

REVIEWS AND SYNTHESIS

TEASing apart alien species risk assessments: a framework for best practices

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Abstract

Some alien species cause substantial impacts, yet most are innocuous. Given limited resources, forecasting risks from alien species will help prioritise management. Given that risk assessment (RA) approaches vary widely, a synthesis is timely to highlight best practices. We reviewed quantitative and scoring RAs, integrating > 300 publications into arguably the most rigorous quantitative RA framework currently existing, and mapping each study onto our framework, which combines Transport, Establishment, Abundance, Spread and Impact (TEASI). Quantitative models generally measured single risk components (78% of studies), often focusing on Establishment alone (79%). Although dominant in academia, quantitative RAs are underused in policy, and should be made more accessible. Accommodating heterogeneous limited data, combining across risk components, and developing generalised RAs across species, space and time *without* requiring new models for each species may increase attractiveness for policy applications. Comparatively, scoring approaches covered more risk components (50% examined > 3 components), with Impact being the most common component (87%), and have been widely applied in policy (> 57%), but primarily employed expert opinion. Our framework provides guidance for questions asked, combining scores and other improvements. Our risk framework need not be completely parameterised to be informative, but instead identifies opportunities for improvement in alien species RA.

Keywords

Colonisation, exotic, habitat suitability, life history trait, non-indigenous, propagule pressure, policy, risk analysis, species distribution, uncertainty.

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INTRODUCTION

Although many alien species are arguably innocuous, some are extremely harmful, to both the environment and economy (Williamson 1996). This distinction between damaging and innocuous species is critical for management and policy purposes, as it is impractical to react to every species which is transported and introduced from one location to another, or to manage all established alien species (Rejmánek & Pitcairn 2002). Nor would it be feasible to end global trade, as it yields substantial economic benefits even at the cost of moving alien organisms around the world (Hulme 2009; Essl *et al.* 2011). Thus, the challenges and costs of preventing species invasions must be balanced against the expected impacts, and difficulties of

control, eradication or adaptation (i.e. changes in behaviour or business practices) (Andreu *et al.* 2009).

Not surprisingly, a central focus of invasion biology has been to try to understand the invasion process and to distinguish between those few alien species that cause harm and those that do not, as a way to characterise the risk associated with alien species (Rejmánek *et al.* 2005). There is a systematic relationship between damages caused by alien species and a set of conditions knowable in advance. The former is the motivation for prioritising efforts, and the latter is the motivation for using risk assessment (RA) tools. In this manuscript, we focus on risk assessment of alien species, where risk is broadly defined as the product of the probability of events and the severity of their impacts (FAO 2007). Here, we do not deal in depth with risk

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management (i.e. evaluating and choosing between potential response options) or their feedbacks with stakeholders (e.g. Horan *et al.* 2011), a topic which deserves its own review article.

Predicting the risk that a species will be transported and introduced, establish, increase in abundance, spread and cause impacts is difficult because we have a scarcity of information for most species, and because the outcomes of introductions may be spatially and temporally context specific (Vilà *et al.* 2006). However, the purpose of risk assessment is to evaluate the likely outcomes of the invasion process for a given species (or a group of species) and to characterise the uncertainty that exists given the data available (see Box 1 for a discussion of uncertainty). This is particularly important given that uncertainty will always exist. Additional research may reduce it, but not eliminate it.

There is an increasing interest in RAs of alien species. Many governmental and intergovernmental bodies (e.g. World Trade Organization, International Maritime Organization, International Plant Protection Convention) recommend or request RAs to be conducted for organisms moving in trade (Pyšek & Richardson 2010; Dahlstrom *et al.* 2011). However, it has become clear that there are many different approaches applied to risk assessments of alien species, and the risk terminology has been used loosely to refer to a number of different end points and objectives (Dahlstrom *et al.* 2011). Thus, it is timely to explicitly compare these RAs, to assess how they relate to the fundamental principles of invasion biology, and to synthesise the advances in both the science and policy of alien species risk assessments.

Our dual objectives in this manuscript are (1) to review and compare existing risk approaches and to assess the current state of the literature, (2) to integrate the > 300 individual RA models reviewed and the major concepts in invasion biology into a coherent full RA model, both verbally and mathematically. To do so, we summarised all RAs into three aspects: the *components* considered, their *dependencies* and the model *structure*. On the basis of the suite of articles examined, we organised the *components* of risk into the major stages in the invasion process: Transport, Establishment, Abundance, Spread and also considered Impact (TEASI), each of which contained sub-components (e.g. the number of individuals transported is determined by uptake before, net growth during and release after transit) (also see Blackburn *et al.* 2011 and ISPM-11, FAO 2004). We defined *dependencies* as the specific factors affecting the outcome of a component or subcomponent, but where the relationship would vary for each system, such that specifying the functional form in our generalised equations would not be useful. For instance, the probability of establishment may depend on environmental conditions in the destination location. Importantly, these dependencies are useful as predictors of TEASI components, and therefore may be used sometimes as surrogate measures. By model *structure*, we were particularly interested in how TEASI components and sub-components combine (e.g. how should propagule pressure from Transport be combined with Establishment?). We begin by presenting the integrated TEASI structure, as this will facilitate succinct comparisons of the > 300 RAs analysed and the identification of the current and future state of the field.

RISK ASSESSMENT COMPONENTS FOR ALIEN SPECIES (TEASI)

In general, risk assessment incorporates the product of the probability of events (invasion process) and the severity of their impact to derive a measure of expected impact, together with their associated

uncertainties (Box 1). The components underlying the invasion process are intimately tied to the concept of probability of an event; thus, much of the predictive invasion biology literature can be integrated into a risk assessment framework. We discuss TEASI components, subcomponents, dependencies, relationships and nuances verbally (see below) and we combine them mathematically into a quantitative RA structure (Box 2 & 3).

Invasion process

Transport/introduction

We combine transport and introduction into one component of the invasion process, because in combination they yield propagule pressure, the variable of actual interest. Propagule pressure (the number of individuals or viable life stages entering a new location) is one of the main predictors of invasion success (Lockwood *et al.* 2005). In general, the different factors leading to propagule pressure occur before, during and after transit of a given vector (Hulme 2009). These can be broadly described by uptake of propagules at the origin, net growth (reproduction or mortality) during transport and fraction released. Uptake at origin may differ due to differences in the species abundance in the source location, the environmental conditions (e.g. causing aggregation of propagules), the vector and pathway characteristics (i.e. some vectors and pathways may be more likely than others to take up propagules), and should also differ depending on the alien species traits (e.g. generation of many propagules per adult). Moreover, net growth in number of individuals depends on factors such as duration of trip, conditions during transport (which may be vector specific) and species traits (e.g. environmental tolerance). Finally, the probability of release may depend on the destination environment, species traits (e.g. ability to escape containment) and the vectors in question. This suite of sub-components and their dependencies are succinctly summarised in eqn 1 (Box 2). Importantly, the subcomponents associated with propagule pressure will often not be measurable directly, and surrogate measures using accessible data may be needed. For instance, volume of trade and human population size may be relevant correlates of vector traffic; characteristics of source populations and extent of spread in source areas may correlate with uptake. Note that in the situations where actual numbers of individuals introduced or release events are known (e.g. some birds and mammals; Cassey *et al.* 2004; Sol *et al.* 2008), we need not estimate transport, given that we already have a direct measure of propagule pressure.

Establishment

The probability of establishment is driven by population dynamics. These dynamics differ between species and environments, and may therefore be predictable by examining species traits and environmental features (Rejmánek & Richardson 1996; Kolar & Lodge 2001). Furthermore, they include factors such as Allee effects and stochasticity, and thus are dependent upon propagule pressure (initial population size) (e.g. Taylor & Hastings 2005). We note that propagule pressure can be complex because we rarely know where and when every propagule is released (propagule dose vs. frequency, Lockwood *et al.* 2005), and we often do not know the spatial scales and time frames needed for propagules to interact (e.g. mate finding), particularly given heterogeneous environments. Thus, any measure of propagule pressure will implicitly aggregate some level of this complexity, which will thus be modelled as statistical probabilities.

Box 1 Uncertainty in risk assessment

No discussion of a risk framework would be complete without consideration of uncertainty, which occurs throughout the invasion process, in virtually every component estimated underlying risk assessments. There are several types of uncertainty that are typically identified in the literature and particularly relevant for risk assessment models. Broadly, these include (1) linguistic uncertainty, (2) stochasticity (also termed natural variation, or irreducible uncertainty) and (3) epistemic uncertainty (also termed incertitude or reducible uncertainty). Below, we discuss these types of uncertainty, and where they fit into the full RA model described in Box 2 & 3.

Linguistic uncertainty

Linguistic uncertainty arises because the language (written and oral) we choose to express ideas is often vague and imprecise (Burgman 2005), and even when precise language is used, interpretation may differ between people. This is particularly a problem for qualitative approaches and scoring approaches, where different people may attribute different meanings to the same words, or the same person may conflate multiple ideas. Furthermore, the logical outcome of given verbal arguments are sometimes difficult to accurately assess. Subjectivity also occurs for quantitative approaches. However, mathematical models force individuals to explicitly define the relationships underlying concepts, and therefore linguistic uncertainty can be more transparent. Furthermore, the consequences of assumptions can be difficult to perceive for both qualitative and quantitative models, but more so in the former.

Stochasticity and natural variation

Stochasticity includes spatial and temporal variability and probabilistic processes. Environments, both abiotic and biotic, may vary across space and time, and these can be expressed as probability distributions. Stochasticity is important because it influences the dynamics of the system and predicted outcomes. In the quantitative framework, for each function ($f(\cdot)$), stochasticity is explicitly identified by the symbol σ , where the subscripts denote different components of stochasticity (Box 2 & 3). Furthermore, probability equations ($pr(\cdot)$) also inherently model stochastic processes.

