Ambient air particulate matter (PM₁₀) satellite monitoring and respiratory health effects assessment

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Received: 1 May 2020 / Revised: 11 September 2020 / Accepted: 14 September 2020 / Published online: 3 October 2020
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Abstract

Purpose Air particulate matter with an aerodynamic diameter of 10 µm or less (PM₁₀) is one of the main causes of acute exacerbation of chronic obstructive pulmonary disease (AECOPD). This study explored the relationship between PM₁₀ by remote sensing and AECOPD in Chaharmahal-o-Bakhtiari province from 2014 to 2018.

Method PM₁₀ concentrations were predicted and validated based on aerosol optical depth (AOD) from 161 images processed by MODIS sensor and ground air quality monitoring station data. Demographic information and spirometric indices of 2038 patients with AECOPD were collected and analyzed from the hospital during the studied periods. SPSS software was used to analyze the relationships between these two categories of information.

Results There was a significant negative relationship between PM₁₀ and FVC, FVC%, FEV₁, FEV₁%, FEF₂₅₋₇₅, FEV₁/FVC, PEF, and FEF₂₅/FVC indices ($p < 0.05$). The results showed that over 2014–2018, the annual mean of PM₁₀ concentrations varied from 35 to 52 µg/m³. The result of the regression model showed that the patient's age, body mass index (BMI), and PM₁₀ concentrations were the most affecting variables on the two important spirometric indices i.e., FVC% and FEV₁%. The PM₁₀ concentrations and number of AECOPD patients had a similar pattern during the studied period. The women group, age group above 74 years, normal BMI, and non-smoking patients showed the most sensitivity to the PM₁₀ concentrations.

Conclusions Our findings provide supplementary scientific information on PM₁₀ concentration related to the incidence of AECOPD and as a variable affecting the most important spirometry indicators by providing local decision-makers information needed to set a priority of air pollution control measures as well as health services.

Keywords PM₁₀ · Satellite Monitoring · MODIS · Acute exacerbation of chronic obstructive pulmonary diseases · Spirometric indices · Chaharmahal-o-Bakhtiari Province

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Introduction

Particulate matter (PM), by depositing more deeply into the lungs, can carry larger concentrations of adsorbed or condensed toxic air pollutants per unit mass with its greater surface area that has been most strongly linked to adverse health effects [1]. In a study conducted by the Global Burden of Diseases in 2015, about 7.6% of global deaths and 4.2% of global disability-adjusted life years were attributed to exposure to PM with an aerodynamic diameter less than 2.5 µm [2]. One of the leading risk factors for global disease burden is a chronic obstructive pulmonary disease (COPD) that persistently limited airflow with chronic inflammation of the lung. COPD can start early in life and progress slowly until the lung decompensate mostly at advanced ages [3, 4]. According to the world health organization (WHO), COPD will become the

third leading cause of death in the world by 2030 [5]. The natural history of COPD is often associated with episodes of acute worsening of symptoms with a variable degree of physiological destruction known as exacerbations [6]. The Epidemiology and Impact of COPD (EPIC) in Asia's study showed that nearly half of the patients with COPD had experienced exacerbations, 19% of them had been hospitalized [7]. Due to the lack of a specific treatment regimen for COPD, identification of the risk factors and action against them will have important consequences in preventing the exacerbation of the disease [8].

Lastly, numerous studies have found associations between mass concentrations of ambient PM air pollution and adverse health outcomes related to mortality, hospitalization, and emergency department visits in acute exacerbation episodes of COPD patients [9–14]. The air pollution problem caused by particulate matter in Iran has become more important due to exposure to middle eastern dust (MED) storms, especially storms from the Arabian Peninsula, Kuwait, and Iraq [15]. Over the past few years, dust particles from the North-Western region of Iraq and eastern Syria [16] and neighboring provinces have reduced air quality, especially in western and southern cities, resulting in increased respiratory referrals to health centers across Chaharmahal-o-Bakhtiari province. Among the respiratory diseases observed in the province, COPD has a high prevalence, with the costs being directly or indirectly spent on the disease, imposing a significant substantial social and economic burden on society. COPD patients may need specialized health care when experiencing an exacerbation of symptoms during this time period. One factor affecting the exacerbation of this disease is the destructive effects of PM.

