the application of recent methodological innovations. This work also serves to bridge the gap between advances in multiple fields of ecology and evolutionary biology and their application to IAS, and methods used in an invasion context that may be helpful for research in other ecological sciences.

II IAS OCCURRENCE DATA

(1) Background

Information on biological invasions is needed to inform three major processes in management: designing surveillance and field surveys, prioritizing locations for management interventions, and supporting regulatory decision-making (Sofaer *et al.*, 2019). The workflow around which this review is organized focuses primarily on the latter process (see Section VI), but the same data are useful across all three. This common data currency consists of spatiotemporally explicit occurrences of focal IAS (Latombe *et al.*, 2017). Here we review the diverse sources of IAS occurrence data with special emphasis on emerging or increasingly popular technologies. Before surveying these diverse data sources, it is worth describing two products that are commonly derived from these data to support proactive management of IAS. The analytical methods involved in these two products (Essential Biodiversity Variables, and Species Distribution Models, see below) and their use in a proactive research and management context are discussed in depth in Section V.

Essential Biodiversity Variables (EBVs), i.e. global information products and indicators for assessing biodiversity change, are designed to set unifying standards for monitoring and modelling important biodiversity parameters. Species populations EBVs (Jetz *et al.*, 2019) describe the abundance and occurrence of species across space and time, providing a conceptual nexus and methodological framework for guiding data collection, integration, and modelling to deliver the predictions needed for invasion research, policy, and management (McGeoch & Jetz, 2019; Myers *et al.*, 2021). EBVs are used to overcome data gaps and biases, and deliver predictions of species' spatial dynamics at appropriate resolutions, and consequently are strongly aligned with the needs of proactive IAS management and invasion forecasting (Battini *et al.*, 2019).

Species distribution models (SDMs; also known as ecological niche models and environmental envelope models) are a key analytical approach to modelling and forecasting the dynamics of IAS across space and time and form the primary scientific basis for monitoring and management (Rodríguez-Rey *et al.*, 2019; Seebens *et al.*, 2020). For example, the U.S. Forest Service used an SDM to guide herbicide treatment activities for highly invasive cheatgrass (*Bromus tectorum*; West *et al.*, 2017; workflow Step V).

Species occurrence data serve multiple purposes in invasion management from IAS introduction and establishment to spread and impact (Cheney *et al.*, 2021) and are the primary targets of surveillance and monitoring efforts. Occurrence records encompass both presences (detections) and probable absences (or non-detections) of an invasive organism collected in either its invasive or native range. Surveillance, in which the absence of IAS propagules is tested across time to enable rapid response, is a major management activity that can produce large amounts of absence data for modelling and risk assessment. Multiple technologies and approaches are now available to prioritize monitoring for local EDRR or SDMs at large geographic scales for forecasting range dynamics (see Section V). The need for rapid, cost-effective surveillance over large areas has driven substantial innovation in methods for collecting IAS occurrence data for monitoring and modelling across diverse disciplines (Larson *et al.*, 2020). In this section, we review current and emerging methods for collecting the necessary data to support monitoring, early detection, and fundamental analyses like these in an invasion science context.

(2) Legacy data and data re-use

Although this review section centres around innovations in occurrence data collection, it is worth acknowledging the importance and utility of IAS occurrence data that have already been collected, and that can be used or repurposed for guiding proactive management. Useful data may be collected by local agencies at varying spatial scales, which can mean that information may be widely scattered in different repositories. Although it can involve significant investments to digitise or centralise these legacy data into usable databases, this can be more cost-efficient than re-collecting data and can offer valuable information about trends over time. Legacy data can also be used to guide the use of other detection methods (see sections below) for quantifying and predicting the range and spread of IAS (e.g. Rubenson & Olden, 2020).

Increasingly sophisticated and comprehensive repositories of legacy information are becoming available, for example the BISON program (Table 1) in North America. Young *et al.* (2020) demonstrated a modelling workflow for guiding IAS management by collating occurrence data from BISON and mobile apps (workflow Step II; see Section II.(6)) to predict the habitat suitability of invasive grasses in the USA (fountain grass *Pennisetum setaceum* and goutweed *Aegopodium podagraria*). We focus in greater depth on IAS data repositories and data centralization efforts in Section IV.

(3) IAS detection *via* remote sensing

Remote sensors on satellite or airborne platforms can detect some IAS through direct and indirect observations, allowing for repeated detection without the need for *in situ* searchers or monitoring devices. Such applications are primarily useful for plants (especially trees and grasses) and species that affect them (Vaz *et al.*, 2019; Reeves *et al.*, 2021), although fishes have been detected using airborne LiDAR (light detection and ranging; e.g. Roddewig *et al.*, 2018). Indirect detection of IAS is achieved by identifying physical changes in the landscape that suggest species presence, such as phenology of plant greening that differs from native species (Tian *et al.*, 2020). Indirect detection can also use multiple sensors in concert; for example, Pontius *et al.* (2017) combined hyperspectral data, LiDAR, and thermal infrared observations to monitor emerald ash borer (*Agrilus planipennis*) through detection of their impacts on tree colour, canopy density, and water uptake.

Hyperspectral imagery, which can describe hundreds of unique spectral 'bands' within the electromagnetic spectrum, is opening the door for more direct species detection using species-specific colour signatures, allowing the detection of IAS that are small, cryptic, or visually similar to native species (Tesfamichael *et al.*, 2018). The rapid advance in hyperspectral libraries opens the possibility for widespread IAS detection (Meerdink *et al.*, 2019); NASA's HyspIRI (Hyperspectral Infrared Imager) and other next-generation satellite hyperspectral imagers offer potential global coverage and frequent sampling of unique spectral signatures in both aquatic and terrestrial ecosystems pertaining to IAS; including, distribution, habitat suitability, and individual health (Reeves *et al.*, 2021). A key enabling technology for hyperspectral data is the development of flexible and efficient machine-learning algorithms and readily accessible computing and storage capacity on the cloud that enable efficient information extraction from massive hyperspectral data volumes (e.g. Abeysinghe *et al.*, 2019).

Unmanned aerial vehicles (UAVs; drones) are an emerging remote sensing platform that provides an increasingly

Table 1. Web addresses (URLs) for data sets, projects, and documents mentioned in this review

Entity	Web address
Aquatic eDNAtlas	https://www.fs.fed.us/rm/boise/AWAE/projects/the-aquatic-eDNAtlas-project.html
Atlas of Living Australia	https://www.ala.org.au
Biodiversity Information Serving Our Nation (BISON)	https://bison.usgs.gov/#home
CABI Horizon Scanning Tool	https://www.cabi.org/publishing-products/horizon-scanning-tool/
CaleDNA	https://ucedna.com/
Corn Disease Working Group	https://corn.ipmpipe.org/tarspot/
Darwin Core	https://dwc.tdwg.org/
Ecological Metadata Language (EML)	https://eml.ecoinformatics.org
EDDMapS database	https://www.eddmaps.org
FAIR data principles	https://www.go-fair.org/fair-principles/
Global Biodiversity Information Facility (GBIF)	https://www.gbif.org
iMapInvasives Mobile	https://www.imapinvasives.org/mobile-tools
iNaturalist	https://www.inaturalist.org/
INSPIRE directive framework (Infrastructure for Spatial Information in Europe)	http://inspire.ec.europa.eu/
Invasive Alien Species Europe	https://easin.jrc.ec.europa.eu/easin/CitizenScience/BecomeACitizen
International Standards Organization's (ISO) 191**	https://www.iso.org/committee/54904/x/catalogue/p/1/u/0/w/0/d/0
Midwest Invasive Species Information Network (MISIN)	https://www.misin.msu.edu/
Non-native Aquatic Species (NAS) database	http://nas.er.usgs.gov
North American Invasive Species Management Association's (NAISMA) mapping standards	https://naisma.org/programs/standards-and-technology/
Reporting IAS sightings with EDDMapS	https://bugwoodcloud.org/CDN/eddmaps/tools/EDDMapS_App_WalkThrough.pdf
Sighting identification with iNaturalist	https://www.inaturalist.org/pages/getting+started#identify
U.S. Federal Geographic Data Committee's Content Standards for Digital Geospatial Metadata	https://www.fgdc.gov/metadata/csdgm-standard

viable alternative to satellite remote sensing for detecting IAS (Dash *et al.*, 2019). UAVs allow greater control over the timing of image capture, are less error prone than observer-based methods, can easily survey challenging or dangerous terrain, and offer control over spatial resolution by adjusting flight altitude. Their use is expanding rapidly for IAS research, and has included deployment of multi- and hyperspectral sensors, as well as LiDAR sensors for relatively high-resolution mapping (Juanes, 2018; Dash *et al.*, 2019). Recent applications for IAS detection have primarily centred on the use of multispectral and LiDAR sensors in conjunction with machine-learning algorithms like artificial neural networks to recognize invasive trees, forbs, and marsh plants (Martin *et al.*, 2018; Abeysinghe *et al.*, 2019; Zhu *et al.*, 2019). Thermal imaging has proven feasible for the detection of animal IAS, but has seen limited use to date (Lioy *et al.*, 2021). Camera traps (also known as trail cameras) and other remote stationary cameras have also been used to great effect in detecting and monitoring the abundance of mammals [e.g. in New Zealand (Anton, Hartley & Wittmer, 2018; Nottingham, Glen & Stanley, 2021)]. Imagery collected by UAVs, camera traps, and other remote automated photographic technology can be combined with machine-learning and artificial intelligence algorithms to automate monitoring across broad areas (e.g. Aota *et al.*, 2021).

(4) Molecular genetic methods for IAS detection and monitoring – eDNA

Environmental DNA (eDNA) sampling infers taxa presence from the detection of genetic material in the environment (e.g. water, sediment, soil, snow, or air samples; Taberlet *et al.*, 2018; Fig. 2). This approach can be used to detect eDNA of specific (targeted) taxa, or multiple taxa from a single environmental sample when combined with DNA amplification technologies [i.e. quantitative polymerase chain reaction (PCR), digital PCR, loop-mediated isothermal amplification, etc.] or high-throughput sequencing. eDNA sampling is widely used in aquatic environments where the use of traditional visual observation methods or conventional capture tools is challenging (Taberlet *et al.*, 2018). eDNA sampling has often proved more sensitive and cost-effective than traditional detection techniques, particularly for cryptic and low-density IAS (Hunter *et al.*, 2015). eDNA detection data help to inform and prioritize sites for traditional surveys. For example, detection of Asian carp (Cyprinidae) eDNA in the Great Lakes region (USA and Canada) prompted calls for intensive (non-molecular) monitoring to locate fish populations (Woldt *et al.*, 2019). In this way, eDNA surveys can improve EDRR programs by triggering focused, non-molecular sampling (Sepulveda *et al.*, 2020a). Further, eDNA sampling is amenable to citizen science (Larson *et al.*, 2020) and has been used to evaluate the success of invasive fish eradication efforts (Carim *et al.*, 2020).

An important caveat of the high sensitivity of eDNA methods is they can also detect genetic material from DNA sources other than immediately local, live individuals, such as upstream populations or carcasses (Merkes *et al.*, 2014). However, confidence in the potential presence of target taxa is increased with study designs that include sufficient sample

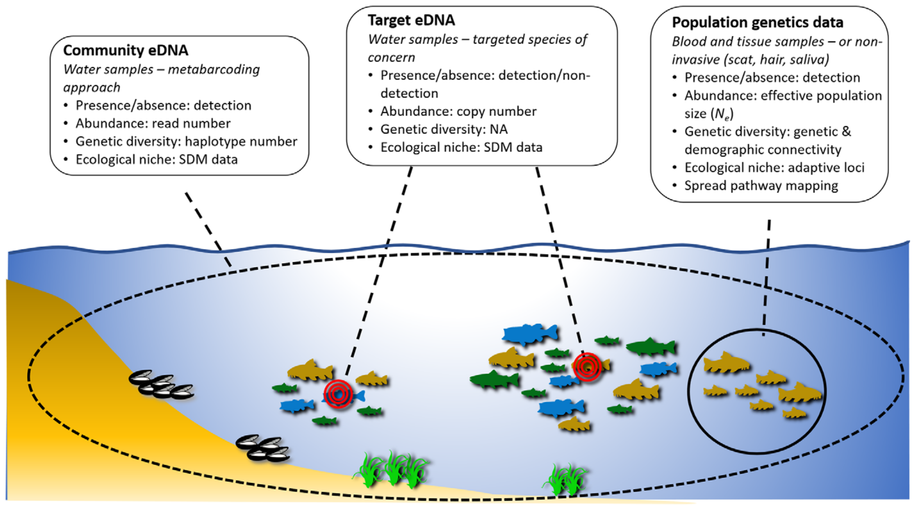

Fig. 2. Visualization of different genetic applications in proactive invasive alien species (IAS) research and management, including associated sampling methods and data types. Population genetics data analysis includes taking DNA samples from individual organisms and allows for a wider understanding of a population's size, genetic diversity, connectivity, origin/source of immigrants, and information on local adaptation (e.g. functional/adaptive genes identified using genome-wide marker scans). Population genetic approaches are being conducted on eDNA samples (Holman *et al.*, 2022). Target eDNA refers to approaches that collect DNA from the environment to identify a target species by using species-specific markers [e.g. Polymerase Chain Reaction (PCR) primers or a quantitative PCR (qPCR) assay] to detect if a species is present, its relative abundance, and distribution across environments or niches [e.g. using species distribution models (SDMs)]. Community eDNA refers to multi-species detection approaches including metabarcoding or metagenomics to test for the presence of several species to understand community diversity and species interactions. Metabarcoding uses next-generation sequencing of an environmental sample to sequence a single locus from each of multiple species (simultaneously) using 'universal' PCR primers for an entire taxonomic group (e.g. salmonids, all fish, or all mussels). Metagenomics approaches use next-generation sequencing of all DNA (all genes/genomes) in an environmental sample including all species present. Metagenomics, unlike metabarcoding, detects the presence (and abundance) of all genes (and species) and thus provides functional information regarding kinds of genes and gene functions, like nitrogen-fixing genes in bacteria in the local environment. Metagenomics allows discovery of new invasive species including parasite/pathogen taxa and simultaneous detection of vector species such as insects or introduced fish that spread pathogens (e.g. Piper *et al.*, 2019). NA, not applicable.

collection and replication (over time and space), appropriate quality controls, and operational best practices (e.g. Goldberg *et al.*, 2016). This is further addressed by the inclusion of statistical modelling of the false negative or positive rate (e.g. Griffin *et al.*, 2020) and incorporation of eDNA sampling data into formal decision models for natural resource managers that account for uncertainty of inference (e.g. Sepulveda *et al.*, 2020a).

Another potential approach to verifying the local presence and the living status of target taxa is the new field of environmental RNA (eRNA). In concept, the identification of target eRNA in an environmental sample provides the researcher with greater confidence that the target organism is both present and living – RNA can only be shed from a live organism – and provides higher temporal resolution for monitoring efforts because RNA degrades faster than DNA (Cristescu, 2019; Tsuri *et al.*, 2021. Environmental RNA from multiple species can be detected simultaneously using metatranscriptomics, which could improve real-time surveillance of known and unknown IAS (Yates, Derry & Cristescu, 2021). Importantly, most work to date has been proof-of-concept and additional empirical data are needed to demonstrate the efficacy of these developing methods in practice.

Emerging applications for rapid or *in-situ* eDNA detection for IAS, which forego the need for most or all laboratory-based work, have benefited from advances in ecogenomic sensors (e.g. Scholin *et al.*, 2017) and low-cost point-of-care molecular diagnostic tools in biomedicine including handheld quantitative PCR (Thomas *et al.*, 2020), clusters of regularly interspaced short palindromic repeats (CRISPR; Williams *et al.*, 2019), loop-mediated isothermal amplification (LAMP; Li *et al.*, 2011), and microfluidic instrumentation (Carvalho *et al.*, 2021). Although not yet widely implemented, these techniques provide rapid, remote, and (when combined with robotics) autonomous eDNA detections (Scholin *et al.*, 2017; Yamahara *et al.*, 2019). For example, Sepulveda *et al.* (2020b) placed robotic autosamplers into U.S. Geological Survey stream-gauges to conduct high-frequency eDNA sampling for fish pathogen and non-native fish DNA in the Yellowstone River (Montana, USA) and Snake River (Idaho, USA) for up to 50 days. They then merged these eDNA sample results with publicly available environmental data (e.g. weather, water quality, water quantity) captured by other automated sensor networks to enhance biosurveillance and forecasting capacity.

