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Classification of air quality using fuzzy synthetic multiplication

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Abstract Proper identification of environment's air quality based on limited observations is an essential task to meet the goals of environmental management. Various classification methods have been used to estimate the change of air quality status and health. However, discrepancies frequently arise from the lack of clear distinction between each air quality, the uncertainty in the quality criteria employed and the vagueness or fuzziness embedded in the decision-making output values. Owing to inherent imprecision, difficulties always exist in some conventional methodologies when describing integrated air quality conditions with respect to various pollutants. Therefore, this paper presents two fuzzy multiplication synthetic techniques to establish classification of air quality. The fuzzy multiplication technique empowers the max–min operations in "or" and "and" in executing the fuzzy arithmetic operations. Based on a set of air pollutants data carbon monoxide, sulfur dioxide, nitrogen dioxide, ozone, and particulate matter (PM_{10}) collected from a network of 51 stations in Klang Valley, East Malaysia, Sabah, and Sarawak were utilized in this evaluation. The two fuzzy multiplication techniques consistently classified Malaysia's air quality as "good." The findings indicated that the techniques may have successfully harmonized inherent discrepancies and interpret complex conditions. It was demonstrated that fuzzy synthetic multiplication techniques are quite appropriate techniques for air quality management.

Keywords Air quality index · Air quality management · Fuzzy synthetic evaluation · Environmental monitoring · Fuzzy sets

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Introduction

It is undeniable that deterioration of air quality and increment of potential environment-polluting activities are the major causes that concern all regions in the world including Malaysia. The three major sources of air pollution in Malaysia are mobile sources, stationary sources, and open burning sources. For the past 5 years, emissions from mobile sources (i.e., motor vehicles) have been the major source of air pollution, contributing to at least 70–75% of the total air pollution. Emissions from stationary sources generally have contributed to 20–25% of the air pollution, while open burning and forest fires have contributed approximately 3–5% (Department of Environment 1996). The environmental threats somehow prompted increasing awareness of the significance of healthy environment. Major observations have been made by Awang et al. (2000) on the long-term trends of major air pollutants in Malaysia including nitrogen dioxide, carbon monoxide (CO), the ozone and total suspended particulate matter (particularly PM10), and sulfur dioxide, emitted from industrial and urban areas from the early 1970s until late 1998. Afroz et al. (2003) reviewed the results of the ambient air quality monitoring and studies related to air pollution and health impacts. Continuous monitoring, proper environmental education, and various assessment methods have been conducted as to ensure healthy air quality to populations. One of the well-known assessment methods in air quality is indices. For environment quality assessment, index assessment has been used by a number of researchers (Inhaber 1976; Ott 1978; Rossbach et al. 1999; Bhuyan et al. 2003). In Malaysia, the government establishes Malaysian Air Quality Guidelines, the Air Pollution Index (API) and the Haze Action Plan to monitor and improve air quality. One of the direct indices that provides quick reference or status of air quality is API. The index for Malaysian API is classified into five scales good, moderate, unhealthy, very unhealthy, and hazardous. For instance, API between 0 and 50 is considered good and if API reads more than 300, the air quality is classified as hazardous. It seems that the index is given in numerical scale and then translated into linguistic terms. Therefore, it could be presumed that the interpretation of air quality status fundamentally depends on the five linguistic classifications.

To strengthen the importance of air quality classification, Flemming et al. (2005) presents an objective air quality classification scheme for observed ozone (O_3), nitrogen dioxide (NO_2), sulfur dioxide (SO_2) and particulate matter (PM10) time series in Germany. The classification is based on the medians of daily average concentration and relative daily variation by means of hierarchical clustering. The stability of the clusters in relation to variable scaling and transformation was validated by a cross-validation test based on resampling. Quick classification rules were developed, which permit a rapid and easy classification of any further observed or modeled annual time series. In assessing indoor air quality, Zhang et al. (2009) introduced nine main factors used which are clustered into three grades that are comfortable, rather comfortable, and uncomfortable. With the favorable assessment functions, they utilized grey classification theory to establish the assessment model of indoor air quality. Alvarez-Guerra et al. (2010) developed a methodology based on artificial neural networks for integrating data of multiple measured pollutants to group monitoring stations according to similar air quality. The method considers the subsequent geographical mapping of the clusters of stations observed which can make it possible to classify geographically different areas but shared similar air pollution problems. Thus a reliable air quality classification not only considers the material contributed to air pollution but proper method of classification is equally important.

