

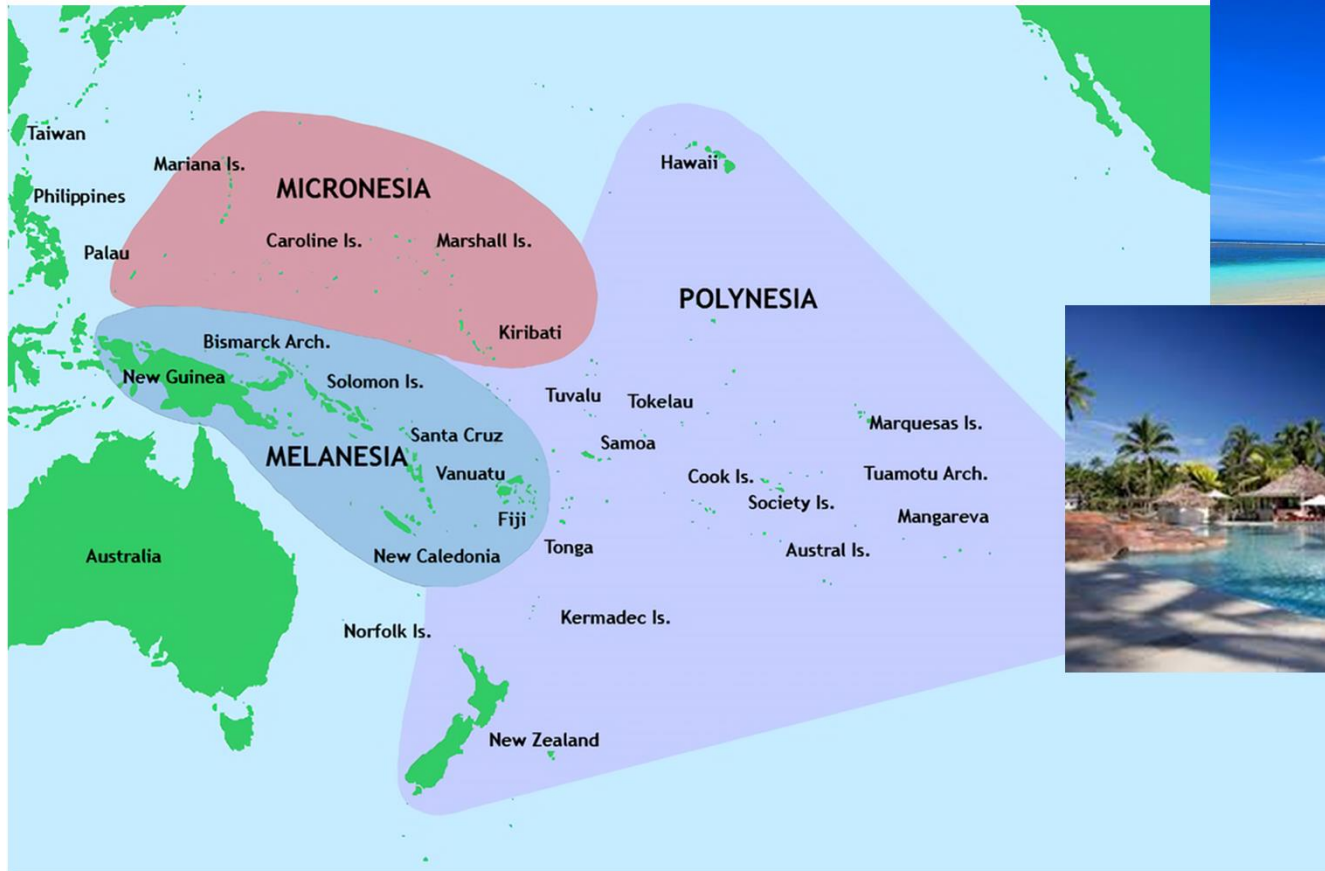
APCC in the Forefront of S2S Forecast: Leading the way in the fight against extreme phenomena

Subseasonal-to-seasonal prediction for tropical cyclone activity in the South Pacific

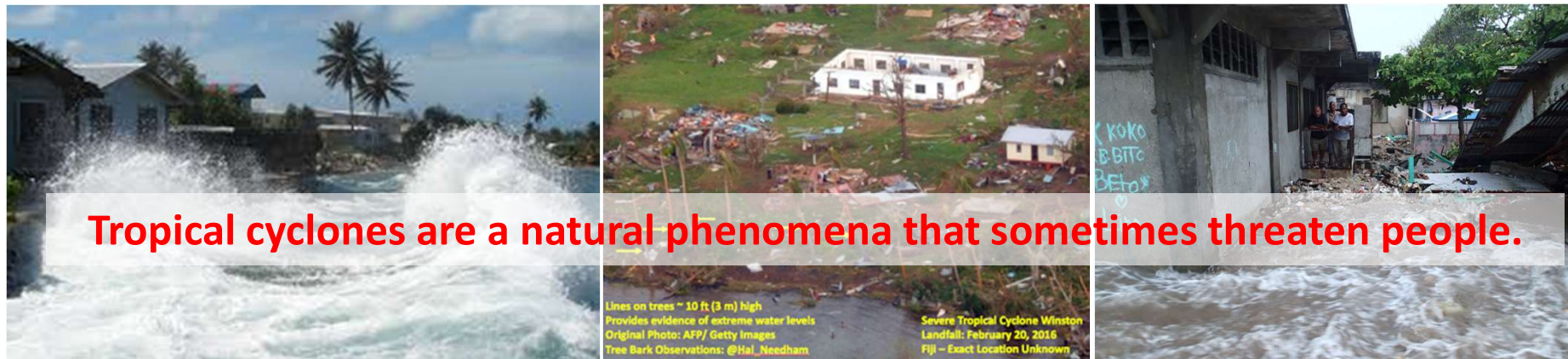
July 25, 2018

OK-Yeon Kim

What happened in the beautiful islands?

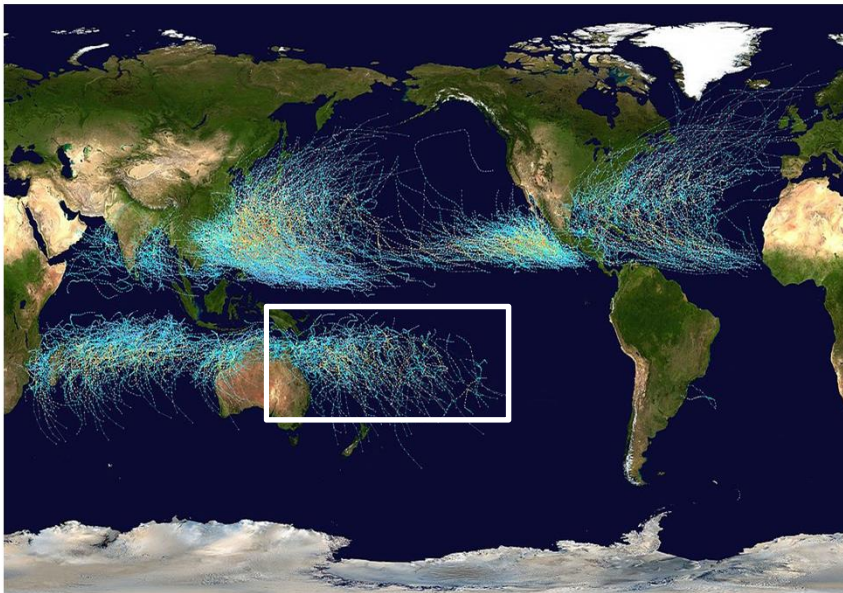


What happened in the beautiful islands?

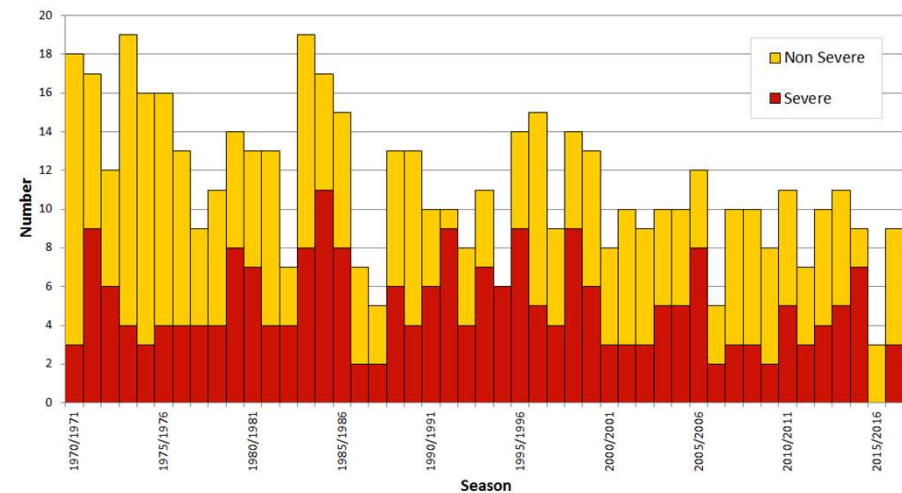
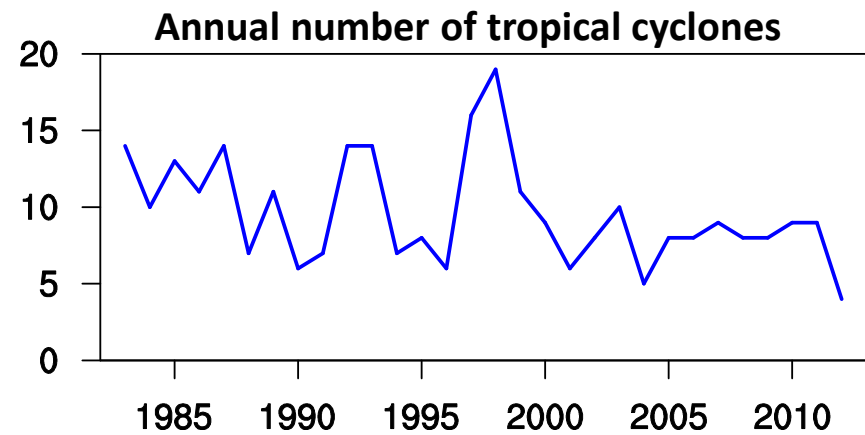


- Tropical cyclones are extremely dangerous to humans because in general **we live on or near the coast.**
- In the South-West Pacific tropical cyclones regularly **devastate the social and economic basis of many countries.**
- Most of the smaller Polynesian countries are at risk from Cyclones. For example Fiji, Tonga or Vanuatu.

What happened in the beautiful islands?

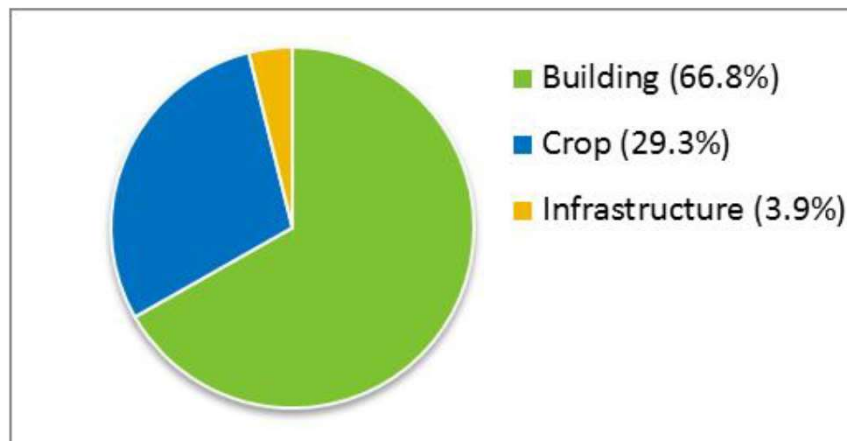


- Based on global and regional studies, tropical cyclones are projected to **become less frequent with a greater proportion of high intensity storms** (stronger winds and greater rainfall)



Current and future tropical cyclone risk in the South Pacific (e.g., Vanuatu)

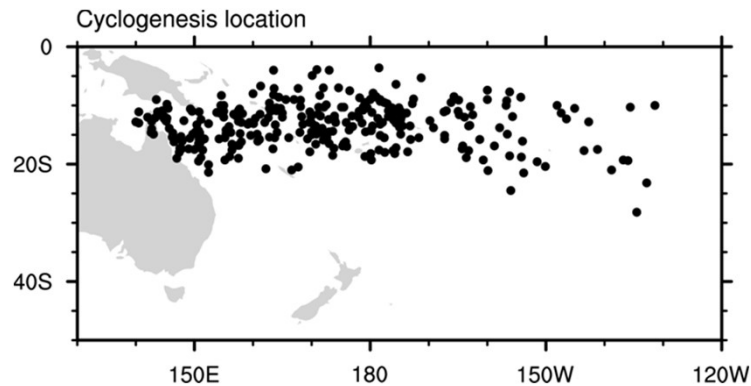
Contribution to total Average Annual Loss (AAL) from the three types of assets considered



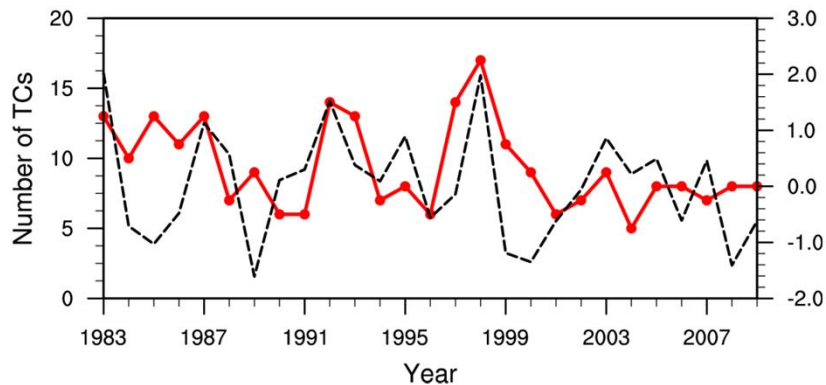
(<https://www.pacificclimatechange.net/>)

- The current climate average annual loss due to tropical cyclones represents about 5% of the country's GDP (36.8 million USD).
- The main contributors to current and future building and infrastructure losses are wind and flood accompanied by tropical cyclones.
- Average annual losses are projected to increase from 36.8 million USD to 37.9 million USD by mid-century and to 39.6 million USD by end-of-century, an increase of 3% and 7.6%, respectively (2010 dollars).

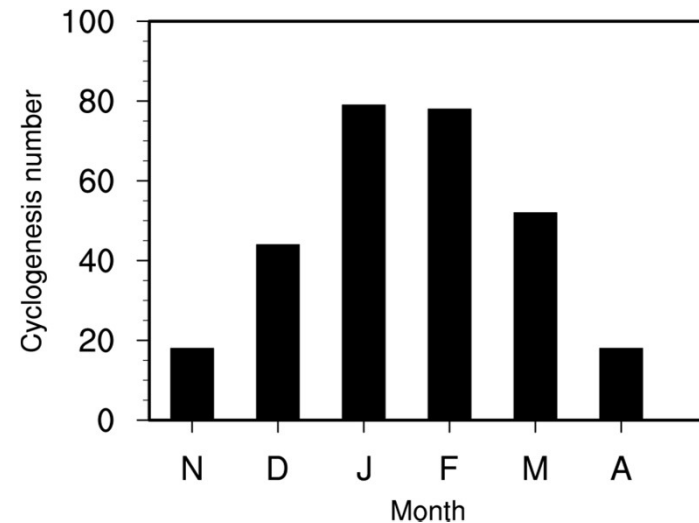
Climatology of TC genesis in SPO and associated basic state



Geographical distribution of TC genesis points

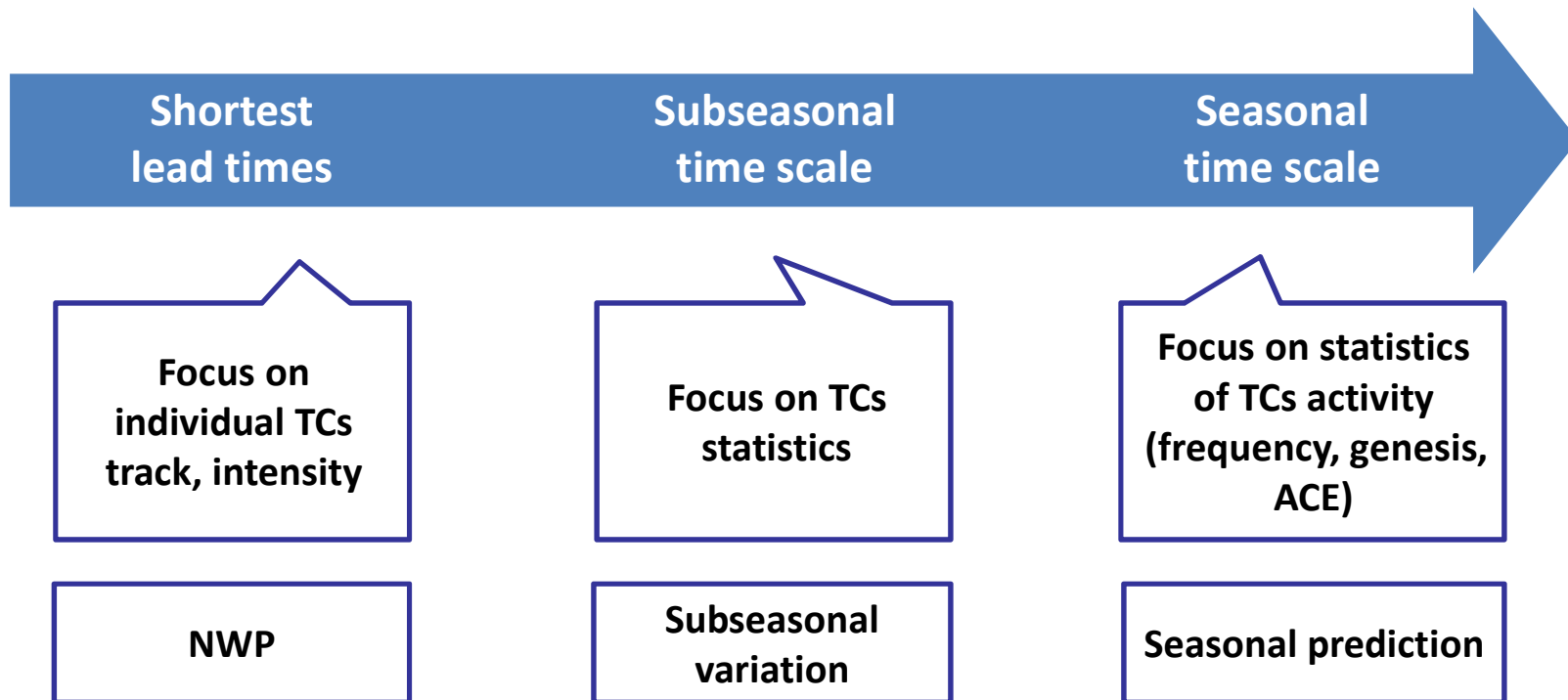


Annual variation of TC occurrence from 1982/1983 to 2008/2009



Monthly variation of TC occurrence

Time scale of TC prediction





How can we predict the TCs activity?

