Dynamic Change in Regional Resilience Indicators After a Disaster: A Comprehensive Assessment of Sichuan After the 2008 Wenchuan Earthquake

Yi Lu
Sichuan University
Xiaoyuan Shi
Sichuan University
Xiai Mao
Sichuan University
Shihang Wang (sw3275@columbia.edu)
Columbia University

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Abstract

Regional resilience after a disaster is a process that encompasses resistance, recovery and redevelopment. However, there have been few longitudinal dynamic analyses using resilience indicators after a disaster. This research proposes an ordination and clustering-based method for regional resilience evaluations focused on short-term disaster-resistance and long-term disaster-recovery capacities in the affected counties. This method was proven to be effective on data from 55 counties before and after the 2008 Wenchuan Earthquake (2005-2016) in Sichuan Province, China. It was found that: (i) economic related indicators were often negatively affected by the disaster over the short term, especially in the severely affected counties; (ii) the degree of economic development and the devastation extent significantly affected the recovery trends of two macro-economic indicators: the primary industry and the private economy; and (iii) the recovery trends in most counties for some economic and social indicators were initially stagnant or had a slow recovery for 1-3 years, after which there was a rapid recovery process. The intuitive and informative results from this evaluation provide a better understanding of the dynamic regional resilience process after a disaster.

1. Introduction

Disasters have negative effects on crop production (Lesk et al. 2016), economic welfare (Cassar et al. 2017) and long and short term macro-economic indicators (Noy 2009). To deal with these effects, international organizations such as the World Bank and the Asian Development Bank focus their disaster prevention work on strengthening the self-recovery powers of disaster-stricken areas through disaster resilience programs, which allow “the system, community or society exposed to the hazard factor to timely and effectively resist, absorb and withstand the effects of disasters, and the ability to recover from it” (UNISDR 2009).

The concept of resilience and particularly disaster resilience is closely associated with regional planning, development, and post-disaster reconstruction (Peng et al. 2017; Huang et al. 2020). Crespo et al. (2013) clarified regional resilience planning thinking into four phases, each of which was related to the accurate measurement and evaluation of the previous phase. Regional resilience assessments involve comprehensive measurements of regional societies (Saja et al. 2019; Qi and Wei 2010) with the aim of evaluating and improving regional resilience strategies (Kwok et al. 2018). However, effectively measuring disaster resilience is challenging (Kwok et al. 2018) as the behavior of individuals, businesses, and government entities before, during, and immediately after a disaster can dramatically affect the impact of the disaster and the recovery time (Walters 2015; Aoki 2016; Aerts et al. 2018). Given that disaster is inevitable in some regions, resilience is not limited to pre-disaster building, but post-disaster resilience building, which is the whole process of preparing for, responding to, recovering from disaster and building back better.

Further to ensure accurate regional disaster resilience assessments, all social, economic, institutional, infrastructure, ecological, and community capability components need to be considered (Cutter et al.

2008), for which there are many different indicators and methods. Many prior studies have developed frameworks and indicators for community or regional disaster resilience, which have provided a basis for comprehensive assessments. An illustration of studies on disaster resilience and the primary indicators and methods used are given in Table 1.

Table 1 An illustration of disaster resilience indicators and methods

Study area and scale	Research focus or result	Primary indicators	Major methods used	Literature citation
Community level	A place-based model for community resilience to disasters	Ecological, social, economic, institutional, infrastructure, and community competences	Theoretical framework	Cutter et al. (2008)
Baluchistan (local level)	A community resilience framework for an earthquake prone area	Social, economic, physical, and institutional	Questionnaire	Ainuddin and Routray (2012)
Southeastern United States (regional level)	A comparative assessment of community resilience in 736 counties	Social, economic, institutional, infrastructure, and community	Correlation analysis	Cutter et al. (2010)
Gulf of Mexico Coast (regional level)	Construction of a Community Disaster Resilience Index	Social, economic, physical, and human	Cross-classification method; Community workshop	Peacock et al. (2010)
Tehran (regional level)	Measurement of disaster resilience for 22 urban regions in Tehran	Social, economic, institutional, infrastructure, and community	Connective factor analysis; Analytic network process;	Asadzadeh et al (2015)
Talcahuano (regional level)	Measurement of urban morphology supporting tsunami rapid resilience	Geophysical and social	Agent-based computer model	León and March (2014)
Indonesia (national level)	A framework to assess the resilience of disaster-prone areas in Indonesia	Social, economic, community capacity, institutional and infrastructure	Delphi method and AHP	Kusumastuti (2014)
Korea (national level)	Resilience degree of 229 local municipalities in Korea to disasters	Human, social, economic, environmental, and institutional	Regression methods	Yoon et al (2015)

Much of the research in Table 1 involved qualitative and spatial analyses, with most assessments being static evaluations based on cross-section community, county or city data from normal situations; however, resilience is not static and can be improved (Ungar 2018). Frommer (2011) and Bertilsson et al. (2019) believed that all highly resilient systems manifest three resilient abilities: resistance, recovery and creativity: that encompass the bearing of the disaster without the need to change the region's basic community structure, a bouncing back to a pre-disruption state, and adapting to the new situation at an even better level (Cutter et al. 2008).

However, there have been few longitudinal dynamic analyses using resilience indicators after a disaster. Even though Karatani (2004) analyzed a citizen recovery process, little is known about the resistance and recovery capacities of other economic or education related indicators. Xiao and Drucker (2013) employed a difference-in-difference model and conducted a temporal and spatial quantitative analysis for regional disaster resilience. However, there have been few analyses on the joint effect of economic development and devastation extent on the resilience of specific indicators, and none that have considered pre-disaster, response, recovery states and regional differences.

Therefore, the question is do regional resilience indicators vary depending on the economic development level and the devastation extent immediately after the disaster and in the following recovery period? Klomp (2016) found that the economic effect partly depended on the size and scope of the natural catastrophe, the geographical location, the degree of financial development, and the quality of the political institutions present, and Fang et al. (2018) suggested that changes in livelihood resilience in rural regions was dominated by livelihood provision and livelihood promotion. However, there has been little research attention in this area; therefore, reliable evaluations of short-term disaster-resistance capacity (SDRC) and long-term disaster-recovery capacity (LDRC) are needed to fully understand and improve regional resilience.

2. Methodology

2.1 Regional disaster resilience indicators

As one of the most well-known and widely used frameworks, the disaster resilience of place model had six dimensions; ecological, social, economic, institutional, infrastructure, and community competence (Cutter et al. 2008). However, the ecological was excluded due to "data inconsistency" (Cutter et al. 2010). Further, the institutional was excluded because disaster-related institutional change has been observed to be a very slow process with the changes being consistent for each county in one region. So, in this study, four dimensions were chosen: economic, social, infrastructure, and community competence. In reference to Kusumastuti et al. (2014)'s indicator selection and considering data accessibility at the county level in Sichuan Province, a regional disaster resilience index was built that had five primary indicators and 28 secondary indicators (Table 2), with all resilience effects of these indicators being positive.

