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Development and validation of a weed screening tool for the United States

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Abstract The Australian weed risk assessment has been promoted as a simple and effective screening tool that can help prevent the entry of weeds and invasive plants into new areas. On average, the Australian model identifies major-invaders more accurately than it does non-invaders (90% vs. 70% accuracy). While this difference in performance emphasizes protection, the overall accuracy of the model will be determined by its performance with non-invaders because the frequency of invasive species among new plant introductions is relatively low. In this study, we develop a new weed risk assessment model for the entire United States that increases non-invader accuracy. The new screening tool uses two elements of risk, establishment/spread potential and impact potential, in a logistic regression model to evaluate the invasive/weedy potential of a species. We selected 204 non-invaders, minor-invaders, and major-invaders to develop and validate the new model, and compare its performance to the Australian model using the same set of species. Performing better than the Australian model, our new model accurately identified 94.1% of major-invaders and 97.1% of non-invaders, without committing any false positives or false negatives. The new secondary screening tool we developed reduced the number of species requiring secondary evaluation from 22 to 12%. We expect that the new weed risk assessment model should significantly enhance the United State's timeliness and accuracy in regulating potential weeds.

Keywords Weed risk assessment · ROC analysis · Predictive screening tool · Base-rate effect · Australian WRA

Introduction

A weed risk assessment (WRA) is a systematic process by which the available evidence is evaluated to estimate the risk of a plant species entering, establishing, spreading, and causing harm in a new area (Groves et al. 2001). Although the content, style, and approach of WRAs vary considerably (e.g., Pheloung et al. 1999; Randall et al. 2008; Reichard and Hamilton 1997), they all consider similar kinds of information. Weed risk assessments that identify or predict potential invaders before they enter a country are sometimes referred to as screening tools or pre-border WRAs. One of the most popular screening tools is the Australian WRA, which consists of 49 primarily "yes/no" questions about plant traits and status elsewhere (Pheloung et al. 1999). The questions evaluate whether a plant possesses traits typically associated with weedy and

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invasive species; the higher the risk score, the more likely a given plant will become invasive or weedy in the WRA area. Nearly a dozen independent tests of the Australian WRA have demonstrated its ability to consistently identify invaders (e.g., Daehler and Carino 2000; Gordon et al. 2008c; Křivánek and Pyšek 2006; Nishida et al. 2009). One group of testers suggested that it should be more broadly used to identify future invaders[1] (Gordon et al. 2008b).

Plant Protection and Quarantine (PPQ) is the United States Department of Agriculture (USDA) agency responsible for safeguarding U.S. agricultural and natural resources from plant pests associated with trade. Since about 1995, PPQ has used a weed risk assessment procedure that evaluates many of the same factors as the Australian system, but in a less structured, more open-ended, narrative process (USDA 2004; Lehtonen 2001). However, while the Australian tool takes only 1–2 days to complete, the PPQ approach usually takes considerably longer, from 2 to 8 weeks (Parker et al. 2007; Gordon and Gantz 2008). Given the importance of preventing the entry of new weeds (White and Schwarz 1998; Pimentel et al. 2000) and of evaluating new incursions quickly (NISC 2008; FICMNEW 2003), PPQ needs a more efficient process for weed screening at the national level. Rapid screening tools have been developed for a U.S. botanical garden (Jefferson et al. 2004), North American woody species (Reichard and Hamilton 1997), and two U.S. states (Gordon et al. 2008c; Daehler and Carino 2000), but never for the entire United States and all plant taxa.

The Australian WRA is a potentially suitable rapid screening tool for PPQ (Gordon et al. 2008b), but a bias in its performance is important to consider (Křivánek and Pyšek 2006). The nearly dozen tests of the Australian WRA have shown that the model identifies major-invaders more accurately (90% accuracy) than it does non-invaders (70%). It also commits relatively more false-positives (10% error rate) than false-negatives (1%) (Gordon et al. 2008b; McClay et al. 2010). From these measures, it may appear the overall accuracy of the Australian WRA is about 80% (the mean of 70 and 90%). However, because non-invaders are expected to be about 100 times more prevalent than major-invaders among new introductions (Williamson and Fitter 1996), the overall accuracy of the Australian model is expected to be closer to 70% due to the base-rate effect (see discussion in Onderdonk et al. 2010; Smith et al. 1999; Křivánek and Pyšek 2006). Because of the diversity of PPQ's stakeholders, it is important that we adopt a screening tool that increases non-invader accuracy so that major-invader and non-invader performance are at the very least similar.

International standards (IPPC 2009) identify several elements of pest risk that should be evaluated in a risk assessment. In this study, we developed a predictive weed screening tool based on the Australian WRA that incorporates two of these risk elements: establishment/spread, and impact. Our goal was to develop a model that maintains the same level of major-invader accuracy associated with the Australian system, but that increases non-invader accuracy. During model development, we evaluated the predictive ability of the screening questions, examined the utility of logistic regression models for prediction, and analyzed receiver operating characteristic (ROC) curves to select decision thresholds. To ensure that our predictive model was at least as accurate as the Australian system, we tested and compared the performance of the PPQ and Australian WRAs with the same set of test plants. By designing a new WRA process for the United States that can be completed in about 2 days, similar to the Australian WRA, we plan to meet increased demand arising from an ongoing revision of the regulations governing imports of plants for planting (APHIS 2009). The new PPQ weed screening process is consistent with our Plant Protection Act authority and international standards on pest risk analysis (NAPPO 2008; IPPC 2009).

Because geographic and climatic suitability affect the likelihood of species establishment (IPPC 2009), many WRAs incorporate one or more of these measures (e.g., Fox et al. 2005; Gordon et al. 2008c). The intent of the criteria is to give species that can establish in the risk assessment area higher risk scores than those that would be less likely to establish. Selection of geographic and climatic criteria for use in WRAs is straightforward when the area

[1] The terms "weed" and "invader" have been defined and used in a variety of different ways in the literature. It is beyond the scope of this paper to review their usage or to bring some clarity to their confounded meanings. We use these terms rather loosely and interchangeably to refer to non-native plants capable of spreading across natural or artificial landscapes and causing some type of economic or environmental harm.

of interest is relatively homogenous and comprised of a limited set of bioclimatic classes. For climatically diverse and heterogeneous regions such as the United States, however, selection of suitable criteria is not simple. Relative to many other countries, the United States (including its territories) is geographically and climatically diverse due not only to its large land area but also to how that land area is distributed across latitudes. This poses unique challenges for WRA model development (Parker et al. 2007). Our approach to this issue was to exclude geographic and climatic suitability from the predictive model developed here.

Materials and methods

Species selection

For model development and validation, we selected 204 exotic plants whose weed and invasive behavior in the United States was already known. As in other studies (reviewed in Gordon et al. (2008b)), these species formed the basis of our three a priori categories: non-invaders, minor-invaders, and major-invaders ($N = 68$ each). We randomly selected half of each group for developing the model (developmental dataset) and used the other half to validate it (validation dataset). Although we did not formally stratify species selection by geographic region (southeast, northwest, pacific, etc.), invasive domain (agricultural, environmental, urban/suburban), plant family, or habit (vine, shrub, tree, aquatic, etc.), we tried to ensure a wide range of plants, including beneficial ones, were selected for model development (Appendix 1).

We define a non-invader as a plant that has been in the United States for 75 years or more and is not known to have naturalized.[2] We required a minimum residency time for non-invaders to ensure enough time for them to escape and establish. Although time lags in invasions can range from 10 to 150 years (Kowarik 1995), we chose 75 years because Bailey and Bailey's *Hortus* (1930) was a convenient reference of North American plants in cultivation in the early part of the century. We primarily used the USDA PLANTS database (http://plants.usda.gov/) to determine whether a plant has naturalized in the United States, but consulted other sources as necessary. Because we found no single national reference categorizing agricultural and environmental weeds, we used several sources to determine if a plant met our criteria for classification as a major-invader. We classified environmental weeds with an impact ranking "I-rank" of high or high-medium on NatureServe's categorization system (NatureServe 2009) as major-invaders. We also classified plants as major-invaders if listed by Holm et al. (1979) as U.S. "serious" or "principal" or by Bridges (1992) as "troublesome". Plants that have naturalized in the United States but did not meet the criteria for major-invaders were classified as minor-invaders. We also considered a plant's a priori status in the Florida (Gordon et al. 2008c) and Hawaiian (Daehler et al. 2004) tests of the Australian WRA. When two or more sources conflicted, we used the more invasive status.

The WRA models

We based the new PPQ model on the Australian WRA, retaining many of the original questions, but excluding some that have proven in other studies to be unimportant or difficult to answer (Gordon, pers. comm.; McClay et al. 2010). After reviewing other WRA systems (e.g., USDA 2004; Parker et al. 2007; Fox et al. 2005; Jefferson et al. 2004; Randall et al. 2008), we selected or created additional questions that we thought would be predictive or indicative of invasive plant risk. We organized the questions into two elements of risk described in international guidelines for pest risk assessment (IPPC 2009): establishment/spread potential (E/S), and impact potential (Imp). The establishment/spread risk element measures the likelihood that a species will establish or naturalize in the area at risk, and then spread to other areas. The impact potential element measures the capacity of the species to cause direct and indirect damage to natural, anthropogenic, and production systems. Greater scores indicate greater likelihood to establish and spread, and/or cause harm. Most of the questions under E/S were the same as those used in the Australian WRA system, while most

[2] We follow Richardson et al.'s (2000) definition of "naturalized" as alien plants that reproduce consistently and sustain populations over many life cycles without direct human intervention in natural or human-made ecosystems. This definition is consistent with the IPPC's (2009) definition of "established."

under Imp were new. We included three questions about the adaptive potential of the species in E/S. This is an important predictor of invasiveness as species with a high adaptive potential will be able to establish in and spread across a large range of environments (Rejmánek 2000; Scott and Panetta 1993; Baker 1965). Unlike the Australian WRA, the PPQ WRA does not make policy recommendations of "accept" or "reject." In risk analysis in PPQ, risk assessment is separate from risk management, where policy decisions (e.g., accept, reject, etc.) are made.