Epistemic uncertainty

Epistemic uncertainty reflects our level of knowledge about a system, and can be reduced with additional information. We build verbal (qualitative) or mathematical (quantitative) models to represent our understanding of processes underlying a system. We use empirical data to parameterise the model. However, given stochastic elements present, we never have perfect estimates of underlying parameters and processes. Furthermore, given that models are our conceptual abstractions of the real world, even the basic structure of the model is uncertain.

In addition, there will always be some uncertainty in our data sources, which may propagate through the risk model. Data are often limited, and may come from heterogeneous sources, ranging from systematic regional sampling (e.g. governmental databases), records of human activity (e.g. economic activity, trade patterns), satellite, remote sensing, aerial and other map types (e.g. GIS layers), laboratory and field experiments and even volunteer programmes amongst others. All these sources are potentially useful, but may have varying reliability. More generally, observation error – a mismatch between a measurement and true value – is inherent in the data sources used, and arises because we often do not have direct measures of the variables of interest (e.g. population size, occurrence records, human valuation of ecosystem impacts), and we often need to rely on sampling or surrogate measures. Even the detection of initial establishment is dependent on observation, which in turn can be affected by the extent of the invasion. Furthermore, given the nature of invasion process, spatial uncertainty is of particular relevance. Models are built and inferences made using spatial maps, which contain its own sources of error (e.g. Messina *et al.* 2008). Importantly, given the coarseness of maps (e.g. often 50 km x 50 km resolution), relevant biological processes may be obscured if they occur at a finer scale, and may lead to greater predictive errors. We also include data gaps in this section as the most extreme form of data uncertainty, which propagate through any model developed. Given logistical limitations in time and resources, such gaps can occur frequently. In these cases, models provide the logical structure and expert opinion, which also contains its own set of biases, is used in place of empirical data (Burgman 2005).

In brief, epistemic uncertainty contains parameter uncertainty, model (structural) uncertainty and data/observation error. In the risk framework (Box 2 & 3), model uncertainty occurs through the choice of the functional forms (i.e. shape of the relationships) for each component ($f(\cdot)$ and $pr(\cdot)$), Box 2 & 3). Parameter uncertainty occurs through estimation of parameter values underlying those functional forms (e.g. r and k , Box 2, eqn 6), and data/observation error propagates through the risk model in the fitting process. In principle, Bayesian hierarchical models and model averaging can explicitly incorporate these three components of epistemic uncertainty (e.g. Clark *et al.* 2005; Ibanez *et al.* 2009).

Additional cautions

Extrapolating beyond the conditions where the data were collected may result in underestimating uncertainty (e.g. extrapolating given climate change, Jeschke & Strayer 2008). While other approaches such as scenario analysis have been suggested (Carpenter *et al.* 2006), one must still conceptualise the models to be able to consider them. Thus, despite these cautions, we should continue to build predictive models based on the best available information.

Box 2 Model of invasion process

Here, we integrate the arguments in the invasion biology literature into a small set of equations. We summarise the components and sub-components underlying the invasion process, their dependencies, and the model structure. We used generalised functions for sub-components, because they were highly system dependent, although we provide simple concrete examples for illustration. In contrast, the structure for the combination of components and sub-components was generalisable. Variables in parentheses identify dependencies, which potentially can be used as predictors/surrogates. The complete list of notations is provided in Table 1.

Transport/introduction

Propagule pressure N is determined by uptake before (O), net growth during (f_g) and release after transit ($pr(R)$):

$$N_{i,t} = \sum_{j=1}^J \sum_{k=1}^{V_{ij,t}} O(E_{j,t'}, v_{i,j,k,t}, S, X_{j,t'}, \sigma_O) * f_g(t - t', D_{ij}, \vec{E}, v_{i,j,k,t}, S, \sigma_g) * pr(R|E_{i,t}, v_{i,j,k,t}, S) \quad (1)$$

where i is the release location (e.g. a bay), j is the source location of uptake and k is a single vector of transport (e.g. a ship) and t is the time of release, t' is the time of uptake, $V_{ij,t}$ is the vector traffic (e.g. 10 ships moving from j to i). Each individual vector can take up propagules, transport and release a fraction of them. Thus, propagule pressure to location i is the sum across all vectors from all source locations. Simple examples of possible functional forms are: $O = c_t X_{j,t'}$ (uptake linearly increases with population size), $f_g = e^{-\alpha(t-t')}$ (constant rate of mortality during transport), $pr(R) = c_3$ (constant probability of release). σ denotes stochasticity (i.e. determining the distribution from which an error term ε_k is chosen, capturing individual variation between each vector k).

Establishment

Establishment can depend on environment–population dynamic interactions (eqn 2), temporal habitat suitability (eqn 3) and spatial habitat suitability (eqns 4 and 5).

$$P_{i,t}^A = 1 - (1 - pr(\lambda_A|E_i, S))^{N_{i,t}^{\beta(E_i, S)}} \quad (2)$$

$$P_{i,T}^B = 1 - \prod_{t=1}^T (1 - P_{i,t}^A * pr(\lambda_B|E_{i,t}, S)) \quad (3)$$

$$P_{i,T}^C = P_{i,T}^B * pr(\lambda_C|E_i, S) \quad (4)$$

$$P_T^C = 1 - \prod_{i=1}^L (1 - P_{i,T}^C) \quad (5)$$

where P_T^C is the probability of establishment in at least one location in the system by time T . $pr(\lambda_A|.)$, $pr(\lambda_B|.)$, and $pr(\lambda_C|.)$, are the probabilities that a single propagule will establish in a suitable site, that it is temporally suitable, and that it is spatially suitable respectively. These are used to calculate joint probabilities, given all propagules within a given site and time interval ($P_{i,t}^A$, eqn 2), across all time intervals within a given site ($P_{i,T}^B$, eqn 3), and across all sites (P_T^C , eqn 4 and 5). Each equation makes use of similar logic, using the complement of the probability of all propagules, time intervals and sites failing to establish, respectively (Leung *et al.* 2004). β is a coefficient allowing interactions between propagules (i.e. Allee effect). By definition, each probability $pr(.)$, reflects stochasticity. $pr(\lambda_A|.)$ implicitly incorporates variability in propagule quality, genetic and phenotypic differences, sampling frequency from different source regions and within-site variation in releases (dose and frequency). $pr(\lambda_B|.)$ incorporates within-site temporal fluctuations and seasonality and $pr(\lambda_C|.)$ incorporates unmeasured spatial site factors that determine establishment.

Local density or abundance

After establishment, local population size/density ($X_{i,t}$) may grow according to population and local ecosystem dynamics:

$$X_{i,t+1} = f_X(X_{i,t}, r(E_{i,t}, S), \kappa(E_{i,t}, S), \sigma_e, \sigma_d) \quad (6)$$

$$E_{i,t+1} = f_E(X_{i,t}, E_{i,t}, S, \sigma_E) \quad (7)$$

To denote environment and species effects, we make the parameters functions of environment (E) at location i and time t , and species (S). For consistency with the literature, we separate stochasticity into two forms – demographic (σ_d) and environmental (σ_e). To allow for environmental feedback with population dynamics, we include the term E_t (eqn 7). We note that establishment may also be modelled using population dynamics (i.e. $P_{i,t}^A = pr(X_{i,t} > threshold | N_{i,t=0})$, or using r as a predictive species trait). However, care must be taken as the conditions experienced by propagules transported to new areas likely differ from those of established populations. Simple examples of f_X is the deterministic logistic growth equation ($X_{i,t+1} = X_{i,t} + rX_{i,t}(1 - X_{i,t}/\kappa)$), and for $E_{i,t+1}$, a reduction in a resource (e.g. space) due to the alien species ($E_{i,t+1} = c_1 - c_2X_{i,t}$).

Spread

Spread models generally allow estimation of the numbers introduced from established sites (j) to new locations (i), and can be related to propagule pressure ($N_{i,t}$) or vector movement ($V_{i,j,t}$). For natural dispersal,

$$N_{i,t} = \sum_{j=1}^J f_{XD}(X_{j,t}, S, \sigma_{XD}) f_D(\vec{E}, D_{i,j}, S, v, \sigma_D) \tag{8}$$

Note that the functions f_{XD} and f_D can be considered analogous to $O(i)$ and $pr(R_i)$ respectively (eqn 1). f_g (eqn 1) is usually not considered in these models, but theoretically could be integrated into f_D . We use \vec{E} to indicate that dispersal can differ across environmentally heterogeneous landscapes (With 2002). A simple example of the functional forms would be $f_{XD} = c_i X_{j,t}$ (a constant function of abundance) and $f_d = c_2 * e^{-c_2 D_{ij}}$ (an integro-difference model, with a negative exponential dispersal kernel, Kot *et al.* 1996). Equation 8 best represents either movement of individual organisms or dispersal of propagules from a stationary source population (e.g. seeds distributed by plants). In contrast, human vector movement can be described as:

$$V_{i,j,t} = V_{j,t} f_D(\vec{E}, \vec{D}_j, E_i, D_{i,j}, v, \sigma_D) \tag{9}$$

where $V_{j,t}$ is the total number of vectors from invaded source location j . Here, E_i are the environmental conditions determining ‘attractiveness’ of specific destination i . Although in practice vector traffic itself (eqn 9) is often used as a simplified surrogate of propagule pressure, in principle this could be merged with eqn 1 to estimate n . An example of functional form f_D would be $f_D = E_i D_{i,j}^{-c} / \sum_{j=1}^L E_j D_{i,j}^{-c}$ (gravity model, e.g. Leung *et al.* 2004).

$$Q_T = \sum_{i=1}^L P_{i,T}^{C2} \tag{10}$$

$P_{i,T}^{C2}$ depends upon propagule pressure (N) from invaded sources (J) (eqns 8 and 9), hence Q_T , the expected number of occupied sites at time T , is dynamically dependent on invasion progress at times $t < T$. Primary and secondary spread can be conceptualised as a difference in scale, and eqns 1–4 can be used to estimate establishment (secondary spread) into new local areas (differentiated from initial establishment using a superscript ‘2’). Note that eqn 5 calculates the probability of establishment in at least one site, whereas eqn 10 sums the individual probabilities across patches.

