nature climate change

SUPPLEMENTARY INFORMATION

DOI: 10.1038/NCLIMATE2646

Q & A on 'Trade-off between intensity and frequency of global tropical cyclones'

Nam-Young Kang & James B. Elsner

List of questions

1. **What is new in this paper?**
2. **What are the merits of the methodology?**
3. **What is orthogonal variability space?**
4. **What is 3-D variability space? How do we find the best explanatory variability direction?**
5. **What is the difference between variability and indicator?**
6. **What are the boundaries for regional ocean basins?**
7. **What are the statistics of TC frequency and intensity?**
8. **What is the implication of A?**
9. **What is the implication of E?**
10. **Why are global SST and SOI chosen as the environmental indicators?**
11. **What is the difference between warm-phase ENSO and warm-year El Niño?**
12. **How can we read Fig. 2?**
13. **How is significance calculated?**
14. **What is the trend of global ocean warmth?**
15. **How much does thermodynamic factor correlate with global ocean warmth?**
16. **How much does dynamic factor correlate with global ocean warmth?**
17. **What is the difference between Fig. 2a and Fig. 4 in the main manuscript?**
18. **What is 'reference σ' in Fig. 4 in the main manuscript?**

19. Does the result in Fig. 4 mean that the TC intensity have increased by 1.3 m s^{-1} on average over the 30 years?

20. How can the process and results in this paper be validated?

1 What is new in this paper?

A global linkage between intensity and frequency of tropical cyclones (TCs) is empirically examined and a physical mechanism is identified. For this, ocean heating is directly compared with global TC response in a continuous variability space.

2 What are the merits of the methodology?

Trend analysis of TC climate, which is popular, could be understood as the correlation with 'time'. In this paper, 'time' is replaced by global mean sea surface temperature (SST), which is an indicator of global ocean warmth, and the response is directly examined on an annual basis. Thus, direct interpretation of 'global warming' is available, instead of the 'climate change' perspective. Moreover, this approach enables understanding the annual variation of TC climate as well as the trend in association with global ocean warmth.

In addition, continuous variability space helps us find the linkage between the TC climate indicators. Thus, the physical connection between frequency and intensity is available to investigate using this framework. This paper examines the trade-off between TC frequency and intensity under global ocean warming.

3 What is orthogonal variability space?

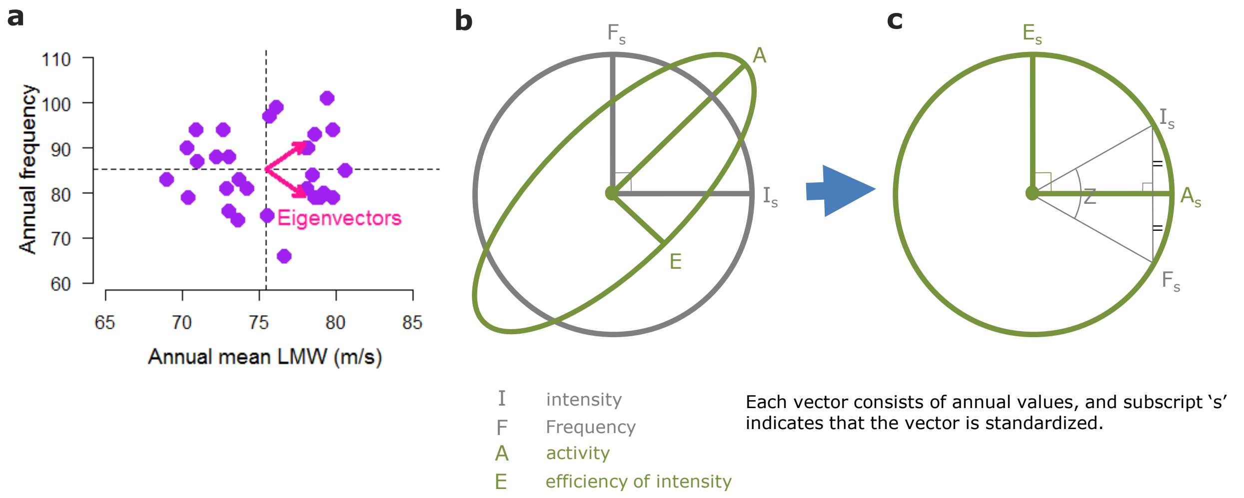
Orthogonal variability space is the variability space whose axes are orthogonal (zero correlation) to each other.

Firstly we can think of XY coordinates for TC intensity (I) and frequency (F) (Suppl. Fig. 1a,b). I and F are vectors of annual values, where mean life-time maximum wind (LMW) speed and number of annual TCs are used as indicators, respectively. Standardized I and F are used, for convenience. Although independent, they are not necessarily orthogonal, forming an angle between the two in an orthogonal variability space. To construct an orthogonal variability space, we need two directional variabilities orthogonally fixed by definition. The two eigenvectors coming from principal component analysis (PCA) are used to construct them. The two directional variabilities are named 'activity (A)' and 'efficiency of intensity (E)', and can be simply calculated by

$$A = \left[\mathrm{s}\left(I\right) + \mathrm{s}\left(F\right)\right] / \sqrt{2} \tag{1}$$

$$E = \left[\mathrm{s}\left(I\right) - \mathrm{s}\left(F\right)\right] / \sqrt{2}, \tag{2}$$

