Scientific
Research
Publishing

Development of an Aggregate Air Quality Index Using a PCA-Based Method: A Case Study of the US Transportation Sector

Jaesung Choi, Yong Shin Park, Ju Dong Park*

Upper Great Plains Transportation Institute, North Dakota State University, Fargo, ND, USA
Email: *judong.park@ndsu.edu

Abstract

For the past couple of decades, the transportation sector has made efforts to preserve and improve air quality for public health and sustainable growth between current and future generations. An easily understandable tool to measure the level of air pollution in the transportation sector by considering multiple air pollutants together might raise awareness about clean air to the public, practitioners, state policy planners, and the government. For this reason, this study develops an aggregate air quality index to help prepare decision makers, which could rank a state according to the different levels of multiple air pollutants. The index is developed for use with principal component analysis and an algebra about a line segment, and then applied to the US transportation sector using data on five air pollutants (CO, NOx, PM, SO_2, and VOCs) in 2008. This study finds that some states were less polluted or more polluted in terms of the index, although their GDP levels for a transport mode were similar to each other. Thus, this finding implies that the necessary actions for stricter air quality standards must be taken in their boundaries.

1. Introduction

Transport modes emit air pollutants such as carbon monoxide (CO), nitrogen oxides (NOx), particulate matter (PM), sulfur dioxide (SO_2), and volatile organic compounds (VOCs) into the air through fossil fuel combustion.

*Corresponding author.

Such air pollution frequently exposes human health to acute and chronic diseases, and in the short- and long-terms might result in premature death and declines in life expectancy [1]. Further, it is reported by several researchers that outdoor air pollution negatively affects the productivity of indoor workers [2]-[7].

Transportation is essential for economic growth at the local and national levels, but it is highly connected to environmental pollution, especially air pollution [8]. Gorham's 2002 report [9] for the United Nations shows how much fossil fuel is being combusted by transportation: the transportation sector consumes 25 percent of total worldwide energy consumption and uses more than 50 percent of the total oil produced. Furthermore, annual demand for transport modes is projected to grow by 3.6 percent in developing countries and by 1.5 percent in developed countries [9]. Finally, it might be appropriate to recognize transportation's air pollution emissions as one of the most serious sources of ongoing atmospheric pollution in the world.

Daily air quality indices that evaluate the levels of air pollutants measured at monitoring stations have been developed by a number of researchers [10]-[22] to inform the public about how polluted their living areas are. However, the indices developed until now have a couple of limitations. First, mathematical models for developing air quality indices are based on daily air pollution data (to report daily levels of health concern to the public); this means that without any data measured per day, the model is useless. Second, air pollution data measured at monitoring stations generally represent the levels of overall air pollution in that area, and thus the model cannot be applied to any specific air emissions source, e.g., transportation, to suggest the degree of pollution by transport mode in a state or city.

Nonetheless, under the Clean Air Act[1] the US Environmental Protection Agency (USEPA) has an obligation to provide national emissions inventory (NEI) data[2]. As a result, air pollution emissions data available to the public have been estimated by the USEPA in order to inform people and the authorities of an air pollutant concentration in an air emissions source every three years by state since 2002.

By using air pollution data by transport mode (airline, rail, truck, and vessel) in 2008[3], this study develops an aggregate air quality index (AAQI) using principal component analysis (PCA) to measure the relative levels of air quality by transport mode in a state in the US. The model developed and findings have the advantage of being useful as an administrative tool for making air pollution regulations in the transportation sector at state and national levels and providing the authorities and people with easily understandable information about the levels of air quality by transport mode in a state. The second section of this study presents a literature review on changes to the development of air quality indices and the third section presents the methodology about developing an AAQI. The fourth section is the data. After the results are presented, the conclusions discuss the developed AAQI and air pollution changes by state based on the index.

2. Literature Review

Thom and Ott [10] in 1975 started to develop a uniform air quality index (AQI) through a detailed survey of the air pollution indices in the US and Canada, since at that time states and cities in the US used different daily informational indices. Indeed, an index value in one state meant something entirely different in other states. However, following the Federal Interagency Task Force [11], a daily pollutant standards index (PSI) was developed to report daily air pollution levels to the public, because the index developed by Thom and Ott [10] was criticized as being poor and confusing. In 1998, Hämekoski [12] introduced a PSI developed by the Federal Interagency Task Force [11] to provide a simple AQI in order to inform the public of daily air quality in Finland.

The USEPA [13] in 1999 adopted some revisions for the uniform AQI, which incorporates new breakpoints for ozone and PM, and changed its name from the PSI to the AQI. The AQI consists of sub-indices calculated for each pollutant, with the maximum index then selected between different indices to represent the level of air quality. Following Trozzi *et al.* [14], Sharma *et al.* [15] [16], Murena [17], Nagendra *et al.* [18], Wen *et al.* [19], and Eder *et al.* [20], the AQI developed by the USEPA was used in several countries for reporting daily air quality. On the other hand, Swamee and Tyagi [21] applied an ambiguity- and eclipsicity-free function to develop an overall AQI from the aggregation of air pollution sub-indices.

The disadvantage of the AQI developed by the USEPA was that it only considered the levels of one pollutant at a time and thus the index could not identify if multiple air pollutants exceeded their daily air quality standards

---

[1]The Clean Air Act was enacted in 1963 and revised in 1970 and 1990 to establish national air quality standards in the US [37].

[2]NEI is an estimate of air emissions from all air emissions sources from 2002 to 2011 every three years [42].

[3]The updated calculation methodology for data in 2008 was not consistent with 2002 and 2005, and air pollution data in 2011 were not available during the study period.

[22]. To address this limitation, a couple of methodologies have been developed by several researchers [22]-[25] to include the combined effects of major air pollutants. On the other hand, Longhurst [26] developed a simplified mathematical formula to measure an AQI for SO_2 and particulates, while a time series regression analysis by Stieb *et al.* [27] [28] has been developed to illustrate the relationship between five air pollutants and mortality. Recently, Mohan and Kandya [29] and Mayer *et al.* [30] analyzed the effect of long-term air pollution, while Sowlat *et al.* [31] developed a computation method of artificial intelligence to assess the performance of a fuzzy-based AQI.

Research using a PCA-based method have been noticed in recent years by several researchers [32]-[36] for developing composite sustainability indicators in a variety of fields. In 2006, Vyas and kumaranayake [32] tried to construct socio-economic status indices to measure household wealth, while Soler-Rovira [33] developed an environmental indicator for 36 countries for agricultural production in 2008. In 2009, Ali [34] suggested a practical way of developing Arab water sustainability index to promote more efficient water use within the Arab countries. On the other hand, Li *et al.* [35] constructed an overall sustainability performance indicator for the manufacturing industry to provide the industry and academia with an integrated methodology, and Hosseini and Kaneko [36] developed dynamic sustainability indicators at the macro level in 2011. **Appendix A** summarizes the literature on changes to the development of air quality indices.