Box 3 Calculating risk and impact

Risk (denoted here as Z) incorporates the probability of exposure (invasion) * impact of that exposure (expected impact). The impact can arise due to direct damages from an alien species and also due to management actions, which can reduce direct damages, but also result in indirect damages (costs).

For clarity, we distinguish between pre-invasion and post-invasion risk, and consider the delays in establishment and invasion progress, due to prevention efforts. The invasion process model (Box 2) provides input into the risk model, which is expressed below as a set of equations (see Table 1 for definition of variables).

Pre-establishment expected impact

$$Z_T = \sum_{t=1}^T ((1 - P_{t1}^C(\alpha^p M^p)) * M^p + U_{t1}(\alpha^p M^p) * Y^A) \tag{11}$$

$$U_{t1} = P_{t1}^C(\alpha^p M^p) - P_{t1-1}^C(\alpha^p M^p) \tag{12}$$

where the risk (Z) is the probability of initial establishment during time $t1$ (U_{t1}) multiplied by the post-establishment impacts of an alien species (Y^A), plus the cost of prevention (M^p) while the system remains uninvaded ($1 - P_{t1}^C(\alpha^p M^p)$), summed to time horizon (T). The greater the delay in invasion ($d1$), the lower the cumulative post-establishment impact experienced (Y^A , eqn 13). The invasion may be delayed because probability of initial establishment (P_{t1}^C) is naturally low, or because prevention is effective ($\alpha^p M^p$) in reducing P_{t1}^C . The delay is simply $d1 = t1 - 1$. Although we do not deal in depth with risk management issues (which would require a separate paper), the benefit of prevention is the balance between averted post-establishment impacts (including direct damages, policy effects such as quarantines, control costs and adaptation costs, eqn 13), vs. the cost of prevention.

Post-establishment expected impact

$$Y^A = \sum_{i2=1}^{T-d1} \left(M^s + M^e + \sum_{i2=1}^{I2} \left((1 - P_{i2,i2}^{C2}(\alpha^{s2} \vec{M}^{s2}, \alpha^{p2} M_{i2}^{p2})) * M_{i2}^{p2} + W_{i2,i2}(\alpha^{s2} \vec{M}^{s2}, \alpha^{p2} M_{i2}^{p2}) * Y_{i2}^B \right) \right) \quad (13)$$

$$W_{i2,i2} = P_{i2,i2}^{C2}(\alpha^{s2} \vec{M}^{s2}, \alpha^{p2} M_{i2}^{p2}) - P_{i2,i2-1}^{C2}(\alpha^{s2} \vec{M}^{s2}, \alpha^{p2} M_{i2}^{p2}) \quad (14)$$

Here, we use superscript and subscript 2 to differentiate pre-establishment from post-establishment processes, because many of the components are analogous, differing primarily in scale (see Table 1). Thus, for instance, one may consider the probability of an alien species establishing in a system (P_{i1}^C) or a local patch $i2$ within that system ($P_{i2,i2}^{C2}$). One can have prevention expenditures to delay establishment to an uninvaded system (M^p), or to an uninvaded patch within the system (M_{i2}^{p2}) (i.e. slow the spread strategies). Once invaded, expenditures may be needed for surveillance and detection (M^s). Trade sanctions and other policies (M^e) may prevent the spread to new systems, which is analogous to management at the set of invaded local patches (\vec{M}^{s2}) to slow the spread of the alien species to uninvaded areas within the system. The delay of establishment of individual patches ($d2$) within the system lowers the cumulative local impact (Y_{i2}^B , eqn 15). The delay of invasion to a local patch is simply $d2 = t1 + t2 - 2$.

$$Y_{i2}^B = \sum_{i3=1}^{T-d2} \left(M_{i2}^{s2}(\alpha^e M^e) + M_{i2}^c(\alpha^e M^e) + \sum_{\gamma1=1}^{G1} \sum_{\gamma2=1}^{G2} w_{\gamma1\gamma2} * f_i^{\gamma1,\gamma2}(t3, X_{i2,i3}, E_{i2}, S, \alpha^e M_{i2}^c(\alpha^e M^e), \sigma_I) \right) \quad (15)$$

Once establishment occurs within a local patch ($\beta = 1$), there is potentially a cost (M_{i2}^{s2}) to slow the spread to other locations, a cost to control or adapt to the alien species (M_{i2}^c), and a direct impact of the invader ($f_i^{\gamma1,\gamma2}$), and can include both economic and ecosystem/environmental effects (see text for explanation of dependencies). The ability to implement these management activities is dependent on detecting the invader ($\alpha^e M^e$). The functional form for the impact of the invader may differ for different economic or ecosystem components ($\gamma2$) and may be valued differently by different stakeholder groups ($\gamma1$). Note that while we express the impact as summed across components and groups, in practice, how to weight ($w_{\gamma1\gamma2}$) components and groups is an open question, and care is needed to avoid double counting (Aukema *et al.* 2011). In addition, although the concept of patches is intuitive, there is sometimes a mismatch in scale between biology (e.g. a series of contiguous farms), management (e.g. applied to an entire county or political unit) and risk models (e.g. 50 km x 50 km squares, based on resolution of GIS maps). Nevertheless, a simple example of a functional form for direct impact within a patch is $f_i = c_1 X_{i2}, t_3 / (1 + \alpha^e M_{i2}^c)$ (impact is directly proportional to density, and reduced asymptotically by management $\alpha^e M_{i2}^c$).

Furthermore, for each species, we expect spatiotemporal variability of the environment to affect establishment in three distinct ways:

(1) *Spatial habitat suitability* (Box 2, eqn 4): For a given alien species, some sites may not be suitable, and thus may be unable to support a self-sustaining population. For instance, climate and nutrient differences between locations can cause differences in suitability. However, predictions may not be perfect due to other unmeasured factors. Thus, we treat suitability as a probability, conditional on known measured factors (Leung and Mandrak 2007). Spatial habitat suitability can be thought of as the long-term invasion pattern once the system has reached equilibrium and can be thought of as the fraction of sites expected to be occupied, for a given set of environmental conditions. However, generally, habitat suitability does not incorporate a temporal dimension, where probabilities of establishment increase with repeated introductions.

(2) *Temporal habitat suitability* (Box 2, eqn 3): Even if a site is generally suitable, establishment may still only be possible under specific conditions (e.g. temporal resource fluctuations, Davis *et al.* 2000; seasonal timing such as spring vs. winter, Drake and Lodge 2006), or some more complex confluence of environmental events. In contrast to spatial habitat suitability, here the probability of establishment increases over time, with repeated windows of opportunity. We include this term also to allow for conditions where introduc-

tions at the wrong time fail to result in an establishment, regardless of the number of propagules arriving in a habitat (compare with Box 2, eqn 2).

(3) *Environment–population dynamics interaction* (Box 2, eqn 2): Importantly, sufficient propagule pressure is needed for establishment, even when a site is spatially and temporally suitable. However, successful establishment will be determined by the interaction of propagule pressure with the vulnerability of the site to colonisation (e.g. presence of a predator) such that higher propagule pressure is often required to overcome more ecologically resistant habitats (Von Holle & Simberloff 2005; Edward *et al.* 2009).

It is important to explicitly consider the above components in a joint model (Box 2, eqns 2–5). Not doing so may result simultaneously in an underestimation of the proportion of sites that can eventually become invaded (long-term forecasts) and an overestimation of the number of propagules needed to result in establishment of suitable sites (Leung & Mandrak 2007). Furthermore, because policies are often aimed at reducing the number of propagules entering a region or habitat (e.g. Andersen *et al.* 2004), the efficacy of policies will also be overestimated if fewer propagules are needed for establishment than expected. This is consistent with arguments in the literature for combined models (e.g. Leung & Mandrak 2007; Roura-Pascual *et al.* 2009; Gallien *et al.* 2010).

Table 1 Parameter and variable list: notations used in the manuscript (see Box 2 & 3), plus a brief description and examples of potential ways to derive values for parameters