As in other tests of the Australian model (e.g., Daehler et al. 2004), we modified the four questions that relate to environmental and climatic suitability of the test region. Our modifications were very similar to those of Gordon et al. (2008a). We changed question 2.01 to read "species suited to USDA cold plant hardiness zones," where low is suitability to grow in 0–25% of the United States, intermediate is 25–50%, and high is 50+%. We changed question 2.03 to read "broad climate suitability (environmental versatility)," where we interpreted broad to mean occurring in four or more Köppen-Geiger climate classes (see Peel et al. (2007) for a description of this classification system). Also, we revised question 2.04 to "native or naturalized in regions with an average of 11–60 inches of annual precipitation." Finally, we changed question 4.10 to "grows on one or more of the following soil types: alfisols, entisols, or mollisols." These three soil types represent the three most frequent soil types of the United States (13.9, 12.3, and 21.5 percent, respectively; NRCS 1999).

Species assessment and review

The 204 species selected for model development and validation were assessed using both WRAs by a small group of people with varying levels of botanical and invasive plant expertise. Variation in expertise helped us design a set of interpretative guidelines for the questions. We adapted guidance developed previously by Gordon et al. (2010) for the Australian WRA, and incorporated guidance for the new questions. To ensure consistency, our group regularly discussed question approaches and interpretations. Furthermore, every assessment was reviewed by a second team member.

As in other studies that have developed or tested predictive tools (Pheloung et al. 1999; Daehler and Carino 2000; Gordon et al. 2008c), we wanted to test the ability of our model to correctly identify a species' a priori status when relying solely on foreign literature. Consequently, we ignored any information from the United States about the invasive status or impact of a species, but used U.S. sources for basic biological traits (e.g., fruit type, life form, seed dormancy, etc.) if available. We took this approach because basic biology is unlikely to change across different parts of a species' range.

Questions that could not be answered due to a lack of information or due to conflicting information were scored as "unknown". In some cases, we used information about congeners to fill knowledge gaps, but we restricted this to questions about biological traits that are likely to be well conserved among closely related species (e.g., dispersal vector, seed dormancy, minimum generation time). We never answered questions about more complex traits (e.g., impact, weediness elsewhere) using congeneric information. We specifically incorporated these directives into our guidance document.

PPQ model development and refinement

We used chi-square tests of independence (JMP v. 8.0.1) to evaluate the association between question response and U.S. invasive status and to help us determine which questions should be weighted more heavily and which ones should be eliminated. Because non-invaders had a greater proportion of questions with answers of "unknown," we excluded these species to avoid biasing the results. We used Kruskal–Wallis tests to evaluate a few questions with ordinal or continuous answers. We retained all questions that were significant ($P \leq 0.05$) or trended towards significance, and eliminated questions that were not significant, were rarely answered, or did not otherwise help separate risk score distributions for the three invasive categories. All analyses were done using the developmental dataset ($N = 102$).

Once we obtained our final set of questions, we used logistic regression to develop predictive models for invasive class (non-invaders, minor-invaders, and major-invaders) with E/S and Imp as the predictor variables. Using Youden's Index, we determined decision thresholds analytically with Receiver Operating Characteristic (ROC) curve analysis[3] (Bewick et al. 2004; Fluss et al. 2005). Youden's Index assumes the relative cost of a false-positive and a false-negative are equal (Bewick et al. 2004; Fluss et al. 2005). Because we wanted three possible model outcomes (low risk, evaluate further, and high risk), we needed two decision thresholds. One ROC curve analysis used the probability of being a non-invader to develop a threshold between non-invaders and invaders. The other analysis used the probability of being a major-invader to develop a threshold between major-invaders and the other two classes.

As with the Hawaiian application of the Australian WRA (Daehler et al. 2004), we developed a secondary screening tool to further assess those species categorized as "evaluate further." These are the species with traits and risk scores intermediate between non- and major-invaders. A secondary screening tool is valuable because it improves model accuracy and reduces the number of species in this category (Kato et al. 2006; Daehler et al. 2004; but see Nishida et al. 2009). In developing the tool, we used only the data for species categorized by the main model as "evaluate further." Thus, we examined the remaining predictive power of all the questions in the WRA after initial classification by the model.

Model comparison and performance

Using the validation dataset (N = 102), we compared the PPQ and Australian models using previously developed performance measures (e.g., Gordon et al. 2008c; Smith et al. 1999; Bewick et al. 2004; Metz 1978). Specifically, we calculated the true-positive fraction (major-invader accuracy), true-negative fraction (non-invader accuracy), the false-positive fraction (percentage of species incorrectly classified as major-invaders), and the false-negative fraction (percentage of species incorrectly classified as non-invaders). These four measures are insensitive to the relative frequencies of the different classes in a test dataset (Bewick et al. 2004, Smith et al. 1999). In addition, we calculated the overall accuracy percentage, overall error percentage, and the positive and negative predictive values, which depend on the relative frequencies of the different classes in the test dataset (Bewick et al. 2004, Smith et al. 1999). We did not consider the population of minor-invaders, because our goal was to develop a WRA model that distinguishes non-invaders and major-invaders (see discussion below).

We also evaluated model performance using ROC curve analysis, which is unaffected by the prevalence of invaders (Smith et al. 1999; Metz 1978). The area under an ROC curve (AUC) measures how well the model discriminates between two classes. It can be interpreted as the probability that a randomly drawn positive case will receive a higher score than a randomly drawn negative case (DeLong et al. 1988). If the model perfectly separates both classes, then the curve rises straight up to point 0,1 and then moves straight across to point 1,1, forming two sides of a square. The AUC for that curve is 1. In contrast, if the model is completely unable to sort the two classes, then the curve is a positive diagonal from 0,0 to 1,1, with an AUC of 0.5. We generated empirical ROC curves for the Australian and PPQ models using the trapezoidal method (Lasko et al. 2005; Fawcett 2004). Because ROC curves only compare two states or conditions, we generated three curves for each model, one comparing non- and minor-invaders to major-invaders, one comparing non-invaders to minor- and major-invaders, and the other comparing just non- and major-invaders. We tested the AUCs for significant differences from 0.5 and from each other using the formulae in Greiner et al. (2000).

Results

Question analysis and PPQ WRA refinement

After excluding species with answers of "unknown", chi-square tests for 41 of the 77 questions across both models were significant at an alpha level of 0.05. This corresponds to 41% of the questions in the Australian WRA and 53% of the questions in the initial PPQ WRA. Questions about weed status elsewhere, dispersal mechanism, and impacts were often significant, whereas relatively few questions about plant type, reproduction, and undesirable traits were

[3] ROC curve analysis is an analytical tool that helps evaluate the sensitivity and specificity of a diagnostic test over a range of decision thresholds (Bewick et al. 2004; Fluss et al. 2005). It is typically used to estimate the overall predictive ability of a test and to evaluate the best decision threshold for the particular system (e.g., Nishida et al. 2009).

significant. In both models, the question about invasive status elsewhere had the greatest association between question response and a priori invasive status (Aus 3.01: $X^2 = 45.45$, Cramer's V = 0.67; PPQ E/S 1: $X^2 = 82.97$, Cramer's V = 0.64). This is consistent with other studies indicating that history elsewhere is one of the best predictors of invasiveness (Dawson et al. 2009; Gordon et al. 2008c).

During model refinement, we monitored the impact of our changes on score distributions using the F statistic from analysis of variance. With respect to our initial WRA model, our changes improved risk score separation, first as we increased the weight of predictive questions, and then as we eliminated useless questions ($F_{E/S}$: 53.07 → 81.83 → 97.33; F_{Imp}: 51.18 → 52.50 → 56.24) (ANOVA; JMP v. 8.0.1). The final PPQ WRA contained 23 questions in the Establishment/Spread (E/S) risk element and 18 questions in the Impact (Imp) risk element (Appendix 2). We found a significant positive correlation between the number of questions answered and the E/S risk scores (Spearman's $\rho = 0.51$, $P < 0.001$), but not the Imp risk scores (Spearman's $\rho = 0.15$, $P = 0.128$).

During model development, we obtained the highest accuracies and lowest error rates when we used logistic-regression probabilities as risk scores in conjunction with ROC-derived risk thresholds. The logistic-regression model was significant ($X^2 = 102.89$; df = 2; $P < 0.0001$), explaining 46% of the variation in the data. The E/S risk element was a significant predictor ($X^2 = 30.75$; $P < 0.0001$) of a priori class, but not the Imp risk element ($X^2 = 2.32$; $P = 0.128$). This is probably due to the strong correlation between the E/S and Imp risk scores (r = 0.8103; $P < 0.0001$). After E/S was considered by the model, inclusion of Imp added only 1% to model R^2 (0.449 vs. 0.459). The final model, with both variables was:

$$P(\text{Major-invader}) = 1/(1 + e^{(4.1348-0.2356\text{ES}-0.6019\text{Imp})})$$

$$P(\text{Minor-invader}) = [1/(1 + e^{(0.6366-0.2356\text{ES}-0.6019\text{Imp})})] - P(\text{Major-invader})$$

$$P(\text{Non-invader}) = 1 - [1/(1 + e^{(0.6366-0.2356\text{ES}-0.6019\text{Imp})})]$$

We determined the decision threshold for low risk to be P(non-invader) ≥ 0.449, and that for high risk to be P(major-invader) ≥ 0.338 (Fig. 1). Species not meeting either criteria are classified as "evaluate further".

