China Economic Sensitivity to Weather Variability

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Abstract. Given the increasing global impacts of climate change and weather extremes on economies, understanding the sensitivity of economic output to weather variables has become crucial. This study investigates the influence of weather variables on the economic output of China across different sectors, provinces, and the whole nation, employing a modified Cobb-Douglas production function. The results reveal significant weather sensitivity across regions and sectors, ranging between 4.9%-12.8% for sectors, and 6.2%-27.7% for provinces. The highest sensitivity was observed in the Agriculture, Forestry, Animal Husbandry and Fishery (AFAHF) sector due to its direct dependence on weather patterns. Among provinces, Qinghai showed the highest sensitivity. The overall sensitivity of the Chinese economy to weather variables is approximately 5.87%, and the Chinese economy sensitivity to weather variables in 2022 is estimated at 7.1 trillion RMB. These findings stress the need for considering weather variability in economic planning and the importance of enhancing adaptation and resilience in highly sensitive sectors and regions.

Keywords: Economic Sectors; Sensitivity; Weather Variables; Cobb-Douglas production function

1 Introduction

Weather can directly or indirectly affect every economic sector at all spatio-temporal scales in China, both positively and negatively. For example, in terms of tourism, favorable weather can increase the pleasure of visitors, while bad weather events such as typhoons or heavy rainfall force tourism to be temporarily suspended. Similarly, weather can affect agriculture, i.e., fine weather can facilitate crop planting and harvesting, while extreme weather events such as droughts and floods can lead to a reduction in production and even crop failure. Traffic flow can also be affected positively or negatively by weather. When the weather is clear, traffic flow is relatively smooth, while snow and ice weather or foggy weather can easily result in traffic congestion or even accidents. However, current research tends to focus on the extreme weather events and their impacts on the economy rather than evaluating the

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overall impact of weather on the Chinese economy. To this end, this study presents a comprehensive quantitative analysis of the sensitivity of Chinese economy to weather variability.

The topics in current research on the sensitivity of economic output to changes in meteorological conditions can be roughly divided into five categories: 1) analysis of the sensitivity of specific economic sectors to meteorological factors, mainly focusing on assessing the impact of meteorological factors on agricultural output [1-4]; 2) analysis of the impact of specific meteorological conditions, especially meteorological disaster events, on economic sectors [5-8]; 3) the impact of long-term climate change on eco-nomic growth [9,10]; 4) using qualitative or semi-qualitative methods to assess the sensitivity of economic sectors to meteorological factors [11,12]; 5) quantitative analysis of the sensitivity of economic sectors to meteorological factors [13-17]. Fewer of this prior work examined the sensitivity of the Chinese economy to the weather variability.

Recent studies have continued to explore the relationship between meteorological conditions and economic performance in various regions worldwide [18,19]. These findings emphasize the importance of understanding and mitigating the potential impacts of weather and climate changes on the economy, particularly considering the increasing prevalence of extreme weather events attributed to climate change [20,21].

However, few studies have been carried out by using a quantitative method to assess the sensitivity of China's economic sector output to meteorological factors, and previous studies mainly focused on the period before 2010. Since 2010, China's socio-economic development and meteorological climate characteristics have undergone certain changes, making it increasingly important to study the impact of weather variables on the output of economic sectors during this period. With the changes in China's socio-economic landscape and weather characteristics, past studies may not accurately reflect the current situation. Hence, this study employs a widely accepted econometric model to examine the sensitivity of China economic output to weather variability by using the latest data.

The remainder of this paper is organized as follows. Section 2 introduces the data and methods used in this study. Section 3 shows the results, including the sectors related to weather based on Delphi method and weather-sensitive economic output based on C-D production function. Finally, the main findings are summarized in Section 4.

