Temporal–spatial decomposition of city-scale changes in sectoral CO2 emissions in southeast China

Yimin HUANG
Fujian Normal University

Yuan Wang (y.wang@fjnu.edu.cn)
Fujian Normal University

Yanmin He
Otemon Gakuin University

Lin Zhu
Nanjing Institute of Environmental Sciences

Wen-ting Lai
Fujian Normal University

Article

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Abstract

Carbon emissions are typically analyzed on a national scale. However, to achieve regional carbon reduction targets, research should be carried out at sub-provincial and municipal scales, and the driving forces of sectoral CO_2 emissions should be analyzed from a more disaggregated perspective. In this study, we apply temporal logarithmic mean Divisia index (LMDI) decomposition for exploring the factors influencing changes in city-scale energy-related CO_2 emissions across industry, transportation, and household sectors in Fujian Province during 2000–2017. Moreover, the spatial LMDI model is employed to investigate spatial discrepancies in the driving forces of CO_2 emissions among nine prefecture-level cities in 2000, 2005, 2010, 2015, and 2017. The results suggest that the magnitude of energy-related CO_2 emission changes in the industry sector was much higher than that in the transportation and household sectors in Fujian Province. Moreover, the income effect was the dominant factor leading to increased CO_2 emissions in the three sectors of each city. Conversely, the energy intensity effect was the primary factor responsible for the mitigation of CO_2 emissions in each city during 2000–2017, except in the transportation sector. The urbanization effect was another crucial factor contributing to increased CO_2 emissions in all sectors, whose contribution was greater in coastal cities than in non-coastal ones. Additionally, the energy intensity effect was the main factor responsible for the discrepancy in CO_2 emissions among cities. The findings of this study can be used to propose targeted policy recommendations for low-carbon development in Fujian Province.

Introduction

Rapid industrialization and urbanization worldwide has led to a significant increase in global energy consumption and carbon emissions [1,2]. The International Energy Agency (2021) predicted global energy-related CO_2 emissions of 33.622 billion tons for 2019, with China accounting for 9.92 billion tons (29.5%) of these emissions, marking it as the world's largest CO_2 emitter. Therefore, CO_2 emission control and low-carbon development have recently become urgent concerns in China. At the Copenhagen and Paris Climate Conferences, China pledged to reduce CO_2 emissions per unit of gross domestic product (GDP) by 40–45% in 2020 from the 2005 level, decrease CO_2 emission intensity by 60–65% in 2030 from the 2005 level, and reach peak CO_2 emissions by 2030. In this context, all provinces in China have proposed distinct emission reduction targets (e.g.[3–5]). However, current carbon emission research, which typically focuses on national and provincial levels, is not conducive to achieving regional carbon reduction targets. Therefore, the research scale should be extended to sub-provincial levels, and the factors influencing CO_2 emissions should be examined from a more disaggregated perspective. Moreover, investigating the spatial and temporal characteristics of carbon emissions and the spatial and temporal discrepancies in driving factors can help formulate more effective regional carbon emission reduction polices.

Decomposition analysis techniques, such as structural decomposition analysis and index decomposition analysis, are commonly used to analyze the driving factors of CO_2 emissions [6,7]. Structural decomposition analysis is mostly employed in national-scale research, whereas index decomposition analysis is universally adopted to analyze energy savings and emission reduction for single or multiple sectors in a given region. The logarithmic mean Divisia index (LMDI) is one of the most popular index decomposition analysis methods [8,9] because of its many advantages, including the absence of decomposition residuals, the aggregation of subsector effects to the same value as the total effects, and the ability to decompose and process datasets containing zero and negative values[10]. The LMDI model was proposed by Ang, et al. [11] for energy and environmental decomposition analysis,

and has since been widely applied to investigate temporal and spatial changes in energy consumption and carbon emissions.

Recent studies in this area can be divided into two main categories: those examining the drivers of CO_2 emission changes over time (temporal LMDI models) and those analyzing spatial differences in the factors influencing carbon emissions between regions (spatial LMDI models). For example, the temporal LMDI model has been applied to examine the drivers of CO_2 emission changes over time on a global scale [12], at the country level [13–15], on a provincial scale [16–18], for individual cities [19,20], and by sector [14,21–24]. Existing research has typically focused on the factors driving changes in carbon emissions from a single sector or all industry; therefore, comparative studies on emissions from different sectors are relatively lacking. The temporal LMDI model has also been applied to analyze differences and similarities between countries [12], provinces [25–27], and cities [22]); however, these comparisons were not quantitative. Therefore, additional methods have been employed to explore the spatial diversity of driving factors. For example, Wang and Feng [28] and Chang, et al. [29] combined the temporal LMDI model with the gravity model to analyze temporal and spatial variations in the drivers of energy-related CO_2 emissions among regions. Moreover, Wang and Feng [30] adopted the Shephard distance functions and temporal LMDI model to explore the driving forces of energy-related CO_2 emissions in China's construction industry. However, although these methods can elucidate the spatial relationships between the drivers of CO_2 emission changes, the quantitative relationships between drivers cannot be defined.

Ang, et al. [31] subsequently expanded the temporal LMDI method to propose a spatial LMDI approach, which included bilateral-regional, radial-regional, and multi-regional models to quantitatively compare the differences in driving forces across regions. This approach, which is static and only valid for the year of the analysis [32], has also been applied to study carbon emissions, mercury emissions [33], and water intensity [34]. A growing body of research has adopted this spatial LMDI approach to study spatial differences in the factors influencing carbon emissions between regions. For example, Roman-Colladoa and Morales-Carrion [35] investigated the driving forces behind the country-scale growth of CO_2 emissions in Latin America. Moreover, Liu, et al. [36] employed the spatial LMDI model to analyze the CO_2 emission performance rate for electricity generating units in 30 Chinese provinces. Li, et al. [37] then used both the temporal and spatial LMDI models to explore the factors influencing differences in CO_2 emissions among 30 provinces in China. Shi, et al. [38] explored the driving factors of CO_2 emissions from the household sector in China at both national and provincial scales. Moreover, Chen, et al. [39] divided China's 30 provinces into four regions, and investigated the factors influencing carbon intensity at regional and provincial levels.

However, decomposition analyses of the temporal and spatial dimensions of CO_2 emissions are typically performed at national and provincial scales, with very few empirical works conducted on the municipal scale. Moreover, the driving forces of CO_2 emissions are commonly categorized into four groups: energy structure, energy intensity, economy scale, and population effects. However, this classification neglects the likely impact of long-term urbanization on carbon emissions (Wang, et al. [1].

Therefore, in this study, we analyze the impact of urbanization on CO_2 emissions by employing the temporal–spatial LMDI model to compare energy-related CO_2 emissions from the industrial sector (ICEs), transportation sector (TCEs), and household sector (HCEs) in nine prefecture-level cities in Fujian Province, China. Fujian Province is the first provincial pilot demonstration zone of ecological civilization in China, encompassing the construction

and development of the West Coast Economic Zone, the core area of the Maritime Silk Road, and the Fujian Free Trade Zone. Therefore, nine prefecture-level cities within Fujian Province are selected as the basic study units for this research.

Results And Discussion

Energy-related CO_2 emissions in Fujian Province.

China has implemented several FYPs to set goals and directions for long-term economic development. As official data from 2018 to 2020 are not yet available, our study period covers 2000–2017. We chose 2000, 2005, 2010, 2015, and 2017 as five specific years to compare the spatial differences among nine prefecture-level cities in Fujian Province.

Total CO_2 emissions in Fujian during 2000–2017 are shown in Fig. 1. Total CO_2 emissions increased rapidly from 78.4 Mt to 432.11 Mt during the study period, with an average annual growth rate of 6.70%. During 2000–2005, CO_2 emissions increased from 143.2 Mt to 194.69 Mt, with an average annual growth rate of 6.34% (moderate rate). Between 2005 and 2010, CO_2 emissions increased more rapidly, with an annual growth rate of 11.41%. Slower growth in CO_2 emissions was observed from 2010 to 2015, with an average annual growth rate of 4.89%. Finally, during 2015–2017, CO_2 emissions increased only slightly and with fluctuations, with an average annual growth rate of 0.93%. The observed change in CO_2 emissions is related to the transformation of economic development patterns, with recent energy saving and emission reduction policies gradually achieving some success. CO_2 emissions from the industry sector accounted for 86.6% of total regional CO_2 emissions during this period. Therefore, this sector was the largest CO_2 emitter in Fujian Province, followed by the transportation sector, whose share in regional CO_2 emissions fluctuated slightly between 2.28% and 5.71% from 2000 to 2017. The third-largest CO_2 emitter was the household sector, which accounted for 4.22% of total CO_2 emissions during 2000–2017. The influence of other sectors on total CO_2 emissions in Fujian Province was negligible so will not be discussed further in this paper.

