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Distribution pattern of poisonous plant species in arid grasslands: a case from Xinjiang, Northwestern China

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Abstract. Poisonous plants threaten the ecosystem health of grasslands and the sustainability of animal husbandry. In arid lands, grassland ecosystems tend to be vulnerable and have been degraded due to the influence of human activities. The total area of the natural grasslands in Xinjiang, a large region in arid north-western China, ranks third in terms of area in China. In the process of grassland degradation, poisonous plants have spread widely and quickly in this region. During recent years, increasing economic losses have been caused by poisonous plants in Xinjiang. Although poisonous plants have been reported at some specific locations, their spatial patterns have rarely been investigated at a large regional scale. To understand the current status of hazards and assess the invasion risks of poisonous plants, we sampled ~150 poisonous plant species from Xinjiang and modelled the present and the future (the 2050s and the 2070s) distribution of 90 species using species distribution modelling. Based on the distribution maps of these poisonous plants, four diversity hotspots of poisonous plants were identified in Xinjiang. The results showed that northern Xinjiang had higher levels of poisonous plant diversity compared with the other part of Xinjiang. The precipitation factors had the most influence on prediction of the poisonous plants distributions in the species distribution modelling. Under the scenarios of future climate change, the results of modelling showed that regions close to the four hotspots of poisonous plants in Xinjiang displayed higher risks of invasion by poisonous plants in the future. In addition, these areas with a high risk of plant invasion will become increasingly large. We propose that policy makers consider implementing monitoring and prevention measures in areas identified as having a high risk of future invasion by poisonous plants.

Additional keywords: arid northwestern China, future environmental changes, grasslands, poisonous plants, Xinjiang.

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Introduction

Poisonous plants have been recognised as a species type that contains toxic components, which could pose a serious risk to grassland ecosystem health and have caused economic losses to the livestock industry throughout the world, such as in the United States (James *et al*. 1992), Australia (Everist 1978) and South America (Tokarnia *et al*. 2002). In China, ~1300 species of poisonous plants have been found (Zhao *et al*. 2013). Based on statistical data from animal husbandry, poisonous plants have caused increasing economic losses since the 1960s in China (Lu *et al*. 2012). Therefore, a need exists to assess the potential risk of poisonous plants for grasslands as it relates to the management of ecosystem health and the sustainability of animal husbandry.

Xinjiang covers ~1/6 of the total land area of the country, and the total area of the natural grasslands there ranks third in terms of area in China (Lu *et al*. 2012; Yan *et al*. 2015). Against the background of climatic drought, the grassland ecosystem in Xinjiang is vulnerable and sensitive to human activities. During recent years, natural grasslands have been seriously degraded because of overgrazing and drought in this region (Yan *et al*. 2015). As grasslands degraded, poisonous plants have spread widely and quickly because they are rarely ingested as feed for livestock. This situation is also displayed in other regions, such as Africa (Mbatha and Ward 2006) and North America (Holechek 2002), so that overgrazed grasslands may be particularly susceptible to degradation and invasion by poisonous plants. In total, ~150 poisonous plants have been listed in Xinjiang (Zhao *et al*. 1997; Sun *et al*. 2004; Li *et al*. 2010). Previous studies have examined the distribution and toxicology of some major poisonous plants in the study area with great detail (Li *et al*. 2010; Yan *et al*. 2015). Many studies have also provided effective approaches to managing these poisonous plants, such as enclosure of pastures on *Aconitum leucostomum* Worosch. (Luo *et al*. 2006; Li *et al*. 2009), and chemical control of *Achnatherum*

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inebrians (Hance) Keng (Dong *et al*. 2014; Jin *et al*. 2014) and *Ligularia narynensis* (C. Winkl.) O. et B. Fedtsch. (Liu *et al*. 2010; Xu *et al*. 2011).

Although poisonous plants from some specific regions have been reported, spatial patterns of these poisonous plants have rarely been investigated at a large regional scale to date. This information is important for helping to make management decisions on poisonous plants. Based on the distribution patterns of plant species, previous studies have planned for conservation and identified priority areas of biodiversity at a regional scale (Zhang *et al*. 2012; Zhang and Zhang 2014; Wang *et al*. 2015). In addition, they assessed the risk of potential biodiversity loss in the face of future environmental changes (Zhang *et al*. 2014). Analogically, investigating spatial patterns of poisonous plants could be beneficial for understanding the status of grassland ecosystem health and for assessing the potential hazards of poisonous plants in grasslands at a regional scale.

Species distribution modelling (SDM) is a widely used approach for determining the distribution of species diversity at a large spatial scale (Raes and ter Steege 2007; Zhang *et al*. 2012; Zhang and Zhang 2014). Profiting from a large number of existing records from the databases of herbarium collections, the power of this approach can now be greatly enhanced and used effectively in a wide range of applications. Comprehensive maps are particularly useful for identifying priority areas where management efforts for the control of poisonous plants are most needed. Under the scenarios of environmental change, this approach can help us predict locations with a high risk of invasion by poisonous plants in the future.

