Supplementary Information for

Greater flood risks in response to slowdown of tropical cyclones over the coast of China

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Supplementary Information

Appendix A: Coastal regions of China

Fig. S1 shows the coastal regions of China. The land area within 200 km from the coastlines of mainland China is delineated. Only TC positions located within 200 km from this land area are considered. Based on the best-track data, a total of 406 TCs made landfall over the coast of China during 1961-2017, with 1224 TC track points over land and 1327 TC track points over sea.
Fig. S1. The land area in the coast of China (red line) and the track points of TCs affecting the study area (blue points). The land area delineated by the red line is that within 200 km from the coastline of China. Blue points indicate TC track points located within 200 km from the study area.
Appendix B: Sampling bias in the best-track data and its impacts on TC slowdown estimates

In previous studies, TC slowdown was estimated using track data of TCs positioned over land and both near and far away from the coast. However, TC track points far away from the coast were less detected in the pre-satellite era and therefore TC translation speed tends to be over-estimated because TCs move slower over sea than over land (1–3). In this connection, the veracity of global TC slowdown estimates has been questioned and the slowdown may have been generally over-estimated. To minimize the potential effect of sampling bias on trend detection, Kossin (4) excluded the TC track points over sea and found a decreasing trend in TC translation speed over the continental USA in 1900-2017. In our study, since our goal is to evaluate the impacts of TC slowdown on the local rainfall total in the coastal region, we only sample TCs making landfall and positioned inside and within 200 km on both sides of the coastal study area (See Methods). Therefore, our estimates of TC slowdown should be less affected by the sampling bias the best-track data compared to previous studies.

The sampling bias in the best-track data can be reflected by the changes in the ratio of the number of TC track points over sea to the total number over sea and over land (3). This ratio increased considerably over the past decades in previous studies, because TC track points far away from the coast were included (1, 2). However, the ratio does not change significantly in our study as shown in Fig. S2A. Furthermore, even only the track points over land are considered, our results do show the significant slowdown of TCs (Fig. S2B). Both findings support the argument that our estimates of TC slowdown are less affected by the sampling bias in the best-track data.
Fig. S2. Temporal changes of annual percentage of TC track points over sea (%) and annual-mean TC translation speed over land (km/hr) in 1961-2017. (A) Changes in annual percentage of TC track points over sea near the coastline of China. (B) Changes in annual-mean TC translation speed over land in the study area along the coast of China. In (A),(B), solid straight line indicates the trend is significant at the 95% level based on the Modified Mann-Kendall test, while dashed straight line means the trend is insignificant. Sen’s slope is shown.
Appendix C: Trends in TC translation speed in Global Climate Model (GCM) simulations

TCs in the simulations of GCMs in the Coupled Model Intercomparison Project Phase 5 (CMIP5) are identified and tracked using the Camargo and Zebiak algorithm (refs. 5, 6; See Methods for details). A total of eight GCMs, namely CSIRO-Mk3-6-0, GFDL-ESM2M, GFDL-CM3, HadGEM2-ES, MIROC5, MPI-ESM-LR, MRI-CGCM3, and NorESM1-M, are selected based on their data availability of 6-hourly sea level pressure, temperature at three pressure levels (850, 500, and 250 hPa), and winds at two pressure levels (850 and 250 hPa). Table S1 shows the information of the eight GCMs. The four thresholds for the Camargo and Zebiak algorithm are different for various basins and GCMs. The values of the thresholds in the western North Pacific for the eight selected GCMs have been given by Camargo (6) as shown in Table S2. Following previous studies on TC simulations, the TC tracks extracted from GCMs are compared with the observations in terms of the root mean square error (RMSE) and the two-sample student’s $t$ test (5, 7).