2 Materials and Methods

2.1 Data

The socio-economic data used in this study are derived from the "China Statistical Yearbook", mainly including GDP, employment (L), and fixed asset investment (K) values for 31 provinces and eight sectors in China over 23 years from 1998 to 2020. These eight sectors consisted of agriculture, forestry, animal husbandry, and fishery (AFAHF), industry, construction, transportation, warehouse and postal services (TWP), wholesale and retail trade (WRT), accommodation and catering (ACC), finance and insurance, and real estate. To mitigate the impact of inflation, we adjusted the GDP and the fixed asset investment using the Consumer Price Index (CPI) published in the “China Statistical Yearbook” based on the current purchasing power (the base year for purchasing power is 2020).

The meteorological data used in this research were obtained from the China Meteorological Data Service Center, mainly including daily average temperature and precipitation meteorological elements for 2600 stations in 31 provinces over a 34-year period from 1987 to 2020. In order to assess the impacts of meteorological variables on China's GDP, it is necessary to comprehensively consider meteorological elements that contribute to all eight sectors. Consequently, temperature and precipitation, which are broadly representative, are chosen for this study [14].

In terms of temperature, we mainly selected the heating degree day (HDD) and cooling degree day (CDD) indexes (Eq. (1) and Eq.(2)). For precipitation, we select the total annual precipitation (Ptota) and standard deviation of precipitation in a year (Pst).

$$\mathrm{HDD} = {}_{i=1}^{365}(18 - T_{\mathrm{mean}(i)}) \tag{1}$$

$$\mathrm{CDD} = {}_{i=1}^{365}(T_{\mathrm{mean}(i)} - 18) \tag{2}$$

where HDD represents the accumulated value of daily average temperature below 18°C in a year. It’s assumed that additional heating is immediately provided when the temperature is below 18°C to keep the temperature in the most comfortable range for business activities. CDD represents the accumulated value of daily average temperature above 18°C in a year. It’s assumed that cooling is immediately provided when the temperature is above 18°C to keep the temperature in the most comfortable range for business activities.

2.2 Delphi Method

The Delphi method is a well-established decision-making technique that entails soliciting expert opinions through a series of iterative consultations and providing feedback based on statistical results to achieve consensus and tackle complex issues [22–24]. In this study, the Delphi method was employed to assess the potential impact of weather and climate on the output value of China's national economic industries and their respective subsectors. A panel of 30 experts was assembled, and the members are from prestigious institutions such as the Chinese Academy of Social Sciences, the University of Chinese Academy of Sciences, Tsinghua University, Beijing Normal University, Shanghai Normal University, and the China Meteorological Administration. These experts possessed extensive expertise and knowledge across various disciplines, including climatology, meteorology, and economics.

A comprehensive questionnaire was developed to elicit the experts' opinions on the potential influence of weather and climate changes on the output value of industries and subsectors. These opinions were collected through organized meetings or written consultations. If the sector's output value is deemed likely to be affected, the associated percentage of the sector's output value is classified as 100% weather-related; otherwise, it is zero [12]. By aggregating the weather-related output values for all industries, the study aims to determine the total output value of China's industries in relation to weather and climate factors.

2.3 Cobb-Douglas Production Function

The Cobb-Douglas (C-D) production function is the most widely used empirical macroeconomic model in current economics, which is widely adopted to analyze the impact of a particular factor on economic output [25]. The early classic C-D function only considered the relationships of labor and capital inputs with output. After years of research practice, numerous scholars have made various modifications to the C-D function as the basic macroeconomic model, adding new variables to study the impact of other factor inputs on output [26]. However, this C-D function still has some deficiencies, such as the inability to capture the interaction between input factors. In order to better evaluate the impact of meteorological factors on economic output, the quadratic and cross terms of input factors are added to improve C-D function [14]. By adding the quadratic and cross terms, the C-D function can capture the non-linear relationship, alternative relationship, and synergistic relationships among different variables, thus improving the accuracy of the model fitting. Therefore, this study uses this model to evaluate the impacts of meteorological factors on economic output in Eq.(3).

