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Interannual variability of terrestrial net ecosystem productivity over China: regional contributions and climate attribution

Li Zhang1,2, Xiaoli Ren1, Junbang Wang1, Honglin He1,2, Shaoqiang Wang1,2, Miaomiao Wang1,2, Shilong Piao1,4, Hao Yan1, Weimin Ju1, Fengxue Gu1, Lei Zhou1, Zhongen Niu1,2, Rong Ge1,2, Yueyue Li1,2, Yan Li1,2, Huimin Yan1,2, Mei Huang1 and Guirui Yu1,2

1 Synthesis Research Center of China’s Ecosystem Research Network, Key Laboratory of Ecosystem Network Observation and Modeling, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, People’s Republic of China
2 College of Resources and Environment, University of Chinese Academy of Sciences, Beijing 100190, People’s Republic of China
3 Sino-French Institute for Earth System Science, College of Urban and Environment Sciences, Peking University, Beijing 100871, People’s Republic of China
4 Key Laboratory of Alpine Ecology and Biodiversity, Institute of Tibetan Plateau Research, CAS Center for Excellence in Tibetan Plateau Earth Science, Chinese Academy of Sciences, Beijing, 100085, People’s Republic of China
5 National Meteorological Center, China Meteorological Administration, Beijing 100081, People’s Republic of China
6 International Institute for Earth System Science and Jiangou Provincial Key Laboratory of Geographic Information Science and Technology, Nanjing University, Nanjing 210023, People’s Republic of China
7 Key Laboratory of Dryland Agriculture, MOA, Institute of Environment and Sustainable Development in Agriculture, Chinese Academy of Agricultural Sciences, Beijing 100081, People’s Republic of China
8 University of Chinese Academy of Sciences, Beijing 100049, People’s Republic of China

E-mail: hehl@igsnrr.ac.cn

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Abstract

China’s terrestrial ecosystems play an important role in the global carbon cycle. Regional contributions to the interannual variation (IAV) of China’s terrestrial carbon sink and the attributions to climate variations are not well understood. Here we have investigated how terrestrial ecosystems in the four climate zones with various climate variabilities contribute to the IAV in China’s terrestrial net ecosystem productivity (NEP) using modeled carbon fluxes data from six ecosystems models. Model results show that the monsoonal region of China dominates national NEP IAV with a contribution of 86% (69%–96%) on average. Yearly national NEP changes are mostly driven by gross primary productivity IAV and half of the annual variation results from NEP changes in summer. Regional contributions to NEP IAV in China are consistent with their contributions to the magnitude of national NEP. Rainfall variability dominates the NEP annual variability in China. Precipitation in the temperate monsoon climate zone makes the largest contribution (23%) to the IAV of NEP in China because of both the high sensitivity of terrestrial ecosystem carbon uptake to rainfall and the large fluctuation in the precipitation caused by the East Asian summer monsoon anomalies. Our results suggest that NEP IAV can be mainly attributed to ecosystems with larger productivity and response to precipitation, and highlight the importance of monsoon climate systems with high seasonal and interannual variability in driving interannual variation in the land carbon sink.

Introduction

Global terrestrial ecosystems have functioned as a strong carbon (C) sink since the 1960s (Le Quere et al 2018), which substantially mitigates climate change by removing around a quarter of anthropogenic CO2 emissions per year, on average. This global land C sink has gradually increased over recent decades (Keenan et al 2016, Ballantyne et al 2017, Le Quere et al 2018) but shows a large interannual variability (IAV) (Fu et al 2017, Niu et al 2017). The IAV of the global land sink is of great importance because it drives the interannual
variability of the atmospheric CO₂ growth rate (Schaef er et al 2002, Keenan et al 2012, Le Quere et al 2018). Our current knowledge of regional contributions to the IAV of the global C sink remains controversial. Recent studies show that tropical ecosystems (Cox et al 2013, Wang et al 2013, Wang et al 2014) and semi-arid ecosystems (Poul ter et al 2014, Ahlstrom et al 2015) play important roles in influencing the IAV of the global land C sink. The dominant climate factors driving yearly land carbon sink changes also show a variation between local and global scales (Jung et al 2017).

