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Impact network analysis and the INA R package: Decision support for regional management interventions

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Abstract

1. The success of intervention projects for species management depends on both the effectiveness of management technologies and the geographical landscape of management adoption. Impact network analysis (INA) is a new framework for evaluating the likely level of success of regional species management before, during and after projects, for project implementers, policymakers and funders. INA evaluates the effects of management performance in a multilayer network analysis. The socioeconomic network represents manager communication about technologies and influence about technology adoption decisions in an agent-based model. The linked biophysical network represents species dispersal, resulting in regional success or failure of species management.
2. The specific objectives of this paper are to (a) introduce the INA framework and INA R package; (b) illustrate the identification of key nodes for smart surveillance strategies; (c) illustrate the application of the INA framework for evaluating the likely degree of success of a project in intervention ecology, before, during and after an intervention; and (d) illustrate the use of INA for evaluating adaptation strategies under global change scenarios with pulse and press stressors, introducing 'adaptation functions' to evaluate the management response required for sustainability and resilience.
3. Examples of use of the INA package show key outcomes of analyses: identifying the limiting factors for effective regional management, pointing out when systems may be non-responsive to the system components that are readily changed through management decisions, and identifying the additional adaptations that may be necessary for intervention success.
4. The broader goals for the development of impact network analysis and the INA package are to provide a common framework that integrates across intervention ecology, to enhance opportunities for lessons learned across systems and scientific disciplines, to support the development of a community of practice, and to create a general platform to operationalize analysis of sustainability, resilience and economic viability in intervention ecology applications.

KEYWORDS
agroecology, decision support, disease ecology, endangered species, intervention ecology, invasive species, multilayer networks, R package

1 | INTRODUCTION

Success in interventions in ecological systems often depends on understanding which system components are limiting factors. Successful regional management of species depends on how effective management methodologies are, whether a critical mass of decision-makers adopts good management, and the resulting efficacy of the geographical landscape of management choices. Achieving this type of effective 'management landscape' is a common challenge for management intervention projects across applied ecology—including invasive and endangered species management, restoration, agricultural development and public health programmes, illustrated prominently by the COVID-19 pandemic—with opportunities for synergies by developing concepts across subdisciplines (Carvajal-Yepes et al., 2019; Chadès et al., 2011; Hobbs et al., 2011; Hulme et al., 2020; Lenzner et al., 2019; Ostrom, 2009). Invasive species dispersal is a key threat to ecological systems while connectivity of reserves is often key to endangered species conservation (Hilty et al., 2012). Sustainable agricultural development depends on technologies for managing the spread of pathogens, arthropod pests and weeds, and for supporting the spread of improved crop genotypes (Henry & Vollan, 2014; McEwan et al., 2021). Public health is supported by technologies for communicating about disease and using methods such as vaccination to slow its spread (Manfredi & d'Onofrio, 2013).

Developing good regional management strategies for species in these related ecological systems requires integration across three system components: (a) the type and quality of management technologies and the research underlying them, (b) socioeconomic networks of decision-makers communicating about management technology use, such as networks of land managers or farmers and (c) biophysical networks of dispersal, such as networks of pathogen invasion or networks of endangered species dispersal, where decisions about use of management technologies influence species establishment probabilities. Here, 'impact networks' are defined as multilayer networks, composed of linked socioeconomic and biophysical networks, through which management may have a regional effect. This paper introduces a framework for scenario analysis (Garrett et al., 2018), 'impact network analysis' (INA; Figure 1) and an R package that implements common scenarios for intervention ecology in which an impact network analysis can provide decision support for formulating project strategies (Garrett, 2021a, 2021b).

The first component in this framework is an intervention technology, such as biocontrol agents, biocides, burning regimens, models indicating the best timing of management activities or some combination of such technologies. These intervention technologies are all the products of scientific research and can be thought of in terms of the 'information' (in the broad sense) resulting from scientific experiments, with an associated uncertainty about their effect (Klerkx et al., 2010). The 'value of information'—the improvement in outcomes when decision-makers take into account information, versus not having the information—is a useful concept for regional management strategies. Analyses of the 'value of information' have been incorporated in, for example, medical decision-making (Bartell et al., 2000; Claxton & Sculpher, 2006; Tappenden et al., 2004), management of species (Canessa et al., 2015; Tallis & Polasky, 2011; Wiles, 2004) and adaptive resource management (Williams et al., 2011). The reproducibility of science is being critically evaluated in multiple disciplines, questioning the quality of information generated by experiments (Ioannidis, 2005; Kenett & Shmueli, 2014; Leek & Peng, 2015). And even if information and technologies are of very high quality, their influence on system-level outcomes will be minimal if decision-makers are unaware of them. Impact network analysis (INA) can be thought of as an evaluation of the realized regional value of information or technologies in landscapes.

The second component is the socioeconomic network, where nodes are decision-makers such as farmers, other land or water resource managers, or individuals managing their families' health (Burgess et al., 2020; Garcia-Figuera et al., 2021; Rebaudo & Dangles, 2011, 2013)—and potentially also include other agents such as scientists (Ekboir, 2003), extension agents, policymakers, consumers and related institutions. Links between these nodes may indicate the spread of ideas, influence and/or money. Individual decision-making about whether to adopt new technologies plays out in the context of the information available through individuals' networks (Garrett, 2012; Rogers, 2003). Agricultural management is often limited by lack of information (Parsa et al., 2014), and in general heuristics for decision-making may or may not be well developed (Ascough et al., 2008; Gigerenzer & Gaissmaier, 2011). The effects of decision-making by agents in the socioeconomic network, with or without information about options, create a management landscape that influences the success or failure of species in the biophysical network.

