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Climate change risks for net primary production of ecosystems in China

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ABSTRACT

Few studies have investigated ecosystem risk under climate change from the perspective of critical thresholds. We presented a framework to assess the climate change risk on ecosystems based on the definition of critical thresholds. Combined with climate scenario, vegetation and soil data, the Atmosphere Vegetation Interaction Model version 2 was used to simulate net primary productivity in the period of 1961--2080. The thresholds of dangerous and unacceptable impacts were then defined; climate change risks on ecosystems in China were assessed. Results showed that risk areas will be closely associated with future climate change, and will mainly occur in the southwest and northwest areas, Inner Mongolia, the southern part of the northeast areas, and South China. The risk regions will expand to 343.66 Mha in the long-term (2051--2080), accounting for 35.80% of China. The risk levels on all ecosystems (eco-regions) are likely to increase continually. The ecosystems of wooded savanna, temperate grassland, and desert grassland, which are typically exhibited strong water stress, will have the maximum risk indices in the future. Northwest Region

is likely to be the most vulnerable because of precipitation restrictions and obvious warming. By contrast, Qinghai--Tibet Region will not be so vulnerable to future climate change.

Key Words

risk, dangerous impact, unacceptable impact, net primary production, climate change.

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INTRODUCTION

The planet's biota and ecosystem processes are strongly affected by past climate changes whose rates were lower than those projected during the 21st century under high warming scenarios (high confidence) (IPCC 2014). Most ecosystems are vulnerable to climate change even at rates of climate change projected under low-to medium-range warming scenarios; moreover, climate change is projected to be a powerful stressor on terrestrial ecosystems in the second half of this century (IPCC 2014). Understanding the ecosystem risks from climate change will assist in implementing mitigation and adaptation measures to reduce the adverse impacts of climate change.

Many recent researchers assessed the ecosystem risks and reported significant progress (Keith *et al.* 2013; Bayliss *et al.* 2012; Munns *et al.* 2015; Matthews *et al.* 2014). Ecological risk assessment (ERA) was the common representative model that is intended to estimate the potential negative effects of human activities and multiple human-induced stressors on ecosystems (Bayliss *et al.* 2012; Munns *et al.* 2015). However, this model mainly assessed the negative effects caused by toxic chemicals and climate change was seldom considered. A few studies have used the risk assessment criteria for ecosystems developed by the International Union for the Conservation of Nature (IUCN) (Keith *et al.* 2013; Wardle *et al.* 2015; Auld and Leishman 2015). For example, Auld and Leishman (2015) assessed the ecosystem risk for Gnarled Mossy Cloud Forest in Lord Howe Island of Australia. A conceptual model of ecosystem dynamics leading to collapse was developed with this method, and facilitated the integrated assessment of multiple processes (Keith 2015). Nevertheless, ecological communities and species represented the most suitable scale, and the risk sources in the IUCN protocol were not restricted to climate change only.

As carbon sequestration of ecosystem has close relationship with climate change, ecosystem has been one of main fields of the United Nations Framework Convention on Climate Change (Sands 1992). Climate change risk on ecosystems has thus attracted much attentions (Graux *et al.* 2013; Chen and Hsu 2014; Hurduzeu *et al.* 2014; Schröter *et al.* 2005; Scholze *et al.* 2006; Matthews *et al.* 2014). A few scholars quantitatively evaluated the climate change risks on ecosystem services (Schröter *et al.* 2005; Scholze *et al.* 2006; Matthews *et al.* 2014). Schröter *et al.* (2005) used a range of ecosystem models and considered climate and land-use change scenarios to conduct a Europe-wide risk assessment of ecosystem services during the 21st century, they found that the supply of many ecosystem services is likely to decrease, such as soil fertility and water availability, whereas the risk of forest fires will increase. By forcing Lund--Potsdam--Jena model with multiple scenarios from 16 climate models, Scholze *et al.* (2006) quantified the climate-induced risks in key global ecosystem processes (freshwater runoff, wildfire frequency and the biome change from forest to non-forest) during the 21st century. Moreover, many researchers selected net primary productivity (NPP) as the representative indicator of ecosystem services to investigate the climate change impact (Gao *et al.* 2013; Piao *et al.* 2013; Reyer *et al.* 2014). For example, Gao *et al.* (2013) applied a light use efficiency model to analyze the NPP response to temperature and precipitation changes in the Tibetan Plateau. Piao *et al.* (2013) employed a set of 10 process-based models to evaluate the sensitivity of NPP to climate variability. These studies evaluated either ecosystem vulnerability or sensitivity to climate change, i.e., the positive or negative effects of climate change on the NPP of ecosystems. Given the lack of critical thresholds identified in these studies, the climate change risks on ecosystems were assessed by the variance percentage of certain indicators to their original status. In fact, these percentages can capture only the impact intensity from climate change, that is, whether the impacts reach a dangerous level or not are lacking in these studies. Therefore, risk assessment should be aided by identifying the critical impact thresholds for ecosystems.

Many scholars have recently realized the importance of thresholds to the assessment of risk from climate change. The definition of these thresholds motivated the quantitative assessment of climate change risks and provided conceptual references for the criteria employed. van Minnen *et al.* (2002) developed the critical climate change method to assess the climate change risks on ecosystems in Europe. They assumed that the unacceptable impact is a 10% loss of NPP due to climate change. This rate was determined through the frequent reduction from the long term average of NPP. The threshold definition in this method can help evaluate risk quantitatively; nonetheless, the differences in NPP reduction across various ecosystems must be distinguished further. To assess the impacts of droughts on the grassland ecosystems, Lei *et al.* (2015) assumed that the unacceptable impact is determined by the difference between the mean NPP of the reference years and the NPP of the drought years. The assigned threshold was particularly suitable for the integrative assessment of the effects of drought events; however, the application to multiple climatic factor risks on ecosystems may be limited.

