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Estimation of health impact using AirQ+ model attributed to surface ozone in sub-regions of Surat city, India

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ABSTRACT

Introduction: Deteriorated air quality in nation like India contributes to the health burden. The AirQ+ is used to estimate short-term and long-term health impact attributable to surface Ozone (O_3) in Surat city. Average hourly ozone concentration data and other criteria pollutants retrieved from January 2018 to December 2019 from two monitoring stations (Limbayat and Varachha).

Materials and methods: In this study, the Respiratory Mortality (RM), Cardiovascular Mortality (CM), Total Mortality (TM), Hospital Admissions with Cardiovascular Disease (HACVD), and Hospital Admissions with Respiratory Disease (HARD), as well as Respiratory Mortality-Long-Term (LT-RM) were quantified. Baseline Incidence (BI) data were obtained from literature and Relative Risk (RR) values were referred from World Health Organization (WHO). An annual Sum of Maximum 8 h Ozone means over 35 ppb (SOMO35), 70 µg/m^3, used as a predictor of potential long-term health effects.

Results: More ozone concentration were observed in winter and pre-monsoon than concentration formed in southwest monsoon and post-monsoon seasons. The average of O_3 concentration for Limbayat are 71.61 (±0.39) µg/m^3 and 29.76 (±1.86) µg/m^3 and for Varachha are 61.17 9 (±6.15) µg/m^3, 11.32 (±1.35) µg/m^3 during 2018 and 2019, respectively and the obtained cumulative number of cases of death are estimated 136, 45, 172 and 18 persons respectively. Total hospital admission due to cardiovascular and respiratory diseases are found 435, 134, 552 and 58 at Limbayat and Varachha during 2018 and 2019. LT-RM is attributed to ozone concentration having the most significant value, 6.8% and 4.62% at Limbayat and Varachha in 2018.

Conclusion: More hospital admissions are found than mortality rates using AirQ+ tool. It can be used to estimate public health in context of mortality and morbidity rates which helps to develop air quality management programs and policy makers to reduce the impact of air pollution on health.

Introduction

Air pollution become a worldwide problem due to unplanned urbanisation [1], most commonly in transportation sector [2]. Developing countries face air pollution as a response element to severe public health impacts [3]. India suffers from high mortality

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and disease burden due to air pollution, which has a significant implication for planetary health [4]. In an urban area, surface Ozone (O_3) acts as a most threatening air pollutant for public health [5]. In the troposphere, ozone is generated with the oxidation of CO (Carbon monoxide), VOCs (Volatile Organic Compounds), CH_4 (methane), and NMHC (Non-Methane Hydrocarbon) in the presence of NO_x (Nitrogen oxides) and solar radiation [6]. Moreover, other climatic factors such as relative humidity, temperature, and wind speed are the influencing parameters to form secondary pollutant surface ozone [7]. Ozone is a highly oxidative compound that can react with some other chemicals rapidly. The ozone reactions can be detrimental to human health [8]. People are exposed to high O_3 concentration and/or increasing exposure time in days, resulting in unwanted health outcomes [9].

Usually, short-term exposure is a daily concentration of surface ozone with a particular time interval and the annual/seasonal average value is represented as long-term exposure to air pollution [10]. Pulmonary diseases, airway inflammation, lung permeability, respiratory symptoms, and increased asthma medication are health effects due to short-term exposures, while morphological changes in the airways, lung complications, persistent structural airway, and reduction in lung function early in life indicate effects of long-term ozone exposure [11]. With immutable emissions by 2050, a 200% increment in mortalities will take place relative to 2015 due to the aging population and more people's susceptibility to air pollution in India [12]. Only a few studies have been carried out on the health effects of surface ozone in India as the unavailability of continuous hourly data because of the lack of constant electrical power supply, instrument maintenance, and service. However, currently, SAFAR (System of Air Quality Forecasting and Research) and SAMEER, developed by Central Pollution Control Board (CPCB), apps are available at the doorstep for monitoring the air quality in many areas of India. Therefore, the aim of study is to estimate possible health impacts of exposure to O_3 from January 2018 to December 2019 in Surat city.