In the biophysical network, the third component, nodes indicate the geographical locations where species or, more generally, 'bioentities' (including functional groups, biotypes, genotypes, crop varieties or genes) may become established (Calabrese & Fagan, 2004; Galpern et al., 2011). Nodes might be people (as hosts to human pathogens), farms, habitat patches or other land or water management units. Links between nodes indicate the potential for the spread of undesirable bioentities, such as antibiotic-resistant pathogens (Epanchin-Niell et al., 2010; Margosian et al., 2009; Sutrave et al., 2012; Xing et al., 2020), or of desirable bioentities, such as endangered species

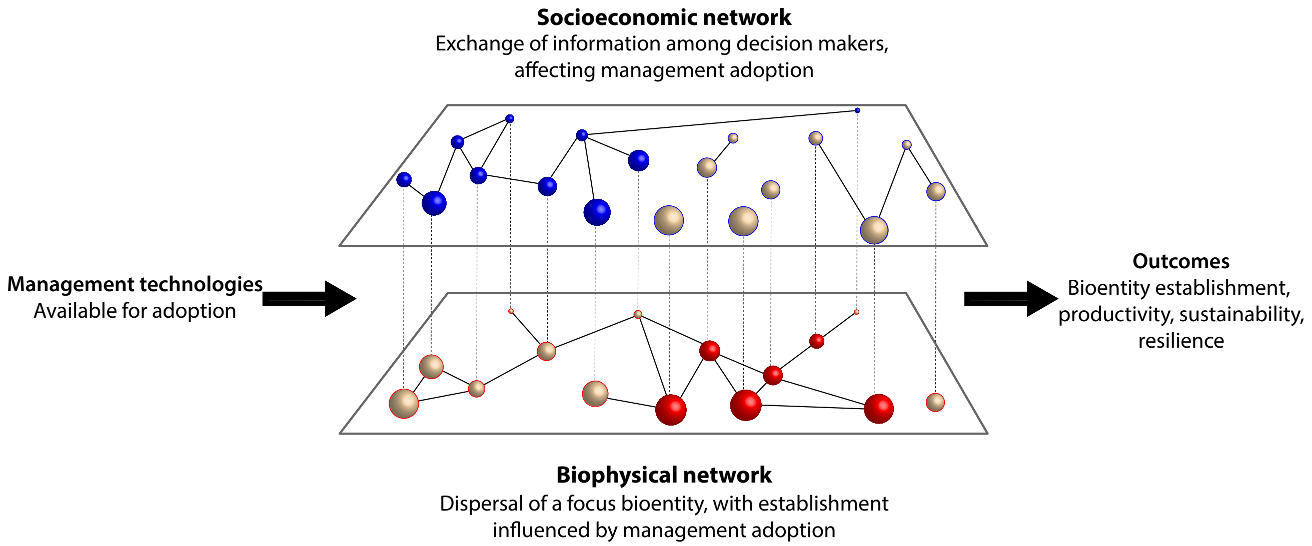

FIGURE 1 Impact network analysis is a framework for the analysis of how management technologies influence regional outcomes for management of a species or biotype ('bioentity') for decision support. Regional outcomes are also a function of whether decision-makers are influenced to adopt management by their socioeconomic networks, and of the geographical landscape of management choices and its ability to effectively manage the bioentity. Nodes in the socioeconomic network are individual decision-makers (such as land managers), with links in this network indicating communication and influence regarding the management technology, in an agent-based model. Some decision-makers manage land nodes in the biophysical network (such as farms or public lands), indicated by a dotted line between network layers. The management technology is or is not applied at a land node, depending on the corresponding manager's decision, and links in the biophysical network represent the potential for bioentity spread. The cumulative effects of the managers' decisions create a landscape of bioentity management, and the effectiveness of this landscape determines regional outcomes [Figure adapted from Garrett et al. (2018) with permission from *Annual Reviews*]

or improved crop varieties, for example orange-fleshed sweetpotatoes to support vitamin A consumption (evaluated in Andersen et al. (2019)). (In some cases, the same type of biophysical network model may usefully be applied to the spread of abiotic components, such as the spread of pollutants, soil erosion and provisioning of fresh water; Baron et al., 2002). Nodes in the biophysical network are linked to the corresponding decision-makers in the socioeconomic network layer such that the probability of bioentity success at a biophysical node is modified by the decisions about management at the corresponding socioeconomic node (Figure 1). Successful management also depends on the quality of management technologies.

Combining these three components provides a systems perspective for decision support based on scenario analyses, to evaluate potential outcomes from research and intervention project investments. INA can also be used to evaluate the likely degree of success of adaptation strategies to pulse (intermittent) or press (continual) system stressors, such as the introduction of a new pathogen or climate change (Harris et al., 2018), to operationalize concepts of system sustainability, resilience or economic viability. Some of these system components have been considered together more-or-less explicitly in disease ecology (Funk et al., 2009, 2010; Garrett, 2012; Harwood et al., 2009; Manfredi & d'Onofrio, 2013; Sahneh et al., 2012) and natural resource management (Bodin & Prell, 2011; Burgess et al., 2020; Conley & Udry, 2010; Epanchin-Niell & Hastings, 2010; Hernandez Nopsa et al., 2015; Magnan et al., 2015; Mills et al., 2011; Rebaudo & Dangles, 2011). Combining the components in INA, a general agent-based model, can help to bridge these related subdisciplines that often have limited interactions. INA also provides a new perspective on the science of science policy (Fealing et al., 2011) by evaluating interactions among agents engaged in developing scientific results and in implementing the new results.

The overall goal for the development of impact network analysis is to provide a common framework that integrates across intervention ecology, to enhance opportunities for lessons learned across systems and scientific disciplines, to support the development of a community of practice, and to create a general platform for analysis of sustainability, resilience and economic viability in intervention ecology for bioentity management. Network analyses, as compared to more aggregated models, allow consideration of the role of geographical and social structures in the likelihood of success of technological innovations. INA is designed to provide decision support to implementers, funders and policymakers about the prioritizations they must consider, as a complement to traditional approaches to monitoring and evaluation.

The specific objectives of this paper are to (a) introduce the INA framework and INA R package (github.com/GarrettLab/INA, Garrett, 2021a, 2021b), (b) illustrate the identification of key nodes for smart surveillance strategies, (c) illustrate the application of the INA framework for evaluating the likely degree of success of a project in intervention ecology, before, during and after an intervention and (d) illustrate the use of INA for evaluating adaptation strategies under global change scenarios with pulse and press stressors, introducing 'adaptation functions' for evaluating the system response required for sustainability and resilience. These experiments illustrate how INA can be used for analysis of hypothetical systems, observed systems or a blend of hypothetical and observed. Data limitations will always be a challenge for scenario analyses, but uncertainty quantification methods, as illustrated here, can inform decisions about investments in interventions. Because of the importance of both socioeconomic networks and biophysical networks in most ecological systems, scenario analysis platforms like INA can provide valuable information about the likelihood of intervention success for current and potential regional management strategies.

