| Model ID | Reference citation | Study type | Name of the developed or applied model | Regions applied | Groups applied | Number of species or diseases assessed | Total number of questions | Question type | Weighting | Rank formation - brief explanation | Rank output | Uncertainty comments | Uncertainty L/S/E | Policy implemented (references at the bottom of the table) | T/E/A/S/I individual components estimated (yes/no) | Model components | Notes |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Ahmed et al (1988) | Development | Ahmed et al | No application | Fish | 0 | 26 | | Inbuilt to scoring | Sum of the questions | The species with the highest score is the most potential candidate | Not necessary to answer all questions, but really intended to be used if the question is not appropriate to the situation. | N/N/N | The authors had no information regarding the use of the model. | Y/Y/Y/N/Y | S: Species trait (9)<br>fg(.): Survival during transport (1)<br>r(.): Reproductive potential (1)<br>fX(.): Population growth (3)<br>fI(.): Impact (2)<br>Management (1)<br>Other (9 not applicable (related to use as biological | The paper is not about invasive species, but employs a similar approach, and is such an early approach that it was included in the sample. |
| 2 | Bomford & Glover (2004), Bomford (2006) | Further development | Australian freshwater fish model | Australia | freshwater fish | 47 | 5 | Different types of predictor variables (continuous, categorical) related to species and environmental traits | No | One rank | Low, moderate, serious, extreme | No | N/N/N | The Australian Federal Government (national level) uses the models to assist decision making when assessing applications to import new exotic vertebrate species into Australia. Several State Governments in Australia (for example the Western Australian Government) also use the models to assist decision making on whether to permit the keeping of non- | N/Y/N/N/N | pr(I) : Probability of establishment (5) | |
| 3 | Bomford (2003) | Development | Australian vertebrate model | Australia | mammals and birds (adapted to herptiles and fish) | 44 mammals / 60 birds | 19 | Different types of predictor variables (continuous, categorical) related to species and environmental traits | Inbuilt to scoring | Three different ranks formed | Low, moderate, serious, extreme: determined from the various combinations of the three risk scores | No | N/N/N | As above | N/Y/N/N/Y | S: Species trait (2)<br>pr(I) : Probability of establishment (7)<br>fI(.): Impact (10) | |
| 4 | Bomford (2005, 2006) | Further development | Australian reptile and amphibian model | Australia, New Zealand | reptiles and amphibians | UK: 40; California: 56; Florida: 68; AUS: 7 | 3 | Different types of predictor variables (continuous, categorical) related to species and environmental traits | No | One rank | Low, moderate, serious, extreme | No | N/N/N | As above | N/Y/N/N/N | pr(I) : Probability of establishment (3) | |
| 5 | Bomford (2008) | Further development | Australian bird and mammal model | Australia, New Zealand | mammals and birds (adapted to herptiles and fish) | AUS: 45 mammals / 54 birds; NZ: 39 mammals / 73 birds | 20 | Different types of predictor variables (continuous, categorical) related to species and environmental traits | Inbuilt to scoring | Three different ranks formed | Low, moderate, serious, extreme: determined from the various combinations of the three risk scores | No | N/N/N | As above | N/Y/N/N/Y | S: Species trait (2)<br>pr(I) : Probability of establishment (8)<br>fI(.): Impact (10) | |
| 6 | Branquart (2007) | Development | Invasive Species Environmental Impact Assessment Protocol (ISEIA) | Belgium | Selected species of several taxa (vascular plants, mosses, mammals, birds, fish, amphibians, reptiles) | 15 | 4 | All answers are scored on a 3-point scale | No | Sum of the four components, no weighting | High, moderate and low environmental risk. (Black list, watch list, no list) | Uncertainty is rated for each question. If not information, no score. If poor information, score 1 (unlikely) and 2 (likely) | N/Y/Y | Applied formally and informally in Belgium | N/Y/N/Y/Y | pr(I) : Probability of establishment (1)<br>fD(.): Dispersal (1)<br>fI(.): Impact (2) | |
| 7 | Brunel et al. (2010) | Development | EPPO prioritization process for invasive alien plants | EPPO region | Plants | 0 | 11 | Yes - no (6) and three scaled responses (5) | No | Decision tree resulting in a matrix of scores combining three levels of impact with three levels of spread potential (phase 1), and decision tree with a three scored result (phase 2) | Phase 1: lists of species of minor concern, observation list and list of invasive alien plants, Phase 2: no, lower or priority for PRA | Phase 1: uncertainty rated for each question as low, medium or high, and one overall uncertainty rating | Y/N/Y | The EPPO system is formally applied to many alien species in the EU to justify regulations. Most widely applied to non-plant pests in Great Britain. | Y/Y/N/Y/Y | O(.): Organisms at uptake (2)<br>pr(I) : Probability of establishment (5)<br>fD(.): Dispersal (1)<br>fI(.): Impact (3) | |
| 8 | Caley and Kuhnert (2006) | Application + Further development + Comparative test | Caley and Kuhnert TREE model (A-WRA) | Australia | Plants | 370 | 4 | Yes/No binary questions | No | Classification regression tree | Weed, non-weed | No | N/N/N | Not applied according to the authors. | Y/Y/N/N/Y | N: Propagule pressure (1)<br>pr(I) : Probability of establishment (1)<br>fD(.): Dispersal (1)<br>fI(.): Impact (1) | |
| 9 | Champion and Clayton (2000) | Development | The New Zealand Aquatic Weed Risk Assessment Model (AWRAM) | New Zealand | Aquatic plants | 21 | 36 | Multiple-choice questions. Questions use different scales (0-10, 0-5, 0-3 and 0-1) depending on their level of importance. | Inbuilt to scoring | Sum of individual questions | Continuous ranking | No | N/N/N | Formally applied to decide on which aquatic species should be banned and also to select species for eradication programmes in New Zealand | N/Y/Y/Y/Y | S: Species trait (5)<br>pr(I) : Probability of establishment (5)<br>r(.): Reproductive potential (4)<br>fE(.): Environment interactions (2)<br>fD(.): Dispersal (4)<br>fI(.): Impact (10)<br>Management (6) | |
| 10 | Cook and Proctor (2007) | Development | Cook & Proctor | Australia | Plant pests and diseases | 10 | 10 | | Explicit | Weighted sum of all sub-categories | Continuous ranking | Formed a "risk index" based on variability of scores by panel members | Y/N/Y | The bioeconomic models that were used to provide expert testimony on the economic impact criterion, continue to be used informally to support decision-making processes in Australia. Used internally by government biosecurity agencies to allocate scarce funds to priority areas. The breeder group based | Y/N/N/N/Y | N: Propagule pressure (1)<br>fI(.): Impact (8)<br>Management (1) | |
| 11 | Copp et al (2005) | Further development | Fish Invasiveness Screening KIT (FISK) / Invasive Fish Risk Assessment (IFRA) based on A-WRA/EPPO | UK | Fish | 9 | 49 | Central components (e.g. rank formation) of FISK are based on A-WRA | Inbuilt to scoring | Equally-weighted sum of answered questions grouped in two sections, with total score compared against a set of critical values that determine the risk of the species to become invasive. Minimum number of answered questions (10/49) | Accept, evaluate (=need further evaluation), reject taxon | No | N/N/N | FISK has been used to inform government policy makers (Department of Environment, Food and Rural Affairs) in the UK as regards the potential invasiveness of non-native freshwater fishes when classifying fishes for regulation under the Import of Live Fish Act (ILFA). The outcome of FISK was taken into consideration when deciding on classifications, but it was not used to classify the species. FISK scores also are part of a decision support tool for assessing management options impacts, but has been applied in a post-priori manner only. | Y/Y/Y/Y/Y | S: Species trait (10)<br>N: Propagule pressure (2)<br>v: Transport vectors (3)<br>O(.): Organisms at uptake (1)<br>pr(I) : Probability of establishment (5)<br>r(.): Reproductive potential (6)<br>fX(.): Population growth (5)<br>fE(.): Environment interactions (2)<br>fD(.): Dispersal (1)<br>fI(.): Impact (12)<br>Management (1)<br>Other (1- quality of the information) | |
| 12 | Copp et al (2005) | Further development | Fish Invasiveness Screening KIT (FISK) / Invasive Fish Risk Assessment (IFRA) based on A-WRA/EPPO | UK | Fish | 1 | 34 | Central components (e.g. rank formation) of IFRA based on EPPO. Use of scoring matrices for questions in which two or more variables contribute to the assessment. Explanatory guides provided with each question, and the assessor expected to provide a brief rational for the score given for each question | No | Sum of the sums for each category | Continuous ranking | Suggest a basic approach to calculate the proportion of "don't know" answers. Alternatively, qualify each answer on scale of confidence (1-3): low, medium; high | Y/N/Y | | Y/Y/Y/Y/Y | N: Propagule pressure (1)<br>O(.): Organisms at uptake (7)<br>O(.)*fg(.):Transport (3)<br>fg(.): Survival during transport (1)<br>pr(RL): Probability of release (1)<br>pr(I) : Probability of establishment (7)<br>fD(.): Dispersal (1)<br>fI(.): Impact (10)<br>Management (2)<br>Other (1 - quality of the information) | |
| 13 | Cowie et al (2009) | Development | Quarantine list of Cowie et al (2009) | USA | Non-marine snails and slugs | 46 | 12 | 3-point scale (0, 0.5, 1) according to a series of thresholds established by the authors | No | Question scores were summed for each species or group, and then divided by the total number of attributes scores | Continuous ranking from 0 to 1 (least to greatest concern) | None | N/N/N | The study was a request of US Department of Agriculture, Animal and Plant Health Inspectin Service, Plant Protection and Quarantine (USSA-APHIS-PPQ) | Y/Y/Y/N/Y | S: Species trait (1)<br>O(.): Organisms at uptake (1)<br>pr(I) : Probability of establishment (4)<br>r(.): Reproductive potential (3)<br>fD(.): Dispersal (1)<br>fI(.): Impact (2) | |
| 14 | Cunningham et al (2004) | Further development | A-WRA + staged assessment | Australia | Plants | 17 | 49 + 6 | Yes/no, some [0-2], [1-3], [1-4], [1-5] | No | Additive ranking within categories, but division between potential impact and feasibility of eradication categories to obtain benefit-cost ratio. Weed risk and benefit-cost ratio not combined. B-C ratio of the species ranking highest in WRA to be observed | Continuous ranking | No, although there is one question in the potential impact category related to data realiability | N/N/N | Unknown | N/Y/Y/N/Y | pr(I) : Probability of establishment (1)<br>r(.): Reproductive potential (1)<br>QT(.): Species range (2)<br>fI(.): Impact (1)<br>Management (1) | The mapping includes only questions in addition to the A-WRA. The framework is not entirely clearly explained, and therefore difficult to map precisely. |
| 15 | Daehler and Carino (2000) | Application + Further development + Comparative test | Daehler and Carino (2002) SAF | Hawaii (USA) | Plants | 111 | 19 | Different types of predictor variables (continuous, categorical) related to species and environmental traits | No | No ranking. High/low risk determined by expert-decision tree system | Low or high risk | Not necessary to answer all questions. If no answer, higher risk path assumed (system explicitly conservative) | N/N/Y | Unknown | N/Y/Y/Y/N | S: Species trait (1)<br>pr(I) : Probability of establishment (6)<br>r(.): Reproductive potential (5)<br>fX(.): Population growth (2)<br>fD(.): Dispersal (5) | |
| 16 | Daehler et al (2004) | Application + Further development + Comparative test | HP-WRA+2nd screening | Hawaii (USA) | Plants | 192 | 49+1 | | Inbuilt to scoring | Higher than 6 is pest, lower than 1/0 not pest, in between (1-6) the second screening process determines whether the species is a pest or requires further evaluation | Accept, evaluate (=need further evaluation), reject taxon | Not necessary to answer all questions | N/N/Y | The assessment system is currently promoted by the Hawaii Department of Agriculture, by the Hawaii Invasive Species Council, and by Hawaii Industry groups (e.g. Landscape Industry Council of Hawaii). The assessments are made by a specialist who is paid by the State of Hawaii. While the risk assessment is endorsed and encouraged by many groups, it is NOT required by law and there is no law that restricts the growth or importation of species that are ranked as "high risk". Instead, the risk assessment is mainly used to raise awareness of | Y/Y/Y/Y/Y | S: Species trait (7)<br>N: Propagule pressure (2)<br>v: Transport vectors (7)<br>pr(I) : Probability of establishment (6)<br>r(.): Reproductive potential (9)<br>fE(.): Environment interactions (2)<br>fI(.): Impact (16)<br>Management (1) | |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 17 | Darin et al. (2011) | Development | WHIPPET (Weed Heuristics: Invasive Population Prioritization Tool) | North America (California) | Plants | 19 | 25 | | Explicit | Score multiplied by weight, first to produce criteria value, and then the same for total score | Continuous ranking | Uncertain information was assigned to middle points so as not to affect the results | N/N/N | Used by the San Francisco Bay Area Early Detection Network to prioritize hundreds of occurrences of 73 target species. Also used by the San Diego County Department of Agriculture to prioritize regionally invasive weed infestations for control/ containment/ eradication. Has also been taken up by United States Forest Service, United States Fish and Wildlife Service, California Department of Water Resources | N/N/Y/Y/Y | r(.): Reproductive potential (5)<br>X: Population size (1)<br>fD(.): Dispersal (5)<br>fI(.): Impact (7)<br>Management (7) | |
| 18 | Department of Primary Industries (2008) | Development | Victorian WRA | Victoria, Australia | Weeds | 2 | 42 | | Explicit | Weight multiplied by score and the scores then summed up | The species with the highest score is the most potential candidate | Each question scored for uncertainty | N/N/Y | Applied in the State of Victoria, Australia | Y/Y/Y/Y/Y | S: Species trait (2)<br>v: Transport vectors (1)<br>pr(I) : Probability of establishment (3)<br>r(.): Reproductive potential (3)<br>fX(.): Population growth (4)<br>fD(.): Dispersal (1)<br>fI(.): Impact (27)<br>Other (Current range / potential range) | |
| 19 | EPPO (2011) | Development | EPPO computer-assisted pest risk assessment scheme (CAPRA) | Europe, North Africa, Great Britain | Plant pests including weeds | 0 | 48 | All answers are scored on a 5-point scale (3-point for impact). | No | No explicit guidance on how to combine scores of individual questions to a final score. | No ranking | Uncertainty rated as low, medium & high for each question | N/N/Y | Formally applied to many alien species in the EU to justify regulations. Most widely applied to non-plant pests in Great Britain. | Y/Y/N/Y/Y | O(.): Organisms at uptake (2)<br>fg(.): Survival during transport (2)<br>pr(R).: Probability of release (3)<br>pr(I) : Probability of establishment (13)<br>r(.): Reproductive potential (1)<br>fD(.): Dispersal (3)<br>QT(.): Species range (1)<br>fI(.): Impact (15)<br>Management (6)<br>Other (1 - adaptability (Is the pest highly adaptable? 1 - transient populations) | |
| 20 | Essl et al. (2011) | Development | GABLIS | Germany, Austria | Many taxa (fish) | 31 | 16 | Criteria are scored on a 3 to 4-point scale. | No | Ranking is based on the highest assessment criteria score, no weighting. Precautionary approach in assigning to groups. | High (=Black List), intermediate (=Grey List), low risk (=White List) | Uncertainty rated low, med, high for each question | N/N/Y | Applied informally, but expected to influence decisions for introduction/release of species in Germany | N/Y/Y/Y/Y | v: Transport vectors (1)<br>pr(I) : Probability of establishment (2)<br>r(.): Reproductive potential (1)<br>fD(.): Dispersal (1)<br>QT(.): Species range (1)<br>fI(.): Impact (8)<br>Management (1)<br>Other (1 - facilitation by climate change) | |
| 21 | European Technology Platform for Global Animal Health (2006) | Development | ETPGAH | Europe | Animal diseases | 30 | 7 | | No | Probably summation, but not explained. | The diseases divided into three groups (major diseases, diseases for surveillance, and neglected zoonoses) | No | N/N/N | Unknown | Y/N/N/N/Y | pr(R).: Probability of release (1)<br>fI(.): Impact (6) | |
| 22 | Fejzic et al (2008) | Development | Bosnia and Herzegovina animal health model | Bosnia and Herzegovina | Animal diseases | 7 | 8 | | Explicit | Weight multiplied by score and the scores then summed up | | No | N/N/N | Unknown | N/N/N/N/Y | fI(.): Impact (5)<br>Management (3) | |
| 23 | Garry Oak Ecosystems Recovery Team (2007) | Development | IAPP Species Scoring Algorithm | Canada | Plants | None | 24 | Yes/no | Explicit | Weighted sum | Continuous output | No | N/N/N | Unknown | N/Y/Y/Y/Y | S: Species trait (7)<br>v: Transport vectors (1)<br>pr(I) : Probability of establishment (2)<br>r(.): Reproductive potential (10)<br>fI(.): Impact (2)<br>Management (2) | |
| 24 | GB Non-native species secretariat (2011) | Further development | GB Non-native species Rapid Risk Assessment (NRRA) | Great Britain | Invasive species | | 17 | The first 7 questions and the management questions are open, the 5 scored questions are five scaled and comments to justify score need to be provided | No | No explicit guidance on how to combine scores of individual questions to a final score. | Conclusion from questions and summarising categories drawn by risk assessor and peer review | Scores in the summarising categories and the final concluding risk assessment are accompanied by a five scaled confidence score | N/N/Y | Officially used in the UK. Have completed 46 full risk assessments and 1 rapid risk assessment. In addition have 34 full risk assessments in progress, with 21 rapid risk assessments in progress. | Y/Y/N/Y/Y | N: Propagule pressure (1)<br>pr(I) : Probability of establishment (5)<br>fD(.): Dispersal (2)<br>QT(.): Species range (1)<br>fI(.): Impact (2)<br>Management (4)<br>Other (1 - facilitation by climate change<br>+ 1 - overall risk) | |
| 25 | Gederaas et al (2007) | Development | Norwegian Black List | Norway | Selected species of several taxa | 217 | Phase 1: 3<br>Phase 2: 4 | Multiple choice questions | No | Phase2 : high: if at least one question is answered with yes to any of the impacts, low: if all four questions are answered with no, unknown: if no answer is yes and at least one cannot be answered because of uncertainty | Phase 1 identifies species as not requiring further assessment. Phase 2 classifies species in 3 risk categories (low, high, unknown risk) | Phase1: if uncertain, need to proceed to phase 2, Phase 2: all questions have an "unknown" category | N/N/Y | Officially used in Norway. Each species is strictly classified on the basis of the set of criteria alone. For management, the system is used informally: management decisions (by DN) are based on the risk assessment of alien species, but may also be informed by other aspects (such as economic constraints and political priorities). So far applied to about 10% of alien species documented in Norway | N/Y/N/N/Y | pr(I) : Probability of establishment (2)<br>fI(.): Impact (5) | |
| 26 | Hayes and Sliwa (2003) | Development | Australian potential marine pests model | Australia | Marine invasive species | 851 | 4 | | No | Did not actually rank them, only distinguished them as potential pests | Checks if survive all the criteria, if yes, identified as pests | Excluded if uncertainty | N/N/N | Was used by the Australian Government Department of Agriculture Fisheries and Forestry in defining next pest lists used to guide monitoring and management regimes. Current status unknown. | Y/N/N/N/Y | v: Transport vectors (2)<br>QT(.): Species range (1)<br>fI(.): Impact (1) | |
| 27 | Hiebert and Stubbendieck (1993) | Development | Exotic Plant Species Ranking System | USA | Plants | 71 | 25 | | No | Sum of components, control reported separately | Matrix with two dimensions (impact and control) | No | N/N/N | Unknown | N/N/N/Y/Y | S: Species trait (1)<br>pr(I) : Probability of establishment (2)<br>r(.): Reproductive potential (4)<br>fE(.): Environment interactions (1)<br>fD(.): Dispersal (1)<br>QT(.): Species range (2)<br>fI(.): Impact (4)<br>Management (10) | |
| 28 | IPPC/FAO (2004) | Development | ISPM11 | World | Plant pests | Many | Only guidelines | Only guidelines | No guidelines | No guidelines | No guidelines | Uncertainty should be documented for transparency | N/N/Y | International plant trade. Risk assessment procedure acknowledged by the World Trade Organization. | Y/Y/N/Y/Y | v: Transport vectors<br>O(.): Organisms at uptake<br>fg(.): Survival during transport<br>pr(R).: Probability of release<br>pr(I) : Probability of establishment<br>fD(.): Dispersal<br>fI(.): Impact<br>Other (adaptability (establishment), management (at each stage)) | |
| 29 | Jefferson et al (2004) | Application + Further development + Comparative test | A-WRA, modified R-H, shortened a-WRA | Chicago (USA) | Plants | 40 | 24 | Yes/No binary questions; magnitudes not considered. | Inbuilt to scoring | Equally-weighted sum of answered questions. Minimum number of answered questions (10/49) | Accept, evaluation (=need further evaluation), reject taxon | Number of questions answered used as indicator of reliability | N/N/Y | Chicago Botanic Gardens have an invasive plant policy that states that any plant that we import from outside the country and that is new to the region (i.e. not already common in the nursery industry) must undergo risk assessment. They use a modified version of the Reichard/Hamilton risk assessment framework. Risk assessment is conducted by the Collections Department after each plant collection trip | N/N/Y/Y/Y | v: Transport vectors (8)<br>r(.): Reproductive potential (8)<br>fE(.): Environment interactions (2)<br>fI(.): Impact (4) | Note on mapping: it was not entirely clear from the paper which questions were included in the shortened WRA and the authors were not available for comment. |
| 30 | Johnson (2009) | Development | Southern Australian Weed Risk Management System | New South Wales, Australia | Plants | 0 | 22 | Multiple-choice questions using different scales. | No | Questions posed in separate sections to determine weed risk and feasibility of control. Weed risk calculated by averaging the scores par section and then calculating: invasiveness x impact x potential distribution. Weed risk and Control feasibility form then a matrix | Very high, high, medium, low, negligible risk. | Index based on number of unanswered questions | Y/N/Y | Applied formally regionally in Australia (New South Wales) | Y/Y/Y/Y/Y | N: Propagule pressure (1)<br>pr(I) : Probability of establishment (1)<br>r(.): Reproductive potential (2)<br>fX(.): Population growth (1)<br>fE(.): Environment interactions (1)<br>fD(.): Dispersal (2)<br>QT(.): Species range (2)<br>fI(.): Impact (6)<br>Management (6) | |
| 31 | Koop et al (2012) | Application + Further development + Comparative test | PPQ (Plant Protection and Quarantine) WRA , based on A-WRA | USA | Plants (non-invaders, minor-invaders and major-invaders) | 204 | 41 | Yes/No binary questions, although a there are a few multi-choice questions; magnitudes not considered. | Inbuilt to scoring | Equally-weighted sum of answered questions at PPQ WRA. However, species categorized as "evaluate further" follow a secondary screening model (i.e. a short decision tree, similar to HP-WRA+2nd screening) | Low risk, evaluate further, high risk | Number of questions answered used as indicator of reliability. Guidance provided on how to answer questions and assessments reviewed by two team members. | Y/N/Y | Unknown | Y/Y/Y/Y/Y | S: Species trait (5)<br>N: Propagule pressure (1)<br>v: Transport vectors (3)<br>pr(I) : Probability of establishment (4)<br>r(.): Reproductive potential (5)<br>fE(.): Environment interactions (1)<br>fI(.): Impact (21)<br>Management (1) | |