At present, few studies have investigated the NPP risk caused by climate change from the perspective of thresholds. Knowing where and when risks will occur is necessary to implement suitable mitigation and adaptation measures into local conditions. Thus, an integrated framework should be established to quantitatively analyze the risks from climate change. The aims of the present work are as follows: (1) to develop a framework to explore the climate change risk on ecosystems from the perspective of thresholds, and (2) to analyze the future risk of NPP on ecosystems in China.

RISK ASSESSMENT FRAMEWORK

Selecting an Indicator to Represent the Ecosystems

The first step in the framework was selecting an appropriate indicator to represent the characteristics of ecosystems. NPP is a main measure for understanding the role of terrestrial ecosystem in the global carbon cycle; changes in this factor can reflect the integrated effects of climate change on potential plant productivity and carbon cycle feedbacks. Moreover, the NPP can be modeled explicitly and spatially by the process model. Thus, it was selected as the representative indicator to evaluate the risk from climate change.

Simulating the NPP of Ecosystems

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Climatic data

Climate scenario data for this research were provided by climate change group in Chinese Academy of Agricultural Sciences. The group used the Providing Regional Climates for Impacts Studies (PRECIS) from UK's Hadley Center to project climate changes in China during the 21st century (Xu *et al.* 2006). The outputs of the third version of the Hadley Centre Coupled Model (HadCM3) and the sea coupled climate model from UK's Hadley Center were employed to drive PRECIS, generating the daily climate change scenarios of China for the future years, with a horizontal resolution of 50 km.

The Intergovernmental Panel on Climate Change (IPCC) Special Report on Emission Scenarios (SRES) have described four different narrative storylines (A1, A2, B1, and B2) (IPCC 2001). The B2 storyline and scenario family describes a world in which local solutions to economic, social, and environmental sustainability are emphasized. In this world, the global population continuously increases at a rate lower than in the A2 storyline, with intermediate levels of economic development as well as less rapid and more diverse technological change than in the B1 and A1 storylines (IPCC 2001). After downscaling the socioeconomic projections from SRES with the approach by Gaffin *et al.* (2004), the B2 family describes a prosperous and fair world that reports low emissions of greenhouse gases as a result of a general orientation toward sustainable development. This storyline fitted with the plan of social and economic development over the medium-to-long term in China and was selected as the climate change scenario for this study.

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Data on vegetation and soil

To simplify the modeling process, a plant functional type (PFT) has been widely proposed as an ecological alternative to traditional ecosystem types. The map of PFTs released by the International Geosphere-Biosphere Programme was used to divide the vegetation into 14 PFTs: evergreen coniferous forest, evergreen broadleaf forest, deciduous coniferous forest, deciduous broadleaf forest, temperate mixed forest, closed scrubland, open scrubland, wooded savanna, temperate grassland, alpine meadow, wetland, cultivated land, desert grassland and desert (Figure 1). The ecosystem types considered in this study accorded with the corresponding PFTs. The vegetation types were resampled with a horizontal resolution of 50 km (Zhang *et al.* 2004). The soil texture data originated from a digital map of 1:14,000,000 soil texture types (ISS CAS 1986). The data indicated the information of the proportions of mineral grains of different sizes in the top soil and the geographical distribution of different soil texture types in a given region. The soil texture dataset was transformed into grid format and resampled with a horizontal resolution of 50 km.

Model

The Atmosphere Vegetation Interaction Model version 2 (AVIM2) was used to simulate the NPP of ecosystems in the period of 1961--2080 (Ji 1995; Lu and Ji 2006; Huang *et al.* 2007). The physical process module, physiological plant growth module, soil carbon and nitrogen dynamics module were the main components of this model, which simulated biogeochemical processes such as the transformation and decomposition of soil organic carbon and nitrogen mineralization. The soil carbon and nitrogen dynamics module was developed based on the same type of modules from CENTURY (Parton *et al.* 1987) and Carbon Exchanges in the Vegetation--Soil--Atmosphere system (CEVSA) model (Cao and Woodward 1998) with some modifications, and can be coupled directly and timely with physical process module and physiological plant growth module. A detailed description of this model is provided in previous works (Ji 1995; Dan *et al.* 2005; Lu and Ji 2006; Ji *et al.* 2008).

AVIM2 has been employed to simulate the carbon fluxes in the ecosystem on global and regional scales, and has previously been validated and tested on China ecosystems several times (Huang *et al.* 2006; Dan *et al.* 2007). Huang *et al.* (2007) compared the measured and simulated daily carbon exchange in 10-d period to examine model output, the simulated gross primary productivity were closed to the measurements ($y = 0.228+0.995x$, $r^2 = 0.82$). A closely correlation was also detected between the simulated and measured ecosystem respiration ($y = 0.054+0.985x$, $r^2 = 0.84$). AVIM2 was included in the Project for Intercomparison of Land surface Parameterization Schemes and was utilized to compare the modeled carbon fluxes with the filed measurements on the Loobos site in Holland (http://www.pilpsc1.cnrs-gif.fr/).

Definition of periods

The periods in this study were segmented according to the IPCC definition: the baseline, near-term, mid-term, and long-term periods were 1961--1990, 1991--2020, 2021--2050, and

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2051--2080, respectively (Carter *et al.* 1999; IPCC 2007). Each term was discussed according to an average of 30 years.

Defining Dangerous and Unacceptable Impacts

Two levels of impact thresholds from climate change were defined in this framework. Each ecosystem type has a natural NPP variability that is generally centered on the long term average NPP over time. When NPP varied within the range of natural variability, we assumed that the NPP changes temporarily and can eventually revert to the average state. Thus, a dangerous impact should incur a particular percentage of NPP loss as a result of climate change; this percentage loss should be somewhat beyond the typical natural variability of NPP (van Minnen *et al.* 2002), that is, the abnormal variability from the average state during normal years. In the presented work, the period of 1961--1990 was regarded as the normal years. As the definition provided by the World Meteorological Organization, abnormal variability is the excess of mean values plus or subtract twice of standard deviation (Jones *et al.* 1999; Hulme *et al.* 2009). If reduction of NPP exceeded the natural variability of a grid in comparison with average NPP in normal years, then the impact was considered to be dangerous.

