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

82　occurrence of wind speed changes (stilling vs. reversal), because their underlying causes are

83　not fully understood (Wu et al., 2018).

84　　While air temperature and precipitation extreme changes have been extensively investigated,

85　studies of extreme wind speed changes, e.g., daily maximum wind speed (DMWS, defined as

86　observed daily maximum 10 minutes average wind speed), an important index for designing

87　building safety, has received limited attention during the last two decades (Azorin-Molina et

88　al., 2016; Zhang et al., 2020). Given the uncertainty of causes in mean wind speed changes

89　(Wu et al., 2018) and a skewed relationship between mean wind speed and maximum wind

90　speed (Minola et al., 2020), the trends in DMWS and in the mean wind may not be consistent.

91　International multi-decadal research into extreme wind variability, as well as changes from

92　anemometer observations, remain inconclusive: both negative and positive trends have been

93　reported in different regions (Azorin-Molina et al., 2016). For instance, DMWS significantly

94　declined from 1975 to 2016 in China (Zhang et al., 2020), as supported by a range of different

95　evidences including declining global dust emissions (Chappell et al., 2016; Shao et al., 2013).

96　In contrast, DMWS has increased at most of coastal stations in the USA since 1990 (Klink,

97　2015).

98

99　　To date, few studies have investigated the causes of extreme wind speed variability and trends

100　(Wu et al., 2018). For example, large-scale atmospheric changes expressed by the North

101　Atlantic Oscillation Index and the Jenkinson and Collison scheme indices showed significant

102　correlation with both frequency and magnitude of daily peak wind gust changes over Spain and

103　Portugal (Azorin-Molina et al., 2016). Overall weakened large-scale atmospheric circulation

104   partly explained the declining annual, winter and autumn DMWS over China, while the causes

105   of increased DMWS in summer and spring are still largely unknown (Zhang et al., 2020). In

106   addition, near-surface wind speed is sensitive to aerodynamic roughness changes according to

107   the wind profile law (Han et al., 2016), and many previous studies have confirmed that changes

108   in surface roughness induced by vegetation growth (Vautard et al., 2010; Wever, 2012) or

109   urbanization (Hou et al., 2013) have played a key role in reducing near-surface mean wind

110   speed. For example, in South Korea during 1993-2015, urban near-surface mean wind speeds

111   observations declined up to -0.63 m s^{-1} decade^{-1}, while those at rural stations increased up to

112   0.41 m s^{-1} decade^{-1}. Rapid urbanization contributed -0.37 m s^{-1} of mean wind speed changes

113   from 1980-2018 over Beijing-Tianjin-Hebei in China (Wang et al., 2020). However, no existing

114   studies have examined the contribution of changed surface roughness to extreme wind speed.

115   The present study addresses this knowledge gap.

116

117   China has experienced rapid urbanization in the last 3-4 decades, with vigorous economic

118   growth (Bai et al., 2014), especially in the Yangtze River Delta (YRD, including Zhejiang,

119   Jiangsu and Shanghai) which accounted for more than 20% of China's GDP (Gross Domestic

120   Product) in 2019 (Statistical Bulletin on National Economic and Social Development in 2019,

121   http://www.stats.gov.cn/tjsj/zxfb/202002/t20200228_1728913.html, last accessed 1 February

122   2022). Previous studies documented that rapid urbanization both in terms of areal extension

123   and constructing more taller buildings has weakened near-surface mean wind speed in some

124   rapidly urbanized areas, e. g., east China (Li et al., 2018) and Beijing (Hou et al., 2013). By

125   increasing roughness, urbanization could weaken the long-term trend of near-surface DMWS

126   (Zhang et al., 2020), yet in contrast, uniform building distributions can induce wind funneling

127   effects (Peng et al., 2018) that can enhance DMWS in some local urban areas: these contrasting

128   responses illustrate the uncertainty regarding the effects of urbanization on DMWS changes.

129

130   For these reasons, our objectives are to (i) investigate DMWS trends in the rapidly urbanized

131   YRD from 1990 to 2015, using quality-controlled and homogenized DMWS observations and

132   reanalysis output; (ii) reveal the potential impacts of the rate of urbanization on DMWS trends,

133   by using night-time lighting data to classify the rate of urbanization at each station; and (iii)

134   simulate how urbanization affects DMWS by conducting sensitivity experiments using a

135   regional climate model. Our research supports the management of social and environmental

136   planning and policy development of urbanization, and contributes to the scientific

137   understanding of long-term variability in wind extremes.