- ❖ **Identification of individual TCs based on objective criteria (*Dynamical*)**
 - TCs are identified and tracked based on the definition of the criteria, i.e., the thresholds and the domain over which they are computed.
 - TCs are identified and tracked as centers of maximum relative vorticities and minimum of surface pressure, with a warm core in high levels and maximum wind in the low layers of the atmosphere.
 - This approach requires a fully coupled high-resolution GCMs.
- ❖ **Use of a genesis parameter from large-scale fields (*Statistical*)**
 - It produces an estimate of the TC activity based on a genesis parameter computed from seasonal means of large-scale fields.
 - It uses the lagged relationship between seasonal TC activity and pre-season atmosphere and ocean conditions.
 - It has been used especially in the analysis of low-resolution model simulations.
 - It obviates the explicit simulations of individual TCs.



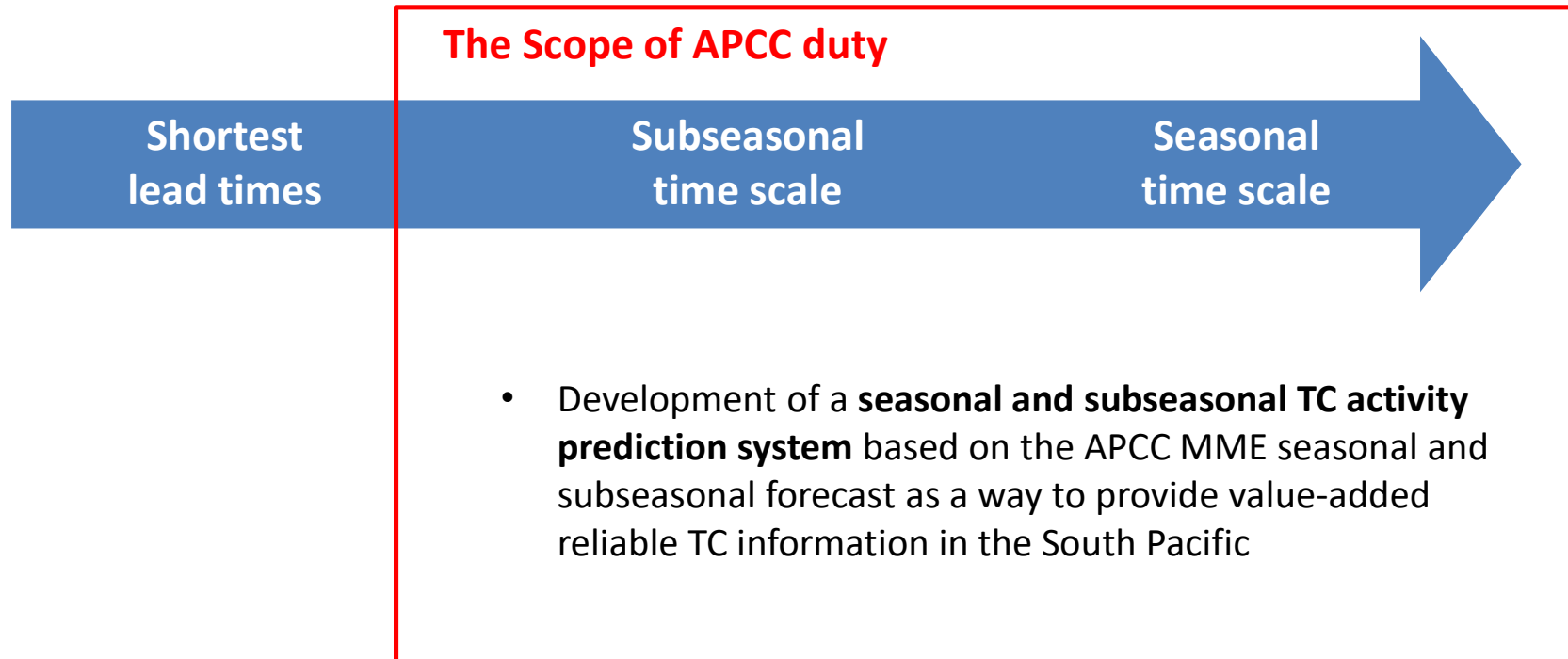


How can we predict the TCs activity?

- ❖ A statistical approach with inputs from dynamical simulations (*Hybrid*)
 - It utilizes **transfer functions** (i.e., regression equations) that related coupled ocean-atmosphere dynamical climate model forecasts of **key atmospheric and oceanic anomalies** to the observed tropical cyclone activity.
(concurrent relationships!!!)



What can APCC do for tropical cyclone forecast in the South Pacific?



- 1) **Seasonal tropical cyclone activity prediction** for the South Pacific using APCC seasonal multi-model ensemble prediction
- 2) **Subseasonal tropical cyclone genesis prediction** in the South Pacific using subseasonal multi-model ensemble prediction



- 1) Seasonal tropical cyclone activity prediction for the South Pacific using APCC multi-model ensemble prediction**
- 2) Subseasonal tropical cyclone genesis prediction in the South Pacific using subseasonal multi-model ensemble prediction**





Seasonal TC activity prediction

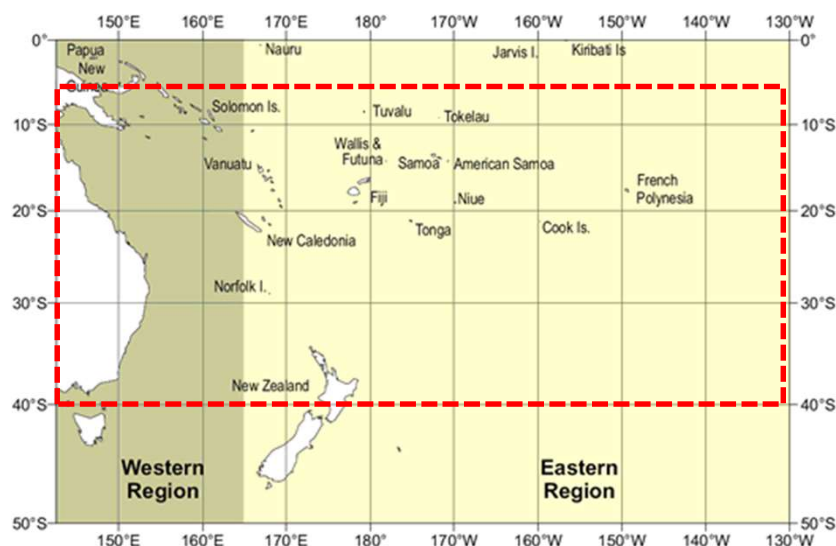
❖ **Three key questions:**

- 1) How well do the APCC MME forecasts explain the **key large-scale atmospheric/oceanic variability** related to the observed seasonal TC activity in the South Pacific?
- 2) How do we build **the empirical model** based on the relationship between the seasonal TC activity and the large-scale variability from the APCC MME forecasts?
- 3) How do we build and produce **the seasonal TC activity map** from a prediction of the APCC MME-empirical model?



Region of interest

❖ TCs-affected area in the South Pacific

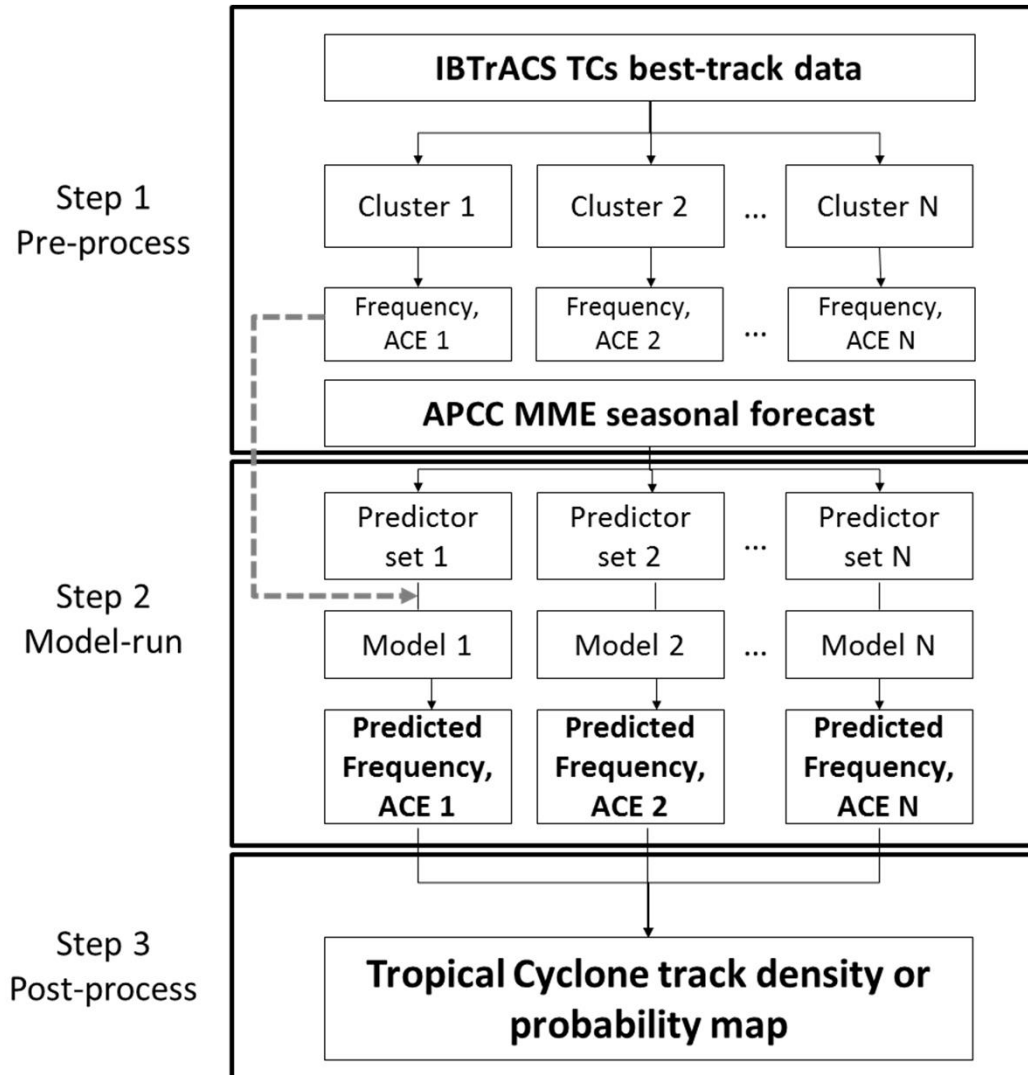


Region	Top	Bottom	Left	Right
Whole South Pacific region	5°S	40°S	140°E	130°W
Western region	5°S	40°S	140°E	165°E
Eastern region	5°S	40°S	165°E	130°W

Operational terminology used in the South Pacific (WMO, 2014)

Category	10-minute sustained winds
Tropical depression	< 34 knots (< 63 km/h)
Category 1 Tropical cyclone (gale)	34–47 knots (63–88 km/h)
Category 2 Tropical cyclone (storm)	48–63 knots (89–117 km/h)
Category 3 (hurricane) Severe tropical cyclone	64–85 knots (118–159 km/h)
Category 4 Severe tropical cyclone	86–107 knots (160–200 km/h)
Category 5 Severe tropical cyclone	> 107 knots (>200 km/h)

Seasonal TC activity prediction procedure



Step1:

- Cluster analysis of TCs best-track in the South Pacific
- APCC MME forecast data handling

Step2:

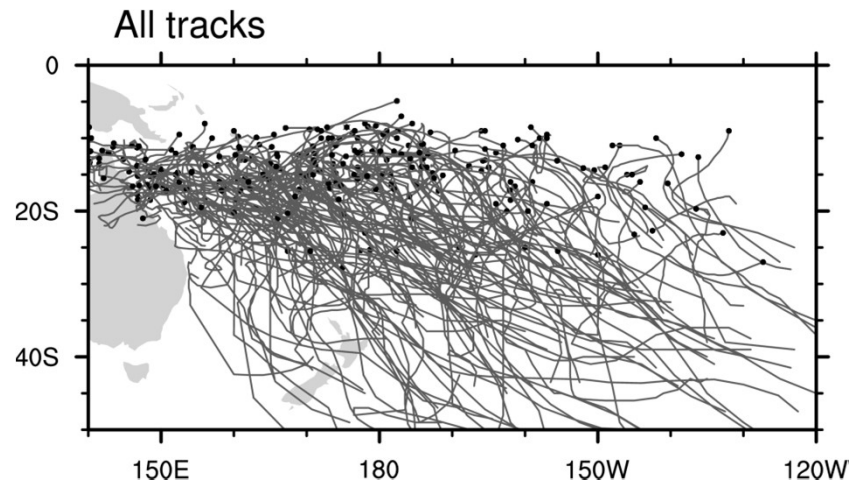
- Selection of predictors from the APCC MME forecasts
- Establishment of the empirical model between predictors and predictand

Step3:

- Construction of the forecasting map of seasonal TCs track density

Cluster analysis of TCs best-track in the South Pacific

TC track for the 27 years
(1982/83-2008/09)



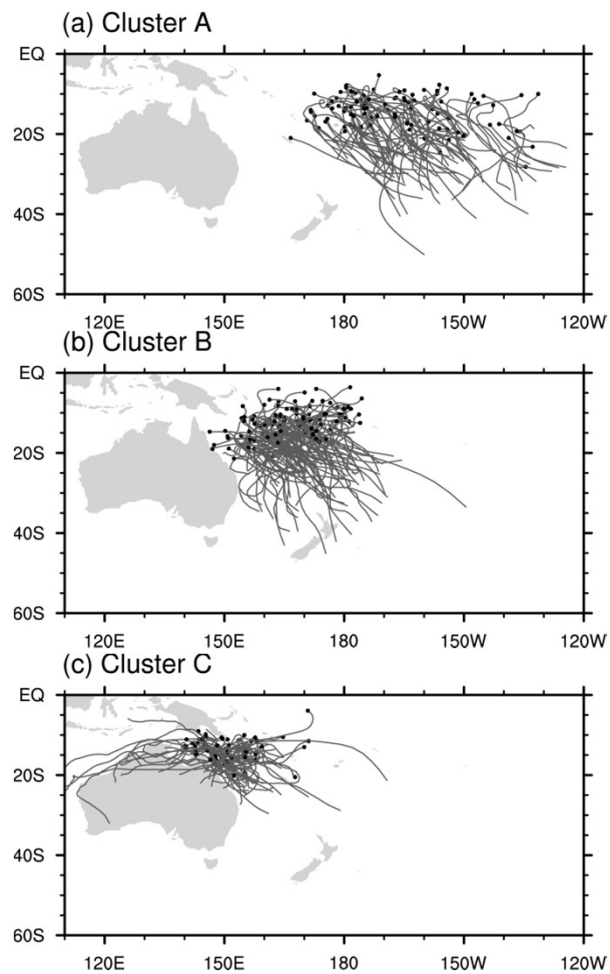
❖ Cyclone-track clustering technique

- A model that provides systematically better fit and more accurate predictions when used to cluster variable-length trajectory data
- A model that incorporates spatio-temporal smoothness in the trajectories in the modeling process, and accommodates cyclone trajectories of different lengths

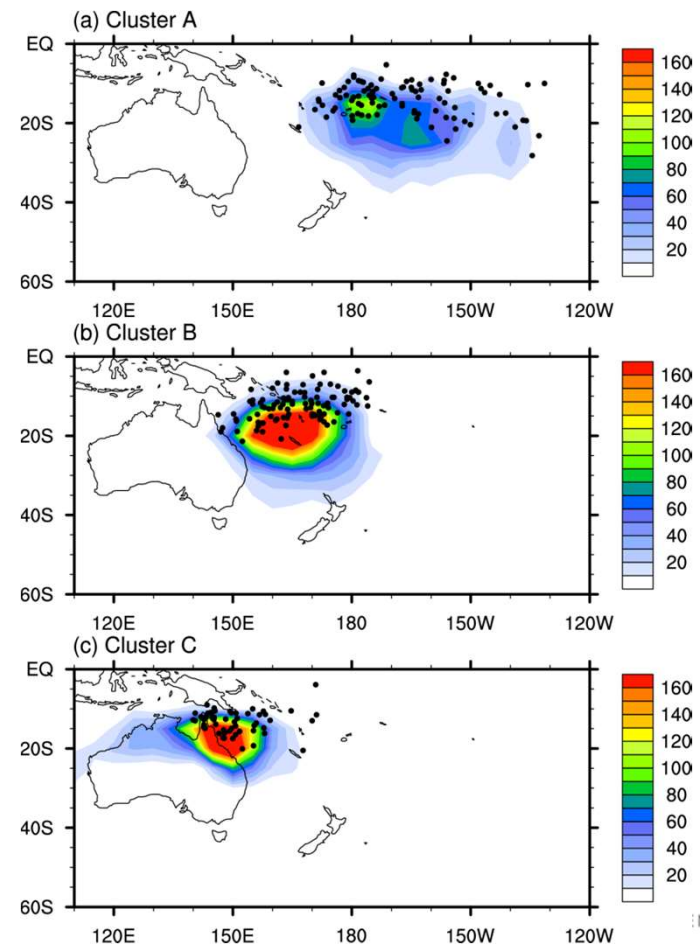
➔ *Optimal choice for the number of clusters*