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| 32 | McKenzie et al (2007) | Development | Rapid Risk Analysis based on IRA by OIE | New Zealand | Animal pathogens | 82 | 12 | | No | Risk: POE x LOS x LOS. Ranked by target population (wildlife, etc.). Also all populations can be considered by summing the individual target | Continuous ranking (also by target population) | If information not available, worst case scenario used. Significant gaps in knowledge were recorded. | Y/N/N | Has not been applied in policy. | Y/Y/N/N/Y | N: Propagule pressure (1)<br>pr(R|.): Probability of release (5)<br>fl(.): Impact (6) |
| 33 | Miller et al (2010) | Development | Miller et al Relative Risk Model | Nebraska (USA) | Plants | 18 | 23 | Magnitudes, converted to 4 categories (0-absent, 2-low, 4-medium, 6-high;) o increments of 1/10th (from 0-absent to 1-high). Yes/no questions at the Effects filter category | No | Multiplication of individual criteria, after adding score values of question subcategories (i.e. 17 land cover categories in Habitat rank, and 4 characteristics in Effect filter) | Continuous ranking | Present median values of uncertainty distributions; assess each question by uncertainty (1-low, 2-medium, 3-high depending on data reliability) | N/N/Y | Authors have no information on any policy application. | N/Y/N/N/Y | O(.): Organisms at uptake (1)<br>pr(I) : Probability of establishment (18)<br>fl(.): Impact (4) |
| 34 | Minnesota Department of Natural Resources (1991) | Further development | Exotic Plant Species Ranking System for Minnesota, based on Hiebert | Minnesota (USA) | Plants | 153 | 23 | | Inbuilt to scoring | Sum of components, control reported separately | Threat category: minimal, moderate, severe, unknown | No | | Unknown | N/N/Y/Y/Y | S: Species trait (1)<br>pr(I) : Probability of establishment (1)<br>r(.): Reproductive potential (4)<br>fE(.): Environment interactions (1)<br>fD(.): Dispersal (1)<br>QT(.): Species range (4)<br>fl(.): Impact (2)<br>Management (9) |
| 35 | More et al (2010) | Development | Irish animal health prioritisation, based on Animal HEalth Strategy of the EU | Ireland | Animal diseases | 13 | 1 | One question scored on a 5-point scale | No | One criterion | [1-5] | No | N/N/N | The framework was applied formally as part of the decision-making process. The framework formed the basis for prioritization of activities within Animal Health Ireland, a relatively new organisation with responsibility for national coordination and facilitation | N/N/N/N/Y | fl(.): Impact (1)<br>Other (after initial prioritization, details on impact and management are collected, but no ranking is made) |
| 36 | Morse et al. (2004) | Development | NatureServe's Invasive Species Assessment Protocol | USA | Plants | 0 | 20 | Four scaled responses plus unknown category. | Inbuilt to scoring | Answers are assigned points that are summed up for the four categories of the scheme and then combined to a final biodiversity impact score. If there is a range of answers, then min and max added separately. | Produces an I-Rank of either "high", "medium", "low", or "insignificant". | "Unknown" category in multiple choice style of four scaled responses included, if no precise answers possible, ranges can be chosen and are accounted for in the rank formation | N/N/Y | According to the paper, used to assess biodiversity impact of about 3,500 plants established outside cultivation in the USA | N/N/Y/Y/Y | pr(I) : Probability of establishment (3)<br>r(.): Reproductive potential (1)<br>fX(.): Population growth (1)<br>fD(.): Dispersal (1)<br>QT(.): Species range (5)<br>fl(.): Impact (5)<br>Management (4) |
| 37 | Nentwig et al. (2010) | Development | Generic Impact-Scoring System | Europe | Invasive species (mammal, birds) | 34 | 10 | All answers are scored on a 5-point scale. | Explicit | Weighted sum of scores, multiplied by proportional area. | Continuous impact ranking | Variability of scores by experts used | Y/N/Y | Applied informally to derive a black list of alien animals in Switzerland | N/N/N/N/Y | fl(.): Impact (10) |
| 38 | OIE (2011a,b) | Development | OIE codes | World | Animal pathogens | Many | Only guidelines | Only guidelines | No guidelines | Although no specific guidance is given, it is made clear that the individual invasion steps should be seen as a pathway, i.e. earlier steps need to be overcome in order to evaluate later steps. | No guidelines | For quantitative risk assessments: probability distributions or confidence intervals for overall uncertainty, sensitivity analysis | N/Y/Y | International animal trade. Risk assessment procedure acknowledged by the World Trade Organization. | Y/Y/N/Y/Y | S: Species trait<br>N: Propagule pressure<br>v: Transport vectors<br>fg(.): Survival during transport<br>pr(I) : Probability of establishment<br>X: Population size<br>fD(.): Dispersal<br>fl(.): Impact<br>Other (ease of contamination (release), management (at each step)) |
| 39 | Olenin et al. (2007) | Development | Biopollution Index | Baltic Sea | Invasive aquatic species | 14 | 5 | Impact questions scored on a 5-point scale, but abundance and distribution ranges on a 3- and 4-point scales respectively | No | Matrix combining three levels of impact with abundance and distribution ranges of species | Biopollution Level on a scale 0 (weak) to 4 (massive). | No | N/N/N | Applied informally in Lithuania (and possibly will be applied in Finland) for implementation of marine strategy directive | N/N/Y/Y/Y | fX(.): Population growth (1)<br>QT(.): Species range (1)<br>fl(.): Impact (3) |
| 40 | Ou et al. (2008) | Development | Chinese WRA | China | Plants | 67 | 19 | Questions structured hierarchically (primary vs. secondary indices) and scored into a continuous scale (from 0 to 100) based on the Analytic hierarchy process (AHP). | Explicit | Weighted sum of six categories (or primary indices) | Species ordered based on their invasion risk | No | N/N/N | According to the paper, has been applied since March 2007 in Xiamen. | Y/Y/Y/Y/Y | N: Propagule pressure (3)<br>pr(I) : Probability of establishment (2)<br>r(.): Reproductive potential (1)<br>fX(.): Population growth (1)<br>fE(.): Environment interactions (1)<br>QT(.): Species range (4)<br>fl(.): Impact (3)<br>Management (4) |
| 41 | Parker et al. (2007) | Development | U.S. Weed Ranking Model | USA | Plants | 249 | 27 (authors say 33) | Multiple-choice questions using different scales (ranging between 0-10 or 0-1 depending on the category) | Explicit | Product of the four categories, the category scores are sums of individual questions/scores. Two categories (geographic potential and entry potential) score 0-1, while the category damage potential ranges between 0.8 and 2.4 and invasive potential (the critical element of the model) can attain scores >30 | Continuous score | Quality of information was ranked; model tested statistically / Use of correlations and sensitivity analysis to determine the influence of categories and factors in the final model scores, as well as comparison of these values to independent scores from previously tested scoring systems | N/N/Y | Was applied to revise plants-for-planting regulations, but also to help select species for early detection of adventive pests. The model has since been superseded by the agency's formal weed risk assessment process. | Y/Y/Y/Y/Y | S: Species trait (6)<br>N: Propagule pressure (1)<br>pr(I) : Probability of establishment (3)<br>r(.): Reproductive potential (4)<br>fD(.): Dispersal (1)<br>QT(.): Species range (1)<br>fl(.): Impact (10)<br>Management (1) |
| 42 | Pheloung 2001 | Development | Hazard model | Australia | Plants | 0 | 12 | | Inbuilt to scoring | Summation | | No | N/N/N | Used in Australia by AQIS until 1997 for decision-making on the importation of plants. | N/Y/Y/Y/Y | S: Species trait (1)<br>pr(I) : Probability of establishment (1)<br>fX(.): Population growth (2)<br>fD(.): Dispersal (4)<br>fl(.): Impact (4) |
| 43 | Pheloung et al (1999) | Development | Australian WRA (A-WRA) | Australia | Plants | 370 | 49 | Yes/No binary questions; magnitudes not considered. | Inbuilt to scoring | Equally-weighted sum of answered questions. Minimum number of answered questions (10/49) | Accept, evaluation (=need further evaluation), reject taxon | Number of questions answered used as indicator of reliability | N/N/Y | Applied formally to thousands of species in Australia and New Zealand | Y/Y/Y/Y/Y | S: Species trait (8)<br>N: Propagule pressure (2)<br>v: Transport vectors (7)<br>pr(I) : Probability of establishment (5)<br>r(.): Reproductive potential (8)<br>fE(.): Environment interactions (2)<br>fl(.): Impact (15)<br>Management (1)<br>Other (1- quality of data) |
| 44 | Reichard and Hamilton (1997) | Development | Reichard and Hamilton scheme (R-H) | North America | Plants | 235 | 8 | Different types of predictor variables (continuous, categorical) related to species' traits. | No | Statistical analysis (classification and regression decision trees) | Accept (low probability of invasiveness), reject (high probability), further analysis/monitoring needed (intermediate probability) | No | N/N/N | Used to reformat the US risk assessment process, but also applied informally by non-governmental organizations. It has been used by a number of botanic gardens, for instance University of Washington, Chicago Botanical Garden and Missouri Botanical Garden. Also some nurseries have used it, | N/Y/Y/Y/N | pr(I) : Probability of establishment (4)<br>r(.): Reproductive potential (3)<br>fD(.): Dispersal (1) |
| 45 | Risk Assessment and Management Committee (1996) | Development | The Generic Nonindigenous Aquatic Organisms Risk Analysis Review Process | USA | Aquatic species | 0 | 7 | | Inbuilt to scoring | In establishment: if any sub-rating is low, then rating is low; in impact: if any sub-rating is high then impact rating is high. Final socre is average, but rounded to a conservative side | Matrix providing a summary score of low, med or high | Each question scored for uncertainty | Y/N/Y | Unknown | Y/Y/N/Y/Y | v: Transport vectors (1)<br>fg(.): Survival during transport (1)<br>pr(R|.): Probability of release (1)<br>fD(.): Dispersal (1)<br>fl(.): Impact (3) |
| 46 | Saether et al. 2010; Sandvik et al. In revision | Development | Criteria System for Ecological Risk Assessment of Alien Species in Norway | Norway | Invasive species | Assessments for 5 species are finished | 4 | Varies (y/N, numbers) | Inbuilt to scoring | Matrix of invasion / spread vs. effect axis | 5 categories: severe impact, high impact, potentially high impact, low impact, no known impact | Not formally included, but uncertainty should be considered by applying the "precautionary principle" | N/N/N | Will be applied to all alien species in Norway as basis for IAS management | N/Y/N/Y/Y | pr(I) : Probability of establishment (1)<br>r(.): Reproductive potential (1)<br>fD(.): Dispersal (1)<br>fl(.): Impact (1) |
| 47 | Smallwood and Salmon (1992) | Development | Smallwood and Salmon Rating System | USA | Birds and mammals | 48 | 40 | Yes/no and multiple-choice questions using different scales. (*) When multiple choices referred to the same component, each choice was considered a separate component in the fourth column. | Explicit | Weighted sum of four section scores, calculated by summing the scores assigned to each component of the section or selecting the highest ones. | Continuous ranking | Correction value attached to uncertain information (0.05 to rating with questionable information / 0.10 to rating with poor or non-documented information) | N/N/Y | Unknown | Y/Y/N/N/Y | S: Species trait (3)<br>v: Transport vectors (2)<br>fg(.): Survival during transport (1)<br>pr(I) : Probability of establishment (2)<br>fl(.): Impact (19)<br>Management (13) |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 48 | SZEID (2006) | Development | AHW Prioritisation Decision Support Tool | UK | Animal diseases | 0 | 40 | Multiple choice questions/criteria | Explicit | Weighted sum of criteria/question, independently of the section/category in which each criteria/question belongs to. | Continuous ranking | Development of the tool with the help of stakeholders and risk/epidemiology experts, as well as few questions in the questionnaire related to availability of data | N/N/Y | Has been applied informally in the UK. D2R2 outputs have been applied in an informal manner to support the decision-making process. D2R2 outputs (including graphs and tables to show the relative rankings) have been produced to inform the monthly Veterinary Risk Group meetings, the selection of diseases for International Disease Monitoring reports, and resource planning and allocation within Defra. There are future plans to expand this process | Y/Y/Y/Y/Y | v: Transport vectors (1)<br>O(.): Organisms at uptake (1)<br>pr(I) : Probability of establishment (1)<br>fD(.): Dispersal (3)<br>QT(.): Species range (3)<br>fI(.): Impact (21)<br>Management (6)<br>Other (1 - data availability / 3 - economics) |
| 49 | Tucker and Richardson (1995) | Development | Expert System for screening potentially invasive alien plants in South African fynbos (SAF) | South Africa | Woody plants | 73 | 24 | Different types of predictor variables (continuous, categorical) related to species and environmental traits | No | No ranking. High/low risk determined by expert-decision tree system | Low or high risk | Not necessary to answer all questions. If no answer, higher risk path assumed (system explicitly conservative) | N/N/Y | Applied informally in regulations for South Africa's "biodiversity act" risk assessment for invasive species | N/Y/Y/Y/N | S: Species trait (1)<br>pr(I) : Probability of establishment (8)<br>r(.): Reproductive potential (8)<br>fX(.): Population growth (2)<br>fD(.): Dispersal (5) |
| 50 | Ward et al (2008) | Development | Invasive Ant Risk Assessment | New Zealand | Ants | 11 | 32 | All answers scored on a 3-point scale (0, 0.5, 1). | No | Question scores averaged by category, and the averages summed to produce an overall score. If two species had same score, one with higher consequences first | High, medium, low risk | No | N/N/N | Applied formally in New Zealand by the Ministry for Agriculture and Forestry" and Biosecurity NZ to assess what ant species would be invasive in New Zealand. | Y/Y/Y/N/Y | v: Transport vectors (2)<br>O(.): Organisms at uptake (4)<br>O(.)*fI(.):Transport (2)<br>pr(I) : Probability of establishment (8)<br>r(.): Reproductive potential (1)<br>κ(.): Carrying capacity (1)<br>fI(.): Impact (12)<br>Management (2) |
| 51 | Warner et al (2003) | Development | CAL-IPC, based on Invasive Species Assessment Protocol | Arizona, California and Nevada (USA) | Plants | 0 | 13 | | Inbuilt to scoring | Uses tables, where all answer combinations are listed | | Not necessary to answer all questions; documentation is assessed based on reliability, but does not affect the rank but can be used to describe degree of confidence in ranking | N/N/Y | According to the paper, applied informally in California, Nevada and Arizona | Y/Y/N/Y/Y | v: Transport vectors (1)<br>pr(I) : Probability of establishment (4)<br>r(.): Reproductive potential (1)<br>fD(.): Dispersal (2)<br>QT(.): Species range (1)<br>fI(.): Impact (4) |
| 52 | Weber and Gut (2004) | Development | Classification key for Neophytes (WG) | Central Europe | Vascular plants | 240 | 12 | Multiple-choice questions with different scales, but always ranging between 0 and 4 | Inbuilt to scoring | Sum of all individual questions | High, intermediate, low risk | No | N/N/N | Unknown | N/Y/Y/Y/Y | S: Species trait (1)<br>pr(I) : Probability of establishment (4)<br>r(.): Reproductive potential (2)<br>fX(.): Population growth (1)<br>fD(.): Dispersal (1)<br>fI(.): Impact (2)<br>Other (1 - habitat vulnerability) |
| 53 | Weber and Gut (2005) | Development | Weed Survey | Europe | Plants | 281 | 3 | Short questions (e.g. "weediness") | Explicit | First listed by most important criterion, then by second criterion | | Used the average of several respondents, but in the model as such no uncertainty included | N/N/Y | Unknown | N/N/N/Y/Y | fD(.): Dispersal (1)<br>fI(.): Impact (1)<br>Management (1) |
| 54 | Widrlechner et al (2004) | Further development + Comparative test | modified R-H, R-H/matrix model, New CART model | Iowa (USA) | Plants | 100 | 3 | Different types of predictor variables (continuous, categorical) related to species' traits. | No | No ranking, high risk/low risk is determined in a hierarchical decision tree | Accept (low probability of invasiveness), reject (high probability), further analysis/monitoring needed (intermediate probability) | No | N/N/N | Iowa Department of Agriculture & Land Stewardship (IDALS) plans to use the models the next time that state weed regulations are modified. Chicago Botanic Gardens has applied the models informally as part of their internal decision-making process. | N/Y/Y/Y/N | pr(I) : Probability of establishment (1)<br>r(.): Reproductive potential (1)<br>fD(.): Dispersal (1) |
| 55 | Widrlechner et al (2004) | Further development + Comparative test | modified R-H, modified R-H/matrix model, New CART model | Iowa (USA) | Plants | 100 | 10 | Different types of predictor variables (continuous, categorical) related to species' traits. | No | No ranking, high risk/low risk is determined in a hierarchical decision tree | Accept (low probability of invasiveness), reject (high probability), further analysis/monitoring needed (intermediate probability) | No | N/N/N | As above | N/Y/Y/Y/N | pr(I) : Probability of establishment (5)<br>r(.): Reproductive potential (3)<br>fD(.): Dispersal (2) |
| 56 | Andreu and Vilà (2010) | Application + Comparative test | A-WRA, WG | Spain | Plants | 80 | | | | | | | | Applied informally in Spain as some species have been listed to an Act on Management on Invasive species in the Annex C Government | | |
| 57 | Barney and Ditomaso (2008) | Application | A-WRA | USA | Biofuel plants | 3 | | | | | | | | | | |
| 58 | Buddenhagen et al (2009) | Application | HP-WRA | Hawaii (USA) | Plants | 80 | | | | | | | | Unknown | | |
| 59 | Copp et al (2009) | Application | FISK (with uncertainty and predictive power improvements) | UK | Fish | 67 | 49 | Central components (e.g. rank formation) of FISK are based on A-WRA | | Equally-weighted sum of answered questions grouped in two sections, with total score compared against a set of critical values that determine the risk of the species to become invasive. Minimum number of answered questions (10/49) | Accept, evaluation (=need further evaluation), reject taxon | Each species scored by two people, difference denotes a delta score. Each response scored for uncertainty on scale 1-4 | Y/N/Y | Applied in the UK as a part of the decision-making process regarding the Import of Live Fish Act. | | |
| 60 | Crosti et al (2010) | Application | A-WRA | Italy | Plants | 20 | | | | | | | | Has not been applied in policy. | | |
| 61 | Dawson et al (2009) | Application | HP-WRA+2nd screening | Tanzania | Plants | 230 | | | | | | | | | | |
| 62 | Gassó et al (2010) | Application | A-WRA | Spain | Plants | 197 | | | | | | | | Has not been applied in policy. | | |
| 63 | Gordon et al (2008) | Application + Comparative test | A-WRA, HP-WRA+2nd screening, Caley and Kuhnert TREE model | Florida (USA) | Plants | 158 | | | | | | | | Has been applied informally in Florida. The tool has been incorporated into the University of Florida's IFAS Assessment of Non-native Plants in Florida, which is the basis for extension faculty recommendations for which species to | | |
| 64 | Kato et al. (2006) | Application | HP-WRA+2nd screening | Japan, Bonin Islands | Plants | 130 | | | | | | | | | | |
| 65 | Křivánek and Pyšek (2006) | Application + Comparative test | A-WRA, HP-WRA+2nd screening, R-H | Czech Republic | Plants | 180 | | | | | | | | | | |
| 66 | Massam et al (2010) | Application | Australian bird and mammal model | Western Australia | Invasive species | 40 | 20 | | | Two different ranks formed (matrix) | | Based on number of references available | | | | |
| 67 | Nishida et al (2009) | Application + Comparative test | A-WRA, HP-WRA+2nd screening | Japan | Plants | 259 | | | | | | | | The AWRA system might have been applied to decide Invasive Alien Species by 'Invasive Alien Species Act'. However, the Invasive Alien Species | | |
| 68 | Pheloung et al (1999) | Application | NZ-WRA | New Zealand | Plants | 291 | 49 | Yes/No binary questions; magnitudes not considered. | | Equally-weighted sum of answered questions. Minimum number of answered questions (10/49) | Accept, evaluation (=need further evaluation), reject taxon | Number of questions answered used as indicator of reliability | N/N/Y | Applied formally to thousands of species in Australia and New Zealand | | |
| 69 | Randall et al (2008) | Application | Invasive Species Assessment Protocol | USA | Plants | 0 | 20 | | | Subranks are summed up, if range of answers, then min and max added separately | Produces an I-Rank of either "high", "medium", "low", or "insignificant". | Can answer unknown (U), can answer ranges | N/N/Y | The nonprofit organization NatureServe is using the protocol to assess the estimated 3,500 nonnative vascular plant species that are established in the United States to create a national list | | |

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| 70 | Tricarico et al (2010) | Application | Freshwater Invertebrates Scoring Kit (FI-ISK), based on FISK | Italy | Invertebrates (crayfish) | 37 | 49 | Yes/No/Don't know questions, with a level of certainty (spread over four rankings) | Sum of the section scores | Total scores range from -4 to 39, but were evaluated in light of the score thresholds used in the original A-WRA and FISK and a statistical computation (ROC) | Each response scored for uncertainty on scale 1-4 (according to the Intergovernmental Panel on Climate Change) | N/N/Y |

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**Appendix 1. References cited**

1

Ahmed S., Linden A. & Cech Jr J. (1988). A rating system and annotated bibliography for the selection of appropriate, indigenous fish species for mosquito and weed control. *Bulletin of the Society of Vector Ecologists*, 13, 1-59.

2

Andreu J. & Vilà M. (2010). Risk analysis of potential invasive plants in Spain. *Journal for Nature Conservation*, 18, 34-44.

3

Barney J.N. & Ditomaso J.M. (2008). Nonnative species and bioenergy: Are we cultivating the next invader? *Bioscience*, 58, 64-70.

4

Bomford M. (2003). *Risk assessment for the import and keeping of exotic vertebrates in Australia*. Bureau of Rural Sciences Canberra, Australia.

5

Bomford M. (2006). Risk assessment for the establishment of exotic vertebrates in Australia: recalibration and refinement of models. *A report produced for the Department of the Environment and Heritage, Commonwealth of Australia*.

6

Bomford M. & Glover J. (2004). Risk assessment model for the import and keeping of exotic freshwater and estuarine finfish. Bureau of Rural Sciences, Canberra.

7

Bomford M., Kraus F., Braysher M., Walter L. & Brown L. (2005). Risk assessment model for the import and keeping of exotic reptiles and amphibians. *A report produced for the Department of Environment and Heritage. Bureau of Rural Sciences, Canberra*, 110.

8

Branquart E. (2007). Guidelines for environmental impact assessment and list classification of non-native organisms in Belgium. *ISEIA Guidelines, Harmonia information system (version 2.5)*, 1-4.

9

Brunel S., Branquart E., Fried G., Van Valkenburg J., Brundu G., Starfinger U., Buholzer S., Uludag A., Joseffson M. & Baker R. (2010). The EPPO prioritization process for invasive alien plants. *EPPO Bulletin*, 40, 407-422.

10

Buddenhagen C.E., Chimera C. & Clifford P. (2009). Assessing biofuel crop invasiveness: a case study. *Plos One*, 4, e5261.

11

Caley P. & Kuhnert P.M. (2006). Application and evaluation of classification trees for screening unwanted plants. *Austral Ecology*, 31, 647-655.

12

Champion P.D. & Clayton J.S. (2000). *Border control for potential aquatic weeds*. Department of Conservation Wellington (New Zealand).

13

Cook D. & Proctor W. (2007). Assessing the threat of exotic plant pests. *Ecological Economics*, 63, 594-604.

14

Copp G.H., Garthwaite R. & Gozlan R. (2005a). Risk identification and assessment of non-native freshwater fishes: concepts and perspectives on protocols for the UK. Technical Report no. 129. Cefas, Lowestoft (UK).

15

Copp G.H., Garthwaite R. & Gozlan R.E. (2005b) Risk identification and assessment of non-native freshwater fishes: a summary of concepts and perspectives on protocols for the UK. *Journal of Applied Ichthyology*, 21, 371-373

16

Copp G.H., Vilizzi L., Mumford J., Fenwick G.V., Godard M.J. & Gozlan R.E. (2009). Calibration of FISK, an invasiveness screening tool for nonnative freshwater fishes. *Risk Analysis*, 29, 457-467.

17

Cowie R.H., Dillon Jr R.T., Robinson D.G. & Smith J.W. (2009). Alien non-marine snails and slugs of priority quarantine importance in the United States: A preliminary risk assessment. *American Malacological Bulletin*, 27, 113-132.

18

Crosti R., Cascone C. & Cipollaro S. (2010). Use of a weed risk assessment for the Mediterranean region of Central Italy to prevent loss of functionality and biodiversity in agro-ecosystems. *Biological Invasions*, 12, 1607-1616.

19

Cunningham D.C., Barry S.C., Woldendorp G. & Burgess M.B. (2004). A Framework for Prioritizing Sleeper Weeds for Eradication 1. *Weed Technology*, 18, 1189-1193.

20

Cunningham D.C., Woldendorp G., Burgess M.B. & Barry S.C. (2003). *Prioritising sleeper weeds for eradication: Selection of species based on potential impacts on agriculture and feasibility of eradication*. Bureau of Rural Sciences.

21

Daehler C.C & Carino D.A. (2000). Predicting invasive plants: prospects for a general screening system based on current regional models. *Biological Invasions*, 2, 93-102.

22

Daehler C.C., Denslow J.S., Ansari S. & Kuo H.-C. (2004). A risk assessment system for screening out invasive pest plants from Hawaii and other Pacific islands. *Conservation Biology*, 18, 360-368.

23

Dawson W., Burslem D.F.R.P. & Hulme P.E. (2009). Factors explaining alien plant invasion success in a tropical ecosystem differ at each stage of invasion. *Journal of Ecology*, 97, 657-665.

24

Department of Primary Industries. (2008). Victorian Weed Risk Assessment (WRA) method. In: (ed. Department of Primary Industries SoV) Victoria, Australia.

25

EPPO (2011). Guidelines on Pest Risk Analysis: Decision support scheme for quarantine pests. European and Mediterranean Plant Protection Organization Europe.

26

Essl F., Nehring S., Klingenstein F., Milasowszky N., Nowack C. & Rabitsch W. (2011). Review of risk assessment systems of IAS in Europe and introducing the German-Austrian Black List Information System (GABLIS). *Journal for Nature Conservation*, 19, 339-350.

27

European Technology Platform for Global Animal Health. (2006). Strategic Research Agenda. Belgium.

28

Fejzic N., Haracic S.S., Dargatz D.A., McCluskey B.J., Cornwell S.M., Salman M. & Mumford E.L. (2008). Development of an animal health surveillance infrastructure in Bosnia and Herzegovina-case report. *Slovenian Veterinary Research* 45, 43-48.

29

Garry Oak Ecosystems Recovery Team. (2007). General decision process for managing invasive plant species in Garry Oak and associated ecosystems (GOEs).

30

Gassó N., Basnou C. & Vilà M. (2010). Predicting plant invaders in the Mediterranean through a weed risk assessment system. *Biological Invasions*, 12, 463-476.

31

GB Non-native species Secretariat. (2011). Great Britain Non-native species Rapid Risk Assessment (NRRA). GB Non-native species Secretariat. York, United Kingdom (Unpublished).

32

Gederaas L., Salvesen I. & Viken A. (2007). *Norsk svarteliste 2007: økologiske risikovurderinger av fremmede arter*. Artsdatabanken.

33

Gibbens J., Houston C., Gibons L., Williams K., Lawton S., Kelly L. & Lysons R. (2006). UK Surveillance: Prioritisation of animal health and welfare issues for government intervention. ISVEE 11: Proceedings of the 11th Symposium of the International Society for Veterinary Epidemiology and Economics, Cairns, Australia.

34

Gordon D.R., Onderdonk D.A., Fox A.M. & Stocker R.K. (2008). Consistent accuracy of the Australian weed risk assessment system across varied geographies. *Diversity and Distributions*, 14, 234-242.

35

Hayes K.R. & Sliwa C. (2003). Identifying potential marine pests - a deductive approach applied to Australia. *Marine Pollution Bulletin*, 46, 91-98.

36

Hiebert R.D. & Stubbendieck J.L. (1993). *Handbook for ranking exotic plants for management and control*. US Department of the Interior, National Park Service, Natural Resources Publication Office.

37

ISPM-11 (2004). Pest Risk Analysis for Quarantine Pests Including Analysis of Environmental Risks and Living Modified Organisms. IPPC/FAO Rome.

38

Jefferson L., Havens K. & Ault J. (2004). Implementing invasive screening procedures: The Chicago Botanic Garden model. *Weed Technology*, 18, 1434-1440.

39

Johnson, S. (2009). NSW Weed Risk Management System. Industry and Investment NSW. Orange, New South Wales, Australia.

40

Kato H., Hata K., Yamamoto H. & Yoshioka T. (2006). Effectiveness of the weed risk assessment system for the Bonin Islands. *Assessment and Control of Biological Invasion Risks. Shoukadoh Book Sellers, Kyoto, Japan and IUCN, Gland, Switzerland*, 65-72.

41

Koop A.L., Fowler L., Newton L.P. & Caton B.P. (2012). Development and validation of a weed screening tool for the United States. *Biological Invasions*, 14, 273-294.

42

Křivánek M. & Pyšek P. (2006). Predicting invasions by woody species in a temperate zone: a test of three risk assessment schemes in the Czech Republic (Central Europe). *Diversity and Distributions*, 12, 319-327.

43

Massam M., Kirkpatrick W. & Page A. (2010). Assessment and prioritisation of risk for 40 exotic animal species. Department of Agriculture and Food, Western Australia. *Invasive Animals Cooperative Research Centre, Canberra*.

44

McKenzie J., Simpson H. & Langstaff I. (2007). Development of methodology to prioritise wildlife pathogens for surveillance. *Preventive Veterinary Medicine*, 81, 194-210.

45

Miller T.K., Allen C.R., Landis W.G. & Merchant J.W. (2010). Risk assessment: Simultaneously prioritizing the control of invasive plant species and the conservation of rare plant species. *Biological Conservation*, 143, 2070-2079.

46

Minnesota Interagency Exotic Species Task Force. (1991). Report and recommendations of the Minnesota Interagency Exotic Species Task Force. Minnesota Department of Natural Resources. Minnesota, USA.

47

More S.J., McKenzie K., O'Flaherty J., Doherty M.L., Cromie A.R. & Magan M.J. (2010). Setting priorities for non-regulatory animal health in Ireland: results from an expert Policy Delphi study and a farmer priority identification survey. *Preventive Veterinary Medicine*, 95, 198-207.

48

Morse L.E., Randall J.M., Benton N., Hiebert R. & Lu S. (2004). An invasive species assessment protocol: Evaluating non-native plants for their impact on biodiversity, Version 1. *US Government Documents (Utah Regional Depository)*, 537.

49

Nentwig W., Kühnel E. & Bacher S. (2010). A generic impact scoring system applied to alien mammals in Europe. *Conservation Biology*, 24, 302-311.

50

Nishida T., Yamashita N., Asai M., Kurokawa S., Enomoto T., Pheloung P.C. & Groves R.H. (2009). Developing a pre-entry weed risk assessment system for use in Japan. *Biological Invasions*, 11, 1319-1333.

51

OIE (World Organization for Animal Health). (2011a). Terrestrial Animal Health Code. OIE (World Organization for Animal Health) Paris, France.

52

OIE (World Organization for Animal Health). (2011b). Aquatic Animal Health Code. OIE (World Organization for Animal Health) Paris, France.

53

Olenin S., Minchin D. & Daunys D. (2007). Assessment of biopollution in aquatic ecosystems. *Marine Pollution Bulletin*, 55, 379-394.

54

Ou J., Lu C. & O'Toole D.K. (2008). A risk assessment system for alien plant bio-invasion in Xiamen, China. *Journal of Environmental Sciences*, 20, 989-997.

55

Parker C., Caton B.P. & Fowler L. (2007). Ranking nonindigenous weed species by their potential to invade the United States. *Weed Science*, 55, 386-397.

56

Pheloung P. (2001). Weed risk assessment for plant introductions to Australia. *Weed Risk Assessment. CSIRO Publishing, Collingwood, Victoria, Australia*, 83-92.

57

Pheloung P., Williams P. & Halloy S. (1999). A weed risk assessment model for use as a biosecurity tool evaluating plant introductions. *Journal of Environmental Management*, 57, 239-251.

58

Randall J.M., Morse L.E., Benton N., Hiebert R., Lu S. & Killeffer T. (2008). The invasive species assessment protocol: a tool for creating regional and national lists of invasive nonnative plants that negatively impact biodiversity. *Invasive Plant Science and Management*, 1, 36-49.

