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Propagation of cloud base to higher levels during Covid-19-Lockdown

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HIGHLIGHTS
• Effect of polluted-to-clean conditions on cloud base height with synoptic conditions unaltered
• Drop in pollutants continuing for a period resulted in upward shift of cloud base.
• Use of ceilometer for cloud base height and assessment of CCN
• Significant negative correlation between cloud base height and CCN, precursor gases

GRAPHICAL ABSTRACT

AEROSOL-CLoud Interactions and feedbacks play an important role in modulating cloud development, microphysical and optical properties thus enhancing or reducing precipitation over polluted/pristine regions. The lockdown enforced on account of Covid-19 pandemic is a unique opportunity to verify the influence of drastic reduction in aerosols on cloud development and its vertical distribution embedded in identical synoptic conditions. Cloud bases measured by ceilometer in Delhi, the capital of India, are observed to propagate from low level to higher levels as the lockdown progresses. It is explained in terms of trends in temporal variation of cloud condensation nuclei (CCN) and precursor gases to secondary hygroscopic aerosols. The large reduction (47%) in CCN estimated from aerosol extinction coefficient during the lockdown results in upward shift of cloud bases. Low clouds with bases located below 3 km are found to have reduced significantly from 63% (of total clouds distributed in the vertical) during pre-lockdown to 12% in lockdown period (less polluted). Cloud base height is found to have an inverse correlation with CCN ($r = -0.64$) and NO$_2$/NH$_3$ concentrations ($r = -0.7$). The role of meteorology and CCN in modulating the cloud vertical profiles is discussed in terms of anomalies of various controlling factors like lifting condensation level (LCL), precipitable water content (PWC) and mixing layer height (MLH).

1. Introduction

Aerosols affect weather and climate in several ways through various mechanisms, the basic among them is through scattering and absorption of solar radiation leading to reduction in insolation of the ground and modification of surface energy budget (Latha et al., 2019, 2018; Murthy et al., 2014; Urankar et al., 2012). The vertical distribution of clouds depend on surface air temperature and moisture content, atmospheric pressure, condensation nuclei (aerosols), their hygroscopicity as well as size distribution. Spatial heterogeneity of Land use land cover (LULC) and mesoscale weather systems also influence altitudinal
variation of clouds (Stull, 1988). CloudSat observations indicate that altocumulus clouds (mean height 5.5 km) preferentially occur over Indian land region during the summer monsoon (Subrahmanya and Kumar, 2013). During pre-monsoon months (April and May) low level clouds obtained from MODIS (Moderate Resolution Imaging Spectroradiometer) are found to be higher in number and middle and higher level clouds over Kolkata (Chakravarty et al., 2013). Cloud base heights can be measured by ground based active remote sensing systems like lidar, ceilometer, etc. while space borne active or passive sensors can detect cloud tops as well as bases.

Absorbing aerosols like black carbon increases the air temperature and alter the instability and convection (Manoj et al., 2011). Aerosols act as cloud condensation nuclei (CCN) and affect microphysical properties of clouds and modify cloud albedo, life time (Kauffman and Nakajima, 1993; Twomey, 1977), warm rain initiation and precipitation (Albrecht, 1989; Rosenfeld, 2000; Rosenfeld et al., 2008). Polluted environment with high amount of aerosols suppress warm rain, invigorate convection, enhance ice nuclei formation and increase total precipitation (Tao et al., 2012). Tornadoes are observed to evade weekends due to reduction in aerosol concentration (Rosenfeld and Bell, 2011). Convective invigoration depends also on absorbing aerosols like soot particles which heats up the aerosol-laden atmosphere and cools the surface, thus increasing the static stability causing reduction of surface evaporation leading to less moisture content inhibiting cloud formation. Cloud top height and cloud fraction over the Amazon during the dry season is observed to increase with aerosol optical depth initially and then decrease with further increase in optical depth (Koren et al., 2008) indicating that invigoration can be offset by absorbing aerosols.