Materials and methods

Study area

Surat is the cleanest city of Gujarat, located at 21.17° N and 72.83° E, on the Tapi river bank of India with a total land area of 440 km^2. It is one of the rapidly growing cities with textile and diamond industries. In this study, an average hourly data is obtained from January 1 to December 31 in 2018 and 2019 with the help of Surat Municipal Corporation (SMC), from two real-time continuous monitoring stations (Fig. 1) i.e., Limbayat (19.492 km^2) and Varachha (37.525 km^2) which cover approximately 13% area of the total city area. Limbayat area is covered by most of the chemical dyeing and weaving industry, which covers approximately 70% of the total area. Varachha is known as the diamond hub of Surat city with a residential and commercial domain. The climate in Surat consists of four seasons; winter, pre-monsoon, southwest monsoon, and post-monsoon. Out of 6,000,000 inhabitants in Surat, in Limbayat and Varachha are 7,48,304 and 11,37,138 respectively [13]. Though exposure variability within the city and data are obtained only from two sampling stations, the estimated health effects are represented by sub-regions (i.e., Limbayat and Varachha) despite the whole city. This study focused on surface ozone only to prove the importance of a single pollutant instead of inter-comparison among multi pollutants.

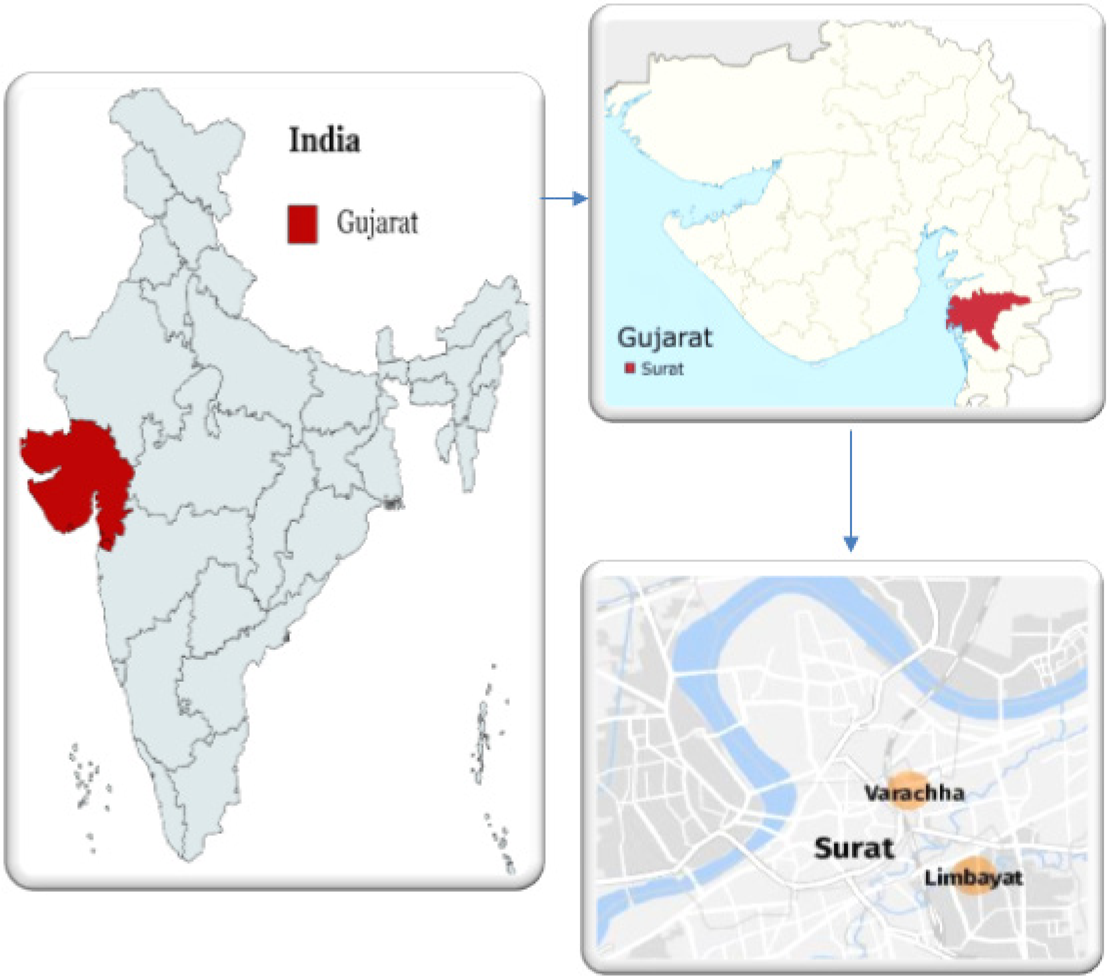

Fig. 1. Location map of monitoring stations

Health evaluation modelling, Air Q+

The AirQ+ version 2.0 package is recommended by world health organisation to quantify the public health effects of exposure to air pollution [14]. The AirQ+ model is used to be aware of the health risk of population exposure. Mortality and morbidity rates have been found attributable to PM_{10}, SO_2, and NO_2 in ten different urban areas in Maharashtra state in India using the AirQ model from 2004 to 2013 [15]. Long-term mortality due to PM_{10} and PM 2.5 exposure has been assessed in the most polluted Indian city, Lucknow, with AirQ+ from 2010 to 2019 [16]. Sum of Ozone Means Over 35 ppb (SOMO35) values for O_3, the at-risk population, Baseline Incidence (BI) rate for the given health endpoint, Relative Risk (RR) values and a cut-off value of concentration are essential parameters to run the AirQ+ model [17].

