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Determination of an Atmospheric Condition Index with Evidential Annotated Paraconsistent Logic Tools

Determinação de um Índice de Condição Atmosférica com Ferramentas da Lógica Paraconsistente Anotada Evidencial

Determinación de un Índice de Condición Atmosférica con Herramientas de Lógica Paraconsistente Anotada Evidencial

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Abstract
The objective of this article is to propose the creation of an atmospheric condition index using Artificial Intelligence tools. The atmospheric condition can be obtained from parameters that the scientific communities – environment, health, labor safety – adopt for the different pollutants in the atmosphere. Parameters were obtained from the scientific literature and specialists, who were consulted about the objective data to allow an analysis through an expert system. As the data are from highly imprecise sources, classic-logic (binary) systems do not fit. We opted to use the Evidential Annotated Paraconsistent Logic. This non-classical logic naturally accommodates imprecisions, contradictions, and paracompleteness without the danger of trivialization. Thus, the Evidential Annotated Paraconsistent Logic can be ideally adopted as a valuable tool for controlling atmospheric conditions, especially in large metropolises.
Keywords: Atmospheric condition index; Expert system; Paraconsistent logic; Degree of certainty; Degree of uncertainty.

Resumo
O objetivo deste artigo é propor a criação de um índice de condição atmosférica utilizando ferramentas de Inteligência Artificial. A condição atmosférica pode ser obtida a partir de parâmetros que as comunidades científicas – meio ambiente, saúde, segurança do trabalho – adotam para os diferentes poluentes da atmosfera. Os parâmetros foram obtidos da literatura científica e de especialistas, que foram consultados sobre os dados objetivos para permitir uma análise por meio de um sistema especialista. Como os dados são de fontes altamente imprecisas, os sistemas de lógica clássica (binários) não se encaixam. Optamos por utilizar a Lógica Paraconsistente Anotada Evidenciada. Essa lógica não clássica acomoda naturalmente imprecisões, contradições e paracompletudes sem o perigo de banalização. Assim, a Lógica Paraconsistente Anotada Evidencial pode ser idealmente adotada como uma ferramenta valiosa para o controle das condições atmosféricas, principalmente em grandes metrópoles.
Palavras-chave: Índice de condição atmosférica; Sistema especialista; Lógica paraconsistente; Grau de certeza; Grau de incerteza.

Resumen
El objectivo de ese artículo es proponer la creación de un índice de condiciones atmosféricas utilizando herramientas de Inteligencia Artificial. La condición atmosférica se puede obtener a partir de los parámetros que las comunidades científicas -ambiental, de salud, de seguridad laboral- adoptan para los diferentes contaminantes de la atmósfera. Los parámetros se obtuvieron de la literatura científica y de especialistas, a quienes se consultó sobre los datos objetivos para permitir un análisis a través de un sistema experto. Como los datos provienen de fuentes muy imprecisas, los sistemas de lógica clásica (binarios) no encajan. Optamos por utilizar la Lógica Paraconsistente Anotada Evidencial. Esta lógica no clásica acomoda naturalmente imprecisiones, contradicciones y paracompletos sin el peligro de la trivialización. Por lo tanto, la Lógica Paraconsistente Anotada Evidencial se puede adoptar idealmente como una herramienta valiosa para controlar las condiciones atmosféricas, especialmente en las grandes metrópolis.
Palabras clave: Índice de condición atmosférica; Sistema experto; Lógica paraconsistente; Grado de certeza; Grado de incertidumbre.

1. Introduction

Several sources and human activities cause air pollution and negatively affect public health and the environment. Thus, knowing how to diagnose threatening atmospheric conditions, get reliable information, and answer to this information can help save lives, especially in large cities. Highly populated cities are becoming more and more common due to the inevitable migration from the countryside to urban regions. This concentrated activity changes the atmosphere composition and brings health problems for men, animals, and plants (Oliveira, 2016; Ostro, 1994; House of Lords, 2017).

Air pollution is a global problem, but national, regional, or local governments set legal limits for concentrations of major air pollutants that impact public health. Therefore, for the authorities to adopt prevention or prompt improvement initiatives, assessing atmospheric conditions in a simple, fast and efficient manner is of utmost importance (Silva, 2015).

The air quality results from a complex combination of independent factors, assuming contradictory and inconsistent values. An appropriate tool to deal with these conflicting values is the Paraconsistent Annotated Evidential Logic, PAL (Abe, 1992), which handles inconsistent and conflicting data without becoming trivial. In this research, an atmospheric condition index (ACI) is proposed to allow a scientifically grounded evaluation of the atmospheric conditions based on logical criteria.

2. Literature Review

Recognizing that modeling and evaluating probabilistic atmospheric conditions and providing helpful information for managing and forecasting the unfavorable effects of air pollution are essential, several approaches have been considered to assess or predict air conditions. Still, when it comes to addressing uncertainties, fuzzy logic is the approach most explored. Some studies cover the issue in urban areas. Alyousifi et al. (2021) proposed applying the Markov chain-based fuzzy states model for analyzing the ambiguity in the incidence of air pollution events in urban areas and unfolding the transition behavior of air pollution. Their outcomes showed that the Markov chain-based fuzzy states could successfully model the air pollution index and provide policymakers with information and understanding about air pollution dynamics. Zheng et al. (2017) built a population-production-pollution nexus for all-inclusive air pollution management and air quality provision. A fuzzy-stochastic mixed quadratic method was used to deal with uncertainty. The results may encourage adapting current policies on the atmospheric crisis through a sustainable production model with a mitigation scheme at the urban level.

In a study proposing a fuzzy factorial-chance-constrained method for designing urban ecosystems under uncertainties, Liu et al. (2018) addressed uncertainties. They quantitatively evaluated the specific and synergistic outcomes of multiple environmental elements on the urban ecosystem. Their results revealed that one of the cities investigated, Foshan, experienced sulfur dioxide pollution discharged from the industrial sector. Their results disclosed multiple uncertainties in system components and eco-environmental constraints and can help decision-makers understand the tradeoff concerning economic development and environmental security in urban agglomerations.

According to Dursun et al. (2015), air quality estimate is complicated, and artificial intelligence methods may be effectively used to model nonlinear approximation problems. They used an artificial neural network and an adaptive neuro-fuzzy logic method to estimate the influence of particular sulfur dioxide pollution levels on the air quality in the Konya city center. The results of their inference system model were assessed and matched to the results achieved from the air quality standards of Turkey and the Environmental Protection Agency. The inference system model was considered a valued tool to predict and assess air quality.

There is also vigorous research on risk assessment. Asif and Chen (2019) applied an integrated fuzzy-based risk assessment approach to assess uncertainty and air quality in open-pit metal mines in North America. The risk level was based on diverse environmental guidelines. Using a triangular fuzzy membership approach, the risk was allocated into loose, medium, and strict. The method was proposed as a tool for decision-making to select the best technology for air pollution control. Claiming that studies of environmental management lack consistent data for risk assessment of pollutant exposure, Chung et al. (2019) used an inference model based on Fuzzy theory allied to a GIS map. Their approach allowed us to understand the risk map of PM2.5 in Taiwan through a quick pollutant measurement to calculate environmental exposure for potential risk.

