Long-term changes in aerosol loading over the ‘BIHAR’ State of India using nineteen years (2001–2019) of high-resolution satellite data (1 × 1 km²)

Moorthy Nair, Sagnik Dey, Hemant Bherwani, Ashok Kumar Ghosh

A B S T R A C T

Indo-Gangetic Plain (IGP) in the Indian sub-continent faces massive aerosol loading, for which it is regarded as a global air pollution hotspot. This study examined the spatial variation in columnar aerosol loading (2001–2019) over the eastern state of Bihar and its 38 administrative districts affected by transboundary transport and local emissions. In the current study, aerosol optical depth (AOD_{550nm}) retrieved at 1 × 1 Km² resolution by the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor using the Multi-Angle Implementation of Atmospheric Correction algorithm (MCD19A2, Collection 6) was analyzed. A significant increase in AOD from 0.49 to 0.68, with an inter-annual variability of 12.0%, was observed. The highest seasonal aerosol loading of the range 0.51–0.75 was observed during the post-monsoon (OND) and winter (JF) seasons due to long-range transport of pollutants from upper and central IGP regions and aerosols emitted locally, which further was aggravated by poor metrological conditions. AOD was not found to vary significantly with the land use pattern (e.g., urban, rural, and background), implying the substantial influence of regional transport. A significant increase in the annual AOD trend (0.0106 year⁻¹) and seasonal trends (0.0072–0.0182 year⁻¹) was observed for the analysis period. Districts located along the Ganga river stretch exhibited the highest annual AOD rate with an overall percentage increase of 40–50%. Low to moderate model performance (R²:0.25–0.65; MAPE: 15.2–26.7%) was exhibited by Auto-Regressive Integrated Moving Average (ARIMA) time series model over the study area for the successive two years (2020 and 2021), emphasizing the districts with a potential for high aerosol loading that requires immediate addressing under Business as usual (BAU) scenarios. The overall study augments policy-makers with decision-making support to instigate air quality measures at the state epicenters. The study also recommends inter-state coordination to develop an integrated airshed management approach for holistic improvement in state air quality.

Keywords:
Aerosol Optical Depth (AOD)
Indo-Gangetic Plain (IGP)
Land use pattern
Time-series trend

1. Introduction

Aerosol Optical Depth (AOD) measurements have been centred in the climatology domain due to their imperative role in altering the properties of incoming solar radiation and cloud formation with an influence on the overall dynamics of the earth’s climatic system. Aerosols largely acknowledged as Particulate Matter (PM) vary in their physiochemical characteristics and morphological structure, forming a major constituent of air pollution causing adverse health effects on humans across the globe (David et al., 2018; Filonchyk et al., 2019; Kumar et al., 2018). With formerly mentioned externalities being no limitation, aerosols extend their significant impact on biodiversity (Steiner, 1994; Walters, 2010), food security (Banerjee et al., 2018; Burney and Ramanathan, 2014), hydrological cycle (Ramanathan et al., 2001), greenhouse gases

---

**Corresponding author. Centre for Atmospheric Sciences, Indian Institute of Technology Delhi, Hauz Khas, New Delhi, 110 016, India.**

**Corresponding author. CSIR-National Environmental Engineering Research Institute (CSIR-NEERI), Nehru Marg, Nagpur, Maharashtra, 440020, India.**

*E-mail addresses:* sagnik@cas.iitd.ac.in (S. Dey), b.bherwani@neeri.res.in (H. Bherwani).

https://doi.org/10.1016/j.apr.2021.101259

Received 27 June 2021; Received in revised form 14 October 2021; Accepted 5 November 2021

Available online 10 November 2021

1309-1042/© 2021 Turkish National Committee for Air Pollution Research and Control. Production and hosting by Elsevier B.V. All rights reserved.
properties (Filonchyk et al., 2019) and contrasted visibility (Wu et al., 2012; Han et al., 2012; Zhang et al., 2017).

Significant aerosol loading exhibiting diverse characteristics due to varying polluting sources, geographical position, topography, land-use, meteorological condition, population density, and socio-economic behaviour (Venkataraman et al., 2005; Tare et al., 2006; Nair et al., 2007; Dey and Tripathi, 2007; Srivastava et al., 2012a, 2012b; Pathak et al., 2015; Kumar et al., 2018; Sharma et al., 2021) along the Indo-Gangetic Plain (IGP) of India has gained global attention in discovering this region as a focal point of aerosol study for years. PM$_{2.5}$ concentration in the India IGP regions was reported to be ranging from 73.4 to 81.5 μg/m$^3$ (Dey et al., 2020) and is 22–35% higher than the National Ambient Air Quality Standards (60 μg/m$^3$) of India. IGP regions are dominated by a complex mixture of aerosols constituting anthropogenic sources (such as fossil fuel burning, industrial pollution, crop residue burning, biofuel cooking, etc.), mineral dust, and sea salt exhibiting seasonal variation in their loadings (Dey et al., 2004; Chin-nam et al., 2006; Srivastava et al., 2012b). IGP Regions is significantly influenced by coarse mode natural emissions by dust and sea salt aerosols mainly during pre-monsoon and monsoon, respectively, as a result of transportation facilitated by southwesterly winds from the neighbouring desert and sea regions augmenting to the local crustal emissions (Dey et al., 2004; Dey and Tripathi, 2007; Srivastava et al., 2012b). During post-monsoon and winters, the regions experience massive fine mode anthropogenic aerosol loadings at near-surface level majorly due to space heating, crop residue burning, vehicular pollution, etc. having larger retention time facilitated by the formation of inversion layer as the planetary boundary layer drops shallow due to lower solar insolation reaching the earth’s surface ceasing the vertical mixing of aerosols (Tripathi et al., 2005; Ramachandran et al., 2012; Kedia et al., 2014; Kumar et al., 2018; David et al., 2018).

From the context of the Indian sub-continent, remote sensing using multiple satellite sensors such as Moderate Resolution Imaging Spectroradiometer (MODIS), Multi-Angle imaging spectroradiometer (MISR), Sea-viewing Wide Field-of-View Sensor (SeaWiFS), POlarization and Directionality of the Earth’s Reflectance (POLDER), etc. is widely being used in monitoring AOD heterogeneity (Sarkar et al., 2005; Dey and Di Girolamo, 2010; Kaskaoutis et al., 2011; Ramachandran et al., 2012; Mehta, 2015; Mhawish et al., 2019) and has improved over the years in terms of spatial resolution and temporal coverage. Ground-based aerosol monitoring stations such as Aerosol Robotic Network (AERONET), Aerosol Radiative Forcing Over India Network (ARFINET), Skyradiometer Network (SKYNET), etc. being a contemporary monitoring approach used extensively (Dey and Tripathi, 2007; Beegum et al., 2008; Kaskaoutis et al., 2012; Srivastava et al., 2012a, 2012b; Babu et al., 2013; Ramachandran and Kedia, 2013; Pathak et al., 2015) has lower spatial coverage and limited station deployment generating a demand for expansion of ground-based aerosol monitoring station network facilitating remote sensing as an efficient approach to cater larger spatial extent. Satellite-derived AOD is widely utilized in assessing the ground level spatial PM$_{2.5}$ patterns using advanced machine learning algorithms (Mhawish et al., 2020; Dey et al., 2020) and sophisticated modelling approaches (Krishna et al., 2019; Lekinwala et al., 2020; Bali et al., 2021) for climate and epidemiology related studies. Meanwhile, to reduce uncertainties in satellite-derived AOD, improvements are required in terms of retrieval algorithm and underlying assumptions related to aerosol microphysical and optical properties (Kaufman et al., 1997; Levy et al., 2013; Babu et al., 2013).