2 | MATERIALS AND METHODS

Many applications of impact network analysis would include a combination of observed data along with simulated data that (a) represent scenarios for regional management strategies being considered or (b) are part of an uncertainty quantification to understand the effects of varying parameters that are difficult to estimate. Three simulation experiments are presented here to illustrate the use of impact network analysis for both purposes, using the INA R package (github.com/GarrettLab/INA, Garrett, 2021a, 2021b). The first experiment using the *smartsurv* function is simpler, based on information about a biophysical network structure describing potential spread of an invasive bioentity. In this experiment, the socioeconomic network structure is implicit: location nodes are weighted based on where the invasive bioentity is likely to enter the biophysical network. The other two experiments use the *INAscene* function and illustrate scenario analyses for linked socioeconomic and biophysical networks in an agent-based model of regional management of the spread of a desirable bioentity, such as an endangered species or improved crop cultivar, or an undesirable bioentity, such as pathogens and other invasive species. Technical details about using INA package functions are available in a user guide (Garrett, 2021b) and in several vignettes at github.com/GarrettLab/INA (Garrett, 2021a).

2.1 | Experiment 1. Identifying key sampling locations for smart surveillance

Surveillance strategies can be informed by knowledge about the structure of the biophysical network of invasive spread. Nodes that function as hubs (high node degree) and bridges (high betweenness) in the biophysical network will tend to be important for sampling (e.g. Andersen et al., 2019), and as networks become more complex other node and network traits may become important (Holme, 2017, 2018). The relative risk of location nodes being the first point of introduction of an invasive bioentity in a dispersal network may be a function of the corresponding decision-maker node's role in communication networks (Buddenhagen et al., 2017).

The *smartsurv* function in the INA package in R can be used to evaluate the importance of each node for sampling to detect spread of an invasive (Table 1). This function evaluates the dispersal network to find, for each node considered as a potential sampling node in turn, how many other nodes remain free from the invasive by the time it is detected at the sampling node. The more nodes that remain uninvaded at the time of detection, the more effective the sampling node is for identifying invasive spread while there is still time to manage the invasion. Sampling nodes are evaluated considering each node as a potential introduction node. The *smartsurv.weight* function uses the output from *smartsurv* to evaluate the value of sampling at each node if the probability that the invasive is introduced to the network can vary from one potential introduction node to another. In this illustration, the differences among three commonly studied types of networks are evaluated. In practice, users of the *smartsurv* function would often want to provide their own estimate of the network structure for their system.

TABLE 1 Questions in simulation experiments evaluating locations to prioritize for sampling in a smart surveillance strategy, using impact network analysis function *smartsurv*

Experiment	Component	Question
1A	Explicit biophysical network	What locations selected for sampling are likely to allow detection of an invasive bioentity before many other locations are invaded?
1B	Added implicit socioeconomic network	How is the selection of sampling locations likely to change if the probability the invasive bioentity enters the region at each location is determined by socioeconomic traits of locations?

In this experiment, key nodes for sampling are identified for a set of biophysical network types, with details shown in a vignette (V1 at github.com/GarrettLab/INA). The importance of nodes for sampling is evaluated in experiment 1 for nine simple scenarios, representing each combination of three types of networks and three types of weighting of the probability that nodes are entry points for invasives. The three types of networks are random (Erdős & Rényi, 1960), small world (Watts & Strogatz, 1998) and scale-free (Barabasi & Albert, 1999). The three types of weighting are unweighted, weights proportional to node degree and weights inversely proportional to node degree.

2.2 | Experiment 2. Evaluating the likelihood of management success in a region, including uncertainty quantification

In experiments 2 and 3, the INA package function *INAscene* was used to perform scenario analyses in simulations in the R programming environment, using the IGRAPH package (Csárdi & Nepusz, 2006) for generating network figures. Details about the agent-based model used in *INAscene* are in the Supplemental Information and a vignette shows how the component functions of *INAscene* work, V2 at github.com/GarrettLab/INA.

Experiment	Timing	Question
2A	Before intervention	What is the likely probability distribution of project outcomes? Over time?
2B	Before intervention	How is the outcome likely to change if the management effect size can be increased?
2C	During intervention	If outcomes are lower than desired, what investments to increase adoption rates would likely be necessary to compensate?
2D	After intervention	If adoption rates decline after the project, what are the likely effects on the outcome over time?

TABLE 2 Example types of simulation experiments using impact network analysis (INA) to evaluate the likely outcomes of general intervention projects for managing a bioentity, using the function *INAscene*. The outcomes might be defined in terms of factors such as spread of an invasive or endangered species, health indicators, agricultural productivity or benefits from a crop variety

First, consider a luxurious case for scenario analysis where there is a lot of high-confidence information available about the system in which a management technology is being promoted for bioentity management, illustrated in a vignette (V3 at github.com/GarrettLab/INA). The impact network analysis evaluates the outcomes by which success of an intervention project will be judged, such as share of region with the bioentity present. In experiment 2A (Table 2), the analysis is performed at the planning stage of a project, to evaluate the probability distribution of outcomes from the project.

In experiment 2B, project planners ask how the results are likely to change if the management effect size can be increased, so outcomes are evaluated for the range of possible values of the mean management effect size. This analysis is also illustrated for cases where the socioeconomic networks are based on the same common network types as in experiment 1, with the addition of a ring network for contrast.

In experiment 2C, during monitoring and evaluation of the project, suppose that the observations are consistent with the initial conceptualization of the project, but the project is performing at the low end of the initial frequency distribution of likely outcomes. If efforts are increased to enhance the probability of technology adoption, perhaps through subsidies or policies to increase uptake, what increase in adoption rates would be necessary to keep progress in the system on track?

In experiment 2D, at the conclusion of the project, the success of the project is evaluated in terms of the current status of the bioentity, and also evaluated in terms of how long the benefits of the project last for successful regional management. If adoption rates decline without project inputs (such as subsidies or educational campaigns), what happens over time? Can increased management effect sizes make up for reductions in management adoption? In this example, the mean management effect size and the mean probability of adoption are varied.

2.2.1 | Uncertainty quantification

Suppose there is less information available about a system. Uncertainty quantification is an evaluation of how model outcomes change as key parameters change. For this case study, a parameter is varied in the inverse power law model used to describe the likelihood of movement as a function of distance. Uncertainty quantification for particular parameters, and scenario analysis of the outcomes for planned changes to the system, may each be implemented similarly. Uncertainty quantification is most relevant to components of the system for which it is difficult to collect data while scenario analysis is most relevant to system components amenable to change by decision-makers.