The study's key objective is to quantify short and long-term health effects due to exposure of the residents of Surat to surface Ozone (O_3). With the help of the AirQ+ model, Respiratory Mortality (RM), Cardiovascular Mortality (CM), Total Mortality (TM), Hospital Admissions with Cardiovascular Disease (HACVD), Hospital Admissions with Respiratory Disease (HARD), Respiratory Mortality-Long Term (LT-RM) are estimated.

Since the obtained O_3 data are in a gravimetric unit (µg/m^3) with average hourly data, they are converted to maximum 8 h average concentrations. All required statistical data such as annual mean, minimum level, maximum level, and standard deviation are calculated and reported in Table 1 to understand the succeeding processes. Compared with Central Pollution Control Board, National Ambient Air Quality Standards (CPCB NAAQS), higher and lower O_3 concentration reported detrimental health effect which needs more improvement in current standards threshold value in favor of public health.

Fig. 2 shows an 8-h mean daily maximum O_3 seasonal bar chart of all four seasons for Surat. Comparatively low O_3 concentrations are found in all seasons in 2019.

Table 1. Descriptive statistics of 8 h average concentration of surface ozone at Limbayat and Varachha (2018-2019)

	Limbayat		Varachha	
O_3 parameters	2018	2019	2018	2019
Annual mean (µg/m^3)	71.45	29.76	61.27	11.26
Annual maximum (µg/m^3)	309.50	115.92	345.9	52.79
Ratio of maximum daily 8-h average value to NAAQS value of maximum 8-h average	3.1	1.2	3.5	0.5
Annual Minimum (µg/m^3)	0.1725	0.5137	0.4625	0.01
Winter mean (µg/m^3)	104.45	50	63.23	21.33
Pre-monsoon mean (µg/m^3)	88.61	23.83	89.6	16.53
Southwest monsoon mean (µg/m^3)	62.95	19.21	47.43	2.24
Post monsoon mean (µg/m^3)	49.20	36.39	33.72	7.40
Standard deviation (µg/m^3)	58.75	15.8	54.43	12.11
n_{valid} (N) (days)	284	276	300	310