Expecting that their work would provide a means for the Chinese government to lead programs to control air pollution, Du et al. (2019) investigated a practical structure to mitigate air pollution in the process of a group negotiation with many decision-makers, including an assortment of vague information and predilections. The authors proposed a new group negotiation decision model employing a hesitant fuzzy set, grey target, grey incidence analysis, and graph model for conflict resolution to resolve the arrangements for treating air pollution. Xu et al. (2017) proposed fuzzy synthetic evaluation to assess pollutants air and quality. The model was described as robust to early warnings and suitable for monitoring air quality, potentially viable for decision-makers.

However, most recent studies are dedicated to forecasting atmospheric conditions and providing early warnings systems. Yang and Wang (2017) proposed a plan to monitor air quality and provide an early warning system. A wide-ranging fuzzy evaluation was presented to establish the key pollutants and estimate the degree of air pollution. The model was validated in two cities in China and proposed to forecast pollutant concentrations. Wang et al. (2018) also developed an early warning system based on fuzzy time series. The model was presented to predict significant air pollutant concentrations, and the model's effectiveness and stability were verified in monitoring air quality.

Using an adaptive neuro-fuzzy inference system and data of the concentrations of atmospheric pollutants recorded by sensors, Zeinalnezhad et al. (2019) developed a system for air pollution forecasting. The method predicted four air pollution indicator levels: carbon monoxide, sulfur dioxide, nitrogen oxides, and trioxygen absolute error less than 15 %. Li et al. (2018) proposed a self-adaptive neuro-fuzzy weighted extreme learning machine combined with a prediction method to improve the accuracy and real-time air pollutant concentration prognosis. Based on the air pollutant concentration data collected in Datong, Taiwan, an integrated model was built to predict each pollutant's concentration collected by a single monitoring point. The experimental results showed that the method had good prediction accuracy and real-time performance.

Bougoudis et al. (2018) proposed a Hybrid Fuzzy Semi-Supervised Forecasting Framework, combining fuzzy logic, semi-supervised clustering, and semi-supervised classification. The framework was applied to model the air quality of Athens city effectively and managed to forecast extreme air pollutants' values and explore the parameters that affect their concentration. A hybrid strategy was also developed by Jiang et al. (2017) to predict and analyze particular matter's concentration (PM2.5). The results showed that the developed hybrid strategy could be a political and administrative method to issue effectively early warnings and design suitable abatement strategies.

Although not very known in environmental studies, paraconsistent logic has been under the concern of philosophers and mathematicians since its appearance at the beginning of the last century. Regarding environmental issues, paraconsistent

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logic was first mentioned by Giannetti et al. (2009) when dealing with the complexity of the ecological demands of composite environmental indexes. The use of Paraconsistent logic allowed to build helpful tools to evaluate environmental indicators and draw attention to environmental conditions and trends for policy purposes. Bonilla et al. (2019) proposed using paraconsistent logic to support decision-making in emergy accounting. Recently, Langa et al. (2021) applied it to verify whether the Global Reporting Initiative (GRI) indicators aligned with the concept of `strong' sustainability. The work contributed to identifying and suggesting improvements to the GRI developers on indicators that may better represent the strong sustainability and achieve its primary goals.

Even if most authors use different logical approaches and different systems of interest, they all agree that logic other than classic is the proper tool to treat systems that present uncertainties, contradictions, and inconsistent data. Among the issues when favorable and unfavorable pieces of evidence simultaneously describe a proposition, paraconsistent logic allows reaching conclusions without trivialness. Thus, it enables decision-making without the necessity of disregarding or discarding data (Da Silva Filho, 2010).

3. Methodology

We will consider an Expert System based on the Paraconsistent Annotated Evidential Logic Eτ - Logic Eτ. Roughly speaking, paraconsistent logic is a logic that can be the underlying logic for unreliable but non-trivial theories. A notable feature of the Logic Eτ is that in addition to being paraconsistent, it is paracomplete and non-alethic. A logic is dubbed paracomplete if theories are based on it, and there are propositions and their negation that are both false. A logic is non-alethic if it is simultaneously paraconsistent and paracomplete (Da Costa et al., 1991; Abe, 1997).

The atomic propositions of the language of the Logic Eτ are of type p(a; b), where p is a proposition in the usual sense and the pair (a; b) belong to the set of true values [0; 1] X [0; 1] = [0; 1]2 where [0; 1] is the actual unitary interval.

The pair (a; b) is called annotation constant. Thus p(a; b) can be intuitively read: a is the favorable evidence expressed by p, and b is the contrary evidence expressed by p. Depending on the application, the values a and b can be read as beliefs or probabilities.

In the set [0; 1] X [0; 1] we consider the order relation * such that (a1; b1) * (a2; b2) if and only if a1 ≤ a2 and b2 ≤ b1, where ≤ is the usual order of real numbers. One can prove that [0; 1]2 with the order relation * constitutes a lattice symbolized by τ (Figure 1).

Each annotation constant (a; b) belongs to a logical state. Some exciting readings of annotation constants stand out (De Carvalho, 2002):

- (1; 0) intuitively means total favorable evidence and no contrary evidence (thus (1; 0) is a logical state which is called truth, which is symbolized by V);
- (0; 1) which intuitively represents no favorable evidence and total contrary evidence (it corresponds to a logical state which is called falsity, which is represented by F);
- (1; 1) means total favorable and contrary evidence (total favorable and total contrary evidence which belong to a logical state that is called inconsistent, which is represented by $\top$), and
- (0; 0) indicates the total lack of favorable and contrary evidence, which belongs to a logical state called paracomplete, which is represented by $\perp$).

The logical state (0.5; 0.5), for example, can be read as undefined.

3a. Degrees of certainty and uncertainty

Now we introduce the concepts regarding Uncertainty and Certainty degrees. As seen previously, each annotation constant belongs to the set [0; 1]2 (Cartesian Product Unitary Square – CPUS). The lattice τ is composed of decision states.

This article will consider twelve decision states, as shown in Figure 1. In the set [0; 1]2, the segment AB is called the perfectly undefined segment (PUS), and CD, called the perfectly defined segment (PDS), stands out (Abe and Da Silva Filho, 2001). Thus, given an annotation constant (a; b), we define:

- Degree of certainty: H = a – b
- Degree of uncertainty: G = a + b – 1

Figure 1 - CPUS and decision states, with limit lines defined by degrees of certainty and uncertainty, in modulus equal to 0.60.