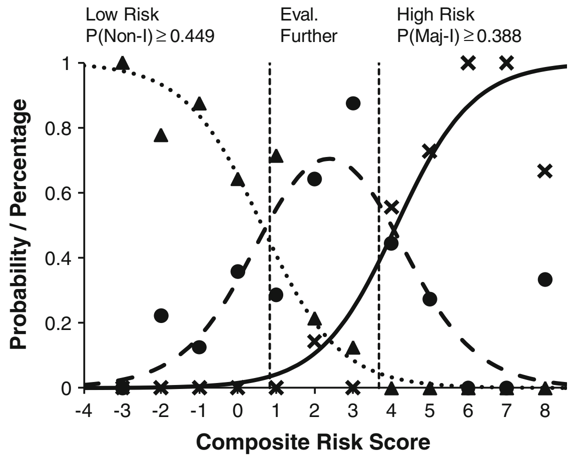

Fig. 1 Logistic regression model of the probability of invasive species class. Composite risk score refers to a linear combination of the risk scores for the establishment/spread (E/S) and impact (Imp) risk elements and is calculated as (0.2356 × E/S) + (0.6019 × Imp). *Filled triangle*, *filled circle*, *multiplication* represent the proportion (fraction) of non-invaders, minor-invaders, and major-invaders, respectively, for each corresponding risk score value (after rounding to the nearest whole number). Logistic regression probabilities for non-invaders (*dotted line*), minor-invaders (*dashed line*) and major-invaders (*solid line*) are shown as a function of the composite risk score. Also shown are the ROC-derived thresholds that establish the three risk regions. If the probability of being a non-invader is ≥0.449 (composite risk score ≤0.841), then the species is classified as "low risk." If the probability of being a major-invader is ≥0.388 (composite risk score ≥3.769), then the species is classified as "high risk." All other species are classified as "evaluate further" pending secondary screening

The secondary screening tool was designed as a short decision tree. Interestingly, after excluding species classified as either low or high risk by the PPQ model, invasive status elsewhere was still useful for distinguishing the three a priori groups. Thus, this question appears first in the decision tree (Fig. 2). If a species is invasive elsewhere, it is categorized as "high risk," whereas if it has been introduced elsewhere for more than 75 years and has not escaped, it is categorized as "low risk." Next in the decision tree, we considered a combination of invasive status elsewhere and a score based on the answers to six of the model's questions: (1) prolific reproduction, (2) minimum generation time, (3) shade tolerance, (4) commodity contaminant, (5) number of

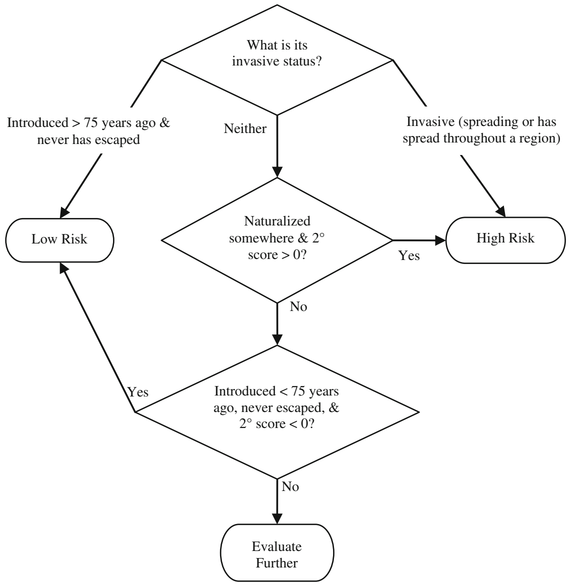

Fig. 2 The secondary screening tool of the PPQ weed risk assessment. This tool uses key questions that are strongly associated with a priori status in the United States. The first and most predictive question refers to the species' invasive status elsewhere in the world. The questions in the next two diamonds represent choices from the status elsewhere question. The secondary score is the sum of the scores for six questions from the WRA model: (1) prolific reproduction, (2) minimum generation time, (3) shade adapted, (4) commodity contaminant, (5) number of natural dispersal vectors, and (6) forms dense thickets

natural dispersal vectors, and (6) forms dense thickets. Species not identified as either "high risk" or "low risk" using this tool remain in the "evaluate further" category.

Comparison of model performance

The Australian and PPQ WRAs effectively separated non- and major-invaders, with little overlap between the two groups (Figs. 3 and 4). As expected, risk scores were lowest for non-invaders, while scores for major invaders were the highest. Scores for minor-invaders ranged widely between those groups, reflecting the large variability in invasiveness in this group. Mean risk scores were significantly different among a priori groups (non-, minor- and major-invaders) at $P < 0.0001$ (Kruskal–Wallis tests; Table 1).

For both models, major-invader accuracy was high, with the Australian model having a slightly higher accuracy than the PPQ model (0.971 vs. 0.941). However, the PPQ model had higher non-invader accuracy than the Australian model (0.971 vs. 0.794; Table 2). Our test results for the Australian model are not unexpected and fall within the range observed in other studies. Compared to the Australian model, the greater non-invader accuracy of the PPQ

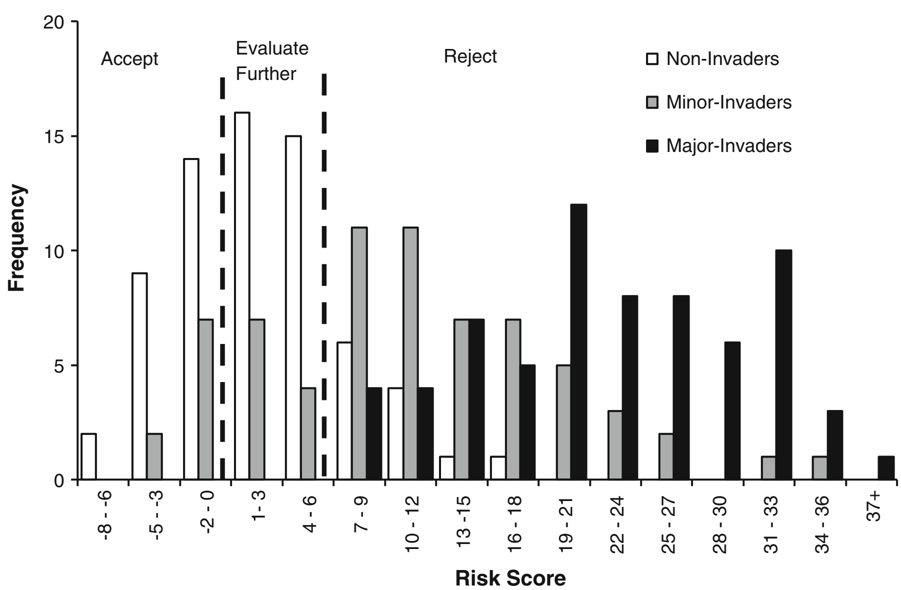

Fig. 3 Risk scores from the U.S. test of the Australian weed risk assessment for all 204 species. *Vertical dashed lines* represent the decision thresholds that separate the "accept", "evaluate further", and "reject" regions

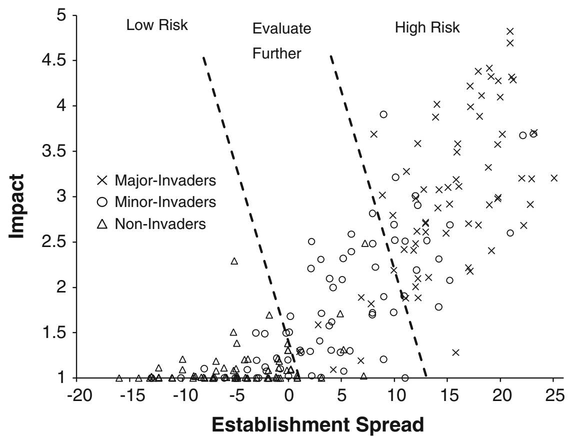

Fig. 4 Risk scores from the PPQ weed risk assessment for all 204 species used in this study. *Dashed lines* represent the decision thresholds that separate the "low risk", "evaluate further", and "high risk" regions. A small random number was added to all risk scores to see overlapping scores

model resulted in higher overall accuracy (Table 2). The PPQ model did not commit any false-positive or false-negative errors. While it may be tempting to claim that this model is error-free, we believe that this unusual result derived from the particular set of species in our validation dataset. In our developmental dataset, the PPQ model erred once by classifying a non-invader as "high risk" (2.9% error). In comparison, the Australian model accepted 0% of the major-invaders and incorrectly rejected about 9% of the non-invaders (Table 2). These results are consistent with other studies showing that the Australian WRA commits more false-positives than false-negatives (0.164 vs. 0.022; Table 2). Because the PPQ model did not commit any errors (with the validation dataset), its positive and negative predictive values equaled 1.0 (Table 2). The positive predictive value of the Australian model was lower than the PPQ model because of those false-positives.

