

Evaluation of species properties used in weed risk assessment and improvement of systems for invasion risk assessment

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Abstract The weed risk assessment (WRA) system is used in Australia for plant species. Results of applying such weed risk assessment in Bonin (Ogasawara) Islands, Japan were analysed to evaluate the effectiveness of the species properties considered. In addition, a comparison was carried out of various risk assessment systems, such as WRA, weight estimation by linear regression, logistic regression and decision tree analysis, with the aim of improving the systems used for risk assessment.

Among species properties considered in WRA, history of naturalisation (establishing self-perpetuating population in regional vegetation) was the most important property, whereas many biological traits did not contribute effectively. A better result was obtained with a risk assessment system based on four groups of variables: 1) naturalisation elsewhere, 2) special biological traits, such as natural enemies, 3) weediness, 4) habitat specific ecological properties (for forests and for disturbed land).

In the short term, the “biogeography and history” components of traditional WRA may provide the best system, although the threshold value for acceptance and rejection needs to be determined. In the slightly longer term, the regression model with grouped variables proposed in this paper is another candidate, although this should be tested with additional data.

Keywords: invasion risk assessment; Bonin (Ogasawara) Islands; Japan; oceanic island; weed risk analysis; ecological trait

INTRODUCTION

Weed risk assessment (WRA) is an invasion risk assessment system for plant species developed in Australia (Pheloung *et al.* 1999), to evaluate the risk that a species proposed for introduction will become a noxious weed. It has been used in Australia to evaluate invasion risks before introduction and in New Zealand to determine the management of alien plant species already introduced. In WRA, species properties relating to climate, domestication history, naturalisation elsewhere, as well as other ecological traits, are considered. The sum of the values assigned to each property gives a total score which is used to evaluate the likely invasion ability and impacts of the focal species. WRA has been adapted to other regions such as Hawaii (Daehler *et al.* 2004). In the Hawaiian WRA, small decision trees have been added as an additional step to decide on species with an ambivalent outcome; nevertheless the properties considered and their weightings were basically those of the original Australian WRA.

The objectives of this research are to evaluate the effectiveness of the species properties considered in WRA, with the aim of improving the invasion risk

assessment system. The WRA results for Bonin (Ogasawara) Islands (Kato *et al.* 2006), Japan were used for analysis. The WRA for the Bonin Islands was successful, but providing the information asked for in the assessment for all species properties is labour intensive and there may be a room to improve weighting for each property.

The Bonin Islands are subtropical oceanic islands with many endemic species. Land use in these islands is different from Australia and grazing in pastures is not common. The shade tolerant tall alien tree *Bischofia javanica* is now the most dominant species in the climax forests, and environmental weeds in natural habitats are a more important issue than weeds in arable lands and pastures. As a result, some properties considered in WRA elsewhere may not be important in the islands. Proper weighting of properties and improvement of formulation will improve evaluation of invasion risk.

METHODS: DATASET AND ANALYSIS OF SPECIES PROPERTIES

Data set

The WRA results in the Bonin Islands (Kato *et al.* 2006), based on the Hawaiian WRA (Daehler *et al.* 2004), were used for analysis. Seed plant species that have a history of introduction to Bonin Islands were listed for analysis. The data set was a table of species (sample) x properties (variable).

Invasiveness value, representing the impact of alien species, was used as a dependent variable to evaluate the risk assessment models. Since a suitable standardised method to classify the impact of a given alien species on the native ecosystem was not yet established, expert opinion was used. Several plant experts living in the Bonin Islands evaluated the impact of the listed alien species, based on their experience, and classified each species as either a “major pest” (established widely in the wild or having substantial impact on ecosystems), “minor pest” (naturalised but no significant impact), and “non-pest” (not naturalised). The majority vote of these experts was used to assign an invasiveness value to a species. Values assigned in quantitative analysis (correlation coefficient and linear regression) were 0 for non-pest, 1 for minor pest, 2 for major pest. Values assigned in qualitative analyses (logistic regression, decision tree analysis) were 0 for non-pest and 1 for major pest. Minor pest species were not used in qualitative analyses.

Independent variables used to predict invasion risk were bio-geographical, historical and biological properties of species with the list of properties used the same as in the WRA. The value for each property was agreed by botanists based on information available in literature and on the Internet (Kato *et al.* 2006). For many properties, the value was one of three states: “yes”, “no” or “unknown”. If the shade tolerance is given quantitatively in the information source, the researcher needed to use judgment in giving values as “tolerant” or “intolerant”. These processes are like a questionnaire based on personal experience. Results obtained may not be very precise, but it is much quicker than requiring quantitative measurements. To calculate the WRA score, numerical values were assigned for “yes”, “no” and “unknown” according to the WRA method (see Appendix 1 in Kato *et al.* 2006, for the list of properties and their weightings).

Species properties were categorised for the two fields of “biogeography and history” and “biology and ecology” (Pheloung *et al.* 1999). “Biogeography and history” was subdivided into “domestication and cultivation”, “climate similarity” and “naturalisation

elsewhere”. “Biology and ecology” was subdivided into “undesirable traits” (such as spines, allelopathy, toxic, etc.), “plant type” (such as aquatic, nitrogen fixer, etc.), “reproduction”, “dispersal”, and “persistence attributes” (such as huge seed production, propagule bank, herbicide tolerance, etc.). Details for the WRA in the Bonin Islands have been described by Kato *et al.* (2006) in this volume.

