Rapid urbanization induced daily maximum wind speed decline in metropolitan areas: a case study in the Yangtze River Delta (China)

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ABSTRACT:

Wind extremes cause many environmental and natural hazard related problems globally, particularly in heavily populated metropolitan areas. However, the underlying causes of maximum wind speed variability in urbanized regions remain largely unknown. Here, we investigated how rapid urbanization in the Yangtze River Delta (YRD), China, impacted daily maximum wind speed (DMWS) between 1990-2015, based on near-surface (10 m height) DMWS observations, reanalysis datasets, and night-time lighting data (a proxy for urbanization). The station observation shows that annual DMWS in the YRD significantly ($p < 0.05$) declined during 1990-2015, by -0.209 m s^{-1} $decade^{-1}$, while slightly ($p > 0.1$) positive trends were found in NCEP-NCAR1 (+0.048 m s^{-1} $decade^{-1}$) and ERA5 (+0.027 m s^{-1} $decade^{-1}$). An increasing divergence between the reanalysis output and the station observation since 2005 was found, and those stations located in areas with high rates of urbanization show the strongest negative annual DMWS trend, implying the key role of urbanization in weakening DMWS. This finding is supported by sensitivity experiments conducted using a regional climate model (RegCM4) forced with both 1990 and 2015 land-use and land-cover (LULC) data, where the simulated DMWS using the 2015 LULC data was lower than that simulated using the 1990 LULC data.

Keywords: daily maximum wind speed, trend, urbanization, regional climate model, Yangtze River Delta.

1. Introduction

Wind speed is an important factor for many environmental issues. For examples, it can influence air quality in megacities through local ventilation and long-distance transportation of air pollutants (Cai et al., 2017; Shi et al., 2019), and it supplies kinetic energy for removing the fine and nutrient-rich topsoil, thereby causing severe soil erosion (Chappell et al., 2016; Zhang et al., 2019) and dust storms (Wang et al., 2017) across the globe in arid regions. Wind energy production is strongly dependent on wind speed variability (Karnauskas et al., 2018; Zeng et al., 2019), as the wind power generation potential varies as the cube of the instantaneous wind speed (Zeng et al., 2019). Strong winds and their associated turbulent eddies can heavily damage infrastructure, buildings (Neumayer et al., 2014) and crops (Gardiner et al., 2016), thus inflicting considerable socioeconomic losses each year (Vautard et al., 2019). For example, storms associated with extreme winds were identified as the costliest among the various types of climate-related and geophysical disasters in 2019, being estimated to have caused about 58 billion US dollars of direct losses (47.5% of the global natural disaster-induced losses) and more than 2,500 deaths worldwide (2019 Global Natural Disaster Assessment Report, 2020).

Global terrestrial mean wind speed has declined since the 1960s, termed stilling (Roderick et al., 2007; McVicar et al., 2012). This slowdown has been most evident in boreal mid-latitude countries, including China (Lin et al., 2013), the United States (Pryor et al., 2009) and European counties (Azorin-Molina et al., 2014; Minola et al., 2016). From ~2010 onward, a reversal of the mean wind speed trend has attracted the attention of the climate community (Zeng et al., 2019; Azorin-Molina et al., 2019). Debate continues in scientific circles regarding the occurrence of wind speed changes (stilling vs. reversal), because their underlying causes are not fully understood (Wu et al., 2018).

While air temperature and precipitation extreme changes have been extensively investigated, studies of extreme wind speed changes, e.g., daily maximum wind speed (DMWS, defined as observed daily maximum 10 minutes average wind speed), an important index for designing building safety, has received limited attention during the last two decades (Azorin-Molina et al., 2016; Zhang et al., 2020). Given the uncertainty of causes in mean wind speed changes (Wu et al., 2018) and a skewed relationship between mean wind speed and maximum wind speed (Minola et al., 2020), the trends in DMWS and in the mean wind may not be consistent. International multi-decadal research into extreme wind variability, as well as changes from anemometer observations, remain inconclusive: both negative and positive trends have been reported in different regions (Azorin-Molina et al., 2016). For instance, DMWS significantly declined from 1975 to 2016 in China (Zhang et al., 2020), as supported by a range of different evidences including declining global dust emissions (Chappell et al., 2016; Shao et al., 2013). In contrast, DMWS has increased at most of coastal stations in the USA since 1990 (Klink, 2015).