IGP regions enduring highest aerosol loading over Indian sub-continent (Prasad et al., 2004; Ramachandran and Kedia, 2013), a study confined to states is envisaged to streamline policy interventions at regulatory levels for robust governance in reducing air pollution and other associated health impacts. Prioritizing this concept, a long-term aerosol trend over the entire State of Bihar and its 38 administrative districts located in the eastern part of India for 19 years (2001–2019) was studied. In addition to local sources of emission, Bihar State is geographically located at the receiving end of the pollution transport pathway subjected to massive aerosol loading. The novelty of the study is in its approach of using high resolution (1 × 1 Km$^2$) Multi-Angle Implementation of Atmospheric Correction (MAIAC) satellite data having larger spatial coverage and retrieval frequency over more complex geographical regions (Mhawish et al., 2019) for monitoring transition and distribution of AOD over Bihar, the 3rd largest state in IGP and 12th in the country. An attempt was made to quantify the variation in AOD based on the shift in land-use patterns from the year 2001–2015. Further, the overall change in AOD trend (Units/Year) was accessed using Thiel-sen’s slope method over the long term, seasonal and monthly variations in AOD over the study period. Time series analysis using Auto-Regressive Integrated Moving average (ARIMA) forecasting was employed to predict the future aerosol trends specific to individual districts. Since IGP regions are prone to the transboundary movement of pollutants (Begum et al., 2011; Kumar et al., 2015), Hybrid Single-Particle Lagrangian Integrated Transport (HYSPLIT) model was used to identify the monthly variation in the airsheds inhibiting potential sources of pollution. The study contemplates building cognizance among the policymakers in premature identification of districts that require immediate attention in terms of the state of the art abatement measures through robust clean air action plan frameworks followed by binding obligation towards its implementation.

2. Methodology

2.1. Study area description and background

Bihar State, with its 38 administrative districts, as shown in Fig. 1, constitutes a total area of 94,163 Km$^2$ and is located in the eastern part of India, accommodating a total population of 104 million (Census, 2011). The landlocked state is surrounded by Uttar Pradesh to its west, Jharkhand to its south, West Bengal to its east, and Nepal to its north. Agriculture is the major occupation of the state and accounts for 77.3% of the total land use, and with rural area share being prominent over urban (approximately six times the urban area) (https://bhuva-appl1.nsrc.gov.in/thematic/thematic/index.php), the consumption of clean cooking fuel in these areas are reported to be very low. As an alternative, the household relies on solid fuel for their livelihood activities ascertaining to be one of the major contributors to escalate air pollution levels in the State (Chowdhury et al., 2019; Purohit et al., 2019). Bihar being a part of IGP faces erratic behaviour in aerosol loading (Sarthi et al., 2019) and remained as the area of interest among researchers to explore the intuitions behind aerosol pooling over the regions (Di Girolamo et al., 2004; Kar et al., 2010; Kumar et al., 2018).

2.2. AOD retrieval and pre-processing

2.2.1. MAIAC AOD

Columnar aerosol features provided using MODIS sensors onboard TERRA and AQUA satellite are processed to retrieve AOD using three different algorithms, namely Dark Target (DT), Deep Blue (DB), and MAIAC. Among the three algorithms, MAIAC has been reported to have higher retrieval quality and accuracy with better spatial variability over various geographical types (Mhawish et al., 2019; Liu et al., 2019). The advanced MAIAC algorithm uses time series analysis to extensively characterize the surface and background aerosols in addition to the combination of pixel to image-based processing technique on MODIS collection 6 records. The algorithm introduced in the year 2011–2012 has evolved to globally adopt improved processing techniques on cloud/snow detection, aerosol retrieval, and atmospheric correction of MODIS data (Lyapustin et al., 2018). The details of the MAIAC processing algorithm are mentioned elsewhere (Lyapustin et al., 2018; Mhawish et al., 2019). In the current study, high resolution (1 × 1 Km$^2$) MAIAC AOD at 0.55 μm covering 19 years from January 2001–December 2019 was used for detailed analysis.
2.2.2. Data pre-processing

Monthly averaged MODIS AOD data were processed using Google earth engine (https://code.earthengine.google.co.in/) cloud platform. Data pre-processing of retrieved AOD data were instigated to maintain consistency in AOD data over the study area by handling missing data gaps formed due to seasonal variation in surface reflectance and aerosol properties (Mhawish et al., 2019) and normalizing the swath edge variation effect on the pixels (Dey et al., 2020). Chances of higher cloud coverage during monsoon significantly hindered the consistency in data retrieval (Fig. S1). The retrieval percentage dropped as low as 23% during monsoon, and a higher percentage of retrieval above 95% was observed for 80 percentile of monthly averaged AOD data during other seasons. Data gaps formed due to enormous cloud masking were filled using the nearest neighbour interpolation technique (Liu et al., 2019). Imputation using nearest-neighbour interpolation is efficient as it preserves the original data structure and substitutes the missing value with plausible value (Beretta and Santaniello, 2016). Savitzky-Golay smoothing technique was used to minimize swath edge variation. The technique was applied along the X-axis of the data matrix followed by the Y-axis, ensuring acceptable deviation between the original and smoothed value ($R^2 > 0.95; \text{RMSE} = 0.089$) (Table S1).

2.3. Influence of landuse pattern on AOD

Land-use types based on population density, pollution sources, and socio-economic behaviour exhibit a significant change in spatial pattern and distribution of AOD (Xie and Sun, 2021). Previous studies that assessed satellite derived PM$_{2.5}$ using AOD have established significant influence of land use/land cover on spatial variation in PM$_{2.5}$ concentration (Xie et al., 2015; Park et al., 2019; Mhawish et al., 2020; Zhang et al., 2021). The current study examines the influence of land use settlement upon AOD and its transition as a shift in settlement layer over the years was observed. Global Human Settlement Layer (GHSL) data package released by European Commission (EC) provides GHS – Population (GHS-POP), GHS- Built-Up (GHS-BUILT), and GHS-settlement Model (GHS-SMOD) gridded information at $1 \times 1 \text{Km}^2$ resolution for the years 1975, 1990, 2000 and 2015. GHS-POP uses extrapolated information from the gridded population of the world version 4.0 (GPW V4.10) disaggregated from population and housing census results that occurred between 2005 and 2014 (https://sedac.ciesin.columbia.edu/data_collection/gpw-v4) to delineate population size per grid (Corbane et al., 2019), whereas GHS-BUILT is classified using multi-temporal Landsat image collections (Freire et al., 2016). GHS-SMOD delineates and classifies settlements as urban, dense urban, semi-dense urban, rural, low density rural, very low density rural, and water bodies based on population size derived from GHS-POP and built-up density derived from GHS-BUILT. Criteria for spatial entities classification and schematic workflow algorithm for the model are detailed elsewhere (Florczyk et al., 2019).

