Attribution Methodologies Applied to Tropical Cyclones

Blackboard Lecture at the Princeton AOS Summer Workshop by Hiro Murakami（August 4th, 2022）

1. Introduction

Tropical cyclones (TCs) are extreme themselves. But there are some extreme TC events recently occurred that arose public interest regarding the effect of anthropogenic climate changes. The latest studies indicate that these recent changes in TC activity could be due to human influences on the climate. However, this view has been challenged for the following reasons: (1) the limited availability of long-term TC observations makes it difficult to infer the effect of anthropogenic climate forcing agents on TC activity; (2) the significant influence of intrinsic internal variability on TC activity makes the signal of anthropogenic climatic changes in TC activity difficult to detect; and (3) expensive computational cost for conducting climate model simulations using high-resolution climate models. Despite these challenges, this lecture introduces the methodologies applied to the attribution of extreme TC events to climate change. The topics of this lecture are as follows.

1. Extreme single TC event (e.g., Cat 5 hurricane; Katrina, Florence)
2. Extreme TC seasons (e.g., the 2015 active hurricane season in the Eastern North Pacific)
3. An unusual decade or trend (e.g., Increased North Atlantic hurricanes during the 2010s)
4. Statistical-dynamical downscaling methodology

2. Single TC event

Suppose we are observing an extremely intense TC event such as Hurricane Florence.

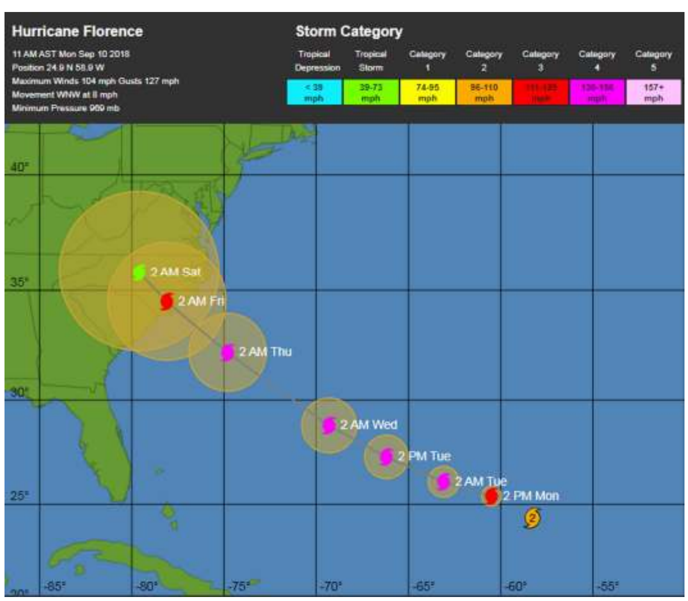


Fig.1 Hurricane Florence (2018)

An open question is "How much anthropogenic warming affected the intensity of Hurricane Florence?". *To answer this question, Wehner et al. (2019), Patricola and Wehner (2020), and Reed et al. (2020, 2022) applied so-called "**pseudo global warming sensitivity experiments**".*

What are pseudo global warming sensitivity experiments?
There are two sets of experiments using a regional climate model. One is an actual experiment and the other is a counter-factual experiment.

As in real-time weather forecast predictions, an actual experiment is conducted given realistic initial and lateral conditions from the reanalysis dataset (Fig. 2).

A counterfactual experiment is the same as the actual experiment, but only temperatures and specific humidity are modified in the initial and lateral boundary conditions. The expected perturbations due to global warming in temperature and humidity are removed from the original lateral boundary and initial conditions (Fig. 3).