Figure 2 presents the energy-related CO_2 emissions of nine cities in 2000, 2005, 2010, 2015, and 2017. Most cities showed growing trends in CO_2 emissions in all years, except for Longyan City from 2010 to 2017 (12th and 13th FYPs) and Xiamen City from 2015 to 2017 (13th FYP), where CO_2 emissions decreased. Moreover, the average annual growth rates of CO_2 emissions in the nine cities were 15.06% (Ningde), 12.60% (Putian), 10.39% (Zhangzhou), 7.69% (Fuzhou), 6.70% (Quanzhou), 6.55% (Sanming), 3.77% (Xiamen), 3.23% (Longyan), and 2.11% (Nangping). In 2017, the two cities with the highest CO_2 emissions, i.e., Quanzhou and Fuzhou, were responsible for 39.22% and 16.61% of total CO_2 emissions, respectively. In comparison, all other cities accounted for less than 10% of total CO_2 emissions, i.e., 9.8% (Sanming), 9.16% (Zhangzhou), 7.14% (Xiamen), 5.92% (Ningde), 5.46% (Longyan), 4.32% (Putian), and 2.37% (Nanping). Therefore, clear spatial differences in CO_2 emissions were observed in Fujian Province, with changes in CO_2 emissions in Quanzhou and Fuzhou playing a crucial role in provincial-level CO_2 emissions.

Spatial-temporal decomposition analysis of energy-related CO_2 emissions

Figures 3–8 show the results of the temporal and spatial decomposition analysis. The temporal decomposition of ICEs, ECEs, and HCEs for the nine cities was calculated for 2000–2017 using Eqs. 3–11 (Figs. 3, 5, and 7). The relative contribution rates of different drivers are shown in Tables A1, A3, and A5 in supplementary material. The spatial decomposition of ICEs, ECEs, and HCEs for the nine cities in 2000, 2005, 2010, 2015, and 2017 was further calculated using Eqs. 12–20 (detailed calculation results are shown in Tables A2, A4, and A6 in supplementary material). We then investigated the spatial relationship among three main driving factors (ΔCEt, ΔCG, and ΔCUr) in different cities, as shown in Figs. 4, 6, and 8.

Spatial-temporal decomposition of energy-related CO_2 emissions from the industry sector

Figure 3 shows that ΔCG was the dominant factor leading to higher CO_2 emissions in each city during 2000–2017. ΔCG was largest in Quanzhou (113.04 Mt), followed by Fuzhou (42.00 Mt), and the relative contribution rate ranged from 50.30% (Fuzhou) to 25.89% (Sanming). This result agrees with those of previous studies (Chang et al., 2019, Chen et al., 2019, Li et al., 2017, Quan et al., 2020, Shi et al., 2019, Xue et al., 2019). ΔCEt was the dominant factor leading to lower CO_2 emissions in all cities except for Ningde and Putian. Quanzhou showed the largest ΔCEt during 2000–2017 (−94.56 Mt), followed by Sanming (−36.96 Mt). The relative contribution rate ranged from −47.07% (Nanping) to −22.2% (Fuzhou). Improvements in productivity and development, and the deployment of clean energy can reduce energy intensity, which is crucial for reducing industrial carbon emissions. ΔCUr was the second largest positive effect on the increase in ICEs, which was especially more prominent in coastal cities (e.g., Quanzhou, Fuzhou, and Putian), for example, ΔCUr in Quanzhou reached 46.25 Mt during 2000–2017. Urbanization can increase ICEs via infrastructure construction, industrial development, and urban population expansion. ΔCP was positive in most cities (most significantly in Xiamen), indicating that the increase in population size from 2000 to 2017 in Xiamen contributed to the observed changes in ICEs, and that the population load in Xiamen is relatively heavy. ΔCIs was also positive in each city, however, there was a discrepancy in the contribution rate among cities, with Sanming, Zhangzhou, Ningde, and Nanping exhibiting higher contribution rates. ΔCEs and ΔCQi had little impact on the changes in ICEs in all cities in Fujian Province from 2000 to 2017.

The spatial decomposition results of the three main driving factors are denoted by dots in Fig. 4, and joined by arrows. The three factors correspond to the X-axis (ΔCEt), Y-axis (ΔCG), and Z-axis (ΔCUr), and the plotting area is divided into four quadrants and two axes according to the projection of each dimension. According to Fig. 4(b), cities located in quadrant □ exhibited lower ΔCG and ΔCUr than the regional average, cities located in quadrant □ had higher ΔCG and lower ΔCUr than the regional average, cities located in quadrant □ had higher ΔCG and ΔCUr than the regional average, and cities located in quadrant □ had lower ΔCG and higher ΔCUr than the regional average. The data displayed in Fig. 4(c) and Fig. 4(d) can be interpreted in a similar way. The spatial decomposition results provide a comprehensive description of the variations in ICEs in the nine cities. Movement over time toward a lower value along an axis indicates a positive development, i.e., ΔCEt in Xiamen (Fig. 4[c]), whereas movement over time toward a higher value along an axis indicates a negative development, i.e., ΔCEt in Quanzhou (Fig. 4[c]).

The difference between ΔCEt and the corresponding average value was much greater than the difference between ΔCUr or ΔCG and their corresponding average values. Moreover, the evolutionary trends of the scattered dots were diverse, in that some cities were always located in one quadrant and some cities covered multiple quadrants. Therefore, we classified the nine cities into four groups according to the spatial decomposition results. The first group, which includes Putian, Nanping, and Ningde, were cities predominantly located in one quadrant (i.e., quadrant). These cities moved toward a lower value over time (Fig. 4[b–d]), indicating higher ΔCEt, ΔCUr, and ΔCG values than the regional average, this inhibitory effect increased over time. The second group includes cities located in both quadrant and quadrant , i.e., Fuzhou and Xiamen. The ΔCEt value of Fuzhou and Xiamen was negative but increased over time, indicating higher energy use efficiency than the regional average, which curbed the excessive growth of carbon emissions. The ΔCG and ΔCUr values of Fuzhou and Xiamen were also higher than the regional average, indicating that economic development and urbanization promoted carbon emissions in these cities. The third group includes cities located in both quadrant and quadrant , i.e., Longyan City. Here, the ΔCEt was positive, whereas ΔCG and ΔCUr were negative, indicating that improving the energy use efficiency is imperative for reducing industrial carbon emissions in this city. Quanzhou, Zhangzhou, and Sanming cities belong to the fourth group as they were located across three or more quadrants. Quanzhou City exhibited the most distinctive characteristics of change, whereby ΔCG and ΔCEt were both positive and ΔCUr changed from negative to positive in 2010, indicating that all three factors had low influence. Therefore, policy priorities to reduce ICEs in each city should be developed according to the spatial decomposition analysis of the driving forces in each city.

The increase in ICEs in Fujian Province was generally affected by the increase in ΔCG, where the ΔCG value in industrially developed areas (e.g., Quanzhou, Zhangzhou, Fuzhou, Sanming, and Xiamen) was higher than the regional average. Since the reform and opening-up, to further meet the demand for economic growth, the government of Fujian Province has been increasing construction and investment in the industry sector, which in turn has increased energy consumption and related CO_2 emissions. ΔCEt was the main factor responsible for the mitigation of ICEs in the study area, energy intensity decreased in each city, except for Ningde City, indicating that carbon emission reduction targets played an important role in enabling regions to improve energy use efficiency by adjusting their energy consumption structure and promoting the use of clean energy.

Spatial-temporal decomposition of energy-related CO_2 emissions from the transportation sector

Figure 5 shows that ΔCG was also the dominant factor influencing the increase in TCEs in Fujian Province. Quanzhou showed the largest ΔCG of 3.35 Mt during 2000–2017, whereas Putian showed the lowest ΔCG of 0.53 Mt, and the relative contribution rate ranged from 62.27% (Nanping) to 31.19% (Xiamen). ΔCUr had the second highest positive effect on the growth of TCEs, especially in Quanzhou (1.37 Mt), Fuzhou (0.62 Mt), and Zhangzhou (0.43 Mt). The relative contribution of ΔCEs to the transportation sector was higher than that to the industry sector, with the relative contribution rate ranging from 15.98% (Zhangzhou) to 6.36% (Putian), therefore, the energy structure of the transportation sector requires adjustment. Unlike for ICEs, ΔCEt showed a positive effect on TCEs in most cities except Putian City (−0.09 Mt), the relative contribution rate ranged from 22.45% (Xiamen) to 0.67% (Fuzhou), indicating that the energy use efficiency of the transportation sector requires further improvement. Moreover, ΔCP was positive in coastal cities (e.g., Quanzhou, Fuzhou, Zhangzhou, and Xiamen), indicating that an increase in population size promoted the increase in TCEs. ΔCIs was negative in most cities except Zhangzhou

(0.17 Mt), the relative contribution rate ranged from −17.95% (Fuzhou) to −2.88% (Longyan) indicating that development of the transportation sector has a suppressive effect on TCEs.