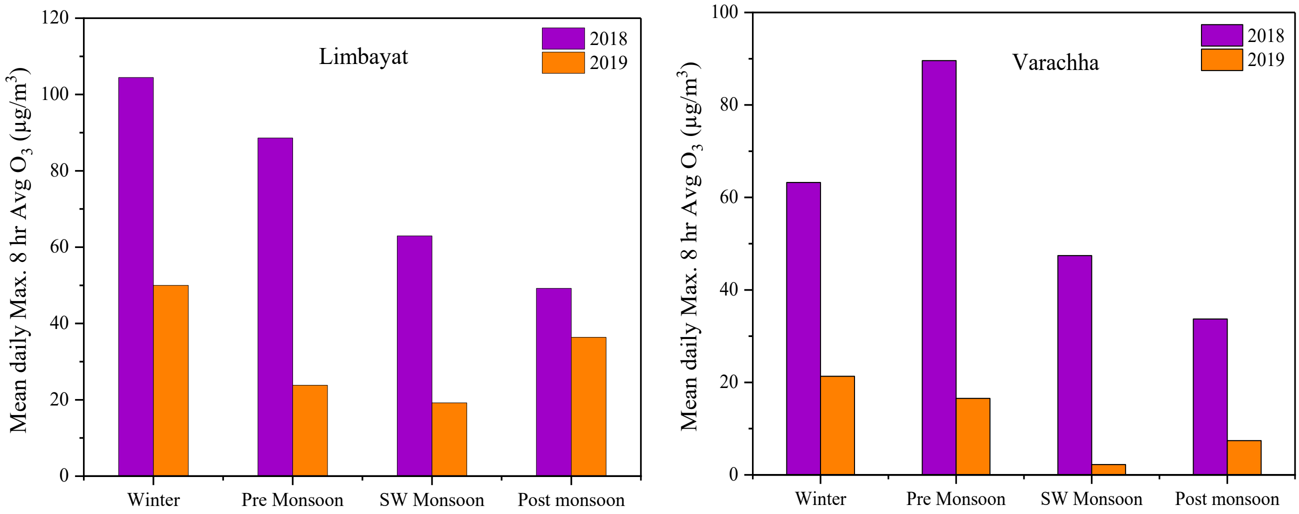

Fig. 2. Seasonwise ozone concentration distribution at Limbayat and Varachha during 2018 and 2019

Working on AirQ+ model using O_3 concentration

The procedure for estimation of various health effects is shown in Fig. 3 with a flow chart. To process with the AirQ+ tool, various categories as ambient analysis type, time perspective (short-term or long-term effects), location, type of pollutant ($PM_{2.5}$, PM_{10}, BC, NO_2, and O_3), and evaluation (Impact or Life Table evaluation) to be fed as input. From input mean value or input air quality data sheet options, one option has been selected as per the selection of long-term or short-term effect of O_3 exposure data respectively.

In the case to assess the short-term effect, a daily maximum 8-h mean concentration of O_3 is calculated. For assessment of the long-term health effects of ozone, the indicator SOMO35 (sum of ozone means over 35 ppb) is used and should be provided by the user. With the help of a survey or from past research incidence rates, Relative Risk (RR) can be determined. Eventually, TM, CM, RM, and HA are estimated by selecting the proper calculation method and a cut-off value of the pollutant.

AirQ+ model analysis

For estimating long-term mortalities due to ozone, the indicator SOMO35 (sum of ozone means over 35 ppb) (µg/m^3 days) is used. It is defined as the annual sum of the daily maximum of 8-h running average for O_3 above (1 ppb=2 µg/m^3 for ozone) 70 µg/m^3. Table 2 reports the SOMO35 (µg/m^3. days) metric in two sub-regions of Surat city. It shows low (1033) at Limbayat and NIL at Varachha in the year 2019.

$$\mathrm{SOMO35}_{\mathrm{uncorrected}} = \sum_{i} \mathrm{Max}\left\{0, C_i - 70\,\mu\frac{g}{m^3}\right\} \quad (1)$$

Eq. 1 indicates for calculation of SOMO35 with a yearly summation. C_i is the daily maximum 8-h average O_3 concentration (µg/m^3), i represents 1 to 365 days per year. Correction is applied to annual coverage when some daily data are missing, according to Eq. 2.

$$\mathrm{SOMO35} = \mathrm{SOMO35}_{\mathrm{uncorrected}} * N_{\mathrm{Total}} \div N_{\mathrm{valid}} \quad (2)$$

N_{total} is the number of days in the period of interest (i.e., 365 days of the year), N_{valid} is the number of valid days.

For respiratory mortality Long Term (LT-RM) exposure assessment, RR is calculated for a 10 µg/m^3 increment in O_3 concentration as shown in Eq. 3 at three levels of lower (5% CI), central (50% CI) and upper (95% CI) category. It estimates the magnitude of an association between exposure and disease and

Create new analysis

Selection of analysis parameters, location, short-term/long-term effects

↓

Impact assessment

Pollutant data processing and calculations as per short-term/long-term effects selection

↓

Impact Evaluation in accordance with morbidity and mortality

Health end point, incidence rate, relative risk details

↓

Outcomes

Results of risk assessment in % and per 100,000 population

Fig. 3. Flowchart of health estimation using AirQ+ model

Table 2. SOMO35 metrics in Surat (2018-2019)

	Limbayat		Varachha	
Metric	2018	2019	2018	2019
Days with O_3>70 µg/m^3 (n)	113	12	77	0
$SOMO35_{uncorrected}$ ((µg/m^3).days)	14440	1033	10208	0

is usually modeled as a log-linear function.

$$RR = \exp\{\beta.SOMO35_{uncorrected} \div N_{valid}\} \quad (3)$$

In the same way, for short-term all types of mortalities, RR is calculated as:

$$RR = \exp\ [\beta.\{C_{max8} - X_0\}] \quad (4)$$

C_{max8} is a maximum daily 8 h average O_3 concentration, X_0 is a daily concentration of O_3 above 70 $\mu g/m^3$ and β is the rate at which RR increases. The Attributable Proportion (AP) defined with given RR values is the percentage of health output in the association with the exposure of pollutants to the exposed population is calculated by Eq. 5.

