REPORT

Generating an agricultural risk map based on limited ecological information: A case study using *Sicyos angulatus*

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Received: 5 January 2016/Revised: 25 February 2016/Accepted: 8 April 2016/Published online: 27 April 2016

Abstract In this study, we propose a method for estimating the risk of agricultural damage caused by an invasive species when species-specific information is lacking. We defined the “risk” as the product of the invasion probability and the area of potentially damaged crop for production. As a case study, we estimated the risk imposed by an invasive weed, *Sicyos angulatus*, based on simple cellular simulations and governmental data on the area of crop that could potentially be damaged in Miyagi Prefecture, Japan. Simulation results revealed that the current distribution range was sufficiently accurate for practical purposes. Using these results and records of crop areas, we present risk maps for *S. angulatus* in agricultural fields. Managers will be able to use these maps to rapidly establish a management plan with minimal cost. Our approach will be valuable for establishing a management plan before or during the early stages of invasion.

Keywords Agricultural risk · Alien invasive species · Management strategy · Risk mapping · Risk management · Virtual ecology

INTRODUCTION

The environmental and economic costs of alien plant invasions have been well documented (Pimentel et al. 2001, 2005). This is one of the most important topics in conservation efforts (Cristescu and Boyce 2013). In agricultural systems, invasive plants may cause economic losses of up to 40 % (Pimentel et al. 2001). To minimize such losses, substantial time and effort must be invested in eradicating invasive populations and preventing their further spread (Pichancourt et al. 2012). Management is most effective when invasion is detected early and comprehensive control

measures are rapidly implemented; any effect is thus confined (Simberloff 2003; Kaplan et al. 2014). Therefore, the early identification of areas where efforts (e.g., prevention, elimination, and monitoring) should be concentrated is crucial for cost-effective management.

However, information on focal invasive species in particular target areas is often very limited during the early stages of invasion (Koike 2006). It requires time, effort, and other resources to obtain detailed information on invasive species and their target areas. The required resources may be in short supply, for social and economic reasons (Humston et al. 2005; Shaw 2005). Therefore, land managers and/or decision makers must identify areas in which to concentrate resources, and must establish management plans based on limited information. Uncertainty is always in play (Millennium Ecosystem Assessment 2005; Suter II 2006; Drolet et al. 2016).

Risk assessment, which is defined as technical support for decision making under uncertainty, is a central theme in environmental management (Suter II 2006). The conventional definition of “risk” is a combination of the severity of the incident and the probability of its occurrence (Suter II 2006). Thus, the risk imposed by invasive plants in agricultural systems can be defined as the product of the invasive probability and the area of fields containing potentially damaged crops. In the present study, we propose a practical approach to estimate the risk of invasive plants to agriculture based on limited information.

Our method does not require detailed ecological information on the target invasive species, as the invasive probability is estimated using a virtual ecology approach that does not require a detailed ecological information model. The virtual ecology approach simulates species dynamics using models, and the species dynamics can be observed “virtually” (Albert et al. 2011; Pagel and Schurr

2012). Here, we used the virtual ecology model previously established by Osawa and Ito (2015) to estimate the invasive probability. This model only requires physical environmental connectivity and can predict the expansion of species that passively expand to some degree, without ecological information on the target species (Osawa and Ito 2015). Specifically, the model focuses only on the form of physical dispersal, and does not require biological information. The dispersal vector is one of the most important features of biological invasion (Parendes and Jones 2000; Holle and Simberloff 2005; Lockwood et al. 2005; Barney 2006; Osawa et al. 2013; Akasaka et al. 2015; Osawa and Ito 2015). Identification of the vector is useful when predicting species dispersion. To represent potential crop damage, we used the area of fields currently in cultivation, which can be strongly influenced by the target invasive plant. A combination of the estimated invasive probability and the area under cultivation allows evaluation of the risk posed of invasive plants in agricultural fields.