However, classifications frequently encountered complex situations, such as overlapping or imprecise boundaries that normally obstruct correct classification (Onkal-Engin et al. 2004). Thus classifications are not a straightforward process as it accounts multipollutant materials. One of the purposes of classification is to group the air pollutant data into a category depending on the type of effect they may have on human health. In this process, the contributions of all pollutants are evaluated according to their own level of importance and are aggregated into a single value. Therefore choosing a proper means of classification method is an important matter in air quality assessment. Apart from classification, there is always a vagueness or fuzziness in air quality assessment due to inconsistency and distinction of each air pollutant. Fuzziness makes the use of sharp boundaries in classification schemes hard to justify. A small amplification or reduction in pollutant data, near its boundary value, will change its class. This fuzziness led some environmental researches to look for advanced assessment methods based on fuzzy set arithmetic operations. For this, Fisher (2003) proposed a decision-making model and its application to uncertainty, particularly in air pollution. At present, a substantial number of studies in environmental sciences are carried out stemming from fuzzy set theory (Zadeh 1965); for example, fuzzy logic rules- based was developed by Sowlat et al. (2011) to obtain air quality index. Different weighting factors were assigned to each pollutant according to its priority. Trapezoidal membership functions were employed for classifications and the final index consisted of 72 inference rules. To assess the performance of the index, a case study was carried out employing air quality data at five different sampling stations in Tehran, Iran. In a case of water quality assessment, Icaga (2007) developed an index model for quality evaluation of surface water quality classification using fuzzy logic. In the method, traditional quality classes are transformed into continuous form and then the concentration values of the different quality parameters are summed up using fuzzy rules. Finally defuzzification of these summed up values develop the index.

Besides index, assessment of air quality can be also in form of classifications. Athanasiadis and Kaburlasos (2006) for example proposed added value based on fuzzy set theory in applying data mining techniques in operational decision making of air quality classification. The application of fuzzy lattice reasoning classifier was investigated. An enhanced fuzzy lattice reasoning algorithm employed a sigmoid valuation function for introducing tunable nonlinearity. The fuzzy lattice reasoning with a sigmoid positive valuation function offers an improved performance on environment dataset from the region of Valencia, Spain. In fact, fuzzy set theory has been used for classification mainly for rivers since the 1980s. The majority of research in water quality modeling has focused on fuzzy synthetic evaluation (FSE) and fuzzy clustering analysis. The FSE is used to classify samples at a known center of classification (or group), whereas the fuzzy clustering analysis is used to classify samples according to their relationships when this center is unknown (Lu et al. 1999). The FSE classifies samples for known standards and guidelines, which is a modified version of traditional synthetic evaluation techniques. At microanalysis, the FSE comprises of simple fuzzy classification (SFC), fuzzy similarity method (FSM), and fuzzy comprehensive assessment (FCA). The FSE methods have been used by a number of researchers in various environmental areas (Lu et al. 1999; Chang et al. 2001; Lu and Lo 2002; Haiyan 2002). In air quality assessment, Onkal-Engin et al. (2004) carried out a case study to assess the urban air quality of the European part of Istanbul using FSE. With FSE method, data are classified into several categories according to predetermined quality criteria which eliminate the possible fuzziness. The FSE method processes all the components according to predetermined weights and decreases the fuzziness by using membership functions. Therefore the sensitivity is quite high compared to the other index evaluation techniques.

Going deeper into the mathematical background of FSE, one should apprehend that the main mathematics operation in FSE is fuzzy number multiplications. In addition, two of three methods under FSE employ the operations of multiplication in fuzzy sets. The so-called fuzzy synthetic multiplications are heavily employed in SFC and FCA computations. Multiplications based on fuzzy arithmetic operation are seemed to be the pivotal roles in FSE. In fact, the fuzzy synthetic multiplications have been tested successfully in human resource management (Abdullah 2007; Termini et al. 2006). However, the roles of fuzzy multiplications in FCA and FSE have been belittled despite its long success in FSE. Against all this background, this paper will focus on fuzzy multiplication operation and extends its application to Malaysian air quality assessment data. Hence, the objective of this paper is to specifically establish classification of Malaysian air quality data using fuzzy synthetic multiplication.