As an important component of the global C sink (Fang et al 2007, Piao et al 2009, Tian et al 2011), China’s terrestrial C uptake accounts for 8%–11% of the global carbon sink (Piao et al 2009) and varies largely from year to year, which is caused by climate variability (Cao et al 2003). During the period 1981–2000, the annual total net ecosystem productivity in China ranged from −0.32 to 0.25 Pg C yr⁻¹ with a coefficient of variation of 196%, and net primary productivity contributed more than heterotrophic respiration to this variation in arid northern China but less in moist southern China (Cao et al 2003). The magnitude (Piao et al 2009), trend (Cao et al 2003, He et al 2018) of land C sink in China, and the contributions from multiple global change factors (Tian et al 2011) also have a distinct regional variation. The high rate of variation in Asian monsoon climate strongly influences variation in terrestrial ecosystems in China (Fu and Wen 1999). However, the relative contributions of ecosystems in different climate regions to the interannual variation in China’s terrestrial C sink and the attributions to climate variations associated with the Asian summer monsoon in different regions have not been well characterized.

The objective of this study was to investigate relative regional contributions to the IAV of China’s terrestrial net ecosystem productivity (NEP) and its climate attribution. Influenced by the East Asia monsoon, terrestrial ecosystems in four climate zones (i.e. temperate continental, temperate monsoon, high cold Tibetan Plateau, and subtropical-tropical monsoon) have experienced various climate changes in both precipitation and temperature (He et al 2018). Here, we used model outputs from six process-based ecosystems models to estimate (1) how terrestrial ecosystems in these four climatic regions contribute to the IAV in China’s NEP; and (2) how the IAV in national NEP can be attributed to climate variability over different climate regions.

Materials and methods

Ecosystems models
To analyze the interannual variability of China’s terrestrial NEP and its attribution, we collected modeled carbon fluxes, i.e., gross primary productivity (GPP), ecosystem respiration (RE), and NEP, from six different ecosystems models: CEVSA2 (Gu et al 2010, Gu et al 2015), BEPS (Liu et al 1997, Ju et al 2010), TEC (Yan et al 2015), CLM4CN (Mao et al 2013), ORCHIDEE (Krinner et al 2005), and CABLE (Wang et al 2010). The first three models were driven by the meteorological data interpolated using the Australian National University Spline (ANUSPLIN) software based on observed data from the Chinese National Meteorological Information Center (http://data.cma.cn/) (Wang et al 2017). All three models use the same driving data, including climate, land cover, and soil texture. The other three models were performed using historical climate fields from the CRUNCEP v4 dataset (http://dods.cea.fr/data/p529viov/cruncep/), which had strong correlations with those used in the first three models (He et al 2018). A detailed description of these six models (including model input data, model evaluation, and simulation protocol) can be found in He et al (2018) and Piao et al (2015). Here we quantified IAV as yearly detrended (i.e. departure from a long-term trend) carbon fluxes or environmental variables. We evaluated the performance of modeled IAV with data-driven carbon flux products (Jung et al 2011) that were upscale from FLUXNET observations. The IAV of the ensemble GPP, RE, and NEP mean from six ecosystems models were very consistent with that of Jung’s products. They had significant correlations (figures S1(a)–(c) in the supplementary material stacks.iop.org/ERL/14/014003/mmmedia), and the standard deviations of the modeled carbon fluxes were close to that of Jung’s products (figure S1(d)).

Modeled outputs from four simulation experiments (He et al 2018) were used to quantify the effects of climate, atmospheric CO₂ concentration, and nitrogen deposition on the terrestrial NEP IAV in China. CEVSA2 and BEPS performed three experiments (I, II, and III). In experiment I, models were forced with constant CO₂ concentration and climate. Models were run with constant CO₂ concentration and changing climate in experiment II. In experiment III, both changing atmospheric CO₂ concentration and climate were used. To assess the relative contribution of nitrogen deposition, CEVSA2 performs another experiment (IV) with varied atmospheric CO₂ concentration, climate and nitrogen deposition. The differences between the modeled NEP in experiment II and experiment I, experiment III and experiment II, experiment IV and experiment III represent the effects of climate, CO₂, and nitrogen deposition on the terrestrial NEP, respectively.

