Ecological Risks

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5.1 Background

Climate change has strong influence on terrestrial ecosystems, and the influence is almost certain to grow in the near future (IPCC 2014). Continuing climate change and climate extremes may cause significant impacts on the terrestrial ecosystems, such as decrease in regional carbon stocks and reduction in vegetation leaf cover (Donohue et al. 2013). China has a variety of ecosystems ranging from alpine tundra to evergreen tropics and from desert to forest. The impact of climate change on terrestrial ecosystems in China has received considerable attention.

Many impact assessments focused on one or a few aspects such as vegetation structure and distribution (Tao and Zhang 2010; Wang 2014), or carbon cycle [e.g., carbon flux and stock, net primary productivity (NPP)] (Tao and Zhang 2010; Piao et al. 2009; Ni 2011). However, it is difficult to identify the main factors influencing ecosystem shifts and to know the degree of climate change tolerated prior to the shift of complex ecological systems. In order to quantify the comprehensive risks of ecosystem alterations under climate change, Heyder et al. (2011) proposed an aggregated metric, Γ , of joint changes in macroscopic ecosystem features. This metric is based on a specific subset of macroscopic variables (e.g., carbon fluxes, carbon stocks, and water fluxes) that characterize the ecosystem state. Essentially, this metric Γ uses aggregated changes in the biogeochemical ecosystem state as a proxy for the risk of ecosystem shifts. Ecosystem shift in this study refers to the state that the ecosystem has been pushed beyond the point of recovering (Scheffer and

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Carpenter 2003). Based on the specific subsets of variables, this metric could also be used to identify the main factors influencing ecosystem shifts. To identify the high-risk areas and the main contributing factors of the predicted ecosystem shifts in China, a multi-model analysis of ecosystem shift risk using the metric Γ was presented over the naturally vegetated land of China in this chapter (Yin et al. 2016).

5.2 Method

In this chapter, the ecosystem change metric Γ was calculated following Heyder et al. (2011) (Eq. 5.1). The metric calculates the difference between an ecosystem state under climate change and the current state. Ecosystem states are characterized as vectors in a multi-dimensional state space by the variables (Table 5.1) simulated by four global gridded vegetation models (GGVMs) in ISI-MIP (Table 5.2), with each dimension representing a specific fluxes change, stock, or process variable. The simulation outputs of the GGVMs were provided from 1971 to 2099. Three GGVMs (JeDi, JULES, and LPJmL) presented simulation results under four representative concentration pathways (RCPs) namely, RCP2.6, RCP4.5, RCP6.0, and RCP8.5 of five general circulation models (GCMs) from the Fifth Coupled Model Inter-comparison Project (CMIP5) while VISIT model offered simulation results exclusively for RCP2.6 and RCP8.5 of three GCMs. The model outputs of LPJmL and VISIT were provided on a $0.5^{\circ} \times 0.5^{\circ}$ grid, and the model outputs of JeDi and JULES were provided on a $1.25^{\circ} \times 1.85^{\circ}$ grid. We assigned the value of a $0.5^\circ \times 0.5^\circ$ grid or 1.25° \times 1.85° grid, to which the central point of a 1 km grid belong, to the 1 km grid (Taylor et al. 2012). All the GGVMs took into account of the CO₂ fertilization effects. As the land surface was assumed to be covered by natural vegetation only during these model simulations, the ecosystem shifts suggested by the GGVMs were only driven through climate change rather than land-use change. Therefore, we focused on the risk of only natural vegetation by excluding sandy desert, swamp, and cultivated areas.

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Q. Tang and Q. Ge (eds.), Atlas of Environmental Risks Facing China Under Climate Change,

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IHDP/Future Earth-Integrated Risk Governance Project Series, DOI 10.1007/978-981-10-4199-0_5

Table 5.1 Variable subsets used for analysis

Subset	Variables
Carbon fluxes	NPP; fire carbon
Carbon stocks	Carbon contained in vegetation and soil
Water fluxes	Transpiration; evaporation; runoff
All	Carbon fluxes; carbon stocks; water fluxes; soil water content (SWC)

Table 5.2	Overview of the	
GCMs and	GGVMs	

	Name	Institute				
GCMs	HadGEM2-ES	Met Office Hadley Centre				
	IPSL-CM5A-LR	Institute Pierre-Simon Laplace				
	MIROC-ESM-CHEM	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies				
	GFDL-ESM2M	Geophysical Fluid Dynamics Laboratory				
	NorESM1-M	Norwegian Climate Centre				
GGVMs	JeDi	Max-Planck-Institut für Biogeochemie (Germany)				
	JULES	Centre for Ecology and Hydrology (UK); Met Office Hadley Centre (UK); University of Exeter (UK)				
	LPJmL	PIK (Germany)				
	VISIT	National Institute for Environmental Studies (Japan)				

$$\Gamma = \left\{ \Delta V + cS(c, \sigma_c) + gS(g, \sigma_g) + bS(b, \sigma_b) \right\} / 4 \quad (5.1)$$

where ΔV is change in vegetation structure; *c* is relative, local change of ecosystem; *g* is absolute, global change of ecosystem; *b* is changes in the relative magnitude of key biogeochemical exchange fluxes; and $S(x, \sigma_x)$ is change in inter-annual variability (a normalized sigmoid function of the ratio to standard deviation in the reference period, and computed for *c*, *g* and *b*). The range of value for the above dimensions is 0–1. Since the vegetation composition data are unavailable, ΔV is not included in the calculation. The remaining three components (*c*, *b*, and *g*) were scaled up accordingly in Eq. (5.1) and the factor in the denominator becomes 3 instead of 4.

