Article

Spatial risk assessment of alien plants in China using biodiversity resistance theory

YouHua Chen
Department of Renewable Resources, University of Alberta, Edmonton, T6G 2H1, Canada
E-mail: haydi@126.com

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Abstract
In the present study, the potential occurrence risk of invasive plants across different provinces of China is studied using disease risk mapping techniques (empirical Bayesian smoothing and Poisson-Gamma model). The biodiversity resistance theory which predicts that high-biodiversity areas will have reduced risk of species invasion serves as the base for performing spatial risk assessment of plant invasion across provinces. The results show that, both risk mapping methods identified that north-eastern part of China have the highest relative risk of plant invasion. In contrast, south-western and south-eastern parts of China, which have high woody plant richness, are predicted to possess low relative risks of plant invasion. Through spatial regression analysis (simultaneous autoregression model), nine environmental variables representing energy availability, water availability, seasonality, and habitat heterogeneity are used to explain the relative risk of plant invasion across provinces of China. The fitting results suggest that, PRECrange and TEMrange are the most two important covariates correlated with the occurrence risks of alien plants at provincial level in China. As indicated by Moran's I index, spatial regression analysis can effectively eliminate the potential biases caused by spatial autocorrelation.

Keywords spatial ecology; risk assessment; invasion biology; plant distribution.

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1 Introduction

Alien plants may cause severe ecological problems onto local ecosystems because they can better compete for the resources than native species (Zhang and Chen, 2011). Biodiversity hotspots are believed to be more resistant to species invasion: more diverse communities would have less species invasions (Law and Morton, 1996; Stachowicz et al., 2002; Zhang, 2011, 2012a). This biodiversity resistance theory can be an option for performing risk assessment of species invasions.

Modeling plant invasion risk in China has been done in some previous studies recently (Bai et al., 2013; Liu et al., 2005; Wu et al., 2006; Feng and Zhu, 2010). However, all these studies only rely on the richness information of alien plants, the dependence of alien plant diversity and native plant diversity has never been considered yet. As such, one may utilize the biodiversity resistance theory to quantify relative risk of alien plants by explicitly incorporating the information of native plant diversity.

In the present study, we perform the relative risk assessment of alien plants in China by using spatial disease mapping methods (including empirical Bayesian smoothing and Poisson-Gamma model) so as to incorporate richness information of native woody plant species.

2 Materials and Methods

2.1 Invasive plant diversity data

The province-level 127 alien plant richness data are collected from previous studies (Chen, 2013; Wang et al., 2009; Wu et al., 2006; Yan et al., 2012). The resultant data include provincial distributional information and physiological trait patterns of each invasive plant found in China.

2.2 Woody plant diversity data

The population size at risk when performing risk mapping is required as an entry. In the present study, we regard the population size at risk as the number of native woody plant species. As such, similar to the disease transmission model, areas where there are higher population sizes would have less relative risk of disease outbreak. In our modeling of relative risk estimation of plant invasion, we hold the recognition that areas with high biological diversity should have less plant invasion risk (Law and Morton, 1996; Stachowicz et al., 2002).

2.3 Risk mapping using empirical Bayesian smoothing and Poisson-Gamma model

We use both empirical Bayesian smoothing and Poisson-Gamma model for predicting the outbreak risk of invasive plants over the provinces of China. For testing whether the relative risk of plant invasion is significantly higher than 1, we utilize Poisson exact test.

2.4 Identification of important covariates associated with the occurrence risk of alien plants

We use generalized linear models to identify important covariates which are closely related to the occurrence risk of alien plants at provincial level in China. The fitting model is given by,

$$\log(\theta) = X\beta + \varepsilon$$

where θ is the relative risk of alien plants across various provinces of China calculated as above; β is the associated coefficients for the covariates presented in terms of columns in the covariate matrix *X*.

We standardize all the covariates in X so that the estimated coefficients β are standardized partial coefficients. We then choose those covariates with high values of β as the important ones for explaining the occurrence risk of alien plants at provincial level in China.