2.4. Thiel-Sen’s slope trend analysis

Growing anthropogenic activities by virtue of rising population and with little to no policy measures on control aspects have increased the severity of aerosol loading in the IGP regions over the years (Sarkar et al., 2005; Prasad et al., 2006). Thiel- Sen’s slope analysis was carried out to study the overall annual trend in terms of long-term, seasonal and monthly variation in AOD values for the study period. Thiel- Sen’s slope, a non-parametric approach that uses the median of slopes estimated between all pairs of data points to assess the linear trend (Thiel 1950; Sen 1968). The method is efficient as it is insensitive to outliers yielding accurate confidence intervals for data with skewed behaviour and
heteroscedasticity (Wilcox, 2001). The analysis was carried out using the ‘openair’ Package in R (Carslaw and Ropkins, 2012). The package is endorsed with functions to handle autocorrelation and seasonality effect in the data that can account for larger uncertainties in trend estimates for a time series of atmospheric parameters (Kumar et al., 2018).

2.5. Time series forecasting using ARIMA

There exist very few studies on time series forecasting of AOD before being measured based on its past behaviour for IGP regions. Box-Jenkins Auto-Regressive Integrated Moving Average (ARIMA) (Box et al., 1994) model is the most commonly used forecasting approach (Soni et al., 2014, 2015; Taneja et al., 2016; Kumar et al., 2018) considering its ability to account for nonlinear dynamics within the time series data (Chelani and Devotta, 2006). The model uses a robust iterative and exploratory process for best fitting long-term observation via identification of stationary time series, estimation of order for ARIMA model, and diagnostic checking of model parameters to build an adequate time series model. The model indicating the lowest normalized Bayesian Information Criteria (BIC) with lagged residuals showing no autocorrelation with each other (i.e., white noise) is considered as the optimum. The accuracy of the model is verified using the Mean Percentage Error (MPE) between the predicted estimates and actual value. In the current study, Box-Jenkins ARIMA was used to forecast AOD for the Bihar State and its 38 administrative districts for the subsequent 24 months (i.e., January 2020 to December 2021). The forecasting was limited for a short-term duration as the model considers previous values to predict the future estimates. The uncertainty in time series forecasting estimates increases with a larger prediction duration as the model after a certain point of time continues with the previously forecasted estimate for prediction.

2.6. Air mass propagation using HYSPLIT back trajectory analysis

Five days (120 h) isentropic air mass back trajectory analysis was carried out at a height 1500 m at the centroid location (25.6790°N, 85.610°E) of the state as the receptor site using National Ocean and Atmospheric Administration – Air Resource Laboratory (NOAA ARL) Hybrid Single-Particle Lagrangian Integrated Transport model (HYSPLIT) (Draxler, 1999; Draxler and Hess, 1998; Stein et al., 2015) to map the Transboundary movement of atmospheric particulates. The model was simulated using Reanalysis meteorological data provided in the meteorology archives of NOAA Air resource laboratory (https://www.ready.noaa.gov/HYSPLIT.php). An elevated height at 850 hPa (=1500 m) was based on top of the Planetary Boundary Height (PBL) reported in the previous studies carried out for IGP and its disaggregated regions (Liu et al., 2018; Bharali et al., 2019; Vinjamuri et al., 2019; Singh et al., 2020). Singh et al. (2020) also reported heavy black carbon loading for IGP at higher elevation (850 hPa - 500 hPa), and to assess the potential air mass propagation, the opted trajectory height should be the ideal. Five days back trajectory was considered with a rationale to capture the desert dust sources of the northeastern regions and potential air mass direction for organic and elemental carbon aerosols as their approximate lifetime in the atmosphere is the same as the back trajectory hours considered in this study (Pan et al., 2013). To understand the transition in predominant directions of the pollutant being transported over the study period, a trajectory cluster analysis for the years 2001, 2005, 2010, 2015, and 2019 were studied. Euclidian distance method is employed in clustering the trajectories to outline the transport pathway of the pollutants by averaging the identical air mass pathways towards the receptor location (Sen et al., 2017).

3. Results and discussion

3.1. Spatial and temporal distribution of long term aerosol over the study region

The analysis interpreted aerosol loading of 0.58 ± 0.17 (mean ±1σ) over the State of Bihar and was comparatively higher than the average AOD for IGP (0.50 ± 0.25) and India (0.38 ± 0.12) as reported previously (Kumar et al., 2018; Mehta et al., 2016). The MODIS AOD data utilized in these previous IGP and regional levels studies vary both in terms of product quality and duration from the current study, and hence any conclusions upon direct comparison may have uncertainties. Fig. 2 shows the district-wise variation in AOD. The districts in the figure are arranged in ascending order of the mean AOD exhibited. District-wise population density and forest cover area (Km²) are shown in Table S2. The districts with natural forest cover and lower population density are conducive to exhibit minimal aerosol loading in the State. The forest cover increases the deposition rate of PM by accelerating the end flow in the surface-atmosphere (Yang et al., 2011; Zhao et al., 2013), whereas, low population results in restricted anthropogenic activities curtailing the overall emission of the pollutants. Despite owing to these favorable conditions, Districts Banka and Jamui exhibited relatively higher AOD (0.62), which possibly may be due to a) Uncertainties in processing swath tile edges by the retrieval algorithm; b) local sources such as dust resuspension from prevalent barren/uncultivable land in the region (https://bhuvan-app1.nrsc.gov.in/thematic/thematic/index.php), household pollution or significant regional contribution. Districts with higher population density exhibited larger aerosol values, which can largely be attributed to the escalating anthropogenic activities at a local scale. District Siwan, Saran, and Gopalganj anticipated as airflow corridors facilitating regional transport of pollutants were found exhibiting higher AOD value. High AOD value is evident over the northwestern and central regions of Bihar, commonly termed as ‘Bihar pollution pool’ (Di Girolamo et al., 2004; Kar et al., 2010) to the subsidence of northwesterly air mass inhibiting the vertical mixing of airborne pollutants favoring the accumulation of the particles (Dey and Di Girolamo, 2011; Kumar et al., 2018).

3.1.1. Long term aerosol trend – year wise

Fig. 3 depicts the comprehensive year-wise variation in AOD over Bihar State and its administrative district for the entire study period (2001–2019). Higher spatial AOD pixel (>0.7) was found to be dominant over the Bihar region after 2010 (Fig. 3(a)). Unrestricted emission from regional and local scales over the years might have exhausted the carrying capacity of the atmosphere, slowing down the rate of dispersion (Shaikh, 2010; Zhou and Zhou, 2017), resulting in massive aerosol loading over the region. Fig. 3(b) shows the gradual shift in AOD over the years towards the higher side with relatively higher value and is apparent that growing population with decadal growth of 25.4% reported for the year 2011 (Economic Survey 2019–20) and emissions from proliferated anthropogenic activities in sectors such as transportation, urbanisation, energy, waste generation, agriculture, industrialisation, residential etc. with no stringent statutory measure against its control at both regional and local levels as the potential for high AOD. The quantification of the growing sectorial activities in Bihar is explained elsewhere (Economic Survey 2019–20). AOD value for the entire State (Fig. 3(c)) ranged between 0.50 and 0.54 till the year 2010, after which a drastic increase up to 0.64 ± 0.05 was observed. Bihar having a larger share of the population residing in the rural region (>89% as per Census, 2011), is likely to use solid fuel for their deemed essentials. Households adopting clean fuel practices are at a moderate phase relative to the rising population has evolved the sector as one of the dominant source introducing enormous emissions conducive to both primary and secondary formation of.