3. Methodology

PCA is generally used for one sample without grouping among the observations, and the technique seeks to find the maximum of the variance of a linear combination of the variables [37]-[41]. The maximum of the variance of a linear combination of the variables is the first principal component, and the second principal component is perpendicular to the first principal component with the maximal variance of the linear combination of the variables. This process keeps going until it finds p principal components, where p is the number of variables [40].

The principal components of the transformed variables are shown with the normalized eigenvectors a_j of the sample covariance matrix S of the sample of observation vectors $y_1, y_2, \cdots, y_n$ [40]:

$$A = C' = \begin{bmatrix} a'_1 \\ a'_2 \\ \vdots \\ a'_p \end{bmatrix} \quad (1)$$

where a_j is the jth normalized eigenvector of S and C is the orthogonal matrix consisting of a_j,

$$z_i = Ay_i = \begin{bmatrix} a_{11}y_{i1} + a_{12}y_{i2} + \cdots + a_{1p}y_{ip} \\ a_{21}y_{i1} + a_{22}y_{i2} + \cdots + a_{2p}y_{ip} \\ \vdots \\ a_{p1}y_{i1} + a_{p2}y_{i2} + \cdots + a_{pp}y_{ip} \end{bmatrix} = \begin{bmatrix} z_{1i} \\ z_{2i} \\ \vdots \\ z_{pi} \end{bmatrix} \quad (2)$$

According to Rencher and Christensen [40], the eigenvalues $\Lambda_1, \Lambda_2, \cdots, \Lambda_p$ are obtained from S, and Λ_1 is the biggest eigenvalue of S. The first principal component z_1 shows the largest sample variance, whereas the variance of the last principal component z_p is the smallest. Since the eigenvalues are equal to the variances of the principal components, the percentage of variance explained by the first k principal components is as follows:

$$\text{Percentage of variance} = \frac{\Lambda_1 + \Lambda_2 + \cdots + \Lambda_k}{\sum_1^p \Lambda_j} \quad (3)$$

We only expect to substitute the variables $y_1, y_2, \cdots, y_p$ for the first principal component

$$\left(z_1 = a_1 y_1 + a_2 y_2 + \cdots + a_p y_p \right),$$

which accounts for more than 80 percent of the total variance[4] since the dependent variables of air pollutants emissions are highly correlated with each other [42]-[44]. If this case is established, then a concept of a line segment is introduced to develop an AAQI in the transportation sector: 1) list all measurements calculated from the first principal component on a line segment and then find the maximum and minimum measurements, which are the most polluted and the least polluted observations, respectively; 2) measure the length of the line segment between the maximum and minimum measurements; and 3) calculate a proportion for each measurement from the ratio of the length of the line segment between the minimum measurement and each measurement to the length measured in 2), and then multiply the calculated values by 100. The least polluted observation indicates 0, while the most polluted observation indicates 100.

In **Figure 1**, this study illustrates a simple example to calculate an AAQI. Four measurements Z_{11}, Z_{12}, Z_{13} and Z_{14} are calculated from the first principal component representing the levels of multiple air pollutants. The length of the line segment for each measurement is as follows: $\overline{Z_{11}Z_{14}} = 12$; $\overline{Z_{11}Z_{12}} = 4$; and $\overline{Z_{11}Z_{13}} = 8$.

Therefore, the proportions of the four measurements are 0, $0.333\left(\dfrac{4}{12}\right)$, $0.666\left(\dfrac{8}{12}\right)$, and 1, respectively. The AAQIs for Z_{11}, Z_{12}, Z_{13} and Z_{14} finally are calculated as 0, 33.3, 66.6, and 100, respectively.

4. Data

An AAQI using PCA and the concept of a line segment was developed in Section 3 for multiple air pollutants. Under the Clean Air Act, the USEPA provides air quality standards for the five common air pollutants to suggest air quality guidelines to state policy planners and industrial sectors and protect public health [42]. For this reason, the five air pollutants of CO, NO_x, PM, SO_2, and VOCs were used for the index. Since principal components are not scale-invariant, all variables should be measured in the same units [3]; therefore, all variables measured in tons were utilized by each transport mode in the 53 states in the US These were obtained from the NEI of the USEPA in 2008, and were the latest estimated air pollutants available during the study period [48].

Table 1 shows the summary statistics for the data utilized in this study. The five air pollutants measured for each transport mode by state do not show any kind of heterogeneity since the coefficient of variation in each variable calculated was less than 10 [45]. For the airline transport mode, Texas emits the largest air pollution for each air pollutant, while District of Columbia shows the least air pollution. On the other hand, Idaho emits the fewest air pollutants for vessel and Louisiana shows the largest air pollution in CO, NO_x, PM, and VOCs, but Texas is the largest SO_2 emission state. For rail, Nebraska contributes to the largest air pollution across the nation for the four air pollutants, but Texas emits the largest SO_2 emission as in the vessel case. For all five air pollutants, Rhode Island emits the least air pollution. For truck, California is the number one air pollution-emitting state for CO, NO_x, and VOCs, while Texas is for PM and SO_2. The least air pollution state for NO_x, PM, and SO_2 is Idaho, but that for CO and VOCs is Rhode Island.

Figure 2 provides a geographic map showing the study area where the five air pollutants were emitted. The NEI provides them by state, but there are no data available for some states for the vessel, rail, and truck transport sectors: Arizona, Colorado, Montana, North Dakota, New Mexico, Nevada, South Dakota, Utah, Virgin Islands, Vermont, and Wyoming in vessel; and Hawaii, Puerto Rico, and Virgin Islands in rail and truck.

5. Empirical Results

Like most multivariate analyses where the data used follow the multivariate normal (or at least approximately multivariate normal) distribution [46], this study uses a multivariate analysis with PCA. Thus, the developed AAQI tests two statistical assumptions. The first assumption is of multivariate normality. In **Figure 3**, the scatter plot matrix on the left indicates that the original data do not suggest any normality and even each variable shows

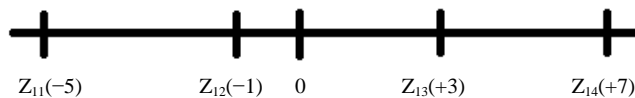$Z_{11}(-5)$ $Z_{12}(-1)$ 0 $Z_{13}(+3)$ $Z_{14}(+7)$

Figure 1. Line segment to calculate an AAQI of the example.

---

[4]Deciding on the number of components followed a recommendation of retaining sufficient components to account for at least 80 percent of the total variance [40].

Table 1. Summary statistics for the five air pollutants emitted by the four transport modes.

