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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 $-0.209 \text{ m s}^{-1} \text{ decade}^{-1}$, while slightly ($p > 0.1$) positive trends were found in NCEP-NCAR1 ($+0.048 \text{ m s}^{-1} \text{ decade}^{-1}$) and ERA5 ($+0.027 \text{ m s}^{-1} \text{ decade}^{-1}$). 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 countries (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 $-0.63 \text{ m s}^{-1} \text{ decade}^{-1}$, while those at rural stations increased up to
112 $0.41 \text{ m s}^{-1} \text{ decade}^{-1}$. 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 1 February 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-

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

153 For comparison with station observations, 6-hourly and hourly 10-m zonal and meridional
154 components of wind from two widely used and reliable reanalyses (Zhang et al., 2021; Torralba
155 et al., 2017) of, i.e., the National Center for Environmental Prediction, National Center for
156 Atmospheric Research (NCEP–NCAR1 Reanalysis, Kalnay et al., 1996),
157 <https://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis.pressure.html>; last accessed
158 1 February 2022), and the European Centre For Medium Range Weather Forecasts (ERA5
159 Reanalysis, Hersbach et al., 2020), <https://cds.climate.copernicus.eu/>; last accessed 1 February
160 2022) were downloaded, both covering 1990–2015. Note that DMWS from NCEP–NCAR1 and
161 ERA5 were calculated as maximum 6-hourly wind speed and hourly wind speed for a day,
162 respectively; this differs from the maximum 10-minute average which is denoted as daily
163 maximum wind speed from observations.

164 **2.2. Remote sensing data**

165 **2.2.1 Night-time light data**

166 Night-time light data are widely used to indicate the distribution of urban areas and
167 urbanization growth (Stokes and Seto, 2019; Zhao et al., 2020). We retrieved night-time light
168 data that from the National Centers for Environmental Information (NCEI,
169 <https://www.ngdc.noaa.gov/eog/download.html>, last accessed on 1 February 2022). The dataset

170 included two types of satellite observations. Operational Linescan System of the Defense
171 Meteorological Satellite Program (DMSP/OLS) observed night-time light from Jan 1992-Dec
172 2013, with a spatial resolution of 0.008333° (~0.92 km at the equator), and Visible Infrared
173 Imaging Radiometer Suite (VIIRS) observed night-time light from Jan 2012 onwards, with a
174 spatial resolution of 0.004167° (~0.46 km at the equator). We used the monthly DMSP/OLS
175 composites product averaged over 1992 to represent the 1990 level of urbanization, and the
176 annual average of the 2015 monthly VIIRS product to represent the 2015 urbanization. Both
177 products were selected with a stable light value, which discarded other sites with persistent
178 lighting, including gas flares and ephemeral events, such as fires. Due to sensor differences
179 between DMSP/OLS and VIIRS, calibration coefficients were applied to the VIIRS data (Yang,
180 2018) to harmonize the two products. We used the night-time light value (0-64, dimensionless)
181 to represent the urbanization level, and the mean night-time lights within a 3 km radius for each
182 station (Li et al., 2018). Then, the difference in night-time light between 1992 and 2015 was
183 used as a proxy for urbanization changes within the 3 km proximity of each station.

184 **2.2.2 Land-use and land-cover (LULC) data**

185 The land-use and land-cover (LULC) data over the YRD in 1990 (1990LULC) and 2015
186 (2015LULC) were downloaded from the Resource and Environmental Science Data Center of
187 the Chinese Academy of Sciences (RESDC-CAS,
188 <http://www.resdc.cn/Datalist1.aspx?FieldTyeID=1,3>; last accessed 1 February 2022), with a 1
189 km resolution. As the regional climate model applied herein (see 2.3) used a different LULC
190 classification, following Ren et al. (2018), we transferred the RESDC-CAS LULC to a format
191 that was used by the model.

192

193 2.2.3 Normalized Difference Vegetation Index (NDVI) data The Normalized Difference
194 Vegetation Index (NDVI, dimensionless) data over the YRD in 1990 is provided by National
195 Cryosphere Desert Data Center. (NCDDC, <http://www.ncdc.ac.cn>; last accessed 1 February
196 2022), with an 8 km resolution. The NDVI data in 2015 is downloaded from the Resource and
197 Environmental Science Data Center of the Chinese Academy of Sciences (RESDC-CAS,
198 <https://www.resdc.cn/DataList1.aspx?FieldTypeID=1,3>; last accessed 1 February 2022), with an
199 1 km resolution. To be congruent with the resolution of the NDVI in 2015, NDVI in 1990 is
200 resampled to a 1 km resolution.