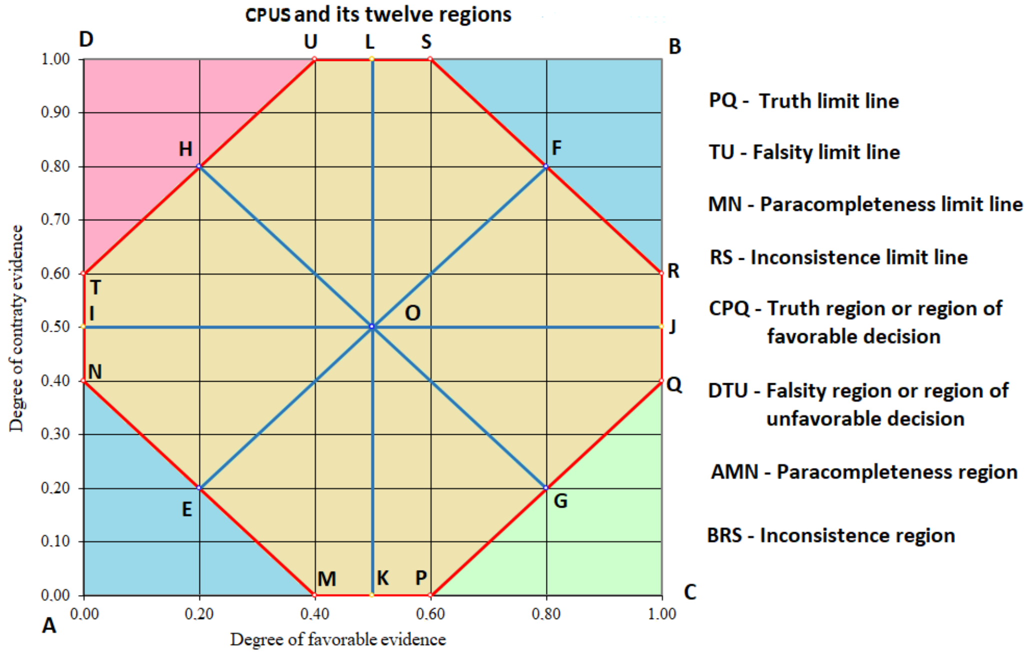

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Figure 1 shows that the proposition is defined as true with the higher value of the favorable evidence and the lower value of the contrary evidence. The less favorable evidence and the greater the contrary evidence, the proposition is false. If both favorable and contrary evidence is high, the proposition is inconsistent; if both favorable and contrary evidence values are low, the proposition is paracomplete; finally, if the evidence values are not extreme, the proposition is undefined (De Carvalho & Abe, 2018). Details for additional definitions can be seen in De Carvalho (2006):

- Paracompleteness limit line: straight MN, such that G = – k1, for 0 < k1 < 1;
- Inconsistency limit line: straight RS, such that G = + k1, for 0 < k1 < 1;
- Falsity limit line: straight TU, such that H = – k2, for 0 < k2 < 1;
- Truth limit line: straight PQ, such that H = + k2, for 0 < k2 < 1.

Usually, k1 = k2 = k is adopted, giving symmetry to the graph, as in Figure 1, where k1 = k2 = k = 0.60. The value of k2 will be called the requirement level, as it represents the minimum value of |H| so that one falls into the region of falsity or truth. One can say that the atmospheric condition index is unfavorable or favorable.

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With the division of the CPUS into twelve regions adopted in Figure 1, four extreme regions stand out, and among those four:

- CPQ region: $0.60 \leq H \leq 1.00 \Rightarrow$ truth region.
- DTU region: $-1.00 \leq H \leq -0.60 \Rightarrow$ falsity region.

Therefore, if the annotation constant (a; b) belongs to one of these regions, there is an excellent indication to qualify the atmospheric condition. There will be an ideal condition if X belongs to the CPQ region or a bad condition in the DTU region.

Therefore, the CPUS, with its division into twelve regions known as a para-analyzer device or algorithm (Abe and Da Silva Filho, 2001), allows analysis for the qualification of the atmospheric condition.

3b. NOT, MAX and MIN operators of PAL (De Carvalho and Abe, 2011)

NOT is defined by: NOT (a; b) = (b; a). The NOT operator must match the negation of the annotated logic. Note: NOT T = T, NOT ⊥ = ⊥, NOT V = F and NOT F = V.

The MAX operator, called maximizing, is defined by (a1; b1) MAX (a2; b2) = (max.{a1, a2}; min{b1, b2}). This operator has the meaning of choosing the best favorable evidence (higher a) and the best unfavorable evidence (lower b) to maximize the degree of certainty.

The MIN operator, called minimizing, is defined by (a1; b1) MIN (a2; b2) = (min{a1, a2}; max{b1, b2}). This operator has the meaning of choosing the worst favorable evidence (lower a) and the worst unfavorable evidence (higher b) to minimize the degree of certainty.

3c. How to obtain the ACI using PAL

The atmospheric condition index (ACI) is determined by analyzing air pollutant indicators against the parameters established by experts. In this work, government norms, entities that take care of the environment, well-reputed scientific work, renowned researchers are considered experts. To apply PAL techniques, experts are initially separated into groups (A, B, C, etc.), adopting their conceptualization as a criterion in the scientific community's eyes, the importance that the respective countries give to the environment, or another criterium deemed appropriate.

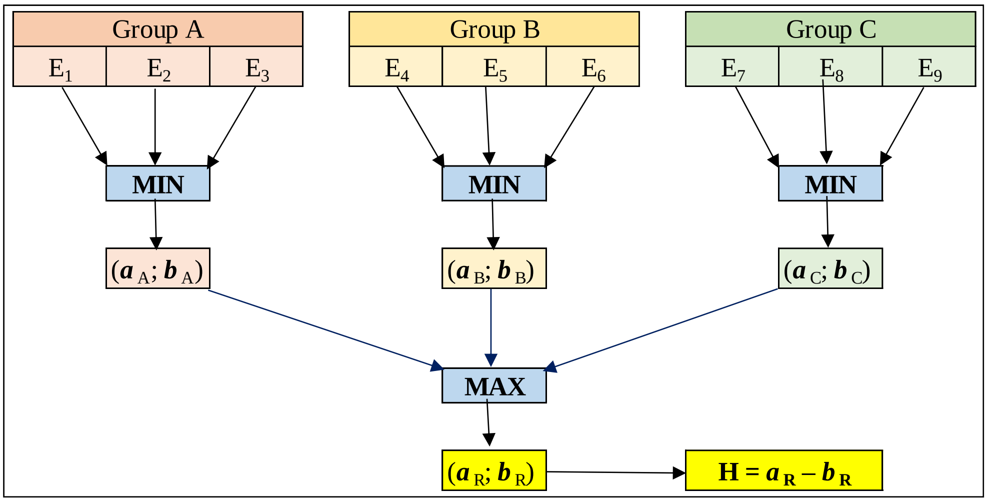
Each group must be made up of specialists, with knowledge in the field, according to some adopted criterion, such as, for example, international credibility. In addition, experts in one group must be independent of experts in other groups. One group's opinion is independent of other groups' views. If an indicator is in bad condition in the opinion of an expert of a group, this will imply that the indicator is in bad condition for the whole group. This is achieved by applying the MIN operator intragroup (De Carvalho and Abe, 2018). By imposing that the group is characterized by the expert's opinion who attributes the worst conditions to the indicator, a criterion in which the result favors safety is adopted.

Once the safety within groups is guaranteed, the MAX operator is applied intergroup to obtain the joint opinion of all experts on the atmospheric condition. According to the criterion known as max-min in decision theory (Shimizu, 2006).

The PAL minimization and maximization techniques allow identifying each specialist's indicator pair (a, b). The pairs (aA, bA), (aB, bB), ..., which translate the opinion of groups A, B, ... of specialists about the analyzed indicator of atmospheric condition, are obtained. Following the procedure, the MAX operator is applied intergroup, maximizing the worst opinions. With this, a resulting pair (aR, bR) estimates the degree of certainty of this indicator, H = aR – bR, which translates the indicator influence on the atmospheric condition (Figure 2).

Suppose the condition for the degree of certainty (H) results is negative. In that case, all the groups have a higher pollutant concentration (X) than the minimum standard (or maximum acceptable concentration value, K).

Figure 2 - Illustrative diagram of the application of the MIN and MAX operators of the PAL in this work.



Source: Authors.

By repeating the process for all the chosen indicators (Pi), a degree of certainty (Hi) is obtained for each one. The joint analysis of all obtained degrees of certainty (Hi) leads to a numerical value that reflects all indicators' joint influence, according to all specialists' opinions. This result will be called the Atmospheric Condition Index (ACI).

