# Conflict or Coordination? The Interactions between Climate Change Mitigation and Adaptation: Evidence from China

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**Author contributions**

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Miao-miao Chen, Yixuan Li and Xinxiao Shao. The first draft of the manuscript was written by Huiqin Jiang and Miao-miao Chen, and was reviewed and edited by Jianqiang Bao. The funding was acquired by Huiqin Jiang. All authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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# Conflict or Coordination? The interactions between climate change mitigation and adaptation: Evidence from China

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**Abstract**

As two important strategies to reduce adverse climate effects, mitigation and adaptation actions can interact, resulting in synergies or trade-offs. Using data from 30 Chinese provinces from 2008 to 2017, this study employs a panel vector autoregression (PVAR) model to study the interactive relationships between mitigation and adaptation. Moreover, based on the coupling coordination model, this paper investigates the coordination degree of mitigation and adaptation in China. The results show that 1) there is Granger causality between mitigation and adaptation, and the positive impact of mitigation on adaptation is greater than the negative impact of adaptation on mitigation. Therefore, an integrated approach that considers these interactions can help enhance synergy and create a win-win situation. 2) The dynamic relationship between mitigation and adaptation in China has reached a barely balanced stage, and there are large regional differences. 3) Compared with the mitigation evaluation value, the adaptation evaluation value has a more positive effect on promoting an increase in the coordination degree. These findings can contribute to the formulation of effective regional sustainable development strategies.

**Key words** mitigation and adaptation, climate change, panel VAR, coupling coordination degree model,

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## 1. Introduction

Climate change has had a visible effect on the natural and human environment, and inevitably, decisions must be made to mitigate greenhouse gases and adapt climate change to cope with the rapidly emerging and escalating climate change risks. *The Emission Gap Report 2020*, released by the United Nations Environment Programme (UNEP), found that over the past ten years, global GHG emissions have increased by 1.4% annually and reached a record high of 59.1 Gt $CO_2$e in 2019. Although $CO_2$ emissions could decrease in 2020 due to COVID-19, current intended nationally determined contribution (INDC) targets remain seriously inadequate to achieve the climate goals of the Paris Agreement, and the global temperature will rise by at least 3° C by the end of the century. Due to historical emissions and the fact that we cannot adapt indefinitely to the worst effects of climate change, taking action on adaptation and mitigation is essential.

However, adaptation and mitigation have historically been regarded and treated as two separate management strategies in both the climate change policy arena and the literature (Xu et al. 2019). This divergence has hindered progress against the fundamental sustainable development challenges of climate change (Howell et al. 2016; Ayers and Huq 2009). Since the mid-2000s, instead of focusing mainly on mitigation or adaptation, the situation has been that 'both mitigation and adaptation are considered significant'. There has been a surge in academic and policy-oriented discussions of the interrelationship between mitigation and adaptation (Landauer et al. 2015; Sharifi, 2020), and new work in this area suggests that global mitigation and adaptation are substitutes (in economic terms) and complementary (in policy terms) (Ingham et al. 2013).

Although the majority of interactions are deemed positive (Berry et al., 2015), there is the possibility of maladaptation (the "problem of increasing risks from adaptation") or malmitigation (i.e., increasing risks from mitigation). Therefore, it is necessary to enhance the synergies between mitigation and adaptation actions to expand shared interests and weaken conflicts. Against this background, there has been a growing body of literature addressing the interaction between mitigation and adaptation from different perspectives, e.g., the feasibility of simultaneously implementing mitigation and adaptation strategies (Locatelli et al. 2011; Wilbanks et al. 2007; Hulme et al. 2009), examples of synergies between mitigation and adaptation measures in different sectors (Sharifi, 2021; Berry et al. 2015), core drivers contributing to or hindering synergies (Landauer et al. 2015; Landauer et al. 2018) and so on.

Despite growing interest in the linkage between mitigation and adaptation, the majority of extant works only discuss mutual relations without empirically testing them. Most generally focus on

"relationship discovery" rather than "relation mining", which means there is a lack of empirical research investigating the level of integration between adaptation and mitigation and how this integration affects outcomes (Grafakos et al. 2020; Grafakos et al. 2019) . In addition, developed countries, particularly European cities, are hot areas for research in this area, while countries in the Global South are underrepresented in the peer-reviewed literature (Sharifi, 2021).

Hence, this paper chooses China, a country with both large greenhouse gas emissions and high climate vulnerability, as a case study. On the one hand, China's large population yields a strong demand for consumption, output and energy sources (Duan et al. 2019), which has triggered major GHG emissions. Moreover, China's large share of energy-intensive industries and high economic dependence on fossil energy make it particularly difficult for China to control GHG emissions. On the other hand, China is also frequently referred to as one of the developing member countries (DMCs) most vulnerable to climate change (Hallegatte and Stephane 2013). The complicated geographical and climatic conditions of China lead to diversified and frequent natural disasters, which requires higher-level emergency response mechanisms for extreme climate events and disaster protection capacity. A report issued by the UN Office for Disaster Risk Reduction (UNDRR) in 2018 found that between 1998 and 2017, disaster-hit countries experienced direct economic losses caused by climate-related disasters valued at US$ 2,245 billion. Among them, China ranked second, with a loss of up to US$492.2 billion (UNDRR, 2018).

Against this background, the aim of this research is to explore the dynamic interrelationship between adaptation and mitigation and to evaluate their integration in China to address the sustainable development challenges of climate change policy. In this context, this article presents a framework, including an evaluation system, to trace the capacity for mitigation and adaptation to climate change in China. The panel VAR model is adopted to empirically examine the relationship between mitigation and adaptation, and a coupling coordination degree model is developed to assess the integration between climate change mitigation and adaptation.

This paper is composed of four sections. The rest of this work is organized as follows: Section 2 briefly introduces the evaluation system, PVAR model and coupling coordination degree model. Section 3 presents the empirical analysis and the main result. The final section discusses the findings and their limitations and highlights gaps to be addressed in future research.

## 2 Methodology and data

### 2.1 The evaluation system

To empirically examine the interrelationship between mitigation and adaptation, this paper first establishes an evaluation system. Within the evaluation system, two subsystems were defined via the

respective indicators.

Based on the definition of mitigation—anthropogenic intervention to reduce the sources or enhance the sinks of greenhouse gases (IPCC, 2007)—this paper evaluated mitigation capacity from 5 aspects: industrial structure, energy structure, carbon intensity, energy efficiency and carbon sinks. The industrial structure (IS) is defined as the share of each sector in the gross national product (Zheng et al. 2019). According to the existing literature, the ratio of the added value of secondary industry to regional GDP is adopted as an indicator in this article. The lower the IS value is, the more reasonable the industrial structure, indicating that the economy is inclined toward developing in the direction of "low pollution and low energy consumption". The energy structure (ES) is a key factor in reducing greenhouse gas emissions. This study adopts the proportion of thermal power generation in electricity generation, and a lower value of ES means a more sustainable energy structure. Energy intensity (EI) refers to the quantity of energy required per unit output or activity, so this paper adopts the energy consumption per 10,000 yuan of real GDP as the indicator. Low EI values are a proxy for energy efficiency improvements and GHG emissions declines. Carbon intensity reflects the amount of carbon dioxide emitted per unit of GDP, and the $CO_2$ emissions per 10,000 yuan of real GDP are adopted here. Generally, the decline in carbon intensity, an important sign of increased mitigation capability, does not indicate an improvement in energy efficiency but is connected with technological progress and economic growth. For carbon sinks (CS), the percentage of forest cover was used as a measure because forests, as the primary natural carbon sink, play an important role in absorbing and storing carbon dioxide from the atmosphere (Pan et al. 2011; Sun et al. 2019 ). Ultimately, as shown in Table 1, these 5 indicators were selected to measure the mitigation evaluation value (MEV).