138 **2.   Materials and methods**

139 **2.1. Anemometer observations and reanalysis outputs**

140   We used daily maximum 10-minute mean near-surface (~10 m height) wind speed for

141   00:00 to 23:59 from the China Meteorological Administration (CMA, http://data.cma.cn/, last

142   accessed 1February 2022). Following Azorin-Molina et al.(2014), the daily maximum wind

143   speed (DMWS) data were firstly aggregated into monthly values, allowing a maximum of five

144   days of missing data each month. Stations with a large amount of missing data (i.e., greater than

145   3 months since 1 January 1990) were excluded. Figure 1 displays the distribution of the 111

146   stations selected for the 26-year (i.e., 1990–2015) study period.

147   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.

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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

214 model MM5 (Giorgi et al., 2012). The RegCM4 model simulations cover the YRD (Fig. S1),

215 with a horizontal resolution of 30 km. The vertical grid includes 23 levels from the surface to

216 50 hPa, and the time step is 30 seconds. The primary physical process schemes contain the

217 MIT–Emanuel cumulus convection scheme for cumulus parameterization (Georg, 1993),

218 Holtslag planetary boundary layer (PBL) scheme (Holtslag et al., 1990), the Zeng scheme for

219 sea flux parameterization (Zeng et al., 1998), Community Land Model version 4.5 (CLM4.5)

220 for land-surface parameterization scheme (Oleson et al., 2013), the NCAR CCM3 radiation

221 scheme (Kiehl et al., 1996), and the Rapid Radiation Transfer Model (RRTM) (Mlawer et al.,

222 1997).   ERA-Interim   reanalysis   data $(0.75° \times 0.75°,$

223 https://apps.ecmwf.int/datasets/data/interim-full-daily/levtype=pl/, last accessed 1 February

224 2022) were used as the lateral boundary condition, which is updated every 6 hours; the sea

225 surface temperature (SST) data were from   the optimal interpolation weekly SST data from

226 NOAA (Reynolds et al., 2002). Full details of the model experiments are found in Wang et al.

227 (2021).

228   To explore possible responses of DMWS changes to the rapid urbanization, using the same

229 meteorological forcings from 1 October 1989 to 31 December 1990, two sensitivity

230 experiments were performed in RegCM4 using (i) 1990LULC; and (ii) 2015LULC respectively,

231 after a one-year' initialization This method has been successfully implemented previously to

232 assess the impact of LULC on wind speed dynamics (e.g., Zha et al., 2019), and air temperature

233 and precipitation changes (e.g., Cao et al., 2015). A full year simulation for a low and high

234 urbanization cases is considered appropriate to identify the impact of urbanization on wind

235 climate between the two years (i.e., 1990 and 2015); noting that our research purpose was not

236   to simulate realistic changes of the wind climate under changing urbanization for each of the

237   26-years. In the analysis, the first three months of each experiment were excluded for model

238   spin-up. DMWS in the model output was taken as the maximum hourly wind speed for each

239   24-hour period (defined as UTC 00:00 to 24:00).

240

241   **2.4 Statistical analyses**

242   To avoid a few series with high-wind speed dominating a regional average series, DMWS

243   anomalies were expressed as the deviation from the 1990-2015 DMWS mean for each station

244   (Azorin-Molina et al., 2021). Following previous studies (Chen et al., 2013; Zhang et al., 2020),

245   regional mean DMWS in the YRD from the NCEP-NCAAR1 and ERA5 were calculated as the

246   mean value of all grids with a majority of area covered by the study site. Sen's slope method

247   was used to calculate the magnitude of DMWS trends (in m s^{-1} decade^{-1}), and an 11-yr Gaussian

248   low-pass filter was used to obtain the DMWS multi-decadal variability. To enable the

249   comparison with reanalysis data, DMWS from station observations were interpolated onto a

250   0.5° resolution grid. Additionally, we computed the statistical significance of the estimated

251   linear trends using the Mann–Kendall's tau-b nonparametric correlation coefficient.