Fuzzy synthetic multiplication: air quality classification

The main purpose of the FSE method is to classify samples at a known center by synthesizing and evaluating several individual components of a process as a whole. FSE classifies samples for known standards and guidelines, which is a modified version of traditional techniques (Lu et al. 1999). Of the three subtitles under the FSE, the SFC and FCA employ the novelty of synthetic multiplication operation in fuzzy sets theory (Zadeh 1965). Multiplication can be derived using the basic fuzzy-processing procedure: the product of fuzzy relations through max–min composition. According to Kantardzic (2003), max–min composition is defined using the fuzzy set operations of union and intersection. The union of two fuzzy sets A and B is a fuzzy set C, written as $C = A \vee B$ whose membership function $\mu_C(x)$ is related to those of A and B by

$$\begin{aligned}\mu_C(x) &= \max(\mu_A(x), \mu_B(x)) \\ &= \mu_A(x) \vee \mu_B(x), \forall x \in X \end{aligned} \tag{1}$$

A more intuitive but equivalent definition of the union of two fuzzy sets A and B is the smallest fuzzy set containing both A and B. The intersection of fuzzy sets can be defined analogously. The intersection of two fuzzy sets A and B is a fuzzy set C, written as $\mathrm{C} = \mathrm{A} \wedge \mathrm{B}$whose membership function $\mu_C(x)$ is related to those of A and B by

$$\mu_C(x) = \min(\mu_A(x), \mu_B(x),) = \mu_A(x), \mu_B(x), \forall x \in X \tag{2}$$

As in the case of the union sets, it is obvious that the intersection of A and B is the largest fuzzy set that is contained in both A and B. These basic fuzzy arithmetic operations are embedded into SFC and FCA. In these two techniques, membership functions are determined according to different air quality levels. The membership functions are used to form a relationship between the air quality measurements and the defined air quality levels. The evaluation matrix, R is then used to multiply with the defined weights to determine air quality classification. To ease the computational risk, the following steps are proposed based on the works of Onkal-Engin et al. (2004). Step 1 to step 4 are the preliminary steps prior to SFC and FCA computations.

Step 1: obtain pollutant concentration index

The conversion of each pollutant concentration to API can be evaluated by the equation below.

$$\text{Index} = \frac{C_i}{S_i} 500 \tag{3}$$

where

C_i is the pollutant concentration
S_i is pollutant standard level

Here, the concentration of the pollutants is expressed as a ratio of the relevant standard.

Step 2: define membership function for linguistic

In fuzzy synthetic multiplication, assessment criteria of air environment quality are classified according to the group set as “good,” “moderate,” “unhealthy,” “very unhealthy,” and “hazardous.” Then, the value of fuzzy membership function of each factor related to five assessment levels is calculated by a set of the following functions:

$$\mu_A = \begin{cases} 1, & 0 \le x \le D_A, \\ \frac{D_B - x}{D_B - D_A}, & D_A \le x \le D_B, \\ 0, & x \ge D_B, \end{cases}$$

$$\mu_B = \begin{cases} 0, & x \le D_A \ or \ x \ge D_C, \\ \frac{x - D_A}{D_B - D_A}, & D_A < x < D_B, \\ 1, & x = D_B, \\ \frac{D_C - x}{D_C - D_B}, & D_B < x < D_C, \end{cases}$$

$$\mu_C = \begin{cases} 0, & x \le D_B \ or \ x \ge D_D, \\ \frac{x - D_B}{D_C - D_B}, & D_B < x < D_C, \\ 1, & x = D_C, \\ \frac{D_D - x}{D_D - D_C}, & D_C \le x \le D_D, \end{cases}$$

$$\mu_D = \begin{cases} 0, & x \le D_C \ or \ x \ge D_E, \\ \frac{x - D_C}{D_D - D_C}, & D_C < x < D_D, \\ 1, & x = D_D, \\ \frac{D_E - x}{D_E - D_D}, & D_D \le x \le D_E, \end{cases}$$

$$\mu_E = \begin{cases} 0, & 0 \le x \le D_D, \\ \frac{x - D_D}{D_E - D_D}, & D_D \le x \le D_E, \\ 1, & x \ge D_E. \end{cases}$$

D_A, D_B, D_C, D_D, and D_E are the boundaries in criterion levels. The functions μ_A, μ_B, μ_c, μ_D, and μ_E represent the five classifications.