Pollutants in the region (Upadhyay et al., 2018; Purohit et al., 2019; Jat and Gurjar, 2021). With more than 70% percentage of the population
in the state engaged in agriculture activities (Economic Survey 2019–20), a recent study by (Purohit et al., 2019) has reported higher Ammonia (NH₃) emissions predominant released from the agriculture and allied sector involving fertilizer application, manure management and livestock farming facilitating as a precursor in secondary PM₂.₅ formation. To have deeper intuition on contribution from the neighbouring states, the spatial variation in AOD over these regions was analyzed (Fig. S2). The dominance of long-range transport of pollutants was found to be prominent after 2011 and might be one of the leading reasons for a sharp increase in AOD thereafter. Further analysis superimposing the meteorological field is carried out in the subsequent section (section 3.5) before concluding. It is also evident that the improvement observed in the year 2016 (AOD: 0.6) can be largely attributed to ameliorated meteorological conditions inhibiting the interference of long-range transport of particles.

3.1.2. Long term aerosol trend – month-wise

Fig. 4 depicts the month-wise variation in AOD over the study region for the entire period of study. The spatial variation (Fig. 4(a)) shows higher AOD accumulation of the range 0.7–0.9 during January, June, November, and December months. The Western region of Bihar was found exhibiting lower AOD in comparison to other regions with substantial evidence that, In addition to the local anthropogenic and natural source emissions, transport of pollutants from neighbouring states contribute to massive aerosol loading. Histogram (Fig. 4(b)) interprets the change in dominant AOD values over the months. High AOD values (0.8–0.9) spreads across major regions of Bihar in January, with a reduction in subsequent months. Reduction observed further reverse in May (0.6–0.7), after which an apparent reduction in AOD (0.4–0.5) during subsequent months due to deposition favored by precipitation. Substantial upsurge thereafter the precipitation from October month resumed till the end of the year with prevalently high AOD (>0.7) over Bihar. Higher AOD (~0.9) observed at the beginning (January) and end of the years (November and December) (Fig. 4(c)) are attributable to the influence of poor meteorological conditions such as low temperature, low relative humidity (RH), anticyclonic circulation of wind, shallow Planetary Boundary Layer (PBL) and weak thermal convection obstructing the vertical mixing of the pollutants (Tripathi et al., 2005; Dey and Di Girolamo, 2011; Ramachandran et al., 2012). As the.

Meteorological conditions improve over the subsequent months (February, March, and April), AOD value decreased to the range 0.56–0.45. The hygroscopic growth of fine particles by absorbing water due to high RH alters the aerosol size, morphology, phase, reactivity and refractive index (Lee et al., 2008) characterising higher AOD in June. In the subsequent years (July, August, September), particles do not grow hygroscopically due to significant precipitation. The long-range transport of pollutants facilitated by northwesterly winds into the region is depicted for January, May, November, and December (Fig. S3), and the same was reported previously (Dey and Di Girolamo, 2011; Kedia et al., 2014; Mehta 2015; Sarthi et al., 2019). To substantiate this inference, prominent wind direction for each month at a higher altitude will be carried out in further sections. Rather than month-wise, a season-wise interpretation was conducted as a holistic approach to grasp the overall transition in pollution scenarios over the study region.

3.1.3. Long term aerosol trend – season-wise

As per Indian Meteorological Department (IMD) standards, the year was divided into four seasons, namely winter (January, February), pre-monsoon (March, April, May), Monsoon (June, July, August, September), and post-monsoon (October, November, December) (https://mausam.imd.gov.in/). Fig. 5 shows the variation in season-wise AOD over Bihar state. At the onset of monsoon, low rainfall and high RH prevail hygroscopic growth of particles capturing larger AOD value and observes reduction in subsequent months due to wet deposition and change in the origin of an air parcel. Massive aerosol loading of the range 0.7–1.1 during post-monsoon compared to other seasons followed by winter and pre-monsoon of the range 0.4–0.6 over prevalent regions of Bihar was observed. Higher AOD (>0.9) engulfing the neighbouring states of Bihar during post-monsoon was observed (Fig. S4). Kumar et al. (2018) in his study reported dominant fine particle (<0.5 µm) pollutants over Bihar during post-monsoon and winter. Kedia et al. (2014) reported more local air mass prevalent during post-monsoon translates to a conclusion that the local anthropogenic activities must be the reason for this peak. Additionally, advection from agricultural field burning in the northern region of IGP is also expected to contribute significantly to high aerosol content (Badarinath et al., 2009). Tare et al. (2006) reported that IGP regions experience disturbance from westerly wind, especially during winters, and the situation is intense while moving from west to east with dropping elevation, narrow topography, reduction in temperature and wind speed (Nair et al., 2007) prevailing haze and fog.

Formation contributing to high AOD. Indeed, this situation is prevalent during December and January and is well captured in Fig. S3. In contrast, Fig. S4 does not depict northwesterly transport during winter, probably due to a false combination of months prevailing the condition. During pre-monsoon, dust influx from southwesterly and northwesterly winds surpassing the Thar desert and Pakistan arid regions respectively.
were reported (Ramachandran and Kedia, 2010; Giles et al., 2011; Srivastava et al., 2012b; Sen et al., 2017). During pre-monsoon, the strong influence of desert dust and biomass burning from north mixed with local pollutants (Srivastava et al., 2012b; Pathak et al., 2015; Sen et al., 2017) fostered mixed aerosol type (Coarse + Fine) to be prevalent over Bihar (Kumar et al., 2018). In addition to natural emission sources, Bihar is bordered by densely populated states having dominant industrial pollution shares in addition to other anthropogenic activities endorsing significant contribution of various aerosol species such as mineral dust, organic, inorganic, and black carbon particles into Bihar landmass, thus making the region an aerosol hotspot (Jat and Gurjar, 2021).