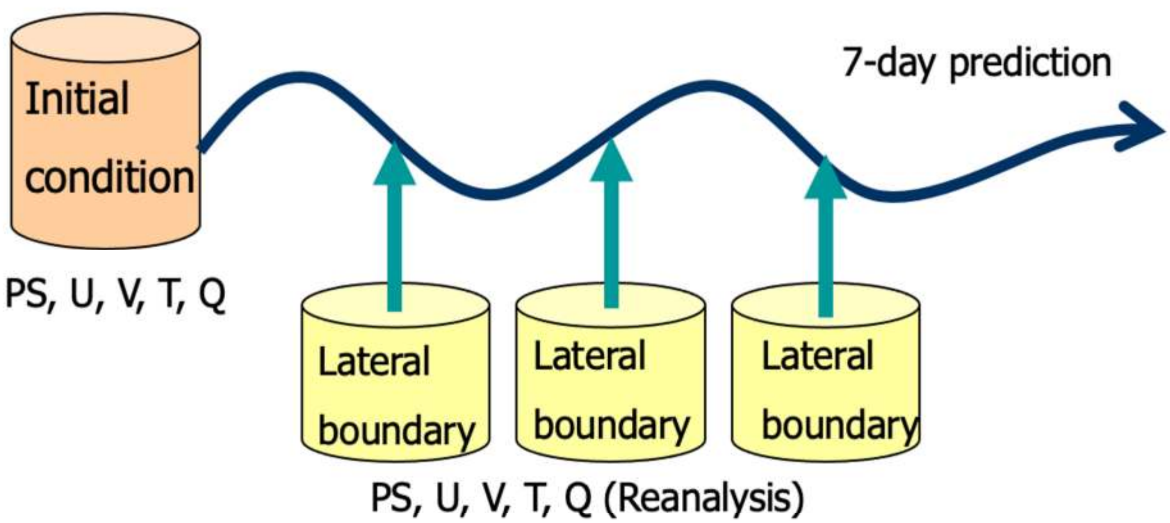


Fig.2 An actual experiment

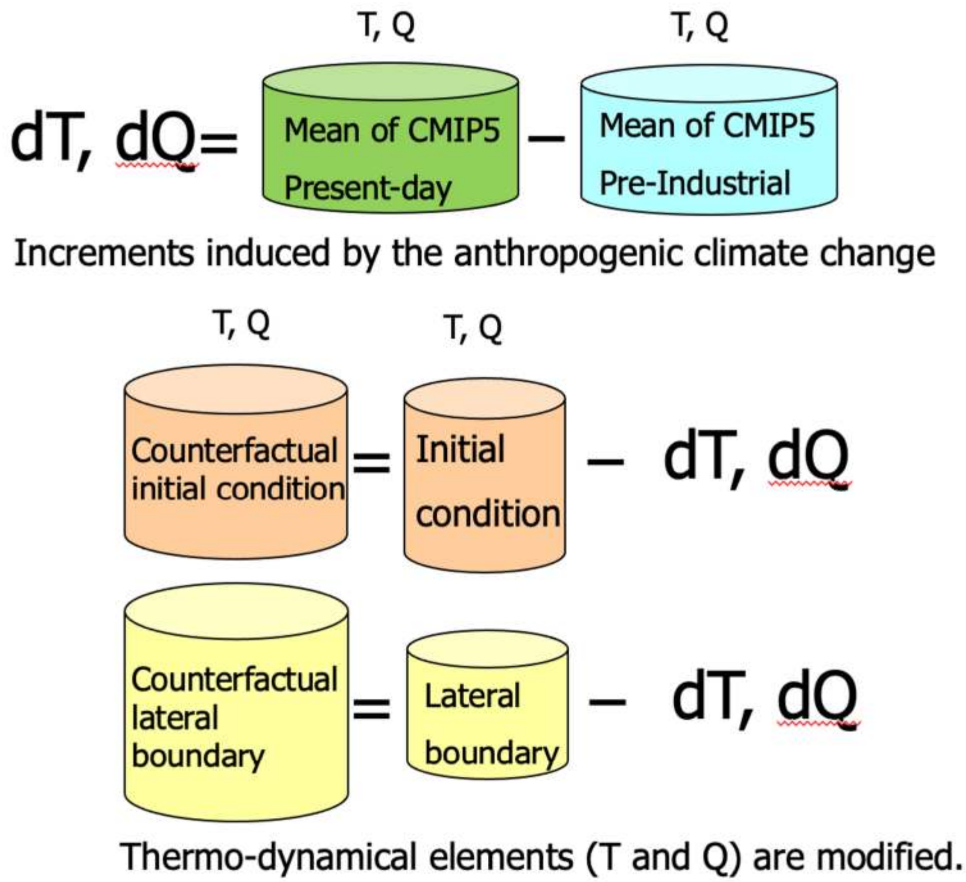


Fig.3 A counterfactual experiment. The initial and lateral boundary conditions were modified by removing the anthropogenic climate change effect, then conducting reforecasts as the actual experiment.

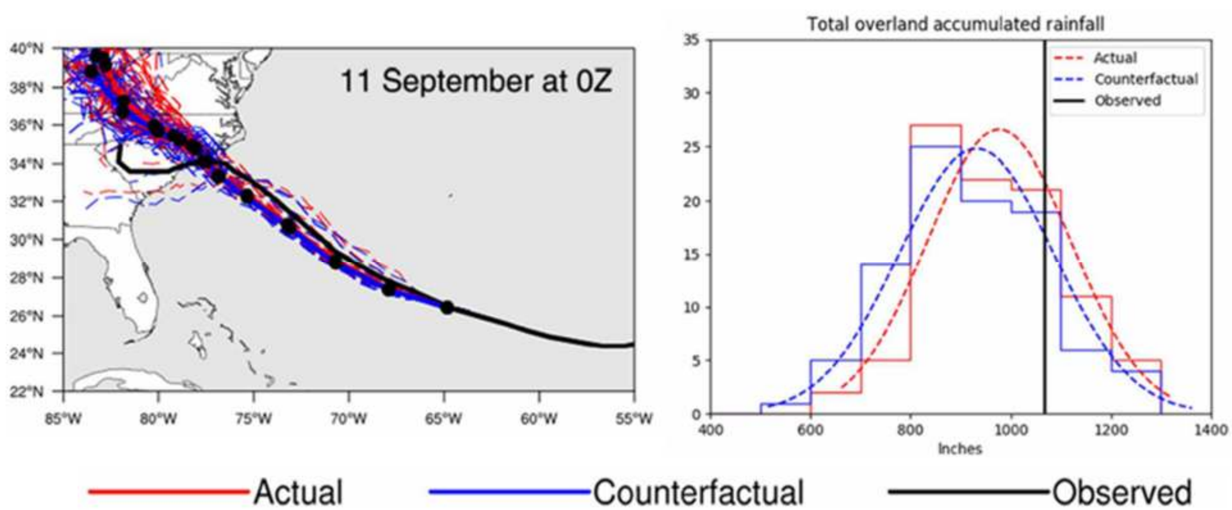


Fig.4. (left) Observed and simulated storm tracks for Hurricane Florence. Model simulated TC tracks of the 7-day Actual (red) and Counterfactual (blue) forecasts initialized on 00Z, 11 September 2018. Black lines are the observed track. (right) Simulated changes in total accumulated rainfall within 200 km and 48 hours of the model landfall for the Actual (red) and Counterfactual (blue) 11 September 00Z ensembles. Dashed lines are Gaussian fits to the data. Only 96 ensemble members that made landfall within 200 km of the observed landfall location were included. The

observations are marked with the vertical black line. Adapted from Reed et al. (2020).

