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Future projections of daily hazy and clear weather conditions over the North China Plain using a Perturbed Parameter Ensemble

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Abstract

We examine past and future changes in both winter haze and clear weather conditions over the North China Plain (NCP) using a Perturbed Parameter Ensemble (PPE) and elucidate the influence of model physical parameterizations on these future projections for the first time. We use a meteorology-based Haze Weather Index (HWI), which was developed to examine the haze conducive weather conditions for Beijing. We find that the HWI can be used as an indicator of winter haze across the entire NCP due to the extended spatial coherence of the local meteorological conditions. The PPE generated using the UK Met Office HadGEM-GC3 model shows that under a high-emission (RCP8.5) scenario, the frequency of haze conducive weather is likely to increase whereas the frequency of clear weather is likely to decrease in future. However, a change of opposite sign with lower magnitude in the frequencies, though less likely, is also possible. In future, the total number of hazy days for a given winter can be as much as ~3.5 times higher than the number of clear days over the NCP. We also examined the changes in the interannual variability of the frequency of hazy and clear days and find no marked changes in the variability for future periods. The future frequencies of winter hazy and clear days in the PPE are largely driven by changes in zonal-mean mid-tropospheric winds and the vertical temperature gradient over the NCP. We do not find any discernible influence of model physical parameterizations on the future projections of trends in the frequency of hazy or clear days. We find a clear impact of anthropogenic climate change on future trends for both hazy and clear days, however, it is only discernible for specific periods due to the large underlying internal variability in the frequencies of hazy and clear days.

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1. Introduction

Over the last decade, a number of severe haze episodes (several days or longer) were reported over the North China Plain (NCP) during boreal winter (December-January-February, DJF). In January 2013, unprecedented $PM_{2.5}$ levels exceeding 450 μg m^{-3} were observed over the NCP (Wang et al., 2014a; Wang et al., 2014b; Zhang et al., 2018; Zhang et al., 2013). Similar events were also observed in November-December 2015 when the $PM_{2.5}$ concentrations reached as high as 1000 μg m^{-3} in Beijing and caused the first-ever 'red alert' for severe air pollution (Liu et al., 2017; Zhang et al., 2017). In December 2016, around 25% of the land area of China was covered with severe haze for around one week (Yin and Wang, 2017). These severe haze events adversely impacted public health including mortality, visibility, and ultimately the economy of the country (Bai et al., 2007; Chen and Wang, 2015; Kan et al., 2012; Kan et al., 2007; Wang et al., 2006; Xu et al., 2013; Hong et al., 2019).

Previous research has shown that the persistence of severe haze for days during winters over the NCP occurred due to the combined effect of local and regional high pollutant emissions and stagnant meteorological conditions (Li et al., 2018; He et al., 2016; Jia et al., 2015; Pei et al., 2018; Zhang et al., 2021). The normal winter meteorological conditions over the NCP are characterized by northwesterly flow near the surface through to the mid-troposphere associated with the East Asian winter monsoon (An et al., 2019; Renhe et al., 2014; Li et al., 2016; Xu et al., 2006). However, during the severe haze episodes, the mid-tropospheric trough was reported to be shallower and shifted northwards leading to a weaker than normal northwesterly flow and reduced horizontal transport of air pollutants from the NCP (Chen and Wang, 2015). The weaker northwesterlies near the surface also reduces the intrusion of cold and clean air from the high-latitudes to the NCP (Xu et al., 2006). In addition to changes in horizontal winds, the vertical temperature gradient between the lower and upper troposphere over the NCP enhances the thermal stability and reduces atmospheric mixing leading to the

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build-up of the atmospheric pollutants over this region (Hou and Wu, 2016; Sun et al., 2014; Wang et al., 2014a; Zhang et al., 2018; Cai et al., 2018). The planetary boundary layer height is also found to be suppressed during extreme haze events leading to accumulation of pollutants, notably $PM_{2.5}$ concentrations (Liu et al., 2018; Petäjä et al., 2016), due to an increase in moisture, reduced vertical mixing and dispersion which aids aerosol growth during high haze events over the NCP (An et al., 2019; Tie et al., 2017).

In this paper, our focus is on the meteorological driven changes leading to daily hazy or clear weather conditions over the NCP. On a daily scale, recent studies suggest an increase in the occurrence of large-scale meteorological conditions favourable for winter haze over the NCP under climate change. Cai et al. (2017) used a meteorology-based daily Haze Weather Index (HWI) and projected a 50% increase in the frequency of winter haze conducive weather conditions, similar to the January 2013 event, over Beijing in the future (2050-2099) as compared to the historical (1950-1999) period under RCP8.5 scenario using 15 CMIP5 models. Han et al. (2017) also examined indicators of haze pollution potential (e.g. horizontal transport, wet-deposition, ventilation conditions) using three regional climate simulations and projected a higher probability of haze pollution risk over Beijing-Tianjin-Hebei region under the RCP4.5 scenario. Liu et al. (2019) projected a 6-9% increase in the winter haze frequency under 1.5° and 2° global warming, respectively based on 20 CMIP5 models. Qiu et al. (2020) also projected an increase of 21% and 18% in severe winter haze episodes under 1.5° and 2° global warming, respectively using an ensemble of climate simulations from the Community Earth System Model 1 (CESM1) for a low warming experiment (Kay et al., 2015). Callahan and Mankin (2020) found 10-15% increase in winter hazy days in CMIP5 multimodel and CESM large ensemble under 3° warming and emphasized a large influence of internal variability in addition to anthropogenic forcing on future haze conducive weather over Beijing. A few studies also find little impact of climate change on future projections of haze (Shen et al., 2018; Pendergrass

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et al., 2019), which could partly arise due to the under-sampling of internal variability associated uncertainty in their projections (Callahan and Mankin, 2020), as well as model-to-model differences. Hence, there is a large uncertainty as to how haze conducive weather conditions may change in the future and these depend on haze metric or underlying processes considered for projections.

In order to account for the uncertainty in the future projections (e.g. of large-scale circulation) particularly at the regional scale (Hawkins and Sutton, 2012; Deser et al., 2012; Deser et al., 2014), it is desirable to use an ensemble of climate change simulations. Whilst a multimodel ensemble, e.g. CMIP5 or CMIP6, is commonly used for climate change studies, several other studies have also emphasised the use of an initialised ensemble or Perturbed Parameter Ensemble (PPE) from a single model to assess the uncertainties and obtain a comprehensive range of possible future climate realisations for the same emission scenario for a given model (Knutti et al., 2010). All three methodologies have different advantages. For instance, using multiple models allows us to sample structural uncertainty in future projections, which cannot be sampled using a single model. On the other hand, using an initialised ensemble from a single model allows us to sample a broader range of internal variability, which is often under-sampled in a multimodel ensemble. The advantage of using the PPE over the initialised or multimodel ensemble is that it not only accounts for internal variability but also model uncertainty arising due to the different settings of the physical parameterisations in a single model.