Table 2 Indicators after data cleaning to analyze the impact of the Wenchuan Earthquake

Dimensions	Primary Indicators	Secondary Indicators	Description
Economic	Macro-economic	Total investment in fixed asset/ CNY, Value-added of private economy/ CNY, Value-added of primary industry/ CNY, Value-added of secondary industry/ CNY, Value-added of tertiary industry/ CNY	Measures the general macro-economic circumstance of each county and the economic structure
	Industrial economics	Industrial value added/ CNY, Post and telecommunications income/ CNY, Retail sales/ CNY, Tourism revenue/ CNY, End-of-year loan balance/ CNY, End-of-year deposit balance/ CNY	Measures the detailed economic performance in each county in several industrial sectors, including industry, post and telecommunications, retail, tourism and finance
Social	People’s livelihoods	Population, Non-agricultural population, Net income of rural residents/ CNY, Net income of urban residents/ CNY	Measures the urban and rural resident income, distribution, and net income
Infrastructure	Transport	Road mileage/ km, Standard road mileage/ km, Passenger traffic volume 10k ppl/km, Freight traffic volume 10k t/km	Measures the road infrastructure construction and the corresponding carrying capacity of each county
Community competence	Education & medical treatment	Primary school num/ PT, Primary school student num/ PT, Primary school teacher num/ PT; Middle school num/ PT, Middle school student num/ PT, Middle school teacher num/ PT; Medical institution num/ PT, Medical technician num/ PT, Medical bed num/ PT	Measures the education and medical institutions, relevant staff and facilities provided as well as school students

2.2 Research site and data processing

The case-study example in this study was the 2008 Wenchuan Earthquake, which affected 417 counties (cities, districts) in 10 provinces (cities) of China, and especially Sichuan Province (Dunford and Li 2011), which is an earthquake-prone province with 21 cities and 183 counties. Due to data accessibility, this research mainly focused on 55 counties and 6 of the most seriously affected cities in Sichuan for which there was accessible data from 2005 to 2016. Based on the extent of the devastation, these 55 counties were divided into three groups: *extremely-affected counties*, *heavily-affected counties* and *not-heavily affected counties:* by the State Council. Therefore, in this study there were 9 extremely affected counties, 22 heavily affected counties, and 24 not-heavily affected counties. The research site was as shown in Fig.1.

This study used authoritative panel data extracted from the Statistical Year Book of each county's statistics bureau. However, as the statistical data varied from county to county and from time to time, due to the different data acquisition policies and the changing statistical policies in different counties, some indicator values were missing. There were also significant value differences; for instance, the GDP in most developed counties, such as Shuangliu near the capital Chengdu, was over 100 times higher than the least developed GDPs. Therefore, in the disaster resilience assessment, the change trends were considered more valuable than the absolute values, for which two data processing methods were implemented.

First, the missing values were imputed from an intermediate bisector line between the global and local lines, after which a variation was added to each imputed value to force the imputed value to follow the shape of the average trajectory (Genolini et al. 2013). However, if there were more than 30% values missing at random of a county for specific indicators, the county was temporarily deleted, which also meant that the samples varied in different sections. Overall, however, even the section with least available samples, i.e., Tourism Revenue for Long-term Disaster-recovering Capability Evaluation, had 16 sample counties, which implied sufficient data in each section from enough counties to allow for a detailed analysis of the relationships between disaster resilience and economic development/devastation extent.

2.3 Resilience Evaluation Models

(a) Correspondence Analysis

To determine the SDRC performance for the Wenchuan Earthquake, correspondence analysis (CA), which has been widely used in the ecological field (Beh and Lombardo 2014; Greenacre 2017), was applied. As an unconstrained ordination analysis method, CA is capable of mapping indicators and samples simultaneously on a 2-dimensional space (biplot), and preserves maximum data features by applying orthogonal component constructions on the distance matrix. Therefore, the resilience indicators and the affected counties could be intuitively obtained by using biplots.

CA can be applied when there are at least 2 rows and 2 columns, no missing data, no negative values and all data is of the same scale (Gauch 1982). Although ordination methods are sensitive to outliers, the ratio transformation in Section 2.2 was able to solve this problem, and the best CA performance was gained by comparing its data feature preservation and ordination results interpretability with three other unconstrained ordination analysis methods: Principle Component Analysis, Principle Coordinate Analysis and Non-metric Multidimensional Scaling.

The biplot analysis logic is the same as when used in ecological evaluations; each row represents the species distribution in a sample plot, with the higher the quantity value of a species, the more preference the species has for the corresponding sample plot. In this research, the higher the ratio, the more the county has positive feedback (a large growth rate) for the corresponding indicator.

The biplot can be explained in several ways according to Gauch (1982):

1. The counties and indicators around the origin share the least unique features and represent the most common counties/indicators that have similar properties.
2. A relative distance between counties or indicators can be applied to measure the similarities between those counties or indicators; the closer the distance, the more similar they are.
3. The correlation between two counties or indicators can be measured by their included angle towards the origin; the smaller the angle, the stronger the correlation.
4. The approximate preference between counties and indicators can be obtained via relevant distance; however, the distance value is meaningless.

(b) Gaussian Mixture Model

To further analyze the regional characteristics, cluster analysis was employed to group the county sets so that counties in the same cluster were more similar in some sense to each of those in the other clusters.

Taking the primary industry changes as an example, although many counties were influenced by the Wenchuan Earthquake and have experienced a steady recovery since then, the change trends have not been homogeneous (Fig. 2). Therefore, the Gaussian Mixture Model (GMM), a model-based clustering method and widely utilized heterogeneous group growth analysis method (Reinecke and Seddig 2011), was used to cluster the counties based on the different changing trends.

In this part, GMM is used to cluster the counties with similar change trends under a certain indicator into one group, so as to form several clusters, and then observe the different characteristics of different clusters under this indicator. After the clustering results were obtained, the general trends in each cluster were analyzed, and the counties' common recovery properties determined in relation to their differing economic development stages and devastation extent.

In this way, the characteristics of different geographical regions can be observed simultaneously, thus forming a horizontal analysis perspective. Then, the change trend of the indicator for several consecutive years is shown in the same plane Cartesian coordinate system, and a longitudinal perspective is obtained. As a result, the comprehensive resilience assessment is realized.

2.4 Research framework

The framework had two parts: preparation and resilience assessment, which had two components: a SDRC analysis using the CA and a LDRC evaluation using the GMM. After the CA, five substantially affected secondary indicators in 2008 were selected to assess their recovery trends as these could possibly take as long a time to recover as the primary indicators. In particular, the three *macro-economic* secondary indicators selected to assess economic development were the core focus of this study, and none of the transport indicators were selected because the substantial transport reconstruction projects were completed in 2008. The model structure is shown in Fig. 3.

2.5 County clustering and coding

The GMM was used to evaluate the economic development of each county before the Wenchuan Earthquake (from 2005 to 2007). As the GMM took the trends in these 3 years into account, it was much more valid than grouping them according to average value.

The counties were renamed based on their economic development and devastation extent, with the former based on the derived clusters, and the latter based on the official devastation extent certification. For instance, Wenchuan County, which had medium development and was extremely affected by the earthquake, was renamed ME1, and counties with similar properties, such as Dujiangyan City and Shifang County, were sequentially renamed as ME2 and ME3. The code names for the 55 counties are listed in Appendix A. Based on the different economic development levels, the average and underdeveloped counties were called *less developed counties*; and the extremely-and heavily-affected counties were called *severely affected counties*.