Grouping of species properties and correlation to invasiveness

WRA considers many closely related properties. Properties were classified by dichotomous cluster analysis according to responses for species using Minna de GIS software (Koike 2004). In the cluster analysis, properties were subjected to principal component analysis, and then properties were divided into two groups based on the first principal component axis. The divided groups were subdivided iteratively. When the contribution of principal component analysis was less than 10% of total variance, division was stopped.

To evaluate the effectiveness of the species properties considered in the WRA, a simple correlation coefficient with “invasiveness” (expert judge score) was calculated for individual properties, and for the sum of values of each property type (with property types being biogeography, biological traits, etc.).

RISK ASSESSMENT MODELS

Various regression models were evaluated to obtain a model predicting species invasiveness from properties. The expert judge score was used as the dependent variable, and various properties were considered as independent variables. SPSS 13.0J was used for analysis.

Linear regression

All properties considered in WRA were used as independent variables. A stepwise variable selection procedure was applied. In this procedure, the most significant variable (property) was taken as the first step. The best two variables model (including the previously selected, most significant variable) was determined in the next step. Steps were iterated, and the number of variables in the model was increased as long as the addition of the new variable was statistically significant. If there were two similar variables with high mutual correlation, only one of

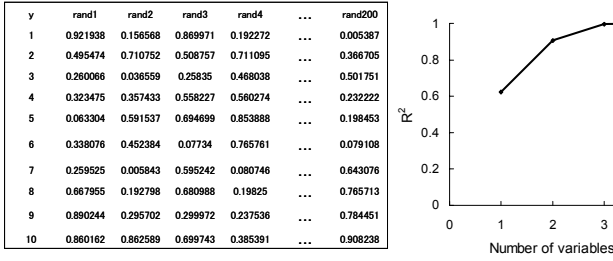


Figure 1 Artificial data of dependent variable y (sequential value from 1 to 10), and random number (0.0 to 1.0) for 200 independent variables. The graph represents the results of stepwise regression using a fixed threshold value of significance level at $P=0.05$. A significant linear regression was obtained. Thus controlling the significance level is essential in the stepwise variable selection procedure.

them was taken.

Although the significance level of $P=0.05$ is often used as a threshold, if we considered many independent variables simultaneously, even a variable with random values becomes significant. In our example (Fig. 1), we generated a test data set with 10 samples and 200 variables; we gave a sequential value from 1 to 10 to the dependent variable (y), and a random value between 0 to 1 for all independent variables ($rand1$ to $rand200$). Even though no variable should correlate to y , a significant regression model was obtained when using the stepwise linear regression (Fig. 1), if P was assumed to be 0.05. This was because the number of variables considered was too large, and hence at least some exceeded the significance level of $P<0.05$. To avoid this phenomenon, we used a threshold significance level of

$$P = 0.05 / (n - i + 1) \quad (1)$$

for the i -th step of the variable selection procedure, where n was the number of whole independent variables considered (Rice 1989). The term, $n - i + 1$, gives the number of variables examined in the i -th step.

Linear regression based on the properties in the category “biogeography and history”

A linear regression based only on the species properties in the category of “biogeography and history” was conducted to evaluate their effectiveness. A step wise variable selection procedure was applied.

Linear regression based on the properties in the category “biology and ecology”

A linear regression based only on species properties in the category “biology and ecology” was conducted to evaluate their effectiveness. A stepwise variable selection procedure was applied.

Logistic regression

A logistic regression with stepwise variable selection was also evaluated. This model gives the probability that the species will become invasive. Two states of “major pest” and “non-pest” were used as dependent variables, and “minor pest” species were not included in this analysis.

Decision tree analysis

Species were divided into two groups depending on a threshold value for a property, and the best combination of property and its threshold value was determined to divide ‘major-pest’ and “non-pest” species. This process was iterated and a tree-like division of species was obtained. There will be a branch of mainly “major pest” species and one of mainly “non-pest” species. ANSWER TREE 3.0J was used for the analyses.

Linear regression with grouped variables

Data used in WRA is provided using a questionnaire and personal experience will affect this to some extent. When we deal with data containing much noise (error of data), a slight fluctuation of a given variable will cause a large difference in the prediction, if only a few variables were considered. This may be the reason why the WRA considers several properties with much redundancy (Pheloung *et al.* 1999). For example, arable weed species usually have a set of traits, such as a long flowering time, short life cycle, and non-synchronous germination. If we use stepwise variable selection, only one, most significant, trait will be used from many traits with high mutual correlation. However, the selected trait will have error. Adding many mutually correlated variables can reduce random noise as

$$S = \frac{V}{N} \quad (2)$$

where S is the variance of averaged value of considered variables, V is the variance of a individual

variable, N is the number of variables averaged. It is possible to improve the reliability of the prediction model by adding mutually correlated variables.

In this research several groups of properties were selected and the sum of property values for each group was calculated. A linear regression with these summed values was conducted, assuming the expert judge score as a dependent variable.

To define property groups, properties were divided by cluster analysis as mentioned above. The important property in each group was selected, based on the correlation coefficients with the expert judge score. Several variables were added to each group to increase redundancy. These grouped variables were used in linear regression with stepwise variable selection.