2.3 | Experiment 3. Adaptation to global change scenarios, including a science of science perspective

This experiment illustrates an analysis of how to modify system components that are potentially under managers' control to compensate for changes outside managers' control, such as changes in the likelihood of establishment—due to climate change or changes in the functional traits of the bioentity being considered. In this analysis, climate change effects are represented by changes in environmental conduciveness to establishment of a bioentity, reflected in the probability of establishment. Details of these analyses are in a vignette (V4 at github.com/GarrettLab/INA). Sustainability and resilience are illustrated here in terms of a system's ability to maintain bioentity incidence at desired levels when establishment probabilities change (in the case of sustainability) or the incidence jumps or plunges and needs to be adjusted back to the previous level (in the case of resilience).

In experiment 3A (Table 3), the 'adaptation for sustainability' scenario, conduciveness to establishment of an invasive bioentity increases and remains steady over time, as a press stressor. The probability of establishment (in the absence of management) at a baseline of 0.5 is compared to a new scenario with the probability of establishment at 0.9.

In experiment 3B, consider an 'adaptation function for sustainability', the required change in a manageable component of the system to maintain system function when an unmanageable component of the system is changing. For the scenario of adaptation to higher establishment rates in the absence of management (such as due to environmental changes or changes in the functional traits of the bioentity), consider the change in the mean adoption probability and

TABLE 3 Example types of simulation experiments using impact network analysis (INA) to evaluate the likely outcomes of strategies for adaptation to global change effects on bioentities, using the function *INAscene*. The outcomes might be defined in terms of factors such as spread of an invasive or endangered species, health indicators, agricultural productivity or benefits from a crop variety

Experiment	Type of stressor	Question
3A	Press	To adapt for sustainability in the face of increased establishment risks, what level of change is needed in manageable system components?
3B	Press	What is the adaptation function for sustainability, describing the needed system change to keep the system failure rate below a threshold, as establishment risks increase?
3C	Pulse	To adapt for resilience in the face of a rapid change in bioentity establishment, what level of change is needed in manageable system components?
3D	Pulse	What is the adaptation function for resilience, describing the needed system change to keep the failure rate below a threshold, if there is a rapid change in establishment?

the mean management effect size necessary to compensate, that is, to keep the rate of 'observed' establishment at the same level as before. In this scenario, the mean probability of establishment in the absence of management for an invasive increases from a baseline of 0.5 and the goal is to keep the 'observed' establishment proportion below 0.2 for sustainable management, that is, at an establishment rate no higher than under baseline conditions.

In experiment 3C, an 'adaptation for resilience' scenario with a pulse stressor, a baseline starting proportion of nodes with an invasive of 0.05 is compared to a new scenario where the starting proportion has leapt to 0.50. What increase in the mean probability of technology adoption would be needed to bring the mean 'observed' establishment back down to the level for the baseline before the leap in establishment occurred?

In experiment 3D, the 'adaptation function for resilience' indicates the adaptation required in terms of modifying the system parameters under managers' direct control to bring the 'observed' establishment rate back to the baseline level before the pulse stressor. This pulse stressor results in an unusually high proportion of locations with an invasive bioentity, and the system must then compensate if it is to be resilient. What adaptation is necessary to bring the proportion locations with the bioentity established below 0.2 during the time steps considered? Suppose the management effect mean is brought up to 0.9. What is the adaptation function for resilience, based on adaptation through modifying the mean technology adoption probability?

2.3.1 | Science of science experiment

In a science of science scenario analysis, the ability of a technology to improve regional management is also influenced by the outcome of an initial experiment. This could represent a scenario where a research group is testing management technologies and deciding whether to promote them or not. Depending on the effort invested by the scientists in the scenario, the management effect size is estimated with greater or lesser precision. When the management effect size estimate generated by the research group is below a threshold, information about the management is not communicated, so some share of scenario realizations does not include the use of management technology. In this case study, the threshold for communication about management ranges from 0 (communication occurs regardless of the estimated management effect) to 1 (communication cannot occur unless there is not uncertainty about the complete effectiveness of management). In the first scenario analysed here, the management effect mean is 0.5 and the management effect standard deviation is fairly high, also 0.5, while the sampling effort is low (1). Additional examples are in vignette V4 at github.com/GarrettLab/INA. Note that these analyses explore the potential costs of not communicating about a technology. There are other types of costs of communicating about a technology if the benefits have been overestimated, where both underestimation and overestimation of technology effects may be part of a reproducibility problem in science.

3 | RESULTS

3.1 | Experiment 1. Identifying key sampling locations for smart surveillance

For the simple *random network* example, nodes more important for sampling for detection occur in several parts of the network, but not in the periphery (Figure 2). When weighting is proportional or inversely proportional to node degree, the relative importance of nodes shifts, as illustrated in a vignette (V1 at github.com/GarrettLab/INA, also with more details of other analyses described in this paragraph). For the *small world network* example, nodes are of similar importance, though some nodes that link across different parts of the network are somewhat more important (Figure 2). When weighting is proportional or inversely proportional to node degree, there is little change because of the similar roles of nodes. For the simple *scale-free network* example, the high degree nodes are clearly more important for sampling (Figure 2). When weighting is proportional or inversely proportional to node degree, there is again only a slight change because the role of high degree nodes in driving the invasion network is so important. When stochastic networks are considered, the clear importance of some nodes for sampling seen in deterministic networks is decreased (V1 at github.com/GarrettLab/INA).