It was established that the atmospheric condition would be terrible or calamitous if the value of one indicator is above the standard value (maximum allowed limit, K). This value must average all indicators' degrees of certainty (Hi). But, what average?

Even though it is positive, the arithmetic average (AA) has the inconvenience of "hiding" the negative values of one or more Hi. Therefore, it does not meet the established requirement and must be discarded. The geometric average (GA) has similar drawbacks: it can be positive and high, even if several Hi are negative. Furthermore, it may not be defined in the set of real numbers if n is even, and there are odd numbers of indicators with negative Hi and no null. GA has the advantage of detecting Hi close to zero, but that is not enough. The solution was to adopt an adjusted geometric average that we call adapted geometric average (AGA). Every negative Hi is replaced by zero; thus, AGA detects Hi close to zero, does not increase with negative values, and turns itself null when at least one Hi is negative.

$$ACI = \sqrt[n]{H_1' \ x \ H_2' \ x \dots x \ H_n'}$$

For a more accurate calculation, which reflects different degrees of importance of the indicators, weights, as considered by the scientific community, can be applied.

3d. A nominal scale to translate the atmospheric condition

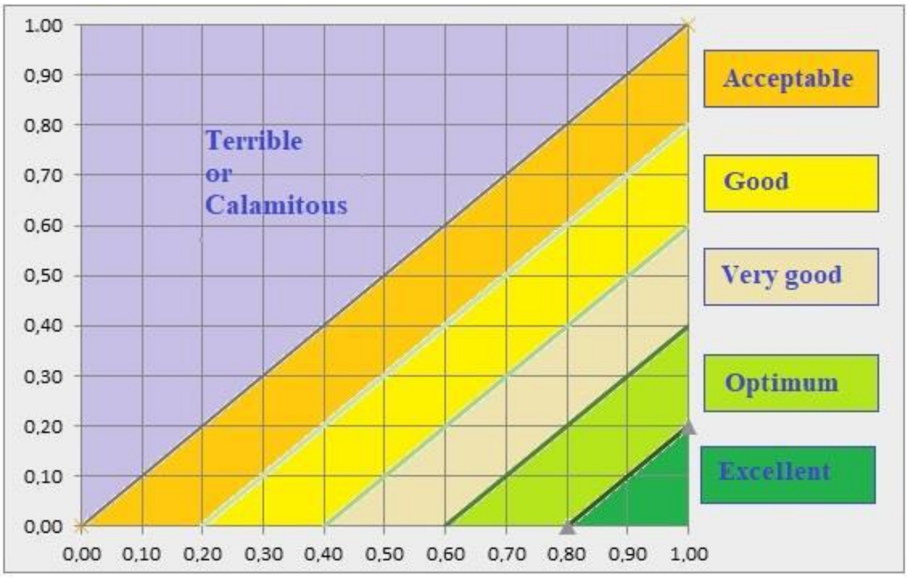
To facilitate the communication of the results, a nominal scale was created to portray the atmospheric condition with less precision than that analyzed in section 3. c but with a more straightforward interpretation (FEAM, 2021). For each interval of the atmospheric condition index (ACI), the corresponding atmospheric condition was categorized according to the scale summarized in Table 1 and Figure 2 (IEMA, 2016).

Table 1 - ACI values and corresponding categories of atmospheric conditions.

ACI	Atmospheric condition
from +0.80 to +1.00	Excellent
from +0.60 to +0.80	Optimum
from +0.40 to +0.60	Very good
from +0.20 to +0.40	Good
from 0.00 to +0.20	Acceptable
equal to 0.00	Terrible or calamitous

Source: Authors.

Figure 3 - Representation of the categories of atmospheric conditions in the para-analyzer device.



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4. The Database

Any substance in the air capable of making it unsuitable and harmful to health is called an air pollutant. These substances can be primary (from the emitting source) or secondary, formed by the interaction between natural components and primary pollutants.

The concentrations of a set of air pollutants (indicators) were used to assess the atmospheric condition (Stossel, 2015; WHO, 2005) since they are the most used by researchers in the area and by Brazilian and other standards (CONAMA 2018; CESTEB, 2020; WHO, 2005; IEMA, 2017):

- P1 - particulate material with a diameter of 2.5 to 10 µm (PM10);
- P2 – particulate material with a diameter of up to 2.5 µm (PM2.5);
- P3 – sulfur dioxide (SO2);
- P4 – nitrogen dioxide (NO2);
- P5 – ozone (O3); and
- P6 – carbon monoxide (CO), although the latter is not always used.

Another problem analyzed and resolved concerned the reference period of available concentration values (annual, 24h, 8h, or less) due to the purpose of this work (to create an index that indicates the atmospheric condition at a given "time" and in a given "region," we adopted the shortest periods, which were readily available in the literature. The periods and units adopted are shown in Table 2 (database), which shows the standard concentration values or the maximum acceptable concentrations (K) of the pollutant assigned by the experts. Class 2, which concerns urban areas, was adopted (CHINA-AQS, 2016), and the minimum concentration equaling zero translates the ideal condition (Stossel, 2015).

Table 2 - Database – standard value or maximum acceptable values (K) for the concentration of pollutants in the atmosphere established by the experts Ei*.

1	2	3	4	5	6	7	8	9	10	11	12	13
Indicator	Pollutant	Period	Unity	E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8	E_9
				WHO	EU	USA (EPA)	China	Japan	Israel	Mexico	India	Brazil
P_1	MP_{10}	24h	$\mu g/m^3$	50	50	150	150	100	50	75	100	120
P_2	$MP_{2.5}$	24 h	$\mu g/m^3$	25	25	35	75	35	25	45	60	60
P_3	SO_2	24h	$\mu g/m^3$	20	125	367	150	105	20	288	80	125
P_4	NO_2	1 h	$\mu g/m^3$	200	200	188	200	200	200	395	395	395
P_5	O_3	8 h	$\mu g/m^3$	100	120	138	160	100	100	138	100	140
P_6	CO	8 h	mg/m^3	10	10	10	10	10	10	13	4	10

* Where: E1 – World Health Organization (WHO, 2005); E2 – EU (European Union Commission, 2019); E3 – Environmental Protection Agency (EPA-USA, 2019); E4 – Chinese standard (CHINA-AQS, 2016); E5 – Japanese standard (JAPAN-EQS, 1999); E6 – Israeli standard (Stossel, 2015); E7 – Mexican standard (MEXICO-AQS, 1994; INECC, 2014); E8 – Indian standard (NAAQS, 1997); E9 – Brazilian standard (CONAMA, 2018; CETESB, 2020; FEAM, 2021).

The data highlighted in blue were converted from p.p.m - 1 ppm ≅ Molecular weight x 40.9 µg/m3 and 1 ppb ≅ Molecular weight x 40.9 / 1,000 mg/m3 - at 25ºC. The data highlighted in red were not found in the respective references. Since minimization is carried out first, and for completing the table, the lowest value of the group was adopted for the missing values. This procedure does not affect either the result of the application of the MIN operator within each group or the final ACI value.

For the application of PAL techniques, three groups were considered: A (E1, E2, and E3) constituted by specialists from renowned institutions of environmental protection; B (E4, E5, and E6) composed by standards values from developed countries; and C (E7, E8, and E9) composed by standard values from developing countries (Table 2).