To date, few studies have investigated the causes of extreme wind speed variability and trends (Wu et al., 2018). For example, large-scale atmospheric changes expressed by the North Atlantic Oscillation Index and the Jenkinson and Collison scheme indices showed significant correlation with both frequency and magnitude of daily peak wind gust changes over Spain and Portugal (Azorin-Molina et al., 2016). Overall weakened large-scale atmospheric circulation partly explained the declining annual, winter and autumn DMWS over China, while the causes of increased DMWS in summer and spring are still largely unknown (Zhang et al., 2020). In addition, near-surface wind speed is sensitive to aerodynamic roughness changes according to the wind profile law (Han et al., 2016), and many previous studies have confirmed that changes in surface roughness induced by vegetation growth (Vautard et al., 2010; Wever, 2012) or urbanization (Hou et al., 2013) have played a key role in reducing near-surface mean wind speed. For example, in South Korea during 1993-2015, urban near-surface mean wind speeds observations declined up to -0.63 m s^{-1} $decade^{-1}$, while those at rural stations increased up to 0.41 m s^{-1} $decade^{-1}$. Rapid urbanization contributed −0.37 m s^{-1} of mean wind speed changes from 1980-2018 over Beijing-Tianjin-Hebei in China (Wang et al., 2020). However, no existing studies have examined the contribution of changed surface roughness to extreme wind speed. The present study addresses this knowledge gap.

China has experienced rapid urbanization in the last 3-4 decades, with vigorous economic growth (Bai et al., 2014), especially in the Yangtze River Delta (YRD, including Zhejiang, Jiangsu and Shanghai) which accounted for more than 20% of China's GDP (Gross Domestic Product) in 2019 (Statistical Bulletin on National Economic and Social Development in 2019, http://www.stats.gov.cn/tjsj/zxfb/202002/t20200228_1728913.html, last accessed 1 February 2022). Previous studies documented that rapid urbanization both in terms of areal extension and constructing more taller buildings has weakened near-surface mean wind speed in some rapidly urbanized areas, e. g., east China (Li et al., 2018) and Beijing (Hou et al., 2013). By increasing roughness, urbanization could weaken the long-term trend of near-surface DMWS

(Zhang et al., 2020), yet in contrast, uniform building distributions can induce wind funneling effects (Peng et al., 2018) that can enhance DMWS in some local urban areas: these contrasting responses illustrate the uncertainty regarding the effects of urbanization on DMWS changes.

For these reasons, our objectives are to (i) investigate DMWS trends in the rapidly urbanized YRD from 1990 to 2015, using quality-controlled and homogenized DMWS observations and reanalysis output; (ii) reveal the potential impacts of the rate of urbanization on DMWS trends, by using night-time lighting data to classify the rate of urbanization at each station; and (iii) simulate how urbanization affects DMWS by conducting sensitivity experiments using a regional climate model. Our research supports the management of social and environmental planning and policy development of urbanization, and contributes to the scientific understanding of long-term variability in wind extremes.

2. Materials and methods

2.1. Anemometer observations and reanalysis outputs

We used daily maximum 10-minute mean near-surface (~10 m height) wind speed for 00:00 to 23:59 from the China Meteorological Administration (CMA, http://data.cma.cn/, last accessed 1February 2022). Following Azorin-Molina et al.(2014), the daily maximum wind speed (DMWS) data were firstly aggregated into monthly values, allowing a maximum of five days of missing data each month. Stations with a large amount of missing data (i.e., greater than 3 months since 1 January 1990) were excluded. Figure 1 displays the distribution of the 111 stations selected for the 26-year (i.e., 1990–2015) study period.

Anemometer height and type changes (Wan et al., 2010), and anemometer aging (Azorin-

Molina et al., 2018), can cause artificial shifts in wind speed series. As has been successfully applied previously to DMWS series (Azorin-Molina et al., 2016; Zhang et al., 2020), the R package Climatol (http://www.climatol.eu/; last accessed 1February 2022) was used to perform quality control, relative homogenization, and missing data infilling on the raw DMWS series. A detailed description of Climatol is found in Guijarro (2018).