3.2. AOD transition influenced by land use pattern

The transition in AOD as an influence of shift in land use pattern between 2001 and 2015 for Bihar state is depicted in Fig. 6(a). Very low-density rural area (VLDRA) and water area (WA) are classified as land with little to no human settlement (Florczyk et al., 2019), and throughout the analysis, AOD captured over VLDRA areas was considered background region accounting for natural dust and regional source loading. WA spreads across relatively smaller areas exhibited larger bias in misclassifying local and regional aerosol loading. WA (≈40 Km²) showed a higher AOD change of 58.9% might be due to natural suspension of silt or anthropogenic activities (such as crematorium rituals, diesel workboats plying). It is noteworthy that major roads are catering to heavy traffic ply close to the banks of the river, which tend to emit huge emissions evidently being captured in the 1 × 1 Km² WA pixel. Analysis showed an overall increase in AOD by 42 ± 2%, consistent with most of the land use pattern that has remained unchanged. Irrespective of the land use pattern, a consistent AOD of the range 0.48–0.50 and...
0.68–0.78 was prevalent over the years 2001 and 2015, respectively. This consistency could be largely attributed to the fact that the classified land use patterns are fragmented in small landholding across the Bihar state, unable to capture their influence on AOD due to the interference of local anthropogenic source from the neighbouring pixel of different class augmented by regional transport in altering the physicochemical properties of aerosols. Fine to medium textured fertile Gangetic alluvium soil is predominant over the Bihar region (ENVIS, 2014) and is most likely to contribute to aerosol loading via dust resuspension directed by moderate to high wind speed and human-influenced agricultural activities. The shift in VLDRA (mostly agricultural land in this case) to any other land use pattern showed a relatively low percentage increase in AOD (38%) which possibly can be attributed to suppression of soil dust due to concretization for human settlement. Analysis depicted massive contribution of regional aerosols from neighbouring states for the year 2015 compared to 2001 in Fig. 3. It is evident from high background loading that besides local anthropogenic sources, regional source contribution significantly influences the AOD in Bihar, which is consistent with the previous study (Purohit et al., 2019). Overall urbanization for Bihar in the year was reported to be 11.3% which is low compared to its neighbouring states such as Uttar Pradesh (22.28%), Jharkhand (24.05%), and West Bengal (31.89%) (Census, 2011). Bihar observed an increase of 8.03% in urbanization for the year 2011 over 2001 inducing a strong instinct about the rural sector to be the major anthropogenic source of emission in the state. In urban regions, 62% of households were reported to be using solid fuel for cooking for the year 2015–16 (NFHS-4), which indeed can have a significant contribution to emission along with other conventional urban sources. It was observed that the criteria used by G-SMOD in classifying the land use (urban and rural) are different from the one used by India during the Census, 2011. Misclassifications among the rural and urban patterns were identified in comparison with the land use/landcover (LU-LC) dataset provided by Bhuvan thematic services (https://bhuvan-app1.nrsc.gov.in/thematic/thematic/index.php), which might be due to difference in spatial
resolution (G-SMOD: 1 Km; Bhuvan: 23.5 m) at which land use patterns are portrayed, thereby limiting the clarity in interpreting their influence on AOD. The district-specific influence of land use patterns over AOD is portrayed in Fig. S5. An increase in mean AOD for Bihar by over 50% for the year 2015 compared to 2001 (Fig. 6(b)) was observed for district Arwal (51%), Begusarai (54%), Bhojpur (55.6%), Buxar (53.3%), Gaya (53.8%), Jahanabad (55.8%), Khagaria (65.17%), Lakhisarai (65.7%), Munger (56.3%), Nalanda (54.2%), Nawada (50.5%), Patna (53.5%), Saharsa (52.9%), Samastipur (53.9%), Saran (51.10%), and Sheikpura (60.4%). Pronounced reduction in AOD over regions situated at northeastern (Paschim Champaran), southwestern (Kaimur, Rhotas), and southeastern (Jamui, Banka) part of Bihar due to substantial forest covers. Incidents of forest fires in the areas of Munger and fringes bordering Jharkhand (Fig. S6) might not have influenced the overall reduction in AOD. An overall increase in AOD over 50% for the year 2019 compared to 2001 (Fig. 6(b)) was observed for district Begusarai (52.1%), Bhagalpur (53.1%), Khagaria (55.7%), Patna (52.4%) and Samastipur (51.1%). Solid fuel cooking prominent in larger rural shares of district Samastipur and Khagaria, and rapid urbanization in district Patna, Begusarai, and Bhagalpur, which allegedly accounts for 31% of the urban population share in the State (Census, 2011), might be a reason for higher AOD value. Fig. 6(b) and (c) clearly depicts a larger accumulation of AOD along the stretch of river Ganga (Ganga stretch over Bihar is shown in Fig. S7), which can be attributed to both natural (fine silt suspension) and anthropogenic sources (construction activities, open crematorium, mining and agricultural activities, plying of diesel operated boats in the river, road transport along the stretches, etc.) prominent over the region. Significant spatial improvement in AOD was observed for districts of Bihar during the year 2019 compared to 2015, which might be due to the larger penetration of clean cooking fuel both at urban (78.6%) and rural (30.3%) sectors (NFHS-5) of the state. Besides the spatial improvement, a smaller decrease in average AOD by 5.5% over Bihar during 2019 compared to 2015, which in turn emphasizes the need for strengthening the strategies to ameliorate air quality in the State.

3.3. Trend analysis

An overall long-term (de-seasonalised) and seasonal change in AOD trend (increasing or decreasing) with a subsequent annual rate of change for Bihar are shown in Fig. 7. A statistically significant (p < 0.001)
increase in long term AOD (0.0106 year \(^{-1}\)) was observed for the Bihar state and is considerably higher than that of trend reported for the entire IGP (0.002 year \(^{-1}\)) by (Kumar et al., 2018) for the period 2006–2015, India (0.005 year \(^{-1}\)) by (Streets et al., 2009) for period 1980–2006 and northern India (0.007 year \(^{-1}\)) by (Moorthy et al., 2013) for period 2001–2011. The inconsistency with the previous studies can be attributed to the difference in the statistical method employed for computation, period and frequency of analysis, satellite type, and its spatial resolution, and geographical extent of observation (Kumar et al., 2018). A significant increase in seasonal AOD for winter (0.0157 year \(^{-1}\)), pre-monsoon (0.0072 year \(^{-1}\)), monsoon (0.0079 year \(^{-1}\)) and post-monsoon (0.0182 year \(^{-1}\)) were computed. Long-term, winter, and post-monsoon computed values were found consistent within the trend range of 0.01–0.04 year \(^{-1}\) predicted on a seasonal basis over the India sub-continent for the period 2001–2010 (Dey and Di Girolamo, 2011). A significantly higher annual AOD rate was observed over Bihar for post-monsoon and winter seasons due to increasing anthropogenic emissions being trapped in subsiding air facilitated by the pollution transported by northwesterly winds. On the other hand, it was otherwise during pre-monsoon and monsoon seasons due to spatial heterogeneity in dust transport and precipitation (Dey and Di Girolamo, 2016; Dey and Di Girolamo, 2011; Ramachandran et al., 2012; Pandey et al., 2017). Districts of Bihar exhibited a statistically significant increase in annual AOD trend for long term (0.0069–0.0014 year \(^{-1}\)), winter (0.0077–0.0206 year \(^{-1}\)), pre-monsoon (0.0016–0.0157 year \(^{-1}\)), Monsoon (0.0004–0.0153 year \(^{-1}\)) and post-Monsoon (0.0077–0.0242 year \(^{-1}\)) with few being exceptions. The same are detailed in Table 1. Begusarai and Kaimur showed the highest and lowest increase in long-term annual AOD rates, respectively. Considering the heterogeneous source characteristics of each district, an unsupervised classification to group the districts that exhibited similar computed annual trend patterns for long-term and seasonal AOD was conducted (Fig. S8). Among the 2 clusters computed, the cluster-1 with the highest number of districts (24) exhibiting a higher AOD value than the cluster-2 is indicated in Table 1. There exists a possibility that the cluster-1 districts are located along the airshed pathway of northwesterly winds (Further analyzed in section 3.5) and are frequently subjected to regional transport of pollutants from neighbouring states and districts along with local emissions from natural and anthropogenic sources. Interestingly, it was also interpreted that most of the districts along the Ganga river stretch are grouped under cluster-1, which is in agreement with Fig. 6(b) and (c) depicting larger aerosols content over the stipulated region. Some part
of Bihar has witnessed an active shift of river Ganga from its original position (Kumar et al., 2014), leaving behind massive fine silt content with a likely potential to re-suspend even at low wind speeds. However, there exists a need for a finer level of scrutiny along the Ganga river stretch to ascertain the predominant sources of emission for better management of air quality in the State.