Figure 6 presents the spatial decomposition results of TCEs, according to which the nine cities were divided into three groups. The first group includes the cities predominantly located within one quadrant (quadrant III), which includes Putian, Nanping, Ninde, and Xiamen. Putian and Nanping consistently appeared in quadrant Ⅲ (Fig. 6[b–d]). For Xiamen, which was consistently located in quadrant Ⅲ, the positive effect of ΔCEt and ΔCUr was larger and increased over time, indicating that the transportation sector was driven by population migration during urbanization. However, the energy efficiency of the transportation sector did not improve, which led to an increase of CO_2 emissions. The second group includes cities mostly located in quadrant II, i.e., Fuzhou, where ΔCUr and ΔCG were higher than the regional average. The third group includes the cities mostly located in quadrant Ⅳ, i.e., Longyan. Here, ΔCUr and ΔCG were consistently negative and increased over time, whereas ΔCEt was positive and increased over time. The fourth group includes cities located across three or more quadrants, i.e., Quanzhou, Zhangzhou, and Sanming, which all exhibit similar characteristics. Specifically, ΔCG had a positive effect in these cities, whereas ΔCEt changed from positive to negative in different years. Income improvement generally drives population mobility and the circulation of goods, and the population tends to flow from developing areas to developed areas. This contributes to development of the transportation sector, and the increasing energy consumption required for transportation leads to an increase in carbon emissions. Therefore, ΔCG was higher than the regional average in industrially developed regions (e.g., Quanzhou, Zhangzhou, Xiamen, Fuzhou, and Sanming). ΔCEt increased TCEs, and the ΔCEt value in Xiamen was much higher than the regional average. These results suggest that it is necessary to improve energy use efficiency in the transportation sector.

Spatial-temporal decomposition of energy-related CO_2 emissions from the household sector

Figure 7 shows that ΔCG was the dominant factor leading to an increase in HCEs, and the relative contribution rate ranged from 147.66% (Fuzhou) to 74.18% (Xiamen). ΔCEt was the dominant factor responsible for the mitigation of HCEs in each city, and the relative contribution rate ranged from −117.01% (Fuzhou) to −34.87% (Longyan). ΔCUr had the second highest positive influence on the increase in HCEs in most cities, and the relative contribution rate ranged from 49.64% (Zhangzhou) to 15.12% (Xiamen), indicating that urbanization led to a concentration of population in urban areas and an improvement of people's living standards, and thus to an increase in HCEs. ΔCEs were positive in each city, indicating that the energy structure led to an increase in HCEs. ΔCP showed a significant positive effect in developed cities, for example, the relative contribution rate in cities with recent rapid population growth (Xiamen, Fuzhou, and Quanzhou) was 44.14%, 19.71%, and 10.69%, respectively, indicating that population growth is a significant factor driving increased HCEs.

The nine cities are divided into three groups in Fig. 8. The first group includes Xiamen and Fuzhou, which were characterized by negative ΔCEt that progressively decreased compared to the regional average, positive ΔCUr that was higher in Xiamen than in Fuzhou, and positive ΔCG, the gap between ΔCG and the regional average decreased over time. The second group includes cities that covered two quadrants, including Nanping, Putian, Ningde, and Longyan. In these cities, ΔCUr and ΔCG were consistently negative and ΔCEt was consistently positive, indicating that the energy efficiency of these cities was lower than the regional average. The third group includes cities that moved across three or more quadrants, including Quanzhou, Zhangzhou, and Sanming. In Zhangzhou, ΔCEt and

ΔCUr were negative, and the ΔCEt gap between the cities and the regional average was relatively small. Conversely, ΔCG was positive, and the gap continued to increase. With an increase in household income and living standards, people prefer to purchase more carbon-emitting products, which leads to an increase in HCEs. ΔCG was more evident in high-income areas, such as Quanzhou, Zhangzhou, Xiamen, and Fuzhou. The observed decrease in energy intensity was likely related to people's awareness of environmental protection and adjustment of their consumption structure. ΔCEt was below the provincial average in developed regions (e.g., Xiamen, Fuzhou, Quanzhou, and Zhangzhou), indicating that improved living standards can promote a reduction of energy intensity in the household sector.

Conclusions And Policy Implications

Conclusions

In this study, we first calculated energy-related CO_2 emissions at the city level then explored the driving forces of CO_2 emissions from the industry sector, transportation sector, and household sector in nine prefecture-level cities in Fujian Province during 2000–2017. Temporal and spatial LMDI models were used to calculate the changes and interregional discrepancies in CO_2 emissions from different sectors. Therein, the corresponding impact factors were divided into seven groups: the carbon emissions coefficient effect, the energy structure effect, the energy intensity effect, the industrial structure effect, the income effect, the urbanization effect, and the population effect. The findings of this study can be summarized as follows.

CO_2 emissions increased in each city during 2000–2017, with the change in energy-related CO_2 emissions from the industry sector being more significant than that in the transportation sector or household sector in Fujian Province. The income effect was the dominant force driving the increase in ICEs, TCEs, and HCEs in each city from 2000 to 2017. Conversely, the energy intensity effect was the major factor responsible for the mitigation of CO_2 emissions in each city during 2000–2017, except for emissions from the transportation sector. The energy intensity effect of the transportation factor was positive, indicating that the energy efficiency of this sector should be adjusted. The urbanization effect was another critical driver contributing to an increase in CO_2 emissions in all sectors, which had a greater positive effect in coastal areas.

Moreover, the intensity effect was the main factor causing discrepancies in CO_2 emissions among cities. We divided the nine prefecture-level cities into four groups (Table 2). The first group, which included Nanping, Ningde, and Putian cities, showed similar spatial variations, i.e., the energy intensity effect, income effect, and urbanization effect in the three sectors were negative, whereas the energy intensity effect of the household sector was positive. The second group, including Xiamen and Fuzhou, also showed similar spatial variations, i.e., the urbanization effect and income effect were positive in the three sectors, whereas the energy intensity effect in industry and household sectors was negative. Moreover, the energy intensity of the transportation sector in Xiamen City was positive. In the third group, (Longyan City), the energy intensity effect was positive across all three sectors, whereas the income and urbanization effects were negative. In the fourth group, the spatial differences in Quanzhou, Zhangzhou, and Sanming cities were more complex across these sectors and over the years, therefore, policy adjustments should be made according to the actual conditions.

Policy implications

National and regional targets have been implemented to achieve a carbon emission peak by 2030 in China. However, the results of this study show that none of the cities in Fujian Province are currently on track to achieve that goal. Therefore, CO_2 emission reduction efforts should be further promoted. Based on the findings of this study, we propose the following targeted recommendations for low-carbon development in the cities of Fujian Province.

As each city in Fujian Province has distinct strengths and weakness in terms of their driving forces of CO_2 emissions, local policies should be developed to reduce the CO_2 emissions in each city. In economically underdeveloped cities (e.g., Nangping, Ningde, and Longyan), the government should learn from the advanced energy utilization methods used in developed regions while improving economic development to achieve a high-quality development path. It is also necessary to strengthen residents' awareness of the important of emission reduction measures and emphasize a low-carbon lifestyle. Conversely, in economically developed areas (e.g., Fuzhou and Xiamen), it is important to promote the popularity of new energy vehicles that can serve as a model for other regions. Moreover, an effective urban growth model should be developed to encourage the population and economy to concentrate in areas suitable for development. Finally, in industrially developed areas (e.g., Quanzhou, Zhangzhou, and Sanming), to improve the quality and efficiency of economic development, governments should promote the widespread use of advanced energy-efficient and low-carbon technologies in the dominant industry sectors.

Methods

Profile of the study area

Fujian Province (115°51'–120°40'E;23°31'–28°22'N) is located on the southeastern coast of China. Since the start of China's reform and opening-up policies, Fujian Province has made substantial progress in economic construction; however, the province is characterized by very high total energy consumption and increasing CO_2 emissions and dependence on imported energy sources. Moreover, the energy structure, economic structure, and industrial structure show an imbalanced across the cities in Fujian Province, leading to substantial regional differences in carbon emissions. Therefore, the government issued the 13th Five-Year Plan (FYP) in an attempt to control greenhouse gas emissions and promote energy conservation (Min Zheng 2017a). Specifically, to reduce emission intensity by 40–45% in 2020 compared to 2005 levels, emission intensity reduction targets were clearly defined for each city, the Pingtan comprehensive experimental zone was delineated, and low-carbon industrial development was vigorously implemented to promote industrial transformation and upgrading.