Parameter/Variable/Function	Description	Example data sources/parameterisation
D_{ij}	Distance between locations i and j	GIS
\vec{D}_j	Vector (array) of distances to all potential destinations from source j	GIS
E	Environmental traits. Includes both biotic and abiotic factors. Can affect each invasion component differently.	Database
\vec{E}	Vector (array) of environments across all local sites	Database
$f(.)$	Generically denotes a function	NA
$f_D(\vec{E}, D_{ij}, S, v, \sigma_D)$	Generalised function for dispersal kernel (how dispersing individuals are spatially distributed)	Fitted model or direct field sampling
$f_D(\vec{E}, \vec{D}_j, E_i, D_{ij}, v, \sigma_D)$	Generalised movement model of pathways (e.g. gravity model)	Survey of human movement, goods and services
$f_E(X_{i,t}, E_{i,t}, S, \sigma_E)$	Generalised environment interaction (ecosystem or community) model.	Fitted model or experiments on species interactions and across environmental gradients.
$f_g(t - t', v_{i,j,k,t}, S, \sigma_g)$	Net growth (mortality or reproduction) during transport as a function of travel time, pathway and species trait.	Experiments or observations before and after transport. Combined O^*f_g may be estimated by interceptions.
$f_I^{i1,i2}(t3, X_{i2,t3}, E_{i2}, S, M_{i2}^i, \sigma_I)$	Direct impact to ecosystem component (γ_2) as experienced by stakeholder group (γ_1).	Experiment, field observations or model to estimate change in ecosystem. Social survey to examine human preferences.
f_s	Denotes that function results in a measure of species richness or abundance over all species. Used for mapping (Table 2), but does not occur in framework (Box 2 & 3).	N/A
$f_X(X_{i,t}, r(E_{i,t}, S), \kappa(E_{i,t}, S), \sigma_e, \sigma_d)$	Generalised population model	Population dynamics model
$f_{XD}(X_{j,t}, S, \sigma_{XD})$	Generalised function for number of individuals dispersing	Fitted model or field sampling
M_{i2}^C	control or adaptation costs applied at local patch $i2$	Documentation. Effectiveness estimated via model, experiment or field comparison (time series, or control site).
M^E	Expenditure for early detection.	Documentation.
M^P	Management expenditure to prevent establishment into a current uninvaded system. Can also be applied to local patches within a system as well.	Documentation. Effectiveness estimated via survey (change in human behaviour), or model or observed change in detections/interceptions.
M^I	Management costs at an invaded system. At the system level, causes indirect impact of alien species immediately after detection (e.g. trade sanction). Also applicable to local invaded patches within a system, where it can be part of a slow the spread strategy.	Legislation, documentation. Effectiveness estimated survey (change in human behaviour), or model or observed change in detections/interceptions.
\vec{M}^{i2}	Vector of M^I across all alien occurrences within a system.	Same as above
$N_{i,t}$	Propagule pressure at a given time interval t and location i .	Calculated or surrogates are used (e.g. goods, produces, imports)
$O(E_{j,t}, v_{i,j,k,t}, S, X_{j,t}, \sigma_O)$	Number of organisms in uptake from location j at time t , as a function of environment, pathway and species trait and local abundance.	Surrogate: e.g. human population density, population dynamics model in source location.
$pr(.)$	Generically denotes a probability	NA
$pr(R E_{i,t}, v_{i,j,k,t}, S)$	Fraction propagules released as a function of environment, species and pathway traits.	Social survey or sampling vectors (e.g. ships) at destinations
$pr(\lambda_A E_i, S)$	Probability that an individual propagule will establish, within a spatially and temporally suitable site. The probability may be dependent on environmental conditions or species traits.	Fitted model. Presence/absence data and propagule pressure estimates (see above), population dynamics model, or experiment
$pr(\lambda_B E_{i,t}, S)$	Probability that a site is suitable within a given time interval (e.g. seasonality).	Habitat suitability model, presence/absence time series data.
$pr(\lambda_C E_i, S)$	Probability that a given site is generally suitable, given a set of environmental conditions and species traits.	Habitat suitability model, presence/absence data.
$P_{i,t}^A$	Joint probability of establishment across all propagules, for a suitable site and invisable time interval	Calculated
$P_{i,T}^B$	Joint probability of establishment across all propagules and all time intervals, for a suitable site	Calculated

Table 1. (continued)

Parameter/Variable/Function	Description	Example data sources/parameterisation
P_T^C	Joint probability of establishment across all propagules, all time intervals, and all suitable sites	Calculated
Q_T	Species range at time T	Fitted model
$r(E_{i,t}, S)$	Intrinsic rate of growth, given environmental conditions and species traits	Fitted model: time-series data or direct field sampling
S	Species traits. Can affect each invasion component differently.	Database
$V_{ij,t}$	Number of vectors travelling from location j to location i at time t .	Database or traffic model (e.g. gravity model)
U_{i1}	Probability that a region (e.g. continent) has a primary invasion at time $t1$.	Calculated
$W_{i2,t2}$	Probability that site $i2$ (e.g. farm or bay) becomes invaded exactly at time $t2$, and not before. This corresponds with secondary spread, rather than primary introduction	Calculated
$X_{i,t}$	Population size or abundance at location i at time t .	Population model, or direct field sampling
Y^A	Post-establishment impact	Calculated
Y_{i2}^B	Impact in local patch $i2$	Calculated
Z_T	Risk by time T as measured by expected impact	Calculated
α	Effectiveness of management. Thus, α^p would refer to effectiveness per unit expenditure in prevention. Presented as a simple scalar, but could be more complex functional forms.	See above under specific types of expenditures.
$\beta(E_i, S)$	Coefficient to allow population dynamics such as Allee effects. May also be a function of environment and species traits.	Fitted model. Presence/absence data and propagule pressure estimates (see above), or population dynamics model.
$\kappa(E_{i,t}, S)$	Carrying capacity, given environmental conditions and species traits.	Fitted model: time series data or direct field sampling
λ	Establishment (see above for different probabilistic notations).	See above.
σ	Term denoting stochasticity. Subscript in equations denote different stochastic estimates for each component.	Fit to data
v	Type of vector or pathway	Database
$w_{\gamma 1 \gamma 2}$	Weighting for component and group.	Social survey to determine relative importance of different factors/groups.

The term 'Calculated' refers to use of equations in text to derive values.

Abundance/local density

Like establishment, abundance or density is also driven by population dynamics, in the context of novel environmental conditions. There are a plethora of well-studied models to describe population dynamics for different organisms with different life history strategies and reproductive behaviour (e.g. logistic growth, Ricker, Beverton-Holt, matrix models, reviewed in Turchin 2003), depending on the specific system. However, common elements of population dynamical models include some form of maximum density (carrying capacity), population growth and autocorrelated dependency on population size in the previous time interval(s). Furthermore, two distinct sources of stochasticity – demographic and environmental are often identified in population models (Taylor & Hastings 2005). In addition, population dynamics may affect and be affected by the environment. These elements are described in eqn 6 (Box 2).

We note that although population dynamics underlie both the Establishment and Abundance components of TEASI, they differ in the following ways and are therefore treated separately:

(1) Establishment is affected by propagule quality immediately after transport, the probability of release into suitable microhabitats within a given habitat and the ability to adapt to a novel environment. In contrast, for abundance, the above factors play no essential role because populations are already present in suitable microhabitats.

(2) Establishment is driven by small population dynamics (Allee effects and demographic stochasticity). In contrast, for abundance, carrying capacity and intraspecific competition are important. An abundant alien species may deplete prey populations and resources, thereby affecting community dynamics with potential feedback on its own abundance over time. Initial high alien abundances might also be followed by declines and maintenance at lower densities, or even by population crashes (Simberloff & Gibbons 2004), although the mechanisms of population collapses are uncertain in many cases.

(3) A newly established population is likely to have too low an abundance to affect community dynamics, and hence dynamic feed-

back interactions can be disregarded in establishment. In contrast, as aliens are sometimes ecosystem engineers, a well-established and abundant population of an alien species can modify its physical environment (Crooks 2002) (Box 2, eqn 7).

Given the above three points, and given the relative infrequency of establishment success even with high numbers of introductions (i.e. most individuals do not establish), we do not include contributions of propagule pressure to the general dynamics of the population (Box 2, eqn 6), although we acknowledge that this is a possibility in special cases (e.g. Ficetola *et al.* 2011).

Spread

Models of dynamical spread generally integrate movement from established sites (sources) to new locations. Spread, in part, depends on the local source abundance of the invader, because individuals either are directly redistributed or produce dispersive propagules (e.g. juveniles or seeds). In addition, the rate of spread also depends on the dispersal ability and environmental tolerance of the species or their vectors (e.g. humans, air and ocean currents), and the spatiotemporal heterogeneity in suitability of the recipient region. Depending on the specific dynamics, time lags may occur between initial establishment and subsequent spread (Aikio *et al.* 2010). In risk assessment, spread describes the spatiotemporal invasion progress, and it is a determinant of regional extent of invasion, and hence its impact and eventual costs of control or eradication (Parker *et al.* 1999; but see Hulme 2012 for exceptions).

The most common approaches to modelling spread dynamics include reaction-diffusion, integro-difference and gravity models (see Hastings *et al.* 2005 for a review). For natural processes, one might model dispersal as a smooth declining function of distance (e.g. integro-difference models, Kot *et al.* 1996). In contrast, for human-mediated dispersal, where travel may skip geographical locations, both distance and 'attractiveness' of destinations are important to consider to account for vector preference of some environments over others (e.g. gravity models, Bossenbroek *et al.* 2001). All of these approaches in essence yield information on propagule pressure to an uninvaded location, albeit at a different scale (Box 2, eqns 8 and 9).

After obtaining information on propagule pressures to uninvaded locations, there are two ways to conceptualise spread. One is as an expanding wave front, encompassing an 'invaded' area (Kot *et al.* 1996). The other is as the accumulation of invasions of local areas (patches), where patches may differ in quality both spatially and temporally, resulting in environmental heterogeneity (With 2002). In the later conceptualisation, spread incorporates propagule pressure and establishment processes. Thus, transport and primary establishment and secondary spread to individual patches differ in terms of scale, but the underlying processes are analogous, albeit likely with different vectors and different parameter values. Here, our interest may be how far the alien species has spread, how many local patches the alien species occupies and over what time frame these events occur (Box 2, eqn 10).

Calculating risk and impact

The growing concern about alien species stems largely from their potential impact to the environment, the economy and society (Andersen *et al.* 2004). Thus, we use expected impact (probability of events * severity of impact) as our measure of risk (Z), but we rec-

ognise that there have been other applications of the term 'risk' in invasion biology (see mappings of Z in Appendix 2). As a good first approximation, expected impact has been characterised by the range * abundance * per capita effect of a given alien species (Parker *et al.* 1999). However, to accommodate other arguments in the literature, we provide a fuller characterisation of risk as applied to alien species (Box 3).

Estimation of direct damages caused by an alien species requires the integration of all the other components of the invasion process: transport and establishment needs to take place; abundance should increase impact; each local area can experience impact due to the alien species, hence the greater the number of invaded local sites, the greater the overall impact for a given alien species; and some species will inherently have greater per capita impact than others. In addition, impact is likely to be heterogeneous across space and time, and this should be considered to properly estimate risk (Vilà *et al.* 2006). Specifically, alien species abundance is expected to vary (Kulhanek *et al.* 2011a, b), and also some environments may be more valuable than others, either because they contain elements of interest (e.g. lakes with power plants affected by zebra mussels, Leung *et al.* 2002 or vulnerable native species, Olden *et al.* 2011). Moreover, alien population size changes over time and both native species and human society may adapt as well, potentially reducing the impact of invaders (Strayer *et al.* 2006) (summarised in Box 3, eqn 15).

