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Industrial Clusters and Their Boundaries : A Case Study for Plants in the Cincinnati Metropolitan Area

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Industrial clusters and their boundaries are identified by factor and hot spot analyses for the greater Cincinnati metropolitan area in USA. While traditional input-output approach identified aspatial industrial clusters, this study combines traditional approach with GIS techniques to identify their boundaries. Combining the results of input-output industrial clusters with the leading industries groups, we have identified five leading industry clusters. They are food (20), chemicals (28), metal manufacturing (32), metal products (33), and machinery (35). We also used hot spot analysis to visualize each industry cluster on the research area by using Arcview software. Determining the degree to which such industries are associated spatially and their spatial delimitation may be an additional approach to measuring the efficiency of the spatial organization of an economy. It is hoped that the industrial clusters and industrial spatial clusters approaches may also proved the basis for the development of new models of the spatial arrangement of industry at a level more aggregated than that of the single plant or firm.

Key words : input-output matrix, industrial clusters, hot spot, industrial spatial cluster

1. Introduction

Recent research has given a good deal of attention to the phenomenon of spatial agglomeration of economic activity (Malmberg, 1996). While a number of industrial location models for single plants are available, models of entire industries, of industrial concentrations, and of the industrial sector of regional economy have been few and weak. One detailed model, the input-output matrix, does describe the relationship among these more aggregated units of industrial structure, but it has been little used for locational analysis because of its complexity and its lack of direct spatial reference.

An input-output matrix which records the transactions between large numbers of industries is of great value for tracing in detail the impact of specific changes upon the economy as a whole; it is too complex to be used to make more general statement of spatial patterns of activities.

The research reported here applies factor analysis to an input-output table as a means of identifying functionally related groups of industries. These results in the identification of

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groups of industries which may be called industrial clusters. An industrial cluster[1] contains a base group of industries that have similar patterns of transactions, and it also includes other industries which are major suppliers of markets for those within the group. The results are empirically reexamined by identifying the leading industries. Then the identified industrial clusters will be mapped on the research area to propose spatial limit of each industrial cluster with a tool of GIS.

This article presents results drawn from secondary data analysis. After describing in detail the methodology of secondary data analysis, it provides a brief introduction to input-output analysis. Industrial clusters are extracted which are highly interrelated in terms of supplier chains within the metropolitan area. It also tries to identify leading industries based on speciali-zation, growth rates and employment share. The last part of this paper presents the spatial industrial clusters of manufacturing plants by importing industrial cluster results on the greater Cincinnati metropolitan area (Figure 1) that is especially not noted for recent unusual economic performance.

1) Literature review

Other investigators have used two different operational definitions of the industrial clusters concept. One definition considers the industrial clusters as a groups of highly interrelated industries contained within some major economic unit. The other definition describes industrial clusters as interdependent industries located at a single center or within a common region. The former, an aspatial type of clusters, can be examined by a straightforward