Both multimodel ensemble and initialised ensemble from a single model have been used to assess the future winter haze conducive conditions over Beijing. In this paper, we use a PPE generated using the UK's Met Office HadGEM-GC3 model to assess for the first time the impact of both model physical parameterisations and anthropogenic climate change on future daily haze conducive weather conditions using the HWI. We first determine the spatial

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extent for which the HWI can be used as an indicator of air quality over China (Section 3). We examine the changes in the frequency of hazy and clear days for historical and three future periods, i.e. near (2006-2032), mid (2033-2059) and far (2060-2086) future, over the NCP (Section 4). We also analyse the changes in the interannual variance of the frequency of hazy and clear days for the future periods as compared to the historical (Section 5). We investigate the importance of the different meteorological variables used in the HWI in determining the future changes in haze conducive conditions in the PPE (Section 6). Finally, we assess the model physical parametrisations and anthropogenic climate change on the frequency of future hazy and clear weather conditions over the NCP (Section 7). More details on the data and methods used in this paper are provided in the next section.

2. Data & Methods

2.1 Observations, Reanalysis Outputs and PPE Model Simulations

Hourly $PM_{2.5}$ concentrations are used from the US embassy site for Beijing for DJF from 2009-2017. Daily mean $PM_{2.5}$ concentrations are constructed using hourly data to identify hazy and clear days and evaluate the performance of the HWI for Beijing (see Section 3). We also used newly released gridded daily $PM_{2.5}$ concentrations for DJF from Chinese Air Quality Reanalysis Datasets (CAQRA) provided by China National Environment Monitoring Centre for 2013-2017 (Kong et al., 2021) to test the performance of the HWI across entire China. The CAQRA data has been produced by assimilating surface air quality observations from over 1000 monitoring sites in China and is available at a high spatial resolution of around 15×15 km and hourly temporal resolution over China. More details on the validation of the CAQRA dataset against the independent station data is provided in (Kong et al., 2021). The visibility data for Beijing (homogenized data for 20 stations in Beijing) is provided by the National

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Meteorological Information Center of China, Chinese Meteorological Agency for DJF 1999-2018.

We used daily ERA-5 reanalysis data of four variables: meridional wind at 850 hPa pressure level (V_{850}), zonal wind at 500 hPa pressure level (U_{500}), temperatures at 850 hPa level (T_{850}) and 250 hPa (T_{250}) to calculate the HWI for DJF 1979-2019. The ERA-5 data used here is available at 0.25° x 0.25° horizontal resolution and hourly temporal resolution (Hersbach et al., 2020).

We used a PPE of climate simulations produced using the recent configuration of the UK Met Office's HadGEM3-GC3.05 coupled model (Sexton et al., 2021; Yamazaki et al., 2021). The base model used for PPE, HadGEM3-GC3.05, has a horizontal resolution of ~60 km with 85 vertical levels. A total of 47 model parameters from seven parameterization schemes were simultaneously perturbed to obtain the PPE (the full list of perturbed parameters is provided in Table 1 of (Sexton et al., 2021). Here, we used daily outputs of V_{850}, U_{500}, T_{850} and T_{250} for DJF for the historical (1969-2005) and future (2006-2089) under the RCP8.5 scenario. In addition, we also assessed internal variability using 200-year control simulations for each PPE member where 1900 boundary conditions were prescribed. Overall, 16 PPE members are available for all the control, historical and RCP8.5 simulations.

2.2 Calculation of the HWI

We analyse the composite differences in the U_{500}, V_{850}, T_{850} and T_{250} for hazy ($PM_{2.5}$ concentrations > 150 μg m^{-3}) and clear ($PM_{2.5}$ concentrations < 35 μg m^{-3}) days across China for DJF 2009-2017 (Fig. 1) (see next section for the cut-offs values used for $PM_{2.5}$ concentration). Figure 1 shows the difference in the zonal wind speed with a dipole pattern suggesting a northward shift in the mid-tropospheric trough (Fig. 1a), weakened northerly flow (Fig. 1b), higher temperatures in the lower troposphere and lower temperatures in the upper

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troposphere (Fig. 1c-d) over the NCP during hazy days as compared to the clear days. These findings are consistent with the previous studies (e.g. Cai et al., 2017) that showed similar changes in these meteorological variables. Cai et al. (2018) have examined the use of other variables such as geopotential height, boundary layer thickness and local stratification instability and do not find any significant differences in the performance of HWI by inclusion of more weather parameters. Therefore, we also use only these four variables for our analysis.

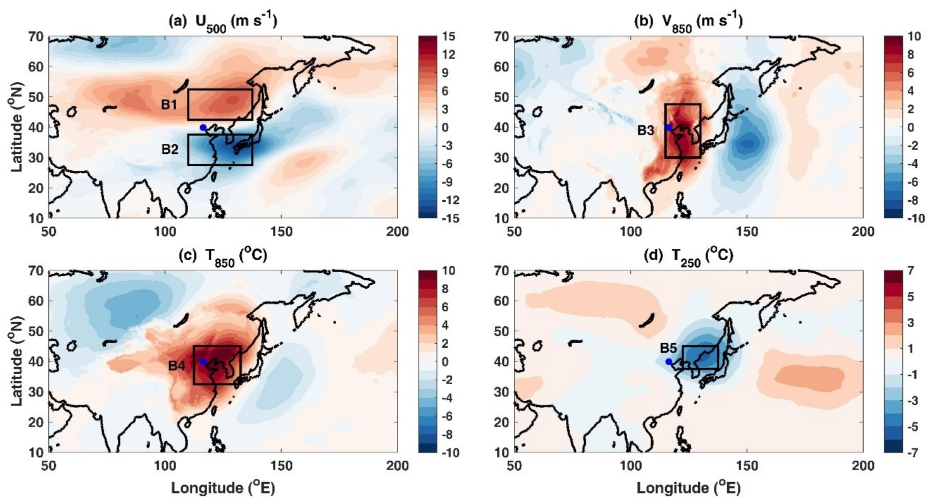

Figure 1 Winter composites of differences in (a) u-wind at 500 hPa level (U_{500}) (b) v-wind at 850 hPa level (V_{850}) (c) temperature at 850 hPa level (T_{850}) and (d) temperature at 250 hPa level (T_{250}) over China for all available days with high $PM_{2.5}$ (>150 µgm m^{-3}) and low $PM_{2.5}$ (<35 µgm m^{-3}) concentration for DJF 2009-2017 for the US embassy station for Beijing. The blue dot shows the location of Beijing. Red colour in (a) and (b) shows strengthened westerlies and weakened northerlies, respectively.