For comparison with station observations, 6-hourly and hourly 10-m zonal and meridional components of wind from two widely used and reliable reanalyses (Zhang et al., 2021; Torralba et al., 2017) of , i.e., the National Center for Environmental Prediction, National Center for Atmospheric Research (NCEP–NCAR1 Reanalysis, Kalnay et al., 1996), https://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis.pressure.html; last accessed 1February 2022), and the European Centre For Medium Range Weather Forecasts (ERA5 Reanalysis, Hersbach et al., 2020), https://cds.climate.copernicus.eu/; last accessed 1 February 2022) were downloaded, both covering 1990-2015. Note that DMWS from NCEP-NCAR1 and ERA5 were calculated as maximum 6-hourly wind speed and hourly wind speed for a day, respectively; this differs from the maximum 10-minute average which is denoted as daily maximum wind speed from observations.

2.2. Remote sensing data

2.2.1 Night-time light data

Night-time light data are widely used to indicate the distribution of urban areas and urbanization growth (Stokes and Seto, 2019; Zhao et al., 2020). We retrieved night-time light data that from the National Centers for Environmental Information (NCEI, https://www.ngdc.noaa.gov/eog/download.html, last accessed on 1 February 2022). The dataset included two types of satellite observations. Operational Linescan System of the Defense Meteorological Satellite Program (DMSP/OLS) observed night-time light from Jan 1992-Dec 2013, with a spatial resolution of 0.008333° (~0.92 km at the equator), and Visible Infrared Imaging Radiometer Suite (VIIRS) observed night-time light from Jan 2012 onwards, with a spatial resolution of 0.004167° (~0.46 km at the equator). We used the monthly DMSP/OLS composites product averaged over 1992 to represent the 1990 level of urbanization, and the annual average of the 2015 monthly VIIRS product to represent the 2015 urbanization. Both products were selected with a stable light value, which discarded other sites with persistent lighting, including gas flares and ephemeral events, such as fires. Due to sensor differences between DMSP/OLS and VIIRS, calibration coefficients were applied to the VIIRS data (Yang, 2018) to harmonize the two products. We used the night-time light value (0-64, dimensionless) to represent the urbanization level, and the mean night-time lights within a 3 km radius for each station (Li et al., 2018). Then, the difference in night-time light between 1992 and 2015 was used as a proxy for urbanization changes within the 3 km proximity of each station.

2.2.2 Land-use and land-cover (LULC) data

The land-use and land-cover (LULC) data over the YRD in 1990 (1990LULC) and 2015 (2015LULC) were downloaded from the Resource and Environmental Science Data Center of the Chinese Academy of Sciences (RESDC-CAS, http://www.resdc.cn/Datalist1.aspx?FieldTyepID=1,3; last accessed 1 February 2022), with a 1 km resolution. As the regional climate model applied herein (see 2.3) used a different LULC classification, following Ren et al. (2018), we transferred the RESDC-CAS LULC to a format that was used by the model.

2.2.3 Normalized Difference Vegetation Index (NDVI) dataThe Normalized Difference Vegetation Index (NDVI, dimensionless) data over the YRD in 1990 is provided by National Cryosphere Desert Data Center. (NCDDC, http://www.ncdc.ac.cn; last accessed 1 February 2022), with an 8 km resolution. The NDVI data in 2015 is downloaded from the Resource and Environmental Science Data Center of the Chinese Academy of Sciences (RESDC-CAS, https://www.resdc.cn/Datalist1.aspx?FieldTyepID=1,3; last accessed 1 February 2022), with an 1 km resolution. To be congruent with the resolution of the NDVI in 2015, NDVI in 1990 is resampled to a 1 km resolution.

2.2.4 Estimation of aerodynamic roughness

Following Chappell et al. (2018), we estimated monthly albedo-derived aerodynamic roughness for each station over the YRD from 2000-2015. The albedo data were retrieved from the MODIS albedo product (https://modis.gsfc.nasa.gov/, last accessed 1February 2022), which provides 500 m resolution data available every 8 days, with 16 days of acquisition, since 2000.