The objective of the present study was to develop a procedure for generating risk maps of invasive plants for agriculture based on limited information. As a case study, we focused on the noxious invasive plant, *Sicyos angulatus*, in Miyagi Prefecture, Japan. *Sicyos angulatus* has already caused substantial agricultural losses (Shimizu 1999; NARO 2013) in several regions of Japan; therefore, practical management strategies are required (Kurokawa et al. 2009; Kobayashi et al. 2012). We calculated the risk posed by *S. angulatus* and created a risk map using a virtual model of plant ecology and agricultural statistics derived from the target area. Based on these results, we discuss the effectiveness of our approach.

MATERIALS AND METHODS

Study area and species

The study was conducted in Miyagi Prefecture, Japan (38°27'N, 140°155'E, 7285.80 km²; Fig. 1a). The area has a mean annual precipitation of 1254 mm, and mean annual temperature of 12.4 °C (Sendai City; Japan Meteorological Agency).

Sicyos angulatus is well known as a problematic invasive vine because of its aggressive attacks on summer crops, such as maize, soybeans, and forage crops (Shimizu 1999). The species is difficult to eradicate when established; thus, strategic prevention and/or eradication programs are essential (Shimizu 1999; Kurokawa et al. 2009; Kobayashi et al. 2012). The species is common in riparian areas and open spaces, suppressing the growth of native vegetation throughout Japan (Watanabe et al. 2002; Kurokawa et al. 2009; Osawa et al. 2013). *Sicyos angulatus* is

currently considered one of the most important environmental weeds in Japan (Kurokawa et al. 2009). For example, Shimizu (1999) reported that *S. angulatus* at a density of one plant/m² reduced forage corn production by 90 % (Shimizu 1999). National Agriculture and food Research Organization (NARO) has reported that farmland in northern Japan, including Miyagi Prefecture, is severely affected by invasive plant species (NARO 2013). Japan's Invasive Species Act classifies the species as an "Invasive Alien Species (IAS)," which is considered the most problematic type of invasive species (Ministry of Environment, Japan).

Virtual ecology model

We used a simple cellular automata (CA) model that can predict the dispersion of the target species based solely on large stream flow (Osawa and Ito 2015). As *S. angulatus* often dominates riparian areas (Watanabe et al. 2002; Kurokawa et al. 2009; Kobayashi et al. 2012; Osawa et al. 2013), it is likely to expand according to stream flow in Japan (Osawa et al. 2013).

The digital space in the CA model consists of a rectangular grid of square cells representing the target area. The grid is set to the same size as the unit of predicted range dispersion. The model yields a theoretical number of invasions in each cell, which serves as an invasive probability (described in detail below). Each cell has three parameters: cell ID, dispersion path vector, and elevation value (Fig. 2a). The cell ID indicates the spatial location of the area of analysis. The dispersion path involves four variables that indicate the four directional vectors of adjacent cells (Fig. 2b; described in detail in the next section). The elevation value indicates the relative height among the cells of analysis and acts as the stream flow direction, i.e., stream flow progresses from high to low cells. The cell space was assumed to be of homogeneous habitat quality for the target species. Also, the model does not have a time axis. Thus, the time required to move from one cell to the next is not considered (Osawa and Ito 2015). We therefore do not consider time-dependent parameters such as flow velocity or dispersion speed.

Dispersion path among cells

In this CA model, the dispersion path is defined as the possibility of dispersion into four adjacent cells: those on the left, right, top, and bottom (Fig. 2b). The dispersion path is defined as a vector with four binomial values:

Dispersion path $x = dx(d1, d2, d3, d4)$,

where d1, d2, d3, and d4 indicate connectivity to the top, left, bottom, and right cells, respectively (Fig. 2b). If all

Fig. 1 Study area and units, data resources for this study. Locations and sizes of the 5 km grids were defined by the Japanese Government. River line data were derived from Governmental data base

dispersion path values are 0, the invasive species in this cell cannot expand to any other cells. The dispersion path is defined based only on habitat continuity. For example, in the present study, if the river line crosses two adjacent cells, then these cells each have a dispersion path (Fig. 2c). The analysis unit of the invasive plant was the local population, i.e., one cell can contain one population. Thus, the model can simulate the capabilities for population dispersion within the target areas. The virtual population can expand only according to the dispersion path. The model processes define population dispersions as occurring via the dispersion path according to elevation, i.e., a population can only expand from a high to a low elevation cell, even if the cells are connected.