Similar to GCM performance in terms of other variables [e.g. temperature and precipitation (8, 9)], the multimodel ensemble mean outperforms individual GCMs as measured by RMSE and the two-sample student’s $t$ test, and the performance of individual GCMs varies considerably (Tables S3,S4). The RMSE value of the multimodel ensemble mean is lower than those of individual GCMs. The two-sample student’s $t$ test shows that the differences in the translation speed between the multimodel ensemble mean and observations are insignificant at the 95% level. The multimodel ensemble mean shows decreasing trends in TC translation speed comparable to observations from 1961-2005 under the historical scenario only (Fig. S3 and Table S3) and from 1961-2017 under the historical and RCP4.5 scenarios (Fig. 1 and Table S4). The decreasing trends of TCs estimated from the CMIP5 GCM ensemble in both periods are significant at the 95% level.
More than half of the GCMs agree on the decreasing trends (some significant and some not) in both periods, while some models simulate insignificant positive trends. The inconsistency of trends among GCMs may partially explain the contradictory results in recent but very limited number of simulation-based studies of TC translation speed. A very recent work based on one atmospheric global circulation model from the Meteorological Research Institute (MRI-AGCM3.2) found an increasing trend of global TC translation speed in the past decades (10). However, another recent study based on a 13-year pseudo-global warming simulations from multiple GCMs found slower translation speed in the eastern coast of North America (11). A most recent study found slower translation speed in a constant 4-K warming scenario relative to the historical scenario based on MRI-AGCM3.2H simulations, while the simulations under the historical scenario were inconsistent with the observed slowdown trend (12). Different from the above studies based on one single model or short-term pseudo-warming simulations, our study, for the first time, uses simulations of multiple CMIP5 GCMs, the most commonly used GCM archive that is the best available to the public, to examine the trends in TC translation speed over the past several decades. The comparable slowdown trends in TCs estimated from the best-track data and the CMIP5 GCM ensemble provide valuable insights into the heated debate on the veracity of translation speed changes.
Fig. S3. Annual-mean TC translation speed from the observations and the multimodel ensemble mean of CMIP5 GCMs in 1961-2005 under the historical scenario. The black (red) curve denotes the observations (multimodel ensemble mean of CMIP5 GCMs). Solid straight line indicates the trend is significant at the 95% level based on the Modified Mann-Kendall test. Sen’s slope is shown.
| GCM          | Institution                                                                 | Resolution (Lon×Lat) |
|--------------|------------------------------------------------------------------------------|----------------------|
| CSIRO-Mk3-6-0 | Commonwealth Scientific and Industrial Research Organization and Queensland Climate Change Centre of Excellence | 1.9°×1.9°            |
| GFDL_ESM2M   | NOAA/Geophysical Fluid Dynamics Laboratory                                   | 2.5°×2.0°            |
| GFDL-CM3     | NOAA/Geophysical Fluid Dynamics Laboratory                                   | 2.5°×2.0°            |
| HadGEM2-ES   | Met Office Hadley Center                                                     | 1.9°×1.2°            |
| MIROC5       | Japan Agency for Marine-Earth Science and Ocean Research Institute (University of Tokyo), and National Institute for Environmental Studies | 1.4°×1.4°            |
| MPI-ESM-LR   | Max Planck Institute for Meteorology                                          | 1.9°×1.9°            |
| MRI-CGCM3    | Meteorological Research Institute                                            | 1.1°×1.2°            |
| NorESM1-M    | Norwegian Climate Centre                                                     | 2.5°×1.9°            |
Table S2. Values of vorticity threshold ($\zeta_m; \ 10^{-5}/s$), wind speed threshold ($v_m; \ m/s$), vertical integrated local temperature anomaly ($T_m; \ ^\circ C$), and relaxed vorticity threshold ($\zeta_r; \ 10^{-5}/s$) for TC identification and tracking in the western North Pacific for the eight selected GCMs. The values are given in Camargo (6).

| GCM            | $\zeta_m$ | $v_m$ | $T_m$ | $\zeta_r$ |
|----------------|-----------|-------|-------|-----------|
| CSIRO-Mk3-6-0  | 3.9       | 13.3  | 2.1   | 2.7       |
| GFDL_ESM2M     | 3.1       | 11.3  | 3.0   | 2.7       |
| GFDL-CM3       | 3.4       | 13.4  | 2.0   | 2.0       |
| HadGEM2-ES     | 4.1       | 13.9  | 2.0   | 2.6       |
| MIROC5         | 3.9       | 11.7  | 1.4   | 2.7       |
| MPI-ESM-LR     | 3.6       | 12.8  | 1.9   | 3.5       |
| MRI-CGCM3      | 4.7       | 13.9  | 2.0   | 3.5       |
| NorESM1-M      | 3.1       | 12.8  | 1.1   | 2.0       |
Table S3. Evaluation metrics and trends of TC translation speed in GCMs during 1961-2005.