2.3 Regional climate model and sensitivity experiment design

The Abdus Salam International Center for Theoretical Physics (ICTP) RegCM4 model (https://www.ictp.it/research/esp/models/regcm4.aspx; last accessed 1February 2022) was applied to conduct sensitivity experiments. The model uses a terrain-following σ-pressure vertical coordinate and an Arakawa B horizontal grid system and includes a convection parameterization scheme, a large-scale cloud and precipitation scheme, expansion and modification of the radiation scheme, and advanced land-surface model within the mesoscale model MM5 (Giorgi et al., 2012). The RegCM4 model simulations cover the YRD (Fig. S1), with a horizontal resolution of 30 km. The vertical grid includes 23 levels from the surface to 50 hPa, and the time step is 30 seconds. The primary physical process schemes contain the MIT–Emanuel cumulus convection scheme for cumulus parameterization (Georg, 1993), Holtslag planetary boundary layer (PBL) scheme (Holtslag et al., 1990), the Zeng scheme for sea flux parameterization (Zeng et al., 1998), Community Land Model version 4.5 (CLM4.5) for land-surface parameterization scheme (Oleson et al., 2013), the NCAR CCM3 radiation scheme (Kiehl et al., 1996), and the Rapid Radiation Transfer Model (RRTM) (Mlawer et al., 1997). ERA-Interim reanalysis data (0.75° × 0.75°, https://apps.ecmwf.int/datasets/data/interim-full-daily/levtype=pl/, last accessed 1 February 2022) were used as the lateral boundary condition, which is updated every 6 hours; the sea surface temperature (SST) data were from the optimal interpolation weekly SST data from NOAA (Reynolds et al., 2002). Full details of the model experiments are found in Wang et al. (2021).

To explore possible responses of DMWS changes to the rapid urbanization, using the same meteorological forcings from 1 October 1989 to 31 December 1990, two sensitivity experiments were performed in RegCM4 using (i) 1990LULC; and (ii) 2015LULC respectively, after a one-year' initialization This method has been successfully implemented previously to assess the impact of LULC on wind speed dynamics (e.g., Zha et al., 2019), and air temperature and precipitation changes (e.g., Cao et al., 2015). A full year simulation for a low and high urbanization cases is considered appropriate to identify the impact of urbanization on wind climate between the two years (i.e., 1990 and 2015); noting that our research purpose was not to simulate realistic changes of the wind climate under changing urbanization for each of the 26-years. In the analysis, the first three months of each experiment were excluded for model spin-up. DMWS in the model output was taken as the maximum hourly wind speed for each 24-hour period (defined as UTC 00:00 to 24:00).

2.4 Statistical analyses

To avoid a few series with high-wind speed dominating a regional average series, DMWS anomalies were expressed as the deviation from the 1990-2015 DMWS mean for each station (Azorin-Molina et al., 2021). Following previous studies (Chen et al., 2013; Zhang et al., 2020), regional mean DMWS in the YRD from the NCEP-NCAAR1 and ERA5 were calculated as the mean value of all grids with a majority of area covered by the study site. Sen's slope method was used to calculate the magnitude of DMWS trends (in m s^{-1} $decade^{-1}$), and an 11-yr Gaussian low-pass filter was used to obtain the DMWS multi-decadal variability. To enable the comparison with reanalysis data, DMWS from station observations were interpolated onto a 0.5° resolution grid. Additionally, we computed the statistical significance of the estimated linear trends using the Mann–Kendall's tau-b nonparametric correlation coefficient.

We also assessed DMWS changes as a function of urbanization rate across the study region. Considering the complex and non-uniform urban morphology (Peng et al., 2018) and that winds are sensitive to urbanization induced surface roughness (Li et al., 2018), homogenized data from the 111 stations were classified into 5 groups with different urbanization rates (Table 1) being: (i) very-low urbanization rate; (ii) low urbanization rate; (iii) moderate urbanization rate; (iv) fast urbanization rate; and (v) very fast urbanization rate. Here the urbanization rates of each station for 1990 to 2015 were calculated as the difference in night-time light value as 2015 minus 1992 (see Table 1).

3 Results

3.1. DMWS changes estimated from the station observations and reanalyses

Figure 2 shows trends in DMWS anomalies for 1990-2015 over the YRD. Annual DMWS observations significantly declined for the whole period (-0.209 m s^{-1} dec^{-1}, $p < 0.05$), with the highest DMWS (actual values: 8.7 m s^{-1}) in 1990 and the lowest DMWS (actual values: 7.8 m s^{-1}) in 2015. DMWS displayed relatively stable interannual variability during 1990-2005, before a dramatic and rapidly weakening trend from 2005 till 2015. However, DMWS from NCEP-NCAR1 shows an insignificant positive trend (+0.048 m s^{-1} dec^{-1}, $p > 0.1$) for 1990-2015. A close relationship between the observed DMWS and NCEP-NCAR1 DMWS was detected from 1990-2005, while the two series diverged from 2005 onwards. Similar variability and a positive trend (+0.027 m s^{-1} dec^{-1}, $p > 0.1$) were found in ERA5 DMWS. The conflicts between observed DMWS and reanalyses indicate the uncertainty of reanalyses on modeling DMWS, as reanalyses have not assimilated roughness changes induced by urbanization (Zhang et al., 2020). Increasing divergence between the reanalyses and the station observation started in 2005, indicating urbanization might have a significant impact on DMWS changes after reaching a certain threshold.