3.4. Time series analysis and forecasting

Time series forecasting for the years 2020 and 2021 based on observed monthly mean AOD from 2001 to 2019 using the ARIMA model for Bihar state is depicted in Fig. 8. An annual average of 0.67 (95%CI: 0.42–0.92) and 0.68 (95%CI: 0.42–0.94) for the years 2020 and 2021, respectively, were computed. The selected model accuracy was found moderate while assessing goodness of fit measures such as R-Squared ($R^2$: 0.47), Root Mean Square Error (RMSE: 0.12), Mean Absolute Percentage Error (MAPE: 16.34). The further details of the model are depicted in Fig. S9. The moderate performance of the model can be attributed to the heterogeneous culture of the IGP regions in terms of aerosol mass loading due to dynamic source emission and meteorological conditions (Kumar et al., 2018). Alternatively, spatial inconsistency exhibited by the MODIS AOD retrieval algorithm can also be a possible reason hindering model performance. The year 2020 and 2021 was anomalous due to the Coronavirus Disease (COVID-19) pandemic induced lockdown restricting major anthropogenic activities across the country thereby improving the air quality (Bherwani et al., 2020, 2021).

It was pronounced to underperform the predictions as this was a peculiar condition limited to forecasting years because of which it was not accounted for in the model training sessions. However, the model was anticipated to perform satisfactorily under Business As Usual (BAU) scenarios. It is envisaged that improvement in air quality under COVID-19 imposed lockdown are short-lived and are likely to reverse under BAU scenarios; and hence any policy framework and decisions must be articulated at BAU scenarios for optimistic outcomes.

Table 2 shows the forecasted AOD value for 38 districts of the Bihar state, which range from 0.57 to 0.77 and 0.58–0.78 for the year 2020 and 2021 respectively, with an overall low to moderate range of fit measure ($R^2$: 0.25–0.65) being exhibited by all the simulated models. Further details of the model and its overall fit assessments are shown in Table S3. Almost all the districts grouped under cluster-1 (Table 1) exhibited higher AOD, with an increase ranging up to 14.8% (2020) and 16.9% (2021) than that for the entire state. The percentage change in AOD from the year 2019 was of the range $6.0\% - 3.79\%$ and $3.5\% - 5.12\%$ for the forecasted years 2020 and 2021, respectively. The percentage change in AOD between 2020 and 2021 ranged from $2.0\% - 2.6\%$. Bihar state showed an agreeable correlation (r: 0.5) between the forecasted values and satellite retrieved AOD for the year 2020 (Detailed in Table S4). Districts exhibited a varying correlation value (r: 0.06–0.87) of which a total of 18 districts exhibited agreeable conditions (r > 0.5) and 13 districts with moderately agreeable conditions (r: 0.3–0.5). A highly agreeable correlation (r > 0.7) was observed for February, March, May, October, November, and December. Correlation of (r: 0.59) was
observed in April attributable to temporary improvement due to COVID-19 imposed lockdowns. The low correlation value ($r < 0.5$) during the month of monsoon can be attributable to heterogeneous patterns of precipitation in the state. Albeit a marginal change in the overall forecasted AOD between 2020 and 2021 exhibited by the state in conjunction with the significant change evident among a few of the districts for the forecasted year, the policymakers are recommended to adopt statewide strategical measures in conjunction with neighbouring states to address the emission sources to ameliorate the quality of air in the state as well the entire eastern IGP belt.

