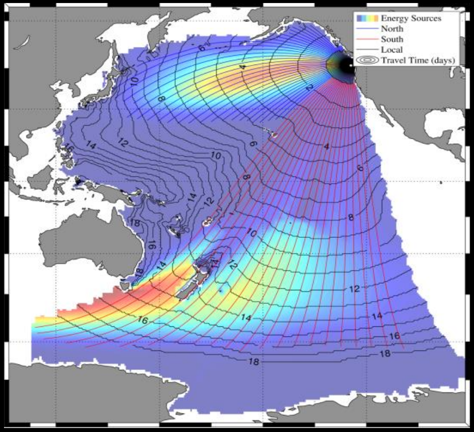
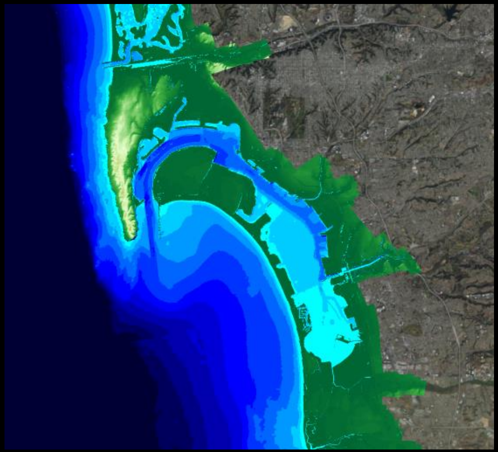
Time-varying **E**mulator for **S**hort- and **L**ong-term **A**nalysis of coastal flooding: **TESLA**-flood

Dylan Anderson[1], Peter Ruggiero[1], Fernando J. Mendez[2], Ana Rueda[2], Jose A.A. Antolinez[2], Laura Cagigal[2], John Marra[3], Curt Storlazzi[4], Patrick Barnard[4]

Oregon State University[1], University of Cantabria[2] , NOAA[3], US Geological Survey[3]