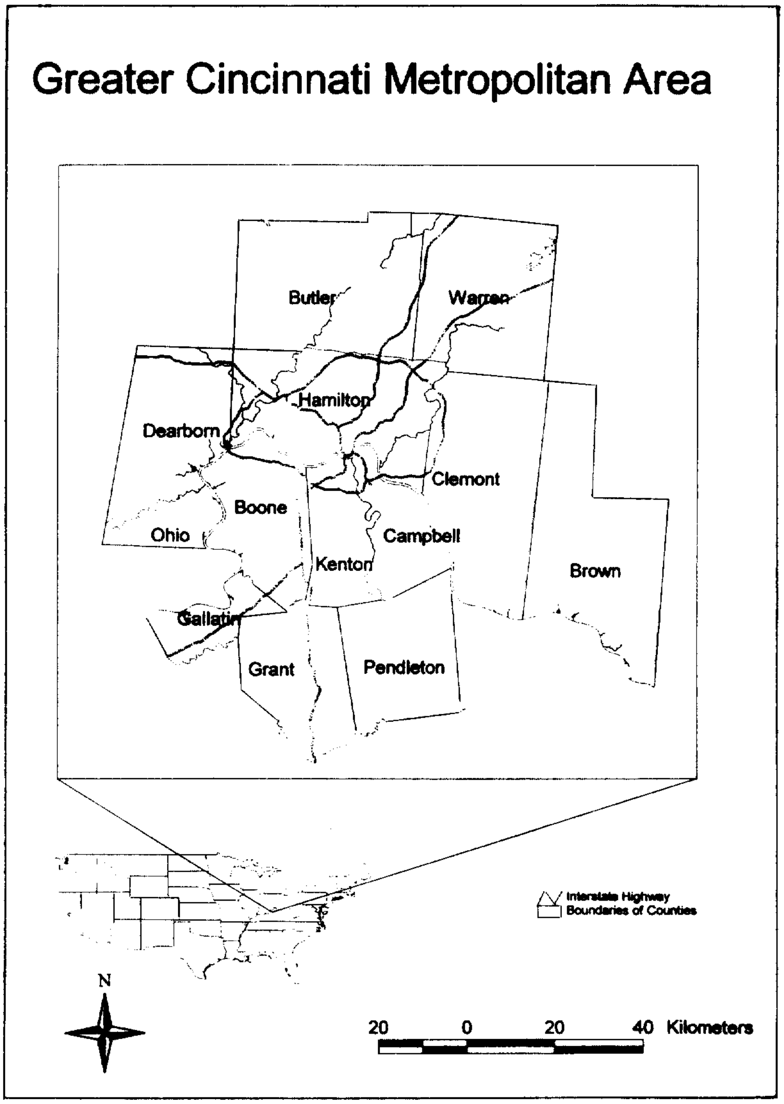

Fig 1. Research Area

analysis of inter-industry flow data. The most common technique for implementation of this analysis has been the triangulation of the inter-industry flows represented in an input-output matrix. Other aspatial approaches to the recognition of industrial clusters include that of Czamanski (1971). Another methodology is found in Campbell's analysis of inter-industry flows as directed graphs (1970).

For the latter, Isard and Smolensky (1963) define an industrial complex is a set of activities occurring at a given location and belonging to a group of activities which reap important external economies because of their close production, marketing or other linkages. The idea is similar to the territorial production complex described by Kolosovsky (1961). Richter and Streit (1969) have used correlation analysis of the number employed by presumably functionally linked industries in order to suggest the existence of both inter dependency and spatial association for certain groups of industries. Karaska (1969) utilized input-output data for the Philadelphia region to identify industries for which local supply and demand linkages were relatively great importance with this particular study area.

Although such searches for agglomerative forces within an industrial economy clearly have major value, there are certain difficulties with these attempts to recognize spatially-defined industrial clusters. As Richter (1969) noted high inter correlations in the data are likely to be in part due to forces other than the tendency for the location of one type of industry to influence the location of another. A more difficult problem is presented by the question of distances that may occur between spatially associated firms. Recently, using survey data from 239 USA-based Japanese-owned manufacturing firms, Reid (1995) finds support for such spatial clustering at the county but not at the state and national scales. The backward and forward-linked manufacturing firms is studied by Smith and Florida(1994), with empirical reference to Japanese auto-related manufacturers in the USA. The hypothesis that agglomeration is a significant factor in the location of such establishments meets the test. In recent years there Krugman examined the spatial concentration of employment by industry at the state level in his 1991 book and found that many industries are indeed highly concentrated geographically. Glaeser et al. (1992) identifies three general models of agglomeration economies and test how each of these economic structures stimulate employment growth in the long run. Anderson (1994) writes the use of industry clusters as a practical approach to development planning in Sillicon Valley. Gollub et al. (1997) do suggest that mathmatical cluster analysis be used to clarify manufacturing structure, however, the specification is sparse and the ability to interpret the resulting cluster groupings is absent. Held (1996) used factor analysis at the two digit level of the SIC supplemented with interviews and a traditional economic base analytical techniques to distinguish between vertically integrated clusters based on buy-sell relationships in all of New York state's counties, plus an aggregation for New York City.

Most researchers examine the scope of an existing pre-determined cluster, or limit their study to dynamic regions where clusters are assumed to be at the heart of the region's success. This brief review of previous work suggests that recognition of industrial clusters has so far been hindered by a lack of sufficiently powerful techniques. In this study, factor analysis with varimax rotation combined with hot spot analysis are proposed as an approach which may avoid some of the problems noted here.

2) Key concepts

It is worthwhile to briefly introduce some key concepts used throughout this study, although more detailed definitions will be provided later. Leading industries are defined as industries that show specialization relative to the national economy structure, occupy a relatively large portion of the regional economy, and have relatively higher growth rates for the past 10 years. Industrial clusters are defined as clusters of related industries in terms of input-output linkage structures. In other words, a subset of industries which trade more strongly with each other than with other industries will be regarded as an economically integrated group. These industrial clusters do not necessarily mean that they are spatially concentrated. Spatial clusters are defined as subsets of industries which are more closely spatially associated with each other than with other industries.

2. Methodology for the Identification of Industrial Clusters

Archival data analyses focus on the identification of leading industries and industrial clusters. Major data sources used in this case study are: the Census of Manufacturers, the County Business Pattern, the Manufacturer Directory of Greater Cincinnati and the Industrial Pin-pointer based on Harris Manufacturer Directory for necessary years. Finally, input-output tables for the Greater Cincinnati(1996) area have been used to identify industrial clusters.

To identify leading industries, three criteria were considered: specialization (location quotient), growth rates, and relative percentage of employment to the total employment. To see which industries are specialized, a location quotient (LQ) has been calculated. In order to see which industries grow faster than others, employment growth rates by industry for the years 1987 and 1996 have been calculated. To measure the relative importance of an industry, its share of employment in 1996 has been calculated.