Furthermore, we note that impact can have differential effects to distinct ecological, economic or social elements. For instance, ecological impacts include loss of biodiversity and ecosystem services among others (Pejchar & Mooney 2009; EFSA P.o.P.H.P 2011); economic and social effects can include loss of industry, reduced property values and disease transmission among others (Crowl *et al.* 2008; Aukema *et al.* 2011; see Lovell *et al.* 2006 for a review). Moreover, stakeholders likely value different attributes in different ways. Although beyond the scope of this review, approaches exist to convert such elements into a common metric and discount costs and benefits over time (e.g. economic valuation, Champ *et al.* 2003) and consider trade-offs between elements (e.g. multicriteria analysis, Hurley *et al.* 2010).

Finally, the expected impact is due in part to management strategies, which can reduce the direct impact of an alien species, but which imposes a cost and can result in other collateral damages. Although our focus here is on risk assessment, and a detailed treatment of risk management is beyond the scope of this manuscript (including analyses of trade-offs and decision theory models), we felt that it was worthwhile to briefly include key management options, and their relation to risk (Box 3). First, management-related costs and impacts can occur at all stages of invasion. Before initial establishment occurs, prevention efforts can be costly, albeit potentially worthwhile if an invasion is delayed and damages are averted for a number of years (Box 3, eqn 11). Once establishment occurs, societal responses such as international trade sanctions and surveillance costs may occur immediately (Mumford 2002), followed by measures to slow the spread of the alien species (e.g. Sharov & Liebhold 1998) (Box 3, eqn 13). Finally, for invaded areas, management actions include eradication, control and adaptation (changing investment and business practices to moderate the effects of the alien species, e.g. into labour and capital, Leung *et al.* 2002). Taken together, the combination of the TEASI components and sub-components allows the calculation of risk over the invasion process (Box 2 & 3).

Table 2 Two examples of risk-scoring mapping onto TEASI framework

Name of system	Group/Regions applied	Main components: T/E/A/S/I Individual components estimated (# questions)	Uncertainty L/S/E	Rank formation	Policy implemented	Comments
1) Australian A-WRA scheme/Pheloung et al. (1999)	Plants/Australia	Main: Y/Y/Y/Y/Y r: types of vectors (7) S: species traits (8) N: propagule pressure (2) r(): population growth (1) pr(λ-c/E): habitat suitability (1) pr(λ-c/E,S): habitat suitability & traits (2) pr(λ-c/): range & history (2) r(S): population growth & traits (7) f _E (E,S): community interactions (2) f _I (S): impact & traits (10) f _I (S): impact & history (5) Other: quality of information and management effectiveness (2)	N/N/Y Number of questions answered used as indicator of reliability	Equally weighted sum of answered questions. Minimum number of answered question (10/49) Recommendation: accept, evaluation (=need further evaluation), reject taxon	Applied formally to thousands of species in Australia and New Zealand. Applications around the world.	Question type: Yes/No binary questions; magnitudes not considered. Strength: Widely tested around the world. Comprehensive questions. Weakness: aspects associated with propagule pressure and temporal dynamics missing.
2) EPPO computer-assisted pest risk assessment scheme (EPPO 2011)	Many taxa (plant pests incl. weeds)/Europe, North Africa, Great Britain	Main: Y/Y/N/Y/Y O(φ _r): probability of being transported along a pathway (2) f _g (t - t _I , v _r): net growth in transport (2) pr(R/E, v): release in suitable habitat (3) pr(λ-c/E _r): abiotic & biotic habitat suitability (12) r(): population growth (1) pr(λ-c/): history (1) f _D (): natural & human-assisted spread (3) Q _r (): Species range (1) f _I (): environmental & agricultural impact (14) f _I (S): impact as a vector (1) Other: adaptability, transient populations, management (9)	N/N/Y Uncertainty rated low, med, high for each question.	No explicit guidance on how to combine scores of individual questions to a final score. Recommendation: continuous ranking	Formally applied to many alien species in the EU to justify regulations. Most widely applied to non-plant pests in Great Britain.	Question type: All answers are scored on a 5-point scale (3-point for impact). Strength: generic, can apply to many taxa, all aspects of invasion sequence. Weakness: Questions relating to local abundance are missing. No guidance on risk aggregation.

We chose analogous equations that best corresponded to the element of risk that could be estimated. Rank formation: method of combining scores. L, Linguistic; S, Stochasticity; E, Epistemic uncertainties; T, Transport; E, Establishment; A, Abundance; S, Spread; I, Impact. Y = Yes, N = No. Numbers of questions for each sub-component are in parentheses. Where possible, we included conditional dependencies (e.g. $F_I(S)$ was dependent on species traits, whereas $F_I(r)$ denoted unspecified dependencies). Two dominant approaches were presented, the A-WRA and EPPO (based on ISPM-11). See appendix 1 for analyses of the complete set of scoring approaches examined, Box 2 & 3 for TEASI model description, and Table 1 for definition of terms.

Table 3 Three examples of quantitative risk assessment mapping onto TEASI framework

Name of model	Analogous equations	Uncertainty examined	Comments
Species distribution models (also called Habitat suitability models or ecological Niche-based model) (e.g. Elith <i>et al.</i> 2006; Stohlgren <i>et al.</i> 2010)	$Z = Q = \sum_{i=1} pr(\lambda_C E_i)$	Accounts for spatial variability, parameter uncertainty via Bayesian methods; model uncertainty via ensemble models. Validation data sets also used.	Many different techniques (e.g. Maxent, GARP, Neural Networks). Implicitly assume equilibrium conditions. Treated as probabilities here, as closest analogue in full model, but discrepancies may exist because of biased sampling, use of pseudoabsences and base-rates effects (see also Jimenez-Valverde <i>et al.</i> 2011). Note that presence of subscript i indicating that spatial locations considered. One ramification of this is that extent of spread (Q) can be estimated. Note absence of t , indicating that temporal dynamics not considered.
Species trait models (e.g. Reichard & Hamilton 1997; Vall-Ilosera & Sol 2009)	$Z = P^e = f_{P^e}(S)$	Validation data sets and error rates.	Species trait models have been applied to a number of the invasion stages, but only establishment shown here. Note that expressed as P^e , indicating the probability of the system as a whole will be invaded. $f_{P^e}(S)$ indicates that it is some function of S (to determine P^e). Species trait models have used numerous statistical approaches with different functional forms to estimate the probability of establishment. Note absence of subscripts i and t , indicating that spatial and temporal heterogeneity and dynamics not considered.
'Propagule pressure-establishment model' (e.g. Leung <i>et al.</i> 2004)	$V_{i,j,t} = V_{j,t} f_D(\vec{E}, \vec{D}_j, E_i, D_{ij})$ $N_{i,t} = \alpha \sum_{j=1}^J V_{i,j,t}$ $P_{i,t}^A = 1 - \prod_{t=1}^T (1 - pr(\lambda_A))^{N_{i,t}^B}$ $Z_T = Q_T = \sum_{i=1} P_{i,t}^A$	Probabilities are stochastic. Uncertainty examined using hindcasts.	Uses vector traffic as a surrogate of propagule pressure, and calculates establishment as a function of propagule pressure. Implicitly assumes all propagules have equal probability and that no interaction occurs with environment (compare with full model, 'establishment'). Note, J refers to all invaded sources, rather than all sources. Note that probability of establishment is also calculated, as with above models, but here is a function of propagule pressure, rather than environment or species trait. Note that subscript t indicates that it is temporally dynamic, and that i indicates that it predicts spatial patterns. Thus, spatial extent Q_T can be modelled over time.

We chose analogous equations that best correspond to the element of risk that could be estimated. Notation has also been converted to be consistent with this manuscript. Subscripts specify location (i), time interval (t), time horizon (T), source (j). Absence of subscript indicates that the model does not consider that element. For comparability, all three examples yield information on probability of establishment; but differ in substantive ways (see *Comments* for explanation and insight into the nuances of the mappings). See appendix 1, for analyses of complete set of 236 quantitative approaches examined, Box 2 & 3 for TEASI model description, and Table 1 for definition of terms.

CURRENT STATE AND FUTURE DIRECTIONS OF ALIEN SPECIES RISK ASSESSMENTS

To elucidate how risk of biological invasions is currently being measured, we used the TEASI components, dependencies and structure developed above (see Box 2 & 3) as a vehicle to compare all RAs that we reviewed, and to identify generalities. We described each article in a few equations, essentially 'mapping' each RA onto our TEASI framework by identifying the components considered in each RA (Tables 2 and 3, see Appendix 1 & 2 for complete set of RAs analysed, and Appendix 3 for illustrative examples of mappings). We also reported on how researchers have sought to include uncertainty, given its relevance in risk assessment (Box 1).

We noted that two streams have progressed in parallel in academia and policy, with much of academic research focused on refining quantitative predictive models and much of policy improvements focused on risk-scoring methods (i.e. questionnaires). As such, we analysed each stream separately. For the risk-scoring methods, we chose analogous equations to the questions considered in each RAs (see some examples in Table 2), while for the quantitative predictive

models, we used equations that best corresponded to the elements of risk estimated (Table 3).

As part of our review, we processed over 700 abstracts from the Web of Science (using the key words (invasive species OR exotic species OR indigenous species OR alien species) AND risk AND model) and also examined the scoring risk approaches from reviews by Heikkila (2011) and Essl *et al.* (2011) and examined two existing guidelines (International Standards for Phytosanitary Measures-11 (ISPM-11), FAO 2004 and Terrestrial and Aquatic Animal Health Code, OIE (World Organization for Animal Health) 2011a; OIE (World Organization for Animal Health). 2011b). This resulted in > 300 relevant individual RA models (70 scoring and 236 quantitative RAs, see Appendix 1 & 2). The minimum criteria for inclusion were that the approach related to prediction of alien species, that the model was documented explicitly and that it was not a review article nor purely theoretical (i.e. it was based on real systems).