The new secondary screening tool we developed for the PPQ model reduced the percentage of species classified as "evaluate further" from 21.6 to 11.8%. This decrease is similar to that observed for our U.S. test of the Australian WRA + Daehler system (21.6 to 9.8%), which used the same set of test species. The final percentage of test species requiring further evaluation with the PPQ model (11.8%) was not much higher than those reported in other tests (Table 3). The percentage of minor-invaders in the "evaluate further" category was 75% for the PPQ model and 50% for the U.S. test of the Australian system. These represent an increase from the initial frequency of minor-invaders (33%) among all test plants. To compare the change in minor-invader frequency among other tests with different initial frequencies of minor-invaders, we calculated the ratio of the frequency of minor-invaders in the "evaluate further" category to their frequency in the initial, validation dataset. These values were 2.25 for the PPQ model and 1.5 for the U.S. test of the Australian WRA. For other tests of the Australian WRA, this ratio varied widely, but had a mean of 0.979 (Table 3), indicating that on average the WRA does not lead to increased minor-invader frequency in the intermediate risk category ("evaluate further").

When we grouped minor-invaders with major-invaders, the AUC for the PPQ model was 0.953 and that for the Australian model was 0.914 (Fig. 5). When we grouped minor-invaders with non-invaders, the AUCs were 0.932 for the PPQ model and 0.929 for the Australian model (Fig. 5). In all cases, the AUCs were significantly different from 0.5, indicating that the models effectively discriminated between invaders and non-invaders, regardless of how minor-invaders were categorized (Fig. 5). In both comparisons, the AUCs for the PPQ and Australian models were very similar and not statistically different from

Table 1 Mean risk scores (and standard deviation) for the Australian and PPQ WRA models

Model	Mean risk score (SD)			Kruskal–Wallis	
	Non-invaders	Minor-invaders	Major-invaders	X^2	*P*
Australian	0.2 (4.3)	9.3 (8.5)	21.9 (7.5)	119	<0.0001
PPQ—E/S potential	−4.2 (3.8)	5.3 (7.1)	14.7 (5.5)	136	<0.0001
PPQ—Imp potential	1.07 (0.14)	1.75 (0.68)	3.00 (0.92)	124	<0.0001

E/S and Imp refer to the establishment/spread and impact risk elements. Differences among means of the three invasive plant classes were tested with Kruskal–Wallis tests

Table 2 Estimates of accuracy, error, and predictive value for the U.S. tests of the PPQ weed risk assessment and the Australian WRA

Test[a]	N	True-positive fraction[b]	True-negative fraction[b]	False-positive fraction[c]	False-negative fraction[c]	Overall accuracy	Overall error	Positive predictive value[d]	Negative predictive value[d]
US—Aus WRA	68	0.971	0.794	0.088	0.000	0.882	0.044	0.917	1.000
US—PPQ WRA	68	0.941	0.971	0.000	0.000	0.956	0.000	1.000	1.000
Bonin Islands	86	0.927	0.622	0.222	0.024	0.767	0.128	0.792	0.966
Canada	102	1.000	0.481	0.442	0.000	0.735	0.225	0.685	1.000
Central Italy	14	1.000	0.800	0.000	0.000	0.929	0.000	1.000	1.000
Czech Republic	174	1.000	0.873	0.019	0.000	0.885	0.017	0.850	1.000
East Africa[e]	161	0.826	0.848	0.087	0.087	0.845	0.087	0.613	0.983
Florida	110	0.919	0.729	0.083	0.016	0.836	0.045	0.934	0.972
Hawaii & Pacific	127	0.818	0.848	0.076	0.045	0.843	0.071	0.692	0.989
Japan	148	1.000	0.520	0.380	0.000	0.838	0.128	0.838	1.000
Mean[f]		0.936	0.715	0.164	0.022	0.835	0.088	0.800	0.989

N represents the number of species used in the tests. We include estimates for other tests of the Australian WRA for comparison, but only for tests that used a minor-invader category and a secondary screen

[a] Hawaii and Pacific (Daehler et al. 2004), Czech Republic (Křivánek and Pyšek 2006), Bonin Islands (Kato et al. 2006), Florida (Gordon et al. 2008c), Japan (Nishida et al. 2009), Canada (McClay et al. 2010), Central Italy (Crosti et al. 2010), East Africa (Dawson et al. 2009)

[b] The true-positive fraction is the proportion of major-invaders that were classified as reject/high risk (major-invader accuracy), while the true-negative fraction is the proportion of non-invaders that were classified as accept/low risk (non-invader accuracy)

[c] The false-positive fraction is the proportion of non-invaders classified as reject/high risk, while the false-negative fraction is the proportion of major-invaders classified as accept/low risk

[d] The positive predictive value is the proportion of major-invaders among all of the taxa predicted to be positive (reject/high risk), while the negative predictive value is the proportion of non-invaders among all of the taxa predicted to be negative (accept/low risk)

[e] This study used four categories of invasive species (Dawson et al. 2009). Here we treated surviving and regenerating species as non-invaders, naturalized as minor invaders, and spreading as major-invaders

[f] Excluding results from this study

each other. Because our goal was to develop a WRA model to discriminate between non-invaders and major-invaders, we also evaluated model performance by excluding minor-invaders entirely from the ROC curve analysis. In that case, the AUCs were 0.999 for the PPQ model, and 0.996 for the Australian model (Fig. 5). These values demonstrate the excellent ability of both models to discriminate between those two classes of species.

Discussion

Model performance and comparison

In this study, we developed a predictive WRA model for the United States, and achieved our goal of improving prediction accuracy over other models (e.g., Reichard and Hamilton 1997; Weber and Gut 2004; Pheloung et al. 1999). Accurately identifying 94.1% of major-invaders and 97.1% of non-invaders, our new model resulted in more balanced accuracies than the Australian model. The PPQ model committed no false-positives or false-negatives, indicating that non- and major-invaders that were not accurately identified remained in the "evaluate further" category (3 of 68 species). Because for some life forms (e.g., epiphytes, aquatics, subshrubs) we were only able to test a few species, additional work is required to evaluate whether the model is equally suitable for all life forms.

Designing a predictive model with both high sensitivity and specificity is difficult because an inherent tradeoff exists between them (Hughes and Madden 2003). Lowering decision thresholds to correctly identify more major-invaders inadvertently

Table 3 Categorization of minor-invaders (Min-I) (shown as proportions) and composition of the "evaluate further" category

Test[a]	Minor-invader categorization			Evaluate further category[b]		
	Accept/low risk	Reject/high risk	Evaluate further	Proportion of test species	Minor-invader proportion	Ratio
US—Aus WRA	0.265	0.588	0.147	0.098	0.500	1.500
US—PPQ WRA	0.265	0.471	0.265	0.118	0.750	2.250
Bonin Islands	0.114	0.795	0.091	0.100	0.308	0.909
Canada	0.140	0.860	0.000	0.026	0.000[e]	0.000[e]
Central Italy	0.167	0.833	0.000	0.050	0.000[e]	0.000[e]
Czech Republic	0.444	0.222	0.333	0.109	0.150	3.050
East Africa[c]	0.426	0.447	0.128	0.082	0.353	1.562
Hawaii and Pacific	0.333	0.600	0.067	0.081	0.214	0.819
Florida	0.354	0.583	0.062	0.101	0.188	0.617
Japan	0.081	0.892	0.027	0.031	0.375	0.875
Mean[d]	0.257	0.654	0.089	0.073	0.198	0.979

As in Table 2, we only included tests with a minor-invader category and a secondary screen. The U.S. test of the Australian system used the Daehler et al. (2004) secondary screening tool, whereas the PPQ model used the new secondary screening tool shown in Fig. 2

[a] Hawaii and Pacific (Daehler et al. 2004), Czech Republic (Křivánek and Pyšek 2006), Bonin Islands (Kato et al. 2006), Florida (Gordon et al. 2008c), Japan (Nishida et al. 2009), Canada (McClay et al. 2010), Central Italy (Crosti et al. 2010), East Africa (Dawson et al. 2009)

[b] Values presented are: proportion of all test species categorized as "evaluate further"; proportion of "evaluate further" that is represented by minor-invaders; and the ratio of the proportion of minor-invaders in the "evaluate further" category to the proportion of minor invaders in the entire dataset

[c] This study used four categories of invasive species (Dawson et al. 2009). Here we treated surviving and regenerating species as non-invaders, naturalized as minor invaders, and spreading as major-invaders

[d] Excluding results from this study

[e] Values were zero because no minor-invaders were classified as "evaluate further"

rejects more non-invaders, and vice versa. Our test results of the Australian model were consistent with previous tests showing a higher sensitivity than specificity (McClay et al. 2010; Gordon et al. 2008b). In previous tests that identified three classes of invaders and used a secondary screening tool, major-invader accuracy was appreciably greater than non-invader accuracy (93.6 vs. 71.5%), while the false-negative rate was less than the false-positive rate (2.2 vs. 16.4%). Thus, the Australian WRA tends to increase the likelihood of correctly rejecting a major-invader at the expense of correctly accepting a non-invader. While this conservative (i.e., risk averse) approach minimizes the risk of introducing weeds and invasive species, it may exclude potentially economically beneficial species.