Prediction of species dispersion

A grid size of approximately 5 km, termed the “Japanese 5-times mesh” (hereafter, 5-km mesh), was used for the analyses (Fig. 1a). The 5-km-mesh grid system is a Japanese standard unit used for several types of statistics, mainly wildlife records, at this scale of geographic resolution (Ministry of the Environment, Japan). We used this unit because the virtual ecology model based on a combination of the 5-km mesh and the national first-grade river line (shown below) performed well (Osawa and Ito 2015).

Specifically, using 1-km mesh, the expansion paths of more than half of all grids were zero, and the predictive performance afforded by the 10-km mesh was relatively lower than that of the 5-km mesh (Osawa and Ito 2015).

We used the mesh ID of the 5-km mesh as the cell ID, which was derived from the Japan Integrated Biodiversity Information System available at the Biodiversity Center of Japan (J-IBIS). The elevation value of each mesh was derived from a numerical map using 250-m values (Japan Map Center). We used minimum rather than average elevation values, because we predicted that in the river habitat used in this study, water likely occurs in lowland areas. Also, Japan has steep mountain ranges that can greatly affect the average grid elevation. The dispersion path of the 5-km mesh was defined according to the above rule (see Fig. 2c) using river line data derived from the National Land Numerical Information Download Service, Japan (Ministry of Land, Infrastructure, Transport and Tourism, Japan; see Fig. 1b). The river lines were derived from GIS line data on national first-grade large rivers (Ministry of Land, Infrastructure, Transport and Tourism, Japan). Thus, we did not consider smaller rivers (second-grade rivers, small streams, or ditches). Using this CA field, we calculated the theoretical number of cells that could expand into each cell as the potential dispersion range for all cells. We summed the number of cells to calculate the number of

Fig. 2 Basic structure of the modified cellular automata (CA) model. **a** each cell has three values; (1) the cell ID x is a unique ID of the cell, (2) the dispersion path dx indicates four directional vectors of adjacent cells (described below), and (3) elevation x_e indicates the elevation value in the cell. **b** values $d1$, $d2$, $d3$, and $d4$ indicate the dispersion path to the *top*, *left*, *bottom*, and *right* cells, respectively. If the dispersion path value is 1, the invasive species in this cell can expand to the adjacent cell. **c** if the river line crossed two adjacent cells, the target species could move to the adjacent cells according to the dispersion path

invasions into each cell. We used these invasion numbers as indices of “invasion probability.” This model was run with 100 iterations to reach a static state of dispersion.

We validated the results of the CA model using partial occurrence records of *S. angulatus* that were collected during occasional censuses from 2009 to 2012. We compared average virtual invasion values between meshes containing occurrence records and all of the meshes analyzed. If the model prediction gave an accurate picture of *S. angulatus* dispersion in the real world, the invasion values should be higher in meshes containing occurrence records than in all of the analyzed meshes. We thus used the Mann–Whitney U test to compare model predictions with field data. We also employed generalized linear models (GLMs), logistic distribution (log-link) tests, and the Wald test to evaluate the accuracy of the model’s prediction of *S. angulatus* invasions (i.e., presence/absence in each grid).

Agricultural land-use dataset

Three crops were selected for estimating damage by invasion of *S. angulatus*: soybean, forage crops, and pasture.

These three crops are known to have already suffered extensive damage from *S. angulatus* (Ministry of Agriculture, Forestry and Fisheries). The datasets for crop area were obtained from the Census for Agriculture, Forestry and Fisheries (CAFF) 2005 dataset (Ministry of Agriculture, Forestry and Fisheries), which was part of a periodic census conducted every 5 years by the Ministry of Agriculture, Forestry and Fisheries. Although no data for the area of soybean crops were available in the CAFF records, we used the area of paddy fields as a proxy of soybean area because 80 % of soybeans grown in Japan are cultivated in upland paddy fields as an after crop and/or conversion crop (Ministry of Agriculture, Forestry and Fisheries, Japan).