$$\begin{aligned}\ln(Q) = {} & \ln(A) + \beta_L \ln(L) + \beta_K \ln(K) + \sum_{i=1}^{n} \beta_{W_i} \ln(W_i) + \frac{1}{2}\beta_{LL} \ln(L)\ln(L) + \\ & \frac{1}{2}\beta_{KK} \ln(K)\ln(K) + \frac{1}{2}\beta_{KL} \ln(K)\ln(L) + \\ & \frac{1}{2}\sum_{i=1}^{n} \beta_{W_iW_i} \ln(W_i)\ln(W_i) + \frac{1}{2}\sum_{i=1}^{n} \beta_{W_iW_{i+1}} \ln(W_i)\ln(W_{i+1}) + \varepsilon\end{aligned} \tag{3}$$

Where Q represents output, L labor input, K capital input, W four meteorological indicators (HDD, CDD, Ptota, Pst), and A a constant. β_L, β_K, and β_w and etc. are elasticity coefficients, representing the sensitivity coefficients of labor L, capital K, and meteorological factor W to the corresponding changes in the explanatory variables of eco-nomic output Q, respectively.

In order to quantitatively analyze the impact of meteorological variables on various regions and sectors in China, we established a panel random-effects model for the economic and meteorological data of 31 provinces from 1998 to 2020. Then, we estimated the model parameters separately for the GDP in eight sectors and obtained eight sets of the regression results of the panel data model (Table 1).

The econometric model developed in this study demonstrates high accuracy across sectors, with R-squared values generally exceeding 0.9 when compared with real GDP. Particularly, the sectors of AFAHF, Industry, Real Estate, and TWP show outstanding fit with R-squared values over 0.95 (Table 1). This indicates the model's strong fitting ability and accuracy in predicting economic output across different sectors.

Table 1. Parameter estimates from the Cobb-Douglas function of different sector models.

Variable Name	AFAHF	Real estate	Industry	Construction	TWP	Finance and insurance	WRT	ACC
(ln(K))	0.06**	0.64***	0.76***	0.35***	0.44***	0.06	0.64***	0.34***
(ln(L))	-0.51***	0.25*	-0.27*	1.31**	-0.31***	3.79***	-0.19*	0.22**
(ln(HDD))	-2.18**	-4.14**	-0.53	-5.10**	-0.72	0.18	-2.69	2.79
(ln(CDD))	-2.16***	-4.43***	-0.68	-5.04**	-0.73	-2.09	-2.49	2.39
(ln(Ptota))	-0.30	-0.32	0.79	-1.87	-0.45	-0.99	-4.22	-2.55
(ln(Pst))	-0.14	0.84	1.21	0.19	1.18	-0.74	3.65**	1.46
ln(K)*ln(K)	0.01***	-0.01	0.01	0.03***	0.01	0.03***	-0.01	0.03***
ln(L)*ln(L)	0.01	0.09***	0.10***	0.02	0.07***	-0.38***	0.09***	0.11***
ln(K)*ln(L)	0.06***	-0.02	-0.05***	-0.14***	0.00	0.02	-0.01	-0.07***
ln(HDD)*ln(HDD)	0.03	0.03	0.03	0.10*	0.03**	-0.08	-0.02	-0.07*
ln(CDD)*ln(CDD)	-0.01	0.07***	0.04***	0.09***	0.02	0.05*	0.06***	0.03
ln(Ptota)*ln(Ptota)	-0.08	0.15*	0.17**	-0.09	0.13	0.09**	0.19	0.32*
ln(Pst)*ln(Pst)	0.06**	0.19	0.15	0.37*	0.01*	0.27*	0.38**	0.39***
ln(HDD)*ln(CDD)	0.19**	0.48***	0.15**	0.29	0.07**	0.11*	0.19	-0.36**
ln(HDD)*ln(Ptota)	0.08*	-0.01	-0.11	0.25**	-0.03	-0.03	0.29*	0.04
ln(HDD)*ln(Pst)	-0.02	0.01*	-0.04	0.02	-0.01	0.02	-0.19*	0.04*
ln(CDD)*ln(Ptota)	0.10	-0.01	-0.14*	0.43**	-0.03	0.16*	0.23*	0.12
ln(CDD)*ln(Pst)	-0.05	0.03	0.04	-0.13	0.06*	0.02	-0.19*	-0.04
ln(Ptota)*ln(Pst)	0.03	-0.37	-0.34*	-0.36	-0.22	-0.27	-0.57*	-0.69**
Constants	24.73***	31.83**	1.63	40.18*	8.24	8.34	28.87*	11.37
Observations	713	698	713	713	713	713	713	713
R-squared	0.98	0.97	0.98	0.84	0.96	0.92	0.94	0.94