METHOD FOR EVALUATION OF ASSESSMENT SYSTEMS

The following regression models, described above, were compared: "traditional" WRA, WRA using only the properties of "biogeography and history", and WRA using the properties of "biology and ecology". The decision tree used for the second screening in the Hawaiian WRA (Daehler *et al.* 2004, see Appendix 1-3

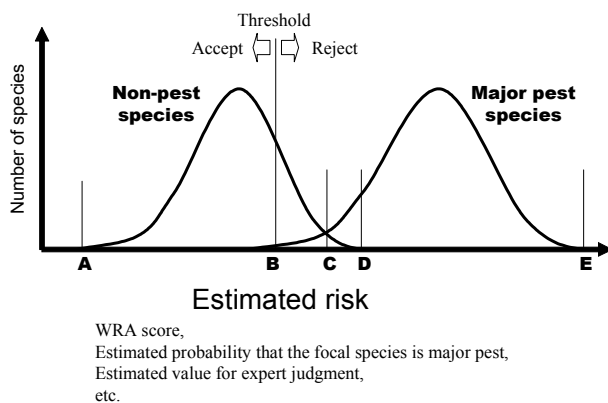


Figure 2 Hypothetical diagram to determine the threshold value that will be used to decide on the acceptance or rejection of a proposed introduction. Many types of scores can be used for the horizontal axis. They are: WRA score in weed risk assessment, estimated probability that the focal species is a major pest in logistic regression, decision tree analysis, and score of expert judge in various linear regression models. **A**: all species will be rejected, **B**: almost all major pest species will be rejected and many non-pest will be accepted (Scenario 2), **C**: maximise the probability that both major pest and non-pest species were judged correctly (Scenario 1), **D**: almost all non-pest species will be accepted and some major pest will also be accepted, and **E**: all species will be accepted.

in Kato *et al.* 2006) was not used in this analysis.

A score of 6 is usually used as a threshold value in WRA, meaning that a species with a value higher than 6 is not allowed to be introduced (Pheloung *et al.* 1999).

We need to determine such a threshold for various risk assessment systems (Fig. 2). Several non-pest species may score above the threshold and be rejected. Some major-pest species might score below the threshold and be accepted. The probabilities that a major pest species is judged as a pest and that a non-pest species is judged as a non-pest, will vary with the threshold value. The threshold should be set to maximise these probabilities simultaneously. We compared a plot of these probabilities for each risk assessment method (Fig. 5). Minor pest species were not considered in this evaluation.

Two scenarios were considered to set a threshold score. One scenario was to maximise the probability that both major pest and non-pest species were judged correctly (Scenario 1, threshold **C** in Fig. 2). This probability is the product of (correctly judged probability for major pest) $\times$ (correctly judged probability for non-pest). In this scenario a model with a high value for this probability is a good risk assessment model. In another scenario, it was assumed that major pests cause unacceptable hazards, thus the probability that the major pest is judged correctly should be as high as 95% (Scenario 2, threshold **B** in Fig. 2). However, this will cause rejection of many non-pest species. A model with a large probability that a non pest is judged correctly is a good risk assessment model under this second scenario.

RESULTS

Structure of species properties

Species properties were classified in six groups (Tab. 1). Group A contains species properties of agricultural and garden weeds. Variables in this group include propagule properties such as likely unintentional dispersal, dispersal as a contaminant, wind dispersal, and short generation time. Group B contains species properties relating to the degree of environmental tolerance. Group C contains species properties of weeds in forests and shrub lands. Group D included records of naturalisation in similar climate. Group E contained various properties. Although this latter group was very divers, contribution of the first principal component was low, and the group was not subdivided. Group F grouped properties of endozoochoric propagule dispersal.

Table 1 Classification of species properties based on the results of weed risk assessment in Bonin (Ogasawara) Islands, Japan (Kato *et al.* 2006). Dichotomous cluster analysis was carried out. Properties were divided into two groups using Division 1 (0 and 1 for Division 1), and each group was subdivided using Division 2 (0 and 1 for Division 2). The second level groups were subdivided using Division 3.