Discussion

What are the pros and cons of the pseudo-warming experiment?

2. Extreme TC season

Attribution of specific active storm seasons was also studied by a few studies (Murakami et al. 2017, 2018; Qian et al. 2020). Here, the methodology used for attribution for the 2015 active storm season in the Eastern North Pacific Ocean (EPO) is described as an example.

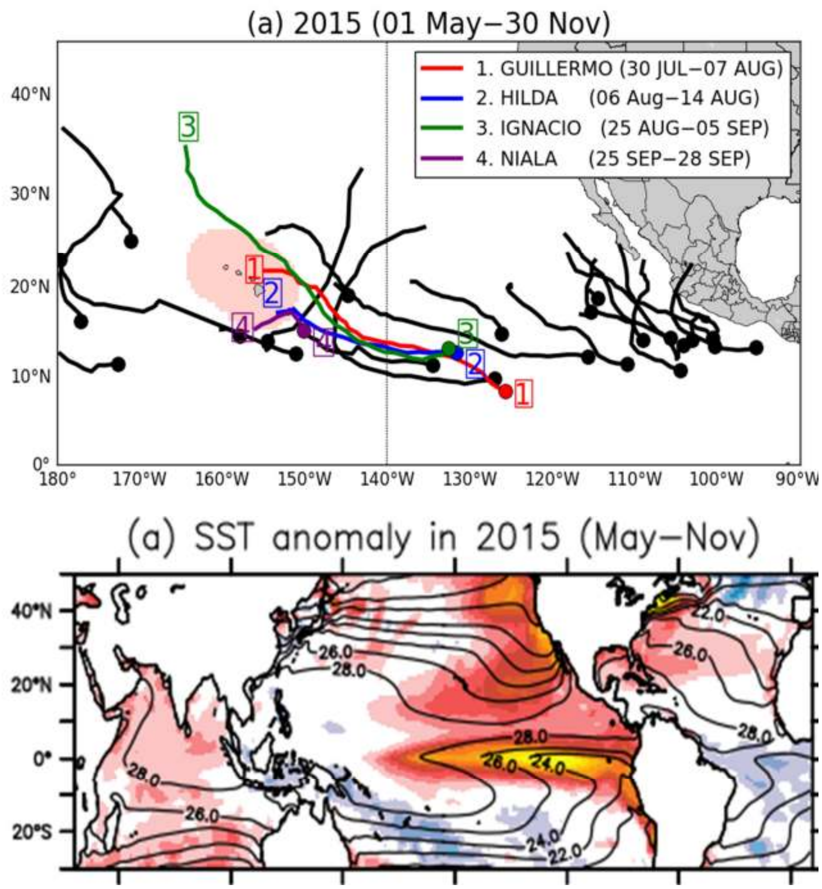


Fig.5 (top) 27 TCs in 2015 in the EPO. (bottom) Observed SST anomaly in 2015 showing strong El Nino.

The 2015 storm season was super active for EPO. There were 27 storms generated. A lot of news media argued that the occurrence of the active season was due to the strong El Nino (Fig. 5). However, it is uncertain if the strong El Nino is the main reason for the active storm season. You can see marked warming in the subtropical eastern Pacific in Fig. 5. Murakami et al. (2016) conducted idealized seasonal predictions to identify which SST anomalies were the most important for the extreme TC season.

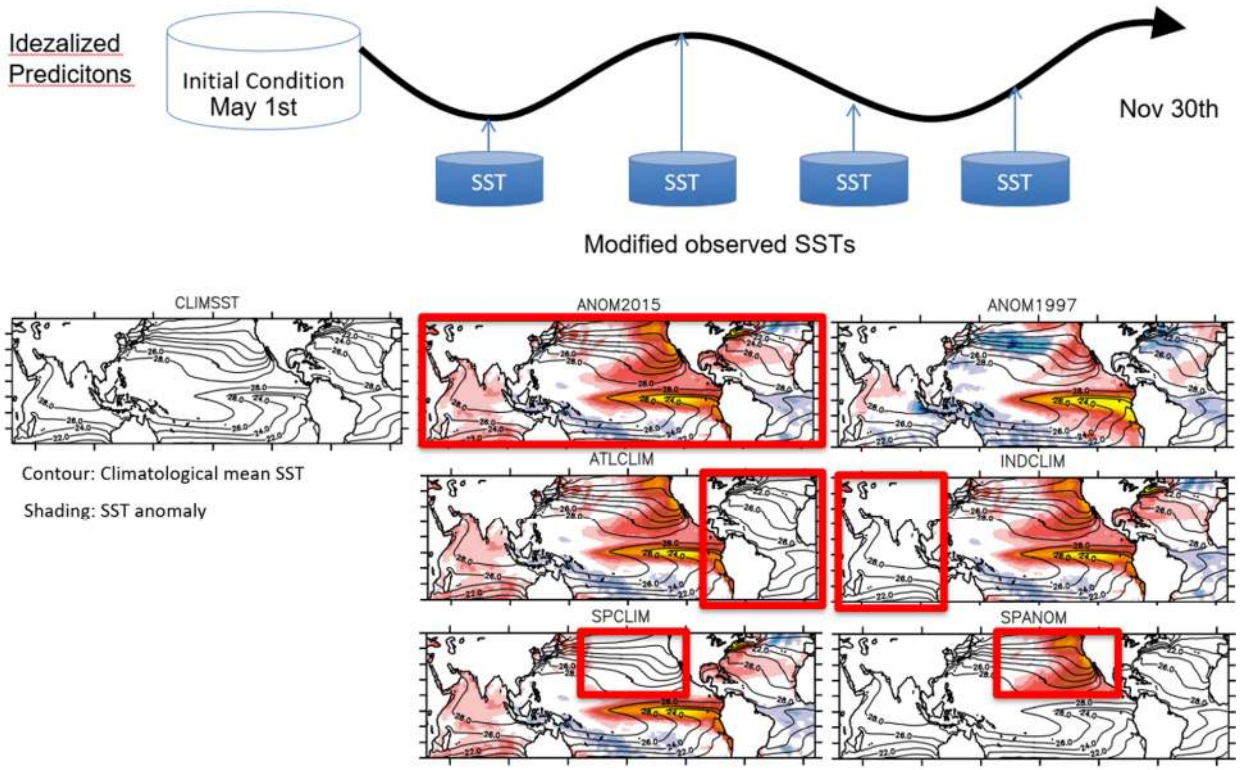


Fig.6. Forced SSTs in the idealized experiments.