Note： “***” represents that the corresponding value passes the significance test at a significance level of less than 1%,“**” indicates that the corresponding value passes the significance test at a significance level of less than 5%, and “*” denotes that the corresponding value passes the significance test at a significance level of less than 10%.

“AFAHF” represents agriculture, forestry, animal husbandry and fishery, ‘’TWP’’ transportation, warehouse and postal services, ‘’WRT’’ wholesale and retail trade, ‘’ACC’’ accommodation and catering, "K" fixed asset investment, "L" employment, "HDD" heating degree day index, "CDD" cooling degree day index, "Ptota" annual total precipitation, and "Pst" the standard deviation of precipitation in a year.

3 Results

3.1 The Sectors Related to the Weather and Climate

Based on the Delphi method, we obtained a table (Table 2) showing the sector output related to weather and climate in China. The first two columns present the major categories of the gross domestic product (GDP) and their respective contributions. The third column indicates sectors that are, to some extent, related to events and changes of weather and climate. The results suggest that about two-fifths of sectors economic output, representing an annual revenue of approximately RMB 47 trillion, are related to weather and climate to some extent. The sectors that are most susceptible to the impacts of weather and climate changes are the AFAHF, construction, TWP, real estate, and ACC (Table 2).

Table 2. Sectors related to weather and climate in China

Sectors	**GDP Composition (RMB Trillions)**	**GDP composition related to weather and climate (RMB Trillions)**
AFAHF	**8.14**	**8.14**
Agriculture	4.47	4.47
Forestry	0.37	0.37
Animal husbandry	2.51	2.51
Fishery	0.79	0.79
Industry	**31.29**	**4.65**
Manufacturing	26.64	—
Mining	2.54	2.54
Production and supply of electricity, heat, gas, and water	2.11	2.11
Construction	**7.24**	**7.24**
TWP	**4.06**	**4.06**
Finance	**8.36**	**1.15**
Financial securities and others	7.21	—
Insurance	1.15	1.15
Real estate	**7.34**	**7.34**
WRT	**9.61**	**4.08**
Wholesale	5.53	—
Retail	4.08	4.08
ACC	**1.52**	**1.52**

Others	**23.84**	**3.66**
Information transmission, software and information technology services	3.82	—
Leasing and business services	3.24	—
Tourism	3.66	3.66
Health and social work	2.62	—
Scientific research and technology services	2.23	—
Others	8.27	—
Gross Domestic Product (GDP)	**114.4**	**47.20**
Weather-related production value as a percentage of the GDP	**41.26%**	

Note: The data in the table come from the 2021 value-added data of various industries released by the National Bureau of Statistics of China, the official websites of the major ministries, and related research reports. Due to the inconsistency in the statistical standard among different reports, there may be slight differences in the related data. Nonetheless, these differences do not affect the overall validity of our analyses.