59

Reichard S.H. & Hamilton C.W. (1997). Predicting invasions of woody plants introduced into North America. *Conservation Biology*, 11, 193-203.

60

Risk Assessment and Management Committee. (1996). Generic nonindigenous aquatic organisms risk analysis review process (for estimating risk associated with the introduction of nonindigenous aquatic organisms and how to manage for that risk). A report.

61

Sæther BE, Holmern T, Tufto J & Engen S. (2010). Forslag til et kvantitativt klassifiseringssystem for risikovurdering av fremmede arter. Senter för bevaringsbiologi. Trondheim, p. 144.

62

Sandvik H., Sæther B.-E., Holmern T., Tufto J., Engen S. (in prep.). Towards a generic ecological impact assessment of alien species: a quantitative set of criteria. Under revision.

63

Skurka Darin G.M., Schoenig S., Barney J.N., Panetta F.D. & DiTomaso J.M. (2011). WHIPPET: A novel tool for prioritizing invasive plant populations for regional eradication. *Journal of Environmental Management*, 92, 131-139.

64

Smallwood K.S. & Salmon T.P. (1992). A rating system for potential exotic bird and mammal pests. *Biological Conservation*, 62, 149-159.

65

SZEID. (2006). Documentation for prototype AHW prioritisation decision support tool. Version 1.1. p. 14.

66

Tricarico E., Vilizzi L., Gherardi F. & Copp G.H. (2010). Calibration of FISK, an invasiveness screening tool for nonnative freshwater invertebrates. *Risk Analysis*, 30, 285-292.

67

Tucker K.C. & Richardson D.M. (1995). An expert-system for screening potentially invasive alien plants in South-African fynbos. *Journal of Environmental Management*, 44, 309-338.

68

Ward D., Stanley M., Toft R., Forgie S. & Harris R. (2008). Assessing the risk of invasive ants: a simple and flexible scorecard approach. *Insectes Sociaux*, 55, 360-363.

69

Warner P., Bossard C., Brooks M., DiTomaso J., Hall J., Howald A., Johnson D., Randall J., Roye C. & Ryan M. (2003). Criteria for categorizing invasive non-native plants that threaten wildlands. *California Exotic Pest Plant Council and Southwest Vegetation Management Association*.

70

Weber E. & Gut D. (2004). Assessing the risk of potentially invasive plant species in central Europe. *Journal for Nature Conservation*, 12, 171-179.

71

Weber E. & Gut D. (2005). A survey of weeds that are increasingly spreading in Europe. *Agronomy for Sustainable Development* 25, 109-121.

72

Widrlechner M.P., Thompson J.R., Iles J.K. & Dixon P.M. (2004). Models for predicting the risk of naturalization of non-native woody plants in Iowa. *Journal of Environmental Horticulture*, 22, 23-31.

| ID manuscript | Citation | Groups applied | Number of species assessed | Regions applied | Uncertainty examined | Model description | T/E/A/S/I components estimated (yes/no) | Mapping | Mapping comments |
|---|---|---|---|---|---|---|---|---|---|
| 1 | Ahrens et al. 2011 | Plant herbicide resistant *(A. stolonifera, A. gigantea, A. perennans, A. scabra, A. capillaris, A. Canina)* | 6 | USA | Yes (cross validation and kappa) | Species distribution model calibrated using occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 2 | Allen et al. 2001 | Molluscs (mussel) | 1 | USA & Canada | Yes (accuracy) | Logistic regression on traffic, hydrology and water chemistry as predictors for *Dreissena* occurence | N/Y/N/N/N | $Z_i = pr(\lambda_C \mid E_i, V_i)$ | |
| 3 | Andrew & Ustin 2010 | Plants | 1 | USA (California) | No | Dispersal model that examines the role of propagule pressure and landscape structure on rate of spread | Y/Y/N/Y/N | $Z_{i,t} = N_{i,t} = \sum_{j=1}^{J_i} \sum_{k=1}^{V_{i,j,t}} f_D(\bar{E}, D_{i,j})$ | Dispersal dependent on environment in pathways (corridors too), as well as general habitat suitability |
| 4 | Aragon & Lobo 2012 | Insect (maize pest western corn rootworm *Diabrotica virgifera* ssp. *virgifera*) | 1 | Northern hemisphere | Yes (misclassification rates) | Species distribution models combined with physiological spatial projections outputs (geographical projections of temperature physiological thresholds based on key fitness components, MDE, and MD categorized as lower or higher climatic favourability) to estimate areas of invasion under both current and future climate scenarios | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 5 | Arriaga et al. 2004 | Plant (buffel grass, *Cenchrus ciliaris* L.) | 1 | Mexico | Yes (kappa) | Species distribution model derived from using climate, habitat and edaphic data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 6 | Ba et al. 2010 | Crustacean (decapode) | 1 | Global | No | Modelling invasion risks on a global scale using SDM. To assess invasion risks in major ports, dispersal distances and major ocean shipping rozes were additionally accounted for. | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i, D_{i,j})$ | Dij is the distance from known source and nearest coastline. Verbally, indicated included it into SDM |
| 7 | Barney & DiTomaso 2010 | Plant (switchgrass, *Panicum virgatum*) | 1 | USA | No | Bioclimatic envelope models used to estimate the potential distribution and suitable habitat based on the climate and distribution data in the native range under both current and future climate scenarios | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 8 | Bartell & Nair 2004 | Insect (Asian longhorned beetle, *Anoplophora glabripennis*) | 1 species/1 pathway (establishment); the study mention other transitions like transport and spread, but they are not really modeled | USA | Uncertainties inherent to the estimation of model parameters that determine the risk of establishment are defined, quantified, and propagated through the population model. The approach takes into account a wide array of factors infuencing establishment: (1) factors that determine the rate of pest entry into the United States; (2) the biology and ecology of the pest species; (3) the availability of suitable hosts and environmental factors that influ- ence pest establishment in different geographical re- gions; (4) the population dynamics of the pest species; and (5) the implications of uncertainties on resulting estimates of risk and risk reduction. | The risk of establishment is modelled considering both the rate of entry and the population size required for persistence (i.e., threshold). Risk of establishment is modelled with a stage-based demographic model, including information on the biology and ecology of pest species, the suitability of potentially susceptible hosts, and the quality of available habitats | N/Y/Y/N/N | $X_{t+1} = f_X(X_t, r + \sigma_d)$<br>$Z = P_t^A = pr(X_t > threshold)$ | Stage based population model more complex than demographic model mapped. Assume demographic stoch, but not entirely sure. No density dependence. Not clea rwhether there were any environmental variables modeled |
| 9 | Beaumont et al. 2009 | Plants (hawkweeds: *Hieracium pilosella, H. aurantiacum* and *H. murorum)* | 3 | Australia | Yes (AUC and kappa) | Ecological niche models combining occurrence data with various climate variable to predict current and future species distributions | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 10 | Bomford et al. 2010 | Freshwater fishes | 280 | Global | Yes (AUC using cross-validation) | Establishment success of species based on the number of countries where introductions occurred (a measure of propagule pressure) and species' genus and family. Climate matching was also tested. | N/Y/N/N/N | $Z = P^c = f_{P^c}(E, S, N, v)$ | |
| 11 | Bomford et al. 2009 | Reptiles and amphibians | 1995 introduction records (1028 successful and 967 failed introductions) for 596 alien species | World, but emphasis on Great Britain, California and Florida | Yes (AUC using cross-validation) | Statistical models examining the association of establishment success and range expansion with environmental conditions, range size and history of establishment | N/Y/N/Y/N | $Z = P^c = f_{P^c}(E, S)$<br>$Z = Q = f_Q(E, S)$ | E is climate match. Also looked at hierarchical models, and therefore components of stochasticity. Not shown explicitly in mapping. Also examined multiple jurisdictions for validation |
| 12 | Bourchier & Van Hezewijk 2010 | Plant (Japanese knotweed, *Polygonum cuspidatum)* | 1 | Canada | Yes (efficiency test with indepedent data) | Climate matching model on predicted the occurrence of invasive species | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 13 | Bradley 2009 | Plant (cheatgrass, Bromus tectorum) | 1 | Western USA | Yes (model prediction comparison) | Bioclimatic model using occurrence data was constructed based on Mahalanobis Distance. Future invasion risk considered | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 14 | Bradley & Mustard 2006 | Plant (cheatgrass, Bromus tectorum) | 1 | USA (North-central Great Basin) | Yes (validation with field data) | Occurrence of species compared to various spatially explicit landscape variables (elevation, aspect, hydrographic channels, cultivation, roads, and power lines) to assess risk of future invasion | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i, f(O, D))$ | Distance to road, cultivated areas here were included as disturbance rather than related to human transport, and thus are in E. f(O,D) is the distance from a source population of cheatgrass (1973 distribution) |
| 15 | Bradley et al. 2010 | Plants (kudzu, *Pueraria lobata*; privet, *Ligustrum sinense* and *L. Vulgare*; cogongrass, *Imperata cylindrica*) | 3 | South-East USA | Yes (AUC) | Climatic habitat using occurrence data was developed using both the Maxent and Mahalanobis distance methodologies. Future invasion risk considered | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 16 | Bradley 2010 | Plants | 1 | USA | Yes (probability models) | Hierarchical risk modeling on the probability of invasion by Chetgrass on Sagebush | N/Y/N/Y/Y | $f_1(E_i) = pr(\lambda_{C2}^{Native} \mid E_i)$<br>$Z = \sum_{i=1}^{L} pr(\lambda_{C2} \mid E_i) f_1(E_i)$ | Also used ensemble models, and mis-classification rates |
| 17 | Bradshaw et al. 2008 | Fabaceae plants | 8906 | World | No | Statistical model that examines the relationship between the ecological and life-history traits and the threat and invasiveness risk of species | N/Y/N/N/N | $Z = P^c = f_{P^c}(S)$ | Although environment is mentioned, it is more a feature of the species than the receiving environment per se (not spatially explicit) |
| 18 | Brickman 2006 | Various | 0 | Canada | Yes (statistical parameter distribution, SE etc) | Introduces a RA model for ballast water dispersion (which is the carrier of transported IAS) after release in seas, including a) time integrated ballast water concentrations, b) time need for an organisms to reach an area, and c) the onshelf average concentrations. | N/N/N/Y/N | $Z_{i,t} = N_{i,t} = \sum_{j=1}^{A_i} \sum_{k=1}^{V_{i,j,t}} f_D(\bar{E}, D_{i,j})$ | fD - from oceanographic model. Ballast water layer captured in Vj across space. N - abundance reacing location i. Also looked at time to reach area, but not included in mapping |
| 19 | Broennimann et al. 2007 | Plant (spotted knapweed; *Centaurea maculosa*) | 1 | North America | Yes (AUC using independent data) | Species distribution model calibrated using occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 20 | Brooks et al 2012 | Plants | 1 | Argentina (native range) & USA (Florida, alien range) | Yes (statistical parameter distribution, SE etc) | Assessment of the role of the environmental envelope as compared with patterns of host–herbivore associations based on collections made in the native range. | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |

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|---|---|---|---|---|---|---|---|---|---|
| 21 | Buckley et al 2005 | Plants | 1 | New Zealand | Yes (sampling from parameter distribution) | Dispersal model incorporating life-history parameters | N/N/Y/Y/N | $X_{j,t+1} = f_X(X_{j,t}, r(E_{j,t}, S))$<br>$N_{i,t} = \sum_{j=1}^{J} f_{XD}(X_{j,t}) f_D(D_{i,j})$ | Simplification - paper had stage structured population model, and had both long and short distance dispersal kernels, but ideas reamin similar. Population rate of change (r) was dependent on species traits, and on grazing |
| 22 | Carrasco et al. 2010a | Insect (maize pest western corn rootworm *Diabrotica virgifera* ssp. *virgifera*) | 1 | Austria | Yes (maximum likelihood and predicted versus observed regression) | Spatially explicit metapopulation model (integrating both natural and human-assisted dispersal) and phenology model (driven by degree-days) | Y/Y/N/Y/Y | $N_{i,t} = \sum_{j=1}^{J} f_D(E_i, E_j, D_{i,j})$<br>$Z = Q_t = \sum_i pr(\lambda_C \mid E_i) * pr(N_{i,t} > 0) * f(V)$ | Included both natural and human mediated dispersal, using pop sizes as attractiveness (environment) of locations (gravity models affecting transport). Indicated population submodel, but no info on it, except to indicate effect of degree day |
| 23 | Carrasco et al. 2010b | Multiple (bacterium, insects) | 3 | United Kingdom | No | Bioeconomic model that considers the exclusion, detection and control of multiple NIS spreading by stratified dispersal and presenting Allee effects | N/Y/N/Y/Y | $P_t^C = f(M^P)$<br>$P_{i,t}^{A2} = 1 - (1 - pr(\lambda_A))^{N_{i,t}^P}$<br>$Q_T = \sum_{i=1}^{I} f(P_{i,T}^{A2})$<br>$Z = \sum_{t,i} P_t^c * P^e * (Q_T * f_I(\alpha^c M^c) + M^e + M^p)$<br>$P_t^c * (1 - P^e) * (Q_T * fI(.) + M^e + M^p) + (1 - P_t^c) * (M^e + M^p)$ | Also examined detection (Pe). From description in paper, not clear whether QT increased as a function of t, or increased after establishment. Also, included efficacy of control, but this was also not stated in paper |
| 24 | Carrasco & Baron 2010 | Mollusc (Pacific oyster, *Crassostrea gigas)* | 1 | South American coast | No | Occurrence Data. Species distribution model combining occurrence data with surface seawater and atmospheric temperature | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 25 | Carrete & Tella 2008 | Birds | 202 | Spain | Yes (standard errors) | Life trade model that uses species origin ( wild-caught versus captive-bred), availbility on international markets and potential phylogenetic effects to explain invasion success | Y/N/N/N/N | $Z = N = f(O(S))$ | Here, O is the potential for uptake, as measured by the number of stores carrying particular species ("popularity") or the number being sold. Propagule pressure was some function (*f*) of popularity |
| 26 | Castro-Díez et al. 2011 | Trees (Australian acacias) | 85 | Australia | Yes (models compared with AIC) | Study of predictors of invasiveness among a set of 85 Australian Acacia species | N/Y/N/N/N | $Z = P^c = f_{P^c}(S, f(V))$ | response variable - invasion success - not clear which component, although we treat this as establishment. Also, looked at env traits, but from the perspective of tolerances of species. Thus, did not include E as a predictor |
| 27 | Catford et al. 2011 | Plants | 441 | Australia | Yes (survey gap analysis using the multivariate environmental similarity surface (MESS) algorithm; CV correlation, AUC, Deviance) | Occupancy and abundance based on environmental, biotic and propagule pressure predictors analysed by boosted regression trees | N/Y/N/N/N | $Z_i = f_{Xs}(E_i, f(V))$<br>$Z_i = f_s(E_i, f(V))$ | Didn't look explicitly at abundance * occurrence, but could do so. fXs denotes abundance of cover of all exotic species. Vproxy is a surrogate (e.g., human population size) of traffic to a location. In using it here, does not consider temporal dynamics or sources |
| 28 | Catterall et al. 2012 | Plants | 1 | United Kingdom | Yes (posterior distributions of parameter estimates) | Habitat suitability and dispersal model built within a Bayesian framework | Y/Y/N/Y/N | $N_{i,t} = \sum_{j=1}^{J} f_D(D_{i,j}); Z = Q_t = \sum_i pr(\lambda_C \mid E_i) * pr(N_{i,t} > 0)$ | |
| 29 | Chen 2008 | Insect (Yellow crazy ant, *Anoplolepis gracilipes)* | 1 | Global | No | Species distribution models calibrated using occurrence data and past, current and future climate data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 30 | Chown et al. 2012 | Plants | >100 | Antarctica | No | Not a risk model per se but a quantification of propagule pressure in different climate environments | Y/Y/N/N/N | $Z = pr(\lambda_C \mid E) \sum_v N_v$ | Env is degree days, and propagule pressure is separated by vector types (v) |
| 31 | Chytry et al. 2008 | Plants | Many (> 1000) | Europe | Yes (sensitivity analysis) | Potential level of invasion (% neophytes in local communities) based on extrapolation from average occurrences at different habitat types | N/Y/N/N/N | $Z_i = f_s(E_i)$ | Looking essentially at whether environment is suitable. Risk given per environment. Not sure how to deal with fraction of total species. Define fs as # of species. Sum across i - is it more insightful to keep separate? |
| 32 | Claudi & Ravishankar 2006 | Not specified (everything in ballast water) | | Canada | Yes (sensitivity analysis) | Probabilistic model to assess the risk of alien species introductions via ballast water, including journey duration and mortality of species | Y/N/N/N/N | $Z_{i,t} = \sum_j V_{j,t} f_g(t - t', \alpha^P M^P)$ | |
| 33 | Cohen et al. 2007 | Aquarium plants | 138 | Montreal, Canada | Yes (stochasticity and parameter uncertainty using a Bayesian approach) | Live trade-release model that estimates propagule pressure by means of Bayesian analysis . It uses a multinomial distribution to calculate the uncertainty distribution associated with all combina tions of disposal pathways. | Y/N/N/N/N | $Z = N = \sum_{j=1}^{J} O_j(S) * pr(R \mid S)$ | Takes into account number of owners (J), number owned per individual (O), weighted by species (S) popularity, and release pr(R\|S) based on percent of individuals who release, and how many are released as a function of species traits. This model estimated total releases into the wild in a year, but does not consider environmental or spatial issues, which should affect probability of survival |
| 34 | Colnar & Landis 2007 | Crustacean (crab) | 1 | USA | Yes (Monte Carlo analysis) | Ranking system for identifying exposure and impact on target taxa but does not include local spread | Y/N/N/N/Y | $N_{i,t} = \sum_v O(E_i, v) f_g(.)$<br>$Z = \sum_i f(N_{i,t}) + \sum_{\gamma 1} f_I^{\gamma 2}(E)$ | Not sure about this./ Also took into account life stages - transitions between life stages and spread between patches not made clear. Considered impact on different ecosystem attributes. Conceptual model |
| 35 | Colunga-Garcia et al. 2009 | Various | 0 | USA (to global) | Yes (statistical parameter distribution; SE etc) | Analysis of regional freight transport to determine the likelihood of establishment of exotic species | Y/N/N/N/N | $Z = N = \sum_{j=1}^{J_i} f(V_{i,j,t})$ | V actually incorporates multiple stages of transport (multiple vectors), which isn't shown in the mapping. Determine relative risk at different locations |
| 36 | Compton et al. 2012 | Plants | 4 | New Zealand | Yes (statistical parameter distribution; AUC, SE etc) | Statistical model examining whether variables that indirectly describe weed spread via human access and use, as well as a lake's position in the landscape, could describe the distribution of species | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i, f(V))$ | f(V) includes pop density and roads, integrated with environments to determine establishment |
| 37 | Cooke & Hill 2010 | Fish | 2 | North America (Great Lakes) | Yes (statistical parameter distribution; SE etc) | Bioenergetic models that relate the metabolic requirements of invaders (under various body sizes, swimming speeds and reproductive stages) to planktonic food resources and environmental temperature to predict when and where they may survive | N/Y/N/N/N | $Z = \sum_{i=1}^{L} pr(\lambda_{C2} \mid E_i, S)$ | Based on bioenergetic model - not linear statistical model like most others examining E,S simultaneously |

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|---|---|---|---|---|---|---|---|---|---|
| 38 | Copp et al. 2010 | Fish | 18 | England | Yes (statistical parameter distribution; SE etc) | Spatial relationships between the occurrence of non-native fishes and human demographic factors associated with propagule pressure | Y/N/N/N/N | $Z = N = f(O(v), f(V))$ | Here, treat O as stores (sources of species) and V proxy as human density. This is partly to remain consistent with previous mappings (e.g.,Table 2). Also, looked at multiple sources (pathways?) |
| 39 | Coredell et al. 2010 | Crustacean (copepods) | 1 | Pacific (coast of North America) | Yes (statistical parameter distribution, SE etc; model comparision approach, sensitivity analysis) | Statistical model that assess areas at risk of invasion by examining the influence of various paramters on species occurrence | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 40 | Costello et al. 2007 | Crustacean (copepods) | Many (alien fauna & flora) | USA (San Francisco Bay) | Yes (statistical parameter distribution, SE etc, and by separating introduction and detection history) | Analytical model linking exotic species introductions and discoveries to trade volumes used to assess if trade origin and history affects new IAS numbers. The model is estimated using a novel historical data set on global trade and species introductions by region | Y/N/N/N/N | $Z_i = P^A_{i,t} = f(\sum_{j=1}^{J_i}(V_{i,j,t}))$ | Examined probability of establishment as a function of trade volume from different areas |
| 41 | Cotner & Schooley 2011 | Mammals | 1 | USA (Illinois) | Yes (statistical parameter distribution; AIC, SE etc) | Distribution model examining the relationship of site occupancy with local habitat conditions and anthropogenic landscape alterations | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 42 | Crossman & Bass 2008 | Tree (Olea europea) | 1 | Australia | Yes (AUC, missclassification measures) | Habitat suitability models applied to a single invasive plant | N/Y/Y/N/N | $Z = \sum_{i=1}^{L} f_X(E_i) pr(\lambda_c \mid E_i)$ | Also looked at Bayesian for uncertainty, and did ensemble models. As with others, did not actually combine both density and occurrence predictions, but could have |
| 43 | Crossman et al. 2011 | Weeds | 33 | Australia | Yes (AUC, missclassification measures) | Spatially-explicit indicator of threat to biodiversity from invasive plants under human-induced climate change by combining both a pattern-based element and a process-based element (dispersal). | Y/Y/N/Y/Y | $V_{i,j,t} = V_{j,t} f_D(\vec{E}, \vec{D}_j, E_i, D_{i,j})$<br>$N_{i,t} = \alpha \sum_{j=1}^{J}(V_{i,j,t})$<br>$Q_T = \sum_{i=1}^{I}(1 - pr(\lambda_A))^{N_{i,t}}$<br>$Z = Q_T * f_I(S)$ | Used a constant for propagule source sizes. Invasion history used for impact fI(S). Also looked at climate change effects (not included in equation). Converted components to relative scores. In actual paper, summed across species s, to obtain a multi-species predictions per location i |
| 44 | Dangles et al. 2008 | Insect (moths) | 3 | Ecuador | Yes (standard errors, and spatial and temperal variation) | Distributed delay models on temperature effect on life history development and demography. GLM on the effect of climate and host type on occurrence and abundance | N/N/Y/N/N | $Z = X = \sum_{i=1}^{L} f_X(E_i)$<br>$Z = X_t = f_X(X_{t-1}, r(E), k)$ | Looked at 2 studies - experimental which basically gave population dynamics parameters, and SDM-abundance. Pop dynamics model more complex (life stages) than the one in box2 |
| 45 | Davis et al. 2011 | Plants | 1 | USA | No | WRA vs. demographic model in relation to habitat suitability. No propagule pressure or dispersal | N/N/Y/N/N | $Z = X_{i,t+1} = f_X(X_{i,t}, r(E_{i,t}), \sigma)$ | Stochasticity included but not distinguished between environmental and demographic. E reported as disturbance, but seemed to be based on management (e.g., herbicide treatments). Also had seedbank and stages, not included in mapping |
| 46 | Dawson et al. 2009 | Plants | 142 | Tanzania | Yes (sensitivity analysis) | Trait-based model that also examines role of propagule pressure on tree survival, regeneration and spread | N/Y/N/N/N | $Z = P^C = f(S, E, N, t, v, D)$ | Also more finely divided establishment. t is the time that the first plot was planted, D is the minimum distance between plot and forest. Not sure whether summed across establishments (i.e., estimate Q). Also looked at linear distance moved, which could be considered Q (wave-front - not sure whether multiple plots were considered) |
| 47 | De Meyer et al. 2008 | Insects (Mediterranean fruit fly, *Ceratitis capitata;* Natal fruit fly, *Ceratitis rosa* ) | 2 | Africa, southern Europe, and world | Yes (binomial tests of correct prediction of both presences and absences) | Species distribution model calibrated using occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 48 | Denslow et al. 2008 | Plants | Many (174-892/island) | Pacific islands | No | Linear regression models on geographic (environmental, socioeconomic) predictors to alien plant richness in island | N/Y/N/N/N | $Z_i = f_s(E_i, V_{proxy})$ | V based on a surrogate of human population attributes, which may affect the number of vectors transporting aliens |
| 49 | DeVaney et al. 2009 | Eurasian cyprinid fishes (Common carp, *Cyprinus carpio* ; Tench, *Tinca tinca* ; Grass carp, *Ctenopharyngodon idella* ; and Black carp, *Mylopharyngodon piceus* ) | 4 | North America | Yes (independent data) | Species distribution models calibrated using occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 50 | Diez et al. 2012 | Plants | >25,000 | New Zealand and Australia | Yes (Bayesian posterior distributions) | Hierachical Bayesian apporach using informed prior information from Australia to derived probabilities of naturalisation in NZ | N/Y/N/N/N | $Z = P^C = f(S)$ | Here S is actually establishment (naturalization) in other locations (australia) as a predictor of establishment in NZ. Priors are also implicit in calculations of probabilities (but not shown in mapping) |
| 51 | Dorcas et al. 2011 | Reptile (Burmese pythons, *Python molurus bivittatus)* | 1 | USA | No | Species distribution model | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 52 | Drake 2005 | Mammal (feral nutria, Myocastor coypus) | 1 pathway (establishment) / 1 species | United Kingdom | Yes (model selection by least squares, AIC and BIC) | Demographic models describing the lag phase of the population, where demographic stochasticity and Allee effects play a major role in extinction; ignores expansion and saturation phases | N/Y/Y/N/N | $X_{i,t+1} = f_X(X_{i,t}, r, \kappa, \beta, \sigma_e, \sigma_d)$<br>$Z = P_t^A = pr(X_{i,t} > threshold)$ | Considered Allee effects (Beta) in population dynamic model. Considered invasion if population size exceeded a threshold (1000) |
| 53 | Drake & Lodge 2004 | Aquatic species | +1 | Global | Yes (uncertainty examined using hindcasts) | Propagule pressure-establishment model that identifies global hotspots of invasion based on worldwide patterns of ship traffic and estimates rate of port-to-port invasion | Y/Y/N/Y/N | $V_{i,j,t} = V_{j,t} f_D(\vec{E}, \vec{D}_j, E_i, D_{i,j})$<br>$N_{i,t} = \alpha \sum_{j=1}^{J}(V_{i,j,t})$<br>$P^A_{i,T} = 1 - \prod_{t=1}^{T}(1 - pr(\lambda_A))^{N^B_{i,t}}$<br>$Z_T = Q_T = \sum_{i=1}^{L} P^A_{i,T}$ | 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 |
| 54 | Drake et al. 2005 | Marine plankton | None | None | Yes (uncertainty indirectly associated with parameters) | Function of diffusive spread and population growth that estimates safe release thresholds | N/N/N/Y/N | $Z = P^C = f(\Delta X_t(S), \Delta Q_t)$ | Function of diffusive spread and pop growth, which is functions of species traits. Establishment occurs if critical density exceeded, given pop growth and spread rate |