In this study, we sampled ~150 poisonous plant species in Xinjiang, collected from all georeferenced locations. Then, we chose 90 of these 150 species because they were present in more than four geographic coordinates from different cells of an approximate area of 100 km^2. We modelled their potential distributions under different environmental conditions, including the present and the future (the 2050s and the 2070s). Based on the maps from the species distribution model, our aims were as follows:

(1) Determine the current distribution pattern of poisonous plant species diversity in Xinjiang and identify areas with high levels of poisonous plant diversity;
(2) Clarify major environmental factors influencing the spatial distribution of poisonous plant species in Xinjiang; and
(3) Assess the risk of invasion by poisonous plants in Xinjiang under possible/diverse scenarios of future environmental changes to predict locations with a high risk of invasion by poisonous plants in the future.

Materials and methods

Species data

Based on the list of poisonous plants recorded in Xinjiang (Sun *et al*. 2004; Zhao *et al*. 1997; Li *et al*. 2010), ~150 poisonous plants were distributed in the study area. They mostly belonged to native plants (see Supplementary materials table S1, as available at journal's website). These species represented ~10% of the poisonous plants in China (Sun *et al*. 2004; Zhao *et al*. 2013). Distribution records of poisonous plants in Xinjiang were obtained from the China National Information Infrastructure database (NSII 2016), which can obtain records of specimens from most of the renowned Chinese herbariums. Based on label information in the specimen records, we were able to translate most of the recorded locations into latitude and longitude data. To avoid the bias of intensive specimen collection in some regions, we selected only one georeferenced location per species in an approximate area of 100 km^2 (at a 5-arcmin solution). Then, we removed the species that had less than five georeferenced collection locations from the analysis because these data lacked statistical power to define an ecological niche in distribution modelling. Finally, we obtained 2261 records from the 90 remaining poisonous plants (Supplementary materials table S1) to model species distributions.

Environmental data

Initially, 27 environmental variables were selected to define the ecological niche for these sampled species. Altitude and 19 bioclimatic variables were obtained from the WorldClim-Global Climate Data database (Hijmans *et al*. 2005; WorldClim 2016); seven soil variables were downloaded from the International Geosphere-Biosphere Program Data and Information System database (Global Soil Data Task Group 2000). These 27 environmental variables were employed at the resolution of 5 arcmin. When species distribution modelling is used, strong collinearity of environmental variables can result in model over-fitting (Graham 2003; Peterson 2006). To avoid this defect, only the lowest correlated variables (Spearman <0.75) were retained (Supplementary materials table S2 and S3). After screening the variables for multicollinearity, 11 remaining environmental variables were used to model the present distributions of these 90 poisonous plant species. These included: (1) ALT: altitude; (2) BIO2: mean diurnal temperature range; (3) BIO4: temperature seasonality (standard deviation); (4) BIO9: mean temperature of driest quarter; (5) BIO12: annual precipitation; (6) BIO15: precipitation seasonality (coefficient of variation); (7) BIO19: precipitation of coldest quarter; (8) BULKDENS: soil bulk density; (9) THERMCAP: soil thermal capacity; (10) SOILCARB: soil carbon density; and (11) FIELDCAP: soil field capacity.

To build species distribution models under future climatic conditions, we acquired 19 future bioclimatic variables during the 2050s and the 2070s based on three global climate models (CCSM4, HadGEM2-AO and MIROC5), each of which contains four representative concentration pathways (RCP), from the WorldClim-Global Climate Data database (Hijmans *et al*. 2005; WorldClim 2016). In total, 24 sets (3 models × 4 RCP × 2 future periods) of future climatic variables were obtained at a 5-arcmin resolution. To constrain the responses of plants to climatic changes in the species distribution modelling, we assumed that soil conditions were not changed between the present and the future (2050s and 2070s) in this study. During the process of species distribution modelling, we used the same 11 environmental variables with low correlation to model their future distributions.

Species distribution model building

To model species distributions, the software package MaxEnt version 3.3.1 (Phillips *et al*. 2006; MaxEnt 2016) was employed.

MaxEnt was specifically developed for presence data. This software has been suggested to perform better than other available modelling algorithms, especially when few presence records are used (Graham *et al*. 2008). MaxEnt predicted a target potential distribution by finding the probability distribution of maximum entropy (i.e. the most spread out, or closest to uniform) under a set of constraints representing incomplete information about the target species distribution. When applied to presence species distribution modelling, MaxEnt defines the probability distribution based on the space compiled by the pixels of the study area. Pixels with known species occurrence records constituted the sample points, and the features were climatic variables, elevation and soil variables (Phillips *et al*. 2006). Calibrated MaxEnt models can be used to project plant species distributions based on past and future climatic conditions to assess habitat suitability at the Last Glacial Maximum or in the future.

To model the present species distributions, we employed these 11 selected environmental variables at present-day conditions in the MaxEnt program. To obtain the future distributions of species during the 2050s and the 2070s, we projected the models on future datasets of the same environmental variables as were used to calibrate the models. SDM of the future distributions was calibrated under the present climatic conditions of the 11 environmental variables using present collection records, and these models were subsequently projected onto the future climatic conditions with the 11 corresponding environmental variables. The approaches of MaxEnt were run under the following modelling rules: (1) linear features were applied when fewer than 10 records were available, (2) quadratic features were added when 10–14 records were available, and (3) hinge features were added when >15 records were available. These rules were employed in MaxEnt to overcome the tendency of SDMs to over-fit, especially when few species presence records are available.