Step 3: create evaluation matrix

Evaluation matrix, R, is created by the membership values and corresponded to air quality parameters:

$$R = \begin{bmatrix} r_{11} & r_{12} & & r_{15} \\ r_{21} & r_{22} & & \\ & & & \\ r_{51} & r_{52} & & r_{55} \end{bmatrix}$$

where $r_{ij} = \mu_j(x)$, i=1, 2,…, 5, j=1, 2,…, 5. For example, $r_{45} = \mu_5(x) = \mu_E$.

Similarly,

$$\{\mu_1, \mu_2, \mu_3, \mu_4, \mu_5\} = \{\mu_A, \mu_B, \mu_C, \mu_D, \mu_E\}.$$

Here r_{ij} represents the values of data evaluated by fuzzy membership functions.

Step 4: obtain weight from expert

An air pollutant cannot be ascertained or observed according to a pollutant because each pollutant has its own contribution to air pollution. Therefore, weight factors here are chosen according to the knowledge and experience of the experts. The opinion from Onkal-Engin et al. (2004) is accounted in this case study where weight factors are defined as

$$W = \{w_{SO_2}(0.15), w_{PM}(0.3), w_{CO}(0.3), w_{NO_2}(0.1), w_{O_3}(0.15)\}$$

where w represents the average concentration for respective pollutants.

This decision making requires information for relative importance of attributes or criteria. The relative importance is established by a set of preference weights, which can be normalized to a sum of 1. In the case of n criteria, a set of weights can be written as: $W=(w_1, w_2, \ldots, w_n)$, where $\sum_{j=1}^{n} w_j = 1$.

The fuzzy synthetic multiplication techniques of SFC and FCA can be proceeded for classification purposes after completing the above four steps. Parts of these two methods are retrieved from Onkal-Engin et al. (2004).

1. Simple fuzzy classification

   For the SFC method, the fuzzy membership functions are used to form a relationship between the air quality measurements and the defined air quality levels. Matrix R is used to determine the degree of similarity between measured values and determined air quality levels. The fuzziness for classification can be observed in step 2.

   Here, the air quality criteria are divided into five groups. For classification, weighted average method is used as stated by Chang et al. (2001). The weighted average method provides a set of weights to express the relative importance of each pollutant.

$$k_j = \sum_{i=1}^{m} w_i \lambda_{ij} \quad j = 1, 2, \ldots, n \tag{4}$$

   w_i is the defined weight associated with each parameter which is subject to the requirements below.

$$\sum_{i=1}^{n} w_i = 1$$
$$k_p = \max\{k_j\} \quad j = 1, \ldots, n$$

   The fuzzy operators, the min–max of synthetic multiplication, are implemented to Eq. 4 to determine the classification.

2. Fuzzy comprehensive assessment

   In FCA, using the membership function and the standards, a fuzzy relationship matrix is formed. The air quality codes or values are given to a fuzzy operator. The total evaluation conclusion is schematically shown in Fig. 1.

   Lastly, the classification can be determined using fuzzy operators of synthetic multiplication. The fuzzy comprehensive assessment result can be obtained from B as:

$$B = W \otimes R = (b_1, b_2, b_3, b_4, b_5)$$

$$\{b_1, b_2, b_3, b_4, b_5\} = \{b_A, b_B, b_C, b_D, b_E\}$$

$$\text{Class} = \max(b_j), \quad j = 1, 2, \ldots, 5$$

   Here, the maximum value of b_j determines the air quality class of the related area. In short, air quality classifications are determined using fuzzy operators, the min–max of synthetic multiplication.