(5) Population/landscape genetics and genomics for IAS detection, and monitoring

Population genomic analyses generally rely on direct sampling (e.g. tissue or blood) or non-invasive forms of sampling (e.g. hair, feathers, skin, urine, or faecal matter) to provide suitable genetic material for powerful molecular approaches that illuminate population demographic histories, identify potentially adaptive genes, and discern landscape connectivity to monitor and predict the direction and rate of IAS spread (Chown *et al.*, 2015; Grummer *et al.*, 2019; Hamelin & Roe, 2020; Allendorf *et al.*, 2022; Fig. 2). Additionally, population genomic analyses of IAS can help to identify introduction source(s), the number of individuals and the spatiotemporal patterns of introductions, and pathways of spread, as well as the role of adaptation in colonization. For example, Roe *et al.* (2019) highlight how genomic tools provided a high-resolution look into the invasion history and routes of spread of the mountain pine beetle (*Dendroctonus ponderosae*) and its origins of introduction, informing efforts to prevent future spread. Although *D. ponderosae* is native to northern boreal forests in North America, it has spread beyond its range and is considered a harmful forestry pest, making it effectively invasive from a management perspective.

Landscape genomics studies identify environmental features associated with connectivity, dispersal, genetic variation, and local abundance, which can facilitate proactive analyses of spread risk and mapping hotspots of current and predicted future invasions (Sacks, Brazeal & Lewis, 2016). Recent works have detected changes in population connectivity and abundance in interacting species, suggesting climate and landscape impacts on dispersal rates (e.g. De Kort *et al.*, 2018); similarly community landscape genomic studies (using neutral and adaptive loci) could help explain and control IAS spread, for example in plant–pathogen, host–parasite, or native–invasive systems (Hand *et al.*, 2015). Finally, studies that employ a range of tools (e.g. population genomics, landscape genomics, and simulation modelling) could also help identify mechanisms underlying adaptive capacity while testing for environmental, demographic, and human-mediated drivers of IAS establishment and spread (Smith *et al.*, 2020).

(6) Community or citizen science

Community science (i.e. citizen science, participatory science) has been defined in various ways across disciplines and cultural contexts (Haklay *et al.*, 2021). Herein, we define it as the collection of IAS occurrence data by non-professional volunteers. It is a rapidly growing approach for meeting the *in-situ* data needs for surveillance and modelling that has great potential for expanded application (Larson *et al.*, 2020; Encarnação, Teodósio & Morais, 2021). While traditional field-based monitoring approaches consisting of ground surveys by teams of professional researchers or staff may seem time-consuming and costly, especially where high visitation rates are needed over large geographical areas, community science may meet such needs at comparably low cost (Johnson *et al.*, 2020; Larson *et al.*, 2020).

Community science, as well as other participatory approaches to enable contribution of information from diverse sources including indigenous or local ecological knowledge, have demonstrably improved the performance of SDMs for various taxa (Zhang *et al.*, 2020; Skroblin *et al.*, 2021). Roy-Dufresne *et al.* (2019) found that predictive SDMs for invasive rabbits in Australia performed better when parameterized with community science data in addition to expert opinion compared to those trained on expert data alone. Community science efforts can also significantly reduce the time until first detection during monitoring; recent examples include the first-ever detection of an invasive, disease-vector mosquito species in Spain (Eritja *et al.*, 2019) and five introduced gastropod species in southern California (Vendetti, Lee & LaFollette, 2018).

The primary limitations of community science are inherent spatiotemporal sampling biases (e.g. people sampling more often on weekends, or in areas that are more accessible or attractive), data quality control, and technology access for volunteers (Callaghan *et al.*, 2019; Encarnação *et al.*, 2021). These issues can be addressed by providing training opportunities and standardized protocols for sampling, employing statistically robust analytical methods (e.g. Bayesian Hierarchical Models, Section V), and prioritizing volunteer sampling in areas that would contribute most to modelling (Callaghan *et al.*, 2019). Mobile apps and open online databases (see Section IV) are also an important part of facilitating and enhancing the role of community science in IAS monitoring (Johnson *et al.*, 2020; Howard *et al.*, 2022).

Historically, community science mainly involved volunteers assisting professional technicians to collect data in the field, but websites and smartphone applications have opened new avenues for participation (Mazumdar *et al.*, 2018; Howard *et al.*, 2022). Digital crowdsourcing allows people to participate virtually in a variety of roles, including as volunteer naturalists, identifying species based on observations (e.g. images, audio) on apps like EDDMapS, and iNaturalist (Table 1). Additionally, smartphone/tablet apps and mobile-friendly websites allow people to document IAS occurrences as they see them and ensure standardized data recording. Recent IAS reporting apps include EDDMapS, MISIN (Midwest Invasive Species Information Network;), Invasive Alien Species Europe, and iMapInvasives Mobile. For most of these apps, generated data are publicly available, in demand, and have been used effectively to study the spread of IAS (Table 1; Pawson, Sullivan & Grant, 2020). There is increasing potential to capture information on the interactions amongst species using such applications (Groom *et al.*, 2021).

The emerging fields of conservation culturomics and iEcology involve the repurposing and utilization of public data uploaded to social media for environmental research (Toivonen *et al.*, 2019; Jarić *et al.*, 2020). This includes a diversity of applications for species occurrences (Ghermandi &

Sinclair, 2019; Edwards *et al*., 2021). Machine-learning and web-scraping algorithms now make it possible to identify and collect information on IAS sightings from platforms like Instagram, Flickr, or Twitter, which are applicable for monitoring spread (Daume, 2016; Laudy *et al*., 2020; Jarić *et al*., 2021).

(7) Conservation detection dogs

Domestic dogs trained for chemical detection are increasingly employed for ecological and conservation applications (Grimm-Seyfarth, Harms & Berger, 2021). These wildlife or conservation detection dogs (hereafter CDDs) can detect organic compounds associated with a variety of organisms and possible physiological states (Bennett, Hauser & Moore, 2020), sometimes at concentrations on the order of hundreds of parts per trillion (Johnston, 1999). Conservation applications of CDDs began with the detection of cryptic endangered species, especially by scat (covered in greater depth in Martinez *et al*., 2020), but have broadened considerably as training techniques and awareness of these methods has advanced (Whitehouse-Tedd, Richards & Parker, 2021). The performance of CDDs across a variety of applications is remarkably high; a recent meta-analysis showed CDDs outperforming other conventional methods of species detection in nearly 90% of >600 research studies (Grimm-Seyfarth *et al*., 2021).

The application of CDDs for invasion research and management has risen rapidly in the last decade, although with a significant geographical bias around North America and Oceania (Martinez *et al*., 2020; Grimm-Seyfarth *et al*., 2021). CDDs are considered especially valuable in the context of biosurveillance, monitoring and early detection, since organisms are harder to detect at low concentrations and abundances (Hoyer-Tomiczek & Hoch, 2020). Dogs are already an integral part of monitoring for invasive dreissenid mussels in North America (Sawchuk, 2018), acting as a valuable complement to eDNA detection methods, and have demonstrated efficacy for early detection of invasive and pest species of the beetle family Cerambycidae, including the emerald ash borer (Hoyer-Tomiczek & Hoch, 2020).

Relative to their clear efficacy and applicability to a variety of IAS systems, the use of CDDs for IAS research and management is still limited. As with other innovations discussed in this review, their greater integration into ongoing research and management pipelines will reduce barriers for their implementation in an IAS context.

III SPATIAL ENVIRONMENTAL DATA

(1) Background

Spatial data on environmental conditions associated with occurrences provide the essential covariates necessary for species distribution modelling and forecasting of new invasions and secondary spread [i.e. spread after initial introduction (Vaz *et al*., 2019; Randin *et al*., 2020)]. These data are essential for defining the characteristics of areas where IAS are detected, enabling statistical inference of the relative probability of spread or habitat suitability of unsurveyed or uncolonized areas (see Section V). These model results are in turn valuable for managersef and decision-makers, making spatially explicit data sets equally important as the occurrence data that are often emphasized for monitoring. An important caveat to the use of remotely sensed spatial environmental data is that, in order to be useful in distribution modelling, especially for predictive purposes (see Section V), the variables derived from these data must be biologically meaningful with respect to the modelled organisms' natural history. A clear understanding of the species' natural history and ecology should be translated into robust hypotheses with respect to the relationship between its occurrence and derived environmental variables.

Spatial information like digital elevation models and hydrographic units are readily available for many regions of the world through large spatial data repositories (e.g. Domisch, Amatulli & Jetz, 2015), and have great utility for informing IAS distribution models. Managers increasingly rely on geospatial information from remote sensing for this purpose (Palumbo *et al*., 2017). In the following sections, we review common, well-established remote-sensing products as used in IAS research and management, then highlight new and emerging products with the potential for new and exciting developments in this applied field.

(2) Common and established remote-sensing approaches for IAS research and management

Remotely sensed environmental variables from global operational satellites have distinct advantages for proactive modelling of IAS for research and management, and they are integral to EBV implementation (Dantas de Paula *et al*., 2020). For example, the NASA Aqua MODIS (moderate resolution imaging spectroradiometer) land surface temperature (LST) product measures the effective 'skin' temperature of the Earth's surface globally with a reported accuracy of $\pm 1^{\circ}$C at 1 km and 8-day resolution (Wan, Hook & Hulley, 2015). Because of the regular mid-day revisit schedule of the Aqua MODIS and next-generation National Oceanic and Atmospheric Administration (NOAA) visible infrared imaging radiometer suite (VIIRS) satellite retrievals, LST (and other products) can monitor the spatial and temporal dynamics of the surface environment (e.g. the frequency and duration of temperature extremes) in addition to longer-term climatological conditions typically used in species distribution modelling (Ibrahim *et al*., 2018). Although the links between many remotely sensed variables and spatial habitat and species distributional characteristics have been well established (Randin *et al*., 2020), the temporal variability inherent in such products has yet to be fully exploited.

While remote-sensing data pertaining to the timing and duration of ecologically relevant events has been used in some models, other data products have yet to reach their full potential for IAS modelling. For example, spectral indices such as the Normalized Difference Moisture Index and their associated temporal variability have been used to assess the periodicity of waterfowl use of perennially flooded wetlands (Donnelly *et al.*, 2019). While not strictly using an SDM, the authors provide a template for harnessing the inherent spatiotemporal variability of such indices and demonstrate the potential utility of combining images taken across different time periods for modelling.

A diverse array of complementary Earth observations from the International Space Station (ISS) is routinely collected and processed by NASA for ecological monitoring and is freely available for public use (Meerdink *et al.*, 2019). Remote-sensing products from the ISS relevant to IAS include multi-channel thermal-infrared based surface temperature retrievals from ECOSTRESS (ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station), which provides 70 m spatial resolution and high radiometric precision ($\pm 0.15^{\circ}$C) suitable for distinguishing thermal heterogeneity in the local environment. The drifting ISS orbit permits daily monitoring of surface skin temperatures over land and water between $\pm 50^{\circ}$ of N/S latitude, with varying local sampling times covering diurnal temperature cycles relevant to species thermal tolerances and habitat suitability. In addition, complementary full-waveform LiDAR observations from the ISS-based GEDI (Global Ecosystem Dynamics Investigation) instrument provide 25 m footprint resolution retrievals of terrain and vegetation structure relevant to plant community composition, animal associations, microclimate variations, and associated habitats (Schneider *et al.*, 2020).

Satellite microwave radiometers, including the JAXA/NASA AMSR (Advanced Microwave Scanning Radiometer) and NASA SMAP (Soil Moisture Active Passive) missions, provide global coverage and near-daily monitoring with consistent day/night sampling from sun-synchronous polar-orbiting satellites. The all-weather capability and strong sensitivity of lower frequency ($\leq$37 GHz) microwave radiometers to changes in the relative abundance of water in the landscape enables effective monitoring of a range of ecological parameters affecting habitat suitability. These include the subnivium (Zhu *et al.*, 2019), surface water inundation and soil moisture dynamics affecting IAS spread (Wimberly *et al.*, 2021), damaging frosts impairing vegetation growth (Kim *et al.*, 2014), and the timing and duration of seasonal ice cover on northern lakes (Du *et al.*, 2017). The relatively long duration of many satellite microwave radiometer missions has enabled the development of consistent global data records spanning multiple decades that are well suited for detecting environmental trends, albeit at relatively coarse ($\sim$25 km) spatial resolution (e.g. Kim *et al.*, 2017). These data can be supplemented with other multispectral optical and synthetic aperture radar (SAR) satellites such as Landsat and Sentinel-1, which provide finer spatial resolution ($\sim$30 m) observations of surface moisture and vegetation conditions, but with less frequent (weekly or longer) intervals (e.g. Das *et al.*, 2019). While satellite optical sensors such as Landsat (TM/ETM+/OLI) are actively used for IAS applications (e.g. Pastick *et al.*, 2021), active and passive microwave sensors have received less attention and offer significant potential for IAS distribution modelling (e.g. Wimberly *et al.*, 2021).

Although remote sensing has strong utility for IAS modelling and monitoring, a significant limitation for these applications is that the sensor retrievals may contain spatial or temporal gaps and other inconsistencies requiring additional preprocessing of the data before it can be effectively used to inform models of species occurrences and habitat conditions. Alternatively, conventional climate data are interpolated from ground-based weather station network measurements or derived from coarse global climate models and can also provide spatially continuous environmental information. Climate models, involving both interpolated historical weather station data (e.g. Daymet, PRISM) and Earth System Model projections of future conditions, can provide insights on how climatic variables (i.e. precipitation, air, and stream temperature) influence the spread of IAS. For instance, accelerated warming and stream flow changes have reportedly increased the rate of hybridization between rainbow trout (*Oncorhynchus mykiss*) and westslope cutthroat trout (*Oncorhynchus clarkii lewisi*), and were closely associated with interactions between precipitation and temperature as described with Daymet precipitation data and statistically derived stream temperature projections (Muhlfeld *et al.*, 2017).

(3) Innovations in environmental data collection for IAS research and management

In addition to the wealth of established environmental data products and acquisition procedures, new technologies are emerging that further facilitate ecological and environmental modelling (Ustin & Middleton, 2021). For example, Cubesats are miniature satellites whose low cost and fast development cycle enables multipoint constellations of coordinated Earth observations offering global coverage with relatively high temporal and spatial resolutions from a mix of passive (e.g. optical-infrared surface reflectance) and active (e.g. Radar, LiDAR) sensors (Poghosyan & Golkar, 2017). Although some Cubesat constellations are designed for commercial applications and may be cost prohibitive to potential users, recent efforts include generating precipitation measurements in difficult-to-reach areas using low-cost Radar sensors (Peral *et al.*, 2019). Furthermore, full-waveform satellite LiDAR now available from the NASA GEDI mission are enabling high-resolution three-dimensional mapping of vegetation structure over large global domains (Dubayah *et al.*, 2020). LiDAR retrievals potentially useful for IAS include local topography, vegetation canopy structure, and above-ground biomass (Davies & Asner, 2014; Gonzalez De Tanago *et al.*, 2018).

Lastly, the development of climate model reanalysis products has expanded access to comprehensive and accurate global weather and climate records. These products are derived by assimilating multiple observations (e.g. satellite, aircraft, buoys, ground stations) within sophisticated Earth System Model frameworks to produce consistent high-quality environmental data records. For instance, the Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2) is a global atmospheric reanalysis that spans four decades (1980–present), providing moderate spatial (50 km) and high temporal (hourly) resolution climate and weather data including temperature, humidity, wind speed, rainfall, and snowfall (Gelaro *et al.*, 2017). This and other reanalysis products, whose integrated frameworks mitigate issues of model and geographic bias ubiquitous to individual earth system models, remote sensing, and interpolated observational products (e.g. WorldClim), have enabled new capability for understanding the spread of IAS worldwide (Atala *et al.*, 2019; Gillard *et al.*, 2020).

IV DATA MANAGEMENT FOR PROACTIVE IAS RESEARCH AND MANAGEMENT

(1) Background

Proactive and predictive IAS research for management requires data that are frequently updated, accurate, standardized (interoperable), and openly accessible to researchers and managers (Groom *et al.*, 2017). As new sources of occurrence data (Section II) and spatial environmental data (Section III) proliferate, accelerate, and diversify, digital infrastructures and bioinformatics must advance to keep pace (Larson *et al.*, 2020; Reaser *et al.*, 2020b). The management, preservation, storage, and sharing of these important IAS data are essential to providing a foundation for IAS research and management over larger spatiotemporal scales, such as detecting long-term patterns or permitting monitoring and predicting spread across countries or continents.

Online databases are already largely responsible for the increased feasibility and success of community science IAS research efforts (Encarnação *et al.*, 2021), and are key for making knowledge accessible to managers by ensuring its accessibility and availability *via* the internet (Beaury *et al.*, 2020; Section VI). IAS data at national and international scales are collected and maintained by diverse institutions with different needs and objectives, making great volumes of data fragmented, difficult to access, and limited in interoperability (Groom *et al.*, 2015; Johnson *et al.*, 2020). Increased coordination among entities that collect, house, and manage data (providers of IAS data infrastructure) is needed to upscale IAS research and management in order to support growing efforts to combat IAS and accomplish relevant biodiversity and SDGs. Such coordination includes improving core biodiversity data standards (Wieczorek *et al.*, 2012) and following workflows for data processing and sharing already developed for biodiversity and IAS data (e.g. Seebens *et al.*, 2020).