The period of 1981–2010 was used as the reference period to estimate the current state of ecosystem. The reference period was also used in calculation of *c*, *g*, and $S(x, \sigma_x)$. The *g* was calculated based on data in China. The relative change of NPP and the ecosystem change metric Γ were computed between future periods (2011–2040, 2041– 2070, and 2071–2099, respectively) and the reference period. The metric Γ was first calculated for each of the variable subset 'carbon fluxes', 'carbon stocks', or 'water fluxes' individually and then was calculated for the variable subset 'all' (Table 1). There were five GCMs and four GGVMs, making a maximum number of 20 model pairs under each RCP. However, this study used 18 model pairs for RCP2.6 and RCP8.5, and 15 model pairs for RCP4.5 and RCP6.0 due to unavailability of some model simulations in ISI-MIP. The Multimodel-ensemble Medians (MMs) of relative change of NPP or Γ were calculated for the periods of 2011–2040, 2041–2070, and 2071–2099, respectively. The MMs of Γ were divided into ten levels (Table 5.3). The standard deviation (SD) of the relative change or Γ from all the available GCM-GGVM pairs was used to quantify the model uncertainty.

5.3 Results

5.3.1 Relative Change of NPP and Risk Ecological Risk Under Climate Change

The relative change of NPP is less than zero in certain regions of transition zone between cropping area and nomadic area and northwest China. The largest increase of NPP is in Tibetan Plateau and in most regions of northwest China. The relative change is predicted to be greater under higher emission scenario.

Depending on the variable subset considered, the spatial patterns of the metric vary greatly. It suggests that the contributing factors to the ecosystem shifts are dissimilar for different regions. For a specified variable subset considered, the spatial pattern of the metric under different RCPs is similar. However, the metric is generally small under the

Table 5.3 Ecological risk levels

Risk level	1	2	3	4	5	6	7	8	9	10
MM of Γ	≤ 0.1	0.1-0.15	0.15-0.2	0.2–0.25	0.25-0.3	0.3–0.35	0.35–0.4	0.4–0.45	0.45-0.5	>0.5

lowest emission scenario and becomes greater under higher emission scenario. The metric Γ for carbon fluxes under RCP8.5 is considerable in the Tibetan Plateau and temperate humid/subhumid regions. The metric Γ for carbon stocks under RCP8.5 is greater than 0.3 in the Tibetan Plateau and the eastern China regions. Based on simulations of the GGVMs, the metric Γ for water fluxes is small in most parts of China under all emission scenarios. The only exception is the Tibetan Plateau region, where the median of the metric Γ for water fluxes is greater than 0.25, indicating a considerable influence of water fluxes change on ecosystem shift, under RCP8.5 scenario.

For all variable subsets, the ecosystem change metric Γ is small in most parts of China excluding for an area in the Tibetan Plateau region under the lowest emission scenario RCP2.6. Under RCP8.5 scenario, the Tibetan Plateau region, part of the temperate humid/subhumid, and cold temperate humid regions would have severe risks of ecosystem shifts. The high value of Γ over the Tibetan Plateau region results from the combined changes of carbon fluxes, carbon stocks, and water fluxes. The temperate humid/subhumid and cold temperate humid regions would have moderate risks of ecosystem shifts. The risk of ecosystem shifts is generally low in the northwest arid region and tropical and subtropical humid regions.

5.3.2 Model Spread and Uncertainty

The standard deviation of relative changes in NPP and Γ (for carbon fluxes, carbon stocks, water fluxes, and all variables) calculated from all available GCM-GGVM pairs over 2071-2099 for RCP8.5 are illustrated in five maps. The model spread of the relative change of NPP is high in the west China, and low in the east China. The model spread of the Γ for carbon fluxes is high in transition zone between cropping area and nomadic area and certain regions in the Tibetan Plateau. The model spread of the Γ for carbon stocks is large than 0.2 in most regions of east China as well as in the Tibetan Plateau region, while it is smaller than 0.2 only in some regions in northwest China. The model spread of the integrated metric Γ is less than 0.1 under all RCPs in the northwest arid region and southern part of the tropical and subtropical humid region, where the risk of ecosystem shift is generally low. The model spread is generally high in those areas, where the estimated risk of ecosystem shift is high. The largest model spread is related to the Tibetan Plateau region and northeast China. The standard deviation of the Γ estimates is about 0.25 under RCP8.5 scenario.

5.4 Maps

















































































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