To measure the accuracy of the SDM, goodness of fit between model and training data were assessed by analysing the area under the receiver operating characteristic curve (AUC) of a receiver operating characteristic (ROC) plot (Fielding and Bell 1997) produced by MaxEnt. An ROC plot is generated by plotting all sensitivity values on the y-axis and their 1-specificity values on the x-axis for all available thresholds. The area under the ROC curve (AUC) is usually taken to be an important goodness-of-fit index and it tests whether a model has classified presence more accurately than random predictions have (Fielding and Bell 1997). Moreover, all measures of SDM accuracy require absences. When these are lacking, as is the case in this study, they are replaced by pseudo-absences or by sites randomly selected at localities where no species presence was recorded (Phillips *et al*. 2006). However, when SDM accuracy measures are based on presence-only data and pseudo-absences, the standard measures of accuracy (e.g. the often-used measure AUC >0.7) do not apply (Raes and ter Steege 2007). To overcome this deficiency, a null-model (Raes and ter Steege 2007) can be used to test the AUC value of an SDM developed with all-presence records against the AUC values expected by chance. This assumes that collection localities represent a randomisation of environmental data. Due to collecting biases, this is not a valid assumption in many cases (Kleidon and Mooney 2000; Zhang *et al*. 2012). To determine whether our 2261 collection localities were random subsamples of the environmental variable space, we first divided each of the 11 environmental variables into 10 equal-interval bins based on the ranges observed for Xinjiang (Zhang *et al*. 2012). We then tested whether the observed frequency distributions represented by the 2261 collection localities differed from those observed for all of Xinjiang using a Chi-square test. The test showed that our collection locations in Xinjiang represented non-random subsamples of the environmental variables for all of the 11 variables in this region. To correct for this bias, we employed a bias-corrected null model (Raes and ter Steege 2007) by testing each species modelled AUC value against 1000 AUC values that were generated randomly by subsampling from all the available collection localities only. When the observed AUC value fell in the top 95% of randomly generated AUC values (for the same sample size as the observed value), the tested species was considered to have a significant non-random distribution and was used in further analyses. Finally, all 90 species showed a significantly non-random distribution (AUC value $\geq$95% C.I.) here (Supplementary materials table S1).

Spatial pattern of species diversity

To estimate spatial patterns of poisonous plant diversity in Xinjiang, a threshold was applied to define whether a species was considered present in a grid cell based on the level of MaxEnt prediction values. For species with $\geq$10 records we used the fixed '10 percentile presence' threshold during SDM procedures; for species with less than 10 records we used either the 'sensitivity specificity equality' or the 'sum maximisation' threshold. This selection method depended on the assumption that a maximum of 10% of collections were wrongly identified or georeferenced (Zhang *et al.* 2012). Once the thresholds were set, a series of presence/absence layers were produced for all species, including (1) a set of presence/absence models under current climate conditions and (2) 24 sets of projected presence/absence models under four RCP, for each of three global climate models (CCSM4, HadGEM2-AO and MIROC5) during the 2050s and the 2070s. Then, current spatial patterns of poisonous plant diversity in Xinjiang were developed by superimposing all SDM layers under current climate conditions using ArcMap 10 (Environmental Systems Research Institute, Redlands, CA, USA). Based on the number of poisonous plant species in a grid cell, we divided them into four levels of species diversity based on categories representing the number of species predicted to be present in a grid cell.

To determine temporal changes in the composition of species in each grid cell, we used an approach of grid cell migration statistics (Hole *et al*. 2011). Species that were modelled as present in grid cells under future climatic conditions, but absent under present climate were defined as immigrants. Species that were modelled as present under current climatic conditions but as absent under future climate were defined as emigrants. Lastly, species that were modelled as present both under current and future climate were defined as persistent. The number of immigrants, emigrants and persistent species were calculated for each grid cell (5 arcmin). Finally, we computed the values of the number of immigrants, emigrants and persistent species in each grid cell (5 arcmin) for each of the 12 datasets of climatic scenarios (3 models $\times$ 4 RCP) during the 2050s and the 2070s.

To ascertain the major environmental factors influencing the distributions of poisonous plant species, we calculated the frequency of the 11 environmental variables in the contribution to their prediction of 90 species distributions. The first and the second important contributions of environmental variables reported from the outputs of the MaxEnt were only considered.

Results

Among the 90 modelled poisonous plant species, all showed a significantly non-random distribution (AUC value $\geq$95% C.I.) in this study (Supplementary materials table S1). The results of 90 modelled distributions based on current climatic conditions were stacked to sum the number of unique plant species for a pixel across all modelled species distributions in order to map spatial patterns of poisonous plant diversity in Xinjiang. After categorising species diversity values into five levels based on the number of unique species in pixel (Fig. 2*a*), four unique hotspots of poisonous plant diversity, having Level 4 species diversity, were identified in Xinjiang. These hotspots were the Central Tianshan Mountains around the Ili Valley, the north slope of the Central Tianshan Mountains from Urumqi to Shawan County, the Western Dzungarian Mountains, and the western side of the Altai Mountains. Mountain regions in the northern part of Xinjiang displayed high levels (Levels 4 and 3) of poisonous species diversity (Fig. 2*a*). In the Dzungarian Basin and the mountain regions around the western part of the Tarim Basin, low levels (Level 2) of species diversity were displayed (Fig. 2*a*). The interior of the Tarim Basin and the eastern ridges of this basin showed low levels (Level 1) of poisonous plant diversity (Fig. 2*a*).