Given that individual ecosystems often have different specific thresholds in temperature, precipitation or other variables, beyond which they are at risk of distribution or extinction (IPCC 2007), this process is irreversible and unacceptable. For a given ecosystem, the minimum value of

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NPP in normal years was defined as the unacceptable NPP impact. If the NPP continuously dropped below the unacceptable impact level, then the ecosystem was assumed to be irreversible.

Classifying the Risk Levels

Risks were classified into no, low and high levels according to the definitions of dangerous and unacceptable impact thresholds. When the NPP value in a certain grid dropped below the dangerous impact threshold, it was classified as low risk. When this value continued to decline below the threshold of unacceptable impact, it was classified as high risk. In a no risk level, NPP may increase continuously, or the NPP loss may not exceed the dangerous impact; otherwise, areas with no NPP data were detected, such as ice and snow regions (Figure 2).

Assessing Integrated Risk

To assess the influence of various risk levels on an entire region or ecosystem, the integrated risk of a given region or ecosystem was calculated with the risk index (Duggan *et al.* 2015). Given the simplistic scoring of risk, the risk index in a region or ecosystem facilitated the comparison of the relative levels of risk among regions and ecosystems rather than enabling the precise estimate of risk at these scales. The scores of no, low, and high risk levels were set to be 0, 1, and 2, respectively. The risk index can be calculated as follows.

$$R_i = (R_{i0}S_{i0} + R_{i1}S_{i1} + R_{i2}S_{i2})/S_i \quad (1)$$

Where R_i was the risk index of region (or ecosystem) i. R_{i0}, R_{i1}, and R_{i2} were the scores of the no, low, and high levels of region (or ecosystem) i respectively. S_{i0}, S_{i1}, and S_{i2} were the areas in which the no, low and high levels of region (or ecosystem) i were detected, respectively; and S_i was the total area of region (or ecosystem) i.

RESULTS

Spatial Pattern

Under the IPCC SRES B2 climate scenario, the mean temperature of China will increase by 0.84°C, 1.77°C and 2.74°C in the near-term (1991--2020), mid-term (2021--2050) and long-term (2051--2080), respectively. Meanwhile, the total risk areas, which are composed of high risk and low risk areas, are likely to expand from 219.68 × 10^6 ha (219.68 Mha) in the near-term to 285.15 Mha in the mid-term. The areas will reach to 343.66 Mha in the long-term, accounting for 35.80% of China's area. Over the three terms, regions with risk are likely to concentrate in the southwest and northwest areas, Inner Mongolia, the southern part of the northeast areas and South China (Figure 3).

Low-risk locations are likely to continue expanding; this level of risk will always dominate the most areas of the risk region. Its area will increase from 141.25 Mha in the near-term to 178.91 Mha in the mid-term and then expand to 204.33 Mha in the long-term. Meanwhile, the high risk region will expand immensely from 1991 to 2080; its area will increase from 78.42 Mha to 139.34 Mha at a rate of 77.68% (Figure 3).

Temporal Change

Risk change grades were defined to analyze the temporal change in risk levels across different periods. I_1 and I_2 imply that the risk level will increase by one and two grades, respectively; D_1 and D_2 indicate that the risk level will decrease by one and two grades, respectively; and C suggests that the risk level will be unchanged. From near-term to mid-term, the risk levels of most regions, with an area of 835.05 Mha (accounting for 86.98% of China's area), will be unchanged. The risk levels of regions with a total area of 108.40 Mha will increase, and most of these areas will belong to the I_1 category (with an area of 102.16 Mha). They will be distributed mainly in the northwest areas, the northeastern part of Inner Mongolia and the southern part of the northeast areas. Meanwhile, the risk levels of regions with a total area of 16.55 Mha will decrease, and most of them will belong to the D_1 category (with an area of 11.75 Mha) (Figure 4a).

From mid-term to long-term, risk levels will also rise as in the case of the former period (from near-term to mid-term). However, the varied area (89.69 Mha) is likely to be smaller than that in the former period, accounting for only 9.34% of China's area. The I_1 category will also dominate the risk level changes (81.54 Mha). Meanwhile, the risk levels of 4.56 Mha ecosystems will decrease (Figure 4b).

Risk Distribution for Different Ecosystems

Temperate grassland will constitute the largest risk area in near-term (42.69 Mha) and mid-term (49.89 Mha), although the total area is not the largest (Table 1). Temperate grassland is mainly distributed in the northwest areas of China, where the environment is arid. In addition, intense

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warming is likely to occur in these areas in the future. In the long-term, desert grassland will have the largest risk area (59.24 Mha), which will be slightly higher than that of temperate grassland (58.03 Mha) and of cultivated land (58.03 Mha). In all the ecosystems, the percentages of land area affected by risk will also increase continually from near-term to long-term. Furthermore, some affected proportions of the ecosystems will exceed 50%, including the wooded savanna in the mid-term (51.11%) and long-term (56.66%), temperate grassland (54.76%), desert grassland (56.01%) and wetland (57.5%) in the long-term. The risk indices of all ecosystems will increase continually from near-term to long-term. The wooded savanna (0.87), temperate grassland (0.65), and desert grassland (0.65) will report high average risk indices over the three terms. Fortunately, the risk of cultivated land (0.34) will not be so serious, whereas the alpine meadow (0.16) will generate the minimum risk index among these ecosystems (Table 1).

