Comparison of Spatial Characteristics of Local Air Quality Reported Using The Air Quality Index in The State of North Carolina of 1999 and 2004

Kuo-Ping Li, Chirayath Suchindran
Department of Biostatistics, University of North Carolina at Chapel Hill

ABSTRACT

Many regions in North Carolina were affected by the economic downturn following the boom in the 1990s. It is interesting to see how this would affect local air quality. In this study, we used the EPA's Air Quality Index (AQI) as the indicator of air quality. The ratio of days with a "good" AQI was computed for North Carolina counties for 1999 and 2004. The spatial correlation of these ratios were analyzed. An increase in the degree of spatial clustering of "good" counties within a range of 50 km was observed. Possible factors contributed to this increase are investigated.

Keywords: spatial statistics, air quality index, clustering, spatial analysis.

Introduction

Similar to many other regions in the United States, North Carolina had experienced an economic downturn following the growth in the mid and late 1990’s. One of the significant impacts to the general population is the unemployment rates.

In table 1, the percentage unemployment rates of the entire North Carolina and of Wake County, one of North Carolina’s highly industrialized counties, of four representative years from 1990 to 2004 were listed. Years 1990 and 1995 can be considered in the “pre-boom” period, in which the unemployment rates were relatively constant. The year 1999 was near the peak (and the end) of the economic boom; that year’s unemployment rates reached decade low in both the state level and in Wake County in particular. Since the economic downturn began at around year 2000, the unemployment rates had been increase rapidly until around 2003 and 2004 when it was stabilized or saw some slight decrease.

In General, the degree of increase of unemployment rates from 1999 to 2004 was more dramatic for industrialized regions than the entire North Carolina. For Wake County, in which many “high-tech” companies are located, the unemployment rate increased by 300% from 1.4% (1999) to 4.3% (2004). On the other hand, the unemployment rate of the entire North Carolina increased by 70% from 1999 to 2004. This suggests that the economic downturns had much bigger impact on unemployment rates for the industrialized counties than other counties.

Year	North Carolina	Wake County
1990	4.2	2.6
1995	4.3	2.4
1999	3.2	1.4
2004	5.5	4.3

Table 1: Percentage Unemployment Rates of (1) entire North Carolina; (2) Wake County, one of North Carolina’s highly industralized counties

It is for sure that the economy downturn had affected social-economical factors such as unemployment rates. It would be interesting to see whether the economy downturn would have some effects on aspects of community life which does not seem to have an immediately link to economy. In this study we attempted to find the local environmental effects of economy downturn, such as the changes of local air quality.

The quality of air that a community’s population breath is largely determined by the presence of air pollutants, such as sulfur dioxide, ground-level ozone, and nitrogen dioxide. The air quality would in turn affect the health of people living in that community. Most of these air pollutants result from industrial activities such as power plants, manufacturing processes, and operation of automobiles. The spatial spread of these industrial activities has a natural tendency of clustering. For example, the presence of some specific natural resources and the existence of good infrastructure in a particular region would attract a certain type of industries to that region. The degree of industrial activities is also affected by the local and/or global economy which might change from time to time. Therefore, in additional to spatial features, there can be longitudinal variation in the degree of industrial activities. Because most air pollutants result from industrial activities, one could reasonably expect both spatial and longitudinal effects in local air qualities of different regions and of different times.

Many cities and regions in the U.S. have a mechanism to monitor local air quality and report the results to the general public on a regular basis. One way to report air quality is to simply list the concentration of air pollution species, typically in units of ppm or $\mu g/m^3$. However, these raw measurements do not provide the general public an intuitive way to assess whether the air quality is "good" or "bad". To address this issue, some local agencies had been reporting some kinds of indexes converted from the raw measurements instead of the raw measurements themselves. On the other hand, the "indexes" reported by different agencies might not be calculated according to a uniform protocol. For example, a 1976 study conducted by U.S. Environmental Protection Agency and the President's Council on Environmental Quality found that 14 different indexes were used by the 55 urban areas in the U.S. and Canada reporting such an index [1]. These different indexes would send confusing messages to the general public.

To address the above issues, EPA developed a uniform Air Quality Index (AQI) to be used by state and local agencies. This index also reflects the degree of health concerns by embracing the National Ambient Air Quality Standards and the significant harm level [2] [3]. In its simplest form, AQI system maps the average concentration of six pollutants, ozone (O_3), fine particular matter ($PM_{2.5}$), coarse particular matter (PM_{10}), carbon monoxide (CO), sulfur dioxide (SO_2), and nitrogen dioxide (NO_2), to a scale that is "normalized" across pollutants, then an AQI level is assigned using one of the 6 air quality categories based on the AQI value. These 6 categories are "good", "moderate", "unhealthy for sensitive groups", "unhealthy", "very unhealthy", and "hazardous" [3].

Currently many state and local agencies report AQI on a daily basis. By using the AQI as a measurement of local air quality, we are able to compare the air quality across different regions as well as different period of times.