3.2 Economic Sensitive to Weather

To quantitatively analyze the impact of meteorological factors on the output value of various sectors in China, we calculate the sensitivity of economic activities of eight sectors across 31 provinces to weather variables. Non-meteorological factors, namely capital and labor, are fixed to the average values in each province and sectors from 2016 to 2020 as the baseline data to control potential annual distortions, which also represents a relatively stable state of socio-economic development at the current level. By keeping K and L at their average levels during 2016-2020 and assuming the same scientific and technological level as in 2020, the changes in the gross state product (GSP) of provinces and sectors can be fully attributed to weather change because non-meteorological factors are controlled. The GSP is a measurement of the economic output of a province, and the sectoral GSP for a sector is a measurement of the economic output of a sector at the national level.

The observational weather data of the HDD, CDD, Ptota, and Pst are collected for 34 years (1987-2020). These data are inputted into the verified C-D function model (Eq.(3) and coefficients in Table 1) to obtain the fitted values of the GSP of each sector. Then, we examine these fitted values to identify the variability of the GSP due to weather variability. This process is carried out through three distinct aggregations. One is to assess sectoral sensitivity across 31 provinces. The second is to assess provincial sensitivity across eight sectors. The third is to gauge overall sensitivity across eight sectors and 31 provinces. This three-tiered analysis enables a comprehensive under-standing of how changes in weather conditions affect China's economic productivity at various geographical and sectoral levels.

3.2.1 Sectoral Sensitivity to Weather.

The coefficient of variation shown in Table 3 is a dimensionless metric denoting the variability of output around its mean. This coefficient ranges from 0.017 for the Real Estate sector to 0.039 for the WRT sector, indicating that in most cases, variability level around the mean is quite low. Given that 95% of observations typically fall within two standard deviations of the mean, we predict that the economic output will hover around 3.4% of the average for sectors akin to Real Estate. Similarly, for the WRT sector, the output is anticipated to be within 7.8% of the average GSP for 95% of the time.

The fifth and sixth columns of Table 3 is the maximum and minimum fitted sectoral GSP for each province. The corresponding years when these values were recorded are denoted in parentheses for each sector. The ranges in Table 3 indicate the difference between the maximum and minimum values of the 34-year simulations. The absolute difference spans from RMB 136 billion in the ACC sector to RMB 2227 billion in the Industrial sector. The column of the range rank in the table denotes the ranking of sectors in terms of their absolute sensitivity to weather variability. Sectors with a higher GSP, such as the Industrial sector, AFAHF, WRT, and the Financial and Insurance sector exhibit relatively high absolute sensitivity. Their absolute sensitivity to weather variability exceeds RMB 500 billion. In previous studies, the discussions on weather sensitivity were rarely extended to these sectors, except for the AFAHF.

The percentage range refers to, the range divided by the average, to facilitate the comparison of the relative impact across sectors. According to the Table 3, sectors are ranked based on the percentage range in descending order as follows: AFAHF, ACC, WRT, TWP, Industry, Finance and Insurance, Real Estate, and Construction. Despite the high absolute weather sensitivity of Industry (RMB 2227 billion, ranking first), and Finance and Insurance sectors ((RMB 571.4 billion, ranking fourth), their proportions of absolute output sensitive to weather rank are relatively low among all sectors (at 7.9% and 7.1%, ranking fifth and sixth, respectively). As expected, the AFAHF (the sector that has studied the weather impact on specific production the most), is one of the most sensitive sectors at 12.8%. Most of the activities in the AFAHF sector rely directly on weather patterns. For example, crops require specific conditions to grow, which include adequate sunlight, rainfall, and specific temperature ranges. These conditions can vary considerably due to weather variable, directly impacting production and long-term decision-making [27]. Additionally, activities within the AFAHF sector, such as forestry and animal husbandry, have relatively long production cycles. It means that they are exposed to weather variability over a long period, which increases their overall sensitivity [2,28].

Table 3 illustrates that the ACC sector ranks second regarding weather sensitivity, and the WRT sector ranks third. The Construction sector demonstrates the lowest weather sensitivity at 4.9%. The sensitivity of each sector to weather is determined by the extent to which its business, consumer demand, and costs are influenced by weather variability. The ACC sector ranks second in terms of weather sensitivity, with a large part of its business depending on weather conditions, that directly influence consumer behavior. For instance, customers may be more willing to dine out or travel in favorable weather conditions, thereby increasing demand for this sector.