Calculation of CO_2 emissions

We adopted the guidelines of the Intergovernmental Panel on Climate Change (2006) to calculate CO_2 emissions from fossil fuel consumption, i.e.;

$$C = E_{kj} \times NCV_j \times EF_j \times O_{kj}$$

1

Here, i represents different types of fossil fuel; j represents different sectors; CE_{ij} represents CO_2 emissions from the combustion of fossil fuel i in sector j; E_{ij} represents the consumption of fossil fuel i in sector j; NCV_j represents the net caloric value; EF_i represents the emission factor; and O_{ij} represents the oxygenation efficiency of different types of fossil fuel.

Decomposition model

Kaya identity

According to the Kaya identity (Ehrlich 1971), energy-related CO_2 emissions are decomposed into seven factors:

$$C = \sum_{ijk} C_{ijk} = \sum_{ijk} \frac{C_{ijk}}{E_{ijk}} \times \frac{E_{ijk}}{E_{ij}} \times \frac{E_{ij}}{G_{ij}} \times \frac{G_{ij}}{G_i} \times \frac{G_i}{P_i} \times \frac{P_i}{P} \times P$$
$$= Qi \times Es \times Ei \times Is \times G \times Ur \times P$$

2

where subscript i represents one of nine cities in Fujian Province (i = 1,2,…9); j represents the sector type (j = 1,2…7, i.e., primary sector, industry sector, construction sector, transport sector, wholesale, retail trade, and hotel and catering services, other sectors, and household sector); k represents the form of energy (k = 1,2,…14); C_{ijk} represents the CO_2 emissions; E_{ijk} represents the energy consumption; E_{ij} represents the total energy consumption in sector j; G_{ij} represents the GDP of industry j; G_i represents the total GDP; P_i is the size of the urban population; and P is the size of the total population. Qi, Es, Ei, Is, G, Ur, and P are the CO_2 emissions coefficient, energy structure, energy intensity, industrial structure, economy scale, urbanization, and population, respectively. We assumed that the CO_2 emissions coefficient was constant, so did not include this coefficient in the decomposition framework of total CO_2 emissions.

Temporal LMDI model

According to the temporal LMDI model (Ang 2005), changes in energy-related CO_2 emissions for region i from the base year 0 to the target year t are decomposed into seven main factors: the carbon emissions coefficient effect (ΔCQ_i), the energy structure effect (ΔCEs), the energy intensity effect (ΔCEi), the industrial structure effect (ΔCIs), the income effect (ΔCG), the urbanization effect (ΔCUr), and the population effect (ΔCP), as shown in Eqs. (3–11).

$$\Delta C_i^{t,0} = \Delta C_i^t - \Delta C_i^0$$
$$= \sum_{ijk} \left(\Delta C^{t,0}_{C_{ijk}} / {}_{E_{ijk}} + \Delta C^{t,0}_{E_{ijk}} / {}_{E_{ij}} + \Delta C^{t,0}_{E_{ij}} / {}_{G_{ij}} + \Delta C^{t,0}_{G_{ij}} / {}_{G_i} + \Delta C^{t,0}_{G_i} / {}_{P_i} + \Delta C^{t,0}_{P_i} / {}_{P} + \Delta C^{t,0}_{P} \right)$$
$$= \Delta CQi^{t,0} + \Delta CEs^{t,0} + \Delta CEi^{t,0} + \Delta CIs^{t,0} + \Delta CG^{t,0} + \Delta CUr^{t,0} + \Delta CP^{t,0}$$

3,

$$\Delta CQi^{t,0} = \sum_{ijk} L(C^t_{ijk}, C^0_{ijk}) \ln \left(\frac{Qi^t}{Qi^0} \right)$$

4,

$$\Delta CEs^{t,0} = \sum_{ijk} L(C_{ijk}^{t}, C_{ijk}^{0}) \ln\left(\frac{Es^{t}}{Es^{0}}\right)$$

5,

$$\Delta CEt^{t,0} = \sum_{ijk} L(C_{ijk}^{t}, C_{ijk}^{0}) \ln\left(\frac{Et^{t}}{Et^{0}}\right)$$

6,

$$\Delta CIs^{t,0} = \sum_{ijk} L(C_{ijk}^{t}, C_{ijk}^{0}) \ln\left(\frac{Is^{t}}{Is^{0}}\right)$$

7,

$$\Delta CG^{t,0} = \sum_{ijk} L(C_{ijk}^{t}, C_{ijk}^{0}) \ln\left(\frac{G^{t}}{G^{0}}\right)$$

8,

$$\Delta CUr^{t,0} = \sum_{ijk} L(C_{ijk}^{t}, C_{ijk}^{0}) \ln\left(\frac{Ur^{t}}{Ur^{0}}\right)$$

9,

$$\Delta CP^{t,0} = \sum_{ijk} L(C_{ijk}^{t}, C_{ijk}^{0}) \ln\left(\frac{P^{t}}{P^{0}}\right)$$

10,
where

$$L(C_{ijk}^{t}, C_{ijk}^{0}) = \frac{C_{ijk}^{t} - C_{ijk}^{0}}{\ln C_{ijk}^{t} - \ln C_{ijk}^{0}}$$

11.
Spatial LMDI model

Regarding the selection of the spatial exponential decomposition model, unlike the bilateral-regional and radial-regional models, the multi-regional model takes the average of all research units during the study period as the reference region, thereby avoiding the complex computational burden of the bilateral-regional model and the

subjectivity of the radial-regional model when selecting reference objects (Ang et al. 2016; Ang et al. 2015). For this reason, the multi-regional model (Ang et al. 2016) was used in this study. The spatial LMDI model for analyzing the driving factors of carbon emission changes is described as follows:

$$\Delta C_i^{i,u} = \Delta C_i^i - \Delta C_i^u$$
$$= \sum_{ijk} \left(\Delta C_{C_{ijk}}^{i,u} / E_{ijk} + \Delta C_{E_{ijk}}^{i,u} / E_{ij} + \Delta C_{E_{ij}}^{i,u} / G_{ij} + \Delta C_{G_{ij}}^{i,u} / G_i + \Delta C_{G_i}^{i,u} / P_i + \Delta C_{P_i}^{i,u} / P + \Delta C_P^{i,u} \right)$$
$$= \Delta CQi^{i,u} + \Delta CEs^{i,u} + \Delta CEi^{i,u} + \Delta CIs^{i,u} + \Delta CG^{i,u} + \Delta CUr^{i,u} + \Delta CP^{i,u}$$

12,

where the benchmark, *u*, is calculated using the arithmetic mean of the values from the nine cities in Fujian Province. The effects of various driving forces were calculated using the following equations:

$$\Delta CQi^{i,u} = \sum_{ijk} L(C_{ijk}^i, C_{ijk}^u) \ln \left(\frac{Qi^i}{Qi^u} \right)$$

13

$$\Delta CEs^{i,u} = \sum_{ijk} L(C_{ijk}^i, C_{ijk}^u) \ln \left(\frac{Es^i}{Es^u} \right)$$

14

$$\Delta CEt^{i,u} = \sum_{ijk} L(C_{ijk}^i, C_{ijk}^u) \ln \left(\frac{Et^i}{Et^u} \right)$$

15

$$\Delta CIs^{i,u} = \sum_{ijk} L(C_{ijk}^i, C_{ijk}^u) \ln \left(\frac{Is^i}{Is^u} \right)$$

16,

$$\Delta CG^{i,u} = \sum_{ijk} L(C_{ijk}^i, C_{ijk}^u) \ln \left(\frac{G^i}{G^u} \right)$$

17,

$$\Delta CUr^{i,u} = \sum_{ijk} L(C_{ijk}^i, C_{ijk}^u) \ln \left(\frac{Ur^i}{Ur^u} \right)$$

18,

$$\Delta CP^{i,u} = \sum_{ijk} L(C_{ijk}^{i}, C_{ijk}^{u}) \ln\left(\frac{P^{i}}{P^{u}}\right)$$

19,
where

$$L(C_{ijk}^{t}, C_{ijk}^{u}) = \frac{C_{ijk}^{t} - C_{ijk}^{u}}{\ln C_{ijk}^{t} - \ln C_{ijk}^{u}}$$

20.
Relative contribution rate

We converted the contribution of each effect to a relative contribution using the ratio of each effect to the sum of its absolute value (Eq. [21]). This approach facilitates the comparison and analysis of the time trend in the contribution of each effect.

$$I(\Delta C_k) = \frac{\Delta C_k}{\sum_k \left|\Delta C_k\right|}$$

21.
Here, $I(\triangle C_k)$ represents the relative contribution rate of each effect and ΔC_k represents the value of each effect.