For industrial clusters, factor analysis using principal component analysis was performed for input-output tables of the Greater Cincinnati metropolitan area. Principal component analysis is a form of factor analysis, used to reduce a set of variables to a smaller representative set of variables. The transformation is based on the intercorrelation among the variables. A basic assumption is that each variable is a linear combination of the hypothesized factors. Because of this, variables and factors are in a standard form, and factor loadings are the weighted coefficients of the common factors. In this case, common factors are uncorrelated between each other and their number is smaller than the number of the original variables. R-mode technique has used to correlate thirty eight industries groups with four hundred seventy one sub industries groups. Communality is the proportion of the variables variance accounted by the common factor. Principal components analysis is a factor analysis with communalities equal to one. Eigenvalues are the numerical values which represent the amount of variance, for which the corresponding factor accounts. In this study, eigenvalues greater than one are used for threshold following the standard suggested by Granda (1965). In an attempt to reduce the complexity of the underlying factors, some forms of rotation are employed. The objective of a rotation is to achieve high loadings on, as few as possible, factors and zero or near zero loadings for all the other factors. For this study, varimax rotation which emphasizes a factors simplification was used.

To identify industrial spatial clusters, the nearest neighbor analysis and cluster analysis were performed. To judge the degree of cluster of the industries, the nearest neighbors index R was calculated based on the absolute coordinates of each plants. To identify the spatial limit of industrial clusters, a cluster analysis was performed for each industry group. In this study, cluster analysis software from the Department of Criminal Justice of the State Illinois was used.

3. Industrial Clusters

1) Identifying the Leading Industries

Which industries lead the regional economy? The reason for focusing on industrial clusters is that they are hypothesized to be a major source of a regional economy's competitive advantage, a term coined by Porter to capture a broader array of forces behind trade than comparative advantage, with its emphasis on factor endowments (Porter, 1990). The major source of cluster economies is generated by the forces of inter-correlation and collaboration in production innovation, the adoption of process innovations, and the encouragement of entrepreneurship to take advantage of perceived market, supply, or distribution gaps with the cluster by leading industry groups. Although there are available data sources about productivity and exports at the two or three digit level, data at the four-digit SIC level is unavailable. This study primarily relied on data from the 1987 and 1996 Industrial Pin-Pointer of Greater Cincinnati, which organizes plants through both a Standard Industrial Classification (SIC) scheme, and spatial information about each plant. Through these data analyses, we identified the region's leading manufacturing industries. We used three criteria to identify the leading industries in terms of employment Location Quotient, growth rates for last ten years and its relative share to the regional manufacturing employment. These three sets of variables are derived from economic base theory and theories of competitive advantage. One measure of competitiveness is the change in the share of an industry's employment with its relative share to all the industry. Another measure of each industry's competitive position is location quotients (LQ). Economic base theory is a major theoretical explanation of regional employment growth and economic development. The theory holds that employment in a regional economy rests with goods and services that are exported to consumers who live outside of the economy.

The threshold for each criterion contains sixty percentage of the region's manufacturing employment respectively (Table 1).

Table 1. Threshold of the Leading Industry

Criteria	Threshold
Location Quotient	greater than 1.35
Growth rates	greater than 2.5%
Employment shares	greater than 0.85%

Out of all the four digit industries, thirty six industries have been extracted as leading industries in the region, which meet any two criteria of three criteria. When all three criteria are applied, the selected industries contain only twenty eight percent of the regional manufacturing employment, which means the criteria are too restrictive and missing a major features of the regional economy (Table 2). If an industry meets any two of three criteria, we selected that industry as a leading industry. The leading industry groups were simplified using two-digit SIC codes (Table 3)[2]. These industries listed in Table 4 with their LQ, share and growth rates.

Of significant note is the employment share of

Table 2. Employment Contained by the Combination of Criteria

Number of Criteria	Three	Two	One	Total
Employment Percentage	42,775 28.18	97,146 63.99	133,084 87.67	151,806 100.00

six main industries-Food (20), Chemicals (28), Metal (33), Metal products (34), Machinery (35), and Motors and Aircrafts (37).

Together the six leading industry groups explains total sixty eight percentage of the selected leading manufacturing employment. As table 4 makes evident, motors and aircraft (37) and metal manufacturing industries mainly consist of large plants, while metal products (34) and food (20) industries are small plants.

These selected industries are combined with input-output industrial clusters for the identification of main leading industries.

2) Industrial Clusters

This research applies factor analysis to an input-output table as a means of identifying functionally related groups of industries. This results in the identification of groups of industries which may be called Industrial Clusters. An Industrial Cluster contains a base group of industries that have similar patterns of transactions. It also includes other industries which are major suppliers of markets for those within the group.