### Table 1

<table>
<thead>
<tr>
<th>District</th>
<th>Long term</th>
<th>Winter</th>
<th>Pre-Monsoon</th>
<th>Monsoon</th>
<th>Post-Monsoon</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arariya</td>
<td>0.0095***</td>
<td>0.0108*</td>
<td>0.0149***</td>
<td>0.0012</td>
<td>0.01*</td>
</tr>
<tr>
<td>Arwal</td>
<td>0.009***</td>
<td>0.0113*</td>
<td>0.0057</td>
<td>0.0049*</td>
<td>0.0166**</td>
</tr>
<tr>
<td>Aurangabad</td>
<td>0.0081***</td>
<td>0.0089***</td>
<td>0.0022</td>
<td>0.0068*</td>
<td>0.0131***</td>
</tr>
<tr>
<td>Banka1</td>
<td>0.0117***</td>
<td>0.0135***</td>
<td>0.0069+</td>
<td>0.0114*</td>
<td>0.0171***</td>
</tr>
<tr>
<td>Begusarai</td>
<td>0.0142***</td>
<td>0.0185***</td>
<td>0.0088+</td>
<td>0.0122**</td>
<td>0.0243***</td>
</tr>
<tr>
<td>Bhabua</td>
<td>0.0069***</td>
<td>0.0091***</td>
<td>0.0017</td>
<td>0.0064+</td>
<td>0.0153***</td>
</tr>
<tr>
<td>Bhagalpur</td>
<td>0.0129***</td>
<td>0.0167***</td>
<td>0.0082*</td>
<td>0.0094*</td>
<td>0.0211***</td>
</tr>
<tr>
<td>Bhojpur</td>
<td>0.0111***</td>
<td>0.014***</td>
<td>0.0051</td>
<td>0.0096*</td>
<td>0.0186***</td>
</tr>
<tr>
<td>Boxur1</td>
<td>0.0098***</td>
<td>0.0119***</td>
<td>0.0034</td>
<td>0.0093*</td>
<td>0.0165***</td>
</tr>
<tr>
<td>Darbhanga</td>
<td>0.0107***</td>
<td>0.015***</td>
<td>0.0078***</td>
<td>0.0051</td>
<td>0.0177***</td>
</tr>
<tr>
<td>Gaya</td>
<td>0.0089***</td>
<td>0.0094***</td>
<td>0.0023</td>
<td>0.0094*</td>
<td>0.0156***</td>
</tr>
<tr>
<td>Gopalganj</td>
<td>0.0103***</td>
<td>0.0166+</td>
<td>0.0074***</td>
<td>0.0084***</td>
<td>0.018***</td>
</tr>
<tr>
<td>Jahanabad</td>
<td>0.01***</td>
<td>0.043***</td>
<td>0.0046</td>
<td>0.0089*</td>
<td>0.0176***</td>
</tr>
<tr>
<td>Jamui1</td>
<td>0.0109***</td>
<td>0.0131***</td>
<td>0.0046</td>
<td>0.0121***</td>
<td>0.0174***</td>
</tr>
<tr>
<td>Katihar</td>
<td>0.012***</td>
<td>0.0184***</td>
<td>0.0141***</td>
<td>0.0086*</td>
<td>0.0164***</td>
</tr>
<tr>
<td>Khagaria1</td>
<td>0.0126***</td>
<td>0.0173***</td>
<td>0.0086*</td>
<td>0.0099*</td>
<td>0.023***</td>
</tr>
<tr>
<td>Kishanganj</td>
<td>0.0089***</td>
<td>0.0096</td>
<td>0.0158***</td>
<td>0.0015</td>
<td>0.0078*</td>
</tr>
<tr>
<td>Lakhisarai</td>
<td>0.0105***</td>
<td>0.0169***</td>
<td>0.005+</td>
<td>0.0067*</td>
<td>0.0203***</td>
</tr>
<tr>
<td>Madhepura1</td>
<td>0.013***</td>
<td>0.0168**</td>
<td>0.0115***</td>
<td>0.0063*</td>
<td>0.0167***</td>
</tr>
<tr>
<td>Madhubani</td>
<td>0.0093***</td>
<td>0.0126</td>
<td>0.0087***</td>
<td>0.0062+</td>
<td>0.0128**</td>
</tr>
<tr>
<td>Munger2</td>
<td>0.0115***</td>
<td>0.014***</td>
<td>0.0064*</td>
<td>0.009*</td>
<td>0.021***</td>
</tr>
<tr>
<td>Muzaffarpur1</td>
<td>0.0094***</td>
<td>0.0184*</td>
<td>0.007+</td>
<td>0.0069+</td>
<td>0.0192***</td>
</tr>
<tr>
<td>Nalanda2</td>
<td>0.0107***</td>
<td>0.0171***</td>
<td>0.0046+</td>
<td>0.0094*</td>
<td>0.0204***</td>
</tr>
<tr>
<td>Nawada</td>
<td>0.0121***</td>
<td>0.014***</td>
<td>0.0054</td>
<td>0.0124***</td>
<td>0.0213***</td>
</tr>
<tr>
<td>Panchchim Champanar</td>
<td>0.0087***</td>
<td>0.0078</td>
<td>0.03***</td>
<td>0.0035</td>
<td>0.012***</td>
</tr>
<tr>
<td>Patna1</td>
<td>0.0119***</td>
<td>0.0165**</td>
<td>0.006+</td>
<td>0.0111**</td>
<td>0.0232***</td>
</tr>
<tr>
<td>Purbi Champaran</td>
<td>0.0088***</td>
<td>0.0095*</td>
<td>0.0064***</td>
<td>0.005</td>
<td>0.0166***</td>
</tr>
<tr>
<td>Purnia</td>
<td>0.0105***</td>
<td>0.0149***</td>
<td>0.0132***</td>
<td>0.003</td>
<td>0.0138***</td>
</tr>
<tr>
<td>Rohtas</td>
<td>0.0075***</td>
<td>0.0091***</td>
<td>0.0017</td>
<td>0.0072*</td>
<td>0.0152***</td>
</tr>
<tr>
<td>Saran2</td>
<td>0.0113***</td>
<td>0.0172***</td>
<td>0.0099***</td>
<td>0.0083+</td>
<td>0.0182***</td>
</tr>
<tr>
<td>Samastipur1</td>
<td>0.0124***</td>
<td>0.0158*</td>
<td>0.0077+</td>
<td>0.008***</td>
<td>0.0229***</td>
</tr>
<tr>
<td>Saran1</td>
<td>0.013***</td>
<td>0.0178***</td>
<td>0.0065*</td>
<td>0.0065+</td>
<td>0.0204***</td>
</tr>
<tr>
<td>Sheikhpura1</td>
<td>0.0094***</td>
<td>0.0168***</td>
<td>0.0043</td>
<td>0.0065+</td>
<td>0.0187***</td>
</tr>
<tr>
<td>Sheohar</td>
<td>0.009***</td>
<td>0.013***</td>
<td>0.007***</td>
<td>0.0031</td>
<td>0.0192***</td>
</tr>
<tr>
<td>Sitamarhi</td>
<td>0.008***</td>
<td>0.0106**</td>
<td>0.0082***</td>
<td>0.0004</td>
<td>0.0148***</td>
</tr>
<tr>
<td>Siwan1</td>
<td>0.0113***</td>
<td>0.0207**</td>
<td>0.0045</td>
<td>0.0107*</td>
<td>0.0181***</td>
</tr>
<tr>
<td>Supaul</td>
<td>0.0107***</td>
<td>0.0117*</td>
<td>0.0124***</td>
<td>0.007+</td>
<td>0.0144**</td>
</tr>
<tr>
<td>Vaishali1</td>
<td>0.0115***</td>
<td>0.0148*</td>
<td>0.0076*</td>
<td>0.0114**</td>
<td>0.0242***</td>
</tr>
</tbody>
</table>

Fig. 8. ARIMA time series forecasting of MODIS AOD$_{0.55\mu m}$ for the Bihar State. The solid blue indicates the original MODIS AOD$_{0.55\mu m}$ value. The red solid and dotted line indicates the forecasted and 95% confidence interval limit, respectively.
Table 2
District wise ARIMA time series forecast for the year 2020 and 2021. The value within parenthesis indicates 95% confidence intervals (CI). The districts with $R^2 \geq 0.5$ are indicated as ($^1$), 0.35 $< R^2 < 0.5$ are indicated as ($^2$).

<table>
<thead>
<tr>
<th>Districts</th>
<th>2020</th>
<th>2021</th>
<th>Change in AOD between 2019 &amp; 2020 (%)</th>
<th>Change in AOD between 2019 &amp; 2021 (%)</th>
<th>Change in AOD between 2020 &amp; 2021 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arariya</td>
<td>0.627</td>
<td>0.615</td>
<td>1.25</td>
<td>−0.75</td>
<td>−1.97</td>
</tr>
<tr>
<td>Buxar</td>
<td>0.671</td>
<td>0.686</td>
<td>−3.30</td>
<td>−1.98</td>
<td>1.37</td>
</tr>
<tr>
<td>Jahanabad</td>
<td>0.665</td>
<td>0.664</td>
<td>2.82</td>
<td>1.43</td>
<td>−1.36</td>
</tr>
<tr>
<td>Patna</td>
<td>0.689</td>
<td>0.688</td>
<td>3.44</td>
<td>1.87</td>
<td>−1.52</td>
</tr>
<tr>
<td>Sheohar</td>
<td>0.667</td>
<td>0.656</td>
<td>−2.26</td>
<td>−0.66</td>
<td>1.64</td>
</tr>
<tr>
<td>Sitamarhi</td>
<td>0.721</td>
<td>0.73 [0.44:1.02]</td>
<td>2.76</td>
<td>4.01</td>
<td>1.22</td>
</tr>
<tr>
<td>Siwan</td>
<td>0.732</td>
<td>0.739</td>
<td>−1.99</td>
<td>−1.05</td>
<td>0.96</td>
</tr>
</tbody>
</table>

(continued on next page)
shown in Fig. 9. The receptor location is located at Samastipur district of Bihar and is the centroid location of the state. Fig. 9(a) clearly depicts the spatial pattern depicted in Fig. S4 for the winter season. During the monsoon (JJAS), a shift in air mass trajectory position from northwesterly region to southwesterly regions was observed. The southwesterly air mass originated from the Arabian Sea traverse over the Indian landmass advancing towards the Bengal Sea (Bay of Bengal) before reaching the receptor location. Post-monsoon (OND) season exhibited similar characteristics as that of the winter season, with upper (10–25%) and central (>25%) IGP being the predominant air mass regions. However, it is also evident from the air mass trajectory frequency (Fig. 9(a)) that the state, along with regional transport, experiences significant contribution from within state local areas.