The significance of the increased non-invader accuracy associated with the PPQ model is more apparent when we consider the base-rate effect (Smith et al. 1999). Most tests of predictive screening systems use relatively similar frequencies of non-, minor- and major-invaders in their study designs (except see Weber and Gut 2004). This is necessary for precise estimates of model performance (Metz 1978). However, some estimates of model performance (i.e., overall accuracy, overall error, and reliability) are affected by the prevalence of the condition being tested (Smith et al. 1999; Fawcett 2004; Metz 1978). The effective accuracy and error of the model will be dominated by model performance with the most frequent group (e.g., Lonsdale 2010; Onderdonk et al. 2010; Křivánek and Pyšek 2006). Because most introduced plant species will likely be non-invaders (Williamson and Fitter 1996) and because the non-invader accuracy of the PPQ model was 97.1%, the effective, *overall* accuracy of the PPQ model is expected to be near 97% based on results with the validation dataset. Additional tests of

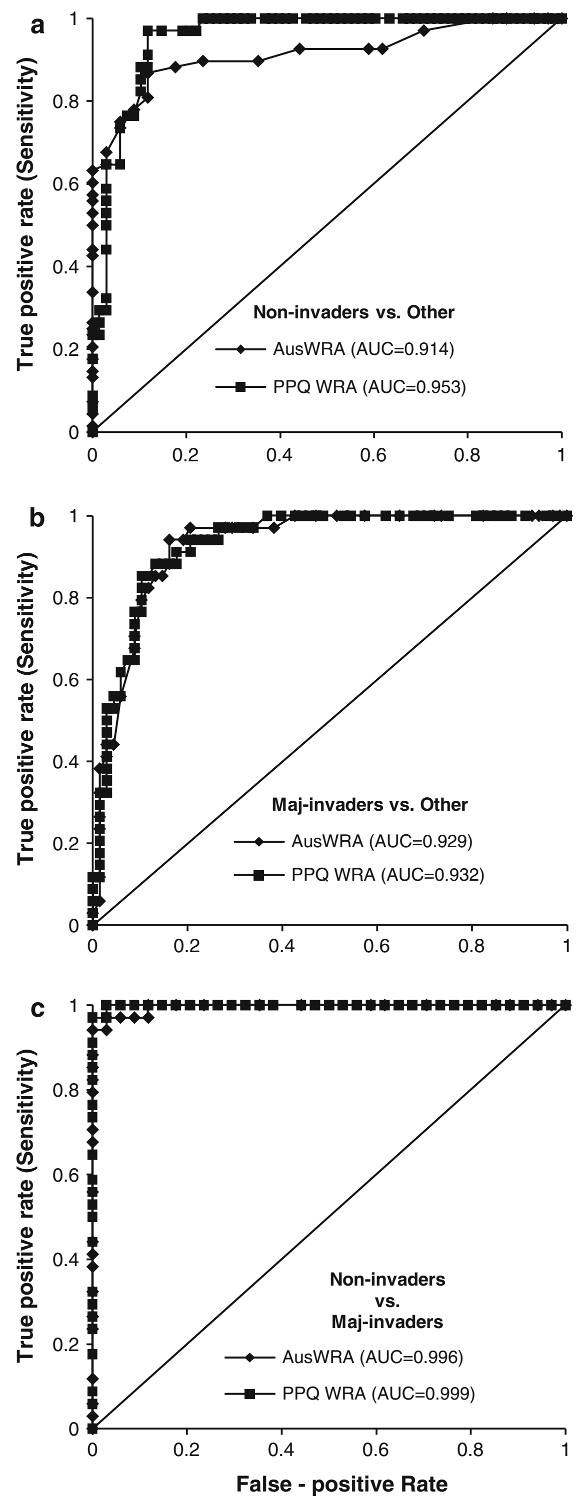

Fig. 5 Receiver operating characteristic (ROC) curves for the ▶ Australian and PPQ WRA models. Because there are three classes of invasive species (non-invaders, minor-invaders, and major-invaders), curves were generated first by treating minor-invaders as major-invaders (**a**), then by treating minor-invaders as non-invaders (**b**), and finally, by excluding minor-invaders (**c**). The area under the curves (AUC) is shown in the figure legend. None of the pairs of AUCs were significantly different from each other, but they were all different from an AUC of 0.5, represented by the diagonal. ROC curves were based on the validation dataset

the PPQ model but with different sets of species would help determine if non-invader accuracy is consistently high.

For the validation dataset, analysis of the AUCs for both models did not detect a significant difference between the PPQ and Australian models; yet test accuracy and error results suggest that the PPQ model improved upon the Australian model. The discrepancy may be partially explained by the differences between those two types of performance measures. The AUC measures the ability of a model to discriminate between two different classes, independently of any decision threshold (Hughes and Madden 2003). However, measures of accuracy, error, and reliability require that a decision threshold be established and are directly affected by the placement of that threshold. Thus a perfect model can have a very low sensitivity or specificity, if the decision threshold is set too high or too low. As in other studies (McClay et al. 2010; Nishida et al. 2009), our results suggest that the performance of the Australian model might be improved by using higher thresholds (5 and 11, vs. 1 and 6 in the original WRA).

"Evaluate further" and minor-invaders

Most tests of WRA models consider three categories of invasive species representing the two extremes and an intermediate category (e.g., Kato et al. 2006; Křivánek and Pyšek 2006). Including the intermediate category may be useful, but it complicates how we interpret model performance because test diagnostics usually consider only two cases. Most tests of the Australian WRA have evaluated model performance by grouping minor-invaders first with non-invaders and then with major-invaders. Because the distribution of risk scores for minor-invaders greatly overlaps the non- and major-invader categories, how the categories are grouped affects performance measures (Gordon et al. 2008b), ROC curve analysis, determination of cutoff scores, and our perception of model performance. However, grouping does not affect a species' risk score or the ability of the WRA to discriminate among species. Because most plant import decisions are to either prohibit or allow entry, an intermediate category also challenges policy-makers wishing to balance opposing viewpoints between plant importers and groups wishing to prevent the entry of invasive species (Reichard 2004; Peters et al. 2006). Should minor-invaders be considered as non-invaders or major-invaders? Ultimately, the answer depends on public perception of risk and on how risk averse regulatory agencies are (Gordon et al. 2008c). Here we took a more neutral approach to minor-invaders. We first grouped them both ways to determine the risk thresholds that separate the low and high risk categories from the "evaluate further" category. However, later, we ignored them when evaluating model performance, allowing us to focus on our goal of maximizing separation of non- and major-invaders.

The PPQ WRA may be better able to separate minor-invaders from non- and major-invaders than the Australian WRA, since it resulted in higher frequencies of minor-invaders in the "evaluate further" category than the other tests. We believe this is because of the way we refined our initial model to eliminate less predictive questions and increase the weights of more predictive ones. Ideally, a predictive model would perfectly separate all three a priori classes from each other, categorizing all non-invaders as low risk, all minor-invaders as the intermediate risk category ("evaluate further" in our system), and all major-invaders as high risk. However, this is never the case due to inadequate discrimination by the model and misclassification of the a priori species. Assuming our model is robust and our assessments were thorough, then the species risk scores may more accurately reflect their current or potential status as weeds and invaders than the original a priori classifications. To our knowledge, the validity of a priori classification has never been discussed.

Generally, after a secondary screening tool is used with the Australian WRA, about 10% of the species remain in the "evaluate further" category (Gordon et al. 2008b). Policy-makers and program managers should be cautious when determining the fate of these species because while most may represent minor-invaders (species with intermediate risk scores), some may be unresolved non- and major-invaders (Gassó et al. 2010). When a taxon categorized as "evaluate further" is not economically beneficial (evaluated by some other tool), denying entry may be prudent. If, on the other hand, the taxon is beneficial, then it should be evaluated further with either a more detailed risk assessment or with greenhouse or field experiments (Ruesink et al. 1995; Mack 2005).

Meeting analytical, regulatory, and management needs

The WRA model that we developed in this study meets many analytical needs in PPQ. Assessments with the new model can be completed in about 2 days, which is considerably faster than with the previous APHIS WRA (USDA 2004) process. Rapid assessments will decrease response time to new and imminent weeds, and allow us to greatly increase the number of assessed species. This should benefit all of PPQ's stakeholders.

Because of the correlation between Establishment/Spread and Impact, the impact risk element was not a significant predictor of plant invasive status in the logistic regression model. We could have omitted this variable to produce a simpler model, losing only 1% of the variability explained by the full model. By doing so, however, we would have been ignoring one of the fundamental components of risk—the consequences of an adverse event (Byrd and Cothern 2005). Understanding the magnitude and types of impacts of weeds and invasive plants is important in weed risk assessment (Groves et al. 2001), weed management (Randall et al. 2008), and necessary for regulating plants as Federal Noxious Weeds (The U.S. Plant Protection Act of 2000).

We did not include the geographic or climatic suitability of the United States as a component of species establishment because it would have unintentionally biased the model against plants of minor U.S. regions (e.g., tropical or Mediterranean climates). Our model's overall high accuracy supports our decision to exclude this factor, and suggests that for climatically diverse regions, climate matching may not be necessary for predicting the invasive success of species. However, for countries or regions with limited climatic diversity, consideration of geographic and climatic suitability through either a few simple questions (Pheloung et al. 1999) or more complex climate matching tools (DPI 2008) is still important and may be critical for model performance (e.g., Canada: McClay et al. 2010). Although not part of our predictive model, climate matching will be an important component of U.S. weed risk management as national, regional, and local managers decide what actions, if any, are appropriate for their jurisdictions. It will also be useful for weed managers as they seek to understand how climate change may affect the distribution of weeds and invasive plants within regions (Kriticos et al. 2003).