$$AP = \sum\{RR(c) - 1.p(c)\}\ /\ \sum\{RR(c).p(c)\} \quad (5)$$

RR(c) represents a relative risk with category c of a pollutant exposure for a given health effect outcome, p(c) is the proportion of the population in category c of the exposure. By assuming a specific baseline incidence rate (BI) of a particular health endpoint from previous research papers, estimation of the Number of Cases per unit of population (NC) is calculated as in Eq. 6.

$$NC = AP \times BI \quad (6)$$

For the N size population, NC is converted to the number of cases attributed to the exposure according to Eq. 7.

$$NP = NC \times N \quad (7)$$

RR values came by the AirQ+ model's default to associating the health impacts of O_3 and BI values obtained from published research papers on the health impacts of air pollution shown in Table 3.

Table 3. Baseline incidence rate and relative risk values getting from past studies

Health endpoint	Baseline incidence	RR (50%CI, 5%CI and 95% CI) per 10 $\mu g/m^3$
TM	1013	1.0029 (1.0014-1.0043)
CM	497	1.0049 (1.0013-1.0085)
RM	66	1.0029 (1-1.007)
HACVD	436	1.0089 (1.005-1.0127)
HARD	1260	1.0044 (1.0007-1.0083)
LT-RM	66	1.014 (1.005-1.024)

Note: Baseline incidence values retrieved from past research papers

Results and discussion

Surface ozone concentrations

The study was performed with the calculation of the O_3 annual mean for the whole years 2018 and 2019 at two monitoring stations in Surat. It is observed that the yearly average of O_3 for Limbayat is 71.61±0.39 µg/m³ and 29.76±1.86 µg/m³ and for Varachha are 61.17±6.15 µg/m³, 11.32±1.35 µg/m³ during 2018 and 2019, respectively. The maximum annual O_3 concentration level at Limbayat is about three times greater in 2018 (309.5 µg/m³) compared to 2019 (115.92 µg/m³) (Table 1). Similarly, at Varachha, the maximum concentrations are 345.93 µg/m³ and 52.79 µg/m³ for 2018 and 2019, respectively. To calculate SOMO35, the number of days with an 8-h average of ozone higher than 70 µg/m³ at Limbayat and Varachha in 2018 and 2019 year is 113, 12, 77, and zero, respectively (Table 2). The ratio for the maximum daily 8-h average concentration of ozone to NAAQS value suggests the crystal-clear contribution to the total number of deaths. In our study, annual maximum concentrations at Limbayat and Varachha in 2018 and 2019 are respectively 3.1, 1.2, 3.5, and 0.5 times higher than the standard value (Table 1), pointing toward insufficient protective levels from the public health perspective. From all the seasons for both years, only at Limbayat, winter 2018 has O_3 concentrations (104.45 µg/m³) that slightly exceeded the WHO standards and National Ambient Air Quality Standards (NAAQS) (100 µg/m³). To improve air quality, the National Air Quality Index with eight major pollutants and a color-coded system was launched by the Union Environmental Ministry of the Government of India in April 2015 [18]. However, some authors reported harmful health impacts of pollutants at a lower concentration than the standard air pollution guidelines, which indicates that the available standards may not be a sufficient preventive shield from the public health point of view.

Person-day exposure

People exposed to O_3 concentration to the percentage of days recorded for the entire years 2018 and 2019 in Surat are displayed in Fig. 4. The maximum percentage time is noticed with 30-40 µg/m³ O_3 concentration range at both locations in 2018, while 20-30 µg/m³ and less than 10 µg/m³ concentrations were found in the year 2019 at Limbayat and Varachha, respectively. Mostly, the O_3 exposures are found below the concentration interval of 90-100 µg/m³ at both locations during 2018 and 2019.