However, the above model is spatially implicit, for which it can not be able to partial out the influence of spatial autocorrelation and may inflate Type I errors. As such, we implemented the alternative model which explicitly incorporate the spatial influence in the model as,

$$\log(\theta) = X\beta + \rho W \log(\theta) + \varepsilon$$

where *W* is the matrix with each element w_{ij} =1 if provinces *i* and *j* are adjacent (i.e., they share some boundaries), otherwise w_{ij} =0. ρ measures the strength of spatial autocorrelation for the response variable (log-transformed relative risk). This is the formula of spatial simultaneous autoregression lag model (SAR) (Dormann et al., 2007; Dormann, 2007). Implication of SAR model has been done using R (R Development Core Team, 2011) package "*spdep*" (Bivand et al., 2013).

The following environmental variables at provincial level are used for fitting the above model (Qian, 2013): mean annual temperature (TEM, °C), mean temperature of the coldest month (TEMmin, °C), mean temperature of the warmest month (TEMmax, °C), annual precipitation (PREC, mm), annual actual evapotranspiration (AET, mm), annual potential evapotranspiration (PET, mm), the range of mean annual temperature within a province (TEMrange, °C), the range of annual precipitation within a province (PRECrange, mm), and the range of elevation within a province (ELEVrange, m). These nine environmental variables represent energy availability, water availability, seasonality, and habitat heterogeneity (Qian, 2013). All these covariates are standardized before performing SAR modeling.

3 Results

As showed in Fig. 1, the woody plant diversity is highest in southern part of China, which was identified as one of the global biodiversity hotspots of the world (Myers et al., 2000; Chen and Bi, 2007). Yunnan has the highest woody plant richness, followed by Guangxi Province.

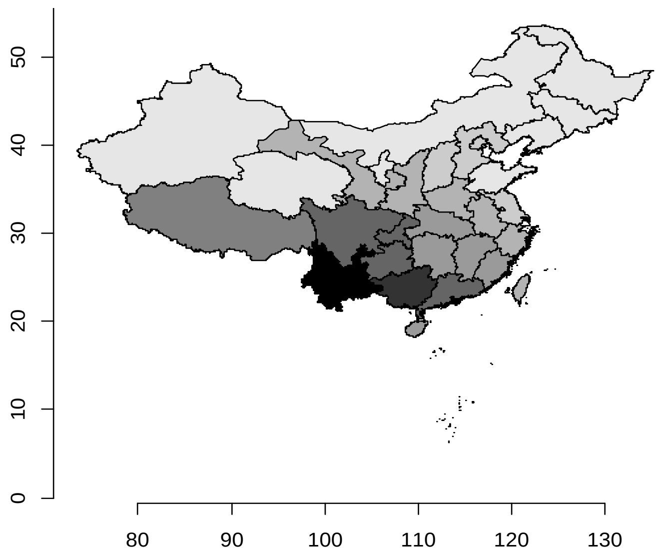

Fig. 1 Observed woody plant diversity at provincial level of China. Colors from light to dark grey indicate diversity from low to high.

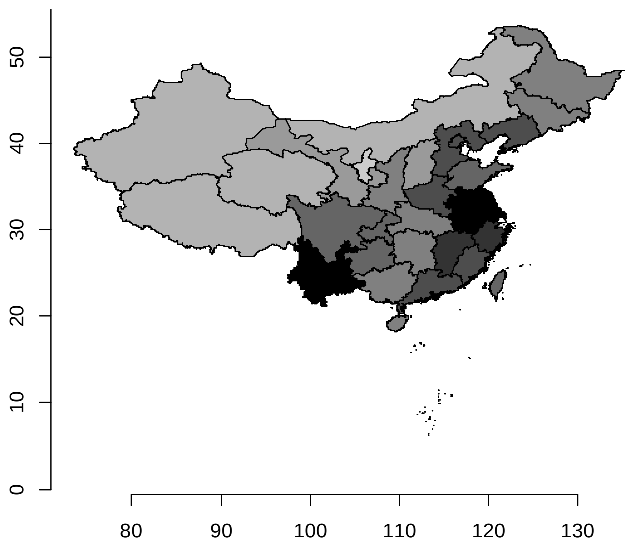

Fig. 2 Observed alien plant diversity at provincial level of China. Colors from light to dark grey indicate diversity from low to high.