Using the FLOR model, so-called SST-nudging experiments were conducted in which the model was forced with SSTs at a 5-day time scale.

$$\underbrace{\frac{\partial SST}{\partial t}(x,y,t)}_{\text{Modified SST tendency}} = \underbrace{\chi(x,y,t)}_{\text{Simulated SST tendency}} + \frac{1}{\tau}(\underbrace{SST_T(x,y,t)}_{\text{Reference SST to restore}} - \underbrace{SST(x,y,t)}_{\text{Simulated SST}})$$

τ: nuding time scale

These reference SSTs are the climatological mean (CLMSST), 2015 SST (ANOM2015), 1997 SST (ANOM1997), ANOM2015 but with climatology in Atlantic (ATLCLM), in the Indian Ocean (INDCLIM), in subtropical Pacific (SPCLIM), and 2015 SST only over subtropical Pacific (SPANOM) (Fig.6).

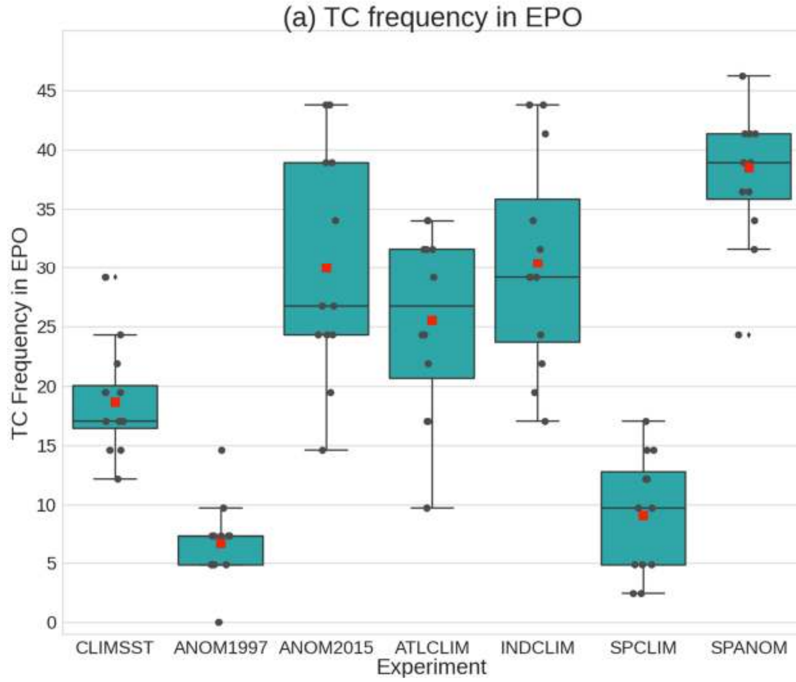
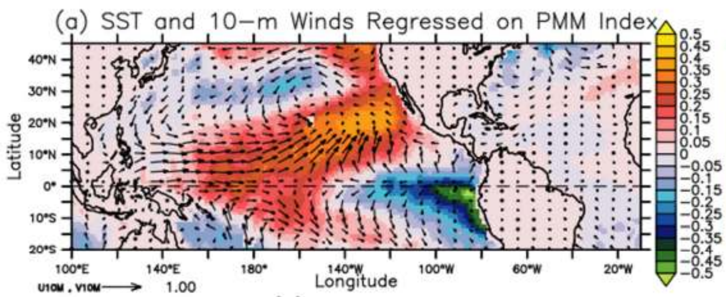


Fig.7 Simulated TC number for SST-nudging experiments. There are 12 ensemble members for each experiment.

The results showed that the subtropical SST anomaly was critical for the extreme TC year of 2015 (Fig. 6).



The PMM is the 1st singular decomposition (SVD) mode for the SST and zonal and meridional components of the 10-m wind field (*Chiang and Vimont* 2004).

	Niño-3.4	PMM
1997 (May–Nov)	+2.4σ	−1.0σ
2015 (May–Nov)	+2.4σ	+0.9σ

Fig.8. The Pacific Meridional Mode (PMM) may be important for the active 2015 TC season.

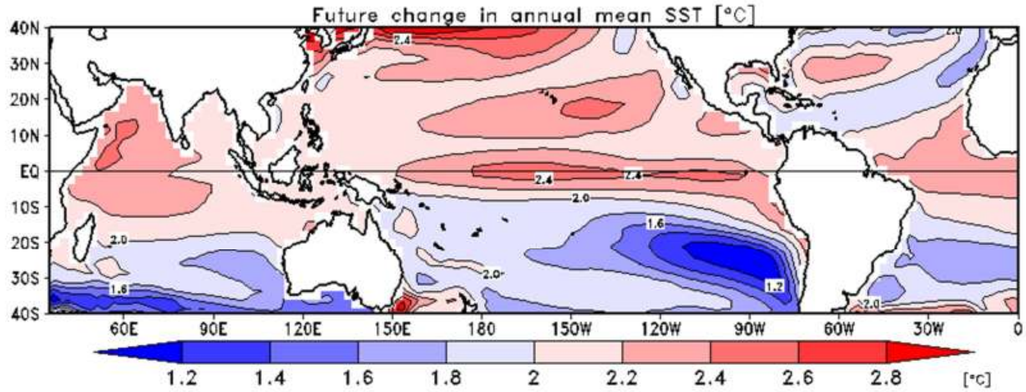


Fig.9. Projected future changes in SST by CMIP5 models.