Adaptive capacity is a complex concept that reflects the integrated capabilities of the economy, society, technology, natural resources and risk management to address climate change risks (Nhuan et al. 2016). Therefore, it is also defined as "the collective ability of a locale (or community) to combine various forms of capital", and there are a number of theoretical and scientific frames developed for related assessments (Engle and Lemos 2010; Hill and Engle 2013; Tinch et al. 2015; Araos et al. 2016; Zheng et al. 2018). Therefore, the capital approach, a bottom-up assessment framework, is applicable to adaptation assessment. This approach has the advantage of considering all tangible and intangible capital that may generate consumption or welfare, including financial, engineering, natural, human and social capital c omponents (Chen et al. 2014). With reference to the extant literature, this paper develops an evaluation index system for adaptation based on the five components of the capital approach, including the natural environment, infrastructure, financial support, human resources and social stability. Considering the availability of data, 14 indicators representing the stock of these five types of capital

were selected to form the framework of adaptation evaluation in this paper (see Table 1).

Since the original data of each indicator have different units, it is impossible to compare them. Accordingly, min-max normalization is applied here so that all the indicators of different units and scales are transformed into the range [0,1]. Considering the difference between positive and negative indicators, it is necessary to standardize them. The specific formula is shown below:

Indicators that have a positive contribution to the AEV and MEV,

$$\mathrm{x_{ij}} = \frac{X_{ij} - \min X_j}{\max X_j - \min X_j} \tag{1}$$

Indicators that have a negative contribution to the AEV and MEV,

$$\mathrm{x_{ij}} = \frac{\max X_j - X_{ij}}{\max X_j - \min X_j} \tag{2}$$

where i refers to the ith sample (i = 1, 2, ⋯, n), j refers to the jth indicator (j =1, 2, ⋯, m), Max is the maximum value of a given indicator, and Min is the minimum value of a given indicator.

To reduce interference from subjective selection factors, the entropy method is used to calculate the indicator weight according to its variability.

Equations 3 and 4 show the methods for calculating the MEV and the AEV, respectively.

$$MEV = w_{is}IS + w_{es}ES + w_{ei}EI + w_{ci}CI + w_{cs}CS \tag{3}$$

where IS, ES, EI, CI and CS refer to standardized values normalized by the maximum and minimum method. $w_{is}$, $w_{es}$, $w_{ei}$, $w_{ci}$ and $w_{cs}$ represent the weights of industrial structure, energy structure, energy intensity, carbon intensity and carbon sinks, respectively.

$$AEV = w_n N + w_e E + w_f F + w_h H + w_s S \tag{4}$$

where N, E, F, H and S refer to dimensionless data normalized by the maximum and minimum methods. $w_n$, $w_e$, $w_f$, $w_h$ and $w_s$ represent the weights of natural, engineering, financial, human and social capital, respectively.

Descriptive statistics for each variable are presented in Table 2. In addition, we visualize the raw data in Fig. 1. Fig. 1 documents at least three facts. First, substantial regional inequality exists in mitigation and adaptive capacity. Second, the regional growth rates of these two variables are quite different. Third, high mitigation indices agglomerate in central and southern China (i.e., Sichuan, Yunnan, Hunan and Hubei provinces), while the high adaptation indices are concentrated in the provinces in the Yangtze River Delta region (such as Jiangsu, Shanghai and Zhejiang), and the western region where is rich in natural resources (i.e., Inner Mongolia, Qinghai and Ningxia provinces).

**Table 1** Evaluation indicators of mitigation and adaptation

| Subsystem | Components | Indices | Indicator | Attribute |
|---|---|---|---|---|
| Mitigation | Reduce the sources of greenhouse gasses | Industrial structure | the ratio of the added value of second industry to the regional GDP | - |
| | | Energy structure | The proportion of thermal power generation in electricity generation | - |
| | | Carbon intensity | $CO_2$ emissions per 10,000 yuan of real GDP | - |
| | | Energy intensity | Energy Consumption per 10,000 yuan of real GDP | - |
| | Enhance the sinks of greenhouse gasses | Carbon sinks | Proportion of forest area | + |
| Adaptation | Natural capital | Water resourse index | Per capita freshwater resources availability | + |
| | | Ecological index | Percentage of natural wetland coverage | + |
| | | Arable land index | Per capita output of grain | + |
| | Engineering capital | Environmental infrastructure index | Investment in the treatment of industrial pollution control to regional GDP ratio | + |
| | | Energy supply index | Power supply per capita | + |
| | | Transpotation index | Per capita freight traffic | + |
| | Financial capital | Economical development index | Per capita regional GDP | + |
| | | Economical health index | Unemployment rate | - |
| | Human capital | Labor index | Proportion of vulnerable population (<18 or >60 years old) | - |
| | | Education index | The number of college students per 10,000 persons | + |
| | | Technology index | Number of invention patents granted | + |
| | Social capital | Medical care index | Number of hospital beds per 10，000 persons | + |
| | | Communication index | Network coverage | + |
| | | Insurance index | Proportion of medical insurance coverage | + |