3. Results

3.1 Short-term disaster-resistance capacity analysis

(a) Macro-economic SDRC analysis

As shown in Fig. 4, the CA biplot preserved 92.3% of the original data features, which allowed for a general view of the indicators that were substantially affected, such as *total investment in fixed assets*, and the counties that had been positively (UE2, ME4) or negatively affected (AH1, ME1) on the corresponding indicator. The points around the coordinate origin shared similar features and indicated the counties or indicators that were not heavily affected. The approximate impact was indicated based on the relevant distance between the indicators or counties and was considered the reference point; that is, the further away the point, the more the indicator or county had been influenced. As can be seen, the earthquake had the most impact on *total investment in fixed asset* and *value-added of secondary* *industry*, especially in the *less developed* and/or *extremely-affected counties* in the right hand side and lower left corner.

The *value-added of secondary industry* and *total investment in fixed assets* in AH2, ME1 and UH2, located in A'ba prefecture north of Sichuan Province, for instance, had the most negative impacts. In the *extremely-affected counties,* such as UE2, ME4, UE3 and ME3, however, the earthquake had a positive impact on *total investment in fixed assets*, probably because of the massive infrastructure rebuilding required post-disaster. However, the *total investment in fixed assets* and *value-added of secondary industry* in counties located closer to Chengdu (the Provincial Capital) that already had more balanced industry structures and better overall economic performances, such as ME2 and AE, were less affected, reflecting high robustness and good disaster resilience.

(b) Industrial Economics SDRC analysis

As shown in Fig. 5, the Wenchuan Earthquake had a relatively lighter impact on the *end-of-year loan balance* and *post and telecommunications income*, while the *industrial value added* and *retail sales* declined considerably in the *severely affected counties*. Generally, the *end-of-year deposit balance* and *tourism revenue* were more affected and except for ME3, the *extremely-affected counties* (UE2, ME1, AE, etc.) had substantially increased *end-of-year deposit balances*, and the *undeveloped counties* had greater increases than the *medium-developed* and *average counties*. Also, most UN counties in the tourist areas were close to the *Tourism revenue* center, which indicated that they had a greater *tourism revenue* compared with the *severely affected counties*.

(c) Education and Medical Treatment SDRC analysis

As shown in Fig. 6, *medical institution number* and *primary school number* were more negatively affected in the *severely affected counties* than in the *not-heavily affected counties* around the coordinate origin. Specifically, there was a significant decline in the *less developed counties*.

Medical bed number and *medical technician num*ber showed a very strong correlation and had a moderate impact. The number of *school teachers* and *students*, on the other hand, were only slightly affected. Additionally, the number of institutions (*medical institutions*, *primary schools* and *middle schools*) was not found to be necessarily correlated with the human resources.

3.2 Long-term disaster-recovering capability evaluation

As in the above analysis, five representative indicators were selected from some of the dimensions that could have long-term impact on the LDRC evaluation: *value-added of primary industry*, *value-added of secondary industry*, *value-added of the private economy*, *tourism revenue* and *medical technician number*. To evaluate the resilience of the different counties for these five indicators, GMM was applied to cluster the different counties based on their resilience trends and distribution features (Table 3 and Appendix B, Fig. 7).

Table 3 P-value for the five secondary indicators from the Contingency Table Test

	Economic	Devastation	Economic & Devastation
Value-added of primary industry	0.0001	0.0895	0.0080
Value-added of secondary industry	0.1237	0.1190	0.2441
Value-added of the private economy	0.0885	0.0033	0.0008
tourism revenue	0.5425	0.1788	0.4978
Medical technician number	0.3729	0.3534	0.5346

As can be seen in Table 3, the economic extent for the *value-added of primary industry* was significantly correlated with its recovery capacity, the devastation extent was significantly correlated with the recovery capacity of *value-added of the private economy,* and the economic development and devastation extent jointly significantly impacted the recovery capacity for both *value-added of primary industry* and *of the private economy*.

Appendix B and Fig. 7 show the cluster results for the five secondary indicators and their recovery trends. Compared with the pre-disaster growth rate*, value-added of primary industry* had no substantial impact on most of the AH, AN, MH, and UH counties. Irrespective of economic development level, the *extremely-affected counties* were generally seriously affected, but recovered to their pre-earthquake state within 2-3 years. The difference was that the *less developed counties* in Class 5 recovered steadily and the MEs in Class 1 recovered faster even though the growth rate in both groups was the same 3-4 years after the Wenchuan Earthquake, which again indicated that the more developed counties appeared to have a greater resilience for primary industry recovery. Most of the counties in Class 4, which were classified as *not-heavily affected counties* suffered from substantial decreases and had slow recoveries, which may have been because of their geographical location as all were in A'ba Prefecture, which is dominated by plateau mountain areas and adjacent to the *extremely-affected counties*; therefore, the regional resilience in these areas is commonly lower.

The *value-added of secondary industry* was not affected in many *heavily-affected counties* and *not-heavily affected counties*, and even if there was an initial effect, the recovery generally took less than 2 years. However, the *value-added of secondary industry* was seriously affected in some *heavily-* and *extremely-affected countie*s. In the *less developed* Class 2 *counties*, the *value-added of secondary industry* recovered to the pre-earthquake state in around 3 years and in the following 1-2 years increased steadily. The *value-added of secondary industry* in the more developed counties in Class 4, however, took 4-5 years to recover and then increased steadily.

The *value-added of the private economy* showed no substantial impact in the *not-heavily affected* and most *heavily-affected counties*, and in the *severely affected counties* in Class 2 and Class 4, the *value-added of the private economy* was slightly affected, recovered quickly and then had a rapid increase. In

Class 3, the more developed and devastated counties such as ME3 and ME4 had a depression in the *value-added of the private economy* for 3 years, recovered and developed at a relatively slow speed. Compared to the state-owned industries that are given more from the central or provincial governments facilitating the recovery process, private capital is more vulnerable to disaster because private investments are more risk averse, which means that the devastation extent plays a more important role in the regional recovery process for the *private economy* than economic development.

The Wenchuan Earthquake had a substantial impact on tourism revenue in most Class 1 and Class 3 counties regardless of the devastation extent as it took 2-4 years for the Tourism revenue to recover, after which there was a rapid rise. The counties in Class 1 and Class 3 encompass Mianyang City and A'ba Prefecture, which are two famous tourism areas in Sichuan Province.

No obvious regularity was observed for *medical technician number* and therefore, there did not appear to be a correlation with the counties' degree of earthquake impact, economic development, or regional effect. The most affected counties, however, rapidly recovered in the year after the Wenchuan Earthquake.

4. Discussion And Conclusions

This research developed a general model suitable for all hazard resilience and provided a case study to analyze the correlations between economic development/ devastation extent and regional resilience. By examining the post-Wenchuan Earthquake scenario in 55 affected counties in China, which has a strong central government, this research avoided the interior and external gaps between regions found in Walters (2015). Counties with similar backgrounds were grouped with same code name to detect the interior factors affecting regional resilience. From the comprehensive assessment of the case, two main conclusions were drawn.