The subtropical Pacific warming associated with Pacific Meridional Mode (PMM) may be important for the active 2015 TC season (i.e., the effect of internal variability). However, the climate models commonly project a substantial warming over the subtropical Pacific in the future projections, so anthropogenic global warming might have also played an important role in the occurrence of the active TC season like 2015 (Fig. 9).

Two sets of long-term fixed anthropogenic forcing experiments were conducted to assess the effect of anthropogenic warming on the extreme TC season relative to that of natural variability.

Experiment	Radiative Forcing	Simulation Years
1860 Control	1860 Level	3500
1990 Control	1990 Level	500

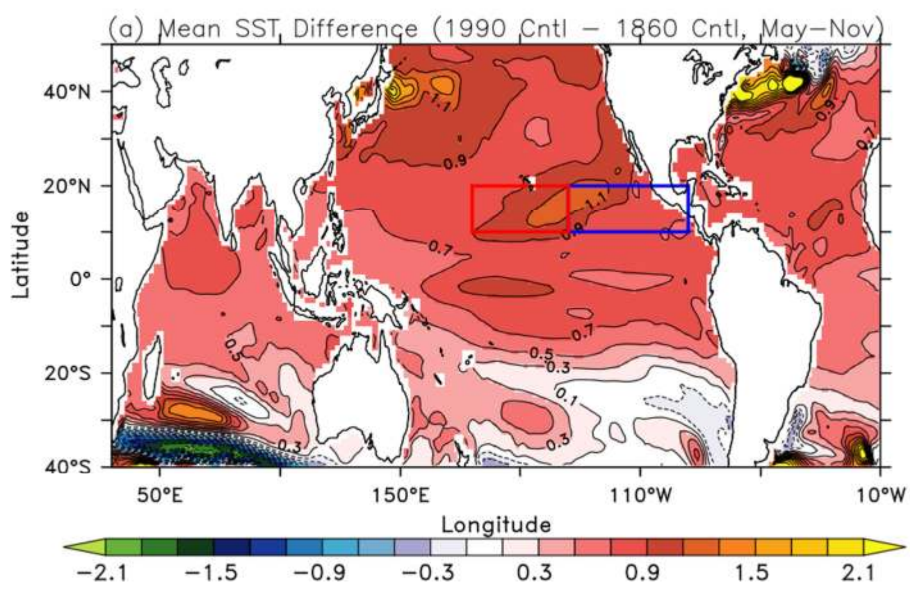


Fig.10. (top) Long-term fixed anthropogenic forcing experiments. (bottom) The difference in the mean SST between 1860 Control and 1990 Control.

Here, we define the probability of occurrence of the year with a TC number equal to *x* or greater.

Probability of Exceedance

$$P(x) \equiv \frac{\text{Number of years with TC number } \geq x}{\text{Total number of years}}$$

x : TC frequency in a year

P(x) is compared between 1860 Control (red) and 1990 Control (blue) (Fig. 11), showing clear separation in *P(27)*.

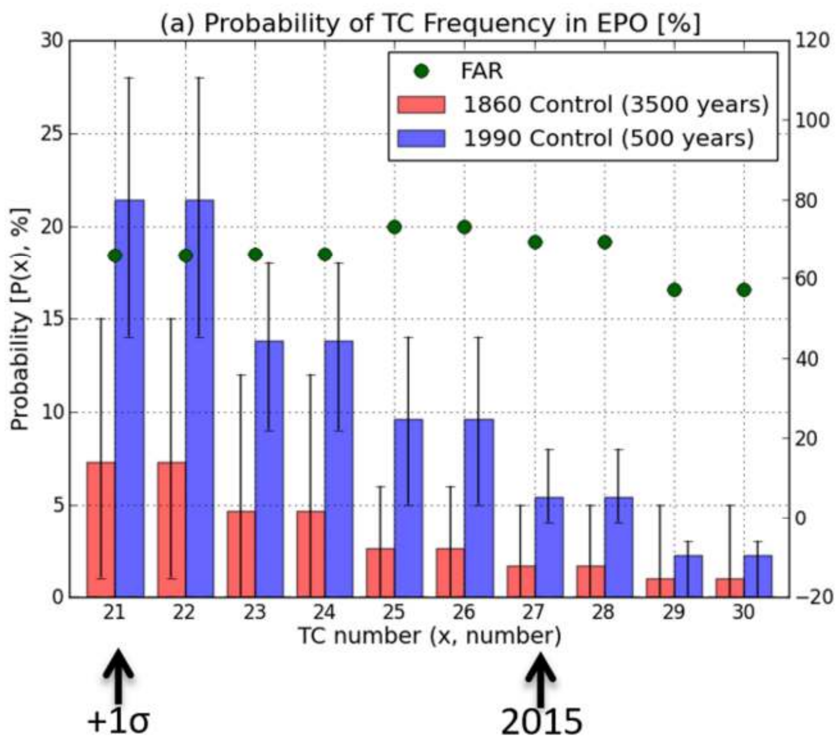


Fig.11. P(x) for 1860 Control (red) and 1990 Control (blue). FAR is shown in green dots.