The winter HWI is calculated using the methodology given by Cai et al. (2017). For the observational HWI, we use ERA-5 reanalysis data for the period 1979-2019. We first create a daily DJF time series of each variable for each reanalyses grid point over China. The daily DJF time series is concatenated for the period 1979-2019. A daily standardised anomaly time series is created for each meteorological variable by first removing the daily mean climatology from each day of the time series and then normalising by the standard deviation. Spatial averages are then obtained over the relevant boxes (B1 to B5) for each meteorological variable following Cai et al. (2017) (Fig. 1). The HWI time-series is calculated by using the following equation:

$$HWI\ (t) = U_{500}\ (t) + V_{850}\ (t) + dT(t)$$

where $U_{500} = U_{500,B1}$ (t) - $U_{500,B2}$ (t), $V_{850} = V_{850,B3}$ (t), and $dT = T_{850,B4}$ (t) – $T_{250,B5}$ (t). The HWI (t) time series is then itself normalized by its own standard deviation.

For the PPE historical and RCP8.5 simulations, the daily HWI time series is calculated for each ensemble member for DJF for 1969-2089 using the same methodology as used for ERA-5, with the difference being that the normalisation of the PPE time-series (1969-2089) is performed using the historical standard deviation (1969-2005), following Cai et al. (2017). Similarly, the HWI time series is calculated for the PPE pre-industrial control simulations for 170 model years out of 200 model years (first 30 years are discarded as model spin-up period). The normalisation of the pre-industrial control time series is performed using the standard deviation for 170 years. The pre-industrial control simulations used here are initialised with past forcings corresponding to the year 1900 and therefore are an approximate representative of the internal variability of the current climate as this does not take into account any temporal changes in the internal variability from 1900 to the historical and future periods used here.

3. Relationship between the Haze Weather Index and air quality indicators

We determine the relationship between HWI and $PM_{2.5}$ concentration for Beijing. As visibility is an optical representative of haze (Wang et al., 2006) and available for a relatively long period (1999-2018) as compared to the $PM_{2.5}$ concentrations, we also correlate the HWI with the visibility over Beijing. We then test the relationship between HWI and $PM_{2.5}$ concentrations over entire China to determine the spatial extent of the region for which HWI can be used as an indicator of air quality. We use the 25th and 75th percentile values of daily mean $PM_{2.5}$ concentrations to identify the clear and hazy days, respectively for each dataset.

For visibility, we use the opposite criterion, i.e. 25th percentile as a threshold for hazy days and 75th percentile as a threshold of clear days, as lower visibility is associated with hazy days and higher visibility with clear days. The days with daily $PM_{2.5}$ concentration or visibility lying between the 25th and 75th percentile values are identified as moderately polluted days.

3.1 $PM_{2.5}$ concentrations for Beijing versus HWI

Figure 2 (a) shows that the daily HWI increases linearly with increasing $PM_{2.5}$ concentrations for up to ~150 μg m^{-3} and for $PM_{2.5}$ > 150 μg m^{-3}, the HWI starts to level-off (note the log scaling in the y-axis). The time-series correlation between the HWI and $PM_{2.5}$ concentration is ~0.58, which is significant at the 1% level. Callahan et al. (2019) have also obtained a correlation coefficient of 0.58 for daily $PM_{2.5}$ concentrations from the U.S. embassy in Beijing and the HWI calculated using NCAR R1 reanalysis.

The 25th and 75th percentile values of daily mean $PM_{2.5}$ concentrations for the US embassy Beijing station for DJF 2009-2017 are ~35 and ~150 μg m^{-3} respectively. We determine the percentage of hazy days (with daily mean $PM_{2.5}$ concentrations >150 μg m^{-3}) and clear days (with daily mean $PM_{2.5}$ concentrations < 35 μg m^{-3}) for different HWI ranges (Fig. 2b). Out of all days with HWI >1, 64% have daily mean $PM_{2.5}$ concentrations > 150 μg m^{-3} and 98% with $PM_{2.5}$ concentrations >35 μg m^{-3}. This suggests that for HWI >1, almost all days are hazy or moderately polluted. Similarly, almost all days with HWI < -1 are clear or moderately polluted. Using HWI thresholds of ±1 demarcates between the clear and hazy days, i.e. almost no clear days occur for HWI >1 and almost no hazy days occur for HWI <-1.

3.2 Visibility for Beijing versus HWI

Figure 2 (c) shows that the HWI is inversely related to the visibility for the Beijing station. The time-series correlation between the HWI and visibility is -0.63, which is significant

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at the 1% level. The days with visibility < 8.5 km are identified as hazy days, days with visibility > 23.8 km are identified as clear days. For days with HWI > 1, no clear days occur

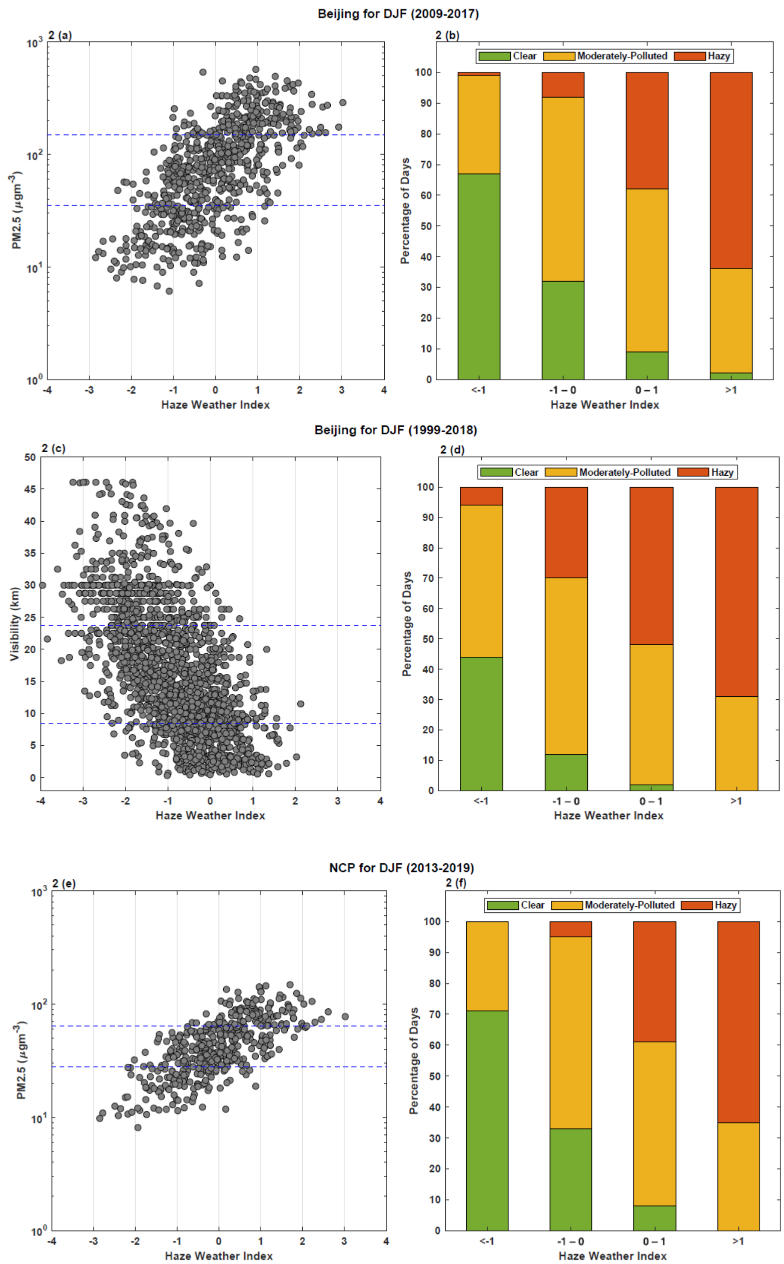

Figure 2 **(a)** Daily mean $PM_{2.5}$ concentrations versus HWI and **(b)** percentage of clear, moderately polluted and hazy days for different HWI ranges for the US embassy Beijing station for DJF 2009-