Conversely, bad weather can discourage customers, and lead to a decline in demand. Similarly, the WRT sector, ranking third in terms of weather sensitivity, displays a comparable pattern to the ACC sector. The WRT sector is significantly influenced by weather patterns, as weather can profoundly affect consumer purchasing behavior. For instance, sales of specific products surge during particular seasons, such as winter clothing during cold months or beach-related items during summer. Contrarily, the Construction sector shows the least weather sensitivity among these sectors, at a mere 4.9%. Construction projects indeed face potential delays due to adverse weather conditions such as heavy rainfall or snowfall. However, advanced planning, risk management techniques, and the application of technology allow this industry to better anticipate and mitigate weather-related disruptions [29]. Thus, compared with other sectors, the overall operations and profitability of the Construction sector are less affected by weather variables.

Table 3. Fitted sectoral weather sensitivity

Sector	2016-2020 actual average 31-province sectoral GDP (billion in a constant year of 2020) *	Fitted sectoral GSP** (RMB billions in constant year of 2020)							
		Average	Coefficient of variation	Maximum (year)	Minimum (year)	Range	Range Rank	Percent Range	Percent Range Rank
AFAHF	7317.4	5190.4	0.021	5596.6 (1998)	4932.2 (1989)	664.4	2	12.8%	1
ACC	1669.9	1209.0	0.027	1279.7 (2018)	1143.7 (1992)	136. 0	8	11.3%	2
WRT	9113.6	6424.7	0.039	6779.4 (2007)	6132.9 (1992)	646.5	3	10.1%	3
TWP	4087.7	3377.4	0.026	3533.1 (2013)	3214.6 (1993)	318.5	6	9.4%	4
Industry	30762.5	27879.0	0.020	28938 (2013)	26711 (1993)	2227	1	7.9%	5
Finance and Insurance	7338.0	8058.9	0.032	8418.7 (2002)	7847.3 (2012)	571.4	4	7.1%	6
Real Estate	6557.7	5429.8	0.017	5611.6 (2016)	5265.1 (2004)	346.5	5	6.4%	7
Construction	6635.2	4922.4	0.032	5138.8 (2005)	4897.8 (1989)	241.0	7	4.9%	8
Total Sectoral GDP	73482.2	62491.9							

* The actual GDP is a value adjusted by purchasing power, to remove the effect of price changes in the statistical series (base year of 2020).

**the GSP is the fitted sectoral GDP (31 provinces/34 years), and K and L are fixed and are the average values of each province from 2016 to 2020

3.2.2 Provincial Sensitivity to Weather.

To estimate the provincial GSP, we can sum across the 8 sectors for each province. The absolute difference ranges (maximum - minimum) and the percentage ranges (the absolute range divided by the average GSP) can be calculated to measure the economic sensitivity of each province. The results are presented in Figure 1.

The impacts of temperature and precipitation on the provincial GSP vary from province to province (Figure 1). The provinces with relatively large impacts are mainly: Qinghai, Xinjiang, Hainan, Ningxia, Shandong, and Tibet, with overall impacts ranging between 17% and 28%. The provinces with relatively smaller impacts are mainly: Fujian, Guangxi, Sichuan, Hubei and Guizhou.