OHUallachain's methodology (1984) is based on the calculation of an intra-regional purchase and

Table 3. Leading Industry Groups at Two Digit Level

Sector	Employment	%	Establishment	%	Average Employment
sic20	**10403**	**10.7**	**55**	**10.1**	**189**
sic23	2603	2.7	3	0.6	868
sic24	380	0.4	2	0.4	190
sic26	299	0.3	7	1.3	43
sic27	4845	5.0	60	11.0	81
sic28	**16187**	**16.7**	**48**	**8.8**	**337**
sic29	1460	1.5	18	3.3	81
sic30	350	0.4	1	0.2	350
sic31	230	0.2	2	0.4	115
sic32	1291	1.3	10	1.8	129
sic33	**10570**	**10.9**	**19**	**3.5**	**556**
sic34	**99370**	**9.6**	**120**	**22.0**	**78**
sic35	**15222**	**15.7**	**115**	**21.1**	**132**
sic36	935	1.0	5	0.9	187
sic37	**19329**	**19.9**	**24**	**4.4**	**805**
sic38	1840	1.9	10	1.8	184
sic39	1853	1.9	29	5.3	64
Total	97167	100.0	546	100.0	258

Table 4. Four-digit Leading Industry Structure

SIC	Employees(1987)	Employees(1996)	LQ(1996)	Share(1996)	Change (1987-1996)
2013	168	3289	2.87	2.17	1857.74
2043	200	290	1.34	0.19	45.00
2051	1991	2132	1.03	1.40	7.08
2052	1030	1365	2.17	0.90	32.52
2082	693	853	1.84	0.56	23.09
2086	1729	1500	1.45	0.99	-13.24
2087	372	974	7.05	0.64	161.83
2812	30	150	1.40	0.10	400.00
2819	379	2375	2.24	1.56	526.65
2821	70	1425	1.74	0.94	1935.71
2841	6035	2140	4.86	1.41	-66.06
2844	2178	6327	7.89	4.17	190.50
2865	1033	1639	5.50	1.08	58.66
2869	1422	2131	1.59	1.40	49.86
3312	7752	4661	2.04	3.07	-39.87
3316	17	4991	24.64	3.29	2925.82
3354	100	260	0.75	0.17	160.00
3369	40	142	2.21	0.09	255.00
3398	254	516	2.20	0.34	103.15
3412	485	556	5.68	0.37	14.64
3442	1251	1291	1.42	0.85	3.20
3443	365	1435	1.36	0.95	293.15
3444	1978	2284	1.64	1.50	15.47
3469	511	1322	1.07	0.87	158.71
3479	121	866	1.46	0.57	615.70
3494	1220	1616	7.44	1.06	32.46
3534	300	390	3.78	0.26	30.00
3535	1133	1921	4.71	1.27	69.55
3541	7325	3906	10.63	2.57	-46.68
3546	78	1783	8.26	1.17	2185.90
3555	617	733	2.85	0.48	18.80
3556	43	606	2.39	0.40	1309.30
3559	2693	2770	2.48	1.82	2.86
3565	612	634	1.79	0.42	3.59
3599	1690	2479	0.74	1.63	46.69

an intra-regional sales coefficient. The intra-regional purchase coefficient is defined as:

kij = Xij/Xj

The intra-regional sales coefficient is defined as :

tij = Xij/XI

where, Xij are the intra-industry flows (from I to j),

Xj are total purchases of the j-th sector, and

Xi are total sales from the i-th sector.

Table 5. Factor Components and Percentage of Explanation at Two-digit level

Industries	Food	Machinery	Metal	Wood&Fur	Electricity	Chemical	Glass	Metal Product
	2011	3511	3483	2411	3612	2812	3229	3312
	2015	3519	3484	2421	3613	2873	3221	3313
	2021	3523	3482	2426	3621	2875	324	3315
	2023	3524	3489	2429	3625	2879	3251	3316
	2024	3531	3411	2431	3624	2861	3253	3317
	2028	3532	3412	2434	3629	2891	3255	3332
	2081	3533	3431	2435	3631	2892	3259	3462
	2032	3534	3432	2439	3632	2893	3261	3398
	2033	3535	3433	2452	3633	2895	3262	3399
S	2034	3536	3441	2451	3634	2899	3263	3331
	2035	3537	3442	2491	3635	2821	3264	3334
	2092	3541	3443	2448	3639	2822	3269	3339
	2037	3542	3444	2499	3641	2823	3271	334*
	2038	3544	3446	2495	3645	2824	3272	3351
I	2041	3546	3448	2441	3643	283*	3273	3353
	2043	3547	3449	2511	3651	2841	3274	3356
	2045	3548	3451	2519	3652	2842	3275	3357
	2047	3543	3465	2517	3661	2843	328*	3363
	2048	3549	3466	2512	3663	2844	3291	3368
C	2044	3556	3469	2514	3671	285*	3292	3369
	2046	3552	3421	2515	3674	291*	3295	3463
	2051	3553	3423	2521	3672	2992	3296	
	2052	3554	3425	2522	3691	2999	3297	
	2053	3555	3429	2531	3692	2951	3299	
C	2061	3559	3471	2541	3694	2952		
	2064	3563	3479	2542	3695			
	2066	3562	3495	2591	3699			
	2067	3564	3493	2599				
	2068	3566	3494					
	2082	3567	3497					
O	2083	3569	3499					
	2084	3565						
	2085	3592						
	2088	3593						
	2087	3596						
D	2074	3599						
	2075	3578						
	2076	3571						
	2077	3575						
	2095	3579						
E	2079	3581						
	2097	3582						
	2098	3585						
	2096	3586						
	2099	3589						
	211*							
	212*							
	213*							
	214*							
N	49	45	31	28	27	25	24	21
% of Exp	16.94	10	7.43	5.67	5.16	4.99	4.81	4.38
Cumulative %	16.94	26.95	34.38	40.04	45.2	50.19	55	59.38

* The original data of input-output matrix has three digit industry classification code

By defining the intra-regional sales and purchase coefficients, the matrices of inter-industry intra-regional requirements (K) and sales (T) are obtained.