Recently, studies have been done on the epidemiology of respiratory diseases associated with dust storms in the western regions of the country. In a study conducted by Daryanoosh et al. (2017) on the incidence of hospitalizations due to respiratory diseases associated with PM₁₀, the result showed that 7.3%, 6.4%, and 3.9% of respiratory diseases in the cities of Ahvaz, Khorramabad, and Ilam were attributed to PM₁₀ [15]. In a study conducted in Tabriz city by Barzeghar et al. during 2006–2017, it was estimated that attributable proportions due to long-term exposure to PM₁₀ were between 7.9% and 28.7% for post neonatal infant mortality and between 20.7% and 61.5% for the incidence of chronic bronchitis in adults [17].

Air quality control at the national and regional scale and the achievement of air quality maps and spatiotemporal variation are essential for assessment of air pollution control [18]. In Iran, air quality monitoring stations for monitoring the concentration of criteria ambient air pollutants (PM₁₀, PM_{2.5}, NO₂, SO₂, CO, O₃) are deployed since 1991. Although ground-based measurement is an efficient method for monitoring the air quality [19], ground measuring stations are limited in numbers and the instruments are expensive, only limited numbers of ground collection locations are available that

makes variability in air pollution in large spatial cannot be measured correctly [20]. Today spatial variability and long-range transport of air pollution can account for satellite-mounted sensors, thus by measuring concentration gradients between stationary monitors it can provide global coverage of aerosols, this data provided better spatial distribution and temporal resolution than the data obtained from in-ground stations. It can be used especially in regions that lack ground monitoring capabilities [21, 22]. For continuous air quality monitoring applications offering a wide coverage area satellite imagery such as Landsat, Moderate-resolution Imaging Spectroradiometer (MODIS), and SPOT can be used [18]. The MODIS data with a high temporal resolution is an ideal data source in simulative monitoring for environmental variability monitoring [23]. One of the most essential parameters of MODIS is the AOD (aerosol optical depth), which measures the amount of columnar light extinction by aerosol particles during satellite transit and shows the columnar optical characteristics [24]. Therefore, understanding the regional and temporal changes in AOD is essential to better quantify the radiation effects of aerosols [25]. Several studies have been carried out focusing on global AOD variations over land and ocean and linear correlation with daily ground-based PM₁₀ measures [26–28]. Despite a good understanding of AOD's spatial and temporal changes on a global scale and in many regions around the world, the properties of aerosols have not been well analyzed throughout Iran [25]. In such studies, the relationship between MODIS AOD satellite data and the ground station particle concentration data is used to determine the concentration of suspended particles [29].

The main aims of this study are satellite monitoring of PM₁₀ (particulate matter with an aerodynamic diameter $\leq 10 \mu\text{m}$) in order to evaluate its effect on acute exacerbation of chronic obstructive pulmonary disease (AECOPD) in Chaharmahal-o-Bakhtiari province in the southwest of Iran during 2014–2018. For the first time, the present study examined the ability of remote sensing to monitor and quantify particulate matter and analyzed the relationship between remote sensing data and information of patients with acute exacerbation of COPD in Chaharmahal-o-Bakhtiari province. This study can provide useful data about the possibility of efficient and low-cost satellite monitoring of particulate matter concentrations in order to provide a pattern of dispersion of particulate matter in the province, as well as provide documentation of the relationship between PM₁₀ concentration and AECOPD.

Materials and methods

Study area

The study area of Chaharmahal-o-Bakhtiari province is located in 31°9'00" to 32°38'00"N latitude and 49°30'00" to 51°26'

00"E longitude (Fig. 1) in the southwest of Iran with an area of 16,421 km² and with a population of 947,763 (in 2016). It has nine counties, namely, Shahrekord (the capital of the province), Saman, Ben, Kouhrang, Ardal, Farsan, Kiar, Boroujen, and Lordegan [30].

Data and methodology

Assessment of the PM₁₀-AECOPD relationships has been performed using three different datasets over five years (2014–2018): (1) Aqua MODIS AOD data (*Collection 6. 1-Level 1, Atmosphere, Land-61*) of Chaharmahal-o-Bakhtiari province; (2) Ground air quality data from a station in Shahrekord city; and (3) spirometric spirometric data of AECOPD hospitalized patients in Chaharmahal-o-Bakhtiari province during the studied period. Figure 2 shows a brief flowchart of the study and an overview for investigating the relationships between PM₁₀-AECOPD. The descriptions of each step are provided in the following.