In terms of percentage range, the most sensitive province is Qinghai, with a GSP variation of up to 27.68%, while the least sensitive province is Guizhou, with a GSP variation of 6.19%. Several factors could contribute to the varying sensitivity levels among provinces. Specifically, the provinces with more diverse climate and topography, such as Qinghai, may experience more weather variability, with higher sensitivity. The provinces with a higher reliance on weather-dependent sectors, such as agriculture or tourism, may also be more sensitive to weather variables. For instance, Hainan, with its strong focus on tourism, could be more susceptible to weather impacts. How-ever, provinces with more advanced infrastructure and technology might be better equipped to handle weather variability, reducing their sensitivity. Provinces that have implemented effective adaptation and mitigation measures in response to climate change may also experience lower sensitivity. For instance, Guizhou's low weather sensitivity can be attributed to its less weather-dependent industries like big data and electronics manufacturing, protective mountainous geography, mild subtropical climate, and government led economic diversification [30–32] .

Figure 1 illustrates the remarkable variance in the sensitivity of economic output to weather across Chinese provinces. A discernible trend is evident, where northern provinces are more susceptible to weather variables than their southern counterparts, and western provinces more so than those in the east, closely mirroring China's climate region divisions. This sensitivity is significantly tied to an intricate interplay of regional characteristics, including meteorological, geographic, and economic conditions.

Considering the latitudinal dimension, northern China's economic production, faced with less water, limited sunlight, and colder temperatures, is inherently more constrained by weather conditions and thus displays a higher degree of sensitivity compared to southern China. From a longitudinal perspective, China's topography divides it into three distinct regions: the eastern coastal, the central mountainous region, and the western plateau. The coastal and central regions, under the influence of a mild monsoon climate, present more favorable conditions for development, whereas the western region, with its challenging terrain comprising plateaus, glaciers, and deserts, is increasingly vulnerable to climate change impacts [33].

However, the provinces of Hainan and Shandong are notable exceptions within their respective regions, manifesting higher than average weather sensitivity. Both regions, although coastal and often affected by typhoons, have relatively simpler economic structures predominantly reliant on weather-sensitive industries compared to their coastal counterparts. Specifically, Hainan, a tropical island, anchors its economy largely on the tourism industry, which encompasses ACC, and the Transportation, WTP sectors. Shandong, known nationwide for its well-developed agriculture and industry, also exhibits significant weather sensitivity. The distinct features of these regions necessitate tailored strategies to mitigate potential weather-related impacts on their economies.

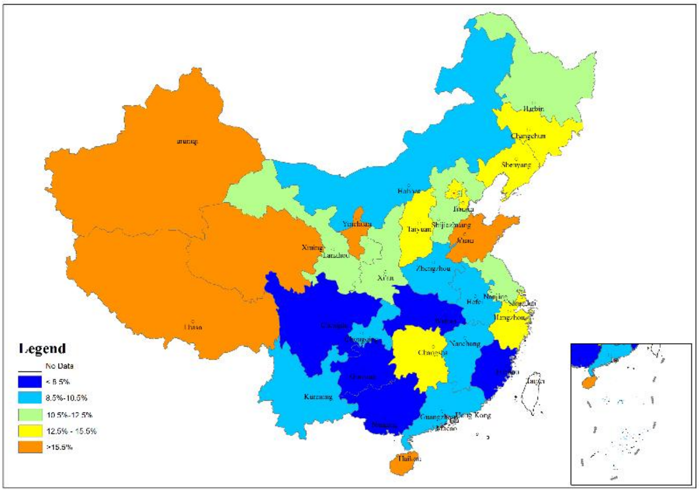

Fig. 1. Province sensitivity to weather variability as a percentage of GSP

3.2.3 National Sensitivity to Weather.

A comprehensive analysis is conducted on the sensitivity of the whole country to weather variability by collating the fitted values of all provinces and sectors derived from 34-year historical data. The results of this aggregation are presented in Table 4.

As indicated in the Table 4, the coefficient of variation for the aggregated national GDP is 0.0084. Considering the statistical norm where 95% of observations fall within two standard deviations of the mean. It can be inferred that the GDP varies less than ±1.68% of the mean for 95% of the time due to weather variability. Furthermore, Table 4 reveals a GDP range of RMB 4,945.51 billion, derived from the minimum total GDP of RMB 81,573.47 billion and the maximum of RMB 86,518.97 billion. This range equates to approximately 5.87% of the average total output of RMB 84,283.05 billion, representing a deviation of ±2.93% from the average. Notably, the range may be extended if the analysis encompasses more years that had markedly different weather conditions. For 2022, the total GDP in China is RMB 121.02 trillion, and the total weather sensitivity of the economy is about at RMB 7.1 trillion (5.87%, as shown in Table 4).