The fraction of attributable risk (FAR) is defined as follows.

Fraction of Attributable Risk (FAR)

$$FAR(x) \equiv \frac{P(x|E_1) - P(x|E_0)}{P(x|E_1)}$$

E_1: Anthropogenic Forcing (1990 Contl)
E_0: Non-anthropogenic Forcing (1860 Contl)

$-\infty$ (not attributable) < FAR ≤ +1.0 (attributable)

FAR(21) = 0.66
FAR(27) = 0.57

FAR ranges from -∞ (not attributable) to 1.0 (attributable). FAR(27) was 57%, indicating that there is a 57% chance that the 2015 extreme TC season had occurred due to increased anthropogenic forcing relative to natural variability alone.

Discussion

What are the pros and cons of the above method?

3. Unusual decade or trend

Tropical cyclones undergo substantial multi-decadal variability influenced by both anthropogenic climate changes and internal variabilities such as Interdecadal Pacific Oscillation (IPO) and Atlantic Multi-decadal Variability (AMV).

We focus on TC density. TC positions were counted every 6 hours over each 5° x5° (or 2.5° x 2.5°) grid box globally. The total count for each grid box is defined as TC density. The left panel in Fig. 12 shows the observed trend in TC density over the period 1980-2018, showing substantial increases in the Hawaiian region, North Atlantic, and the Arabian Sea as well as decreases in Western North Pacific and South Indian Ocean in the recent decades.

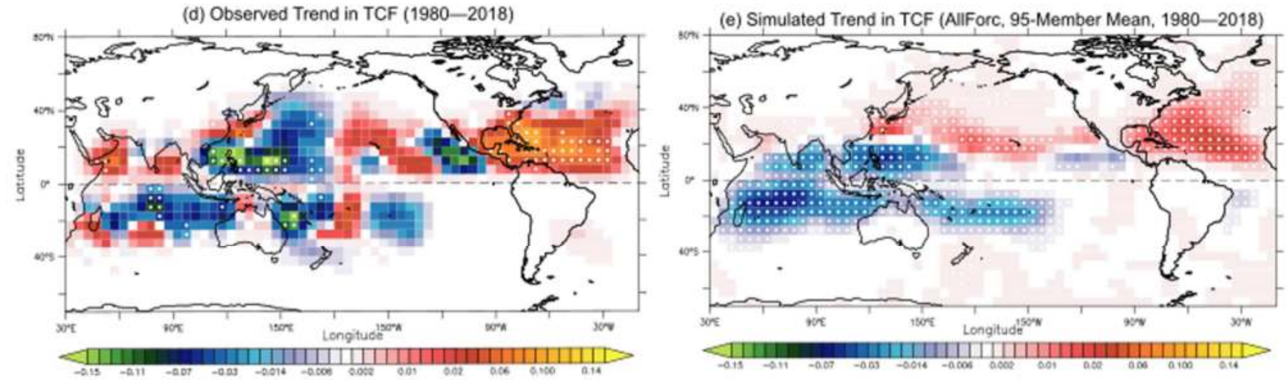


Fig.12. (Left) Observed TC density trend over the period 1980-2018. (Right) As in left, but for the ensemble mean of the AllForc large-ensemble simulations. Adapted from Murakami et al. (2020).

Because of the short duration of the observed record, we primarily rely on climate model simulations to understand forced climate change (e.g., anthropogenic forcing) and internal natural variability (e.g., IPO and AMV). Large-ensemble simulations allow one to better define a model's forced response and to distinguish it from internal variability, taking advantage of ensemble statistics given a sufficiently large ensemble.

There are more than 30 ensemble members in the simulations. Each ensemble member was initialized from a different year from the long-term control simulations and integrated forward by prescribing time-varying historical external forcing such as greenhouse gases, aerosols, volcanic aerosols, and solar radiation (hereafter referred to as AllForc). The simulated global mean temperature rises year by year, as observed (red lines in Fig. 13a). Because each ensemble member shows a different phase of internal variability at a specific time, taking the mean of the ensemble members can filter out the internal variability (e.g., Fig. 13b); thus, the resultant mean field can be regarded as an estimated modeled response to the external forcing.