Ground-based PM₁₀ contents

Chaharmahal-o-Bakhtiari province has only one air quality control station, which has been located in Shahrekord city since 2014 and managed by the Environmental Protection Organization. The station has sensors for measuring the 24-hour average concentration of air pollutants, i.e., NO, NO₂, NO_x, PM₁₀, PM_{2.5}, and CO. In this study, in the first step, the data about Shahrekord air quality control station were collected from March 2014 to December 2018 as an Excel file. After

that, according to the monthly information, the date of two to seven days with a maximum average concentration of PM₁₀ 24-hour was recognized (days in upper quartile). The reason for choosing the days in the upper quarter was that these days have the greatest impact on the health of the province's residents and determine the frequency of hospital visits. Finally, 161 days over the studied period were selected and the concentrations of PM₁₀ in the selected days were used for validating the satellite data.

Satellite-based aerosol data

In this study, remote sensing data to estimate PM₁₀ concentrations of the province were collected from NASA (<https://ladsweb.modaps.eosdis.nasa.gov>) over the studied period (from 2014 to 2018). Accordingly, MODIS collection 6 level 2 AOD data from aqua satellite (MYD04-3K) at 550 nm with a spatial resolution of 3 km (MODIS C6.1 daily aerosol level-2 product MOD04) were downloaded to develop a statistical model between AOD-PM₁₀. MODIS instrument was on board of the Terra and Aqua satellites, which were launched in December 1999 and in May 2002 respectively, to retrieve aerosol properties over land and ocean [31]. The NASA research team released retrieved AOD with a resolution of 3 km as part of collection 6. The algorithm is used to retrieve 3 km AOD product is the same as the original MODIS dark target aerosol algorithm especially for lookup tables and inverse method and the mere difference is the organization and selection of pixels to retrieve AOD product [32]. Aqua observes the study region at approximately 14:00 local time (as an average time).

Fig. 1 Location of Chaharmahal-o-Bakhtiari province and its nine cities in Iran

Fig. 2 Flowchart of the study methodology; investigating the relationships between PM₁₀-AECOPD

AOD data has been autonomous highly correlated with ambient air PM₁₀ concentrations [33–36]. These data can more accurately estimate and model the concentration of PM₁₀ when combined with data from numerous ground-based stations, as well as meteorological and topographic data [31, 37, 38]. It should be noted that Chaharmahal-o-Bakhtiari is an underdevelopment province in Iran and we have had restrictions on the number of ground-station and access to meteorological maps. On the other hand, the need to use satellite data to investigate its relationship with the health of the province's residents has led us to suffice with a traditional linear regression model between PM₁₀ concentrations and AOD values. Therefore, we used the data obtained from the single air quality control station in Shahrekord to calibrate the pixel corresponding to it in the satellite image and then generalized the obtained model to the whole province. Similarly, in the study of Pratama (2018) [36], there were limitations of air quality monitoring data and they used MODIS-AOD data to estimate PM concentrations based on a linear regression model.

It must be kept in mind that we have not sought to measure the absolute concentration of PM₁₀, and we only need to have its relative changes over the studied years and among the cities of the province. Therefore, the data obtained in this study has no value for measuring the absolute PM₁₀ concentrations and only represents the relative spatial-temporal comparison.

In this regard, after selecting and downloading 161 satellite images, Terrset software was used for the pre-processing of downloaded images. In the first processing step, while changing the format of the downloaded images to RST format, the *image_optical_Depth_Land_And_Ocean* (680 × 451) field was extracted to get the AOD values [39]. Then, geometrical corrections of images were considered and the image subset tool was used to clip the study boundary from the MODIS image frame. All image's calculation and spatial and temporal trends extractions were done in the Terrset software

environment. Finally, Arc GIS (version 10.1) software was used to design and export the maps.