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| 55 | Duggan et al. 2006 | Aquarium fishes | 308 | Canada, USA | Yes (standard errors) | Live trade model that uses occurrence frequency in aquarium stores to explain introduction and establishment of aquarium fishes in freshwater habitats | Y/N/N/N/N | $Z = N = f(O(S))$ | Here, O is the potential for uptake, as measured by the number of stores carrying particular species ("popularity") or the number being sold. Propagule pressure was some function (f') of popularity |
| 56 | Epanchin-Niell et al. 2009 | Weeds (*Bromus tectorum*) | 1 | USA | Yes (sensitivity analysis) | Vegetation dynamic model to predict vegetation changes and management costs under different intensities and types of post-fire revegetation. Results estimate species dominance | N/N/Y/N/Y | $X_{t+1} = f_X(X_t, E_t)$<br>$E_{t+1} = f_E(X_t, E_t)$<br>$Z = f(E, M^c)$ | Space not considered. Uses probability transition matrix between states (E), and has more states than presented in equations, but dynamics would be similar to interactions between species |
| 57 | Essl et al. 2010 | Plants | 86 | Global (Temperate and subtropical countries and regions (n = 60) from five continents spanning both hemispheres) | No | Uses forest usage and forestry area across 60 global regions as a measure of possible "propagule pressure" and maps this on to regional environmental suitability. | N/Y/N/N/N | $Z = P^C = f(E, S, v)$ | S is origin of species, E is regions area, and v is use in forestry |
| 58 | Fabregas et al. 2010 | Animals | 1 pathway (introduction) | Spain | No | Risk of potential animal escape at zoological parks by assessing the security of enclosures | Y/N/N/N/N | $Z = N = O(S) * pr(R \mid S)$ | O is the number of enclosures given S (taxonomic groups), and pr(R\|S) are the proportion of unsecured enclosures |
| 59 | Ficetola et al. 2007 | Amphibian (American bullfrog, *Rana catesbeiana*) | 1 | Global | Yes (AUC and r^2) | Species distribution model calibrated with occurrence data, included hunting pressure | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 60 | Fitzpatrick et al. 2012 | Insect (hemlock woolly adelgid, *Adelges tsugae*) | 1 | Eastern North America | Yes (AUC) | Dynamic model using both abundabce and dispersal data | N/Y/Y/Y/N | $X_{i,t+1} = f_X(X_{i,t}, r(E_{i,t}), \kappa(E_{i,t}), \sigma_e)$<br>$N_{i,t} = \sum_{j=1}^{J} f_{XD}(X_{j,t}, S, \sigma_{XD}) f_D(D_{i,j})$<br>$P_{i,t}^{A2} = 1 - (1 - pr(\lambda_{A2} \mid E_i))^{N_{i,t}}$ | Environment for k and IA was host levels, whereas for r it was winter temp. Stochasticity was incorporated at all levels. For pop dynamics, we called it environmental stochasticity, since per capita rates did not decrease with population size. Stochasticity in dispersal occurred in number of dispersers, not in the dispersal kernel |
| 61 | Floerl et al. 2005 | Various (alien hull fouling species) | Many | New Zealand | Yes (statistical parameter distribution; SE etc) | Quantitative risk screening techniques that predicts the abundance and variety of organisms being transported by ocean-going yachts | N/N/N/N/Y | $Z_{i,j,k,t} = N_{i,j,k,t} = f(M^p, t' - t)$ | Risk of vector k, traveling from i to j in time t is a function of prevention (e.g., paint) and of time. In this case time is voyage history. Provides a metric of propagule pressure, but does not consider release |
| 62 | Floyd et al. 2006 | Weeds | 8 | USA | Yes (ANOVA using different site categories, with and without management) | Each soil series and each vegetation community was ranked using a ordinal scale 1-3 representing low to high density of invasive non-native species, based on soil analyses | N/Y/N/N/N | $Z_i = f_{xs}(E_i, M^c)$ | converted to ranks |
| 63 | Follak & Strauss 2010 | Plant (Horse nettle, *Solanum carolinense)* | 1 | Central Europe and North America | Yes (model predictions evaluated with independent data) | Species distribution model calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 64 | Follak 2011 | Plant (kudzu, *Pueraria lobata*) | 1 | Switzerland, Austria and Slovenia and parts of northern Italy | Yes (visual inspection and using independent data) | Species distribution model calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 65 | Forsyth et al. 2004 | Mammals | 40 | Australia | Yes (standard error applied to the fitted model) | GLM considering both occurrence and various explanatory variables (climate matching, life-history traits, introduction efforts) on the introduction and spread of species | N/Y/N/N/N | $Z = P^c = f_{pr}(S, N)$ | |
| 66 | Foxcroft et al. 2007 | Plants | 231 | South Africa | Yes (r^2) | Risk assessment that alien species invade a protected area from surrounding watersheds; include species abundance or, as a proxy, species richness as a method of incorporating propagule pressure | N/Y/N/N/N | $Z = \sum_s \sum_{i=1} pr(\lambda_{C,s} \mid E_i)$ | Summed across species for a given location, or range for each species. Different than ones that use species richness as a response variable |
| 67 | Frank et al. 2008 | Fungi (rust) | 1 | USA | Yes (patial and temporal variation) | Synoptic classification meteorological data from upper (geopotential height, specific humidity, and u- and v-wind components) and surface (humidity and temperature) level used to simulate establishment likelihood | Y/Y/N/Y/N | $N_{i,t} = \sum_{j=1}^{J} f_D(\vec{E}, D_{i,j}, v)$<br>$Z_i = f(N_{i,t}) + f(pr(\lambda_B \mid E_{i,t}))$ | paper good for pr(IB). Converted to scores, and then summed to determine risk according to date. Weird way of going about it |
| 68 | Fujisaki et al. 2010 | Reptiles | 68 | USA | Yes (error rates) | Discriminant analysis, logistic regression and recursive partitioning and regression trees on species traits, live release, manageability and environmental variables to predict establishment success | N/Y/N/N/N | $Z = P^C = f(S, E, f(N))$ | Authors discuss manageability, but mapped as species traits (e.g., aggresiveness) rather than related than as a management component (M) |
| 69 | Gassó et al. 2009 | Plants | 106 | Spain | Yes (explained variance) | Joint species trait-environment model that examines occurrence data based on plant attributes and plant richness on environmental factors | N/Y/N/N/N | $pr(\lambda_{C2} \mid E_i, S) = f(E_{i,1} + E_{i,2} ... + S_{i,1} + S_{i,2} ...)$<br>$Z = \sum_{i=1}^{L} pr(\lambda_{C2} \mid E_i, S)$ | Incorporates both species traits and environmental suitabilities, simultaneously. Has only been done using linear models. Standard errors also provided, but not on validation set |
| 70 | Gertzen & Leung 2011 | Crustacean (Spiny water flea, *Bythotrephes*) | 1 | Canada | Yes (stochasticity (probabilistic spread and establishment), epistemic uncertainty (missing data, modeled via simulation)) | Extention of Leung et al. (2004). Extensions were to deal with unknown times of invasion, imperfect knowledge of invasion status, and multiple vectors. | Y/Y/N/Y/N | $V_{i,j,t} = V_{j,t}(v) f_D(\vec{E}, \vec{D}_j, E_i, D_{i,j}, v)$<br>$N_{i,t} = \alpha \sum_{j=1}^{J} V_{i,j,t}$<br>$P_{i,T}^A = 1 - \prod_{t=1}^{T} (1 - pr(\lambda_A))^{N_{i,t}}$<br>$Z_T = Q_T = \sum_{i=1}^{L} P^A_{i,T}$ | Extention of Leung et al. (2004). Note that v was for fluvial dispersal and boater movement (combined into a single dispersal equation for simplicity, but could have had 2 equations) |
| 71 | Gertzen et al. 2008 | Aquarium fishes | 252 | Montreal, Canada | Yes (stochasticity and parameter uncertainty using a Bayesian approach) | Life trade-release model that models propagule pressure using Bayesian analysis. The model was then extended to take into account specific characteristics and population size (species-specific propagule pressure) | Y/N/N/N/N | $Z = N = \sum_{j=1}^{S} O_j(S) * pr(R \mid S)$ | Takes into account number of owners (J), number owned per individual (O), weighted by species (S) popularity, and release pr(R\|S) based on percent of individuals who release, and how many are released as a function of species traits. This model estimated total releases into the wild in a year, but does not consider environmental or spatial issues, which should affect probability of survival |
| 72 | Gertzen & Leung 2011 | Crustacean (Spiny water flea, *Bythotrephes*) | 1 | Canada | Yes (stochasiticy modeled demographic and environmental) | Demographic model incorporating Allee effects, stochasticity, and mesocosm experiments. Looking at the effect of initial population size (propagule pressure) versus establishment success. | N/Y/Y/N/N | $X_{t+1} = f_X(X_t, r(E_t), \beta, \sigma_e, \sigma_d)$<br>$Z = P_T^A = pr(X_t > threshold)$ | Demographic model incorporating Allee effects, stochasticity, and mesocosm experiments. Looking at the effect of initial population size (propagule pressure) versus establishment success |

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| 73 | Gevrey et al. 2006 | Insects | 844 | Global | No | Self-organising map used to link species assemblages globally to identify potential group membership | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | Looked at pest assemblages/co-occurrence. Could consider it a special case of E refering to biotic predictors (other pests) |
| 74 | Gillham et al. 2004 | Plants (black henbane, *Hyoscyamus niger*; *hoary cress, Cardaria draba* ; leafy spurge, *Euphorbia esula* ; perennial pepperweed, *Lepidium latifolium* ; spotted knapweed, *Centaurea maculosa* ) | 5 | USA (Wyoming) | Yes (independent data) | Occurrence data. degree of disturbance.WISP model (automated extension within the GIS program) | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 75 | Glardon et al. 2008 | Plant (green alga, *Caulerpa taxifolia)* | 1 | USA (Florida) | Yes (r^2) | Species distribution model calibrated with occurrence data, including biotic factors (native species presence, human population density) | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i, f(V))$ | |
| 76 | Goodwin & Piggot 2009 | Bacteria | 1 | USA (Florida) | Yes (comparision of model performance of three model variants) | Spatiotemporal models of the risks of citrus canker transmission | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | Not sure where the spatiotemporal aspect is - seemed to be based solely on host/acreage |
| 77 | Goslee et al. 2003 | Plant (Russian knapweed, *Acroptilon repens* ) | 1 | USA (Colorado) | Yes (model predictions compared with abundance maps) | Species distribution model calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 78 | Goslee et al. 2006 | Plants | 1 | USA | No | Demographic model applied to cells in landscape | N/N/Y/N/N | $Z = X_{i,t+1} = f_X(X_{i,t}, r(S), \kappa, \sigma)$ | Not enough info provided to be sure (IBM approach). Also looked at above vs below biomass. S was photosynthetic pathway & water use efficiency |
| 79 | Gravuer et al. 2008 | Plants | 70 | New Zealand | Yes (variation explained) | Boosted-tree methods on human, biogeographic, species trait predictors on introduction, naturalization and spread | Y/Y/N/Y/N | $N = f(S, f(V), E)$<br>$Z = N * pr(\lambda_{C2} \mid S, E, T, f(V)) * \Delta Q(S, E, T, f(V))$ | Also looked at error rates. deltaQ here is the spread rate |
| 80 | Gray 2010 | Insect | 1 | USA | Yes (probability models, standard errors) | Phenology model on probability of introduction and establishment | Y/Y/N/N/N | $N = O(X_t) * f_g(\bar{E})$<br>$Z = P_{i,T}^{A} = 1 - \prod_{t=1}^{T}(1 - pr(\lambda_A))^{N_{i,t}}$ | O-predarture phenology dev, fg |
| 81 | Gross 2001 | Mammals (mountain goats, Oreamnos americanus) | 1 species / 1 pathway (impact) | USA | | Spatially explicit, individual-based model that forecasts population dynamics of a native and an exotic species | N/N/Y/Y/Y | $N_{i,t} = \sum_{j=1}^{J} f_{XD}(X_{j,t}) f_D(\bar{E}, D_{i,j})$<br>$X_{i,t+1} = f_X(X_{i,t}, r(E_{i,t}), \kappa(E_{i,t}), \sigma_e, \sigma_d)$<br>$E_{i,t+1} = f_E(X_{i,t}, E_{i,t})$<br>$Z_T = \sum_{t=1}^{T}\sum_{i=1}^{N} f_I(X_{i,t}, E_{i,t})$ | Decriptions verbal, so am not sure. E is mainly biotic - includes competition from species of interest Big Horn Sheep and disease, as well as abiotic environmental factors. Impact is also effect on Big Horn Sheep (i.e., a function of biotic environment wrt invasive mountain goats.). Dispersal causes immigration (emmigration implicit in fX in our mapping) |
| 82 | Haight et al. 2011 | Plant pathogenic fungus (oak wilt) | 1 | USA (Minnesota) | Yes (sensitivity analysis) | Spread model that combines historic data on short- and long-distance dispersal with costs of removing infected trees to simulate future development and costs of the disease | N/N/N/N/Y | $Z_T = Y^A = \sum_{t2=1}^{T}\left(\sum_{t2=1}^{t2}\left(W_{t2,t2} * Y_{t2}^{B}\right)\right)$<br>$Y_{t2}^{B} = \sum_{t3=1}^{T-t2}\left(M_{t2}^{c} + f_I(t3, X_{t2,t3}, E_{t2}, \alpha^c M_{t2}^{c})\right)$ | Wi2,t2 is the probability of establishment of new pockets at time t2 (taken here as a constant rate). Damage is a function of pocket age (t3), we use X as area infested within cell, E is the environment (Oaks), and MC is the management (cutting down trees). Estimates expected damages in absence of other preventative measures. Also calculated post-establishment |
| 83 | Hallstan et al. 2010 | Mollusc (zebra mussel, *Dreissena polymorpha* ) | 1 | Sweden | Yes (percentage correct prection and AUC using cross-validations) | Hierarchical partitioning and stepwise selection of water chemistry variables in a multiple logistic model using occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 84 | Hamilton et al. 2005 | Plants | +150 | Eastern Australia | Yes (validation data sets and error rates) | Species trait model that compares life-history correlates of invasion success between regional and continental spatial scales | N/N/Y/N/N | $Z = \bar{X} = f_X(S)$ | Predicting average abundance |
| 85 | Hanson et al. 2008 | Crustacean (crab) | 1 | USA | No | Verbal analsysis of hidrographic and water quality variables as predictors of crab occurrence and larval development | N/Y/N/N/N | $P_{i,T}^{B} = 1 - \prod_{t=1}^{T}(1 - pr(\lambda_B \mid E_{i,t}, S))$<br>$Z = P^{C}{}_{i,T} = P^{B}{}_{i,T} * pr(\lambda_C \mid E_t, S)$ | Note that prB did not include any propagule pressure component, but was included to indicate that timing issues were considered. Species traits here was determined for a specific species, using experimental studies rather than statistically across many species (as a discriminator) |
| 86 | Harris & Barker 2007 | Insects (ants) | 12 | New Zealand | No | GIS-based modelling tool for management of biosecurity risks to New Zealand's indigenous ecosystems based on occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 87 | Hartley et al. 2006 | Insect (Argentine ant, *Linepithema humile)* | 1 | Global | Yes (concordance probability and misclassification errors) | Species distribution model calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 88 | Henderson et al. 2011 | Vertebrates | 137 | Australia | Yes (generalised linear models between the risk of establishment and vertebrate classes or detection categories) | Four-factor risk assessment based on the outcomes of historical introductions of exotic species and climate matches | N/Y/N/N/N | $Z_{s,v} = f_{s,v}(O_s * f_{g,s}(.)) * pr(\lambda_{C,s} \mid E)$ | Separated by vector type (v) and calculated for a series of indivdual species explicitly (not generalizing beyond species) (denoted here as fs,v). i.e., calculating risk ranks for the combination of species and vector. Used interception data (fs,v) which therefore we make a function of uptake and survival (but not release) |
| 89 | Herbert et al. 2012 | Mollusc (Manila clam, *Ruditapes philippinarum)* | 1 | United Kingdom | Yes (independent data) | Hydrodynamic models coupled with a water salinity model and an individual behaviour model of Manila clam larvae | N/N/N/Y/N | $N_{i,t} = \sum_{j=1}^{J} f_D(\bar{E}, D_{i,j}, S, v, \sigma_D)$ | v included because explicitly hydrodynamic model, and behavioural movement. E is salinity |
| 90 | Herborg et al. 2007 | Crustacean (crab) | 1 | North America | Yes (misclassification rates) | Potential distribution of species by combining the use of habitat suitability models with data on the intensity of shipping activity | Y/Y/N/N/N | $Z = \sum_{i} f(V_i, v) * pr(\lambda_C \mid E_i)$ | f(Vi,v) here is the vector density map at each given location i. Multiple vectors examined, and a combined score generated for each location. This was multiplied by niche model output |
| 91 | Herborg et al. 2009 | Tunicate | 1 | North America | Yes (AUC) | Establishment probability of invasive species by combining vector and environmental niche models | Y/Y/N/N/N | $Z = \sum_{i}\sum_{v} f(V_{i,v}, v) * pr(\lambda_C \mid E_i)$ | Develped a risk map, cumulating over pathways (v), and the number of vectors in that pathway Vv, weighted by risk of transport by that vector. And then standard SDM. Separated for each location i |

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| 92 | Herrera et al. 2012 | Plants | 1 | Venezuela | Yes (sensitivity analysis) | Demographic model of weeds integrated with simulations of management | N/Y/Y/N/N | $Z = P_t^A = pr(X_t > threshold)$<br>$X_{t+1} = f_X(X_t, r(S), \kappa, \sigma_e, \sigma_d, M^c)$ | Looked at probability of establishment using PVA. Also considered stage structured population model, not shown in mapping |
| 93 | Hoddle 2003 | Insect (glassy-winged sharpshooter, *Homalodisca coagulata* ) and bacteria (grape pathogen, *Xylella fastidiosa* ) | 2 | Global | No | Species distribution model calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 94 | Hortal et al. 2010 | Plant (sweet pittosporum, *Pittosporum undulatum* ) | 1 | Azores | Yes (cross validation) | Species distribution model calibrated with occurrence data, human impact considered | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i, f(V))$ | |
| 95 | Hyvonen et al. 2010 | Plants | 163 | Finland | Yes (explained variance) | GLMM and redundancy analysis on land-use and climate predictors on alien weed richness, occurrence and abundance in crop fields | N/Y/N/N/N | $Z_i = f_{Xi}(E_i)$<br>$Z_i = f_x(E_i)$<br>$Zi = pr(\lambda_C \mid E_i)$ | Ei (land use) here could also be considered management options, but followed authors usage |
| 96 | Ibáñez et al. 2009 | Plants (*Berberis thumbergii, Celastrus orbiculatus, Euonymus alata, Elaeagnus umbellata* and *Rosa multiflora)* | 5 | New England, eastern North America | Yes (spatial variability and parameter uncertainty via Bayesian methods; model uncertainty via ensemble models. Validation data sets also used. Also, looked at error rates extrapolated to new areas) | Species distribution abundance model that combine species richness and species per cent ground cover with several environmental predictors (related to climate, local habitat and land cover) | N/Y/Y/N/N | $Z = \sum_{i=1}^{L} f_X(E_i) pr(\lambda_c \mid E_i)$ | Using same logic and techniques associated with habitat suitability models but applied to predict species abundance |
| 97 | Inglis et al. 2006 | Molluscs | 2 | New Zealand | Yes (sensitivity analysis) | Model comparision between simple expert-based habitat suitability models and regression models | N/Y/N/Y/N | $N_{i,t} = f_D(D_{ij}, \vec{E})$<br>$Z = \sum_{i=1}^{L} pr(\lambda_{C2} \mid E_i, N_{i,t})$ | Included SDM and oceanographic dispersal model within regression model to predict establishment. Vector E is the ocean circulation environment, and Dij is distance to nearest source |
| 98 | Jacobs & MacIsaac 2009 | Plants | 1 | Canada | Yes (ensemble modelling) | Passive and active dispersal models coupled with an environmental suitability model. Measures of propagule pressure incorporated both human-mediated dispersal and advective flow from invaded to non-invaded systems, while habitat suitability was forecasted by combining native and global data sets and using statistical models | Y/Y/N/Y/N | $V_{i,j,t} = V_{j,t} f_D(\vec{E}, \vec{D}_j, E_i, D_{i,j})$<br>$N_{i,t} = \alpha \sum_{j=1}^{J} V_{i,j,t}$<br>$N'_{i,t} = \sum_{j'} f_D(D_{i,j})$<br>$Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)(f_N(N_{i,t}) + f_N(N'_{i,t}))$ | 2 vectors were considered human and natural (differentiated with a ' superscript). Propagule pressure estimates converted to probability, and combined as shown below |
| 99 | Jakubowski et al. 2010 | Plant (reed canarygrass, *Phalaris arundinacea L.* ) | 1 | USA (southern Wisconsin) | No | Species distribution model with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 100 | Jarosik et al. 2011 | Plants (*Ageratum houstonianum, Argemone ochroleuca, Chromolaena odorata, Opuntia stricta, Xanthium strumarium* and *Lantana camara*) | 6 | South Africa (Kruger National park) | Yes (cross validation to estimate relative errors) | Species distribution model with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i, f(V))$ | 6 species examined. F(V) was roads |
| 101 | Jokela & Ricciardi 2008 | Mollusc (Eurasian zebra mussel, *Dreissena polymorpha* ) | 1 | Canada-Quebec | Yes (r^2) | Regression model relating mean fouling intensity to environmental variables | N/N/N/N/Y | $Z_i = f_I(E_i)$ | Empirical study, looking at several sites and environmental correlates of fouling (impact) |
| 102 | Jones et al. 2010 | Plants (*Geranium robertianum, Hedera helix, Ilex aquifolium)* | 3 | USA (Olympic Peninsula) | Yes (AUC and true skill statistic) | Species distribution model calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 103 | Kadoya & Washitani 2010 | Insect (bumblebee) | 1 | Japan | Yes (Bayesian posterior distributions) | Stochastic spatio-temporal model that incorporates immigration and establishment processes to asses spatial dynamics of invasion | Y/Y/N/Y/N | $Q_T = \sum_{i=1}^{L} \sum_{j=1}^{J} (f_D(D_{i,j}) + f(O) * pr(\lambda_C \mid E_i))$<br>$Z_T = Q_T(M^c)$ | f(O) amount of tomatoes (source area). 2 paths considered, which in our mapping we sum. Management also modeled as eradication of N number of cells, in different configurations, and the effect of this on spread |
| 104 | Kaiser & Burnett 2010 | Reptile (brown treesnake, *Boiga irregularis* ) | | | They do not formally model uncertainty beyond that regarding the point of entry, using expected values for marginal damages, marginal costs, and an area's invasion population at a given time. The model is parameterized using data from Hawaii and Guam, and investigate across 30 years of potential snake presence on the island of Oahu to identify the net benefits of EDRR. The model assumes that dispersion is through a diffusion model (it is said that this is the best way to model it based on the invasion of Guam, but it is not validated with data from Oahu), taking into account accessibility (based on distance to closest road) but not other environmental factors (e.g. habitat suitability). | Spatial–dynamic model for optimal early detection and rapid response that consists of search activities beyond the ports of entry, where search (and potentially removal) efforts are targeted toward areas where credible evidence suggests the presence of an invader. Costs are a spatially dependent variable related to the ease or difficulty of searching an area, while damages are assumed to be a population-dependent variable. The spread and population model of the invader considers the accesibility of the terrain (distance to roads) | Y/N/Y/Y/Y | $N_{i,t} = \sum_{j=1}^{J} f_{XD}(X_{j,t}) f_D(D_{i,j}, E_i)$<br>$X_{i,t+1} = f_X(X_{i,t}, r, \kappa) + N_{i,t}$<br>$Z_T = \sum_{t=1}^{T} \sum_{i=1}^{L} M^c + M^s + f_I(X_{i,t}, E_{i,t}, M^c, M^s)$ | E in fD is distance to road.E om fI is other species. Ms is surveillance effort, which also affects fI since can only apply strategies once detection occurs |
| 105 | Keller et al. 2007 | Molluscs | 18 | Great Lakes basin and the 48 contiguous states of USA | Yes (validation data sets and error rates) | Species trait model that differentiate between characteristics of benign and nuisance species. Time since establishment used to explain negative impacts of molluscs | N/N/N/N/Y | $Z = f_I(S)$ | Species trait models have been applied to a number of the invasion stages, but never integrated. Metrics of impact questionable. Not a quantification of severity of damage, but a probability of any damage occurring. |
| 106 | Keller et al. 2008 | Crustacean (rusty crayfish) | 1 | USA (Wisconsin) | Yes (AIC and AUC) | Predictive occurrence model applied with different management options to calculate cost benefit scenarios | N/Y/N/N/Y | $Z = \sum_{i2=1}^{L} pr(\lambda_C \mid E_{i2}, f(V), \alpha^{p2} M_{i2}^{p2}) * f_I(X_{i2}, E_{i2}, M_{i2})$ | Vproxy is cabins. Assumed 100% effectiveness in management |
| 107 | Kelly et al. 2007 | Fungi (*Phytophthora ramorum* ) | 1 | USA | Yes (cross-validation) | Species distribution models calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 108 | Kikillus et al. 2010 | Reptile (red-eared slider turtle, *Trachemys scripta elegans)* | 1 | New Zealand | Yes (partical AUC using cross-validation) | Species distribution model calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 109 | Kilroy et al. 2008 | Diatom (*Didymosphenia geminata)* | 1 | New Zealand | No | Multivariate environmental distance using occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 110 | Kimberling 2004 | Insects | 83 | USA | No | Traits-based prediction of success/failure and non-target impacts of biocontrol agents | N/N/N/N/Y | $Z = f_I(S)$ | Only considered analysis with respect to non-target effects (i.e., the risk of this introduction), rather than the management effectiveness |
| 111 | Kleinbauer et al. 2010 | Plant (black locus, *Robinia pseudacacia* L.) | 1 | Austria | Yes (AUC and kappa using cross-validation) | Species distribution models calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |