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2017. **(c)** Daily mean visibility versus HWI and **(d)** percentage of clear, moderately polluted and hazy days for different HWI ranges for the Beijing stations for DJF 1999-2018. **(e)** Daily mean $PM_{2.5}$ concentrations versus HWI and **(f)** percentage of clear, moderately polluted and hazy days for different HWI ranges for the NCP for DJF 2009-2017. Blue lines show the 25th and 75th percentile thresholds used to define clear and hazy days for each dataset.

and similarly for days with HWI< -1, only 6% of days are hazy (Fig 2d). This further confirms that the correlation between the HWI and haze is significant for a longer period (1999-2018) using visibility as a metric for haze (alternative to the $PM_{2.5}$ concentrations used above).

3.3 $PM_{2.5}$ concentrations over North China Plain versus HWI

We now determine the spatial extent for which HWI can be used as an indicator of $PM_{2.5}$ concentrations using data from CAQRA reanalysis. We correlate the daily time-series of $PM_{2.5}$ concentration at each grid point with the HWI for DJF 2013-2017 (Fig. 3). Over the entire NCP (36-43.5 °N, 107-122 °E), the correlation coefficient between the daily HWI and gridded $PM_{2.5}$ concentration is ~0.7, significant at the 1% level. The correlation is considerably lower but still significant over other eastern China regions, e.g. north easternmost China and the Sichuan Basin (27-32 °N, 102-107 °E).

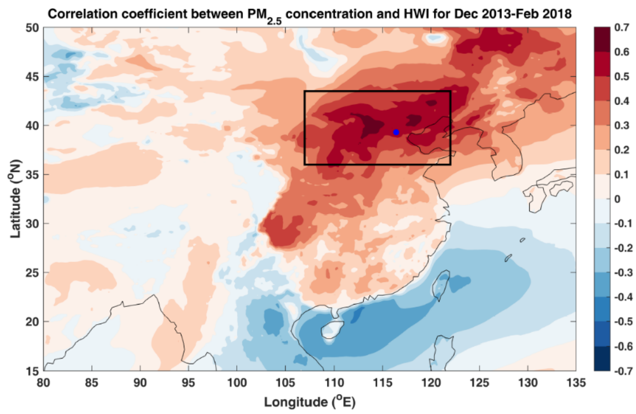

Figure 3 Spatial distribution of correlation between winter $PM_{2.5}$ concentrations and HWI time series at each grid point. Blue dot shows the Beijing station (39.3 °N, 116.4 °E) and the black rectangle shows the North China Plain (36-43.5 °N, 107-122 °E).

Considering daily mean $PM_{2.5}$ concentrations averaged over the NCP, we also find a linear relationship with the daily HWI (r = 0.66; significant at the 1% level; Fig 2e). The values of $PM_{2.5}$ concentrations for NCP are lower as compared to the station values of $PM_{2.5}$ concentrations at the US Embassy Beijing and the correlation coefficient is higher. This could be due to the different time periods for the two dataset, i.e. 2009-2017 for the US embassy and 2013-2017 for the CAQRA reanalyses, and spatial averaging of $PM_{2.5}$ concentrations over the NCP region. We also calculate the percentage of clear and hazy days for different HWI ranges for the larger domain of the NCP using the 25th and 75th percentile values, respectively. The percentage of hazy and clear days for HWI > 1 and HWI < -1 for NCP in CAQRA reanalyses are very similar to the values obtained for the US embassy Beijing station (Fig 2f).

Overall, our results confirm that the daily HWI has a robust relationship with daily $PM_{2.5}$ concentrations not only for the Beijing station but across the NCP for the given time periods. Therefore, we use HWI > 1 as a threshold for hazy days and HWI < -1 as a threshold of clear days across the NCP region. This threshold is also consistent with several other studies (e.g., Cai et al., 2017; Callahan and Mankin, 2020; Callahan et al., 2019), that have used HWI >1 as a cut-off for hazy days for Beijing. We now use the HWI to calculate the frequency of hazy and clear conditions for past and future using ERA-5 reanalysis and PPE members.

4. Historical and future changes in the frequency of hazy and clear conditions

The changes in the number of hazy and clear days per winter, as defined by HWI thresholds, from the ERA-5 reanalyses and the PPE are shown in Fig. 4. For ERA-5, the frequency of hazy days has increased, whereas the frequency of clear days has reduced for the period 1979-2018. The mean frequency of hazy days using 16 PPE members shows a relatively larger increase than ERA-5 for the same 1979-2018 time-period (Fig. 4a). In contrast, the mean frequency of clear days from the PPE for this period shows a similar reduction to that obtained using the ERA-5 reanalyses (Fig. 4b).

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We examine the changes in the frequency of hazy and clear days for the historical (1979-2005) and three future periods, i.e. near (2006-2032), mid (2033-2059) and far (2060-2086) future. The mean frequency of hazy days is 14.7 days per winter obtained from the ERA-5 reanalysis and 15.0 days per winter from the PPE mean for the historical period. The corresponding values for clear days are 15.0 days and 15.2 days per winter for ERA-5 and PPE, respectively. This shows a good agreement between the mean frequencies of hazy and clear days for the ERA-5 data and the PPE mean for the historical period.