The threshold level selected by OHUallachain (1984) has the value of 0.40. This corresponds to the value of loadings which are statistically significant at the one percent significance level, according to the Burt-Banks formula (p.425). Eight dimensions are derived from the aggregated transactions matrix about which industries are grouped by similarities of transaction flows. Together they account for sixty percent of the variance found in the data. Table 5 and 6 (with a simplified format) show that Factor I (Food), containing seventeen percent of the total variance and is composed primarily of food industries. Factor II (Machinery) represents a grouping made up entirely of machinery and equipment industries; it accounts for ten percent of the total variance.

An examination of the transactions shown in the input-output data confirms that the most important flows for each industry link it with another in the group. In a similar manner, the remaining industrial clusters are defined and described from the results of the analysis presented in Table 5. Factors III (Metal Products), IV (Wood and Furnitures), V (Electrical Equipments), VI (Chemicals), VII (Glass and Stone) and VIII (Metal manufacturing) are drawn for further research for the formation of possible industrial districts.

Combining the results of input-output industrial clusters with the leading industries groups which are identified in the previous section, we have five leading industry clusters. They are food (20), chemicals (28), metal manufacturing (32), metal products (33), and machinery (35). Together the five leading industries made up fifty percent of the regions manufacturing employment.

4. Industrial Spatial Clusters

These industrial clusters are economically interrelated, that is, linked by flows of goods stronger among them than with the rest of the economy, and following similar sales or purchase pattern. From an employment analysis, the leading industry which mainly drives the regional economy was identified. What is missing is the spatial aspect of those analyses, because industrial districts theses emphasized the importance of spatial proximity, which facilitates close interrelationships among plants within the districts.

In this section, two analyses of industrial spatial clusters are considered. The first, whether

Table 6. Factor Components and Percent of Explanation at Two-digit level

Factors	1	2	3	4	5	6	7	8
Industry	Food	Machinery	Metal	Wood	Electricity	Chemical	Glass	Metal Product
SIC code	20	35	34	24	36	28	32	33
N	49	45	31	28	27	25	24	21
% of Explanation	16.94	10.0	7.43	5.67	5.16	4.99	4.81	4.38
Cummu-lative %	16.94	26.95	34.38	40.04	45.20	50.19	55.00	59.38

the distribution of plants in the area is dispersed or agglomerated is determined. To this end, we have calculated the nearest neighborhood index R for selected industry groups. Second, a series of maps are presented which not only show the distribution of plants, but also the range of spatial delimitation of clusters of selected industry groups.

1) Cluster Analysis of Industrial Clusters

A standardized nearest neighbor index R is to determine the difference in the degree of cluster among industry groups. The R index can be calculate by dividing the average nearest neighbor distance by the corresponding value for a random distribution with the same point density. With the standardized index, a perfectly clustered pattern produces an R value of 0.0, a random distribution of 1.0, and a perfectly dispersed arrangement generates the maximum R value of 2.149.

Table 7. Nearest Neighbor Index R by Type of Activities

SIC	R
Total	0.22
Food	0.33
Machinery	0.31
Metal	0.28
Wood & Furniture	0.53
Electricity	0.36
Chemicals	0.28
Glass	0.42
Metal Products	0.29
Textile	0.39
Paper	0.29
Printing	0.25
Rubber & Leather	0.33
Motor & Aircraft	0.34
Instrument	0.24
Miscellaneous	0.46

The Nearest Neighbor index R for all selected manufacturing shows that their distribution is almost perfectly clustered, except the wood and furniture industry which has an R indices of than 0.5.

Industrial districts can be organized around buy-sell relationships between the leading industries and others in the complex, the use of common technologies among plants in the driver industries and other industries in the cluster, and by sharing the local labor market. However, table 7. shows no significant differences between industries which belong to industrial clusters and those that do not. One concludes that industrial clusters identified by input-output analysis do not have higher degree of cluster than those of other industries or leading industry groups.

2) Industrial Spatial Clusters

Five industrial clusters are identified using factor analysis of input-out tables of the Greater Cincinnati Metropolitan Area. This section analyzes their spatial clusters using Cluster Analysis Software from the Criminal Justice Department of Illinois State, called STAC[3]. It is a spatial analysis tool designed to identify hot spots of criminal occurrences. Based on X and Y coordinates of position, this software finds spatially delimited area of clustered spots. Essentially, the hot spot area routine in the STAC creates areal units from point data by identifying the major concentrations of incidents for a given distribution. Each dense area is represented by a standard deviational ellipse[4]. The ellipses are calculated in the STAC program then imported to ArcView software where we geocoded location of all manufacturing plants of the research area.