Emissions from pollution sources especially vehicles and industries have reduced drastically during the implementation of lockdown 1.0 due to Covid19 pandemic in India. As a result air quality has improved significantly due to associated reductions in air pollutant (particulate matter and trace gases) concentrations (Mahato et al., 2020). Many studies have reported the percentage drop in pollutant concentrations due to Covid-19 pandemic and their variability pan India and the world (Otmani et al., 2020; Sicard et al., 2020). Since particulate matter (aerosols) are a proxy for CCN, any reduction in aerosol concentration is expected to affect not only surface solar radiation and air temperature but also CCN-dependent cloud microphysical properties like cloud drop number, size and chemical composition (Dusek et al., 2006; Farmer et al., 2015).

Routine concurrent measurements of cloud profiles, particulate matter and trace gases along with meteorological parameters in the megalopolis Delhi have given us an opportunity to study the implications of lockdown-induced reduction in aerosols and trace gases on cloud profiles in comparison to the pre-lockdown period. The objective of this study is to understand the changes in cloud base heights and their vertical distribution during the lockdown 1.0 from the perspective of the controlling parameters like PM2.5, PM10, precursors to secondary aerosols, CCN, aerosol extinction coefficient, lifting condensation level (LCL), and mixing layer height.

2. Location, data and analysis

The Indian Government has imposed Covid-19-Lockdown phase 1.0 from March 25 to April 14, 2020 as an initial attempt to decelerate the spread of pandemic. Particulate matter (PM) levels in Delhi often rise to high values leading to severe air quality in winter due to trapping of local and transported pollutants and sometimes in summer due to dust storms. The emission inventories for Delhi report vehicular and industrial emissions as the major anthropogenic sources (Beig et al., 2018; Guttkunda and Calori, 2013) which have been severely curtailed during the lockdown period.

Aerosol back scatter profiles and cloud base heights (CBH) are being measured routinely by ceilometer (Vaisala, CL51) in Delhi along with SAFAR network where PM2.5, PM10, NO2, NH3, UV radiation, wind speed, direction, air temperature and relative humidity are recorded continuously. Details of SAFAR network are available elsewhere (Beig et al., 2015). All the sensors in SAFAR network stations are regularly calibrated (once a month) and maintained by dedicated team. Ceilometer transmits a laser pulse of 910 nm into the atmosphere and measures the backscattered signal intensity which is proportional to the aerosol number concentration in the scattering volume. The received signals are processed to remove background noise and averaged in space and time to determine aerosol backscatter coefficient profiles at a time interval of 16 s. The output from ceilometer consists of three cloud base heights, three mixing layer heights and extinction coefficient integrated up to 4 km. Details of ceilometers specifications are given in Table 1. Since the backscatter from cloud is much higher than that from aerosols, clouds can be easily detected with precision. Mixing layer height is detected by relatively large negative gradients in aerosol concentration (Murthy et al., 2020). Hourly-mean parameters are analyzed in this study. The analysis is done for the lockdown period (March 25–April 15) and compared with the pre-lockdown period i.e. March 01-24, 2020.

3. Results and discussion

3.1. Vertical distribution of clouds

Time-height distribution of clouds and the associated instantaneous backscatter coefficient profile is illustrated in Fig. 1. The profile shows large backscatter coefficient at 2300 h Indian Standard Time caused by cloud water droplets located at 15 k foot (~4.5 km). Presence of clouds during 1000–1700 h at 4.5 k ft and also at 1800 h around 17 k ft can be noted. Presence of multilayer clouds and falling rain droplets are indicated.

Time series of vertical distribution of hourly cloud base heights is shown in Fig. 2a for the pre-lockdown period. The ceilometer (Vaisala, CL51) can detect up to 3 cloud bases, namely CLD1, CLD2 and CLD3. When multi-layer clouds are present there could be up to 3 outputs and if single layer only one, and none in the case of no clouds. It may be noted that ceilometer can detect only overhead clouds. If no clouds pass overhead then no CBH is recorded even if there are clouds in the horizon. Quality flags (1, 2 and 3) are applied by the processing software of CL51 to the raw data (16 s backscatter profiles) based on statistical