Cluster analysis of TCs best-track in the South Pacific

TC genesis position and trajectories



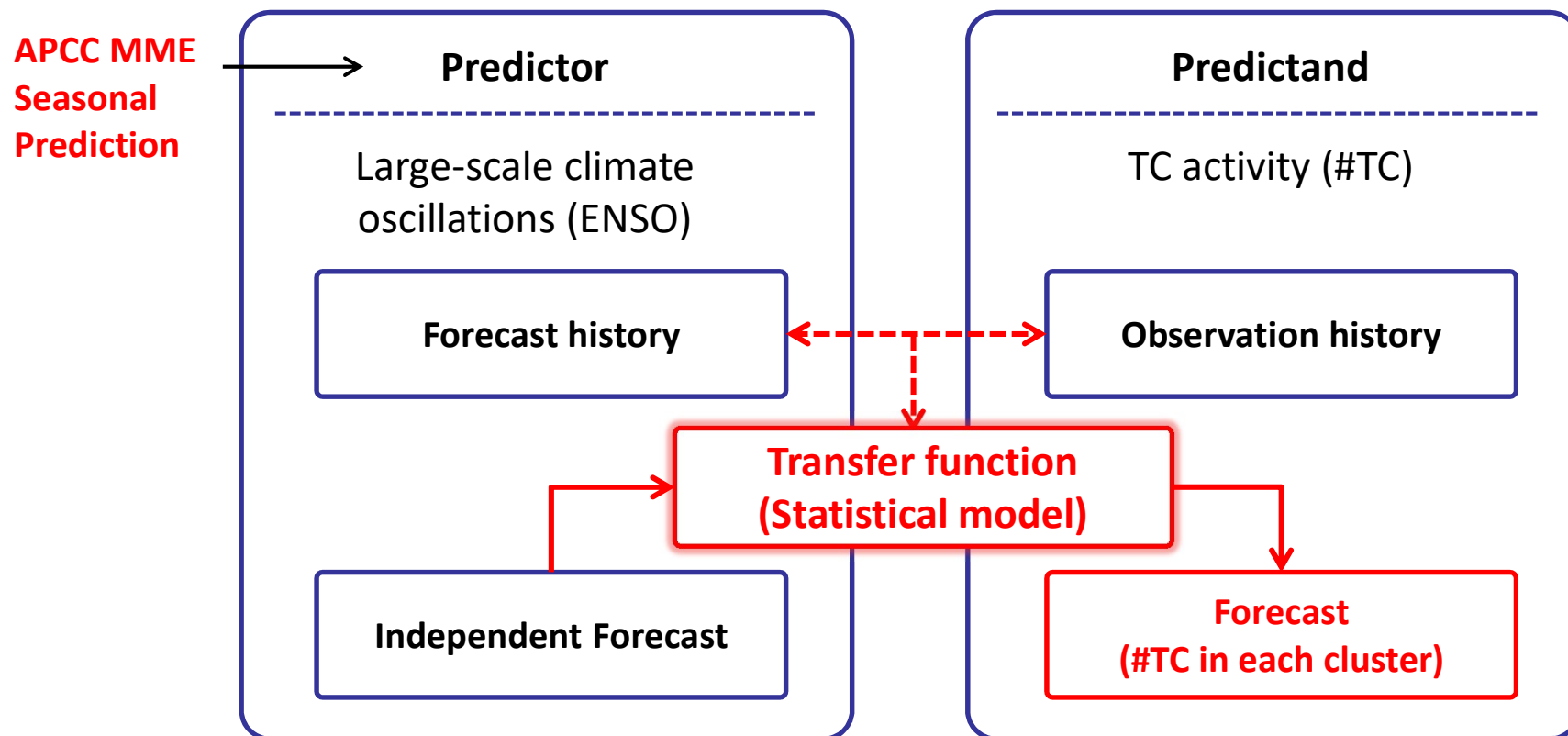
TC track density



Dynamical-Statistical Model

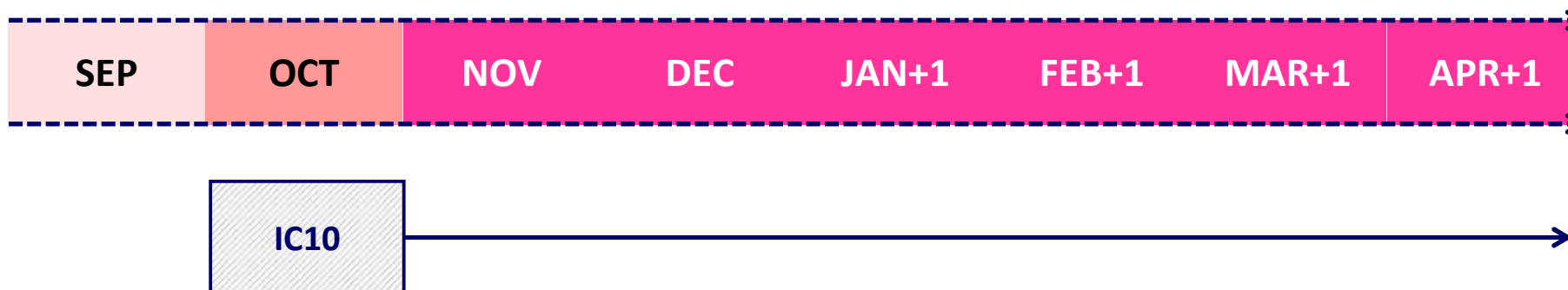
Hybrid forecast

Statistical prediction based on dynamical model predictors



Data: Observations

Active Tropical Cyclone Season in the South Pacific



- **Potential predictor fields:** SST, VWS, VOR, U850 and U200 in the forecast month
 - ✓ Extended Reconstructed SST version 3 (Smith et al., 2008)
 - ✓ NCEP/DOE reanalysis 2 U850 and U200 (Kanamitsu et al., 2002a)
 - ✓ Vertical wind shear (VWS): the difference in zonal wind between 200 and 850 hPa
 - ✓ Relative vorticity (VOR) at 850 hPa
- **Predictand: TC genesis frequency (NTC)**
 - ✓ **International Best Track Archive for Climate Stewardship (IBTrACS)** maintained by NCDC
 - ✓ From November to April+1, 1983/84-2008/09 (26 years), 243 storms

Data: APCC 6-month forecast models

- 5 models, 61 ensemble members
- Common period: 1983-2008 (26 years)

Model Acronym (Organization)	Resolution	No. Ens (F/H)	Hindcast Period	Reference
CGCM3 (MSC)	T63L31	10/10	1981-2010	http://www.ec.gc.ca/ccmac-cccma/default.asp?lang=En&n=1299529F-1
CGCM4 (MSC)	T63L31	10/10	1981-2010	http://www.ec.gc.ca/ccmac-cccma/default.asp?lang=En&n=3701CEFE-1
CFSv2 (NCEP)	T62L64	20/20	1982-2008	Saha et al. (2014)
PNU (PNU)	T42L18	5/5	1980-2012	Park et al. (2004)
GMAO (NASA)	288x181 grid L72	11/11	1982-2012	http://www.gfdl.noaa.gov/ocean-model

Environmental conditions that affect tropical cyclone activity

Global effects

- **El-Niño-Southern Oscillation**
 - alters the lower tropospheric source of **vorticity** and changes the **vertical shear** profile
- **Quasi-Biennial Oscillation**
 - upper tropospheric to lower stratospheric vertical shear variations and/or upper tropospheric static stability changes may be responsible

Local effects

- **Local sea level pressure**
 - directly impact the strength of the **vertical wind shear**
- **SSTs**
 - have a direct thermodynamic effect on TCs through their influence on moist static stability
- **Tradewind / monsoon circulations**
 - variations in the Australian monsoon could alter the TCs activity, independent of any pronounced ENSO events

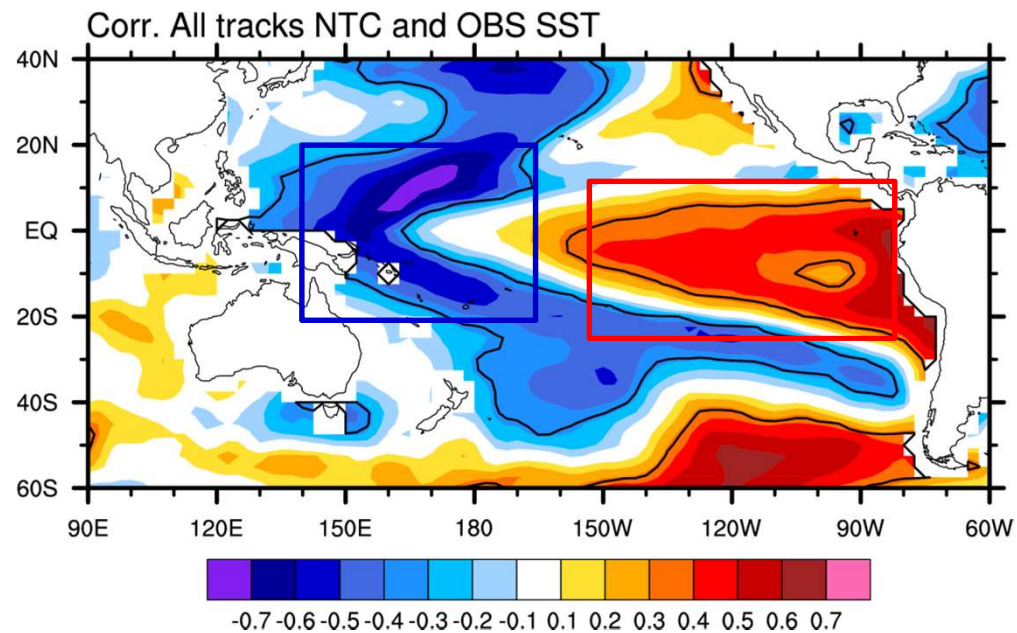
Southern Pacific Tropical Cyclone Activity

Potential predictor identification

- The key driver of TC interannual variability → ENSO

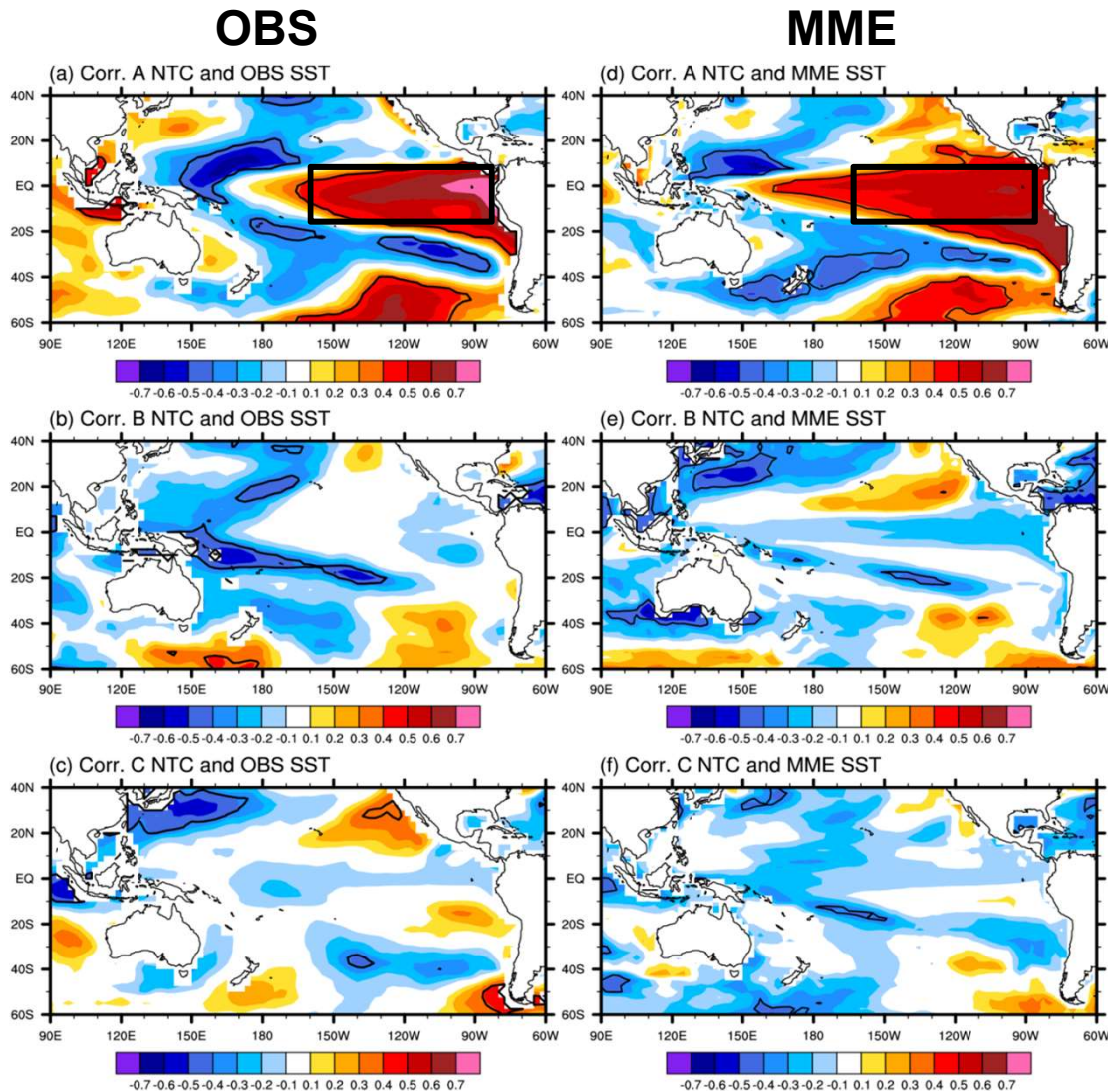
Observations for all tracks

Negative correlations
over the western and
the southern Pacific



Positive correlations
over the eastern
equatorial Pacific

Potential predictor identification: SST

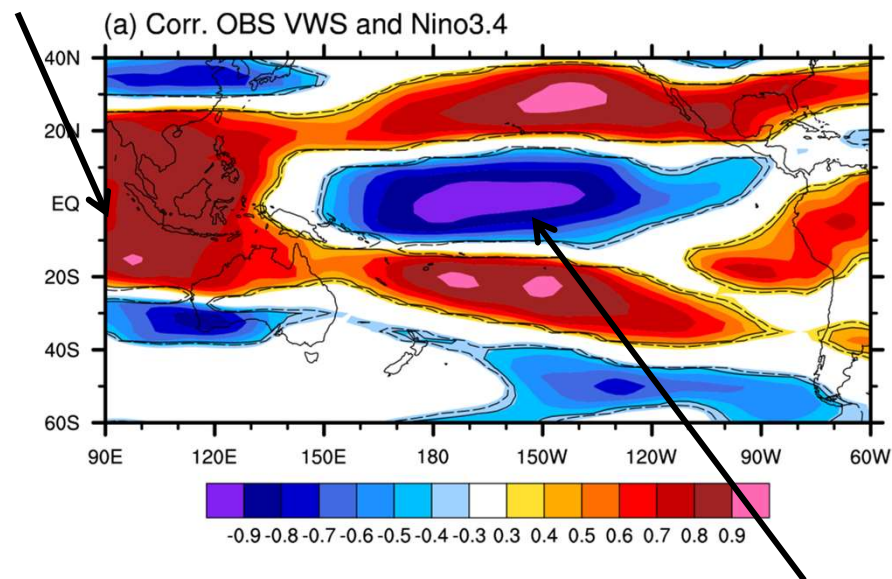


In Cluster A: **Warm-phase of ENSO**
→ increased convection near dateline

Potential predictor identification: VWS

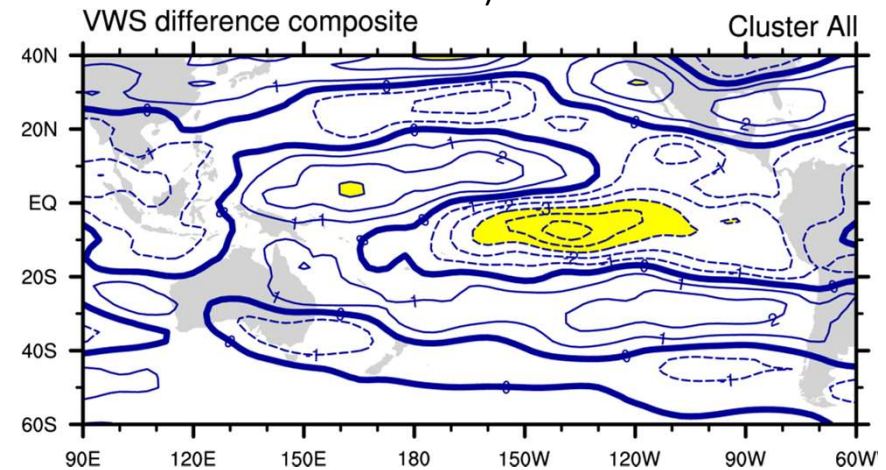
- Atmospheric parameter favorable for TC development → **Weak to moderate VWS**

Influence of Nino-3.4 SST on the VWS is pronounced

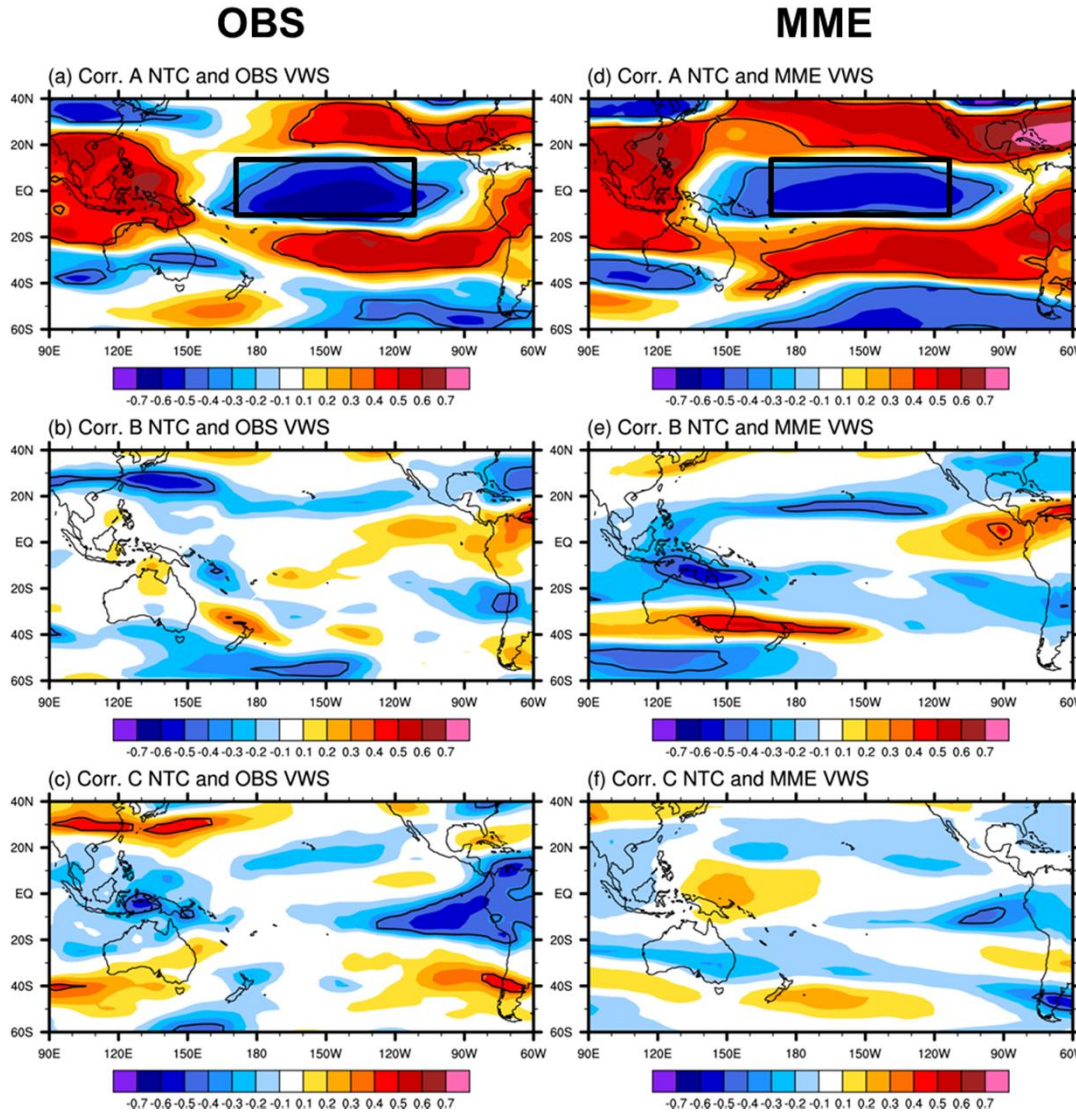


Nino-3.4 SST is highly negatively correlated with VWS of the zonal wind over the central equatorial Pacific.

