Monoxide), NO_2 (Nitrogen Dioxide), O_3 (Ozone), $PM_{2.5}$(Particulate matter) in the air. The main factors of air pollution are high population density, growth of the industrial activities, oil refining, high rise buildings, increased vehicular movements and agricultural activities, etc. Long- and short-term exposure to air suspended toxicants has an alternate toxicological effect on human including respiratory diseases, skin diseases, eye irritation, etc. Air contamination is considered as the major environmental risk factor in the incidence and progression of some diseases such as asthma, lung cancer, low birth weight, etc. Several authors have been working in this direction (Türk and Kavraz, 2011; Ghorani-Azam et al., 2016; Schwartz and Dockery, 1992). Air Quality Index (AQI) is a number used to communicate the level of pollution in the air.

Fuzzy sets were introduced by Zadeh (1965). Several authors have been working for providing fuzzy theoretic approach for dealing with the problem of air pollution (Saddek et al., 2014; Kumaravel and Vallinayagam, 2012; Swarna and Nirmala, 2017; Upadhyay et al., 2014; Upadhyaya and Dhashore, 2011).

The present study was confined to the three different cities, Patna, Gaya and Muzaffarpur of Bihar. Air pollution in these cities has degraded alarmingly. These three Bihar cities has been figured among the "very poor" air quality index. The CPCB (Central Pollution Control Board) states that 'very poor' category of air quality index can lead to respiratory diseases on prolonged exposure while 'severe' category can affect healthy people and seriously impact those with existing diseases.

In this paper, we have constructed a fuzzy model (by using MATLAB R2013a) that predicts the risk of respiratory diseases due to different air pollutants. We have then used our constructed fuzzy model to analyze the risk of respiratory diseases in the three cities of Bihar. The time interval of the study is taken between Jan 2018- Dec 2018. The four inputs in the fuzzy model are the different air pollutants, namely, $RM_{2.5}$, NO_2, CO, O_3 which are affecting human respiratory system while the output gives the risk of respiratory diseases.

Materials and Methods:

A fuzzy set A in X is a mapping $_A$:X → [0, 1], where X is the universe of discourse, $_A$ is called the membership function of A and $_A(x)$ is called the membership value of x in A. The height of a fuzzy set A is the largest membership value of any element in A. A triangular membership function for a fuzzy set A is specified by three parameters {a,b,c} and is given by

$$_A(x) = \{0, \quad x \le a \qquad \frac{x-a}{b-a}, \quad a \le x \le b \qquad \frac{c-x}{c-b}, \quad b \le x \le c \quad 0, \qquad c \le x$$

By a linguistic variable, we mean a variable whose values are words or sentences in a natural or artificial language (cf. Zadeh, 1975). For example, age is linguistic variable if its values are linguistic rather than numerical, i.e., young, very young, not young, etc. rather than 21, 15, 50.

To obtain a fuzzy model for analyzing the risk of respiratory diseases in the considered cities, we have collected index values of input pollutants $PM_{2.5}$, NO_2, CO and O_3 from the Central Pollution Control Board (CPCB) database for the year 2018. CPCB continuously monitors the level of pollutions in different parts of India. The daily data on air pollution levels were obtained directly from the CPCB for monitoring stations IGSC Planetarium complex, Patna-BSPCB, Muzaffarpur collectorate, Muzaffarpur-BSPCB and Gaya collectorate, Gaya-BSPCB. For our study, we have further calculated monthly average of each pollutant's index for each city separately. We have used triangular membership functions for both input and output variables and constructed 81 if-then rules to obtain the risk values.

The construction of our fuzzy model comprised of following steps:

Step 1: Fuzzification of input variables: For our study, we have considered four major air pollutants, $PM_{2.5}$ (Particulate matter), NO_2 (Nitrogen dioxide), CO (Carbon dioxide) and O_3 (Ozone), as input variables and for each input variable, we have used three linguistic variables, namely, Good, High and Very-High.

Step 2: Fuzzification of the output variable: The output variable is 'risk' of respiratory diseases due to air pollutants present in air. We have used four linguistic variables for the risk, namely, low, moderate, high and very high.

Step 3: Construction of inference rules : In this step, we have formed several rules which establish the connection between the input variables and the output variable. In this construction, we have used 'IF-THEN' rules along with connectors 'OR' or 'AND'. 81 combinations (IF-THEN rules) were constructed in this step.

Step 4: Defuzzification of the output variable : In this step, fuzzy output will be converted into crisp value. This step performs the inverse process of fuzzification. We have used MOM defuzzification method.