Oregon State University

UC UNIVERSIDAD DE CANTABRIA

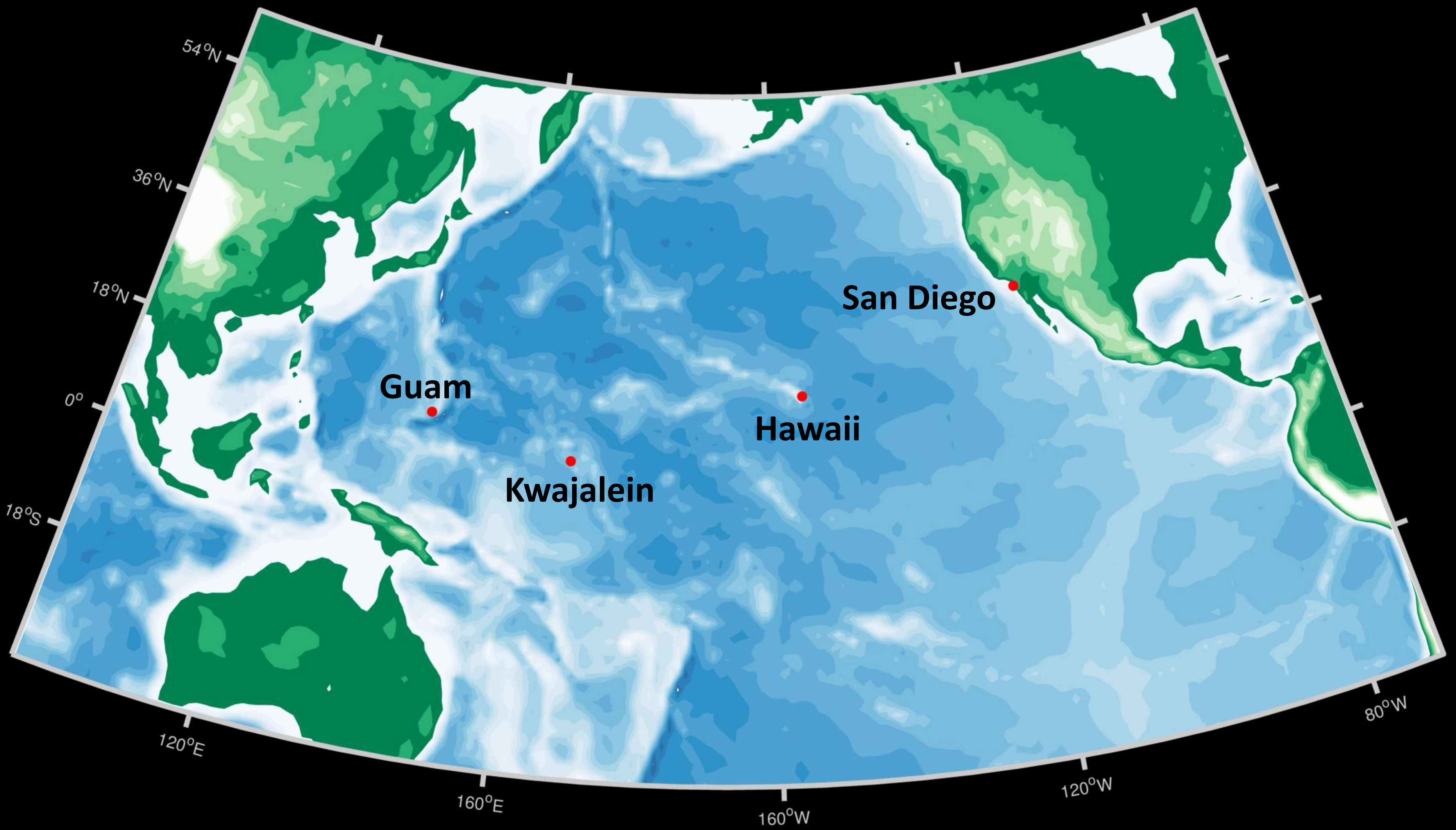
NOAA

USGS

NSF

SERDP DOD • EPA • DOE

Military installations across the Pacific Ocean Basin



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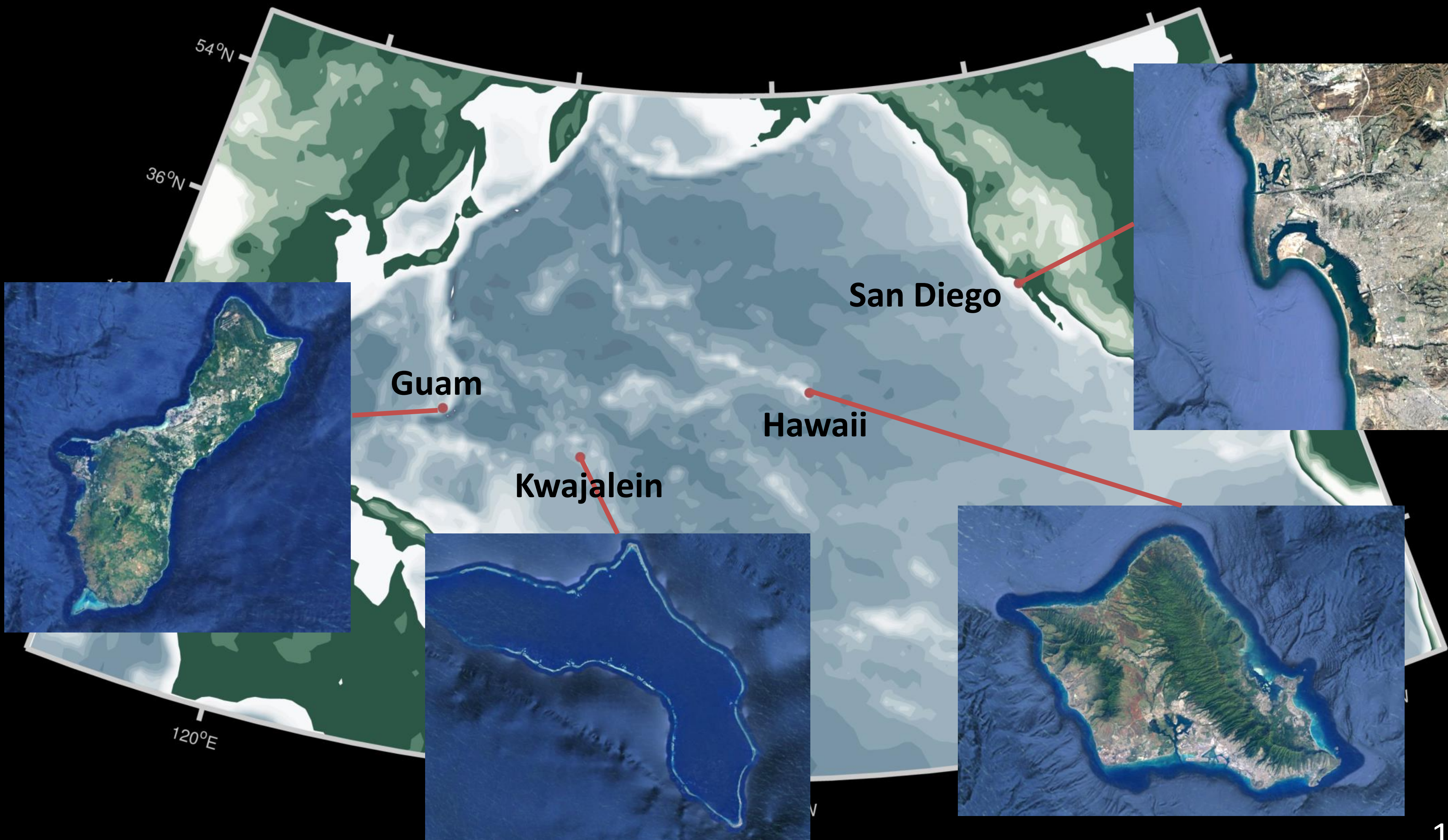
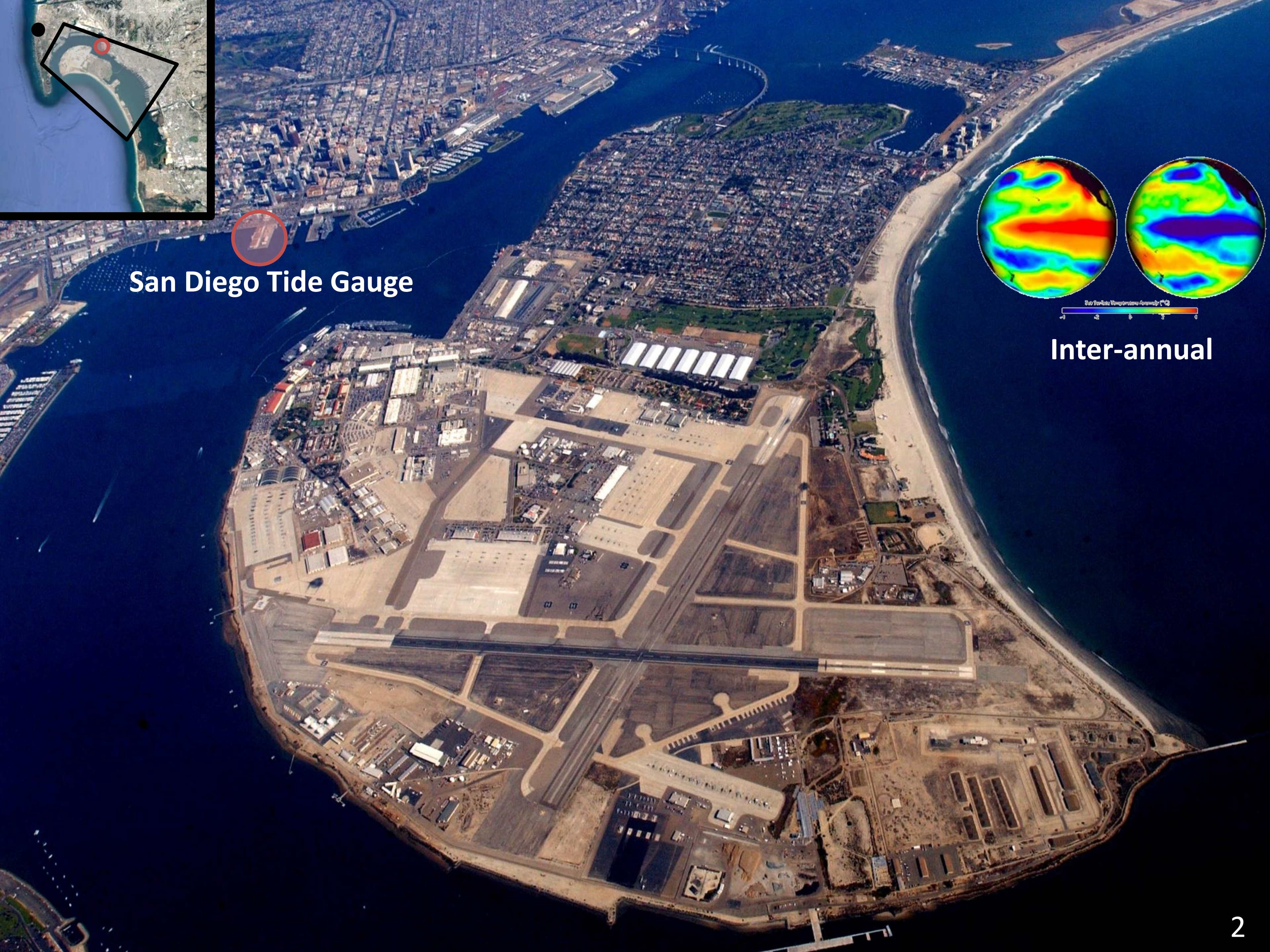
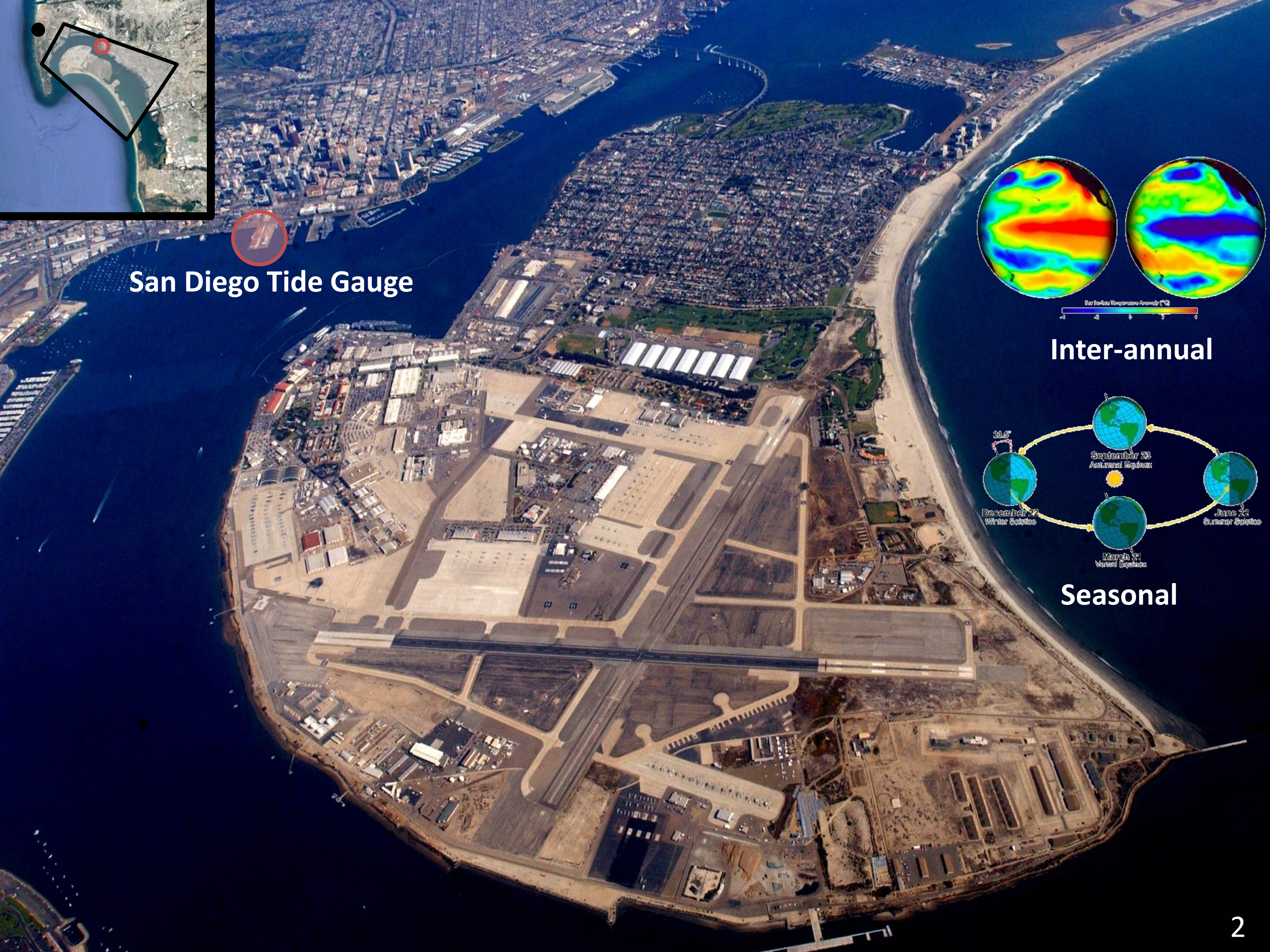
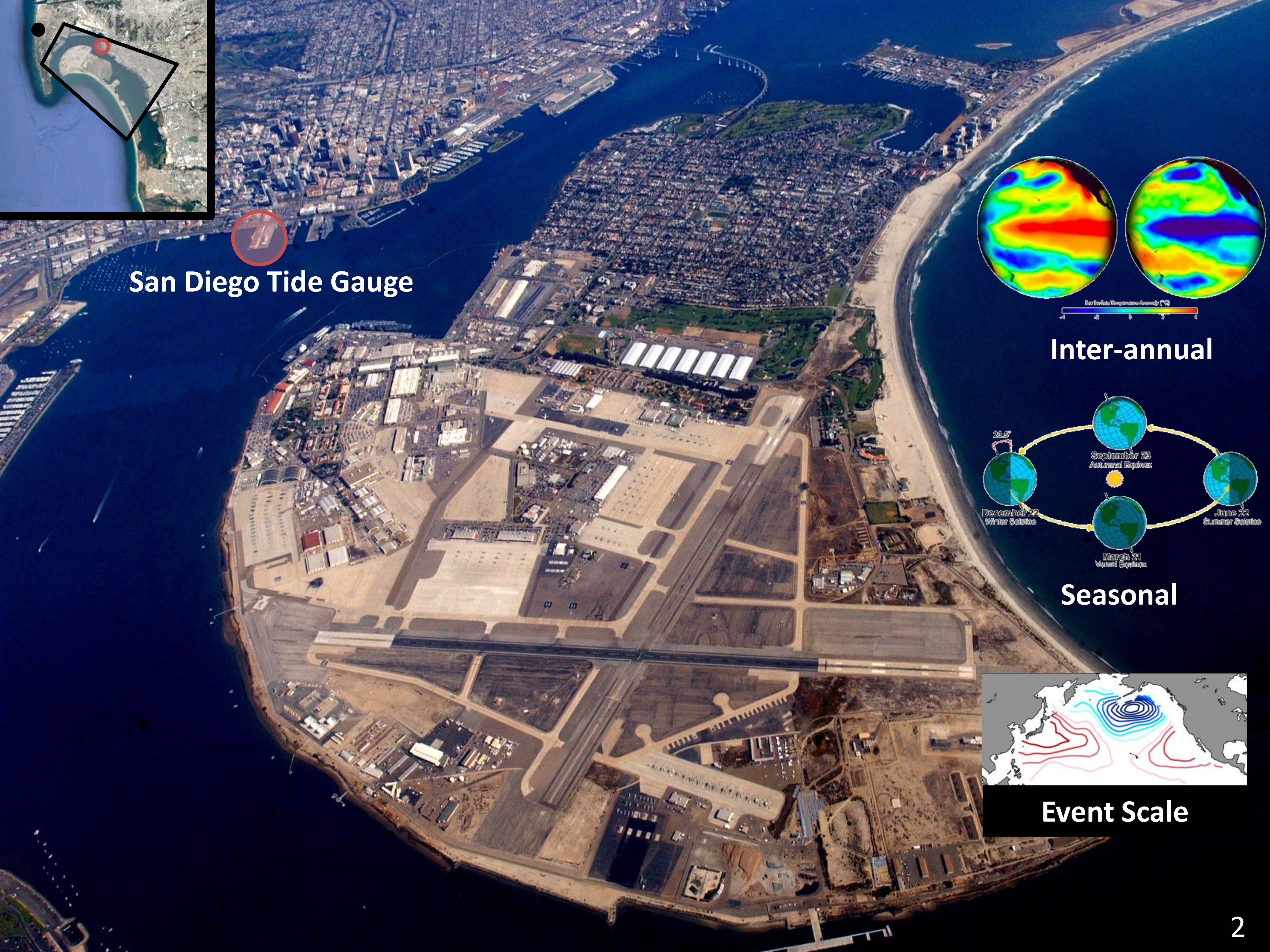