| Table 1 |
|----------|
| **Technical specifications of ceilometer.** |
| Model no. & make | CL51, Vaisala |
| **Transmitter** | |
| Laser source | Indium gallium arsenide (InGaAs) diode laser |
| Center wavelength | 910 ± 10 nm at 25 °C (77 °F) |
| Operating mode | Pulsed |
| Pulse energy | 3.0 µJ ± 20% (factory adjustment) |
| **Peak power** | 27 W typical |
| **Repetition rate** | 6.5 kHz |
| **Average power** | 19.5 mW |
| Beam divergence | ≤0.15 x ±0.25 mrad |
| **Receiver** | |
| Detector | Silicon avalanche photodiode (APD) |
| **Surface diameter** | 0.5 mm (0.02 in.) |
| **Receiver bandwidth** | 3 MHz (−3 dB) |
| **Performance** | |
| Cloud detection range | 0 ... 13 km |
| Measurement range | 0 ... 15 km |
| Measurement resolution | 10 m |
| Cloud reporting resolution | 5 m |
| Reporting interval | 6 s ... 120 s, selectable, 16 s selected |
| Measurement interval | 6 s |
| **Mixing layer (MLH) and cloud height** | |
| MLH | 4 km maximum – report 3 layers |
| Cloud detection | 13 km maximum - report 3 heights |
consistency in space and time as well as signal to noise ratio. The most reliable is flag 3. Noisy signals with low signal to noise ratio are rejected automatically by the software while processing. Additional filtering of data is not applied by the user. In this study clouds are classified as Low, Middle and High clouds based on the heights of their bases located in 0–3 km, 3–6 km and 6-9 km range respectively. Most of the cloud bases are located below 3 km while a few are seen in 3-6 km and 6-9 km range indicating denser low level cloud coverage. Fig. 2b shows the cloud distribution in the lockdown period which illustrates the propagation of clouds to higher levels through a gradual reduction and complete absence of low level clouds below 3 km while middle and high level clouds increasing in number.

Statistical analysis of cloud base heights in terms of frequency count or percentage of clouds in each height range designated as low, middle and high level clouds is shown in Fig. 3 for the pre-lockdown and the lockdown periods. During the pre-lockdown there were 63% low clouds, 27% middle clouds and 10% high level clouds. In the lockdown period low clouds reduced to 12%, middle clouds increased to 40% and high level clouds increased further to 48%.

3.2. Controlling factors - meteorology

The reduction in low level clouds during the lockdown period in 2020 could be due to change in meteorological parameters like air temperature (AT), relative humidity (RH), radiation (UV), wind speed (WS). These parameters are shown in Fig. 4a along with UV (ultra violet) radiation and mixing layer height (MLH) derived from aerosol backscatter coefficient profiles. The vertical line in the figure indicates the...
start date of the lockdown (25th March). Rainfall (RF) is shown in the time series of AT. The increase in MLH, UV radiation, AT (and decrease in RH) and WS can be seen which is obvious as this is the transition period from late winter to pre-monsoon (April). Increase in radiation, AT and WS leads to more turbulent mixing resulting in increase in MLH.

The change in meteorological and thermodynamic parameters in the lockdown period with respect to that in the pre-lockdown period is illustrated in Fig. 4b. The percentage change in AT, RH, WS, MLH, and UV is 24, −20, 48, 44, 47 respectively. Thermodynamic parameters obtained from radiosonde profiles like CAPE (convective available potential energy) decreased by −56% while CINE (convective inhibition energy) increased by 88% (Fig. 4b). The large increase (44%) in MLH is an artefact of low MLH in pre-lockdown period due to the presence of too many (62%) low level clouds. It is to be evaluated whether this increase in controlling meteorological parameters could explain the cloud distribution in the lockdown period.

The theoretical cloud base height, LCL is the height at which water vapour in the adiabatically rising air parcel from the surface reaches saturation and starts condensing and this is computed based on near surface air temperature, dew point or RH and atmospheric pressure. Daily mean time series of LCL computed from hourly values following Stull (1988) is shown in Fig. 5 along with the cloud base height (CBH). There is an increase in CBH as well as LCL from the pre-lock down to the lockdown period. However the difference between CBH and LCL is much higher in lockdown period as compared to that in the pre-lockdown. CBH not only depends on temperature and moisture content of the rising air parcel but also on aerosol concentration in the form of CCN for cloud droplet formation. Some of the earlier studies have found that CBH has positive correlation (Wang et al., 2019) with particulate matter concentration while the difference between CBH and LCL (lifting condensation level) has negative correlation (Gebremariam et al., 2018). According to Li et al. (2011), CBH is independent of CN concentration. Thus the relationship among CBH, PM2.5 and LCL seems to depend on many other factors like geographical location, aerosol size, composition, cloud type, etc. Decrease in CAPE and increase in CINE (Fig. 4b) and absence of rain (except one spell with <1 mm) indicates that the lockdown period is characterized by layered cumulus clouds.