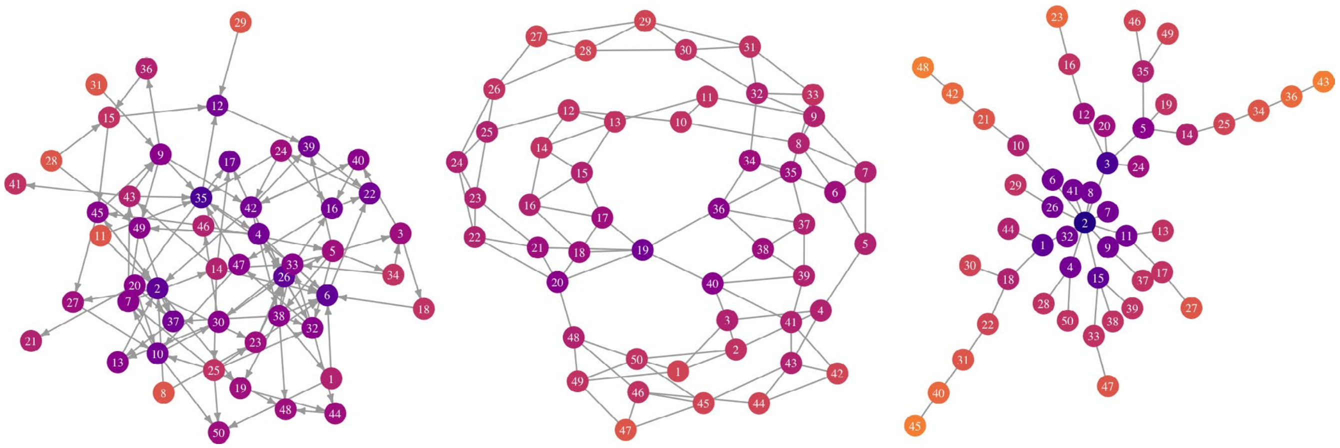

FIGURE 2 Identifying key nodes for sampling for an invasive 'bioentity' as part of a smart surveillance strategy (experiment 1). This analysis identifies the nodes where sampling can detect the bioentity before it has spread widely through the network. In these simple examples based on commonly studied network types, darker nodes would detect the epidemic sooner. (Left) In a random network, nodes at the periphery of the network will be less important for sampling. (Centre) In a small world network, nodes may be of similar value for sampling, but those that link across sections of the network may be more useful. (Right) In a scale-free network, nodes with high degree are more useful for sampling. As real networks diverge from these simpler structures, and become too large for simple visualization, this method for identifying key nodes for sampling can be used to identify important nodes

3.2 | Experiment 2. Evaluating the likelihood of management success in a region, including uncertainty quantification

In experiment 2A, at the planning stage of a project, analysis of the probability distribution of outcomes from the project indicates that the bioentity would become established in less than half the nodes (Figure 3, with more details in vignette V3 at github.com/GarrettLab/INA).

In experiment 2B, network types are compared in terms of how responsive the system is to changes in the management effect size. The small world and scale-free networks generally have a greater benefit from increasing the management effect while the ring network generally has the least benefit of the systems considered (Figure 3).

In experiment 2C, the system has a weak response to changing the mean probability of adoption (Figure 3) so that even when adoption is certain (for nodes with information about the management technology), other changes in the system would be necessary to keep the 'observed' establishment rate below 0.2.

In experiment 2D, evaluating how benefits of a project intervention can persist over time, a combination of higher mean management effect size and higher mean adoption rate can push the 'observed' establishment rate below 0.2 (Figure 3).

In an uncertainty quantification, the effect of changing an inverse power law parameter (determining the dispersal gradient for the bioentity, often difficult to estimate) was evaluated. For the scenario considered, the 'observed' rate of establishment is similar across ranges of the parameter between 0 and 0.7 and between 1.2 and 2.0 (Figure 4). However, if the true parameter value is between 0.7 and 1.2, obtaining a more precise estimate of the parameter may be important for understanding system outcomes.

3.3 | Experiment 3. Adaptation to global change scenarios, including a science of science perspective

In experiment 3A, the probability of establishment increases from a baseline of 0.5 to a new scenario of 0.9, and both the probability of adoption and the management effect size must change to compensate (Figure 5, with more details about this and other results for experiment 3 in vignette V4 at github.com/GarrettLab/INA).

In experiment 3B, the adaptation function for sustainability is evaluated. This function indicates the required change in a manageable component of the system to maintain system function when an unmanageable component of the system changes. The adaptation function for sustainability shows how the mean adoption rate must change (given also an increase in the management effect size) to compensate for changes in the mean probability of establishment (Figure 5).

In experiment 3C, adaptation for resilience is evaluated in response to a pulse stressor that pushes the baseline proportion of nodes with the bioentity from 0.05 to 0.50. Increasing the mean probability of adoption can keep the 'observed' establishment proportion down about to 0.2 (Figure 5), but more adaptation actions would likely be necessary to keep the establishment proportion reliability lower.

In experiment 3D, the adaptation function for resilience is evaluated. This system recovers from the pulse stress of 0.50 nodes with the bioentity. The adaptation function for resilience when responding to the pulse stressor evaluates the technology adoption rates required to compensate for an increasing initial number of nodes with the bioentity established (Figure 5).

In science of science experiments, as the management effect size threshold for communication about the management technology increases, the 'observed' rate of establishment increases, as expected (V4 at github.com/GarrettLab/INA). For the second case in which