| GCM              | Averaged translation speed (km/hr) | RMSE  | Sen’s slope (km/hr/yr) |
|------------------|-----------------------------------|-------|------------------------|
| CSIRO-Mk3-6-0    | 20.6"                             | 4.7   | -0.134*                |
| GFDL_ESM2M       | 18.3#                             | 8.6   | 0.021                  |
| GFDL-CM3         | 22.2#                             | 9.3   | -0.074                 |
| HadGEM2-ES       | 19.7#                             | 11.5  | -0.093                 |
| MIROC5           | 19.0#                             | 5.7   | -0.015                 |
| MPI-ESM-LR       | 21.0#                             | 6.2   | -0.053                 |
| MRI-CGCM3        | 17.7                              | 5.9   | 0.012                  |
| NorESM1-M        | 24.0                              | 9.8   | 0.128                  |
| Ensemble mean    | 20.4#                             | 3.1   | -0.047*                |

Note: The averaged translation speed is the mean value of TC translation speed during 1961-2005. # denotes the t test indicates the observed and simulated TC translation speed are not significantly different at the 95% level. * indicates the trend is significant at the 95% level based on the Modified Mann-Kendall test.
Table S4. Evaluation metrics and trends of TC translation speed in GCMs during 1961-2017.

| GCM                | Averaged translation speed (km/hr) | RMSE  | Sen’s slope (km/hr/yr⁻) |
|--------------------|------------------------------------|-------|--------------------------|
| CSIRO-Mk3-6-0      | 20.1"                              | 4.8   | -0.106*                  |
| GFDL_ESM2M         | 17.0                               | 8.8   | -0.134*                  |
| GFDL-CM3           | 21.3"                              | 8.6   | -0.093*                  |
| HadGEM2-ES         | 19.4"                              | 10.5  | -0.033                   |
| MIROC5             | 19.3"                              | 5.5   | 0.039                    |
| MPI-ESM-LR         | 21.5                               | 6.0   | 0.021                    |
| MRI-CGCM3          | 17.6                               | 5.9   | -0.030                   |
| NorESM1-M          | 24.4                               | 10.1  | 0.131*                   |
| Ensemble mean      | 20.1"                              | 3.2   | -0.038*                  |

Note: The averaged translation speed is the mean value of TC translation speed during periods of 1961-2017. " denotes the t test indicates the observed and simulated TC translation speed are not significantly different at the 95% level. * indicates the trend is significant at the 95% level based on the Modified Mann-Kendall test.
Appendix D: Correlation between translation speeds and local rainfall totals of TCs with rainfall intensities in different ranges

The spatial patterns of Spearman correlation coefficients of translation speeds and local rainfall totals of TCs with rainfall intensities in different ranges are shown in Fig. S4. When rainfall intensity $\geq 10$ mm/day, the southern and eastern parts of the coast of China show significant negative correlations between TC translation speeds and local rainfall totals. When rainfall intensity $\geq 20$ mm/day, significant negative correlations can be observed over most parts of the coast of China. As the rainfall intensity increases from 20 mm/day to 50 mm/day, the negative correlations tend to be more evident. We obtain similar findings using the Pearson correlation coefficients for the analysis (Fig. S5).
Fig. S4. Spatial pattern of correlation coefficients of translation speeds and local rainfall totals of individual TCs with rainfall intensities (I) in different ranges. In (A),(B),(C),(D), only TCs with I ≥ 10 mm/day, ≥ 20 mm/day, ≥ 40 mm/day, and ≥ 50 mm/day are considered, respectively. Only areas that have at least 4 TCs passing are used in the analysis. Stippled regions represent areas with Spearman correlation coefficients significant at the 95% level.
Fig. S5. Same as Fig. S4, but for the Pearson correlation coefficients.
Appendix E: Detection and attribution analysis of changes in TC translation speed

To examine the possible linkage between climate change and the slowdown of TCs, we conduct a detection and attribution analysis using the optimal fingerprinting method (13). The optimal fingerprinting method has been widely used for the detection and attribution of anthropogenic impacts on changes in hydrologic and climatic variables, such as precipitation, temperature, and soil moisture (14–16). For example, Stott et al. (14) estimated the influence of anthropogenic forcing on changes in the seasonal mean temperature in 1920-1999 based on the CRUTEM2(v) observations and the HadCM3 simulations. In the optimal fingerprinting method, a generalized linear regression model is developed to represent observed changes as a linear combination of signals:

\[ y = \sum_{i=1}^{n} (x_i - v_i)\beta_i + \varepsilon \]  