AECOPD data

In this study, spirometric data of AECOPD hospitalized patients between January 2014 and December 2018 were extracted from the spirometry division of a central hospital in Chaharmahal-o-Bakhtiari. This hospital is the first and the reference hospital in which the province's spirometry equipment has been built and patients are tested and hospitalized for respiratory problems (patients who have referred to this hospital from other provinces have been excluded from the study). A total of 2038 patients' information was processed and these visits date and residence locations in the nine cities of Chaharmahal-o-Bakhtiari were recorded. In addition, the health information system (HIS) of the central hospital provided patients' information by self-report including gender, age, smoking status, admission, and pulmonary function test. By assigning a code to each city, the patients' residential address was recorded as 1–9, representing the cities of Shahrekord, Saman, Ben, Koohrang, Farsan, Ardal, Kiar, Borujen, and Lordegan, respectively. Patients have been selected who met the following criteria:

- 1 They were hospitalized in the Lung Division of the central hospital between January 2014 and December 2018;
- 2 They resided in the study area;
- 3 Their pulmonary function test that showed an obstructive pattern (a ratio of forced expiratory volume in the first, second [FEV₁] to forced vital capacity [FVC] of less than 70%) [40, 41];
- 4 They had FEV₁ and FVC percent predict less than 80%;
- 5 They were over 40 years old to exclude people those likely to have asthma rather than COPD [42] and

- 6 They had chronic obstructive pulmonary disease with (acute) exacerbation with 2019 ICD-10-CM Diagnosis Code J44.100 and J44.101 [13].

Statistical methods, modeling and validation

According to the coordinates of the ground-station, the amount of data in these coordinates was recorded on each image and after relevant analyzes, then the general formula for the prediction of particulate matter (PM_{10}) was used. In this study, due to the quantitative nature of the ground-based PM_{10} concentration and AOD values, Pierson's correlation and univariate linear regression were applied to test the relationships and model the linkage between AOD- PM_{10} (at a significance level of 0.05). All achieved data in this study were randomly separated into two sections; 70% as training data and 30% as testing data and to assess the estimation performance of the modeling process the coefficient of determination (R^2) was used. The general form of the univariate linear regression equation is as follows:

$$Y = \beta_0 + \sum(\beta_i X_i) \quad (1)$$

Where:

Y = Dependent variable including PM_{10} contents;

X_i = Independent variable (AOD values);

β_i = Coefficients obtained from SPSS (non-standardized regression coefficient or B) and,

β_0 = Width of Source (Constant Value)

The multivariate regression model shows the relationship between image values and pollutant levels.

Furthermore, to test data distribution and compared the quantitative variables between the two and three groups, the Kolmogorov-Smirnov test, independent t-test, and ANOVA were used, respectively (at a significance level of 0.05). Statistical analysis and graph drawing were done with Microsoft Excel 2010 and the SPSS version 16.

Results and discussion

Verification

The relationship between MODIS-based AOD and PM_{10} was investigated. According to Fig. 3, the high correlation coefficient (R^2) is 0.76 between the AOD parameter and PM_{10} . This finding is consistent with both a study by Ferrero et al. in Italy (2019), with a result of R^2 greater than 0.83 [43], and a study by Li et al. in China (2016) that estimated the concentration of PM_{10} using MODIS satellite data, with R^2 of 0.804 [44].

Fig. 3 Comparison of data obtained from the AOD parameter and ground sensing station (n = 161)

According to Table 1, the non-standard regression coefficient is used to create the regression equation. The regression equation is used to predict the values of the dependent variable accurately which is as follows:

$$\text{Field measurement} = 30.5 + 0.23 \times \text{MODIS pixel value} \quad (2)$$

In this equation, PM_{10} concentration in the region was predicted by placing the values of the satellite sensor data.

Spatial-temporal variations of PM_{10} concentrations in the study area

PM_{10} concentration was evaluated by using of 60 images during the months of study after averaging by province cities (Fig. 4). The mean and standard deviation of PM_{10} concentration was $41 \pm 16 \mu\text{g}/\text{m}^3$ ($30\text{--}158 \mu\text{g}/\text{m}^3$).