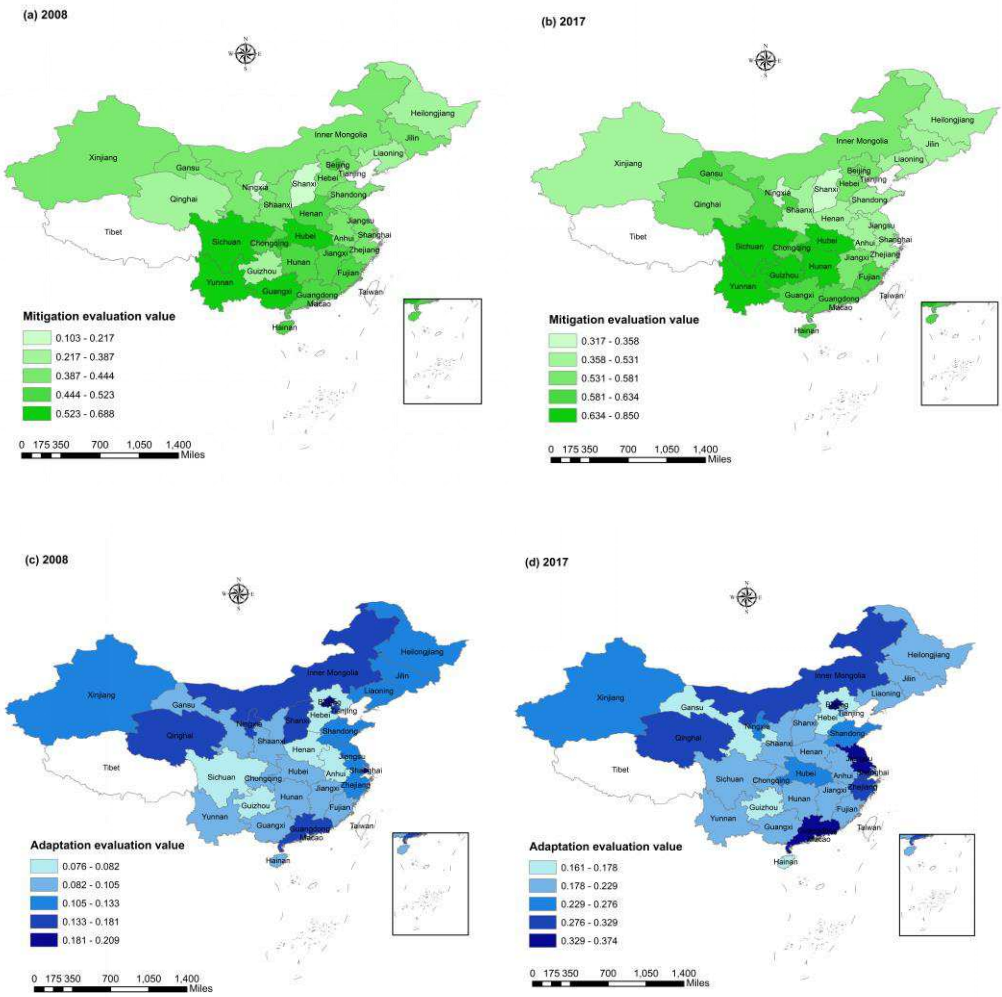


**Fig. 1** Distribution of China's MEV and AEV in 2008 and 2017

**Table 2** Descriptive Statistics

| Variable | Mean | Std | Min | Max | Observation |
|---|---|---|---|---|---|
| MEV | 0.4997 | 0.1072 | 0.1025 | 0.8496 | 300 |
| AEV | 0.1809 | 0.0624 | 0.0764 | 0.3743 | 300 |

### 2.2 The panel VAR model

The PVAR model was empirically applied in this paper to examine the interrelationship between mitigation and adaptation. This model combines the advantages of panel data with the VAR model, which can not only address endogeneity problems but also allow the existence of unobserved individual heterogeneity and heteroscedasticity in the data (Yang et al. 2020; Love and Zicchino 2007; Yang and Pan 2020). With reference to the PAVR model proposed by Abrigo and Love (2016), the specific model constructed in this paper is shown below:

$$Z_{it} = f_i + d_t + \sum_{i=1}^{n} A_j Z_{it-j} + \varepsilon_{it}, \quad (5)$$

Where $Z_{it}$ is a two-factor column vector containing the MEV and the AEV. $i \in \{1,2,...N\}$ represents 30 provinces in China, and $t$ refers to the time period. $f_i$ refers to the fixed effect of the individual variable, while $d_t$ is the fixed effect of time. $A_j$ represents the lagged-term regression coefficient of the endogenous variables, and $\varepsilon_{it}$ represents the disturbance term.

### 2.3 Coupling coordination degree model

"Coupling", a phenomenon originating in the physical sciences, occurs when two or more systems influence each other through various interactions (Song et al. 2018). The coupling coordination model is widely used to assess the integration of two or more systems as criteria of the coupling stage (Chen et al. 2020; Tian et al. 2020). It is employed in this article to assess the integration between mitigation and adaptation to reveal whether the two subsystems are balanced and whether they have beneficial effects upon each other. Analyzing the high-low and temporal-spatial characteristics of the coupling coordination degree can provide suggestions for achieving relatively sustainable development between two systems. The coupled coordination model of mitigation and adaptation was established as follows:

$$D_i = \sqrt{C_i \times T_i} \quad (6)$$

$$C_i = \left\{ \frac{MEV \times AEV}{\left[ (MEV + AEV) \div 2 \right]^2} \right\}^{1/2} \quad (6a)$$

$$T_i = \alpha \times MEV + \beta \times AEV \quad (6b)$$

where $D \in \{0,1\}$ represents the extent of coupling coordination between the mitigation and adaptation systems. $C$ is the coupling degree of the two subsystems, indicating the interaction intensity. T refers to the comprehensive value of mitigation and adaptation subsystems. $\alpha$ and $\beta$ are undetermined coefficients, reflecting the contributions of mitigation and adaptation systems. Considering that mitigation and adaptation are equally important to China in addressing climate risks, the evaluated subsystems were assumed to have equal status. Therefore, $\alpha = \beta = 1/2$

### 2.4 Data

Thirty provinces in China were selected as the research objects; Tibet, Hong Kong, Macau, and Taiwan were omitted, as they lack data on some indicators. The statistical yearbooks at the national, provincial and municipal levels from 2009 to 2018 provide the main relevant socioeconomic data. Specifically, all indicator data in currency units in this article have been adjusted to 2005 constant prices to clarify the effects of inflation. Provincial carbon emissions data from fossil fuel sources were acquired

from the *China Emission Accounts and Datasets* (CEADs, 2015). The proportion of thermal power generation in total power generation by region and the total energy consumption by region were derived from the *China Energy Statistical Yearbook*. The Internet penetration rate was derived from the *China Tertiary Industry Statistical Yearbook*.

## 3 Results

### 3.1 Baseline results

For the purpose of analyzing the dynamic relationship between mitigation and adaptation in China, the PVAR model is constructed to conduct empirical testing. Before implementing the PVAR model, the stationarity of each variable needs to be tested to avoid the possibility of "spurious regression". This paper employs the LLC and IPS methods for the unit root test, and according to the results shown in Table 3, the LLC test and IPS test of the MEV and AEV are significant, indicating that the variables can be considered stationary.

**Table 3** Panel data unit root tests

| | LLC test | IPS test | Result |
|---|---|---|---|
| MEV | -7.7356*** | -3.1680*** | Stationary |
| AEV | -8.2345*** | -1.4992* | Stationary |

*p < 0.1, **p < 0.05, ***p < 0.01.

After the panel unit root test is completed, it is also necessary to determine the lag length of the panel VAR model. The Akaike information criterion (AIC), Bayesian information criterion (BIC) and Hannan-Quinn information criterion (HQIC) are common methods employed to determine the lag length. Only when the BIC, AIC and HQIC have the minimum information content can the model be judged to be optimal (Lin and Zhu 2017). According to Table 4, a four-period lag is considered the best lag length according to the principle of parsimony.

**Table 4** Selection order criteria for panel VAR

| lag | AIC | BIC | HQIC |
|---|---|---|---|
| 1 | -8.0194 | -7.0912 | -7.6454 |
| 2 | -8.8996 | -7.8158 | -8.4615 |
| 3 | -9.3227 | -8.0455 | -8.8049 |
| 4 | -9.8831* | -8.3577* | -9.2634* |
| 5 | -9.3887 | -7.5304 | -8.6341 |

The Granger causality test was applied in this paper to better understand the suggestive relationship

between mitigation and adaptation, and the results are shown in Table 4. The null hypotheses of the Granger causality test for panel data are that mitigation is not the cause of adaptation and adaptation is not the cause of mitigation, while the results showed that both were denied. This means that mitigation and adaptation are mutually causal, with both $p < 0.05$.

**Table 5** Granger causality tests result

| Null hypothesis | $Chi^2$ | df | Prob |
|---|---|---|---|
| Adapation are not the Granger cause of Mitigation | 14.044 | 4 | 0.007 |
| Mitigation are not the Granger cause of Adaptation | 11.772 | 4 | 0.019 |

### 3.2 Impulse response analysis

The impulse response function and variance decomposition can better reflect the fluctuations and influences among endogenous variables, thereby obtaining long-term predictions. In particular, the impulse response function is used to identify the effect of one shock at a time while holding other shocks constant. Fig. 2 presents the results from the simulations of the impulse response for 4 lags by using Monte Carlo simulations with 200 repetitions.

First, the shocks to mitigation and adaptation both have a positive and significant impact on them (Fig 2a and Fig 2d), which means that both are progressive and self-reinforcing over time. However, this positive effect tends to decrease with time. The results are further evidence that a development model that relies solely on adaptation or mitigation is not sustainable. In addressing climate change risks, policy makers should strike a balance between adaptation and mitigation and carry out overall planning to achieve coordinated development.