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| 112 | Knowler & Barbier 2005 | Plants | 1 | USA | No | Cost benefits analysis of introductions into nurseries | Y/N/N/Y/Y | $N_{t1} = \sum_{j=1}^{J_t} O_j$<br>$Y^A = \sum_{t=1}^{T-d1} cQ_t$<br>$Z_T = \sum_{t1=1}^{T} \left( f(N_{t1}) * Y^A \right)$ | O was # per nursery, J is # nurseries. F(N) is a hazard function, and here is the probability of invasion during time interval t1. In paper, these are modeled as continuous functions, but discretized for consistency with full model. d1=t1 and is the delay to invasion, and c is the average impact. Article also looked at discounting, which we don't do here, and don't consider the cost-benefit (risk management) side |
| 113 | Koch et al. 2011 | Forest insects from border interception | Not specified | USA | no | Prediction of species establishment from commodity import data | N/Y/N/N/N | $Z = f_x(V^{proxy})$ | Examined at 2 levels, initial introduction (Vproxy is amount of trade), and into urban areas (Vproxy is also goods into urban areas). Not combined. Looked at # species introduced |
| 114 | Koch et al. 2012 | Forest insects | 0 (they model the pathway) | USA | Yes (use AIC for model selection, likelihood ratio tests and standard errors) | An analysis of the dispersal potential of pest species via transport of firewood to campsite (consider travel distances, but do not include any assumptions on number of insects carried) | N/N/N/Y/N | $Z_{i,t} = N_{i,t} = \sum_j V_{j,t} f_D(D_{i,j})$ | Where V is the numbe r of campers. Then used a integrodifference model, with multiple dispersal kernels. Determine transport of firewood to location i |
| 115 | Kolar & Lodge 2002 | Fishes | 45+66+14 | USA | Yes (jackknife validations of discriminant functions, and cross-validation of CART trees) | Statistical model examining the relationship between a series of predictors and establishment risk, followed by an additional analysis | N/Y/N/Y/Y | $Z = P^c = f_{P^c}(S)$<br>$Z = \Delta Q = f_Q(S)$<br>$Z = f_I(S)$ | Also included invasion history |
| 116 | Konishi et al. 2009 | Fish | 1 | Japan | Yes (statistical parameter distribution; SE etc) | Occurrence pattern of a species in relation to 16 environmental habitat variables | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | includes both abiotic and biotic factors |
| 117 | Kraus et al. 2012 | Reptile (lizard) | 1 | USA | No? | Climate matching model on predicted distribution in Hawaii and Global. Impact not integrated in the model | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 118 | Kriticos et al. 2003 | Plant (Prickly acacia, *Acacia nilotica)* | 1 | Australia | Yes (fitted parameters considering the species known distribution) | Species distribution model calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 119 | Kueffer et al. 2010 | Plants | 383 | Many | Yes (standard errors/r^2) | Global analysis of alien species richness across islands using island geographic and economic predictors. Explores species traits but does not include them in the model | N/Y/N/N/N | $Z_i = f_x(E_i, f(V_i))$ | i is each separate island |
| 120 | Kulhanek et al. 2011a | Fish (common carp, *Cyprinus carpio)* | 1 | USA (Minnesota) | Yes (spatial variability and parameter uncertainty via Bayesian methods; model uncertainty via ensemble models. Validation data sets also used. Also, looked at error rates extrapolated to new areas) | Species distribution abundance model | N/Y/Y/N/N | $Z = \sum_{i=1}^{L} f_X(E_i) pr(\lambda_c \mid E_i)$ | Using same logic and techniques associated with habitat suitability models but applied to predict species abundance |
| 121 | Kulhanek et al. 2011b | Aquatic invaders (especially common carp, *Cyprinus carpio* ) | 19 | Global | Yes (explained variance) | Model used invasion history data to predict severity of impacts (biotic and abiotic). Meta- analysis of common carp impacts based biomass and time since introduction as predictive variables. | N/N/N/N/Y | $Z_i = f_I(X_i)$ | Has primarily used previous observed relations between abundance and metrics of impact. Note that invasion history has been used in species trait models, as a dichotomous variable (has species caused impact anywhere) |
| 122 | Küster et al. 2008 | Plants (neophytes) | 388 | Germany | Yes (explained variance) | Statistical models examining the effects of traits (related to morpho-physio-phenological traits, ecological performances and variables describing introduction history) on species frequency | N/Y/N/N/N | $Z = P^c = f_{P^c}(S,t)$ | t is the time of first occurrence |
| 123 | Lambdon & Hulme 2006 | Plants | 862 | Mediterranean | Yes (sensitivity analysis) | Introduction traits used to predict invasion risk categories using canonical discriminant analysis | N/Y/N/N/N | $Z = P^c = f_{P^c}(S,v,t,N)$ | v is the mode of introduction, and t is the first time of first introduction |
| 124 | Lambdon et al. 2008 | Plants | 382 | Mediterranean | Yes (elasticity analysis) | Introduction traits used to predict naturalisation using GLM | N/Y/N/N/N | $Z = P^c = f_{P^c}(S,v,t,N)$ | v is the mode of introduction, and t is the first time of first introduction |
| 125 | Larson et al. 2001 | Plants | 38 | USA | Yes (standard errors/r^2) | Statistical model assessing the effect of vegetation, anthropic and park unit as predictors for alien species distribution (occurrence) and frequency | N/Y/N/N/N | $Z_i = f_x(E_i)$<br>$Zi = pr(\lambda_C \mid E_i)$ | Seems to look at total # plants (richness?) |
| 126 | Leung et al. 2006 | Molluscs (zebra mussel) | 1 | USA (Michigan) | Yes (least square analysis) | Gravity model used to model boat traffic between lakes as vectors for the spead of zebra mussel (i.e. surrogate for propagule pressure). Potential establishment is not considered. | N/N/N/Y/N | $Z_{i,t} = \sum_j V_{j,t} f_D(\bar{E}, \bar{D}_j, E_i, D_{i,j})$ | |
| 127 | Leung & Mandrak 2007 | Mollusc (zebra mussel, *Dreissena polymorpha* ) | 1 | USA (Michigan) | Yes (uncertainty examined using hindcasts) | Joint propagule pressure-species distribution model that simultaneously incorporates invasibility and propagule pressure to predict invasion risk | Y/Y/N/Y/N | $V_{i,j,t} = V_{j,t} f_D(\bar{E}, \bar{D}_j, E_i, D_{\lambda,j})$<br>$N_{i,t} = \alpha \sum_{j=1}^{J} V_{i,j,t}$<br>$P_{i,T}^A = 1 - \prod_{t=1}^{T} \left(1 - pr(\lambda_A)\right)^{N_{i,t}^{\beta}}$<br>$Z = Q_T = \sum_{i=1}^{L} P^A{}_{i,T} * pr(\lambda_C \mid E_i)$ | Extend of propagule pressure-establishment model (e.g. Leung et al 2004) by also considering environmental differences between locations. pr(I\|C\|E) is estimated using SDM. As opposed to SDM this does not suffer from requiring equilibrium. Note that species distribution model was termed "site invasibility" in Leung & Mandrak 2007, which we change here to be consistent with the majority of the literature |
| 128 | Leung et al. 2004 | Mollusc (zebra mussel, *Dreissena polymorpha* ) | 1 | USA (Michigan) | Yes (uncertainty examined using hindcasts) | Propagule pressure-establishment model that estimates the probability of population establishment taking into account propagule pressure and allee effects using survival analysis and maximum likelihood techniques | Y/Y/N/Y/N | $V_{i,j,t} = V_{j,t} f_D(\bar{E}, \bar{D}_j, E_i, D_{i,j})$<br>$N_{i,t} = \alpha \sum_{j=1}^{J} V_{i,j,t}$<br>$P_{i,T}^A = 1 - \prod_{t=1}^{T} \left(1 - pr(\lambda_A)\right)^{N_{i,t}^{\beta}}$<br>$Z = Q_T = \sum_{i=1}^{L} P^A{}_{i,T} * pr(\lambda_C \mid E_i)$ | 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 |
| 129 | Leung et al. 2002 | Mollusc (Zebra mussel) | 1 | North America | Yes (stochasticity included in dynamic model, sensitivity analysis) | Bioeconomic model taking into account population dynamics of zebra mussel, and economic losses experienced by a power plant. Adaptation occurred via different investment into labor and capital | N/Y/Y/N/Y | $X_{t+1} = f_x(X_t, r, \kappa, \sigma)$<br>$Y^B = \sum_{t3=1}^{T-t3} \left(M_{t2}^c + f_I(t3, X_{t3}, \alpha^c M_{t2}^c)\right)$<br>$Z_T = \sum_{t1=1}^{T} \left((1 - P_{t1}^C(\alpha^p M^p)) * M^p + U_{t1}(\alpha^p M^p) * M^p\right)$ | Bioeconomic approach. Not spatially explicit. Took into account population dynamics, and losses experienced by a power plant. Control was also in a power plant, and reduced the Zebra Mussel population size in the power plant only. Adaptation occurred via different investment into labor and capital. Was not spatially explicit |

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| 130 | Liddle et al. 2006 | Vertebrates | 3 | Australia | Yes (sensitivity analysis) | Assessment of the level of impact by an invader | N/N/N/N/Y | $\sum_{i=1} f_i\ (t, E, M^c)$ | Looked at impact due to invader in terms of palm trees. Simulated management effects, and also looked at environment over time. Looked at several sites, but analysis not spatially explicit |
| 131 | Lindgren et al. 2010 | Plants (*Tamarix ramosissima Ledeb., T. chinensis Lour.* and hybrids) | 3 | Canada | No | Species distribution model calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 132 | Lippitt et al. 2008 | Insect (gypsy moth, *Lymantria dispar L.)* | 1 | Contiguous USA | Yes (AUC) | Species distribution model using occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i, V)$ | V is human traffic from source locations |
| 133 | Liu et al. 2011 | Crustacean (red swamp crayfish, *Procambarus clarkii)* | 1 | Global | Yes (model predictions compared to null models; AUC) | Species distribution model calibrated with occurrence data, considered human impact | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 134 | Liu 2009 | Amphibian (frog) | 1 | China | Yes (test for alternative predictors) | GLMM for numerous predictors related to farming, propagule pressure, geographic and hydrology as predictors for establishment probability | N/Y/N/N/N | $Z = Q_T = \sum_{i=1}^{L} pr(\lambda_C \mid E_i, O_i, D_{ij}, t_j, \alpha^p M^p)$ | O frog density at source, Dij because distance from a source. Time since source pop existed also considered (tj) and enclosure type was mapped as prevention effort |
| 135 | Logan et al. 2007 | Insect (gypsy moth, *Lymantria dispar L.)* | 1 | USA (Utah) | Yes (cross-validation) | Species distribution model with occurrence data | N/Y/Y/N/N | $X_{i,t+1} = f_X(X_{i,t}, r(E_{i,t}), \sigma)$<br>$Z = P_t^A = pr(X_t > threshold)$ | Based on verbal description of model. Pop growth parameters function of environment, not clear from description whether K present, or relevant. Assume that sigma included, given that simulations stochastic |
| 136 | Mandle et al. 2010 | Plant (*Impatiens walleriana)* | 1 | Global | Yes (r^2) | Species distribution model calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 137 | Marchetti et al. 2004 | Fishes | 49 / 22 / 38 | USA (California) | No | Three stage-models examining the relationships between species establishment, spread and integration and 10 life history predictor variables | N/Y/Y/Y/N | $Z = P^c = f_{P^c}(S, D, N)$<br>$Z = Q = f_Q(S, D, N)$<br>$Z = \overline{X} = f_X(S, D, N)$ | D here is the distance from the nearest source |
| 138 | Maret et al. 2006 | Vertebrates | introduced fish and bullfrog | North America | No | Metapopulation model to predict changes in the proportion of ponds occupied by different species | N/N/N/Y/Y | $Q_t = f(Q_{t-1}, E_{t-1})$<br>$\sum_{t=1} Q_t f_t\ (E_t)$ | Modified to just look at major factors considered, and to be centered on the invasive species dynamics. Their functional form is just Levin's meta-pop model with parameterizations. E is fish, drying. Impact is on salamander. Because Levin's model is spatially implicit, do not consider patches i, as with other approaches |
| 139 | Marini et al. 2011 | Insects (beatles) | Many | USA and 20 European countries | Yes (r^2) | Multi-model inference and hierarchical partitioning of human activity (trading) and environmental variables on species richness and establishment | N/Y/N/N/N | $Z_i = f_s(E_i, V_{proxy})$ | Not sure what they mean by multimodal inference - seems like a regular multiple regression |
| 140 | Mason et al. 2011 | Insect (Leek moth, *Acrolepiopsis assectella* ) | 1 | Canada and eastern USA | Yes (compared with species distribution) | Species distribution model calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 141 | Mau-Crimmins et al. 2006 | Plant (Lehmann lovegrass, *Eragrostis lehmanniana)* | 1 | Southeastern USA | Yes (misspecification error rates and r^2) | Comparison between invaded-range versus native-range dataset using species distribution models calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 142 | Medley 2010 | Insect (Asian tiger mosquito, *Aedes albopictus* ) | 1 | North and South America, Europe | Yes (AUC) | Species distribution model calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 143 | Mika & Newman 2010 | Insect (pea leafminer, *Liriomyza huidobrensis* ) | 1 | North America | Yes (misspecification error rates and r^2) | Species distribution model calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 144 | Mika et al. 2008 | Insect (swede midge, *Contarinia nasturtii)* | 1 | North America | Yes (misspecification error rates) | Species distribution model calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 145 | Miller et al. 2007 | Molluscs (bivalve and gasteropod molluscs associated with oyster) | 93 | USA (San Francisco Bay, California) | Yes (model sensitivity and specificity, but also percent correct classification when testing the model applied to 3 different regions using a bootstrap analysis) | Statistical model employing biological attributes to determine establishment success | N/Y/N/N/N | $Z = P^c = f_{P^c}(S)$ | Not sure what to do about historical abundance. Treating habitat characteristics a factor relating to species (i.e., S rather than E) |
| 146 | Miller et al. 2010 | Plants | 8 | USA | Yes (Monte Carlo simulations) | So called Relative risk model on occurrence data for invasive and rare plants | Y/Y/N/N/Y | $f_I(S, E_i) = f_I(S)\, pr(\lambda_C^{Native} \mid E_i)$<br>$Z = \sum_{i=1}^{L} f(O, d_{ij})\, pr(\lambda_C \mid E_i) * f_I(S, E_i)$ | f(O) is the sources, which I didn't know how to place in notation - they have uninvaded_adjacent_toInvade /uninvaded |
| 147 | Mondor et al. 2007 | Insects (aphids) | 174 (96 introduced species - 78 native congeners) | USA-Hawaii | No | Morphological and ecological variables used to predict colonization success | N/Y/N/N/N | $Z = P^c = f_{P^c}(f(O), S)$ | f(O) is presence in continental USA |
| 148 | Moore et al. 2010 | Vertebrates | 1 | Australia | No | Stochastic dynamic programming used to assess the optimum allocation of resources to quarantine and surveillance | N/N/N/N/Y | $Z_T = M^p + M^e + U(\alpha^p M^p) * Y^A$<br>$Q = f(M^e)$<br>$Y^A = f(Q, M^C)$ | SDP model used, and could not entirely map matrix into a small set of equations. Here MP is quarantine and Me is surveillance (which slows the spread). YA is the cost of eradication (Mc), depending on probabiilty of extensive spread Q (a function of Me). Eradication is assumed to successful. Space is implicit, so do not use notation for patches |
| 149 | Muirhead & MacIsaac 2005 | Insect (bumblebee) | 1 | Canada | Yes (Monte Carlo analysis) | Vector traffic model from invaded to non-invaded lakes that assess the patterns of spread of alien species by risky activities | N/N/N/Y/N | $Z_j = \sum_i V_{j,i} f_D(\bar{E}, \bar{D}_j, E_i, D_{i,j})$ | Double constrained gravity model, looking at the risk associated with hub lake j. Discussed management, but did not model it |
| 150 | Muirhead & MacIsaac 2011 | Crustacean (spiny waterflea, *Bythotrephes longimanus)* | 1 | Canada (Ontario) | | Establishment probability and dispersal models | Y/N/N/Y/N | $V_{i,j,t} = V_{j,t} f_D(\bar{E}, \bar{D}_j, E_i, D_{i,j}, \sigma_D)$<br>$N_{i,t} = \alpha \sum_{j=1}^{L} V_{i,j,t}$<br>$Z_i = Q_i = \sum_{i=1}^{L} f(N_{i,t})$ | f(N) is a generic functional form using boosted regression trees |
| 151 | Muirhead et al. 2006 | Insect (Emeral ash borer) | 1 | Canada | Yes (Stochasticity in establishment probabilistic; cross validation examined) | Dispersal model that considers both natural and human-assisted dispersal | N/Y/N/Y/N | $Z_t = Q_t = \sum_i \sum_j pr(\lambda_A) f_D(\bar{E}, \bar{D}_j, E_i, D_{i,j})$ | Containment examined, but not explicitly modeled, and therefore not included in the mapping. Two dispersal modes considered (long-distance, human mediated) and natural dispersal. fD converted to a probability of reaching I from j, and pr(LA) is a fixed fitted probability |
| 152 | Mwebaze et al. 2010 | Plant insect pests | 2253 interceptions at border inspections | United Kingdom | Yes (sensitivity analysis) | Bioceconomic model using the volume of imports and interception data of insect pests at border controls to estimate the number of pests coming in per volume of trade and country. This is used to model the optimal inspection effort allocation to different countries of import origins | N/Y/N/N/N | $Z_i = f_s(M^P, \sum_j f(V_{i,j}))$ | MP is inspection, V is the imports from country j to country i, and fs is the number of species introduced. Also did other trade-off analyses, which would be part of risk management |

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| 153 | Naddafi et al. 2011 | Molluscs (zebra mussel) | 1 | USA, Europe | Yes (model comparisons) | GLM-GAM models on physicochemical variables determining zebra mussel density (abundance) | N/N/Y/N/N | $Z_i = f_X(E_i)$ | |
| 154 | Neteler et al. 2011 | Insect (Asian tiger mosquito, *Aedes albopictus)* | 1 | North-eastern Italy | Yes (misspecification error rates) | Species distribution model calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 155 | Nietschke et al. 2008 | Insect (*Scirtothrips dorsalis* ) | 1 | USA | Yes (misspecification error rates) | Species distribution model with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 156 | Økland et al. 2010 | Pinewood nematode | 1 | Norway | Yes (sensitivity analysis) | Distribution model of a vector species linked to a surveillance/monitoring model to test how contingency plans work | N/Y/Y/Y/Y | $X_{j,t+1} = f_X(X_{j,t}, r(E_{j,t}), \kappa(E_{j,t}))$<br>$N_{i2,t} = \sum_{j2=1}^{J} f_{XD}(X_{j2,t}) f_D(D_{i2,j2}, \sigma_D)$<br>$Z = P^A_{i2,t} = pr(X_t > threshold)$<br>$Z_t = \sum_{i2} f(P^C_{i2,t}, M^C, M^S)$ | Dispersal random - indicates movement to location i2, at which time establishment occurs. Risk a function of everywhere establishment occurs, given eradication and monitoring efforts. Paper actually about probability of eradication |
| 157 | Olden et al. 2006 | Fishes (native and nonnative) | 90 (28 + 62) | USA (Colorado River Basin) | No | Statistical models assessing the relationship between life between life-history overlap and species distributional changes | N/N/N/Y/N | $Z = \Delta Q = f_Q(S)$ | Looked at changes in distribution. Delta Q is the spread rate |
| 158 | Olden et al. 2011 | Crustacean (rusty crayfish, *Orconectes rusticus)* | 1 | USA (Wisconsin) | Yes (error rates; takes into account spatial variability) | Joint suitability-vulnerability model that quantifies ecosystem vulnerability to species distribution as a function of exposure risk (i.e., likelihood of introduction and establishment based on a species distribution model) and the sensitivity of the recipient community (i.e., likelihood of impacts on native species) | N/Y/N/Y/N | $Z = \sum_{i=1}^{L} pr(\lambda_{C2} \mid E_i) pr(\lambda_{C2}^{Native} \mid E_i)$ | Linked habitat suitability models for invader and native species of interest. The probability of both occurring simultaneously over all sites determines the risk. Like other habitat suitability models, does not consider temporal dynamics of invasion process |
| 159 | Olfert et al. 2006 | Insect (swede midge, *Contarinia nasturtii)* | 1 | Canada | Yes (misspecification error rates) | Species distribution model calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 160 | Olfert et al. 2004 | Insect (Oulema melanopus) | 1 | Canada | Yes (misspecification error rates) | Species distribution model calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 161 | Olson et al. 2012 | Plant *(Myriophyllum spicatum L.)* | 1 | USA (Wisconsin) | Yes (AUC and explained variance, error type I and II) | Multivariate logistic and multiple linear regressions using both occurrence and abundance data. Human impact and other biotic factors included | N/Y/Y/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i, f(V)) f_X(E_i)$ | |
| 162 | Otfinowski et al. 2007 | Plants | 251 | Canada | Yes (spatial variation) | Climate, habitat and species traits explaining establishment and proliferation (abundance?). Not very clear, it does not integrate climate match with native range with species traits, close to a qualitative analysis | N/Y/N/N/Y | $Z = pr(\lambda_C \mid E) * pr(\lambda_C \mid S) * f_i(S)$ | Looked at probability of existing in region at all, and probability that traits would occur in park, in susceptible areas. Used a decision tree (convert to 0/1 instead of continuous). Each component fit independently to same data |
| 163 | Paini et al. 2011 | Fungus | 486 | Global | Yes (validation with a virtual world, ensemble model) | Self organizing map by artificial neural network on establishment likelihood | N/Y/N/Y/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_{C2} \mid E_i)$ | Looked at pest assemblages/co-occurrence. Could consider it a special case of E refering to biotic predictors (other pests). Validation of theory, not consideration of real world uncertainty |
| 164 | Parker et al. 1999 | All invaders | Not specified | Global | No | Conceptual model for understanding the impacts of an invader including three fundamental dimensions: range, abundance and its per-capita or per-biomass effect. No models were used | N/N/N/Y/Y | $Z_T = Q_T * \overline{X} * c$ | Implicitly assumes that locations are all equal, abundances are all equal, and that consequences of abundance are linear, scaled by a per unit impact constant © |
| 165 | Peacock& Worner 2006 | Insect pests | 1 | New Zealand | No | Species distribution model calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 166 | Perry & Vice 2008 | Reptile (brown tree snake, *Boiga irregularis)* | 1 | Global | No | Probability of establishment. Included propagule pressure in the model, also incorporated the likelihood of an organism entering the transportation system, avoiding detection, surviving to arrive at another location, and establishing at the receiving end | Y/Y/N/N/N | $Z_{i,t} = N_{i,t} = pr(\lambda_A) \sum_{j=1}^{J} \sum_{k=1}^{V_{i,j,t}} O(v_{i,,j,k,t}) * f_g(v_{i,j,k,t})$ | Multiplies probability of a given individual establishing, times the frequency of vectors (V) times the probability of survival transport (fg), times the probablity of being taken up and remaining undetected. These are functions of the vector (transport vessel size) |
| 167 | Peterson et al. 2003 | Plants (Hydrilla, *Hydrilla verticillata* ; Russian olive, *Elaeagnus angustifolia* ; sericea lespedeza, *Lespedeza cuneata* ; garlic mustard, *Alliaria petiolata)* | 4 | North America | Yes (misspecification error rates) | Species distribution model calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 168 | Pitt et al. 2009 | Insect (Argentine ant, *Linepithema humil)* | 1 | New Zealand | Yes (misspecification error rates) | Occurrence and Spread Data. Spatially explicit stochastic model and uniform radial spread model | Y/Y/N/Y/N | $N_{i,t} = \sum_{j} f_D(D_{i,,j}, v, \sigma_D)$<br>$Z = Q = \sum_{i=1} pr(\lambda_C \mid E_i) pr(N_{i,t} > 0)$ | Based on verbal description of model. Both local and long distance dispersal considered. fD seemed to yield a probability of that dispersal would reach i, so we treated this as at least one dispersal event would reach i from all infested locations |
| 169 | Potapov et al. 2011 | Zooplankton | 1 | Canada | Yes (variation explained) | Stochastic gravity model for propagule pressure and logistic regression model on water physicochemical conditions for establishment | Y/Y/N/Y/N | $V_{i,j,t} = V_{j,t} f_D(\bar{E}, \bar{D}_j, E_i, D_{i,j}, \sigma_D)$<br>$N_{i,t} = \alpha \sum_{j=1}^{J} (V_{i,j,t})$<br>$Z = Q_c = \sum_{i=1}^{I} (1 - pr(\lambda_A))^{n_i^C} * pr(\lambda_C \mid E_i)$ | |
| 170 | Potter et al. 2009 | Plant (*Cytisus scoparius)* | 1 | Global | Yes (misspecification error rates) | Species distribution model calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 171 | Pysek et al. 2009 | Plants | Ambiguos; it includes tranport, introduction, establishment and spread but the boundaries are poorly defined | Global | No | Effects of species' biological traits and their distributional characteristics on invasion success | N/N/N/Y/N | $Z = Q = f(S, f(O), v)$ | Response variable number of locations found (analogous to spread at a global level), which is a function of species traits and vector types (v). Oproxy is how widespread it is in native range, as a proxy for uptake |
| 172 | Pysek et al. 2009 | Plants (neophytes) | 170 (109+44+17) | Czech Republic | No | Examining the probability of introduction, naturalization and invasions by mean of statistical models using introduction data and species life-traits | Y/Y/N/Y/N | $Z = N = f_N(f(O), v, S)$<br>$Z = P^c = f_{P^c}(f(O), v, S)$<br>$Z = \Delta Q = f_Q(f(O), v, S)$ | N equates propagule pressure with the number of escapes, f(O) is the number of stores selling a species, v is the pathway (here the usage of the species) |
| 173 | Raghu et al. 2007 | Insect (beetle for biologial control) | 1 | Australia | Yes (sensitivity analysis) | Life-cycle model for a biological control insect is combined with a model for a target and non-target plant growth model to assess potential benefits (control of target species) and risks (of non-target native species) | N/N/Y/N/Y | $X_{t+1} = f_X(X_t, r(E_t), \kappa(E_t))$<br>$Z = f_t(X_t, E)$ | E is plants present (one for biocontrol and one a non-target effect). Population dynamics model actually had many stages and more complex than mapped. Was modelled per patch (i.e., spread not considered) |
| 174 | Raimundo et al. 2008 | Terrestrial vertebrates | 13 | Spain | Yes (discrimination power of favourability functions; AUC, correct classification rates) | Species presence/absence related to independent variables | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i, f(V))$ | |

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| 175 | Raimundo et al. 2007 | Plant (Siamweed, *Chromolaena odorata)* | 1 | Neotropics (native range) and global (introduced range) | Yes (jackknife evaluation and misspecification error rates) | Species distribution model calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 176 | Reed 2005 | Reptiles (boas, phytons, and relatives) | 6067 shipments representing 404177 individuals, 17 genera and 40 species of snakes | USA | No | Model estimating the likelihood of establishment with legal commerical imports by summing risk associated with commercial trade and risk associated with ecological variables | Y/Y/N/N/N | $N = f(O,S)$<br>$P^C = f_{P^C}(S)$<br>$Z = N + P^C$ | Species traits here are related to their value, and the way they were caught (wild vs raised). O is the number being traded (consider survival and release after that) |
| 177 | Reichard & Hamilton 1997 | Woody plants | 235 | North America | Yes (validation data sets and error rates) | Species trait model that determines which traits (several structural, life history, and biogeographical attributes) characterize establishment of invasive woody plant species using discriminant analysis | N/Y/N/N/N | $Z = P^c = f_{P^c}(S)$ | Species trait models have been applied to a number of the invasion stages, but never integrated. Metrics of impact questionable. Not a quantification of severity of damage, but a probability of any damage occurring. Although applied separately, these approaches could be integrated for a fuller analysis of risk |
| 178 | Reino et al. 2009 | Bird | 1 | Portugal | Yes (statistical parameter distribution; SE etc) | Survival analysis based on information available up to the first invasion peak used to predict pattern of invasion in the second peak, as well as future invasion hazards using climate change scenarios | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | Used survival analysis, but all aspects were looking at colonization using climate as a predictor |
| 179 | Reshetnikov & Ficetola 2011 | Fish (*Perccottus glenii)* | 1 | Holarctic | Yes (AUC and cross-validation) | Species distribution model calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 180 | Ricciardi 2003 | Mollusc (zebra mussel, *Dreissena polymorpha)* | 1 | Europe and North America | Yes (explained variance) | Regression analysis of data (invasion history) from multiple invaded sites to generate empirical models of impact | N/N/N/N/Y | $Z_i = f_1(X_i)$ | Has primarily used previous observed relations between abundance and metrics of impact. Note that invasion history has been used in species trait models, as a dichotomous variable (has species caused impact anywhere) |
| 181 | Richards et al. 2008 | Insect (whitefly) | 4 | USA | Yes (use of three different models and each is made to vary according to a geometric Brownian motion, to simulate random variation in the deterministic model. The models are fitted to empirical data) | Econometric model that takes into account the spatio-temporal process underlying a particular population and apply it to the economic costs of the species damage | Y/N/Y/Y/N | $Z_{i,t} = N_{i,t} = \sum_{j=1}^{J} f_{XD}(X_{j,t}) f_D(D_{i,j})$<br>$X_{i,t+1} = f_X(X_{i,t}, r(E_{i,t}), \kappa(E_{i,t}), \sigma) + N_{i,t}$ | Pricing model. Not sure what risk is. E incorporates space and time differences (could also be expressed as an exogenous matrix). Sigma causes variance, is also autoregressive |
| 182 | Richardson & Thuiller 2007 | Plants | 1 | Global (regions similar to South Africa) | Yes (AUC) | Species distribution model calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 183 | Robertson et al. 2004 | Plants (*Lantana camara; Ricinus communis; Solanum mauritianum) and* native cicada species (*Capicada decora; Platypleura deusta; P. capensis*) | 6 | South Africa, Lesotho, Swaziland | Yes (kappa) | Species distribution model calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 184 | Robinet et al. 2011 | Pine wood nematode (*Bursaphelenchus xylophilus)* | 1 | Europe | Yes (sensitivity analysis) | Occurrence and spread data. Includes human populations | Y/Y/N/Y/N | $N_{i,t} = \sum_{j=1}^{J} f_{XD}(X_{j,t}) f_D(E_i, D_{i,j}, \nu)$<br>$Z = Q = \sum_{i=1} pr(\lambda_C \mid E_i) pr(N_{i,t} > 0)$ | Has both local and long distance. Human population size in dispersla kernel is mapped as Ei here because it is a metric of attractiveness, rather than a vector. Verbally discussed probability of establishment based on host and temperature, but not clear what relations were |
| 185 | Robinson et al. 2010 | Plants | 1 | Australia | Yes (AUC) | Multicriteria evaluation tool coupled with a risk-adjusting technique to develop a series of alternative decision strategies for identifying the distribution of an invasive species | N/Y/N/N/N | $Z = P^c = f_{P^c}(S)$ | Not sure, but paper look at decisions (risk preferences, which is part of risk management), and does not affect risk itself. |
| 186 | Rodder 2009 | Amphibian *(Eleutherodactylus johnstonei)* | 1 | Global | Yes (AUC and jackknife analysis) | Species distribution model calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 187 | Rogers et al. 2007 | Plant (Upland Cotton, *Gossypium hirsutum* var. *hirsutum)* | 1 | Australia | Yes (misspecification error rates) | Species distribution model calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 188 | Rothlisberger & Lodge 2010 | Plants | 1 | USA | Yes (AUC) | Gravity model to predict spread | Y/Y/N/Y/N | $V_{i,j,t} = V_{j,t} f_D(\vec{E}, \vec{D}_j, E_i, D_{i,j})$<br>$N_{i,t} = \alpha \sum_{j=1}^{J} (V_{i,j,t})$<br>$Z = Q_T = \sum_{i=1}^{L} (1 - pr(\lambda_A))^{N_{i,t}}$ | 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 |
| 189 | Roura-Pascual et al. 2010 | Plants | Many | South Africa | Yes (sensitivity analysis) | Spatially-explicit analysis that evaluates the sensitivity of model-based management prescriptions to changes in the relative importance assigned to different decision criteria | N/N/Y/Y/N | $Z_t = w_1 Q_t + w_2 X_t + w_3 f(t) + w_4 E_t + w_5 M + w_6 A_t$ | risk in a given area dependent on spread, abundance, time (age of stand), environment (fire and fire risk), last management, and species type present |
| 190 | Rout et al. 2011 | Vertebrates | 1 | Australia | No | Model optimum allocation of resources to quarantine and surveillance | N/N/N/N/Y | $Z_T = M^P + M^c + U(\alpha^P M^P) * Y^A$<br>$Q = f(M^c)$<br>$Y^A = f(Q, M^C)$ | SDP model used, and could not entirely map matrix into a small set of equations. Here MP is quarantine and Me is surveillance (which slows the spread). YA is the cost of eradication (Mc), depending on probabiilty of extensive spread Q (a function of Me). Eradication is assumed to successful. Space is implicit, so do not use notation for patches |
| 191 | Ruesink & Collado-Vides 2006 | Plant (macroalga, *Caulerpa taxifolia)* | 1 | Mediterranean sea | Yes (confidence intervals) | Non-spatial, discrete, linear model to describe the increase in area covered by patches of an invader | Y/Y/Y/N/N | $X_{j,t+1} = f_X(X_{j,t}, r, \sigma_e)$<br>$Q_t = \sum_j X_{j,t}$<br>$Z = \sum_i pr(\lambda_A) O(Q_t)$ | We use X for Area infested, O for fragments as a function of area and pr(IA) for probability of a given individual reattaching |
| 192 | Ruesink 2005 | Freshwater fishes | 1 pathway (establishment) / 200 species | Global | Yes (model evaluation with independent data) | Multiple logistic regression and tree classifications to explore four classes of predictor variables (species traits, environmental traits, match between species and environment, and propagule pressure) susceptible to explain the risk of establishment | N/Y/N/N/N | $Z = P^C = f(E_1 + E_2 ... + S_1 + S_2 ... + v_1 + v_2 ...)$ | Linear models. All information at the country level. v are reasons for introduction (i.e., pathways such as use in fisheries, etc). Not spatially explicit |