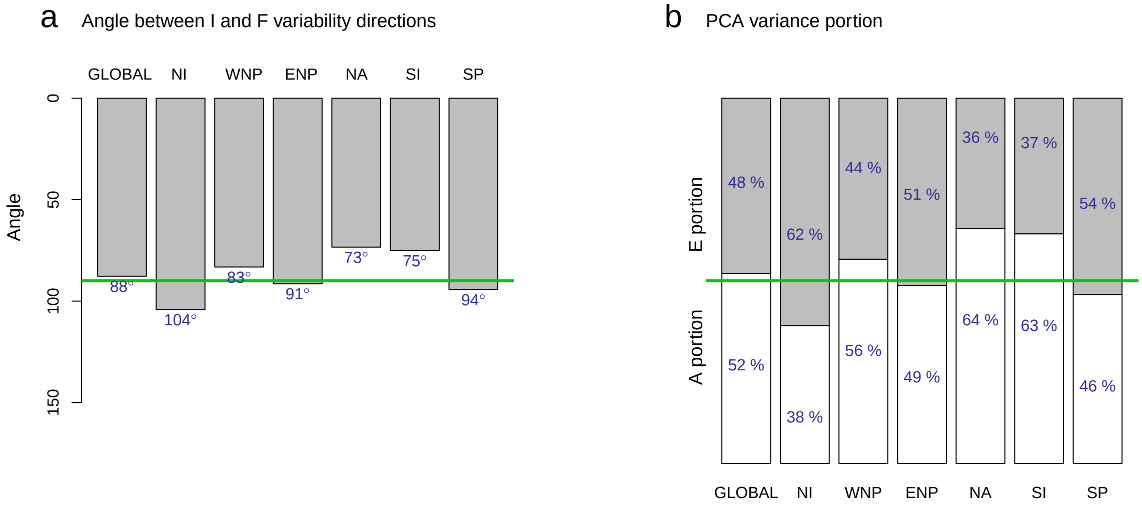
where the operator 's( )' returns standardized values of an input vector.



Suppl. Figure 1 : Schematic diagram of TC climate variability space. **a** example data points of 29 annual values (1984–2012) of global observation, **b** XY coordinates and **c** orthogonal variability space.

By the two principal components, orthogonal variability space is formed where *I* and *F* has an angle (Suppl. Fig. 1b). The angle (Z) shows collinearity between *I* and *F*, which implies PCA variance. The climate characteristics differ by global and each regional ocean basins.

One of the merits of using the orthogonal framework is that statistical solutions are easily obtained from geometry. For example, PCA variance of *A* and *E* are simply calculated by $\cos(Z/2)^2$ and $\sin(Z/2)^2$, respectively. Suppl. Figure. 2 shows the results.

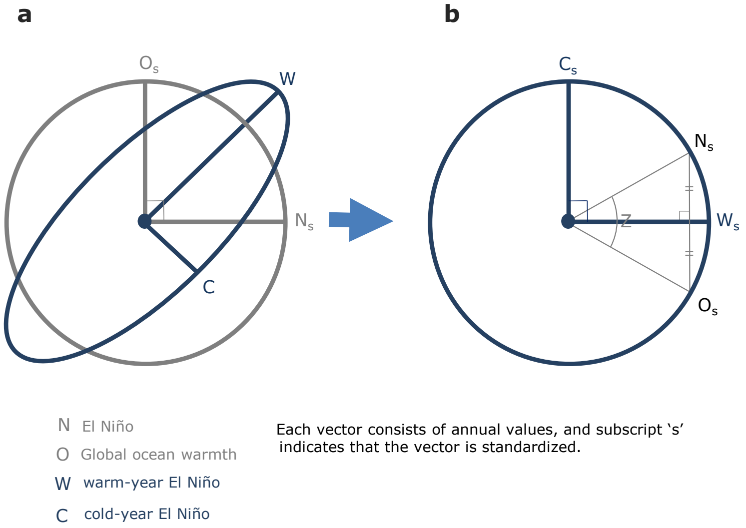


Suppl. Figure 2 : **a** Angles between *I* and *F* variability directions and **b** PCA variance portions.

To avoid the wind-conversion problem, global TC data set is organized by 1-minute wind observations from the Joint Typhoon Warning Center (JTWC, `www.usno.navy.mil/NOOC/nmfc-ph/RSS/jtwc/best_tracks`) and the National Oceanic and Atmospheric Administration (NOAA) National Hurricane Center (NHC, `www.nhc.noaa.gov/data`). 29-year annual values (1984–2012) are used.

4 What is 3-D variability space? How do we find the best explanatory variability direction?

3-D variability space is the variability space where TC climate variabilities and environmental variabilities coexist. For this, the environmental variability space is formed in the same way as the TC climate variability space (Suppl. Fig. 3). In this paper, El Niño (*N*) and global ocean warmth (*O*) are used as the two primary variability directions, which are indicated by negative Southern Oscillation Index (SOI) and global mean SST, respectively. Two orthogonal variabilities come from the PCA. In this paper, those are named as warm-year El Niño (*W*) and cold-year El Niño (*C*) for each.



Each vector consists of annual values, and subscript ‘s’ indicates that the vector is standardized.