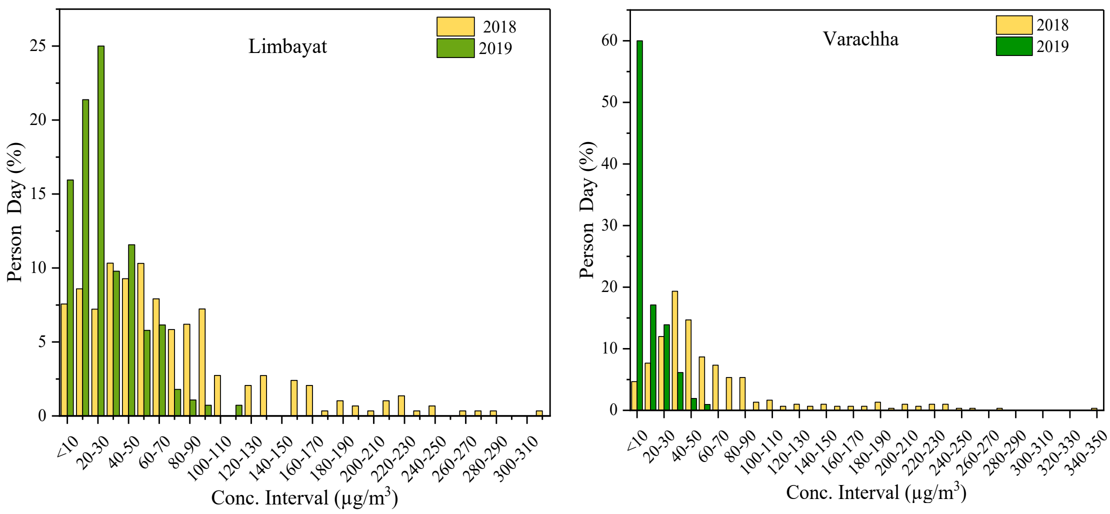

Fig. 4. Exposure levels of surface ozone concentrations intervals (µg/m³) to the population exposed with time (days) at [A] Limbayat, and [B] Varachha during 2018 and 2019

Short-term and long-term health effects estimation

Table 4 and Table 5 report the Attributable Proportion (AP), NP, and the Number of Cases per 100000 (NC) for long-term and short-term health endpoints in Surat for 2018 and 2019. However, O_3 concentrations in the 2019 year are significantly lower than the concentrations in the previous year. Therefore, according to Table 4 and Table 5, the mortality and morbidity rates for O_3 for 2019 are decreasing. In the present study, on an average 45-50% of short-term mortality and morbidity are attributable to ozone concentrations lower than 100 μg/m^3 in 2018, while more than 90% of cases occurred during 2019.

Table 4. Estimation of Attributable Proportion (AP%), NP and NC per 100000, at Limbayat for 2018 and 2019

Health end points	Estimated AP (%)		Attributable Cases (NP)		Attributable Cases per 100000 (NC)	
	2018	2019	2018	2019	2018	2019
TM	1.79(0.387-2.66)	0.59(0.28-0.87)	136 (66-201)	45(22-66)	18(9-27)	6(3-9)
CM	3.02(0.8-5.23)	0.99(0.26-1.72)	112 (30-194)	37(10-64)	15(4-26)	5(1-9)
RM	1.79(0-1.31)	0.59(0-1.42)	9 (0-21)	3(0-7)	1(0-3)	0(0-1)
HACVD	5.47(3.09-7.78)	1.8(1.01-2.56)	179 (101-254)	59(33-84)	24(13-34)	8(4-11)
HARD	2.73(0.43-5.11)	0.89(0.14-1.68)	256 (41-481)	84(13-158)	34(5-64)	11(2-21)
(LT-RM)	6.8(2.5-11.32)	0.52(0.19-0.88)	34 (12-56)	3(1-4)	4(2-7)	0(0-1)

Note: TM: Total Mortality, CM: Cardiovascular Mortality, RM: Respiratory Mortality, HACVD: Hospital Admissions with Cardiovascular Disease, HARD: Hospital Admissions with Respiratory Disease, LT-RM: Respiratory Mortality- Long Term

Table 5. Estimation of Attributable Proportion (AP%), number of cases (NP) and Number of Cases per 100000 (NC) at Varachha for 2018 and 2019

Health end points	Estimated AP (%)		Attributable Cases (NP)		Attributable Cases per 100000 (NC)	
	2018	2019	2018	2019	2018	2019
TM	1.79(0.387-2.66)	0.59(0.28-0.87)	136(66-201)	45(22-66)	18(9-27)	6(3-9)
CM	3.02(0.8-5.23)	0.99(0.26-1.72)	112(30-194)	37(10-64)	15(4-26)	5(1-9)
RM	1.79(0-1.31)	0.59(0-1.42)	9(0-21)	3(0-7)	1(0-3)	0(0-1)
HACVD	5.47(3.09-7.78)	1.8(1.01-2.56)	179(101-254)	59(33-84)	24(13-34)	8(4-11)
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(LT-RM)	6.8(2.5-11.32)	0.52(0.19-0.88)	34(12-56)	3(1-4)	4(2-7)	0(0-1)