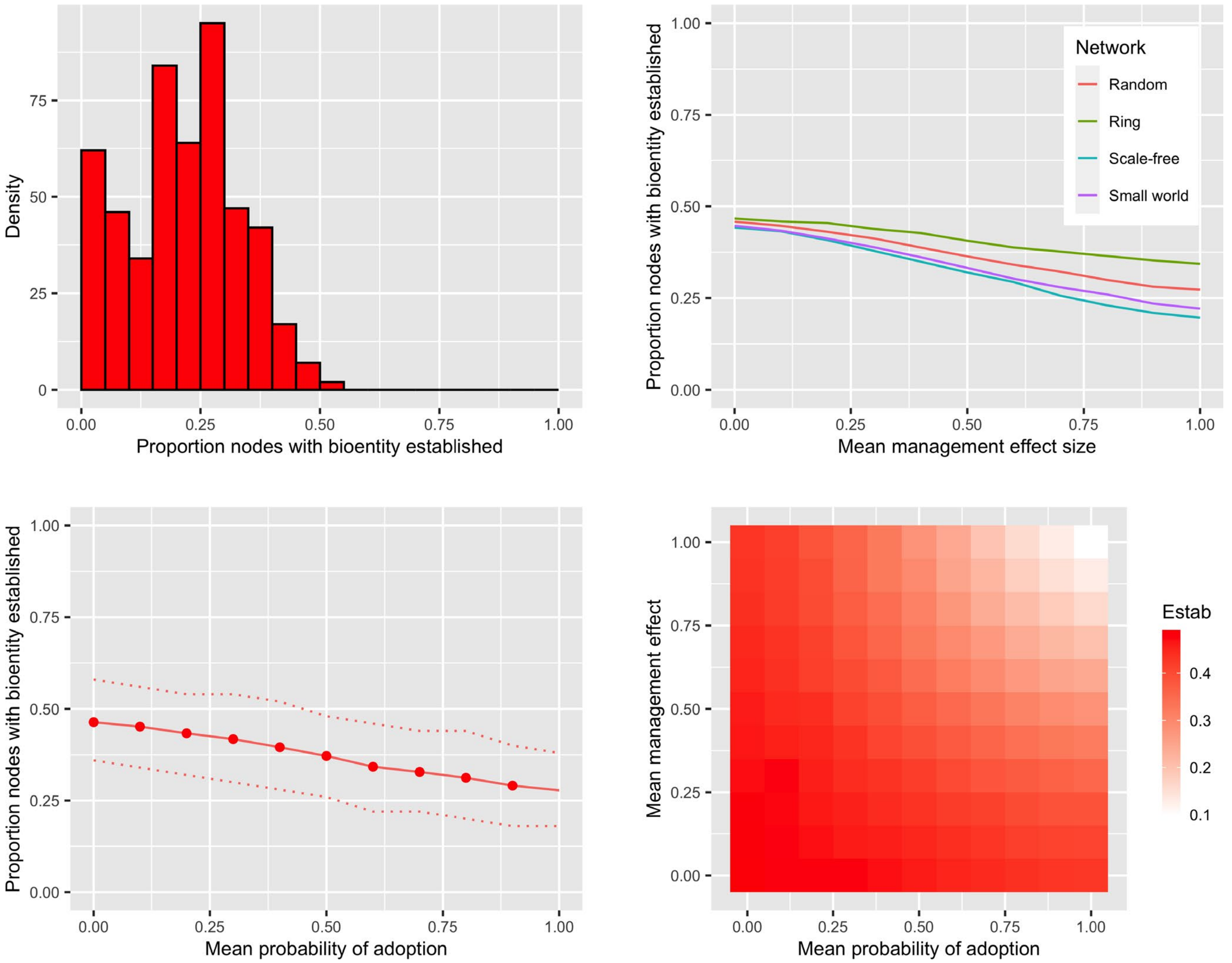

FIGURE 3 Evaluating the likelihood that management is successful in a set of scenario analyses (experiment 2, with more details in vignette V3 at github.com/GarrettLab/INA). (Upper left) At the outset of a project, the analysis focuses on the likely distribution of outcomes, the 'observed' proportion of nodes with the 'bioentity' established. (Upper right) If the project must be adjusted when performance needs to be improved, the analysis focuses on the response of the system to changes in the mean management effect size, illustrated here for four different types of socioeconomic networks in what is otherwise the same system. (Lower left) If the performance of the system is weak, the analysis focuses on whether the results can be improved by boosting performance in a feature such as the mean probability of adoption (where dotted lines indicate the 5th and 95th percentiles of simulation results). (Lower right) Considering how project benefits can persist over time, the analysis focuses on what combinations of 'manageable' components—in this case, the mean management effect size and the mean adoption rate—are needed to keep the 'observed' establishment rate ('Estab') acceptably low for an unwanted bioentity (e.g. the lightly shaded region)

the probability of establishment and the probability of adoption are both 0.9, when the communication threshold is between 0.2 and 0.8, the uncertainty in the outcome is high, as the simulated experiment to evaluate the technology may or may not be adequate to ascertain that the technology is worthy of communication (Figure 6).

4 | DISCUSSION

These case studies illustrate some potential applications of INA and how to use the INA R package. In the examples, all components such as initial distributions and networks are simulated for hypothetical scenarios while many INA applications would use a mixture of observed and simulated data. This section presents ideas for expanding on these types of experiments with observed data and a combination of scenario analyses and uncertainty quantification to address missing information. The INA R package is intended to expand in future versions to incorporate new types of related analyses, and some ideas follow about useful future applications.

The simple scenarios above illustrate a couple potential outcomes from INA. One is identification of thresholds in response to stressors, a problem often discussed. Another point is the potential for flat responses to adaptation strategies, which is less commonly considered but can be an important challenge in regional management. Projects may stall until the components of the system that are limiting factors are understood, as a system may be insensitive to

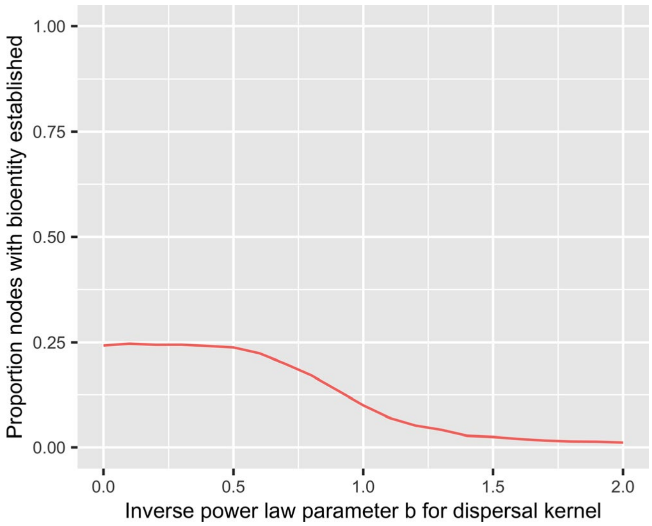

FIGURE 4 An uncertainty quantification to evaluate the effect of changing an inverse power law parameter describing the dispersal gradient for a bioentity

changes in readily managed components. The use of INA to identify limiting factors and necessary adaptations can be expanded by integrating relevant data layers, such as maps of environmental conduciveness or satellite images with information about the locations of species, in a more detailed decision support system. There is often a critical window of opportunity for management in impact networks, and efficient INA applications have the potential to help target efforts effectively.

In analyses of the potential roles of nodes in a smart surveillance strategy (using the function *smartsurv*) in experiment 1, the results for the hypothetical cases illustrate expected patterns of node importance for surveillance in typical random, small world and scale-free networks (Figure 2). In analyses of the value of locations for surveillance, the socioeconomic network may only be implicit, in terms of likely entry points into the biophysical network, as in Buddenhagen et al. (2017) where nodes with less reliable information sources may be more likely invasive entry points. Other reasons for higher risk of being the starting node might include a node's role as a port, weather conditions associated with a node or lack of resources for management at the node. Beyond these archetypal networks, observed networks may have unique properties (Holme, 2017, 2018). Users can evaluate the importance of nodes in their specific biophysical networks, and potentially include new analyses such as evaluating whether node demographic or other traits are associated with higher or lower importance for surveillance. The connectivity of host populations (e.g. Xing et al., 2020) can be used to characterize landscapes for application with *smartsurv*. In ongoing surveillance analyses, the priority given to specific nodes could be updated as more information about the system becomes available.