The following series of maps show the distribution of manufacturing plants and their

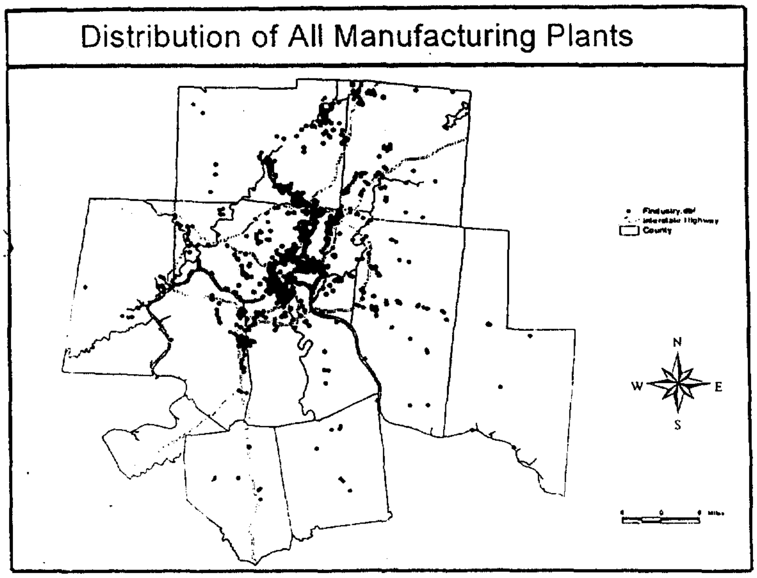

Fig. 2 Distribution of All Manufacturing Plants

spatial industrial clusters.

The distribution of whole manufacturing plants and their spatial industrial clusters are shown on Figure 2. Urban manufacturers cluster together for several reasons.

Topography restricts where industry can locate, and land use controls increasingly circumscribe the areas in which manufacturing can take place. The clustered pattern resulting from regulation is often exaggerated by the development of urgan industrial parks, which frequently are located close to the access points of major transportation routes. With completing of the interstate and intraurban highway networks, these points of access tend to be in the urban periphery and it's also true for the research area. The plants are mainly located along the corridor between inter-state highways 71 and 75.

The answer to a question such as whether or not the features within a certain area on the map are densely clustered, or just one permutation of random distribution, depends on the eye of the observer. To identify high-density areas without regard to artificial boundaries we used the STAC software. The predefined, arbitrary boundaries of areal analysis are an obstacle to the identification of such real high-density areas.

The STAC identifies three Industrial Clusters: a down-town cluster; traditional industrial core, a Springfield- Sharon wood cluster, and a Florence