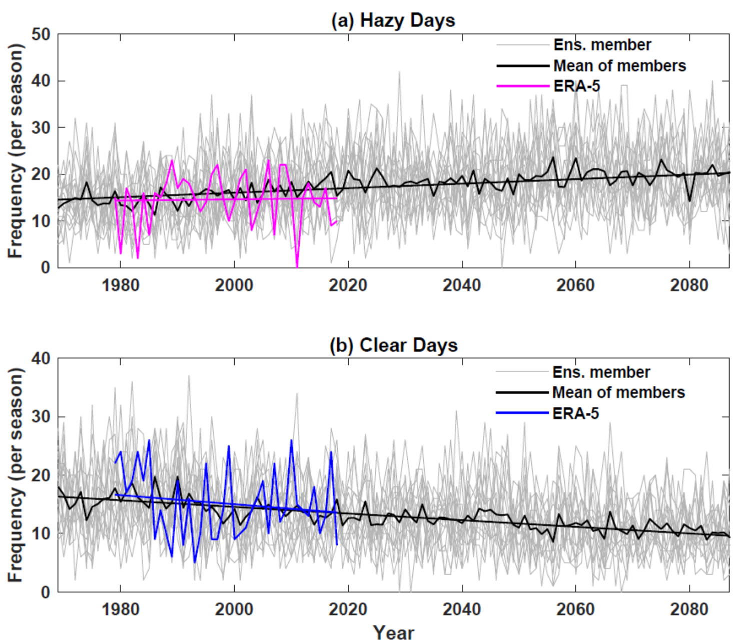

Figure 4 Frequency of hazy (pink line) and clear days (blue line) per winter from ERA-5 reanalysis (1979 to 2018). Year 1979 represents period from 1 December 1979 to 28 February 1980 and so on. For each winter (DJF), we calculate the total number of hazy days with HWI >1 and clear days with HWI < -1. Grey lines show frequencies from 16 individual PPE members and black line shows the mean of frequency using all 16 PPE members for 1969-2087 under the RCP8.5 scenario. Linear trend is calculated using line of best fit.

The mean change in the frequency of hazy days averaging across all PPE members is 26%, 24% and 33% for the near, mid and far future respectively as compared to the historical period, suggesting that the frequency of hazy days will likely increase for all future periods

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(Fig. 5). However, there exists a very large range in the projected change for all three future periods suggesting internal variability or parametric effect could influence the future projections of haze conducive weather. For near and mid future, hazy days are projected to change by -8% to 65% and -12% to 65% across the 16 PPE members, respectively, as compared to the frequency for historical period. For far future, the range of projected change is even larger, and an increase of ~87% in the frequency of hazy days is also possible. It should be noted, for all three periods, only one of the sixteen ensemble members suggests a decrease in daily haze frequency.

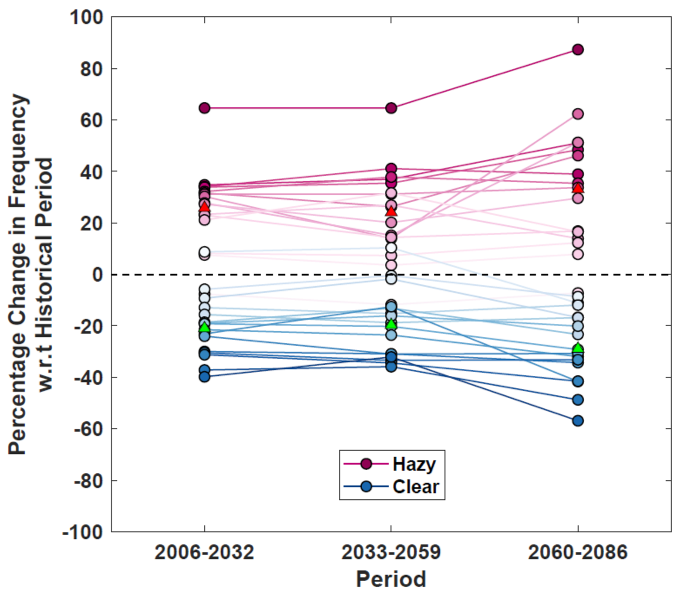

Figure 5 Percentage change in the frequency of winter hazy and clear days averaged over the near (2006-2032), mid (2033-2059) and far (2060-2086) futures under RCP8.5 as compared to the historical period (1979-2005). The length of near, mid and far future is the same as historical (i.e. 27 years). Small coloured circles (blue and pink) represent PPE members and triangles (red and green) represents the mean of PPE members.

For the clear days, the mean change in the frequency of clear days averaging across all PPE members is -21%, -20% and -29% for near, mid and far future, respectively (Fig 5). Considering the range across the 16 PPE members, the frequency for near, mid and far future is projected to change by -40% to 9%, -36% to 10% and -57% to -9%, respectively. Overall,

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most ensemble members show an increase in the frequency of hazy days and a reduction in the frequency of clear days for all three future periods however negligible change or even the opposite change, though less likely, but possible for all periods.

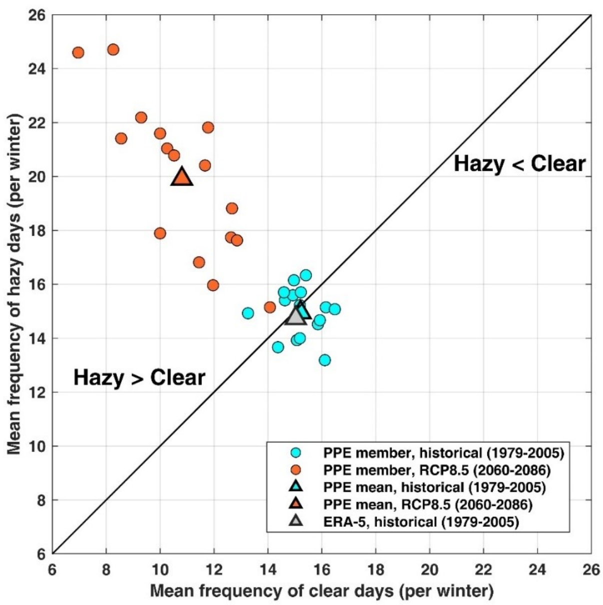

Figure 6 Frequency of winter hazy days versus clear days averaged over the historical period (1979-2005) and the far-future (2060-2086) period under RCP8.5 using all PPE members. Circles denote individual PPE members whereas triangles denote the mean of the members. Grey triangle shows mean frequency from ERA-5 reanalysis for the historical period (1979-2005). The black solid line shows the 1:1 (identity) line.

In addition to the changes in the frequencies over time, we also investigate the relative changes in the frequency of hazy days versus clear days for a given winter. The average frequency of hazy days and clear days over the historical period are almost equal for each PPE member (Fig 6). All PPE members show higher frequency of hazy days than clear days under the far future (2060-2085), however, there exists a substantial range in this change. The frequency of winter haze days can be similar or up to 3.5 times the frequency of clear days (Fig. 6). Similar results are also obtained for near and mid-future. Averaged across the PPE members, the number of hazy days can increase by ~2 times as compared to the number of clear days in future. As noted in Fig. 6, the spread in the frequency of hazy days amongst individual ensemble members is also larger for the far future (2060-2086) compared to the historical period. This suggests a larger uncertainty and a larger range of possible future meteorological conditions affecting haze and air quality as compared to the historical period. Other studies have (e.g.,Cai et al., 2017; Callahan and Mankin, 2020) also found similar increases in the frequency of hazy days for the future. However, the range of projected change differ substantially across models as well as ensemble members. In our study, in addition to the frequency of hazy days, we also evaluate the changes in the frequency of clear days across different future periods and compared the relative changes in both the frequencies, which is not examined in the past studies.