Group	No	Query	Division 1	Division 2	Division 3
A	Q302	Garden/amenity/disturbance weed	0	0	0
	Q303	Agricultural/forestry/horticultural weed	0	0	0
	Q402	Allelopathic	0	0	0
	Q501	Aquatic	0	0	0
	Q502	Grass	0	0	0
	Q504	Geophyte (herbaceous with underground storage organs)	0	0	0
	Q607	Minimum generative time (years)	0	0	0
	Q701	Propagules likely to be dispersed unintentionally	0	0	0
	Q703	Propagules likely to disperse as a produce contaminant	0	0	0
	Q704	Propagules adapted to wind dispersal	0	0	0
	Q707	Propagules dispersed by other animals (externally)	0	0	0
B	Q203	Broad climate suitability (environmental versatility)	0	0	1
	Q410	Tolerates a wide range of soil conditions	0	0	1
	Q606	Reproduction by vegetative fragmentation	0	0	1
C	Q304	Environmental weed	0	1	0
	Q412	Forms dense thickets	0	1	0
	Q801	Prolific seed production (>1000/m ²)	0	1	0
	Q804	Tolerates, or benefits from, mutilation, cultivation, or fire	0	1	0
D	Q301	Naturalised beyond native range	0	1	1
	Q305	Congeneric weed	0	1	1
E	Q102	Has the species become naturalised where grown?	1	0	0
	Q205	History of repeated introductions outside its natural range	1	0	0
	Q401	Produces spines, thorns or burrs	1	0	0
	Q406	Host for recognised pests and pathogens	1	0	0
	Q407	Causes allergies or is otherwise toxic to humans	1	0	0
	Q408	Creates a fire hazard in natural ecosystems	1	0	0
	Q411	Climbing or smothering growth habit	1	0	0
	Q503	Nitrogen fixing woody plant	1	0	0
	Q601	Evidence of substantial reproductive failure in native habitat	1	0	0
	Q603	Hybridises naturally	1	0	0
	Q604	Self-compatible or apomictic	1	0	0
	Q101	Is the species highly domesticated?	1	0	0
	Q103	Does the species have weedy races?	1	0	0
	Q201	Species suited to tropical or subtropical climate(s)	1	0	0
	Q202	Quality of climate match data	1	0	0
	Q204	Native or naturalised in regions with tropical or subtropical climates	1	0	0
	Q404	Unpalatable to grazing animals	1	0	0
	Q405	Toxic to animals	1	0	0
	Q409	Is a shade tolerant plant at some stage of its life cycle	1	0	0
	Q602	Produces viable seed.	1	0	0
	Q605	Requires specialist pollinators	1	0	0
	Q702	Propagules dispersed intentionally by people	1	0	0
	Q705	Propagules water dispersed	1	0	0
	Q802	Evidence that a persistent propagule bank is formed (>1 yr)	1	0	0
	Q803	Well controlled by herbicides	1	0	0
	Q805	Effective natural enemies present locally	1	0	0
F	Q706	Propagules bird dispersed	1	1	0
	Q708	Propagules survive passage through the gut	1	1	0

Importance of properties

High correlation to the expert judge score suggests importance of species properties. In our study, naturalisation beyond the native range (Q301) was the most important property in the WRA (Tab. 2). Domestication (Q101), environmental weediness (Q304) and existence of natural enemies (Q805) were the next most important.. High correlation to the WRA score suggests that there were many similar species properties used in the WRA or that the WRA gives high weighting to the property.

The WRA score showed high correlation to the expert judge score (v1, Table 3). However, correlation

between the expert judge score and the sum of properties of "biogeography and history" (v3, including naturalisation and domestication) was almost the same as the correlation between the expert judge score and the WRA score. The sum of properties of "biology and ecology" (v4) showed lower correlation than "biogeography and history" (v3). The properties of "biogeography and history" determine a significant part of the WRA score.

In linear regression and logistic regression with stepwise variable selection, naturalisation records (Q301) was the most important variable (Table 4). Existence of natural enemies (Q805) and domestication (Q101) followed it. In the decision tree

Table 2 Correlation coefficient of score by expert judge and WRA score. Variables were sorted according to the correlation with the expert judge score. Correlation for Q403 was not calculated because there was no parasitic plant on the list. High correlation with expert judge score represents importance of the property for WRA, and high correlation with WRA score suggests that the focal property correlated with many other properties, or that the weight of the property in calculating the WRA score was large.

No.	Species property	Expert judge score	WRA score	Group
Q301	Naturalised beyond native range	0.49**	0.68**	D
Q304	Environmental weed	0.38**	0.52**	C
Q101	Is the species highly domesticated?	0.38**	0.43**	E
Q805	Effective natural enemies present locally	0.34**	0.1	E
Q303	Agricultural/forestry/horticultural weed	0.33**	0.60**	A
Q704	Propagules adapted to wind dispersal	0.33**	0.37**	A
Q103	Does the species have weedy races?	0.32**	0.39**	E
Q302	Garden/amenity/disturbance weed	0.29**	0.56**	A
Q804	Tolerates, or benefits from, mutilation, cultivation, or fire	0.29**	0.45**	C
Q607	Minimum generative time (years)	0.27**	0.45**	A
Q605	Requires specialist pollinators	0.27**	0.18*	E
Q703	Propagules likely to disperse as a produce contaminant	0.25**	0.42**	A
Q305	Congeneric weed	0.25**	0.35**	D
Q412	Forms dense thickets	0.24**	0.45**	C
Q801	Prolific seed production (>1000/m ²)	0.23**	0.45**	C
Q402	Allelopathic	0.22*	0.49**	A
Q701	Propagules likely to be dispersed unintentionally	0.19*	0.45**	A
Q606	Reproduction by vegetative fragmentation	0.19*	0.28**	B
Q802	Evidence that a persistent propagule bank is formed (>1 yr)	0.18*	0.24**	E
Q602	Produces viable seed.	0.17*	0.22*	E
Q504	Geophyte (herbaceous with underground storage organs)	0.16	0.02	A
Q604	Self-compatible or apomictic	0.15	0.39**	E
Q407	Causes allergies or is otherwise toxic to humans	0.15	0.07	E
Q707	Propagules dispersed by other animals (externally)	0.13	0.34**	A
Q405	Toxic to animals	0.13	0.19*	E
Q204	Native or naturalised in regions with tropical or subtropical climates	0.13	0.17*	E
Q803	Well controlled by herbicides	0.12	0.38**	E
Q408	Creates a fire hazard in natural ecosystems	0.11	0.26**	E
Q203	Broad climate suitability (environmental versatility)	0.11	0.25**	B
Q503	Nitrogen fixing woody plant	0.11	0.18*	E
Q705	Propagules water dispersed	0.1	0.25**	E
Q501	Aquatic	0.1	0.22*	A
Q502	Grass	0.1	0.17*	A
Q201	Species suited to tropical or subtropical climate(s)	0.08	0.13	E
Q601	Evidence of substantial reproductive failure in native habitat	0.08	0.06	E
Q205	History of repeated introductions outside its natural range	0.08	-0.05	E
Q409	Is a shade tolerant plant at some stage of its life cycle	0.07	-0.18*	E
Q410	Tolerates a wide range of soil conditions	0.07	0.1	B
Q404	Unpalatable to grazing animals	0.06	-0.04	E
Q411	Climbing or smothering growth habit	0.04	0.1	E
Q406	Host for recognised pests and pathogens	0.02	0.15	E
Q102	Has the species become naturalised where grown?	0.02	0.13	E
Q202	Quality of climate match data	0.01	0.14	E
Q702	Propagules dispersed intentionally by people	-0.01	-0.06	E
Q603	Hybridises naturally	-0.04	0.11	E
Q708	Propagules survive passage through the gut	-0.08	-0.01	F
Q401	Produces spines, thorns or burrs	-0.08	-0.06	E
Q706	Propagules bird dispersed	-0.09	-0.04	F
Q403	Parasitic			