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| 193 | Sahlin et al. 2011 | Plants | 113 | Europe | Yes (Bayesian posterior distributions) | Using Bayesian analysis to assess the cost-benefit of invasive species screening based on traits | N/Y/N/N/N | $Z = P^c = f_{P^c}(S)$ | Exclude - main point is base-rate (which we can reference), but mapping will not reflect any of this |
| 194 | Sato et al. 2010 | Fish (*Opsariichthys uncirostris uncirostris* ) | 1 | Japan | Yes (AUC) | Species distribution model calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 195 | Sebert-Cuvillier et al. 2007 | Plant (American black cherry, *Prunus serotina Ehrh.)* | 1 | Global | Yes (standard error or amount of explained variation applied to the fitted model) | Stage-classified matrix population model describing its population dynamics at the local scale, i.e., within a forest stand, integrating environmental stochasticity | N/N/Y/N/N | $Z = X_{i,t+1} = f_X(X_{i,t}, r, \kappa, \sigma_e)$ | Stage based model, only mapping presented. Environment considered in terms of stochasticity |
| 196 | Shah et al. 2012 | Plants | 88 | Kashmir Himalya | Yes (r^2) | Model assessing species invasiveness from native range size | N/N/N/Y/N | $Z = Q = f(S)$ | S is how widespread it is in native range |
| 197 | Sharma et al. 2009 | Fish | 1 | Canada | Yes (standard errors/r^2) | Classification tree analysis for introduction, stepwise multiple logistic regression models for establishment and native species occurrence in lakes with risk of invasion | Y/Y/N/N/Y | $Z = \sum_{i=1}^{L} f(V_i) * pr(\lambda_C \mid E_i) * f_I(E_i)$ | Vproxy was human population size, and lake area. Impact - biotic environment - occurrence of species of interest. Multiplied 2 processes based on same data, but fitted independently |
| 198 | Siesa et al. 2011 | Mollusc (crayfish, *Procambarus clarkii)* | 1 | Lombardy, northern Italy | Yes (r^2) | Species distribution model using occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 199 | Skarpaas & Okland 2009 | Invertebrate (European spruce bark beetle) | 1 | Europe | Yes (sensitivity analysis) | Generic model for the first step of the invasion process for trade-imported pests, with an additional development to assess the risk of introductions and alternative management options | N/N/Y/Y/N | $X_{j,t+1} = f_X(X_{j,t}, r, \kappa(V_{j,t}), e(X_{j,t}), I(O * V_{j,t}))$ $Z = N_{i,t} = f_{XD}(X_{j,t}) f_D(D_{i,j})$ | Also looked at management effects (but not costs) by modifying parameters (not mapped). Here V (timber imports) is also the habitat. E is the emigration rate, and I is the immigration (propagule pressure here). O is the natural pest density in wood. Special case because vector is also habitat |
| 200 | Speek et al. 2011 | Plants | 111 | The Netherlands | Yes (r^2) | Use of plant traits, origin and human uses as predictors of regional and local frequency | N/Y/Y/N/N | $Z = P^c = \sum_{i=1}^{L} f_{P^c}(S, v, t)$ $Z = \overline{X} = \sum_{i=1}^{L} f_X(S, t)$ | Dominance not abundance - not sure how to deal with relative nature. T- period of naturalizatino time. Human use (yes/no) denoted as a pathway of introduction v |
| 201 | Spens et al. 2007 | Fish (northern pike, *Esox lucius)* | 1 | Northern boreal region of Sweden | Yes (misspecification error rates) | Connectivity model considering dispersal barriers | Y/N/N/N/N | $Z = N = f(E)$ | E are connectivity related measures, surrogates of propagule pressure |
| 202 | Stanaway et al. 2011 | Insect (whitefly) | 1 | Australia | Yes (Bayesian posterior distributions) | Gravity model to predict spread on plants | Y/Y/N/N/N | $N_{i,t} = \alpha \sum_{j=1}^{L} O(X_j) * V_{i,j,t}$ $P_{i,T}^A = 1 - \prod_{t=1}^{T} (1 - pr(\lambda_A))^{N_{i,t}^P}$ $Z_T = Q_T = \sum_{i=1}^{L} P^A_{i,T}$ | Also looked at detection (observation) error. - look at stochasticity? |
| 203 | Stephens et al. 2007 | Insect (oriental fruit fly, *Bactrocera dorsalis)* | 1 | Global | Yes (misspecification error rates) | Species distribution model calibrated with occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 204 | Stohlgren et al. 2010 | Plants (*Linaria dalmatica, Carduus nutans, Bromus tectorum, Melilotus officianalis* ) | 4 | USA (Yellowstone and Grand Teton National Parks, Wyoming; Sequoia and Kings Canyon National Parks, California, and areas of interior Alaska) | Yes (spatial variability and parameter uncertainty via Bayesian methods; model uncertainty via ensemble models. Validation data sets also used) | Species distribution model calibrated with occurrence data and various predictors related to topography, climate and vegetation | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | Species Distribution Models . Many different techniques (e.g., Maxent, GARP, Neural Networks). Implicitly assume equilibrium conditions, but see models in Leung & Mandrak (2007) and Williams et al (2008) for improvements. 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 Jiménez-Valverde et al. 2011) |
| 205 | Strubbe et al. 2010 | Alein bird (ringnecked parakeets *Psittacula krameri) and native bird (* nuthatches *Sitta europaea)* | 2 | Belgium, Brussel | Yes (AUC and cross-validation) | Abundance data using boosted regression trees. Biotic interaction considered in the model | N/N/Y/N/Y | $X_i = f_X(E_i)$ $Z = \sum_{i=1}^{L} f_I(X_i, E_i)$ | |
| 206 | Sutherst & Maywald 2005 | Insect (Red imported fire ant, *Solenopsis invicta)* | 1 | USA, Australia and New Zealand | Yes (misspecification error rates) | Species distribution model calibrated with occurrence data, considered nonclimatic factors | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 207 | Sutherst et al. 2007 | Insect (ticks: *Boophilus microplus, Boophilus decolloratus;* fruit fly: *Ceratitis capitata, Bactrocera tryoni)* | 1 | Australia, Africa | Yes (standard deviation) | Species distribution model calibrated with occurrence data, considered species interactions | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 208 | Therriault & Herborg 2008 | Tunicate (*Ciona intestinalis)* | 1 | Canada | Yes (hierarchical partitioning and AUC) | Species distribution model calibrated with occurrence data and two environmental variables (temperature and salinity tolerances) | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 209 | Thuiller et al. 2005 | Plants (*Carpobrotus edulis, Senecio glastifolius, Vellereophyton dealbatum*) | 3 | Global | Yes (AUC) | Species distribution model calibrated with occurrence data, considered propagule pressure (trade and tourisem as a proxy) | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i, f(V))$ | |
| 210 | Thuiller et al. 2006 | Plants | +500 | South Africa | Yes (explained variance) | Joint species trait-environmental model that explains the spatial patterns of invasive plants using a multivariate method (predictors considered related to land use, life-history traits, residence time, origin and human usage) | N/Y/N/N/N | $pr(\lambda_{C2} \mid E_i, S) = f(E_{i,1} + E_{i,2} ... + S_{i,1} + S_{i,2} ...)$ $Z = \sum_{i=1}^{L} pr(\lambda_{C2} \mid E_i, S)$ | Incorporates both species traits and environmental suitabilities, simultaneously. Has only been done using linear models. Standard errors also provided, but not on validation set |
| 211 | Trethowan et al. 2011 | Plant (Pompom weed, *Campuloclinium macrocephalum)* and biological control agents (*Liothrips tractabilis and Cochylis campuloclinium)* | 3 | South Africa | Yes (AUC and misspecification error rates) | Species distribution model calibrated using occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 212 | Trnka et al. 2007 | Insect (European corn borer, *Ostrinia nubilalis, Hubner)* | 1 | Global | Yes (misspecification error rates) | Multi-generational phenology model based on occurrence data. | N/N/Y/N/N | $Z = f_x(E)$ | E is degree days - looked at development times rather than populations per se. Not sure about dynamical aspect fo model. Not sure where multi-generational component comes in |
| 213 | Vaclavik & Meentemeyer 2012 | Plant pathogen *(Phytophthora ramorum)* | 1 | Western USA | Yes (AUC and standard deviation using jackknife cross-validation) | Potential distribution at different stages of invasion using occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i, t)$ | By stages he means time since invasion or nearness to equilibrium (denoted as t). - testing the issue of equilibrium distributions in SDMs |
| 214 | Vall-llosera & Sol 2009 | Birds | 202 | Global | Yes (misspecification error rates) | Generalized linear mixed models and hierarchical tree models to be used with occurrence and introduction data | N/Y/N/N/N | $Z = P^c = f_{P^c}(S, N)$ | Actual info on propagule size, in addition to species traits |
| 215 | van klinken et al. 2009 | Plants *(Parkinsonia aculeata)* | 1 | Australia | Yes (sensitivity analysis and r^2) | Species distribution model calibrated using both occurrence and abundance data | N/Y/Y/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i) f_X(E_i)$ | |
| 216 | van Wilgen et al. 2009 | Reptile and amphibians | 67 | USA (California and Florida) | Yes (AUC, kappa and misspecification error rates) | Climate matching model calibrated using occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |

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| 217 | Vanderhood et al. 2009 | Plants (Pepperweed, *Lepidium latifolium)* | 1 | USA (California) | Yes (likelihood ratio, Nagelkerke r^2, Hosmer and Lemeshow goodness of fit, % absent classified correctly, % present classified correctly) | Species distribution model calibrated using occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 218 | Veale et al. 2012 | Mammals (stoats, *Mustela ermine)* | 1 | New Zealand | Yes (AUC) | Species distribution model calibrated using occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 219 | Venette & Cohen 2006 | Plant pathogen *(Phytophthora ramorum)* | 1 | USA | Yes (sensitivity analysis and misspecification error rates) | Species distribution model calibrated using occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 220 | Verling et al. 2005 | Zooplankton | +1 | USA | Yes (standard errors) | Vector traffic model that does not simply estimate propagule pressure from total ship arrivals. Significant differences exist in (i) the frequency and volume of ballast water discharge among vessel types, (ii) the frequency of vessel types and routes (source regions) among recipient ports, and (iii) the transit success (survivorship) of zooplankton in ballast tanks among voyage routes, | Y/N/N/N/N | $Z = N = \sum_{i=1}^{L} \sum_{j=1}^{I_i} \sum_{k=1}^{V_{i,j,t}} f_g(t-t') * pr(R \mid v)$ | Uses amount of anthropogenic traffic in a pathway (ballast water) as a metric of risk. Takes into account mortality depending on source, and hence time. Also takes into account different releases of ballast water depending on vector (ship) type, with the assumption that ballast volume released relates to propagule pressure. The amount and type of traffic V also differs to destinations, and this is implicitly captured in different values of Vi,j,k. and pr(R\|v) which is specific to a given vector. No knowledge of uptake, or variability |
| 221 | Vicente et al. 2011 | Native plant (*Ruscus aculeatus L)* and introduced plant *(Acacia dealbata)* | 2 | North-West of portugal | Yes (AUC and cross-validation) | Species distribution model calibrated using occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 222 | Villemant et al. 2011 | Insect (Asian bee-hawking hornet, *Vespa velutina nigrithorax)* | 1 | South-Western France | Yes (AUC and cross-validation) | Species distribution models calibrated using occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 223 | Wang & Jackson 2011 | Crustacean (*Bythotrephes longimanus)* | 1 | Canada (Ontario) | Yes (AUC and cross-validation) | Species distribution models calibrated using occurrence data, considered biotic interactions with predators | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 224 | | Plants (*Buddleja davidii* ) | 1 | New Zealand | Yes (model evaluation with independent data) | Parameters from current species distribution were used to predict future distribution under climate change | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 225 | Watt et al. 2008 | Plant (broad-leaved paperbark, *Melaleuca quinquenervia* ) | 1 | Global | Yes (misspecification error rates) | Species distribution model calibrated using occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 226 | Watt et al. 2011 | Fungi (*Phaeocryptopus gaeumannii)* and plant *(D* ouglas-fir, *Pseudotsuga menziesii)* | 2 | New Zealand | Yes (misspecification error rates) | Species distribution model calibrated using occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 227 | Welk et al. 2002 | Plant (garlic mustard, *Alliaria petiolata)* | 1 | North America | Yes (Jaccard index and misspecification error rates) | Climate matching model calibrated using occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 228 | Williams et al. 2008 | Plant (orange hawkweed, *Hieracium aurantiacum)* | 1 | Australia | Yes (probabilities are stochastic. Uncertainty examined using hindcasts) | Dispersal constrained habitat suitability model that combines a habitat suitability index (developed from disturbance, site wetness and vegetation community parameters) with a phenomenological dispersal kernet that uses wind direction and observed dispersal distances | N/Y/N/Y/N | $N_{i,t} = \sum_{j=1}^{J} f_D(D_{i,j}, E)$ <br> $Z = P_T^A = \sum_j pr(\lambda_C \mid E_i) * pr(N_{i,t} > threshold)$ | Uses dispersal kernel for probability of reaching an area in combination with habitat suitability. Like model 7, does not require equilibrium. Does not consider propagule pressure versus establishment relation. Here J are occupied sources, which result in temporal dynamics |
| 229 | Wilson et al. 2009 | Fish | 2 | USA | Yes (standard errors/r^2) | Mayfield logistic regression on temperature variables and species traits (strain and mass-lenght ratio) on dayly survival as a proxy for establishment success | N/Y/N/N/N | $Z = pr(\lambda_{C2} \mid E_i, S) = f(E_{i,1} + E_{i,2} ... + S_{i,1} + S_{i,2} ...)$ | Purely experimental, and looks at survival only |
| 230 | Wu et al. 2010 | Mollusc (zebra mussel, *Dreissena polymorpha)* | 1 | USA (Wisconsin) | Yes (misspecification error rates) | Risk-based decision model based on occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | E was the habitat suitability index (HIS). Paper presented conceptual demographic model as well with management (CASM), but results were all based on HIS analysis. Also, not enough info on CASM to map |
| 231 | Yan et al. 2006 | Plant (Pinus radiata) | 1 | Southwest China | Yes (misspecification error rates) | Climate matching model calibrated using occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 232 | Yemshanov et al. 2009 | Insect *(Sirex noctilio)* | 1 | Cross-border USA-Canada | Yes (misspecification error rates) | Bioeconomic Model based on occurrence and spread data. Propagule pressure considered | Y/Y/N/Y/Y | $N_t = \sum_{i=1} V_{i,t}$ <br> $P_{i,t}^{A2} = f_D(D_i)$ <br> $Z = \sum_{t1=1}^{T} f(N_{t1}) \sum_{t2=1}^{T-t1} \sum_i (P_{i,t2}^{A2} - P_{i,t2-1}^{A2}) * f_I(E_i)$ | N used shipping as a proxy. N was rescaled to be a probability. Pr(IA) was dependent on distance (D) to closest source only. fI was dependent on host (Pine) characteristics, and climate. Combination of factors not explicit and was assumed. Time elements not indicated either, and assumed |
| 233 | Zalba et al. 2000 | Plant (old man saltbush, *Atriplex nummularia)* | 1 | Argentina (Buenos Aires) | No | Species distribution model based on occurrence data and considering species germination, establishment, growth and reproduction. | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i, S)$ | |
| 234 | Zenni et al. 2009 | Plant (Kangaroo thorn, *Acacia paradoxa)* | 1 | South Africa | Yes (AUC and misspecification error rates) | Species distribution model calibrated using occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 235 | Zhu et al. 2012 | Insect (Brown marmorated stink bug invasion, *Halyomorpha halys)* | 1 | Global | Yes (cross-validation, AUC and binary omission rate) | Species distribution model for both native and exotic species calibrated using occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |
| 236 | Zimmermann et al. 2011 | Plant (*Rosa rubiginosa)* | 1 | Southern Argentina | Yes (AUC and explained variance) | Species distribution model calibrated using occurrence data | N/Y/N/N/N | $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$ | |

**Appendix 2. References**


1

Ahrens C., Chung J., Meyer T. & Auer C. (2011). Bentgrass distribution surveys and habitat suitability maps support ecological risk assessment in cultural landscapes. *Weed Science*, 59, 145-154.

2

Allen Y.C. & Ramcharan C.W. (2001). *Dreissena* distribution in commercial waterways of the US: using failed invasions to identify limiting factors. *Canadian Journal of Fisheries and Aquatic Sciences*, 58, 898-907.

3

Andrew M.E. & Ustin S.L. (2010). The effects of temporally variable dispersal and landscape structure on invasive species spread. *Ecological Applications*, 20, 593-608.

4

Aragon P. & Lobo J.M. (2012). Predicted effect of climate change on the invasibility and distribution of the Western corn root-worm. *Agricultural and Forest Entomology*, 14, 13-18.

5

Arriaga L., Castellanos A.E., Moreno E. & Alarcon J. (2004). Potential ecological distribution of alien invasive species and risk assessment: a case study of buffel grass in arid regions of Mexico. *Conservation Biology*, 18, 1504-1514.

6

Ba J.W., Hou Z.E., Platvoet D., Zhu L. & Li S.Q. (2010). Is *Gammarus tigrinus* (Crustacea, Amphipoda) becoming cosmopolitan through shipping? Predicting its potential invasive range using ecological niche modeling. *Hydrobiologia*, 649, 183-194.

7

Barney J.N. & DiTomaso J.M. (2010). Bioclimatic predictions of habitat suitability for the biofuel switchgrass in North America under current and future climate scenarios. *Biomass & Bioenergy*, 34, 124-133.

8

Bartell S.M. & Nair S.K. (2004). Establishment risks for invasive species. *Risk Analysis*, 24, 833-845.

9

Beaumont L.J., Gallagher R.V., Downey P.O., Thuiller W., Leishman M.R. & Hughes L. (2009). Modelling the impact of *Hieracium spp*. on protected areas in Australia under future climates. *Ecography*, 32, 757-764.

10

Bomford M., Barry S.C. & Lawrence E. (2010). Predicting establishment success for introduced freshwater fishes: a role for climate matching. *Biological Invasions*, 12, 2559-2571.

11

Bomford M., Kraus F., Barry S.C. & Lawrence E. (2009). Predicting establishment success for alien reptiles and amphibians: a role for climate matching. *Biological Invasions*, 11, 713-724.

12

Bourchier R.S. & Van Hezewijk B.H. (2010). Distribution and Potential Spread of Japanese Knotweed (*Polygonum cuspidatum*) in Canada Relative to Climatic Thresholds. *Invasive Plant Science and Management*, 3, 32-39.

13

Bradley B.A. (2009). Regional analysis of the impacts of climate change on cheatgrass invasion shows potential risk and opportunity. *Global Change Biology*, 15, 196-208.
14
Bradley B.A. (2010). Assessing ecosystem threats from global and regional change: hierarchical modeling of risk to sagebrush ecosystems from climate change, land use and invasive species in Nevada, USA. *Ecography*, 33, 198-208.
15
Bradley B.A., Wilcove D.S. & Oppenheimer M. (2010). Climate change increases risk of plant invasion in the Eastern United States. *Biological Invasions*, 12, 1855-1872.
16
Bradley B.A. & Mustard J.F. (2006). Characterizing the landscape dynamics of an invasive plant and risk of invasion using remote sensing. *Ecological Applications*, 16, 1132-1147.
17
Bradshaw C.J.A., Giam X.L., Tan H.T.W., Brook B.W. & Sodhi N.S. (2008). Threat or invasive status in legumes is related to opposite extremes of the same ecological and life-history attributes. *Journal of Ecology*, 96, 869-883.
18
Brickman D. (2006). Risk assessment model for dispersion of ballast water organisms in shelf seas. *Canadian Journal of Fisheries and Aquatic Sciences*, 63, 2748-2759.
19
Broennimann O., Treier U.A., Muller-Scharer H., Thuiller W., Peterson A.T. & Guisan A. (2007). Evidence of climatic niche shift during biological invasion. *Ecology Letters*, 10, 701-709.
20
Brooks C.P., Ervin G.N., Varone L. & Logarzo G.A. (2012). Native ecotypic variation and the role of host identity in the spread of an invasive herbivore, *Cactoblastis cactorum*. *Ecology*, 93, 402-410.
21
Buckley Y.M., Brockerhoff E., Langer L., Ledgard N., North H. & Rees M. (2005). Slowing down a pine invasion despite uncertainty in demography and dispersal. *Journal of Applied Ecology*, 42, 1020-1030.
22
Carrasco L.R., Mumford J.D., MacLeod A., Harwood T., Grabenweger G., Leach A.W., Knight J.D. & Baker R.H.A. (2010a). Unveiling human-assisted dispersal mechanisms in invasive alien insects: Integration of spatial stochastic simulation and phenology models. *Ecological Modelling*, 221, 2068-2075.
23
Carrasco L.R., Mumford J.D., MacLeod A., Knight J.D. & Baker R.H.A. (2010b). Comprehensive bioeconomic modelling of multiple harmful non-indigenous species. *Ecological Economics*, 69, 1303-1312.
24
Carrasco M.F. & Baron P.J. (2010). Analysis of the potential geographic range of the Pacific oyster *Crassostrea gigas* (Thunberg, 1793) based on surface seawater temperature satellite data and climate charts: the coast of South America as a study case. *Biological Invasions*, 12, 2597-2607.
25

Carrete M. & Tella J.L. (2008). Wild-bird trade and exotic invasions: a new link of conservation concern? *Frontiers in Ecology and the Environment*, 6, 207-211.
26
Castro-Diez P., Godoy O., Saldana A. & Richardson D.M. (2011). Predicting invasiveness of Australian acacias on the basis of their native climatic affinities, life history traits and human use. *Diversity and Distributions*, 17, 934-945.
27
Catford J.A., Vesk P.A., White M.D. & Wintle B.A. (2011). Hotspots of plant invasion predicted by propagule pressure and ecosystem characteristics. *Diversity and Distributions*, 17, 1099-1110.
28
Catterall S., Cook A.R., Marion G., Butler A. & Hulme P.E. (2011). Accounting for uncertainty in colonisation times: a novel approach to modelling the spatio- temporal dynamics of alien invasions using distribution data. *Ecography*.
29
Chen Y.H. (2008). Global potential distribution of an invasive species, the yellow crazy ant (*Anoplolepis gracilipes*) under climate change. *Integrative Zoology*, 3, 166-175.
30
Chown S.L., Huiskes A.H.L., Gremmen N.J.M., Lee J.E., Terauds A., Crosbie K., Frenot Y., Hughes K.A., Imura S., Kiefer K., Lebouvier M., Raymond B., Tsujimoto M., Ware C., Van de Vijver B. & Bergstrom D.M. (2012). Continent-wide risk assessment for the establishment of nonindigenous species in Antarctica. *Proceedings of the National Academy of Sciences of the United States of America*, 109, 4938-4943.
31
Chytry M., Pysek P., Wild J., Pino J., Maskell L.C. & Vila M. (2009). European map of alien plant invasions based on the quantitative assessment across habitats. *Diversity and Distributions*, 15, 98-107.
32
Claudi R. & Ravishankar T.J. (2006). Quantification of risks of alien species introductions associated with ballast water discharge in the Gulf of St. Lawrence. *Biological Invasions*, 8, 25-44.
33
Cohen J., Mirotchnick N. & Leung B. (2007). Thousands introduced annually: the aquarium pathway for non-indigenous plants to the St Lawrence Seaway. *Frontiers in Ecology and the Environment*, 5, 528-532.
34
Colnar A.M. & Landis W.G. (2007). Conceptual model development for invasive species and a regional risk assessment case study: The European green crab, *Carcinus maenas*, at Cherry Point, Washington, USA. *Human and Ecological Risk Assessment*, 13, 120-155.
35
Colunga-Garcia M., Haack R.A. & Adelaja A.O. (2009). Freight Transportation and the Potential for Invasions of Exotic Insects in Urban and Periurban Forests of the United States. *Journal of Economic Entomology*, 102, 237-246.
36
Compton T.J., de Winton M., Leathwick J.R. & Wadhwa S. (2012). Predicting spread of invasive macrophytes in New Zealand lakes using indirect measures of human accessibility. *Freshwater Biology*, 57, 938-948.