The purpose of this study is answering these questions: (1) Is there a spatial structure in the air quality represented by AQI? (2) Could this structure, if any, be confirmed with raw measurement of air pollutant? (3) Could this spatial structure, if any, be linked to economical trends such as changes of unemployment rates?

Data

Twenty North Carolina counties considered relatively industrialized were initially selected for this study. These include Wake County (the state capital), counties surrounding Research Triangle Park where many high-tech companies are located, and adjacent counties along interstate highway 40, 85, and 95.

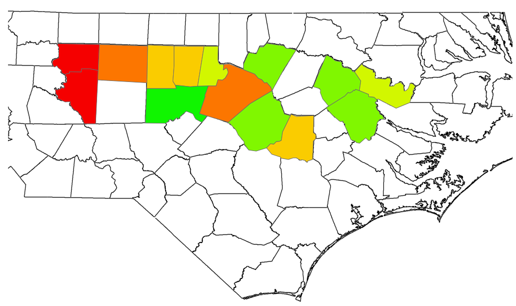

Figure 1: 14 North Carolina counties analyzed in this study. The color codes represent the air quality in 2004, with red being the worst.

The daily AQI levels of these North Carolina counties were then obtained from U.S. EPA data archive (available from EPA's web site). AQI data of only 14 among these 20 counties are available. Therefore, we analyzed these 14 counties in this study. Figure 1 shows the location of these counties.

In this study, we are interested in comparison of air quality of 1999 and 2004. We "measure" a county's air quality by the parameter p_{good} of a given year:

$$p_{\text{good}} = \frac{\text{Number of days AQI was "good"}}{\text{Number of days AQI data were available}}$$

The values of p_{good} of each county of both 1999 and 2004 were then calculated.

Table 2 lists simple statistics (mean and standard deviation) of p_{good}.

	Year 1999	Year 2004
Mean of p_{good}	0.64	0.70
Std. Dev. of p_{good}	0.13	0.17

Table 2: Mean and standard deviation of p_{good}

We also obtained various social-economical data of the counties from North Carolina state government. These include: county population, county population density, number of registered automobiles, density of automobiles (number of registered automobiles per square miles), farmland area, and unemployment rates.

We obtained annual emissions of four major air pollutants: CO, NO_2, SO_2, and Volatile Organic Compounds (VOCs). VOCs emissions was used because ground-level ozone is formed by a chemical reaction that involves VOCs and in the presence of sunlight. These data were obtained from North Carolina Department of Environment and Natural Resources.

The centroids of counties were used for spatial analysis.

Spatial Analysis

To measure the spatial correlation of a variable, the Moran's I statistic was used [4]. Moran's I is defined as:

$$I = \frac{n}{\sum_{i \neq j} w_{ij}} \frac{\sum_{i,j} w_{ij} z_i z_j}{\sum_i z_i^2}, \quad \text{where} \quad z_i = x_i - \bar{x}$$

In this definition, x_i is the variable p_{good} in consideration (p_{good} or one of the social-economical factors) of county i, n is the total number of counties, and w_{ij} is the waiting factor that reflects the "interaction" between the pair of county i and county j. We chose w_{ij} to be inversely proportional to the distance between county i and county j:

$$w_{ij} = (d_{ij})^{-1}, \quad \text{where} \quad d = \text{distance}$$

This was based on two assumptions. First, we assume air pollutants spread from sources to nearby areas in two dimensions, that is, in a planar manner. This yields a pollutant concentration that is inversely proportional from the distance from the location of observation to the source of pollution. Second, we assume the interactions affect air quality (such as the diffusion of pollutants) are symmetric in space. Therefore, the weighting factors do not depend on orientations; only the distance is important.

Results of Moran's I were then standardized by subtracting the expected value, and dividing the result by the corresponding standard deviation. It was shown that a positive standardized Moran's I indicates a positive spatial autocorrelation, that is, nearby regions tend to have similar values, and vice versa [5]. We then use the standardized Moran's I as a measure of degree of spatial association.

Results

At first, we calculated the averaged relative growth of p_{good} as well as the social-economical factors mentioned above. Figure 2 shows the results. It is obvious that the 100% increase of averaged unemployment rates is the most profound change, indicating the impacts due to the changes of local economy between 1999 and 2004. On the other hand, air quality represented by p_{good} had only a mild improvement (about 10%).

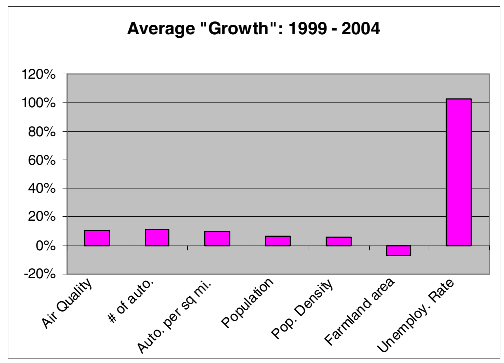

Figure 2: Averaged relative growth of p_{good} and social-economical factors of counties analyzed in this study

Figure 3 shows the standardized Moran's I of 1999 and 2004 of the same variables plotted in Figure 2.