We calculated the East Asian summer monsoon index (EASMI) in 1982–2010 using the method proposed by Guo et al (2003) and the air pressure data from the CRUNCEP v4 dataset. EASMI is defined as the accumulative pressure difference (less than −5 hPa) between 110°E (land) and 160°E (sea) from 10°N to 50°N at 10 degree latitude intervals from June
to August of one year, normalized by the long-term mean (i.e. 1948–2016 in this study).

**Contribution index**

We used the contribution index \( f_j \) as defined in Ahlstrom et al (2015) to calculate the contribution of individual regions (i.e. climate zones) and carbon flux components (i.e. annual or monthly GPP and RE) to national NEP IAV. The contribution index \( f_j \) is expressed as

\[
f_j = \frac{x_i - \bar{x}_i}{\sum_j \bar{x}_j} \]

where \( x_{ij} \) is the detrended flux for region \( j \) at time \( t \) (in years or months), and \( X_i \) is the detrended national flux \( X_i = \sum_j x_{ij} \). Regions or flux components with higher and positive values of \( f_j \) are regarded as contributing more to national NEP IAV. This method was also used to partition the national NEP IAV among different months.

To estimate the contributions of climate factors (i.e., air temperature \((\text{T})\), precipitation \((\text{P})\), and shortwave radiation \((\text{R}_\text{sw})\) in four climate zones to the national NEP IAV, we first estimated the responses of the GPP, RE, and NEP to climate variables in each climate zone over the past three decades using a multiple regression approach (Piao et al 2013):

\[
y_i = a_i X_{iT} + b_i X_{IP} + c_i X_{IR} + \varepsilon_i
\]

where \( y_i \) is detrended estimated NEP for the climate zone \( i \), \( X_{iT} \), \( X_{IP} \), \( X_{IR} \) are the detrended temperature, precipitation, and shortwave radiation for the climate zone \( i \), respectively. The regression coefficients \( a_i \), \( b_i \), and \( c_i \) represent the sensitivities of the carbon fluxes to these climate variables for the climate zone \( i \), and \( \varepsilon_i \) is the residual error. The sum of \( y_i \) (i = 1, 2, 3, 4) is equal to the detrended national NEP. We then used equation (1) to quantify the contribution indexes of the above three climatic drivers in determining the national NEP IAV.

**Results**

**Interannual variability in climate variables**

Detrended mean air temperature \((\text{T})\), annual precipitation \((\text{P})\), and shortwave radiation \((\text{R}_\text{sw})\) on the national scale ranged from \(-0.44^\circ \text{C}\) to \(0.77^\circ \text{C}\), \(-49.3\ \text{mm}\) to \(69.0\ \text{mm}\), and \(-45.1\ \text{W m}^{-2}\) to \(57.3\ \text{W m}^{-2}\), respectively (figure 1). The four climate zones have similar interannual variation in mean air temperature (figure 1(a)) but differ significantly in annual precipitation IAV (figure 1(b)) and solar radiation (figure 1(c)). The ranges of annual precipitation variability in the subtropical and tropical climate zone and the temperate monsoonal climate zone were 336.6 mm and 220.6 mm, which were 2.5 to 3.6, and 1.6 to 2.4 times that in the other two climate zones. The range of shortwave radiation IAV in the temperate monsoonal climate zone reaches up to 262.3 W m\(^{-2}\), followed by that in the subtropical and tropical climate zone, with a value of 179.7 W m\(^{-2}\), which are 1.9 to 3.3, and 1.2 to 2.2 times that of the other two climate zones.

**Contributions of regional ecosystems to NEP variation**

China’s terrestrial NEP has a large interannual variation over the period 1982–2010, the average detrended anomaly of which varies from \(-0.147\ \text{Pg C}\) in 2001, during severe drought, to 0.155 Pg C in 1990 with a wet and warm climate (figure 2(a)). Figure 2(b) shows spatial patterns of the mean absolute detrended NEP derived from six models during the period 1982–2010. Mean absolute detrended NEP in China reaches up to 15% of that in the globe modeled by the three global models. Ecosystems in the whole monsoonal region (including both zones II and IV) dominate national NEP IAV with the average contribution of 86% (ranging from 69% for ORCHIDEE to 96% for BEPS). The IAV of ensemble national NEP mean shows a strong correlation with NEP IAV in the temperate \((r = 0.90, p < 0.001)\) and subtropical and tropical \((r = 0.52, p < 0.01)\) monsoon climate zones (figures 2(c)–(d)). Although estimated contributions of the two monsoonal climate zones differ markedly among individual models (figure 2(e)), the average contributions over six models show that the subtropical and tropical monsoon climate zone accounts for the largest fraction (47% ± 10%) of the national NEP IAV, followed by the temperate monsoonal climate zone with a relative contribution of 39% ± 6%.