As per the given baseline incidence rate and from the RR value (at 50% CI), the AP assessed for total mortality attributable to O_3 at Limbayat and Varachha in the year 2018 and 2019 are 1.79%, 0.59%, 1.49%, 0.16% and the corresponding cumulative number of cases of death are estimated 136, 45, 172 and 18 persons respectively. The AP estimated for total deaths caused by respiratory mortality attributed to O_3 are the same as total mortality with deaths are 9, 3, 1, and 1 person at Limbayat and Varachha in 2018 and 2019 respectively. AirQ+ model estimates AP are 3.02%, 0.99%, 2.52%, and 0.26% of the cardiovascular mortality and corresponding death cases are estimated at 112, 37, 15, and 13 persons respectively. For morbidity, the AirQ+ model estimates AP of HACVD is 5.47%, 1.8%, 4.58%, and 0.48%, while AP of HARD is 2.73%, 0.89%, 2.27%, and 0.24% computed at Limbayat and Varachha during 2018 and 2019. Similarly, the long-term mortality quantified in the number of cases of LT-RM is 34, 3, 35, and zero.

Fig. 5 depicted the number of attributable cases in each mortality and hospital admission on a logarithmic scale at Limbayat during 2018. Attributable cases are compared with BI on a log10 scale. The number of hospital admissions is closer to BI.

Fig. 6 illustrates the increment in the cumulative number of cases with broader distribution of ozone concentration. It also indicates that cardiovascular mortality has more contribution than respiratory mortality in total mortality due to the high baseline incidence rates recorded in the previous study [19]. Also, the impact of ozone on respiratory mortality was low and negligible [20]. Moreover, hospital admissions are in more numbers due to cardiovascular

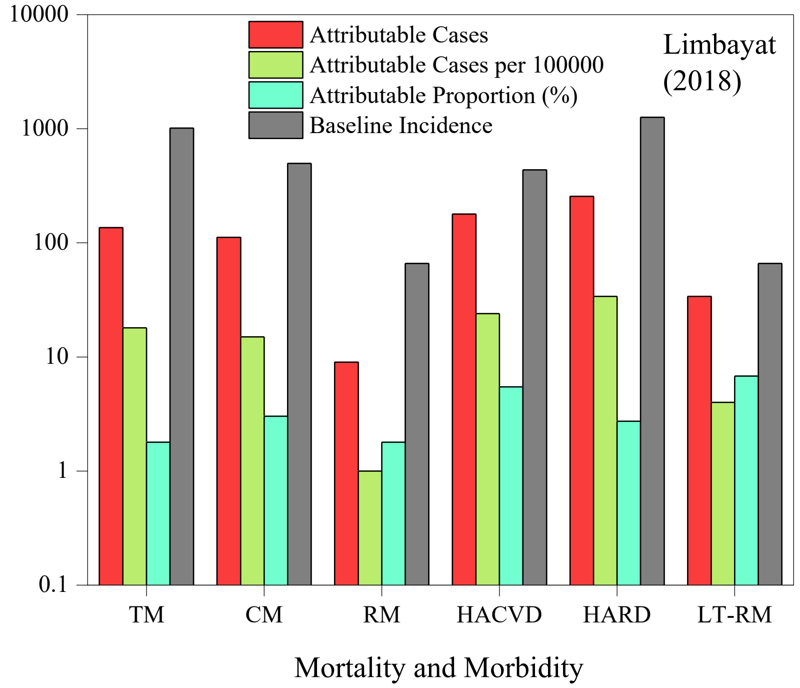

Fig. 5. Estimated AP, Attributable cases, Attributable cases per 100000 with BI of endpoint mortality and morbidity due to Ozone exposure at Limbayat (2018)