Airline						
Pollutant	N. of Obs.	Mean	Std. Dev.	Min.	Max.	CV
CO (tons)	53	8268.350	9963.030	11.979	54029.810	1.205
NO_X (tons)	53	2277.850	3401.790	0.266	17043.920	1.493
PM (tons)	53	180.919	211.983	0.272	1145.140	1.172
SO_2 (tons)	53	239.642	351.130	0.058	1866.450	1.465
VOCs (tons)	53	625.677	1018.070	0.465	6144.000	1.627
Vessel						
Pollutant	N. of Obs.	Mean	Std. Dev.	Min.	Max.	CV
CO (tons)	42	2065.370	4053.190	0.005	23719.810	1.962
NO_X (tons)	42	12771.610	23159.440	0.027	132292.350	1.813
PM (tons)	42	645.534	1074.950	0.001	5677.870	1.665
SO_2 (tons)	42	3403.410	5582.650	0.002	23870.760	1.640
VOCs (tons)	42	342.995	564.392	0.001	3110.910	1.645
Rail						
Pollutant	N. of Obs.	Mean	Std. Dev.	Min.	Max.	CV
CO (tons)	50	2398.720	2082.860	8.592	10858.510	0.868
NO_X (tons)	50	16913.600	14342.040	87.267	74404.650	0.848
PM (tons)	50	551.335	476.072	2.148	2484.400	0.863
SO_2 (tons)	50	215.729	273.284	0.607	1736.870	1.267
VOCs (tons)	50	883.754	763.524	3.222	3760.480	0.864
Truck						
Pollutant	N. of Obs.	Mean	Std. Dev.	Min.	Max.	CV
CO (tons)	50	18677.270	20442.930	918.432	99166.890	1.095
NO_X (tons)	50	63501.130	69821.420	2577.990	363276.210	1.100
PM (tons)	50	3524.960	3706.050	159.779	18699.870	1.051
SO_2 (tons)	50	92.377	92.783	3.666	467.146	1.004
VOCs (tons)	50	4214.540	4634.510	225.378	24122.660	1.100

Note: All air pollutants data come from the NEI in the USEPA [48].

Figure 2. Geographic map showing the study area where the five air pollutants were emitted.

a positive skew. On the other hand, after the transformation of the original data[5], the right side in **Figure 3** shows the approximate normal distribution for each variable. The Q-Q plot for each variable does not show any distinct nonlinear relationship, not indicating a departure from the multivariate normality distribution [40].

The second assumption is that this study can only use one principal component to sufficiently represent the five air pollutants y_1, y_2, y_3, y_4, y_5. To check this, the scree plots and proportion of variance explained by each principal component were tested (see **Figure 4**). The scree plots in all the transport modes reveal an evident natural break between the first and second principal components. Further, the proportion of the first principal component calculated[6] shows more than 90 percent in each transport, which is much higher than a recommendation of retaining enough components to account for 80 percent of the total variance [40]. Being able to use only a first principal component to explain most of the total variance provides a significantly practical and convenient tool to interpret multiple air pollutants. For example, in the original data in 2008 by airline transport, two states, Iowa and Idaho, emitted the five air pollutants of CO, NO_x, PM, SO_2, and VOCs as follows: 2679, 272, 59, 37, and 119 (tons) and 3975, 255, 91, 35, and 147 (tons), respectively. In terms of individual air pollutants, Idaho emitted more (less) air pollution in CO, PM, and VOCs (NO_x and SO_2) than Iowa, but practitioners, state policy planners, and the public might want to know the overall air quality level from this kind of conservative situation. The first principal component calculated from the normalized eigenvectors of the sample covariance matrix was used to address this problem.

By using PCA and a little bit of algebra about a line segment with the transformed data, the first principal component and the AAQI by state in the airline, vessel, rail, and truck transport sectors were calculated, as shown in **Table 2** and **Table 3**. In addition, to compare the relative levels of air quality by state from the indices, the state GDP in each transport mode was added in these tables. Each state is ranked relative to all other observed values of states in the first principal component, from smallest to largest in order of magnitude. The rank of each state is denoted by its AAQI. The index increases from 0 to 100, and this indicates more air pollution when it approaches a higher index value. The index of a state showing 100 means the largest air pollution-emitting state of all. On the other hand, a state index indicating 0 implies that the state is the least air pollution-emitting state.

(A) Scatter plot matrix before the transformation   (B) Scatter plot matrix after the transformation
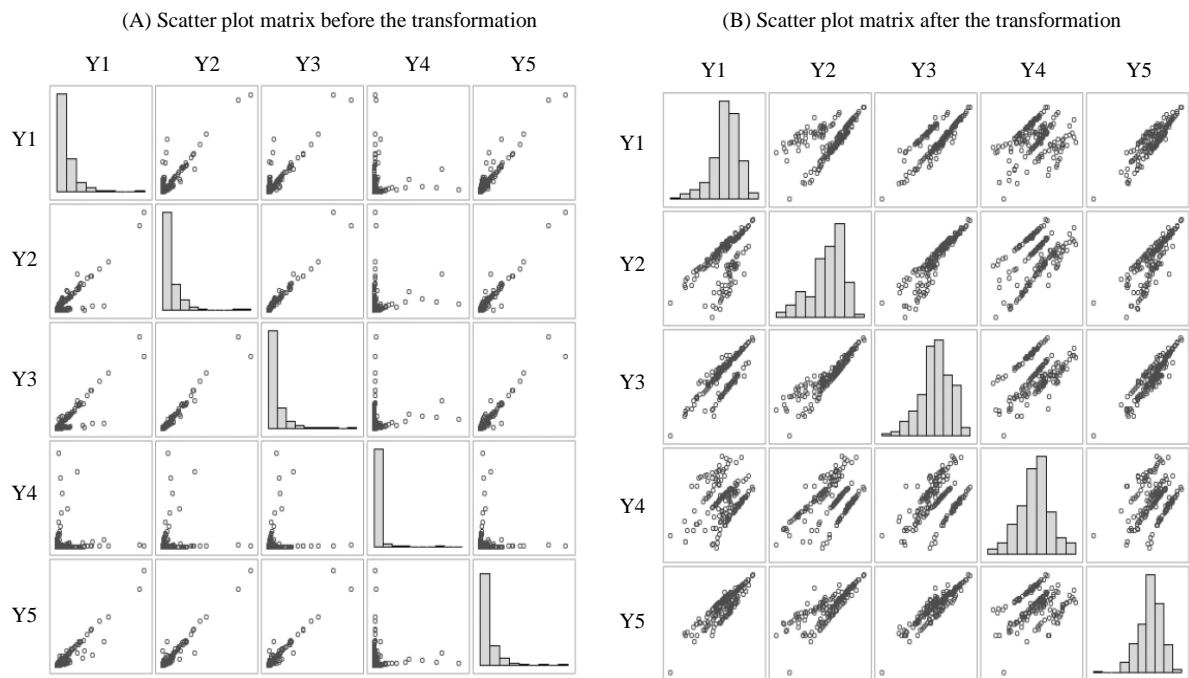
Figure 3. Tests for departures from multivariate normality in the data set before and after the transformation.