According to Fig. 3, the highest and lowest concentrations of PM_{10} were observed in Ardal and Ben, respectively. Other cities in descending order of PM_{10} concentration were Lordegan, Kiar, Borojen, Farsan, Koohrang, Saman, Shahrekord. One reason for the high concentration of PM_{10} in Ardal and Lordegan cities can be the neighboring provinces of Khuzestan and Kohgiluyeh and Boyer Ahmad, which are affected by west and southwest dust storms [45]. Other factors affecting the concentration differences in cities include differences in their altitude codes. According to a study by Rezaei et al. in 2018, the concentration of aerosols is related to the altitude of the points, where points with lower altitudes have higher aerosol concentrations, and points with higher altitudes have lower aerosol concentrations [46]. It is possible that the high concentration of PM_{10} in Ardal and Lordegan cities (with lowest altitude code) and the low concentration in Koohrang (with highest altitude code) may be due to this reason. The mean concentration of PM_{10} during different years of the study period is depicted in Fig. 5. According to WHO air

Table 1 Regression Coefficients

Model	Unstandardized Coefficient		Standardized Coefficients		t	P
	β	Std. Error	Beta			
Constant	30.50316	4.536905	-		6.723342	0.001
MODIS	0.226787	0.010085	0.87224		22.48833	0.001

quality guideline (AQG), Chaharmahal-o-Bakhtiari province was exposed to concentrations of annual PM₁₀ more than 20 $\mu\text{g}/\text{m}^3$ (<https://www.who.int/airpollution/publications/aqg2005/en/>). In a study by Yunesian et al. annual mean concentrations of PM₁₀ in ten selected air quality monitoring stations of Tehran varied from 62.5 to 104.3 $\mu\text{g}/\text{m}^3$ during 2016–2017 [47]. Also in other studies, the annual mean PM₁₀ concentrations in Tehran from 2012 to 2017 fluctuated between approximately 78.9 and 89.9 $\mu\text{g}/\text{m}^3$ [48]. In Ahvaz, Western city of Iran during 2009–2014 the mean PM₁₀ level estimated 249.5 $\mu\text{g}/\text{m}^3$ [49]. In addition, the annual average concentration of PM₁₀ in Kermanshah was equal to 85.7 $\mu\text{g}/\text{m}^3$ during the years 2014 and 2015 [50]. By discussing the concentration of PM₁₀ in different time periods compared to the study area, this province has the lowest level of particulate pollution.

The average value of particulate matter concentrations in 2015 was the highest, and in other years in order were: 2014 >

2016 > 2017 > 2018. According to a study conducted by Ashrafi et al. in 2017 on dust storm modeling and its impact on the overall air quality of Iran, they stimulated a dust storm that occurred in April 2015 with the average concentration of dust in the range of 515 $\mu\text{g}/\text{m}^3$ [51]. The reason for the high concentration of PM₁₀ in 2015 is probably because of this phenomenon. Also, according to a study by Dadashi-Roudbari et al., the annual average AOD index from 2014 to 2015 has been increasing in the western provinces of Iran that it can be related to increasing in PM₁₀ concentration in these two years [52].

Distribution of AECOPD patients

2038 patients (975 men and 1063 women) with a mean age of 69.63 years (standard deviation of 12.54 years) were included in the study. According to Fig. 6, the rates of COPD's patients from 2014 to 2018 were 25, 59, 57, 50, and 24 in every 100,000 people, respectively. There was not a significant difference between the two genders. Baseline quantitative characteristics of the studied population are presented in Table 2. According to the spirometric indicators disaggregated by the patient's gender, there is no significant difference in the number of spirometric indices between men and women.

Patients were categorized by age groups, BMI and smoking status according to Table 3. From 303 subjects, almost 28% of

Fig. 4 Average PM₁₀ concentration by counties

Fig. 5 PM₁₀ concentrations during the studied years

the males and 1% of the females were current smokers. The number of patients in terms of gender status was: 2015 < 2014 < 2016 < 2017 < 2018 (Fig. 5).

Possible reasons for the lower number of patients in 2014 and 2018 than in other years of study include the lack of patient's information in the electronic system of spirometry of the central hospital in January, February, and March 2014 and April, May, June, and July 2018. In addition, the number of patients in 2015, 2016, and 2017 have been declining, may be due to an increase in spirometry testing equipment in other medical centers in the province which has reduced the burden of referrals to the central hospital.