5. Role of individual meteorological variables

We now investigate the role of individual constituent meteorological variables in driving the changes in the HWI between the far-future (2060-86) and the historical (1979-2005) period. The probability distribution of the HWI shows a shift in the distribution towards higher magnitudes for the far-future as compared to the historical period (Fig 8). This implies an increased frequency in hazy days, as values with HWI >1 increase. A similar shift is apparent in the zonal-mean wind (U_{500}) and the vertical temperature profiles (dT), whereas no shift is noted in V_{850} suggesting a relatively less important role of V_{850} in driving the future changes in the HWI. We also find that the shift in the HWI as well as U_{500} and dT distribution is consistent across the 16 PPE members and is continual over time from the historical to the far-future period. Despite using a multimodel ensemble and a different time-period than used here, similar result with a relatively larger shift in the PDFs of U_{500} and dT as compared to V_{850} can also be noted in the Cai et al. (2017).

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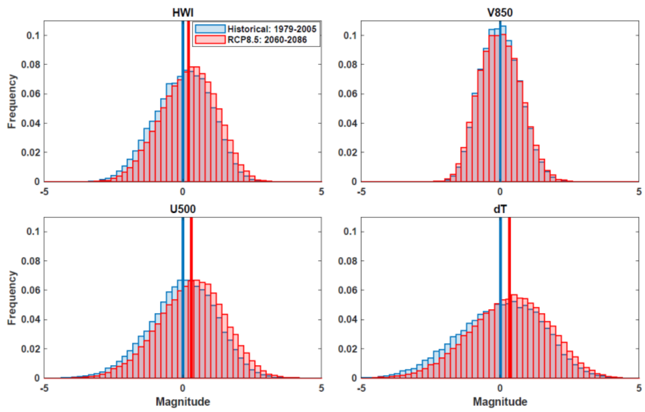

Figure 7 Probability Distribution Functions (PDF) for the winter HWI, meridional winds at 850 hPa pressure level (V_{850}), zonal winds at 500 hPa pressure level (U_{500}) and temperature gradient between the lower and upper troposphere (dT). PDFs are created using daily DJF values for the historical (blue) and far-future (red) under RCP 8.5 by pooling in all 16 PPE members. Blue and red solid lines show the mean values of the PDF for historical and far future, respectively.

6. Interannual variability in the frequency of hazy and clear weather conditions

Large interannual variability in the frequency of hazy and clear days is apparent in both individual PPE members and ERA-5 reanalysis (Section 4). Therefore, we examine the changes in the interannual variance of the frequencies for future periods as compared to the historical period. We also compare the variance in historical and future time-periods with the variance in the control simulation to discern the influence of the model physical parameterisations, i.e. parametric effect, on the variance.

The interannual variance for ERA-5 data is 27 days^2 and 39 days^2 for hazy and clear days, respectively, for the historical period (1979-2005) (triangles in Fig. 8a-b). The interannual variance in the frequency of hazy days derived from the PPE members for the historical period is larger than that for the ERA-5, whereas for the clear days the variance for ERA-5 lies within the range of the PPE members. No consistent change in the interannual variance of hazy days is noted for any of the PPE members (note the changes in colour ranking) from the historical to the future periods suggesting little influence of the parametric effect on the interannual variance of hazy days.

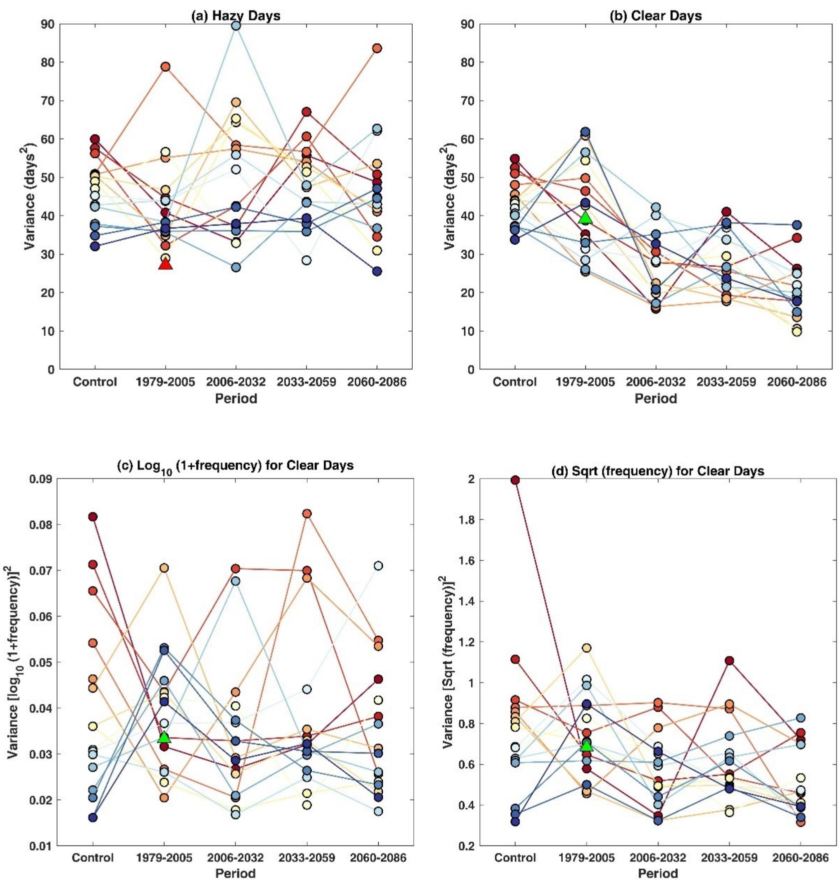

Figure 8 Interannual variance in frequency of winter **(a)** hazy and **(b)** clear days for the control simulation, historical (1979-2005), and near (2006-2032), mid (2033-2059) and far-future (2060-2086) under RCP8.5 for all 16 PPE members. Coloured circles are for individual PPE members and triangles for ERA-5 reanalysis. **(c-d)** are same as **(b)** but with $\log_{10}$ and square root power transformations. For (c-d), we first calculate the $\log_{10}$ of (1+frequency) and square-root of the frequency of clear days for the control simulation and each time-period, and then estimate variance for each respective period. The length of control simulation and all future periods is the same as historical, i.e. 27 years. The 27 years used for control here are randomly selected from 170-year control simulation for each member.

