land

Brief Report

Effects of Habitat Heterogeneity and Topographic Variation on Insect Pest Risks in Alpine Regions

Lei Wang [1], Fei-Xue Zhang [2], Lan-Ping Li [2], Chun-Jing Wang [2,*] and Ji-Zhong Wan [2]

[1] College of Wildlife and Protected Area, Northeast Forestry University, Harbin 150040, China
[2] State Key Laboratory of Plateau Ecology and Agriculture, Qinghai University, Xining 810016, China; wan1276@qhu.edu.cn (J.-Z.W.)
* Correspondence: wangchunjing00@163.com

Abstract: Insect pests pose a significant threat to alpine ecosystems, especially under rapid environmental change conditions. Therefore, it is necessary to explore the effects of environmental factors on insect pest risks and provide methods for pest management in alpine regions. Habitat heterogeneity and topographic variation are the indicators of insect pest risks. However, few studies have explored the effects of habitat heterogeneity and topographic variation on insect pest risks in alpine regions. We used species distribution modeling (i.e., maxent modeling) to project the distributions of insect pests in this alpine region based on occurrence records. Then, we delineated the high-risk areas for insect pests based on the species distributions under a conceptual risk framework using Zonation software for different ecoregional types. We determined the alpine conifer and mixed forests of the Nujiang Langcang Gorge, the conifer forests of the Qilian Mountains, and the shrublands and meadows of Southeast Tibet as the key areas requiring monitoring for insect pests in Qinghai province based on the scoring of insect pest risk rank with >0.7. Habitat heterogeneity and topographic variation could be developed as indicators of risk exposure to insect pests in alpine regions. Our study suggests that the prevention and control of insect pests should be conducted in areas with high habitat heterogeneity and topographic roughness in alpine regions. We provided new insights into the application of species distribution modeling based on habitat heterogeneity and topographic variation. The results of our study indicate that habitat heterogeneity and topographic variation should be considered for improving pest management effectiveness in alpine regions.

Keywords: alpine region; environmental heterogeneity; insect pest; risk assessment; Tibetan Plateau; topography

check for updates

Citation: Wang, L.; Zhang, F.-X.; Li, L.-P.; Wang, C.-J.; Wan, J.-Z. Effects of Habitat Heterogeneity and Topographic Variation on Insect Pest Risks in Alpine Regions. *Land* **2023**, *12*, 1314. https://doi.org/10.3390/land12071314

Academic Editors: Linshan Liu, Prem Sagar Chapagain, Jie Gong and Md. Nurul Islam

Received: 14 May 2023
Revised: 28 June 2023
Accepted: 28 June 2023
Published: 29 June 2023

1. Introduction

The biodiversity found in alpine ecosystems is vulnerable to global environmental change [1,2]. Rapid environmental change (i.e., rapid climate change and land cover change) can lead to high biological invasion risk, mainly affecting sensitive alpine ecosystems [2–4]. Alpine ecosystems are beneficial to recreation, resource extraction, and seasonal grazing of livestock [5,6]. Furthermore, the water that melts off glaciers and flows down through the mountains is a major freshwater source for many populations in alpine regions. Under global environmental change, biological invasion may be enhanced in alpine ecosystems [7,8]. Numerous prediction studies have shown that ecosystem functions and services may be lost under biological invasion [9,10]. For example, climate change could drive species redistribution, which may drive invasive plants into regions of high altitude [11]. Predicting biological invasion can provide insight into biodiversity responses to rapid environmental changes and inform the development of modeling for ecosystem services across different spatial scales [12]. Hence, more detailed predictions on biological invasions (e.g., insect pest invasion) in alpine regions are required to improve the effectiveness of ecosystem management.

Insect pests significantly threaten natural resources, societal development, and food security in alpine regions [13]. Environmental changes (i.e., climate and land cover changes) could result in pest outbreaks, and species distribution prediction modeling indicates that the probability of pest outbreaks may increase under environmental changes [14,15]. Climate change, as one major factor of environmental change, has a large potential to cause a high risk of insect pests, leading to the vulnerability of alpine ecosystems [13–15]. For example, there may be northward range shifts and increased frequency of pest outbreaks (e.g., bark beetle) in the alpine regions under climate change [5]. Direct effects of temperature warming include increases in the development and survival rates of bark beetles [16–18]. Moreover, landscape habitat fragmentation and ecosystem homogenization can exacerbate new environmental damage, allowing for altered inter-species interactions while also enhancing ecosystem susceptibility to pests [19]. Hence, it is necessary to explore the effects of ecological landscapes and fragmentation on insect pest species distributions for assessing insect pest risk in alpine regions. Studies show that habitat heterogeneity and topographic changes can affect natural habitat fragmentation and loss, which potentially affect insect pest risk [20].

Indeed, a fundamental tenet of the theory of biodiversity and ecosystem functioning is that there is also a positive correlation between habitat heterogeneity and ecosystem stability [19–21]. Studies have shown that habitat specificity plays an important role in maintaining biodiversity [22,23]. Habitat heterogeneity is a key factor influencing pest species richness, abundance, and species composition among different types of habitats [21], while higher vegetation richness in a habitat provides sufficient food resources and refuge for natural enemies in the landscape, resulting in higher pest diversity [19–23]. Alpine ecosystems are closely associated with redistribution in determining the relations between landscape and patch-scale interaction [24–26]. Due to low-patch-scale interaction, the constraints that control the ecological dynamics of alpine ecosystems are small for insect pest damage [25,26]. Hence, an alpine ecosystem may develop into a more sensitive ecological landscape, resulting in a limited ability to prevent and control ecological dynamics. Topographic factors have a strong driving force on pest distribution patterns in alpine areas due to the constant changes in hydrological, geomorphological, and biological processes in the terrain [27]. Therefore, exploring the effects of habitat heterogeneity and topographic variation on insect pest risks in alpine regions is necessary. Our study provides insight into pest prevention and control using habitat heterogeneity and topographic variation as ecological indicators of insect pest risks.