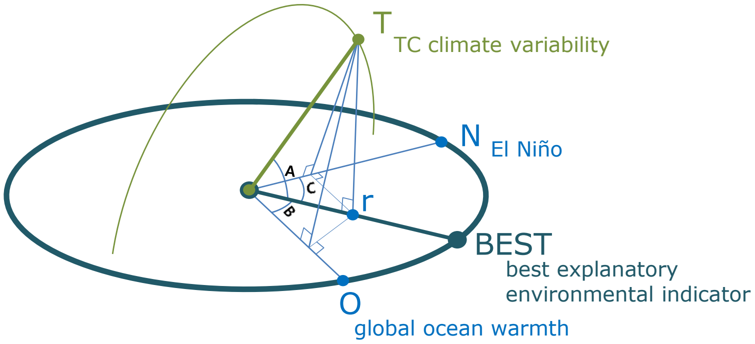
Suppl. Figure 3 : Schematic diagram of environmental variability space. **a** XY coordinates and **b** orthogonal variability space.

Now, Suppl. Figure 4 demonstrates the structure of 3-D variability space. T is an arbitrary TC climate variability at θ direction. The vector of T is obtained by

$$T_\theta = A \cdot \cos\theta + E \cdot \sin\theta, \tag{3}$$

where θ starts from A direction and increases anticyclonically. *BEST* is the variability direction on which *T* is projected. Thus, *BEST* indicates the best explanatory variability direction. The location of *BEST* is identified by *B* and *C*. Angles (*B* and *C*) are calculated by the relationship between the correlation and the cosine function. Projection of *T* onto *BEST* can also be calculated using the geometry of the 3-D variability space.

Let's denote the variance portions of *N* and *O* in *BEST* as V_o and V_N. If *BEST* is located at an acute angle (between *O* and *N*), the sum of V_o and V_N exceeds one. This excess represents the positive collinearity. Otherwise (when located at an obtuse angle), the sum of proportions becomes less than one. The shortfall comes from the negative collinearity. In Fig. 2 from the main manuscript, the area of positively collinearity is shown as overlapping colors, while the area of negatively collinearity as white empty space between the purple and yellow areas. Since the correlation between the negative SOI and the global mean SST is small, the collinearity areas are very narrow and hard to see.



Calcuation of angles (B and C) (in R language format)

BEST=β1*predict(lm(T~N+O))+β2   # β1, β2 : constants

B=acos(cos(B)) = acos(cor(BEST,O))   ;   C=acos(cos(C)) = acos(cor(BEST,N))

Calcuation of the contribution of BEST to T (in R language format)

r=cos(A)=cor(T, BEST)   # correlation between T and BEST

r.sq=r^2   # variance proportion that BEST can explain T

Calcuation of the contributions of O and N to BEST (in R language format)

r_O=cos(B)=cor(BEST,O)   # correlation between BEST and O

V_O=r.sq*(r_O^2)   # variance portion of O

r_N=cos(C)=cor(BEST,N)   # correlation between BEST and N

V_N=r.sq*(r_N^2)   # variance portion of N

Suppl. Figure 4 :   3-D variability space.

5 What is the difference between variability and indicator?

In the 3-D variability space, each variability should have its own variability direction. A name is given to the direction, which is the ‘variability name’. It is qualitative. For example, El Niño is not a quantitative one. Indicator is a quantitative variable to indicate the variability. Usually, there is more than one choice to indicate the variability. For example, indicators such as NINO3, NINO3.4, NINO4, SOI and so forth, can be candidates for an El Niño indicator. Some choices will be better than others.

Variability names and their indicators used in this paper are listed in Suppl. Tab. 1. All values for the indicators are on an annual basis.

Variability name	Indicator
	TC climate
frequency (F)	number of annual TCs
intensity (I)	mean life-time maximum wind speed of annual TCs
activity (A)	principal component 1 (in-phase variation)
efficiency of intensity (E)	principal component 2 (out-of-phase variation)
	Environment
El Niño (N)	negative Southern Oscillation Index (SOI)
global ocean warmth (O)	global mean SST (area-weight applied)
warm-year El Niño (W)	principal component 1 (in-phase variation)
cold-year El Niño (C)	principal component 2 (out-of-phase variation)

Suppl. Table 1: Variability and indicator.

6 What are the boundaries for regional ocean basins?

The western and eastern boundaries applied to regional ocean basins are shown in Suppl. Tab. 2.

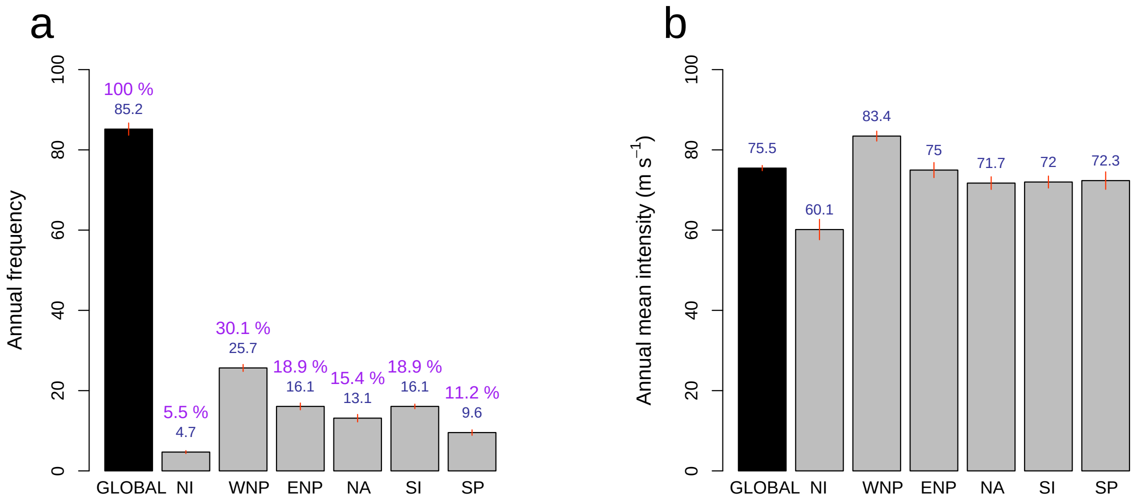
Basin	western bound	eastern bound
North Indian (NI)	land	100°E
western North Pacific (WNP)	100°E	180°E
eastern North Pacific (ENP)	180°E	land
North Atlantic (NA)	land	land
South Indian (SI)	land	135°E
South Pacific (SP)	135°E	land