[5]In an attempt to make the individual variables distributed more closely to a normal distribution and them distributed more closely to a multivariate normal distribution, the following variables were used in this study: $y_1^* = \sqrt[2]{\ln y_1}$; $y_2^* = \sqrt[2]{\ln y_2}$; $y_3^* = \sqrt[2]{\ln y_3}$; $y_4^* = \sqrt[2]{\ln y_4}$; and $y_5^* = \sqrt[2]{\ln y_5}$.

[6]The first principal component in airline: 93.4 percent; in vessel: 95 percent; in rail: 97.8 percent; and in truck: 97.3 percent.

Figure 4. The eigenvalues and proportion of variance explained by the first k principal components by each transport mode ($k = 1, 2, 3, 4, 5$).
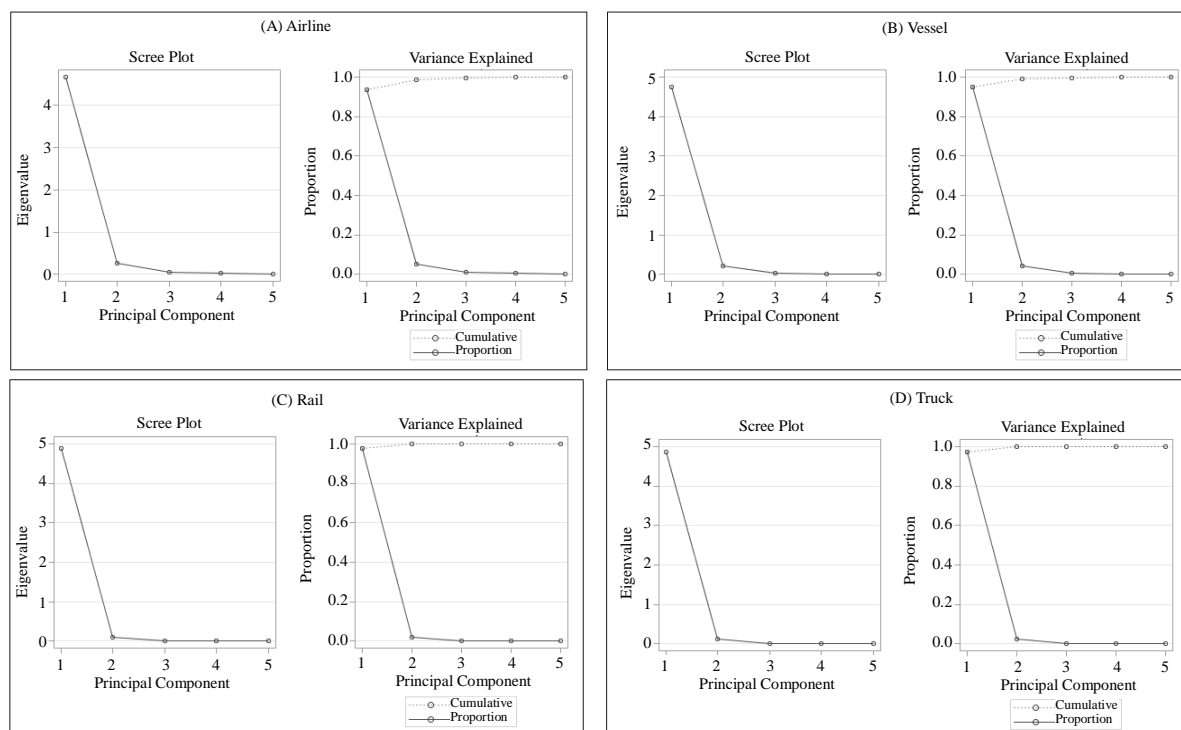
The AAQIs in **Table 2** and **Table 3** are on the ordinal scale; in other words, it is only possible to distinguish each state on the basis of the relative amounts of multiple air pollutants. For instance, in vessel transport in **Table 2**, the index of Iowa shows 34.01, while that of Kentucky is 70.55. This does not tell us whether the air pollution by vessel in Kentucky is twice more polluted than that in Iowa, but rather it is interpretable in the way that Kentucky shows worse air pollution in terms of considering multiple air pollutants than Iowa. In fact, in 2008 Iowa emitted 151, 786, 27, 46, and 17 (tons) of CO, NO_x, PM, SO_2, and VOCs, respectively, whereas Kentucky emitted a considerable amount of air pollutants: 1847, 11370, 441, 594, and 300 (tons).

In **Table 2**, the vessel and rail transport sectors are first analyzed. In vessel transport, Oklahoma is the least air pollution-emitting state, but Louisiana shows the largest air pollution. Indiana, Illinois, Missouri, North Carolina, West Virginia, and Tennessee account for a relatively low AAQI compared with their high GDP levels, whereas Alaska, Michigan, Wisconsin, and Washington hold high ranks in the AAQI compared with their low GDP levels. For rail transport, Delaware takes the lowest rank in the index and Nebraska accounts for the highest rank. Florida, Georgia, and Texas show relatively low air pollution against their high GDP level. Massachusetts, Maryland, Missouri, Oregon, and Pennsylvania in vessel transport, consisting of a similar GDP scale, are differently ranked in the AQI, and this happens to rail transport with Arizona, Colorado, Florida, Montana, Tennessee, and Washington.

In **Table 3**, as this study expected based on the original data for the airline transport sector, where Texas was the largest air pollution-emitting state with respect to the five air pollutants, the Texas AAQI now reaches the highest. By contrast, Delaware holds the lowest rank in the AAQI. Connecticut, Minnesota, and New Jersey emit relatively low air pollution compared with their high GDP levels, while Alabama, Alaska, Massachusetts, Mississippi, Tennessee, and Wisconsin hold high ranks in the AAQI against their relatively low GDP levels. In truck transport, Idaho is ranked the least air pollution-emitting state, which even shows a relatively high GDP level. Truck transport was a little conservative to choosing the largest air polluting state with multiple air pollutants in the original data between Texas and California, but California is chosen as the largest air pollution-emitting state and Texas is ranked right behind it. Florida, Georgia, Michigan, New Mexico, and North Carolina, showing relatively low GDP levels, hold a high rank in the AAQI, whereas Arkansas, Iowa, Nevada, Nebraska, North Dakota, and South Dakota are ranked low in the index compared with their high GDP levels. In airline,

Table 2. The first principal component and AAQI by state in the vessel and rail transport sectors.