Analyses of how well an intervention project is likely to succeed at regional management of a bioentity (using the function *INAscene*) are illustrated in experiment 2. The results for these hypothetical cases show how management options singly or in combination may be adjusted to make projects more likely to succeed, and how network structures may modify system responsiveness to changing management effect size (Figure 3). Changes in the management effect size might be attainable through further experimentation, and the probability of management technology adoption might be modified through policies such as subsidies. In applications using *INAscene*, users could provide a combination of observed and hypothetical components to evaluate the likelihood of project success, updating as new information becomes available. Analyses might evaluate the likely outcomes for categories of nodes, perhaps testing hypotheses about how well systems perform as a function of manager traits such as gender or wealth, or as a function of geographical traits such as environmental factors.

The illustration of uncertainty quantification shows how the effect of parameters that may be challenging to estimate with precision, such as parameters describing dispersal gradients, can be evaluated (Figure 4). It is convenient when the results of scenario analyses are similar across parameter values in uncertainty quantification (e.g. in Andersen et al., 2019), but if not, it is still helpful to know what new data would be particularly valuable to collect for understanding the system better. The value of information estimated by these analyses can be combined with estimates of the cost of information, to prioritize the next rounds of data collection for system management.

Achieving sustainability and resilience of systems and their ecosystem services is a key challenge in intervention ecology, and often operationalizing these concepts is an additional challenge (Biggs et al., 2012; Clark et al., 2011; Howden et al., 2007; Standish et al., 2014). Experiment 3 introduces and illustrations 'adaptation functions'. Adaptation functions are defined here to represent the change in one or more manageable system parameters necessary to maintain desired system outcomes, in the case of sustainability, or to return to desired outcomes, in the case of resilience (Figure 5). The study of adaptation functions can be combined with uncertainty quantification to address uncertainty about the magnitude of global change factors and the response required for adaptation. Other types of global change, such as increased trade, might lead to system changes such as biophysical networks with more links.

The science of science experiment illustrates the effects of decision-making about communication based on research results (Figure 6). Variations in the science of science experiments can address issues in the reproducibility of research, and can be integrated with ideas about how to optimize the design of experiments to inform strategies for regional management benefits.

Agroecological seed systems are an important example of multilayer networks supporting agricultural sustainability and resilience. Layers include the network of seed movement in formal and informal systems, the network of pathogen or pest movement through seed, and the network of information and influence related to integrated seed health strategies (Thomas-Sharma et al., 2016, 2017). Successful seed systems will optimize the maintenance and spread of desirable crop varieties (Labeyrie et al., 2016; Pautasso, 2015; Pautasso et al., 2013) while minimizing the spread of pathogens through seed or grain movement (Andersen et al., 2019; Andersen