Data sources

This study is based on annual data spanning the period of 2000–2017. The GDP of different sectors (primary, industry, construction, transport, wholesale, retail trade, and hotel/catering services, household, and other sectors) and the population size of the nine cities in Fujian Province were derived from Fujian statistical yearbooks (2000–2017) (Statistics 2000–2017). To remove the effect of inflation, all economic data were converted to constant 2000 prices. We adopted the method recommended by Shan et al. (2017) to calculate the energy consumption and carbon emission inventory for the nine cities in Fujian Province. Basic CO_2 emission data included energy balance sheets, sectoral energy consumption, and total energy consumption for the nine cities. As the statistical yearbooks of the nine cities lack energy balance sheets, energy consumption at the city scale was calculated using the provincial energy balance sheet.

Declarations

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Author contributions statement

Yimin Huang: Conceptualization, Methodology, Writing-Original draft preparation, Data curation, Formal analysis, Visualization. **Yuan Wang**: Supervision, Conceptualization, Writing-Review & Editing. **Yanmin He**: Data curation and Writing-Review & Editing. **Lin Zhu** and **Wen-ting Lai**: Writing-Review & Editing.

Declaration of interests

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.

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Tables

Table 1 Abbreviations used in this study

Abbreviation	Definition
ICEs	industry energy-related CO_2 emissions
TCEs	transportation sector energy-related CO_2 emissions
HCEs	household sector energy-related CO_2 emissions
ΔCQ_i	carbon emissions coefficient effect
ΔCEs	energy structure effect
ΔCEt	energy intensity effect
ΔCIs	industrial structure effect
ΔCG	income effect
ΔCUr	urbanization effect
ΔCP	population effect

Table 2 Summary of the spatial decomposition results

		Industry Sector			Transportation Sector			Household Sector		
		ΔCEt	ΔCG	ΔCUr	ΔCEt	ΔCG	ΔCUr	ΔCEt	ΔCG	ΔCUr
First group	Nanping	-	-	-	-	-	-	+	-	-
	Ningde	-	-	-	-	-	-	+	-	-
	Putian	-	-	-	-	-	-	+	-	-
Second group	Xiamen	-	+	+	+	+	+	-	+	+
	Fuzhou	-	+	+	-	+	+	-	+	+
Third group	Longyan	+	-	-	+	-	-	+	-	
Fourth group	Quanzhou	+/-	+	-/+	+/-	+	-/+	-	+	-/+
	Zhangzhou	+/-	+	-	+/-	+	-	-	+	-
	Sanming	+/-	-/+	-	+/-	-/+	-	-/+	-/+	-

Note: “–” represents a negative effect, and “+” represents a positive effect.

Figures

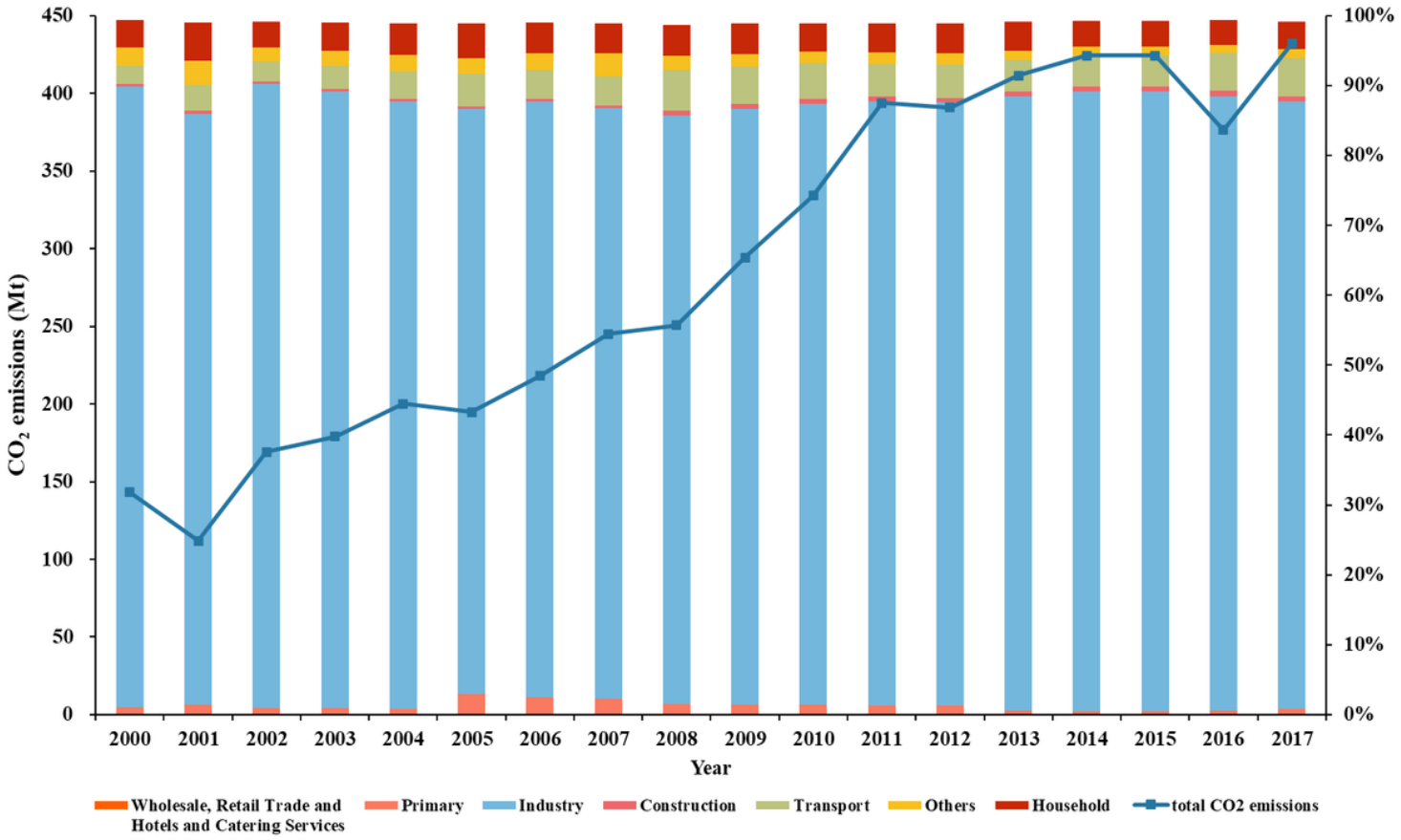


Figure 1

Total CO_2 emissions across seven sectors of the Chinese economy in Fujian Province.