The CAFF datasets were summarized using municipality units. To convert the municipality units into 5-km mesh units, they were divided into 100-m (i.e., 1-ha) mesh units, and the second mesh was reconstructed. The second mesh contained 10 000 m² divided into 100-m meshes. We initially divided the municipality units into 100-m mesh units and partitioned both total farmland and agriculturally abandoned areas equally. If one of these mesh units included two or more municipality units, we assigned the mesh unit to

the dominant municipality, i.e., we assigned the mesh to the single municipality that represented the largest portion of the mesh area. Thus, we assumed that the proportions of total farmland and abandoned area were equally distributed in the 100-m grid within the same municipality. Subsequently, we reconstructed the 5-km mesh units using 50×50 -m meshes and summed the area values for the areas of the three crops. We ignored numerical error that may occur by dividing the municipality units into the 100-m meshes, because the 5-km mesh size was sufficiently larger than the 100-m mesh. We reconstructed the 5-km meshes and calculated the three crops in each 5-km mesh unit.

Estimating risk values

We calculated the risk values of *S. angulatus* following the formula below (see the Introduction for the basis of this definition of risk):

$$\text{Risk} = \text{Probability of invasion} \\ \times \text{Area of potentially damaged cropland}$$

We calculated the risk values of *S. angulatus* upon the three focal crops. Finally, we presented the distribution of risk values as a risk map composed of 5-km mesh units. All GIS data management used ArcGIS 10.1 (ESRI, Redlands, CA, USA), and all statistical analyses, including simulations, were performed with R version 3.1.2 (R Development Core Team 2014).

RESULTS

Analyzing the grid

A total of 602 5-km meshes were used as the units of analysis in the model; 74 of these were occurrence meshes of *S. angulatus* based on periodic censuses. Occurrence records were distributed in a globally balanced manner (Fig. 3a). For the dataset including all of the 5-km meshes, the average value of elevation (m) was 130.24 ± 165.296 m (average $\pm$ SD). The areas of the crops were 208.25 ± 311.62 ha for paddy fields, 5.35 ± 10.53 ha for forage crops, and 9.32 ± 15.71 ha for pasture. The distribution of the area of each crop was biased to some degree (Fig. 3b–c).

Accuracy of the CA model simulation

The number of virtual invasions in meshes containing occurrence records (27.20 ± 24.34) differed significantly from that in all of the meshes analyzed (13.77 ± 19.26) (Mann–Whitney *U* test, $p < 0.001$; Fig. 3a). Also, the GLM showed that the simulation data were significantly correlated with real occurrences (the estimated coefficient of

simulation: 0.30 ± 0.005 , $p < 0.001$). Although our occurrence records included pseudo-absences (i.e., the species was not detected but did occur), we found that our analysis yielded useful general trend information. Thus, we conclude that our virtual ecology model was realistic.

Mapping

The high-risk areas for each crop were distributed within different locations, but the central area and the area slightly to the north exhibited relatively high-risk values for all crops (Fig. 4). For soybean, the area of highest risk occurred in the center of Miyagi Prefecture (Fig. 4a). In contrast, the high-risk areas of pasture and forage crop were located in both central and southwest areas of the prefecture (Fig. 4b, c).

DISCUSSION

We established risk maps for *S. angulatus* in agricultural areas without the use of detailed ecological information, thus using only simulations based on a theoretical model and agricultural statistical records. The predictions of the simulation model were sufficiently accurate for field use. The crops that could be potentially damaged by *S. angulatus* were selected based on previous reports; thus, both the risk values and map will be practical for establishing management plans.

Estimation of risk based on limited information

The most cost-effective way of managing invasive species is to prevent their introduction and establishment within high-risk areas (Leung et al. 2002; Koike and Iwasaki 2011). Thus, our approach provides support for establishing cost-effective management plans, as it actualizes the timely prediction of high-risk areas without the use of detailed ecological information on the target species before or during the early stages of invasion. Based on the results of this approach, decision makers such as land managers can preemptively establish management plans by identifying areas in which to concentrate efforts before or during the early stages of invasion. In addition, our method offers the practical advantage that it can be implemented by land managers immediately before or just after detecting the problem, that is, without specific preparations, such as securing a budget for detection of invasive species or meeting with stakeholders to explain the potential problems posed by invasive species. Our method provides a valuable first step in establishing management plans.