Second, the response of mitigation to adaptation is weakly negative and registers a decreasing trend (Fig. 2b). There are several reasons behind this sign: in the first place, there appears to be a crowding-out effect of investment between adaptation and mitigation, given a limited investment budget. Generally, the crowding-out effect of adaptation on mitigation is much larger than that of mitigation on adaptation. That is, under budget shortages, more financial resources tend to be concentrated on mitigation actions than adaptation actions. (Bosello et al. 2010; Agrawala et al. 2011; Duan et al. 2019). Second, the sign of this response is also in line with some practical cases. For example, urban planners may have to consider the decentralization of urban structures to reduce population density and thereby reduce the damage caused by climate change. However, urban decentralization can negatively impact mitigation by increasing transport fuel demand (Hallegatte 2011).

Focusing next on the responses of adaptation (Fig. 2c), we note that the response of adaptation to mitigation is positive. This result is consistent with theoretical predictions from previous literature

(Ayers and Huq 2009; Landauer et al. 2015). High mitigation capacity means that there is limited room for improvement, and more resources, especially financial resources, can be focused on adaptation activities. Second, in the long run, mitigation activities can reduce the concentration of greenhouse gases in the atmosphere, which will decrease the intensity and frequency of events such as meteorological disasters. In addition, studies have shown that established mitigation policies rather than local climate risk profiles drive cities to join municipal adaptation networks. Cities committed to actual progress on mitigation policy (i.e., with a monitoring system in place) are more likely to adopt adaptation policies (Lee et al., 2020).

### 3.3 Variance decomposition results

We next conduct a study of the variance decompositions to complement the impulse response analysis; this can reflect the relative cumulative contribution of each of the variables in the system. Through 200 iterations of the Monte Carlo simulation, the variance decomposition of the two variables for 30 prediction periods can be acquired. As is reported in Table 5, each variable holds a different degree of importance in explaining the variation of all other variables.

Overall, there is a positive relationship between each variable and its predicted values. The results in Table 5 report that the interpretability of the MEV to its predicted values accounts for 91% in the $10^{th}$ period, and it remains at the 90% level in the $30^{th}$ period, indicating that the MEV follows a process of continuous accumulation. In other words, the predicted values of the MEV are to a large extent determined by its current values. By contrast, the error term decomposition results for the AEV show that its own interpretability is lower than that of the MEV to its predicted values.

In addition, the explanatory power of each variable toward the other variables gradually increased. In the 30th forecast period, the impact of the MEV on the AEV (44.1%) was greater than the impact of the AEV on the MEV (10%). This is indicative of that mitigation take a more significant impact on reducing adverse climate effects than adaptation in the long run. Mitigation works in a more basic way, aiming to reduce climate risks by controlling the accumulation of GHGs in the atmosphere, while adaptation focus on the improvement of adaptive capacity and reduction of vulnerability so as to cope with climate change. Although with the same goal, they are very different in approach, which lead to the benefits varied in terms of temporal scale , and the benefits of mitigation tend to be more significant over the longer term.

Through impulse response analysis in the last section, we have found that mitigation is beneficial to the increase in adaptive capacity in the long term, while adaptation has a slight negative effect on mitigation. The Variance decomposition result showed that the impact of mitigation on the adaptation

was greater than the impact of the adaptation on the mitigation.Taken together, these results suggest that the positive impact of mitigation on adaptation is greater than the negative impact of adaptation on mitigation, indicating that it would be a better option to adopt a combination strategy instead of taking action on adaptation or mitigation alone to reduce adverse climate effects.

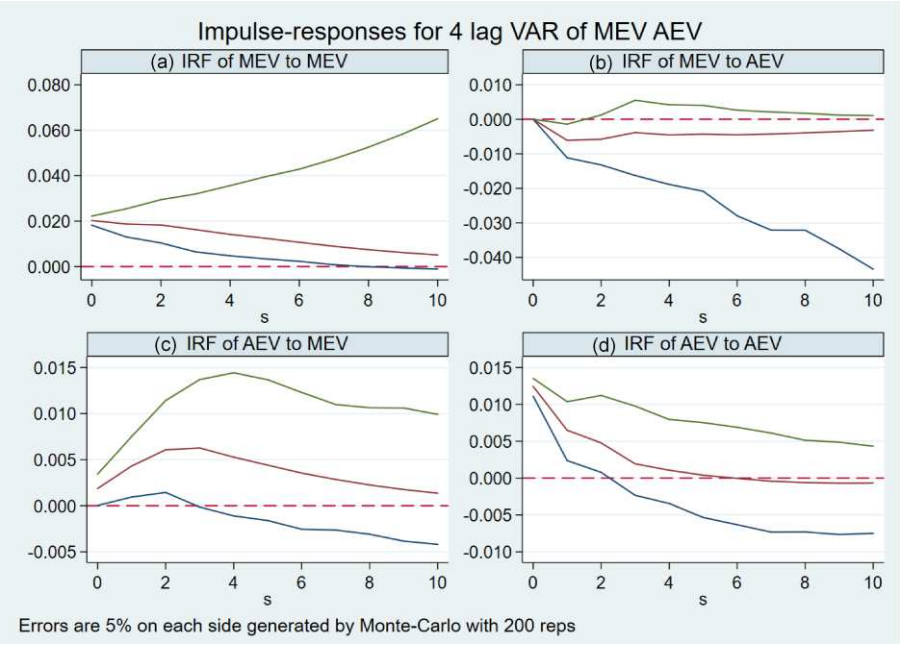


**Fig. 2** Results of impulse response between mitigation capacity and adaptive capacity

**Table 6** Results of variance decomposition

| | Prediction period | MEV | AEV |
|---|---|---|---|
| MEV | 10 | 0.913 | 0.087 |
| AEV | 10 | 0.436 | 0.564 |
| MEV | 20 | 0.901 | 0.099 |
| AEV | 20 | 0.441 | 0.559 |
| MEV | 30 | 0.900 | 0.100 |
| AEV | 30 | 0.441 | 0.559 |