On average, in January, February, November, and December, the highest number of hospitalizations was observed, which is probably due to the cold seasons of the year and the increase in patient visits to medical centers. Also, the average of the lowest number of patients was in September, and October, which is likely to decrease in the summer of the year. The findings are consistent with the results of a study conducted by Djman et al., in The Netherlands [53] and Wilkinson et al., in the UK [54]. Among the reasons studied in this study are the possibilities of more infections related to influenza viruses, colds, presence of influential pathogens,

Table 2 Quantitative characteristics of subjects

Variable	Male		Female	
	Mean	SD	Mean	SD
Age	69.50	12.64	69.74	12.46
BMI	25.39	4.85	27.74	5.80
FVC% predict	45.65	16.76	45.87	16.62
FEV1% predict	49.24	18.19	50.36	17.78
FEF25–75%	1.76	1.14	1.43	0.8
FEV1/FVC	0.85	0.14	0.92	0.12
PEF(L/MIN)	45.34	20.79	42.79	18.60
FEF25%FVC	45.98	24.61	44.69	20.87
FEF50%FVC	51.04	31.87	49.42	25.97
FEF75%FVC	78.37	59.31	80.35	51.18

and human metapneumovirus in cold seasons and exacerbation of COPD.

The increase or decrease of PM₁₀ concentrations and the number of the AECOPD patients were similar during the study period (Fig. 7). This may be evidence of the effect of PM₁₀ concentration on the incidence of acute exacerbation of the disease. In a study conducted by Qian Sun et al. (2018) entitled “correlation between fine particulate matter (PM_{2.5}) and acute exacerbation of COPD in Yancheng, China”, showed that by increasing 10 µg/m³ of PM_{2.5} concentration leads to increasing 1.05% in the number of patients with AECOPD [13]. Also, in a study by Choi et al. (2018), when the air quality index is above 50, the incidence of acute exacerbation of COPD has increased significantly. In addition, the level of particulate matter was statistically significant three days prior to hospitalization [10]. In another study by Omid Khaniabadi (2019), entitled “disease and mortality related to ambient air pollution in Iran” found that 4.97% of respiratory patients and 2.5% of COPD patients received 10 µg/m³ of additional concentration of PM₁₀ [55]. According to Wang

Fig. 6 Temporal trend AECOPD patients in Chaharmahal-o-Bakhtiari province (2014–2018)

Table 3 Qualitative variable of subjects

Variable		Frequency (%)
Age	40–64	706 (34.64)
	65–74	529 (25.95)
	74<	803 (39.4)
	> 74	100 (4.8)
BMI	< 18.5	84 (4.12)
	18.5–24.9	773 (37.92)
	25–29.9	691 (33.9)
	30–34.9	330 (16.19)
	≥ 35	160 (7.85)
Smoker	Male	282 (93)
	Female	21 (7)

et al. study in Jinan, showed the effect of increasing the concentration of suspended particulate matter (per $10 \mu\text{g}/\text{m}^3$) on the number of hospitalized patients (7% increases) in the hospital [56]. The results of these studies, like our study, show a significant relationship between the concentration of suspended particles and the incidence of acute exacerbation.

The number of patients studied by provincial cities is reported in Table 4. As can be seen, the largest number of patients belonged to Shahrekord and its neighboring cities, which is justified due to the presence of the central hospital in Shahrekord and more patients' accessibility to doing clinical spirometry tests in this hospital.

Relationship between spirometric indices in patients and PM_{10} concentration

Pearson correlation coefficient was used to investigate the relationship between spirometric indices and PM_{10} concentrations. Given the amount of P-value in Table 5, there was a significant relationship between PM_{10} and FVC, FVC%, FEV1, FEV1%, FEV1/FVC, PEF, and FEF25FVC indices ($p < 0.05$). According to the negative sign of the Pearson coefficient, with increasing PM_{10} concentration, spirometric indices decreased, and the relationship was inversed.

Heinrich et al. in 2018, reported a small but statistically significant decline of FEV1 [-3.38 mL] per increment of $10 \mu\text{g}/\text{m}^3 \text{PM}_{10}$, supporting an impact on respiratory health with increasing PM_{10} exposure [3]. This finding is consistent with the results of a study by Bloemsma et al., entitled “air pollution panel studies in COPD patients: a systematic review and meta-analysis” in 2016, showing a decrease of 3.38 mL by increasing each $10 \mu\text{g}/\text{m}^3 \text{PM}_{10}$ concentration. The FEV1 and the PEF indices decreased by $0.61 \text{ L}/\text{min}$, consistent with both studies showing a statistically significant association between COPD and lung function in COPD patients [34].