Collating, managing, and maintaining large data sets of IAS occurrence and spatial environmental data from the diverse sources reviewed in Sections II and III is critical to bridging the gap between raw data and aggregated analytical products better suited to inform research, management, and control of biological invasions (Hardisty *et al.*, 2019). The widespread implementation of EBVs for IAS, for example, is nearly impossible without better interoperability among databases, and would be a major step forward for upscaling invasion biology (Latombe *et al.*, 2017; Hardisty *et al.*, 2019). Data sharing through public databases increases data accessibility, allowing for replication of experiments and verification, re-use, and long-term preservation.

The EDDMapS database integrates community science data from numerous initiatives with federal and state data sets into a spatially explicit database describing the current extent and impact of IAS in the USA (Reeves *et al.*, 2021). EDDMapS data have been used for research to model the predicted future distributions of hundreds of invasive plant species across the contiguous USA (Allen & Bradley, 2016). The U.S. Geological Survey's Nonindigenous Aquatic Species (NAS) database is the primary U.S. Federal repository and integrator of spatially explicit data on IAS, combining data from federal and state natural resource management agencies, museum collections, and citizen science initiatives. NAS data have been used in SDMs to predict the potential range and spread of non-native fishes, and provide actionable tools for assisting with EDRR and IAS management including email notifications on novel occurrences and short-term assessments of spread in newly invaded areas (Fuller & Neilson, 2015). The NAS database allows for highly customized data queries, and the ability to overlay species distribution data with administrative, hydrologic, and environmental data layers.

The ability to identify, aggregate, and integrate data from multiple sources is necessary for documenting the status and trends of IAS, but is just as critical for informing predictions necessary for EDRR implementation. Despite repeated calls for, and efforts towards, greater interoperability and coordination of data management (e.g. Groom *et al.*, 2015) these systems still face numerous challenges (Reaser *et al.*, 2020b). For example, the Global Invasive Species Information Network (GISIN) was conceptualized in 2004 and provided cyberinfrastructure to access data from ~30 IAS databases between 2008 and 2015 (Jarnevich *et al.*, 2015), but has not been updated since then. Changing technologies, reorganization of institutional structure and priorities, and a lack of sustained financial commitment have hampered continuing support for the network (C.S. Jarnevich, personal communication). Reducing the barriers to data sharing, as outlined below, will have far-reaching benefits for addressing the threat of IAS (Groom *et al.*, 2015).

(2) Innovations and developments in IAS databases

Multiple metadata standards exist to facilitate sharing and integration of foundational data for proactive IAS management and research. Geospatial data standards include the U.S. Federal Geographic Data Committee's Content Standards for Digital Geospatial Metadata, the International Standards Organization's (ISO) 191** series (including

ISO 19115 and associated updates and extensions), and the INSPIRE directive framework (Infrastructure for Spatial Information in Europe; Table 1). Standards for describing biological data sets include Ecological Metadata Language (EML), Darwin Core [see Groom *et al.*, 2019a for proposed enhancements for IAS data], and the North American Invasive Species Management Association's (NAISMA) mapping standards. The FAIR principles (Wilkinson *et al.*, 2016) offer general guidance for promoting the reuse and integration of scientific data (Table 1).

Recent efforts to facilitate database integration include R software packages that use translation tables and automated workflows to standardize varied terminology so that multiple alien species databases can be integrated, as in the SInAS workflow (Seebens *et al.*, 2020). The Global Register of Introduced and Invasive Species also aims to provide a common backbone to support standardized species inventories by countries (Pagad *et al.*, 2018). Future progress is likely to be made *via* open-source and open-access approaches to integrating, updating, and delivering the data needed for invasion management at multiple scales. For example, IAS databases could provide data [through direct download or *via* Application Programming Interface (API) access] using one or more data standards described above and using a common controlled vocabulary (Groom *et al.*, 2019a), or database metadata and schemas could be collated and used to help develop translation tables.

eDNA data are a new and potentially challenging data type in need of standardization and collation at larger scales for IAS management. They have been stored in specialized, moderate to large-scale databases (e.g. CaleDNA and Aquatic eDNAtlas; Table 1) and recently incorporated into broader species detection databases (e.g. GBIF, Atlas of Living Australia, NAS; Berry *et al.*, 2020; Table 1). Notably, IAS occurrence data from eDNA methods require additional metadata fields to understand the data quality and study scope (e.g. markers used, DNA purification and other laboratory protocols, sample collection information) which complicate database interoperability and standardization and require careful attention in the implementation of this detection method (Sepulveda *et al.*, 2020a).

Interoperable databases housing long-term data sets are likely to be important in the future for understanding real-time management and frontline experiences in IAS management. Information on other aspects of biological invasions, like implementation and impacts of management interventions, or the interactions of IAS with other species, could support evidence-based conservation practice and a broader ecological understanding of IAS impacts if collated in larger databases.

V SPATIAL ANALYSIS FOR PROACTIVE IAS RESEARCH AND MANAGEMENT

(1) Background

Despite the intended role of quantitative SDMs as guides for risk assessments, invasion monitoring, and adaptive management (Chapman *et al.*, 2019; Rodríguez-Rey *et al.*, 2019; see Section II), their use in implementation remains limited, in many cases due to insufficient access to data and analytical (computational) capacity for managers (Bazzichetto *et al.*, 2018). SDMs are the core analytical tool by which foundational monitoring or occurrence data (Section II) and spatial environmental data (Section III) can be converted into a useful form for stakeholders, making them a central part of our proposed workflow (Fig. 1). They also play a prominent role in emerging disease monitoring (Machado *et al.*, 2019; Wimberly *et al.*, 2021), upon which this workflow is based (Fig. 1). SDMs and associated spatial analytical models are at the heart of this workflow, generating the probabilistic spatial inferences that are ultimately intended to guide management decisions in one form or another. For this reason, we devote this section to reviewing the advantages and disadvantages of different frameworks used for the spatial modelling of IAS, and the special concerns and limitations that are common to such modelling.

Analytical methods for proactive IAS research vary in complexity and degree of user involvement, where more complex models require an abundance of high-quality data and more expert knowledge of the study species and the modelling frameworks used; and where simpler models are more easily applied across multiple species, are compatible with often limited data availability, and can be automated with less need for user input (Young *et al.*, 2020; Table 2). Complex approaches, meanwhile, may better accommodate diverse data types and the statistical difficulties of dealing with IAS populations (see Bayesian Hierarchical Modeling in Section V.(3)). Correlational models, which examine the quantitative relationships between occurrence or spread and environmental covariates, fall more on the simple side of this spectrum, while complex approaches are typically mechanistic, explicitly utilizing species-specific knowledge. There can be hybrid models such as species-specific predictors in correlative models (e.g. boat traffic to capture anthropogenic dispersal; Cook *et al.*, 2019) or models encompassing traits of the IAS (Barwell *et al.*, 2021).

SDM applications for IAS typically estimate a species' current distribution (West *et al.*, 2017), the most likely locations for spread and establishment (Cook *et al.*, 2019), or, most often, suitable habitat that could support viable populations (e.g. Chapman *et al.*, 2019). In the latter case, SDMs are effectively simple assessments of the relative risk of spread. While occurrence data are most common, abundance data used in this framework can provide information on where an invader may have impact (Bradley *et al.*, 2018). Horizon scans are a simple application of climate and habitat matching along with assessment of introduction pathways, propagule pressure, and species traits proactively to identify potentially problematic species (Fournier *et al.*, 2019; Roy *et al.*, 2020).

(2) Limitations and statistical concerns with distribution modelling of IAS

Before reviewing innovations in spatial modelling for IAS, it is worth exploring the idiosyncrasies of such modelling in

Table 2. Model types used in invasive alien species (IAS) distribution modelling, including the type of data used, the output data type, and the strength and weaknesses of each model type

Model type	Input data type(s)	Output data and information	Why use this model type?	Potential issues
Correlation-based and machine learning (MAXENT, boosted regression trees, random forests, artificial neural networks)	Presence/ absence	Prediction of occurrence given new environmental data or projections	Useful for data-poor systems (opportunistic occurrence data, thresholded abundance data) to make predictions on where future and additional sampling could or should occur	Can be simplistic, need careful consideration of inputs and interpretation, sometimes high computational demand
Bayesian hierarchical models	Presence/ absence, ecological observations	Prediction of presence, along with predictions of other population metrics, such as abundance	Can make use of more complex data types and propagate uncertainty; can transfer information from data-rich to data-poor regions; can provide probabilistic estimates of future states	Often requires a large amount of varied observational data that can be hard to collect; computationally intensive and requires expertise
Mechanistic (future simulations and prediction)	Information from experiments or other model types (e.g. machine learning and Bayesian)	Detailed predictions of future spread and invasion (e.g. under climate or environmental change)	Higher potential accuracy rates, and can integrate many different types of biological data including genetic information; can also be at the population or individual level which can further improve model control	Data intensive, and requires the most data or information of all model types; outcomes dependent on functional mechanisms assumed

invasive systems and how these are handled in practice. IAS violate a major assumption of SDMs: that the focal population is at equilibrium with the environment (i.e. not presently increasing or decreasing in abundance or extent; Jiménez-Valverde *et al.*, 2011). As a consequence, there are unoccupied regions that may be suitable for establishment if IAS could reach them, biasing the strength and effect of drivers of species occurrence. One potential solution is to include distributional data from both native and invaded ranges of an IAS (Jiménez-Valverde *et al.*, 2011; Srivastava, Lafond & Griess, 2019), although invaded range-only models may be preferable later in the invasion stage (e.g. Liu *et al.*, 2020a). Predictors linked to physiology or natural history of the species and simpler models perform better when predicting in novel geographic regions or times (Jiménez-Valverde *et al.*, 2011; Liu *et al.*, 2020a). Predictors capturing anthropogenic propagule pressure (e.g. boat traffic) may be particularly useful for species dispersed by human activities (Rodríguez-Rey *et al.*, 2019).

This review focuses on distribution modelling using presence-only data sets because of the poor availability of systematically sampled presence–absence data, but the assumptions involved in modelling presence-only data provide weaker inference (Guillera-Arroita *et al.*, 2015). Researchers should be aware of the limitations of these data sets and consider them only when options for presence–absence modelling are not available. Presence-only modelling must be based on some representative sample of potentially available locations across space that characterize the available but unused environment. These types of data, alternatively called background, available, or pseudo-absence data, and the selection of these locations can affect model estimates (e.g. Chapman *et al.*, 2019) and inflate model evaluation statistics. There are various methods for overcoming these issues of bias related to selection of background data based on density of records for new invaders (Elith, Kearney & Phillips, 2010) and modelling sampling bias (Elith, 2017). Presence-only methods can be used with occurrence or abundance to model the 'impact niche', where IAS may cause more problems (Bradley *et al.*, 2018). Despite the issues described, these types of models, when developed following best practices and understanding assumptions, can be very useful (Sofaer *et al.*, 2019). Other approaches have been developed to deal with non-equilibrium conditions such as IAS spatial distribution models (iSDMs), which try to distinguish absences that are due to environmental conditions (i.e. non-suitable habitats) from absences that are due to dispersal limitations (i.e. suitable habitat without ability to disperse to; Hattab *et al.*, 2017).

The non-equilibrium nature of the distributions of IAS also makes standard model evaluation metrics such as area under the curve (AUC) and true skill statistic (TSS) potentially inappropriate. These emphasize true negatives along with positives; and given that most IAS are still spreading, an absence could be due to the invasion stage. One alternative is evaluating the true positive rate in relation to predicted suitable areas (Jiménez & Soberón, 2020).

Although predicting the influence of changing climate on species distributions is often a goal, SDM applications often assume that climate is a limiting factor on current distributions. However, other factors, such as biotic interactions which may alter with changing climate, could be more important (e.g. Sax, Early & Bellemare, 2013). Additionally, retrospective models projected onto current data have done poorly at capturing changes in suitability (e.g. Sofaer, Jarnevich & Flather, 2018) and transferability in space can be poor (Liu *et al*., 2020b).

(3) Innovations in IAS distribution modelling

The advent of large IAS databases (Reaser *et al*., 2020b; see Section IV.(2)) and unstructured data sets due to new monitoring and detection methods necessitate new analytical strategies capable of integrating diverse, low-latency, and high-volume data (Reaser *et al*., 2020b). Two major analytical approaches to predicting distributions and spread of IAS that can accommodate such data are machine-learning algorithms and Bayesian hierarchical models (Farley *et al*., 2018). These two methods represent a trade-off between automation and interpretability of results and outcomes. Machine learning can identify complex patterns and trends with little user input, but requires careful interpretation of results generated by the algorithms. Meanwhile, Bayesian hierarchical modelling provides a high degree of control, including the ability explicitly to accommodate biological dynamics and differing variance structures between data types, but requires significant user input (Farley *et al*., 2018).

Machine-learning applications to IAS distribution and potential spread have been implemented using a variety of algorithms, including MAXENT (maximum entropy; Phillips *et al*., 2017), boosted regression trees (Elith, Leathwick & Hastie, 2008), random forests (Daliakopoulos, Katsanevakis & Moustakas, 2017), and artificial neural networks (Benkendorf & Hawkins, 2020). Their core functionality is to extract knowledge and identify patterns from data sets with a model which can describe these patterns and allow predictions given new data or projections (Lorena *et al*., 2011), and they are advocated as a scalable and low-effort way to develop predictions of future species distributions (Elith, 2017). It is common for multiple machine-learning algorithms to be explored in ensemble to capture better the uncertainty around predictions (Elith, 2017). One potential trade-off between regression tree and random forest model types *versus* more conventional modelling approaches (e.g. generalized linear models) is the potential for overfitting at unsampled sites (Temesgen & Ver Hoef, 2015), as well as an increase in computational demand. However, more recent work suggests that the ability to forecast future IAS spread to new geographic regions could be similarly limited across all model approaches, and that these approaches are nonetheless still useful (Charney *et al*., 2021). The computational demands of machine-learning methods, which might impede their wider application due to inequities in funding and access to computing resources, could be addressed by making such tools available through affordable cloud computing services (Candela *et al*., 2016). Carter *et al*. (2021) recently developed a machine-learning SDM workflow for aquatic IAS in North America that yielded similar insights to highly mechanistic and time-intensive modelling methods with considerably less user input.

Bayesian hierarchical models are a powerful and flexible class of models that can handle multiple layers of complexity in ecological processes, observations, and uncertainty. They provide many benefits for IAS distribution modelling, such as allowing information to be shared from data-rich regions to data-poor regions and better characterization of uncertainty, which is critical for assessing risk and prioritizing management strategies and interventions (Farley *et al*., 2018). By accounting for this uncertainty and how it propagates or changes across variables and processes, these models are well suited for ecological forecasting because they provide probabilistic estimates of future states in a temporally explicit modelling framework (Dietze, 2017).

Users can explicitly design error structures in models to account for bias or complexity in data sets from multiple sources [e.g. state-space models, integrated models (Isaac *et al*., 2020); spatiotemporal models (Thorson *et al*., 2016)], and thus rigorously accommodate heterogeneous data sets (Isaac *et al*., 2020). Such integrated models leverage multiple data types to describe unobserved latent states (e.g. the 'true' distribution of a species) while accounting for differing error structures among data types. For example, such a model might account for decreased detection at the leading edge of invasion by incorporating changing detection probabilities explicitly into the model.

Mechanistic simulations of future IAS spread under climate change are a yet more involved analytical approach in which the actual dynamics of invasion and climate change are reproduced and projected into the future (Chapman *et al*., 2016). Although much less commonly implemented due to their greater data needs, these process-based models potentially offer greater predictive accuracy and a higher degree of control while integrating multiple types of useful biological knowledge in replicating future invasions. Mechanistic models can be based around population dynamics, simulating parameters like species traits, competition, and propagule pressure (e.g. Carboni *et al*., 2018), or can be individual-based, with specified rates of reproduction, survival among age classes, dispersal, and other demographic variables (Messager & Olden, 2018; Dominguez-Almela *et al*., 2020). Such approaches are useful where demographic rates, ecological relationships, and mechanisms of spread are well understood, but these conditions may not be met for many new invasions.