252   We also assessed DMWS changes as a function of urbanization rate across the study region.

253   Considering the complex and non-uniform urban morphology (Peng et al., 2018) and that winds

254   are sensitive to urbanization induced surface roughness (Li et al., 2018), homogenized data

255   from the 111 stations were classified into 5 groups with different urbanization rates (Table 1)

256   being: (i) very-low urbanization rate; (ii) low urbanization rate; (iii) moderate urbanization rate;

257   (iv) fast urbanization rate; and (v) very fast urbanization rate. Here the urbanization rates of

258 each station for 1990 to 2015 were calculated as the difference in night-time light value as 2015

259 minus 1992 (see Table 1).

260

261 **3   Results**

262 **3.1. DMWS changes estimated from the station observations and reanalyses**

263   Figure 2 shows trends in DMWS anomalies for 1990-2015 over the YRD. Annual DMWS

264 observations significantly declined for the whole period (-0.209 m s^{-1} dec^{-1}, $p < 0.05$), with the

265 highest DMWS (actual values: 8.7 m s^{-1}) in 1990 and the lowest DMWS (actual values: 7.8 m

266 s^{-1}) in 2015. DMWS displayed relatively stable interannual variability during 1990-2005, before

267 a dramatic and rapidly weakening trend from 2005 till 2015. However, DMWS from NCEP-

268 NCAR1 shows an insignificant positive trend (+0.048 m s^{-1} dec^{-1}, $p > 0.1$) for 1990-2015. A

269 close relationship between the observed DMWS and NCEP-NCAR1 DMWS was detected from

270 1990-2005, while the two series diverged from 2005 onwards. Similar variability and a positive

271 trend (+0.027 m s^{-1} dec^{-1}, $p > 0.1$) were found in ERA5 DMWS. The conflicts between observed

272 DMWS and reanalyses indicate the uncertainty of reanalyses on modeling DMWS, as

273 reanalyses have not assimilated roughness changes induced by urbanization (Zhang et al., 2020).

274 Increasing divergence between the reanalyses and the station observation started in 2005,

275 indicating urbanization might have a significant impact on DMWS changes after reaching a

276 certain threshold.

277

278   Figure 3 displays the spatial distribution of DMWS trends across the YRD for 1990-2015.

279 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)).

302

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.

316

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

324   urbanization and DMWS are nonlinear. These results clearly show that DWMS in the YRD has

325   been weakened by urban growth during 1990-2015.

326

327   **3.4 Impact of urbanization on DMWS changes revealed by climate model simulations**

328   Figure 6 shows the distribution of urban areas in 1990 and 2015 in the YRD from the LULC

329   data sources, and Table 2 displays the changes in the areas of various LULC types between

330   1990 and 2015. In 1990 (Fig. 6a), urban areas were quite sparse; with most located in the central

331   and northern parts of the YRD. This pattern is strongly consistent with the night-time light

332   distribution in 1992 (2 years later than 1990, see Fig. 4a). Further, urban areas in 2015 mainly

333   occupied the central, northern and southeast coastal parts, which is again highly consistent with

334   the 2015 night-time light pattern (Fig. 4b). Note that much greater urbanization was detected in

335   2015 when compared to 1992 (Fig. 6b), especially for those regions that already (in 1992) had

336   a high proportion of urbanization. When compared to other LULC types, it is clearly seen that

337   urban area increases represent the dominant LULC changes between 1990 and 2015 over the

338   YRD (Table 2). The similar patterns of night-time lighting and urban extent confirm that night-

339   time light data are a reliable proxy of the rapid urbanization across the YRD during 1990-2015.

340   To confirm our hypothesis that the rapid urbanization weakened DMWS, two sensitivity

341   experiments configured with the same settings and forcing but with different LULC data (i.e.,

342   1990LULC and 2015LULC) were implemented using RegCM4. The spatial distributions of

343   RegCM4 simulated DMWS in 1990 (forced with 1990LULC) and 2015 (forced with

344   2015LULC), as well as their difference, are shown in Figure 7. Overall, DMWS for the

345   1990LULC simulation exhibited a distinctly heterogeneous spatial pattern, manifested as a high

346 DMWS from the central to northern YRD, and weak DMWS over the southern part (Fig. 7a).

347 A similar spatial pattern of DMWS was found for the 2015LULC simulation (Fig. 7b). This

348 indicates that changes in LULC have not caused the change in the spatial distribution of DMWS

349 in YRD. When considering the difference in DMWS between the two simulations (i.e.,

350 2015LULC minus 1990LULC, Fig. 7c), negative DMWS differences were found in most

351 metropolitan central and northern ($p < 0.1$) parts of YRD, and a few in southern coastal regions.