(S1)

where \( y \) is the vector of observation anomalies (i.e. annual-mean TC translation speed anomalies estimated from observations in this study), \( n \) is the number of signal patterns, \( x \) is the vector of signal pattern anomalies, \( v \) is the noise from internal variability in the signal pattern, \( \beta \) is the unknown scaling factor to be estimated, and \( \varepsilon \) is the regression residual. The annual-mean TC translation speed anomalies estimated from the CMIP5 GCM simulations under all external historical forcings combined [ALL; anthropogenic (greenhouse gas and aerosol emissions) and natural radiative (volcanic and solar) forcings], and natural forcing (NAT; solar and volcanic combined) are the signal patterns \( x \). The simulations from the unforced preindustrial control runs (Control) are employed to estimate the internal climate variability \( v \). The Control simulations are divided into chunks with a double length of the vector \( y \) to estimate the covariance structure of internal variability. Each of the chunks is split into two segments with the same length as vector \( y \).
to obtain two noise matrices, of which one is used to estimate the internal climate, and the other to
test the residual consistency. The total least square method that considers the sampling uncertainty
in signal patterns is used to estimate the scaling factor $\beta$. If $\beta$ and its 90% confidence interval (CI)
are above zero, the signal is considered detected in the changes of observations $y$. $\beta = 1$ indicates
that the response obtained from the model simulations is identical to the observed changes. The
observed changes attributable to a signal pattern are estimated by multiplying the trend in the signal
pattern (i.e. ALL or NAT) by the respective estimate of $\beta$.

Among the eight GCMs selected for this study, only CSIRO-Mk3-6-0 and GDFL-ESM2M provide
complete 6-hourly outputs of ALL, NAT, and Control simulations (Table S5). Therefore, we
choose these two GCMs to conduct the detection and attribution analysis. The NAT simulations
of CSIRO-Mk3-6-0 span from 1961-2012, while the ALL simulations end in 2005. Therefore, we
use the 2006-2012 simulations under the RCP4.5 scenario to extend the ALL simulations of
CSIRO-Mk3-6-0. Given the length of Control run is only 30 years for CSIRO-Mk3-6-0, a
bootstrap resampling technology is used to extend the Control run (17). First, the annual TC
translation speed is extracted from the 30-year Control run. Second, we use a random seed to obtain
a 52-year (i.e. the length of 1961-2012) sample from the 30-year Control run through random
resampling with replacement. Third, using this seed, the resampling process is repeated 600 times,
and hence a $52 \times 600$ noise matrix is generated. We then divide the noise matrix into two $52 \times 300$
matrices as explained above. The two noise matrices are used to conduct the detection and
attribution analysis. Furthermore, we repeat this procedure 1000 times to examine the robustness
of the detection and attribution results based on the bootstrap resampling technique.
The temporal changes of the signal pattern anomalies (i.e. ALL and NAT) from CSIRO-Mk3-6-0 over 1961-2012 are shown in Fig. S6. The ALL forcing can simulate the significant decreasing trend in the TC translation speed as found in observations, but the NAT forcing only shows an insignificant increasing trend. Before we conduct the detect and attribution analysis, the vector of observation anomalies is divided to a vector of non-overlapping five-year means. The use of five-year average is a compromise between suppressing the natural variability, particularly that at inter-annual timescales, and the desire to detect the effects of natural forcing including the relatively short-lived responses to volcanic activities (17). Therefore, the 52-year values are divided into 10 non-overlapping five-year means and 1 non-overlapping two-year mean, which is \( y \) in Eq. S1. The two vectors of signal pattern anomalies (i.e. ALL and NAT) are separately divided into 11 non-overlapping averages, which are \( x \) in Eq. S1. We first conduct the one-signal analysis, in which each signal pattern is separately regressed according to Eq. S1, to examine if a specific signal is detectable in the observations. We also perform the two-signal analysis in which ALL and NAT signal patterns are together regressed into Eq. S1. The two-signal analysis, on one hand, can verify the result of the one-signal analysis, and on the other hand, can evaluate whether the ALL signal can be separated from the NAT forcing in the observed changes. The scaling factors of ALL and NAT in both one-signal and two-signal analyses are estimated in the 1000 experiments (Fig. S7 and Table S6). Fig. S7 shows the magnitudes of estimated scaling factors are stable for both ALL and NAT forcings in the 1000 experiments. The frequencies of ALL signal detected in the 1000 experiments are 16, 465, and 942 in the 5-95% \( (p < 0.05) \), 7.5-92.5% \( (p < 0.075) \), and 10-90% \( (p < 0.1) \) CIs in the one-signal analysis (Table S6). The ALL signal is detected 719 times in the 10-90% CI in the two-signal analysis. No NAT signal is detected in the three CIs. The scaling factors
of ALL and NAT forcings and their CIs in the 1000 experiments are averaged separately (Fig. S8). For both one-signal and two-signals analyses, we detect the ALL signal in observational changes at the 10-90% CI (i.e. the 10-90% CI of ALL forcing is above zero), but no NAT signal is detected. Therefore, based on results obtained from the CSIRO-Mk3-6-0 simulations, it is probable (p < 0.1) that there is a climate change component associated with anthropogenic forcing in the observed TC slowdown. The attribution results show that the total decrease in observed landfalling TC speeds is 4.7 km/hour (3.3-5.9 km/hr, 5-95% CI), and the ALL forcing contributes a total decrease of 1.8 km/hour (0.3-4.6 km/hr) over 1961-2012.