In this study, the areas at high risk of exposure to insect pests were identified for insect pests in alpine regions based on habitat heterogeneity and topographic variation. Furthermore, we determined potential risk areas for insect pest invasion. We propose the central hypothesis that the risk levels of insect pests are different in high mountain areas without habitat heterogeneity and topographic variation. To test this hypothesis, we applied an adapted risk framework to insect pests to delineate the areas of high risk in alpine regions based on Probert et al. and Wan and Wang [28,29].

2. Materials and Methods

2.1. Pest Species Data

The data on insect pest species were obtained from the study of Wang et al. [30]. Qinghai province is a region of the Qinghai–Tibetan Plateau. The altitude of this region ranges from 1650 m to 6860 m, with an average altitude higher than 3000 m [31]. Damage caused by insect pests has occurred widely in the alpine ecosystems of Qinghai. Vulnerable ecosystems to insect pests include the Central Tibetan Plateau alpine steppe, the Qilian Mountain conifer forests, the Qilian Mountain subalpine meadows, the Southeast Tibet shrublands and meadows, and the Tibetan Plateau alpine shrublands and meadows. From 2014 to 2016, 5513 field plots were investigated for insect pest species in Qinghai, China (Figure 1). In total, 58 insect pest species were studied for our analysis. We identified the damage caused by a particular insect pest based on the percentage of leaf loss, levels of stunting, and proportion of seedling death in host species in the field, and we conducted insect pest identification based on the knowledge of biocontrol and pest science experts. The pest species with greater than 10 occurrence records were used as the input for species distribution modeling (SDM). In total, 58 insect pest species were used as the input for SDM for further analysis.

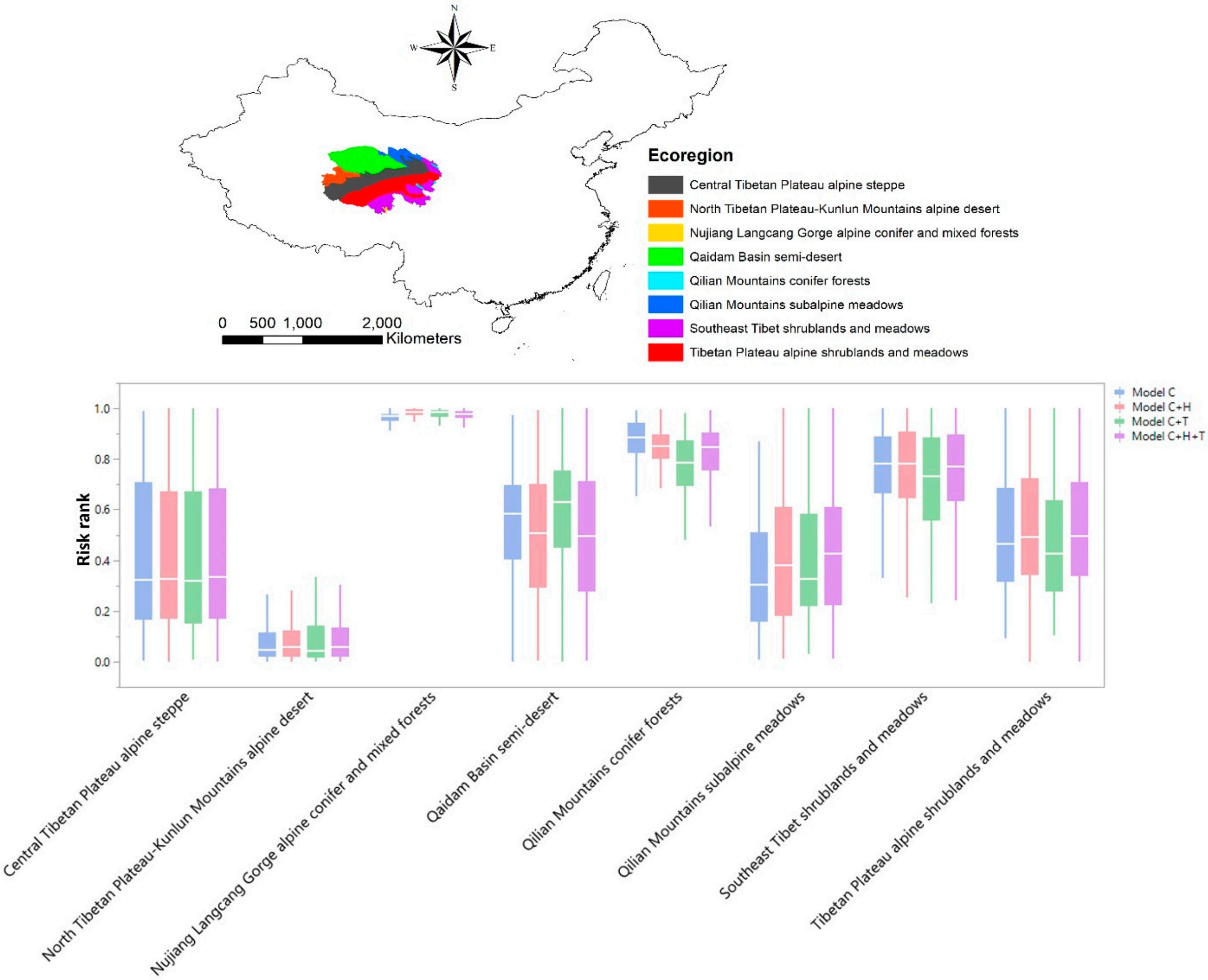

Figure 1. Ecoregions and ecoregional risk rank exposure to insect pests in Qinghai province, China. The upper and lower bars represent the 95% confidence interval ranges of ecoregional risk rank exposure to insect pests in Qinghai province, China, and the lines represent the mean values of ecoregional risk rank.

2.2. Environmental Data

Previous studies have shown that climate, topography, and habitat heterogeneity have strong explanatory power for pest distribution [32–35]. Therefore, we used climatic variables, topographic variables, and habitat heterogeneity as environmental variables in our species distribution model to predict the distribution of 105 pest species in Qinghai Province. Climatic variables were obtained from the WorldClim database (https://www.worldclim.org/, accessed on 20 June 2023) [36]. The WorldClim database includes monthly temperature (minimum, maximum, and average) and precipitation aggregated across a target temporal range from 1970–2000, using data from between 9000 and 60,000 weather stations. In this study, 19 bioclimatic variables were used in a Pearson correlation analysis for 19 variables of climate to determine the relationship between various climate variables.