VI KNOWLEDGE TRANSFER, DECISION SUPPORT, AND CO-PRODUCTION

(1) Background

A crucial final step in the analytical pipeline of proactive IAS management is the transfer of research insights to managers, stakeholders, and decision-makers (Groom *et al.*, 2019b; Reaser *et al.*, 2020a). Once spatial data on occurrences and environmental characteristics (workflow Steps II–IV) have been analysed using an appropriate analytical approach (Step V), primary analytical results must be made relevant and communicable to data users. This interface with data users can then feed back into study design and species prioritization based on user needs (Fig. 1). This knowledge transfer step closes the implementation or 'knowing–doing' gap, a top priority for IAS research (Pyšek *et al.*, 2020). The diverse technological and methodological innovations from the preceding sections can be translated better into on-the-ground results if synthesized into products that are usable for those affected by or responsible for managing IAS impacts (Shackleton *et al.*, 2019a; Kokotovich *et al.*, 2020). Information uptake and use are increased by the inclusion of practitioners, decision-makers and stakeholders throughout the research process (Lemos *et al.*, 2018; Table 3). Integrating end-user communities into research and development increases credibility and legitimacy from an exchange of knowledge and perspectives (Lemos *et al.*, 2018). It can be as simple as co-designing visualization or decision-support tools with end-user input to communicate findings better with data users, or (ideally) a more in-depth process in which data users are directly involved in planning, data collection, sharing, and analysis decisions.

This integrated approach has manifested in a variety of sub-disciplines and frameworks, including structured decision-making, translational ecology, adaptive management, participatory modelling, transdisciplinary research, and knowledge co-production (Novoa *et al.*, 2018; Gaydos *et al.*, 2019; Beaury *et al.*, 2020). These methods convene multiple stakeholders and decision-makers with diverse expertise and knowledge through an iterative, collaborative, and reflexive process to co-create context-specific and decision-relevant knowledge (Norström *et al.*, 2020). Although potentially time- and resource-intensive, these approaches can enhance the applicability of scientific inquiry to decision-making (Fujitani *et al.*, 2017; Owen, Ferguson & McMahan, 2019). This is particularly important for invasion research, which takes place on a complex cultural and socio-economic landscape where numerous, diverse stakeholder values and practices affect management action (Shackleton *et al.*, 2019b; van Poorten & Beck, 2021).

Natural resources managers are increasingly cognizant of the threats posed by global change and the need for forecasting hotspots of IAS spread and colonization (Carlson *et al.*, 2019; Beaury *et al.*, 2020). Near-term ecoforecasting of IAS spatial distributions can be co-produced between researchers with scientific and modelling expertise and stakeholders with on-the-ground knowledge of target species' occurrence and ecological responses (Dietze, 2017; Gaydos *et al.*, 2019). Co-production allows for key feedback loops between model development and data collection in which models can be improved over time, iteratively generating and testing decision-relevant hypotheses and predictions (Uden *et al.*, 2015). Since decision-makers and managers are often conducting monitoring and surveillance, better communication with researchers could thus facilitate data collection in specific areas that address data gaps or maximally improve SDM performance. This process promotes a better mutual understanding of the IAS problem, and desired outcomes, and increases agility in adjusting to changing conditions across time (Sofaer *et al.*, 2019).

Table 3. Key questions for integrating stakeholders, decision-makers, managers, and other information end-users over the course of the IAS workflow

Framework stage	Example questions for co-production
I. Problem identification	Which species are of greatest concern to stakeholders? Which systems can be protected by early action and spatial prioritization? Which systems or environmental assets can be protected?
II. Occurrence data	What data are needed for informing management? What data formats are most useful for end users?
III. Spatial environmental data	At what scales should data be collected to address management-relevant questions? Which data can best be collected *via* community science approaches?
IV. Data management and sharing	How will data be shared and made available to stakeholders? How will the rights and agency of stakeholders (especially indigenous people and local communities) be protected in data storage and sharing? Which tools best enable data access?
V. Data analysis	Which stakeholders or decision-makers should be involved in participatory modelling? What types of analysis outputs are most helpful to end-users? How can parameter uncertainty be encompassed and accounted for in modelling? What degree of model structure and mechanistic realism is best applicable to end-user needs?
VI. Knowledge transfer & decision support	What are the most important key messages to guide decision-making? How can the extent of knowledge gaps within the specific context be assessed? How can uncertainty in model outputs be effectively communicated to stakeholders? How can results be communicated in a two-way exchange with end-users? What end-user feedback needs to be built into the next iteration of modelling?

The U.S. Forest Service has operationalized such an iterative loop with their spongy moth (*Lymantria dispar*) program. This involves developing models of risk for the uninvaded western USA annually (workflow Step V; Fig. 1), using this model to coordinate with federal, tribal, and state stakeholders trapping in the next year, then re-fitting models including the new year's surveillance data. Communication between modellers and data collectors improves the adaptive cycle (Cook *et al.*, 2019).

Clearly communicated information on IAS spread under climate change is a priority for land managers so they can adjust monitoring, intervention, education, and outreach strategies (Beaury *et al.*, 2020; Wallingford *et al.*, 2020). Projections of invasion retractions and expansions allow managers to prioritize species of interest for monitoring and management (Reinhardt *et al.*, 2020). When generating such predictive outputs (i.e. spatially explicit visualizations like maps), researchers should be sure to conduct assessments at scales that are relevant to practitioners and stakeholders, and their options for management and intervention. Quantitative uncertainty and its sources must also be clearly communicated (Crimmins *et al.*, 2020). The production of visualization tools that allow user specification of analytical scales, and that use cyberinfrastructure to make data readily accessible to users, helps get useful information to decision-makers flexibly and efficiently (Blackburn *et al.*, 2020).

Deliberately co-creating proactive invasion research requires time and investment that is not always possible, particularly when scientists, managers, and stakeholders are embedded in institutions with different priorities and incentives that can disincentivize collaboration (Cvitanovic *et al.*, 2019). Other barriers to co-production include a lack of training and capacity among scientists and practitioners on how to work across sectors and integrate different knowledge, uneven power dynamics or lack of trust that limits interactions and knowledge sharing (Gaydos *et al.*, 2019; Rozance *et al.*, 2020). These approaches require significant time and willingness to engage in social learning, trust building, and shared decision-making, especially when advanced and novel technologies are being used (Kokotovich *et al.*, 2020).

A key aspect of co-production approaches is that stakeholders and knowledge users are involved in all stages of the research in an iterative process. Local stakeholders can participate directly in knowledge collection *via* community science (Section II), provide field data on habitat variables potentially to downscale environmental data for modelling (Enquist *et al.*, 2017; Section III), and be encouraged to format their existing databases to match global standards and contribute data to larger repositories (workflow Step IV). Participatory modelling methods are an increasingly sophisticated way to include stakeholders in actual data analysis by creating designated forums for reviewing shared data (Morisette *et al.*, 2017), and collaboration with stakeholders can also improve adaptive modelling by opening avenues for communication around data collection and monitoring. Furthermore, stakeholders, including amateur experts in wildlife recording communities and traditional ecological knowledge holders can bring extensive insights into life-history traits and ecology that can inform interpretation of model outputs (Pocock *et al.*, 2015; Biró *et al.*, 2019).

(2) Examples and innovations in co-production for IAS research and management

Lessons learned from collaborative science processes in other areas (e.g. climate risk assessments) demonstrate that co-production can foster a community of practice that yields future benefits (Morisette *et al.*, 2017). For example, decision-makers, scientists, and stakeholders connected to co-production activities around climate change in the Great Lakes region are linked across regions and knowledge communities (e.g. science and policy), which helps mobilize climate information in ways that shape policy and decision-making, resulting in a coordinated network of professional relationships that increases research-to-management efficacy (Kalafatis *et al.*, 2015). Similar efforts to establish a community of practice between managers, scientists, and stakeholders around the intersection of IAS and climate change are underway through Regional Invasive Species and Climate Change Management Networks in the USA, which facilitate knowledge sharing and curation (workflow Step IV) and communication with decision-makers (Step VI).

Beginning in 2018, the USA National Phenology Network (USA-NPN) released a suite of 'Pheno Forecast' products which provide real-time maps and short-term forecasts of key insect pest activity at fine spatial and temporal resolutions across the USA (Crimmins *et al.*, 2020; workflow Steps V and VI). These maps rely on accumulated growing degree days (GDDs) and input from both experts and published GDD thresholds for management-relevant life-cycle events in key insect pests. The Pheno Forecast maps depict, on a given day, the status of the insect's life-cycle stage across the contiguous USA. Locations are categorized into one of the four conditions: not yet approaching the life stage of management interest, approaching the stage, experiencing the stage, and past the stage. This effort uses a consultative mode of engagement with practitioners and stakeholders as a way continuously to improve the products so that they become more useful for the forest-pest-management community. The incorporation of gridded temperature data, insect phenology, and consultative engagement provide insight into forest-pest-management strategies (Crimmins *et al.*, 2020; Morisette, Macaluso & Burgiel, 2020).

The Corn Disease Working Group in the USA collated occurrence data (workflow Step I) of black spot of maize (*Phyllachora maydis*), produced spatially explicit visualization tools (Steps V & VI) for stakeholders (e.g. growers) *via* social media (Kleczewski *et al.*, 2020; Table 1) and allowed reporting *via* a web-hosted platform that automatically generated and shared maps in real time. This provided in-season knowledge of disease movement and spread at temporal scales that were helpful to growers (Kleczewski *et al.*, 2020). This concept is also demonstrated by the Soybean Rust - Pest

Information Platform for Extension and Education (SBR-PIPE) program, a collaboration to monitor the distribution and impacts of soybean rust (*Phakopsora pachyrhizi*) in North America (Hershman, Sikora & Giesler, 2011; Sikora *et al.*, 2014). Data of current conditions from an international network of sentinel plots are shared with state specialists, crop consultants, and growers to inform farm management decisions by a stakeholder network and collaborative monitoring program (Kelly *et al.*, 2015). These allowed contributors to submit data for the various projects *via* a mobile app and website (Steps II and IV). Data from the programs were made available to the public as value-added products, such as maps, on the project websites (Kelly *et al.*, 2015).

(3) Formal knowledge transfer tools

The rapid change associated with both IAS themselves and the fields of study dedicated to their management complicates effective communication with decision-makers across jurisdictional scales. The ecological and methodological complexity of IAS and their management are not amenable to high-level government and inter-government processes, which require clear, concise, and distilled accounts of potential IAS impacts on which to act. This necessitates formal methodologies for translating the complexities of proactive, forward-looking IAS research into formats that can be used to make decisions beyond the local scale.

In this final section, we describe practice and innovations in two approaches that facilitate the translation of IAS knowledge to decision-makers and society at large to spur timely and necessary action. The analytical techniques involved with these approaches may differ superficially from the workflow presented herein, but their thematic process is parallel, so we focus on their applications here and refer the reader to existing reviews for a more in-depth treatment of these topics.

Scenario planning and analysis centre around generating scenarios that can be used to communicate potential socio-ecological futures to decision-makers and the public. Scenarios are coherent, plausible, and internally consistent descriptions of the future state of a region or the planet under a given management or decision regime (IPCC, 2014). Researchers generate scenarios through a mixture of expert opinion and multi-scale modelling to assess ecological and societal drivers of change, and how they produce different plausible futures (Peterson, Cumming & Carpenter, 2003). Ultimately, scenarios can highlight key uncertainties and incorporate different societal perspectives into the analysis of planned management actions and their anticipated consequences. In this way, they can be used as a synergistic co-production practice that helps stakeholders communicate their values in envisioning potential futures [known as participatory modelling or scenario development (Caceres-Escobar *et al.*, 2019; Harmáčková *et al.*, 2021)].

Scenario planning exercises have been used to great effect in communicating the science of global climate change to world leaders (IPCC, 2014), but have only recently been applied to the ecological and economic realities of IAS (Lenzner *et al.*, 2019). A long-term perspective of IAS impacts is urgently needed, to help give decision-makers a forward-looking perspective on the consequences of biological invasion (Essl *et al.*, 2019; Lenzner *et al.*, 2019). Recent work has begun to address this need in providing frameworks and guidance for conducting scenario analysis for IAS.

One such study explored the potential pathways and invasion scenarios of IAS spread globally with a focus on intercountry connections and including country-specific biosecurity measures (Faulkner, Robertson & Wilson, 2020). Regional biosecurity is likely to play a large part in the spread of IAS between countries as in most cases invasions occurred prominently from a country that either had no incentive (e.g. no harmful effects locally) or low capacity to prevent the spread of IAS (Faulkner *et al.*, 2020). Pathways of biological invasions, in general, will be important in scenario planning as these types of analyses and planning incorporate many factors (e.g. socioeconomic, sociopolitical, environmental, and management effort and success) related to invasion prevention (Essl *et al.*, 2015).

The AlienScenarios project, started in 2019, is a multi-pronged effort to generate scenarios and models of biological invasions for the 21st century at a variety of analytical scales (Essl *et al.*, 2019). The project framework is centred around a set of Alien Species Narratives (ASNs): storylines based on a set of seven key drivers of biological invasions that illustrate a range of plausible futures. These ASNs can in turn inform major global initiatives on biodiversity conservation, including the Convention on Biological Diversity (CBD) and Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES). More recently, the group produced a participatory workflow for the co-production of ASNs and implemented it in a series of workshops to generate a suite of relevant scenarios (Roura-Pascual *et al.*, 2021).

Horizon scanning – the systematic examination of potential threats and opportunities for future change within a given context – has been used to determine global research priorities for broader conservation science (Sutherland *et al.*, 2020). Experts convene to share their knowledge and, through detailed discussions, aim to reach consensus within the scope of a specific question. Horizon scanning studies often include structured expert-elicitation approaches (Roy *et al.*, 2020), which can be valuable to address knowledge gaps and limited availability of empirical evidence (Sutherland & Woodroof, 2009). The importance of horizon scanning as a tool for decision-makers has been demonstrated *via* collaborative solutions to complex environmental issues (Palomino *et al.*, 2012; Sutherland *et al.*, 2020). Many approaches have been implemented to reduce or quantify the bias associated with expert-elicitation methods, including Delphi techniques (Mukherjee *et al.*, 2015). Horizon scanning has been used specifically within the context of biological invasions to rank research priorities (Gallardo *et al.*, 2016), develop risk assessment protocols (Roy *et al.*, 2020), inform prevention (Lucy *et al.*, 2020; Tsiamis *et al.*, 2020), and management (Booy *et al.*, 2017).

The most widespread use of horizon scanning within the context of biological invasions has been to derive ranked lists of IAS that are not yet established within a region but have the potential to arrive, establish, and impact biodiversity and ecosystems. This enables groups of experts rapidly to assess and compare the impact of thousands of IAS using a simple scoring approach to inform discussions within a consensus workshop (Roy *et al.*, 2020). Modelling approaches can be included to guide the horizon scanning (Matthews *et al.*, 2017) or implemented at a later stage through detailed risk assessments on the IAS prioritized through the horizon scanning (Chapman *et al.*, 2019). Future developments could include the integration of societal perspectives of alien species alongside consideration of both negative and positive ecological impacts (Verbrugge *et al.*, 2019).

Tools (e.g. the CABI Horizon Scanning Tool; Table 1) are being developed to assist with horizon scanning by using online databases to generate a list of species that are absent from a defined area but present in an area that may be nearby or have a similar climate or linked through trade. However, there is potential to expand the information accessed to underpin horizon scanning, for example through data mining of social media (Moustakas & Katsanevakis, 2018). Expert opinion will continue to be important to address gaps across regions and taxa (Verbrugge *et al.*, 2019). It is critical that structured expert elicitation processes ensure social inclusion, recognizing the importance of social engagement to address the complexities of conservation issues like biological invasions (Seymour *et al.*, 2020).

VII CONCLUSIONS

(1) Cost-effective and appropriately rapid management of IAS requires a predictive or proactive approach coordinated across researchers, practitioners, decision-makers, and stakeholders. As the global extent and severity of biological invasions worsens and grows more complex with global change, the prevailing reactive management and research paradigm becomes increasingly untenable. IAS occurrence data, environmental information, and other relevant data (e.g. population genetic data; Fig. 2) must be collected, collated, and mobilized at large scales to promote the necessarily rapid, coordinated, and anticipatory responses to biological invasions.

(2) Our review shows that a diversity of new and emerging tools can support this multidisciplinary approach to invasion biology and management if widely adopted and coordinated among institutions and in functional communities of practice. A broader awareness and appreciation of the efficacy and relevance of these technologies and methodological approaches among researchers, managers, and decision-makers is needed, along with support to facilitate their broader application and integration.

(3) We outline a conceptual framework and generalized analytical pipeline to implement these technologies, methods, and workflows in an adaptive, iterative and scalable fashion (Fig. 1). This framework ultimately embraces the abundance and diversity of IAS and spatiotemporal environmental data becoming available, encourages its coordinated use, management and availability, and prioritizes its translation and distillation into timely, actionable products that are co-designed with stakeholders to support their decision-making.