Composite differences between active and inactive TC years (Shaded areas: difference of VWS $\geq |3.0|$ ms^{-1})



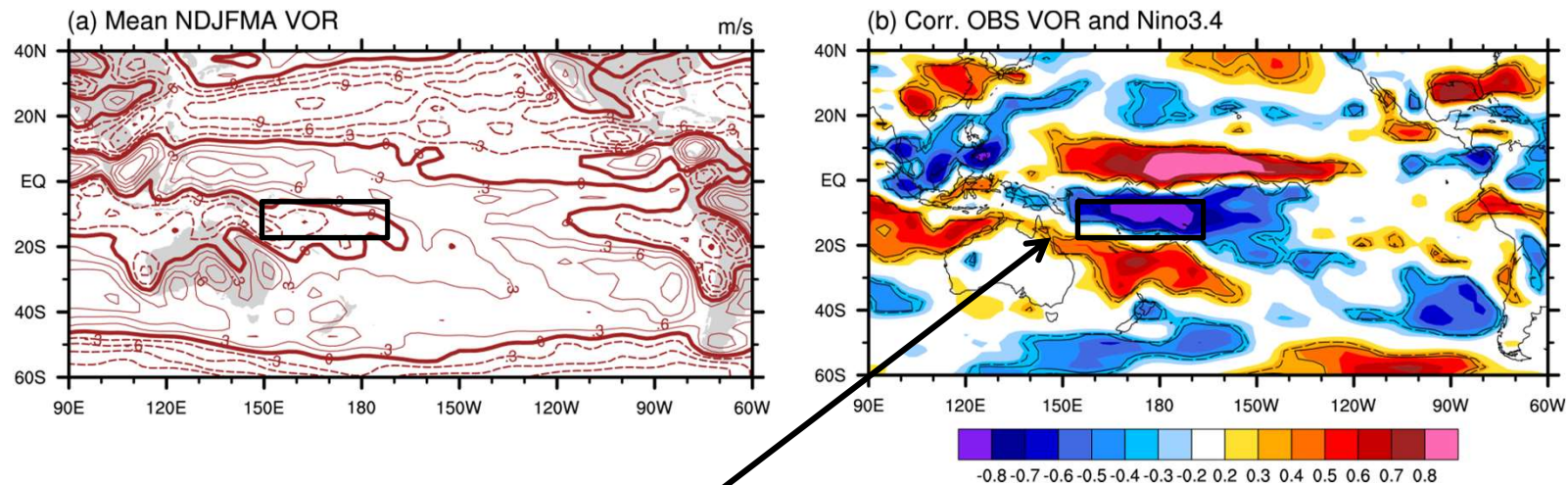
Potential predictor identification: VWS



Most signals come from the VWS variation in the central Pacific, which is modulated by ENSO.

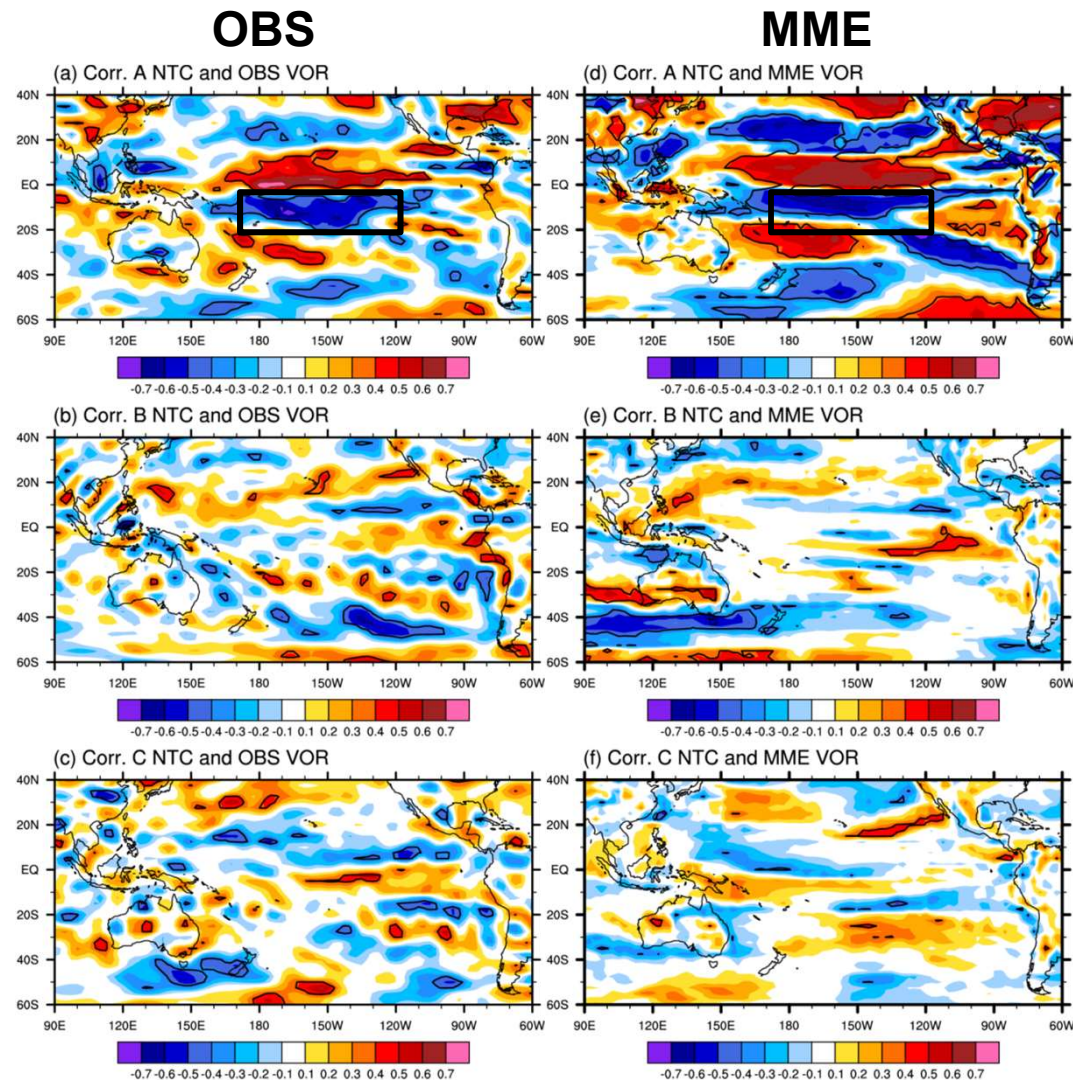
Potential predictor identification: VOR

- Atmospheric parameter favorable for TC development → **Large cyclonic VOR**



The VOR variation: broadly consistent with ENSO phases (e.g., Andrew et al. 2012)
reduced cyclonic vorticity in La Niña → westward contraction of TC activity
enhanced cyclonic vorticity in El Niño → eastward expansion of TC activity
(associated with eastward extension of the Australian monsoon trough)

Potential predictor identification: VOR

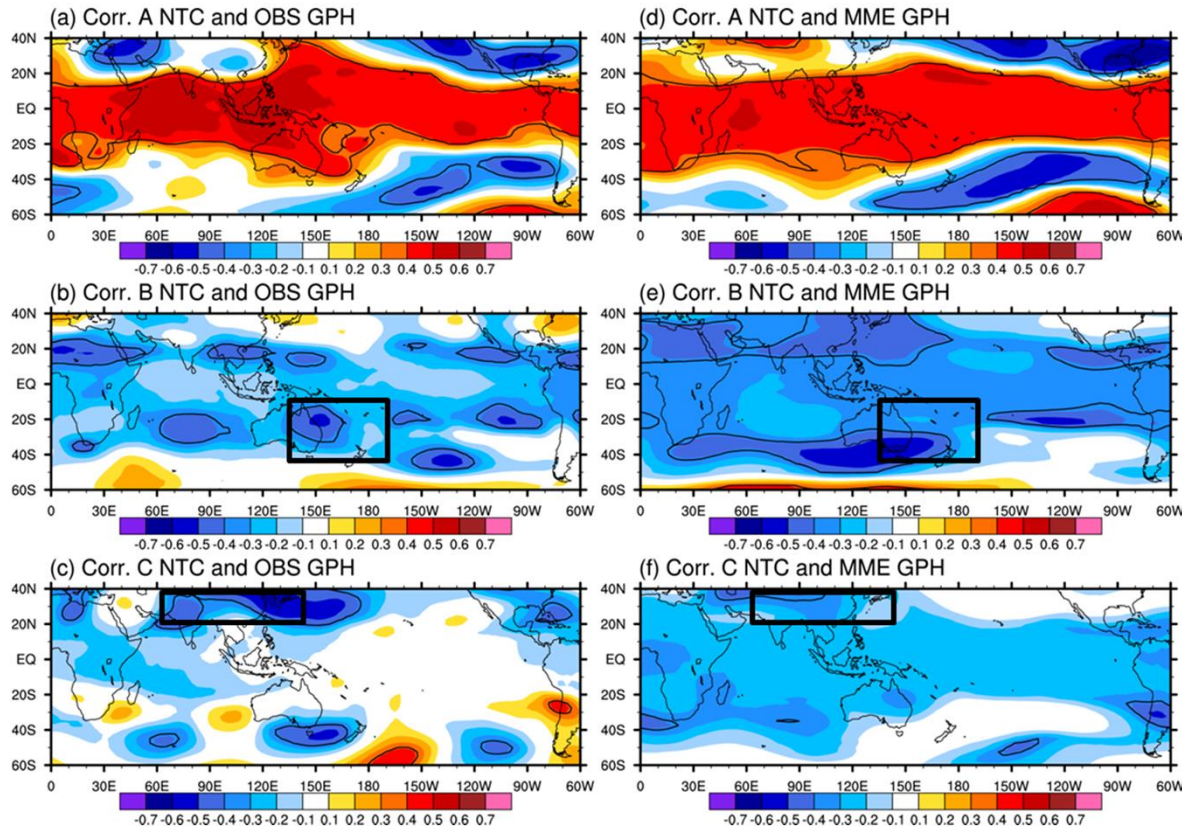


Relative vorticity is found to have strong local correlation with the annual number of cyclones associated with the TC genesis in cluster A.

Potential predictor identification: GPH

OBS

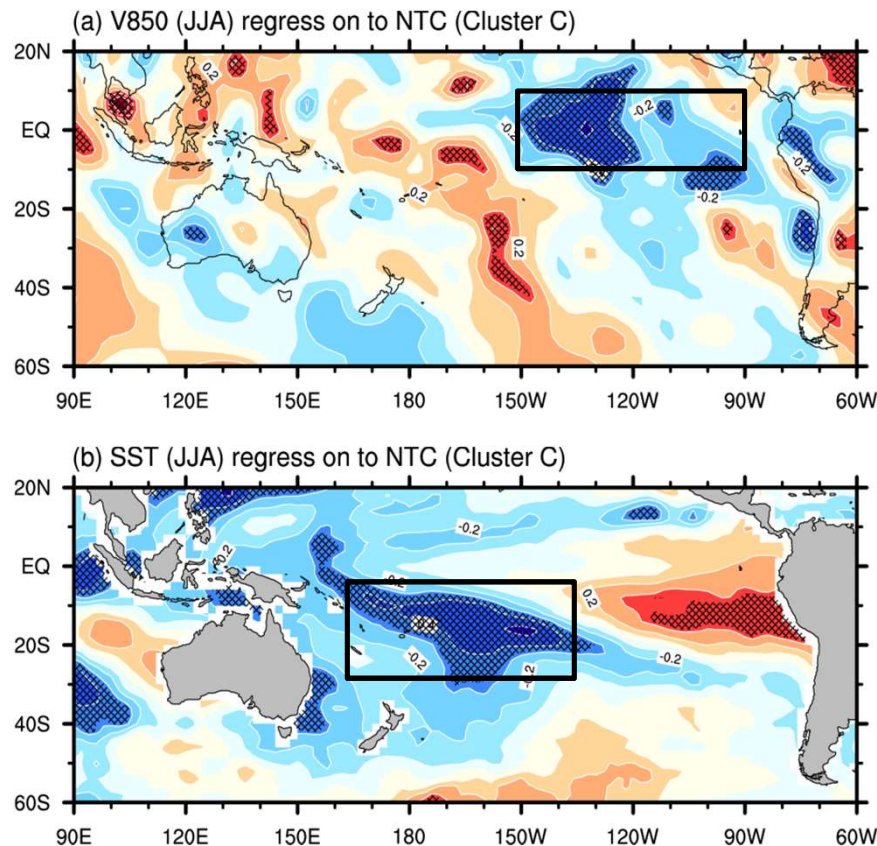
MME



strong negative correlation throughout subtropical convergence zone (ITCZ) whereby colder lower- and mid-troposphere air masses support convection and the TC development

Lagged-relationship with the number of TCs

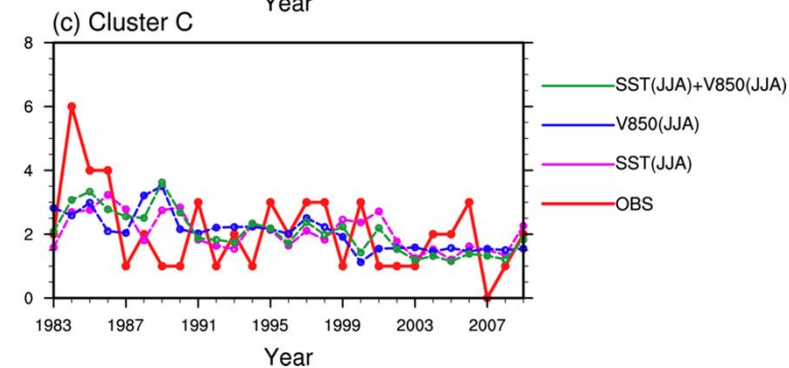
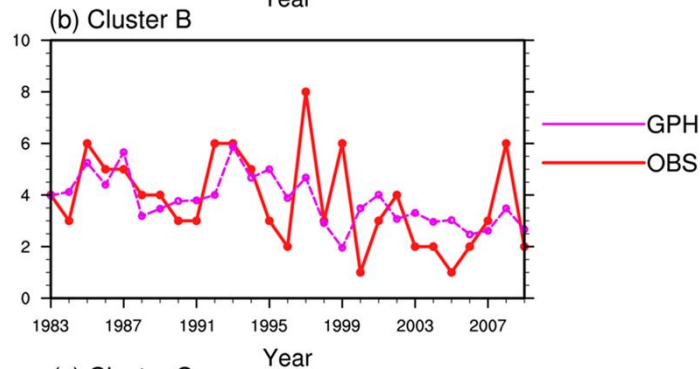
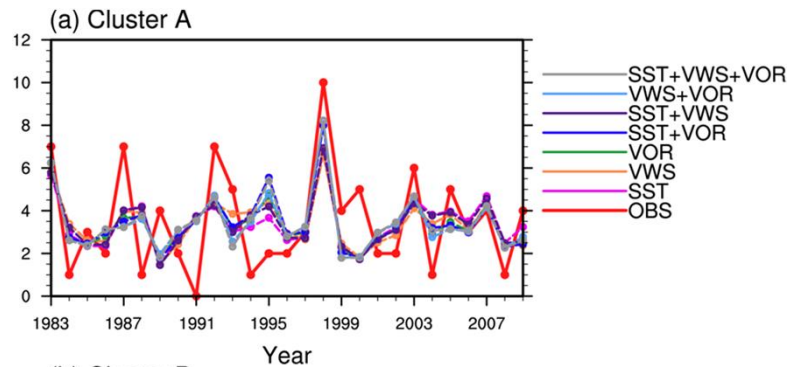
Can observed fields in the pre-season be considered as meaningful potential predictors based on lagged relationship?