Any climate variable with a correlation (r) ≥ |0.60| was removed from the analysis. The final four bioclimatic variables (annual mean temperature, mean diurnal range (mean of monthly (max temp—min temp)), temperature seasonality (standard deviation ×100), annual precipitation, and precipitation seasonality (coefficient of variation) [36,37]) were included in the analysis of this study [36–38]. These four climatic variables were extracted as the mask of the Qinghai map.

Habitat heterogeneity index data were downloaded from https://www.earthenv.org/, accessed on 20 June 2023). The four habitat heterogeneity indices we used were coefficients of variations of Enhanced Vegetation Index (EVI), evenness of EVI, range of EVI, and Shannon of EVI [39]. The topographic variation was downloaded from (https://www.earthenv.org/, accessed on 20 June 2023). We used Terrain Ruggedness Index (TRI), Topographic Position Index (TPI), Vector Ruggedness Measure (VRM), and roughness, respectively. These four indices can describe the heterogeneity of terrain profiles and surface landscapes. The grid resolution is 2.5 arcmin (~5 km). Here, we used the occurrence records of 105 pest species and data on habitat heterogeneity and topographic variability at background points as inputs to the SDM.

2.3. Species Distribution Modeling

In Maxent SDM (Version 3.4.4; https://biodiversityinformatics.amnh.org/open_source/maxent/, accessed on 1 January 2020), we ran the pest occurrence records of Qinghai Province with four sets of environmental variables (i.e., climate (C), climate + heterogeneity (C+H), climate + topography (C+T), and climate + heterogeneity + topography (C+H+T)) as input variables in the model. The distribution of pests in Qinghai Province was predicted under four models (model C, model C+H, model C+T, and model C+H+T). We constructed the ensemble of Maxent SDM as suggested by Merow et al. and Phillips et al. to produce a relatively low modeling complexity to accomplish minimizing overfitting [40,41]. The detailed set of Maxent modeling has the following points: (1) The regularization multiplier (beta) 2.0 was used to produce a smooth and general response shape that is representative of biologically realistic behavior; (2) The maximum number of background points was set to 10,000; (3) The output of Maxent modeling was set to complement log–log (clog–log); and (4) Five replications were conducted with randomized training trial data (auctrain, 80%) and test data (auctest, 20%) to remove bias from the pest species distribution records and, thus, improve the accuracy of the SDM [40,41]. The results of the Maxent model indicated that the species distribution probabilities ranged from 0 to 1. In this paper, the accuracy of the model was assessed using AUC with a range of values from 0 to 1; the higher the value, the greater the deviation of the species distribution from a random distribution (i.e., AUC = 0.5). [38,42]. By maximizing the sensitivity and specificity in cross-validation, the continuous prediction was set as a threshold for binary prediction [38,42]. Based on the cross-validation approach, we evaluated SDM for each pest species using five AUCs. Here, the SDM predicted 105 pest species in Qinghai Province with high accuracy, with all AUCs exceeding 0.7 [42]. Previous studies have shown that the larger the AUC, the higher the performance of the prediction model [42]. Based on maximizing training sensitivity and specificity, the pest species map was quantified using presence thresholds [42]. We calculated the area of presence of each pest by the number of grid cells.

2.4. Delineating the Risk Areas

We used Zonation software coupled with SDM to delineate the areas of high risk for pest species based on the conceptual risk framework described by Probert et al. [28]. The use of this analysis provides a basis for assessing the ecological risk of pest species in order to facilitate justifiable management decisions. Both the species and the potential recipient areas should be considered for the delineation of high-risk areas. SDM can predict the distribution of pest species across a landscape pre- or post-establishment. Priority areas most at risk of exposure to the pest species can be identified using Zonation software [43]. The Zonation framework identified the high-risk areas via a post-hoc analysis of ecologically optimized prioritization and the removal of sites. We used the "core-area Zonation" (CAZ) cell-removal rule, which maximizes core areas of high risk for each individual pest species [44]. We set the warp factor to 1 to maintain output reliability [44]. The monitoring objectives of this study were the distributions of 58 pest species based on Model C, Model C + H, Model C + T, and Model C + H + T; these were used as the input for the Zonation software. We identified priority areas with different risks of exposure to the pest species (exposed assets). Hence, we obtained four maps of the areas at risk for insect pests based on the distributions of pest species from Model C, Model C + H, Model C + T, and Model C + H + T.

2.5. Synthesis

We compared the effects of habitat heterogeneity and topographic variation on the risk of exposure to pests using linear regression modeling. We used the fitted equations of linear regression modeling between Model C, Model C + H, Model C + T, and Model C + H + T. The slope of the linear regression model was applied to compare the risk of exposure to pests with and without habitat heterogeneity and topographic variation. The ecoregion map was downloaded from https://www.worldwildlife.org/publications/terrestrial-ecoregions-of-the-world, (accessed on 6 March 2020) [45]. The ecoregions of Qinghai province included the alpine steppe of the Central Tibetan Plateau, the alpine desert of the North Tibetan Plateau–Kunlun Mountains, the alpine conifer and mixed forests of the Nujiang Langcang Gorge, the semi-desert of the Qaidam Basin, the conifer forests of the Qilian Mountains, the subalpine meadows of the Qilian Mountains, and the shrublands and meadows of Southeast Tibet (Figure 1). We used ANOVA tests to compare the mean of pest distribution probabilities among four models (Model C, Model C+H, Model C+T, and Model C+H+T) in the ecoregion. All analyses were performed in R (https://www.r-project.org/, accessed on 6 March 2020), JMP 11.0 (https://www.jmp.com/en_us/software.html, accessed on 6 June 2019) and ArcGIS 10.6 (https://desktop.arcgis.com/es/, accessed on 2 May 2020).