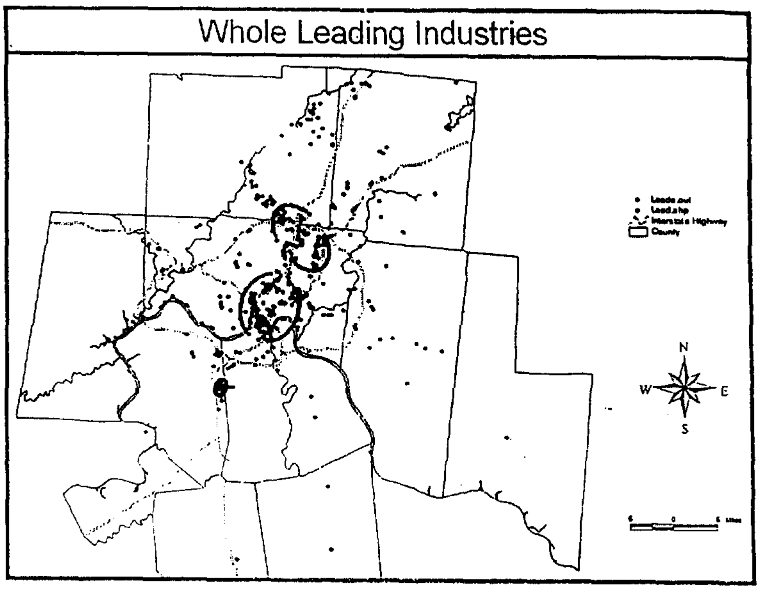

Fig. 3 Industrial Spatial Clusters of Leading Industries

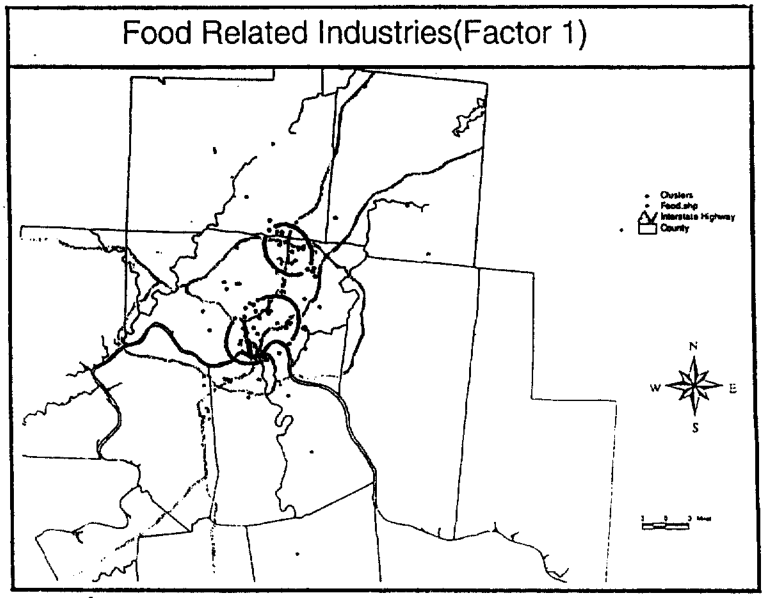

Fig. 4 Industrial Spatial Clusters of Food Industry

cluster in Kentucky; periphery and modern clusters. These results suggest a high possibilities of the formation of an industrial districts among these industrial spatial clusters. The selected area encompasses sixty five percentage of all manufacturing plants in the region. Figure 3 shows the all leading industry groups. Not surprisingly, it has a pattern almost similar to the manufacturing plants of all, in terms of their distribution and their spatial clusters encompassing seventy one percentage of total leading manufacturing industry groups. Among five industry groups that identified as both leading industry groups and input-output industrial cluster, chemical and metal products industries are excluded for the spatial industrial cluster analysis, because two industry groups do not have enough number of plants in the region.

Figure 4 shows the food industries distribution and their spatial clusters. They are concentrated in the inner metropolitan area and are characterized by two spatial clusters. One in the downtown area along the Mill Creek, and the other in the Springfield area. The selected area includes ninety percentage of food related manufacturing plants of the region. The machinery and metal industries show similar spatial distribution and spatial clusters (Fig.5 and Fig.6). Considering that both industries are closely related, these results confirm that they have similar location

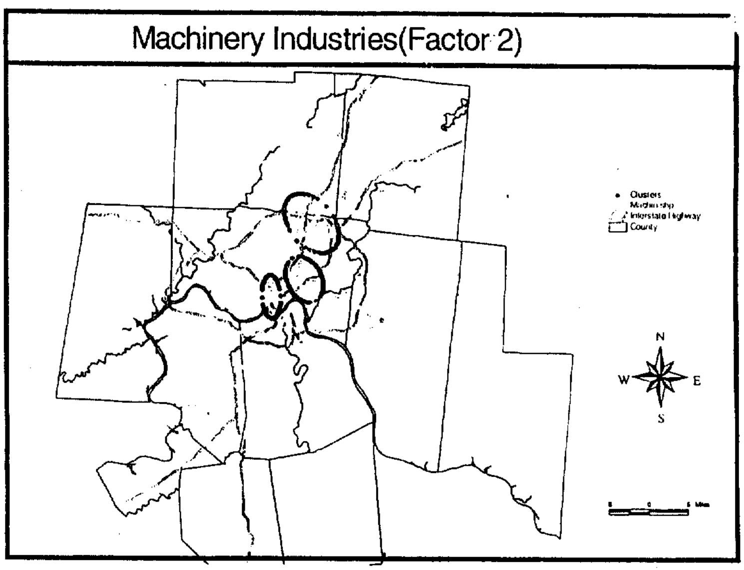

Fig. 5. Industrial Spatial Clusters of Machinery Industry

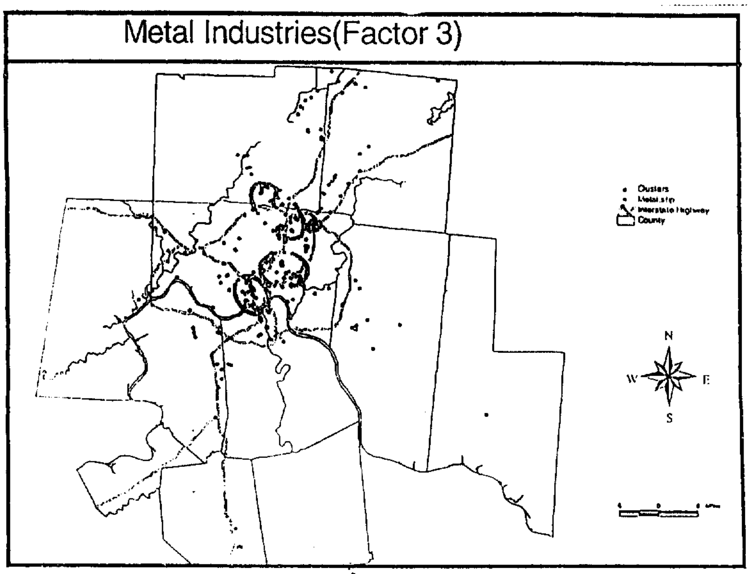

Fig. 6. Industrial Spatial Clusters of Metal Industry

tendencies. The software identified three spatial clusters. One in the downtown area and the other in Springfield- Shronwood area. The new cluster added is located in Norwood area. The selected areas include sixty eight percentage and seventy one percentage of each manufacturing plant respectively.