San Diego Tide Gauge


San Diego Tide Gauge
Inter-annual


San Diego Tide Gauge
Inter-annual
23.5°
September 23
Autumnal Equinox
December 22
Winter Solstice
June 22
Summer Solstice
March 21
Vernal Equinox
Seasonal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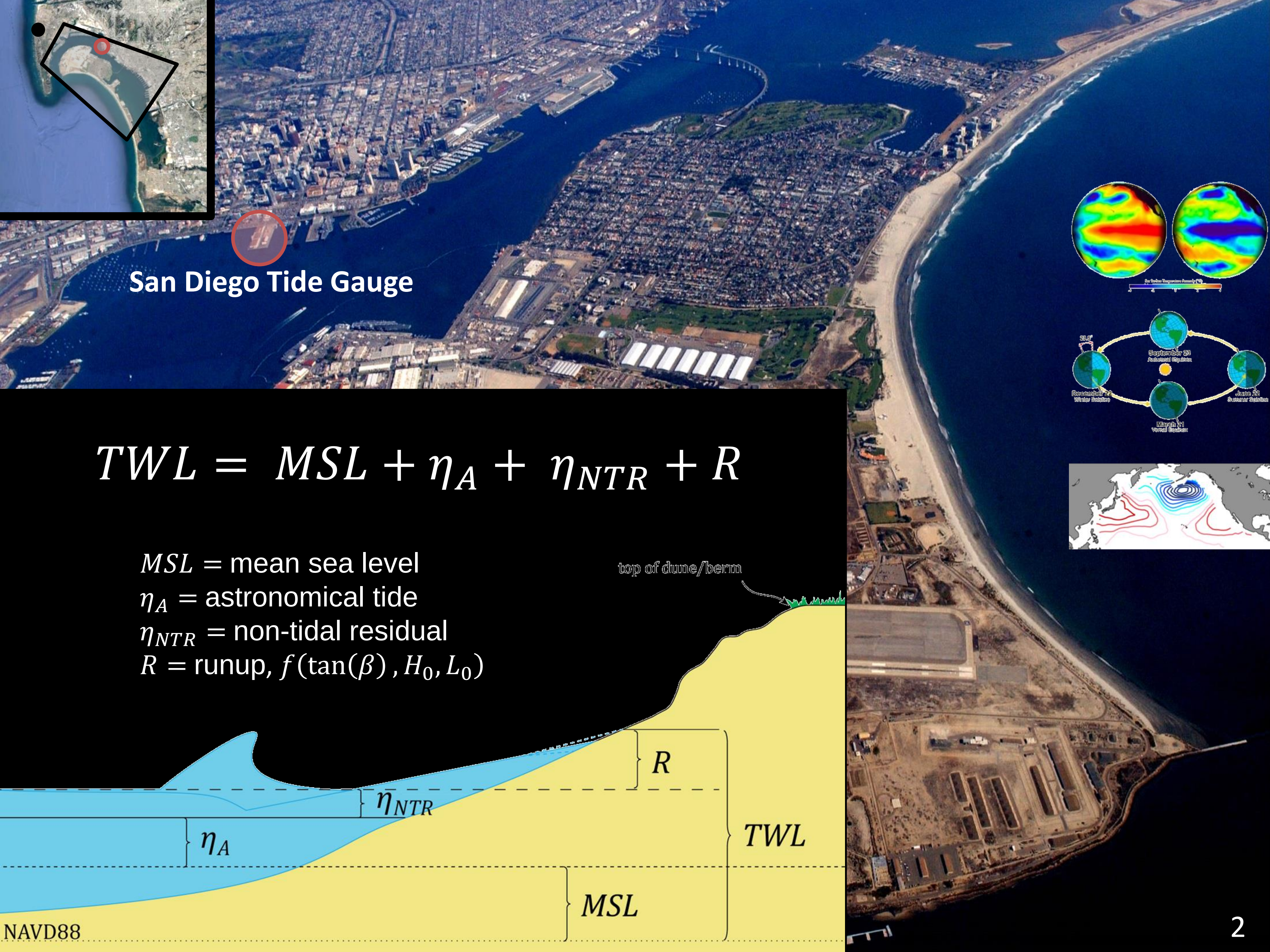
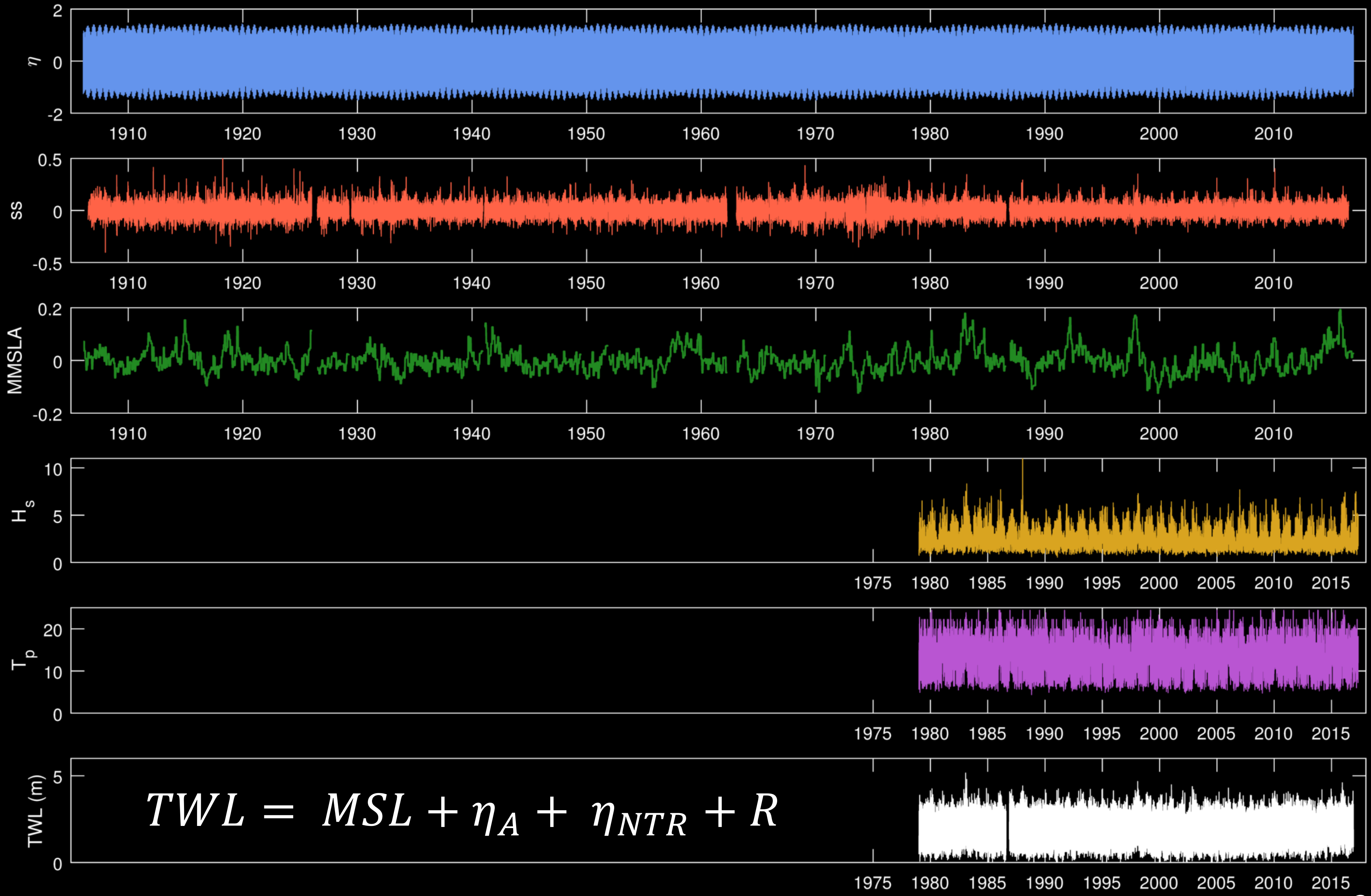
Event Scale



$$TWL = MSL + \eta_A + \eta_{NTR} + R$$

MSL = mean sea level
η_A = astronomical tide
η_{NTR} = non-tidal residual
R = runup, $f(\tan(\beta), H_0, L_0)$

San Diego Observational Record



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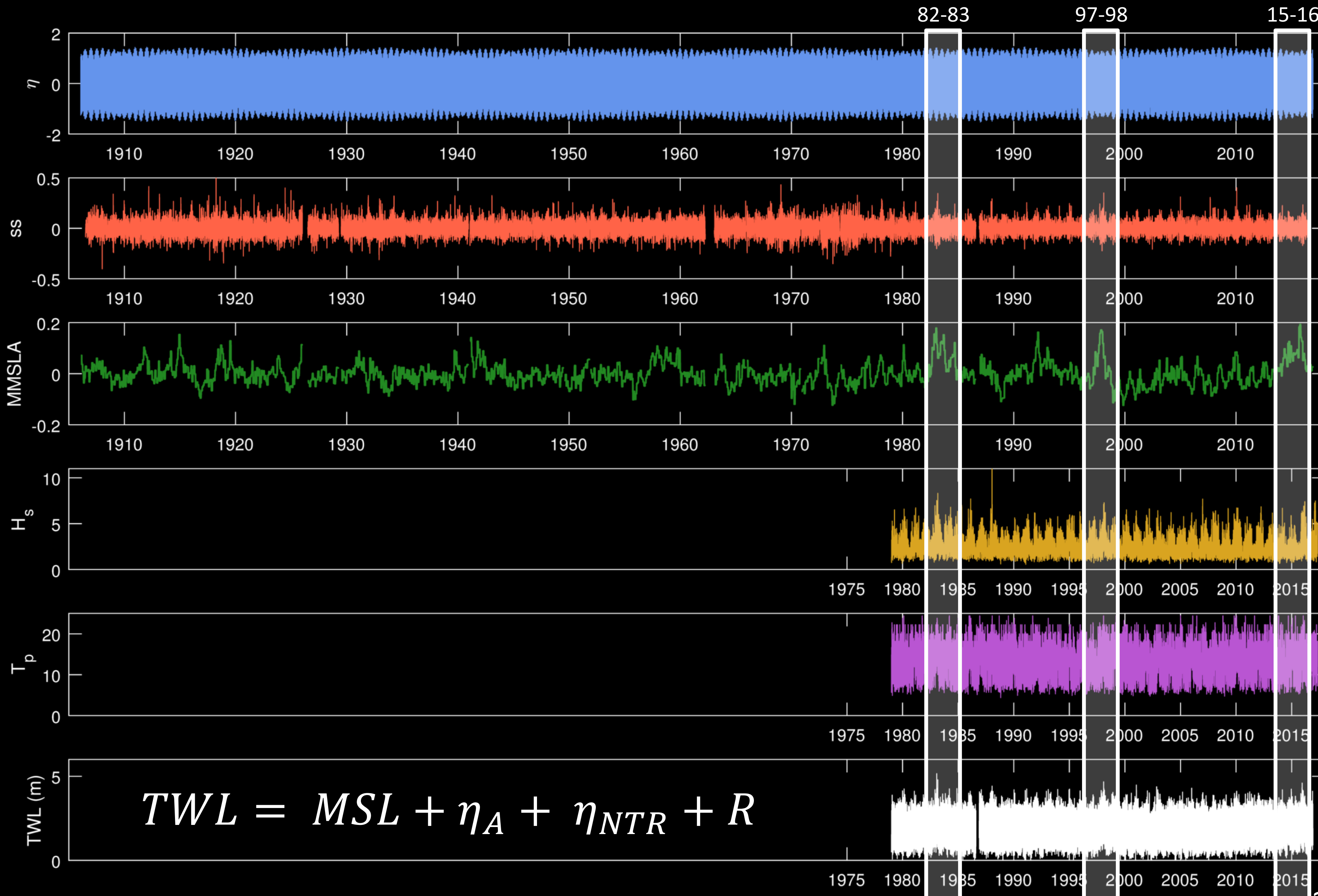
Serafin et al. 2014