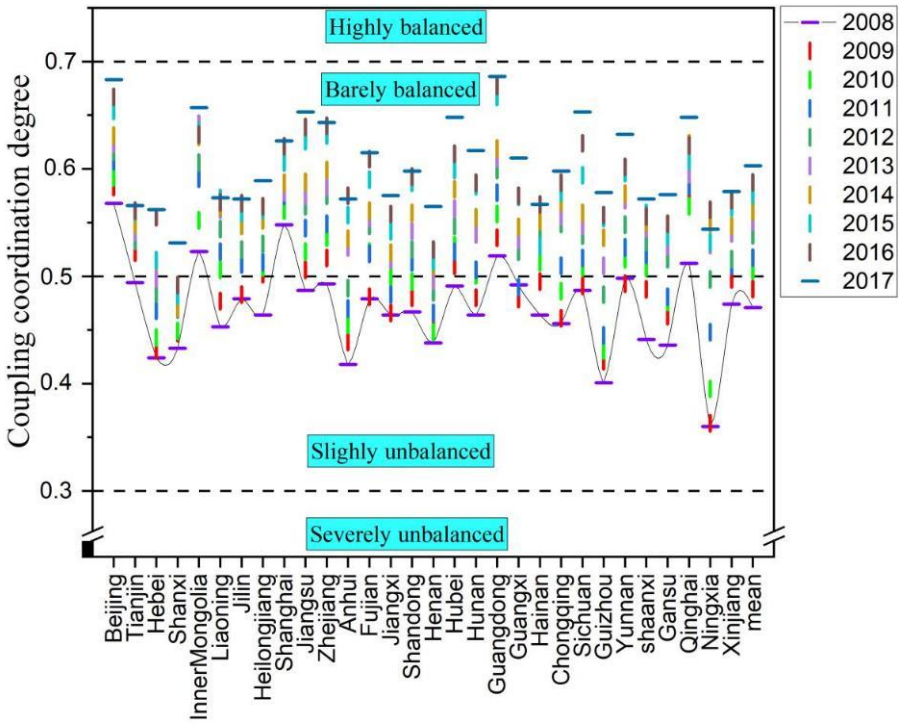


**Fig. 3** The coupling coordination degree between China's mitigation and adaptation from 2008 to 2017

### 3.4 Coordinated trends in the mitigation and adaptation systems

In this section, we focus on investigating the integration of mitigation and adaptation systems. As shown in Fig. 3, there is a significant upward trend in the coordination degree between mitigation and adaptation systems in China. The mean value rose from 0.471 in 2008 to 0.603 in 2017, an increase of over 28%, which means that most provinces in China have achieved a leap from a slightly imbalanced stage to a barely balanced stage. In 2008, the coupling coordination degree exceeded 0.5 only in Beijing, Shanghai, Guangdong, Inner Mongolia and Ningxia, while in 2017, the coupling between the mitigation and adaptation systems in all provinces reached a barely balanced stage.

These results confirm that China has achieved basic coordination between mitigation and adaptation systems, while there are large regional differences in terms of coordination development. As shown in Fig. 4, the coordination degree of most provinces was between 0.5 and 0.6. Only a handful of provinces with both higher development stages and environmental quality scored higher than 0.6, such as Beijing, Guangdong and Inner Mongolia. Meanwhile, there were still some provinces with a lower degree of coordinated development, such as Hebei, Shanxi, Henan, Ningxia and Guizhou.

By and large, China's eastern provinces scored highest in coordinated development, followed by its western provinces, while provinces in central China had the lowest degree of coordinated development. This is mainly due to the rich mineral resources and convenient transportation in the

central provinces of China, which has concentrated a large number of energy-intensive industrial enterprises. This yields a strong demand for energy consumption and greenhouse gas emissions, which are sources of anthropocentric climate change. At the same time, the central provinces also concentrate crowds, buildings, and infrastructure, making them more vulnerable to climate risk.

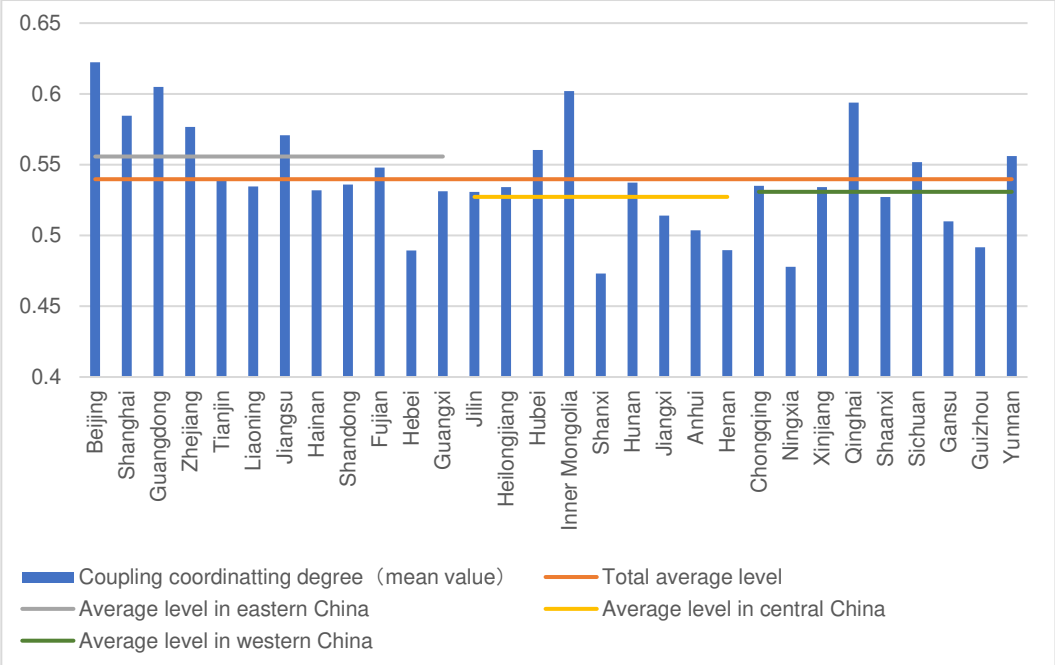


**Fig. 4** The coupling coordination development in different regions

To determine the reasons for the non-ideal coordinated development between mitigation and adaptation, Fig. 5 shows the spatial distribution of mitigation system evaluation and adaptation system evaluation values (mean value). Most of the provinces showed unbalanced development between the mitigation and adaptation systems. All 30 provinces performed better for the mitigation system than for the adaptation system, mainly because successful policy entrepreneurs have been reframing mitigation as an issue of local importance by linking it with economic imperatives within visions of green or low-carbon development. In addition, under international pressure to reduce greenhouse gas emissions, Chinese policy makers have long invested attention in how to control and mitigate greenhouse gas emissions to achieve INDCs rather than adapt to diversified climate risks. As a consequence, local adaptation policies often lag behind mitigation policies.

Moreover, there is strong consistency between the distribution of the degree of coordinated development and the AEVs. The provinces with a higher coordination degree tended to score higher in the adaptation system, while provinces with a lower coordination degree were usually characterized by a low adaptation system evaluation value or by low mitigation and adaptation system evaluation values, e.g., Ningxia and Shanxi, which have a high proportion of energy-intensive industries, a relatively fragile eco-environment and relatively lagging environmental infrastructure construction. This is

indicative of the fact that although the AEV and MEV both play a positive role in improving the coordination degree, the AEV is a more critical factor in determining the trend in coordinated regional development.

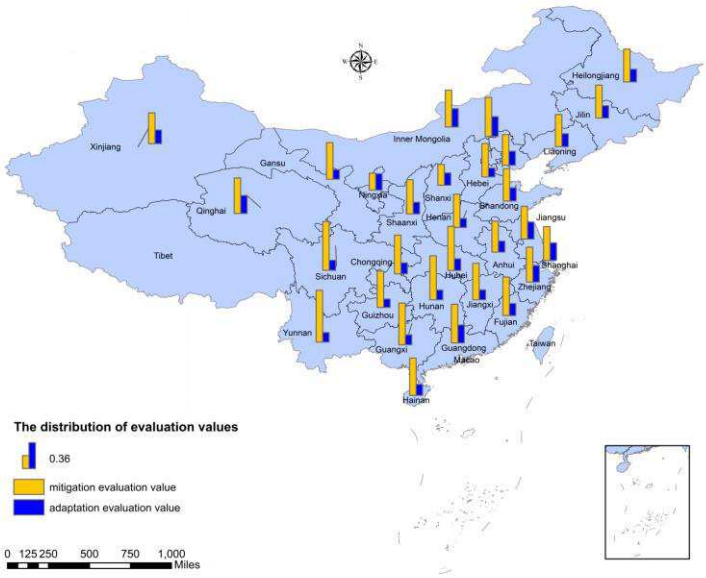


**Fig. 5** Distribution of the MEV and AEV in China

## 4 Conclusions and discussion

With rapidly emerging and escalating climate change risks, both mitigation and adaptation to climate disasters are inevitable for sustainable development. Unlike previous studies that only discussed the relationship, this article attempted to employ a panel vector autoregression model to examine the interactive relationships between mitigation and adaptation in China. Bidirectional Granger causality was observed between mitigation and adaptation in China, and the positive impact of mitigation on adaptation was greater than the negative impact of adaptation on mitigation, which means that a combination of the strategies is a better option than individual adaptation or mitigation actions for reducing climate change damage.