The V850 north of the equator in the far eastern Pacific has statistically significant negative relationship with TC number in cluster C.
→ changes in large-scale circulation due to changes in ENSO phase

Correlation patterns with pre-season SST and TC numbers in cluster C are characterized by the developing ENSO pattern across the tropical and subtropical Pacific.
→ atmospheric teleconnection

Cross-validation for the dynamical-statistical TC prediction



Cluster	Predictors	CORR	RMSE	MSSS
A	SST+WVS+VOR	0.53*	2.01	0.27
	SST+WVS	0.49*	2.06	0.24
	SST+VOR	0.57*	1.95	0.32
	VWS+VOR	0.57*	1.94	0.33
	SST	0.55*	1.99	0.29
	VWS	0.53*	2.01	0.28
	VOR	0.61*	1.88	0.36
B	GPH	0.46*	1.56	0.20
C	GPH	0.08	1.30	-0.04
	SST(JJA)	0.29	1.23	0.06
	V850(JJA)	0.23	1.27	0.00
	SST(JJA)+V850(JJA)	0.34*	1.22	0.08
	GPH+SST(JJA)+V850(JJ)	0.22	1.3	-0.04
	A)			

Construction of the forecasting map of seasonal TC track density

The seasonal TC track density for a particular year is represented by the probability of TC tracks (P) at each grid point defined as

$$P_l(\text{lat}, \text{lon}) = \frac{N_{\text{within } 5^\circ \text{ from a grid point}(\text{lat}, \text{lon}),l}}{N_{\text{Total},l}}, \quad (2)$$

where l denotes the year index, lat and lon are the degrees of latitude and longitude, and N indicates the number of TCs (e.g., $N_{\text{Total},l}$ is the total number of TCs for a TC season of year l): P_l can be calculated using the *observed* TC tracks for all WNP grid points in year l . We can convert P_l into two probability terms using the relation based on the seven track patterns as follows:

$$\begin{aligned} & N_{\text{within } 5^\circ \text{ from a grid point}(\text{lat}, \text{lon}),l} \\ &= \sum_{i=1}^C N_{Ci \text{ within } 5^\circ \text{ from a grid point}(\text{lat}, \text{lon}),l}, \end{aligned} \quad (3)$$

where C_i denotes the i th pattern, and C is the number of patterns (i.e., 7). Then, the converted P_l becomes

Kim et al. (2012, JC)

N: predictand of the model

$$\begin{aligned} P_l(\text{lat}, \text{lon}) &= \sum_{i=1}^C \frac{N_{Ci,l}}{N_{\text{Total},l}} \times \frac{N_{Ci \text{ within } 5^\circ \text{ from grid point}(\text{lat}, \text{lon}),l}}{N_{Ci,l}} \\ &= \sum_{i=1}^C \frac{N_{Ci,l}}{N_{\text{Total},l}} \times \boxed{P_{Ci,l}(\text{lat}, \text{lon})}. \quad ? \rightarrow \text{Climatological probabilities} \end{aligned}$$

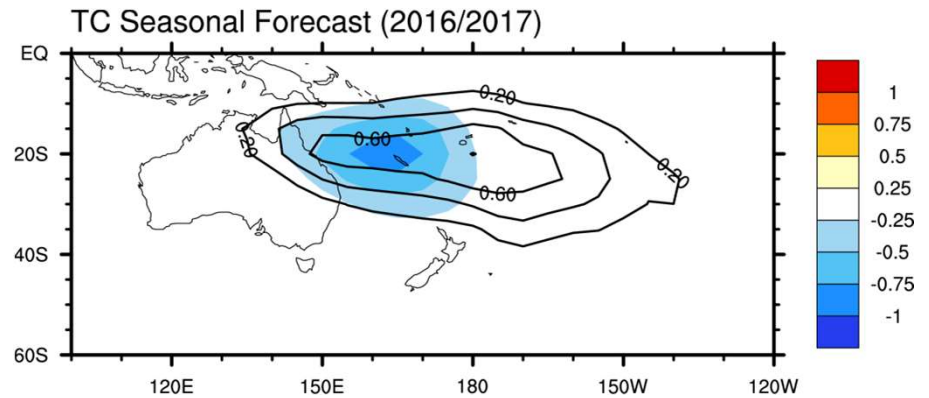
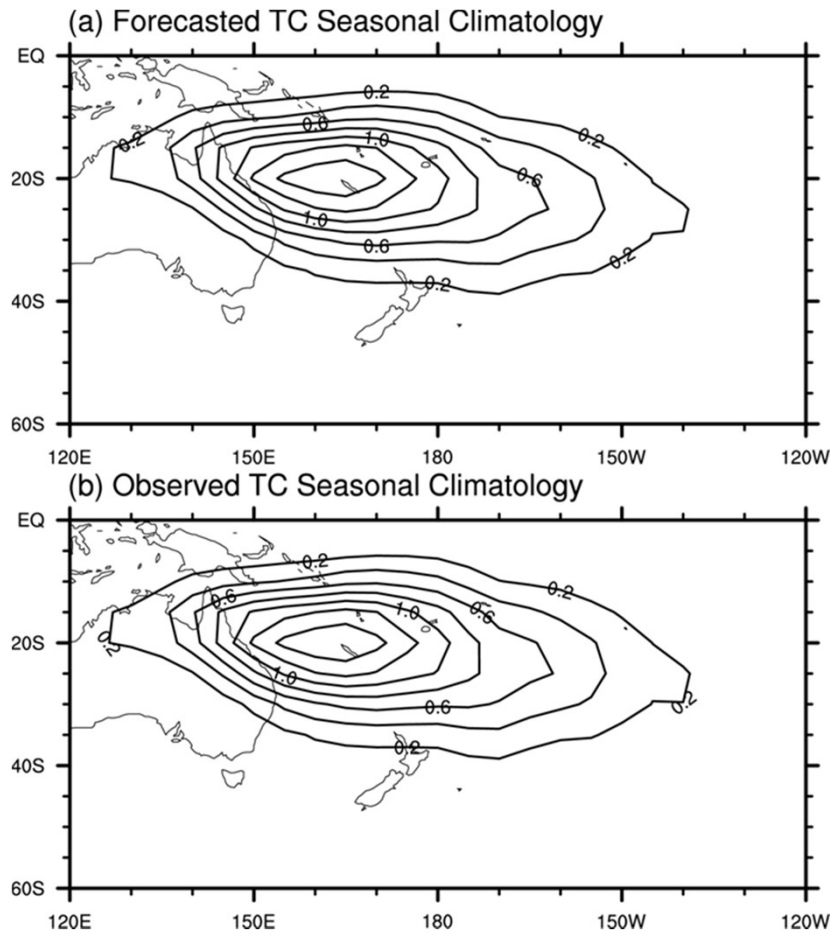
Here $N_{Ci,l}$ is the predictand of the hybrid statistical-dynamical model for C_i in year l , and $N_{\text{Total},l}$ is calculated by summing the predictands of the seven patterns; that is, $N_{\text{Total},l} = \sum_{i=1}^C N_{Ci,l}$. In Eq. (4), however, $P_{Ci,l}$ remains unknown because we do not know the observed probability of the year prior to the TC season. Therefore, an alternative is adopted where the climatological probabilities of the seven patterns (P_{Ci}) are substituted for $P_{Ci,l}$ (Fig. 8). Using the TC tracks of each pattern

wide map of TC track density. Using Eq. (4) the spatial distribution of the TC track density for a forecasting year l (\tilde{P}_l) results from the sum of the climatological probability (P_{Ci}) weighted by the predicted number of TCs for the seven patterns [i.e., $\tilde{y}_{i,l}$ in Eq. (1)], which is

$$\boxed{\tilde{P}_l = \frac{\sum_{i=1}^C \tilde{y}_{i,l} P_{Ci}}{\sum_{i=1}^C \tilde{y}_{i,l}}.} \quad (5)$$

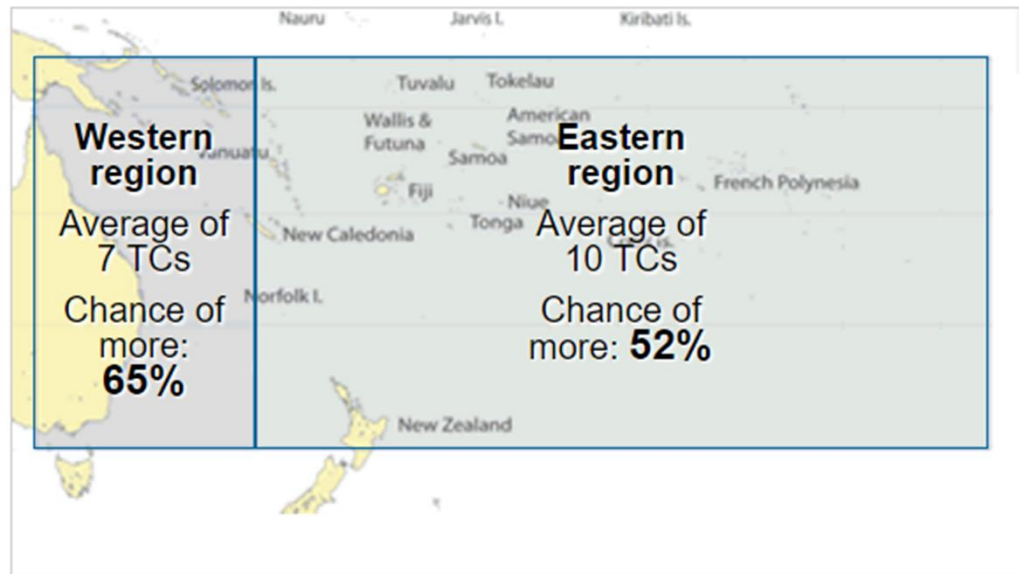
The sum of the climatological probability weighted by the predicted number of TCs for each cluster

Seasonal TC forecasts in 2016/17 (APCC)



The model predicts the highest TC track density in the area near 160°E-180° and 15°S-20°S. The TC track density anomaly, on the other hand, shows near-normal TC track probability near and east of dateline compared to the climatological distribution, but a bit lower TC track probability west of the dateline.

Seasonal TC forecasts in 2016/17 (BoM)



Near-average cyclone numbers are likely for the eastern South Pacific but model accuracy is very low.

Region	Long-term* average number of tropical cyclones	Chance of more tropical cyclones
Western	7	65%
Eastern	10	52%

The long-term average number of tropical cyclones is calculated using data from the 1969–70 season up to this (2016) season.

Seasonal TC forecasts in 2016/17 (RSMC)

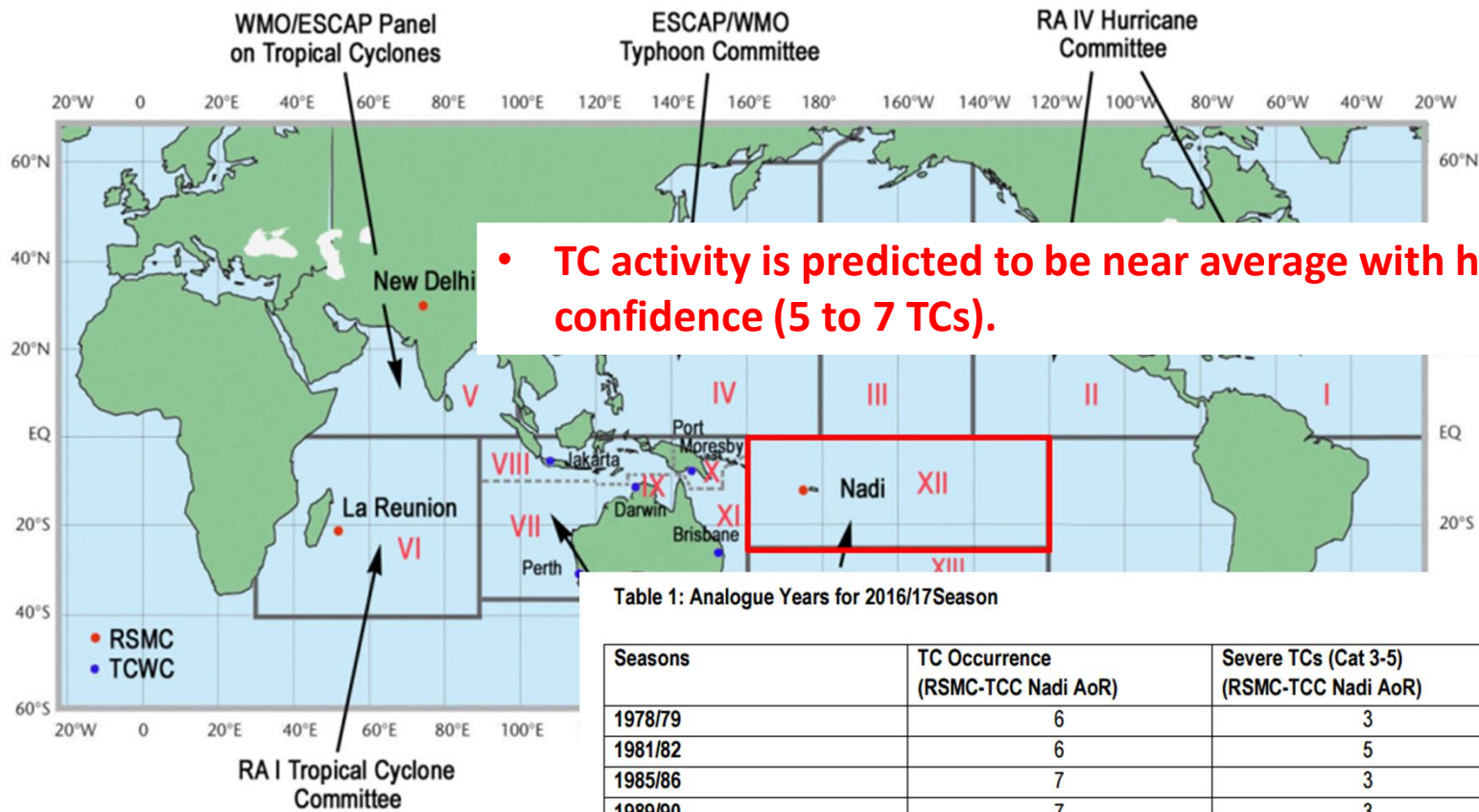
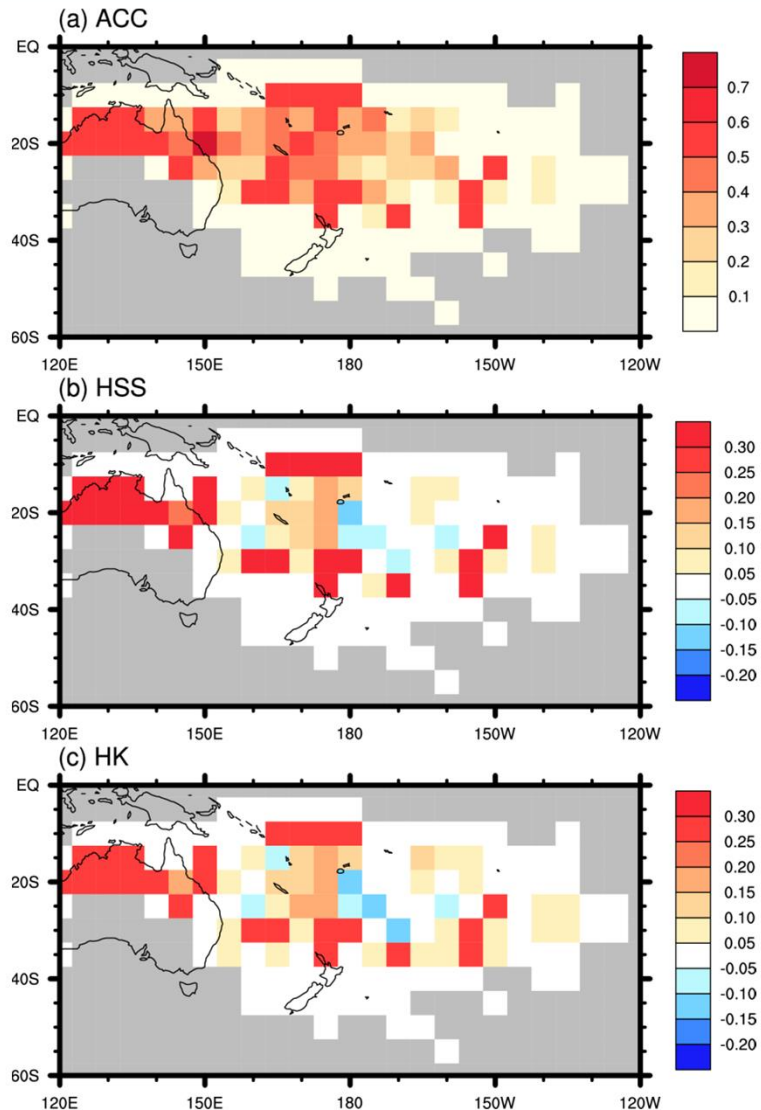


Table 1: Analogue Years for 2016/17 Season

Seasons	TC Occurrence (RSMC-TCC Nadi AoR)	Severe TCs (Cat 3-5) (RSMC-TCC Nadi AoR)
1978/79	6	3
1981/82	6	5
1985/86	7	3
1989/90	7	3
2008/09	5	0
2013/14	6	2
Average (Median)	6.2 (6)	2.7 (3)

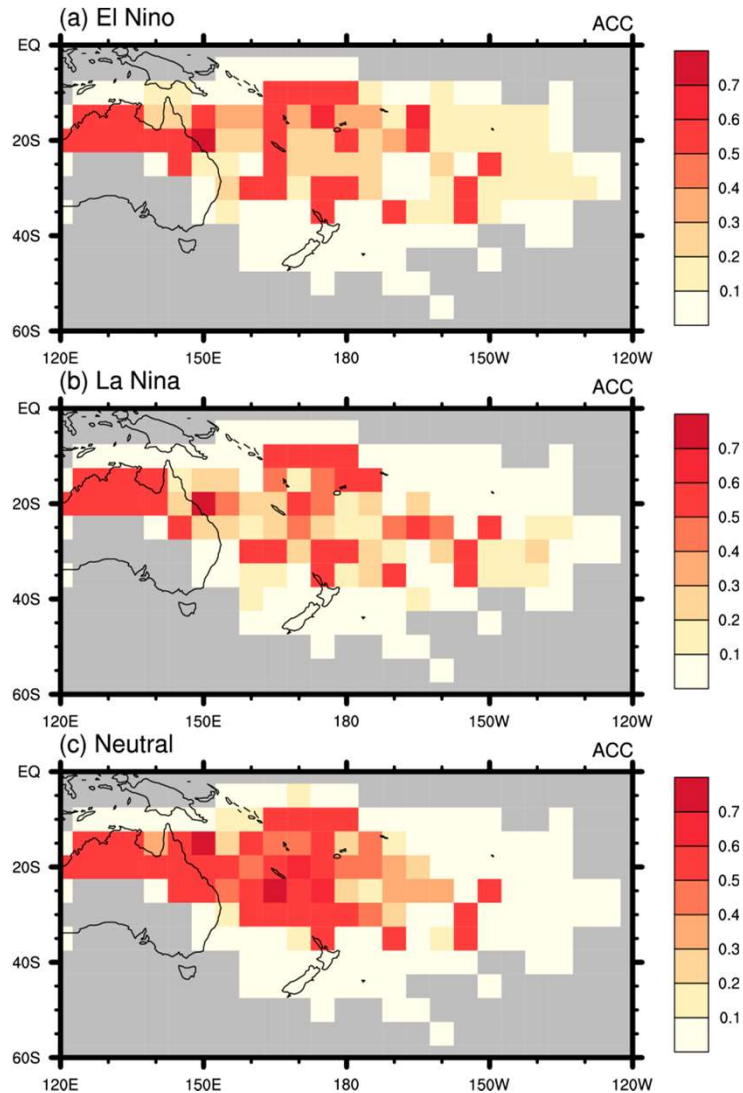
Skill scores for the seasonal TC track density predicted from APCC MME hindcasts



The APCC MME-statistical based TC prediction shows **higher level of accuracy in near and the west of dateline**, but rather lower level of accuracy in the far east of dateline.