Our modeling approach could be improved in several ways. Most importantly, the accuracy of the simulation

Fig. 3 Maps of occurrence points of *Sicyos angulatus* with predicted occurrence units based on our model, potential damaged crops based on statistical records

Fig. 4 Risk maps of *Sicyos angulatus*. Dark color indicates high risk of agriculture. Dashed circles indicate the particularly high-risk area

model should be maximized. To improve the accuracy of predictions, ecological information could be incorporated, such as population growth rates, habitat suitability, and mortality rates (Moles et al. 2008). Furthermore, several techniques involving species distribution models would allow the incorporation of several ecological parameters (Engler et al. 2004; Guisan and Thuiller 2005). In addition, refining the geographic grain and extent of the model is very important to both implementation of the management plan and field-level activities (Foxcroft et al. 2009; Osawa et al. 2011; Akasaka et al. 2012). In the present study, we used the 5-km mesh on a prefectural scale (i.e., local government) as the unit of analysis. This scale is useful for decision makers in establishing a management strategy for broad-scale perspectives of local governments. However, this unit is rather coarse for those actually working in the field, such as individual farmers. Future studies should generate detailed risk maps with high-resolution units for use in the field. Such maps would require more detailed river line data (including ditches and drains) and detailed farm maps showing crop types. Also, the ecological characteristics may vary by the sensitivity of spatial resolution (Akasaka et al. 2012). Thus, not only stream flow but also other dispersal factors may require attention (Osawa et al. 2013). Combinations of and interactions among the spatial scale, the environment, and various and ecological parameters should be explored (Davies et al. 2005; Akasaka et al. 2012; Pysek et al. 2012).

Nevertheless, we were able to practically predict the dispersion of *S. angulatus* without the use of such detailed information. We used a 5-km mesh on the prefectural scale. In a previous study, Osawa and Ito (2015) also successfully predicted the dispersion of golden mussel by placing a grid of the same size over a similar area. These results suggest that our approach could be applied to several invasive species that expand based on stream flow. Also, our approach may be applicable to other vectors, such as roads and railways. Therefore, additional simulations using other problematic invasive species, particularly those in rivers and/or riparian areas, are warranted. The basic dispersal vectors of invasive species are partially understood (Barney 2006; Leuven et al. 2009; Osawa et al. 2013) and are available from international databases (CABI; EPPO).

Application to a management plan

Decision makers such as land managers will ideally use the risk maps derived from this approach for practical management activities, even if information on the target invasive species is lacking. If a target area has already been invaded by the invasive species, managers should concentrate their eradication efforts within high-risk areas. Similarly, if the target area has not yet been invaded,

managers should implement monitoring efforts in high-risk areas to prevent invasion. Such effort allocation would need to be broadly applicable because of limited resources (Giljohann et al. 2011; Januchowski-Hartley et al. 2011; Osawa and Ito 2015). The establishment of such plans should consider specific details for each situation, e.g., funding and human resources. The next challenge would be to establish and implement a management plan based on the risk map.

Management plans based on detailed field information would be preferable; virtual ecology models may over- or under-estimate the extent of invasion. In this context, our approach should ideally be used in combination with field surveys to refine or adapt management plans (Berkes et al. 2000). We used the census records we could find to validate the simulation data, but this information was lacking for some areas. The results might change when field data are added. Managers could use our approach as a first rapid step when developing a basic management plan (Osawa and Ito 2015), which could then be improved by additional field data.

CONCLUSION

Predicting the risk imposed by invasive species will enable the development of pre-arrival countermeasures and will help to avoid social issues, such as the need to reach consensus regarding countermeasures (Koike and Iwasaki 2011). Biological invasions can sometimes cause very severe damage, whereas practitioners usually try to solve the problem after the damage occurs. Our approach of predicting the risk of invasion and establishing a risk map based on limited information can be practically implemented by various stakeholders before or during the early stages of biological invasion.

Acknowledgments We would like to thank Dr. M. Akasaka for giving us good suggestions. Two anonymous reviewers gave us many constructive suggestions. We also would like to thank Dr. D. Sprague for checking English.

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