In view of the differences in natural conditions, climate change awareness, policies, etc., there is no single answer to the coordinated development of mitigation and adaptation for different region. So the another contribution of this article is an empirical research investigating the integration of mitigation and adaptation in China. This provide some meaningful analysis and policy recommendations for China, even for other regions with high climate vulnerability and large greenhouse gas emissions, in how to achieve both mitigation and adaptation goals through limited resources.

It is worth noting that there are some uncertainties regarding the priorities of climate policy in this work. The empirical findings of our study indicate that the impact of mitigation on adaptation is greater

than the impact of adaptation on mitigation, which suggests that mitigation action may matter more to climate policy than adaptation. However, almost all provinces performed better on the mitigation system than on the adaptation system, and there is stronger consistency between the coupling coordination degree and the AEVs, which means that adaptation may be a more significant obstacle to climate risks in China. These results make it hard for government policymakers to ascertain the priorities of climate policy. Further research is needed to quantify the contribution of mitigation and adaptation to synergy.

The provinces under investigation vary considerably in their size, population, GDP, etc. Although the study explored the dynamic interrelationship between adaptation and mitigation in China, it would also be worthwhile to examine whether there is heterogeneity in the interrelation between mitigation and adaptation among regions of China. Given that each province has a different location, infrastructure, governance, resources and society, further research is needed to formulate targeted regional climate change policies.

While the study found that adaptation may matter more to coordinated development than mitigation, further research is needed to ascertain whether other factors not measured here, such as institutional pressures (Daddi et al. 2019) and perception of local climate hazards (Lee and Hughes 2017), might play an important role in driving integration. In this context, further research on influencing factors is needed to explore the opportunities and challenges of integrating adaptation and mitigation in climate change action planning and implementation.

**Declarations**

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**Conflicts of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

**Availability of data and material:** The datasets used or analysed during the current study are available from the corresponding author on reasonable request.

**Code availability:** The code used during the study were provided by a third party. Direct requests for these materials may be made to the provider as indicated in the Acknowledgments.

**Authors' contributions:** All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Miao-miao Chen, Yixuan Li and Xinxiao Shao. The first draft of the manuscript was written by Huiqin Jiang and Miao-miao Chen, and was reviewed and edited by Jianqiang Bao. The funding was acquired by Huiqin Jiang. All authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

**Appendix**

Weight of the indicators

| Indicator | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 |
|---|---|---|---|---|---|---|---|---|---|---|
| the ratio of the added value of second industry to the regional GDP | 0.1125 | 0.1287 | 0.1289 | 0.1305 | 0.1227 | 0.1304 | 0.1343 | 0.1463 | 0.1478 | 0.1396 |
| The proportion of thermal power generation in electricity generation | 0.2544 | 0.2297 | 0.2048 | 0.1941 | 0.219 | 0.231 | 0.2145 | 0.2075 | 0.1819 | 0.1796 |
| CO2 emissions per 10,000 yuan of real GDP | 0.1938 | 0.1949 | 0.2074 | 0.2075 | 0.2211 | 0.1848 | 0.1713 | 0.1711 | 0.1568 | 0.1785 |
| Energy Consumption per 10,000 yuan of real GDP | 0.2053 | 0.2113 | 0.2161 | 0.2512 | 0.2501 | 0.2761 | 0.2611 | 0.2519 | 0.2433 | 0.2295 |
| Proportion of forest area | 0.234 | 0.2354 | 0.2428 | 0.2167 | 0.1871 | 0.1777 | 0.2187 | 0.2232 | 0.2703 | 0.2728 |
| Per capita freshwater resources availability | 0.1009 | 0.147 | 0.127 | 0.1549 | 0.1534 | 0.1447 | 0.1611 | 0.1487 | 0.1328 | 0.1617 |
| Percentage of natural wetland coverage | 0.1149 | 0.1366 | 0.1529 | 0.161 | 0.1678 | 0.182 | 0.1754 | 0.1878 | 0.1817 | 0.1825 |
| Per capita output of grain | 0.0375 | 0.0423 | 0.0551 | 0.064 | 0.0683 | 0.077 | 0.0765 | 0.0837 | 0.0808 | 0.1 |
| Investment in the treatment of industrial pollution control to regional GDP ratio | 0.0546 | 0.0579 | 0.0743 | 0.0592 | 0.0781 | 0.0747 | 0.0909 | 0.0538 | 0.1158 | 0.086 |
| Power supply per capita | 0.0732 | 0.0838 | 0.0832 | 0.0954 | 0.0997 | 0.0989 | 0.0968 | 0.1012 | 0.0906 | 0.1013 |
| Per capita freight traffic | 0.0588 | 0.0598 | 0.0539 | 0.051 | 0.0479 | 0.0501 | 0.0464 | 0.0495 | 0.0465 | 0.0442 |
| Per capita regional GDP | 0.0616 | 0.0642 | 0.0496 | 0.0414 | 0.0377 | 0.0359 | 0.0328 | 0.0355 | 0.0353 | 0.0346 |
| Unemployment rate | 0.0367 | 0.0429 | 0.045 | 0.0415 | 0.0332 | 0.0387 | 0.0363 | 0.0396 | 0.0373 | 0.0305 |

# Figures

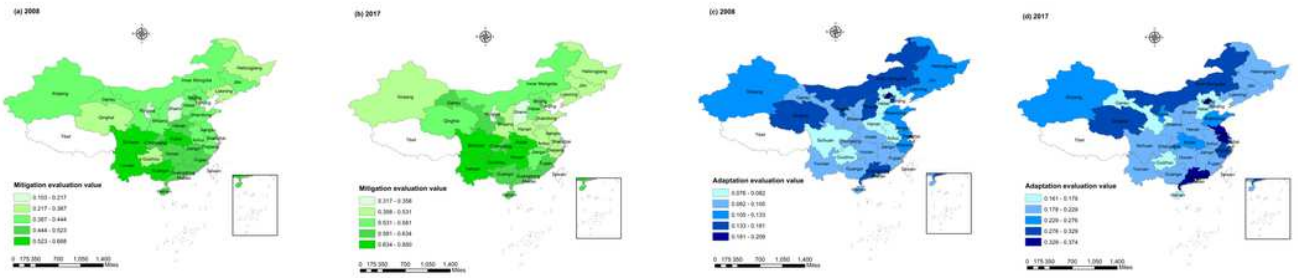


**Figure 1**

Distribution of China's MEV and AEV in 2008 and 2017 Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