In risk analysis, our knowledge is never perfect about most of the factors we are assessing. For most questions in an assessment, we usually have some information on which to base the assessment, but for others we may have less or no information. Incomplete and missing information represents one component of the uncertainty of an assessment (Byrd and Cothern 2005; IPPC 2009). In this study, non-invaders had more unanswered questions than major-invaders. This led to a significant correlation between the number of questions answered and the E/S risk score, suggesting that the model's ability to identify invaders may be limited by missing information. Given our model's high accuracy, however, this did not appear to be true here. Our model may be sensitive enough even without full information to identify most major-invaders as high risk. How risk assessments handle missing information and other types of uncertainty may be just as important as how they handle positive or negative evidence. No one has yet developed a method to evaluate how uncertainty affects the outcome of WRAs.

While our results indicate the new PPQ WRA model is likely to be a valuable tool, we recognize that this is still a rather simple approach to predicting the behavior of plant species because it focuses primarily on species traits. Environmental properties, propagule pressure, chance events, biotic interactions, and human intervention also interact in complex ways to determine the outcome of species introductions (Daehler and Strong 1993; Kolar and Lodge 2001; Lodge 1993; Mack 2005). Several authors have argued that screening tools need to consider these factors (Rejmánek 2000; Mack 1996; Stohlgren and Schnase 2006; Moles et al. 2008). However, evaluating all of these factors for all species is impractical and unrealistic due to the large number of taxa we expect to be analyzing and the tremendous environmental diversity represented by the United States and its territories (Lodge 1993). Our model is meant to be a preliminary screening, the first in a series of defenses against invasive species (NISC 2008). More detailed assessments that consider the above factors may be appropriate for certain species with moderate risk scores or high uncertainty (i.e., species in the "evaluate further" category), proposed biofuel species (Barney and DiTomaso 2008), or genetically modified organisms.

We achieved our goal of developing a streamlined WRA that distinguishes between non- and major-invaders, characterizes risk using traditional elements of pest risk (*sensu* IPPC 2009), and improves prediction of non-invaders. The new PPQ WRA combines the question–answer style of rapid screening tools with the structure typically associated with pest risk analysis (IPPC 2009). By summarizing risk in two separate risk elements rather than one, we essentially create a risk profile for every plant that should be more useful for managers than a single risk score (Gassó et al. 2010). We have already begun using the new model to evaluate the risk potential of plant species. We intend to continue testing the model as we add additional species to the validation dataset.

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Appendix 1

Risk scores and model results after secondary screening for species used in the U.S. tests of the Australian and PPQ weed risk assessments. ES and Imp represent the Establishment/Spread and Impact risk elements of the PPQ model. Model results are accept, evaluate further, or reject for the Australian WRA, and low risk, evaluate further, or high risk for the PPQ WRA. Results based on the secondary screening are indicated with a superscripted "SS" after the result (Tables 4 and 5).

Table 4 Scores and results from the two models for species in the developmental dataset

Species	Family	Habit	Aus WRA		PPQ WRA		
			Score	Result	ES	Imp	Result
Major-invaders							
Abrus precatorius	Fabaceae	Vine	9	Reject	11	2.4	High
Abutilon theophrasti	Malvaceae	Herb	21	Reject	17	2.7	High
Alnus glutinosa	Betulaceae	Tree	15	Reject	12	2	High
Ardisia elliptica	Myrsinaceae	Shrub	8	Reject	13	2.6	High
Avena fatua	Poaceae	Graminoid	25	Reject	20	3.7	High
Bassia scoparia	Chenopodiaceae	Herb	11	Reject	10	2.2	High
Brachypodium sylvaticum	Poaceae	Graminoid	12	Reject	16	1.3	High
Cardaria draba	Brassicaceae	Herb	18	Reject	13	3.1	High
Centaurea solstitialis	Asteraceae	Herb	24	Reject	19	4.3	High
Cirsium arvense	Asteraceae	Herb	29	Reject	18	4.4	High
Convolvulus arvensis	Convolvulaceae	Vine	22	Reject	14	3.1	High
Cupaniopsis anacardioides	Anacardiaceae	Tree	6	Eval^{SS}	4	1.1	High^{SS}
Cyperus rotundus	Cyperaceae	Graminoid	19	Reject	16	3.6	High
Datura stramonium	Solanaceae	Herb	29	Reject	20	4.1	High
Eichhornia crassipes	Pontederiaceae	Herb	31	Reject	20	4.3	High
Eugenia uniflora	Myrtaceae	Shrub	6	Reject^{SS}	12	2.6	High
Hydrilla verticillata	Hydrocharitaceae	Aquatic	31	Reject	21	4.3	High
Lactuca serriola	Asteraceae	Herb	22	Reject	14	3.9	High
Lonicera maackii	Caprifoliaceae	Shrub	7	Reject	7	1.2	High^{SS}
Miconia calvescens	Melastomataceae	Tree	9	Reject	14	2.9	High
Mimosa pigra	Fabaceae	Shrub	19	Reject	19	4.4	High
Pittosporum undulatum	Pittosporaceae	Tree	13	Reject	16	3.2	High
Portulaca oleracea	Portulacaceae	Herb	21	Reject	18	2.7	High
Psidium guajava	Myrtaceae	Tree	16	Reject	16	3.5	High
Rumex crispus	Polgonaceae	Herb	25	Reject	17	2.2	High
Senecio vulgaris	Asteraceae	Herb	31	Reject	25	3.2	High
Setaria italica subsp. *viridis*	Poaceae	Graminoid	23	Reject	19	2.4	High
Sisymbrium irio	Brassicaceae	Herb	25	Reject	19	2.9	High
Solanum nigrum	Solanaceae	Subshrub	24	Reject	20	3	High
Sorghum halepense	Poaceae	Graminoid	29	Reject	23	2.9	High
Tamarix ramosissima	Tamaricaceae	Shrub	17	Reject	9	3	High
Thlaspi arvense	Brassicaceae	Herb	26	Reject	20	3	High
Tradescantia fluminensis	Commelinaceae	Herb	14	Reject	12	3.6	High
Triadica sebifera	Euphorbiaceae	Tree	11	Reject	11	3.3	High
Minor-invaders							
Abutilon hirtum	Malvaceae	Shrub	9	Reject	6	1.3	Eval^{SS}
Acanthospermum australe	Asteraceae	Herb	16	Reject	14	2.3	High
Actinidia chinensis	Actinidiaceae	Vine	16	Reject	6	2.6	High^{SS}
Agrostemma githago	Caryophyllaceae	Herb	12	Reject	8	2.5	Eval^{SS}
Aira caryophyllea	Poaceae	Graminoid	5	Accept^{SS}	2	2.2	Eval^{SS}
Akebia quinata	Lardizabalaceae	Vine	16	Reject	9	1.9	High^{SS}
Antirrhinum majus	Scrophulariaceae	Herb	1	Accept^{SS}	−3	1.5	Low

Table 4 continued

Species	Family	Habit	Aus WRA		PPQ WRA		
			Score	Result	ES	Imp	Result
Archontophoenix alexandrae	Arecaceae	Tree	5	Accept[SS]	5	1.3	High[SS]
Arctium minus	Asteraceae	Herb	23	Reject	13	2.5	High
Bassia hyssopifolia	Chenopodiaceae	Herb	9	Reject	4	1.6	High[SS]
Betula pendula	Betulaceae	Tree	6	Eval[SS]	4	2	High[SS]
Castilla elastica	Moraceae	Tree	0	Accept	0	1.7	High[SS]
Conium maculatum	Apiaceae	Herb	30	Reject	23	3.7	High
Costus dubius	Zingiberaceae	Herb	−5	Accept	−10	1	Low
Dendrobium crumenatum	Orchidaceae	Epiphyte	−1	Accept	−5	1	Low
Eucalyptus camaldulensis	Myrtaceae	Tree	15	Reject	9	3.9	High
Euonymus alatus	Celastraceae	Shrub	4	Eval[SS]	9	1.2	High[SS]
Glechoma hederacea	Lamiaceae	Herb	12	Reject	5	2.3	High[SS]
Guzmania lindenii	Bromeliaceae	Epiphyte	0	Accept	−3	1	Low
Helichrysum petiolare	Asteraceae	Subshrub	3	Accept[SS]	−3	1.2	Low
Hygrophila polysperma	Acanthaceae	Aquatic	17	Reject	11	1	High[SS]
Ligustrum sinense	Oleaceae	Shrub	9	Reject	2	2.5	High[SS]
Luma apiculata	Myrtaceae	Tree	7	Reject	4	1.3	High[SS]
Luziola subintegra	Poaceae	Aquatic	13	Reject	3	2.3	Eval[SS]
Pittosporum pentandrum	Pittosporaceae	Tree	1	Accept[SS]	0	1	Low
Rosa multiflora	Rosaceae	Shrub	22	Reject	12	2.9	High
Setaria palmifolia	Poaceae	Graminoid	9	Reject	10	3.2	High
Spartina densiflora	Poaceae	Graminoid	11	Reject	12	2.2	High
Theobroma cacao	Sterculiaceae	Tree	−3	Accept	−4	1.1	Low
Trachelospermum jasminoides	Apocynaceae	Vine	−2	Accept	−3	1	Low
Ulmus procera	Ulmaceae	Tree	12	Reject	6	2.4	High[SS]
Verbena bonariensis	Verbenaceae	Subshrub	18	Reject	10	2.7	High
Wisteria sinensis/W. floribunda	Fabaceae	Vine	10	Reject	4	1.6	Eval[SS]
Xanthosoma atrovirens	Araceae	Herb	−5	Accept	−13	1	Low
Non-invaders							
Agave filifera	Agavaceae	Shrub	−1	Accept	−13	1	Low
Allium giganteum	Liliaceae	Herb	3	Accept[SS]	−10	1.2	Low
Asarum europaeum	Aristolochiaceae	Herb	3	Accept[SS]	−4	1	Low
Bombax ceiba	Bombacaceae	Tree	1	Eval[SS]	−2	1	Low
Brugmansia sanguinea	Solanaceae	Shrub	2	Accept[SS]	−5	1.5	Low
Buxus microphylla	Buxaceae	Shrub	−6	Accept	−13	1	Low
Catalpa bungei	Bignoniaceae	Tree	−1	Accept	−7	1.1	Low
Cedrus libani	Pinaceae	Tree	−4	Accept	−6	1	Low
Centaurea dealbata	Asteraceae	Herb	9	Reject	7	1	Eval[SS]
Cupressus sempervirens	Cupressaceae	Tree	3	Accept[SS]	−5	2.3	Low
Delosperma echinatum	Aizoaceae	Shrub	−9	Accept	−16	1	Low
Dianthus caryophyllus	Caryophyllaceae	Herb	−3	Accept	−6	1	Low
Festuca amethystina	Poaceae	Graminoid	5	Accept[SS]	−4	1	Low
Fortunella japonica	Rutaceae	Shrub	−7	Accept	−14	1	Low
Gazania rigens	Asteraceae	Herb	10	Reject	7	2.5	High[SS]