4. Summary and Conclusion

An obvious research direction of interest is to investigate the extent to which industries identified in an industrial complex as functionally related are also spatially proximate. This problem is being pursued in connection with analysis of the greater Cincinnati metropolitan area input-output table. Determining the degree to which such industries are associated spatially may be an additional approach to measuring the efficiency of the spatial organization of an economy. Among all manufacturing industries, six leading industries groups have been extracted based on their employment specialization, growth rates and share of total manufacturing: food, chemicals, metal manufacturing, metal products, motors and aircraft, and machinery. Eight input-output industrial clusters have been extracted through factor analysis of input-out tables: food, machinery, metal manufacturing, wood and furniture, electrical equipment, chemicals, glass and stone, and metal products. Five industry groups (machinery, metal manufacturing, chemicals, food, and metal products) are major components of the regional economy in that they appear on both the list of leading industry groups and input-output industrial clusters, suggesting possible formation of industrial districts. All industries groups are clustered, with no significant differences among groups. Two industrial spatial clusters have been identified within the metropolitan area. One is in the downtown area and the other in the Springfield-Sharon wood area. Based on the distribution of plants and spatial cluster analysis, it is possible to identify three metal and machinery related clusters within metropolitan industrial spatial clusters.

It is hoped that the industrial clusters approach may also provide the basis for the development of new models of the spatial arrangement of industry at a level more aggregated than that of the single plant or firm. The main intentions of the paper is not to clarify characteristics of industrial spatial clusters at the plant level but to incorporate aspatial approach with spatial approach to visualize industrial clusters for further research. If we could get certain degree of specific data of plant's local linkage, then we may be able to clarify the characteristics of the spatially delimited regions for the future project[5].

A further application of this technique may lie in the making of comparisons between different economic units. It will be interesting to determine whether similar industrial clusters may be identified in areas of different size and with varying resources. Further research using this approach, as well as that suggested by Czamanski, might furnish initial guidance in economic development efforts. In summary, it seems that the factor analysis of input-output data and hot spot analysis may prove to be a technique of value in both aspatial and spatial analysis. It is hoped that it will be applied by other investigators in order that both its potential and its problems may be better understood.

Note

1) Reviewing the literature in this area, one finds the terms 'cluster' and 'complex' used interchangeabley. Cluster is usually taken to mean a group of industries tied together by relatively strong interindustry linkages. For example, see Hoover, Isard et al., Streit, Beyers, Czamanski, Bergsman et al., Slater, Czamanski and de Q. Ablas and Giarrantani and McNelis
2) For industry information of each SIC code, refer to Appendix A.
3) For detailed algorithms and explanation, refer to Space user manual(1996) and Block(1993)
4) For the mathematical derivation of a standard deviational ellipse, read SPACE technical manual (1996).
5) Lee et al. (2000) tries to clarify the internal mechanism of the metropolitan area.

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Industrial Clusters and Defining Their Boundaries of Plants in the Greater Cincinnati Metropolitan Area

씬씨내티 대도시지역의 산업군집과 경계설정

이 보 영*

국문요약

미국의 씬씨내티 대도시지역을 대상으로 인자분석 및 Hot Spot 분석에 의해 산업 군집과 그것의 경계가 확인되어졌다. 전통적 투입 산출 접근법이 비공간적 산업 군집을 추출하는 반면 이 연구는 전통적 접근을 GIS 기법과 결합하여 경계를 설정한다. 투입 산출 산업 군집의 결과를 선도산업 부문과 결합하여 5개 선도 산업 군집을 추출하였는데 그것은 음식료품, 화학, 금속, 금속제품, 기계공업 부분이다. 그리고 Hot Spot 기법을 이용하여 연구지역의 산업 군집을 Arcview에 통합하여 시각화하였다. 산업 군집의 공간적 결합정도와 공간적 한계를 결정하는 것은 경제의 공간구조의 효율성을 측정하는 부가적 접근이 될 수 있다. 산업 군집과 산업의 공간적 군집 접근은 하나의 공장이나 기업의 수준보다 집계적인 차원에서 산업의 공간적 배열의 새로운 모형 개발 기초의 가능성을 제시한다.

주요어 : 투입-산출 행렬, 산업 군집, 핫스팟, 산업 공간 군집

Appendix A. List of Two-digit SIC Industries

SIC Code	Industries
20	Food
21	Tobacco
22	Textile & Apparel
23	Fabricated Textile
24	Wood
25	Furniture
26	Paper
27	Printing
28	Chemicals
29	Petroleum
30	Rubber
31	Leather
32	Glass & Stone
33	Metal Manufacturing
34	Metal Products
35	Machinery
36	Electrical Equipment
37	Motor & Aircraft
38	Instruments
39	Miscellaneous

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