The freezing level as determined from radiosonde ascents at 00 and 12 UTC lies at 3–4 km in pre-lockdown and 4.5 km in lockdown period. Cloud thickness is not possible to estimate accurately as there were apparently multilayer clouds. Li et al. (2011) observed that convective invigoration due to increase in CN happens only when the cloud top is above −4 °C, cloud base temperature > 15 °C and liquid water path > 0.8 mm. Our results pertaining to a specific event of lockdown are unlikely to fit into the cloud properties and CN statistics derived from a long period of observations. Moreover, the location of current study is vastly different in geographical nature and associated pollution levels.

Fig. 3. Statistical analysis (frequency count percentage) of cloud base heights in the range 0–3000 m (low clouds), 3000–6000 m (middle clouds), 6000–9000 m (high clouds) during the periods of March 1–24, 2020 and March 25 – April 15, 2020.

Fig. 4. (a) Hourly time series of wind speed (WS, m s⁻¹), relative humidity (RH, %), air temperature (AT, °C), rainfall (RF, mm), ultraviolet radiation (UV, W m⁻²), and mixing layer height (MLH, m) from March 01 to April 15, 2020. (b) Change in meteorological and thermodynamic parameters during the lockdown relative to that in pre-lockdown period. AT-air temperature (°C), RH-relative humidity (%), WS-wind speed (m s⁻¹), MLH-mixing layer height (m), UV-ultraviolet radiation (W m⁻²), PWC-precipitable water content (mm), CAPE-convective available potential energy (J kg⁻¹), CINE-convective inhibition energy (J kg⁻¹).
3.3. Role of CCN

In order to understand the relationship between aerosol mass concentration (particulate matter with size less than 2.5 mm and 10 mm; PM2.5 and PM10) and CBH, we have analyzed PM2.5, PM10 and trace gases like NO2, NH3 which are precursors of secondary hygroscopic particles that activate into cloud droplets. PM2.5 and PM10 reduced by 30% and 36% respectively during the lockdown period relative to that in pre-lockdown period while NO2 and NH3 reduced by 62% and 57% respectively. The same is depicted in daily time series of CBH, NO2 and NH3 (Fig. 5).

Clouds with bases below 3 km are few during the lockdown period. This could be due to drastic reduction in aerosol concentration, a fraction of which become CCN. The ratio of CCN to aerosol concentration (activation ratio) is a function of aerosol chemical composition and size distribution. Larger aerosols easily get activated to CCN while smaller particle activation depends on hygroscopicity. The ratio of PM2.5 to PM10 increased from 0.46 in pre-lockdown to 0.64 in...
lockdown period indicating more reduction in bigger (size > 2.5 μm) particles. As shown in Fig. 6, PM10 reduced by 35% while PM2.5 reduced by 30%. Absolute value of PM2.5 has reduced from ~58 μg m⁻³ in pre-lockdown to ~20 μg m⁻³ in lockdown (Beig et al., 2020) due to the reduction in gas pollutants and in formation of secondary particles. Water soluble inorganic secondary hygroscopic particles like nitrates and ammonium salts are generated from its precursor gases NO₂ and NH₃. PM2.5 mass closure in Delhi in winter is dominated by ions like chlorides, ammonium, nitrates and sulphates that account about 30% of mass (Perrino et al., 2011). The reduction in NO₂ and NH₃ gases leads to corresponding decrease in hygroscopic ion concentration and hence CCN. It is observed that under warmer conditions this fraction further reduces as compared to that in cold environment. Thus relatively higher air temperature in the lockdown period leads to a further reduction of water soluble inorganic ions (Voutsa et al., 2014) that serve as CCN.