Table 4 continued

Species	Family	Habit	Aus WRA		PPQ WRA		
			Score	Result	ES	Imp	Result
Kniphofia caulescens	Liliaceae	Herb	3	Accept[SS]	−7	1	Low
Linaria alpina	Schrophulariaceae	Herb	2	Accept[SS]	1	1	Low
Listera ovata	Orchidaceae	Herb	10	Reject	5	1.3	Eval[SS]
Medicago arborea	Fabaceae	Shrub	14	Reject	5	1.7	Eval[SS]
Pistacia chinensis	Anacardiaceae	Tree	1	Eval[SS]	−5	1.4	Low
Podophyllum hexandrum	Berberidaceae	Herb	5	Accept[SS]	0	1.1	Low
Polygonum amplexicaule	Polygonaceae	Herb	5	Accept[SS]	−1	1	Low
Pouteria sapota	Sapotaceae	Tree	−3	Accept	−12	1	Low
Primula elatior	Primulaceae	Herb	−2	Accept	−8	1	Low
Primula pulverulenta	Primulaceae	Herb	0	Accept	−7	1	Low
Prunus japonica	Rosaceae	Shrub	6	Accept[SS]	0	1.3	Low
Rhododendron simsii	Ericaceae	Shrub	−7	Accept	−7	1	Low
Ribes orientale	Grossulariaceae	Shrub	−1	Accept	−4	1.2	Low
Rondeletia odorata	Rubiaceae	Shrub	−5	Accept	−13	1	Low
Saintpaulia ionantha	Gesneriaceae	Herb	−3	Accept	−12	1	Low
Styphnolobium japonicum	Fabaceae	Tree	0	Accept	−2	1.1	Low
Teucrium chamaedrys	Lamiaceae	Subshrub	4	Accept[SS]	0	1.4	Low[SS]
Tulipa gesneriana	Liliaceae	Herb	−5	Accept	−12	1.1	Low
Yucca guatemalensis	Agavaceae	Tree	−5	Accept	0	1.1	Low

Table 5 Scores and results from the two models for species in the validation dataset

Species	Family	Habit	Aust WRA		PPQ WRA		
			Score	Result	ES	Imp	Result
Major-invaders							
Aegilops cylindrica	Poaceae	Graminoid	20	Reject	12	2.1	High
Albizia julibrissin	Fabaceae	Tree	16	Reject	11	1.9	High
Allium vineale	Lilliaceae	Herb	19	Reject	13	2.7	High
Alternanthera philoxeroides	Amaranthaceae	Aquatic	30	Reject	21	4.8	High
Barbarea vulgaris	Brassicaceae	Herb	20	Reject	15	2.9	High
Berberis thunbergii	Berberidaceae	Shrub	19	Reject	10	2.8	High
Bromus tectorum	Poaceae	Graminoid	26	Reject	17	4	High
Capsella bursa-pastoris	Brassicaceae	Herb	13	Reject	15	2.6	High
Carduus nutans	Asteraceae	Herb	28	Reject	17	4.2	High
Carpobrotus chilensis	Aizoaceae	Herb	12	Reject	8	1.8	Eval[SS]
Casuarina equisetifolia	Casuarinaceae	Tree	17	Reject	16	3.1	High
Cayratia japonica	Vitaceae	Vine	19	Reject	12	1.9	High
Cytisus scoparius	Fabaceae	Shrub	30	Reject	18	4.1	High
Daucus carota subsp. *carota*	Apiaceae	Herb	30	Reject	19	3.3	High
Elaeagnus umbellata	Elaeagnaceae	Shrub	19	Reject	13	2.7	High
Emex spinosa	Polygonaceae	Herb	25	Reject	15	3.1	High
Euphorbia esula	Euphorbiaceae	Herb	37	Reject	23	3.7	High
Galinsoga parviflora	Asteraceae	Herb	24	Reject	22	2.7	High

Table 5 continued

Species	Family	Habit	Aust WRA		PPQ WRA		
			Score	Result	ES	Imp	Result
Hypericum perforatum	Hypericaceae	Herb	30	Reject	20	3.6	High
Imperata cylindrica	Poaceae	Graminoid	33	Reject	21	4.3	High
Lamium amplexicaule	Lamiaceae	Herb	20	Reject	12	3	High
Lygodium japonicum	Lygodiaceae	Vine	26	Reject	13	2.1	High
Lythrum salicaria	Lythraceae	Aquatic	32	Reject	22	3.2	High
Malva parviflora	Malvaceae	Herb	15	Reject	12	2.5	High
Myrica faya	Myricaceae	Tree	5	Eval^{SS}	1	1.3	High^{SS}
Myriophyllum spicatum	Haloragaceae	Aquatic	32	Reject	21	4.7	High
Nandina domestica	Berberidaceae	Shrub	17	Reject	3	1.6	Eval^{SS}
Neyraudia reynaudiana	Poaceae	Graminoid	12	Reject	7	1.9	High^{SS}
Pennisetum ciliare	Poaceae	Graminoid	20	Reject	14	4	High
Poa annua	Poaceae	Graminoid	27	Reject	23	3.2	High
Polygonum aviculare	Polygonaceae	Herb	27	Reject	18	3.9	High
Polygonum convolvulus	Polygonaceae	Vine	18	Reject	12	2.4	High
Rottboellia cochinchinensis	Poaceae	Graminoid	17	Reject	17	2.2	High
Schefflera actinophylla	Araliaceae	Tree	10	Reject	8	3.7	High
Minor-invaders							
Acer palmatum	Aceraceae	Tree	5	Eval^{SS}	0	1.5	Eval^{SS}
Artocarpus heterophyllus	Moraceae	Tree	−3	Accept	−2	1.1	Low
Bellardia trixago	Scrophulariaceae	Herb	7	Reject	4	2.1	High^{SS}
Cichorium intybus	Asteraceae	Herb	9	Reject	5	2.1	Eval^{SS}
Cissus rotundifolia	Vitaceae	Vine	−2	Accept	−1	1.1	Low
Clematis terniflora	Ranunculaceae	Vine	4	Eval^{SS}	−2	1.5	Low
Costus speciosus	Zingiberaceae	Herb	−2	Accept	−1	1.2	Low
Cotoneaster coriaceus	Rosaceae	Shrub	19	Reject	10	1.7	High^{SS}
Dioscorea oppositifolia	Dioscoreaceae	Vine	10	Reject	3	1	Eval^{SS}
Epipactis helleborine	Orchidaceae	Herb	13	Reject	8	1.7	High^{SS}
Euryops multifidus	Asteraceae	Subshrub	11	Reject	5	1.1	Eval^{SS}
Geranium pusillum	Geraniaceae	Herb	9	Reject	8	1.7	High^{SS}
Gloriosa superba	Colchicaceae	Vine	17	Reject	15	2.1	High
Gomphrena globosa	Amaranthaceae	Herb	6	Accept^{SS}	1	1.3	Eval^{SS}
Hiptage benghalensis	Malphigiaceae	Vine	6	Eval^{SS}	11	2.5	High
Hylotelephium telephium	Crassulaceae	Herb	9	Reject	1	1.3	Eval^{SS}
Ilex paraguariensis	Aquifoliaceae	Tree	−3	Accept	−8	1.1	Low
Ligustrum obtusifolium	Oleaceae	Shrub	−2	Accept	−2	1.1	Low
Linaria vulgaris	Scrophulariaceae	Herb	33	Reject	22	3.7	High
Lysimachia punctata	Primulaceae	Herb	7	Reject	3	1.4	High^{SS}
Melilotus indicus	Fabaceae	Herb	21	Reject	15	2.7	High
Orobanche minor	Orobanchaceae	Herb	19	Reject	21	2.6	High
Prunus armeniaca	Rosaceae	Tree	8	Reject	2	1.3	Eval^{SS}
Pyracantha coccinea	Rosaceae	Shrub	16	Reject	8	2.2	High^{SS}
Quisqualis indica	Combretaceae	Vine	9	Reject	3	1.7	Eval^{SS}
Ranunculus acris	Ranunculaceae	Herb	25	Reject	12	3	High