In contrast, the frequency of clear days for most PPE members show a marked reduction in the interannual variance from historical to near-future (Fig. 8b). However, as the frequency of clear days show a decreasing trend in time (see Fig. 4b), the mean frequency would be

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expected to reduce for the three future periods. Also, the reduction in variance could arise as the frequencies of clear days approach their lower bound of zero. With count data, a power transformation is often applied to stabilize the variance across all time periods. We tried two power transformations, i.e. $\log_{10}(1+x)$ and square-root (x), where x is the count data (Fig. 8c-d). We find the spread in the variance in the control simulation across the PPE members is comparable with the historical as well as future periods (Fig. 8c-d). Note that for control simulation we randomly selected 27 years (length same as historical and future periods) from 170 years of control simulation from each PPE member, however, we note comparable variance for the other randomly selected samples. Figure 8 (c-d) also shows that the individual PPE members show inconsistent changes in the variance (noting changes in the colour ranking) from control to historical and future periods. Therefore, no robust changes in the interannual variance of hazy or $\log_{10}$(1+ frequency of clear days) can be detected from control to historical and future periods. This means we can use the variance in the control simulation as a representative estimate of internal variability. This enables us to quantify the influence of the parametric effect and anthropogenic climate change on the trends across the different periods (see next section).

7. Influence of the parametric effect and anthropogenic climate change on trends

We discern the influence of the parametric effect and anthropogenic climate change on the future projections of the trends in the frequency of hazy and clear days. Figure 9 shows the time series of the frequency of winter hazy and clear days from ERA-5 and the 16 PPE members for the historical and future periods. The 95th percentile values (blue shaded region) and the range (blue dotted lines) in the frequency of hazy and clear days from the respective control simulation for each PPE member are also shown.

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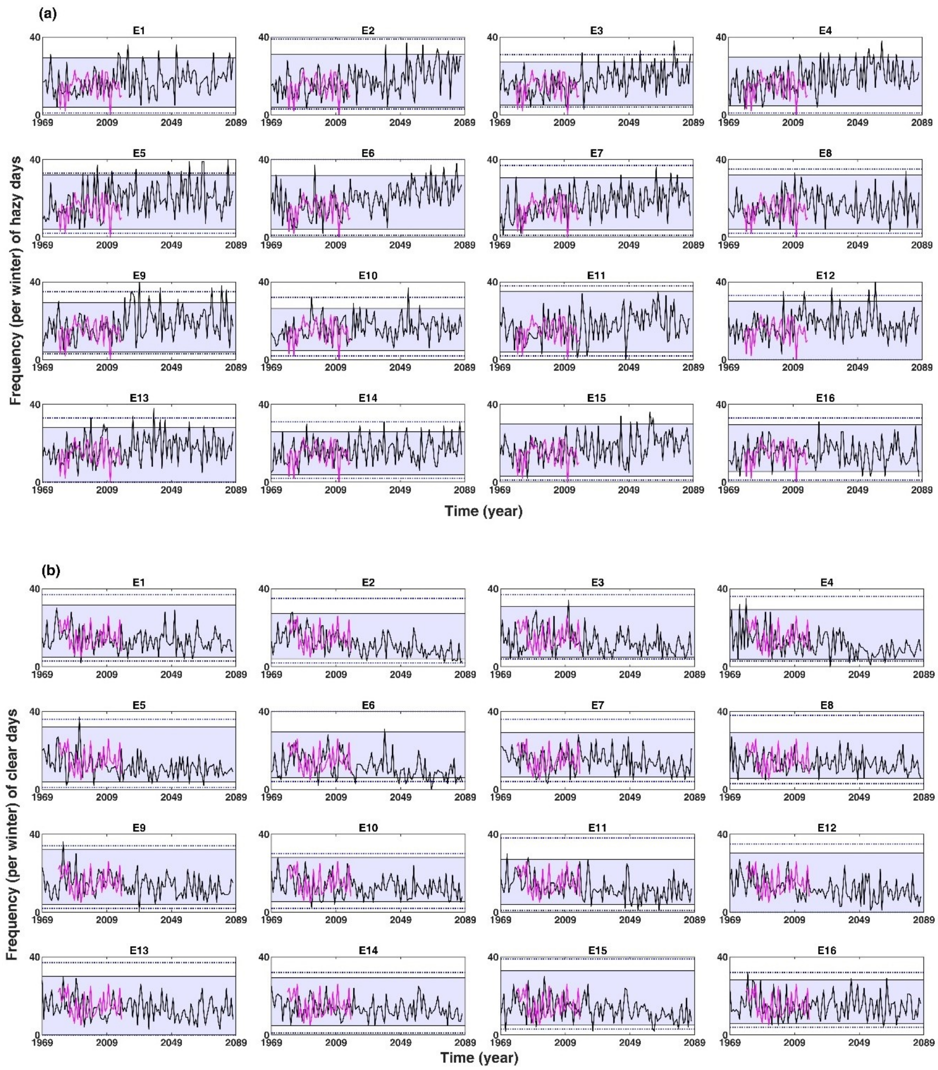

Figure 9 Frequency of **(a)** hazy and **(b)** clear days per winter for individual PPE members (black line) under the historical and RCP8.5 scenarios for 1969-2087 and ERA5 reanalysis (pink line) for 1979-2018. Blue shaded region shows the 95th confidence interval and blue dashed line shows the range of the frequency of hazy and clear days for the pre-industrial control simulation of 170-years.

For hazy days, the time series for selected PPE members (e.g. E3, E4) show increasing positive trends. In particular towards the end of the 21st century (Fig. 9a), the lower half of the control range is seldom sampled and more than the expected number of values lie above the

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97.5th percentile of the control frequencies. In contrast, for other PPE members (e.g. E8, E10), the full time series sample the control distribution evenly throughout the full period. For clear days, some members (e.g. E3, E4) show a clear reduction during the 21st century whilst others (e.g. E16) show that no trend and explore the control distribution evenly (Fig 9b).

We first examine the influence of the parametric effect on the trends in the frequency of hazy and clear days. As can be noted in section 6, for hazy days and $\log_{10}$ (1+ frequency of clear days), the estimate of interannual variance from the control is representative of all time periods and shows no discernible parametric effect. Therefore, we pool the 16 PPE control simulations to sample the internal variability. In Fig. 10 (a) and (b), we show the variance in trends for the time series resampled using the control simulation (see captions for details on resampling). The grey box and whiskers show the 95th confidence interval of the control variance used to represent the internal variability. The variance in PPE trends calculated using 16 PPE members for selected time periods is overlaid (circles). In Fig. 10 (a-b), if the variance for historical or future periods lies outside the whiskers, we conclude an impact of the parametric effect on the trends. Note that the variance in trends for clear days is in log-transformed space. As can be seen in Fig. 10a and 10b, the variance in PPE trends for historical and future periods lies within the envelope of the internal variability for both hazy and clear days. Therefore, we do not find any discernible influence of the parametric effect on the trends in the frequency of hazy and clear days.