Figure 3 displays the spatial distribution of DMWS trends across the YRD for 1990-2015. Observed DMWS declined across most of the study region, with the three sub-regions showing the strongest and most significant negative trends (<-0.200 m s^{-1} dec^{-1}, $p < 0.05$) located in the north, east and coastal zones of the southeastern parts of the study region. Stations that displayed low-magnitude negative trends (-0.100 to 0.000 m s^{-1} dec^{-1}, $p > 0.05$) are located in the southwestern part of the study region, where complex topography is characterized by hills and mountains (Fig. 1). However, barely significant and different spatial patterns of DMWS trends were found in the NCEP-NCAR reanalysis: in this case, DMWS weakly increased (+0.000 to +0.100 m s^{-1} dec^{-1}, $p > 0.05$) in most of the YRD, and weakly declined (-0.000 to -0.200 m s^{-1} dec^{-1}, $p < 0.05$) in the northern and southern corners. Similarly, ERA5 DMWS widely increased (+0.000 to +0.100 m s^{-1} dec^{-1}), but was only significant ($p < 0.05$) over a few southern parts of the study region. The divergences between reanalyses and station observations indicate the crucial role played by urbanization on weakening DMWS, as reanalyses mostly represent the change of climate variability (Vautard et al., 2010).

3.2. Impact of urbanization on DMWS trends

Figure 4 displays the distribution of night-time lighting in 1992 and 2015, as a proxy for urbanization intensity, with urbanization rate revealed by the difference in night-time lighting between these years across the YRD. Figure 4(a) clearly shows that in 1992, the majority of the YRD had very weak night-time lighting (< 10), and only a few (mainly central) regions contained strong lighting. By 2015, Figure 4(b) shows night-time lighting had widely increased over the YRD. Areas with strong night-time lighting (> 40) were primarily located in metropolitan central, coastal and western parts of the region, while night-time lighting in the mountainous southwestern part of the region remained quite small (< 10; Fig. 4(b)).

Figure 4(c) shows that rapid urbanization occurred in most of the central the YRD, with the highest 2015 minus 1992 night-time light difference (NLD > 30) in regions covered by the megacities (> 10 million inhabitants), e.g., Shanghai, Hangzhou, Suzhou and Nanjing. Additionally, some coastal cities in the southeastern and inland cities in the north of the study region also experienced fast urbanization (NLD > 30), due to rapid economic development associated with international and domestic goods transport networks (e.g., ports and railways). The lowest NLD values (< 10) were mainly found in the mountainous and hilly southwestern YRD. Comparing urbanization rates with the magnitude of DMWS trends (Figure 4c, blue circles) revealed that areas with rapid urbanization growth were accompanied by the largest decreases of DMWS, and vice-versa. In other words, the spatial distribution of DMWS trends is correlated with urbanization rates across the YRD. Later, section 3.4, using a regional climate model simulation, we assess to what degree the physical representation of these urban changes drives this high correlation.

Box-and-whisker plots in Figure 5 show DMWS trends in station groups with varied urbanization rates (see Table 1). Station groups with very low urbanization rates have relatively weak negative trends of DMWS, while the strongest declining DMWS trends were found in station groups with the highest urbanization rates. Note that the minimum magnitude of DMWS trends (represented by the upper whisker in Fig. 5) was stable between the station groups from low to high urbanization rate (ranging from +0.02 to -0.05 m s^{-1} dec^{-1}), in contrast to its maximum magnitude (i.e., the lower whiskers on Fig. 5), suggesting the relationship between urbanization and DMWS are nonlinear. These results clearly show that DWMS in the YRD has been weakened by urban growth during 1990-2015.