As shown in Fig. 2, the alien plant diversity is highest in southern and eastern part of China. Interestingly, the biodiversity hotspot, Yunnan Province, also has very high alien plant diversity following Jiangsu Province (Wang et al., 2009).

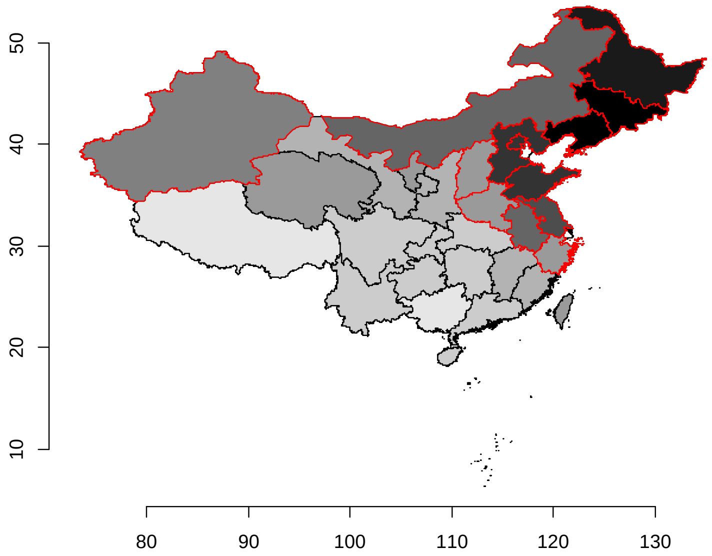

Fig. 3 Relative risk of plant invasiveness at provincial level of China using empirical Bayesian smoothing method. Provinces which have red boundaries indicate that their relative risks of plant invasion are significantly higher than 1. Colors from light to dark grey indicate invasive risks from low to high.

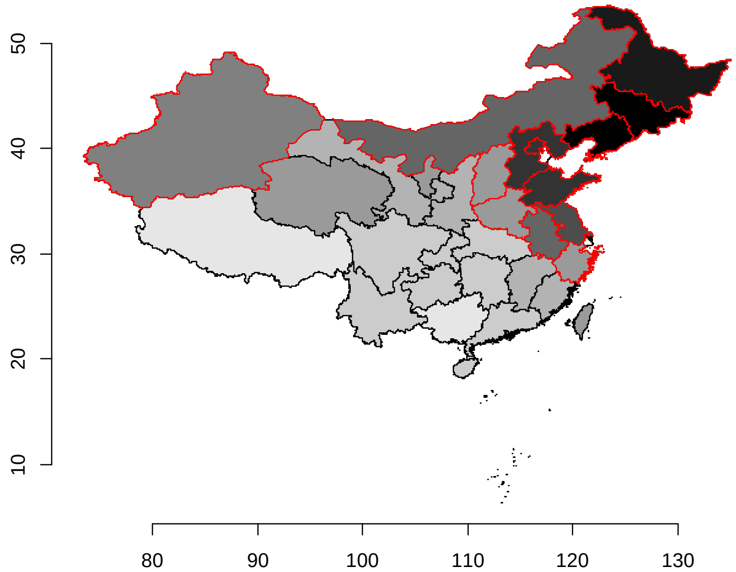

Fig. 4 Relative risk of plant invasiveness at provincial level of China using Poisson-Gamma model. Provinces which have red boundaries indicate that their relative risks of plant invasion are significantly higher than 1. Colors from light to dark grey indicate invasive risks from low to high.