(4) Species distribution modelling, when integrated with participatory and big data approaches, is a key analytical approach for supporting proactive management across spatiotemporal and analytical scales using currently available data and information from new and emerging monitoring and biosurveillance technologies. SDMs support the generation of useful products like horizon scans, spatial relative risk assessments, and EBVs from the best available data. Predictive modelling methods with the ability to handle diverse and numerous data sets compiled across sources (e.g. machine-learning ensembles, Bayesian hierarchical, and mechanistic simulation models) are especially important to take advantage of new and diverse data sources. Access to computing resources and expertise for conducting such modelling, especially on an iterative basis, is a major limiting factor for the applied execution of this workflow. Cloud computing services with machine-learning functionality may be key for applying these models at larger scales and at time intervals that are relevant to management and decision-making.

(5) Among methodological improvements, better frameworks for data format standardization and sharing and interoperability, and early involvement of IAS managers, decision-makers, and other stakeholders, could greatly increase the efficacy and accessibility of existing data and subsequent knowledge products (e.g. distribution of spread-risk models). Significant logistical challenges remain around the collation, interoperability, and wider availability of IAS occurrence data which constitute a bottleneck to achieving global-scale proactive management of biological invasions. Different professional incentives and social networks between researchers, managers, and decision-makers may also hamper coordination and knowledge co-production, a second roadblock for this applied workflow that reduces the usability of data products for intended user groups.

(6) Population genomic, transcriptomic, and remote-sensing methods represent major technological frontiers of innovation for invasion monitoring and spread prevention by facilitating semi-autonomous and high-frequency monitoring of species occurrence and predictive modelling of the pathways of spread. Modern hyperspectral imaging, remote photography (e.g. trail cameras), and active observation missions may allow for direct observation of certain IAS, promoting continuous spatiotemporal surveillance of high-risk areas and providing requisite occurrence data to predictive models. In this way, existing temporally explicit data layers can be formulated into point data, enabling the mechanistic modelling of spread and stepwise occurrence for invasion events across broad taxonomic and spatiotemporal scales.

Integrating remote-sensing, environmental, and population genetic data (e.g. in landscape genomic modelling approaches) allows tracking, mapping, and prediction of spatiotemporal pathways of spread.

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IX. REFERENCES

Abeysinghe, T., Simic Milas, A., Arend, K., Hohman, B., Reil, P., Gregory, A. & Vázquez-Ortega, A. (2019). Mapping invasive *Phragmites australis* in the Old Woman Creek Estuary using UAV remote sensing and machine learning classifiers. *Remote Sensing* **11**, 1380.

Allen, J. M. & Bradley, B. A. (2016). Out of the weeds? Reduced plant invasion risk with climate change in the continental United States. *Biological Conservation* **203**, 306–312.

Allendorf, F. W., Funk, W. C., Aitken, S. N., Byrne, M. & Luikart, G. (2022). *Conservation and the Genomics of Populations*, Third Edition (). Oxford University Press, Oxford, UK.

Anton, V., Hartley, S. & Wittmer, H. U. (2018). Evaluation of remote cameras for monitoring multiple invasive mammals in New Zealand. *New Zealand Journal of Ecology* **42**, 74–79.

Aota, T., Ashizawa, K., Mori, H., Toda, M. & Chiba, S. (2021). Detection of *Anolis carolinensis* using drone images and a deep neural network: an effective tool for controlling invasive species. *Biological Invasions* **23**, 1321–1327.

Atala, C., Pertierra, L. R., Aragón, P., Carrasco-Urra, F., Lavín, P., Gallardo-Cerda, J., Ricote-Martínez, N., Torres-Díaz, C. & Molina-Montenegro, M. A. (2019). Positive interactions among native and invasive vascular plants in Antarctica: assessing the "nurse effect" at different spatial scales. *Biological Invasions* **21**, 2819–2836.

Barwell, L. J., Perez-Sierra, A., Henricot, B., Harris, A., Burgess, T. I., Hardy, G., Scott, P., Williams, N., Cooke, D. E. L., Green, S., Chapman, D. S. & Purse, B. V. (2021). Evolutionary trait-based approaches for predicting future global impacts of plant pathogens in the genus *Phytophthora*. *Journal of Applied Ecology* **58**, 718–730.

Battini, N., Farías, N., Giachetti, C. B., Schwindt, E. & Bortolus, A. (2019). Staying ahead of invaders: using species distribution modeling to predict alien species potential niche shifts. *Marine Ecology Progress Series* **612**, 127–140.

Bazzichetto, M., Malavasi, M., Bartak, V., Acosta, A. T. R., Rocchini, D. & Carranza, M. L. (2018). Plant invasion risk: a quest for invasive species distribution modeling in managing protected areas. *Ecological Indicators* **95**, 311–319.

Beaury, E. M., Fusco, E. J., Jackson, M. R., Laginhas, B. B., Morelli, T. L., Allen, J. M., Pasquarella, V. J. & Bradley, B. A. (2020). Incorporating climate change into invasive species management: insights from managers. *Biological Invasions* **22**, 233–252.

Bellard, C., Cassey, P. & Blackburn, T. M. (2016). Alien species as a driver of recent extinctions. *Biology Letters* **12**, 20150623.

Benkendorf, D. J. & Hawkins, C. P. (2020). Effects of sample size and network depth on a deep learning approach to species distribution modeling. *Ecological Informatics* **60**, 101137.

Bennett, E. M., Hauser, C. E. & Moore, J. L. (2020). Evaluating conservation dogs in the search for rare species. *Conservation Biology* **34**, 314–325.

Berry, O., Jarman, S., Bissett, A., Hope, M., Paeper, C., Bessey, C., Schwartz, M. K., Hale, J. & Bunce, M. (2020). Making environmental DNA (eDNA) biodiversity records globally accessible. *Environmental DNA* **3**, 699–705.

Biró, M., Molnár, Z., Babai, D., Dénes, A., Fehér, A., Barta, S., Sáfián, L., Szabados, K., Kiš, A. & Demeter, L. (2019). Reviewing historical traditional knowledge for innovative conservation management: a re-evaluation of wetland grazing. *Science of the Total Environment* **666**, 1114–1125.

Blackburn, G. S., Bilodeau, P., Cooke, T., Cui, M., Cusson, M., Hamelin, R. C., Keena, M. A., Picq, S., Roe, A. D., Shi, J., Wu, Y. & Porth, I. (2020). An applied empirical framework for invasion science: confronting biological invasion through collaborative research aimed at tool production. *Annals of the Entomological Society of America* **113**, 230–245.

Booy, O., Mill, A. C., Roy, H. E., Hiley, A., Moore, N., Robertson, P., Baker, S., Brazier, M., Bue, M., Bullock, R., Campbell, S., Eyre, D., Foster, J., Hatton-Ellis, M., Long, J., et al. (2017). Risk management to prioritise the eradication of new and emerging invasive non-native species. *Biological Invasions* **19**, 2401–2417.

Bradley, B. A., Allen, J. M., O'Neill, M. W., Wallace, R. D., Bargeron, C. T., Richburg, J. A. & Stinson, K. (2018). Invasive species risk assessments need more consistent spatial abundance data. *Ecosphere* **9**, e02302.

Bradshaw, C. J. A., Leroy, B., Bellard, C., Roiz, D., Albert, C., Fournier, A., Barbet-Massin, M., Salles, J.-M., Simard, F. & Courchamp, F. (2016). Massive yet grossly underestimated global costs of invasive insects. *Nature Communications* **7**, 12986.

Caceres-Escobar, H., Kark, S., Atkinson, S. C., Possingham, H. P. & Davis, K. J. (2019). Integrating local knowledge to prioritise invasive species management. *People and Nature* **1**, 220–233.

Callaghan, C. T., Poore, A. G. B., Major, R. E., Rowley, J. J. L. & Cornwell, W. K. (2019). Optimizing future biodiversity sampling by citizen scientists. *Proceedings of the Royal Society B: Biological Sciences* **286**, 20191487.

Candela, L., Castelli, D., Coro, G., Pagano, P. & Sinibaldi, F. (2016). Species distribution modeling in the cloud. *Concurrency and Computation: Practice and Experience* **28**, 1056–1079.

Carboni, M., Guéguen, M., Barros, C., Georges, D., Boulangeat, I., Douzet, R., Dullinger, S., Klonner, G., van Kleunen, M., Essl, F., Bossdorf, O., Haeuser, E., Talluto, M. V., Moser, D., Block, S., et al. (2018). Simulating plant invasion dynamics in mountain ecosystems under global change scenarios. *Global Change Biology* **24**, e289–e302.

Carim, K. J., Bean, N. J., Connor, J. M., Baker, W. P., Jaeger, M., Ruggles, M. P., McKelvey, K. S., Franklin, T. W., Young, M. K. & Schwartz, M. K. (2020). Environmental DNA sampling informs fish eradication efforts: case studies and lessons learned. *North American Journal of Fisheries Management* **40**, 488–508.

Carlson, A. K., Taylor, W. W., Kinnison, M. T., Sullivan, S. M. P., Weber, M. J., Melstrom, R. T., Venturelli, P. A., Wuellner, M. R., Newman, R. M., Hartman, K. J., Zydlewski, G. B., DeVries, D. R., Gray, S. M., Infante, D. M., Pegg, M. A., et al. (2019). Threats to freshwater fisheries in the United States: perspectives and investments of state fisheries administrators and agricultural experiment station directors. *Fisheries* **44**, 276–287.

Carter, S. C., van Rees, C. B., Hand, B. K., Muhlfeld, C., Luikart, G. & Kimball, J. S. (2021). Testing a generalizable machine learning workflow for aquatic invasive species on rainbow trout (*Oncorhynchus mykiss*) in Northwest Montana. *Frontiers in Big Data* **4**, 734990.

Carvalho, J., Diéguez, L., Ipatov, A., Guerreiro, J. R., Garrido-Maestu, A., Azinheiro, S. & Prado, M. (2021). Single-use microfluidic device for purification and concentration of environmental DNA from river water. *Talanta* **226**, 122109.

Chapman, D. S., Makra, L., Albertini, R., Bonini, M., Páldy, A., Rodinkova, V., Šikoparija, B., Weryszko-Chmielewska, E. & Bullock, J. M. (2016). Modeling the introduction and spread of non-native species: international trade and climate change drive ragweed invasion. *Global Change Biology* **22**, 3067–3079.

Chapman, D., Pescott, O. L., Roy, H. E. & Tanner, R. (2019). Improving species distribution models for invasive non-native species with biologically informed pseudo-absence selection. *Journal of Biogeography* **46**, 1029–1040.

Charney, N. D., Record, S., Gerstner, B. E., Merow, C., Zarnetske, P. L. & Enquist, B. J. (2021). A test of species distribution model transferability across environmental and geographic space for 2018 Western North American tree species. *Frontiers in Ecology and Evolution* **9**, 393.

Cheney, C., van Wilgen, N. J., Esler, K. J., Foxcroft, L. C. & McGeoch, M. A. (2021). Quantifying range structure to inform management in invaded landscapes. *Journal of Applied Ecology* **58**, 338–349.

Chown, S. L., Hodgins, K. A., Griffin, P. C., Oakeshott, J. G., Byrne, M. & Hoffman, A. A. (2015). Biological invasions, climate change and genomics. *Evolutionary Applications* **8**, 23–46.

Cook, G., Jarnevich, C., Warden, M., Downing, M., Withrow, J. & Leinwand, I. (2019). Iterative models for early detection of invasive species across spread pathways. *Forests* **10**, 108.

Crimmins, T. M., Gerst, K. L., Huerta, D. G., Marsh, R. L., Posthumus, E. E., Rosemartin, A. H., Switzer, J., Weltzin, J. F., Coop, L., Dietschler, N., Herms, D. A., Limbu, S., Trotter, R. T. III & Whitmore, M. (2020). Short-term forecasts of insect phenology inform pest management. *Annals of the Entomological Society of America* **113**, 139–148.

Cristescu, M. E. (2019). Can environmental RNA revolutionize biodiversity science? *Trends in Ecology & Evolution* **34**, 694–697.

Cvitanovic, C., Howden, M., Colvin, R. M., Norström, A., Meadow, A. M. & Addison, P. F. E. (2019). Maximising the benefits of participatory climate adaptation research by understanding and managing the associated challenges and risks. *Environmental Science & Policy* **94**, 20–31.

Daliakopoulos, I. N., Katsanevakis, S. & Moustakas, A. (2017). Spatial downscaling of alien species presences using machine learning. *Frontiers in Earth Science* **5**, 60.

Dantas de Paula, M., Gómez Giménez, M., Niamir, A., Thurner, M. & Hickler, T. (2020). Combining European Earth observation products with dynamic global vegetation models for estimating essential biodiversity variables. *International Journal of Digital Earth* **13**, 262–277.

Das, N. N., Entekhabi, D., Dunbar, R. S., Chaubell, M. J., Colliander, A., Yueh, S., Jagdhuber, T., Chen, F., Crow, W., O'Neill, P. E., Walker, J. P., Berg, A., Bosch, D. D., Caldwell, T., Cosh, M. H., et al. (2019). The SMAP and Copernicus Sentinel 1A/B microwave active-passive high resolution surface soil moisture product. *Remote Sensing of Environment* **233**, 111380.

Dash, J. P., Watt, M. S., Paul, T. S. H., Morgenroth, J. & Pearse, G. D. (2019). Early detection of invasive exotic trees using UAV and manned aircraft multispectral and LiDAR data. *Remote Sensing* **11**, 1812.

Daume, S. (2016). Mining Twitter to monitor invasive alien species—an analytical framework and sample information topologies. *Ecological Informatics* **31**, 70–82.

Dauwalter, D. C., Fesenmyer, K. A., Bjork, R., Leasure, D. R. & Wenger, S. J. (2017). Satellite and airborne remote sensing applications for freshwater fisheries. *Fisheries* **42**, 526–537.

Davies, A. B. & Asner, G. P. (2014). Advances in animal ecology from 3D-LiDAR ecosystem mapping. *Trends in Ecology & Evolution* **29**, 681–691.

De Kort, H., Baguette, M., Prunier, J. G., Tessier, M., Monsimet, J., Turlure, C. & Stevens, V. (2018). Genetic costructure in a meta-community under threat of habitat fragmentation. *Molecular Ecology* **27**, 2193–2203.

Dehnen-Schmutz, K., Boivin, T., Essl, F., Groom, Q. J., Harrison, L., Touza, J. M. & Bayliss, H. (2018). Alien futures: what is on the horizon for biological invasions? *Diversity and Distributions* **24**, 1149–1157.

Diagne, C., Leroy, B., Vaissière, A.-C., Gozlan, R. E., Roiz, D., Jarić, I., Salles, J.-M., Bradshaw, C. J. A. & Courchamp, F. (2021). High and rising economic costs of biological invasions worldwide. *Nature* **592**, 571–576.

Dietze, M. (2017). *Ecological Forecasting*. Princeton University Press, Princeton, NJ, USA.

Dominguez-Almela, V., Palmer, S. C. F., Gillingham, P. K., Travis, J. M. J. & Britton, J. R. (2020). Integrating an individual-based model with approximate Bayesian computation to predict the invasion of a freshwater fish provides insights into dispersal and range expansion dynamics. *Biological Invasions* **22**, 1461–1480.

Domisch, S., Amatulli, G. & Jetz, W. (2015). Near-global freshwater-specific environmental variables for biodiversity analyses in 1 km resolution. *Scientific Data* **2**, 150073.

Donnelly, J. P., Naugle, D. E., Collins, D. P., Dugger, B. D., Allred, B. W., Tack, J. D. & Dreitz, V. J. (2019). Synchronizing conservation to seasonal wetland hydrology and waterbird migration in semi-arid landscapes. *Ecosphere* **10**, e02758.

Du, J., Kimball, J. S., Duguay, C., Kim, Y. & Watts, J. D. (2017). Satellite microwave assessment of Northern Hemisphere lake ice phenology from 2002 to 2015. *The Cryosphere* **11**, 47–63.

Dubayah, S., Luthcke, S., Blair, J., Hofton, M., Armston, J. & Tang, H. (2020). *GEDI L1B Geolocated Waveform Data Global Footprint Level V001*. National Aeronautics and Space Administration, Washington, DC.

Edwards, T., Jones, C. B., Perkins, S. E. & Corcoran, P. (2021). Passive citizen science: the role of social media in wildlife observations. *PLoS One* **16**, e0255416.

Elith, J. (2017). Predicting distributions of invasive species. In *Invasive Species: Risk Assessment and Management* (eds A. P. Robinson, T. Walshe, M. A. Burgman and M. Nunn), pp. 93–129. Cambridge University Press, Cambridge.

Elith, J., Leathwick, J. R. & Hastie, T. (2008). A working guide to boosted regression trees. *Journal of Animal Ecology* **77**, 802–813.