201 **2.2.4 Estimation of aerodynamic roughness**

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

206

207 **2.3 Regional climate model and sensitivity experiment design**

208 The Abdus Salam International Center for Theoretical Physics (ICTP) RegCM4 model
209 (<https://www.ictp.it/research/esp/models/regcm4.aspx>; last accessed 1 February 2022) was
210 applied to conduct sensitivity experiments. The model uses a terrain-following σ -pressure
211 vertical coordinate and an Arakawa B horizontal grid system and includes a convection
212 parameterization scheme, a large-scale cloud and precipitation scheme, expansion and
213 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° × 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 $\text{m s}^{-1} \text{decade}^{-1}$), 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 ($-0.209 \text{ m s}^{-1} \text{ dec}^{-1}$, $p < 0.05$), 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 ($+0.048 \text{ m s}^{-1} \text{ dec}^{-1}$, $p > 0.1$) 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 ($+0.027 \text{ m s}^{-1} \text{ dec}^{-1}$, $p > 0.1$) 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

280 the strongest and most significant negative trends ($< -0.200 \text{ m s}^{-1} \text{ dec}^{-1}$, $p < 0.05$) located in the
281 north, east and coastal zones of the southeastern parts of the study region. Stations that
282 displayed low-magnitude negative trends (-0.100 to $0.000 \text{ m s}^{-1} \text{ dec}^{-1}$, $p > 0.05$) are located in
283 the southwestern part of the study region, where complex topography is characterized by hills
284 and mountains (Fig. 1). However, barely significant and different spatial patterns of DMWS
285 trends were found in the NCEP-NCAR reanalysis: in this case, DMWS weakly increased
286 ($+0.000$ to $+0.100 \text{ m s}^{-1} \text{ dec}^{-1}$, $p > 0.05$) in most of the YRD, and weakly declined (-0.000 to -
287 $0.200 \text{ m s}^{-1} \text{ dec}^{-1}$, $p < 0.05$) in the northern and southern corners. Similarly, ERA5 DMWS
288 widely increased ($+0.000$ to $+0.100 \text{ m s}^{-1} \text{ dec}^{-1}$), but was only significant ($p < 0.05$) over a few
289 southern parts of the study region. The divergences between reanalyses and station observations
290 indicate the crucial role played by urbanization on weakening DMWS, as reanalyses mostly
291 represent the change of climate variability (Vautard et al., 2010).

292

293 3.2. Impact of urbanization on DMWS trends

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

302

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

316

317 Box-and-whisker plots in **Figure 5** show DMWS trends in station groups with varied
318 urbanization rates (see **Table 1**). Station groups with very low urbanization rates have relatively
319 weak negative trends of DMWS, while the strongest declining DMWS trends were found in
320 station groups with the highest urbanization rates. Note that the minimum magnitude of DMWS
321 trends (represented by the upper whisker in **Fig. 5**) was stable between the station groups from
322 low to high urbanization rate (ranging from +0.02 to -0.05 m s⁻¹ dec⁻¹), in contrast to its
323 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 DMWS 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

456 weakened DMWS in the YRD. In summary, our findings provide clear evidence that recent
457 rapid urbanization in the YRD has weakened both mean wind speed and the extreme winds.
458 This finding contributes to improved understanding of the underlying causes behind extreme
459 wind speed changes in urban environments.

460

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472 **Author Contributions**

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

476 **Data Availability**

477 Daily maximum wind speed were accessed accessed at China Meteorological Administration

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

485 NDVI data over YRD in 2015 and the land-use and land-cover (LULC) data over YRD in 1990
486 (1990LULC) and 2015 (2015LULC) were downloaded from the Resource and
487 Environmental Science Data Center of the Chinese Academy of Sciences (RESDC-CAS,
488 <http://www.resdc.cn/Datalist1.aspx?FieldTypeID=1,3>). MODIS albedo product albedo data
489 were retrieved from the National Aeronautics and Space Administration (NASA,
490 <https://modis.gsfc.nasa.gov/>).

491

492 **Conflict of interest**

493 The authors declare that they have no competing interests. Data and materials availability: all
494 data needed to evaluate the conclusions in the paper are present in the paper and/or the
495 Supplementary Materials. Additional data related to this paper may be requested from the
496 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
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Night light difference	$0 \leq \text{NLD} < 10$	$10 \leq \text{NLD} < 20$	$20 \leq \text{NLD} < 30$	$30 \leq \text{NLD} < 40$	$\text{NLD} \geq 40$
Number of stations	5	14	22	40	30
Level of urbanization	Very Low(VL)	Low(L)	Moderate(M)	High(H)	Very High(VH)

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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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