Risk Distribution for Different Eco-regions

On the basis of *The Chinese Physical Regionalization* presented by Zheng (2008), China was divided into eight eco-regions, namely, Northeast Region, Inner Mongolian Region, North China, Central China, South China, Southwest Region, Northwest Region and Qinghai--Tibet Region (Figure 5a). According to the risk assessment results of these eco-regions, Northwest Region will have the highest risk index over the three terms, followed by Inner Mongolian Region. By contrast, Qinghai--Tibet Region will obtain the lowest risk index in the future. In terms of temporal change, the risks on all eight eco-regions are all likely to increase in severity with warming (Figure 5a).

DISCUSSION

Under the IPCC SRES B2 scenario, climate change is likely to introduce risk to the NPP of ecosystems in China. The risk distribution will be related to the future climate change. In the arid and semi-arid areas of Northwest and Inner Mongolian Region, low precipitation restricts vegetation growth. In addition, obvious warming will stress the risk (Figures 5b and 5c). Ravi *et al.* (2010) found that the changing climate and land use have resulted in increased aridity and drought frequency in dry lands worldwide, with increasing dominance of abiotic controls of land degradation and changes in hydrology and the erosion of soil by wind. However, in the temperature-constrained regions, such as Qinghai--Tibet Region and the northern part of Northeast Region, warming will relieve the low temperature limitation on the vegetation. This influence is likely to be more remarkable in Qinghai--Tibet Region (Figure 5b). South China and Southwest Region have higher temperatures than other regions do; further warming will induce an increase in respiration (Ji *et al.* 2008). In addition, the increasing precipitation will be accompanied by enhanced clouds cover as well as decreasing sunlight and radiation, the NPP increase will be limited (Ji *et al.* 2008) (Figures 5b and 5c). The findings of other similar studies were compared with our results. Scholze *et al.* (2006) reported that high risks of forest loss will exist in the northwest and northeast areas of China, forests in the southwest areas and South China will also be at risk. Yu (2006) found that highly vulnerable ecosystems will be mainly distributed in the southern part of the northeast areas, Inner Mongolia and the northwest areas of China.

The common feature of wooded savanna, temperate grassland and desert grassland is that they are typically exhibited strong water stress for several months each year. The geographical distribution of these ecosystems is determined by temperature, the seasonal availability of water, and fire and soil conditions; therefore, this distribution is inferred to be susceptible to climate change (Walker and Langridge 1997; Staver *et al.* 2011). Cultivated lands are often located in areas where the niche characteristics are suitable to crop growing, such as soil, temperature, precipitation, and solar radiation. Thus, the capability to resist climate change risk may be stronger than that in other ecosystems. Thomson *et al.* (2006) projected the yield changes in the Huang--Huai--Hai Plain, China's most productive wheat growing region; the modeling process conducted under the A2 and B2 scenarios with the HadCM3 model indicated that winter wheat yields will increase by 0.2 and 0.8 Mg ha^{-1} on average in 2015--2045 and in 2070--2099, respectively, due to warm nighttime temperatures and increased precipitation. Some researchers recognized that deserts are expected to become warmer and drier at faster rates than other terrestrial regions are (Lapola *et al.* 2009; Stahlschmidt *et al.* 2011). Most deserts are already extremely hot; therefore, further warming is likely to be physiologically injurious rather than beneficial (IPCC 2014). However, in the presented study, the risk on deserts will not be so serious, possibly because 58% of deserts are located in Qinghai--Tibet Region, which has the lowest average temperature among the eight eco-regions. Thus, further warming will be beneficial to these deserts.

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For some ecosystems, the warmer and drier climate change may increase their risk levels. The cultivated land will have the largest area of increased risk levels; its precipitation is projected to decrease by 18.85 mm from the near-term to the mid-term. Furthermore, the temperature of cultivated land is projected to increase by 0.98°C simultaneously. The climate is projected to be warm and dry, thus intensifying the risk on cultivated land. This phenomenon is also observed in the deciduous broadleaf forest, wetland, temperate mixed forest, and closed scrubland. Nonetheless, the risks will still heighten with increases in both temperature and precipitation in other ecosystems; this outcome may be explained by other influence factors (humidity index) that should be explored in future researches.

The definition of critical impact thresholds is the key step in the risk assessment framework. The approach to determining such thresholds is flexible and can be adapted to other impact indicators or risk categories. Due to the limitation in data and methodology, some uncertainties were detected in the study. First, CO_2 effects were not included in the model simulation of NPP. In the study conducted by Piao *et al.* (2013), NPP will increase with CO_2 concentration on average by 16% (5--20%) per 100 ppm, while this value was 13% per 100 ppm in the Free-Air CO_2 Enrichment experiment locations (Norby *et al.* 2005). Second, the mortality of a forest ecosystem may influence productivity considerably, the mortality of trees in the long-term was 2.5% yr^{-1} based on fall exclusion experiments plot over the experimental period, mortality was also a major flux determining above-ground biomass (da Costa *et al.* 2010). Moreover, the unchanged ecosystem

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pattern, which was limited by the AVIM2 hypothesis, will influence the risk assessment results. Land use change is also a potential driver of risk assessment; Scholze *et al.* (2006) evaluated the risk in a shift between forest and non-forest states from climate change. In the presented work, human disturbance was not considered carefully as well, especially for cultivated lands, this lack will probably influence the adaptation capability to climate change. For example, the increasing water-use efficiency of plants may counteract drought. Even with the lack of disturbance, the adaption of vegetation to climate change may offset the effects of warming on NPP in many regions. Therefore, the risk assessment presented in this study represented only a preliminary result to explore the critical thresholds on a quantitative scale. Further comprehensive analysis should be conducted and endeavored to investigate the natural variability of ecosystem NPP in China to generate an accurate risk criterion. Moreover, the Representative Concentration Pathways (RCPs) have been defined as the new set of scenarios for the Fifth Assessment Report of IPCC (IPCC 2013). After considering the scenarios difference, the projected climate change based on RCPs is similar to SRES emission scenarios in terms of both patterns and magnitude. However, the RCPs can provide spatially explicit data on land use change and sector-based emissions of air pollutants (IPCC 2013). Therefore, future researches should focus on the risk assessment under the new scenarios. To understand the risks under various future climate scenarios and simulation model can help reduce the uncertainty of risk assessment.