37
Cooke S.L. & Hill W.R. (2010). Can filter-feeding Asian carp invade the Laurentian Great Lakes? A bioenergetic modelling exercise. *Freshwater Biology*, 55, 2138-2152.
38
Copp G.H., Vilizzi L. & Gozlan R.E. (2010). The demography of introduction pathways, propagule pressure and occurrences of non-native freshwater fish in England. *Aquatic Conservation-Marine and Freshwater Ecosystems*, 20, 595-601.
39
Cordell J.R., Tear L.M. & Bollens S.M. (2010). Modelling physico-chemical factors affecting occurrences of a non-indigenous planktonic copepod in northeast Pacific estuaries. *Biological Invasions*, 12, 1427-1445.
40
Costello C., Springborn M., McAusland C. & Solow A. (2007). Unintended biological invasions: Does risk vary by trading partner? *Journal of Environmental Economics and Management*, 54, 262-276.
41
Cotner L.A. & Schooley R.L. (2011). Habitat Occupancy by Riparian Muskrats Reveals Tolerance to Urbanization and Invasive Vegetation. *Journal of Wildlife Management*, 75, 1637-1645.
42
Crossman N.D. & Bass D.A. (2008). Application of common predictive habitat techniques for post-border weed risk management. *Diversity and Distributions*, 14, 213-224.
43
Crossman N.D., Bryan B.A. & Cooke D.A. (2011). An invasive plant and climate change threat index for weed risk management: Integrating habitat distribution pattern and dispersal process. *Ecological Indicators*, 11, 183-198.
44
Dangles O., Carpio C., Barragan A.R., Zeddam J.L. & Silvain J.F. (2008). Temperature as a key driver of ecological sorting among invasive pest species in the tropical Andes. *Ecological Applications*, 18, 1795-1809.
45
Davis P.B., Menalled F.D., Peterson R.K.D. & Maxwell B.D. (2011). Refinement of weed risk assessments for biofuels using *Camelina sativa* as a model species. *Journal of Applied Ecology*, 48, 989-997.
46
Dawson W., Burslem D.F.R.P. & Hulme P.E. (2009). Factors explaining alien plant invasion success in a tropical ecosystem differ at each stage of invasion. *Journal of Ecology*, 97, 657-665.
47
De Meyer M., Robertson M.P., Peterson A.T. & Mansell M.W. (2008). Ecological niches and potential geographical distributions of Mediterranean fruit fly (*Ceratitis capitata*) and Natal fruit fly (*Ceratitis rosa*). *Journal of Biogeography*, 35, 270-281.
48
Denslow J.S., Space J.C. & Thomas P.A. (2009). Invasive Exotic Plants in the Tropical Pacific Islands: Patterns of Diversity. *Biotropica*, 41, 162-170.
49

DeVaney S.C., McNyset K.M., Williams J.B., Peterson A.T. & Wiley E.O. (2009). A Tale of Four "Carp": Invasion Potential and Ecological Niche Modeling. *Plos One*, 4.
50
Diez J.M., Hulme P.E. & Duncan R.P. (2012). Using prior information to build probabilistic invasive species risk assessments. *Biological Invasions*, 14, 681-691.
51
Dorcas M.E., Willson J.D. & Gibbons J.W. (2011). Can invasive Burmese pythons inhabit temperate regions of the southeastern United States? *Biological Invasions*, 13, 793-802.
52
Drake J.M. (2005a). Risk analysis for invasive species and emerging infectious diseases: Concepts and applications. *American Midland Naturalist*, 153, 4-19.
53
Drake J.M. & Lodge D.M. (2004). Global hot spots of biological invasions: Evaluating options for ballast–water management. *Proceedings of the Royal Society of London. Series B: Biological Sciences*, 271, 575-580.
54
Drake J.M., Lodge D.M. & Lewis M. (2005). Theory and preliminary analysis of species invasions from ballast water: Controlling discharge volume and location. *American Midland Naturalist*, 154, 459-470.
55
Duggan I.C., Rixon C.A.M. & MacIsaac H.J. (2006). Popularity and propagule pressure: determinants of introduction and establishment of aquarium fish. *Biological Invasions*, 8, 377-382.
56
Epanchin-Niell R., Englin J. & Nalle D. (2009). Investing in rangeland restoration in the Arid West, USA: Countering the effects of an invasive weed on the long-term fire cycle. *Journal of Environmental Management*, 91, 370-379.
57
Essl F., Moser D., Dullinger S., Mang T. & Hulme P.E. (2010). Selection for commercial forestry determines global patterns of alien conifer invasions. *Diversity and Distributions*, 16, 911-921.
58
Fabregas M.C., Guillen-Salazar F. & Garces-Narro C. (2010). The risk of zoological parks as potential pathways for the introduction of non-indigenous species. *Biological Invasions*, 12, 3627-3636.
59
Ficetola G.F., Thuiller W. & Miaud C. (2007). Prediction and validation of the potential global distribution of a problematic alien invasive species - the American bullfrog. *Diversity and Distributions*, 13, 476-485.
60
Fitzpatrick M.C., Preisser E.L., Porter A., Elkinton J. & Ellison A.M. (2012). Modeling range dynamics in heterogeneous landscapes: invasion of the hemlock woolly adelgid in eastern North America. *Ecological Applications*, 22, 472-486.
61
Floerl O., Inglis G.J. & Hayden B.J. (2005). A risk-based predictive tool to prevent accidental introductions of nonindigenous marine species. *Environmental Management*, 35, 765-778.

62
Floyd M.L., Hanna D., Romme W.H. & Crews T.E. (2006). Predicting and mitigating weed invasions to restore natural post-fire succession in Mesa Verde National Park, Colorado, USA. *International Journal of Wildland Fire*, 15, 247-259.
63
Follak S. (2011). Potential distribution and environmental threat of Pueraria lobata. *Central European Journal of Biology*, 6, 457-469.
64
Follak S. & Strauss G. (2010). Potential distribution and management of the invasive weed *Solanum carolinense* in Central Europe. *Weed Research*, 50, 544-552.
65
Forsyth D.M., Duncan R.P., Bomford M. & Moore G. (2004). Climatic suitability, life-history traits, introduction effort, and the establishment and spread of introduced mammals in Australia. *Conservation Biology*, 18, 557-569.
66
Foxcroft L.C., Rouget M. & Richardson D.M. (2007). Risk assessment of riparian plant invasions into protected areas. *Conservation Biology*, 21, 412-421.
67
Frank K.L., Geils B.W., Kalkstein L.S. & Thistle H.W. (2008). Synoptic climatology of the long-distance dispersal of white pine blister rust II. Combination of surface and upper-level conditions. *International Journal of Biometeorology*, 52, 653-666.
68
Fujisaki I., Hart K.M., Mazzotti F.J., Rice K.G., Snow S. & Rochford M. (2010). Risk assessment of potential invasiveness of exotic reptiles imported to south Florida. *Biological Invasions*, 12, 2585-2596.
69
Gassó N., Sol D., Pino J., Dana E.D., Lloret F., Sanz‐Elorza M., Sobrino E. & Vilà M. (2009). Exploring species attributes and site characteristics to assess plant invasions in Spain. *Diversity and Distributions*, 15, 50-58.
70
Gertzen E., Familiar O. & Leung B. (2008). Quantifying invasion pathways: fish introductions from the aquarium trade. *Canadian Journal of Fisheries and Aquatic Sciences*, 65, 1265-1273.
71
Gertzen E., Leung B. & Yan N. (2011). Propagule pressure, Allee effects and the probability of establishment of an invasive species (*Bythotrephes longimanus*). *Ecosphere*, 2.
72
Gertzen E.L. & Leung B. (2011). Predicting the spread of invasive species in an uncertain world: accommodating multiple vectors and gaps in temporal and spatial data for *Bythotrephes longimanus*. *Biological Invasions*, 13, 2433-2444.
73
Gevrey M., Worner S., Kasabov N., Pitt J. & Giraudel J.L. (2006). Estimating risk of events using SOM models: A case study on invasive species establishment. *Ecological Modelling*, 197, 361-372.
74

Gillham J.H., Hild A.L., Johnson J.H., Hunt E.R. & Whitson T.D. (2004). Weed Invasion Susceptibility Prediction (WISP) model for use with geographic information systems. *Arid Land Research and Management*, 18, 1-12.

75

Glardon C.G., Walters L.J., Quintana-Ascencio P.F., McCauley L.A., Stam W.T. & Olsen J.L. (2008). Predicting risks of invasion of macroalgae in the genus *Caulerpa* in Florida. *Biological Invasions*, 10, 1147-1157.

76

Goodwin B.K. & Piggott N.E. (2009). Spatiotemporal modeling of Asian citrus canker risks: implications for insurance and indemnification fund models. *American Journal of Agricultural Economics*, 91, 1038-1055.

77

Goslee S.C., Beck K.G. & Peters D.P.C. (2003). Distribution of Russian knapweed in Colorado: climate and environmental factors. *Journal of Range Management*, 56, 206-212.

78

Goslee S.C., Peters D.P.C. & Beck K.G. (2006). Spatial prediction of invasion success across heterogeneous landscapes using an individual-based model. *Biological Invasions*, 8, 193-200.

79

Gravuer K., Sullivan J.J., Williams P.A. & Duncan R.P. (2008). Strong human association with plant invasion success for *Trifolium* introductions to New Zealand. *Proceedings of the National Academy of Sciences of the United States of America*, 105, 6344-6349.

80

Gray D.R. (2010). Hitchhikers on trade routes: A phenology model estimates the probabilities of gypsy moth introduction and establishment. *Ecological Applications*, 20, 2300-2309.

81

Gross J.E. (2001). Evaluating effects of an expanding mountain goat population on native bighorn sheep: a simulation model of competition and disease. *Biological Conservation*, 101, 171-185.

82

Haight R.G., Homans F.R., Horie T., Mehta S.V., Smith D.J. & Venette R.C. (2011). Assessing the Cost of an Invasive Forest Pathogen: A Case Study with Oak Wilt. *Environmental Management*, 47, 506-517.

83

Hallstan S., Grandin U. & Goedkoop W. (2010). Current and modeled potential distribution of the zebra mussel (*Dreissena polymorpha*) in Sweden. *Biological Invasions*, 12, 285-296.

84

Hamilton M.A., Murray B.R., Cadotte M.W., Hose G.C., Baker A.C., Harris C.J. & Licari D. (2005). Life history correlates of plant invasiveness at regional and continental scales. *Ecology Letters*, 8, 1066-1074.

85

Hanson E. & Sytsma M. (2008). The potential for mitten crab *Eriocheir sinensis* H. Milne Edwards, 1853 (Crustacea : Brachyura) invasion of Pacific Northwest and Alaskan estuaries. *Biological Invasions*, 10, 603-614.

86

Harris R.J. & Barker G. (2007). Relative risk of invasive ants (Hymenoptera: Formicidae) establishing in New Zealand. *New Zealand Journal of Zoology*, 34, 161-178.

87
Hartley S., Harris R. & Lester P.J. (2006). Quantifying uncertainty in the potential distribution of an invasive species: climate and the Argentine ant. *Ecology Letters*, 9, 1068-1079.
88
Henderson W., Bomford M. & Cassey P. (2011). Managing the risk of exotic vertebrate incursions in Australia. *Wildlife Research*, 38, 501-508.
89
Herbert R.J.H., Willis J., Jones E., Ross K., Huebner R., Humphreys J., Jensen A. & Baugh J. (2012). Invasion in tidal zones on complex coastlines: modelling larvae of the non-native Manila clam, *Ruditapes philippinarum*, in the UK. *Journal of Biogeography*, 39, 585-599.
90
Herborg L.M., Jerde C.L., Lodge D.M., Ruiz G.M. & MacIsaac H.J. (2007). Predicting invasion risk using measures of introduction effort and environmental niche models. *Ecological Applications*, 17, 663-674.
91
Herborg L.M., O'Hara P. & Therriault T.W. (2009). Forecasting the potential distribution of the invasive tunicate *Didemnum vexillum*. *Journal of Applied Ecology*, 46, 64-72.
92
Herrera I., Hernandez M.J., Lampo M. & Nassar J.M. (2012). Plantlet recruitment is the key demographic transition in invasion by *Kalanchoe daigremontiana*. *Population Ecology*, 54, 225-237.
93
Hoddle M.S. (2004). The potential adventive geographic range of glassy-winged sharpshooter, *Homalodisca coagulata* and the grape pathogen *Xylella fastidiosa*: implications for California and other grape growing regions of the world. *Crop Protection*, 23, 691-699.
94
Hortal J., Borges P.A.V., Jimenez-Valverde A., de Azevedo E.B. & Silva L. (2010). Assessing the areas under risk of invasion within islands through potential distribution modelling: The case of *Pittosporum undulatum* in Sao Miguel, Azores. *Journal for Nature Conservation*, 18, 247-257.
95
Hyvonen T., Glemnitz M., Radics L. & Hoffmann J. (2011). Impact of climate and land use type on the distribution of Finnish casual arable weeds in Europe. *Weed Research*, 51, 201-208.
96
Ibanez I., Silander J.A., Allen J.M., Treanor S.A. & Wilson A. (2009). Identifying hotspots for plant invasions and forecasting focal points of further spread. *Journal of Applied Ecology*, 46, 1219-1228.
97
Inglis G.J., Hurren H., Oldman J. & Haskew R. (2006). Using habitat suitability index and particle dispersion models for early detection of marine invaders. *Ecological Applications*, 16, 1377-1390.
98
Jacobs M.J. & Macisaac H.J. (2009). Modelling spread of the invasive macrophyte *Cabomba caroliniana*. *Freshwater Biology*, 54, 296-305.
99

Jakubowski A.R., Casler M.D. & Jackson R.D. (2010). Landscape context predicts reed canary grass invasion: implications for management. *Wetlands*, 30, 685-692.
100
Jarosik V., Pysek P., Foxcroft L.C., Richardson D.M., Rouget M. & MacFadyen S. (2011). Predicting incursion of plant invaders into Kruger national park, South Africa: the interplay of general drivers and species-specific factors. *Plos One*, 6.
101
Jokela A. & Ricciardi A. (2008). Predicting zebra mussel fouling on native mussels from physicochemical variables. *Freshwater Biology*, 53, 1845-1856.
102
Jones C.C., Acker S.A. & Halpern C.B. (2010). Combining local- and large-scale models to predict the distributions of invasive plant species. *Ecological Applications*, 20, 311-326.
103
Kadoya T. & Washitani I. (2010). Predicting the rate of range expansion of an invasive alien bumblebee (Bombus terrestris) using a stochastic spatio-temporal model. *Biological Conservation*, 143, 1228-1235.
104
Kaiser B.A. & Burnett K.M. (2010). Spatial economic analysis of early detection and rapid response strategies for an invasive species. *Resource and Energy Economics*, 32, 566-585.
105
Keller R.P., Drake J.M. & Lodge D.M. (2007a). Fecundity as a basis for risk assessment of nonindigenous freshwater molluscs. *Conservation Biology*, 21, 191-200.
106
Keller R.P., Frang K. & Lodge D.M. (2008). Preventing the spread of invasive species: Economic benefits of intervention guided by ecological predictions. *Conservation Biology*, 22, 80-88.
107
Kelly M., Guo Q., Liu D. & Shaari D. (2007). Modeling the risk for a new invasive forest disease in the United States: An evaluation of five environmental niche models. *Computers Environment and Urban Systems*, 31, 689-710.
108
Kikillus K.H., Hare K.M. & Hartley S. (2010). Minimizing false-negatives when predicting the potential distribution of an invasive species: a bioclimatic envelope for the red-eared slider at global and regional scales. *Animal Conservation*, 13, 5-15.
109
Kilroy C., Snelder T.H., Floerl O., Vieglais C.C. & Dey K.L. (2008). A rapid technique for assessing the suitability of areas for invasive species applied to New Zealand's rivers. *Diversity and Distributions*, 14, 262-272.
110
Kimberling D.N. (2004). Lessons from history: predicting successes and risks of intentional introductions for arthropod biological control. *Biological Invasions*, 6, 301-318.
111
Kleinbauer I., Dullinger S., Peterseil J. & Essl F. (2010). Climate change might drive the invasive tree *Robinia pseudacacia* into nature reserves and endangered habitats. *Biological Conservation*, 143, 382-390.
112

Knowler D. & Barbier E. (2005). Importing exotic plants and the risk of invasion: are market-based instruments adequate? *Ecological Economics*, 52, 341-354.

113

Koch F.H., Yemshanov D., Colunga-Garcia M., Magarey R.D. & Smith W.D. (2011). Potential establishment of alien-invasive forest insect species in the United States: where and how many? *Biological Invasions*, 13, 969-985.

114

Koch F.H., Yemshanov D., Magarey R.D. & Smith W.D. (2012). Dispersal of invasive forest insects via recreational firewood: a quantitative analysis. *Journal of Economic Entomology*, 105, 438-450.

115

Kolar C.S. & Lodge D.M. (2002). Ecological predictions and risk assessment for alien fishes in North America. *Science*, 298, 1233-1236.

116

Konishi M., Sakano H. & Iguchi K. (2009). Identifying conservation priority ponds of an endangered minnow, *Pseudorasbora pumila*, in the area invaded by *Pseudorasbora parva*. *Ichthyological Research*, 56, 346-353.

117

Kraus F., Medeiros A., Preston D., Jarnevich C.S. & Rodda G.H. (2012). Diet and conservation implications of an invasive chameleon, *Chamaeleo jacksonii* (Squamata: Chamaeleonidae) in Hawaii. *Biological Invasions*, 14, 579-593.

118

Kriticos D.J., Sutherst R.W., Brown J.R., Adkins S.W. & Maywald G.F. (2003). Climate change and the potential distribution of an invasive alien plant: *Acacia nilotica ssp indica* in Australia. *Journal of Applied Ecology*, 40, 111-124.

119

Kueffer C., Daehler C.C., Torres-Santana C.W., Lavergne C., Meyer J.Y., Otto R. & Silva L. (2010). A global comparison of plant invasions on oceanic islands. *Perspectives in Plant Ecology Evolution and Systematics*, 12, 145-161.

120

Kulhanek S.A., Leung B. & Ricciardi A. (2011a). Using ecological niche models to predict the abundance and impact of invasive species: application to the common carp. *Ecological Applications*, 21, 203-213.

121

Kulhanek S.A., Ricciardi A. & Leung B. (2011b). Is invasion history a useful tool for predicting the impacts of the world's worst aquatic invasive species? *Ecological Applications*, 21, 189-202.

122

Küster E.C., Kühn I., Bruelheide H. & Klotz S. (2008). Trait interactions help explain plant invasion success in the German flora. *Journal of Ecology*, 96, 860-868.

123

Lambdon P.W. & Hulme P.E. (2006). Predicting the invasion success of Mediterranean alien plants from their introduction characteristics. *Ecography*, 29, 853-865.

124

Lambdon P.W., Lloret F. & Hulme P.E. (2008). How do introduction characteristics influence the invasion success of Mediterranean alien plants? *Perspectives in Plant Ecology Evolution and Systematics*, 10, 143-159.

125
Larson D.L., Anderson P.J. & Newton W. (2001). Alien plant invasion in mixed-grass prairie: Effects of vegetation type and anthropogenic disturbance. *Ecological Applications*, 11, 128-141.
126
Leung B., Bossenbroek J.M. & Lodge D.M. (2006). Boats, pathways, and aquatic biological invasions: Estimating dispersal potential with gravity models. *Biological Invasions*, 8, 241-254.
127
Leung B., Drake J.M. & Lodge D.M. (2004). Predicting invasions: Propagule pressure and the gravity of allee effects. *Ecology*, 85, 1651-1660.
128
Leung B., Lodge D.M., Finnoff D., Shogren J.F., Lewis M.A. & Lamberti G. (2002). An ounce of prevention or a pound of cure: bioeconomic risk analysis of invasive species. *Proceedings of the Royal Society of London Series B-Biological Sciences*, 269, 2407-2413.
129
Leung B. & Mandrak N.E. (2007). The risk of establishment of aquatic invasive species: joining invasibility and propagule pressure. *Proceedings of the Royal Society B-Biological Sciences*, 274, 2603-2609.
130
Liddle D.T., Brook B.W., Matthews J., Taylor S.M. & Caley P. (2006). Threat and response: A decade of decline in a regionally endangered rainforest palm affected by fire and introduced animals. *Biological Conservation*, 132, 362-375.
131
Lindgren C., Pearce C. & Allison K. (2010). The Biology of Invasive Alien Plants in Canada. 11. *Tamarix ramosissima* Ledeb., *T. chinensis* Lour. and hybrids. *Canadian Journal of Plant Science*, 90, 111-124.
132
Lippitt C.D., Rogan J., Toledano J., Saylgermano F., Eastmana J.R., Mastro V. & Sawyer A. (2008). Incorporating anthropogenic variables into a species distribution model to map gypsy moth risk. *Ecological Modelling*, 210, 339-350.
133
Liu X. & Li Y.M. (2009). Aquaculture enclosures relate to the establishment of feral populations of introduced species. *Plos One*, 4.
134
Liu X.A., Guo Z.W., Ke Z.W., Wang S.P. & Li Y.M. (2011). Increasing potential risk of a global aquatic invader in Europe in contrast to other continents under future climate change. *Plos One*, 6.
135
Logan J.A., Regniere J., Gray D.R. & Munson A.S. (2007). Risk assessment in the face of a changing environment: Gypsy moth and climate change in Utah. *Ecological Applications*, 17, 101-117.
136
Mandle L., Warren D.L., Hoffmann M.H., Peterson A.T., Schmitt J. & von Wettberg E.J. (2010). Conclusions about Niche Expansion in Introduced *Impatiens walleriana* Populations Depend on Method of Analysis. *Plos One*, 5.
137

Marchetti M.P., Moyle P.B. & Levine R. (2004). Invasive species profiling? Exploring the characteristics of non-native fishes across invasion stages in California. *Freshwater Biology*, 49, 646-661.

Maret T.J., Snyder J.D. & Collins J.P. (2006). Altered drying regime controls distribution of endangered salamanders and introduced predators. *Biological Conservation*, 127, 129-138.

Marini L., Haack R.A., Rabaglia R.J., Toffolo E.P., Battisti A. & Faccoli M. (2011). Exploring associations between international trade and environmental factors with establishment patterns of exotic Scolytinae. *Biological Invasions*, 13, 2275-2288.

Mason P.G., Weiss R.M., Olfert O., Appleby M. & Landry J.F. (2011). Actual and potential distribution of *Acrolepiopsis assectella* (Lepidoptera: Acrolepiidae), an invasive alien pest of *Allium spp*. in Canada. *Canadian Entomologist*, 143, 185-196.

Mau-Crimmins T.M., Schussman H.R. & Geiger E.L. (2006). Can the invaded range of a species be predicted sufficiently using only native-range data? Lehmann lovegrass (*Eragrostis lehmanniana*) in the southwestern United States. *Ecological Modelling*, 193, 736-746.

Medley K.A. (2010). Niche shifts during the global invasion of the Asian tiger mosquito, *Aedes albopictus Skuse* (Culicidae), revealed by reciprocal distribution models. *Global Ecology and Biogeography*, 19, 122-133.

Mika A.M. & Newman J.A. (2010). Climate change scenarios and models yield conflicting predictions about the future risk of an invasive species in North America. *Agricultural and Forest Entomology*, 12, 213-221.

Mika A.M., Weiss R.M., Olfert O., Hallett R.H. & Newman J.A. (2008). Will climate change be beneficial or detrimental to the invasive swede midge in North America? Contrasting predictions using climate projections from different general circulation models. *Global Change Biology*, 14, 1721-1733.

Miller A.W., Ruiz G.M., Minton M.S. & Ambrose R.F. (2007). Differentiating successful and failed molluscan invaders in estuarine ecosystems. *Marine Ecology-Progress Series*, 332, 41-51.

Miller T.K., Allen C.R., Landis W.G. & Merchant J.W. (2010). Risk assessment: Simultaneously prioritizing the control of invasive plant species and the conservation of rare plant species. *Biological Conservation*, 143, 2070-2079.

Mondor E.B., Tremblay M.N. & Messing R.H. (2007). Morphological and ecological traits promoting aphid colonization of the Hawaiian Islands. *Biological Invasions*, 9, 87-100.

Moore J.L., Rout T.M., Hauser C.E., Moro D., Jones M., Wilcox C. & Possingham H.P. (2010). Protecting islands from pest invasion: optimal allocation of biosecurity resources between quarantine and surveillance. *Biological Conservation*, 143, 1068-1078.

Muirhead J.R., Leung B., van Overdijk C., Kelly D.W., Nandakumar K., Marchant K.R. & MacIsaac H.J. (2006). Modelling local and long-distance dispersal of invasive emerald ash borer *Agrilus planipennis* (Coleoptera) in North America. *Diversity and Distributions*, 12, 71-79.

Muirhead J.R. & Macisaac H.J. (2005). Development of inland lakes as hubs in an invasion network. *Journal of Applied Ecology*, 42, 80-90.

Muirhead J.R. & MacIsaac H.J. (2011). Evaluation of stochastic gravity model selection for use in estimating non-indigenous species dispersal and establishment. *Biological Invasions*, 13, 2445-2458.

Mwebaze P., Monaghan J., Spence N., MacLeod A., Hare M. & Revell B. (2010). Modelling the Risks Associated with the Increased Importation of Fresh Produce from Emerging Supply Sources Outside the EU to the UK. *Journal of Agricultural Economics*, 61, 97-121.

Naddafi R., Blenckner T., Eklov P. & Pettersson K. (2011). Physical and chemical properties determine zebra mussel invasion success in lakes. *Hydrobiologia*, 669, 227-236.

Neteler M., Roiz D., Rocchini D., Castellani C. & Rizzoli A. (2011). Terra and Aqua satellites track tiger mosquito invasion: modelling the potential distribution of *Aedes albopictus* in north-eastern Italy. *International Journal of Health Geographics*, 10.

Nietschke B.S., Borchert D.M., Magarey R.D. & Ciomperlik M.A. (2008). Climatological potential for *Scirtothrips dorsalis* (Thysanoptera : Thripidae) establishment in the United States. *Florida Entomologist*, 91, 79-86.

Okland B., Skarpaas O., Schroeder M., Magnusson C., Lindelow A. & Thunes K. (2010). Is eradication of the pinewood nematode (*Bursaphelenchus xylophilus*) Likely? An evaluation of current contingency plans. *Risk Analysis*, 30, 1424-1439.

Olden J.D., Poff N.L. & Bestgen K.R. (2006). Life-history strategies predict fish invasions and extirpations in the Colorado River Basin. *Ecological Monographs*, 76, 25-40.

Olden J.D., Vander Zanden M.J. & Johnson P.T.J. (2011). Assessing ecosystem vulnerability to invasive rusty crayfish (*Orconectes rusticus*). *Ecological Applications*, 21, 2587-2599.

Olfert O., Hallett R., Weiss R.M., Soroka J. & Goodfellow S. (2006). Potential distribution and relative abundance of swede midge, *Contarinia nasturtii*, an invasive pest in Canada. *Entomologia Experimentalis Et Applicata*, 120, 221-228.

Olfert O., Weiss R.M., Woods S., Philip H. & Dosdall L. (2004). Potential distribution and relative abundance of an invasive cereal crop pest, *Oulema melanopus* (Coleoptera : Chrysomelidae), in Canada. *Canadian Entomologist*, 136, 277-287.

Olson E.R., Ventura S.J. & Zedler J.B. (2012). Merging geospatial and field data to predict the distribution and abundance of an exotic macrophyte in a large Wisconsin reservoir. *Aquatic Botany*, 96, 31-41.

Otfinowski R., Kenkel N.C., Dixon P. & Wilmshurst J.F. (2007). Integrating climate and trait models to predict,the invasiveness of exotic plants in Canada's Riding Mountain National Park. *Canadian Journal of Plant Science*, 87, 1001-1012.

Paini D.R., Bianchi F., Northfield T.D. & De Barro P.J. (2011). Predicting invasive fungal pathogens using invasive pest assemblages: testing model predictions in a virtual world. *Plos One*, 6.

Parker I., Simberloff D., Lonsdale W., Goodell K., Wonham M., Kareiva P., Williamson M., Von Holle B., Moyle P. & Byers J. (1999). Impact: toward a framework for understanding the ecological effects of invaders. *Biological Invasions*, 1, 3-19.

Peacock L. & Worner S. (2006). Using analogous climates and global insect distribution data to identify potential sources of new invasive insect pests in New Zealand. *New Zealand Journal of Zoology*, 33, 141-145.