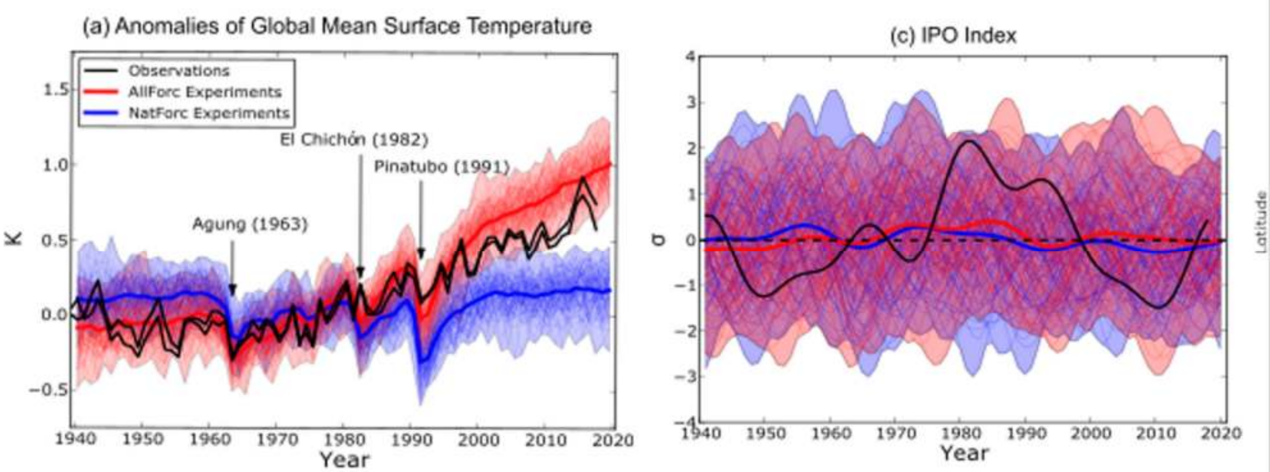


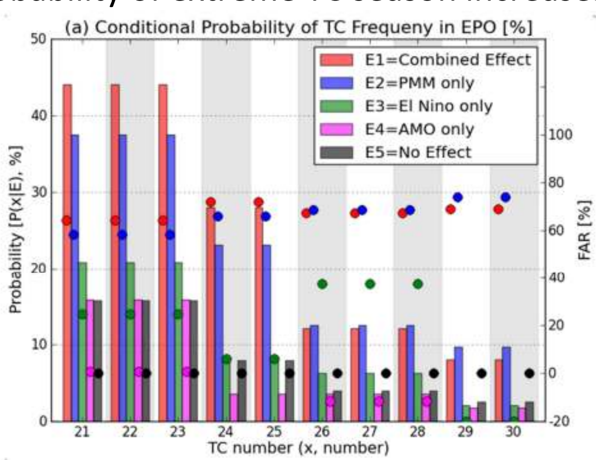
Fig.13. (left) Anomalies of global mean surface temperature relative to 1961–1990 mean based on observations (black), the AllForc large-ensemble experiments (red), and the NatForc experiments (blue). (right) As in right, but for IPO index. Thick red and blue

lines are the ensemble mean of the large-ensemble simulations. Adapted from Murakami et al. (2020).

The right panel in Fig. 13 is the trend in TC density by the ensemble mean of AllForc large ensemble experiments, showing substantial similarity to the observed trend (left panel in Fig. 13). Because taking an average of the ensemble members can filter out the internal variability, the similarity indicates the substantial influence of the external forcing (greenhouse gases, aerosols, and volcanic eruptions) on the trend of TC density.

Large-ensemble simulations are also useful to estimate the effect of internal variability on specific extreme TC seasons. For example, you can pick up the ensemble members showing a positive PMM phase and then calculate the probability of occurrence of the extreme TC season like 2015 to identify the influence of the PMM positive phase on the occurrence.

Figure 14 shows the simulated probability of occurrence of storm season as a function of TC number on the x-axis but grouped into five specific phases of natural variability. Here, evaluated were 35 ensemble members from the AllForc simulations between 2001-2020 so that there are 700 samples (i.e., 35 x 20). E5 is the group showing all PMM, ENSO, and AMO were under neutral phases. E4 is the group showing a negative AMO phase only; E3 is the group showing a positive ENSO phase only; and E2 is the group showing a positive PMM phase only. Finally, E1 is the group showing negative PMM, positive ENSO, and negative AMO simultaneously. The probability of extreme TC season increases during the positive PMM phase in this case.



Using the 700 samples during 2001–2020 period in the AllForc, additional five conditional provability P(x|E$_n$) are computed.

PMM(+) >> Nino-3.4 (+) > AMO (–)

E$_n$	PMM ≥ +1σ	Niño-3.4 ≥ +1σ	AMO ≤ –1σ	Sample size	Effect
E1	✓	✓	✓	44/700	Combined Effect
E2	✓			94/700	Positive PMM only
E3		✓		83/700	Positive Niño-3.4 only
E4			✓	55/700	Negative AMO only
E5				282/700	No Effect

Fig.14. Conditional probability of occurrence of active storm season in the Eastern

North Pacific depending on a specific phase of internal variability. Adapted from Murakami et al. (2017).

FAR for internal variability can be computed as follows.

$$FAR(x|E_i) \equiv \frac{P(x|E_i) - P(x|E_5)}{P(x|E_5)}$$

$$i = 1, \ldots, 4$$

E_i: A group of members showing a specific phase of natural variability

E_5: A group of members under neutral conditions

$-\infty$ (not attributable) $<$ FAR ≤ 1.0 (attributable)

FAR for internal variability can be computed as follows. The dot plots in Fig. 14a show FARs for internal variability, showing greater than 80% for the PMM phase (E2) and combined modes (E1) for the case of the 2015 storm season (i.e., x=27), indicating PMM phase also played an important role to increase the probability of occurrence of extreme storm season.

5. Statistical-dynamical downscaling

One of the problems for a climate modeling study is its computational cost. As the typical horizontal scale of a tropical cyclone ranges from 100 km to 1,000 km, a horizontal resolution finer than a 25-km mesh is required to simulate realistic tropical cyclones. However, running multi-ensemble and multi-decadal simulations using such a high horizontal resolution is very expensive. To save on computational cost, a new downscaling method, statistical-dynamical downscaling, has been implemented to quantify projected future changes in tropical cyclone activity.