Suppl. Table 2: Boundaries for regional ocean basins.

Here, 'land' represents the geographical track limit in each basin. TCs whose genesis locations are within the boundary, are chosen from each regional best-tracks. South Atlantic TCs are not considered in this study.

7 What are the statistics of TC frequency and intensity?

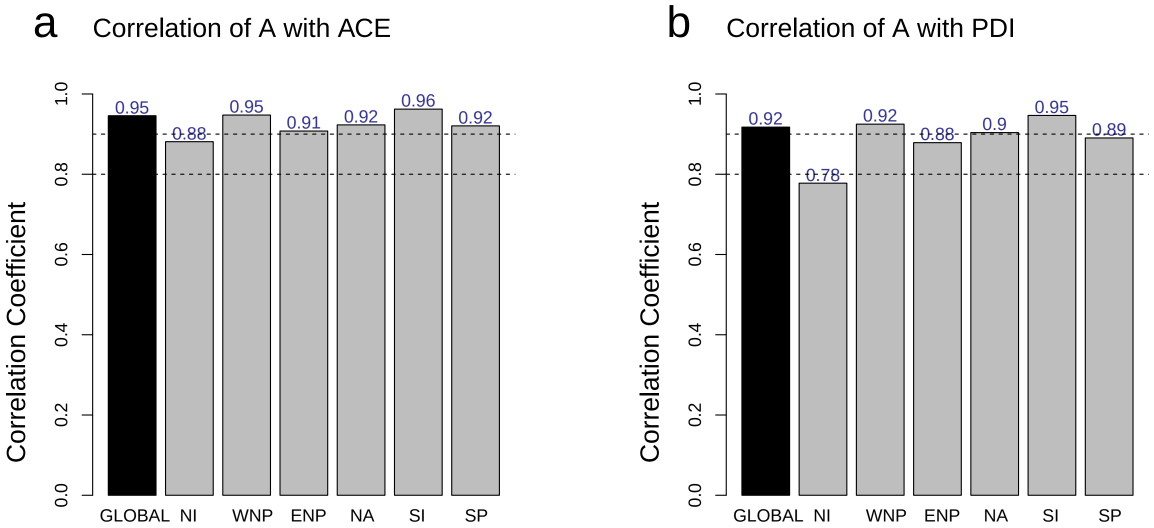
Statistics of TC frequency and intensity are shown in Suppl. Fig. 5. Western North Pacific TCs occupy nearly one-third of the global total based on the past 29-year observations (1984–2012). Even the mean intensity is the highest in this region. *E* in this region significantly increases in a year when the global ocean warms by decreasing frequency but increasing intensity (see Fig. 2 in the main manuscript). Despite the largest frequency fall in this region, the contribution to the global *E* variation is not clear (see Fig. 4 in the main manuscript), since removing high intensity TCs lowers the global mean intensity at the same time.



Suppl. Figure 5 : **a** Annual TC frequency and **b** annual mean intensity. Regional proportion of annual frequency is labeled in purple. Each standard error is shown in red line. Data come from JTWC and NHC. 29-year annual values (1984–2012) are used to calculate correlations.

8 What is the implication of *A*?

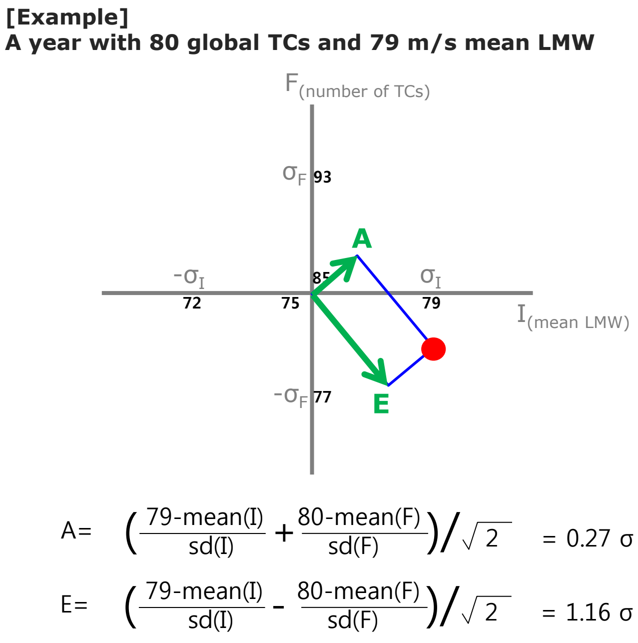
'*A*' is an activity indicator which indicates the in-phase relationship between the frequency and the intensity variations. *A* shows very high correlations with ACE and PDI in all basins (Suppl. Fig. 6), although *A* does not include the 'duration' factor. *A* can be understood as indicating a similar variability direction to that of ACE or PDI.