Aerosol optical properties of scattering and extinction are related to CCN (Liu and Li, 2014) through aerosol scattering index which is the product of scattering coefficient and scattering angstrom exponent. CCN concentration can be estimated from a regression equation developed based on the aircraft observations over the Indo-Gangetic Plain through extinction aerosol index (Jayachandran et al., 2020). Extinction aerosol index, \( \text{Al} = \sigma_{\alpha} \times \alpha \), where \( \sigma_{\alpha} \) is aerosol extinction coefficient at 450 nm and \( \alpha \) is angstrom exponent. The regression equation fitted to aircraft observations at Jodhpur (as surface observations indicate the upslope flow for Delhi is from west or north-west direction) is used in this study. Since we used extinction coefficient at 910 nm measured by ceilometer instead of 450 nm, our CCN values are an underestimate as aerosol optical depth (extinction coefficient profile integrated vertically) decreases with increasing wavelength. The angstrom exponent (\( \alpha \)) for the spectral band of 370–840 nm in Delhi is ~0.7 during March-April as reported by Soni et al. (2010). Aerosol optical depth for dusty conditions changes by 0.01 for the spectral band 870-1030 nm (Toledano et al., 2009), thus \( \alpha \) changes a little (<0.01) in the two spectral bands.

A little uncertainty in Al, due to change in wavelength and the location, may not matter much because our objective is to estimate the reduction in CCN (not absolute values) during the lockdown period. Mean extinction coefficient for the layer 0–4 km is obtained by vertically integrating the profile for each hour from which daily mean \( \sigma_{\alpha} \) (910) is computed. Precaution has been taken to exclude clouds and low signal to noise ratio signals while integrating extinction coefficient profile. We used the regression equation \( \text{CCN}_{\alpha} = \text{Al} \times (17.6 \pm 1.6) \) to estimate CCN at 0.4% supersaturation. CCN spectra (CCN concentrations vs supersaturation, SS %) obtained from aircraft observations over IGB show most sensitivity up to SS = 0.4%, beyond which dependency of CCN on SS considerably reduces. This indicates that majority of aerosols get activated as CCN as SS reaches 0.4%. Hence the empirical formula derived at 0.4% super-saturation is used in this study (Jayachandran et al., 2020). The time series of CCN is portrayed in Fig. 5 along with CBH. CCN has reduced significantly from the pre-lockdown to the lockdown period. Before the lockdown, CCN varies from 1275 to 3300 cm⁻³ and the range drops to 600–1900 cm⁻³ during the lockdown. CCN over Jodhpur decreases with height from 3000 cm⁻³ at 500 m to 500 cm⁻³ at 3 km (Jayachandran et al., 2020). Aircraft measurement of CCN at 0.4% supersaturation and at an altitude of 1.5 km over Hyderabad and the Western Ghats in India varies from 500 cm⁻³ to 1500 cm⁻³ (Leena et al., 2016; Varghese et al., 2016).

The inverse relationship shown in Fig. 5 between CBH and NH₃ and NO₂ is depicted in Fig. 6a and b through scatter plots which show a correlation of ~0.7 (\( p < 0.001 \)). The percentage change in various controlling parameters of cloud formation from the pre-lockdown to the lockdown period is shown in Fig. 6c. One can notice that CCN reduced by 50% during the lockdown period while PM2.5 and PM10 decreased by 30% and 35% respectively. Fig. 7 shows an inverse correlation of ~0.64 (\( p < 0.001 \)) between CBH and CCN.

Several studies (Arub et al., 2020; Burkart et al., 2011; Gebremariam et al., 2018; Rosenfeld, 2000; Rosenfeld et al., 2008; Rosenfeld and Ulbrich, 2003; Wang et al., 2019) have reported the dependence of cloud drop number on CCN concentration. Low CCN concentration in ambient air leads to formation of lesser number of droplets when water vapour reaches saturation in the rising adiabatic air parcel. Higher supersaturations are required to generate sufficient number droplets to grow into a cloud that occurs as air parcel ascends further by updrafts. Sufficient number of cloud droplets form at larger heights under low CCN environment leading to formation of elevated cloud base that can be detected by ground based remote sensing technique. A positive correlation has been found between aerosol loading and CBH at Wuhhan by analyzing ground based CBH over four years (Wang et al., 2019). Analysis of 8 year data of monthly mean CBH and PM2.5 at Baltimore and New York reports decreasing trend in PM2.5 but no significant trend in CBH and LCL (Gebremariam et al., 2018). However, there is a significant negative correlation between PM2.5 and (CBH-LCL). In this study at Delhi the difference between CBH and LCL is higher for very less polluted conditions of the lockdown period with reference to that in pre-lockdown period. Thus the relationships among CBH, PM2.5 and LCL seem to depend on many other factors like geographical location, aerosol size, composition, cloud type, etc. The results of the current study are unique in the way of lockdown applied mainly to transport and industrial sector with hardly any change in domestic activities i.e. sudden change of heavy load in pollutants to some reduced level which might have affected mainly only precursor gases those generate hygroscopic secondary particulates.