In general, there have been substantial advances in the science and the policy applications of alien species risk assessments over the last decade (e.g. ISPM-11 – FAO 2004; Baker *et al.* 2009). While previous reviews and guidelines have done well identifying the com-

ponents, they have offered less guidance regarding the dependencies underlying each component, and the structure of how those components should be combined to determine risk. Furthermore, there was considerable heterogeneity between the > 300 RAs examined, and virtually all articles had gaps in their analyses (Appendix 1 & 2). We summarise the main generalities and differences between both approaches:

Scoring approaches

(1) The scoring approaches have been important for policy, with 57% of the approaches having been applied formally or informally by government or by some other stakeholders (e.g. botanic gardens) (Appendix 1). We could not obtain information from authors for 26% of the approaches, and 11% were not applicable as they were comparative tests of other approaches. The Australian Weed Risk Assessment (A-WRA, Pheloung *et al.* 1999) has been the most influential scoring approach (Table 2), with 30% of the 70 scoring RA studies being applications or further developments of A-WRA (Appendix 1). To avoid having A-WRA dominate trends in our analysis, we excluded applications or comparative tests with no model development from the remainder of the analysis of scoring approaches.

(2) The frequency of TEASI components included ranged from 47% (Transport) to 87% (Impact) (Fig. 1b). Scoring approaches had reasonably broad coverage of TEASI components, with 50% of them including at least three components and 18% including all five (Fig. 1a). Interestingly, models developed in the last 8 years were more likely to include either high or low numbers of components, with 22% including five components and 30% having only one to two components (prior to 2004, 7% had five components and no RA had only a single component). Interestingly, over time, both Transport and Impact inclusion has increased, whereas Abundance has decreased. In comparison to quantitative approaches (discussed below), component coverage was generally much greater, likely, because scoring approaches could be done much more quickly than their quantitative counterparts as they were based primarily on expert opinion (consequences discussed in Vall-Ilosera & Sol 2009). We also note that the scoring approaches reviewed have been applied to a large number of species (average 100, median 47, maximum 851, Appendix 1), although predominantly for vascular plants. Given limitations in time, data and resources, such scoring approaches will likely continue to be needed for the foreseeable future.

(3) In addition to variation in TEASI components, the subcomponents were also highly variable (Fig. 1d). Impact f_I was the most common determinant (69% of all models), followed by spatial habitat suitability $pr(\lambda_c)$ (61%), population dynamics f_x (50%) and spread f_D (46%) (see Table 1 for subcomponents description). Likewise, within studies, the coverage of questions was uneven. For instance, for the Australian WRA, there were 15 questions on impact, seven on vectors/pathways of dispersal, one on population growth, three on habitat suitability and two on propagule pressure (Table 2). Of course, depending on the purpose of the risk assessment, some components of the TEASI risk model may not be relevant. For instance, prioritisation of already established alien species for control or eradication need not consider the first stages of the invasion process. In contrast, prioritisation of invasion prevention should logically consider the entire process identified in the TEASI risk model. The applications of most approaches were geared

towards prioritisation of invasion prevention. Furthermore, guidance has been lacking on the disproportionate number of questions asked for some elements vs. others. A potential improvement would be to consider the suite of components and subcomponents identified in the TEASI risk model to ensure coverage, to determine the relative numbers of questions asked for each component and to weight appropriately. Roughly half (39%) of the studies did weigh questionnaire answers (e.g. V-WRA, Appendix 1, model ID 18, Benke *et al.* 2011), which is a good protocol, although the methods of weighting have been variable.

(4) Usage of dependencies as predictors of TEASI components (e.g. environment or species traits) was substantially less important than for quantitative models (discussed below), likely because these scoring approaches were primarily based on expert opinion. Nevertheless, dependencies still played a role, possibly because some questions based on dependencies were more intuitive than direct questions on TEASI components, with dependencies on environment and species traits each occurring in 20% of the questions (Fig. 1c, Appendix 1).

(5) The types of questions included for Impact, the most commonly analysed component, could be classified into several general categories including: (1) undesired characteristics of the alien species (e.g. does it sting or burn or bite or spread disease or is it toxic or parasitic), (2) environmental effects (e.g. physical obstruction, reducing biodiversity, predation or competition), asked in either detail (e.g. impact through hybridisation, or impact through physical obstruction of the water flow, or damage potential to endangered species) or generally (e.g. impact on native species, impact on ecosystems, environmental impact), (3) economic or social effects (e.g. agriculture, forestry, livestock, human health, infrastructure, gardens), asked in either detail (e.g. yield loss, impact on production costs, impact on animal export) or generally (e.g. impact on economy, negative economic effects, societal relevance) and (4) the potential range and/or severity of impacts in either the native range or the range of interest, potentially also accounting for special interests (e.g. vulnerable groups potentially placed at risk, or the value of the sites at risk).

(6) We noted that most scoring approaches did not estimate magnitudes of expected impact, nor of individual TEASI components or subcomponents. For instance, while vectors are necessary for propagules to be transported, the magnitude of propagule pressure was not queried (e.g. A-WRA, Table 2). Similarly, the severity of impact typically was not estimated (but see Generic Impact Scoring System, Appendix 1, model ID 37, Nentwig *et al.* 2010). Given the low base rate often associated with invasive species, yes/no answers may be too insensitive (Smith *et al.* 1999; Hulme 2012; but see Keller *et al.* 2007), and some metric of severity could be useful. Furthermore, quantification would permit more sophisticated analyses of trade-offs (e.g. cost-benefit or cost-effectiveness analysis). A potential compromise between dichotomous questions and a quantitative approach may be to use Likert-type scales (a multiple-choice type of question, e.g. EPPO scheme, EPPO 2011; Table 2), which was relatively common (Appendix 1). However, linguistic uncertainty may be an issue (Box 1).

(7) Invasions are inherently dynamic, heterogeneous processes. However, no scoring method accounted for temporal dynamics or spatial heterogeneity (but see Van Wilgen *et al.* 2009), perhaps reflecting the difficulties of including these factors in a questionnaire format.

Inclusion of TEASI by model completeness

Percent inclusion of TEASI

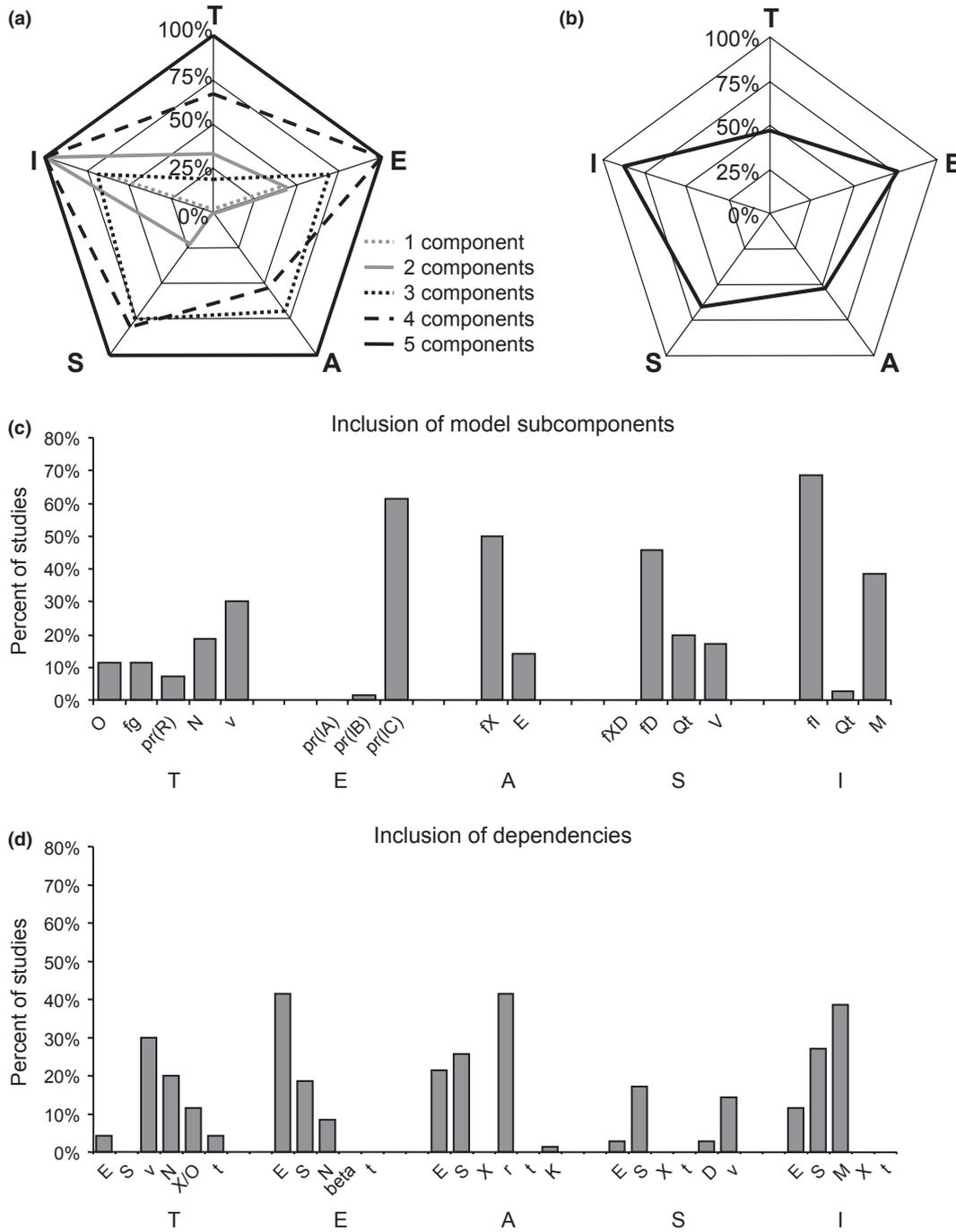


Figure 1 Summary of qualitative/semi-quantitative (scoring) risk assessments. (a) Percent of models considering the different stages of the invasion process, split into models containing different numbers of TEASI components (Transport, Establishment, Abundance, Spread, Impact). (b) Average consideration of TEASI in models. (c) Percent of models considering different TEASI subcomponents and (d) dependencies (model notation explained in Table 1, see also Box 2 & 3 for description of TEASI model).