3. Results

In Qinghai province, habitat heterogeneity and topographic variation could affect the risk of plants being exposed to pests (Figure 2). There were significant relationships of risk rank exposure to pests among Model C, Model C + H, Model C + T, and Model C + H + T across different ecoregions ($p < 0.05$; Figure 2). The slope values were lower than 1 for all the linear regression models except for Model C + T in conifer forests of the Qilian Mountains (Figure 2). In Mode C + T, the risk rank of the Qaidam Basin semi-desert is higher, and there is a significant difference in risk level compared with other models (Table 1; Figure 3).

Table 1. Scoring of insect pest risk rank in ecoregions of Qinghai province, China.

Ecoregion	Code	Clim	Clim + H	Clim + T	Clim + H + T
Central Tibetan Plateau alpine steppe	CTPAS	0.424	0.413	0.415	0.419
North Tibetan Plateau–Kunlun Mountains alpine desert	NTPKMAD	0.070	0.087	0.110	0.101
Nujiang Langcang Gorge alpine conifer and mixed forests	NLGACMF	0.962	0.982	0.977	0.973
Qaidam Basin semi-desert	QBSD	0.566	0.517	0.607	0.509
Qilian Mountains conifer forests	QMCF	0.878	0.839	0.777	0.822
Qilian Mountains subalpine meadows	QMSM	0.354	0.441	0.419	0.468
Southeast Tibet shrublands and meadows	STSM	0.751	0.767	0.716	0.758
Tibetan Plateau alpine shrublands and meadows	TPASM	0.516	0.530	0.479	0.527

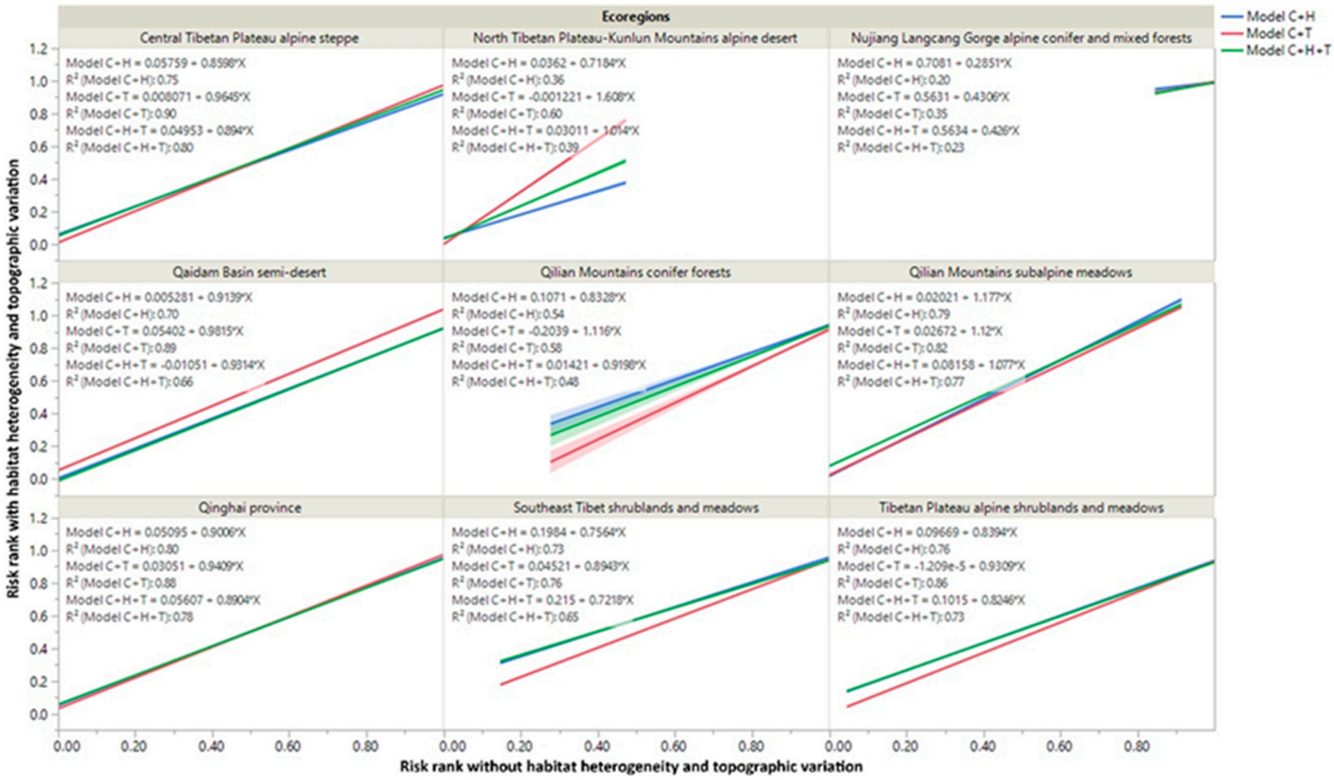

Figure 2. Results of linear regression modeling for risk rank exposure to insect pests with and without habitat heterogeneity and topographic variation. The shaded area surrounding some of the lines represents the 95% confidence interval of risk rank exposure to insect pests based on grid cells.