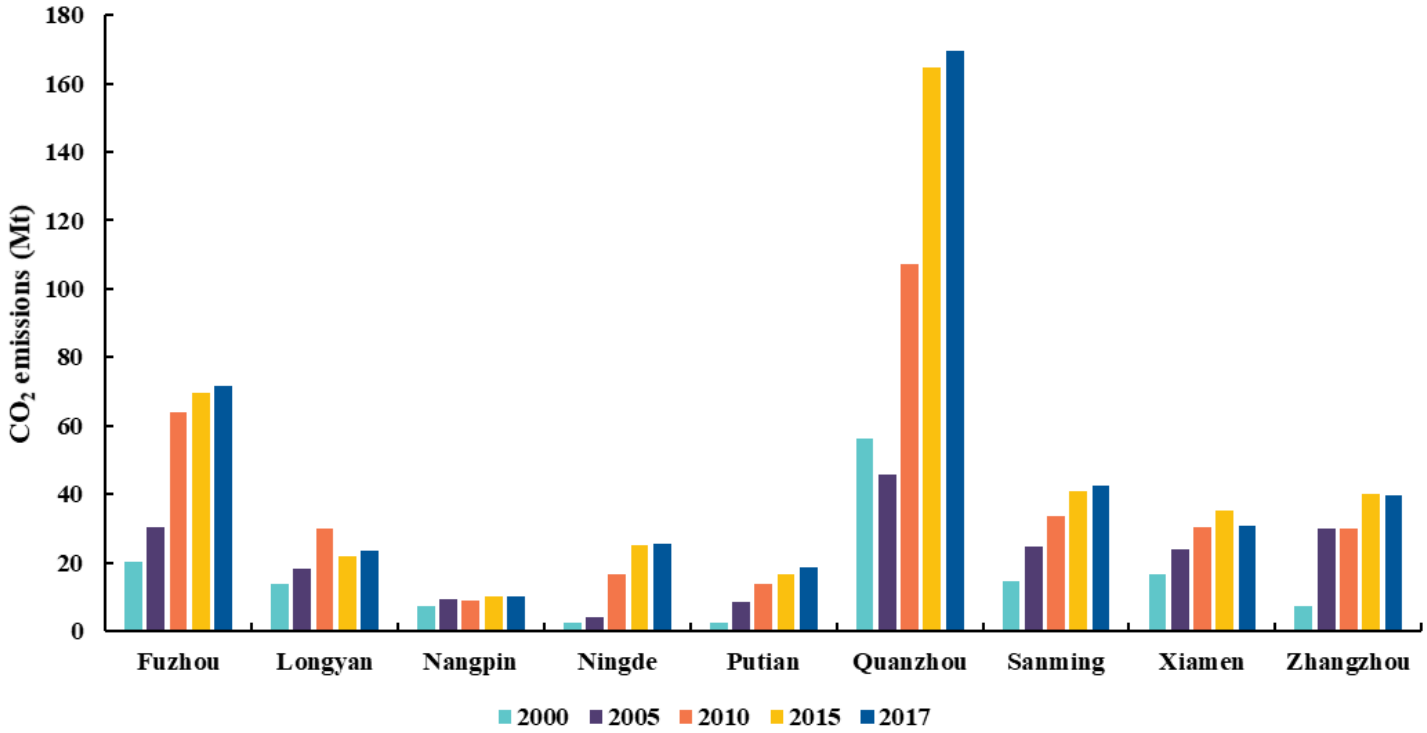


Figure 2

CO_2 emissions of nine prefecture-level cities in Fujian Province for selected years.

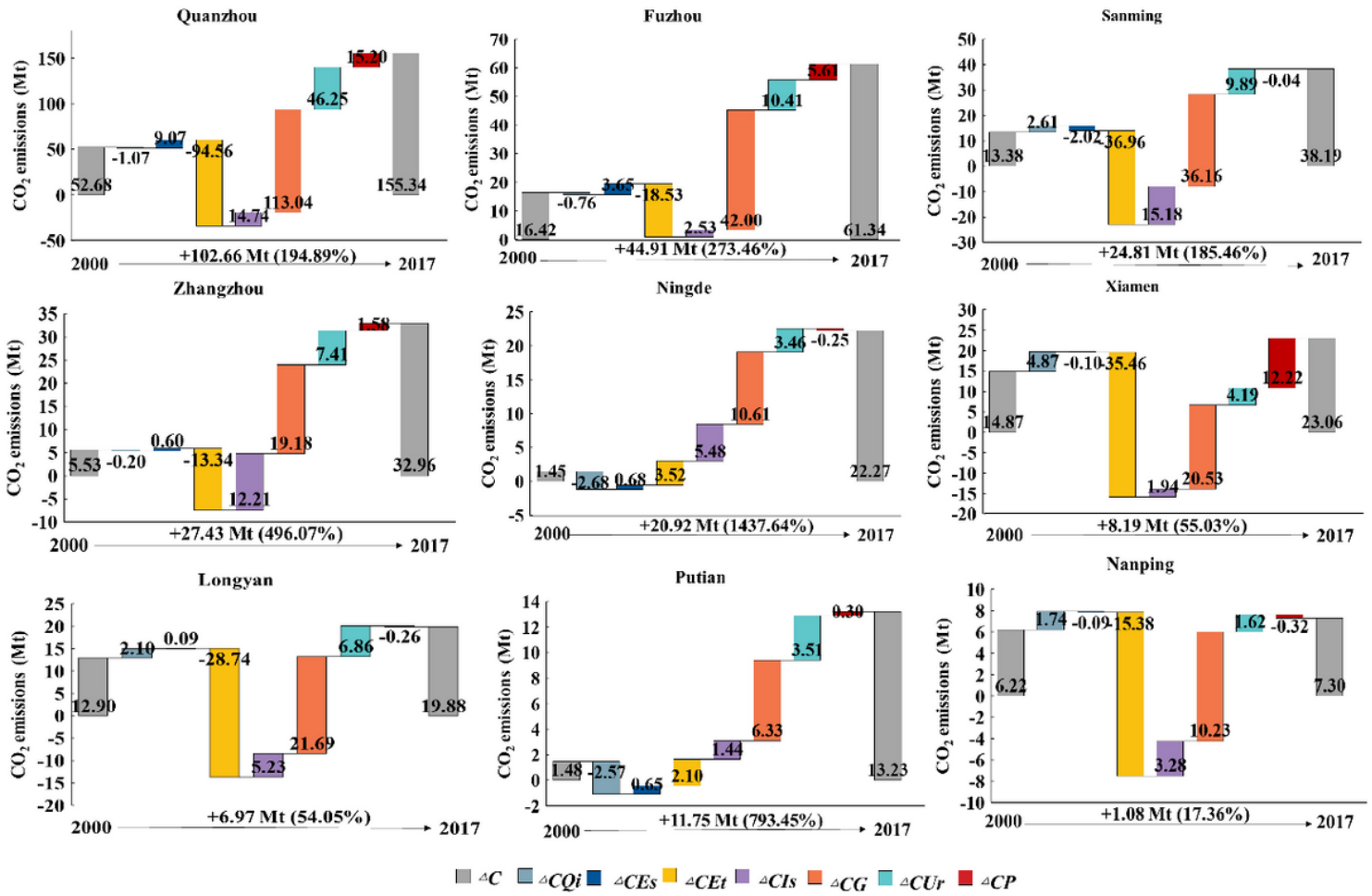


Figure 3

Temporal decomposition of ICEs in nine prefecture-level cities in Fujian Province from 2000 to 2017.

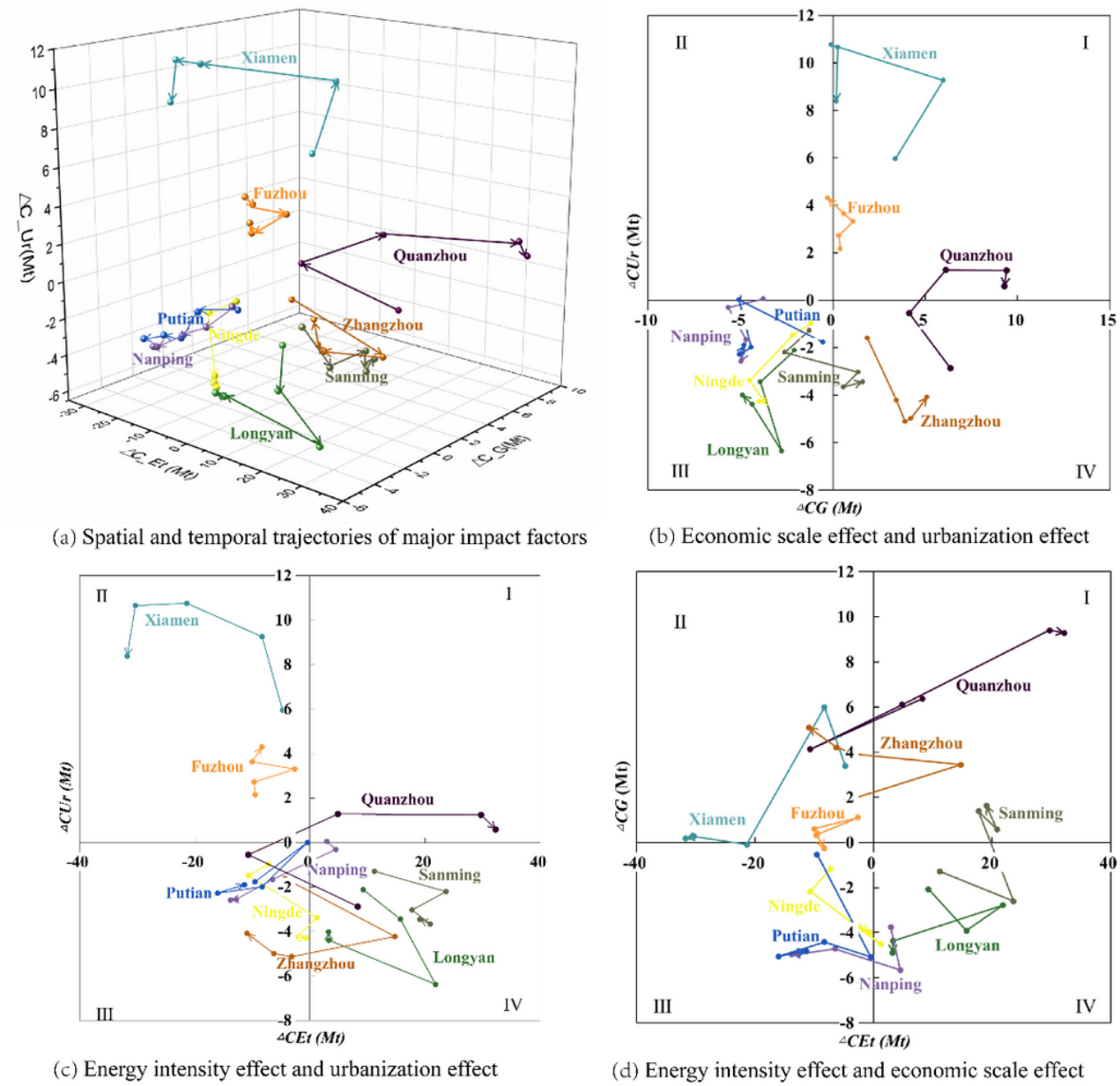


Figure 4

Spatial decomposition of the main factors influencing ICEs for nine prefecture-level cities in Fujian Province for 2000, 2005, 2010, 2015, and 2017.