When the spatial pattern of the occurrence of poisonous plant diversity was overlapped with the grassland map, the grasslands in the northern part of Xinjiang had high hazard ratings (Fig. 2*b*). In the south-western part of the Tianshan Mountains and the Pamir region, grasslands had low hazard risk rankings for poisonous plants (Fig. 2*b*). The precipitation factors of BIO12 and BIO19 showed high levels of frequency in the first important contribution to the prediction of 90 poisonous plants distributions in Xinjiang; whereas, the soil factor of SOILCARB and the altitude showed high level of frequency in the second important contribution to these predicted distributions (Fig. 3).

In their future distributions, poisonous plants displayed similar spatial patterns as the current distributions. Most of species persisted and were mainly distributed in the four hotpots of the mountains of northern Xinjiang during the 2050s and the 2070s (Supplementary materials figs S1 and S2). Under future climate change scenarios, a high risk of potential range expansions of poisonous plants mostly occurred at the eastern side of the Altai Mountains, the foothill of the Western Dzungarian Mountains, the eastern part of the Tianshan Mountains and the Central Tianshan Mountains (Figs 4 and 5). The largest areas of potential range expansion, which was increasing under the intensified tendency of projected global warming, were shown under RCP8.5 scenario within the four RCP scenarios (Supplementary materials table S4; Figs 4 and 5). During the different time periods, spatial patterns of expanding poisonous plants were mostly similar between the 2050s and the 2070s, although the range of expanding poisonous plants during the 2070s was a little larger than it was during the 2050s (Supplementary materials table S4; Figs 4 and 5). Meanwhile, a small number of poisonous plants will undergo range contraction under the future climatic scenarios (Supplementary materials table S5; figs S5 and S6).

Discussion

Spatial pattern of poisonous plant species in grasslands

Xinjiang was confirmed to be seriously threatened by poisonous plants. Approximately 150 poisonous plants are distributed in this region (Zhao *et al*. 1997; Sun *et al*. 2004; Li *et al*. 2010), 90 of which are not stenochoric species (Zhao *et al*. 1997; Yan *et al*. 2015). During recent years, a comprehensive list of poisonous plants collected in Xinjiang has been published (Zhao *et al*. 1997; Sun *et al*. 2004; Li *et al*. 2010). However, the spatial pattern of poisonous species diversity has not been examined, which is important for making strategic decisions on grasslands management at a regional scale in Xinjiang. In this study, the hotspots of poisonous plant species diversity (Level 4) were shown to be the Central Tianshan Mountains around the Ili Valley, the northern slope of the Central Tianshan Mountains from Urumqi to Shawan County, the Western Dzungarian Mountains, and the western side of the Altai Mountains (Fig. 2*a*). The locations of current poisonous plant hotspots were important production bases of animal husbandry in Xinjiang (Yan *et al*. 2015). We suggest that management actions such as pasture enclosure, chemical control, or plant removal and subsequent revegetation be established to control and decrease the damage of poisonous plants to animal husbandry in these areas identified as hotspots in Xinjiang (Fig. 2).

Against the background of climatic drought, grasslands were mainly distributed along the mountain ranges and foothills (Fig. 1*c*) in Xinjiang. In this study, we found that grasslands in northern Xinjiang were covered by high levels of poisonous plant diversity (Fig. 2*b*). Meanwhile, the precipitation factors of annual precipitation (BIO12) and precipitation of coldest quarter (BIO19) made major contributions to the prediction of these poisonous plants distributions in Xinjiang (Fig. 3). The regions with high levels of poisonous plant diversity in Xinjiang, such as the Central Tianshan Mountains around the Ili Valley, the northern slope of the Central Tianshan Mountains from Urumqi to Shawan County, the Western Dzungarian Mountains, and the western side of the Altai Mountains, were shown to have higher precipitation. This finding indicates that modern environmental factors play an important role in shaping the distribution pattern of poisonous plant species. In and around the Tarim Basin, an extremely dry area like the Taklimakan Desert, few poisonous plant species were distributed (Fig. 2*a*). This pattern was similar to other types of plants in Xinjiang (Zhang and Zhang 2014). In grasslands of the Qinghai-Tibet Plateau, it has also been shown that climatic variables (Wu *et al*. 2015) and soil quality (Li *et al*. 2014) have influenced the spatial pattern of poisonous plant species, including poisonous plants coverage and diversity.