Elith, J., Kearney, M. & Phillips, S. (2010). The art of modeling range-shifting species. *Methods in Ecology and Evolution* **1**, 330–342.

Encarnaçao, J., Teodósio, M. A. & Morais, P. (2021). Citizen science and biological invasions: a review. *Frontiers in Environmental Science* **8**, 303.

Enquist, C. A., Jackson, S. T., Garfin, G. M., Davis, F. W., Gerber, L. R., Littell, J. A., Tank, J. L., Terando, A. J., Wall, T. U., Halpern, B., Hiers, J. K., Morelli, T. L., McNie, E., Stephenson, N. L., Williamson, M. A., et al. (2017). Foundations of translational ecology. *Frontiers in Ecology and the Environment* **15**, 541–550.

Eritja, R., Ruiz-Arrondo, I., Delacour-Estrella, S., Schaffner, F., Álvarez-Chachero, J., Bengoa, M., Puig, M.-Á., Melero-Alcíbar, R., Oltra, A. & Bartumeus, F. (2019). First detection of *Aedes japonicus* in Spain: an unexpected finding triggered by citizen science. *Parasites & Vectors* **12**, 53.

Essl, F., Bacher, S., Blackburn, T. M., Booy, O., Brundu, G., Brunel, S., Cardoso, A.-C., Eschen, R., Gallardo, B., Galil, B., García-Berthou, E., Genovesi, P., Groom, Q., Harrower, C., Hulme, P. E., et al. (2015). Crossing frontiers in tackling pathways of biological invasions. *Bioscience* **65**, 769–782.

Essl, F., Lenzner, B., Courchamp, F., Dullinger, S., Jeschke, J. M., Kühn, I., Leung, B., Moser, D., Roura-Pascual, N. & Seebens, H. (2019). Introducing AlienScenarios: a project to develop scenarios and models of biological invasions for the 21st century. *NeoBiota* **45**, 1–17.

Essl, F., Latombe, G., Lenzner, B., Pagad, S., Seebens, H., Smith, K., Wilson, J. R. & Genovesi, P. (2020). The Convention on Biological Diversity (CBD)'s Post-2020 target on invasive alien species–what should it include and how should it be monitored? *NeoBiota* **62**, 99–121.

Farley, S. S., Dawson, A., Goring, S. J. & Williams, J. W. (2018). Situating ecology as a big-data science: current advances, challenges, and solutions. *Bioscience* **68**, 563–576.

Faulkner, K. T., Robertson, M. P. & Wilson, J. R. U. (2020). Stronger regional biosecurity is essential to prevent hundreds of harmful biological invasions. *Global Change Biology* **26**, 2449–2462.

Fournier, A., Penone, C., Pennino, M. G. & Courchamp, F. (2019). Predicting future invaders and future invasions. *Proceedings of the National Academy of Sciences* **116**, 7905–7910.

Fujitani, M., McFall, A., Randler, C. & Arlinghaus, R. (2017). Participatory adaptive management leads to environmental learning outcomes extending beyond the sphere of science. *Science Advances* **3**, e1602516.

Fuller, P. & Neilson, M. E. (2015). The US Geological Survey's Nonindigenous Aquatic Species database: over thirty years of tracking introduced aquatic species in the United States (and counting). *Management of Biological Invasions* **6**, 159–170.

Gallardo, B., Zieritz, A., Adriaens, T., Bellard, C., Boets, P., Britton, J. R., Newman, J. R., van Valkenburg, J. L. & Aldridge, D. C. (2016). Trans-national horizon scanning for invasive non-native species: a case study in western Europe. *Biological Invasions* **18**, 17–30.

Gaydos, D. A., Petrasova, A., Cobb, R. C. & Meentemeyer, R. K. (2019). Forecasting and control of emerging infectious forest disease through participatory modelling. *Philosophical Transactions of the Royal Society B: Biological Sciences* **374**, 20180283.

Gelaro, R., McCarty, W., Suárez, M. J., Todling, R., Molod, A., Takacs, L., Randles, C. A., Darmenov, A., Bosilovich, M. G. & Reichle, R. (2017). The modern-era retrospective analysis for research and applications, version 2 (MERRA-2). *Journal of Climate* **30**, 5419–5454.

Ghermandi, A. & Sinclair, M. (2019). Passive crowdsourcing of social media in environmental research: a systematic map. *Global Environmental Change* **55**, 36–47.

Gillard, M. B., Drenovsky, R. E., Thiébaut, G., Tarayre, M., Futrell, C. J. & Grewell, B. J. (2020). Seed source regions drive fitness differences in invasive macrophytes. *American Journal of Botany* **107**, 749–760.

Goldberg, C. S., Turner, C. R., Deiner, K., Klymus, K. E., Thomsen, P. F., Murphy, M. A., Spear, S. F., McKee, A., Oyler-McCance, S. J., Cornman, R. S., Laramie, M. B., Mahon, A. R., Lance, R. F., Pilliod, D. S., Strickler, K. M., et al. (2016). Critical considerations for the application of environmental DNA methods to detect aquatic species. *Methods in Ecology and Evolution* **7**, 1299–1307.

Gonzalez de Tanago, J., Lau, A., Bartholomeus, H., Herold, M., Avitabile, V., Raumonen, P., Martius, C., Goodman, R. C., Disney, M., Manuri, S., Burt, A. & Calders, K. (2018). Estimation of above-ground biomass of large tropical trees with terrestrial LiDAR. *Methods in Ecology and Evolution* **9**, 223–234.

Griffin, J. E., Matechou, E., Buxton, A. S., Bormpoudakis, D. & Griffiths, R. A. (2020). Modeling environmental DNA data; Bayesian variable selection accounting for false positive and false negative errors. *Journal of the Royal Statistical Society: Series C (Applied Statistics)* **69**, 377–392.

Grimm-Seyfarth, A., Harms, W. & Berger, A. (2021). Detection dogs in nature conservation: a database on their world-wide deployment with a review on breeds used and their performance compared to other methods. *Methods in Ecology and Evolution* **12**, 568–579.

Groom, Q. J., Desmet, P., Vanderhoeven, S. & Adriaens, T. (2015). The importance of open data for invasive alien species research, policy and management. *Management of Biological Invasions* **6**, 119–125.

Groom, Q. J., Adriaens, T., Desmet, P., Simpson, A., De Wever, A., Bazos, I., Cardoso, A. C., Charles, L., Christopoulou, A., Gazda, A., Helmisaari, H., Hobern, D., Josefsson, M., Lucy, F., Marisavljevic, D., et al. (2017). Seven recommendations to make your invasive alien species data more useful. *Frontiers in Applied Mathematics and Statistics* **3**, 13.

Groom, Q., Desmet, P., Reyserhove, L., Adriaens, T., Oldoni, D., Vanderhoeven, S., Baskauf, S. J., Chapman, A., McGeoch, M. & Walls, R. (2019a). Improving Darwin Core for research and management of alien species. *Biodiversity Information Science and Standards* **3**, e38084.

Groom, Q., Strubbe, D., Adriaens, T., Davis, A., Desmet, P., Oldoni, D., Reyserhove, L., Roy, H. E. & Vanderhoeven, S. (2019b). Empowering citizens to inform decision-making as a way forward to support invasive alien species policy. *Citizen Science: Theory and Practice* **4**, 1–11.

Groom, Q., Pernat, N., Adriaens, T., de Groot, M., Jelaska, S. D., Marčiulynienė, D., Martinou, A. F., Skuhrovec, J., Tricarico, E., Wit, E. C. & Roy, H. E. (2021). Species interactions: next-level citizen science. *Ecography* **44**, 1781–1789.

Grummer, J. A., Beheregaray, L. B., Bernatchez, L., Hand, B. K., Luikart, G., Narum, S. R. & Taylor, E. B. (2019). Aquatic landscape genomics and environmental effects on genetic variation. *Trends in Ecology & Evolution* **34**, 641–665.

Guillera-Arroita, G., Lahoz-Monfort, J. J., Elith, J., Gordon, A., Kujala, H., Lentini, P. E., McCarthy, M. A., Tingley, R. & Wintle, B. A. (2015). Is my species distribution model fit for purpose? Matching data and models to applications. *Global Ecology and Biogeography* **24**, 276–292.

Haklay, M., Dörler, D., Heigl, F., Manzoni, M., Hecker, S. & Vohland, K. (2021). What is citizen science? The challenges of definition. In *The Science of Citizen Science* (eds K. Vohland, A. Land-Zandstra, L. Ceccaroni, R. Lemmens, J. Perelló, M. Ponti, R. Samson and K. Wagenknecht), pp. 13–33. Springer International Publishing, Cham, Switzerland.

Hamelin, R. C. & Roe, A. D. (2020). Genomic biosurveillance of forest invasive alien enemies: a story written in code. *Evolutionary Applications* **13**, 95–115.

Hand, B. K., Lowe, W. H., Kovach, R. P., Muhlfeld, C. C. & Luikart, G. (2015). Landscape community genomics: understanding eco-evolutionary processes in complex environments. *Trends in Ecology & Evolution* **30**, 161–168.

Hardisty, A. R., Belbin, L., Hobern, D., McGeoch, M. A., Pirzl, R., Williams, K. J. & Kissling, W. D. (2019). Research infrastructure challenges in preparing essential biodiversity variables data products for alien invasive species. *Environmental Research Letters* **14**, 025005.

Harmáčková, Z. V., Blättler, L., Aguiar, A. P. D., Daněk, J., Krpec, P. & Vačkárová, D. (2021). Linking multiple values of nature with future impacts: value-based participatory scenario development for sustainable landscape governance. *Sustainability Science* **12**, 1–16.

Hattab, T., Garzón-López, C. X., Ewald, M., Skowronek, S., Aerts, R., Horen, H., Brasseur, B., Gallet-Moron, E., Spicher, F., Decocq, G., Feilhauer, H., Honnay, O., Kempeneers, P., Schmidtlein, S., Somers, B., et al. (2017). A unified framework to model the potential and realized distributions of invasive species within the invaded range. *Diversity and Distributions* **23**, 806–819.

Hershman, D., Sikora, E. & Giesler, L. J. (2011). Soybean rust PIPE: past, present, and future. *Journal of Integrated Pest Management* **2**, D1–D7.

Holman, L. E., Parker-Nance, S., de Bruyn, M., Creer, S., Carvalho, G. & Rius, M. (2022). Managing human-mediated range shifts: understanding spatial, temporal and genetic variation in marine non-native species. *Philosophical Transactions of the Royal Society B: Biological Sciences* **377**(1846). https://doi.org/10.1098/rstb.2021.0025.

Howard, L., van Rees, C. B., Dahlquist, Z., Luikart, G. & Hand, B. K. (2022). A review of invasive species reporting apps for citizen science and opportunities for innovation. *NeoBiota* **71**, 165–188.

Hoyer-Tomiczek, U. & Hoch, G. (2020). Progress in the use of detection dogs for emerald ash borer monitoring. *Forestry* **93**, 326–330.

Hunter, M. E., Oyler-McCance, S. J., Dorazio, R. M., Fike, J. A., Smith, B. J., Hunter, C. T., Reed, R. N. & Hart, K. M. (2015). Environmental DNA (eDNA) sampling improves occurrence and detection estimates of invasive Burmese pythons. *PLoS One* **10**, e0121655.

Iacona, G., Ramachandra, A., McGowan, J., Davies, A., Joppa, L., Koh, L. P., Fegraus, E., Game, E., Guillera-Arroita, G., Harcourt, R., Indraswari, K., Lahoz-Monfort, J. J., Oliver, J. L., Possingham, H. P., Ward, A., et al. (2019). Identifying technology solutions to bring conservation into the innovation era. *Frontiers in Ecology and the Environment* **17**, 591–598.

Ibrahim, S., Balzter, H., Tansey, K., Tsutsumida, N. & Mathieu, R. (2018). Estimating fractional cover of plant functional types in African savannah from harmonic analysis of MODIS time-series data. *International Journal of Remote Sensing* **39**, 2718–2745.

Intergovernmental Panel on Climate Change (IPCC) (2014). Climate change 2014: synthesis report. Contribution of Working Groups I, II, and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.

Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) (2019). Summary for policymakers of the IPBES global assessment report on biodiversity and ecosystem services. (eds S. Díaz, J. Settele, E. S. Brondízio, H. T. Ngo, M. Guèze, J. Agard, A. Arneth, P. Balvanera, K. A. Brauman, S. H. M. Butchart, K. M. A. Chan, L. A. Garibaldi, K. Ichii, J. Liu, S. M. Subramanian, et al.), 56 pages. IPBES Secretariat, Bonn, Germany.

Isaac, N. J. B., Jarzyna, M. A., Keil, P., Dambly, L. I., Boersch-Supan, P. H., Browning, E., Freeman, S. N., Golding, N., Guillera-Arroita, G., Henrys, P. A., Jarvis, S., Lahoz-Monfort, J., Pagel, J., Pescott, O. L., Schmucki, R., et al. (2020). Data integration for large-scale models of species distributions. *Trends in Ecology & Evolution* **35**, 56–67.

Jarić, I., Correia, R. A., Brook, B. W., Buettel, J. C., Courchamp, F., Di Minin, E., Firth, J. A., Gaston, K. J., Jepson, P., Kalinkat, G., Ladle, R., Soriano-Redondo, A., Souza, A. T. & Roll, U. (2020). iEcology: harnessing large online resources to generate ecological insights. *Trends in Ecology & Evolution* **35**, 630–639.

Jarić, I., Bellard, C., Correia, R., Courchamp, F., Douda, K., Essl, F., Jeschke, J., Kalinkat, G., Kalous, L., Lennox, R., Novoa, A., Proulx, R., Pyšek, P., Soriano-Redondo, A., Souza, A. T., et al. (2021). Invasion Culturomics and iEcology. *Conservation Biology* **35**, 447–451.

Jarnevich, C. S., Simpson, A., Graham, J. J., Newman, G. J. & Bargeron, C. T. (2015). Running a network on a shoestring: the Global Invasive Species Information Network. *Management of Biological Invasions* **6**, 137–146.

Jetz, W., McGeoch, M. A., Guralnick, R., Ferrier, S., Beck, J., Costello, M. J., Fernandez, M., Geller, G. N., Keil, P., Merow, C., Meyer, C., Muller-Karger, F. E., Pereira, H. M., Regan, E. C., Schmeller, D. S., et al. (2019). Essential biodiversity variables for mapping and monitoring species populations. *Nature Ecology & Evolution* **3**, 539–551.

Jiménez, L. & Soberón, J. (2020). Leaving the area under the receiving operating characteristic curve behind: an evaluation method for species distribution modeling applications based on presence-only data. *Methods in Ecology and Evolution* **11**, 1571–1586.

Jiménez-Valverde, A., Peterson, A. T., Soberón, J., Overton, J. M., Aragón, P. & Lobo, J. M. (2011). Use of niche models in invasive species risk assessments. *Biological Invasions* **13**, 2785–2797.

Johnson, B. A., Mader, A. D., Dasgupta, R. & Kumar, P. (2020). Citizen science and invasive alien species: an analysis of citizen science initiatives using information and communications technology (ICT) to collect invasive alien species observations. *Global Ecology and Conservation* **21**, e00812.

Johnston, J. M. (1999). *Canine Detection Capabilities: Operational Implications of Recent R&D Findings*, p. 7. Auburn, AL, Institute for Biological Detection Systems, Auburn University.

Jourdan, J., O'Hara, R. B., Bottarin, R., Huttunen, K.-L., Kuemmerlen, M., Monteith, D., Muotka, T., Ozoliņš, D., Paavola, R. & Pilotto, F. (2018). Effects of changing climate on European stream invertebrate communities: a long-term data analysis. *Science of the Total Environment* **621**, 588–599.

Juanes, F. (2018). Visual and acoustic sensors for early detection of biological invasions: current uses and future potential. *Journal for Nature Conservation* **42**, 7–11.

Kalafatis, S. E., Lemos, M. C., Lo, Y.-J. & Frank, K. A. (2015). Increasing information usability for climate adaptation: the role of knowledge networks and communities of practice. *Global Environmental Change* **32**, 30–39.

Kelly, H. Y., Dufault, N. S., Walker, D. R., Isard, S. A., Schneider, R. W., Giesler, L. J., Wright, D. L., Marois, J. J. & Hartman, G. L. (2015). From select agent to an established pathogen: the response to *Phakopsora pachyrhizi* (soybean rust) in North America. *Phytopathology* **105**, 905–916.

Kim, Y., Kimball, J. S., Didan, K. & Henebry, G. M. (2014). Response of vegetation growth and productivity to spring climate indicators in the conterminous United States derived from satellite remote sensing data fusion. *Agricultural and Forest Meteorology* **194**, 132–143.