Table 5 continued

Species	Family	Habit	Aust WRA		PPQ WRA		
			Score	Result	ES	Imp	Result
Rhamnus utilis	Rhamnaceae	Shrub	1	Accept^{SS}	−6	1	Low
Ribes rubrum	Grossulariaceae	Shrub	5	Accept^{SS}	0	1.5	Eval^{SS}
Rumex pulcher	Polgonaceae	Herb	20	Reject	14	1.8	High
Saponaria officinalis	Caryophyllaceae	Herb	14	Reject	11	1.9	High
Senecio jacobaea	Asteraceae	Herb	15	Reject	8	2.8	High^{SS}
Spermacoce latifolia	Rubiaceae	Herb	5	Eval^{SS}	10	2.5	High
Stapelia gigantea	Asclepiadaceae	Herb	1	Accept^{SS}	0	1.2	Low
Tillandsia gardneri	Bromeliaceae	Epiphyte	3	Eval^{SS}	2	1	Low^{SS}
Non-invaders							
Abutilon megapotamicum	Malvaceae	Shrub	2	Accept^{SS}	−1	1.2	Low
Acer buergerianum	Aceraceae	Tree	6	Accept^{SS}	−2	1.7	Low
Acorus gramineus	Acoraceae	Aquatic	9	Reject	−2	1	Low
Bergenia crassifolia	Saxifragaceae	Herb	−4	Accept	−6	1.1	Low
Blechnum brasiliense	Blechnaceae	Herb	0	Accept	−5	1	Low
Brachycome iberidifolia	Asteraceae	Herb	0	Accept	−8	1	Low
Ceiba speciosa	Bombacaceae	Tree	−7	Accept	−5	1	Low
Combretum coccineum	Combretaceae	Shrub	−2	Accept	−4	1	Low
Davallia canariensis	Polypodiaceae	Herb	0	Accept	1	1	Low
Dendrocalamus latiflorus	Poaceae	Tree	−6	Accept	−10	1.1	Low
Diospyros kaki	Ebenaceae	Tree	−2	Accept	−4	1.2	Low
Erica carnea	Ericaceae	Subshrub	3	Accept^{SS}	−1	1.1	Low
Fatsia japonica	Araliaceae	Shrub	1	Eval^{SS}	−1	1	Low
Gardenia thunbergii	Rubiaceae	Shrub	−2	Accept	−9	1	Low
Ginkgo biloba	Ginkgoaceae	Tree	−3	Accept	−5	1.1	Low
Hydrangea anomala	Hydrangeaceae	Vine	−3	Accept	−2	1	Low
Lavandula latifolia	Lamiaceae	Subshrub	0	Accept	−3	1	Low
Libertia grandiflora	Iridaceae	Herb	1	Accept^{SS}	−8	1	Low
Lilium martagon	Liliaceae	Herb	7	Reject	3	1	Eval^{SS}
Myrtus communis	Myrtaceae	Shrub	3	Eval^{SS}	0	1.3	Low
Penstemon campanulatus	Scrophulariaceae	Herb	2	Accept^{SS}	−7	1.2	Low
Pinus wallichiana	Pinaceae	Tree	1	Accept^{SS}	0	1.1	Low
Pittosporum bicolor	Pittosporaceae	Tree	4	Eval^{SS}	1	1	Low
Prunus maackii	Rosaceae	Tree	2	Accept^{SS}	−5	1.1	Low
Quercus serrata	Fagaceae	Tree	−3	Accept	−7	1	Low
Rodgersia sambucifolia	Saxifragaceae	Herb	2	Accept^{SS}	−11	1	Low
Salix glabra	Salicaceae	Shrub	−1	Accept	−9	1	Low
Stenocarpus sinuatus	Proteaceae	Tree	−8	Accept	−11	1	Low
Stephanandra tanakae	Rosaceae	Shrub	0	Accept	−5	1	Low
Syzygium eucalyptoides	Myrtaceae	Tree	4	Eval^{SS}	−1	1	Low
Torreya nucifera	Taxaceae	Tree	−3	Accept	−5	1	Low
Trollius europaeus	Ranunculaceae	Herb	−3	Accept	−1	1	Low
Viburnum farreri	Adoxaceae	Shrub	−6	Accept	−9	1	Low
Wisteria brachybotrys	Fabaceae	Vine	11	Reject	−1	1.2	Low

Appendix 2

See Table 6.

Table 6 Questions and scoring used in the final PPQ weed risk assessment

Establishment/spread potential	
ES-1	Select one: (A) Introduced elsewhere long ago (>75 years) but not escaped (−5). (B) Introduced recently (<75 years) but not escaped (−2). (C) Never introduced elsewhere (0). (D) Escaped/Casual (0). (E) Naturalized (2). (F) Invader (5)
ES-2	Is the species highly domesticated (y = −3, n = 0, or ? = 0)
ES-3	Congeneric weed (y = 1, n = 0, or ? = 0)
ES-4	Shade tolerant at some stage of life cycle (y = 1, n = 0, or ? = 0)
ES-5	Climbing or smothering growth habit (y = 1, n = 0, or ? = 0)
ES-6	Forms dense thickets (y = 2, n = 0, or ? = 0)
ES-7	Aquatic (y = 1, n = 0, or ? = 0)
ES-8	Grass (y = 1, n = 0, or ? = 0)
ES-9	Nitrogen-fixing woody plant (y = 1, n = 0, or ? = 0)
ES-10	Produces viable seed or spores (y = 1, n = −1, or ? = 0)
ES-11	Self-compatible or apomictic (y = 1, n = −1, or ? = 0)
ES-12	Requires specialist pollinators (y = −1, n = 0, or ? = 0)
ES-13	Minimum generative time: (A) Less than 1 (multiple generations per year) (2). (B) 1 Year (annual-1 gen per year) (1). (C) 2 or 3 years (0). (D) >3 Years (−1). ? = 0
ES-14	Prolific seed/spore production (see scoring guide) (y = 1, n = −1, or ? = 0)
ES-15	Propagules likely to be dispersed unintentionally by people (y = 1, n = −1, or ? = 0)
ES-16	Propagules likely to disperse in trade as contaminants and hitchhikers (y = 2, n = −1, or ? = 0)
ES-17[a]	No. natural dispersal vectors (none = −4, one = −2, two = 0, three = 2, four or five = 4)
ES-18	Evidence that a persistent (>1 year) propagule bank (seed bank) is formed (y = 1, n = −1, or ? = 0)
ES-19	Tolerates/benefits from mutilation, cultivation or fire (y = 1, n = −1, or ? = 0)
ES-20	Is resistant to some herbicides or has potential to acquire herbicide resistance (y = 1, n = 0, or ? = 0)
ES-21	Number of USDA cold hardiness zones suitable for survival (out of 13) (zero-three = −1, four-nine = 0, ten-thirteen = 1)
ES-22	Number of climate types suitable for survival (out of 12) (zero-two = −2, three = 0, four-twelve = 2)
ES-23	Number of precipitation bands suitable for survival (out of 11) (zero-four = −1, five-seven = 0, eight-eleven = 1)
Impact potential	
Imp-G1	Allelopathic (y = 0.1, n = 0, or ? = 0)
Imp-G2	Parasitic (y = 0.1, n = 0, or ? = 0)
Imp-N1	Change ecosystem processes and parameters that affect other species? (y = 0.4, n = 0, or ? = 0)
Imp-N2	Change community structure? (y = 0.2, n = 0, or ? = 0)
Imp-N3	Change community composition? (y = 0.2, n = 0, or ? = 0)
Imp-N4	Likely to affect any federal Threatened and Endangered plant species? (y = 0.1, n = 0, or ? = 0)
Imp-N5	Likely to affect any globally outstanding ecoregions? (y = 0.1, n = 0, or ? = 0)
Imp-N6	For conservation/natural areas, choose the best answer. (A) Plant not a weed (0); (B) Plant a weed but no evidence of control efforts (0.2); (C) Plant a weed and evidence of control efforts (0.6)

Table 6 continued

Imp-A1	Impacts human property, processes, civilization, or safety? (y = 0.1, n = 0, or ? = 0)
Imp-A2	Changes or limits recreational use of an area? (y = 0.1, n = 0, or ? = 0)
Imp-A3	Outcompetes, replaces or otherwise affects desirable plants and vegetation? (y = 0.1, n = 0, or ? = 0)
Imp-A4	For urban/suburban areas, choose the best answer. (A) Plant not a weed (0); (B) Plant a weed but no evidence of control efforts (0.1); (C) Plant a weed and evidence of control efforts (0.4)
Imp-P1	Reduces crop/product yield? (y = 0.4, n = 0, or ? = 0)
Imp-P2	Lowers commodity value? (y = 0.2, n = 0, or ? = 0)
Imp-P3	Is it likely to impact trade? (y = 0.2, n = 0, or ? = 0)
Imp-P4	Reduces the quality or availability of irrigation, or strongly competes with plants for water? (y = 0.1, n = 0, or ? = 0)
Imp-P5	Toxic to animals, including livestock/range animals and poultry (y = 0.1, n = 0, or ? = 0)
Imp-P6	For production systems, choose the best answer. (A) Plant not a weed (0); (B) Plant a weed but no evidence of control efforts (0.2); (C) Plant a weed and evidence of control efforts (0.6)

Only shown are questions for the establishment/spread (ES) and impact (Imp) risk elements, which comprise the predictive component of the model

[a] We consider up to five possible dispersal vectors: wind, water, bird, animal internal, animal external. These correspond to the same five in the Australian weed risk assessment (questions 7.04–7.08)

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