The relative risk of plant invasion based on empirical Bayesian smoothing and Poisson-Gamma models are highly similar (Figs. 3-4). As seen, northern and western parts of China have high risk of plant invasion (dark grey colors). In contrast, southern part of China is less sensitive to plant invasion (light grey colors). Using Poisson exact test, it is identified that 13 provinces from northern part of China have significant relative risk values higher 1 (those provinces with red boundaries in Figs. 3-4).

As indicated by Table 1, the SAR model predicted that PRECrange was the most significant covariate (P<0.05) predicting the relative risk of plant invasion across different provinces of China. The next two important variables are TEMrange and PET respectively, but their coefficients are marginally significant (P<0.1). The coefficient ρ for quantifying the strength of spatial autocorrelation is equal to 0.7903, which is a quite large value given that the interval for ρ is [0, 1].

Before applying SAR model, there is significant spatial autocorrelation for the relative risk of plant invasion with Moran's I=0.639 (P<0.001) (Table 1 and Figs. 3-4). However, after SAR model has been done, the spatial autocorrelation has been removed to a great extent as indicated by the non-significant Moran's I value for the residuals of the model (Moran's I=0.131, P>0.05).

Table 1 Coefficient estimation for the covariates in the SAR model used for predicting relative risk of plant invasion across different provinces of China. Here the relative risk values are from empirical Bayesian smoothing method, the result for Poisson-Gamma method is almost identical and thus not presented here.

Covariates	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.083	0.049	1.695	0.09
Area	0.119	0.102	1.171	0.242
Elev	0.527	0.883	0.597	0.55
TEM	-0.496	1.219	-0.407	0.684
TEMmin	-0.721	0.755	-0.955	0.339
TEMmax	0.505	0.669	0.755	0.45
PET	0.81	0.486	1.668	0.095
PREC	-0.384	0.375	-1.026	0.305
AET	0.341	0.376	0.907	0.364
ElevRange	-0.21	0.789	-0.267	0.79
TEMrange	-0.267	0.151	-1.768	0.077
PRECrange	-0.214	0.076	-2.827	0.005

	Moran's I	P value
Before SAR	0.639	0.001
After SAR	0.131	0.717

4 Discussion

Different from previous studies, which showed that areas with high relative outbreak risk of alien plants are typically those with high richness of alien plants, the present study found that those areas with low native plant diversity would have higher risk of alien plant occurrence. The remarkable difference on the risk assessment is due to the inclusion of biodiversity information from native woody plant species. As mentioned above, all the previous studies (Bai et al., 2013; Liu et al., 2005; Wu et al., 2006; Feng and Zhu, 2010) did not explicitly consider the interaction between native and alien plant diversity. The biodiversity resistance hypothesis (Law and Morton, 1996; Stachowicz et al., 2002) provides a way to effectively incorporate diversity information from native plants for quantifying invasive risk of alien plants over provinces.

Based on the comparative results (Figs 3-4), both Poisson-Gamma and empirical Bayesian smoothing methods consistently identified that provinces from northern part of China are remarkably higher than those provinces in southern part of China. This is expected, since we applied biodiversity resistance hypothesis when modeling the invasive risk of alien plants. In southern and south-western part of China, the provinces there have very high species richness in comparison to those provinces in northern part of China. In particular, Yunnan province constitutes a well recognized biodiversity hotspot of the world (Chen and Bi, 2007; Myers et al., 2000; Zhang et al., 2010; Hua, 2008; Zhang, 2012b). Thus, even though this province is found to have a very high number of alien plants (Fig. 2), its relative risk of alien plant invasion is still comparatively low (Figs. 3-4). The very reason is that the calculation of relative risk of alien plant invasion requires the population at risk in the denominator, for which we use the native woody plant richness as the surrogate. Yunnan Province has the highest woody plant diversity (Fig. 1), thus its relative risk is predicted to be low accordingly.

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