Case study

The Department of Environment, Malaysia (DOE) has provided the air quality trend from 1998 to 2006 in the Environmental Quality Report (Department of Environment 2006). The namely Air Quality Report was computed by averaging direct measurements from the monitoring sites on a yearly basis and cross-reference with the Malaysia Ambient Air Quality Guidelines. The five criteria pollutants, namely CO, SO_2, NO_2, (O_3), and particulate matter PM_{10} were monitored continuously in 51 locations nationwide. The present study has gathered all these data to propose classification of air quality. The method of the present case study leading to the classification can be depicted in Fig. 2. Based on the proposed steps in

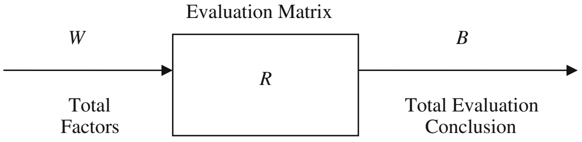

Fig. 1 Fuzzy comprehensive assessment

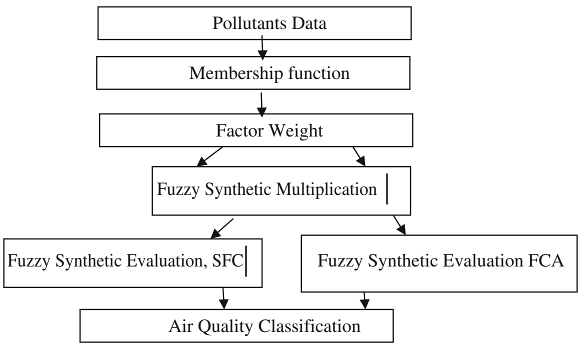

Fig. 2 Classification framework

the "Case Study" section, the computations for this case study are executed as follows.

Computations and results

Data on pollution issued by DOE Malaysia from 1998 until 2006 were used to obtain the index. Using step 1, pollutants' concentration indices were obtained. The pollutant's index for PM_{10} in year 1998, for example, was obtained as

$$\begin{aligned}\text{Index } PM_{10} &= \tfrac{41}{50}500\\ &= 410\end{aligned}$$

The index for all pollutants was computed with the same manner and presented in Table 1. API in Malaysia has five assessment levels, so there would be only five membership functions used to fit in the API which are μ_A, μ_B, μ_C, μ_D, and μ_E. The assessment criterion level from Malaysian Air Quality standard was used as a guide to form the membership function. Details of levels and pollutants set by Malaysian Air Quality Standards can be seen in Table 2.

Based on the standards on Table 2, membership functions for each criterion level and pollutant were defined (refer to step 2). For example, membership function for criterion level of "good" and pollutant SO_2 was defined as

$$\mu_A = \begin{cases} 1, & 0 \le x \le 11.3, \\ \frac{22.6-x}{22.6-11.3}, & 11.3 \le x \le 22.6, \\ 0, & x \ge 22.6,. \end{cases}$$

Membership function for criterion level of hazardous for pollutant of O_3 is defined as

$$\mu_E = \begin{cases} 0, & 0 \le x \le 126.6, \\ \frac{x-126.6}{344-206.4}, & 126.6 \le x \le 211, \\ 1, & x \ge 211. \end{cases}$$

Data from DOE over the criterion level for 9 years were averaged to obtain averaged pollutants for each criterion level. The averaged data are given in Table 3. The averaged data were then used in obtaining membership value for each criterion.

Finally using the proposed step 3, all the membership values was pooled in a matrix R as to ease the next computations.

$$R = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0.1504 & 0 & 0 & 0 & 0 \end{bmatrix}$$

The 9-year data were again used to find average concentration for each pollutant.

Table 1 Index for each pollutant per year

Year	PM_{10}	SO_2	NO_2	CO	O_3
1998	410	92.48	25.29	41.33	190.28
1999	410	43.67	21.80	32.55	170.38
2000	400	47.35	20.06	39.55	195.26
2001	440	37.43	21.51	40.07	185.31
2002	500	36.19	22.97	38.86	191.23
2003	440	32.43	22.96	46.26	176.78
2004	480	28.72	23.26	41.05	194.31
2005	490	29.96	27.91	43.99	210.90
2006	490	26.19	26.74	32.81	204.26

Table 2 Assessment criterion levels from the Malaysian Air Quality Standards

Criterion levels		SO_2	PM	CO	NO_2	O_3
D_A	Good	11.3	5	1,110	34.4	21.1
D_B	Moderate	22.6	10	2,220	68.8	42.2
D_C	Unhealthy	45.2	20	4,440	137.6	84.4
D_D	Very unhealthy	67.8	30	6,660	206.4	126.6
D_E	Hazardous	113	50	11,100	344	211