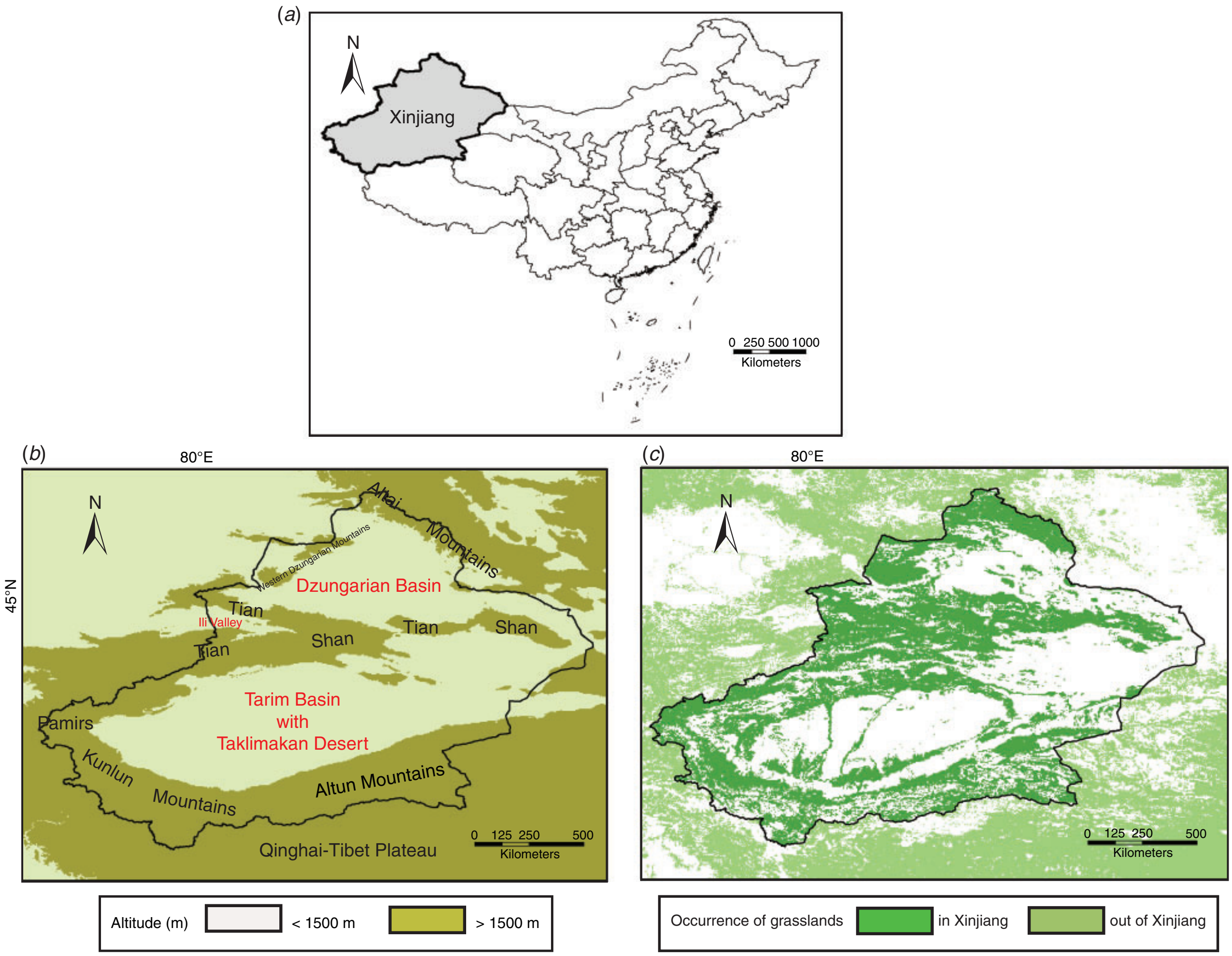

Fig. 1. Geographical overview of (*a*) Xinjiang, (*b*) topography pattern and (*c*) distribution of grasslands in the study area.

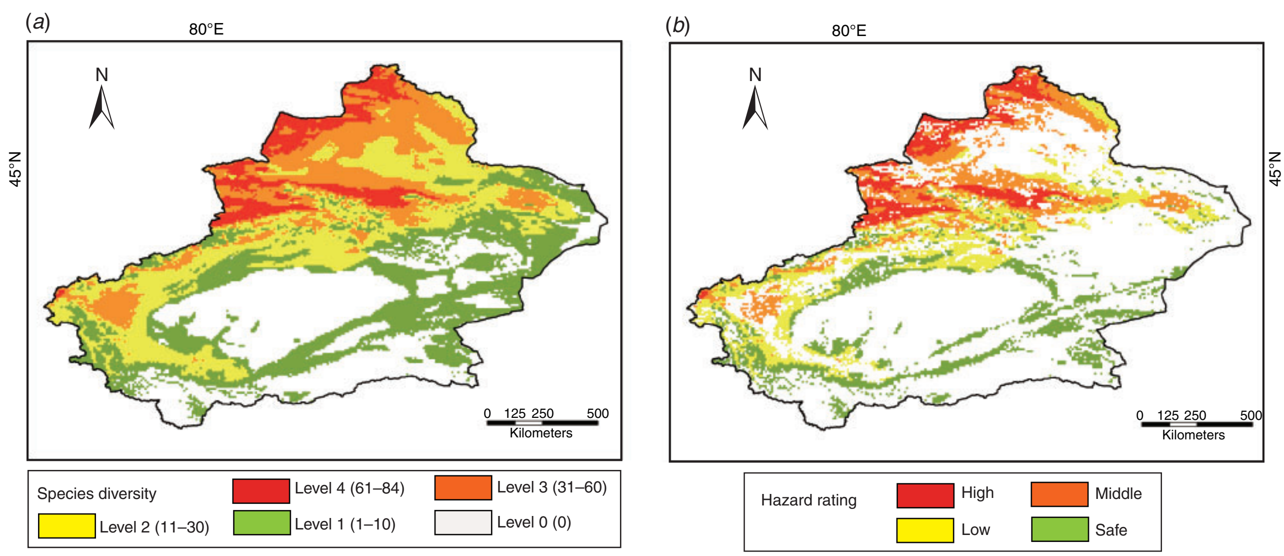

Fig. 2. (*a*) The five quartiles of current poisonous plant diversity in Xinjiang (Level 0 = the lowest group, and Level 4 = the highest group). (*b*) The four levels of hazard rating in Xinjiang grasslands.