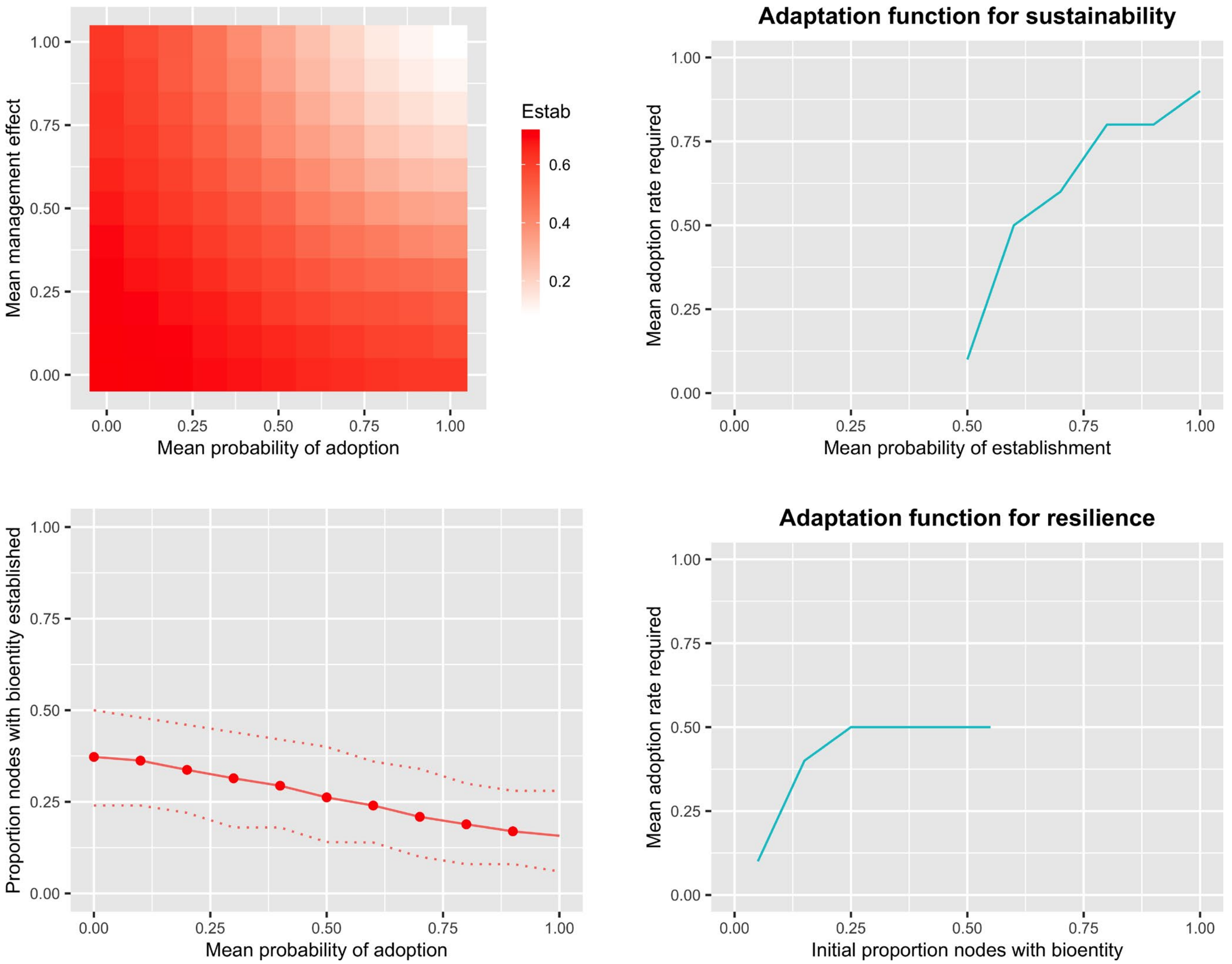

FIGURE 5 Sustainable or resilient adaptation requirements in global change scenarios (experiment 3). (Top left) The sustainability of a system—in terms of its ability to keep invasive bioentity establishment ('Estab') below a threshold even as a press stressor increases the probability of establishment—is evaluated as the probability of establishment moves from a baseline of 0.5 to a new level of 0.9 and both the mean management effect size and the mean probability of adoption increase to compensate. (Top right) The 'adaptation function for sustainability' indicates the required change in a manageable component of the system (mean probability of adoption of a management technology) to keep the 'observed' establishment rate at the baseline level as the mean probability of establishment (in the absence of management) increases. (Bottom left) The resilience of a system—in terms of its ability to return invasive bioentity establishment to a baseline level after a pulse stressor elevates establishment—is evaluated in terms of how well adjusting the mean probability of adoption can compensate. (Bottom right) The 'adaptation function for resilience' indicates the required change in a manageable component of the system (mean probability of adoption of a management technology) to return the 'observed' establishment rate to the baseline level after a pulse stressor boosts the establishment

Onofre et al., 2021; Buddenhagen et al., 2017; Hernandez Nopsa et al., 2015). Linked networks include the global network of crop breeders who exchange genetic material (Garrett et al., 2017).

Priorities for defining scenarios will differ from one application to another (Figure 7). When evaluating the likely success of interventions that are under immediate consideration, analyses will often try to achieve the greatest level of precision possible given the data available. When considering the potential for specific types of future interventions, or the theory of effective interventions, other priorities may be at least as important. There are often trade-offs in the ability of a model to achieve precision, realism and generality (Gross, 2013; Levins, 1966). Other applications of impact network analysis could focus on developing general theories for future intervention strategies, including which combinations of system traits lead to successful regional management. Networks can be characterized using methods such as exponential random graph models (ERGMs), to test hypotheses about system outcomes for specific types of ERGMs (Lusher et al., 2013).

The INA package is designed to be the basis for future expansions to better address specific types of systems. For smart surveillance strategies using the *smartsurv* function, next steps would include incorporating specific types of sampling strategies and their relative performance for sets of specified starting locations for the bioentity. For scenario analyses using the *INAscene* function, next steps would

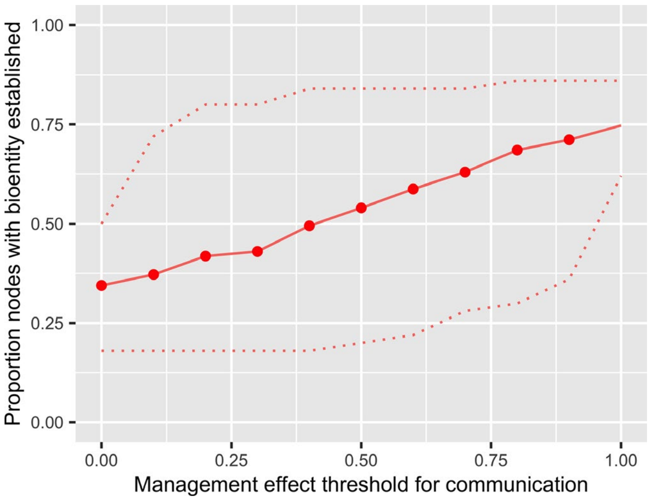

FIGURE 6 A science of science experiment to evaluate the effects of changes in a threshold determining whether there is communication about a new management technology. A simulated experiment may result in estimates of the management effect size above or below the threshold. The outcome is a function of the true management effect size, the variance in the effect and the research effort invested. Dotted lines indicate the 5th and 95th percentiles of simulation results

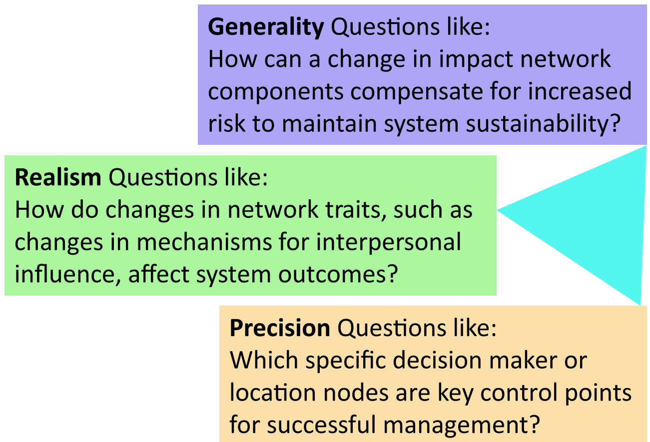

FIGURE 7 Three potential priorities in impact network analysis, and examples of the types of questions that might be asked in each context. As more information about a system is available, questions can address greater realism and precision

include options for tracking population sizes at nodes. This could include multi-scale network analyses, with population viability analysis in finer-resolution networks that helps to determine whether a bioentity is likely to move from one coarser-resolution node to another. Another focus would be generation and evaluation of observations of management success in a heterogeneous landscape, addressing 'big data' in the form of information that is generated throughout, and potentially spread throughout, a network, such that managers may evaluate this information (Cui et al., 2016). For global change scenarios, new components would include the potential for temporal or spatial trends in parameters. For science of science scenarios, useful new model components would include addressing the costs of research and the cost of management implementation, and addressing technology upscaling and the formation and dissolution of links. Another useful extension would be consideration of multiple bioentities and their interactions.

Operationalizing the concepts of sustainability and resilience are ongoing challenges in intervention ecology (Standish et al., 2014) and INA is an option for evaluating the limits of responsiveness of a system and what is likely to be feasible within those limits for management adaptation. Major challenges remain for management of biodiversity while meeting needs for food production (Leclère et al., 2020), and the different scientific communities addressing these problems often have related interests in intervention ecology that can be addressed by methods such as INA, with the potential to integrate across many different types of socioeconomic and biophysical networks (De Domenico et al., 2016; Harwood et al., 2009). The broader goal of the INA framework is to support a community of practice through application across a wide range of system contexts and questions, providing research spill-over and cross-disciplinary lessons learned. As regional management strategies incorporate new approaches, including artificial intelligence for decision support, INA can be applied to integrate data layers rapidly to aim for effective management during critical periods when success is more likely.

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PEER REVIEW

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DATA AVAILABILITY STATEMENT

The INA package R code and several vignettes illustrating analyses in this paper are available at https://github.com/GarrettLab/INA. An archived version of the code and vignettes for INA version 1.0.0 is available in Zenodo (Garrett, 2021a).

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

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