First, regional resilience after the Wenchuan Earthquake underwent a "resistance - recovery - redevelopment" process. The SDRC analysis indicated that most indicators and counties had been positively or negatively, and severely or mildly affected by the earthquake, but none were completely damaged. The LDRC analysis indicated that although the recovery trends varied, most resilience indicator clusters had a stagnant or slow recovery period for 1-3 years and then increased steadily and, entered a period of rapid development. This 1-3 year period was in accordance with most recovery patterns after the 1995 Hanshin-Awaji Earthquake (Karatani and Hayashi 2004); it was the rapid recovery period that made the post-Wenchuan Earthquake reconstruction unique.

There are several reasons why the recovery process after Wenchuan Earthquake was different. The Chinese government launched a three-year reconstruction plan with the intention that the economic development level reach or exceed pre-disaster levels (Dunford and Li 2011). To carry out this plan, the Chinese government provided timely, forceful and substantial national disaster aid, financial assistance, a wave of investments, and innovatively designed a 3-year national counterpart aid program, in which severely affected counties were aided by a partner province. All these efforts proved to be successful in aiding recovery in the affected regions (Zhao et al. 2018; Peng et al. 2018). In particular, the national counterpart aid outstripped the efficiencies of the other three typical aid programs (central government-oriented aid, national NGO aid, and international humanitarian aid) possibly because of the strong central government (Xu and Lu 2013).

Second, the regional resilience indicators varied depending on the specific situations in the affected counties. The SDRC analysis indicated that the Wenchuan Earthquake had an immediate negative impact on most counties near the seismic center on most indicators and especially on the economic related indicators, and that both economic development and devastation extent affected the disaster resistance of the *macro-economic*, *industrial economic* and *traffic volume* indicators. *Primary school numbers* were affected by the devastation extent but there were no obvious correlations observed between *educational* & *medical treatment* and economic development and devastation extent. While there was some regional commonality in some cities, the disaster resistance of the people's livelihood was also not obviously correlated with economic development and devastation extent.

Total investment in fixed assets and *value-added of secondary industry* had the lowest SDRC performances in most counties, and especially in the *less developed* and *severely affected counties*, which were substantially negatively affected. However, *value-added of secondary, tertiary industry* and *the private economy* were found to be more sensitive in both *medium developed* and *underdeveloped counties* in the extremely affected counties. The *average counties* were observed to have relatively better resistance capabilities for the *macro-economic* indicators in the short run.

The *end-of-year deposit balance* increased in many of the *less developed and severely affected counties*, with most UN counties in the tourist areas appearing to be greater beneficiaries for *tourism revenue* than the affected counties.

After the Wenchuan Earthquake, the *net-income of rural residents* decreased in the *severely affected counties* and many of the *less developed counties* in A'ba prefecture, possibly because the earthquake worsened the environmental conditions in this remote plateau area and in the neighborhood counties. While the *traffic volume* and *road mileage* were negatively correlated after the earthquake, the *number of medical* and *educational institutions* was not found to be necessarily correlated with the human resources.

The LDRC evaluation indicated that the *value-added of primary industry* recovery capacity was correlated with the county's economic development, especially in the *severely affected counties*, which tended to have a faster recovery. While the correlation was rejected by the contingency table test, it was observed that the *less developed counties'value-added of secondary industry* had better recovery. The *value-added of the private economy* recovery process was more driven by the devastation extent due to the inherent risk aversion of private capital. *Tourism revenue* and *net income of rural residents'* recovery, on the other hand, were determined more by the county's geographical location, and perhaps by municipal government policies and investments. In particular, economic development or the devastation extent was only observed to correlate with the recovery capacity of the *macro-economic* indicators, that is, the *value-added of primary industry* and the *private economy.*

CA has its strength on reflecting the associations between samples and indicators, while it is also sensitive to outliers, though this problem is kind of mitigated since the original data is transformed to the ratio forms. Besides, as it is necessary to assign the number of clusters for the GMM before clustering; and sometimes it is difficult to determine the features of each cluster when many clusters are required to obtain an acceptable AIC/BIC.

The proposed methods are also highly flexible, since researchers can code county names based on infrastructure states, public awareness of disaster risks, eco-system strengthening and many other factors that may correlate with the disaster resilience in specific counties. By assessing those samples using CA and GMM, very intuitive and reliable SDRC and LDRC results can be obtained. Therefore, a more general view on how the economic or social indicators would recover under different backgrounds could be further studied, which would work as good references for academic researchers and policy makers.

Declarations

Data Availability Statement: Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

Declaration of Conflicting Interests: The authors declare no conflict of interest.

Appendix

Appendix A

Counties based on the different extent of the disaster

Disaster devastation extent	Economic development extent	Code Name	County Names
Extremely-affected counties	Medium	ME	Wenchuan County (ME1), Dujiangyan City (ME2), Shifang County (ME3), Mianzhu County (ME4);
	Average	AE	Pengzhou City (AE);
	Underdeveloped	UE	Mao County (UE1), Beichuan County (UE2), Anzhou District (UE3), Pingwu County (UE4)
Heavily-affected counties	Developed	DH	Jingyang District (DH1), Fucheng District (DH2);
	Medium	MH	Guanghan City (MH1), Baoxing County (MH2), Shimian County (MH3);
	Average	AH	Jiuzhaigou County (AH1), Li County (AH2), Heishui County (AH3), Dayi County (AH4), Chongzhou City (AH5), Luojiang District (AH6), Jiangyou City (AH7), Youxian District (AH8), Lushan County (AH9);
	Underdeveloped	UH	Xiaojin County (UH1), Songpan County (UH2), Zhongjiang County (UH3), Santai County (UH4), Zitong County (UH5), Yanting County (UH6), Langzhong City (UH7), Hanyuan County (UH8)
Not-heavily affected counties	Developed	DN	Shuangliu County (DN1), Xinjin County (DN2), Pi County (DN3);
	Medium d	MN	Shunqing District (MN);
	Average	AN	Ma’erkang County (AN1), Pujiang County (AN2), Qionglai City (AN3), Jintang County (AN4), Tianquan County (AN5), Yingjing County (AN6), Yucheng District (AN7);
	Underdeveloped	UN	Rangtang County (UN1), Hongyuan County (UN2), Ruo’ergai County (UN3), Jinchuan County (UN4), A’ba County (UN5), Yilong County (UN6), Nanbu County (UN7), Jialing District (UN8), Yingshan County (UN9), Peng’an County (UN10), Xichong County (UN11), Gaoping District (UN12), Mingshan County (UN13)