Relationship between spirometric indices in patients and PM_{10} concentration by gender, age, BMI, and smoking status categories

In terms of gender status, there was a significant relationship between PM_{10} and FVC, FVC%, FEV1, FEV1%, FEF25-75, FEV1/FVC, and PEF in men, while in women, PM_{10} has a significant relation with FVC, FVC%, FEV1, FEV1%, FEV1/FVC, PEF, FEF25FVC, and FEF50FVC ($p < 0.05$). There was little difference between the two genders in terms of the Pearson coefficient, but in women more indices were affected by PM_{10} concentration. Also, in the age group 40–64 years FVC%, FEV1%, FEV1/FVC, and PEF indices, in the age group 65–74 years FVC%, FEV1%, PEF, and FEF25FVC indices and in the age group above 74 years, all indices except FEF25-75 and FEF75FVC had a significant relationship with PM_{10} concentration that indicates an increase in patients' sensitivity to PM_{10} at older ages. These results are similar to a study conducted by Liang et al. (2017) in China that showed women and elderly COPD patients and also patients over 65 years of age were more sensitive to air particulate pollutants [57].

In the BMI range of 18.5 to 24.9, FVC, FVC%, FEV1, FEV1%, FEV1/FVC, PEF, FEF25% FVC indices, in the BMI range of 25 to 29.9, FVC, FVC%, FEV1%, FEV1/FVC, PEF, FEF25% FVC indices, in the BMI range of 30 to 34.9, the FVC%, FEV1%, FEV1/FVC indices and in the BMI range of 35 to 39.9, the FVC, FVC%, FEV1% indices were related to the PM_{10} concentration ($p < 0.05$). BMI less than 18.5 and above 40 had no relationship with PM_{10} . Based on Chan et al., (2014) study, the estimated prevalence of moderate to severe COPD among adults aged ≥ 30 years was 5.4% in Taiwan, while the average prevalence in the 12 Asia-Pacific countries, including Taiwan was 6.3%, and in the United States, it was 4.8% [58].

Fig. 7 Temporal trend AECOPD patients and PM_{10} concentration in Chaharmahal-o-Bakhtiari province (2014–2018)

Table 4 Spatial distribution of AECOPD in Chaharmahal-o-Bakhtiari province (2014–2018)

Cities	Shahrekord	Saman	Ben	Koohrang	Farsan	Ardal	Kiar	Borujen	Lordegan
Number	951	136	131	73	239	136	174	82	139
Percent (%)	46.14	6.6	6.36	3.54	11.6	6.6	8.44	3.98	6.74

In separating the status of tobacco use, in the smoker group, FEF25-75 indices and non-smoker group all indices except FEF25-75 and FEF75FVC were related to PM_{10} concentration ($p < 0.05$). According to the results, patients with normal BMI and non-smoking were more sensitive to PM_{10} . In a study conducted by Kerkhof et al., (2015), they were concluded that demographic variables including, gender, age, weight, height, BMI, smoking status, only gender, and age variables had a significant relationship with the particulate concentration [59].

Linear regression analysis

The linear regression model was used to investigate the effect of variables on two relevant spirometric indices, FVC%, and FEV1%. The variables such as age, BMI, smoking status, gender, and concentration of PM_{10} were used. Given the amount of P-value in Table 6 patient's age, body mass index, and PM_{10} concentrations in the residence address were the most affecting variables on dependent variables, FVC%, and FEV1%.

According to the results, the following variables were related to the FVC% and FEV1% by formulas below:

$$FVC\% = 65.155 - 0.273(\text{age}) + 0.210(\text{BMI}) - 0.139(\text{PM}) \quad (3)$$

Table 5 Relationship between PM_{10} Concentrations with Spirometric Indices

Spirometric indices	Pearson correlation		P value
FVC	-0.086	0.001	
FVC%	-0.162	0.001	
FEV ₁	-0.064	0.003	
FEV ₁ %	-0.157	0.001	
FEF25-75	-0.017	0.440	
FEV ₁ /FVC	-0.144	0.001	
PEF(L/MIN)	-0.114	0.001	
FEF25FVC	-0.083	0.001	
FEF50FVC	-0.040	0.067	
FEF75FVC	-0.009	0.664	

$$FEV1\% = 61.438 - 0.180(\text{age}) + 0.297(\text{BMI}) - 0.149(\text{PM}) \quad (4)$$