* P<0.05; **P<0.01

analysis, large values for naturalisation (Q301) and existence of natural enemies (Q805) were selected (Fig. 3).

Regression models

In stepwise linear regression based on all variables, naturalisation beyond native range (Q301) was the most effective variable, and existence of natural enemies (Q805) and domestication level (Q101) followed it (Table 4). The equation was

$$\text{Estimates of expert judge} = 0.222 \text{ Q301} + 0.463 \text{ Q805} + 0.175 \text{ Q101} + 0.510 \quad (3)$$

If only the variables of "biogeography and history" were considered, Q301 and Q101 were important variables. Q805 was the most important trait in the analysis of "biology and ecology" type variables. Variables selected in logistic regression were similar to those in linear regression. Naturalisation beyond native range (Q301) was also the most important variable in the decision tree analysis (Fig. 3).

Table 3 Correlation coefficients of summed variables. Sum of individual properties gives the value for higher level category (v5 to v12). Biogeographical score was the sum of categories belonging to biogeography and history (v3 = v5 + v6 + v7). Biological trait (v4) was the sum of categories belonging to it (v4 = v8 + v9 + v10 + v11 + v12). WRA score was the sum of v3 and v4 (v2 = v3 + v4).

Variables	v1	v2	v3	v4	Biogeography and history			Biological trait				
					v5	v6	v7	v8	v9	v10	v11	v12
v1 Expert judge score	1.00											
v2 WRA score	0.61**	1.00										
v3 Biogeography	0.60**	0.88**	1.00									
v4 Biological trait	0.52**	0.82**	0.49**	1.00								
v5 Domestication	0.39**	0.48**	0.62**	0.21*	1.00							
v6 Climate	0.18*	0.29**	0.38**	0.09	0.14	1.00						
v7 Naturalisation	0.57**	0.87**	0.95**	0.51**	0.39**	0.24**	1.00					
v8 Undesirable trait	0.29**	0.37**	0.30**	0.35**	0.05	0.14	0.33**	1.00				
v9 Plant type	0.19*	0.29**	0.14	0.43**	0.06	-0.02	0.16	-0.09	1.00			
v10 Reproduction	0.39**	0.65**	0.38**	0.76**	0.04	0.16	0.44**	0.11	0.25**	1.00		
v11 Dispersal	0.26**	0.56**	0.26**	0.72**	0.22*	-0.04	0.25**	-0.01	0.10	0.47**	1.00	
v12 Persistence	0.43**	0.49**	0.35**	0.62**	0.22*	0.05	0.35**	0.12	0.24**	0.30**	0.25**	1.00

Table 4 Selected variables using a stepwise variable selection procedure. Significance level was determined by equation 1. Species properties are in Tab. 1.

Number of variables	Linear regression	Linear regression with bio-geographical variables	Linear regression with biological traits	Logistic regression	Linear regression with grouped variables
1	Q301	Q301	Q805	Q301	<i>Naturalisation</i>
2	Q301, Q805	Q301, Q101	Q805, Q804	Q301, Q805	<i>Naturalisation, SpecialTrait</i>
3	Q301, Q805, Q101	ns	Q805, Q804, Q605	ns	<i>Naturalisation, SpecialTrait, MaxVegetation</i>
4	ns	ns	ns	ns	<i>Naturalisation, SpecialTrait, MaxVegetation, Weediness</i>

$MaxVegetation = \text{Max}(\text{Forest}, \text{DisturbedHabitat})$; $Naturalisation = Z(Q101 + Q301 + Q305)$; $Weediness = Z(Q302 + Q303/2 + Q304/2)$;

$SpecialTrait = Z(Q503 + Q605 + Q805)$; $Forest = Z(Q409 + Q602)$; $DisturbedHabitat = Z(Q607 + Q701 + Q703 + Q704)$

$Z(x)$ represents standardised value of the variable x , using mean (μ_x) and standard deviation (σ_x) of x as $Z(x) = (x - \mu_x) / \sigma_x$.