352 As those areas experienced rapid urbanization from 1990 to 2015, this confirms that the

353 decline in DMWS was mainly driven by urbanization (i.e., the LULC changes). Furthermore,

354 we compared regional means of DMWS in the 1990LULC and 2015LULC simulations and

355 found that DMWS for the 2015LULC simulation is lower than that for the 1990LULC

356 simulation by -0.03 m s^{-1}. Note that positive DMWS differences were found over a few southern

357 and western parts, indicating that vegetation changes rather than urbanization appear to have

358 increased DMWS in mountainous areas with complex terrain.

359

360 **4   Discussion**

361   In this study, we first examined DMWS trends over the YRD, a region that has evidently

362 increased its urban area according to LULC and night-time lighting during 1990-2015. The

363 results from station observations showed that DMWS experienced a secular decline during

364 1990-2015, which is consistent with a previous study of DMWS trends across China, although

365 different periods were used (Zhang et al., 2020). A previous study reported negative trends in

366 mean wind speed from 1990-2015 based on station observations over a region containing the

367 YRD (Li et al., 2018), which along with our findings shows that both mean wind speed and

368 DMWS experienced a slowdown in recent decades. In contrast, NCEP-NCAR1 and ERA5

369 reanalysis shows a weakly positive trend in DMWS from 1990 to 2015, leading to increasing

370 divergence between the reanalysis DMWS and station observed DMWS since 2005. Wind

371 speed from reanalysis mostly represent the impact of climate variability (e.g., atmospheric

372 circulation) on wind speed changes (Vautard et al., 2010), as surface roughness changes are not

373 explicitly taken into account in the assimilation process (Kalnay et al., 1996). Therefore,

374 opposite trends between the station observations and reanalysis indicate that climate variability

375 is very likely not be the cause of DMWS change in our study region, and declined DMWS may

376 well be induced by surface roughness increases (e.g., urbanization, Fig. 8). Albedo-based

377 surface roughness in the vicinity of many stations located in urban area increased from 2000-

378 2015 too, and annual DMWS shows a negative correlation (-0.32, $p > 0.1$) with mean annual

379 surface roughness (Fig. 8). Wu et al. (2017) reported that wind speed change over east China is

380 not consistent with East Asian summer monsoon variability, , coupled with the results presented

381 herein, means that the detected observed DMWS declines were most likely driven by rapid

382 urbanization after reaching a certain threshold (2005).

383   The change in night-time lighting between 1992 and 2015 revealed this rapid urbanization

384 during recent decades in the YRD, which is supported by increases in population, GDP, and the

385 number of cars in the region (see Fig. S2). By comparing DMWS trends with urbanization rates

386 (i.e., night-time light increases), it was clearly seen that stations with the strongest negative

387 DMWS trends were mainly located in metropolitan areas with the fastest urbanization rates,

388 while stations with the weakest negative DMWS trends (or even slightly positive trends) were

389 largely distributed over the mountain or hilly areas that experienced the lowest urbanization

390   rates. This demonstrates that recent DMWS changes over the YRD were mainly driven by the

391   rapid urbanization during 1990-2015. As urban expansion and development increased both the

392   number and the height of buildings, the resulting increase in surface roughness could have

393   weakened the near-surface wind speed, e.g., DMWS, according to the theoretical wind speed

394   profile (Han et al., 2016). Existing studies have documented a similar relationship between

395   mean wind speed trend and urbanization-induced surface roughness changes (Li et al., 2018;

396   Chen et al., 2020), while our study is one of the few to provide empirical evidence for the effect

397   of urbanization on extreme winds (Li et al., 2011).