The results of the regression's analysis of the present study were similar to many studies. For example, in a study was done by Tran et al., (2011), on demographic data of patients, including age, gender, BMI, education, smoking, and alcohol use with COPD, they were concluded, among these variables, age, gender, smoking, and education level were at risk level for this disease [60]. Similar to the results of our study, in a systematic review study conducted in 2016 by Jinui et al., with 59 studies, a significant association was found between the risk of exacerbating COPD and all gaseous and particulate pollutants. Among particulate pollutants, PM_{10} with a mean of $46.44 \mu\text{g}/\text{m}^3$ for every additional $10 \mu\text{g}/\text{m}^3$ with a P value of less than 0.001 was significantly associated with exacerbation of the disease [61]. Also, a study conducted by Sharifi et al., in 2018 on the prevalence and risk factors of COPD in five provinces of Iran, showed that the prevalence of the disease was strongly correlated with smoking status, age, and gender [41].

Conclusions

In the present study, satellite monitoring for PM_{10} concentration prediction was used as an efficient method, and its effect on acute exacerbation of COPD was investigated in Chaharmahal-o-Bakhtiari province during 2014–2018 in Iran. The results showed that the increase or decrease of

Table 6 Linear regression test for the dependent variable of FVC% and FEV1%

Variable	FVC%		FEV1%	
	Coef.	P value	Coef.	P value
Age	-0.273	0.000	-0.180	0.000
BMI	0.210	0.002	0.297	0.000
Smoking	0.952	0.387	-1.938	0.107
Gender	0.186	0.811	0.091	0.914
PM	-0.139	0.000	-0.149	0.000
Cons	65.155	0.000	61.438	0.000

PM₁₀ concentrations and the number of the AECOPD patients were similar during the studied period. The correlation between PM₁₀ concentrations and ten spirometric indices in the studied patients was revealed that the increase of PM₁₀ could be decreased the spirometric indices ($p < 0.05$). The linear regression model demonstrated that the patient's age, body mass index, and PM₁₀ concentrations in the residence address were the most affecting variables on the two important spirometric indices, namely, FVC% and FEV1%. Our findings provide supplement scientific information on PM₁₀ concentration related to the incidence of acute exacerbation of COPD for Chaharmahal-o-Bakhtiari province by providing local decision-makers with information needed to set the priority of air pollution control measures as well as health services. Further research using satellite monitoring will be needed to find out the effects of various pollutants and their health outcomes.

Limitations and strengths of the study

This study has not been without some constraints for the interpretation of our results. First, in this study, there was only one air quality ground-station. This constraint in ground-based data has led to a decrease in the ability to calibrate the relationship between AOD-PM₁₀. Second, the use of auxiliary variables such as meteorological parameters can play an important role in improving the accuracy and precision of PM₁₀ maps obtained from satellite data. Nevertheless, meteorological data were not used in this study. Third, hospital data also had limitations, for example, not all patients may have referred to the central hospital or some patients may have referred to hospitals in the neighboring provinces e.g., Isfahan province. Carrying out an interdisciplinary project related to health and the possibilities of using the results of this study in the relevant organizations and the low cost of the study process are strengths of the study.

Acknowledgements The authors gratefully acknowledge the financial support from the SKUMS and Spirometry Center assistance of Hajar Hospital.

Authors' contributions M.M. conducted the experiments and wrote the manuscript, M.A. supervised and supported and funding the project and edited and wrote the manuscript, M.M. designed, methodology and advised satellite selection and monitoring, A.A. designed and advised epidemiological and statistical method, M.S.H. observed the scientific content of the paper, H.R. advised patient's sampling on pulmonary disease. All authors have read and agreed to the published version of the manuscript.

Funding This research was funded by the Deputy of Research and Technology of Shahrekord University of Medical Sciences (Grant No. SKUMS 3648 – 2019).

Data Availability All data generated or analyzed during this study are included in this published article.

Compliance with ethical standards

Ethics approval and consent to participate This study has been approved by the ethical committee of The Shahrekord University of Medical Sciences (SKUMS).

Consent for publication Not applicable.

Conflicts of Interest The authors declare no conflict of interest.

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