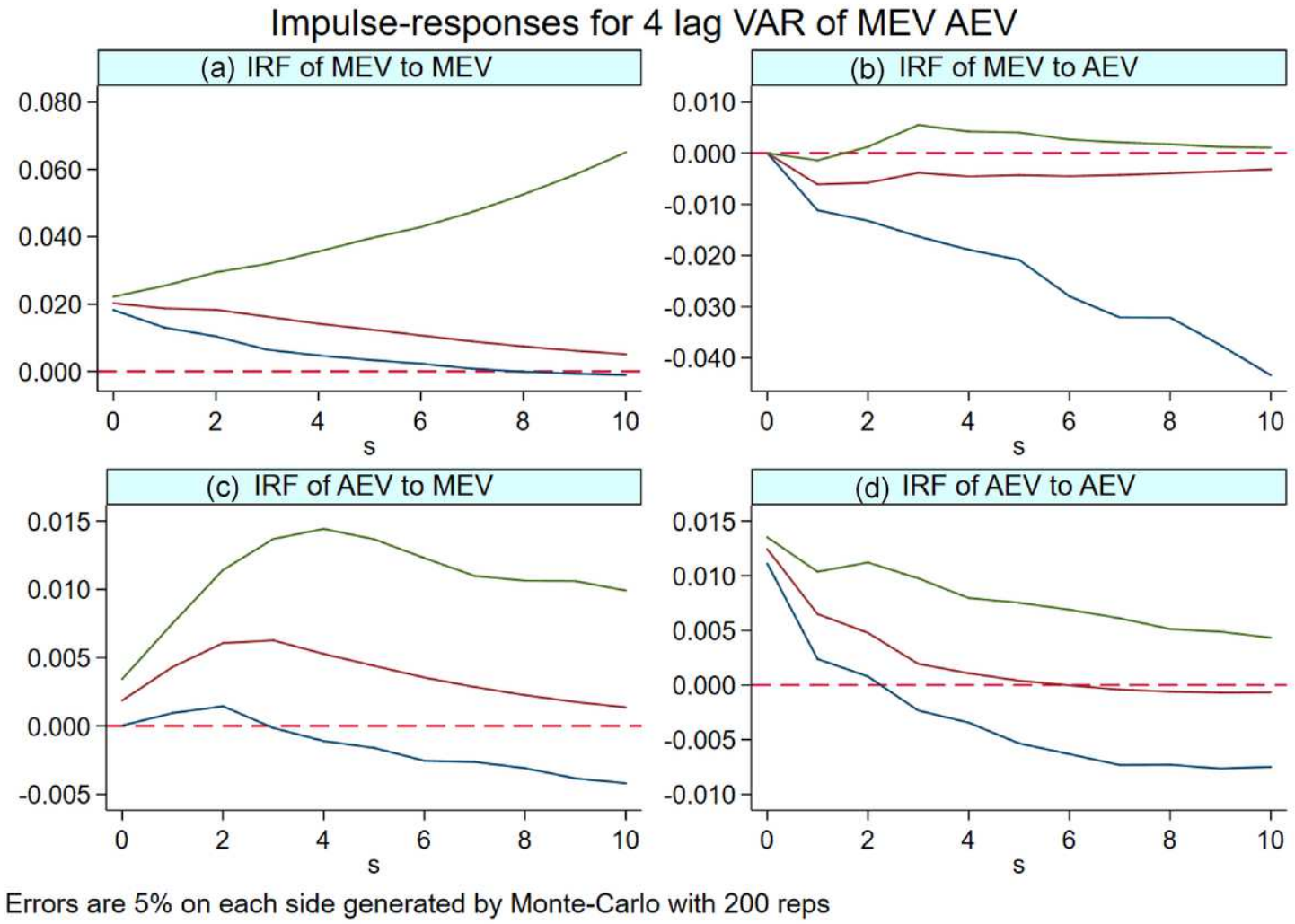


**Figure 2**

Results of impulse response between mitigation capacity and adaptive capacity

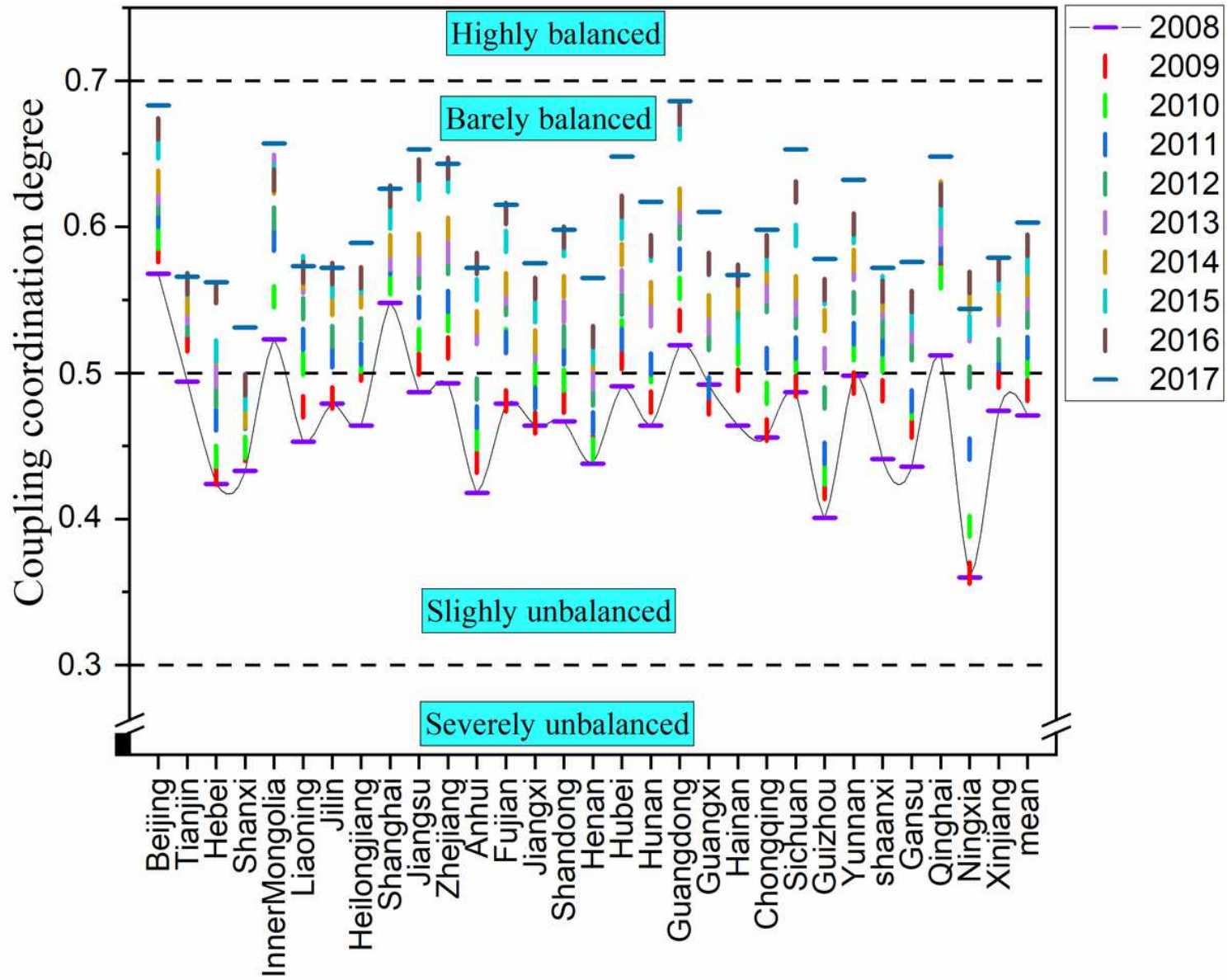



**Figure 3**

The coupling coordination degree between China's mitigation and adaptation from 2008 to 2017