Appendix B

Cluster results for the five secondary indicators based on the GMM

Index	Cluster	Counties
Value-added of primary industry	Class1	ME1, ME2, ME3, ME4, MH2, MH3, AH8, AH9, AN5, AN7, UH6
	Class2	UN6, UN8, UN12, UN13
	Class3	DH2, MH1, AE, AH4, AH6, AH7, AN3, AN6, UH3, UH4, UH5, UN9
	Class4	AH2, AN1, UE1, UH1, UN1, UN2, UN3, UN4, UN5
	Class5	DN1, AH1, AH3, AN4, UE3, UE4, UH2, UH8
	Class6	MN, UE2, UH7, UN10, UN11, UN7
	Class7	DH1, DN2, DN3, AH5, AN2
Value-added of secondary industry	Class1	DH1, DH2, DN1, MH2, MH3, MN, AH4, AH5, AN3, AN5, AN7, UE2, UH4, UH6, UN4
	Class2	ME2, AH2, AH7, AN1, UE1, UE3, UE4, UH1, UH2, UN1, UN2, UN3, UN5
	Class3	AN4, UH5, UH8, UN6, UN7
	Class4	ME1, ME3, ME4, AH1
	Class5	DN2, DN3, MH1, AE, AH6, AH9, AN2, AN6, UH3, UH7, UN10, UN12, UN8
	Class6	UN13
	Class7	AH8, UN9, UN11
Value-added of the private economy	Class1	DH1, DH2, MH1, MH2, MH3, AH6, AH7, AH9, AN5, AN6, AN7, UH3, UH7, UH8, UN10, UN11, UN12, UN13, UN8, UN9
	Class2	AH8, UE2, UH5
	Class3	ME3, ME4
	Class4	UE3, UE4, UH4, UH6
Tourism revenue	Class1	ME1, AH7, UE1, UE3, UE4, UH4, UH5
	Class2	UE2, UH7, UN6
	Class3	DH2, AH1, AH8, UH2, UN2, UN3
Medical technician num	Class1	DH2, DN1, DN2, DN3, MN, AE, AH4, AH5, AH7, AN2, AN3, AN4, UE3, UE4, UH5, UH6
	Class2	AH8, UE2, UH4
	Class3	ME1, ME2, AH1, AH2, AH3, UH1
	Class4	AH9, AN6, UH8, UN13

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Figures

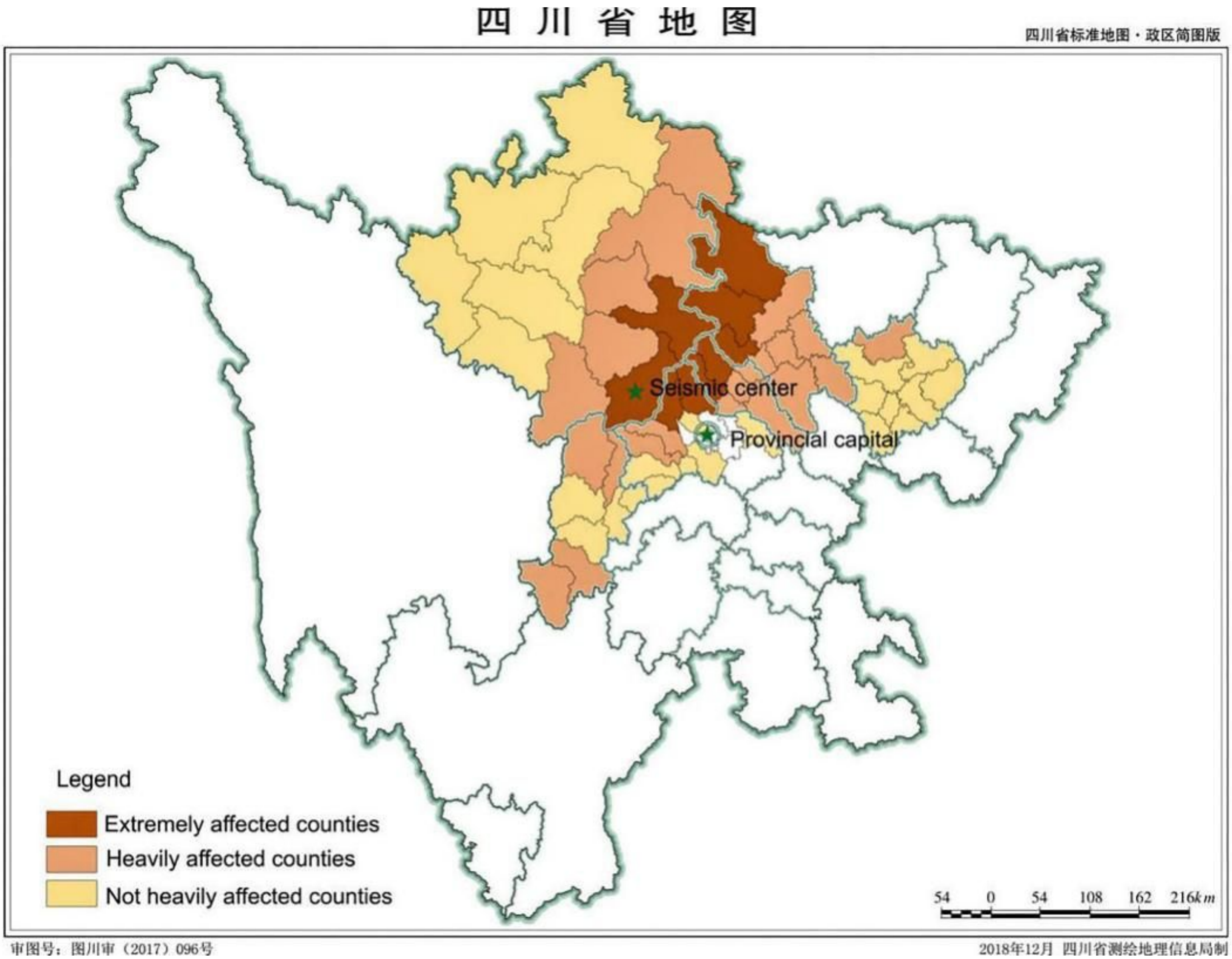

Figure 1

Research sites in Sichuan Province struck by the 2008 Wenchuan Earthquake 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.