CONCLUSION

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In this study, two types of critical threshold were distinguished in the proposed framework: one was the dangerous impact threshold, which indicated the adverse variance beyond of the typical natural variability of NPP from climate change, and the other was the unacceptable impact threshold, which was considered the irreversible tipping point. The critical status of ecosystem change due to climate change could be identified by defining critical thresholds; in addition, the geographical or ecological meanings could be reflected comprehensively and risk distribution could be described objectively. The risk of climate change on the NPP for ecosystems in China was assessed on per-pixel scale; the results can not only indicate the influence intensity on ecosystems from climate change but also show whether the affected ecosystems can be recovered or are irreversible.

Under the IPCC SRES B2 scenario, the scope of risk regions is likely to expand with climate change; such areas are likely to concentrate in the southwest and northwest areas, Inner Mongolia, the southern part of the northeast areas, and South China over the three terms. Risk distribution will also be related to future climate change. In Northwest and Inner Mongolian Region, low precipitation and obvious warming will stress the risk. In South China and Southwest Region, the increasing respiration from warming as well as the decreasing sunlight and radiation from the enhancing precipitation will induce risk. The risk areas are likely to expand from 219.68 Mha in the near-term (1991--2020) to 343.66 Mha in the long-term (2051--2080) (accounting for 35.80% of China's area). Both low and high risks are likely to expand, and low-risk locations will always dominate large areas of the risk region. With respect to the temporal change, risk levels are likely to intensify gradually from the former period (from near-term to mid-term) to the latter (from mid-term to long-term). Furthermore, varied scopes in the former period will be larger than those in the latter period.

The risk levels of all ecosystems (eco-regions) will increase continually from near-term to long-term. The wooded savanna, temperate grassland, and desert grassland ecosystems will report the highest risk indices in the future. Northwest Region will gain the maximum risk index over the three terms, followed by Inner Mongolian Region. By contrast, Qinghai--Tibet Region will not be so vulnerable to future climate change.

Certain countermeasures may be taken to mitigate the ecosystem risk from climate change. For example, the new heat-resistant varieties should be cultivated for adaptation to climate warming. Meanwhile, management measures should be implemented as well, such as irrigation or change the sowing date. In addition, an early warning system, which involves the long term monitoring of ecophysiological studies and the predictive modeling of ecosystems, should be established.

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Table 1. Risk area, the affected proportion and risk index for each ecosystem over the three terms.

Ecosystem type	Risk area/Mha (the affected proportion/%)						Total area/ Mha	Risk index			Mean value of risk index
	Near-term		Mid-term		Long-term						
	high	low	high	low	high	low		Near-term	Mid-term	Long-term	
Wooded savanna	5.28 (24.44)	4.80 (22.22)	8.15 (37.78)	2.88 (13.33)	9.35 (43.33)	2.88 (13.33)	21.58	0.71	0.89	1	0.87
Temperate grassland	16.07 (15.16)	26.62 (25.11)	17.75 (16.74)	32.14 (30.32)	23.26 (21.95)	34.77 (32.81)	106	0.55	0.64	0.77	0.65

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Desert grassland	14.15 (13.38)	19.91 (18.82)	21.58 (20.41)	25.42 (24.04)	31.18 (29.48)	28.06 (26.53)	105.76	0.46	0.65	0.85	0.65
Evergreen broadleaf forest	3.36 (14.00)	4.08 (17.00)	4.50 (19.00)	4.08 (17.00)	4.56 (19.00)	5.52 (23.00)	23.98	0.45	0.55	0.61	0.54
Ecosystem type	Risk area/Mha (the affected proportion/%)						Total area /Mha	Risk index			Mean value of risk index
	Near-term		Mid-term		Long-term			Near-term	Mid-term	Long-term	
	high	low	high	low	high	low					
Deciduous	1.20	4.32	1.92	4.56	3.36	4.08	17.51	0.38	0.48	0.62	0.4

broadleaf forest	(6.85)	(24.66)	(10.96)	(26.03)	(19.18)	(23.29)					9
Temperate mixed forest	3.36 (13.08)	3.12 (12.15)	3.84 (14.95)	4.80 (18.69)	4.08 (15.89)	7.19 (28.04)	25.66	0.38	0.49	0.6	0.49
Wetland	0.24 (2.50)	1.68 (17.50)	0.48 (5.00)	3.60 (37.50)	0.48 (5.00)	5.04 (52.50)	9.59	0.23	0.48	0.63	0.44
Closed scrubland	6.48 (6.46)	13.67 (13.64)	9.11 (9.09)	18.95 (18.90)	12.23 (12.20)	23.50 (23.44)	100.24	0.27	0.37	0.48	0.37
Ecosystem type	Risk area/Mha (the affected proportion/%)						Total area /Mha	Risk index			Mean value of ris
	Near-term		Mid-term		Long-term			Near-term	Mid-term	Long-term	
	high	low	high	low	high	low					