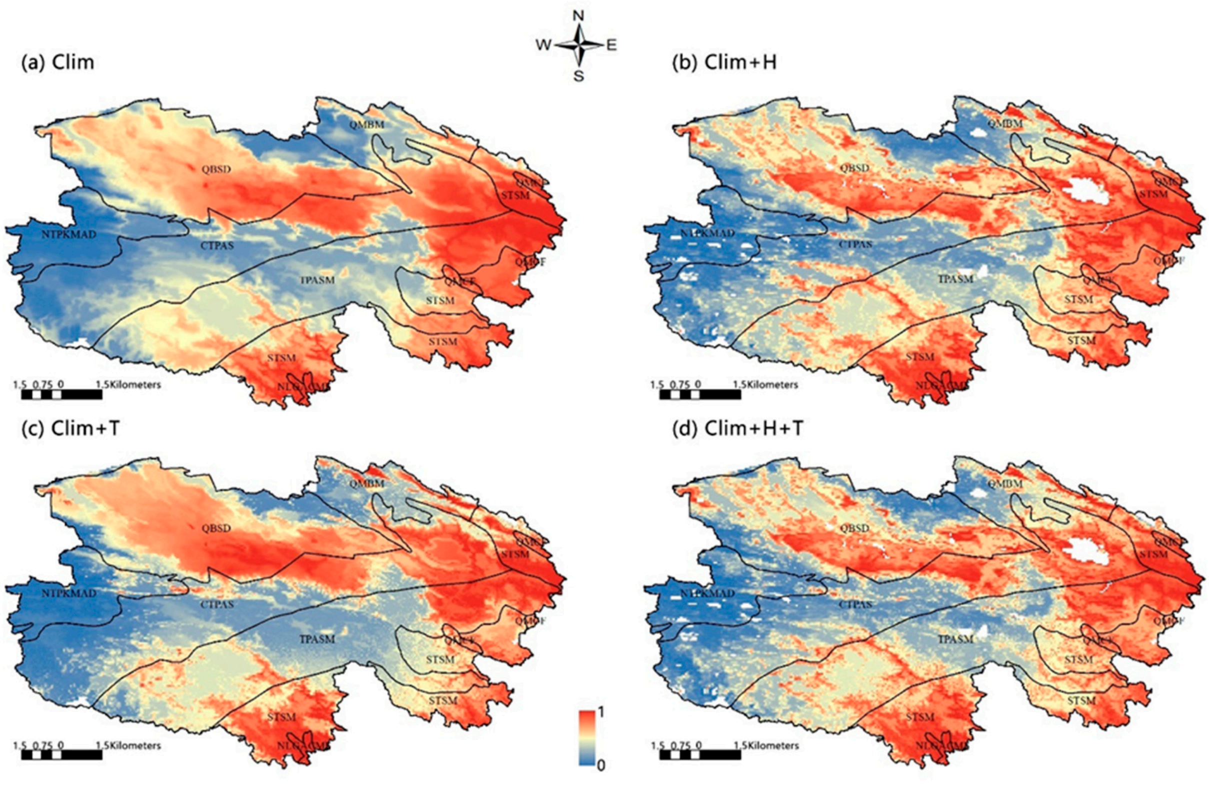

Figure 3. Key risk areas for insect pests in Qinghai province under different modes. Red, yellow, and blue indicate high, medium, and low pest risks, respectively. The ecoregion codes are shown in Table 1.

There was a large area for high risk of plants being exposed to pests in Qinghai province (Figure 3). The areas with high risk were distributed in Northeastern and Southwestern Qinghai province (Figure 3). The areas with a high risk of plants being exposed to pests included the alpine conifer and mixed forests of Nujiang Langcang Gorge, the conifer forests of the Qilian Mountains, and the shrublands and meadows of Southeast Tibet for Model C, Model C + H, Model C + T, and Model C + H + T, with the scoring of insect pest risk rank over 0.7 (Table 1; Figure 3).

4. Discussion

We used the conceptual risk framework described by Probert et al. [28] to delineate the areas of high-risk exposure to insect pests in alpine regions in Qinghai province, China. Climatic factors are the main drivers of insect pests [2–4]. Hence, a map of the climatic distribution of insect pests could guide the prevention and control of insect pests in alpine regions. However, the effects of habitat heterogeneity and topographic variation on insect pest distributions should be considered for pest management. Based on the results of linear regression modeling, there were significant relationships among Model C, Model C + H, Model C + T, and Model C + H + T across different ecoregions. The linear regression modeling equations indicated that habitat heterogeneity and topographic variation could correct the risk of exposure to insect pests in alpine regions. Considering the relationships between habitat heterogeneity, topographic variation, and the probability of insect pest distribution, habitat heterogeneity and topographic variation could be developed as indicators for the prevention and control of insect pests in alpine regions. Therefore, our study provides implications for pest management in alpine regions.

Qinghai province is a representative alpine region and is a part of the Qinghai–Tibetan plateau [31]. However, the invasion of insect pests is a major threat to the ecosystems and biodiversity of Qinghai. Tree species diversity mainly reduced the damage of specialist insect herbivores in mixed stands with phylogenetically distant tree species [46–48]. Increasing forest diversity is a promising management tool to reduce pest damage across different ecoregions [48–51]. Hence, it is recommended to increase tree species diversity to enhance insect pest resistance in forest ecoregions. Furthermore, determining the regions with a high risk of exposure to insect pests is urgent. Our study determined the alpine conifer and mixed forests of the Nujiang Langcang Gorge, the conifer forests of the Qilian Mountains, and the shrublands and meadows of Southeast Tibet as the key areas requiring monitoring for insect pests in Qinghai province. Ecosystems of the Qinghai–Tibetan Plateau have been damaged over the past decades [45,52]; therefore, habitats should be restored for plant species in these ecoregions of Qinghai province. The recovery of plant diversity could contribute to both the maintenance of ecosystem function and the prevention and control of insect pests in alpine regions [51]. Furthermore, topographic conditions should be considered for pest management in alpine regions. Based on the results of linear regression modeling, we developed equations to determine the risk of exposure to insect pests with and without habitat heterogeneity and topographic variation in alpine regions. These equations provide references for the assessment of the risk of insect pests along the gradient of habitat heterogeneity and topographic variation in alpine regions.

Pest management is urgent across different regions around the world. Our study provides new evidence highlighting the urgency of pest management in alpine regions. Stenberg developed a conceptual framework for integrated pest management (IPM) [53]. Our data suggest that actions should be implemented for at least two pest management elements of IPM. Pest prevention and control should be used to reduce the population density or impact of insect pests by predators, parasitoids, and pathogens.

Our study determined the areas where pest prevention and control efforts should be focused. We considered the risk of multiple insect pest species for environmental management, which benefit biodiversity conservation and ecosystem maintenance. Furthermore, 30% of lands should be monitored for insect pest risk due to the scoring of insect pest risk rank over 0.7 considering biodiversity conservation requirements. In these lands, forest resources and diversity should be conserved for promoting ecosystem functions and services [54,55]. Our results indicate that we should preferentially attend to the areas with high habitat heterogeneity and topographic roughness in alpine regions. Land-cover and land-use complexity have the potential for sustainable pest management with complete prevention of pest damage on natural resources [56,57]. However, natural ecosystems may not benefit from plant diversity and habitat heterogeneity in alpine regions because of the potential increase in the diversity of host species [19,20]. In addition, the existing available resources may support insect pests. For specific pest species, relevant indicators should be developed based on the response curves of insect pest distribution probability to habitat heterogeneity and topographic variation in alpine regions.