Interannual variation in NEP in China’s terrestrial ecosystems is mostly driven by GPP based on both the model ensemble mean and analysis across six models. As shown in figures S2(a) and (b) in the supplementary material, national terrestrial NEP IAV in China across the six models is more strongly correlated with interannual GPP anomalies \((r = 0.79, p < 0.01)\) than variation in RE \((r = 0.37, p < 0.01)\). We then used equation (1) to partition the national NEP IAV among GPP and RE and among ecosystems in four climate zones. On average, interannual GPP anomalies contribute 145% (ranging from 100% for BEPS to 183% for CLM4CN) of the national NEP IAV. The GPP anomalies of ecosystems in the temperate climate zone and the subtropical and tropical climate zone contribute 57% and 62% in the model ensemble to national NEP IAV in China (figure 3(a)).

When the national terrestrial NEP IAV is partitioned among months (figure 3(b)), we find that the interannual variability of NEP in the summer season (June, July, and August) accounts for 50%, exceeding that in April, May, September, and October (42%), and the other five months (8%) in the nongrowing season (from November to March). Terrestrial ecosystems in the temperate monsoon climate zone during
Figure 1. Detrended mean air temperature ($T$) (a), annual precipitation ($P$) (b), and shortwave radiation ($R_{sw}$) (c) in the whole nation and the four climate zones (i.e. temperate continental (I), temperate monsoonal (II), high-cold Tibetan Plateau (III), and subtropical-tropical monsoonal (IV) climate zones).

Figure 2. IAV of China’s terrestrial net ecosystem productivity (NEP) and regional contributions over the period 1982–2010 estimated by six ecosystems models. (a) Detrended NEP in the nation. (b) Spatial patterns of the mean absolute detrended NEP. (c) Detrended NEP in the temperate monsoonal climate zone. (d) Detrended NEP in the subtropical-tropical monsoonal climate zone. (e) Relative contributions of the four climate zones to the national NEPIAV. The shaded envelope in panels (a), (c), and (d) indicates the 95% confidence interval using model outputs from six ecosystems models. For details on climate zones I, II, III, and IV, see figure 1.
summer season (JJA) has the largest variation in NEP, which accounts for the largest fraction (28%) of the national NEP IAV, followed by those in the subtropical and tropical monsoon climate zone for the spring (MAM, 12%), autumn (SON, 11%), and summer (10%) seasons, as well as those in the temperate continental climate zone for the summer season (12%) and the temperate monsoon climate zone for the spring season (11%) (figure 3(c)). The GPP anomalies of ecosystems in the temperate climate zone during the summer season and the subtropical and tropical climate zone during the autumn and summer seasons contribute 35%, 24%, and 21%, respectively, in the model ensemble to national NEP IAV in China (supplementary material, figure S3).

**Figure 3.** Relative contributions of gross primary productivity (GPP), ecosystem respiration (RE) IAV (a) and seasonal NEP variation in the nation (b) and four climate zones (c) to China’s terrestrial NEP IAV estimated by six ecosystems models. For details on climate zones I, II, III, and IV, see figure 1.

| Table 1. Correlation coefficients between detrended modeled annual national NEP, GPP and RE in China and mean annual climate variables including air temperature (T), precipitation (P), shortwave radiation ($R_{SW}$), atmospheric CO2 concentration (CO2), and atmospheric nitrogen (N) deposition. Statistically significant correlations are marked with * ($p < 0.01$) and * ($p < 0.05$). |
|------------------|------------------|------------------|------------------|------------------|
|                  | NEP              | GPP              | RE               |
| T                | -0.13            | 0.28             | 0.52**           |
| P                | 0.45*            | 0.60**           | 0.35**           |
| $R_{SW}$         | -0.16            | -0.15            | -0.10            |
| CO2              | 0.31             | 0.24             | 0.12             |
| N deposition     | 0.43*            | 0.38*            | 0.23             |