The prediction model developed in this study shows **higher skills in the region where there is climatologically higher TC track density**.

Skill scores for the seasonal TC track density predicted from APCC MME hindcasts



The ACC in non-ENSO years is higher in the region where there is climatologically higher TC track density compared to that in the El Niño or La Niña years.

These regions have a mixed response with respect to ENSO, which results in higher skill in non-ENSO years compared to that in ENSO years.

Climate outlook for Pacific Islands

South Pacific Tropical Cyclone Outlook for 2017-2018:

APCC has established a seasonal TC activity prediction system for the South Pacific by combining the APCC MME dynamical prediction system with a statistical model. Dynamical model-based predictions of large-scale variables are used as a set of predictors in the statistical forecasts of TC activity over an extended range (November to April in the next year) with lead times of 6 months. For regions having relatively poor predictability (western part of the South Pacific Ocean), a lag relationship from observations during last several months is used as predictors for statistical TC forecast. The model predicts the highest TC track density in the area near 160°E-180° and 15°S-20°S. The TC track density anomaly, on the other hand, shows near-normal TC track probability near and east of dateline compared to the climatological distribution, but a bit lower or near-normal TC track probability west of the dateline. Thus, for countries near and east of dateline, there would be a chance of TC occurrence near the climatological average. For countries near Coral Sea and west of dateline, there would be a chance of below-normal or near-normal TC occurrence.

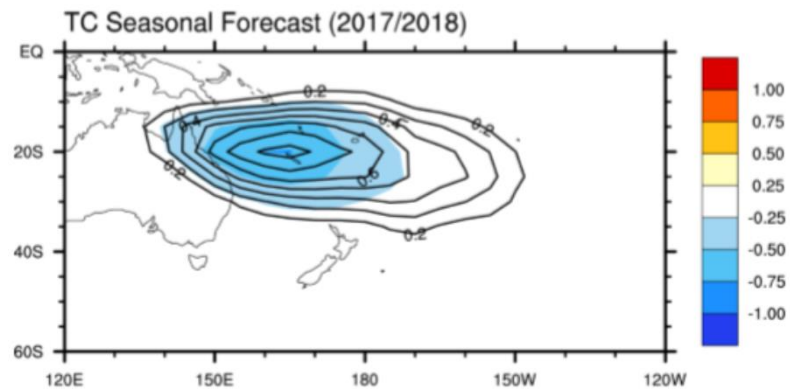


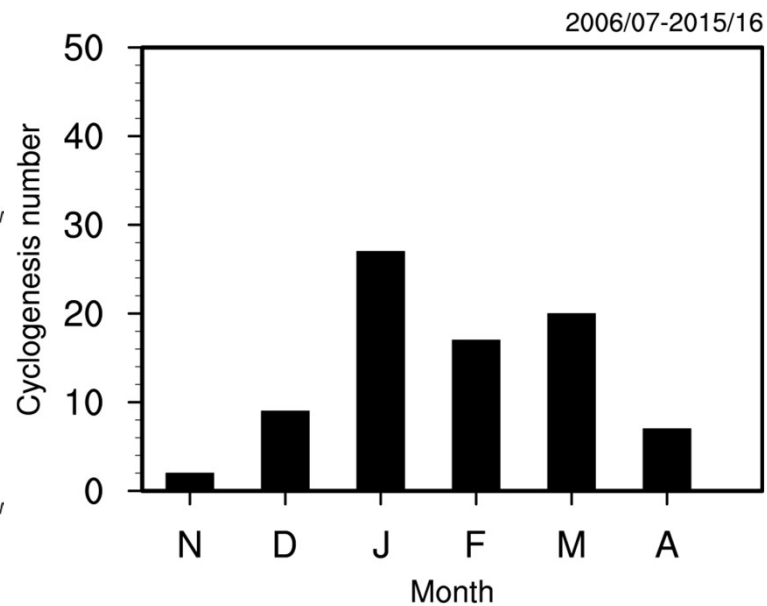
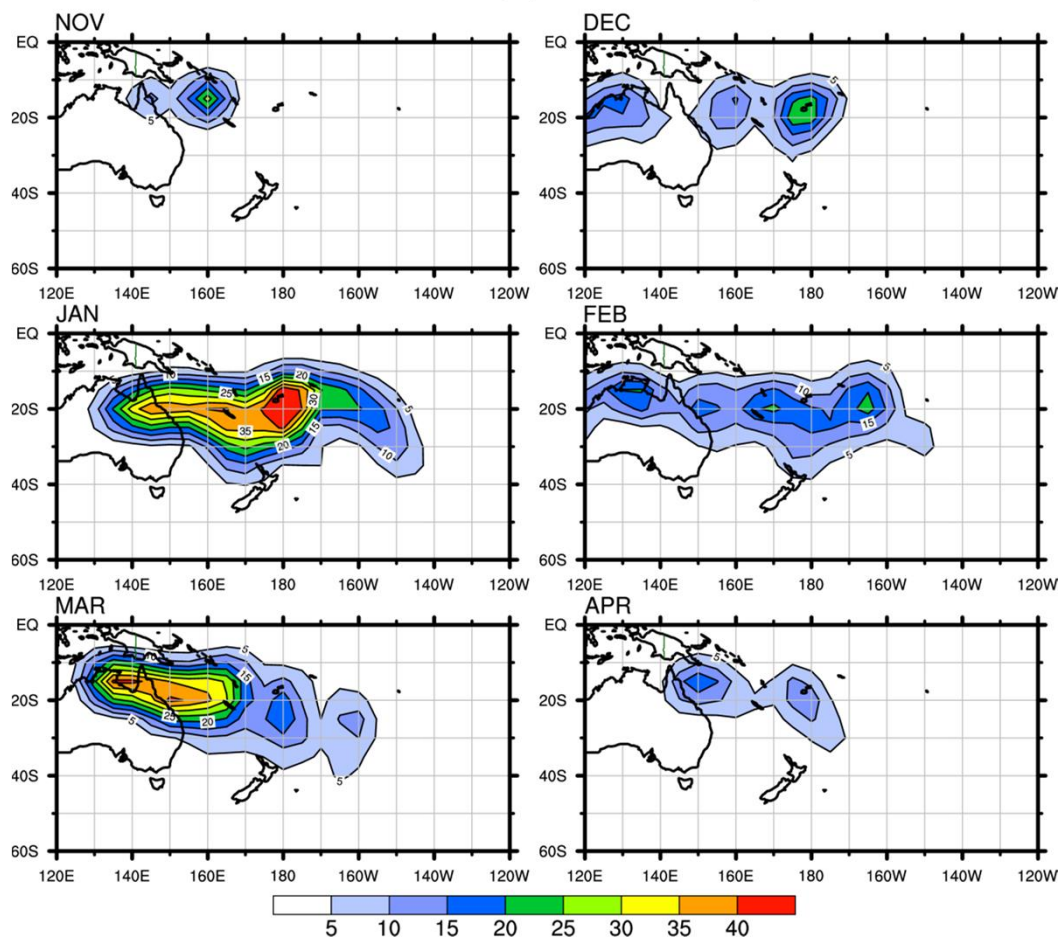
Fig. 11. Seasonal TC forecast track density (contour) and its anomaly compared to the climatological TC track density (shaded) during NDJFMA in 2017/2018 from the hybrid statistical-dynamical model based on APCC MME forecasts. (Note that the climatological TC track density covers 1982/83 to 2008/09.)



- 1) Seasonal tropical cyclone activity prediction for the South Pacific using APCC multi-model ensemble prediction
- 2) Subseasonal tropical cyclone genesis prediction in the South Pacific using subseasonal multi-model ensemble prediction – under development

TC genesis in the SPO

TC track density (2006/07-2015/16)





Subseasonal TC genesis prediction

❖ **Three key questions:**

- 1) Investigation of physically meaningful **weekly TC variability**, which is predictable
- 2) Identification of **potential predictors** associated with subseasonal TC variability from physical consideration
- 3) Development of the **forecast model** with selected predictors and examination of the model's performance in predicting the subseasonal TC genesis – *future plan*



Operational Medium-Range Ensemble Forecast

(available at the TIGGE portal; <http://tigge.ecmwf.int/models.html> for more details)

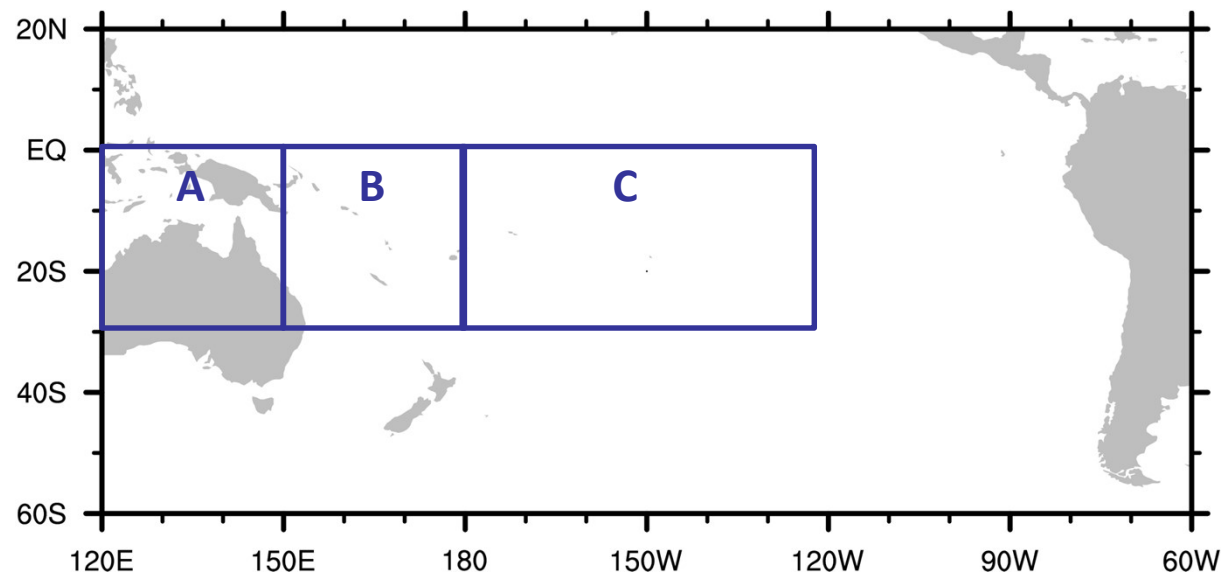
NWP centre	Forecast model resolution	Perturbation method	Perturbed area	Ensemble size/run	Maximum forecast length
BOM	TL119L19	SV ¹	90°–20°S, 20°–90°N	33	10 days
CMA	TL213L31	BV ²	Global	15	10 days
CMC	0.9degL28	EnKF ³	Global	21	16 days
CPTEC	T126L28	EOF-based	45°S–30°N	15	15 days
ECMWF	TL639L62 (0–10 day) TL319L62 (10–15 day)	SV ¹	90°–30°S, 30°–90°N + up to 6 tropical areas	51 (1 cntl + 50 perb)	15 days
JMA	TL319L60	SV ¹	20°S–90°N	51	9 days
KMA	T213L40	BV ²	20°–90°N	17	10.5 days
NCEP	T213L40	ETR ⁴	Global	21	16 days
UKMO	0.5555° (lat.) × 0.8333° (lon.) L70	ETKF ⁵	Global	24	15 days

¹SV: Singular Vector, ²BV: Bred Vector, ³EnKF: Ensemble Kalman Filter,

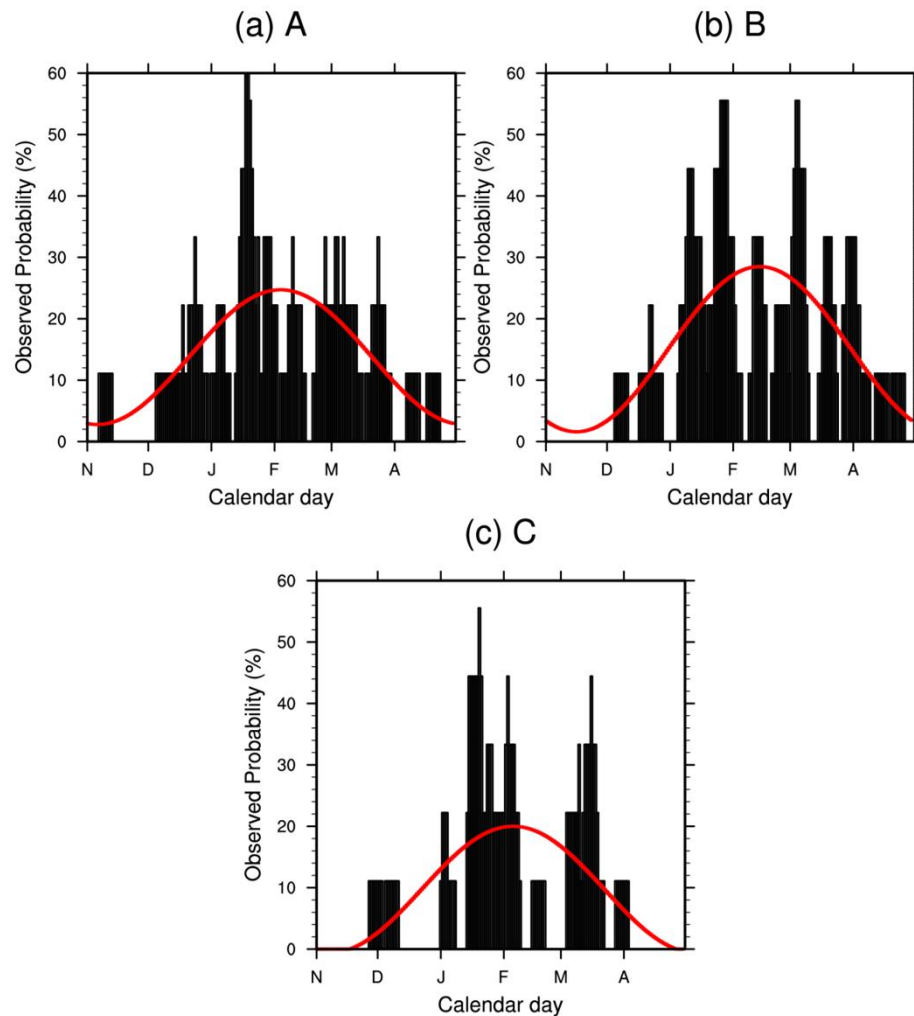
⁴ETR: Ensemble Transform with Rescaling, ⁵ETKF: Ensemble Transform Kalman Filter

Region of interest


- Several different zones; for each, subseasonal TC occurrence prediction system are developed.



Climatological seasonal cycle of weekly TC genesis probabilities



- Probabilities refer to the probability of a TC genesis in the week starting on the day that is specified on the axis.
- Smooth by Fourier analysis applied to the 365-day climatology and reconstruct using only the mean and the first of annual harmonics
→ a more accurate reflection of the real seasonal cycle of TC genesis



Possible sources of TC predictability on subseasonal time scale

❖ Possible sources of subseasonal predictability for TC?

→ potential predictors

- Current and projected state of the Madden-Julian Oscillation (**MJO**)
 - monitoring values of RMM1 and RMM2
- **ENSO**
- Large-scale patterns of **tropical Pacific SST**
- **South Pacific Convergence Zone (SPCZ)**
- Use of other interannual predictors?
- Use of other predictor of the seasonality?



Possible sources of TC predictability on subseasonal time scale

- ❖ **Madden-Julian Oscillation (MJO)** is the strongest mode of tropical subseasonal atmospheric variability (Madden and Julian 1994).