Emanuel (2006, 2008, 2013, 2021) was the first to develop a new statistical-downscaling approach. To put it simply, this approach includes three processes: *Genesis*; *Tracks*; and *Intensity*. In general, the downscaling technique applies a storm intensity model (*Intensity*) to tropical cyclone tracks initiated by random seeding in space and time (*Genesis*), and propagates forward using a beta-and-advection model driven by winds derived from the output by dynamical climate models (*Tracks*). More specifically, in the approach of Emanuel (2006), about 1,000 weak vortices (12 m s^{-1} in terms of maximum wind speed) were randomly placed over the global tropics (i.e., *Genesis*). Second, these vortices were propagated following large-scale flows using an advection model (*Tracks*). The large-scale flows were derived from some existing climate simulations that were not required to be high-resolution models. Third, a hurricane intensity model computed development (or decay) for each vortex along the vortex propagation (i.e., *Intensity*) forced with thermodynamic and dynamic large-scale parameters derived from the same existing climate simulations. Most vortices decay due to strong vertical wind shear or dry conditions in the mid-troposphere. Emanuel (2006) utilized a hurricane intensity model called the Coupled Hurricane Intensity Prediction System (CHIPS). CHIPS is based on a simple axisymmetric hurricane model that can compute attainable tropical cyclone intensity given large-scale environmental conditions, such as SST, atmospheric vertical structure of moisture, and temperature as input. Similar downscaling approaches have been also developed by Lee et al. (2018). Unlike the model by Emanuel (2006), Lee et al. (2018) incorporated a statistical assumption that the seeding rate varies with thermodynamic and dynamic large-scale conditions. These downscaling models are computationally cheap so that you can simulate thousands of years even with your laptop.

The statistical-downscaling model had been used for both future projections for the mean changes in TC activity and attributing studies for extreme TC events. However, there are some uncertainties in the method. For example, Lee et al. (2018) used the two versions of the seeding rate. One depends on large-scale parameters including column-integrated relative humidity (CRH), and the other depends on those including saturation deficit (SD). Figure 15 reveals that the projected future changes in the global number of TCs are the opposite between TCHR and SD. When CRH was used, most of the results showed projected increases in TC numbers in the future; whereas, when SD was used, they showed projected decreases. The results were dependent on the random seeding rate (Fig. 17b), where SD GPI led to a decreasing trend toward the end of the 21st century while CRH GPI led to an increasing trend in the random seeding rate. It is difficult to identify which of the results is the more plausible.

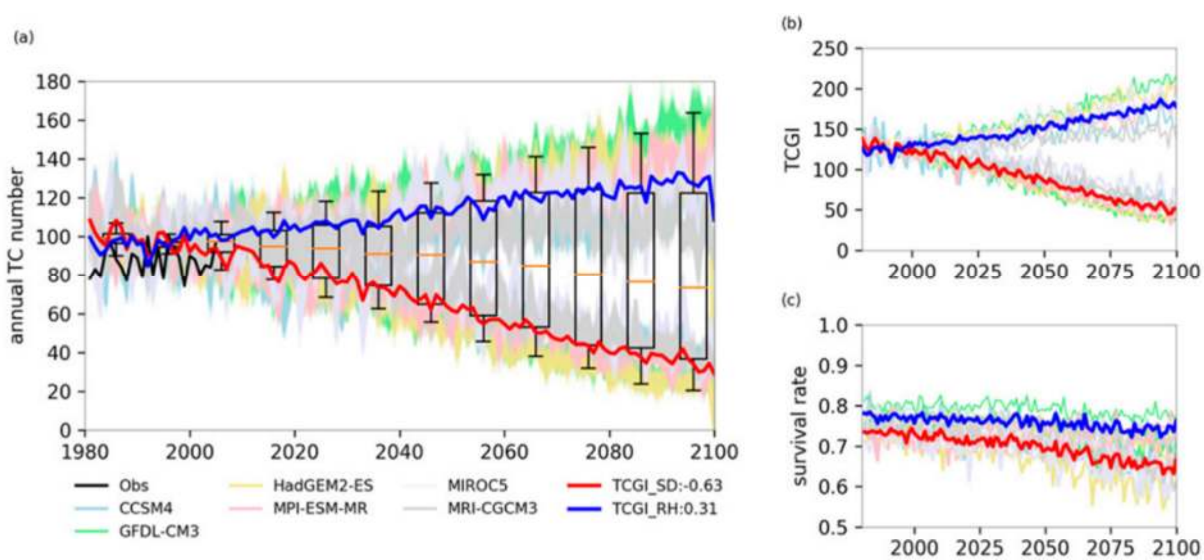


Fig.15. Time series of (a) the simulated annual global number of tropical cyclones (TCs),

(b) the simulated seeding rate, and (c) the survival rate of the synthetic storms. Thin lines show downscaling results from each of the CMIP5 models, indicated by color. The box-and-whisker diagram in (a) shows the median (orange) and the 5^{th}, 25^{th}, 75^{th}, and 95^{th} percentiles. The thick blue and red lines show the ensemble mean from the CHR and SD experiments, respectively. Adapted from Lee et al.(2018).

As indicated by Emanuel (2020) and Lee et al. (2018), the projected future changes in the global number of TCs are largely dependent on the large-scale parameters derived from global models. Specifically, the dependency of the results on the thermodynamic parameters is large in the statistical-downscaling technique. Previous studies indicate that the large-scale controlling variables for TC genesis would be different between the present-day climate and projected future climate (Nolan and Rappin, 2008; Murakami et al. 2013). The projected future changes in TC genesis number assuming unchanged sensitivity of large-scale parameters to the TC genesis leaves substantial uncertainty.

6. Conclusion

In conclusion, attribution of extreme TC events to climate changes as well as future projections remains a challenging scientific topic despite considerable progress having been made in response to the sizeable societal impacts. The challenge is mainly because 1) there are no reliable long-term observations to identify the effect of anthropogenic climate change on TC activity, 2) substantial effect of internal variability on TC activity, and 3) expensive computational cost to perform large-ensemble simulations with high-resolution dynamical models. There are some attribution methodologies had been developed, although they have pros and cons. We can say it is the beginning of the era for the attribution studies applied to TCs. New studies using dynamical and statistical models, long-term observations, and theories are needed to shed further light on the uncertainties involved in the effect of anthropogenic climate changes on TC activity.

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