Although it is necessary to explore the effects of habitat heterogeneity and topographic variation on insect pest risks in alpine regions, our study has the following limitations: (1) A limitation of the consensus dataset on habitat heterogeneity and topographic variation is its low resolution. We could not assess the effects of small-patch landscapes on insect pest risks. (2) The sample size of the studied insect pest species is too small to make broad conclusions, and the distribution data of each species are uneven. (3) This study only considered the distribution probability of insect pest species, but the distributions of their host species were not considered for risk assessment. Although our study has a limited amount of ecological validation, such as field investigation and ecological monitoring, we urgently need innovative evaluation approaches and tools to predict insect pest species distributions and evaluate the pest risk. Finally, we hope that future studies can expand the application of SDM to provide feasible suggestions for the impact of scale effect on pest prevention and control.

5. Conclusions

This study provides some theoretical basis for the effects of habitat heterogeneity and topographic changes on pest distribution in alpine regions. The risk levels of insect pests are different in high mountain areas without habitat heterogeneity and topographic variation. It improves the effectiveness and accuracy of pest management, and we suggest that future studies should elucidate the musculature of habitat heterogeneity and topographic variation affecting pest distribution. Based on the effects of habitat heterogeneity and topographic variation on the insect pest species, we used the conceptual risk framework of Probert et al. [18] to delineate the areas of high-risk exposure to insect pests in alpine regions in Qinghai province, China. In future studies, habitat heterogeneity and topographic variation should be used to delineate areas with high-risk exposure to insect pests in alpine regions for biological control. Furthermore, we need to pay extra attention to the minor factors (any sensitive plant species or high-risk insect species). Our study provides new insights into pest management worldwide.

Author Contributions: C.-J.W., J.-Z.W. and L.W. conceived the ideas and designed the study; F.-X.Z. and J.-Z.W. managed the data; C.-J.W. and J.-Z.W. conducted the fieldwork; C.-J.W., F.-X.Z. and J.-Z.W. collaborated on the statistical analysis and interpretation of the data; C.-J.W. wrote the first version of the manuscript with substantial contributions from L.W. and L.-P.L. All authors contributed to subsequent drafts and gave final approval for publication. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by a project of the Qinghai Science and Technology Department (2020-ZJ-744).

Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgments: We are grateful to Pablo Marquet for the support of our study.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Ernakovich, J.G.; Hopping, K.A.; Berdanier, A.B.; Simpson, R.T.; Kachergis, E.J.; Steltzer, H.; Wallenstein, M.D. Predicted responses of arctic and alpine ecosystems to altered seasonality under climate change. *Glob. Chang. Biol.* **2014**, *20*, 3256–3269. [CrossRef]
2. Pellissier, L.; Rasmann, S. The functional decoupling of processes in alpine ecosystems under climate change. *Curr. Opin. Insect Sci.* **2018**, *29*, 126–132. [CrossRef]
3. Grimm, N.B.; Chapin, F.S., III; Bierwagen, B.; Gonzalez, P.; Groffman, P.M.; Luo, Y.; Melton, F.; Nadelhoffer, K.; Pairis, A.; Raymond, P.A.; et al. The impacts of climate change on ecosystem structure and function. *Front. Ecol. Environ.* **2013**, *11*, 474–482. [CrossRef]
4. Logan, J.A.; Régnière, J.; Powell, J.A. Assessing the impacts of global warming on forest pest dynamics. *Front. Ecol. Environ.* **2003**, *1*, 130–137. [CrossRef]
5. Netherer, S.; Schopf, A. Potential effects of climate change on insect herbivores in European forests—General aspects and the pine processionary moth as specific example. *For. Ecol. Manag.* **2010**, *259*, 831–838. [CrossRef]
6. Comiti, F.; Mao, L.; Penna, D.; Dell'Agnese, A.; Engel, M.; Rathburn, S.; Cavalli, M. Glacier melt runoff controls bedload transport in Alpine catchments. *Earth Planet. Sci. Lett.* **2019**, *520*, 77–86. [CrossRef]
7. Potter, T.S.; Bowman, W.D. Testing invasion filters for the alpine: The roles of temperature, nitrogen deposition and soil. *Biol. Invasions* **2020**, *22*, 1889–1901. [CrossRef]
8. Nicolosi, G.; Mammola, S.; Verbrugge, L.; Isaia, M. Aliens in caves: The global dimension of biological invasions in subterranean ecosystems. *Biol. Rev.* **2023**, *98*, 849–867. [CrossRef] [PubMed]
9. Cornelissen, B.; Neumann, P.; Schweiger, O. Global warming promotes biological invasion of a honey bee pest. *Glob. Chang. Biol.* **2019**, *25*, 3642–3655. [CrossRef]
10. Cramer, W.; Bondeau, A.; Woodward, F.I.; Prentice, I.C.; Betts, R.A.; Brovkin, V.; Cox, P.M.; Fisher, V.; Foley, J.A.; Friend, A.D.; et al. Global response of terrestrial ecosystem structure and function to CO_2 and climate change: Results from six dynamic global vegetation models. *Glob. Chang. Biol.* **2001**, *7*, 357–373. [CrossRef]
11. Pecl, G.T.; Araújo, M.B.; Bell, J.D.; Blanchard, J.; Bonebrake, T.C.; Chen, I.C.; Clark, T.D.; Colwell, R.K.; Danielsen, F.; Evengård, B.; et al. Biodiversity redistribution under climate change: Impacts on ecosystems and human well-being. *Science* **2017**, *355*, eaai9214. [CrossRef]
12. Soliman, T.; Mourits, M.C.M.; Lansink, A.O.; Van der Werf, W. Economic impact assessment in pest risk analysis. *Crop. Prot.* **2010**, *29*, 517–524. [CrossRef]
13. Oliveira, C.M.; Auad, A.M.; Mendes, S.M.; Frizzas, M.R. Economic impact of exotic insect pests in Brazilian agriculture. *J. Appl. Entomol.* **2013**, *137*, 1–15. [CrossRef]
14. Lu, Y.; Jenkins, A.; Ferrier, R.C.; Bailey, M.; Gordon, I.J.; Song, S.; Huang, J.; Jia, S.; Zhang, F.; Liu, X.; et al. Addressing China's grand challenge of achieving food security while ensuring environmental sustainability. *Sci. Adv.* **2015**, *1*, e1400039. [CrossRef] [PubMed]
15. Biber-Freudenberger, L.; Ziemacki, J.; Tonnang, H.E.; Borgemeister, C. Future risks of pest species under changing climatic conditions. *PLoS ONE* **2016**, *11*, e0153237. [CrossRef] [PubMed]
16. Jakoby, O.; Lischke, H.; Wermelinger, B. Climate change alters elevational phenology patterns of the European spruce bark beetle (*Ips typographus*). *Glob. Chang. Biol.* **2019**, *25*, 4048–4063. [CrossRef]
17. Hlásny, T.; Zimová, S.; Bentz, B. Scientific response to intensifying bark beetle outbreaks in Europe and North America. *For. Ecol. Manag.* **2021**, *499*, 119599. [CrossRef]
18. Wermelinger, B.; Rigling, A.; Schneider Mathis, D.; Kenis, M.; Gossner, M.M. Climate change effects on trophic interactions of bark beetles in inner alpine Scots pine forests. *Forests* **2021**, *12*, 136. [CrossRef]
19. Bellone, D.; Klapwijk, M.J.; Bjorkman, C. Habitat heterogeneity affects predation of European pine sawfly cocoons. *Ecol. Evol.* **2017**, *7*, 11011–11020. [CrossRef]
20. Barbaro, L.; Rusch, A.; Muiruri, E.W.; Gravellier, B.; Thiery, D.; Castagneyrol, B. Avian pest control in vineyards is driven by interactions between bird functional diversity and landscape heterogeneity. *J. Appl. Ecol.* **2017**, *54*, 500–508. [CrossRef]
21. Pimenta, M.; De Marco, P. Leaf Beetle (*Chrysomelidae*: Coleoptera) Assemblages in a Mosaic of Natural and Altered Areas in the Brazilian Cerrado. *Neotrop. Entomol.* **2015**, *44*, 242–255. [CrossRef]
22. Haan, N.L.; Zhang, Y.; Landis, D.A. Predicting landscape configuration effects on agricultural pest suppression. *Trends Ecol. Evol.* **2020**, *35*, 175–186. [CrossRef] [PubMed]
23. Beaumelle, L.; Auriol, A.; Grasset, M.; Pavy, A.; Thiéry, D.; Rusch, A. Benefits of increased cover crop diversity for predators and biological pest control depend on the landscape context. *Ecol. Solut. Evid.* **2021**, *2*, e12086. [CrossRef]
24. Forman, R.T.; Godron, M. Patches and structural components for a landscape ecology. *BioScience* **1981**, *31*, 733–740.
25. Turner, M.G. Landscape ecology: The effect of pattern on process. *Annu. Rev. Ecol. Syst.* **1989**, *20*, 171–197. [CrossRef]
26. Cardina, J.; Johnson, G.A.; Sparrow, D.H. The nature and consequence of weed spatial distribution. *Weed Sci.* **1997**, *45*, 364–373. [CrossRef]
27. Kharuk, V.I.; Ranson, K.J.; Fedotova, E.V. Spatial pattern of Siberian silkmoth outbreak and taiga mortality. *Scand. J. For. Res.* **2007**, *22*, 531–536. [CrossRef]
28. Probert, A.F.; Ward, D.F.; Beggs, J.R.; Lin, S.L.; Stanley, M.C. Conceptual risk framework: Integrating ecological risk of introduced species with recipient ecosystems. *Bioscience* **2020**, *70*, 71–79. [CrossRef]