Extended-range predictability (out to about 20 days) of the MJO

(e.g., Waliser et al. 1999; Lo and Hendon 2000)

Existence of strong contemporaneous relationship between MJO and TC activity

(e.g., Maloney and Hartmann 2000; Hall et al. 2001)

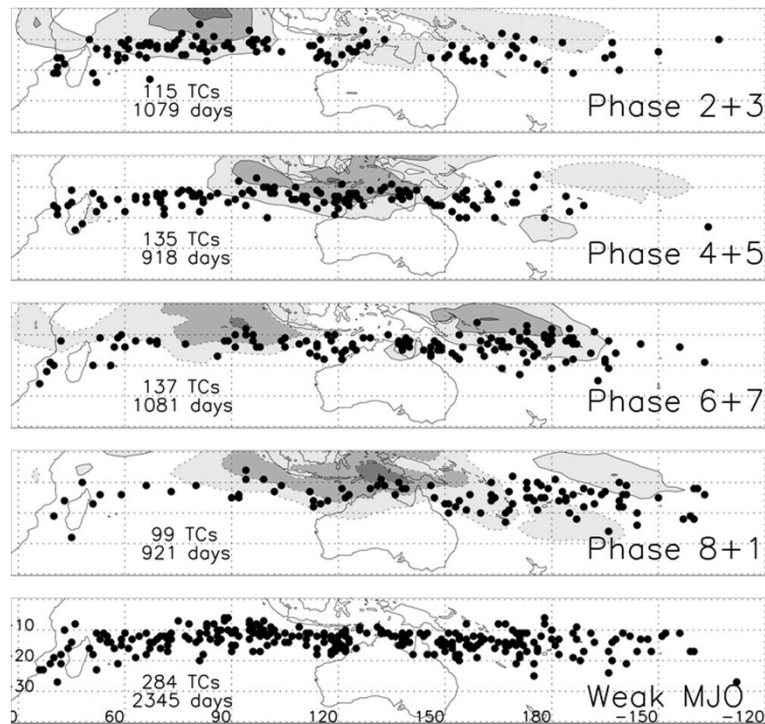


Skillful subseasonal TC prediction with the use of MJO



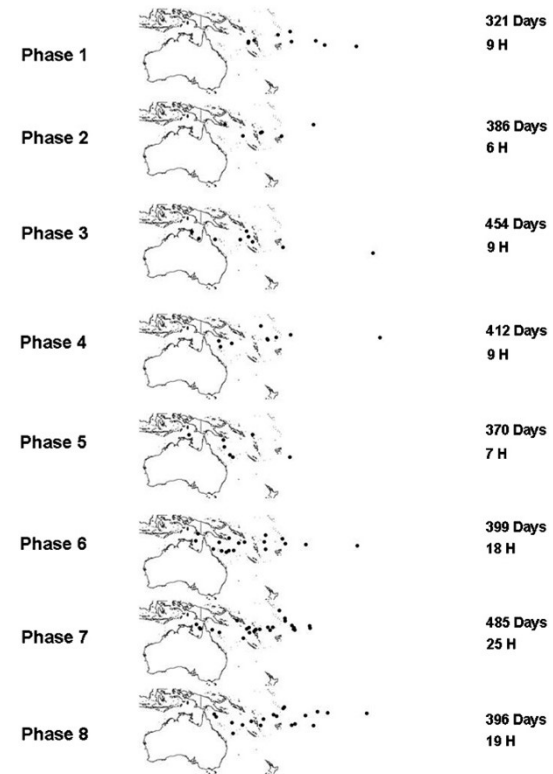
Relationship between MJO and TC

1969-2004



(Leroy and Wheeler 2008)

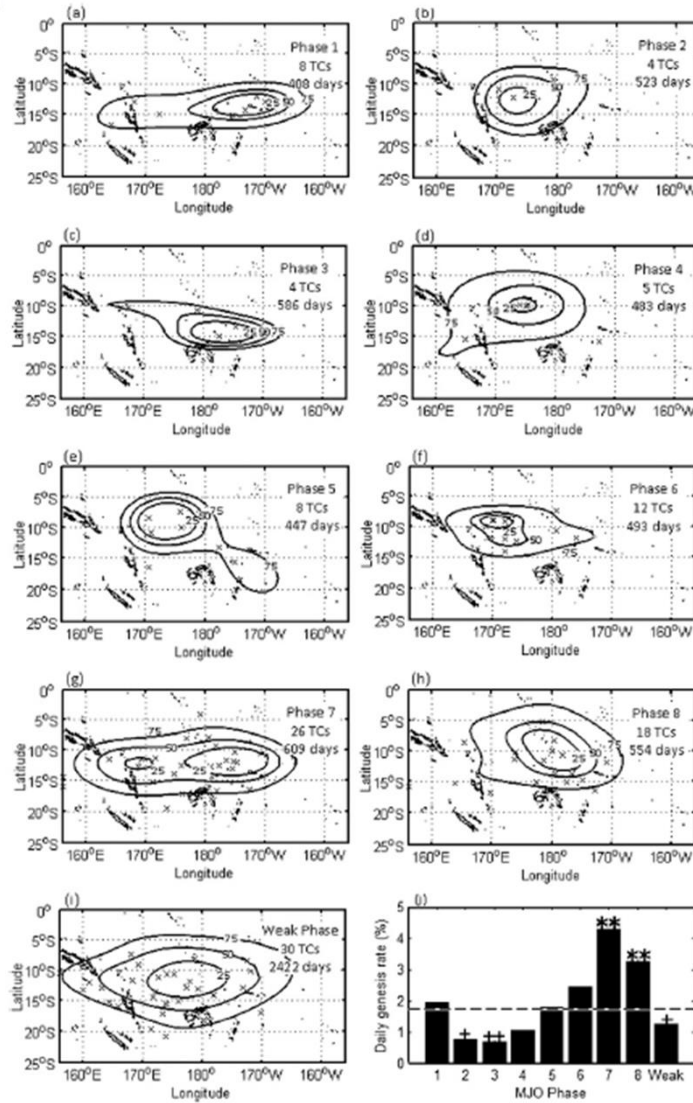
Peak in phase 4+5 and 6+7 near Australia, 6+7 and 8+1 for Pacific



(Klotzbach 2014)

TC-favorable in phases 6, 7, and 8, unfavorable in phases 1, 2, 3 and 4

Relationship between MJO and TC



(Chand and Walsh 2010)

Peak in phase 7 and 8 for Fiji region

Operational Medium-Range Ensemble Forecast

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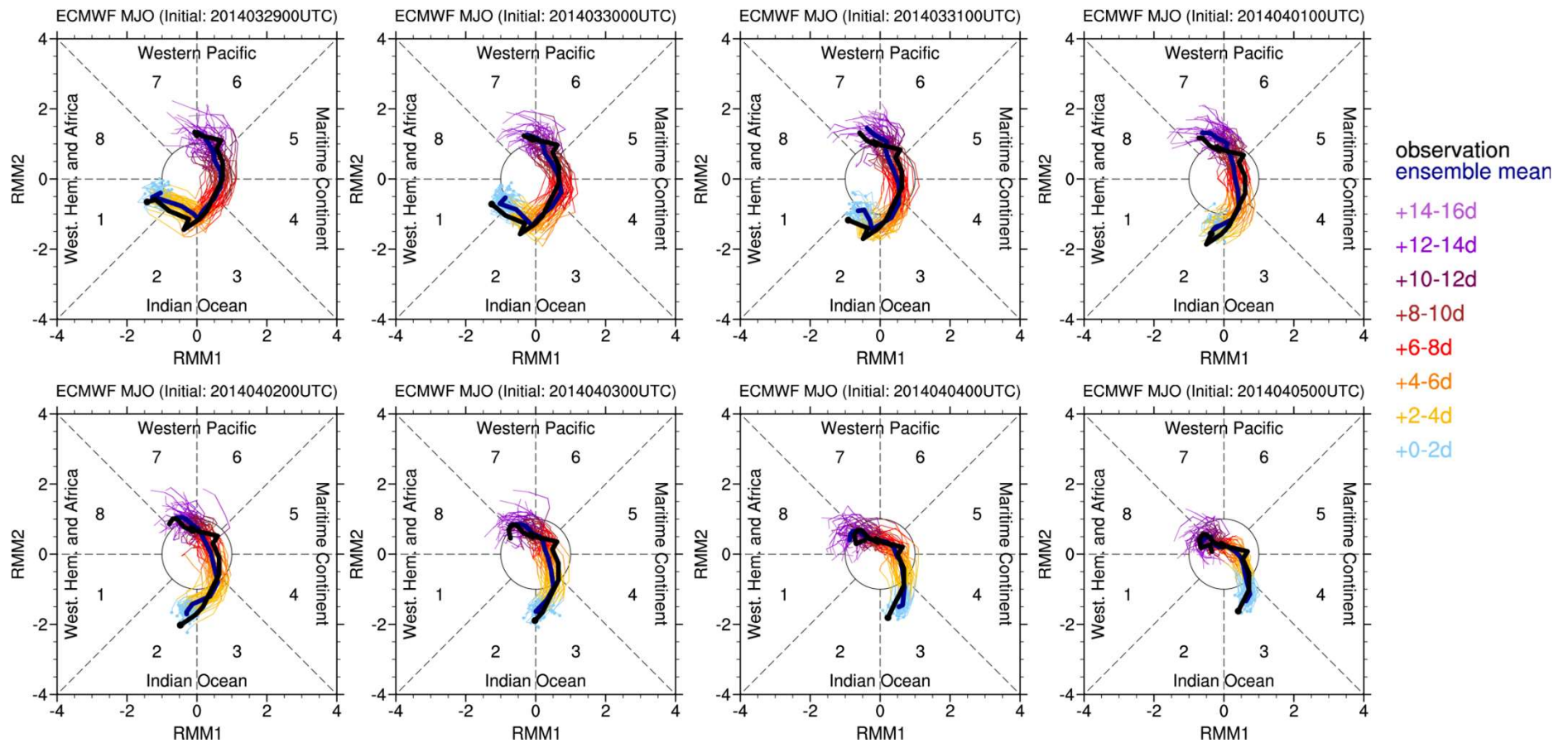
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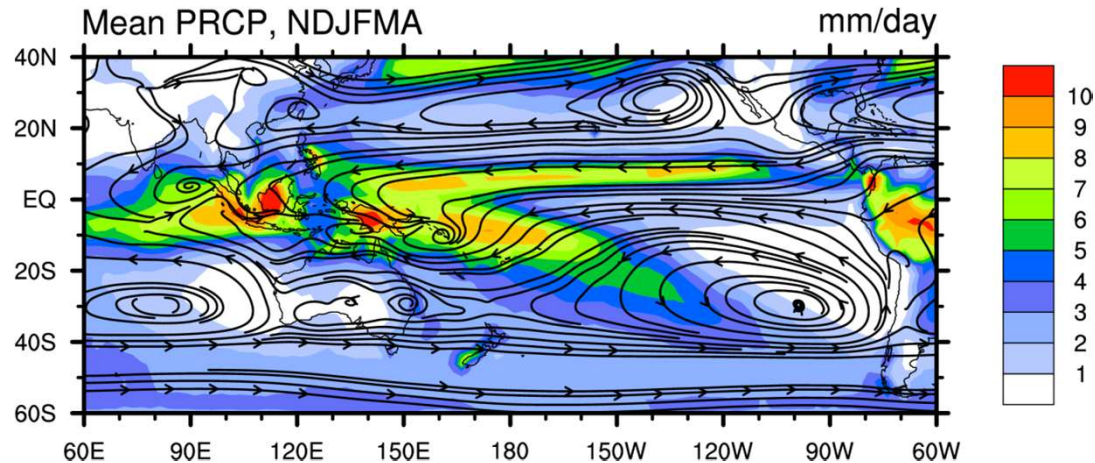
Database: ECMWF (OLR, U200, U850, 2006.11.1-2015.4.30), 51 ensemble size DATE CENTER

Verification of MJO forecasts with TIGGE (2010-2015, NDJFMA)

ECMWF MJO index forecast (initial: 2014/03/29-2014/04/05)

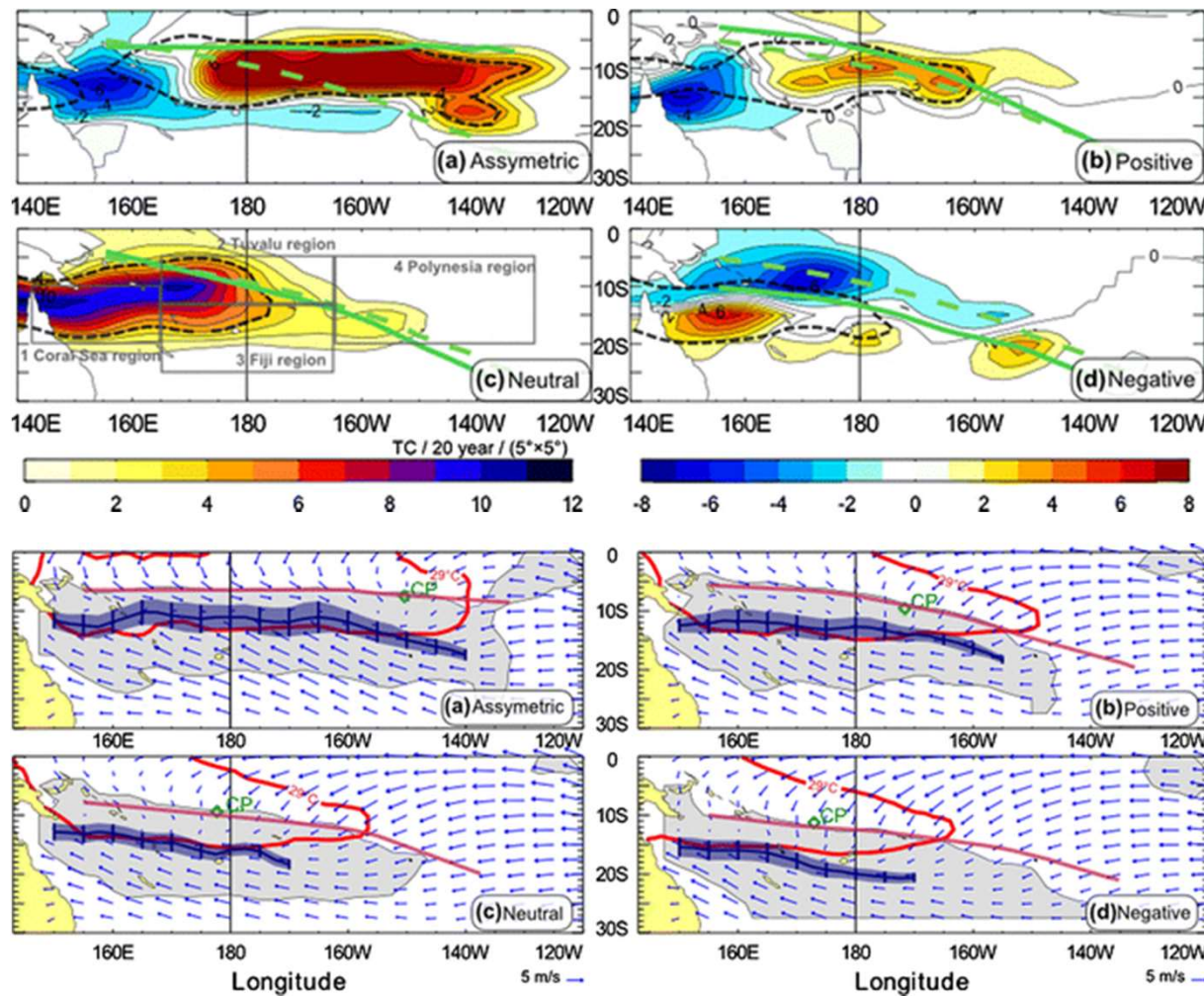


Variability of SPCZ



western portion	eastern portion
<p>Interannual position: influenced by both the underlying SST gradients and the land-ocean distribution (Kiladis et al. 1989; Matthews 2012; Chung et al. 2013)</p> <p>Strongly influenced by the monsoon trough that affects the Indian Ocean and Australian region, with monsoon winds extending eastward until the dateline</p>	<p>Interannual position: rely on the interactions with higher latitude depressions and on the existence of a dry zone in the southeastern Pacific (Kiladis et al. 1989)</p> <p>Daily to weekly scale position: controlled by the zonal dry air inflow associated with trade wind strength (Lintner and Neelin 2008)</p>

Variability of SPCZ



- Black dashed line: TC genesis region
- Green dashed line: climatological GPCP SPCZ
- Green solid line: composite SPCZ line

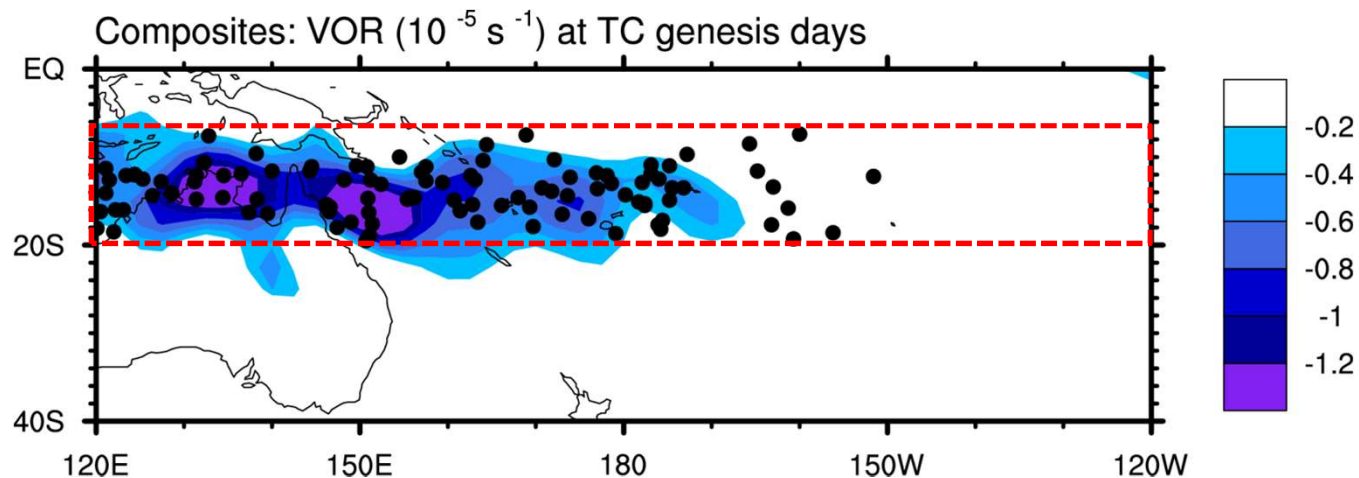
The SPCZ is always collocated with the zero relative vorticity at low levels while the maximum vorticity axis lies 6° to the south of the SPCZ position.