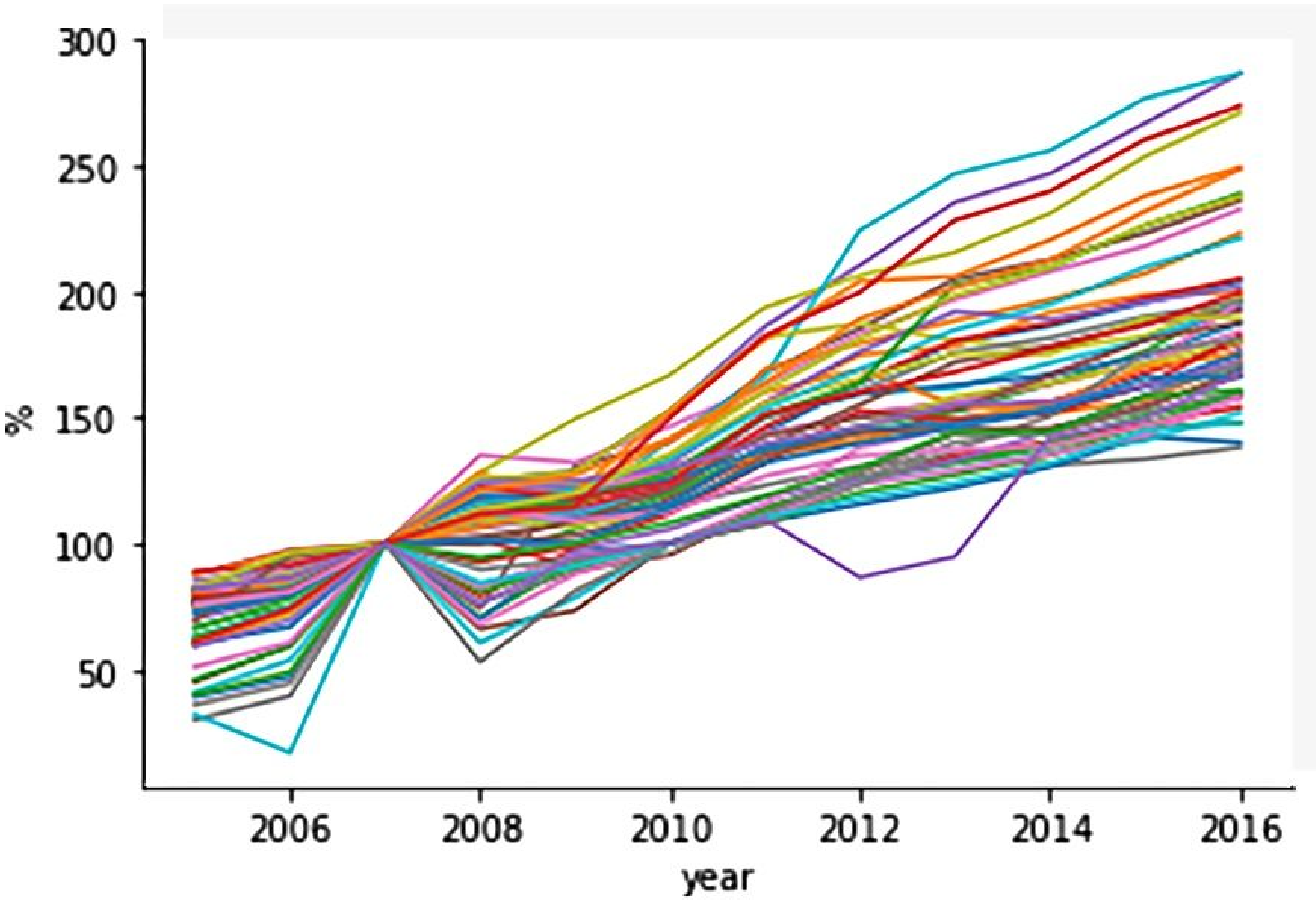

Figure 2

Primary Industry annual trends in the 55 counties

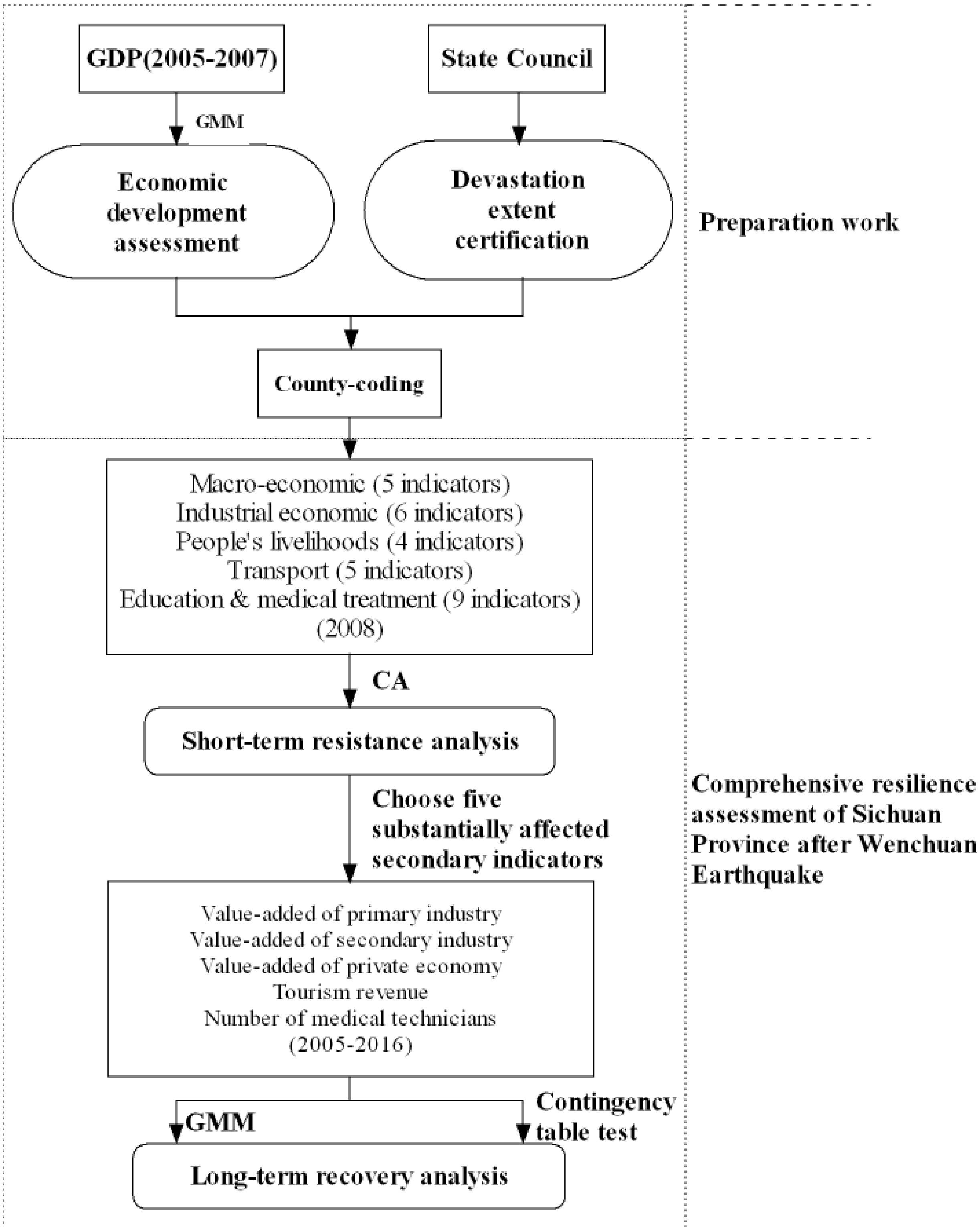

Figure 3

Key structure for the framework