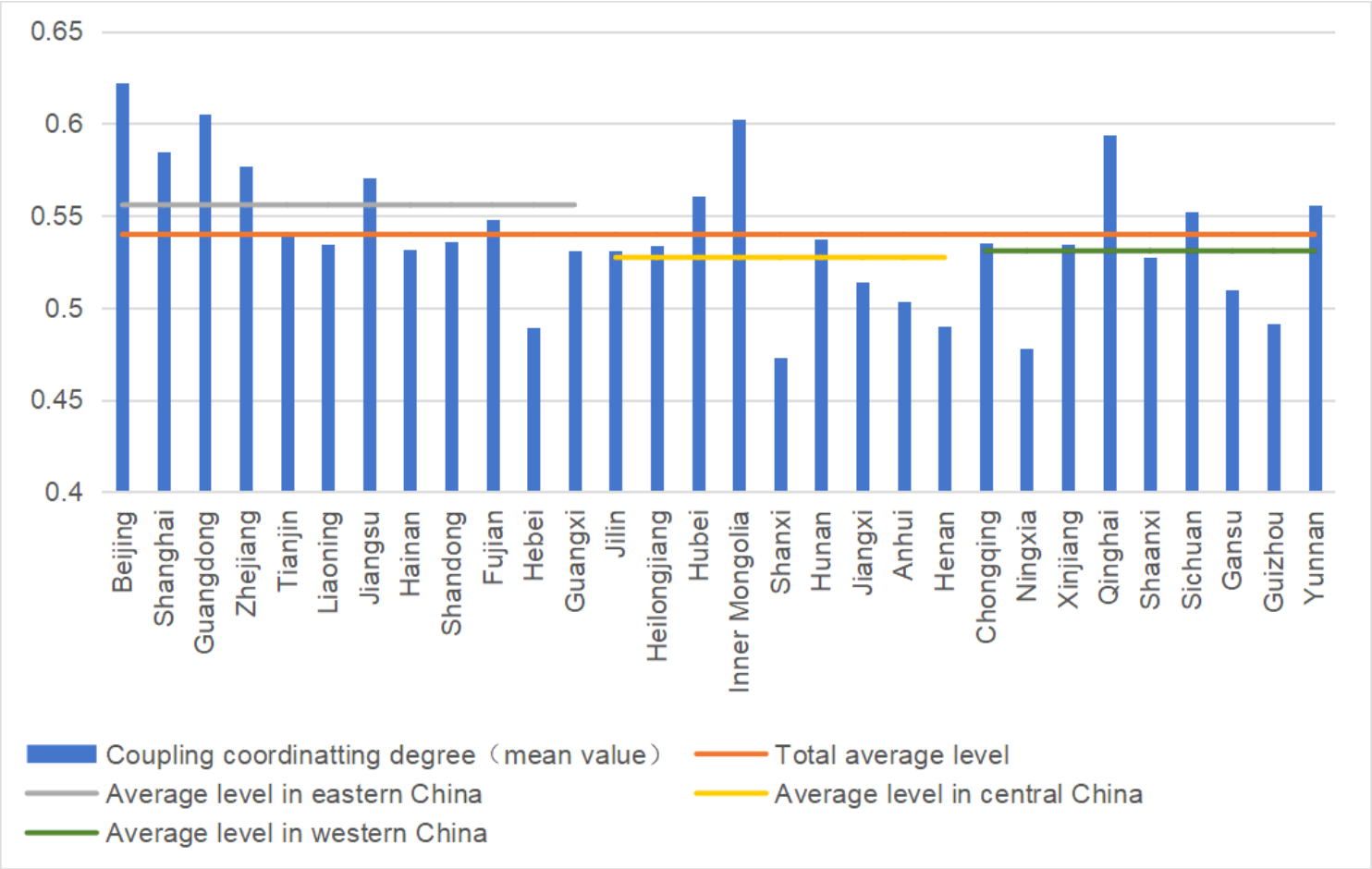
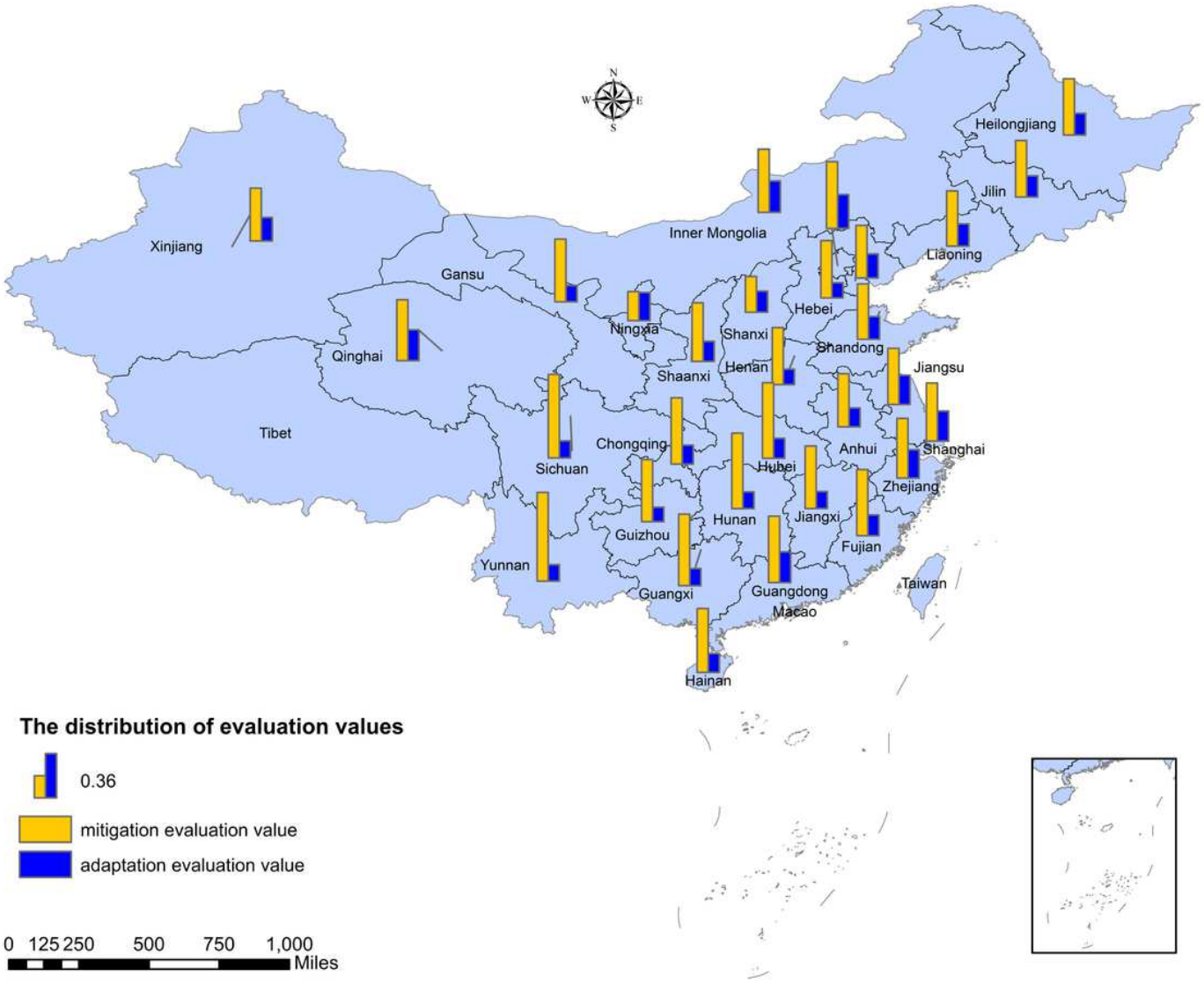



**Figure 4**

The coupling coordination development in different regions




## Figure 5

Distribution of the MEV and AEV in China Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.