Kim, Y., Kimball, J. S., Glassy, J. & Du, J. (2017). An extended global earth system data record on daily landscape freeze–thaw status determined from satellite passive microwave remote sensing. *Earth System Science Data* **9**, 133–147.

Kleczewski, N. M., Plewa, D. E., Bissonnette, K. M., Bowman, N. D., Byrne, J. M., LaForest, J., Dalla-Lana, F., Malvick, D. K., Mueller, D. S., Chilvers, M. I., Paul, P. A., Raid, R. N., Robertson, A. E., Ruhl, G. E., Smith, D. L., et al. (2020). Documenting the establishment, spread, and severity of *Phyllachora maydis* on corn, in the United States. *Journal of Integrated Pest Management* **11**, 14.

Kokotovich, A. E., Delborne, J. A., Elsensohn, J. & Burrack, H. (2020). Emerging technologies for invasive insects: the role of engagement. *Annals of the Entomological Society of America* **113**, 266–279.

Kress, W. J., Mazet, J. A. K. & Hebert, P. D. N. (2020). Opinion: intercepting pandemics through genomics. *Proceedings of the National Academy of Sciences* **117**, 13852–13855.

Lahoz-Monfort, J. J., Chadès, I., Davies, A., Fegraus, E., Game, E., Guillera-Arroita, G., Harcourt, R., Indraswari, K., McGowan, J., Oliver, J. L., Refisch, J., Rhodes, J., Roe, P., Rogers, A., Ward, A., et al. (2019). A call for international leadership and coordination to realize the potential of conservation technology. *Bioscience* **69**, 823–832.

Larson, E. R., Graham, B. M., Achury, R., Coon, J. J., Daniels, M. K., Gambrell, D. K., Jonasen, K. L., King, G. D., LaRacuente, N., Perrin-Stowe, T. I., Reed, E. M., Rice, C. J., Ruzi, S. A., Thairu, M. W., Wilson, J. C., et al. (2020). From eDNA to citizen science: emerging tools for the early detection of invasive species. *Frontiers in Ecology and the Environment* **18**, 194–202.

Latombe, G., Pyšek, P., Jeschke, J. M., Blackburn, T. M., Bacher, S., Capinha, C., Costello, M. J., Fernández, M., Gregory, R. D., Hobern, D., Hui, C., Jetz, W., Kumschick, S., McGrannachan, C., Pergl, J., et al. (2017). A vision for global monitoring of biological invasions. *Biological Conservation* **213**, 295–308.

Laudy, C., Mészáros, L., Wanke, S. & de Juan, M. (2020). Mixing social media analysis and physical models to monitor invasive species. 2020 IEEE 23rd International Conference on Information Fusion (FUSION), pp. 1–8.

Lemos, M. C., Arnott, J. C., Ardoin, N. M., Baja, K., Bednarek, A. T., Dewulf, A., Fieseler, C., Goodrich, K. A., Jagannathan, K., Klenk, N., Mach, K. J., Meadow, A. M., Meyer, R., Moss, R., Nichols, L., et al. (2018). To co-produce or not to co-produce. *Nature Sustainability* **1**, 722–724.

Lenzner, B., Leclère, D., Franklin, O., Seebens, H., Roura-Pascual, N., Obersteiner, M., Dullinger, S. & Essl, F. (2019). A framework for global twenty-first century scenarios and models of biological invasions. *Bioscience* **69**, 697–710.

Li, C., Li, Z., Jia, H. & Yan, J. (2011). One-step ultrasensitive detection of microRNAs with loop-mediated isothermal amplification (LAMP). *Chemical Communications* **47**, 2595–2597.

Lioy, S., Bianchi, E., Biglia, A., Bessone, M., Laurino, D. & Porporato, M. (2021). Viability of thermal imaging in detecting nests of the invasive hornet Vespa velutina. *Insect Sci.* **28**, 271–277.

Liu, C., Wolter, C., Xian, W. & Jeschke, J. M. (2020a). Most invasive species largely conserve their climatic niche. *Proceedings of the National Academy of Sciences* **117**, 23643–23651.

Liu, C., Wolter, C., Xian, W. & Jeschke, J. M. (2020b). Species distribution models have limited spatial transferability for invasive species. *Ecology Letters* **23**, 1682–1692.

Lorena, A. C., Jacintho, L. F. O., Siqueira, M. F., Giovanni, R. D., Lohmann, L. G., de Carvalho, A. C. P. L. F. & Yamamoto, M. (2011). Comparing machine learning classifiers in potential distribution modeling. *Expert Systems with Applications* **38**, 5268–5275.

Lucy, F. E., Davis, E., Anderson, R., Booy, O., Bradley, K., Britton, J. R., Byrne, C., Caffrey, J. M., Coughlan, N. E. & Crane, K. (2020). Horizon scan of invasive alien species for the Island of Ireland. *Management of Biological Invasions* **11**, 155–177.

Machado, G., Korennoy, F., Alvarez, J., Picasso-Risso, C., Perez, A. & VanderWaal, K. (2019). Mapping changes in the spatiotemporal distribution of lumpy skin disease virus. *Transboundary and Emerging Diseases* **66**, 2045–2057.

Martin, F.-M., Müllerová, J., Borgniet, L., Dommanget, F., Breton, V. & Evette, A. (2018). Using single- and multi-date UAV and satellite imagery to accurately monitor invasive knotweed species. *Remote Sensing* **10**, 1662.

Martinez, B., Reaser, J. K., Dehgan, A., Zamft, B., Baisch, D., McCormick, C., Giordano, A. J., Aicher, R. & Selbe, S. (2020). Technology innovation: advancing capacities for the early detection of and rapid response to invasive species. *Biological Invasions* **22**, 75–100.

Matthews, J., Beringen, R., Creemers, R., Hollander, H. D., van Kessel, N., van Kleef, H., Koppel, S., Lemaire, A., Odé, B. & Verbrugge, L. N. (2017). A new approach to horizon-scanning: identifying potentially invasive alien species and their introduction pathways. *Management of Biological Invasions* **8**, 37–52.

Mazumdar, S., Ceccaroni, L., Piera, J., Hölker, F., Berre, A., Arlinghaus, R. & Bowser, A. (2018). *Citizen Science Technologies and New Opportunities for Participation*. UCL Press, London, UK.

McGeoch, M. & Jetz, W. (2019). Measure and reduce the harm caused by biological invasions. *One Earth* **1**, 171–174.

Meerdink, S. K., Roberts, D. A., Roth, K. L., King, J. Y., Gader, P. D. & Koltunov, A. (2019). Classifying California plant species temporally using airborne hyperspectral imagery. *Remote Sensing of Environment* **232**, 111308.

Merkes, C. M., McCalla, S. G., Jensen, N. R., Gaikowski, M. P. & Amberg, J. J. (2014). Persistence of DNA in carcasses, slime and avian feces may affect interpretation of environmental DNA data. *PLoS One* **9**, e113346.

Messager, M. L. & Olden, J. D. (2018). Individual-based models forecast the spread and inform the management of an emerging riverine invader. *Diversity and Distributions* **24**, 1816–1829.

Mollot, G., Pantel, J. H. & Romanuk, T. N. (2017). The effects of invasive species on the decline in species richness: a global meta-analysis. In *Advances in Ecological Research* (eds D. A. Bohan, A. J. Dumbrell and F. Massol), pp. 61–83. Academic Press, London, UK.

Morisette, J. T., Cravens, A. E., Miller, B. W., Talbert, M., Talbert, C., Jarnevich, C., Fink, M., Decker, K. & Odell, E. A. (2017). Crossing boundaries in a collaborative modeling workspace. *Society & Natural Resources* **30**, 1158–1167.

Morisette, J. T., Macaluso, K. & Burgiel, S. W. (2020). Overview of a special issue on geospatial analysis of invasive arthropod alien species. *Annals of the Entomological Society of America* **113**, 67–70.

Moustakas, A. & Katsanevakis, S. (2018). Editorial: data mining and methods for early detection, horizon scanning, modeling, and risk assessment of invasive species. *Frontiers in Applied Mathematics and Statistics* **4**, 5.

Muhlfeld, C. C., Kovach, R. P., Al-Chokhachy, R., Amish, S. J., Kershner, J. L., Leary, R. F., Lowe, W. H., Luikart, G., Matson, P., Schmetterling, D. A., Shepard, B. B., Westley, P. A. H., Whited, D., Whiteley, A. & Allendorf, F. W. (2017). Legacy introductions and climatic variation explain spatiotemporal patterns of invasive hybridization in a native trout. *Global Change Biology* **23**, 4663–4674.

Mukherjee, N., Hugé, J., Sutherland, W. J., McNeill, J., Van Opstal, M., Dahdouh-Guebas, F. & Koedam, N. (2015). The Delphi technique in ecology and biological conservation: applications and guidelines. *Methods in Ecology and Evolution* **6**, 1097–1109.

Myers, B. J., Weiskopf, S. R., Shiklomanov, A. N., Ferrier, S., Weng, E., Casey, K. A., Harfoot, M., Jackson, S. T., Leidner, A. K., Lenton, T. M., Luikart, G., Matsuda, H., Pettorelli, N., Rosa, I. M. D., Ruane, A. C., et al. (2021). A new approach to evaluate and reduce uncertainty of model-based biodiversity projections for conservation policy formulation. *Biosciences* **71**, 1261–1273.

Norström, A. V., Cvitanovic, C., Löf, M. F., West, S., Wyborn, C., Balvanera, P., Bednarek, A. T., Bennett, E. M., Biggs, R. & de Bremond, A. (2020). Principles for knowledge co-production in sustainability research. *Nature Sustainability* **3**, 182–190.

Nottingham, C. M., Glen, A. S. & Stanley, M. C. (2021). Relative efficacy of chew card and camera trap indices for use in hedgehog and rat monitoring. *New Zealand Journal of Zoology* **48**, 32–46.

Novoa, A., Shackleton, R., Canavan, S., Cybele, C., Davies, S. G., Dehnen-Schmutz, K., Fried, J., Gaertner, M., Geerts, S., Griffiths, C. L. & Kaplan, H. (2018). A framework for engaging stakeholders on the management of alien species. *Journal of Environmental Management* **205**, 286–297.

Owen, G., Ferguson, D. B. & McMahan, B. (2019). Contextualizing climate science: applying social learning systems theory to knowledge production, climate services, and use-inspired research. *Climatic Change* **157**, 151–170.

Pagad, S., Genovesi, P., Carnevali, L., Schigel, D. & McGeoch, M. A. (2018). Introducing the global register of introduced and invasive species. *Scientific Data* **5**, 170202.

Palomino, M. A., Bardsley, S., Bown, K., De Lurio, J., Ellwood, P., Holland-Smith, D., Huggins, B., Vincenti, A., Woodroof, H. & Owen, R. (2012). Web-based horizon scanning: concepts and practice. *Foresight* **14**, 355–373.

Palumbo, I., Rose, R. A., Headley, R. M. K., Nackoney, J., Vodacek, A. & Wegmann, M. (2017). Building capacity in remote sensing for conservation: present and future challenges. *Remote Sensing in Ecology and Conservation* **3**, 21–29.

Pastick, N. J., Wylie, B. K., Rigge, M. B., Dahal, D., Boyte, S. P., Jones, M. O., Allred, B. W., Parajuli, S. & Wu, Z. (2021). Rapid monitoring of the abundance and spread of exotic annual grasses in the western United States using remote sensing and machine learning. *AGU Advances* **2**, e2020AV000298.

Pawson, S. M., Sullivan, J. J & Grant, A. (2020). Expanding general surveillance of invasive species by integrating citizens as both observers and identifiers. *Journal of Pest Science* **93**, 1155–1166.

Peral, E., Tanelli, S., Statham, S., Joshi, S., Imken, T., Price, D., Sauder, J., Chahat, N. & Williams, A. (2019). RainCube: the first ever radar measurements from a CubeSat in space. *Journal of Applied Remote Sensing* **13**, 032504.

Peterson, G. D., Cumming, G. S. & Carpenter, S. R. (2003). Scenario planning: a tool for conservation in an uncertain world. *Conservation Biology* **17**, 358–366.

Phillips, S. J., Anderson, R. P., Dudík, M., Schapire, R. E. & Blair, M. E. (2017). Opening the black box: an open-source release of Maxent. *Ecography* **40**, 887–893.

Piper, A. M., Batovska, J., Cogan, N. O. I., Weiss, J., Cunningham, J. P., Rodoni, B. C. & Blacket, M. J. (2019). Prospects and challenges of implementing DNA metabarcoding for high-throughput insect surveillance. *GigaScience* **8**, giz092.

Pocock, M. J. O., Roy, H. E., Preston, C. D. & Roy, D. B. (2015). The biological records Centre: a pioneer of citizen science. *Biological Journal of the Linnean Society* **115**, 475–493.

Poghosyan, A. & Golkar, A. (2017). CubeSat evolution: analyzing CubeSat capabilities for conducting science missions. *Progress in Aerospace Sciences* **88**, 59–83.

Pontius, J., Hanavan, R. P., Hallett, R. A., Cook, B. D. & Corp, L. A. (2017). High spatial resolution spectral unmixing for mapping ash species across a complex urban environment. *Remote Sensing of Environment* **199**, 360–369.

van Poorten, B. & Beck, M. (2021). Getting to a decision: using structured decision-making to gain consensus on approaches to invasive species control. *Management of Biological Invasions* **12**, 25–48.

Preece, J. (2016). Citizen science: new research challenges for human–computer interaction. *International Journal of Human–Computer Interaction* **32**, 585–612.

Pyšek, P., Hulme, P. E., Simberloff, D., Bacher, S., Blackburn, T. M., Carlton, J. T., Dawson, W., Essl, F., Foxcroft, L. C., Genovesi, P., Jeschke, J. M., Kühn, I., Liebhold, A. M., Mandrak, N. E., Meyerson, L. A., et al. (2020). Scientists' warning on invasive alien species. *Biological Reviews* **95**, 1511–1534.

Randin, C. F., Ashcroft, M. B., Bolliger, J., Cavender-Bares, J., Coops, N. C., Dullinger, S., Dirnböck, T., Eckert, S., Ellis, E., Fernández, N., Giuliani, G., Guisan, A., Jetz, W., Joost, S., Karger, D., et al. (2020). Monitoring biodiversity in the Anthropocene using remote sensing in species distribution models. *Remote Sensing of Environment* **239**, 111626.

Reaser, J. K., Burgiel, S. W., Kirkey, J., Brantley, K. A., Veatch, S. D. & Burgos-Rodríguez, J. (2020a). The early detection of and rapid response (EDRR) to invasive species: a conceptual framework and federal capacities assessment. *Biological Invasions* **22**, 1–19.

Reaser, J. K., Simpson, A., Guala, G. F., Morisette, J. T. & Fuller, P. (2020b). Envisioning a national invasive species information framework. *Biological Invasions* **22**, 21–36.

van Rees, C. B., Waylen, K. A., Schmidt-Kloiber, A., Thackeray, S. J., Kalinkat, G., Martens, K., Domisch, S., Lillebø, A. I., Hermoso, V., Grossart, H.-P., Schinegger, R., Decleer, K., Adriaens, T., Denys, L., Jarić, I., et al. (2021). Safeguarding freshwater life beyond 2020: recommendations for the new global biodiversity framework from the European experience. *Conservation Letters* **14**, e12771.

Reeves, M., Ibáñez, I., Blumenthal, D., Chen, G., Guo, Q., Jarnevich, C., Koch, J., Sapio, F., Schwartz, M. K., Meentemeyer, R. K., Wylie, B. K. & Boyte, S. (2021). Tools and technologies for quantifying spread and impacts of invasive species. In *Invasive Species in Forests and Rangelands of the United States: A Comprehensive Science Synthesis for the United States Forest Sector* (eds T. M. Poland, T. Patel-Weynand, D. M. Finch, C. F. Miniat, D. C. Hayes and V. M. Lopez), pp. 243–265. Springer International Publishing, Cham.

Reinhardt, J. R., Russell, M. B., Senay, S. & Lazarus, W. (2020). Assessing the current and potential future distribution of four invasive forest plants in Minnesota, U.S.A., using mixed sources of data. *Scientific Reports* **10**, 12738.

Ricciardi, A., Blackburn, T. M., Carlton, J. T., Dick, J. T. A., Hulme, P. E., Iacarella, J. C., Jeschke, J. M., Liebhold, A. M., Lockwood, J. L., MacIsaac, H. J., Pyšek, P., Richardson, D. M., Ruiz, G. M., Simberloff, D., Sutherland, W. J., et al. (2017). Invasion science: a horizon scan of emerging challenges and opportunities. *Trends in Ecology & Evolution* **32**, 464–474.

Robinson, T. B., Martin, N., Loureiro, T. G., Matikinca, P. & Robertson, M. P. (2020). Double trouble: the implications of climate change for biological invasions. *NeoBiota* **62**, 463–487.