Suppl. Figure 6 : Correlation of activity indicator(*A*) with **a** ACE and **b** PDI. Data come from JTWC and NHC. 29-year annual values (1984–2012) are used to calculate correlations.

9 What is the implication of *E*?

Cartesian coordinates can be helpful in understanding *E* (Suppl. Fig. 7). Here, an example observation is represented as red dot, which indicates an annual record of TC number and mean LMW. As shown in the figure, the lengths of green lines show the values of *A* and *E*. The point of our study is that *E* is the most significantly responding variability direction to global ocean warmth. As it were, new year red dot in the figure is likely to have the larger length of *E*. Larger *E* implies greater trade-off amount between *I* and *F*, which is possible by negative collinearity constrained by the thermodynamic conditions under global ocean warming.



$$A = \left(\frac{79-\mathrm{mean(I)}}{\mathrm{sd(I)}} + \frac{80-\mathrm{mean(F)}}{\mathrm{sd(F)}}\right)\Big/\sqrt{2} \quad = 0.27\ \sigma$$

$$E = \left(\frac{79-\mathrm{mean(I)}}{\mathrm{sd(I)}} - \frac{80-\mathrm{mean(F)}}{\mathrm{sd(F)}}\right)\Big/\sqrt{2} \quad = 1.16\ \sigma$$

Suppl. Figure 7 : Diagram of annual TC observation

10 Why are global SST and SOI chosen as the environmental indicators?

Global mean SST is an indicator of global warmth specialized for TC climate since TCs occur in the ocean. Global mean SST and global mean air temperature are well known to be very close to each other. As we use global mean SST as the indicator, the variability is named as 'Global ocean warmth' in this paper.

In this paper, an environmental variability space is formed to link global ocean warmth and El Niño. For this, an El Niño indicator should be chosen to have the least correlation with global mean SST (which is set as the indicator of global ocean warmth). A variability plane constructed with highly correlated variabilities would make it more difficult to differentiate signal from noise. Among El Niño indicators such as NINO3, NINO3.4, NINO4, SOI and so forth, SOI is chosen to be the indicator, since it has the smallest correlation with global mean SST.

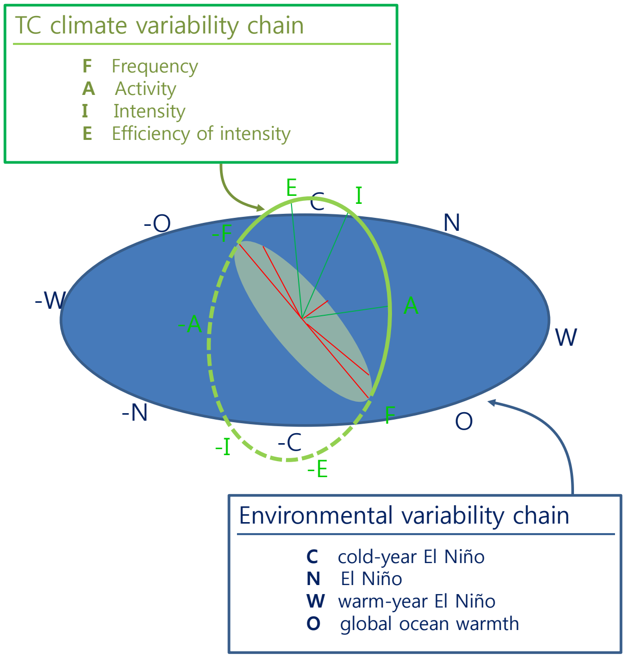
11 What is the difference between warm-phase ENSO and warm-year El Niño?

Warm-phase ENSO is often referred to as El Niño. In this study, warm-year Niño is the combination of global ocean warmth and warm-phase ENSO. Thus, this value increases in a year when negative SOI increases and global SST increases at the same time.

12 How can we read Fig. 2?

As shown in Suppl. Fig. 8, variabilities are circularly chained around the variability plane. TC climate variabilities are projected onto the environmental variability plane. The closest environmental variability direction to any TC climate is determined. Since the projection length is measured by the correlation, we can understand how much the projected TC climate variability can be explained by the determined best environmental variability.

Figure 2 in the main manuscript presents the same information in X-Y plot. For each TC climate variability (lower abscissa), we can confirm the closest environmental variability direction (upper abscissa) and the variance portions. Note that projections could lie in a narrow range of environmental variability direction when the TC climate variability plane is steeply tilted as in Suppl. Fig. 8, which is the eastern North Pacific case. Frequency and activity of eastern North Pacific TCs significantly (red line) respond to environmental variabilities in such a narrow range between El Niño and cold-year El Niño. If the TC climate variability plane is too small, the projection length can not be deciphered, which is the North Indian case.