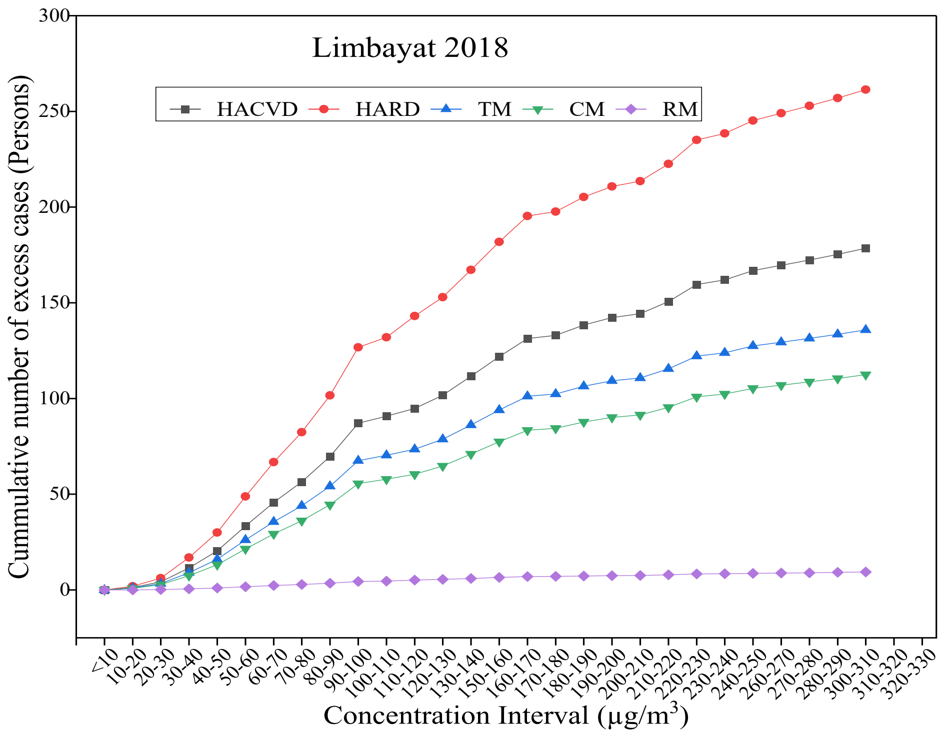

Fig. 6. Relationship between cumulative number of morbidity rates, mortality rates (RR at 95% CI) and ozone concentration

and respiratory diseases than other short-term and long-term mortality rates. Though in Iran, Ahvaz city, focused on a high percentage of hospital admissions associated with a high concentration of surface ozone in 2013 [21]. Limited short and long-term assessment of O_3 in Surat is conducted due to hospital admission's unavailability of physical data.

This model is adopted and applied with certain limitations. The synergistic effect due to multi pollutants has not been considered because of insufficient knowledge about the interaction of chemical agents with living organisms of the different compounds [22]. RR used in this study is obtained from the USA and European countries; therefore, there may be a possibility to get different results compared to what really exists. The model has low reliability in morbidity estimation due to less assurance related to hospitalization entries [23]. Total city area, number of total monitoring stations situated in the city, and the distance between two stations are vital parameters to represent the whole city. Data obtained from only two areas (i.e., 13% area of the total city) of the whole city, cannot express the entire city.

Conclusion

The main focus of the present study is to work out on health effects due to single pollutants rather than multiple pollutants exposure to Surat citizens. WHO's approved AirQ+ software is estimated the short-term TM, CM, and RM; long-term RM and hospital admissions due to surface ozone exposure from 2018 to 2019. More attributable cases of TM, CM, RM, HARD, and HACVD are found in 2018 than in 2019 in Surat at both locations. Higher O_3 concentration is a noticeable factor contributing to the number of deaths in 2018 compared with 2019. TM and CM are the crucial health endpoints followed by hospital admissions with the highest risks for both 2018 and 2019. As per BI and RR values, the AP estimated for total mortality at Limbayat and Varachha during 2018 and 2019 are 1.79%, 0.59%, 1.49%, and 0.16%, respectively deaths are 136, 45, 172, and 18. More cases are found for hospital admissions (respiratory and cardiovascular) at both locations for the year 2018 and 2019 compared to short-term and long-term mortality rates.

A proper physical survey can minimize health deterioration. It can be prevented by developing an air pollution control strategy by creating more online applications to prevail about air quality index values in advance. Though day by day more diversity is found in pollutants, more research should be done on ozone formation chemistry. By controlling the emissions of ozone precursors at the source, enhancing to vehicle inspection program can decrease the O_3 concentration. Public awareness is essential for health impacts and ultimately long-term and short-term exposure to air pollution. This health estimation study can be helpful in public awareness of morbidity and mortality to exposure to surface ozone and environmental control agencies. Advantages of the AirQ+ model can be utilized to implement air quality-based new strategies in favor of better public health. Substantially obtaining real human health data with the physical survey is critical in a developing country. In that case, it is easier to acquire scenarios of human health assessment from software such as AirQ+.

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Competing interests

The authors have no competing interests to declare.

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Ethical considerations

Ethical issues (Including plagiarism, Informed Consent, misconduct, data fabrication and/ or falsification, double publication and/ or submission, redundancy, etc) have been completely observed by the authors.

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