$\text{Max}(x_1, x_2, x_3, \dots, x_n)$ gives the maximum value among values of $x_1, x_2, x_3, \dots, x_n$.

Construction of linear regression model with grouped variables

Variable groups were determined based on the results of the cluster analysis of properties (Tab. 1), regression and correlation to expert judge scores, and empirical experiences. At first, the most closely correlated variable to the expert judge score (Tab. 2) was listed for the groups of A to F. These were Q303, Q304, Q301 and Q101 for Groups of A, C, D and E respectively. Group B and F were not considered because of low correlation. Ecologically similar variables were combined into one group. They were Q301 and Q101 of the variable *Naturalisation*, and Q303 and Q304 of the variable *Weediness*. The variable chosen in the stepwise linear regression was also added (Q805, Table 4) as the variable *SpecialTrait*. Ecologically similar variables were added to each group, and the number of variables in each group was

adjusted to about three, to increase redundancy and to reduce stochastic noise (equation 2).

The variable *Naturalisation* represented the naturalisation of the species elsewhere in similar climate, and domestication history. The variable *Weediness* represent records of weediness elsewhere in a similar climate and having an undesirable impact. *SpecialTrait* was collected from Group E. Existence of natural enemies (Q805) was significant in the regression model, and other biological traits such as requirement for specialist pollinator (Q605), and nitrogen fixing woody plant (Q503) were added to it.

Almost all of the above selected variables were properties of the “biogeography and history” type, except for *SpecialTrait*. However, risk assessment based on biological traits is necessary for species not known as invasive yet. Key traits to assess invasion risk into climax forest communities were shade tolerance and maximum tree height (Koike 2001);

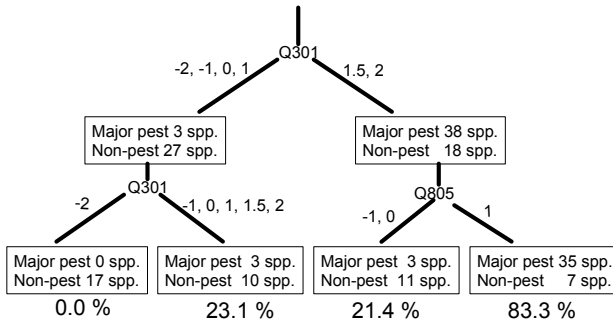


Figure 3 Result of decision tree analysis (C&RT, ANSWER TREE 3.0J). Three variables significant in the linear regression model were used (Q101, Q301, and Q805). The values shown for each branch (-2, -1, 0, 1, 1.5, 2) are the value of the variable assigned by WRA (see Appendix 1-1 in Kato *et al.* 2006). Large value in Q301 suggests that the species have the record of naturalisation, and climate in Bonin Island is suitable for it. Large value of Q805 represents absence of natural enemies. Percentages under the boxes represent the probability that a species in a box is a major pest. If we set the threshold value for this probability, we can make a judgement to accept or reject new species. For example, only the right side box will be rejected if we use the threshold probability of 50%, but three boxes of species, except the left one, will be rejected if we use 5% as threshold value. Correctly judged probability for major pest is 95% in the latter case (Scenario 2).

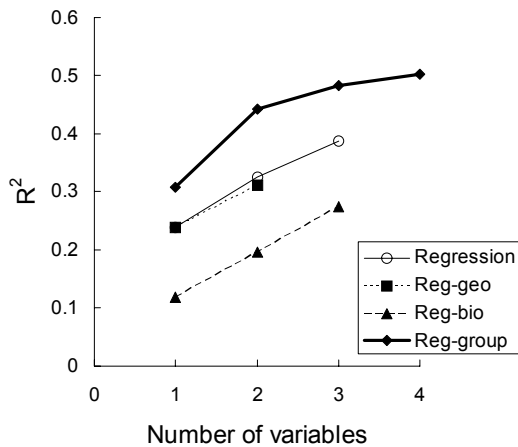


Figure 4 R^2 values for regression models.

Abbreviations are as follows; Regression: stepwise linear regression with all variables, Reg-geo: stepwise linear regression with biogeographical variables only, Reg-bio: stepwise linear regression with biological properties only, and Grouped: stepwise linear regression with grouped variables.

however, these traits will prevent invasion into arable weed communities. Shade tolerance will work positively for forest habitats, but negatively for disturbed habitats. A simple sum including such variables may cause an underestimation of the invasiveness risk for species originating from disturbed habitat, when using WRA. Because of

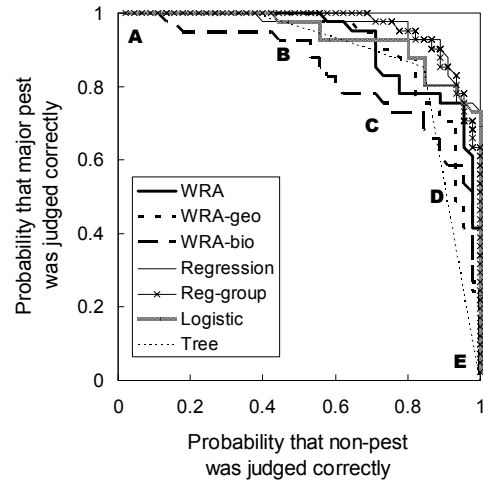


Figure 5 The diagram of two probabilities that a “major pest” is judged correctly, and “non-pest” is judged correctly. Five positions, A-E, correspond to the approximate position of threshold value shown in Fig. 2. The model closest to the upper and right point (1, 1) is the best one in Scenario 1 (C), and B corresponds to Scenario 2. Abbreviations are as follows; WRA: WRA score, WRA-geo: sum of WRA scores only for “biogeographical and historical” species properties, WRA-bio: sum of WRA scores only for “biology and ecology” properties, Regression: stepwise linear regression with all variables, Reg-group: stepwise linear regression with grouped variables, Logistic: stepwise logistic regression with all variables, and Tree: decision tree analysis shown in Fig. 3.