(8) There was diversity in the methods used to combine scores across the components and subcomponents to obtain a risk score, with additive approaches being the most common (44%). However, based on the structure of the full model (Box 2 & 3), adding scores between components (e.g. vector transport and impact) does not make sense. One should at least multiply scores of major TEASI components (e.g. Southern Australian Weed Risk Management

scheme, Appendix 1, model ID 30, Johnson 2009). Elaborate decision matrices have also been used (e.g. Biopollution index, Appendix 1, model ID 39, Olenin *et al.* 2007). These may make sense, but were not transparent so we could not evaluate their logic. We suggest that one should consider how components and subcomponents combine in the TEASI risk assessment framework to provide guidance on how scores should be combined. This would take no

additional time or expertise on the part of the risk assessor, and would happen in the risk assessment formulation stage.

(9) In terms of uncertainty, for these scoring RAs, stochasticity generally was not considered, whereas epistemic uncertainty was considered in some approaches, but varied in methodology (Appendix 1). For instance, some indices were based on number of

unanswered questions (e.g. A-WRA Table 2). However, even if all questions were answered, epistemic uncertainty could still be very high. Analyses have been done separately, examining uncertainty associated with A-WRA (Caley *et al.* 2006), but are not part of the general procedure. Approaches using variation between expert judgement (Generic Impact Scoring System, Appendix 1, model ID

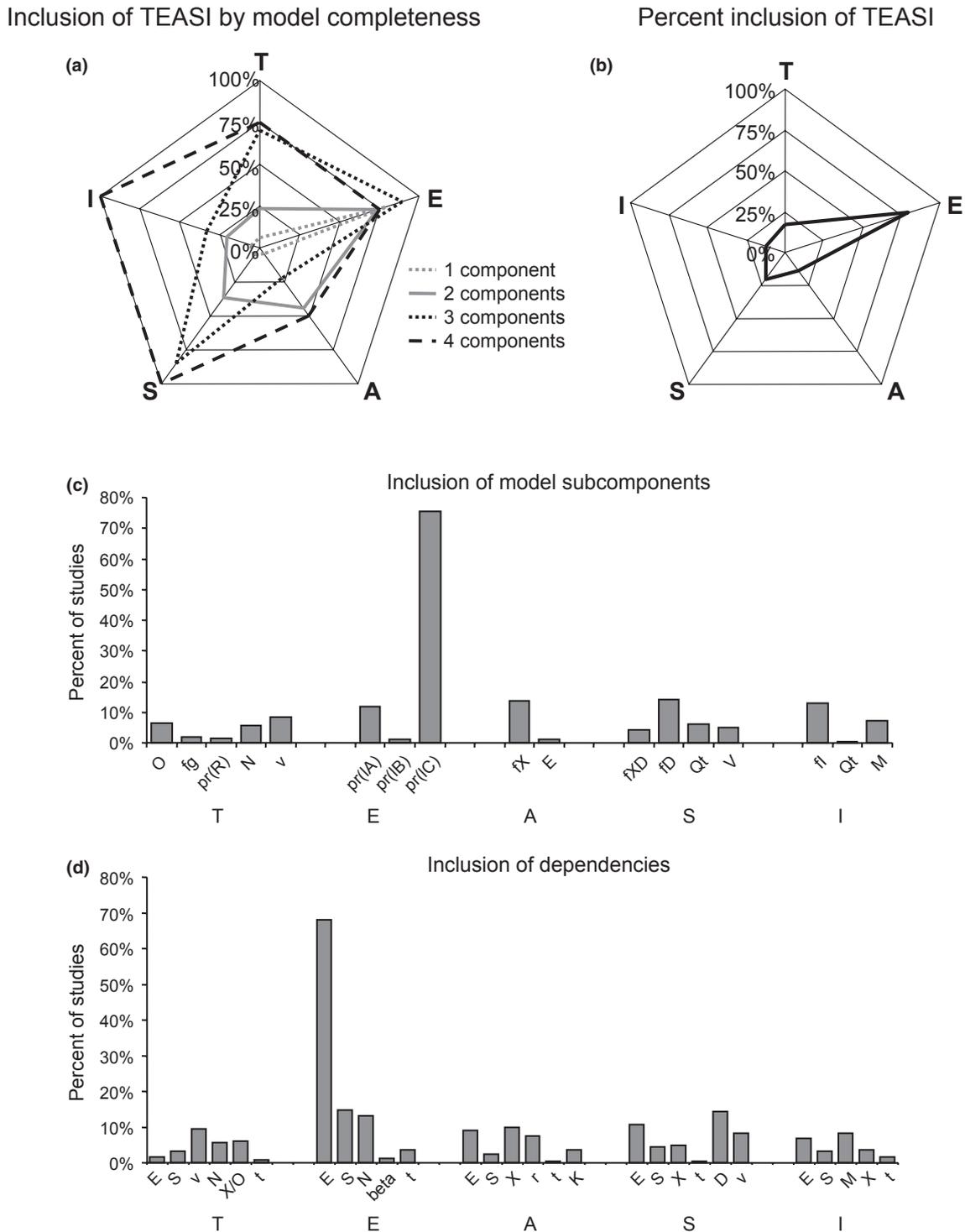


Figure 2 Summary of quantitative risk assessments. (a) Percent of models considering the different stages of the invasion process, split into models containing different numbers of TEASI components (Transport, Establishment, Abundance, Spread, Impact). (b) Average consideration of TEASI in models. (c) Percent of models considering different TEASI subcomponents and (d) dependencies (model notation explained in Table 1, see also Box 2 & 3 for description of TEASI model).

37, Nentwig *et al.* 2010) or ranked as low, medium and high (EPP0, Table 2) may be more reflective of epistemic uncertainty (despite issues of linguistic uncertainty). Others have also used sensitivity analysis as part of their process (V-WRA –Appendix 1, Model ID 18, Department of Primary Industries 2008), although this does not indicate how much uncertainty actually exists, but rather the potential consequence of uncertainty. Finally, we found that linguistic uncertainty occurred, in terms of how each question actually mapped onto risk, and the quantitative meaning of Likert scales (e.g. EPP0, Table 2). In developing or applying a scoring framework, clear guidance should be given as to what each alternative actually means (e.g. what is considered high and what is low) (Gordon *et al.* 2010).

Quantitative models

(1) Most quantitative models examined a single TEASI component (78%, Fig. 2a). Across all studies, establishment was the most commonly estimated component (in 79% of all models, Fig. 2b). Particularly, the probability that a habitat is generally suitable *pr* (λ_C) was the most commonly estimated subcomponent (42%, Fig. 2c), in part because of the popularity and accessibility of species distribution models (also often called habitat suitability models, or ecological niche-based models; Guisan & Thuiller 2005; Elith *et al.* 2006; Stohlgren *et al.* 2010). More recently, there have been cogent arguments for models integrating multiple TEASI components (analogously termed ‘joint models’ – Leung & Mandrak 2007; and ‘hybrid models’ – Gallien *et al.* 2010), but most often these have still only synthesised a small subset of the components underlying risk (Appendix 2). Nevertheless, the field appears mature enough to start synthesising a full TEASI risk assessment model, depending on data availability.

(2) In contrast to the scoring approaches, most of the quantitative RAs have been based on single species risk assessments (96%), except for a few studies using alien species richness or total alien abundance as a measure of risk (4%). However, because impacts are heterogeneous across species (Aukema *et al.* 2011), alternative metrics other than species richness should be explored. Developing analogous frameworks for multispecies risk assessments would be a useful area of future research.

(3) Dependencies were often used as surrogate measures of TEASI components, likely because TEASI components and sub-components can be difficult to measure directly. Environmental dependencies were the most commonly used surrogates for most TEASI components (42%, Fig. 2d, Appendix 2) probably due to the above-mentioned use of species distribution models, in which the suitability of a habitat is dependent on some set of environmental characteristics. Usually, environmental predictors have been abiotic conditions, but as a special note, the biotic environment (i.e. species assemblages) has also been modelled in a few studies using SOM neural networks (e.g. Appendix 2, model ID 73, Gevrey *et al.* 2006), although this has been much rarer. In addition to establishment, the estimation of spread in terms of the potential spatial extent follows naturally from the summation of all potentially established locations (Box 2, eqn 10). Furthermore, environmental predictors have also been used to estimate abundance and impact (e.g. the probability of occurrence of a vulnerable native species, superimposed on the occurrence of the alien species). The simpler versions of species distribution models do not take into account temporal dynamics, although existing ‘joint’ or ‘hybrid’ models sur-

mount this limitation. More broadly, environmental dependencies exist for virtually all components in the full model (Box 2 & 3), and we believe that these predictors could be even more fully exploited, and that this is a fruitful avenue of research. For instance, one should be able to modify species distribution models to parameterise (or scale) dynamical models. This would more fully capture the temporal and spatial dynamics than currently achieved.

(4) Other common dependencies include species traits (12%, Fig. 2d, Appendix 2), which also have been used to estimate most TEASI components. The advantage of species-trait models is that they examine multiple species using reasonably accessible data on species characteristics. The disadvantage is that they typically do not consider either spatial or temporal dynamics. Surrogates of transport (propagule pressure) have included the number of pathways, functions of uptake (e.g. source population size, number of stores selling alien species), functions of survivorship and time, surrogates of vector traffic (e.g. human density, distance from roads) and models of vector traffic. These in turn have been used sometimes as predictors of establishment. A fruitful avenue of research would be to develop approaches to integrate the different dependencies. There have been a few models integrating species traits with habitat suitability models, although these have generally been limited to linear models (e.g. Thuiller *et al.* 2006). Development is needed for non-linear analogues. Furthermore, the combination of species distribution models, propagule pressure, dynamical models and species-trait models could yield a very powerful combination that is generalised across species, space and time, depending on data available.