Roddewig, M. R., Churnside, J. H., Hauer, F. R., Williams, J., Bigelow, P. E., Koel, T. M. & Shaw, J. A. (2018). Airborne lidar detection and mapping of invasive lake trout in Yellowstone lake. *Applied Optics* **57**, 4111–4116.

Rodríguez-Rey, M., Consuegra, S., Börger, L. & Garcia de Leaniz, C. (2019). Improving species distribution modeling of freshwater invasive species for management applications. *PLoS One* **14**, e0217896.

Roe, A. D., Torson, A. S., Bilodeau, G., Bilodeau, P., Blackburn, G. S., Cui, M., Cusson, M., Doucet, D., Griess, V. C., Lafond, V., Paradis, G., Porth, I., Prunier, J., Srivastava, V., Tremblay, E., et al. (2019). Biosurveillance of forest insects: part I—integration and application of genomic tools to the surveillance of non-native forest insects. *Journal of Pest Science* **92**, 51–70.

Roura-Pascual, N., Leung, B., Rabitsch, W., Rutting, L., Vervoort, J., Bacher, S., Dullinger, S., Erb, K.-H., Jeschke, J. M., Katsanevakis, S., Kühn, I., Lenzner, B., Liebhold, A. M., Obersteiner, M., Pauchard, A., et al. (2021). Alternative futures for global biological invasions. *Sustainability Science* **16**, 1637–1650.

Roy, H. E., Peyton, J. M. & Booy, O. (2020). Guiding principles for utilizing social influence within expert-elicitation to inform conservation decision-making. *Global Change Biology* **26**, 3181–3184.

Roy-Dufresne, E., Saltré, F., Cooke, B. D., Mellin, C., Mutze, G., Cox, T. & Fordham, D. A. (2019). Modeling the distribution of a wide-ranging invasive species using the sampling efforts of expert and citizen scientists. *Ecology and Evolution* **9**, 11053–11063.

Rozance, M. A., Krosby, M., Meadow, A. M., Snover, A., Ferguson, D. B. & Owen, G. (2020). Building capacity for societally engaged climate science by transforming science training. *Environmental Research Letters* **15**, 125008.

Rubenson, E. S. & Olden, J. D. (2020). An invader in salmonid rearing habitat: current and future distributions of smallmouth bass (*Micropterus dolomieu*) in the Columbia River basin. *Canadian Journal of Fisheries and Aquatic Sciences* **77**, 314–325.

Sacks, B. N., Brazeal, J. L. & Lewis, J. C. (2016). Landscape genetics of the nonnative red fox of California. *Ecology and Evolution* **6**, 4775–4791.

Sawchuk, C. (2018). Intercepting invasive invertebrate species before they infest waterbodies: the interception of Alberta's dedicated canine mussel inspection program. In *Using Detection Dogs to Monitor Aquatic Ecosystem Health and Protect Aquatic Resources* (ed. N. L. Richards), pp. 119–165. Palgrave Macmillan, Cham.

Sax, D. F., Early, R. & Bellemare, J. (2013). Niche syndromes, species extinction risks, and management under climate change. *Trends in Ecology & Evolution* **28**, 517–523.

Schneider, F. D., Ferraz, A., Hancock, S., Duncanson, L. I., Dubayah, R. O., Pavlick, R. P. & Schimel, D. S. (2020). Towards mapping the diversity of canopy structure from space with GEDI. *Environmental Research Letters* **15**, 115006.

Scholin, C. A., Birch, J., Jensen, S., Marin, R. III, Massion, E., Pargett, D., Preston, C., Roman, B. & Ussler, W. III (2017). The quest to develop ecogenomic sensors: a 25-year history of the environmental sample processor (ESP) as a case study. *Oceanography* **30**, 100–113.

Seebens, H., Blackburn, T. M., Dyer, E. E., Genovesi, P., Hulme, P. E., Jeschke, J. M., Pagad, S., Pyšek, P., Winter, M., Arianoutsou, M., Bacher, S., Blasius, B., Brundu, G., Capinha, C., Celesti-Grapow, L., et al. (2017). No saturation in the accumulation of alien species worldwide. *Nature Communications* **8**, 14435.

Seebens, H., Clarke, D. A., Groom, Q., Wilson, J. R., García-Berthou, E., Kühn, I., Roigé, M., Pagad, S., Essl, F. & Vicente, J. (2020). A workflow for standardising and integrating alien species distribution data. *NeoBiota* **59**, 39–59.

Sepulveda, A. J., Birch, J. M., Barnhart, E. P., Merkes, C. M., Yamahara, K. M., Marin, R., Kinsey, S. M., Wright, P. R. & Schmidt, C. (2020a). Robotic environmental DNA bio-surveillance of freshwater health. *Scientific Reports* **10**, 14389.

Sepulveda, A. J., Nelson, N. M., Jerde, C. L. & Luikart, G. (2020b). Are environmental DNA methods ready for aquatic invasive species management? *Trends in Ecology & Evolution* **35**, 668–678.

Seymour, C. L., Gillson, L., Child, M. F., Tolley, K. A., Curie, J. C., da Silva, J. M., Alexander, G. J., Anderson, P., Downs, C. T., Egoh, B. N., Ehlers Smith, D. A., Ehlers Smith, Y. C., Esler, K. J., O'Farrell, P. J., Skowno, A. L., et al. (2020). Horizon scanning for south African biodiversity: a need for social engagement as well as science. *Ambio* **49**, 1211–1221.

Shackleton, R. T., Adriaens, T., Brundu, G., Dehnen-Schmutz, K., Estévez, R. A., Fried, J., Larson, B. M. H., Liu, S., Marchante, E., Marchante, H., Moshobane, M. C., Novoa, A., Reed, M. & Richardson, D. M. (2019a). Stakeholder engagement in the study and management of invasive alien species. *Journal of Environmental Management* **229**, 88–101.

Shackleton, R. T., Larson, B. M., Novoa, A., Richardson, D. M. & Kull, C. A. (2019b). The human and social dimensions of invasion science and management. *Journal of Environmental Management* **229**, 1–9.

Sikora, E., Allen, T., Wise, K., Bergstrom, G., Bradley, C., Bond, J., Brown-Rytlewski, D., Chilvers, M., Damicone, J. & DeWolf, E. (2014). A coordinated effort to manage soybean rust in North America: a success story in soybean disease monitoring. *Plant Disease* **98**, 864–875.

Skroblin, A., Carboon, T., Bidu, G., Chapman, N., Miller, M., Taylor, K., Taylor, W., Game, E. T. & Wintle, B. A. (2021). Including indigenous knowledge in species distribution modeling for increased ecological insights. *Conservation Biology* **35**, 587–597.

Smith, A. L., Hodkinson, T. R., Villellas, J., Catford, J. A., Csergő, A. M., Blomberg, S. P., Crone, E. E., Ehrlén, J., Garcia, M. B., Laine, A.-L., Roach, D. A., Salguero-Gómez, R., Wardle, G. M., Childs, D. Z., Elderd, B. D., et al. (2020). Global gene flow releases invasive plants from environmental constraints on genetic diversity. *Proceedings of the National Academy of Sciences* **117**, 4218–4227.

Sofaer, H. R., Jarnevich, C. S. & Flather, C. H. (2018). Misleading prioritizations from modeling range shifts under climate change. *Global Ecology and Biogeography* **27**, 658–666.

Sofaer, H. R., Jarnevich, C. S., Pearse, I. S., Smyth, R. L., Auer, S., Cook, G. L., Edwards, T. C. Jr., Guala, G. F., Howard, T. G., Morisette, J. T. & Hamilton, H. (2019). Development and delivery of species distribution models to inform decision-making. *Bioscience* **69**, 544–557.

Srivastava, V., Lafond, V. & Griess, V. C. (2019). Species distribution models (SDM): applications, benefits and challenges in invasive species management. *CAB Reviews Perspectives in Agriculture Veterinary Science Nutrition and Natural Resources* **14**, 1–13.

Sutherland, W. J. & Woodroof, H. J. (2009). The need for environmental horizon scanning. *Trends in Ecology & Evolution* **24**, 523–527.

Sutherland, W. J., Dias, M. P., Dicks, L. V., Doran, H., Entwistle, A. C., Fleishman, E., Gibbons, D. W., Hails, R., Hughes, A. C., Hughes, J., Kelman, R., Le Roux, X., LeAnstey, B., Lickorish, F. A., Maggs, L., et al. (2020). A horizon scan of emerging global biological conservation issues for 2020. *Trends in Ecology & Evolution* **35**, 81–90.

Taberlet, P., Bonin, A., Zinger, L. & Coissac, E. (2018). *Environmental DNA: For Biodiversity Research and Monitoring*. Oxford University Press, Oxford, UK.

Temesgen, H. & Ver Hoef, J. M. (2015). Evaluation of the spatial linear model, random forest and gradient nearest-neighbour methods for imputing potential productivity and biomass of the Pacific northwest forests. *Forestry* **88**, 131–142.

Tesfamichael, S. G., Newete, S. W., Adam, E. & Dubula, B. (2018). Field spectroradiometer and simulated multispectral bands for discriminating invasive species from morphologically similar cohabitant plants. *GIScience & Remote Sensing* **55**, 417–436.

Thomas, A. C., Tank, S., Nguyen, P. L., Ponce, J., Sinnesael, M. & Goldberg, C. S. (2020). A system for rapid eDNA detection of aquatic invasive species. *Environmental DNA* **2**, 261–270.

Thorson, J. T., Ianelli, J. N., Larsen, E. A., Ries, L., Scheuerell, M. D., Szuwalski, C. & Zipkin, E. F. (2016). Joint dynamic species distribution models: a tool for community ordination and spatio-temporal monitoring. *Global Ecology and Biogeography* **25**, 1144–1158.

Tian, J., Wang, L., Yin, D., Li, X., Diao, C., Gong, H., Shi, C., Menenti, M., Ge, Y., Nie, S., Ou, Y., Song, X. & Liu, X. (2020). Development of spectral-phenological features for deep learning to understand *Spartina alterniflora* invasion. *Remote Sensing of Environment* **242**, 111745.

Toivonen, T., Heikinheimo, V., Fink, C., Hausmann, A., Hiippala, T., Järv, O., Tenkanen, H. & Di Minin, E. (2019). Social media data for conservation science: a methodological overview. *Biological Conservation* **233**, 298–315.

Tsiamis, K., Azzurro, E., Bariche, M., Çinar, M. E., Crocetta, F., De Clerck, O., Galil, B., Gómez, F., Hoffman, R., Jensen, K. R., Kamburska, L., Langeneck, J., Langer, M. R., Levitt-Barmats, Y., Lezzi, M., et al. (2020). Prioritizing marine invasive alien species in the European Union through horizon scanning. *Aquatic Conservation: Marine and Freshwater Ecosystems* **30**, 794–845.

Tsuri, K., Ikeda, S., Hirohara, T., Shimada, Y., Minamoto, T. & Yamanaka, H. (2021). Messenger RNA typing of environmental RNA (eRNA): a case study on zebrafish tank water with perspectives for the future development of eRNA analysis on aquatic vertebrates. *Environmental DNA* **3**, 14–21.

Uden, D. R., Allen, C. R., Angeler, D. G., Corral, L. & Fricke, K. A. (2015). Adaptive invasive species distribution models: a framework for modeling incipient invasions. *Biological Invasions* **17**, 2831–2850.

Ustin, S. L. & Middleton, E. M. (2021). Current and near-term advances in earth observation for ecological applications. *Ecological Processes* **10**, 1.

Vaz, A. S., Alcaraz-Segura, D., Vicente, J. R. & Honrado, J. P. (2019). The many roles of remote sensing in invasion science. *Frontiers in Ecology and Evolution* **7**, 370.

Vendetti, J. E., Lee, C. & LaFollette, P. (2018). Five new records of introduced terrestrial gastropods in Southern California discovered by citizen science. *American Malacological Bulletin* **36**, 232–247.

Verbrugge, L. N. H., de Hoop, L., Aukema, R., Beringen, R., Creemers, R. C. M., van Duinen, G. A., Hollander, H., de Hullu, E., Scherpenisse, M., Spikmans, F., van Turnhout, C. A. M., Wijnhoven, S. & Leuven, R. S. E. W. (2019). Lessons learned from rapid environmental risk assessments for prioritization of alien species using expert panels. *Journal of Environmental Management* **249**, 109405.

Wallingford, P. D., Morelli, T. L., Allen, J. M., Beaury, E. M., Blumenthal, D. M., Bradley, B. A., Dukes, J. S., Early, R., Fusco, E. J., Goldberg, D. E., Ibáñez, I., Laginhas, B. B., Vilà, M. & Sorte, C. J. B. (2020). Adjusting the lens of invasion biology to focus on the impacts of climate-driven range shifts. *Nature Climate Change* **10**, 398–405.

Wan, Z., Hook, S. & Hulley, G. (2015). MYD11A2 MODIS/aqua land surface temperature/emissivity 8-day l3 global 1 km SIN grid V006. NASA EOSDIS land processes DAAC.

West, A. M., Evangelista, P. H., Jarnevich, C. S., Kumar, S., Swallow, A., Luizza, M. W. & Chignell, S. M. (2017). Using multi-date satellite imagery to monitor invasive grass species distribution in post-wildfire landscapes: an iterative, adaptable approach that employs open-source data and software. *International Journal of Applied Earth Observation and Geoinformation* **59**, 135–146.

Whitehouse-Tedd, K., Richards, N. & Parker, P. (2021). Dogs and conservation: emerging themes and considerations. *Journal of Vertebrate Biology* **69**, E2004–E2001.

Wieczorek, J., Bloom, D., Guralnick, R., Blum, S., Doring, M., Giovanni, R., Robertson, T. & Vieglais, D. (2012). Darwin Core: an evolving community-developed biodiversity data standard. *PLoS One* **7**, e29715.

Wilkinson, M. D., Dumontier, M., Aalbersberg, I. J., Appleton, G., Axton, M., Baak, A., Blomberg, N., Boiten, J.-W., da Silva Santos, L. B., Bourne, P. E., Bouwman, J., Brookes, A. J., Clark, T., Crosas, M., Dillo, I., Dumon, O., et al. (2016). The FAIR guiding principles for scientific data management and stewardship. *Scientific Data* **3**, 1–9.

Williams, M.-A., O'Grady, J., Ball, B., Carlsson, J., de Eyto, E., McGinnity, P., Jennings, E., Regan, F. & Parle-McDermott, A. (2019). The application of CRISPR-Cas for single species identification from environmental DNA. *Molecular Ecology Resources* **19**, 1106–1114.

Wilson, J. R. U., Bacher, S., Daehler, C. C., Groom, Q. J., Kumschick, S., Lockwood, J. L., Robinson, T. B., Zengeya, T. A. & Richardson, D. M. (2020). Frameworks used in invasion science: progress and prospects. *NeoBiota* **62**, 1–30.

Wimberly, M. C., de Beurs, K. M., Loboda, T. V. & Pan, W. K. (2021). Satellite observations and malaria: new opportunities for research and applications. *Trends in Parasitology* **37**, 525–537.

Woldt, A., McGovern, A., Lewis, T.D. & Tuttle-Lau, M. (2019). Quality assurance project plan: eDNA monitoring of Bighead and Silver carps. U.S. Fish and Wildlife Service Region 3, Bloomington, MN. Electronic file available at Accessed April 26 2021. https://www.fws.gov/midwest/fisheries/eDNA/documents/QAPp.pdf.

Yamahara, K. M., Preston, C. M., Birch, J., Walz, K., Marin, R. III, Jensen, S., Pargett, D., Roman, B., Ussler, W. III & Zhang, Y. (2019). In situ autonomous acquisition and preservation of marine environmental DNA using an autonomous underwater vehicle. *Frontiers in Marine Science* **6**, 373.

Yates, M. C., Derry, A. M. & Cristescu, M. E. (2021). Environmental RNA: a revolution in ecological resolution? *Trends in Ecology & Evolution* **36**, 601–609.

Young, N. E., Jarnevich, C. S., Sofaer, H. R., Pearse, I., Sullivan, J., Engelstad, P. & Stohlgren, T. J. (2020). A modeling workflow that balances automation and human intervention to inform invasive plant management decisions at multiple spatial scales. *PLoS One* **15**, e0229253.

Zhang, C., Chen, Y., Xu, B., Xue, Y. & Ren, Y. (2020). Improving prediction of rare species' distribution from community data. *Scientific Reports* **10**, 12230.

Zhu, X., Meng, L., Zhang, Y., Weng, Q. & Morris, J. (2019). Tidal and meteorological influences on the growth of invasive *Spartina alterniflora*: evidence from UAV remote sensing. *Remote Sensing* **11**, 1208.

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