In the MOM method, the defuzzified value is taken as the element with highest membership value. When there are more than one element having maximum membership values, the mean of the maximum is taken. Let A be a fuzzy set in X with membership function$_A$. Then the defuzzified value is, let say x*, of A is defined as,

$$x^* = \frac{\sum x_i \in M \quad x_i}{|M|}$$

Here, $M = \{x_i| \ _A(x_i)$ is equal to the height of the fuzzy set $A\}$ and $|M|$ is the cardinality of the set M.

Results and Discussion:

Total ranges of input variables are given in Table 1.

Table 1. Total ranges of the input variables

Pollutant	Range
$PM_{2.5}$(Particulate matter)	[0, 400]
NO_2 (Nitrogen dioxide)	[0, 150]
CO (Carbon dioxide)	[0, 120]
O_3 (Ozone)	[0, 230]

The linguistic variables and corresponding membership functions for the input variables are as follows:

1. The linguistic variables for $PM_{2.5}$ are given in Table 2 and the corresponding membership function of $PM_{2.5}$ is given in Fig.1.

Table 2. Linguistic variables for $PM_{2.5}$

Range	Interval	Linguistic variable
0-100	[0 0 100]	Good
95-215	[95 155 215]	High
210-400	[210 400 400]	Very-high

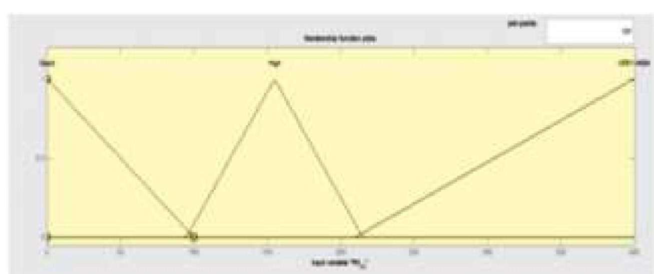

Fig 1. Membership function of $PM_{2.5}$

2. The linguistic variables for NO_2 are given in Table 3 and the corresponding membership function of NO_2 is given in Fig.2.

Table 3. Linguistic variables for NO_2

Range	Interval	Linguistic variable
0-50	[0 0 50]	Good
45-100	[45 75 100]	High
95-150	[95 150 150]	Very-high

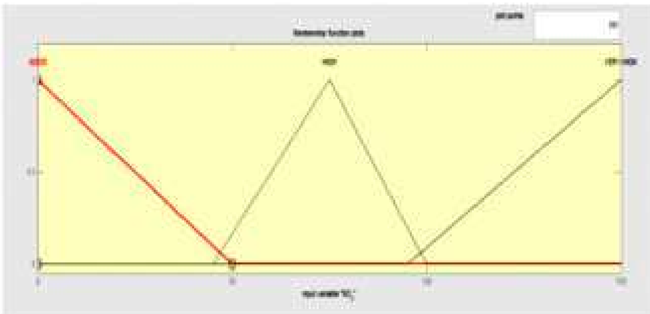

Fig. 2. Membership function of NO_2

3. The linguistic variables for CO are given in Table 4 and the corresponding membership function of CO is given in Fig.3.

Table 4. Linguistic variables for CO

Range	Interval	Linguistic variable
0-40	[0 0 40]	Good
35-80	[35 50 80]	High
75-120	[75 120 120]	Very-high

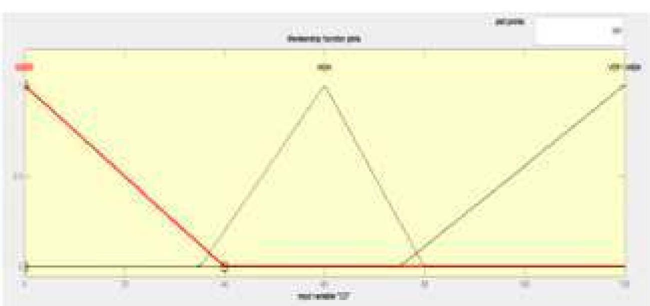

Fig.3. Membership function of CO

4. The linguistic variables for O_3 are given in Table 5 and the corresponding membership function of O_3 is given in Fig.4.