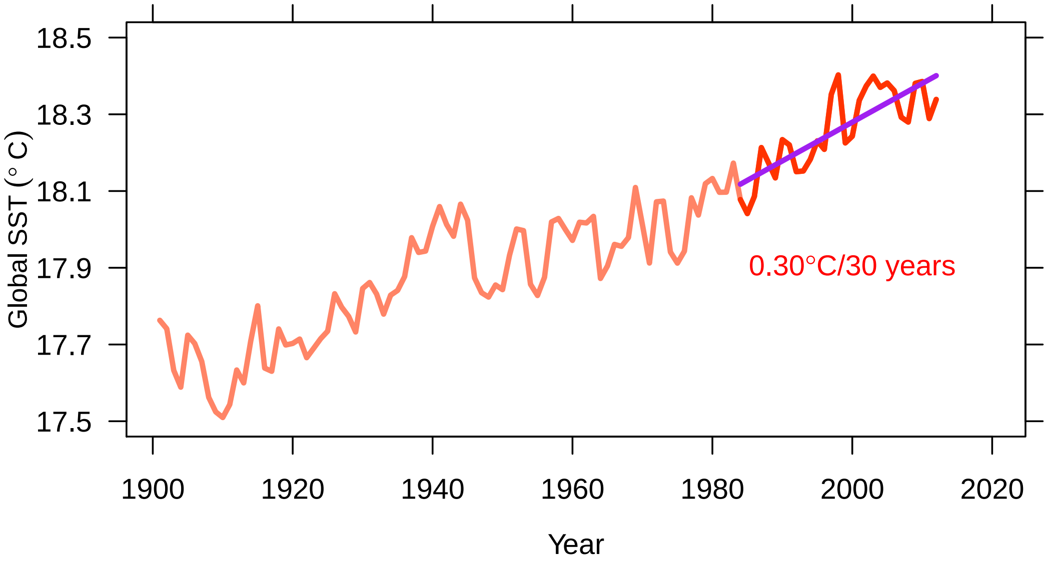
Suppl. Figure 8 : Diagram of variability chain and projection

13 How is significance calculated?

The best explanatory variability direction is that showing the highest correlation with a certain TC climate variability direction. Correlation is calculated using the two vectors, and the significance of the correlation coefficient is done using t-values in a standard way. A significant result is one in which the p-value is less than an alpha level of .05. How to calculate confidence intervals for Figure 3 and Figure 4 is described in `rpubs.com/Namyoung/P2014a`.

14 What is the trend of global ocean warmth?

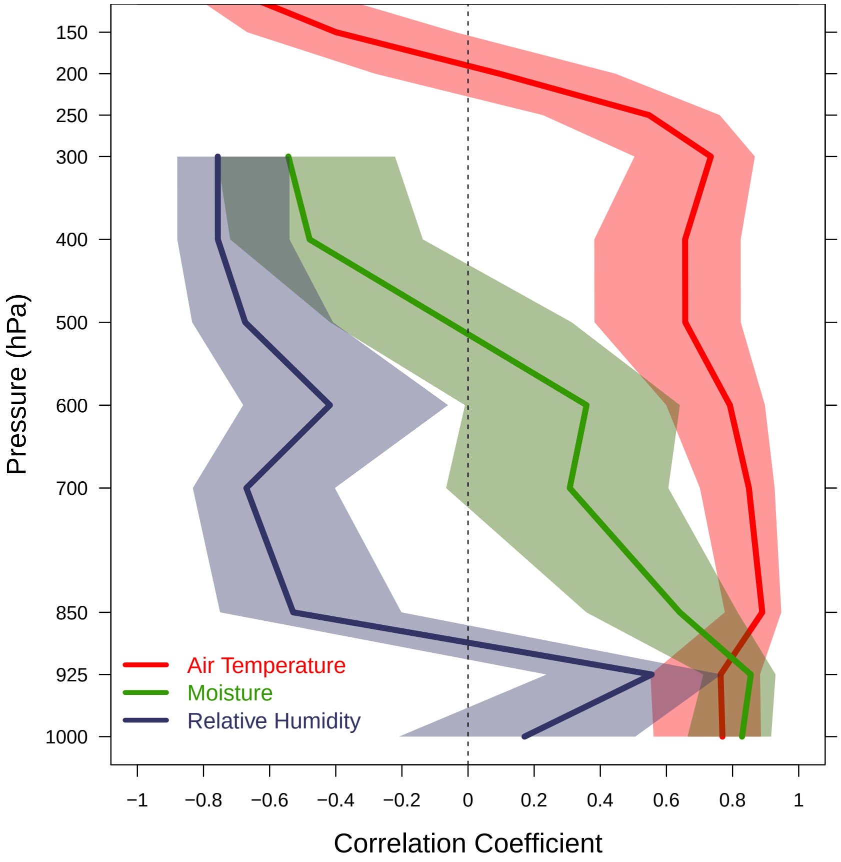
Suppl. Figure 9 shows the annual variation of global mean SST. Annual variation is colored in red, and the slope of the trend (purple line) is calculated as 0.30°C per 30 years. The calculation is based on 29-year (1984–2012) observations.



Suppl. Figure 9 : Global ocean warming. Annual mean of global SST is used as the indicator. NOAA Extended Reconstructed Sea Surface Temperature (ERSST) V3b (`www.esrl.noaa.gov/psd/data/gridded`) is used as the dataset.