Moreover, Table 4 also illustrates an important aspect of national resilience to weather variability. The overall Chinese economy is less sensitive to weather than individual provinces and individual sectors because economic production can shift among provinces and sectors. As shown in Table 3, the maximum or minimum GSP generally appears in different years for different sectors or provinces, since the situation in an advantageous year for a sector or province may be offset by the situation in an unfavorable year for another [14]. National resilience to weather variability derives from the inherent diversity of geographic and economic characteristics in a country, particularly in a country as large and diverse as China. This can be attributed to regional and sectoral differences in weather patterns and their impacts on economic productivity. When the effect of weather on a nation's economy is assessed, these regional and sectoral differences can somewhat counterbalance each other, resulting in a reduction in sensitivity at the national level [34]. For instance, a severe drought event may negatively impact agricultural output in one province, while it can provide concurrently favorable conditions for solar energy production in another. Similarly, this drought event may have minimal impact on the manufacturing or service sectors in urban areas. As economic production shifts among provinces and sectors in response to these different conditions, the national economy displays greater resilience to weather variability [35]. The national resilience to weather variability also suggests potential adaptive strategies. Promoting economic diversification, enhancing cross-regional and cross-sectoral cooperation, and incorporating weather variability into economic strategies and policies can strengthen a nation's resilience.

Table 4. Overall sensitivity of China to weather

Measure	National GDP (RMB billions in a constant year of 2020)
Average	84283.05
Standard deviation	70.7
Coefficient of variation	0.0084
Maximum (2013)	86518.97
Minimum (1993)	81573.47
Absolute range	4945.51
Percent range	5.87%
2022 GDP (RMB billions in 2022)	121020.7
5.87% of the 2022 GDP (RMB billions in 2022)	7103.92

4 Conclusions

This study aims to comprehensively analyze the impact of weather variability on the economy of China, particularly for different sectors and provinces. Based on a quantitative analysis approach, the results reveal high sensitivity of China’s economy to weather variability in the studied sectors and provinces, and the ranges are between 4.9% and 12.8% for sectoral sensitivity and 6.2% to 27.7% for provincial sensitivity.

At the sectoral level, the AFAHF sector has the highest weather sensitivity since its activities are directly dependent on weather patterns. It's followed by the ACC, and WRT sector, where a large part of the businesses and consumer behavior is influenced by weather conditions. In contrast, the construction sector is the least sensitive to weather change, mainly due to effective risk management and the use of technology to predict and mitigate meteorological-related disruptions.

Regarding provinces, Qinghai is the most sensitive province with a GSP variation of up to 27.68%, while Guizhou is the least sensitive province with a GSP variation of 6.19%. Factors contributing to the varying sensitivity levels among provinces included the diversity of climate and topography, reliance on weather-dependent sectors, advanced infrastructure, technology, and effective climate change adaptation and mitigation measures.

At the national level, the overall sensitivity of China's economy to weather variables is found to be approximately 5.87% of the total output. The total weather sensitivity for China's economy in 2022 is estimated at RMB 7.1 trillion.

These findings underscore the importance of considering weather variability in economic planning and development strategies, and they also highlight the necessity of strengthening adaptation and resilience measures in sectors and regions with high weather sensitivity. Furthermore, given the likely increase in weather extremes due to climate change, this analysis provides a vital basis for decision-makers to develop informed strategies, in order to mitigate the economic impacts of such changes in the future. Future research could expand this analysis to specific sector and province, or apply the methodology to other countries for a global comparison of weather sensitivity to the economy.

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