	Vessel				Rail		
State	GDP	PC1	AAQI	State	GDP	PC1	AAQI
Oklahoma	1	−7.60	0	Delaware	86	−5.85	0
Iowa	31	−3.66	34.01	Vermont	17	−5.50	3.96
New Hampshire	3	−3.21	37.80	District of Columbia	107	−5.22	7.03
Rhode Island	19	−2.37	45.10	New Hampshire	8	−4.85	11.16
Arkansas	17	−2.16	46.84	Maine	47	−4.00	20.66
Indiana*	291	−1.89	49.23	Connecticut	40	−3.45	26.84
Tennessee*	335	−1.66	51.21	Alaska	0	−3.44	26.89
Missouri*°	165	−1.41	53.31	New Jersey	171	−2.98	32.04
West Virginia*	110	−1.04	56.52	South Dakota	159	−1.59	47.56
South Carolina	37	−1.04	56.57	Maryland	242	−0.89	55.44
Georgia	45	−0.98	57.01	Massachusetts	263	−0.88	55.50
North Carolina*	224	−0.76	58.93	Michigan	428	−0.60	58.67
Maine	12	−0.74	59.07	Nevada	188	−0.39	60.97
Illinois*	352	−0.64	59.99	Mississippi	298	−0.28	62.20
Minnesota	85	−0.28	63.06	South Carolina	267	−0.24	62.70
Delaware	5	−0.13	64.37	Florida*°	789	−0.09	64.31
Oregon°	150	0.06	66.00	Idaho	314	0.07	66.14
Mississippi	134	0.11	66.45	North Carolina	351	0.19	67.48
Connecticut	338	0.25	67.67	West Virginia	490	0.22	67.77
Alabama	258	0.32	68.27	Louisiana	513	0.24	68.06
Hawaii	309	0.36	68.59	Wisconsin	524	0.39	69.67
Ohio	119	0.56	70.28	Oregon	359	0.44	70.23
Kentucky	302	0.59	70.55	New York	337	0.69	73.07
Wisconsin†	15	0.78	72.20	Utah	340	0.72	73.38
Massachusetts°	156	0.97	73.80	North Dakota	478	0.77	73.89
Pennsylvania°	153	1.05	74.51	Colorado°	766	0.82	74.51
Maryland°	145	1.07	74.66	Kentucky	617	0.83	74.56
Virginia	616	1.35	77.08	Alabama	587	0.89	75.32
New Jersey	604	1.38	77.38	Washington°	754	0.94	75.81
New York	1107	1.62	79.39	Virginia	943	0.97	76.21
Alaska†	166	1.97	82.49	Minnesota	874	1.03	76.79
Texas	1081	2.24	84.73	Oklahoma	540	1.06	77.16
California	1273	2.29	85.20	Arkansas	608	1.07	77.33
Florida	2948	2.58	87.70	Tennessee°	745	1.10	77.60
Washington†	638	2.81	89.70	Pennsylvania	989	1.18	78.53
Michigan†	76	3.22	93.17	Indiana	889	1.30	79.83
Louisiana	1895	4.01	100	Georgia*	1,064	1.36	80.49
				Montana°	762	1.45	81.52
				Arizona°	703	1.48	81.90
				New Mexico	595	1.48	81.90
				Iowa	985	1.55	82.68
				Missouri	1485	1.99	87.59
				Texas*	3249	2.04	88.10
				Ohio	1217	2.05	88.26
				Kansas	1494	2.07	88.46
				Wyoming	1220	2.14	89.23
				California	1377	2.26	90.55
				Illinois	2206	2.36	91.66
				Nebraska	3547	3.11	100

Notes: Data on District of Columbia, Idaho, Kansas, Nebraska, and Puerto Rico by vessel and on Rhode Island by rail were not available after the data transformation; the state GDPs by vessel and rail were obtained from the United States Bureau of Economic Analysis, and measured in millions of dollars [47]; the GDP of Alaska in rail transport shows 0, which is explained by the value being much lower than one million; * means a state showing a relatively low AAQI compared with its high GDP level; † indicates a state holding a high rank in the AAQI compared with its low GDP level; ° means that a state showing a GDP level similar to other states, but it is differently ranked to others in the AAQI.

Table 3. The first principal component and AAQI by state in the airline and truck transport sectors.

Airline				Truck			
State	GDP	PC1	AAQI	State	GDP	PC1	AAQI
Delaware	18	−5.05	0	Idaho	734	−5.24	0
Virgin Islands	N/A	−4.48	6.00	Rhode Island	202	−5.24	0.05
Vermont	24	−3.96	11.31	District of Columbia	18	−4.45	8.63
Wyoming	46	−3.47	16.42	Vermont	221	−4.28	10.46
Rhode Island	79	−3.44	16.68	Delaware	232	−3.87	14.94
West Virginia	16	−2.96	21.67	North Dakota[*]	560	−2.51	29.72
North Dakota	15	−2.51	26.38	Nevada[*]	683	−2.34	31.62
South Dakota	19	−2.36	27.86	South Dakota[*]	506	−2.12	33.96
New Hampshire	86	−2.23	29.27	Alaska	285	−2.07	34.51
Maine	43	−2.04	31.19	New Hampshire	289	−1.92	36.13
Montana	59	−1.64	35.38	Wyoming	456	−1.82	37.30
Iowa	58	−1.62	35.58	Montana	441	−1.60	39.71
Connecticut[*]	270	−1.57	36.09	Maine	490	−1.56	40.11
Nebraska	75	−1.55	36.33	Connecticut	660	−1.50	40.78
Kansas	55	−1.22	39.69	West Virginia	697	−1.10	45.07
Idaho	80	−1.18	40.13	Nebraska[*]	1,957	−0.41	52.65
Puerto Rico	N/A	−1.17	40.23	Utah	1,551	−0.28	54.01
New Mexico	163	−0.95	42.56	Kansas	1,508	−0.18	55.17
Mississippi[†]	38	−0.94	42.57	New Mexico[†]	700	−0.15	55.41
Arkansas	129	−0.53	46.83	Arkansas[*]	2,549	−0.06	56.41
South Carolina	110	−0.41	48.14	Iowa[*]	2,407	−0.03	56.81
Utah	782	−0.28	49.48	Oregon	1,616	0.00	57.03
Oklahoma	723	−0.17	50.65	Mississippi	1,475	0.19	59.12
Oregon	524	0.18	54.20	Colorado	1,634	0.22	59.53
Louisiana[°]	370	0.21	54.57	Maryland	1400	0.33	60.65
Maryland	622	0.27	55.11	Massachusetts	1462	0.48	62.30
Kentucky	553	0.35	55.99	South Carolina	1584	0.49	62.45
Indiana	493	0.45	57.04	Louisiana	1696	0.57	63.25
Missouri	764	0.60	58.54	Wisconsin[°]	3767	0.66	64.22
Alabama[†]	95	0.66	59.24	Alabama	2125	0.75	65.30
Hawaii	1037	0.79	60.52	New Jersey[°]	3669	0.76	65.35
Nevada	1102	0.81	60.75	Oklahoma	1736	0.94	67.27
Minnesota[*]	2094	0.96	62.26	Kentucky	1812	1.02	68.14
New Jersey[*]	2390	1.00	62.70	Virginia	2420	1.18	69.93
Massachusetts[†]	865	1.00	62.73	Minnesota	2278	1.21	70.28
Virginia	1784	1.44	67.29	Washington[°]	3767	1.45	72.82
Colorado	1624	1.48	67.66	New York	3388	1.45	72.89
Michigan	1683	1.54	68.32	Arizona	1834	1.59	74.35
Tennessee[†]	610	1.56	68.54	Missouri[°]	3646	1.61	74.58
Washington	1489	1.60	68.88	Indiana	4490	1.65	75.10
Pennsylvania	1355	1.61	69.05	Pennsylvania	5493	1.72	75.85
Ohio	1494	1.62	69.19	Tennessee	4702	1.83	77.06
Alaska[†]	593	1.63	69.23	North Carolina[†°]	3640	1.85	77.20
Arizona	1888	2.04	73.50	Ohio	5990	2.22	81.22
North Carolina	1309	2.08	73.89	Michigan[†]	3453	2.38	83.04
Illinois	4510	2.31	76.32	Illinois	6435	2.43	83.51
Wisconsin[†°]	403	2.35	76.74	Georgia[†]	3979	2.79	87.42
New York	4223	2.47	77.90	Florida[†]	4003	3.10	90.83
Georgia	4966	2.69	80.20	Texas	10,926	3.94	99.98
Florida	4120	3.43	87.90	California	11,948	3.94	100
California	6555	4.01	93.86				
Texas	7474	4.60	100				