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											k index
Deciduous coniferous forest	1.44 (5.83)	3.36 (13.59)	1.44 (5.83)	6.24 (25.24)	2.16 (8.74)	6.71 (27.18)	24.7	0.25	0.37	0.45	0.36
Evergreen coniferous forest	4.32 (7.69)	6.95 (12.39)	5.76 (10.26)	7.67 (13.68)	7.19 (12.82)	8.87 (15.81)	56.12	0.28	0.34	0.41	0.35
Cultivated land	11.27 (6.09)	23.26 (12.56)	17.75 (9.59)	29.74 (16.06)	22.06 (11.92)	35.97 (19.43)	185.14	0.25	0.35	0.43	0.34
Desert	4.32 (5.98)	6.48 (8.97)	5.28 (7.31)	14.87 (20.60)	7.19 (9.97)	18.23 (25.25)	72.19	0.21	0.35	0.45	0.34
Ecosystem	Risk area/Mha (the affected						Total	Risk index			Me

type	proportion/%)						area/Mha				annual value of risk index
	Near-term		Mid-term		Long-term						
	high	low	high	low	high	low		Near-term	Mid-term	Long-term	
Open scrubland	4.08	10.79	5.28	11.51	7.91	11.03	86.1	0.22	0.26	0.31	0.26
	(4.74)	(12.53)	(6.13)	(13.37)	(9.19)	(12.81)					
Alpine meadow	2.88	12.23	3.36	12.47	4.32	12.47	125.43	0.14	0.15	0.17	0.16
	(2.29)	(9.75)	(2.68)	(9.94)	(3.44)	(9.94)					

Note: The percentages of land areas affected by the high risk and low risk are included in parentheses.

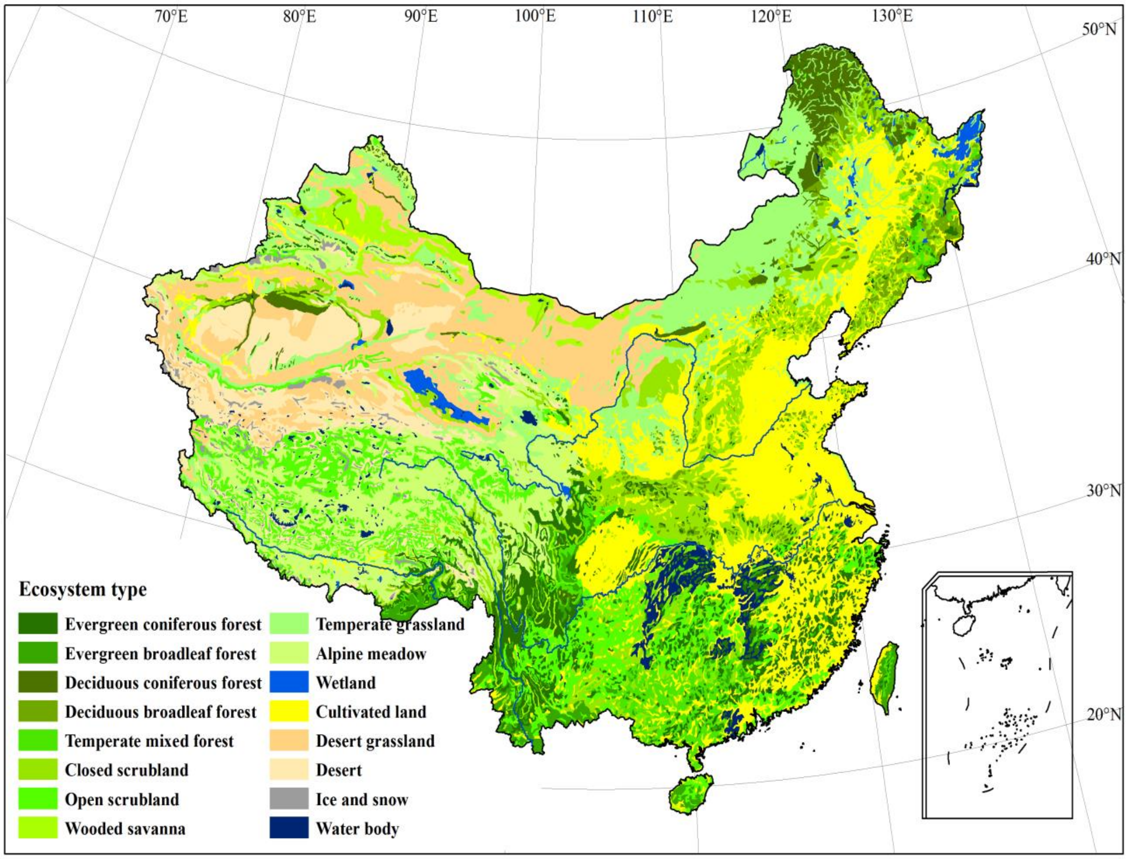

Figure 1. Distribution of ecosystem types in China.

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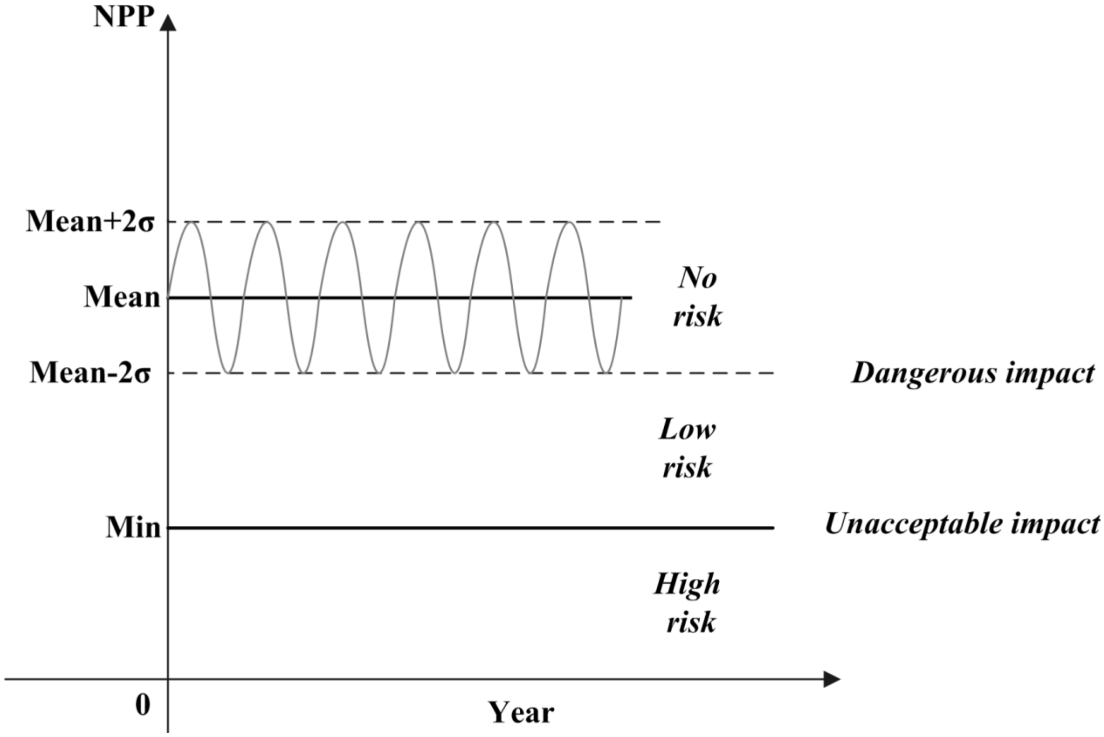