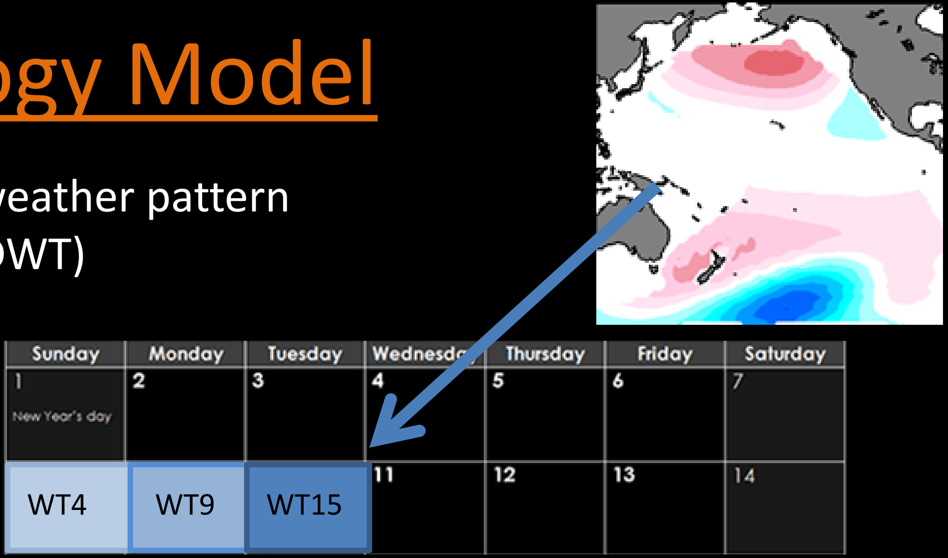
San Diego Observational Record



Serafin et al. 2014

Daily Chronology Model

Each day is assigned a weather pattern
(Daily Weather Type – DWT)



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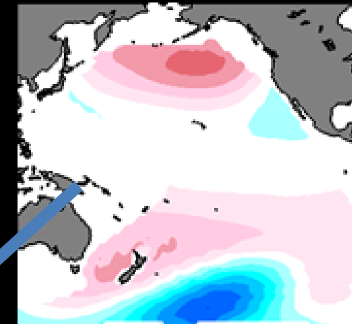

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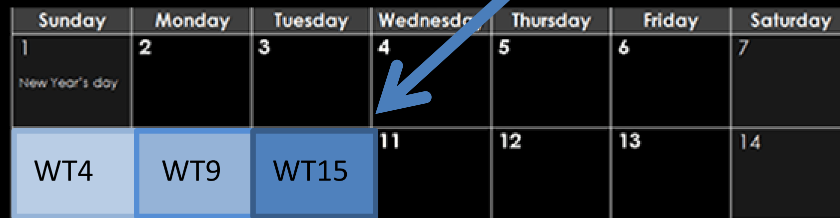

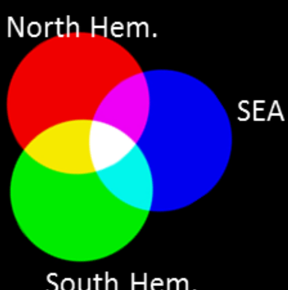

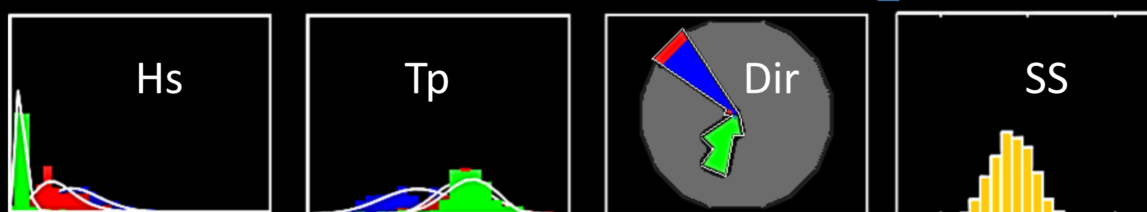

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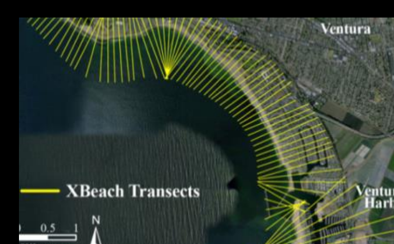
COSMOS

(Barnard et al. 2014)

Delft3d+SWAN

+

Xbeach



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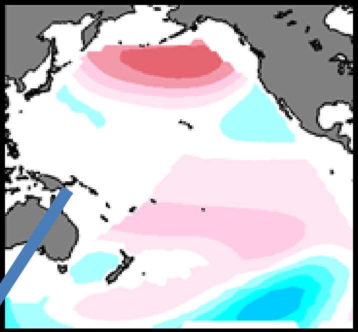

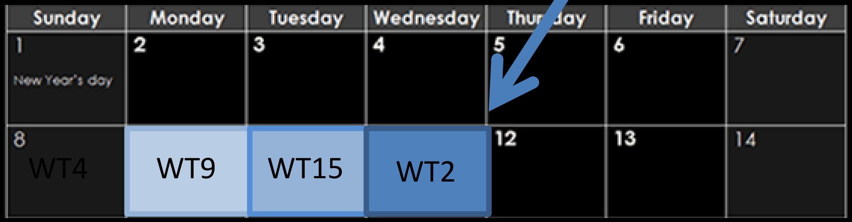

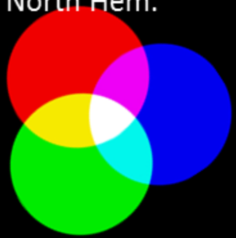

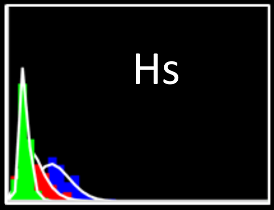

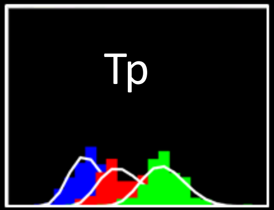

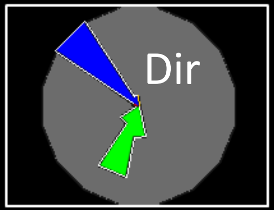

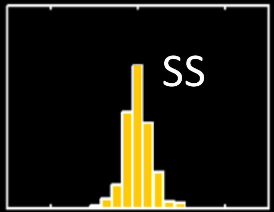

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COSMOS

(Barnard et al. 2014)

Delft3d+SWAN

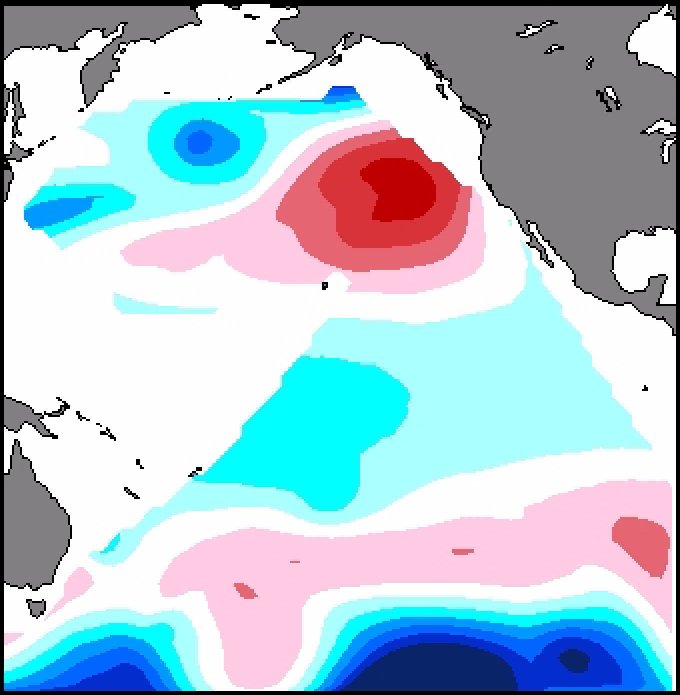
+

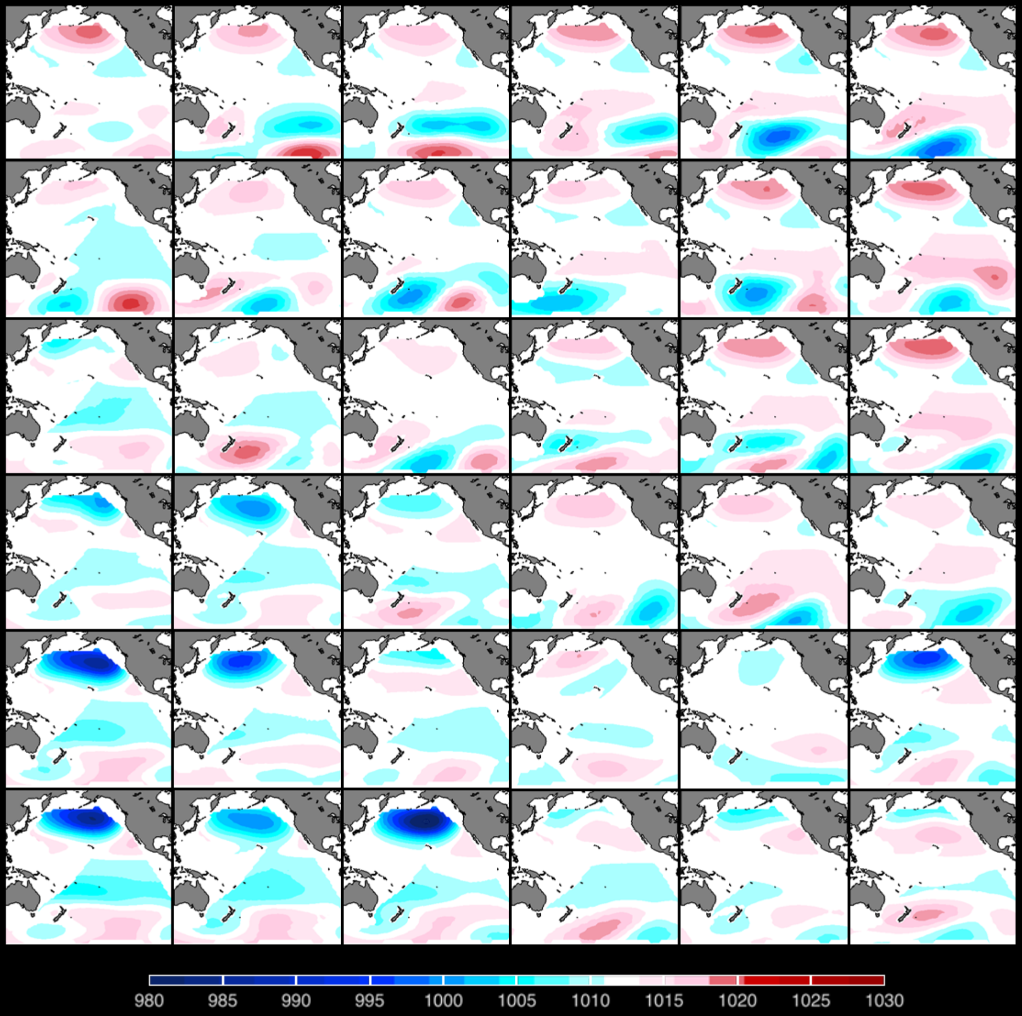
Xbeach

Daily Weather Type

Cluster historical Sea Level Pressures – all SLP fields assigned to a "representative" weather pattern (Kmeans of PCA space)