Note: Data on District of Columbia by airline transport were not available after the data transformation; * means a state showing a relatively low AAQI compared with its high GDP level; † indicates a state holding a high rank in the AAQI compared with its low GDP level; ° means that a state showing a GDP level similar to other states, but it is differently ranked to others in the AAQI.

Louisiana and Wisconsin, showing a similar GDP scale, are differently ranked in the AAQI, which also arises in rail transport with Missouri, New Jersey, North Carolina Washington, and Wisconsin.

6. Conclusions

Transportation is an essential part of the socioeconomic development of a nation, but it has been needed to accompany the undesirable output called air pollution even though advances in technology for modern transport have contributed to reducing air pollution emissions in comparison with past transport modes. On the other hand, the continuous increase in a clean air environment for public health and sustainable growth between current and future generations has had a positive effect on the transportation sector, corresponding to the growing tide of preserving and improving air quality over the past decades.

An easily understandable tool to measure the level of air pollution in the transportation sector by considering multiple air pollutants might raise awareness about clean air to the public, practitioners, state policy planners, and the government. In this study, an AAQI was developed to help prepare decision makers, which could rank a state according to different levels of multiple air pollutants. In the US empirical case, some states were shown as less polluted or more polluted in terms of the index, although their GDP levels for a transport mode were similar to each other. The authors would carefully guess that a possible hypothesis of these differences might be attributed to the degree of the use of eco-friendly transport, strictness of air quality standards, and differences in gasoline prices in their boundaries.

This study, however, has a limitation based on the use of the index developed. The index is only available for one sample, not multiple samples together, since each sample has its own different normalized eigenvectors of the sample covariance matrix according to PCA. Thus, the index value of the same state in different two samples by transport mode, e.g., in 2005 and 2008 if 2005 data were available cannot be theoretically compared with each other. However, one possible advantage of the AAQI developed here is that it can be applied to other numerous index development projects, not limited to the transportation sector.

Acknowledgements

Author Contributions

Jaesung Choi conceived of the research and wrote the paper. Ju Dong Park and Yong Shin Park analyzed the data and performed the multivariate analysis. All authors discussed and commented the results and implications.

Conflicts of Interests

The authors declare no conflict of interest.

References

[1] Kampa, M. and Castanas, E. (2008) Human Health Effects of Air Pollution. *Environmental Pollution*, **151**, 362-367. http://dx.doi.org/10.1016/j.envpol.2007.06.012

[2] Chang, T. and Gross, T. (2014) Particulate Pollution and the Productivity of Pear Packers. http://www.nber.org/papers/w19944.pdf

[3] Zivin, J.S.G. and Neidell, M.J. (2014) The Impact of Pollution on Worker Productivity. http://www.nber.org/papers/w17004.pdf

[4] Greenstone, M. and Looney, A. (2011) We Are What We Breathe: The Impacts of Air Pollution on Employment and Productivity. http://www.brookings.edu/blogs/jobs/posts/2011/05/06-jobs-greenstone-looney

[5] Wyon, D. (2014) The Effects of Indoor Air Quality on Performance and Productivity. http://www.ncbi.nlm.nih.gov/pubmed/15330777

[6] Kosonen, R. and Tan, F. (2004) The Effect of Perceived Indoor Air Quality on Productivity Loss. *Energy and Buildings*, **36**, 981-986. http://dx.doi.org/10.1016/j.enbuild.2004.06.005

[7] Wargocki, P., Wyon, D.P. and Fanger, P.O. (2000) Productivity Is Affected by the Air Quality in Offices. *Proceedings of Healthy Buildings*, **1**, 635-640.

[8] Peck, W. and Harmelink, M. (2014) Transportation Air Pollution. http://trid.trb.org/view.aspx?id=114537

[9] Gorham, R. (2014) Air Pollution from Ground Transportation. http://www.un.org/esa/gite/csd/gorham.pdf

[10] Thom, G.C. and Ott, W.R. (1975) Air Pollution Indices: A Compendium and Assessment of Indices Used in the U.S. and Canada. Ann Arbor Science Publishers, Ann Arbor.

[11] The Federal Interagency Task Force (1976) A Recommended Air Pollution Index. United States Government Printing Office, Washington DC.

[12] Hämekoski, K. (1998) The Use of a Simple Air Quality Index in the Helsinki Area, Finland. *Environmental Management*, **22**, 517-520. http://dx.doi.org/10.1007/s002679900124

[13] The United States Environmental Protection Agency. Air Quality Index Reporting: Final Rule. http://www.epa.gov/ttn/oarpg/t1/fr_notices/airqual.pdf

[14] Trozzi, C., Vaccaro, R. and Crocetti, S. (1999) Air Quality Index and Its Use in Italy's Management Plans. *Science of the Total Environment*, **235**, 387-389. http://dx.doi.org/10.1016/S0048-9697(99)00242-9

[15] Sharma, M., Maheshwari, M., Sengupta, B. and Shukla, B. (2003) Design of a Website for Dissemination of Air Quality Index in India. *Environmental Modelling & Software*, **18**, 405-411. http://dx.doi.org/10.1016/S1364-8152(03)00003-3

[16] Sharma, M., Pandey, R., Maheshwari, M., Sengupta, B., Shukla, B., Gupta, N. and Johri, S. (2003) Interpretation of Air Quality Data Using an Air Quality Index for the City of Kanpur, India. *Journal of Environmental Engineering and Science*, **2**, 435-462.