5. Obtaining the Degrees of Favorable Evidence (a) and Contrary Evidence (b) for a Given Observation

The situation of each pollutant in the atmosphere (an indicator of the atmospheric condition, Pi) is translated by the measure (X), which must be converted into the corresponding degrees of favorable evidence (a) and contrary evidence (b). For each indicator (Pi), the expert (Ej) sets a maximum value (Ki,j) acceptable (or admissible or bearable), known as a standard value, for its concentration (Xi max = Ki,j). Thus, for each indicator (Pi) and the specialist (Ej), a value of the degree of favorable evidence (ai,j) results in a (Xi) measure of Pi concentration, the place and time considered. The degree of contrary evidence (bi,j) is assumed to be the Boolean complement of ai,j, that is, bi,j = 1 – ai,j.

The measure (X) must be standardized to the interval [0, 1] as a function of the standard value or maximum acceptable (allowable) concentration values (K) indicated by the specialists. The minimum or optimum value adopted is zero (Xi min. = 0) when the condition is considered ideal (Stossel, 2015). Thus, as a function of Xi and Ki,j, the degree of favorable evidence ai,j = f (Xi, Ki,j) or, simply, a = f (X, K), is calculated. This function is the same for all indicators Pi and experts Ej; and can be linear, polynomial, exponential, logistic, etc.

In this paper, the second-degree polynomial function is adopted, according to the following reasoning:

1. it is assumed a = 0.5 for the maximum acceptable concentration (X = K). This is justified because, for a = 0.5, b = 0.5 and the degree of certainty is H = a – b = 0. In other words, when the concentration (X) of the pollutant in the atmosphere is at its maximum admissible value (K), the degree of certainty, which translates to the atmospheric condition, will be zero. The degree of certainty will be negative when the concentration (X) is greater than the maximum admissible value (K).

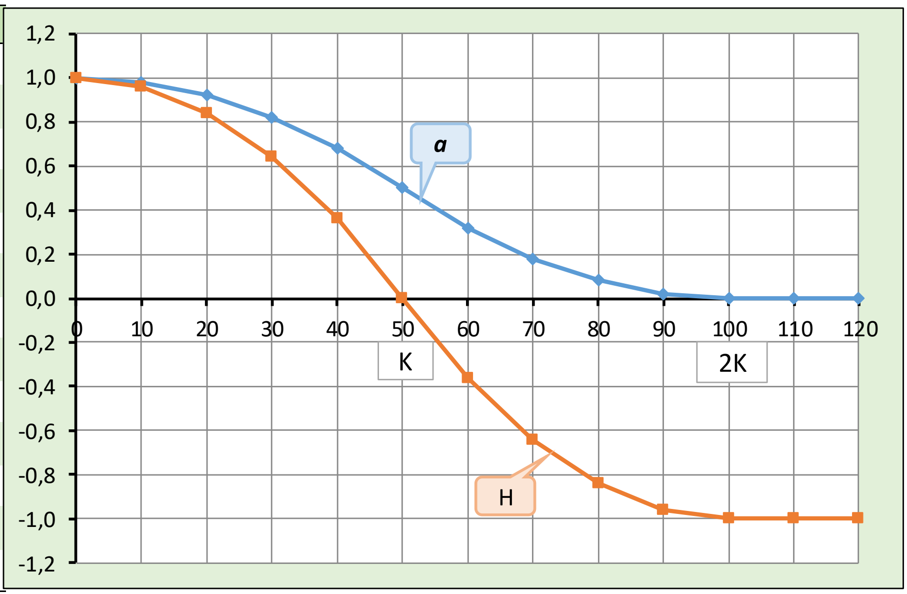
2. when a = 0 (zero), H = –1, and the value of X is equal to or greater than 2K; there is a situation in which the concentration of the pollutant (indicator) is already highly compromising.

3. if the concentration is not zero but close to zero, it does not significantly compromise the atmospheric condition.

Thus, a second-degree polynomial function with two branches, with maximum and minimum points at X = 0 and X = 2K, respectively, and with an inflection at X = K can represent the function a = f (X, K) illustrated in Figure 4, for K=50 as an example.

Figure 4 - The degree of favorable evidence (a) and the degree of certainty (H) as a function of the pollutant concentration (X), for K = 50.

X	*a*	H
0	1,00	1,00
10	0,98	0,96
20	0,92	0,84
30	0,82	0,64
40	0,68	0,36
50	0,50	0,00
60	0,32	-0,36
70	0,18	-0,64
80	0,08	-0,84
90	0,02	-0,96
100	0,00	-1,00
110	0,00	-1,00
120	0,00	-1,00



Source: Authors.

6. The Method Application

To show an application of the method, it will determine the ACI of a particular place (city, neighborhood, etc.) at one specific time (day, hour), three examples (cases) featuring three different situations concerning the location and/or time are explored. Table 3 shows the indicator concentrations (Xi) for the three cases analyzed.

Table 3 - Values of concentration X of pollutants measured at three places and/or time.

1	2	3	4	14 - case 1	14 - case 2	14 - case 3
Indicator	Pollutant	Period	Unity	X_i (Case 1)	X_i (Case 2)	X_i (Case 3)
P_1	MP_{10}	24h	µg/m^3	60	60	60
P_2	$MP_{2.5}$	24 h	µg/m^3	30	30	30
P_3	SO_2	24h	µg/m^3	24	24	24
P_4	NO_2	1 h	µg/m^3	47	47	47
P_5	O_3	8 h	µg/m^3	60	120	120
P_6	CO	8 h	mg/m^3	3,5	3,5	11

Source: Authors.

In the first case, no indicator has a concentration greater than the minimum standard value (acceptable maximum concentration K, see Table 2) of all the groups. For example, the P1 concentration is 60 µg/m^3, greater than the minimum standard values (K) in groups A and B (50 µg/m^3). Still, it is not greater than 75 µg/m^3, the minimum of the standard values in group C. In this case, H1 will result positive, a condition not fulfilled in the second and third cases.

Case 1 - All concentrations of pollutants are below at least one of each group's minimum

From the Xi values (Table 3) and applying the criteria defined in section 5, the **a** values and the respective b (1 – a) can be calculated for each indicator (pollutant) corresponding to each of the experts (Table 4). Following the procedure, the PAL's MIN and the MAX operators were applied, and the final calculations for case 1 are summarized in Table 5 and shown in the para-analyzer device (Figure 5).

Table 4 - Values of degrees of favorable and contrary evidence, obtained as a function of measured concentrations Xi – Case 1.