Table 5. Linguistic variables for O_3

Range	Interval	Linguistic variable
0-75	[0 0 75]	Good
70-145	[70 110 145]	High
110-230	[110 130 230]	Very-high

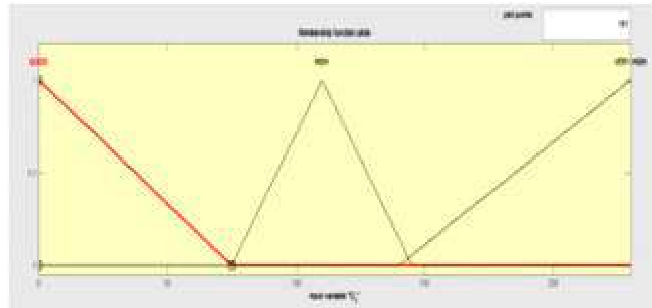

Fig.4. Membership function of O_3

For output variable 'risk', the total range was chosen between 0 and 10. The linguistic variables for risk is given in Table 6 and the corresponding membership function is given in Fig.5:

Table 6. Linguistic variables for risk

Range	Interval	Linguistic variable
0-2	[0 0 2]	Low
1.5-5	[1.5 3.25 5]	Moderate
4.5-8	[4.5 6.25 8]	High
7.5-10	[7.5 10 10]	Very high

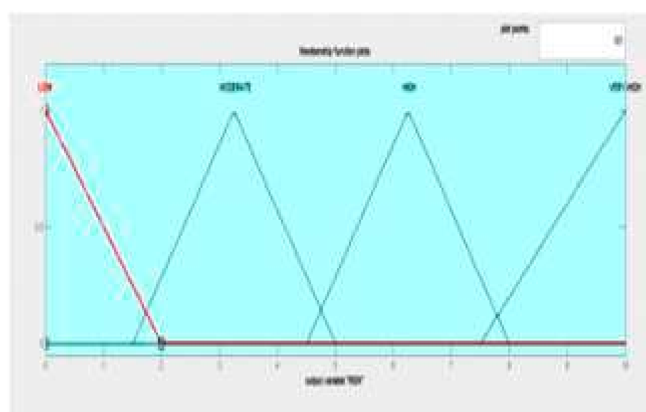

Fig.5. Membership function of risk

The combinations of few inference rules are as follow:

1. If "$PM_{2.5}$"is G and "NO_2" is G and "CO" is G and "O_3" is G then risk value is L
2. If "$PM_{2.5}$"is G and "NO_2" is G and "CO" is G and "O_3" is H then risk value is M
3. If "$PM_{2.5}$"is G and "NO_2" is G and "CO" is G and "O_3" is VH then risk value is M
4. If "$PM_{2.5}$"is G and "NO_2" is G and "CO" is H and "O_3" is G then risk value is M
5. If "$PM_{2.5}$"is G and "NO_2" is G and "CO" is H and "O_3" is H then risk value is M

Table 7. Defuzzified values of output variable 'risk'

MONTH / CITY	PATNA	GAYA	MUZAFFARPUR
JANUARY	9.35	3.25	9
FEBRUARY	6.25	9.35	9
MARCH	8.9	9.35	8.9
APRIL	6.25	8.95	6.25
MAY	6.25	6.25	6.25
JUNE	6.25	6.25	6.25
JULY	3.25	3.25	6.25
AUGUST	6.25	3.25	6.25
SEPTEMBER	3.25	6.25	6.25
OCTOBER	6.25	6.25	6.25
NOVEMBER	8.9	8.8	9.55
DECEMBER	8.9	6.25	6.25

The constructed fuzzy model was used for evaluation of pollutants effect on respiratory diseases in three cities (Patna, Gaya, and Muzaffarpur) for each month in the year 2018 after application on the collected data.

Table 7 shows the risk of respiratory diseases in all the different months of year 2018 for Patna, Gaya, and Muzaffarpur.

The study shows that mostly in the months of November, January, February and March, the risk of respiratory diseases is very high with the risk value of more than 8, whereas in the months of May, June, December and October, the risk is high but risk value lies between 6 and 8. From the result we can also see that the month of July has the lowest risk with the risk value less than 5, so the risk is moderate in this month.

In addition, the pollutants concentration of the cities was poorer in winter and autumn as compared to that in spring and summer. It was found that air pollution in Bihar has a very serious impact on human health and there is an increase in the air pollution related diseases, mainly in winter times. This increase is a clear indication of the relationship between air pollutants and respiratory diseases.

Conclusion:

The output 'risk' gives us clear view about the risk of respiratory diseases in different months of the year 2018 in these cities. It was observed in our study that 'risk' of respiratory diseases varies from season to season. It is highest in the months of November, January, February and March and moderate in May, June, December and October. In winters, risk is possibly due to the presence of high concentration of CO in cold weather and in summers, risk is possibly due to the high concentration of ozone in this season. Our study reveals that $PM_{2.5}$ is the dominant pollutant. Obtained results are consistent with the present status of respiratory diseases in these areas.

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