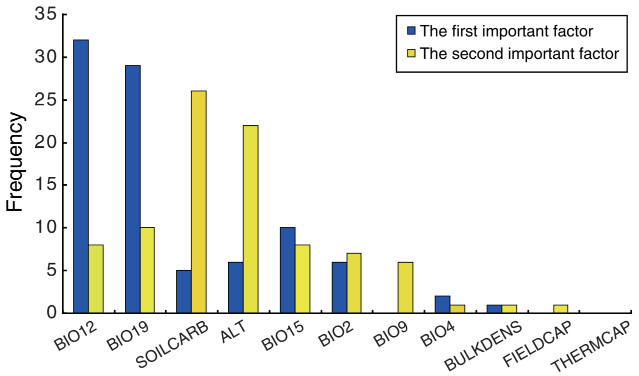

Fig. 3. The frequency of the 11 environmental variables in the contribution to their prediction of 90 poisonous species distributions.

Future range expansion of poisonous plant species in grasslands

Increases in poisonous plants could lead to livestock poisoning, reduce biodiversity and cause a decline in grass yield in grasslands. During recent years, the frequency of reports of the impact of poisonous plants on animal husbandry has increased in Xinjiang (Guo *et al*. 2011; Ma and Sayiremuguli 2012). Although some hazardous events have been reported, the potential hazards of poisonous plants in grasslands have rarely been evaluated. Some biological characteristics could trigger the spread of these poisonous plants in grasslands. Poisonous plant species usually have a stronger tolerance to drought and barren soil than forage grasses, such as *Achnatherum inebrians* (Zhang *et al*. 2010). The seed density of some poisonous plant species, such as *Aconitum leucostomum*, has been estimated to be high in