CFSR Sea Level Pressures: 1979-present

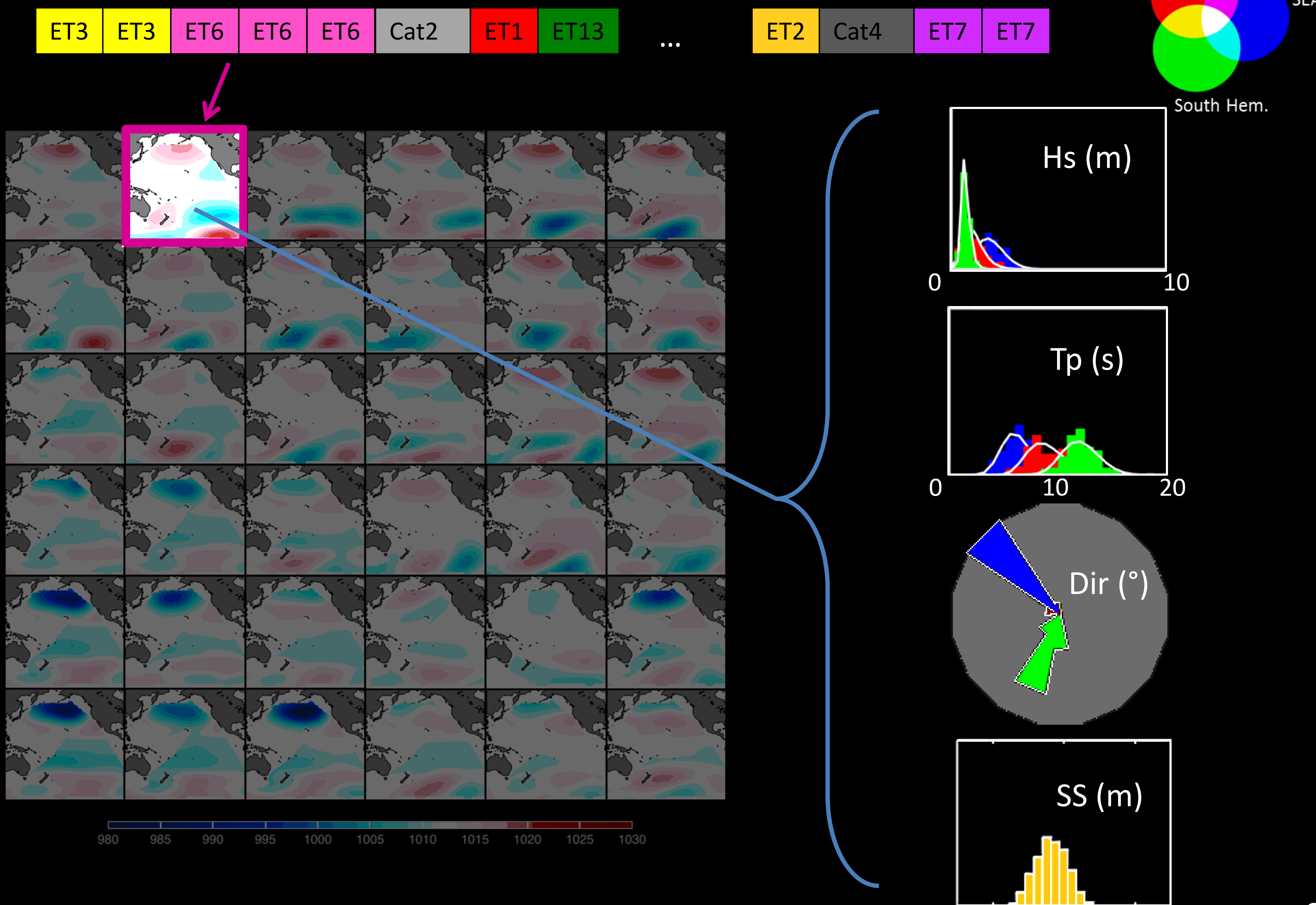




Perez et. al. (204) & Camus et. al. (2014)

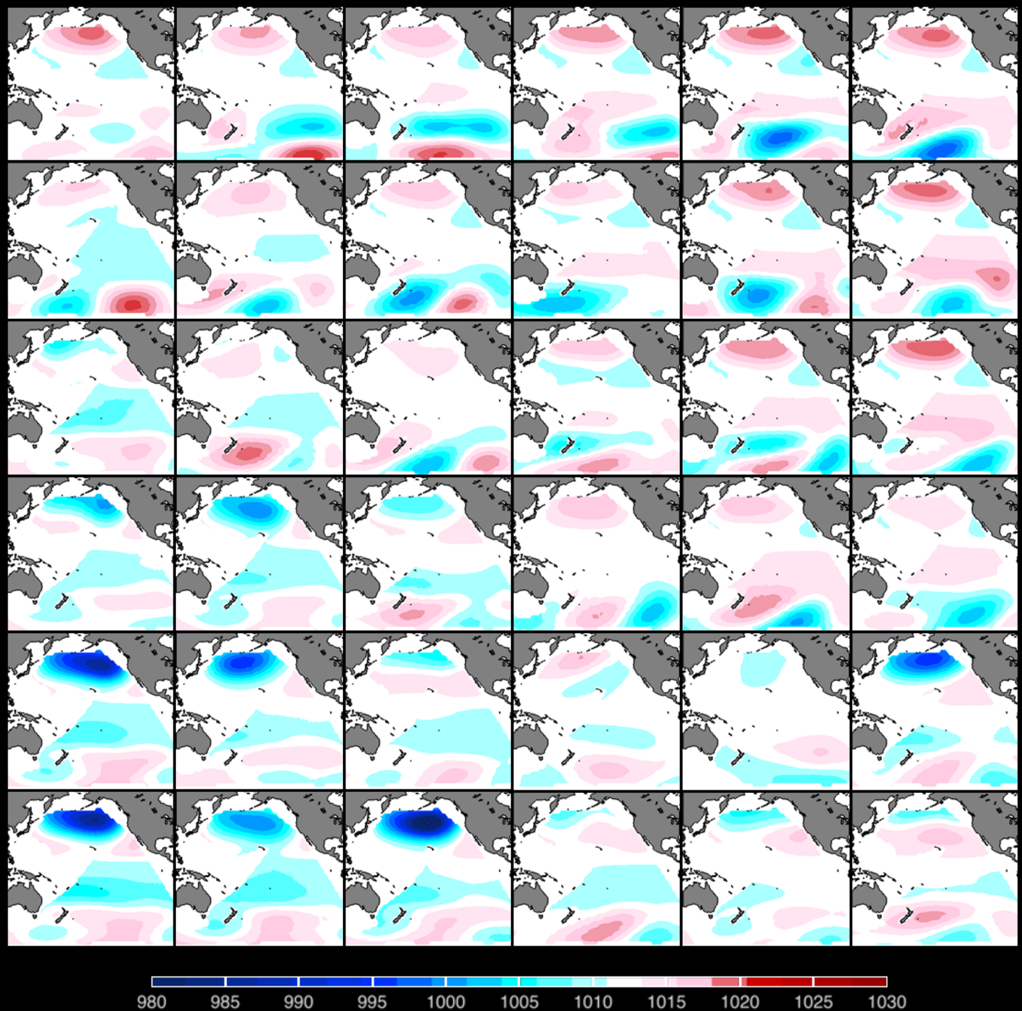
Daily Weather Types

GOW2 wave hindcast: IH Cantabria; NOAA water levels: 9410170

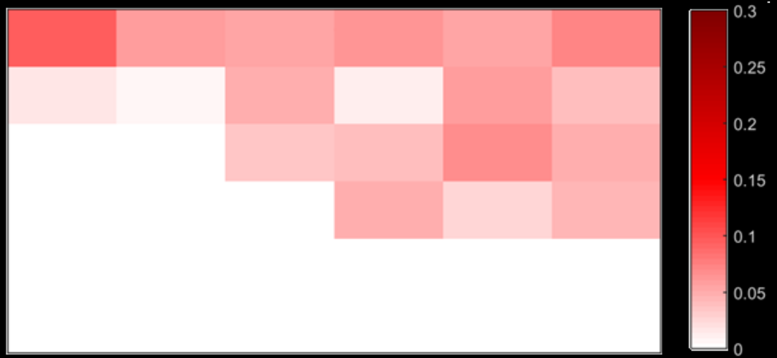


Rueda et. al. 2017

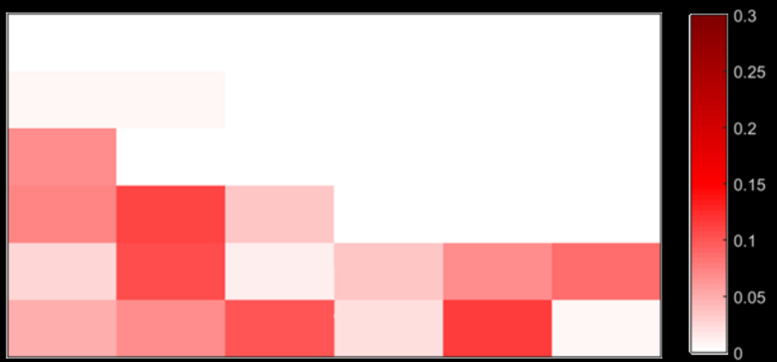
Daily Weather Type



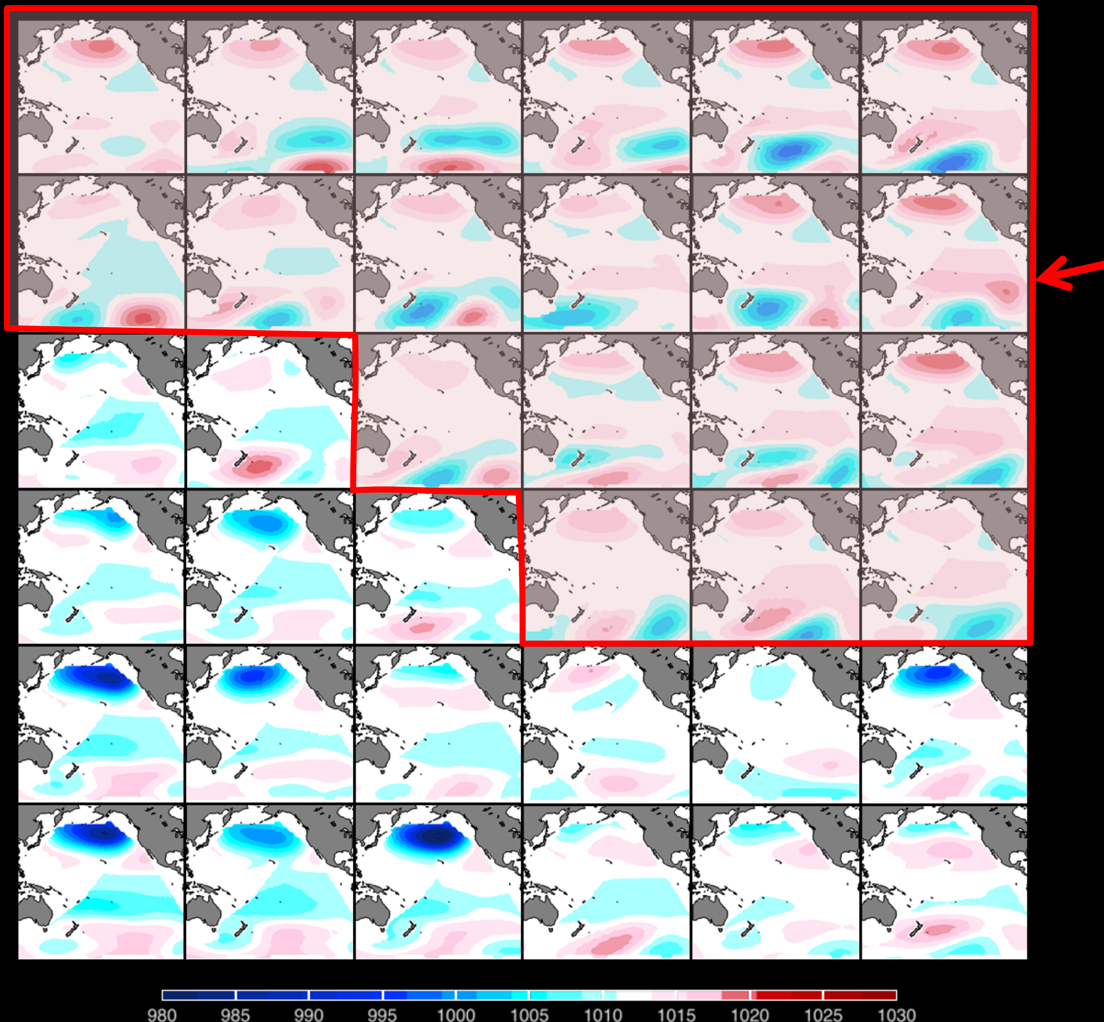
Summer (Jun, Jul, Aug)