Figure 2. Schematic of risk level classification. *Note: Min is the minimum NPP value of a certain ecosystem in normal years, Mean is the average NPP value of a certain grid in normal years; and σ is the standard deviation of NPP in normal years for each grid.*

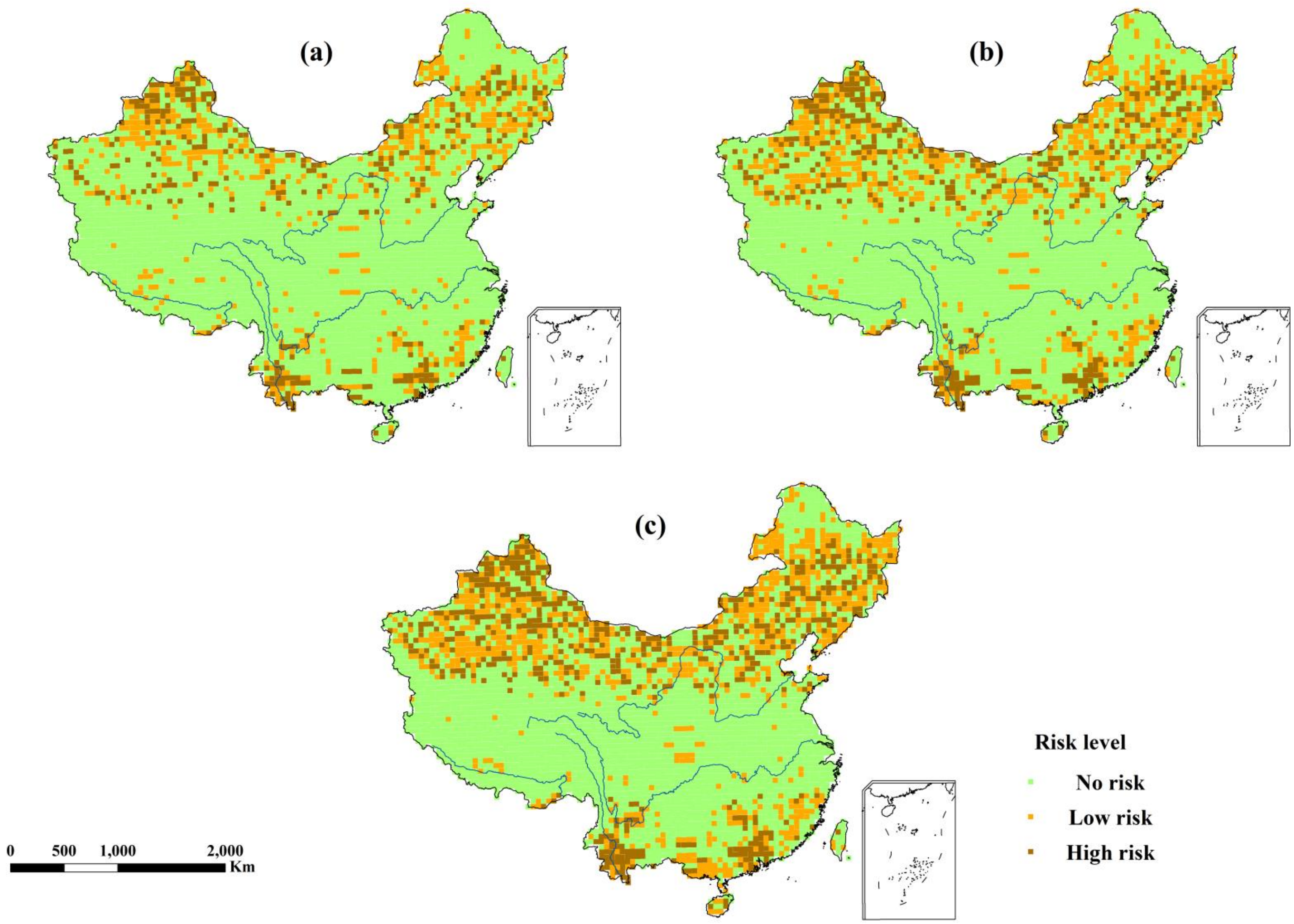

Figure 3. Risk distribution of ecosystems in China during the (a) near, (b) middle and (c) long terms.