3.4 Impact of urbanization on DMWS changes revealed by climate model simulations

Figure 6 shows the distribution of urban areas in 1990 and 2015 in the YRD from the LULC data sources, and Table 2 displays the changes in the areas of various LULC types between 1990 and 2015. In 1990 (Fig. 6a), urban areas were quite sparse; with most located in the central and northern parts of the YRD. This pattern is strongly consistent with the night-time light distribution in 1992 (2 years later than 1990, see Fig. 4a). Further, urban areas in 2015 mainly occupied the central, northern and southeast coastal parts, which is again highly consistent with the 2015 night-time light pattern (Fig. 4b). Note that much greater urbanization was detected in 2015 when compared to 1992 (Fig. 6b), especially for those regions that already (in 1992) had a high proportion of urbanization. When compared to other LULC types, it is clearly seen that urban area increases represent the dominant LULC changes between 1990 and 2015 over the YRD (Table 2). The similar patterns of night-time lighting and urban extent confirm that night-time light data are a reliable proxy of the rapid urbanization across the YRD during 1990-2015.

To confirm our hypothesis that the rapid urbanization weakened DMWS, two sensitivity experiments configured with the same settings and forcing but with different LULC data (i.e., 1990LULC and 2015LULC) were implemented using RegCM4. The spatial distributions of RegCM4 simulated DMWS in 1990 (forced with 1990LULC) and 2015 (forced with 2015LULC), as well as their difference, are shown in Figure 7. Overall, DMWS for the 1990LULC simulation exhibited a distinctly heterogeneous spatial pattern, manifested as a high

DMWS from the central to northern YRD, and weak DMWS over the southern part (Fig. 7a). A similar spatial pattern of DMWS was found for the 2015LULC simulation (Fig. 7b). This indicates that changes in LULC have not caused the change in the spatial distribution of DMWS in YRD. When considering the difference in DMWS between the two simulations (i.e., 2015LULC minus 1990LULC, Fig. 7c), negative DMWS differences were found in most metropolitan central and northern ($p < 0.1$) parts of YRD, and a few in southern coastal regions. As those areas experienced rapid urbanization from 1990 to 2015, this confirms that the decline in DMWS was mainly driven by urbanization (i.e., the LULC changes). Furthermore, we compared regional means of DMWS in the 1990LULC and 2015LULC simulations and found that DMWS for the 2015LULC simulation is lower than that for the 1990LULC simulation by -0.03 m s^{-1}. Note that positive DMWS differences were found over a few southern and western parts, indicating that vegetation changes rather than urbanization appear to have increased DMWS in mountainous areas with complex terrain.

4 Discussion

In this study, we first examined DMWS trends over the YRD, a region that has evidently increased its urban area according to LULC and night-time lighting during 1990-2015. The results from station observations showed that DMWS experienced a secular decline during 1990-2015, which is consistent with a previous study of DMWS trends across China, although different periods were used (Zhang et al., 2020). A previous study reported negative trends in mean wind speed from 1990-2015 based on station observations over a region containing the YRD (Li et al., 2018), which along with our findings shows that both mean wind speed and

DMWS experienced a slowdown in recent decades. In contrast, NCEP-NCAR1 and ERA5 reanalysis shows a weakly positive trend in DMWS from 1990 to 2015, leading to increasing divergence between the reanalysis DMWS and station observed DMWS since 2005. Wind speed from reanalysis mostly represent the impact of climate variability (e.g., atmospheric circulation) on wind speed changes (Vautard et al., 2010), as surface roughness changes are not explicitly taken into account in the assimilation process (Kalnay et al., 1996). Therefore, opposite trends between the station observations and reanalysis indicate that climate variability is very likely not be the cause of DMWS change in our study region, and declined DMWS may well be induced by surface roughness increases (e.g., urbanization, Fig. 8). Albedo-based surface roughness in the vicinity of many stations located in urban area increased from 2000-2015 too, and annual DMWS shows a negative correlation (-0.32, $p > 0.1$) with mean annual surface roughness (Fig. 8). Wu et al. (2017) reported that wind speed change over east China is not consistent with East Asian summer monsoon variability, , coupled with the results presented herein, means that the detected observed DMWS declines were most likely driven by rapid urbanization after reaching a certain threshold (2005).