Winter (Dec, Jan, Feb)



Daily Weather Type



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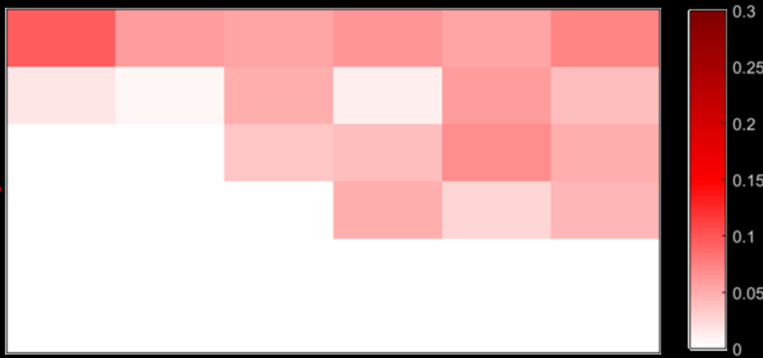

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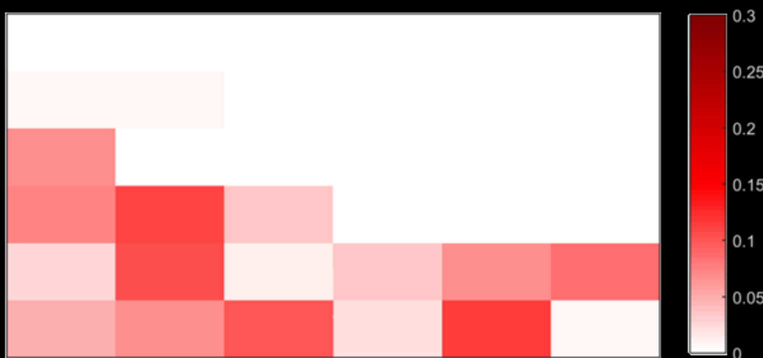
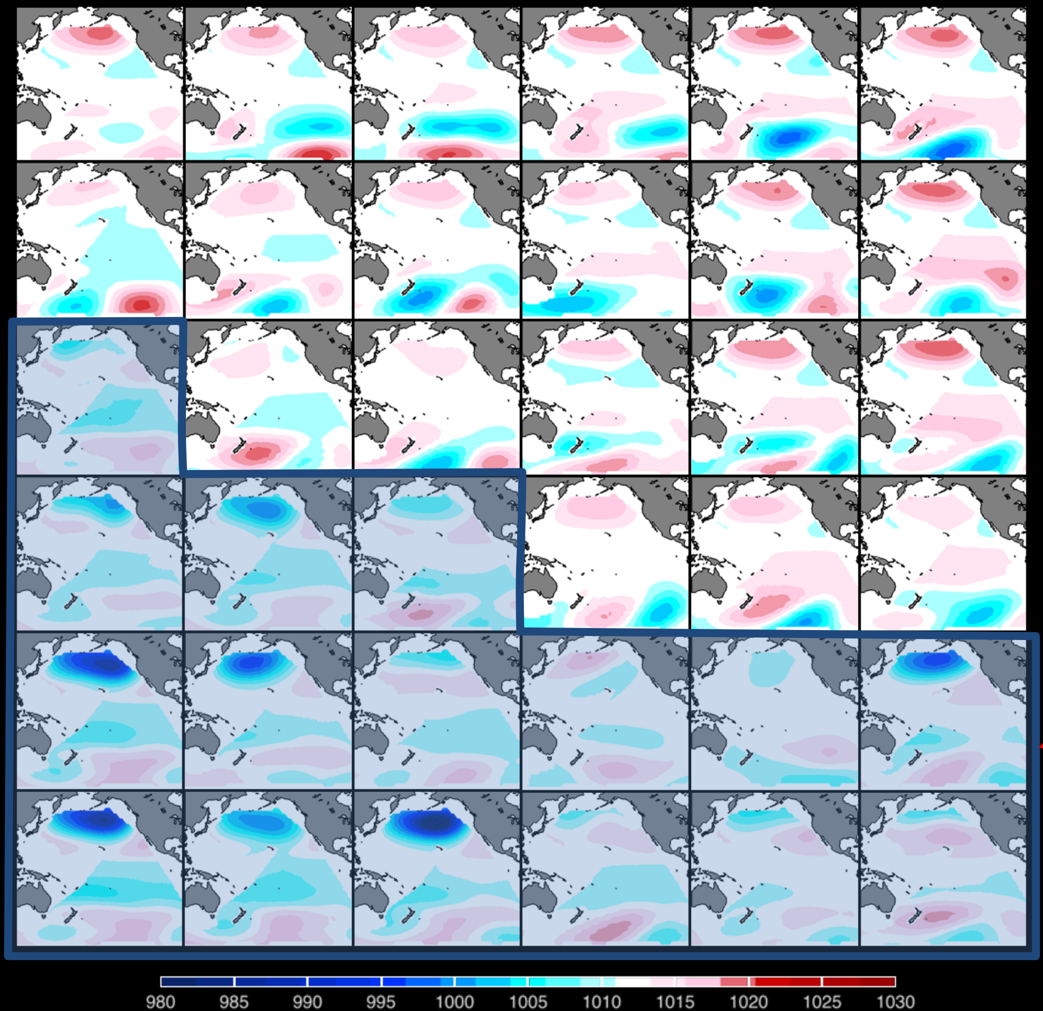


Daily Weather Type



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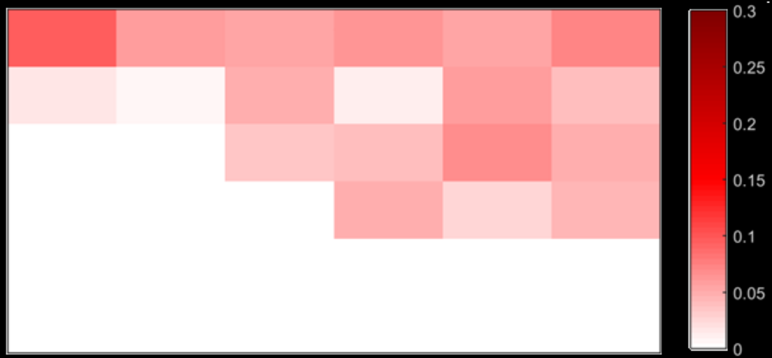

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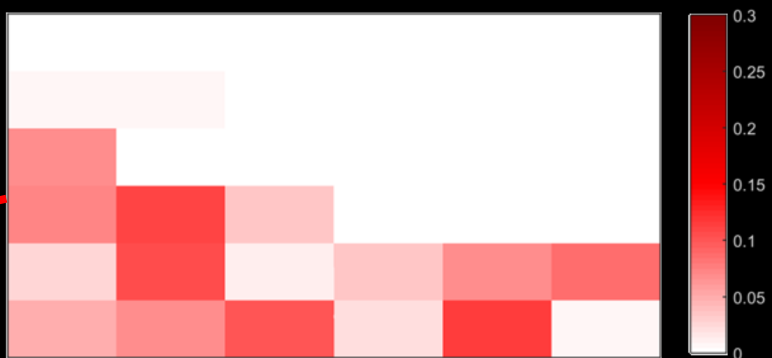
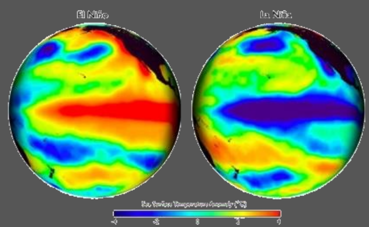


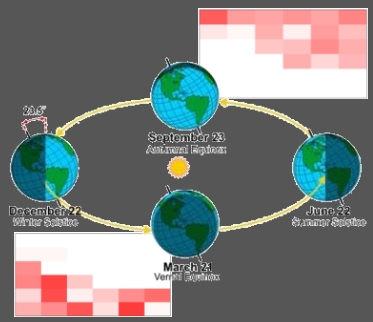
Goal: Daily Chronology model…

Annual Predictor

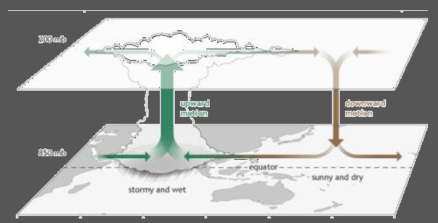


Inter-annual to decadal ocean heat content

Seasonality

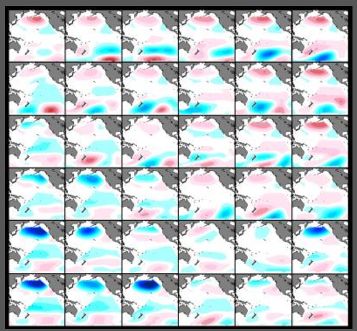


Intra-seasonal Predictor



1 to 2 month
Global atmospheric circ.

Daily Predictor



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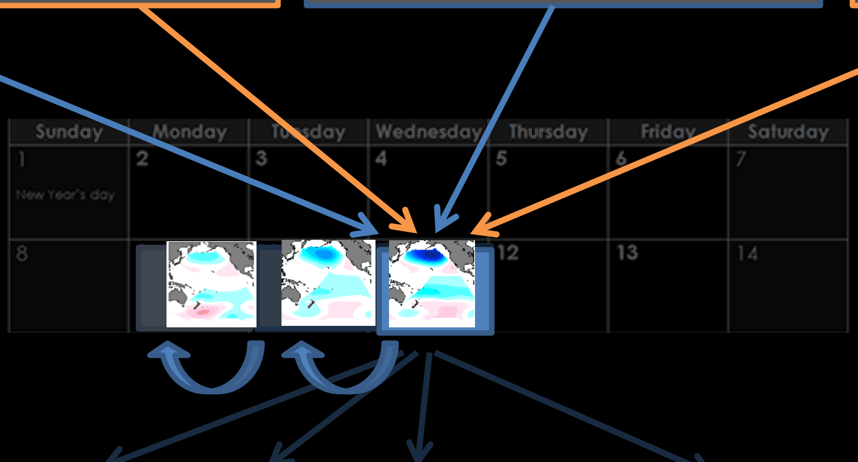
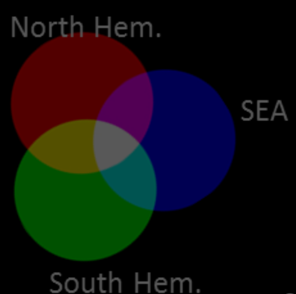
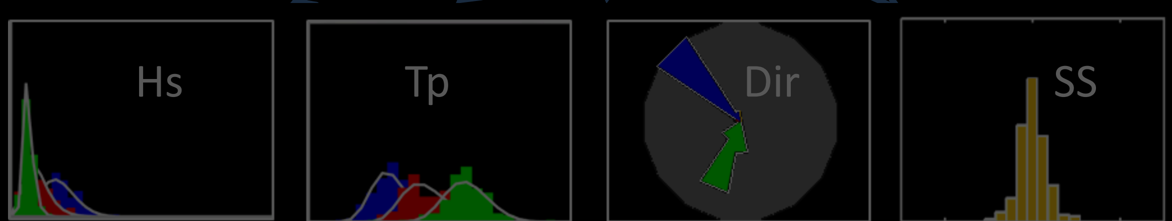