15 How well do thermodynamic factors correlate with global ocean warmth?

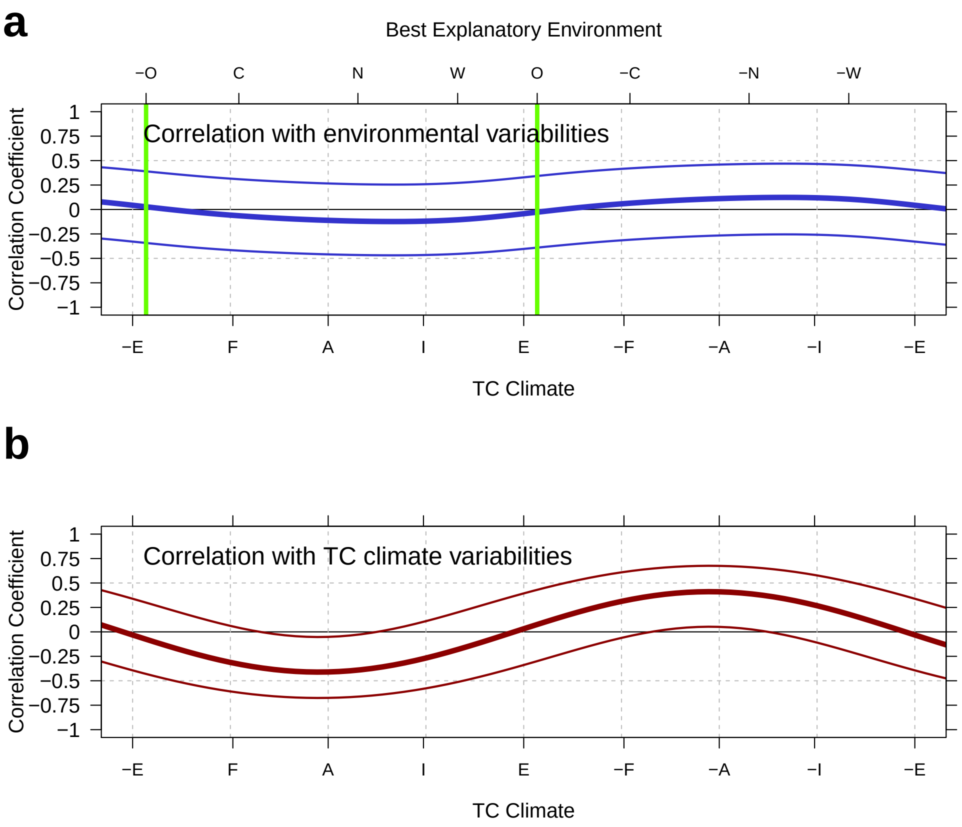
Suppl. Figure 10 shows the correlation coefficients of thermodynamic variables with global mean SST. Air temperature, moisture, and relative humidity are the annual values which are averaged in the tropic region (30°S–30°N). Environmental variables come from the NOAA National Centers for Environmental Prediction (NCEP) reanalysis (`www.esrl.noaa.gov/psd/data/gridded`). At each pressure level, correlation coefficient with annual mean global SST is examined. Correlation coefficient implies how sensitively a variable responds to global ocean warming. It is seen that changing air temperature leads to drier troposphere, which is reflected in the dominant high pressure anomaly over the upper and the middle troposphere.



Suppl. Figure 10 : Correlation of atmospheric variables in the tropics (30°S–30°N) with global mean SST at each pressure level. Shaded area represents 95 % confidence interval. 29-year annual values (1984–2012) are used to calculate correlations.

16 How well do dynamic factors correlate with global ocean warmth variations?

The response of dynamic factors to each environmental variability is also examined in this study. Hadley circulation strength (HCS) is chosen for the dynamic factor. For this, annual HCS is defined by an average of the two maximum absolute mass stream functions (one in N.H, and the other in S.H.). Suppl. Fig. 11a shows the correlation of HCS at each environmental variability direction. The lower and upper abscissas follow the same format as in Fig. 3 of the main manuscript. Besides, the correlation of HCS at each TC climate variability direction is also presented in Suppl. Fig. 11b. Results show that dynamic factor's connection appears insignificant with *O* and as well as with *E*, at least in this research period (1984–2012). Even the correlations are seen to have the lowest values around these variability directions.



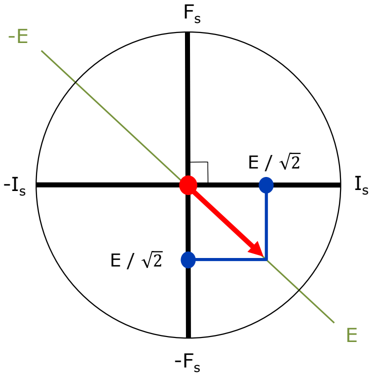
Suppl. Figure 11 : Correlation of Hadley circulation strength with **a** environmental variabilities, and **b** TC climate variabilities. 95 % confidence limits are shown in thin lines. 29-year annual values (1984–2012) are used to calculate correlations.

17 What is the difference between Fig. 2a and Fig. 4 in the main manuscript?

In the main manuscript, Fig. 2a reveals the best explanatory variability for each global TC climate variability. Contributions of global ocean warmth and El Niño are shaded in yellow and purple colors, respectively. Fig. 4 focuses on the contribution of global ocean warming to *E*. Here, regional contributions to global *E* are also shown with color bars.