shortwave solar radiation, atmospheric CO2 concentration, and atmospheric nitrogen deposition. Among the three climate variables, precipitation IAV is positively correlated with IAV of GPP ($r = 0.60$, $p < 0.01$), RE ($r = 0.55$, $p < 0.01$), and NEP ($r = 0.45$, $p < 0.05$), and explained 20.0% of the variation in detrended national NEP, while mean annual temperature IAV is significantly correlated with RE IAV ($r = 0.52$, $p < 0.01$) but not with IAV of GPP and NEP. Moreover, the multi-model mean CV values of GPP (5%–9%), which increase significantly
with that of precipitation ($p < 0.01$), are larger than those of RE (3%–6%) across these four climate zones (figure S4). These results suggest that the variability in precipitation dominates the national NEP annual variability in China because there is larger variation in GPP than in RE due to precipitation fluctuation. In addition, the variation in atmospheric nitrogen deposition has a significant positive correlation with the IAV of GPP and NEP (table 1).

The simulation experiments reveal that climate is the primary factor that determines NEP IAV in the terrestrial ecosystems of China (figure 4(a)). The NEP IAV attributed to climate, N deposition, and CO$_2$ can explain 48%, 28%, and 1% of the variance in detrended national NEP, respectively. We then quantified the contributions of the three climatic drivers—air temperature ($T$), precipitation ($P$), and shortwave radiation ($R_{sw}$)—in governing national NEP IAV in China using equations (1) and (2) (figure 4(b)). The results show that precipitation in the temperate monsoon climate zone accounts for the largest fraction (23%), followed by precipitation in the continental climate zone (10%), and shortwave radiation in the subtropical and tropical monsoon climate zone (8%) and temperate monsoon climate zone (8%). The analysis of the correlation between the interannual variability of national NEP with climate variables in four climate zones also shows that national NEP IAV is significantly correlated with precipitation IAV in the temperate monsoon climate zone ($R = 0.56$, $p < 0.01$) and temperate continental climate zone ($R = 0.58$, $p < 0.01$). In the temperate monsoon climate zone, precipitation is highly correlated with GPP and RE, and the increase in precipitation stimulated GPP larger than RE (figure S5(a)). We also find that the precipitation IAV in the temperate monsoonal climate zone has a strong positive correlation ($p < 0.05$) with the East Asia summer monsoon index (EASMI) anomalies (figure S5(b)), indicating that the strengthening of the East Asian summer monsoon tends to result in increasing rainfall in this region.

For the subtropical and tropical monsoonal climate zone, its large contribution to the national NEP IAV in China mainly results from the GPP IAV in this region (figure 3(a)), where the GPP IAV has a larger positive response than the RE IAV to $R_{sw}$ IAV (figure S6(a)). Furthermore, there is a negative effect of rising temperature on NEP in this region (figure S6(c)), particularly during May to October (figure S6(c)), within which the NEP variability can explain 84% of the variation of annual NEP in this region (figure S6(d)).

**Discussion**

The monsoonal area, i.e. the temperate monsoonal climate zone (II) and the subtropical and tropical monsoonal climate zone (IV), not only dominates both the magnitude and trend of national NEP (1982–2010) in China (He et al 2018), but also plays an important role in influencing the NEP IAV in China (figure 2). Our results suggested that rainfall variability dominated the NEP annual variability in China, which has a strong positive correlation with precipitation in the whole country and the temperate monsoon climate zone. Specifically, precipitation in the
temperate monsoon climate zone made the largest contribution to the IAV of NEP in China, which was caused by both high sensitivity of terrestrial ecosystem carbon uptake to rainfall (57.9 Tg C 100 mm$^{-1}$ reported in He et al. (2018)) and large fluctuation in the precipitation in this region (figure 1(b)). The large precipitation annual variability in the temperate monsoon climate zone is associated with the fluctuation in the East Asia summer monsoon (figure S5(b)). A strong summer monsoon usually means the major rain belt in eastern China moving north, which brings more rainfall to northern China because strong southerly flows transport more moisture northward (Fu and Wen 1999, Liu et al. 2012). Variation in the intensity of the East Asia summer monsoon is likely caused by the change in sea surface temperature anomaly that greatly influences the land–sea thermal contrast between the Asian land area and tropical Pacific oceanic regions (Ding et al. 2009). The East Asian summer monsoon has been projected to become stronger with increasing monsoon precipitation in the future, as revealed by CMIP5 models (Bao 2012, Chen and Sun 2013), which might benefit the terrestrial carbon sink in China and the globe.