The change in night-time lighting between 1992 and 2015 revealed this rapid urbanization during recent decades in the YRD, which is supported by increases in population, GDP, and the number of cars in the region (see Fig. S2). By comparing DMWS trends with urbanization rates (i.e., night-time light increases), it was clearly seen that stations with the strongest negative DMWS trends were mainly located in metropolitan areas with the fastest urbanization rates, while stations with the weakest negative DMWS trends (or even slightly positive trends) were largely distributed over the mountain or hilly areas that experienced the lowest urbanization rates. This demonstrates that recent DMWS changes over the YRD were mainly driven by the rapid urbanization during 1990-2015. As urban expansion and development increased both the number and the height of buildings, the resulting increase in surface roughness could have weakened the near-surface wind speed, e.g., DMWS, according to the theoretical wind speed profile (Han et al., 2016). Existing studies have documented a similar relationship between mean wind speed trend and urbanization-induced surface roughness changes (Li et al., 2018; Chen et al., 2020), while our study is one of the few to provide empirical evidence for the effect of urbanization on extreme winds (Li et al., 2011).

Additionally, we classified stations into five groups based on urbanization rate, and found that maximum negative trends in DMWS increased with increasing urbanization rate, while the minimum magnitudes of DMWS trends were generally stable among the five groups. This is quite a different result when compared to mean wind speed (Li et al., 2018), as both maximum and minimum magnitudes of negative trends increased with urbanization (Li et al., 2018). This suggests that the relationship between urbanization-induced roughness and DMWS trends is more complex than that for mean wind speed. Previous studies have reported an exponential relationship between magnitude of wind speed and surface roughness (Han et al., 2016; Zeng et al., 2019), which means surface roughness may have had a stronger impact on stronger winds, thus extreme winds are more sensitive to local environmental changes (Azorin-Molina et al., 2016; Zhang et al., 2020)than more typical (i.e. more average) winds. Further, we have explored the associations between the NDVI and DMWS (Fig. 9) and found that NDVI decreased in most urban area and increased in most mountainous areas in the YRD during 1990-2015. This indicates that vegetation changes might not be the main cause of declined DMWS in the YRD.

As the increased urban area has been the dominant LULC change over the YRD during recent decades (Table 2 and Fig. S3) (Zha et al., 2019), the difference between the simulated DMWS under the 1990LULC and 2015LULC forcing to a large extent reflects the impact of urbanization on DMWS changes. The results clearly demonstrate that the simulated DMWS forced by the 2015LULC was much lower in those regions (e.g., central, north and coastal parts of the YRD) which experienced rapid urbanization when compared to the simulation forced by the 1990LULC. This pattern is strongly consistent with the distribution of DMWS changes based on the station observations and night-time light difference (Fig. 3) and further confirms that rapid urbanization has weakened DMWS over the YRD from 1990 to 2015. Similar sensitivity experiments for wind speed using the WRF model demonstrated that regional mean wind speed in the Beijing metropolitan area has decreased due to urbanization (Hou et al., 2013). Furthermore, the regional mean difference between DMWS in two sensitivity experiments is -0.03 m s^{-1}, which is much lower than that between 1990 and 2015 based on the station observations. This is likely due to two main reasons. First, DMWS is the maximum 10-minute mean wind speed observation during 24 hours of such 10-minute observations, while simulated DMWS corresponds to maximum hourly mean wind speed over the same 24 hours, noting that the mean peak value of wind speed in a certain period generally decreases with the increase in recording frequency (Azorin-Molina et al., 2017). Second, LULC data used in the climate model cannot realistically capture the building density and height, thus the impact of urbanization on winds is underestimated in the model simulations (Zha et al., 2019).

For the first time, our study based on sensitivity experiments with a regional climate model has demonstrated that urbanization weakens the extreme winds defined in the study. Besides the roughness argument proposed above, the greater atmospheric stability caused by aerosol-induced reductions in the land-surface insolation (Jacobson and Kaufman, 2006) may also affect DMWS variability. Thus, pollution control in the areas of rapid urbanization may also play a role. Further studies in other rapidly developing urban regions across the globe are needed. This is especially the case in rapidly developing economies where urban pollution can be problematic for human health (Landrigan et al., 2018; Dedoussi et al., 2020) and where DMWS decreases may exacerbate the existing pollution-induced health problems in such rapidly growing urban areas.