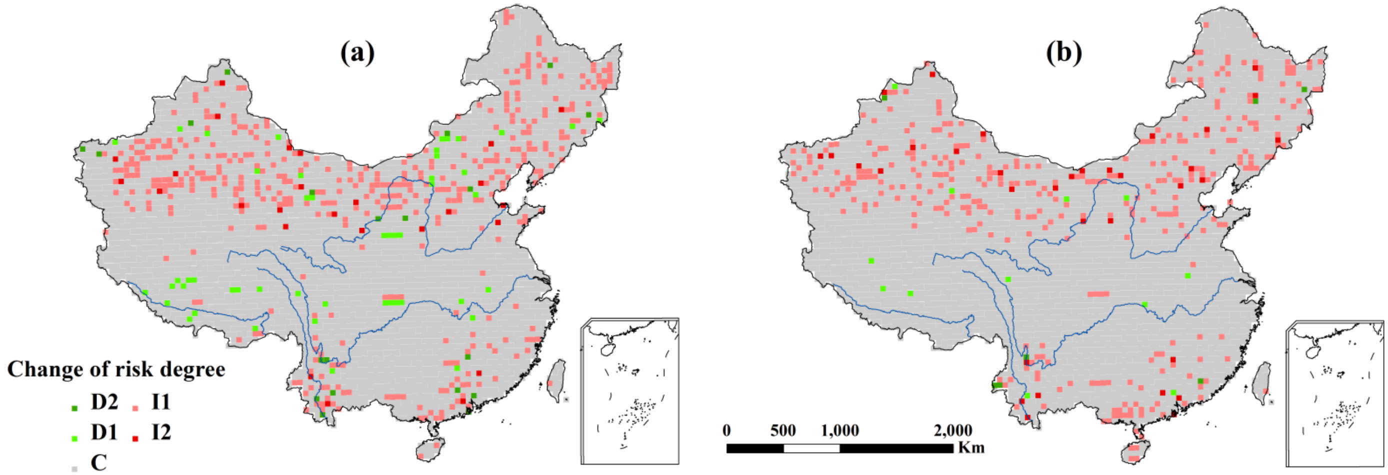

Figure 4. Change in risk levels on the ecosystems of China in the (a) near to mid-term, and (b) mid to long-term. *Note: I_1 and I_2 imply that the risk level will increase by one and two grades, respectively; D_1 and D_2 indicate that the risk level will decrease by one and two grades, respectively; and C suggests that the level will be unchanged.*

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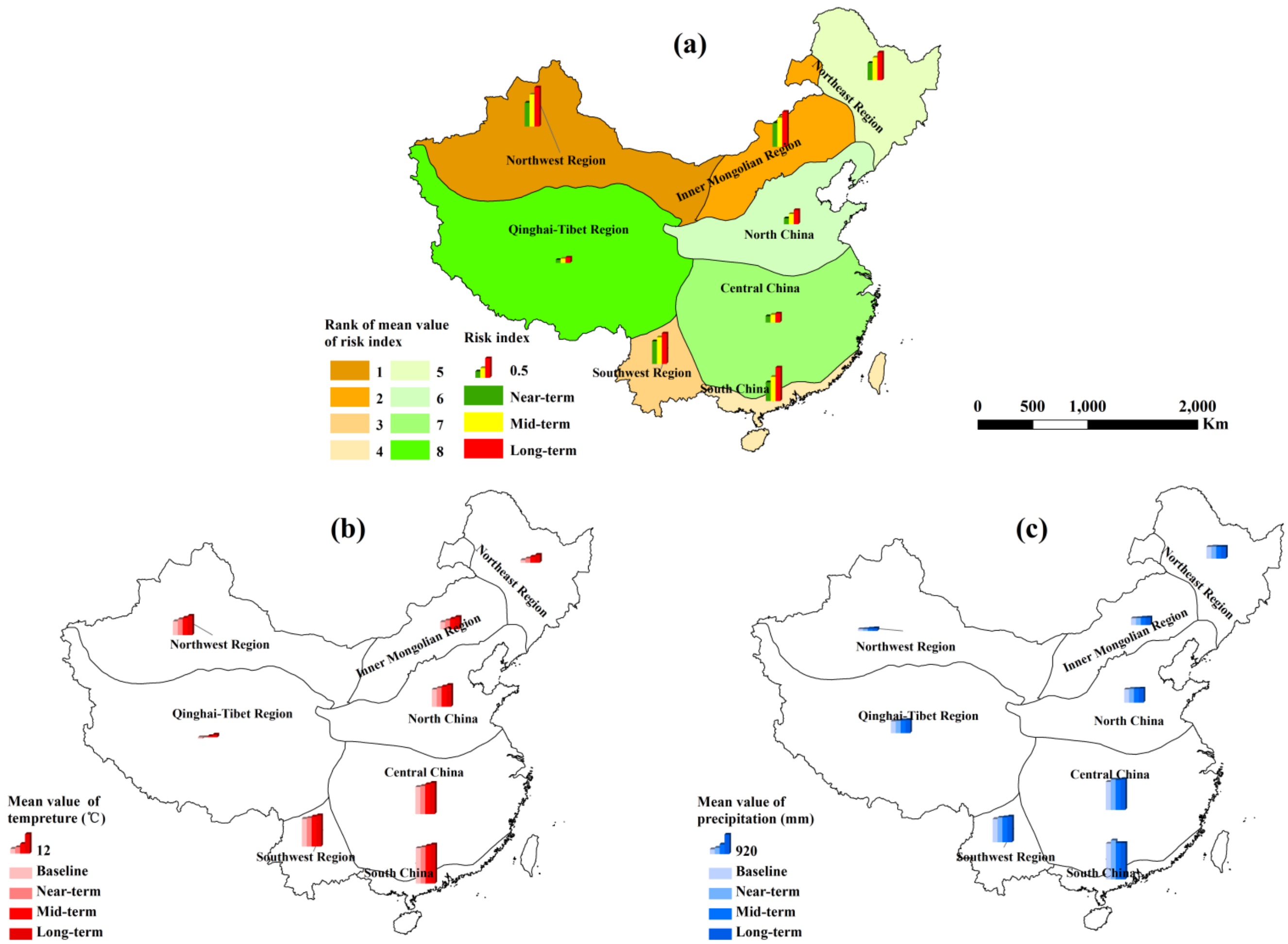

Figure 5. Risk index (a), temperature (b), and precipitation (c) for each eco-region over the three terms.