			Degrees of favorable evidence									Degrees of contrary evidence								
Indicator	Pollutant	X_i	E_1 $a_{i,1}$	E_2 $a_{i,2}$	E_3 $a_{i,3}$	E_4 $a_{i,4}$	E_5 $a_{i,5}$	E_6 $a_{i,6}$	E_7 $a_{i,7}$	E_8 $a_{i,8}$	E_9 $a_{i,9}$	E_1 $b_{i,1}$	E_2 $b_{i,2}$	E_3 $b_{i,3}$	E_4 $b_{i,4}$	E_5 $b_{i,5}$	E_6 $b_{i,6}$	E_7 $b_{i,7}$	E_8 $b_{i,8}$	E_9 $b_{i,9}$
P_1	MP_{10}	60	0.32	0.32	0.92	0.92	0.82	0.32	0.68	0.82	0.88	0.68	0.68	0.08	0.08	0.18	0.68	0.32	0.18	0.13
P_2	$MP_{2.5}$	30	0.32	0.32	0.63	0.92	0.63	0.32	0.78	0.88	0.88	0.68	0.68	0.37	0.08	0.37	0.68	0.22	0.13	0.13
P_3	SO_2	24	0.32	0.98	1.00	0.99	0.97	0.32	1.00	0.96	0.98	0.68	0.02	0.00	0.01	0.03	0.68	0.00	0.05	0.02
P_4	NO_2	47	0.97	0.97	0.97	0.97	0.97	0.97	0.99	0.99	0.99	0.03	0.03	0.03	0.03	0.03	0.03	0.01	0.01	0.01
P_5	O_3	60	0.82	0.88	0.90	0.93	0.82	0.82	0.90	0.82	0.91	0.18	0.13	0.10	0.07	0.18	0.18	0.10	0.18	0.09
P_6	CO	3.5	0.94	0.94	0.94	0.94	0.94	0.94	0.96	0.62	0.94	0.06	0.06	0.06	0.06	0.06	0.06	0.04	0.38	0.06

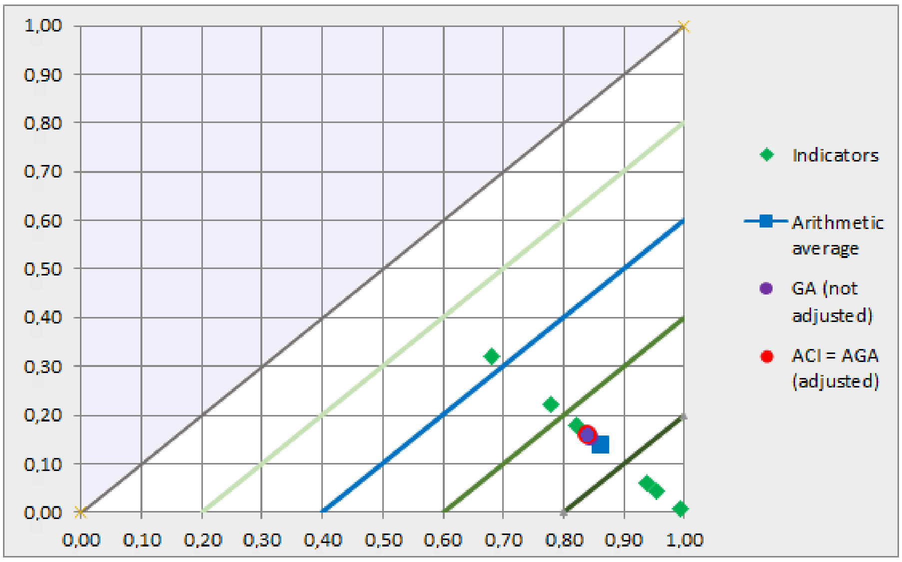
Source: Authors.

Table 5 - Results of the application of the MIN and MAX operators of PAL – Case 1.

Indicator	Pollutant	X_i	Group A MIN (1, 2, 3) $a_{i,A}$	$b_{i,A}$	Group B MIN (4, 5, 6) $a_{i,B}$	$b_{i,B}$	Group C MIN (7, 8, 9) $a_{i,C}$	$b_{i,C}$	MAX (A, B, C) $a_{i,R}$	$b_{i,R}$	H	H'
P_1	MP_{10}	30	0.32	0.68	0.32	0.68	0.68	0.32	0.68	0.32	0.36	0.36
P_2	$MP_{2.5}$	15	0.32	0.68	0.32	0.68	0.78	0.22	0.78	0.22	0.56	0.56
P_3	SO_2	12	0.32	0.68	0.32	0.68	0.96	0.05	0.96	0.05	0.91	0.91
P_4	NO_2	47	0.97	0.03	0.97	0.03	0.99	0.01	0.99	0.01	0.99	0.99
P_5	O_3	90	0.82	0.18	0.82	0.18	0.82	0.18	0.82	0.18	0.64	0.64
P_6	CO	1.2	0.94	0.06	0.94	0.06	0.62	0.38	0.94	0.06	0.88	0.88
										Arithmetic	0.72	0.72
										Geometric	0.68	0.68
											ACI not adjusted	ACI adjusted

Source: Authors.

Figure 5 - Para-analyzer algorithm for case 1 (GA coincides with AGA = ACI).



Source: Authors.

The resulting ACI = 0.68 indicates that the atmosphere condition is optimum according to the scale established in Section 3. d. In this case, in which no Hi is negative, AG coincides with AGA = ACI.

Case 2 - The concentration of one of the pollutants is above all the minimum for all groups

In the second case, the concentration (120 µg/m^3, Table 3) of P5 is greater than the minimum (100 µg/m^3, Table 2) of the standard values (acceptable maximums concentration K) in all the three groups. The **a** and b values for each pollutant and each expert are shown in Table 6). In this case, H5 will result negative and, consequently, $H'_5 = 0$, Table 7.

Table 6 - Values of favorable and contrary evidence degrees, obtained as a function of the new measures (Xi) – Case 2.

			Degrees of favorable evidence									Degrees of contrary evidence								
Indicator	Pollutant	X_i	E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8	E_9	E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8	E_9
			$a_{i,1}$	$a_{i,2}$	$a_{i,3}$	$a_{i,4}$	$a_{i,5}$	$a_{i,6}$	$a_{i,7}$	$a_{i,8}$	$a_{i,9}$	$b_{i,1}$	$b_{i,2}$	$b_{i,3}$	$b_{i,4}$	$b_{i,5}$	$b_{i,6}$	$b_{i,7}$	$b_{i,8}$	$b_{i,9}$
P_1	MP_{10}	60	0.32	0.32	0.92	0.92	0.82	0.32	0.68	0.82	0.88	0.68	0.68	0.08	0.08	0.18	0.68	0.32	0.18	0.13
P_2	$MP_{2.5}$	30	0.32	0.32	0.63	0.92	0.63	0.32	0.78	0.88	0.88	0.68	0.68	0.37	0.08	0.37	0.68	0.22	0.13	0.13
P_3	SO_2	24	0.32	0.98	1.00	0.99	0.97	0.32	1.00	0.96	0.98	0.68	0.02	0.00	0.01	0.03	0.68	0.00	0.05	0.02
P_4	NO_2	47	0.97	0.97	0.97	0.97	0.97	0.97	0.99	0.99	0.99	0.03	0.03	0.03	0.03	0.03	0.03	0.01	0.01	0.01
P_5	O_3	120	0.32	0.50	0.62	0.72	0.32	0.32	0.62	0.32	0.63	0.68	0.50	0.38	0.28	0.68	0.68	0.38	0.68	0.37
P_6	CO	3.5	0.94	0.94	0.94	0.94	0.94	0.94	0.96	0.62	0.94	0.06	0.06	0.06	0.06	0.06	0.06	0.04	0.38	0.06

Source: Authors.