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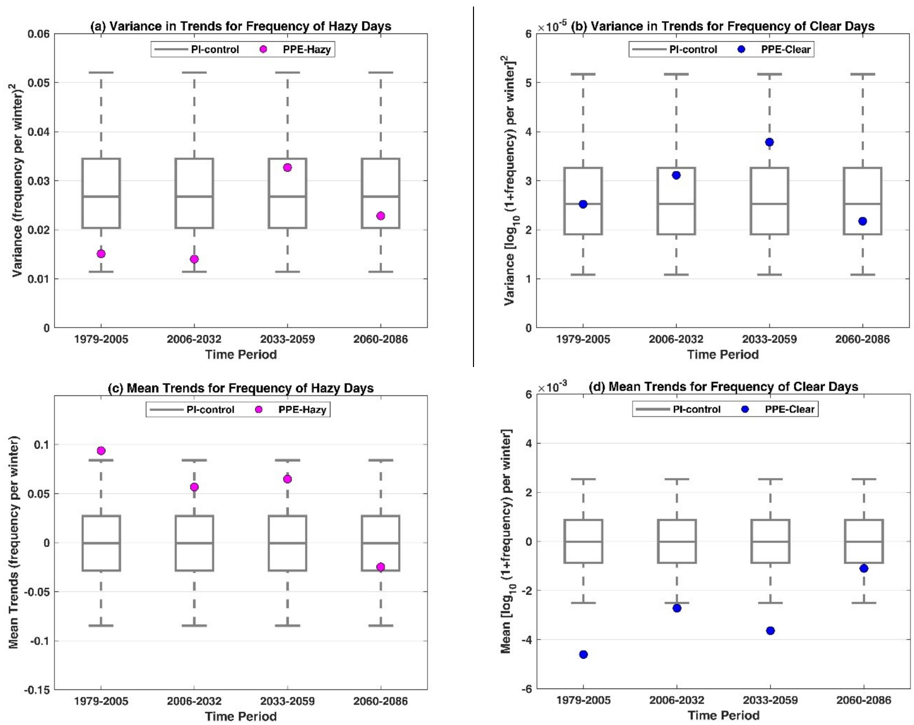

Figure 10 Variance in PPE trends for the frequency of winter **(a)** hazy and **(b)** clear days. Circles show the variance in trends from 16 PPE members for the historical (1979-2005) and near (2006-2032), mid (2033-2059) and far (2060-2086) future under the RCP8.5 scenario. Grey box and whiskers show the distribution of 10,000 values of variance in trends sub-sampled from the control simulation. **(c-d)** same as (a-b) but variance is replaced by mean. For box and whiskers, we first randomly sampled 10,000 time series of length 27 years using 2704 years of pre-industrial control simulation and calculated 10,000 values of trends. We then randomly sub-sample 16 trends values from the 10,000 trend values and calculate the variance and mean of 16 trend values. The boxes are at 25th and 75th percentile and the whiskers at 2.5th and 97.5th percentile of mean and variance distribution. For clear days, the frequencies were transformed to log space by applying a power transformation of $\log_{10}$ (1+ frequency) before calculating trends.

We now examine the influence of anthropogenic climate change on the trends in the frequency of hazy and clear conditions. We calculate the mean trend obtained from the 16 individual PPE member trends (Fig. 10c-d), to determine the influence of climate change across selected time periods. The grey whiskers in Fig. 10 (c) and (d) cover the range of trends that can be explained by internal variability and any trend values lying outside the grey whiskers represent the influence of anthropogenic climate change.

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The mean trend in the frequency of both hazy and clear days for the historical period (1979-2005) lie outside the 95% confidence interval of the control simulations, suggesting a substantial impact of anthropogenic climate change on the historical trends in the PPE. Similarly, the mean trends for clear days for near (2006-2032) and mid future (2033-2059) lie outside the 95% confidence interval of the control simulation. Thus, we find the impact of the climate change on both hazy and clear days. However, it is only discernible for specific periods due to the underlying large internal variability in the frequency of hazy and clear days.

8. Conclusions

In this study, we elucidate for the first time the influence of model physical parametrisations, in addition to internal variability and climate change, on the future hazy and clear weather conditions over the North China Plain (NCP) using the Perturbed Parameter Ensemble (PPE) from the Met Office HadGEM3-GC3 model. We use a meteorology-based daily Haze Weather Index (HWI), which has been previously used by a number of studies to examine the winter (December-February) haze conducive weather conditions over Beijing. We first identify the regional extent of the application of the HWI over China. We find that the HWI can be used as an indicator of hazy and clear weather conditions for the entire NCP due to the spatial coherence of regional meteorological conditions over this region.

The PPE shows that under the RCP8.5 scenario, the mean frequency of hazy days can increase by up to ~65% in near (2006-2032) and mid (2033-2059) future and by ~87% in far-future (2060-2086) as compared to the historical period (1979-2005). In contrast, the frequency of clear days can reduce by up to ~40% in near and mid-future and by ~57% in far-future. However, the opposite change of relatively lower magnitude or negligible change in frequency of hazy and clear, though less likely, is possible. The absolute number of hazy days for the far future can remain same or up to ~3.5 times higher than the clear days for any given winter.

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There also exist a large interannual variability in the frequency of hazy and clear weather conditions. However, no systematic change in the interannual variance of the frequency of hazy or clear days is projected in future as compared to the historical period. We also find that the future changes in hazy or clear weather conditions are largely influenced by changes in the zonal wind component and strong vertical temperature gradient between the lower to upper troposphere over the North China Plain. We do not find any discernible influence of the parametric effect on the future projections of trends in the frequency of hazy and clear days. However, we find the impact of anthropogenic climate change on the trends for both hazy and clear days for historical and specific future periods, suggesting climate change can exacerbate the increase in the number of hazy and the reduction in the number of clear days in future.

This study considers four atmospheric variables to examine the changes in future hazy and clear weather conditions, however, other atmospheric variables (e.g., boundary layer height) or processes may also influence the hazy or clear weather conditions. Furthermore, even though our study shows the potential for an increase in hazy weather conditions and a reduction in clear weather conditions for the future periods examined using the HWI, the formation of haze also depends on future emissions of air pollutants and their precursors. If the source emissions are cut-off or reduced in the future, the risk of haze formation would naturally reduce. Nevertheless, the projections of changes in the frequency and interannual variance in haze conducive weather conditions can be very useful for developing successful adaptation and mitigation policies for the future that consider both emissions and climate change, and therefore can be beneficial for near and long-term planning and decision-making in relation to improving future $PM_{2.5}$ air quality.

Data Availability

The Copernicus Climate Change Service (C3S) (2017): ERA5: Fifth generation of ECMWF atmospheric reanalyses of the global climate data are available through Copernicus Climate Change Service Climate Data Store (CDS) (https://cds.climate.copernicus.eu/). The PM2.5 concentrations for the US Embassy station in Beijing are archived at the following website (http://www.stateair.net/web/historical/1/1.html). The haze weather index time series for PPE and visibility data used in this paper can be obtained from the authors. The CAQRA dataset can be freely downloaded at https://doi.org/10.11922/sciencedb.00053.

Author Contribution

SJ and RMD conceived and designed the manuscript; DS conducted PPE simulations using Met Office HadGEM model; LP provided the visibility data; SJ performed data analysis, produced figures, wrote the first draft; all co-authors provided comments on the manuscript and contributed to writing.

Competing interests

The authors declare no financial or non-financial conflict of interest.

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