[17] Murena, F. (2004) Measuring Air Quality over Large Urban Areas: Development and Application of an Air Pollution Index at the Urban Area of Naples. *Atmospheric Environment*, **38**, 6195-6202. http://dx.doi.org/10.1016/j.atmosenv.2004.07.023

[18] Nagendra, S.S., Venugopal, K. and Jones, S.L. (2007) Assessment of Air Quality near Traffic Intersections in Bangalore City Using Air Quality Indices. *Transportation Research Part D*: *Transport and Environment*, **12**, 167-176. http://dx.doi.org/10.1016/j.trd.2007.01.005

[19] Wen, X.-J., Balluz, L. and Mokdad, A. (2009) Association between Media Alerts of Air Quality Index and Change of Outdoor Activity among Adult Asthma in Six States, BRFSS, 2005. *Journal of Community Health*, **34**, 40-46. http://dx.doi.org/10.1007/s10900-008-9126-4

[20] Eder, B., Kang, D.W., Trivikrama, R.S., Rohit, M., Shaocai, Y., Tanya, O., Ken, S., Richard, W., Scott, J., Paula, D., Jeff, M. and George, B. (2010) Using National Air Quality Forecast Guidance to Develop Local Air Quality Index Forecasts. *Bulletin of the American Meteorological Society*, **91**, 313-326.

[21] Swamee, P.K. and Tyagi, A. (1999) Formation of an Air Pollution Index. *Journal of the Air & Waste Management Association*, **49**, 88-91. http://dx.doi.org/10.1080/10473289.1999.10463776

[22] Cheng, W.-L., Kuo, Y.-C., Lin, P.-L., Chang, K.-H., Chen, Y.-S., Lin, T.-M. and Huang, R. (2004) Revised Air Quality Index Derived from an Entropy Function. *Atmospheric Environment*, **38**, 383-391. http://dx.doi.org/10.1016/j.atmosenv.2003.10.006

[23] Cheng, W.-L., Chen, Y.-S., Zhang, J., Lyons, T., Pai, J.-L. and Chang, S.-H. (2007) Comparison of the Revised Air Quality Index with the PSI and AQI Indices. *Science of the Total Environment*, **382**, 191-198. http://dx.doi.org/10.1016/j.scitotenv.2007.04.036

[24] Kyrkilis, G., Chaloulakou, A. and Kassomenos, P.A. (2007) Development of an Aggregate Air Quality Index for an Urban Mediterranean Agglomeration: Relation to Potential Health Effects. *Environment International*, **33**, 670-676. http://dx.doi.org/10.1016/j.envint.2007.01.010

[25] Bishoi, B., Prakash, A. and Jain, V. (2009) A Comparative Study of Air Quality Index Based on Factor Analysis and US-EPA Methods for an Urban Environment. *Aerosol and Air Quality Research*, **9**, 1-17.

[26] Longhurst, J. (2005) 1 to 100: Creating an Air Quality Index in Pittsburgh. *Environmental Monitoring and Assessment*, **106**, 27-42.

[27] Stieb, D.M., Doiron, M.S., Blagden, P. and Burnett, R.T. (2005) Estimating the Public Health Burden Attributable to Air Pollution: An Illustration Using the Development of an Alternative Air Quality Index. *Journal of Toxicology and Environmental Health*, *Part A*: *Current Issues*, **68**, 1275-1288. http://dx.doi.org/10.1080/15287390590936120

[28] Stieb, D.M., Burnett, R.T., Marc, S.-D., Brion, O., Shin, H.H. and Economou, V. (2008) A New Multipollutant, No-Threshold Air Quality Health Index Based on Short-Term Associations Observed in Daily Time-Series Analyses. *Journal of the Air & Waste Management Association*, **58**, 435-450.

[29] Mohan, M. and Kandya, A. (2007) An Analysis of the Annual and Seasonal Trends of Air Quality Index of Delhi. *Environmental Monitoring and Assessment*, **131**, 267-277. http://dx.doi.org/10.1007/s10661-006-9474-4

[30] Mayera, H., Holsta, J., Schindlera, D. and Ahrensb, D. (2008) Evolution of the Air Pollution in SW Germany Evaluated by the Long-Term Air Quality Index LAQx. *Atmospheric Environment*, **42**, 5071-5078. http://dx.doi.org/10.1016/j.atmosenv.2008.02.020

[31] Sowlat, M.H., Gharibi, H., Yunesian, M., Mahmoudi, M. and Lotfi, S. (2011) A Novel, Fuzzy-Based Air Quality Index (FAQI) for Air Quality Assessment. *Atmospheric Environment*, **45**, 2050-2059. http://dx.doi.org/10.1016/j.atmosenv.2011.01.060

[32] Vyas, S. and Kumaranayake, L. (2006) Constructing Socio-Economic Status Indices: How to Use Principal Components Analysis. *Health Policy Plan*, **21**, 459-468. http://dx.doi.org/10.1093/heapol/czl029

[33] Soler-Rovira, J. and Soler-Rovira, P. (2008) Assessment of Aggregated Indicators of Sustainability Using PCA: The Case of Apple Trade in Spain. *Proceedings of the 6th International Conference on LCA in the Agri-Food Sector*, Zurich, 12-14 November 2008, 133-143.

[34] Ali Hatem, M.M. (2009) Development of Arab Water Sustainability Index Using Principal Component Analysis. *Proceedings of the 13th International Water Technology Conference*, Hurghada, 1563-1578.

[35] Li, T., Zhang, H., Yuan, C. and Liu, Z. (2012) A PCA-Based Method for Construction of Composite Sustainability Indicators. *The International Journal of Life Cycle Assessment*, **17**, 593-603. http://dx.doi.org/10.1007/s11367-012-0394-y

[36] Hosseini, H.M. and Kaneko, S. (2011) Dynamic Sustainability Assessment of Countries at the Macro Level: A Principal Component Analysis. *Ecological Indicators*, **11**, 811-823. http://dx.doi.org/10.1016/j.ecolind.2010.10.007

[37] Park, Y.S., Egilmez, G. and Kucukvar, M. (2015) A Novel Life Cycle-Based Principal Component Analysis Framework for Eco-Efficiency Analysis: Case of the U.S. Manufacturing and Transportation Nexus. *Journal of Cleaner Production*, in Press.