398   Additionally, we classified stations into five groups based on urbanization rate, and found that

399   maximum negative trends in DMWS increased with increasing urbanization rate, while the

400   minimum magnitudes of DMWS trends were generally stable among the five groups. This is

401   quite a different result when compared to mean wind speed (Li et al., 2018), as both maximum

402   and minimum magnitudes of negative trends increased with urbanization (Li et al., 2018). This

403   suggests that the relationship between urbanization-induced roughness and DMWS trends is

404   more complex than that for mean wind speed. Previous studies have reported an exponential

405   relationship between magnitude of wind speed and surface roughness (Han et al., 2016; Zeng

406   et al., 2019), which means surface roughness may have had a stronger impact on stronger winds,

407   thus extreme winds are more sensitive to local environmental changes (Azorin-Molina et al.,

408   2016; Zhang et al., 2020)than more typical (i.e. more average) winds.   Further, we have

409   explored the associations between the NDVI and DMWS (Fig. 9) and found that NDVI

410   decreased in most urban area and increased in most mountainous areas in the YRD during 1990-

411   2015. This indicates that vegetation changes might not be the main cause of declined DMWS

412   in the YRD.

413   As the increased urban area has been the dominant LULC change over the YRD during recent

414   decades (Table 2 and Fig. S3) (Zha et al., 2019), the difference between the simulated DMWS

415   under the 1990LULC and 2015LULC forcing to a large extent reflects the impact of

416   urbanization on DMWS changes. The results clearly demonstrate that the simulated DMWS

417   forced by the 2015LULC was much lower in those regions (e.g., central, north and coastal parts

418   of the YRD) which experienced rapid urbanization when compared to the simulation forced by

419   the 1990LULC. This pattern is strongly consistent with the distribution of DMWS changes

420   based on the station observations and night-time light difference (Fig. 3) and further confirms

421   that rapid urbanization has weakened DMWS over the YRD from 1990 to 2015. Similar

422   sensitivity experiments for wind speed using the WRF model demonstrated that regional mean

423   wind speed in the Beijing metropolitan area has decreased due to urbanization (Hou et al., 2013).

424   Furthermore, the regional mean difference between DMWS in two sensitivity experiments is -

425   0.03 m s^{-1}, which is much lower than that between 1990 and 2015 based on the station

426   observations. This is likely due to two main reasons. First, DMWS is the maximum 10-minute

427   mean wind speed observation during 24 hours of such 10-minute observations, while simulated

428   DMWS corresponds to maximum hourly mean wind speed over the same 24 hours, noting that

429   the mean peak value of wind speed in a certain period generally decreases with the increase in

430   recording frequency (Azorin-Molina et al., 2017). Second, LULC data used in the climate

431   model cannot realistically capture the building density and height, thus the impact of

432   urbanization on winds is underestimated in the model simulations (Zha et al., 2019).

433   For the first time, our study based on sensitivity experiments with a regional climate model

434   has demonstrated that urbanization weakens the extreme winds defined in the study. Besides

435   the roughness argument proposed above, the greater atmospheric stability caused by aerosol-

436   induced reductions in the land-surface insolation (Jacobson and Kaufman, 2006) may also

437   affect DMWS variability. Thus, pollution control in the areas of rapid urbanization may also

438   play a role. Further studies in other rapidly developing urban regions across the globe are

439   needed. This is especially the case in rapidly developing economies where urban pollution can

440   be problematic for human health (Landrigan et al., 2018; Dedoussi et al., 2020) and where

441   DMWS decreases may exacerbate the existing pollution-induced health problems in such

442   rapidly growing urban areas.

443

444   **5   Conclusions**

445   We found that observed DMWS over the YRD which is a region that has experienced a high

446   rate of urbanization significantly declined from 1990 to 2015,. Meanwhile, a weak increase in

447   DMWS was found in the NCEP-NCAR and ERA-5 reanalysis, suggesting that changes in the

448   large-scale atmospheric circulation might not be responsible for the observed DMWS decreases,

449   and that reanalysis output is not useful when assessing wind speed trends. Stations showing the

450   largest negative DMWS trends are mainly located in areas with high urbanization rates as

451   indicated by night-time light differences between 1992 and 2015. In contrast, no significant

452   trends in DMWS were found in areas with small urbanization rates. The increased magnitude

453   of the differences between the reanalyses and the station data since 2005 points to the significant

454   impact of urbanization after a certain threshold. Two sensitivity experiments conducted with

455   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.

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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708   Table 1. Classification of stations with different urbanization rates as indicated by night-time

709   light difference (NLD, dimensionless) between 1992 and 2015 for each station.

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Types of Station	I	II	III	IV	V

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

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714 Table 2. Areas and proportions of LULC types in 1990 and 2015, and area of LULC changes

715 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

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