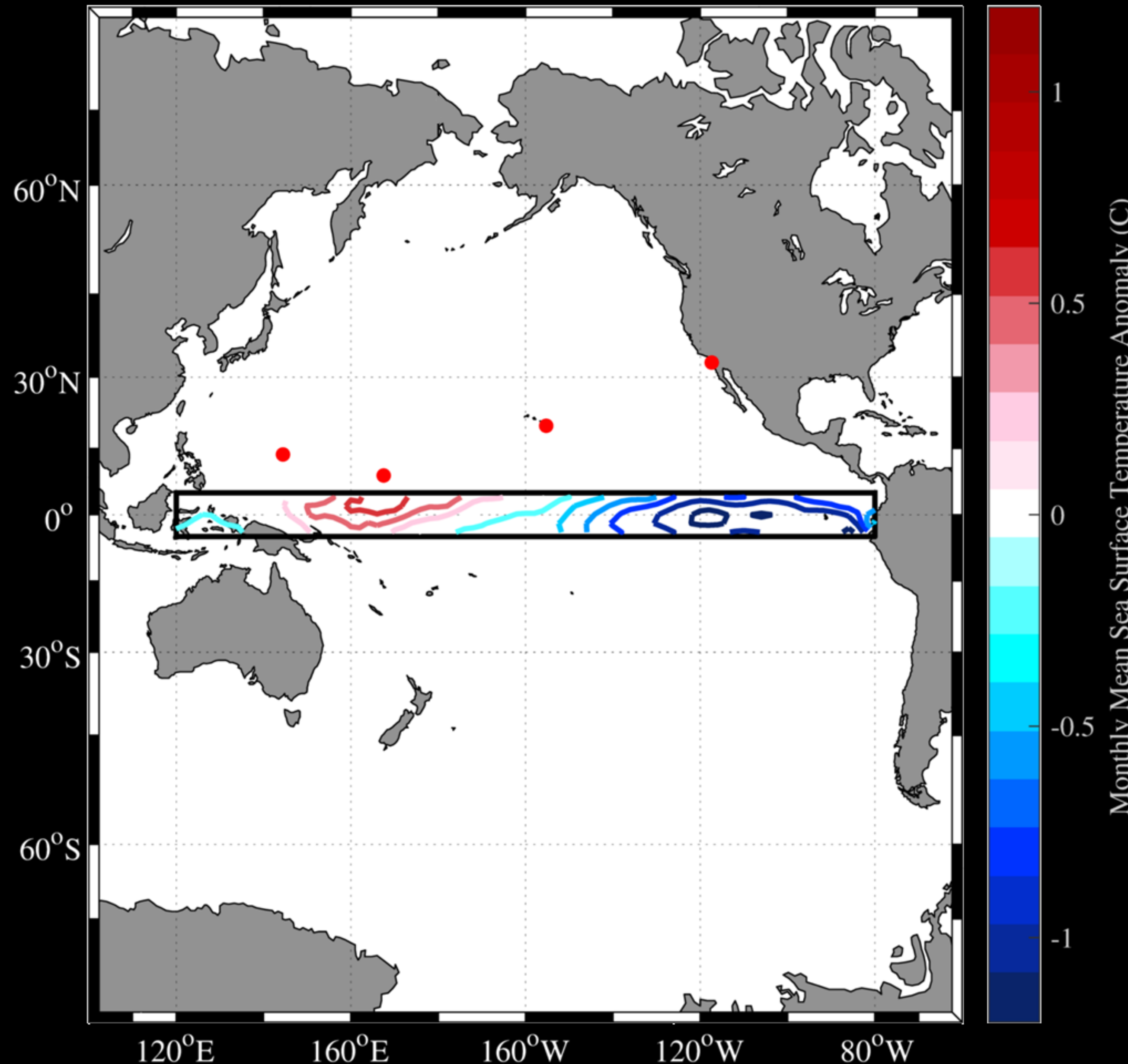


… each DWT has defined wave parameter and water level distributions, which are fed to process-based models

Creating Annual Predictor: X^a

How to simulate large-scale ENSO variability?

Philosophy: a dynamic predictor, capturing changes in both time and space…
Hovmoller Diagrams



ERSSTv4 (NOAA): 1880-present

Creating Annual Predictor: **X**[a]

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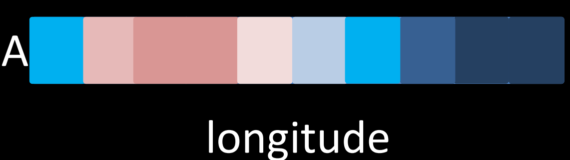

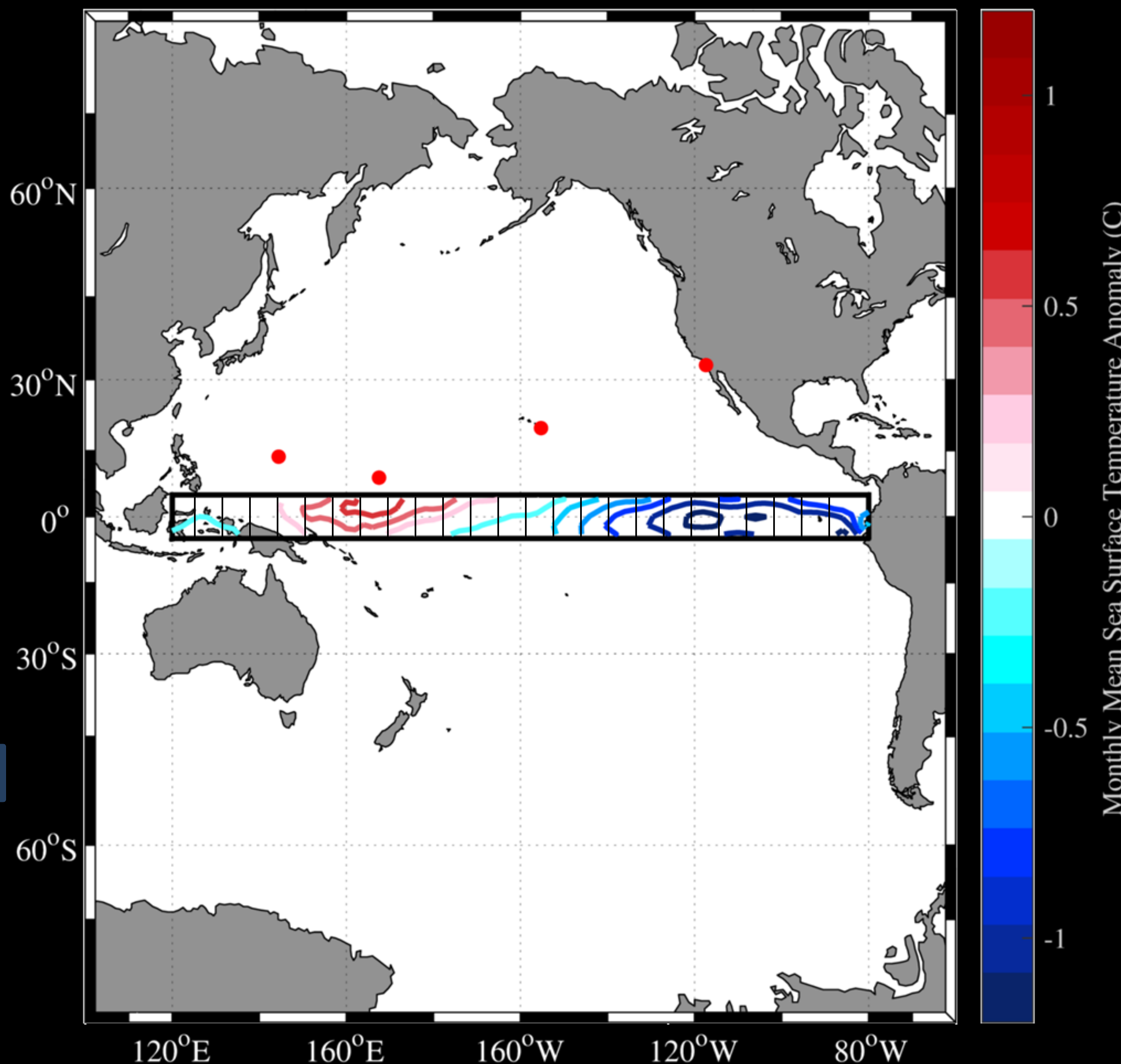

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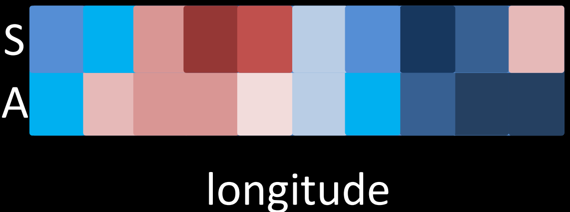