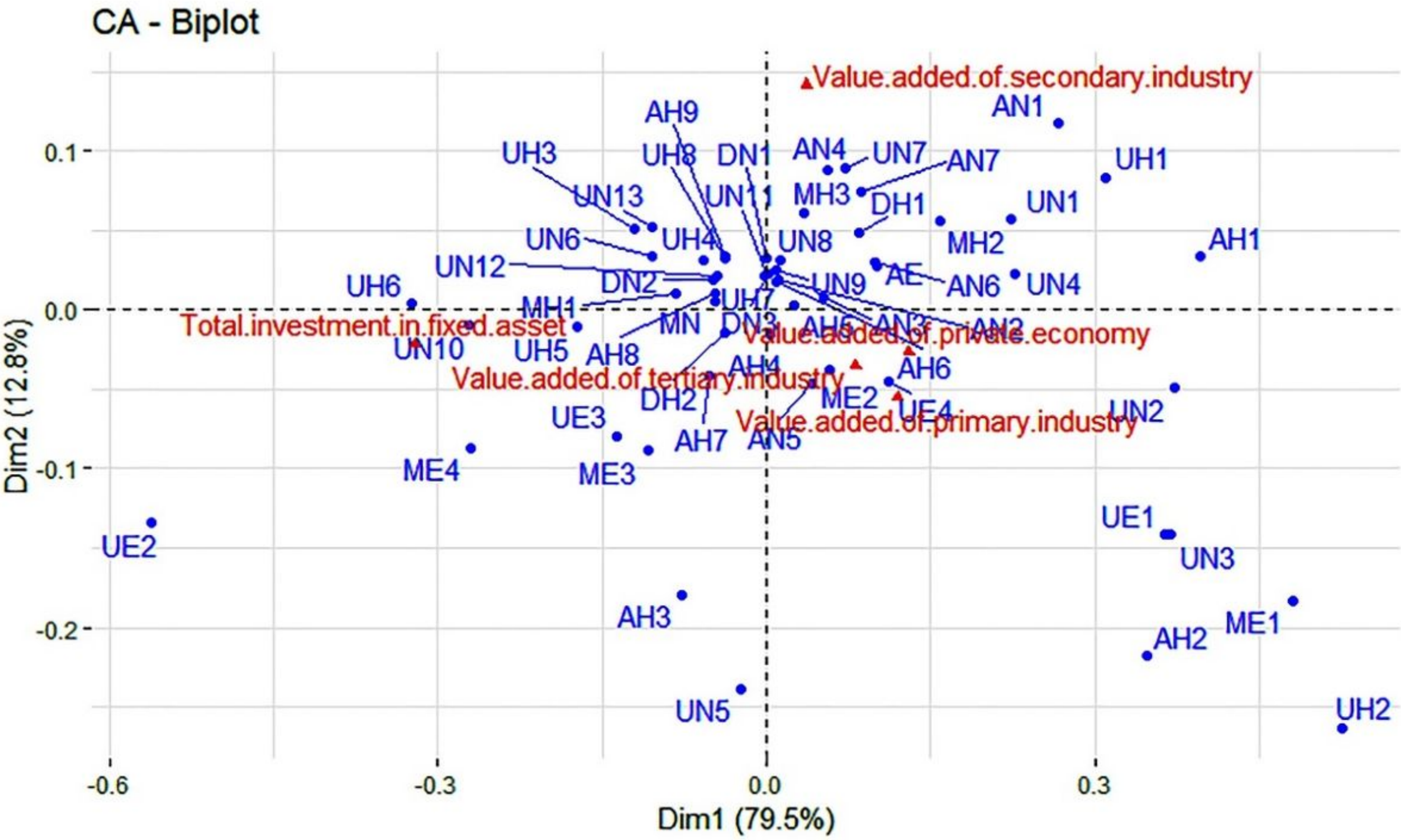

Figure 4

Macro-economic correspondence analysis biplot

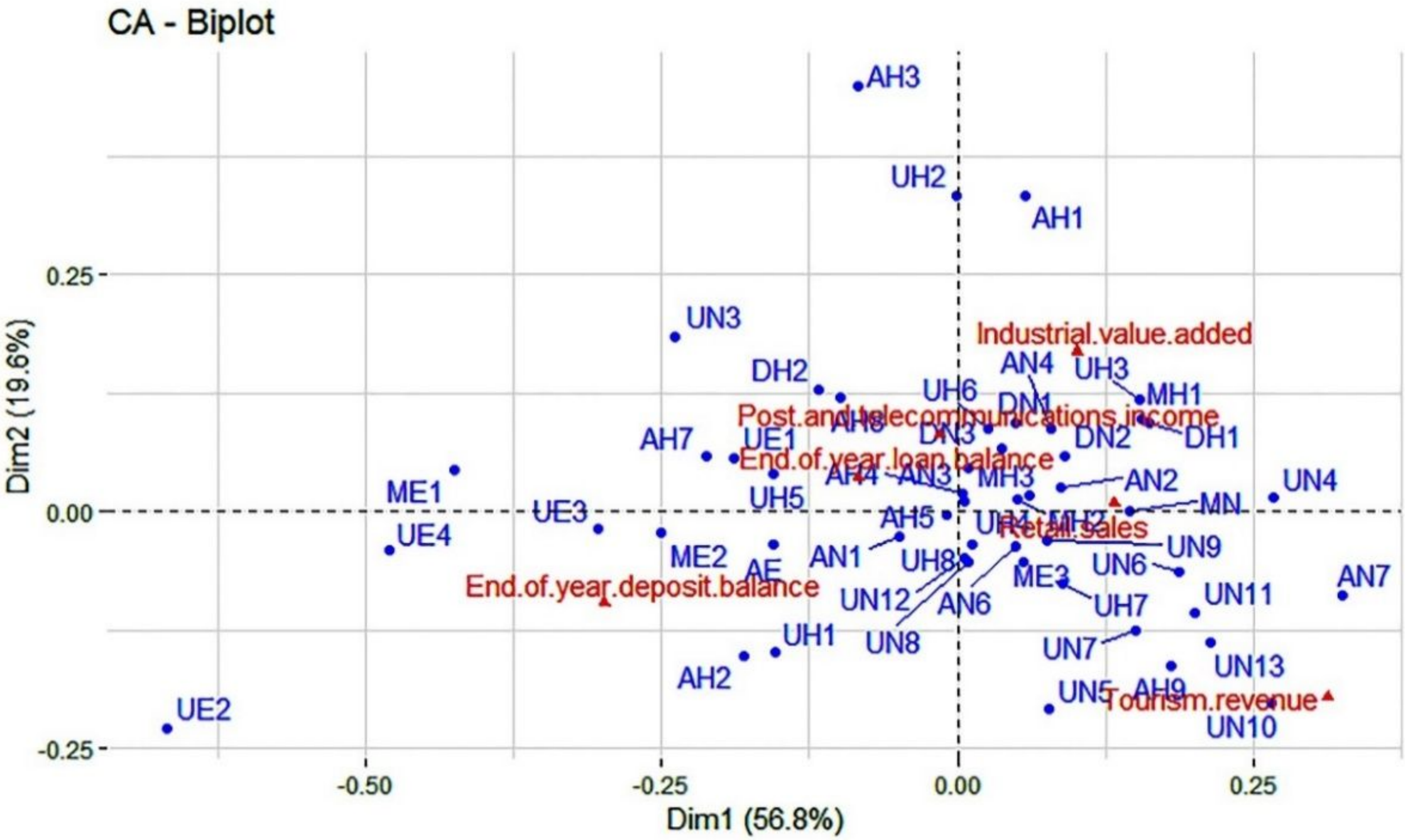

Figure 5

Industrial economics correspondence analysis biplot