[38] Tripping, M.E. and Bishop, C.M. (2002) Probabilistic Principal Component Analysis. *Journal of the Royal Statistical Society*: *Series B* (*Statistical Methodology*), **61**, 611-622. http://dx.doi.org/10.1111/1467-9868.00196

[39] Nagendra, S.S. and Khare, M. (2003) Principal Component Analysis of Urban Traffic Characteristics and Meteorological Data. *Transportation Research Part D*: *Transport and Environment*, **8**, 285-297. http://dx.doi.org/10.1016/S1361-9209(03)00006-3

[40] Rencher, A.C. and Christensen, W.F. (2012) Methods of Multivariate Analysis. 3rd Edition, John Wiley & Sons, Inc., Hoboken. http://dx.doi.org/10.1002/9781118391686

[41] Han, B., Bai, Z., Ji, H., Guo, G., Wang, F., Shi, G. and Li, X. (2009) Chemical Characterizations of PM10 Fraction of Paved Road Dust in Anshan, China. *Transportation Research Part D*: *Transport and Environment*, **14**, 599-603. http://dx.doi.org/10.1016/j.trd.2009.07.010

[42] The United States Environmental Protection Agency (2014) Air Quality Trends. http://www.epa.gov/airtrends/aqtrends.html

[43] Choi, J., Roberts, D.C. and Lee, E. (2014) Forecast of CO2 Emissions from the U.S. Transportation Sector: Estimation from a Double Exponential Smoothing Model. *Journal of the Transportation Research Forum*, **53**, 63-82.

[44] The United States Environmental Protection Agency (2014) Air Pollution and the Clean Air Act. http://www.epa.gov/air/caa/

[45] Mendenhall, W. and Sincich, T. (2011) A Second Course in Statistics: Regression Analysis. 7th Edition, Prentice Hall, Upper Saddle River, 797.

[46] Ramzan, S., Zahid, F.M. and Ramzan, S. (2013) Evaluating Multivariate Normality: A Graphical Approach. *Middle-East Journal of Scientific Research*, **13**, 254-263.

[47] The United States Bureau of Economic Analysis (2014) Industry Data. http://www.bea.gov/iTable/index_industry_gdpIndy.cfm

[48] The United States Environmental Protection Agency (2014) Emission Inventories. http://www.epa.gov/ttn/chief/eiinformation.html

Appendix A. Summary of the literature on changes to air quality indices.

Author(s)	Year	Study area	Pollutants measured	Methodology	Objective(s)
Thom and Ott	1975	US and Canada	CO, NO_X, Oxidants, PM, and SO_2	Standardized AQI	Developing a uniform AQI
Federal Interagency Task Force	1976	US	CO, NO_X, O_3, SO_2, and TSP[7]	PSI	Developing an AQI to report daily air quality by state
Hämekoski	1998	Finland	CO, NO_X, O_3, PM, and SO_2	PSI	Applying a PSI in the Helsinki area, Finland
Swamee and Tyagi	1999	India	CO, Haze, NO_X, O_3, SO_2, and TSP	Ambiguity- and eclipsicity-free function	Developing an overall AQI from the aggregation of air pollution sub-indices
Trozzi *et al.*	1999	Italy	CO, NO_X, O_3, PM, and SO_2	AQI	Applying an AQI developed by the USEPA for Italy
USEPA	1999	US	CO, NO_X, O_3, PM, and SO_2	AQI	Revisions from the PSI to provide additional air quality information
Sharma *et al.*	2003A	India	CO, NO_X, O_3, PM, and SO_2, and SPM[8]	AQI	Describing the design of a website for the dissemination of AQIs
Sharma *et al.*	2003B	India	CO, NO_X, O_3, PM, and SO_2, and SPM	AQI	Applying an AQI developed by the USEPA for the City of Kanpur, India
Cheng *et al.*	2004	Taiwan	CO, NO_X, O_3, PM, and SO_2	Revised AQI (RAQI)	Developing an RAQI as combining a PSI with an entropy function
Murena	2004	Italy	CO, NO_X, O_3, PM, and SO_2	AQI	Implementing an AQI in the urban area of Naples to measure the level of air pollution
Longhurst	2005	US	SO_2 and particulates	Simple formula[9]	Presenting the case study of an AQI in Pittsburgh, Pennsylvania
Stieb *et al.*	2005	Canada	CO, NO_X, O_3, PM, and SO_2	Time series regression on five air pollutants on mortality	Developing an alternative AQI to illustrate the public health burden attributable to air pollution
Cheng *et al.*	2007	Taiwan	CO, NO_X, O_3, PM, and SO_2	RAQI	Comparisons between an RAQI and a PSI or AQI for evaluating the feasibility and effectiveness of several air pollution conditions
Kyrkilis *et al.*	2007	Greece	CO, NO_X, O_3, PM, and SO_2	AAQI	Calculating potential health effects considering five criteria pollutants
Mohan and Kandya	2007	India	CO, NO_X, O_3, PM, and SO_2	AQI	Measuring the annual and seasonal variations of AQI from 1996 to 2004
Nagendra *et al.*	2007	India	Ammonia, CO, lead, NO_X, O_3, SO_2, SPM, and RPM[10]	AQI	Assessing the level of ambient air quality at traffic intersections in Bangalore, India using an AQI developed by the USEPA
Mayer *et al.*	2008	Germany	Benzene, NO_X, PM, and SO_2	Long-term AQI (LAQI)	Analyzing the effect of the integral long-term air pollution for 1985-2005
Stieb *et al.*	2008	Canada	CO, NO_X, O_3, PM, and SO_2	Air quality health index (AQHI) using time series regression on five air pollutants on mortality	Developing an AQHI and applying it in multiple Canadian cities
Bishoi and Jain	2009	India	CO, NO_X, O_3, PM, and SO_2	New AQI (NAQI) with factor analysis	Comparing an NAQI to an AQI developed by the USEPA
Wen *et al.*	2009	US	CO, NO_X, O_3, PM, and SO_2	AQI	Studying the relationship between media alerts of AQI and level of outdoor activity
Eder *et al.*	2010	US	CO, NO_X, O_3, PM, and SO_2	AQI	Developing local AQI forecasts using an AQI developed by the USEPA
Sowlat *et al.*	2011	Iran	CO, NO_X, O_3, PM, SO_2, benzene, toluene, ethyl-benzene, xylene, and 1, 3-butadiene	Fuzzy-based AQI (FAQI)	Developing a FAQI based on the computational method of artificial intelligence and assessing the performance of the index as a case study of Iran

---

[7]TSP stands for total suspended particulates.

[8]SPM stands for suspended particulate matter.

[9]Simple formula is as follows: $50\left(\left(SO_2/0.14\right)+\left(COH/1.73\right)\right)$, where SO_2 represents its measurement and COH means the coefficient of haze; the denominators in the formula are based on National Ambient Air Quality Standards [26].

[10]RPM stands for Respirable Particulate Matter.