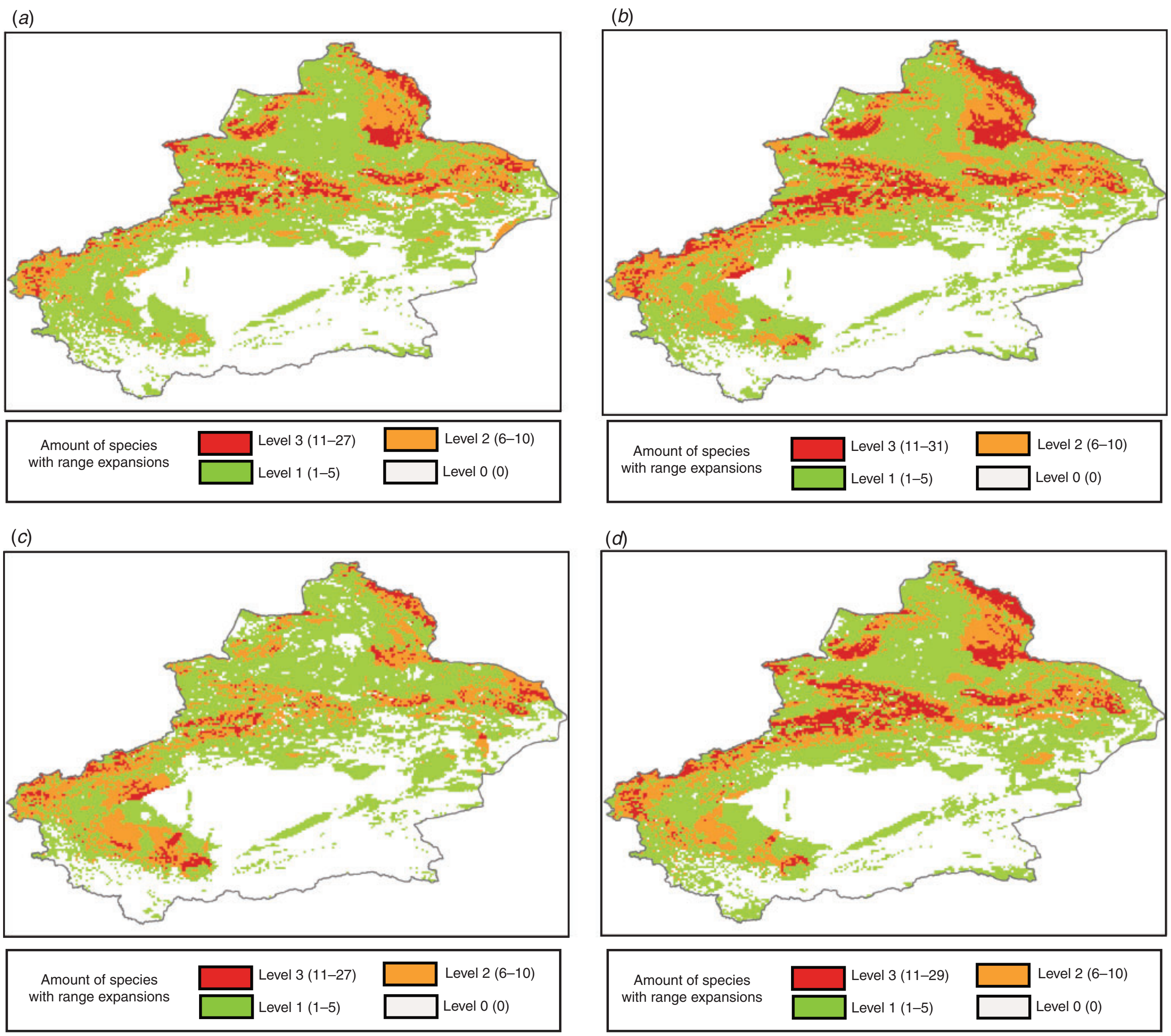

Fig. 4. Four levels of poisonous plants with potential range expansions during the 2050s (MIROC5 model) based on four RCP scenarios, (*a*) RCP2.6; (*b*) RCP4.5; (*c*) RCP6.0; (*d*) RCP8.5 compared with the current distribution pattern.

soil seed banks from deteriorated grasslands (Luo 2006). Some poisonous plants, such as *Sophora alopecuroides*, had high dispersal ability with clonal reproduction, which allows many clonal individuals to be grown from its roots during the spring (Yang 2005).

Future environmental changes will affect the spatial distributions of plant species (Zhang *et al*. 2014). It has been agreed that environmental changes will prevail in arid Central Asia in the future (Lioubimtseva and Henebry 2009). Under changing climatic conditions, many plant species have been predicted to lose their distribution ranges (Zhang *et al*. 2013, 2014). With regard to poisonous plants in this study, the concern is whether they will experience range expansion under future climate changes. In this study, the results of SDM showed that the eastern part of the Altai Mountains, the foothills of the Western Dzungarian Mountains, the eastern part of the Tianshan Mountains and the Central Tianshan Mountains (Figs 4 and 5) were associated with a high risk of potential range expansion for poisonous plants in the future. These regions were close to four hotspots of poisonous plant diversity (Fig. 2*a*) in Xinjiang. This finding indicated that neighbouring areas of these four hotspots of poisonous plants were considered to be at high risk of invasion by poisonous plants in the future. Given the projected expansion of poisonous plants identified in this study, our results indicate the need for policies to reduce risk of invasion by poisonous plants. The areas of highest risk for expansion were adjacent to four current hotspots of poisonous plants, where seed resources and suitable habitats likely increase opportunities for the expansion. We propose that monitoring and prevention measures should be introduced in these areas