CBH may also increase if the columnar moisture content reduces which is represented by precipitable water content (PWC). Analysis of Wyoming university radiosonde ascents at 0000 and 1200 UTC at Delhi during the pre-lockdown and the lockdown periods indicates an increase of 12% in PWC (Fig. 4b) in the lockdown period and LCL increases by 25%. Thus significant increase in CBH seems to be mainly due to drastic reduction in CCN concentration.

CPCB has commissioned source apportionment study in Delhi and released a report ‘Impact of Lockdown on Air Quality’ (CPCB, 2020). Size and chemical composition are important for the CCN activation and then the cloud formation, but in this study, no size information is available, the chemical information from the CPCB shows that hygroscopic components in PM2.5 viz., nitrate and sulphate reduced from 13% and 5% in pre-lockdown to 8% and 6% respectively during the lockdown period. Sulphur in PM2.5 reduced from 33% in pre-lockdown to 18% in lockdown, potassium reduced from 8% to 6%. Vehicular emissions reduced from 19% to 5% while Industrial emissions reduced from 26% to
22% and biomass burning emissions reduced from 21% to 17%. It is clear from above that in the partition of PM2.5, hygroscopic particles with high potential of turning into CCN, have reduced significantly in the lockdown period. Emissions from vehicles and industries reduced leading to reductions in NO₂ and NH₃ which are gaseous precursors for CCN.

3.4. Model simulation

The Weather Research and Forecasting model coupled with Chemistry (WRF-Chem) version 3.9.1 (Fast et al., 2006; Grell et al., 2005) is configured for Delhi city as the focussed region. The processes are treated interactively to get feedback of meteorology into chemistry and vice-versa. It consists of four domains where the innermost domain focussed the area in and around Delhi (Srinivas et al., 2016). First coarser domain covering most of South Asia at a horizontal resolution of 45 km, with 131 × 131 grid cells. The second domain focusses on the northern part of India covering the Indo-Gangetic plain at a resolution of 15 km with 127 × 127 grid cells. The third domain covered the Delhi and surrounding region at a resolution of 5 km with 55 × 55 grid cells whereas fourth domain covers exclusively Delhi city at a resolution of 1.67 km with 75 × 75 grid cells. Meteorological initial and lateral boundary conditions to WRF-Chem model are taken from NCEP-GFS (National Centers for Environmental Prediction-Global Forecast System). Chemical species boundary conditions are obtained from NCAR’s the Whole Atmosphere Community Climate Model (WACCM).

The Yonsei University (YSU) PBL scheme (Hong et al., 2006), the NOAH land-surface model (Chen and Dudhia, 2001), the Lin cloud microphysics scheme and the Grell-3D cumulus parameterization that is an updated version of the Grell-Devenyi scheme (Grell and Dévényi, 2002) with radiative feedback and shallow convection. The Rapid Radiative Transfer Method for Global (RRTMG) long-wave and short-wave radiation scheme (Iacono et al., 2008) is applied. The gas-phase chemistry is based on the Carbon-Bond Mechanism version Z (Zaveri and Peters, 1999) mechanism. It has 67 species and 164 reactions in a lumped structure approach that classifies organic compounds according to their internal bond types. Rates for photolytic reactions are derived using the Fast-J photolysis rate scheme (Wild et al., 2000). The aerosol module is the Model for Simulating Aerosol Interactions and Chemistry (MOSAIC) (Zaveri et al., 2008). MOSAIC includes sulphate, methanosulphonate, nitrate, chloride, carbonate, ammonium, sodium, calcium, black carbon (BC), primary organic mass (OC), liquid water, and other inorganic mass (OIN). Secondary organic aerosol formation is not considered. MOSAIC simulates major aerosol processes (e.g., inorganic aerosol thermodynamic equilibrium, binary nucleation, coagulation, condensation). Dust emission and transport is included. Simulations account for the effect of simulated aerosol concentrations

![Fig. 8](image-url) (Top panel) Time series of CBH from ceilometer observations and model simulation; dashed line indicates commencement of lockdown. (Bottom panel) CBH derived from satellite observations.
on radiation. The direct effect of aerosols on shortwave radiation is simulated based on Mie theory following the approach of Fast et al. (2006). The system is routinely used to generate 72-hour air quality forecast every day for Delhi city.