Our findings pointed out the importance of monsoon climate systems with high seasonal and interannual variability in driving interannual variation in China’s carbon fluxes, which provided a new insight into understanding the interannual variation of the global land carbon sink. Previous studies have shown that the IAV of NPP or NEP exhibits positive coherence with temporal variability in the precipitation in monsoon areas such as China (Fang et al. 2001), India (Nayak et al. 2013), Asia (Tian et al. 2003), and Australia (Poulter et al. 2014, Trudinger et al. 2016), but not related to fluctuations in precipitation in other regions of the world, e.g., North America (Knapp and Smith 2001). Moreover, the MsTMIP models show that global monsoon regions dominate the interannual variation of the global carbon sink with the contribution of 60% on average. These results indicated the importance of the role played by monsoon
systems in the interannual variation of global carbon sink.

Although estimated regional contributions to national NEP IAV in China differ markedly among individual models, all six models agree that the regional contributions to NEP IAV in China is consistent with their contributions to the magnitude of national NEP. As illustrated in figure 5(a), relative contributions from ecosystems in four climate zones to national NEP IAV in China across six models correlate significantly with their contributions to the magnitude of national NEP. Since estimated contributions of different climate zones significantly correlated with modeled mean absolute detrended NEP across six models (figure 5(b), we then did linear regression analysis between the latter and ecosystem responses to precipitation and temperature, which were calculated by multiplying mean absolute detrended precipitation or temperature by modeled NEP sensitivities to precipitation and temperature. The regression results show that the NEP IAV significantly increased with the increasing variability in precipitation (figure 5(c)) but shows no correlation with the increasing variability in temperature (figure 5(d)). This analysis across six models confirms the dominant role of rainfall variability in NEP annual variability in China, as shown in figure 4(b).

Since models tend to have a higher carbon flux response to precipitation than observations (Piao et al 2013), we recommend future work compares the carbon flux response to climate factors between models with data-driven upscaling of fluxes based on China-FLUX sites and results from long-term field manipulation experiments in China. In addition to climate, other environmental factors such as atmospheric CO2 concentration and atmospheric nitrogen deposition also influence NEP IAV in China. Although enhanced CO2 concentration and nitrogen deposition stimulate the plant growth and carbon sequestration in China (Gu et al 2015, Piao et al 2015), their contributions to national NEP IAV are weaker than climate (figure 6(a)). Since the models used in this study did not consider the spatial variation of atmospheric CO2 concentration, how the changes in atmospheric CO2 concentration in different climate zones contribute to the national NEP IAV remains unclear. Moreover, disturbances such as land use change and fire may influence the quantification of regional contributions to national NEP IAV in China, which should be further investigated in the future.

Conclusion

We quantified regional contributions to China’s terrestrial NEP IAV and attributions to climate variability associated with the East Asian summer monsoon using modeled carbon fluxes data from six ecosystems models. We found that ecosystems in the monsoonal region dominated national NEP IAV in China, which was associated with the variability in rainfall rather than temperature. Precipitation in the temperate monsoon climate zone contributed the most to the IAV of NEP in China because of both high sensitivity of terrestrial ecosystem carbon uptake to rainfall and the large fluctuation in the precipitation caused by the East Asian summer monsoon anomalies. These results indicate that strengthened East Asian summer monsoon, with increasing monsoon precipitation in the future, might benefit the terrestrial carbon sink in China and the globe. In addition, our results suggest that monsoon climate systems with high seasonal and interannual variability in precipitation may serve as an important driving force for variation in the regional and global carbon cycle. We therefore recommend that more attention is paid to the prediction of monsoon climate systems, especially the monsoon precipitation anomaly, in projecting future climate change and carbon cycle feedbacks.

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ORCID iDs

Li Zhang @ https://orcid.org/0000-0002-0423-5494
Shilong Piao @ https://orcid.org/0000-0001-8057-2292

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