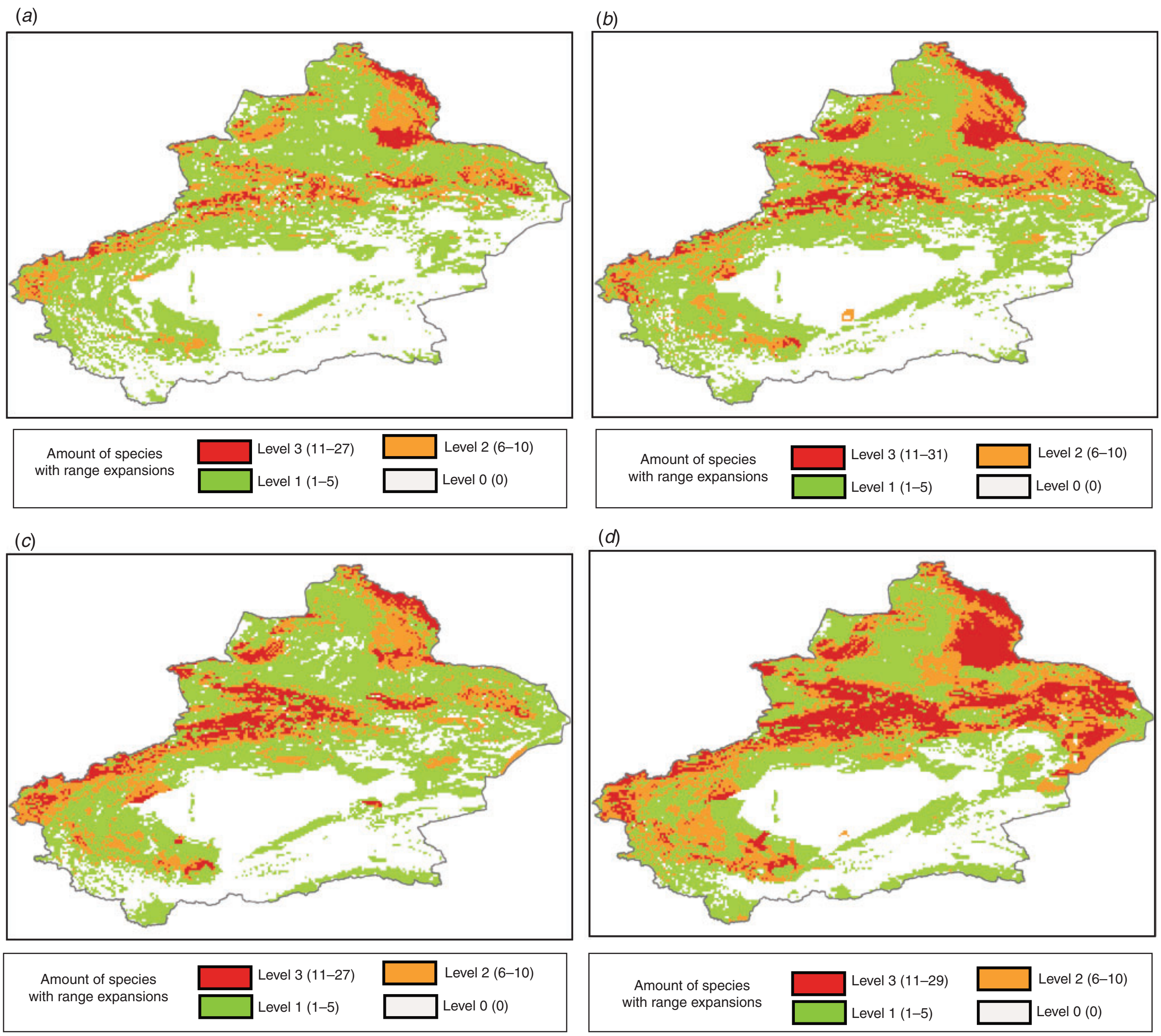

Fig. 5. Four levels of poisonous plants with potential range expansions during the 2070s (MIROC5 model) based on four RCP scenarios, (*a*) RCP2.6; (*b*) RCP4.5; (*c*) RCP6.0; (*d*) RCP8.5 compared with the current distribution pattern.

identified as having high risk (Figs 4 and 5) to reduce opportunities for expansion in the future.

Based on the four RCP scenarios, RCP8.5 scenario showed largest area of high risk of potential range expansion for poisonous plants (Figs 4*d* and 5*d*), which indicated the mean values of global temperature would increase 2.0°C during 2050s and 3.7°C during 2070s (IPCC AR5 WG1 2013). The region of potential range expansion for poisonous plants was increasing under the intensified tendency of projected global warming in Xinjiang (Figs 4 and 5). Based on climate change projected by IPCC SRES, annual temperature increases gradually, and annual precipitation increases, but is projected to have larger fluctuations in annual amounts, during 2050s and 2070s in Xinjiang (Li *et al*. 2013). Compared with different time periods (2050s versus 2070s), the scale of the areas at high risk of invasion by poisonous plants could become increasingly large in the future (Figs 4 and 5). This finding showed that poisonous plants can expand their potential distribution range with the projected global change and could potentially cause serious problems for livestock production on grasslands in Xinjiang.

In this study, some limitations of SDM modelling for the future projections of species distribution also exist. On the one hand, the predicted range expansions of these poisonous plant species are highly tied to the given climatic scenarios. Potential ranges of poisonous plants based on the RCP 4.5 scenario during the 2050s have greater expansion than the results projected on the progression in RCP 4.5 and RCP 8.5 scenarios or the progression during the 2070s (Supplementary materials table S4; Figs 4 and 5). This shortcoming could be caused by the over-interpretation of climatic changes in the study area based on the RCP 4.5 scenario during the 2050s. On the other hand, the predicted future ranges of these poisonous plants are greatly affected by their current distributions with less consideration for their ability to spread via seed transport. Here, three invasive species are among those poisonous species (Supplementary materials table S1), which are *Linum usitatissimum*, *Vicia sativa* and *Robinia pseudoacacia*. Invasiveness in exotic plant species has been linked to vectors transporting the seeds (Phillips and Murray 2012), which could affect the future distributions of these plants. The exotic plant species could have higher potential to spread than the native plants. Then, the predicted future distributions of exotic plants could be underestimated in the SDM modelling. However, because only a small number of exotic plants (3/90) were considered in this study, the distribution pattern of poisonous plant species cannot be seriously affected by these exotic plants.

Conclusions

In this study, we have clarified the spatial pattern of poisonous plant diversity and assessed the potential expansion of poisonous plants in the grasslands of Xinjiang, which may be a hazard to animal husbandry. Four hotspots of poisonous plant diversity were shown to exist in the Central Tianshan Mountains around the Ili Valley, the north slope of the Central Tianshan Mountains from Urumqi to Shawan County, the Western Dzungarian Mountains, and the western side of the Altai Mountains. The precipitation factors made major contributions to the prediction of these poisonous plants distributions in Xinjiang. Under the conditions of future environmental change, regions close to the four hotspots of poisonous plants in Xinjiang were shown to be associated with a high risk of potential range expansion. The region of potential range expansion for poisonous plants will be increasing under the intensified tendency of projected global warming based on the four RCP scenarios. Moreover, the scale of the areas at high risk of invasion by poisonous plants could become increasingly large in the future. Finally, we propose that management actions should be established to control and decrease the impacts of poisonous plants to animal husbandry in the areas identified as current hotspots in Xinjiang. These areas were also identified as having greater risk of expanding under future climate scenarios. Therefore, policies that promote monitoring and preventions measures that would reduce expansion are recommended.

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