18 What is the 'reference σ' in Fig. 4 in the main manuscript?

To understand reference σ, Suppl. Fig. 1a is modified into Suppl. Fig. 12. Reference σ is defined as σ_I (standard deviation of *I*) and σ_F (standard deviation of *F*), simultaneously. The length of red arrow represents the response of *E* to global ocean warmth increase. Employing the concept of reference σ, the trade-off amount between *I* and *F* can be represented as $\sigma \cdot E/\sqrt{2}$.



Reference σ : σ_I (standard deviation of *I*) and σ_F (standard deviation of *F*), simultaneously.
Trade-off rate : Trade-off rate is a fixed value which is determined by σ_I and σ_F.
For example, global trade-off rate is 0.21 ms^{-1} per TC.
As *E* increase, the trade-off amounts increase -at this fixed rate.
Trade-off amount : [intensity] $(E / \sqrt{2}) \times \sigma_I$ **[frequency]** $(E / \sqrt{2}) \times \sigma_F$

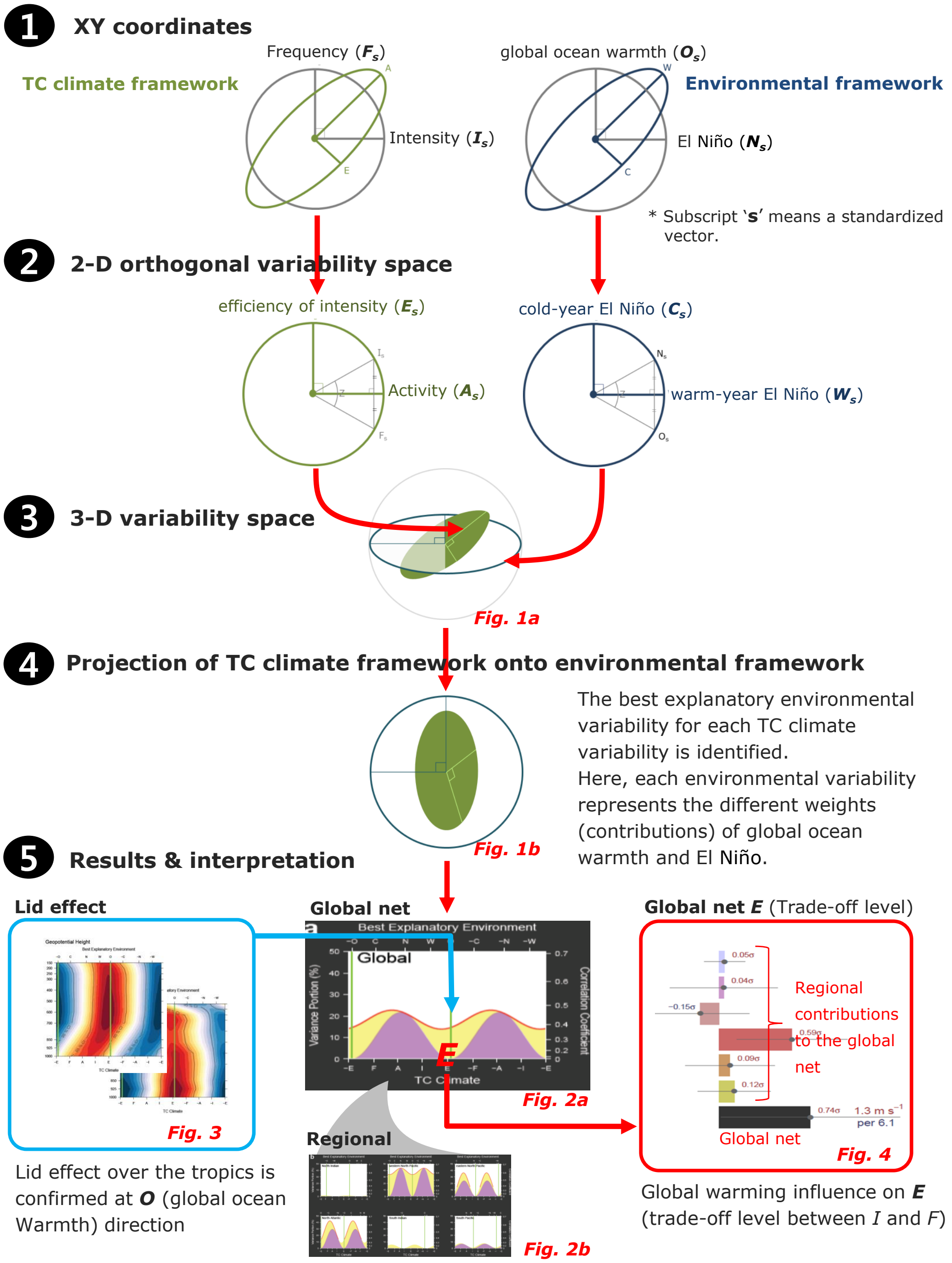
Suppl. Figure 12 : Schematic diagram of *E* and trade-off between *I* and *F*.

19 Does the result in Fig. 4 mean that the TC intensity have increased by 1.3 m s^{-1} on average over the 30 years?

No. 1.3 m s^{-1} (annual mean LMW) and 6.1 TCs are the trade-off amounts occurring over the 30 years of global ocean warming. This tells us how much the decrease of TC numbers has contributed to intensity increases under global warming.

20 How can the process and results in this paper be validated?

The detailed calculations and results are provided in `rpubs.com/Namyoung/P2014a`. For better understanding, the process is summarized in Suppl. Fig. 13.



Suppl. Figure 13 : Summary of the process.