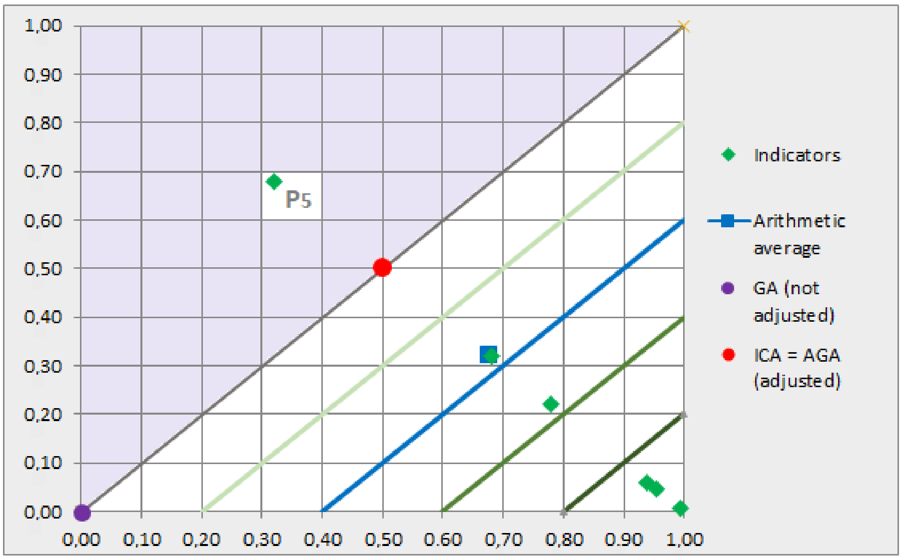
Table 7 - Results of applying the MIN and MAX operators for case 2.

			Group A		Group B		Group C		MAX (A, B, C)		H	H'
Indicator	Pollutant	X_i	MIN (1, 2, 3)		MIN (4, 5, 6)		MIN (7, 8, 9)					
			$a_{i,A}$	$b_{i,A}$	$a_{i,B}$	$b_{i,B}$	$a_{i,C}$	$b_{i,C}$	$a_{i,R}$	$b_{i,R}$		
P_1	MP_{10}	60	0.32	0.68	0.32	0.68	0.68	0.32	0.68	0.32	0.36	0.36
P_2	$MP_{2.5}$	30	0.32	0.68	0.32	0.68	0.78	0.22	0.78	0.22	0.56	0.56
P_3	SO_2	24	0.32	0.68	0.32	0.68	0.96	0.05	0.96	0.05	0.91	0.91
P_4	NO_2	47	0.97	0.03	0.97	0.03	0.99	0.01	0.99	0.01	0.99	0.99
P_5	O_3	120	0.32	0.68	0.32	0.68	0.32	0.68	0.32	0.68	-0.36	0.00
P_6	CO	3.5	0.94	0.06	0.94	0.06	0.62	0.38	0.94	0.06	0.88	0.88
									Arithmetic		0.55	0.61
									Geometric		#NÚM!	0.00
											ACI not adjusted	ACI adjusted

Source: Authors.

For this case, ACI = 0 indicates that the atmospheric condition at the place and moment considered is terrible or calamitous (Figure 6), according to the scale in Section 6.d. It is worthy to note that as n is even and the product of all Hi is negative, the GA value does not exist in the real field (even root of a negative number). This was one of the reasons for adopting the adjusted geometric mean, AGA = ACI, and not the geometric mean, GA, simply.

Figure 6 - Para-analyzer algorithm – Case 2.



Source: Authors.

Although some indicators pointed out a good condition, P5 indicated a terrible or calamitous condition (H5 = -0.36) – with a concentration greater than the minimum of the standard values of groups A, B, and C. The general analysis results in a terrible or calamitous situation (see criteria in Section 5 - for the atmospheric condition to be considered terrible or calamitous, it is enough that one indicator is above the standard value (maximum allowed limit, K).

It should also be noticed that the arithmetic mean (AA = 0.55) does not point to a very good condition, and the geometric mean, not adjusted, cannot be calculated as seen above (GA = #NÚM!). This is another reason why the arithmetic and geometric averages were not adopted. However, the total condition is terrible, with only one indicator above the acceptable concentration (see Section 5). This was another reason for adopting the adjusted geometric average that accuses terrible or calamitous situation (AGA = ACI = 0) with only one indicator in very bad condition.

Case 3 - The concentrations of two pollutants are above all the minima for all groups

The **a** and **b** values for each pollutant and each expert are shown in Table 8. In this third case, P5 concentration (120 μg/m^3) and P6 concentration (11 mg/m^3) are greater than the minimum standard values (acceptable maximums concentration K) in all the groups (see Table 2). In this case, H5 e H6 will be negative and, consequently, $H_5' = 0$ and $H_6' = 0$, Table 9.

Table 8 - Values of favorable and contrary evidence degrees, obtained as a function of the new measures (Xi) – Case 3.

			Degrees of favorable evidence									Degrees of contrary evidence								
Indicator	Pollutant	X_i	E_1 $a_{i,1}$	E_2 $a_{i,2}$	E_3 $a_{i,3}$	E_4 $a_{i,4}$	E_5 $a_{i,5}$	E_6 $a_{i,6}$	E_7 $a_{i,7}$	E_8 $a_{i,8}$	E_9 $a_{i,9}$	E_1 $b_{i,1}$	E_2 $b_{i,2}$	E_3 $b_{i,3}$	E_4 $b_{i,4}$	E_5 $b_{i,5}$	E_6 $b_{i,6}$	E_7 $b_{i,7}$	E_8 $b_{i,8}$	E_9 $b_{i,9}$
P_1	MP_{10}	60	0.32	0.32	0.92	0.92	0.82	0.32	0.68	0.82	0.88	0.68	0.68	0.08	0.08	0.18	0.68	0.32	0.18	0.13
P_2	$MP_{2.5}$	30	0.32	0.32	0.63	0.92	0.63	0.32	0.78	0.88	0.88	0.68	0.68	0.37	0.08	0.37	0.68	0.22	0.13	0.13
P_3	SO_2	24	0.32	0.98	1.00	0.99	0.97	0.32	1.00	0.96	0.98	0.68	0.02	0.00	0.01	0.03	0.68	0.00	0.05	0.02
P_4	NO_2	47	0.97	0.97	0.97	0.97	0.97	0.97	0.99	0.99	0.99	0.03	0.03	0.03	0.03	0.03	0.03	0.01	0.01	0.01
P_5	O_3	120	0.32	0.50	0.62	0.72	0.32	0.32	0.62	0.32	0.63	0.68	0.50	0.38	0.28	0.68	0.68	0.38	0.68	0.37
P_6	CO	11	0.41	0.41	0.44	0.41	0.41	0.41	0.62	0.00	0.44	0.60	0.60	0.56	0.60	0.60	0.60	0.38	1.00	0.56

Source: Authors.

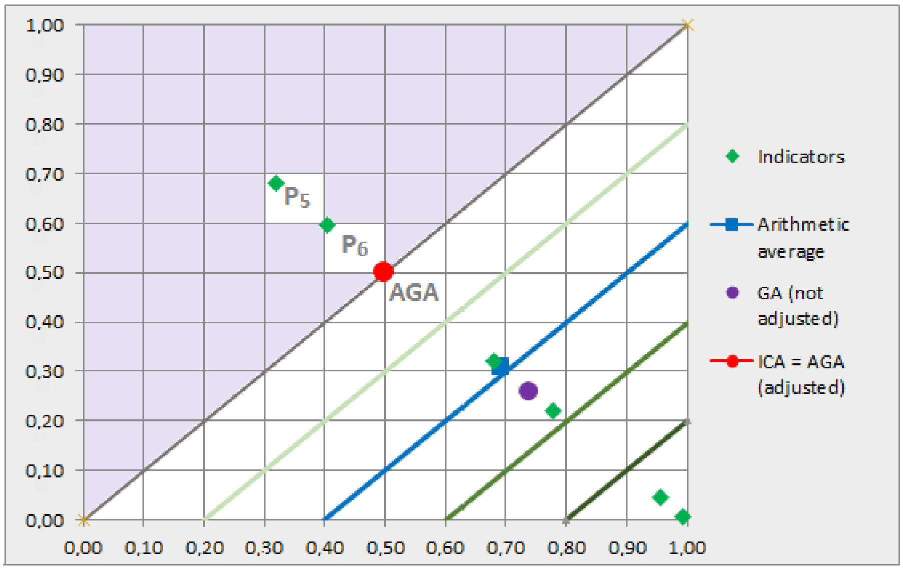
There are two indicators with a concentration greater than the minimum standard values (maximum acceptable concentrations) of groups A, B, and C (with Hi negative). Therefore, according to the adopted criterion (see Section 5), the atmospheric condition is terrible or calamitous. However, in this case, the arithmetic average (AA = 0.38) does not capture this issue and would indicate the good atmospheric condition, according to the scale of Section 6.d; similarly, the not adapted geometric average (GA = 0.48) indicating very good conditions.