Relative vorticity amplitude (in $10^{-6} s^{-1}$)
7, 5, 3

- Purple solid line: composite SPCZ line
- Thick blue line: maximum cyclonic relative vorticity
- Shaded in grey: cyclonic relative vorticity

(Vincent et al. 2009)

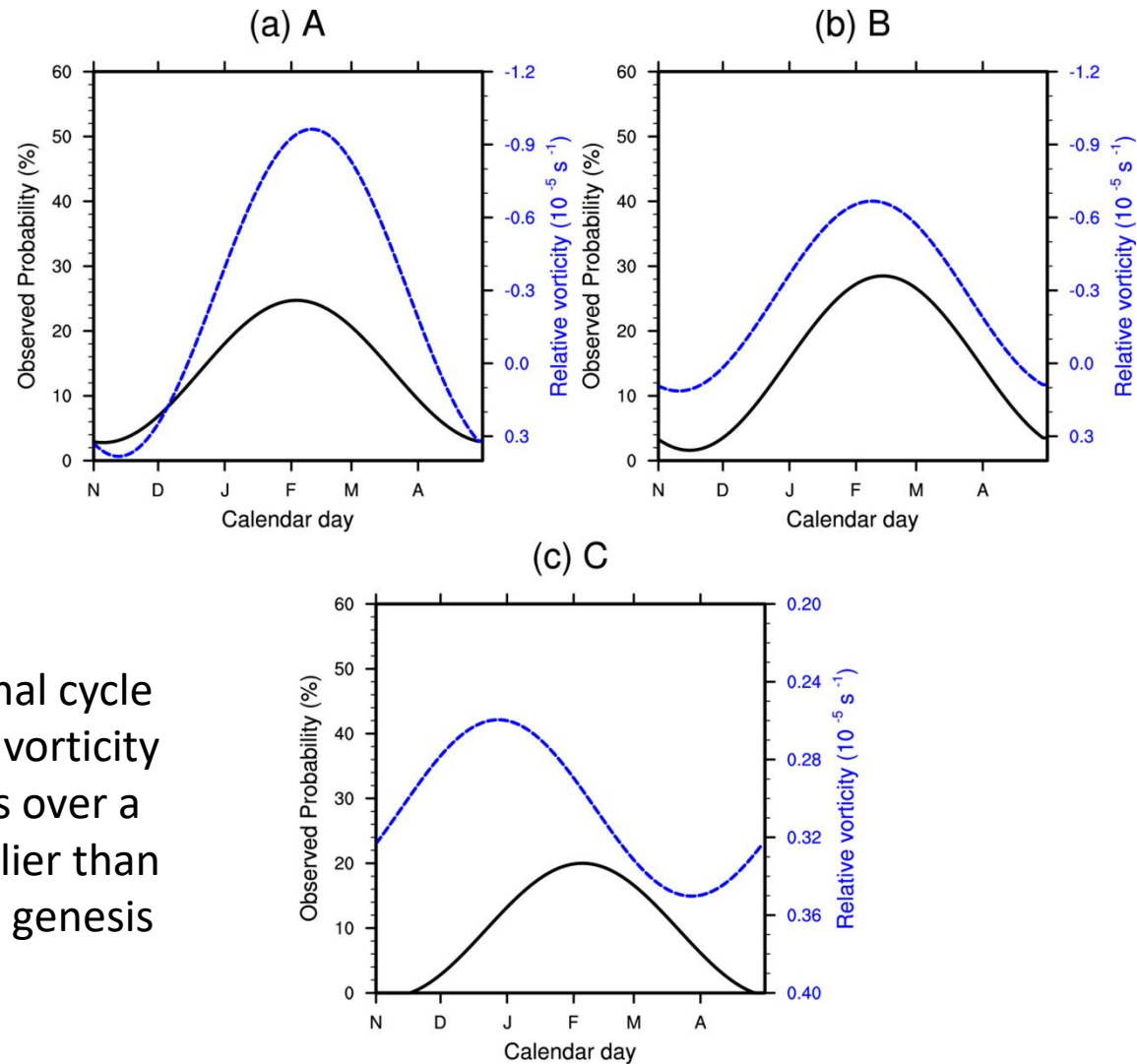
Composite of 850hPa VOR for TC genesis days (2006-2015, NDJFMA)



Black dot: TC genesis location
Shaded area: cyclonic relative vorticity

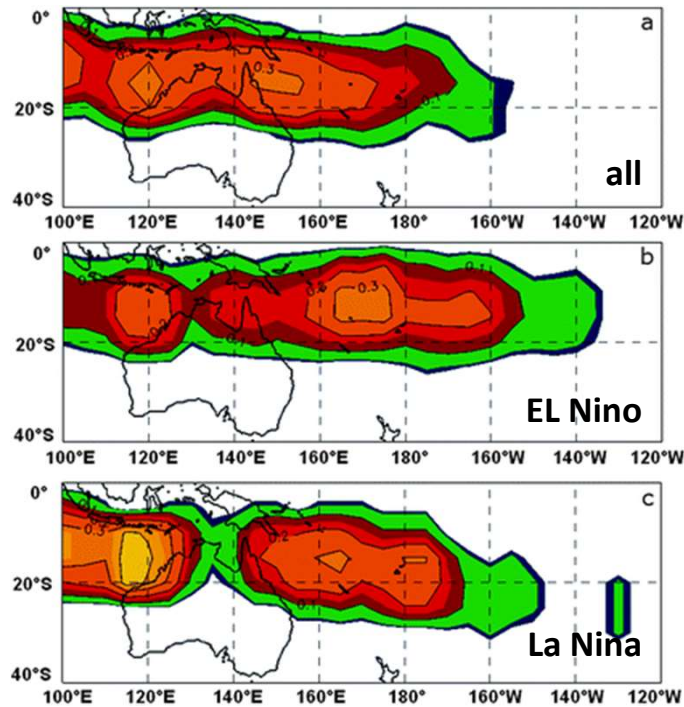
The TC genesis location is considerably collocated with the large relative cyclonic vorticity around 10°S - 20°S , especially west of the dateline.

Relationship between vorticity and TC genesis

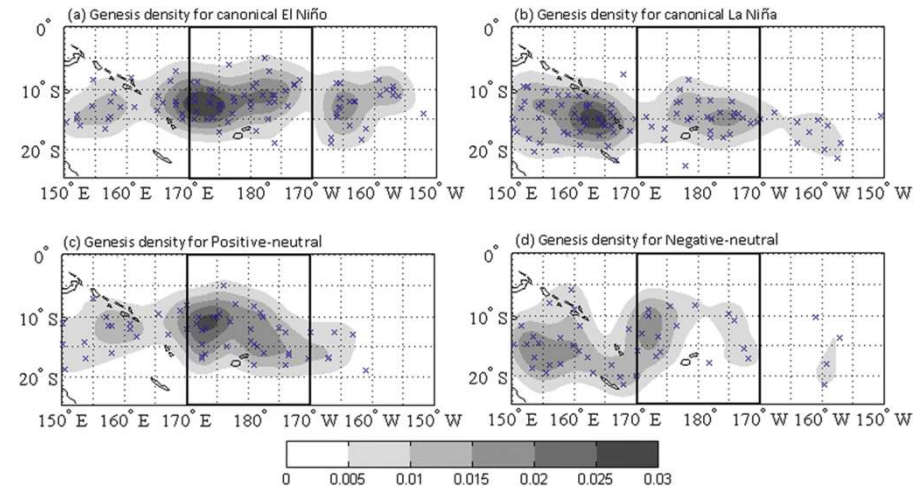


The seasonal cycle of relative vorticity for C peaks over a month earlier than that for TC genesis

Relationship of TC genesis with ENSO



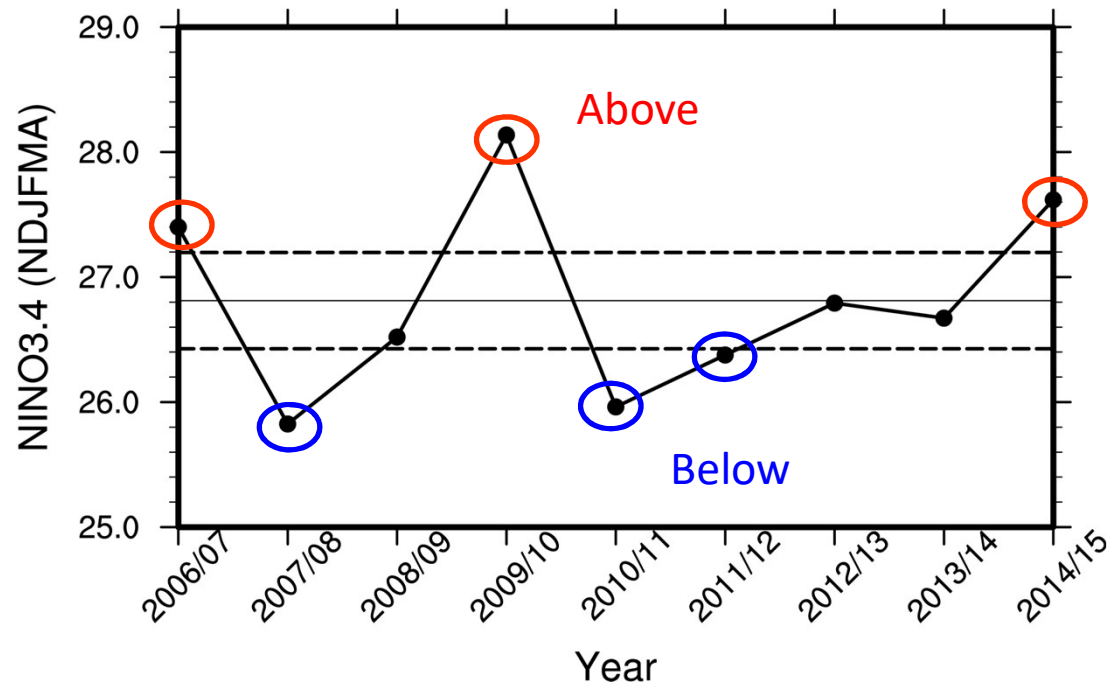
(Dowdy et al. 2012)



(Chand et al. 2013)

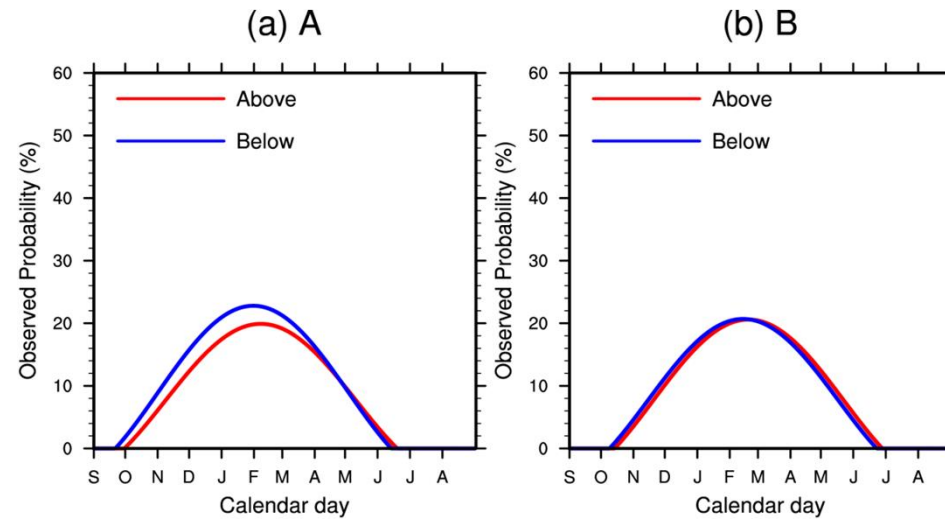
In the positive phase of ENSO: the TC genesis is enhanced eastward, maximum on the dateline
 In the negative phase of ENSO: the TC genesis positions have their maximum density further west of the dateline

Interannual variability of SST

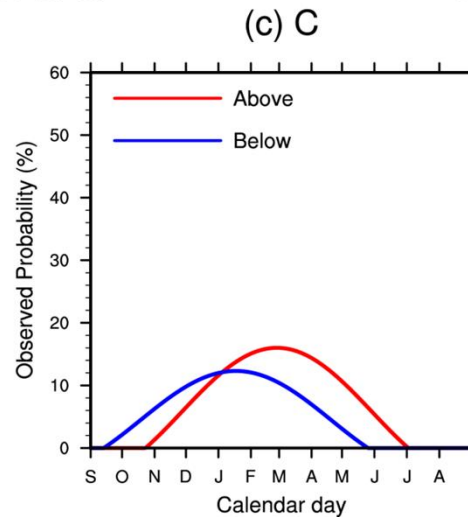


Relationship between SST and TC genesis

TC genesis increase
in the cold ENSO
phase



remain the same



TC genesis increase in the
warm ENSO phase



Future plans

- ❖ Improvement of predictors
 - Use of other interannual predictors?
 - Use of other predictor of the seasonality?
- ❖ Stepwise predictor screening
 - Stepwise regression method to select a best set of predictor variables for each zone and each forecast lead time
- ❖ Statistical modeling issues
 - Critical to pre-define the region of interest
 - Trade-off between forecast skill and usefulness
- ❖ Verification and real-time forecast



TC Forecast model development

Logistic regression:

- suited for making probabilistic forecasts as it has the property that it will always forecast a probability of positive and less than 1

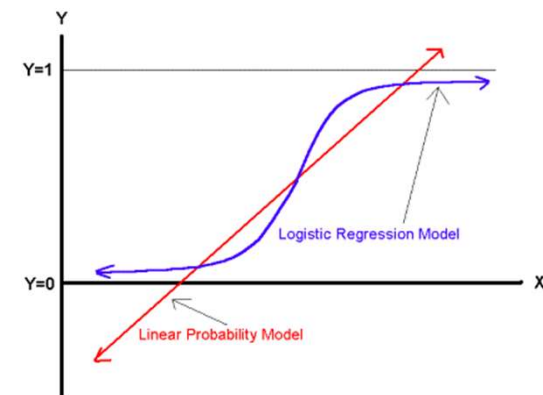
$$y^* = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_m x_m$$

$$P(x) = \frac{e^{y^*}}{e^{y^*} + 1}$$

Predicted probability of TC formation

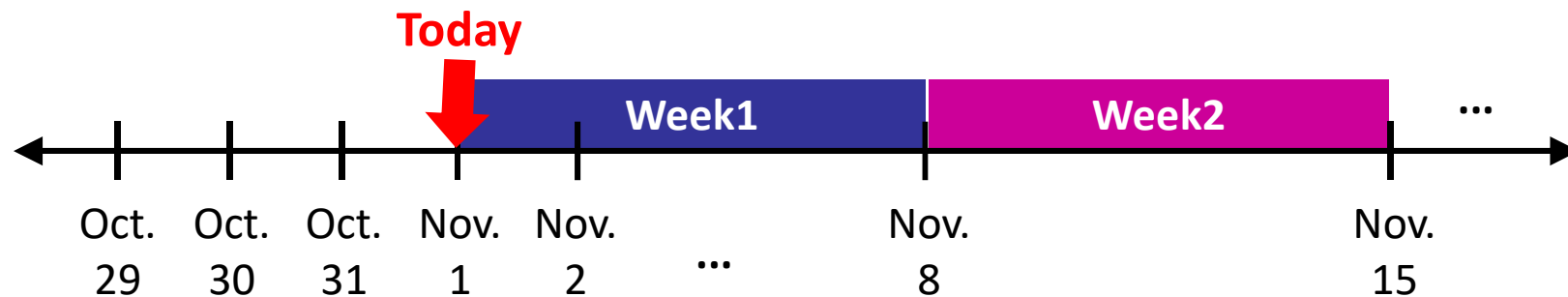
- Once we identify potential predictors from physical considerations, we select which predictors to use for each zone and each lead.

Comparing the LP and Logit Models

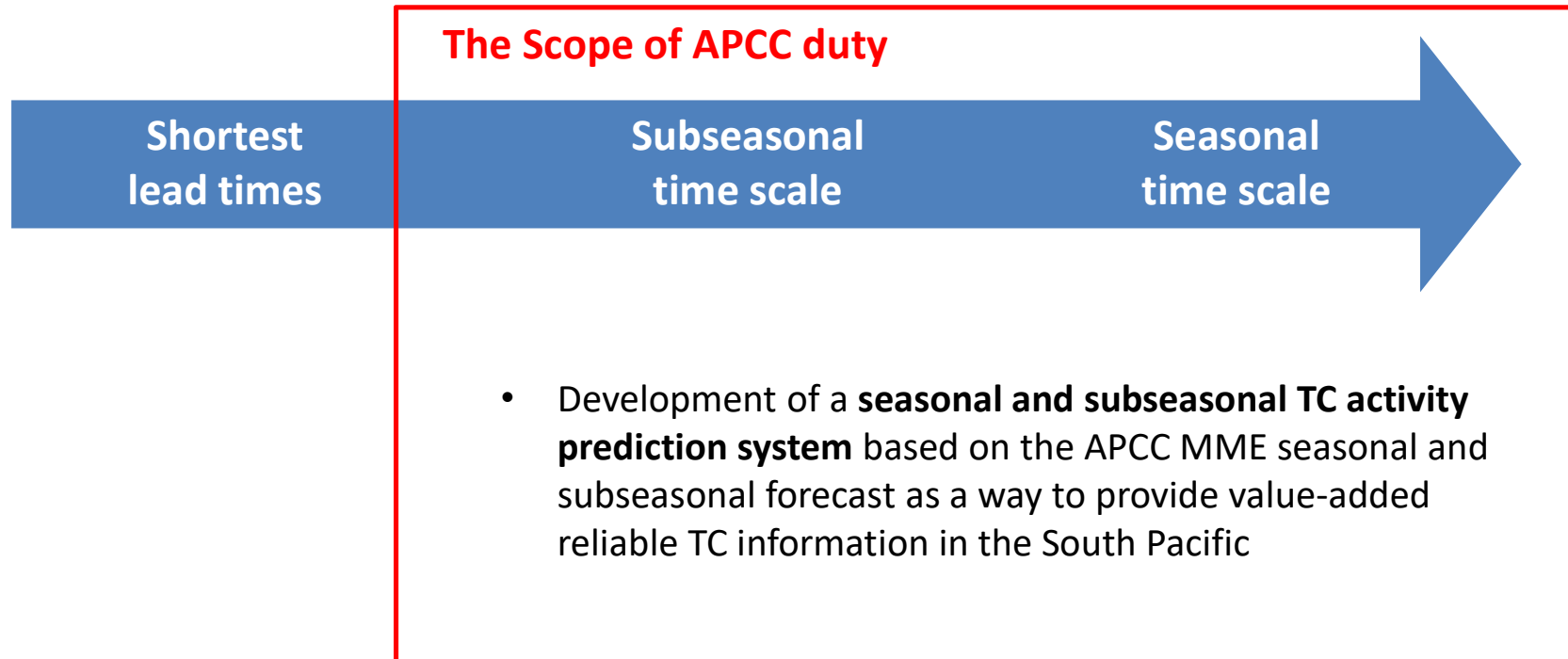


TC Forecast model development

- TC activity will be predicted in several different zones. Divided into several zones that clustered based on the extent to which each predictor exerts its influence.
- Apply the model separately for each regional zone, and for each forecast lead time.
- Develop the model during overlapping weeks, starting on every day
- Activity Tropical Cyclone Season in the SPO: NDJFMA (2016-2010)



What can APCC do for tropical cyclone forecast in the South Pacific?



- 1) **Seasonal tropical cyclone activity prediction** for the South Pacific using APCC multi-model ensemble prediction
- 2) **Subseasonal tropical cyclone genesis prediction** in the South Pacific using subseasonal multi-model ensemble prediction