Fig. 9(b) shows the Euclidian clustering of air mass trajectories (computed four clusters) for the years 2001, 2005, 2010, 2015, and 2019. All the analyzed years exhibited more or less similar trajectory patterns, with northwesterly being the predominant wind direction accounting for more than 50% of air mass origins. Within the northwesterly direction, two sub-air masses originating from the India-Pakistan border and Middle Eastern countries were computed. The former was found to be dominant (40–43%) than the latter (9–17.5%), advancing as the major airshed of the state. The year 2010 showed slight variation in air mass originating from northwesterly direction computing three sets of air mass trajectory clusters originating from the same direction. The dominant air mass cluster from northwesterly direction passes through the densely populated states of Punjab, Haryana, Delhi (Union Territory), and Uttar Pradesh, significantly being influenced by their distinct local sources of pollution (crop residue burning, on-road transport, construction, and road dust resuspension, industrial combustion and process, household emissions, power generation, etc.) (Purohit et al., 2019; Ganguly et al., 2020) before arriving at the receptor location. Contemporarily, southwestern was found to be the next dominant direction accounting for 10–36% of air mass origins. Despite air mass was found traversing over some of the polluted stretches of landmass (such as coal beneficiary regions of Jharkhand, Industrial regions of Maharashtra, Gujarat, and West Bengal in addition to the contribution from other local anthropogenic sources of emission) (Guptikunda et al., 2019), Air mass was reported to be cleaner due to suppression of particles contingent upon wet deposition (Arif et al., 2017).

### 3.5. HYSPLIT back trajectory analysis

120 h back trajectory computed at receptor location of Bihar state is shown in Fig. 9. The receptor location is located at Samastipur district of Bihar and is the centroid location of the state. Fig. 9(a) clearly depicts northwesterly as a prominent wind direction with a high frequency of air mass during the months of winter, pre-monsoon, and post-monsoon season and are consistent with the previous studies for IGP regions (Arif et al., 2017; Kumar et al., 2018; Devi et al., 2020; Kumar et al., 2020). During Winter (JF), air mass was found concentrated in the northern (10–25%) and central regions (>25%) of IGP while traversing over some of the most polluted rural, urban and industrial stretches facilitating advection of regional pollutants. This is also in alignment with the spatial pattern depicted in Fig. S4 for the winter season. During pre-monsoon (MAM), air mass (>25%) was found traversing closer to the semi-arid regions of the Thar desert. Due to significantly low concurrence of air mass (<10%) over these regions, transportation of desert dust toward eastern IGP is lower compared to upper and central IGP regions (Kumar et al., 2018). Besides, significant transport was also observed from northern and central IGP regions during pre-monsoon. During the monsoon (JJAS), a shift in air mass trajectory position from northwesterly region to southwesterly regions was observed. The southwesterly air mass originated from the Arabian Sea traverse over the Indian landmass advancing towards the Bengal Sea (Bay of Bengal) before reaching the receptor location. Post-monsoon (OND) season exhibited similar characteristics as that of the winter season, with upper (10–25%) and central (>25%) IGP to be the predominant air mass regions. However, it is also evident from the air mass trajectory frequency (Fig. 9(a)) that the state, along with regional transport, experiences significant contribution from within state local areas.  

### Conclusion

The current study presents the results of Spatio-temporal variation in MODIS AOD<sub>0.55µm</sub> over Bihar state and its 38 administrative districts for the period 2001–2019. The key highlights of the study are:

1. A significant increase in AOD over the long term was observed throughout the study area. A minor improvement was observed since 2015, which might be due to escalating penetration of clean cooking fuel in Bihar and its neighbouring states. Enforcement of Bharat
Stage IV (BS-IV) emission norms in the transport sector may also have significantly contributed to the improvement.

2. Urban, rural and regional area sources have a significant influence on overall Bihar AOD and were found contingent upon population shares specific to land use patterns. The regions with substantial forest cover area revealed lower AOD values provided, a lower number of forest burning incidences were recorded besides the minor influence from the transboundary movement of pollutants. The districts situated along the Ganga river stretch exhibited higher AOD difference (2001–2019) as it is influenced by both local and anthropogenic sources. Additional these densely populated districts also fall within the major airshed receiving a significant contribution of pollution transported by northwesterly air masses.

3. A significant increase in the long-term and seasonal AOD trend was observed for Bihar State. The districts exhibited an increasing trend in AOD with varying significance levels. A total of 24 districts were grouped as a cluster exhibiting high AOD trend scenarios, among which Sitamarhi was situated along the stretch of river Ganga.

4. ARIMA forecasting of AOD under BAU exhibited moderate model performance for Bihar and its administrative district. Such simulations can be handy under the absence of robust ground-based measurements to facilitate the policymakers in prioritizing the districts from the context of integrating sustainable strategies well in advance to control pollution levels.

5. HYSSPLIT back trajectory depicted air mass originating from northern westerly and south westerly to be predominant. The directions remained more or less consistent throughout the study. Air mass from northwesterly is likely to traverse over the extremely polluted stretches picking up natural and local emissions towards Bihar. Conversely, air mass originating from southwesterly apparently during monsoon is cleaner due to deposition of particles contingent upon precipitation.

The overall satellite-based study suggests the need for abatement strategies to control both local and regional sources of emissions in the State. Besides the spatial heterogeneity and uncertainties being an integral part of any satellite retrievals, it is also vital to consider the complex and dynamic nature of aerosols which emphasizes the need for further investigation at the ground level to distinguish the source-specific contribution in building legislative and technology-driven strategies for clean air. Taking into account the massive state area and underlying challenges of implementing statewide abatement measures, it is anticipated that utilization of such satellite-based findings to prioritize the areas to instigate district-specific actions for tangible air quality improvement can be the way forward.

Credit author statement

Nair MM: all aspects except supervision, funding acquisition and project administration. S Dey: all aspects except formal analysis. H Bherwani: methodology, review and editing. AK Ghost: review and editing.

Data availability statement

All data generated or analyzed during this study are included in this published article and its Supplementary Information files. The corresponding codes generated during and/or analyzed during the current study are available in the Long-Term-AOD-analysis repository, https://github.com/moorthyNair/Long-Term-AOD-analysis.git.

Declaration of competing interest

We declare no competing interest.

Acknowledgment

The present submission is supported by Bihar State Pollution Control Board (BSPCB), Patna. The authors acknowledge NASA for MODIS aerosol product, European Commission for Global Human Settlement Layer dataset, and NOAA-ARI for HYSSPLIT model. The authors acknowledge Google Earth Engine platform, Python and R open access software packages. SD acknowledges IIT Delhi for the Institute Chair position.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apr.2021.101259.

References