this we evaluated invasiveness into forests (*Forest*) and disturbed land (*DisturbedHabitat*) independently, and the maximum value for invasiveness of the different habitats (*MaxVegetation*) was used. By taking the maximum value, the invasiveness to forest was used for forest species, and invasiveness to disturbed land was used for arable weeds. Shade tolerant (Q409) and viable seed production (Q602) were considered as properties of invasive species to forest (*Forest*). Short lived (Q607) species with specific properties of dispersal (Q701, Q703 and Q704) were considered as invasive species to disturbed land (*DisturbedHabitat*).

The obtained equation was

$$\begin{aligned} \text{Estimates of expert judge} = & 0.310 \text{ Naturalisation} \\ & + 0.260 \text{ SpecialTrait} \\ & + 0.191 \text{ MaxVegetation} + 0.131 \text{ Weediness} \\ & + 0.857 \end{aligned} \quad (4)$$

where

$$\begin{aligned} \text{MaxVegetation} &= \text{Max}(\text{Forest}, \text{DisturbedHabitat}) \\ \text{Naturalisation} &= Z(Q101 + Q301 + Q305) \\ \text{Weediness} &= Z(Q302 + Q303/2 + Q304/2) \end{aligned}$$

$$\begin{aligned}
\text{SpecialTrait} &= Z(Q503 + Q605 + Q805) \\
\text{Forest} &= Z(Q409 + Q602) \\
\text{DisturbedHabitat} &= Z(Q607 + Q701 + Q703 \\
&\quad + Q704)
\end{aligned}$$

$Z(x)$ represents standardised value of the variable x , using mean (μ_x) and standard deviation (σ_x) of x as $Z(x) = (x - \mu_x) / \sigma_x$. $\text{Max}(x_1, x_2, x_3, \dots, x_n)$ gives the maximum value among values of $x_1, x_2, x_3, \dots, x_n$. Weightings for Q303 and Q304 were reduced because weightings for these variables were heavier than Q302 in the traditional WRA. All four grouped variables (*Naturalisation*, *SpecialTrait*, *Weediness* and *MaxVegetation*) were significant in stepwise variable selection at the significance level of equation 1.

Evaluation of risk assessment systems

In various linear regressions, the regression with grouped variable had highest R^2 value (Fig. 4). Stepwise linear regression with all variables followed

it. Linear regression with biological traits had the lowest predictability.

The plot of two probabilities: “major pest was judged correctly”, and “non-pest was judged correctly”, was used to evaluate various risk assessment models (Fig. 5). Each model gives a single line on this graph. A point on the line in Fig. 5 corresponds to the threshold value used (for example, threshold in WRA scores, threshold for the predicted value of expert judge in linear regressions, etc).

In Scenario 1, the position closest to the coordinate (1, 1) gives the best threshold value, and models closest to the (1, 1) position are the best (threshold value **C** in Fig. 2 and 5). In Scenario 2, the point where the line crosses the horizontal of [(probability that major pest was judged correctly) = 0.95] gives the best threshold value (**B**). The more to the right this point is, the better the model.

In Scenario 1, the linear regression model and the model with grouped variables were similarly best risk assessment models (Table 5, Fig. 5), although the grouped variables model was the best in the measure

Table 5 Comparisons of risk assessment models based on WRA in Bonin (Ogasawara) Islands (Kato *et al.* 2006). Two scenarios that both major pest and non pest are treated equally (Scenario 1), and that to reduce the risk by major pest up to 0.05% (Scenario 2). Larger probability suggests better risk assessment system in both scenarios. These variables were determined based on the data shown in Fig. 5.

Model	Scenario 1: threshold value to maximise probability that both major pest and non pest were judged correctly	Scenario 2: threshold value at (correctly judged probability for major pest) = 0.95
Traditional WRA	Threshold value = 8.25 ^a Maximum probability = 0.72	Threshold value = 3 ^a Correctly judged probability for non-pest = 0.71
WRA-geo	Threshold value = 6.2 ^b Maximum probability = 0.72	Threshold value = 5 ^b Correctly judged probability for non-pest = 0.71
WRA-bio	Threshold value = 1 ^c Maximum probability = 0.62	Threshold value = -2 ^c Correctly judged probability for non-pest = 0.42
Linear regression	Threshold value = 0.97 ^d Maximum probability = 0.82	Threshold value = 0.95 ^d Correctly judged probability for non-pest = 0.80
Reg-geo	Threshold value = 1.13 ^d Maximum probability = 0.68	Threshold value = 1.05 ^d Correctly judged probability for non-pest = 0.71
Reg-bio	Threshold value = 1.1 ^d Maximum probability = 0.63	Threshold value = 0.41 ^d Correctly judged probability for non-pest = 0.18
Reg-group	Threshold value = 0.89 ^d Maximum probability = 0.80	Threshold value = 0.80 ^d Correctly judged probability for non-pest = 0.82
Logistic regression	Threshold value = 0.81 ^e Maximum probability = 0.75	Threshold value = 0.22 ^e Correctly judged probability for non-pest = 0.56
Decision tree	Threshold value = any value between 0.23 to 0.83 ^e Maximum probability = 0.72	Threshold value = any value between 0 to 0.21 ^e Correctly judged probability for non-pest = 0.38

^a WRA score (Pheloung *et al.* 1999)

^b Sum of values assigned for species properties in WRA, only biogeographical and historical properties were considered.