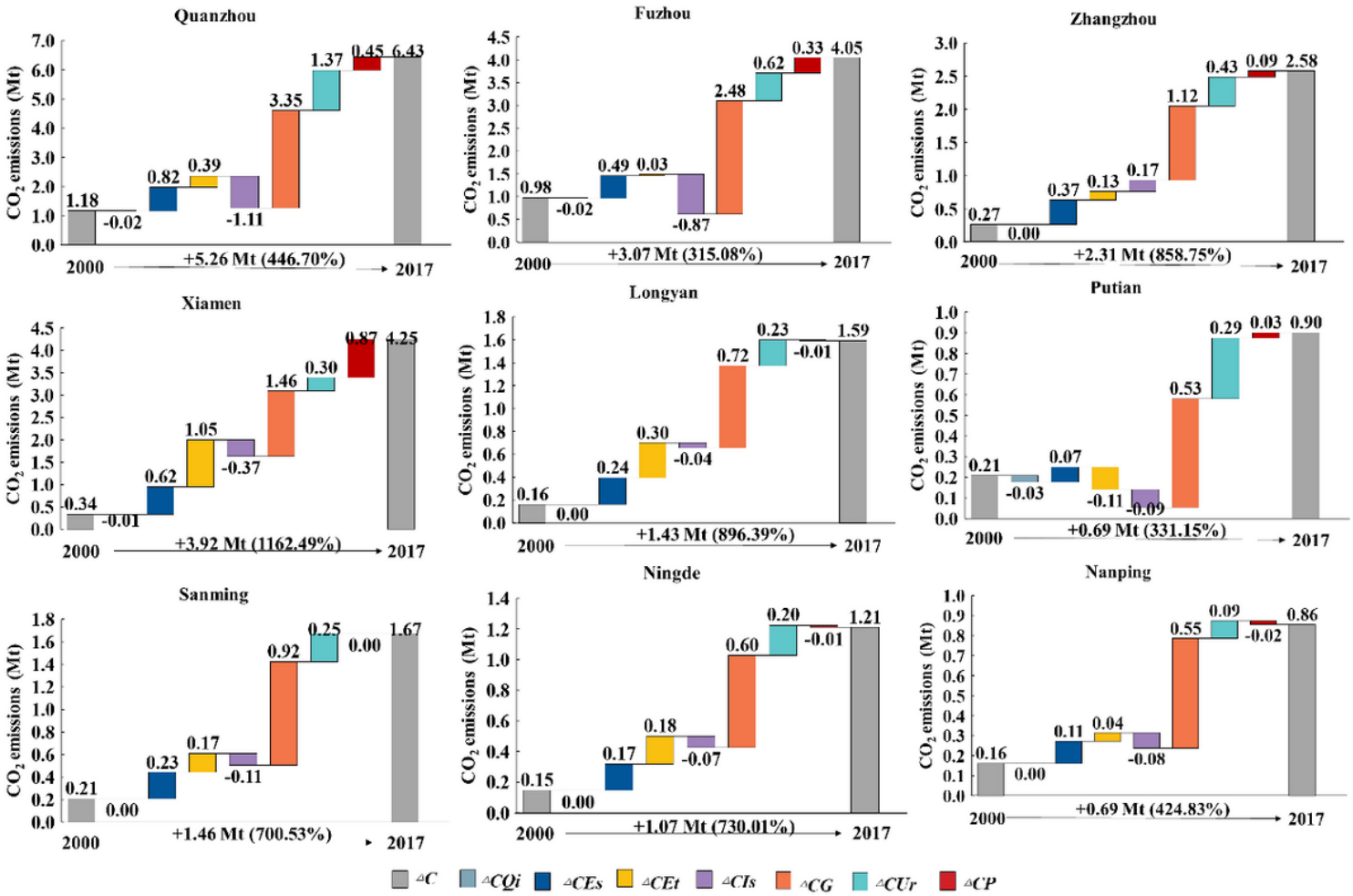
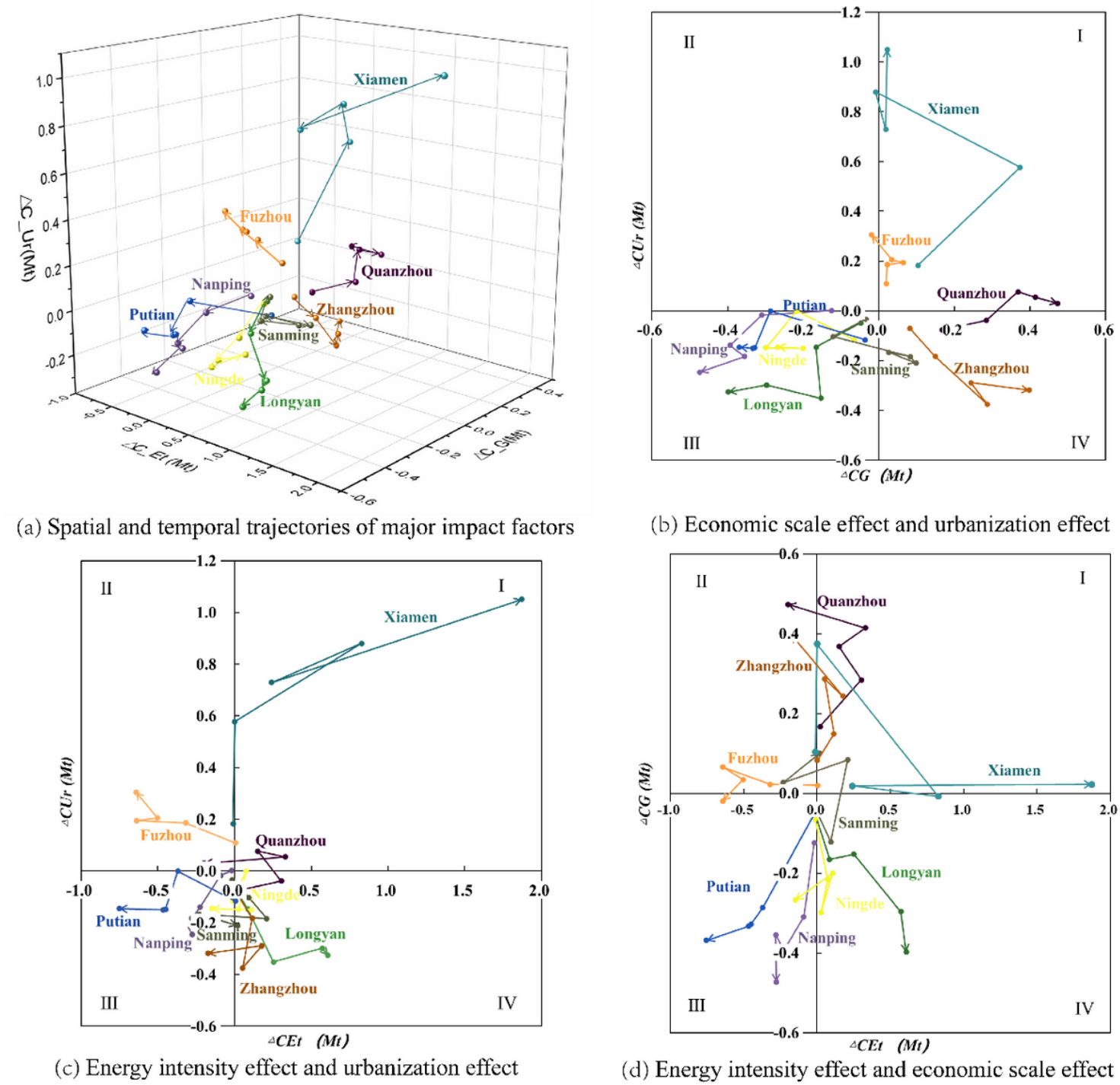


Figure 5

Temporal decomposition of TCEs for nine prefecture-level cities in Fujian Province from 2000 to 2017.