Table 9 - Results of applying the MIN and MAX operators for case 3.

Indicator	Pollutant	X_i	Group A MIN (1, 2, 3) $a_{i,A}$	$b_{i,A}$	Group B MIN (4, 5, 6) $a_{i,B}$	$b_{i,B}$	Group C MIN (7, 8, 9) $a_{i,C}$	$b_{i,C}$	MAX (A, B, C) $a_{i,R}$	$b_{i,R}$	H	H'
P_1	MP_{10}	60	0.32	0.68	0.32	0.68	0.68	0.32	0.68	0.32	0.36	0.36
P_2	$MP_{2.5}$	30	0.32	0.68	0.32	0.68	0.78	0.22	0.78	0.22	0.56	0.56
P_3	SO_2	24	0.32	0.68	0.32	0.68	0.96	0.05	0.96	0.05	0.91	0.91
P_4	NO_2	47	0.97	0.03	0.97	0.03	0.99	0.01	0.99	0.01	0.99	0.99
P_5	O_3	120	0.32	0.68	0.32	0.68	0.32	0.68	0.32	0.68	-0.36	0.00
P_6	CO	11	0.41	0.60	0.41	0.60	0.00	1.00	0.41	0.60	-0.19	0.00
										Arithmetic	0.38	0.47
										Geometric	0.48	0.00
											ACI not adjusted	ACI adjusted

Source: Authors.

Figure 7 - Para-analyzer algorithm – Case 3.



Source: Authors.

By the considerations analyzed, the ACI, as defined, fully meets the requirements that are expected from an environmental condition index. Fulfills safety conditions, accurately indicating even if only one indicator is in poor condition. The ACI showed reliability and consistency with the results; it is quick and practical to calculate, because, using a simple Excel sheet created for its calculation, it is enough to place the concentrations of pollutants in the proper column (14th) and, immediately, obtain the result at the end of 42nd column. Table 10 shows an overview of the Excel sheet fragmented into two parts).

Table 10 - Overview of ACI calculation program, as applied for Case 3.

CALCULATION PROGRAM OF THE ACI - ATMOSPHERIC CONDITION INDEX

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
														Degrees of favorable evidence								
Indicator	Pollutant	Period	Unity	E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8	E_9	X_i	E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8	E_9
				WHO	EU	USA	China	Japan	Israel	Mexico	India	Brazil		$a_{i,1}$	$a_{i,2}$	$a_{i,3}$	$a_{i,4}$	$a_{i,5}$	$a_{i,6}$	$a_{i,7}$	$a_{i,8}$	$a_{i,9}$
P_1	MP_{10}	24h	µg/m³	50	50	150	150	100	50	75	100	120	60	0,32	0,32	0,92	0,92	0,82	0,32	0,68	0,82	0,88
P_2	$MP_{2.5}$	24 h	µg/m³	25	25	35	75	35	25	45	60	60	30	0,32	0,32	0,63	0,92	0,63	0,32	0,78	0,88	0,88
P_3	SO_2	24h	µg/m³	20	125	367	150	105	20	288	80	125	24	0,32	0,98	1,00	0,99	0,97	0,32	1,00	0,96	0,98
P_4	NO_2	1 h	µg/m³	200	200	188	200	200	200	395	395	395	47	0,97	0,97	0,97	0,97	0,97	0,97	0,99	0,99	0,99
P_5	O_3	8 h	µg/m³	100	120	138	160	100	100	138	100	140	120	0,32	0,50	0,62	0,72	0,32	0,32	0,62	0,32	0,63
P_6	CO	8 h	mg/m³	10	10	10	10	10	10	13	4	10	11	0,41	0,41	0,44	0,41	0,41	0,41	0,62	0,00	0,44

24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42
Degrees of contrary evidence									Grup A		Grup B		Grup C		MAX (A, B, C)		H	H'
E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8	E_9	MIN (1, 2, 3)		MIN (4, 5, 6)		MIN (7, 8, 9)					
$b_{i,1}$	$b_{i,2}$	$b_{i,3}$	$b_{i,4}$	$b_{i,5}$	$b_{i,6}$	$b_{i,7}$	$b_{i,8}$	$b_{i,9}$	$a_{i,A}$	$b_{i,A}$	$a_{i,B}$	$b_{i,B}$	$a_{i,C}$	$b_{i,C}$	$a_{i,R}$	$b_{i,R}$		
0,68	0,68	0,08	0,08	0,18	0,68	0,32	0,18	0,13	0,32	0,68	0,32	0,68	0,68	0,32	0,68	0,32	0,36	0,36
0,68	0,68	0,37	0,08	0,37	0,68	0,22	0,13	0,13	0,32	0,68	0,32	0,68	0,78	0,22	0,78	0,22	0,56	0,56
0,68	0,02	0,00	0,01	0,03	0,68	0,00	0,05	0,02	0,32	0,68	0,32	0,68	0,96	0,05	0,96	0,05	0,91	0,91
0,03	0,03	0,03	0,03	0,03	0,03	0,01	0,01	0,01	0,97	0,03	0,97	0,03	0,99	0,01	0,99	0,01	0,99	0,99
0,68	0,50	0,38	0,28	0,68	0,68	0,38	0,68	0,37	0,32	0,68	0,32	0,68	0,32	0,68	0,32	0,68	-0,36	0,00
0,60	0,60	0,56	0,60	0,60	0,60	0,38	1,00	0,56	0,41	0,60	0,41	0,60	0,00	1,00	0,41	0,60	-0,19	0,00
															Arithmetic		0,38	0,47
															Geometric		0,48	0,00
																	ACI not	ACI adjusted

Source: Authors.

7. Conclusions

With atmospheric environmental pollution becoming increasingly severe, developing measurement systems for air quality conditions are vital to monitoring and controlling air quality. However, considering the large fluctuations in the concentration of pollutants, most previous studies have focused on quality forecasting or risk assessments. Therefore, a different atmospheric condition index was successfully developed using Artificial Intelligence tools and based on paraconsistent logic. An uncertainty analysis was generated to analyze further and explore the uncertainties involved for different pollutant quantities. Finally, an overview of the program provides a valuable tool for controlling atmospheric conditions. The cases exposed revealed that the proposed model outperforms the comparison models and baselines, and paraconsistent logic is a good option for analyzing and monitoring air pollution. As suggestions for future researches and articles, authors would recommend the use and examination of the proposed atmospheric condition index in different scenarios and considering different pollutants. In this way, the atmospheric condition index can be improved and turned into a practical tool to evaluate air quality conditions.

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