29. Wan, J.Z.; Wang, C.J. Determining key monitoring areas for the 10 most important weed species under a changing climate. *Sci. Total Environ.* **2019**, *683*, 568–577. [CrossRef]
30. Wang, C.J.; Wang, R.; Yu, C.M.; Dang, X.P.; Sun, W.G.; Li, Q.F.; Wang, X.T.; Wan, J.Z. Risk assessment of insect pest expansion in alpine ecosystems under climate change. *Pest Manag. Sci.* **2021**, *77*, 3165–3178. [CrossRef]
31. Wang, P.; Deng, X.Z.; Jiang, S.J. Diffused impact of grassland degradation over space: A case study in Qinghai province. *Phys. Chem. Earth* **2017**, *101*, 166–171. [CrossRef]
32. Fløjgaard, C.; Normand, S.; Skov, F.; Svenning, J.C. Deconstructing the mammal species richness pattern in Europe–towards an understanding of the relative importance of climate, biogeographic history, habitat heterogeneity and humans. *Glob. Ecol. Biogeogr.* **2011**, *20*, 218–230. [CrossRef]
33. Xu, Y.; Shen, Z.; Ying, L.; Zang, R.; Jiang, Y. Effects of current climate, paleo-climate, and habitat heterogeneity in determining biogeographical patterns of evergreen broad-leaved woody plants in China. *J. Geogr. Sci.* **2019**, *29*, 1142–1158. [CrossRef]
34. Muscarella, R.; Kolyaie, S.; Morton, D.C.; Zimmerman, J.K.; Uriarte, M. Effects of topography on tropical forest structure depend on climate context. *J. Ecol.* **2020**, *108*, 145–159. [CrossRef]
35. Wang, C.J.; Wang, S.J.; Yu, C.M.; Wang, X.T.; Wang, R.; Wan, J.Z. Habitat heterogeneity and topographic variation as the drivers of insect pest distributions in alpine landscapes. *Acta Ecol. Sin.* **2023**, *43*, 596–603. [CrossRef]
36. Fick, S.E.; Hijmans, R.J. WorldClim 2: New 1-km spatial resolution climate surfaces for global land areas. *Int. J. Climatol.* **2017**, *37*, 4302–4315. [CrossRef]
37. Hijmans, R.J.; Cameron, S.E.; Parra, J.L.; Jones, P.G.; Jarvis, A. Very high-resolution interpolated climate surfaces for global land areas. *Int. J. Climatol.* **2005**, *25*, 1965–1978. [CrossRef]
38. Elith, J.; Phillips, S.J.; Hastie, T.; Dudı, K.M.; Chee, Y.E.; Yates, C.J. Astatistical explanation of MaxEnt for ecologists. *Divers. Distrib.* **2011**, *17*, 43–57. [CrossRef]
39. Li, R.Q.; Xu, M.; Wong, M.H.G.; Qiu, S.; Li, X.H.; Ehrenfeld, D.; Li, D.M. Climate change threatens giant panda protection in the 21st century. *Biol. Conserv.* **2015**, *182*, 93–101. [CrossRef]
40. Merow, C.; Smith, M.J.; Silander, J.A. A practical guide to MaxEnt for modeling species' distributions: What it does, and why inputs and settings matter. *Ecography* **2013**, *36*, 1058–1069. [CrossRef]
41. Phillips, S.J.; Anderson, R.P.; Dudík, M.; Schapire, R.E.; Blair, M.E. Opening the black box: An open-source release of Maxent. *Ecography* **2017**, *40*, 887–893. [CrossRef]
42. Wan, J.Z.; Wang, C.J.; Zimmermann, N.E.; Pouteau, R.; Yu, F.H. Current and future plant invasions in protected areas: Does clonality matter? *Divers. Distrib.* **2021**, *27*, 2465–2478. [CrossRef]
43. Moilanen, A.; Franco, A.M.A.; Early, R.I.; Fox, R.; Wintle, B.; Thomas, C.D. Prioritizing multiple-use landscapes for conservation: Methods for large multispecies planning problems. *Proc. R. Soc. B Biol. Sci.* **2005**, *272*, 1885–1891. [CrossRef] [PubMed]
44. Lehtomaki, J.; Moilanen, A. Methods and workflow for spatial conservation prioritization using Zonation. *Environ. Model. Softw.* **2013**, *47*, 128–137. [CrossRef]
45. Olson, D.M.; Dinerstein, E.; Wikramanayake, E.D.; Burgess, N.D.; Powell, G.V.; Underwood, E.C.; D'amico, J.A.; Itoua, I.; Strand, H.E.; Morrison, J.C.; et al. Terrestrial ecoregions of the world: A new map of life on Earth. A new global map of terrestrial ecoregions provides an innovative tool for conserving biodiversity. *Bioscience* **2001**, *51*, 933–938. [CrossRef]
46. Vehviläinen, H.; Koricheva, J.; Ruohomäki, K. Tree species diversity influences herbivore abundance and damage: Meta-analysis of long-term forest experiments. *Oecologia* **2007**, *152*, 287–298. [CrossRef]
47. Moreira, X.; Abdala-Roberts, L.; Rasmann, S.; Castagneyrol, B.; Mooney, K.A. Plant diversity effects on insect herbivores and their natural enemies: Current thinking, recent findings, and future directions. *Curr. Opin. Insect Sci.* **2016**, *14*, 1–7. [CrossRef]
48. Jactel, H.; Moreira, X.; Castagneyrol, B. Tree diversity and forest resistance to insect pests: Patterns, mechanisms, and prospects. *Annu. Rev. Entomol.* **2021**, *66*, 277–296. [CrossRef]
49. Guyot, V.; Castagneyrol, B.; Vialatte, A.; Deconchat, M.; Selvi, F.; Bussotti, F.; Jactel, H. Tree diversity limits the impact of an invasive forest pest. *PLoS ONE* **2015**, *10*, e0136469. [CrossRef]
50. Guyot, V.; Castagneyrol, B.; Vialatte, A.; Deconchat, M.; Jactel, H. Tree diversity reduces pest damage in mature forests across Europe. *Biol. Lett.* **2016**, *12*, 20151037. [CrossRef]
51. Guo, Q.; Fei, S.; Potter, K.M.; Liebhold, A.M.; Wen, J. Tree diversity regulates forest pest invasion. *Proc. Natl. Acad. Sci. USA* **2019**, *116*, 7382–7386. [CrossRef]
52. Cui, G.W.; Ji, G.X.; Liu, S.Y.; Li, B.; Lian, L.; He, W.H.; Zhang, P. Physiological adaptations of Elymus dahuricus to high altitude on the Qinghai-Tibetan Plateau. *Acta Physiol. Plant* **2019**, *41*, 115. [CrossRef]
53. Stenberg, J.A. A conceptual framework for integrated pest management. *Trends Plant Sci.* **2017**, *22*, 759–769. [CrossRef] [PubMed]
54. Edwards, D.P.; Tobias, J.A.; Sheil, D.; Meijaard, E.; Laurance, W.F. Maintaining ecosystem function and services in logged tropical forests. *Trends Ecol. Evol.* **2014**, *29*, 511–520. [CrossRef] [PubMed]
55. Keesstra, S.; Nunes, J.; Novara, A.; Finger, D.; Avelar, D.; Kalantari, Z.; Cerdà, A. The superior effect of nature based solutions in land management for enhancing ecosystem services. *Sci. Total Environ.* **2018**, *610*, 997–1009. [CrossRef] [PubMed]

56. Grecchi, R.C.; Gwyn, Q.H.J.; Bénié, G.B.; Formaggio, A.R.; Fahl, F.C. Land use and land cover changes in the Brazilian Cerrado: A multidisciplinary approach to assess the impacts of agricultural expansion. *Appl. Geogr.* **2014**, *55*, 300–312. [CrossRef]
57. Lai, L.; Huang, X.; Yang, H.; Chuai, X.; Zhang, M.; Zhong, T.; Chen, Z.; Chen, Y.; Wang, X.; Thompson, J.R. Carbon emissions from land-use change and management in China between 1990 and 2010. *Sci. Adv.* **2016**, *2*, e1601063. [CrossRef]