Anthropogenic emissions of aerosols and trace gases are based on EDGAR-HTAP version 2.2 (Janssens-Maenhout et al., 2015) and over Delhi region high resolution emission inventory developed by System of Air Quality and Weather Forecasting and Research (SAFAR) project (Sahu et al., 2015) is used. During the local down period the emissions estimated by the Central Pollution Control Board (CPCB) based on activity data (CPCB, 2020) are used in the model to account for significant reduction in anthropogenic emissions. The parameter commonly used in WRF model to identify the presence of cloud is the cloud fraction (CF). It is defined at each model 3-D grid cell and represents the volume of the cell which is occupied by clouds and ranges from 0 to 1. It describes clouds in a macroscopic manner, and can be used to verify the simulated cloud structures with observations like ceilometers (Arbizu-Barrena et al., 2015). The WRF-modelled CBH is estimated as the height of the lowest model layer where CF is greater than zero over the location of ceilometer.

As shown in Fig. 8 model simulated CBH tend to increase from pre-lockdown to lockdown similar to the observed CBH, although sometimes clouds are not resolved by the model. This could be due to mismatch in spatial scale as ceilometer can detect only the overhead clouds. Satellite observations of CBH are also used to determine the trend from pre-lockdown to lockdown. Passive hyperspectral spectrometer named as TROPOMI (TROPOspheric Monitoring Instrument) is on board Sentinel 5 P and measures several physical properties of clouds with a resolution of 7 km × 3.5 km. In this study, TROPOMI offline stream was used to analyse the variation of cloud base height. CBH data (Copernicus Sentinel data processed by ESA, 2018) was acquired over the region of Delhi, India for the period from March 15, 2020 to April 15, 2020. The data was analyzed using the open source the QGIS software. As illustrated in Fig. 8, satellite derived CBH is also observed to have an increasing trend that corroborates the ground-based observations. No significant change in cloud thickness and cloud optical depth is observed in Sentinel satellite data except on the days of precipitation (not shown).

4. Conclusions

The complete lockdown during March 25–April 14, 2020 on account of Covid-19 outbreak in India– during which industries, construction, vehicular traffic and people movement is severely curtailed, resulted in steep reduction in air pollutants (particulate matter and trace gases). Significant reduction in PM10, PM2.5 as well as precursor gases like NOx, NH3 that generate water soluble secondary aerosols and associated aerosol optical property (scattering and extinction coefficient) lead to a considerable drop in CCN concentration during the lockdown period. CCN being a critical parameter for cloud drop number concentration, cloud formation depends on the availability of CCN. Under low CCN environment higher supersaturation is needed to generate sufficient cloud base drop concentration. As air parcel ascends in convective clouds higher supersaturation occurs in response to drop in parcel temperature. Consequently low level clouds with CBH less than 3 km in pre-lockdown have propagated to higher levels during the lock-down period. The same is corroborated by satellite observations as well as model simulation of CBH. In the absence of any significant change in the ambient synoptic scenario (western disturbance occurred intermittently), the shifting of low clouds to higher level appears to be due to non-availability of sufficient CCN to activate into cloud base droplet concentration in spite of increase in PWC. The lockdown episode is unique in the sense that it is associated with a drastic reduction in anthropogenic sources which are known to emit majorly hygroscopic aerosols as evidenced by enhancement of rainfall over urban areas (Sarangi et al., 2018).

**CRediT authorship contribution statement**

R Latha: Conceptualization, Analysis, Writing and review. B S Murthy: Editing and review, Investigation, Group head. B S Sandeepan: Model simulation. Vinayak Bhanage: Satellite data retrieval and processing. Aditi Rathod: Data curation and collection. Arpit Tiwari: Ceiling meter handling & maintenance. Gufran Beig: General facilitation. Siddhartha Singh: Logistic support & Study location administration.

**Declaration of competing interest**

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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