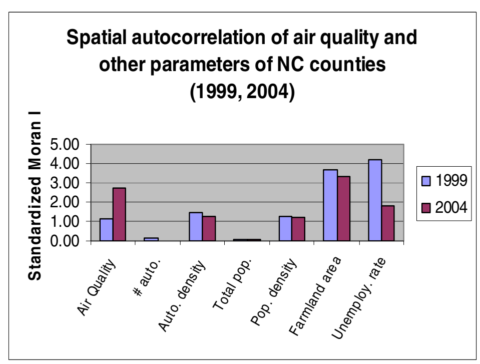

Figure 3: Spatial autocorrelation, represented by the standardized Moran's I, of air quality (represented by pgood) as well as social-economical factors

It can be seen from Figure 3 that the air quality represented by p_{good} had a higher degree of spatial association (more than doubled) in 2004 than in 1999. This suggests an increased degree of spatial clustering of production of air pollutants.

On the other hand, the degree of spatial association of unemployment rates decreased from 1999 to 2004. This probably suggests that, in addition to the increased numbers of unemployed people, there was also a wider spread-out of occurrences of unemployment. A consequence of it is that unemployment had become more common in more areas, therefore reduced its degree of spatial clustering.

Figure 4 shows the relative growth of averaged pollutant emissions of CO, NO2, SO2, and VOCs from 1999 to 2004.

It can be seen from Figure 4 that the emissions of VOCs were increased while emissions of the other air pollutants were reduced.

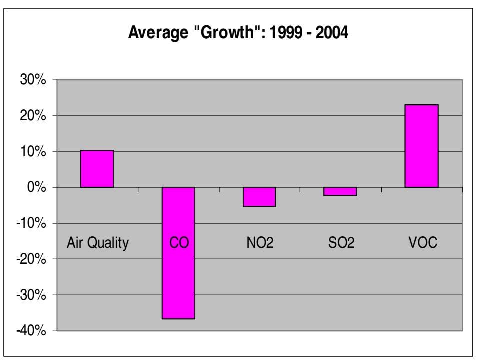

Figure 4: Growth of p_{good} and averaged annual emissions four major air pollutant emissions

Figure 5 shows the standardized Moran's *I* of 1999 and 2004 of the same variables plotted in Figure 4. Notice that both the air quality (p_{good}) and the VOCs emissions have positive spatial autocorrelation, while other pollutants have only very weak spatial association. This is not surprising, because a closer look to the AQI records shows that in 80%-90% of days the air pollutants were dominated by ground-level ozone, and presence of VOCs were the major factor that enhance the formation of ground-level ozone. This also validates the approach of using Moran's I statistic as a measure of spatial autocorrelation.

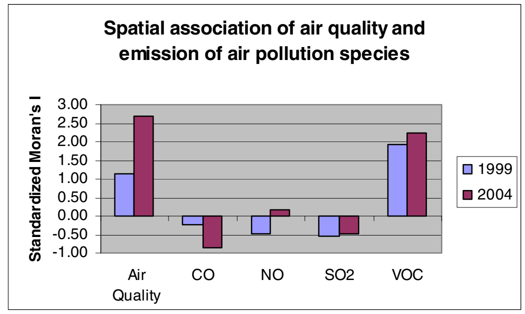

Figure 5: Spatial autocorrelation, represented by the standardized Moran's

Discussion

We have found that, from 1999 to 2004, the air quality represented by p_{good} in the studied counties improved by about 10%, while the averaged unemployment rates were doubled. The increase of unemployment rates were clearly the results of local economic downturns.

We analyzed the spatial association of p_{good} and the unemployment rates of 1999 and 2004. The p_{good} shows a higher degree of spatial association in 2004 than in 1999. This suggests an increased degree of spatial clustering of production of air pollutants.

We also analyzed the spatial association of unemployment rates, which shows a decreased spatial association from 1999 and 2004. This could possibly be explained by a wider spatial spread-out of occurrences of unemployment. This means that the economic downturn not only resulted in increased unemployment rates, it also made the occurrences of unemployment more common in more areas, thus even widen its impact to local population.

Other social-economical factors and air pollutants might have some contributions to the "improvement" of air quality, but their spatial structures are not obvious as seen from Moran's *I* statistic. This means either they have no spatial structures, or that more sensitive and/or robust methods are needed in order to see their spatial structures.

6. REFERENCES

[1] A Recommended Air Pollution Index, report prepared by the Federal Interagency Task Force on Air Quality Indicators, Council on Environmental Quality,

Environmental Protection Agency, and Department of Commerce, 1976.

[2] Environmental Protection Agency Code of Federal Regulations (CFR) Title 40, Part 51.151

[3] Environmental Protection Agency Code of Federal Regulations (CFR) Title 40, Part 58

[4] Moran, P. (1948). The interpretation of statistical maps. *Journal of the Royal Statistical Society*, **B 10**, 24351.

[5] Cliff, A.D. and J.K. Ord (1973), *Spatial Autocorrelation*. Pion, London.