(a) Spatial and temporal trajectories of major impact factors

(b) Economic scale effect and urbanization effect

(c) Energy intensity effect and urbanization effect

(d) Energy intensity effect and economic scale effect

Figure 6

Spatial decomposition of the main factors influencing TCEs for nine prefecture-level cities in Fujian Province for 2000, 2005, 2010, 2015, and 2017.

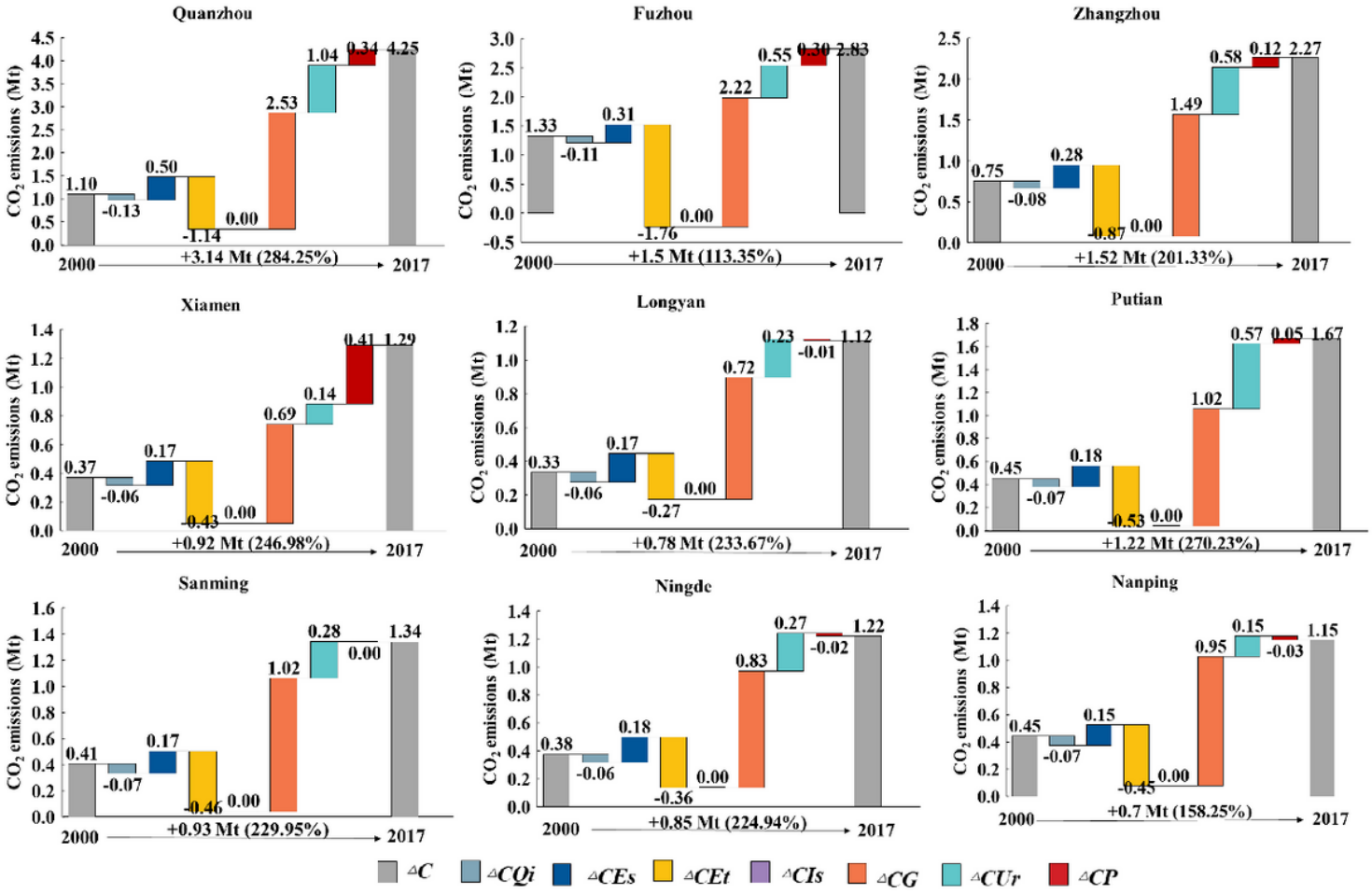


Figure 7

Temporal decomposition of HCEs for nine prefecture-level cities in Fujian Province from 2000 to 2017.

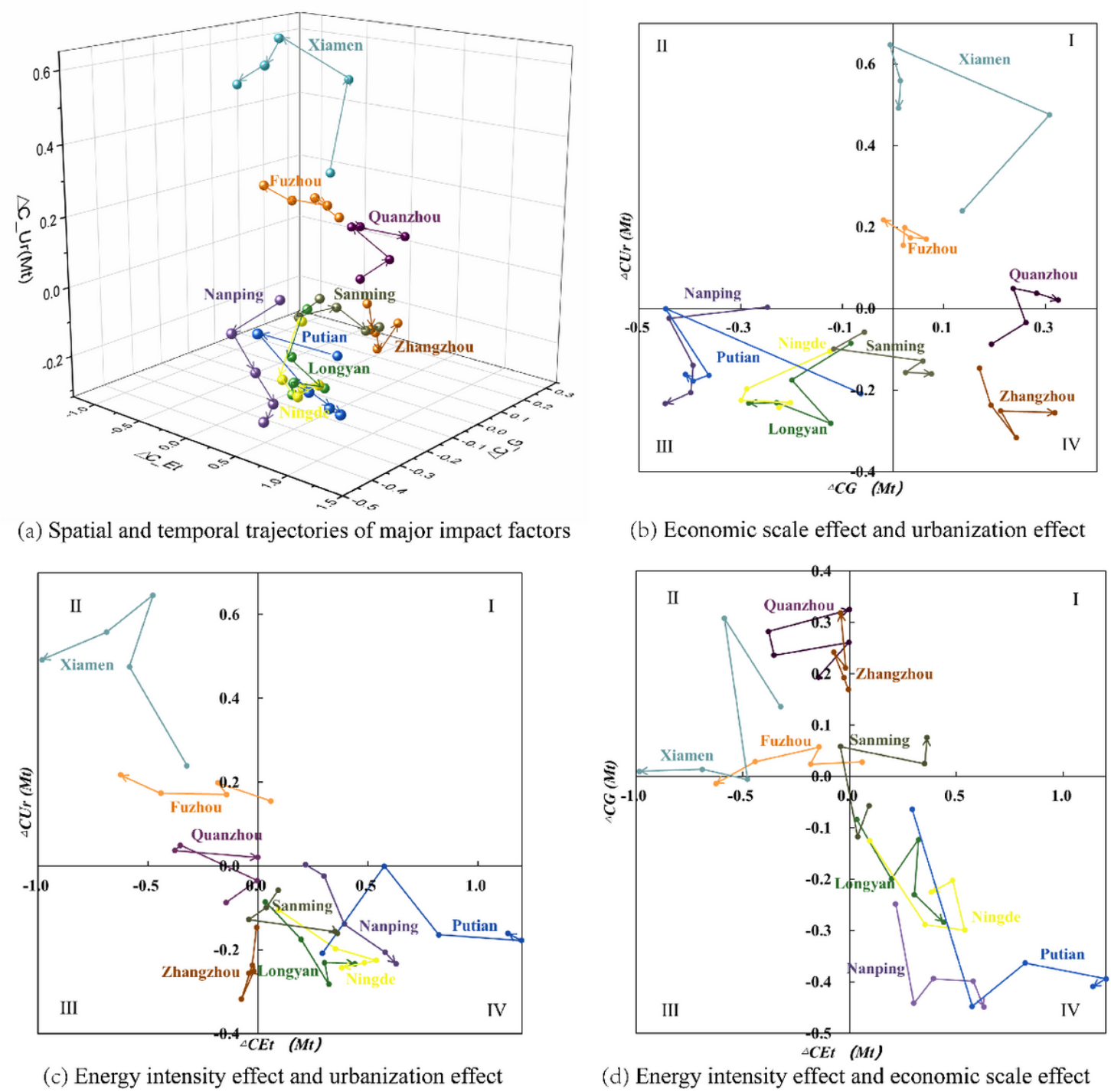


Figure 8

Spatial decomposition of the main factors influencing ICEs for nine prefecture-level cities in Fujian Province for 2000, 2005, 2010, 2015, and 2017.

Supplementary Files

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- SupplementaryMaterial.docx