Perry G. & Vice D. (2009). Forecasting the risk of brown tree snake dispersal from Guam: a mixed transport-establishment model. *Conservation Biology*, 23, 992-1000.

Peterson A.T., Papes M. & Kluza D.A. (2003). Predicting the potential invasive distributions of four alien plant species in North America. *Weed Science*, 51, 863-868.

Pitt J.P.W., Worner S.P. & Suarez A.V. (2009). Predicting Argentine ant spread over the heterogeneous landscape using a spatially explicit stochastic model. *Ecological Applications*, 19, 1176-1186.

Potapov A., Muirhead J., Yan N., Lele S. & Lewis M. (2011). Models of lake invasibility by *Bythotrephes longimanus*, a non-indigenous zooplankton. *Biological Invasions*, 13, 2459-2476.

Potter K.J.B., Kriticos D.J., Watt M.S. & Leriche A. (2009). The current and future potential distribution of *Cytisus scoparius*: a weed of pastoral systems, natural ecosystems and plantation forestry. *Weed Research*, 49, 271-282.

Pysek P., Jarosik V., Pergl J., Randall R., Chytry M., Kuhn I., Tichy L., Danihelka J., Chrtek J.J. & Sadlo J. (2009). The global invasion success of Central European plants is related to distribution characteristics in their native range and species traits. *Diversity and Distributions*, 15, 891-903.

Pysek P., Krivanek M. & Jarosik V. (2009). Planting intensity, residence time, and species traits determine invasion success of alien woody species. *Ecology*, 90, 2734-2744.

Raghua S., Dhileepan K. & Scanlan J.C. (2007). Predicting risk and benefit a priori in biological control of invasive plant species: A systems modelling approach. *Ecological Modelling*, 208, 247-262.

Raimundo R.L.G., Fonseca R.L., Schachetti-Pereira R., Peterson A.T. & Lewinsohn T.M. (2007). Native and exotic distributions of siamweed (*Chromolaena odorata*) modeled using the genetic algorithm for rule-set production. *Weed Science*, 55, 41-48.

Real R., Márquez A.L., Estrada A., Muñoz A.R. & Vargas J.M. (2008). Modelling chorotypes of invasive vertebrates in mainland Spain. *Diversity and Distributions*, 14, 364-373.

Reed R.N. (2005). An ecological risk assessment of nonnative boas and pythons as potentially invasive species in the United States. *Risk Analysis*, 25, 753-766.

Reichard S.H. & Hamilton C.W. (1997). Predicting invasions of woody plants introduced into North America. *Conservation Biology*, 11, 193-203.

Reino L., Moya-Larano J. & Heitor A.C. (2009). Using survival regression to study patterns of expansion of invasive species: will the common waxbill expand with global warming? *Ecography*, 32, 237-246.

Reshetnikov A.N. & Ficetola G.F. (2011). Potential range of the invasive fish rotan (*Perccottus glenii*) in the Holarctic. *Biological Invasions*, 13, 2967-2980.

Ricciardi A. (2003). Predicting the impacts of an introduced species from its invasion history: an empirical approach applied to zebra mussel invasions. *Freshwater Biology*, 48, 972-981.

Richards T.J., Eaves J., Manfredo M., Naranjo S.E., Chu C.C. & Henneberry T.J. (2008). Spatial-temporal model of insect growth, diffusion and derivative pricing. *American Journal of Agricultural Economics*, 90, 962-978.

Richardson D.M. & Thuiller W. (2007). Home away from home - objective mapping of high-risk source areas for plant introductions. *Diversity and Distributions*, 13, 299-312.

Robertson M.P., Villet M.H. & Palmer A.R. (2004). A fuzzy classification technique for predicting species' distributions: applications using invasive alien plants and indigenous insects. *Diversity and Distributions*, 10, 461-474.

Robinet C., Van Opstal N., Baker R. & Roques A. (2011). Applying a spread model to identify the entry points from which the pine wood nematode, the vector of pine wilt disease, would spread most rapidly across Europe. *Biological Invasions*, 13, 2981-2995.

Robinson T.P., van Klinken R.D. & Metternicht G. (2010). Comparison of alternative strategies for invasive species distribution modeling. *Ecological Modelling*, 221, 2261-2269.

Rodder D. (2009). Human Footprint, facilitated jump dispersal, and the potential distribution of the invasive *Eleutherodactylus johnstonei* Barbour 1914 (Anura Eleutherodactylidae). *Tropical Zoology*, 22, 205-217.

Rogers D.J., Reid R.E., Rogers J.J. & Addison S.J. (2007). Prediction of the naturalisation potential and weediness risk of transgenic cotton in Australia. *Agriculture, ecosystems & environment*, 119, 177-189.

Rothlisberger J.D. & Lodge D.M. (2011). Limitations of Gravity Models in Predicting the Spread of Eurasian Watermilfoil. *Conservation Biology*, 25, 64-72.

Roura-Pascual N., Krug R.M., Richardson D.M. & Hui C. (2010). Spatially-explicit sensitivity analysis for conservation management: exploring the influence of decisions in invasive alien plant management. *Diversity and Distributions*, 16, 426-438.

Rout T.M., Moore J.L., Possingham H.P. & McCarthy M.A. (2011). Allocating biosecurity resources between preventing, detecting, and eradicating island invasions. *Ecological Economics*, 71, 54-62.

Ruesink J.L. (2005). Global analysis of factors affecting the outcome of freshwater fish introductions. *Conservation Biology*, 19, 1883-1893.

Ruesink J.L. & Collado-Vides L. (2006). Modeling the increase and control of Caulerpa taxifolia, an invasive marine macroalga. *Biological Invasions*, 8, 309-325.

Sahlin U., Ryden T., Nyberg C.D. & Smith H.G. (2011). A benefit analysis of screening for invasive species - base-rate uncertainty and the value of information. *Methods in Ecology and Evolution*, 2, 500-508.

Sato M., Kawaguchi Y., Yamanaka H., Okunaka T., Nakajima J., Mitani Y., Shimatani Y., Mukai T. & Onikura N. (2010). Predicting the spatial distribution of the invasive piscivorous chub (Opsariichthys uncirostris uncirostris) in the irrigation ditches of Kyushu, Japan: a tool for the risk management of biological invasions. *Biological Invasions*, 12, 3677-3686.

Sebert-Cuvillier E., Paccaut F., Chabrerie O., Endels P., Goubet O. & Decocq G. (2007). Local population dynamics of an invasive tree species with a complex life-history cycle: A stochastic matrix model. *Ecological Modelling*, 201, 127-143.

Shah M.A., Reshi Z.A. & Lavoie C. (2012). Predicting plant invasiveness from native range size: clues from the Kashmir Himalaya. *Journal of Plant Ecology-Uk*, 5, 167-173.

Sharma S., Herborg L.M. & Therriault T.W. (2009). Predicting introduction, establishment and potential impacts of smallmouth bass. *Diversity and Distributions*, 15, 831-840.

Siesa M.E., Manenti R., Padoa-Schioppa E., De Bernardi F. & Ficetola G.F. (2011). Spatial autocorrelation and the analysis of invasion processes from distribution data: a study with the crayfish *Procambarus clarkii*. *Biological Invasions*, 13, 2147-2160.

Skarpaas O. & Okland B. (2009). Timber import and the risk of forest pest introductions. *Journal of Applied Ecology*, 46, 55-63.

Speek T.A.A., Lotz L.A.P., Ozinga W.A., Tamis W.L.M., Schaminee J.H.J. & van der Putten W.H. (2011). Factors relating to regional and local success of exotic plant species in their new range. *Diversity and Distributions*, 17, 542-551.

Spens J., Englund G. & Lundqvist H. (2007). Network connectivity and dispersal barriers: using geographical information system (GIS) tools to predict landscape scale distribution of a key predator (*Esox lucius*) among lakes. *Journal of Applied Ecology*, 44, 1127-1137.

Stanaway M.A., Reeves R. & Mengersen K.L. (2011). Hierarchical Bayesian modelling of plant pest invasions with human-mediated dispersal. *Ecological Modelling*, 222, 3531-3540.

Stephens A.E.A., Kriticos D.J. & Leriche A. (2007). The current and future potential geographical distribution of the oriental fruit fly, *Bactrocera dorsalis* (Diptera : Tephritidae). *Bulletin of Entomological Research*, 97, 369-378.

Stohlgren T.J., Ma P., Kumar S., Rocca M., Morisette J.T., Jarnevich C.S. & Benson N. (2010). Ensemble Habitat Mapping of Invasive Plant Species. *Risk Analysis*, 30, 224-235.

Strubbe D., Matthysen E. & Graham C.H. (2010). Assessing the potential impact of invasive ring-necked parakeets *Psittacula krameri* on native nuthatches *Sitta europeae* in Belgium. *Journal of Applied Ecology*, 47, 549-557.

Sutherst R.W. & Maywald G. (2005). A climate model of the red imported fire ant, *Solenopsis invicta* Buren (Hymenoptera : Formicidae): Implications for invasion of new regions, particularly Oceania. *Environmental Entomology*, 34, 317-335.

Sutherst R.W., Maywald G.F. & Bourne A.S. (2007). Including species interactions in risk assessments for global change. *Global Change Biology*, 13, 1843-1859.

Therriault T.W. & Herborg L.M. (2008). A qualitative biological risk assessment for vase tunicate *Ciona intestinalis* in Canadian waters: using expert knowledge. *Ices Journal of Marine Science*, 65, 781-787.

Thuiller W., Richardson D.M., Pysek P., Midgley G.F., Hughes G.O. & Rouget M. (2005). Niche-based modelling as a tool for predicting the risk of alien plant invasions at a global scale. *Global Change Biology*, 11, 2234-2250.

Thuiller W., Richardson D.M., Rouget M., Proches S. & Wilson J.R.U. (2006). Interactions between environment, species traits, and human uses describe patterns of plant invasions. *Ecology*, 87, 1755-1769.

Trethowan P.D., Robertson M.P. & McConnachie A.J. (2011). Ecological niche modelling of an invasive alien plant and its potential biological control agents. *South African Journal of Botany*, 77, 137-146.

Trnka M., Muska F., Semeradova D., Dubrovsky M., Kocmankova E. & Zalud Z. (2007). European Corn Borer life stage model: Regional estimates of pest development and spatial distribution under present and future climate. *Ecological Modelling*, 207, 61-84.

Vaclavik T. & Meentemeyer R.K. (2012). Equilibrium or not? Modelling potential distribution of invasive species in different stages of invasion. *Diversity and Distributions*, 18, 73-83.

Vall-llosera M. & Sol D. (2009). A global risk assessment for the success of bird introductions. *Journal of Applied Ecology*, 46, 787-795.

van Klinken R.D., Lawson B.E. & Zalucki M.P. (2009). Predicting invasions in Australia by a Neotropical shrub under climate change: the challenge of novel climates and parameter estimation. *Global Ecology and Biogeography*, 18, 688-700.

van Wilgen N.J., Roura-Pascual N. & Richardson D.M. (2009). A Quantitative Climate-Match Score for Risk-Assessment Screening of Reptile and Amphibian Introductions. *Environmental Management*, 44, 590-607.

Vanderhoof M., Holzman B.A. & Rogers C. (2009). Predicting the Distribution of Perennial Pepperweed (*Lepidium latifolium*), San Francisco Bay Area, California. *Invasive Plant Science and Management*, 2, 260-269.

Veale A.J., Hannaford O.D., Russell J.C. & Clout M.N. (2012). Modelling the distribution of stoats on New Zealand offshore islands. *New Zealand Journal of Ecology*, 36, 38-47.

Venette R.C. & Cohen S.D. (2006). Potential climatic suitability for establishment of *Phytophthora ramorum* within the contiguous United States. *Forest Ecology and Management*, 231, 18-26.

Verling E., Ruiz G.M., Smith L.D., Galil B., Miller A.W. & Murphy K.R. (2005). Supply-side invasion ecology: characterizing propagule pressure in coastal ecosystems. *Proceedings of the Royal Society B: Biological Sciences*, 272, 1249-1257.

Vicente J., Randin C.F., Goncalves J., Metzger M.J., Lomba A., Honrado J. & Guisan A. (2011). Where will conflicts between alien and rare species occur after climate and land-use change? A test with a novel combined modelling approach. *Biological Invasions*, 13, 1209-1227.

Villemant C., Barbet-Massin M., Perrard A., Muller F., Gargominy O., Jiguet F. & Rome Q. (2011). Predicting the invasion risk by the alien bee-hawking Yellow-legged hornet *Vespa velutina nigrithorax* across Europe and other continents with niche models. *Biological Conservation*, 144, 2142-2150.

Wang L.F. & Jackson D.A. (2011). Modeling the establishment of invasive species: habitat and biotic interactions influencing the establishment of *Bythotrephes longimanus*. *Biological Invasions*, 13, 2499-2512.

Watt M.S., Kriticos D.J. & Manning L.K. (2009). The current and future potential distribution of *Melaleuca quinquenervia*. *Weed Research*, 49, 381-390.

Watt M.S., Kriticos D.J., Potter K.J.B., Manning L.K., Tallent-Halsell N. & Bourdot G.W. (2010). Using species niche models to inform strategic management of weeds in a changing climate. *Biological Invasions*, 12, 3711-3725.

Watt M.S., Stone J.K., Hood I.A. & Manning L.K. (2011). Using a climatic niche model to predict the direct and indirect impacts of climate change on the distribution of Douglas-fir in New Zealand. *Global Change Biology*, 17, 3608-3619.

Welk E., Schubert K. & Hoffmann M.H. (2002). Present and potential distribution of invasive garlic mustard (*Alliaria petiolata*) in North America. *Diversity and Distributions*, 8, 219-233.

Williams N.S.G., Hahs A.K. & Morgan J.W. (2008). A dispersal-constrained habitat suitability model for predicting invasion of alpine vegetation. *Ecological Applications*, 18, 347-359.

Wilson J.C., Nibbelink N.P. & Peterson D.L. (2009). Thermal tolerance experiments help establish survival probabilities for tilapia, a group of potentially invasive aquatic species. *Freshwater Biology*, 54, 1642-1650.

Wu Y.G., Bartell S.M., Orr J., Ragland J. & Anderson D. (2010). A risk-based decision model and risk assessment of invasive mussels. *Ecological Complexity*, 7, 243-255.

Yan H., Bi H., Li R., Eldridge R., Wu Z., Li Y. & Simpson J. (2006). Assessing climatic suitability of *Pinus radiata* (D. Don) for summer rainfall environment of southwest China. *Forest Ecology and Management*, 234, 199-208.

Yemshanov D., Koch F.H., McKenney D.W., Downing M.C. & Sapio F. (2009). Mapping invasive species risks with stochastic models: a cross-border United States-Canada application for *Sirex noctilio* Fabricius. *Risk Analysis*, 29, 868-884.

Zalba S.M., Sonaglioni M.I., Compagnoni C.A. & Belenguer C.J. (2000). Using a habitat model to assess the risk of invasion by an exotic plant. *Biological Conservation*, 93, 203-208.

Zenni R.D., Wilson J.R.U., Le Roux J.J. & Richardson D.M. (2009). Evaluating the invasiveness of *Acacia paradoxa* in South Africa. *South African Journal of Botany*, 75, 485-496.

235
Zhu G.P., Bu W.J., Gao Y.B. & Liu G.Q. (2012). Potential geographic distribution of brown marmorated stink bug invasion (*Halyomorpha halys*). *Plos One*, 7.
236
Zimmermann H., Von Wehrden H., Damascos M.A., Bran D., Welk E., Renison D. & Hensen I. (2011). Habitat invasion risk assessment based on Landsat 5 data, exemplified by the shrub *Rosa rubiginosa* in southern Argentina. *Austral Ecology*, 36, 870-880.

## Appendix 3: Mapping examples of scoring RAs and quantitative RAs onto the TEASI model

Here, we walk through and compare specific examples of RAs (two scoring RAs and two quantitative RAs). We identify the general elements of RAs, and illustrate how they may be mapped onto the TEASI model structure (see Box 2 & 3 for model structure, and Table 1 for a glossary of notation). By detailing sample RAs, readers should be able to extrapolate to other papers examined, and use Appendix 1 & 2 as a summary of each of the 300+ RAs examined in this study.

Generally, each RA can be described by the components/sub-components that they include, the way that these components are combined (model structure), and the dependencies (surrogates) used to estimate them. For scoring approaches, the components and sub-components are framed in terms of the questions asked within a questionnaire, whereas in the quantitative RAs, they are framed as explicit variables included in a model. The individual questions/variables were mapped to match the closest counterpart in the TEASI model. Where relevant, we noted conditional dependencies (e.g., $F_I(S)$ is explicitly dependent on species traits, whereas $F_I(.)$ denotes unspecified dependencies). More generally, we also determined which model components (TEASI) each RA included (see Appendix 1 & 2). For model structure, in scoring RAs, the methods of combination are explained verbally (e.g., scores are summed), whereas in quantitative RAs, the model structure can be expressed more succinctly as an equation.

### *Example 1: EPPO Risk Assessment*

The EPPO decision-support scheme (EPPO 2011) for quarantine pests is intended to be used to assess the potential importance of a particular pest for a clearly defined area. The scheme provides detailed instructions for the following stages of pest risk analysis: initiation, pest categorization, probability of introduction, potential economic consequences and pest risk management. The EPPO risk assessment firstly estimates the probability of the pest being introduced into the pest risk assessment area (its entry, establishment and spread) and secondly makes an assessment of the likely environmental and economic impact if that should happen. The evaluation is based on the replies to a series of questions, expressed as the choice of an appropriate phrase out of a set of five alternatives (e.g. very unlikely, unlikely, moderately likely, likely, very likely).

To map the EPPO RA (see Table 2 and Appendix 1, Model ID 7), we converted questions into a common notation, based on the TEASI model. The EPPO assessment starts with the identification of all pathways that allow entry or spread of a pest. For each pathway, two questions relate to the number of propagules $O$ transported in this pathway: the probability of a pest to be associated with this pathway and the volume of movement along the pathway. Since they are pathway-specific, they were mapped as $O(v,.)$. Two questions are about population dynamics during transport, namely the likelihood of survival and the likelihood to increase in numbers during transport $f_g(t\text{-}t_1,v,.)$, and another two questions about the likelihood to be released in a suitable habitat, i.e. that the release will support entry of the pest $pr(R|E,v)$. After having answered these 6 questions, one is then asked to assess the overall probability of entry of each pathway and the overall probability of all pathways. To answer these questions, no specific guidance is given as to how combine the specific questions into an overall score or probability.

The next part of the EPPO RA assesses in 12 questions the suitability of the release site for establishment, or in other words, the overall probability of establishment in a given environment $pr(l_C|E,.)$. The questions asked for host plants and suitable habitats, alternate hosts and other essential species, climatic suitability, other abiotic factors, competition and natural enemies, the

spatial distribution of (alternate) hosts or suitable habitats. This is followed by general questions on the pest's reproductive strategy *r(.)*, its adaptability (not mapped; this is not a part of the full model), and the species's history as a pest elsewhere, i.e. its distribution outside its native range, which was mapped as the general likelihood to establish $pr(l_C|.)$. At the end of this part, again an overall assessment of the establishment probability should be made. Again, the connection to the previous questions is not made explicit in the EPPO scheme.

The probability of spread is assessed in 4 questions. Three questions are about the rate of spread by natural and human means, without specifying any dependencies like species traits or environmental characteristics $f_D(.)$, followed by one question about the expected area invaded after 5 years $Q_T(.)$.

Finally, there are 8 questions about general economic impact (crop yield and/or quality, production costs, loss in export markets, transmission of diseases), 4 questions about environmental impact (without giving any details) and 2 questions about social impact (again, without details), all without qualifiers $f_I(.)$.

The EPPO RA covers all TEASI components except local abundance. Uncertainty (only epistemic) should be documented for each question (on a scale of 3: low, medium, high) for transparency and identification of future research needs. However, there is no guidance on how to incorporate uncertainty into assessing risk. Likewise, no guidance is given how to combine scores of individual questions to an overall risk score.

***Example 2: Australian Weed Risk Assessment***

The Australian WRA (Pheloung *et al.* 1999) includes 49 questions divided into three larger sections, which are further divided into a total of eight sub-sections. The questions are in most cases answered yes/no, which typically yield a score of 0 for no and 1 for yes, but in some questions different scales are used (e.g. 0 vs. -3, -1 vs. 1, and 0 vs. 5). In a few questions the score scale is 0-2 (low, intermediate, high). It is not obligatory to answer all the questions, but a sufficient number of questions in each category need to be answered (2, 2 and 6 subsequently). This accounts for uncertainty in the sense that if the answer to some question is not known, it is not necessarily required in order to complete the assessment. The aggregate score is achieved by summation of the individual question scores. Based on their aggregate score, the species are then categorized to three risk categories: accept, reject, or evaluate further, based on pre-determined score boundaries. Each question is also denoted as relating to agriculture, environment, or both. Therefore it is also possible to aggregate the score to assess the importance of the species as, say, an agricultural weed.

The mapping is discussed below in the order of the full invasion model (see Table 2 and Appendix 1, Model ID 43).

There are eight questions mapped as estimating the species traits ($S$). These do not link directly to any particular component (TEASI) of the full model --- rather they are questions that attempt to estimate whether the species in general makes a good invader. The questions relate to shade tolerance, growth on infertile soils, being aquatic, grass plant, nitrogen fixing woody plant or geophyte, toleration of mutilation, cultivation or fire, and whether the propagules are buoyant. A further two questions were mapped related to environmental interactions ($f(E)$): whether the species requires specialist pollination, and whether effective natural enemies are present in the area. These could not be directly linked to any specific invasion model component either.

The seven questions mapped as relating to the Transport component (and *v* more specifically) were related to propagule dispersal by people intentionally and unintentionally, as a produce contaminant, by wind, by bird and by other animals either internally or externally. Propagule buoyancy was mapped as a species trait, although it can relate to water dispersal. The dispersal questions can be interpreted as belonging to either Transport or Spread phase of the invasion – we interpreted them as covering both.

Two questions were mapped related to propagule pressure ($N$): Is the species highly domesticated, and does the species have a history of repeated introductions outside its natural range. These characteristics may be related to either Transport or Establishment phase. In the case of the Australian WRA we did not have to assess whether they link to one or another (or both), as there were other questions relating to both Transport and Establishment, ensuring that the model covered these components.

Five questions were directly mapped relating to establishment probability ($pr(\lambda_C)$), and therefore to the Establishment component of the model. There were two questions with unspecified dependencies: has the species become naturalised where grown, and is it naturalised beyond its native range. There was a further question with environmental dependency ($pr(\lambda_C|E)$) (Does the species have broad climate suitability), and two questions with both environmental and species traits as dependencies ($pr(\lambda_C|E,S)$) (Is the species suited to Australian climates, and is the species native or naturalised in regions with extended dry periods).

Eight questions were mapped to the reproductive potential of the species ($r$), and therefore presenting the Abundance component in the model. There was one question with unspecified dependency (Is there evidence of substantial reproductive failure in native habitat), and seven questions that were dependent on species traits $(r|S)$.

The Impact component was also strongly present, as the Australian WRA includes 15 questions on impacts of the species, with 10 of those especially interpreted as being related to species traits $(F_I(S))$. The five questions that were interpreted as having unspecified dependencies $(F_I(.))$ were related to whether the species has weedy races, and whether it is regarded as a weed in different contexts (e.g. garden, agriculture, environment).

The management question, mapped as $\alpha_C M_C$ (i.e. related to control and control effectiveness of the species), was related to the ability of herbicides to control the species. This one question results in the model mapped as considering the management of the species. The final remaining question regarding the quality of climate match data was mapped as “other”.

Therefore, all the five TEASI components were considered to be covered by the Australian WRA. In comparison with the EPPO approach, the Australian WRA includes a systematic method for aggregating the scores to form a final score. The EPPO system on the other hand includes a more careful consideration of uncertainty related to the assessment, although it provides no guidance on how that should affect the final evaluation. The overall scope of the questions in both schemes was relatively similar.

***Example 3: Species distribution models***

Species distribution models have seen wide development within invasion biology, with numerous statistical approaches linking environmental characteristics with the probability of establishment (Table 3). While often many different predictor variables are used (e.g., hydrology and water

chemistry, Appendix 2, Model ID 2, climate, edaphic data, Model ID 4, etc), and a number of different statistical approaches are available (e.g., Maxent, GARP, Neural Networks, Generalized Linear Models), in essence they all fit environmental predictors of establishment to occurrence data, and are thus denoted as $pr(\lambda_C | E_i)$. Thus, this approach yields much more in depth predictive ability compared to the scoring approaches described above, but is much more abbreviated in scope, examining only a single subcomponent in the TEASI model (and is therefore much simpler to describe).

Given that these models are often based on GIS environmental layers, a simple extension of the fitting technique allows a prediction of spatial extent ($Q$), which we denote in our estimate of risk as $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i)$. Here, $E_i$ typically refers to abiotic environmental traits, but can also include biotic factors such as native species presence (e.g., Appendix 2, Model ID 75). Moreover, researchers have also included aspects related to transport into these models, which thus enters our notation as well. For instance, Appendix 2, Model ID 2 included a measure of vector traffic and is denoted as $Z_i = pr(\lambda_C \mid E_i, V_i)$; Model ID 4 included a measure of distance from known source locations and is denoted as $Z = Q = \sum_{i=1}^{L} pr(\lambda_C \mid E_i, D_{i,j})$. In these ways, multiple TEASI components can be included into the same statistical structure, although with subtle ramifications, as discussed in the next paragraph.

Note the presence of subscript $i$ indicates that spatial locations were considered. Note also the absence of $t$, indicating that temporal dynamics were not considered (i.e., these models implicitly assume equilibrium conditions, although joint models are becoming more popular). Further note that we are treating these as probabilities, as closest analogue in the TEASI model, but discrepancies may exist because of biased sampling, use of pseudoabsences and base-rate effects.

***Example 4: Species trait models***

Species trait models help predict whether a given species will be able to invade a system, using a variety of statistical techniques (e.g., discriminant analysis, generalized linear models, boosted regression trees), and a variety of species traits (e.g., brain size, ecological niches breadth, Appendix 2, Model ID 214; reproductive mode, phenology, invasion history, Model ID 177). These models were mapped to the TEASI framework as $Z = P^c = f_{P^c}(S)$; $P^c$ indicates the probability of the system as a whole will be invaded. $f_{P^c}$ indicates that it is some function of species trait (S) (to determine $P^c$).

Analogously to species distribution models, these provide quantitative predictions, but are also typically more limited in scope compared to scoring methods. However, note that species traits have been used to predict other aspects of the TEASI model besides establishment, and were denoted as such (e.g., to predict average abundance, $Z = \overline{X} = f_X(S)$, Model ID 85; to predict impact, $Z = f_I(S)$, model ID 105), although they are typically not integrated. As another comparison with species distribution models, note the absence of subscripts $i$ and $t$, indicating that spatial and temporal heterogeneity and dynamics were not considered. Although these differences in notation are subtle, they are important as they dramatically change the implications of the models.

As another subtle variation in notation between studies, the predictive dependencies could also extend beyond species traits, and be incorporated into the same statistical method. For instance, environmental conditions (e.g., climate matches between native and introduced ranges) could be included in the model (denoted as $Z = P^c = f_{P^c}(E, S)$, e.g., Model ID 11). As a subtle judgment call, environmental tolerances were treated as a species trait (e.g., minimum temperature, Model ID 115; temperature variability in native range, Model ID 26). Researchers also included factors related to transport (e.g., human usage factors relate to vector movements, denoted as $Z = P^c = f_{P^c}(S, f(V))$, Model ID 26). As mentioned above, these all lacked temporal and spatial resolution.

**References**

1
EPPO (2011). Guidelines on Pest Risk Analysis: Decision support scheme for quarantine pests. In. European and Mediterranean Plant Protection Organization Europe.

2
Pheloung P., Williams P. & Halloy S. (1999). A weed risk assessment model for use as a biosecurity tool evaluating plant introductions. *Journal of Environmental Management*, 57, 239-251.