5 Conclusions

We found that observed DMWS over the YRD which is a region that has experienced a high rate of urbanization significantly declined from 1990 to 2015,. Meanwhile, a weak increase in DMWS was found in the NCEP-NCAR and ERA-5 reanalysis, suggesting that changes in the large-scale atmospheric circulation might not be responsible for the observed DMWS decreases, and that reanalysis output is not useful when assessing wind speed trends. Stations showing the largest negative DMWS trends are mainly located in areas with high urbanization rates as indicated by night-time light differences between 1992 and 2015. In contrast, no significant trends in DMWS were found in areas with small urbanization rates. The increased magnitude of the differences between the reanalyses and the station data since 2005 points to the significant impact of urbanization after a certain threshold. Two sensitivity experiments conducted with the RegCM4 model indicate that the increased urban area from 1990 to 2015 could have weakened DMWS in the YRD. In summary, our findings provide clear evidence that recent rapid urbanization in the YRD has weakened both mean wind speed and the extreme winds. This finding contributes to improved understanding of the underlying causes behind extreme wind speed changes in urban environments.

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Author Contributions

G.Z. and P.S. designed the research and conducted analysis. X.W implemented the sensitivity experiment in the RegCM4 model. G.Z. wrote the majority of the manuscript. All of the authors discussed the results and reviewed the manuscript.

Data Availability

Daily maximum wind speed were accessed accessed at China Meteorological Administration

(CMA, http://data.cma.cn/), NCEP–NCAR1 Reanalysis data was retrieved from NOAA (https://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis.pressure.html), and ERA5 Reanalysis data was downloaded from ECMWF (https://cds.climate.copernicus.eu/). The night-time light data were retrieved from the National Centers for Environmental Information (NCEI, https://www.ngdc.noaa.gov/eog/download.html), and NDVI data over the YRD in 1990 were provided by the National Cryosphere Desert Data Center. (NCDDC, http://www.ncdc.ac.cn).

NDVI data over YRD in 2015 and the land-use and land-cover (LULC) data over YRD in 1990 (1990LULC) and 2015 (2015LULC) were downloaded from the Resource and Environmental Science Data Center of the Chinese Academy of Sciences (RESDC-CAS, http://www.resdc.cn/Datalist1.aspx?FieldTyepID=1,3). MODIS albedo product albedo data were retrieved from the National Aeronautics and Space Administration (NASA, https://modis.gsfc.nasa.gov/).

Conflict of interest

The authors declare that they have no competing interests. Data and materials availability: all data needed to evaluate the conclusions in the paper are present in the paper and/or the Supplementary Materials. Additional data related to this paper may be requested from the authors.

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Table 1. Classification of stations with different urbanization rates as indicated by night-time light difference (NLD, dimensionless) between 1992 and 2015 for each station.

Types of Station	I	II	III	IV	V

Night light difference	$0 \leq NLD < 10$	$10 \leq NLD < 20$	$20 \leq NLD < 30$	$30 \leq NLD < 40$	$NLD \geq 40$
Number of stations	5	14	22	40	30
Level of urbanization	Very Low(VL)	Low(L)	Moderate(M)	High (H)	Very High(VH)

Table 2. Areas and proportions of LULC types in 1990 and 2015, and area of LULC changes between 1990 and 2015 over the Yangtze River Delta.

LULC types	1990		2015		LULC Changes (km^2)
	Area (km^2)	Proportion	Area (km^2)	Proportion	
Crops/mixed farming	29754.78	14.40%	28054.98	13.64%	-1699.80
Short grass	556.11	0.27%	558.61	0.27%	2.50
Tall grass	2723.15	1.32%	2516.72	1.22%	-206.43
Irrigated crop	74475.01	36.03%	64510.86	31.37%	-9964.15
Semi-desert	93.01	0.05%	49.35	0.02%	-43.67
Bog or marsh	1820.71	0.88%	1569.25	0.76%	-251.46
Inland water	5905.44	2.86%	5817.07	2.83%	-88.37
Evergreen shrub	1931.54	0.93%	1784.40	0.87%	-147.14
Mixed woodland	9301.46	4.50%	7818.60	3.80%	-1482.86
Forest/field mosaic	58654.61	28.38%	59299.78	28.84%	645.16
Water and land mixture	5929.19	2.87%	6961.93	3.39%	1032.74
Urban	4526.05	2.19%	11926.28	5.80%	7400.23
Sub-Urban	11007.39	5.33%	14766.71	7.18%	3759.33