^c Sum of values assigned for species properties in WRA, only biological and ecological properties were considered.

^d Predicted value of expert judge score; 0: non-pest, 1: minor pest, 2: major pest

^e Predicted probability that the species is major pest

of R^2 (Fig. 4). The probability that both major pest and non pest were judged correctly was 0.82 at the threshold value of [(estimates of expert judge score) = 0.97] in the linear regression model.

In Scenario 2, the model with grouped variables correctly judged 82% of non-pest species at the threshold value of 0.80. The next best model was linear regression with three individual variables selected by stepwise procedure from all of variables.

DISCUSSION

Weed Risk Assessment (WRA)

Bio-geographical and historical variables, especially for naturalisation beyond native range and intensity of domestication, are key species properties in WRA. Biological traits scarcely contribute to risk assessment. Although our research identified “natural enemies” as an important biological variable, it is difficult to estimate it prior to introduction of an alien species and the reliability of this property is hence, low. The high value for prediction of naturalisation history and the low one of biological properties have been described for various species (Williamson 1996, Goodwin *et al.* 1999, Gollasch 2006). WRA can be considered as a system to evaluate the history of prior invasion. Since so many biological properties were not effective predictors, biological properties could possibly be removed from use in WRA. Low effectiveness of these properties may be one reason why WRA is not sensitive to missing values for them.

When social aspects are considered, WRA is not solely a system to predict invasion risk, but also a system for input by stakeholders. All possible hazards should be considered, even if the weighting is low and the system may not estimate that risk correctly. Use of qualitative values in WRA (“yes”, “no”, “unknown”) enables speedy results and could contribute to avoiding controversy among stakeholders on the weighting of properties.

In conclusion, WRA is a well designed system that is robust and provides for stakeholder consideration. It can be applied quickly in various regions because it only requires qualitative information. However, it can not use biological traits effectively in prediction.

Invasion risk assessment systems available for immediate use

We need to consider time scale in the search for suitable systems of invasion risk assessment. The Japanese Government brought into force the Invasive

Alien Species Act in 2005, and needs a suitable risk assessment system to determine what species to act on. For such immediate application, the information should be qualitative, because quantitative information of consistent quality is not available. Properties for which information is difficult to obtain should be excluded (e.g. existence of natural enemies). The “biogeography and history” part of WRA may be the best system, although the threshold value for acceptance (of a proposed introduction of an alien species) needs to be re-determined for Japan’s purposes (Fig. 5). WRA can be applied immediately to a wide range of species, including animals.

Australia and New Zealand have different biota from the Northern Hemisphere, and Hawaii and the Bonin Islands are oceanic islands with disharmonic biota. Applying the “biogeography and history” component of WRA for mainland situations in the Northern Hemisphere, while adjusting the threshold value (see Fig. 5) will have some effectiveness. It is also possible to evaluate “naturalisation” only for those mainland areas with similar biota, while excluding information from invasion in oceanic islands and in the Southern Hemisphere.

Invasion risk assessment systems for the near future

In the near future, it will be possible to improve the system for weighting and calculation, but qualitative data will need to be used, like in WRA. The regression model with grouped variables proposed in this paper is one candidate (equation 4), although it should be tested with additional data. The simple regression model (equation 3) gave similar results when minor pests were removed from the evaluation. However, the grouped variable model showed a higher R^2 value than the simple regression model did if minor pest species were included, and such inconsistency may be caused by stochastic noises. In the grouped variable model, stochastic error from individuals evaluating the species will be averaged (equation 2). Since the redundancy of this model is lower than in WRA (even if higher than in simple regression model), missing values should be avoided.

Risk assessment based on biological properties is required in the prediction of invasions by species not known as invasive yet. In order to use biological properties, we may need to assess the risk of invasions independently for various habitats (i.e. risk of invasion for arable land, for forests, etc.), as was done in the model with grouped variables in our research. We applied this to two habitats: forests and disturbed land. However, we need further study to determine the key properties for various other

habitats, such as dry rocky cliffs or wetlands.

By evaluating risks of invasion for individual habitats, it might be possible to account for the conservation importance of such habitats. The mere establishment of an alien species can be a significant issue in an area of endangered natural vegetation, whereas a certain level of dominance by an alien species might be acceptable in the case of urban situations.

Invasion risk assessment system for use in the distant future

In the distant future, plant properties should be measured quantitatively. Properties of native species in the local flora should be used in the risk assessment, because the success of invasion depends on local flora (Koike 2001). Impact of invasive alien species (dependent variable in regression) on native ecosystems should be measured quantitatively by standardised methods. It might be possible, in future, to estimate the impact on ecosystems using a community prediction model (Koike 2001).

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