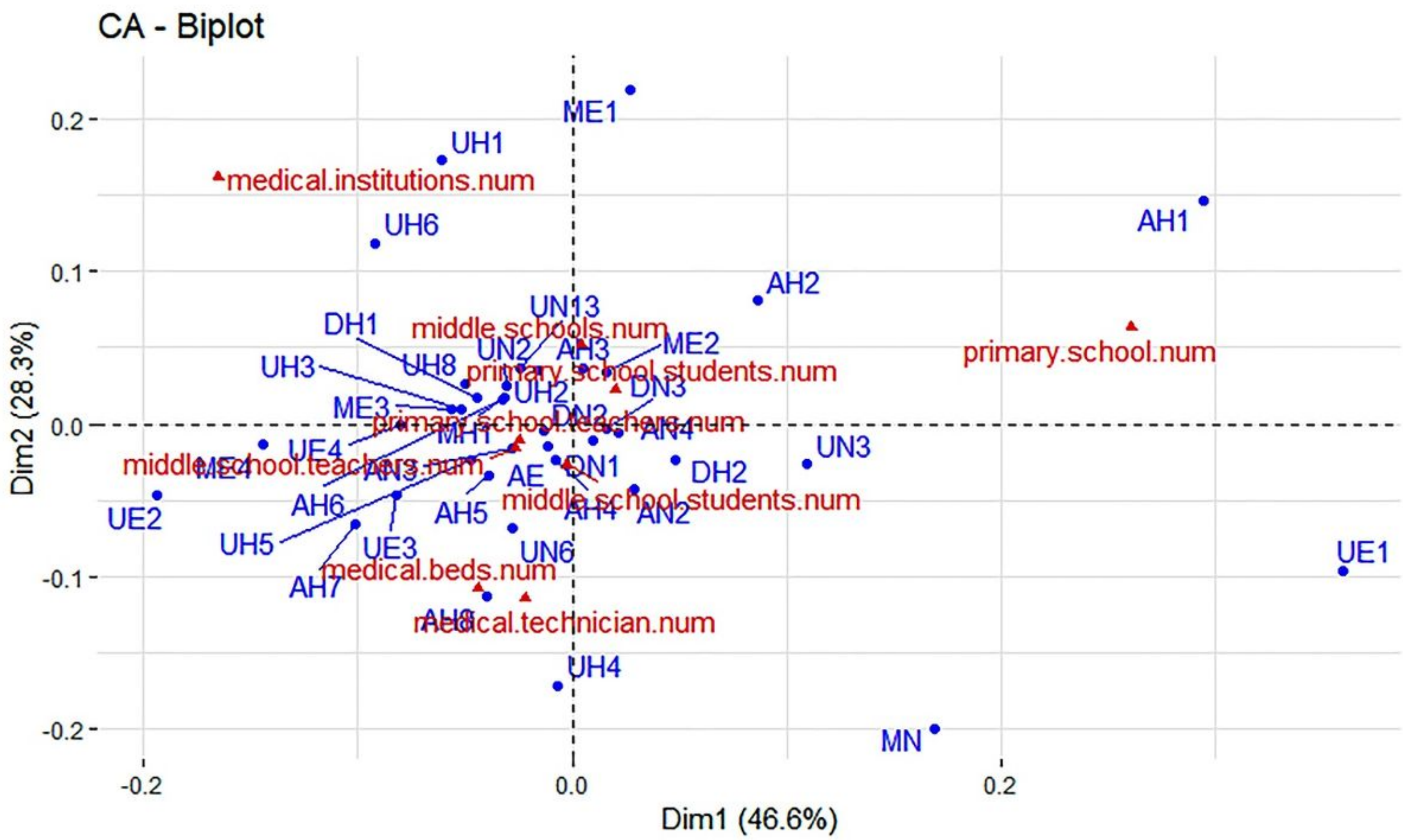

Figure 6

Education & medical treatment correspondence analysis biplot

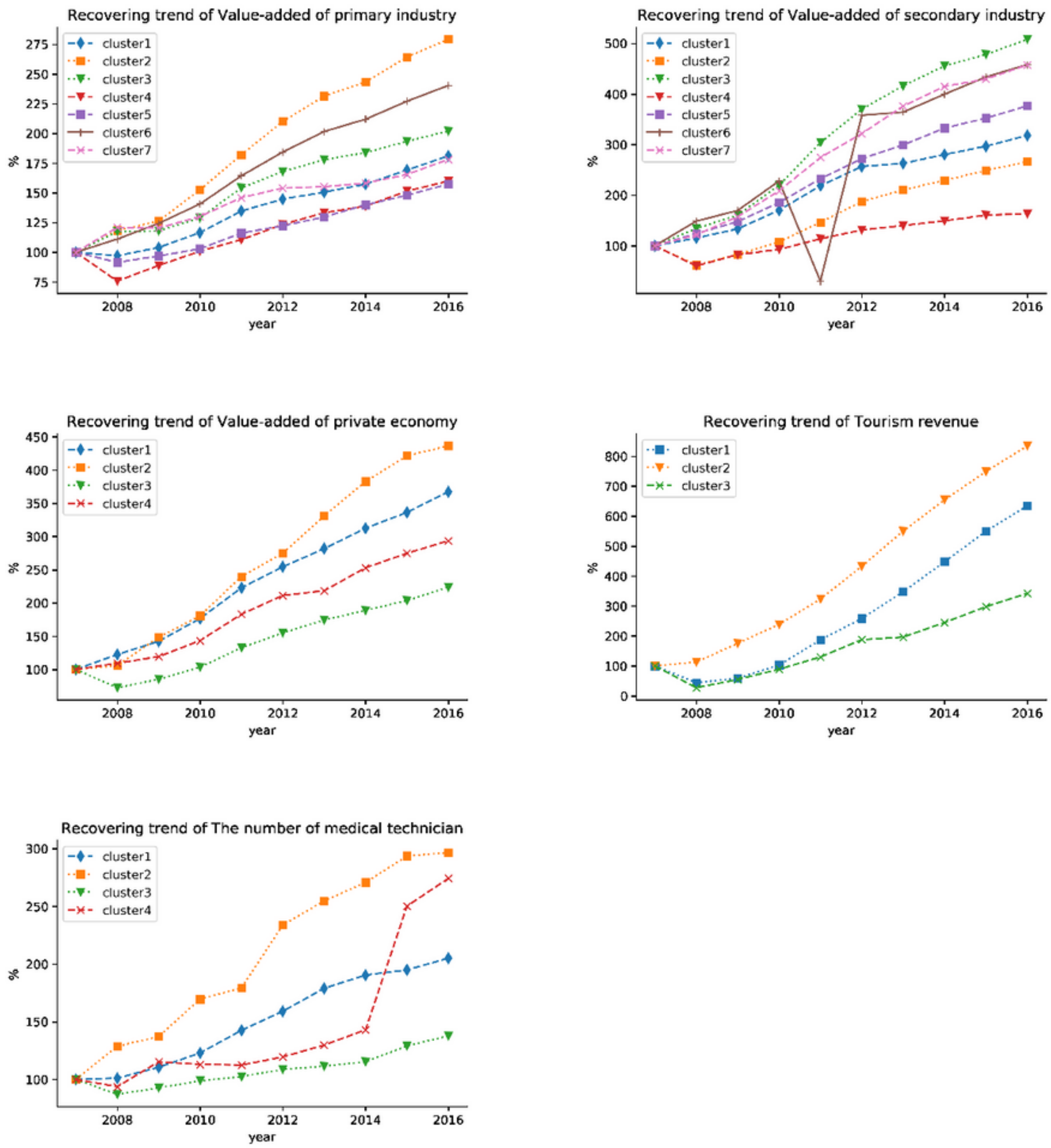

Figure 7

Recovery trends for each cluster for the secondary indicators