(5) The method of combination of TEASI components (i.e. model structure) is nuanced, but potentially important as well. For instance, species distribution models determining the suitability of environments have been combined with transport models to more fully predict establishment. This has been done in a number of ways: using an explicit propagule pressure submodel (e.g. Appendix 2, model ID 90, Herborg *et al.* 2007), dispersal model (e.g. Appendix 2, model ID 28, Catterall *et al.* 2012) or population model (e.g. Appendix 2, model ID 42, Crossman & Bass 2008). They all yield temporal dynamics, and the propagule pressure and dispersal submodels yield spatial dynamics. Alternatively, one could simply insert a transport dependency (e.g. distance to roads) as a factor in a species distribution model (e.g. Appendix 2, model ID 104, Kaiser & Burnett 2010). The benefit is that this is likely the simplest approach. However, temporal dynamics inherent in the invasion process are lost. Other examples of nuanced differences in combination approach include summing components to obtain a relative score (Appendix 2, model ID 229, Wilson *et al.* 2009) or fitting each component in sequence to patterns of occurrence (Appendix 2, model ID 197, Sharma *et al.* 2009). The key point is that the theoretical or empirical ramifications of such choices have typically not been explored (a source of epistemic model uncertainty).

(6) Given the logistical issues of limited data, time and resources, as an avenue of research, we suggest exploration of the relative importance of the components/sub-components identified in the TEASI risk assessment model. For instance, arguments exist that propagule pressure should be more predictive early in an invasion and habitat suitability later (Leung & Mandrak 2007). Some of the traits that make species successful may also make them more readily available for transport and introduction (Cassey *et al.* 2004), whereas others may cancel out in different stages (Dawson *et al.* 2009). Arguably, analyses of the relative importance of model components should be evaluated

for species with different life history traits, and in different environments/ecosystems. Nevertheless, analyses have been virtually non-existent on general rules for which elements are most important, under what circumstances and what the consequences are of omission. This too would be a fruitful avenue of research.

(7) Almost all quantitative models examined some form of uncertainty, but the approaches were diverse (Appendix 2). These included (1) standard error or the amount of variation explained, applied to the fitted model, (2) misspecification (error) rates on validation set, either interpolated within region where data were fit or extrapolated to new regions, (3) temporal hindcasting (building model on the first number of years in a data set, and predicting subsequent years), (4) Bayesian posterior distributions, (5) explicit probability (stochastic) models, (6) sensitivity analyses and (7) ensemble models. Each approach yields nuanced, but important differences. Approaches 1–3 yield combined effect of all uncertainty (stochasticity and epistemic uncertainty), based on the best-fitting model. This is useful for descriptive purposes; however, mixing the effect of stochasticity and epistemic uncertainty can have negative consequences for forecasting (Clark *et al.* 2005) and restriction to the best-fitting model can result in undesirable management outcomes (Peterson *et al.* 2003). Bayesian statistics are more robust to these effects, as they consider the probability of each parameter value being true (parameter uncertainty), can examine model uncertainty via model averaging (Buckland *et al.* 1997) and can separate stochasticity and epistemic uncertainty via hierarchical approaches (e.g. Clark *et al.* 2005). Importantly, Bayesian and stochastic models allow uncertainty to be incorporated into risk-forecast models. However, they do not consider the consequences if all model structures examined are wrong, in contrast to misspecification rates applied to validation data sets. Sensitivity analysis is useful for directing research or management by identifying which parameters most strongly affect model outcomes, and also reporting possible (but not necessarily realised) magnitudes of uncertainty (e.g. Roura-Pascual *et al.* 2010). Finally, ensemble models are useful for identify-

ing model uncertainty, and reducing that uncertainty through averaging (it is analogous to Bayesian model averaging). More powerfully, a combination of Bayesian, misspecification/validation, sensitivity analyses and ensemble models could be used.

CONCLUSIONS

We compared and summarised > 300 quantitative and scoring risk assessment articles, which allowed us to analyse the application of existing ideas in invasion biology. Our review provides a quantitative counterpart to guidelines such as ISPM-11, which provide a qualitative structure (FAO 2004) and conceptual frameworks of the invasion process (e.g. Blackburn *et al.* 2011). We extended these guidelines by explicitly identifying how TEASI components and subcomponents should be combined to determine risk, explicitly considering space and time and more fully considering uncertainty (Box 1). We also identified the dependencies for each subcomponent underlying risk, which may provide predictive surrogates for subcomponents (Box 2 & 3). We specifically did not address the challenges of parameterizing RA models such as the problems of obtaining an objective measure of the impacts, challenges of predicting complex hierarchical and non-linear systems and cognitive biases in expert judgement as these have been addressed elsewhere (Burgman *et al.* 2011; Hulme 2012).

We argue that the principles underlying biological invasions are generalisable, regardless of the application to academia or policy, although the logistical constraints differ. We illustrate that the qualitative/semi-quantitative scoring methods are special cases of quantitative models by mapping each question to a component in the quantitative TEASI risk model. Thus, this framework can provide the skeleton structure and serve as a starting point for future advances in risk modelling. Importantly, our aim in promoting such an integrative approach was not to suggest that all elements need to be estimated to yield a useful risk assessment, but rather to identify opportunities for improvement (Box 4).

Box 4 Principles for balancing complexity in alien species risk assessment

There has been much work done in risk assessment of alien species, offering numerous techniques and predictive approaches, yet substantial limitations still exist (see also Hulme 2012). There is a tendency on the one hand to desire completeness, and on the other hand to disregard available empirical data, because they are limited. Thus, there is a problem of balancing increased complexity and missing opportunities for improved performance. In this regard, we make three assertions to structure thinking for alien species risk assessments.

(1) *Uncertainty exists, but regardless, decisions must be made.* Limitations of time, information and resources are ubiquitous, but should not prevent decisions, as lack of action is also a decision. Thus, risk assessments should be based on best accessible information, while characterising the levels of uncertainty that exist.

(2) *The world is complex and heterogeneous, but the numbers of end points of interest are few and manageable.* Genotype, biochemistry and physiology vary between individuals; individuals interact in the context of their populations and communities; interactions change in different environments. Cataloguing every possible combination of interaction would be infeasible. However, this complexity can be modelled as a frequency distribution of end points (e.g. unexplained variation described by error term ϵ in linear regression $y = b_0 + b_1x + \epsilon$). Where additional predictors exist, we can more finely resolve the error distribution. For invasion biology, the end points of interest coincide with the major invasion stages and impact. In our full model, we balanced complexity and completeness, including those general subcomponents and dependencies previously identified as important.

(3) *All models are abstractions of nature, but some are better than others.* The appropriate question is: which is the best choice amongst available models? Can we identify a model that provides an improvement over current approaches? We emphasise that the full risk model should not be viewed as prescriptive, but rather as a vehicle to understand what current approaches are actually measuring and to identify opportunities for improvement, given realities of data, time and resources.

Thus, for policy, we assumed substantial time and resource constraints, and focused on the major aspects of risk-scoring approaches to risk assessment: composition of questions, weighting of questionnaire responses and combination of scores. For academia, we focused on research avenues for the greatest improvements in predictive power. However, progress in RA would arguably be strongest if the approaches of policymakers and academia converge.

We note that although the quantitative advances in invasion biology have been substantial, they have often not been applied in policy (in contrast to scoring approaches), likely because available data are sometimes too limited and the time required to develop species-specific models is too great. Given the heterogeneity in data sources, development of approaches to integrate diverse sources of (often poor) information would open greater opportunities for analyses, and would be a useful research direction. Given the effort that has gone into developing these quantitative models, research also would be worthwhile that explicitly demonstrate when such quantitative approaches yield benefits over qualitative ones. Possible advantages of quantitative RAs include quantification of severity, which in turn may ameliorate criticisms that RAs are not accurate enough given low base rates of invasion (e.g. Smith *et al.* 1999; Hulme 2012) – i.e. higher severity species may be worth preventing even with low base rates. Furthermore, such quantification would yield more informative estimates of the benefits vs. the cost of management actions, including prevention and slowing the spread of an alien species (e.g. Leung *et al.* 2002). Other advantages of quantitative RAs include potentially higher spatial and temporal resolution, and a fuller characterisation of uncertainty.

In terms of uncertainty, for both quantitative and scoring approaches, it may be useful to identify generalities of which uncertainties are important to include and under what circumstances. For instance, Ranjan *et al.* (2008) found that uncertainty in timing of invasion could have a substantial impact on the optimal management strategy, but others found uncertainty to be unimportant (Russell *et al.* 2006). As another example, we are often limited to using surrogate measures rather than measuring quantities of interest directly (e.g. propagule pressure, Verling *et al.* 2005). Thus, observation error can be substantial. It would be useful to derive rules for exclusion of subcomponents, given non-linear functional forms underlying risk (e.g. is there a signal-to-noise ratio at which predictiveness improves by *excluding* a subcomponent?).

More generally, continuing to increase the accessibility of quantitative models that have seen great development in academia should be a priority. For instance, the development of synthetic models which are generalisable across a number of species (e.g. a taxonomic group), environmental conditions, and the invasion process could allow these quantitative approaches to be broadly applied, *without* species-specific model development. As such, synthetic, generalised models may actually be more accessible for policy purposes, despite the increase in model complexity. For instance, we believe that the prevalence of species distribution models in large part is due to the accessibility of user-friendly software and data. Likewise, software could be developed to more broadly incorporate dependencies beyond environmental suitability, which could see the application of quantitative approaches increase in policy. The increase in complexity would be handled in the model development phase, rather than

by risk assessors. Furthermore, the development and standardisation of large publically available data bases such as DAISIE (DAISIE 2009; see also key datasets identified in PRATIQUE, Baker *et al.* 2009, <http://capra.eppo.org/dataset/>) may make such policy applications much more feasible. Taken together, this article identifies the current state of the science of alien species risk assessments, and provides guidance for the development of future risk assessments approaches.

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