We also similarly conduct the detection and attribution analysis based on the GFDL-ESM2M simulations. The ALL and NAT simulations of GFDL-ESM2M end in 2005. Therefore, 1961-2005 is the period used for the detection and attribution analysis. GFDL-ESM2M provides a relative long Control run (i.e. 438 years) which can be directly used in the detection and attribution analysis. However, it turns out that the regression-based optimal fingerprint of GFDL-ESM2M cannot pass the residual consistency test (18). It seems that there could be signal errors in the ALL simulations of GFDL-ESM2M which contribute to the residual variance (15).

Therefore, the detection and attribution results show that it is likely (> 90%) to have a climate change component associated with anthropogenic forcing in the observed TC slowdown based on the CSIRO-Mk3-6-0 simulations. GFDL-ESM2M fails in the residual consistency test of the optimal fingerprinting method. These two GCMs are the only two models that provide complete 6-hourly outputs of ALL and NAT simulations and Control run in the CMIP5 archive. Given the
uncertainties of different GCMs that may affect the detection and attribution results, further research efforts on detection and attribution analyses using multiple climate models are necessary.
Fig. S6. Temporal changes in TC translation speed anomalies (km/hr) relative to 1961-1990 of (A) ALL and (B) NAT simulations in 1961-2012 from CSIRO-Mk3-6-0. Solid straight line indicates the trend is significant at the 95% level based on the Modified Mann-Kendall test, while dashed straight line means the trend is insignificant. Sen’s slope is shown.
Fig. S7. The estimated scaling factors of TC translation speed over 1961-2012 in CSIRO-Mk3-6-0 driven by ALL and NAT forcings in the one-signal and two-signal analyses based on the 1000 bootstrap samples.
Fig. S8. The averaged scaling factors (A) and corresponding attributable changes (B) of TC translation speeds estimated from ALL and NAT simulations of CSIRO-Mk3-6-0 over 1961-2012 in the one-signal (left) and two-signal (right) analyses based on the 1000 bootstrap samples. The scaling factors and CIs are the means of the corresponding 1000 estimations shown in Fig. S7, which are hence used to estimate the contributions of ALL and NAT forcings.
Table S5. Availability of 6-hour outputs of CSIRO-Mk3-6-0 and GFDL-ESM2M

| GCM            | Forcing | Temporal length |
|----------------|---------|-----------------|
| CSIRO-Mk3-6-0  | ALL     | 1950-2005       |
|                | NAT     | 1950-2012       |
|                | Control | 30 years        |
| GFDL-ESM2M     | ALL     | 1861-2005       |
|                | NAT     | 1861-2005       |
|                | Control | 438 years       |
**Table S6. Frequency of signal detected in TC translation speed in CSIRO-Mk3-6-0 over 1961-2012 in the 1000-time detection and attribution experiments.** The numbers in 5-95% CI, 7.5-92.5% CI, and 10-90% CI indicate the frequencies of signal detected in the corresponding CIs.

| Detection | Forcing | 5-95% CI | 7.5-92.5% CI | 10-90% CI |
|-----------|---------|----------|--------------|-----------|
| One-signal | ALL     | 16       | 465          | 942       |
|           | NAT     | 0        | 0            | 0         |
| Two-signal| ALL     | 0        | 128          | 719       |
|           | NAT     | 0        | 0            | 0         |
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