So, the average concentration for each pollutant is given as

SO_2=9.402 μg/m^3
PM_{10}=45.11 μg/m^3
NO_2=16.24 μg/m^3
CO=879.3 μg/m^3
O_3=80.59 μg/m^3

Using step 4, weight for each pollutant is defined as w= {(0.15), (0.3), (0.3), (0.1), (0.15)}where $\sum_{i=1}^{5} w_i = 1$

Weight factor $W = \{w_{\mathrm{SO_2}}(0.15), w_{\mathrm{PM}}(0.3), w_{CO}(0.3), w_{\mathrm{NO_2}}(0.1), w_{\mathrm{O_3}}(0.15)\}$

From this set of data, the value of W:

$$W=\{9.402(0.15),45.11(0.3),16.24(0.3),879.3(0.1),80.59(0.15)\}$$
$$=\{1.4103, 13.53, 4.872, 87.93, 12.09\}$$

These values were required before continuing with the classification.

Classifications

The classifications were then determined under two techniques:

1. SFC by using weighted average;

$$k_j = \sum_{j=1}^{5} w_j\, \lambda_{ij} \quad j = 1, 2, \ldots, 5$$

Table 4 Classification obtained using SFC and FCA

Fuzzy evaluation techniques	SFC	FCA
Classification	D_A	D_A
Criterion level	Good	Good

λ_{ij} here represents the matrix R evaluated by fuzzy membership function. Thus, fuzzy synthetic multiplication,

$$kj = [0.15\ \ 0.3\ \ 0.3\ \ 0.1\ \ 0.15] \otimes \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0.1504 & 0 & 0 & 0 & 0 \end{bmatrix}, \text{is executed.}$$

Since kp is the maximum value of k_j, thus it could be seen from the fuzzy min–max operation that the maximum value of k_j is k_1=1 which indicates the class by using weighted average method, D_A.

2. Fuzzy comprehensive assessment

Under the technique of FCA, weight factors considering expert opinion and averaged data of the pollutants were utilized. The synthetic multiplication

$$B = [1.410\ \ 13.53\ \ 4.872\ \ 87.93\ \ 12.09] \otimes \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0.1504 & 0 & 0 & 0 & 0 \end{bmatrix} \text{is executed.}$$

Thus, B=(1, 0, 0, 0, 0) and the maximum value of b_j determine the class which is b_1. So the class

Table 3 Averaged data for criterion levels and pollutants

Criterion levels		SO_2	PM	CO	NO_2	O_3
D_A	Good	5.92	40	725.5	14.3	73.25
D_B	Moderate	6.86	41	876.8	15.5	78.2
D_C	Unhealthy	8.32	44	911.3	16.7	81.0
D_D	Very unhealthy	10.29	49	976.5	18.4	86.2
D_E	Hazardous	20.9	50	1,027.0	19.2	89.0

by using fuzzy comprehensive assessment is D_A. The results from the two classification techniques using fuzzy synthetic multiplication are summarized in Table 4.

Of the five classifications from "good" to "hazardous," the two techniques classified criterion level of air quality in Malaysia as "good." The results concur with the API readings throughout the country where the air quality has been considered "generally good."

Conclusions

An important element in air quality assessment are methods which can take into account the multi-pollutants and expert's knowledge. The method should establish a decision to reflect the contribution of each accounted factor. Furthermore the method should be practical, direct analysis, and the most important is the results are clearly comprehensible. Air quality data are generally very complex to assess due to multipollutant characteristics. In this study, two synthetic multiplication decision-making techniques were used for the classification of air quality data. The two multiplication methods used the fuzzy arithmetic operation of multiplication that can translate pollutants concentrations and their respective weights to reach decision. The classification obtained from fuzzy comprehensive assessment was identical to simple fuzzy classification. The simple fuzzy classification and fuzzy comprehensive assessment used the same membership function but with different approaches of weights to indicate the class. The two techniques are banked mainly from the usage of membership functions and predetermined weights. The multiplication techniques overcome the classification problem by implying the fuzziness in the boundaries of the standard values from the membership function evaluation. In addition, the predetermined weights also allow each pollutant to be used at its own level of importance. The consistency in classification from the two methods indicates the possibility of using fuzzy techniques in air quality management.

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