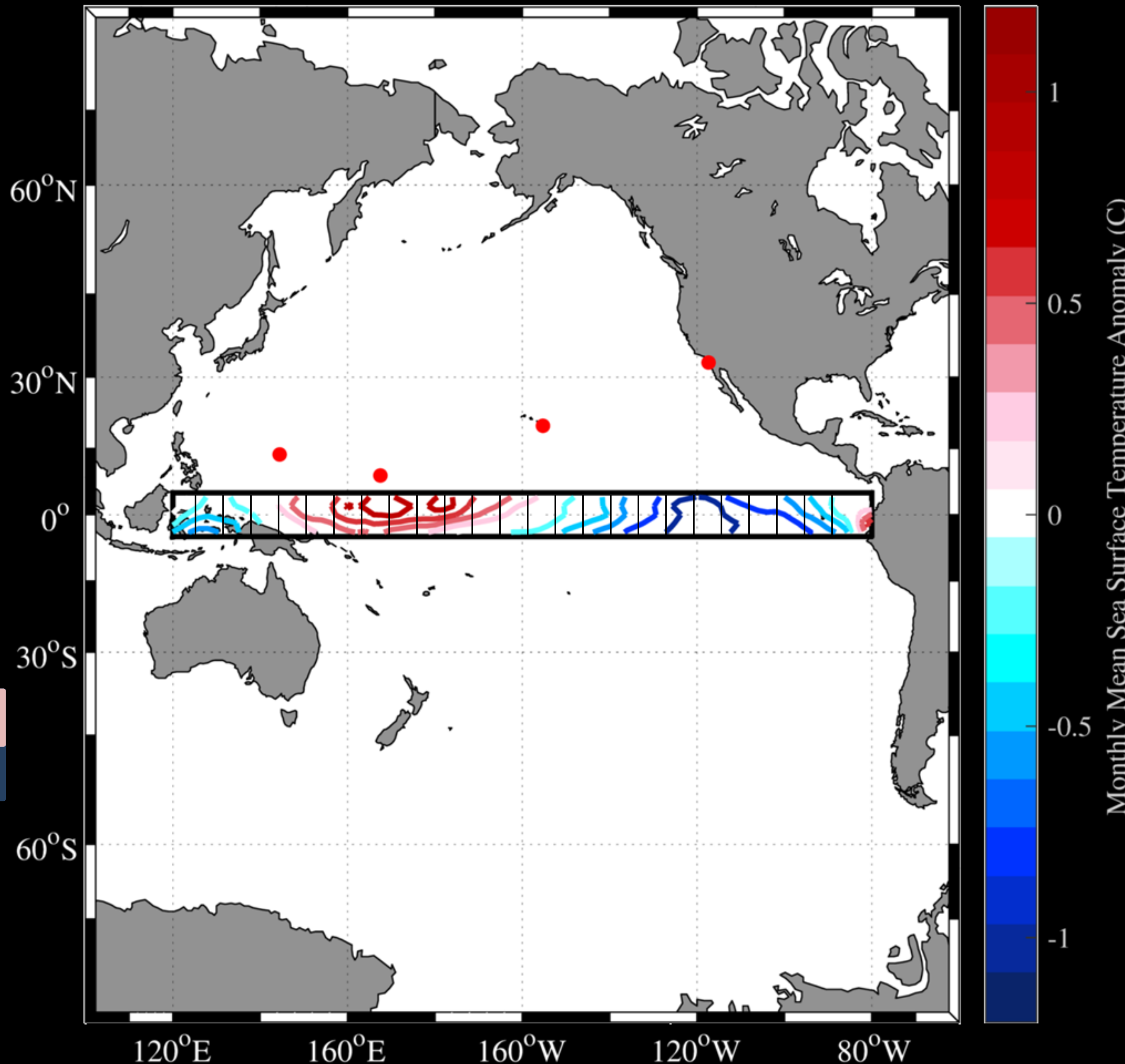

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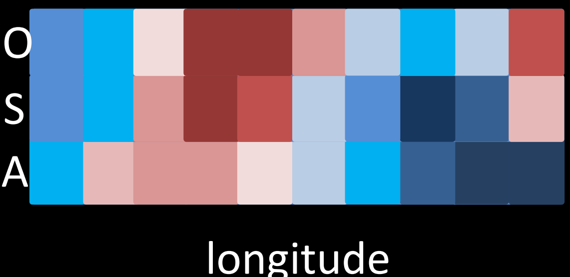

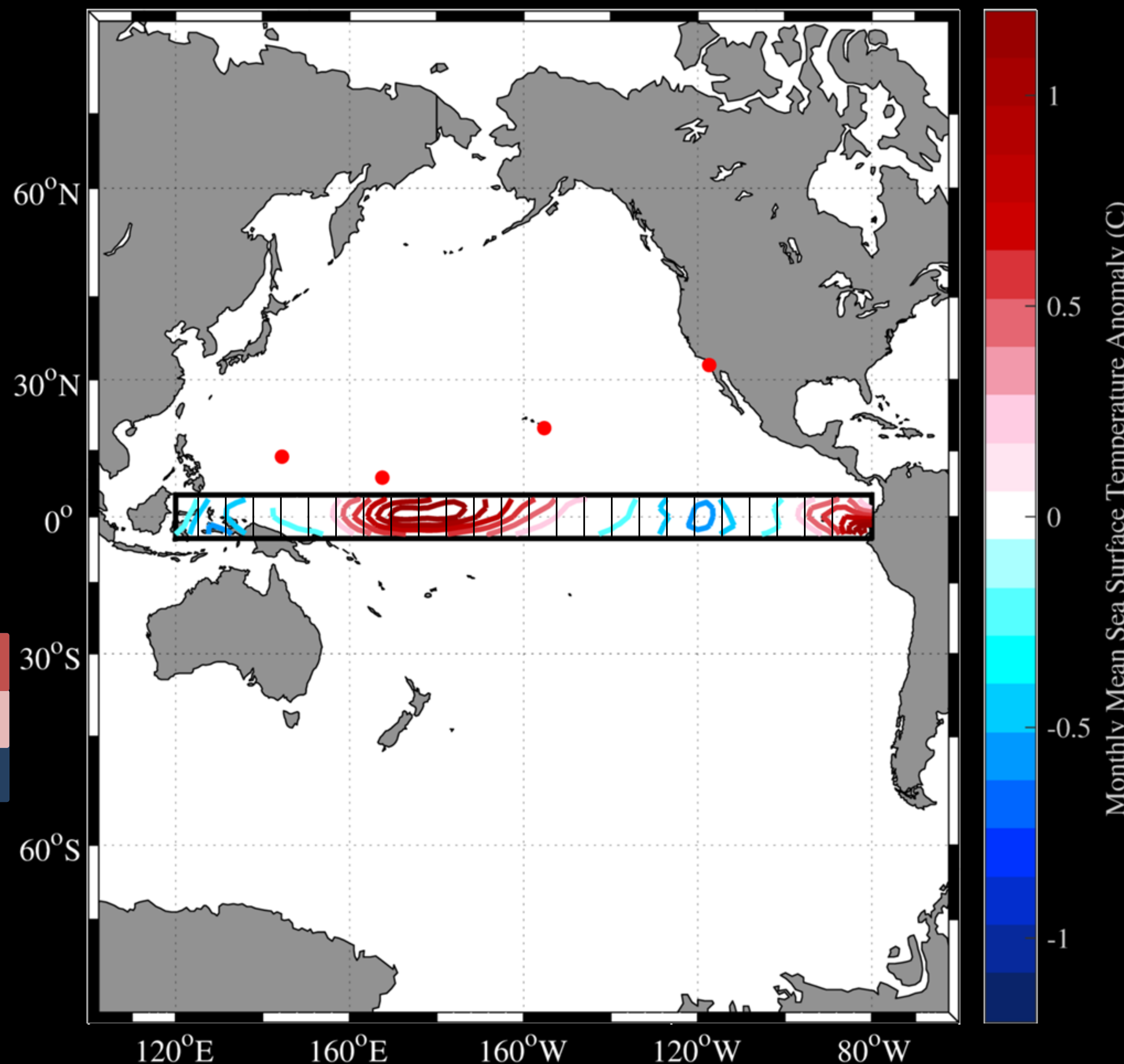

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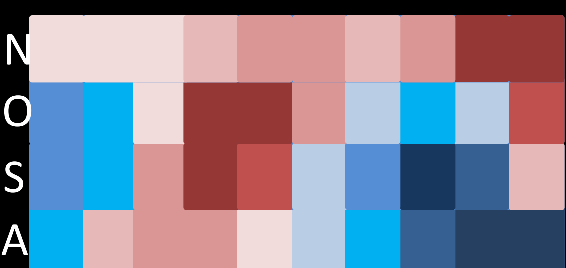

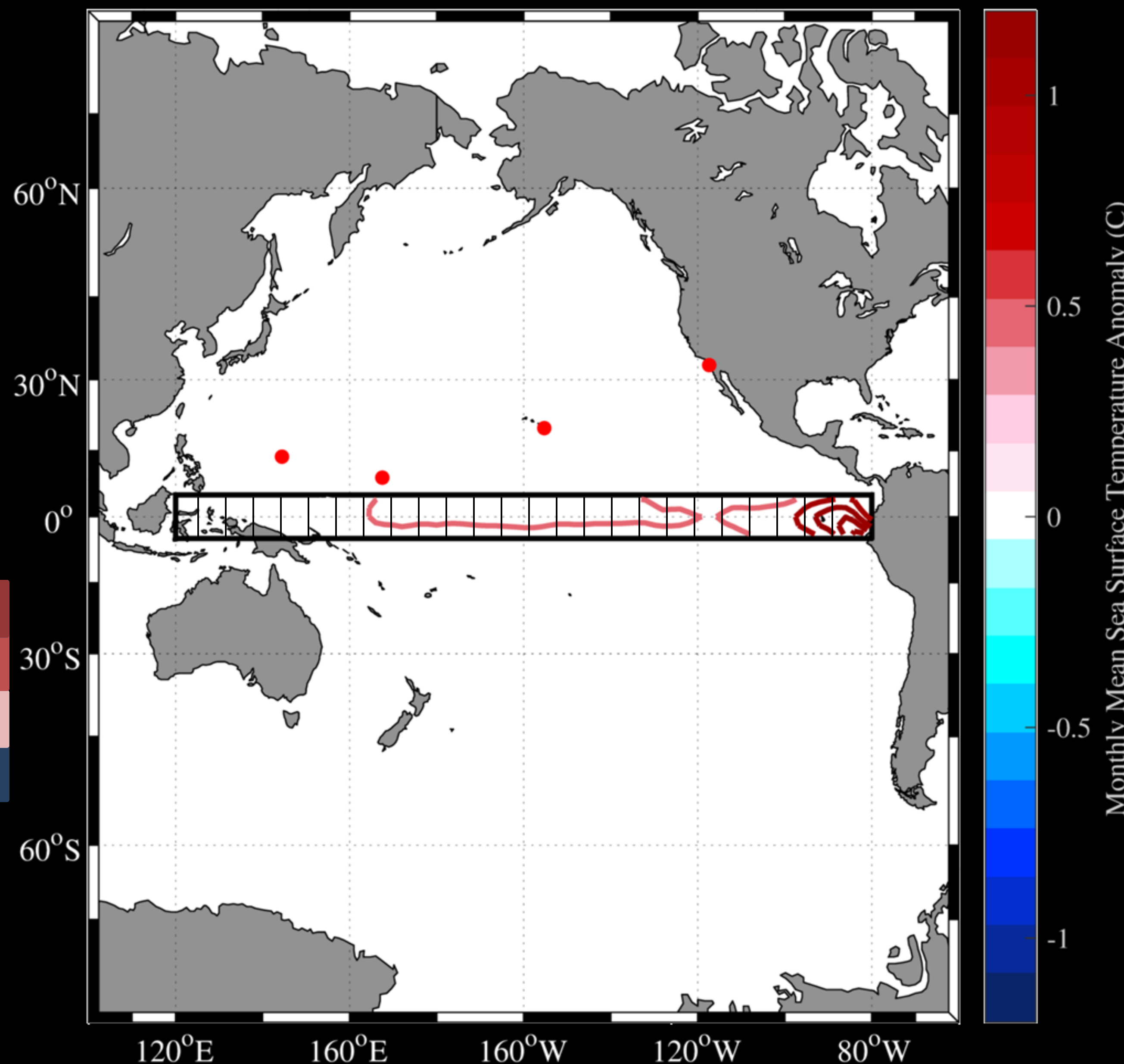

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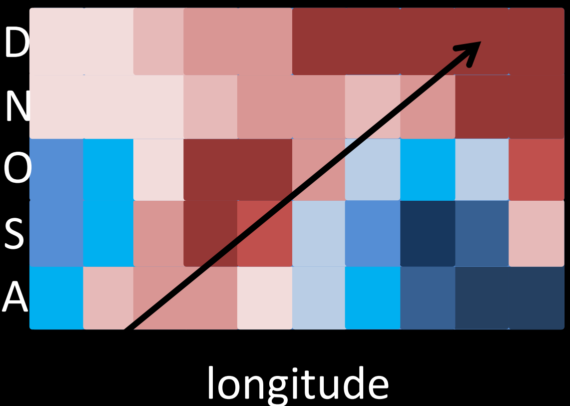
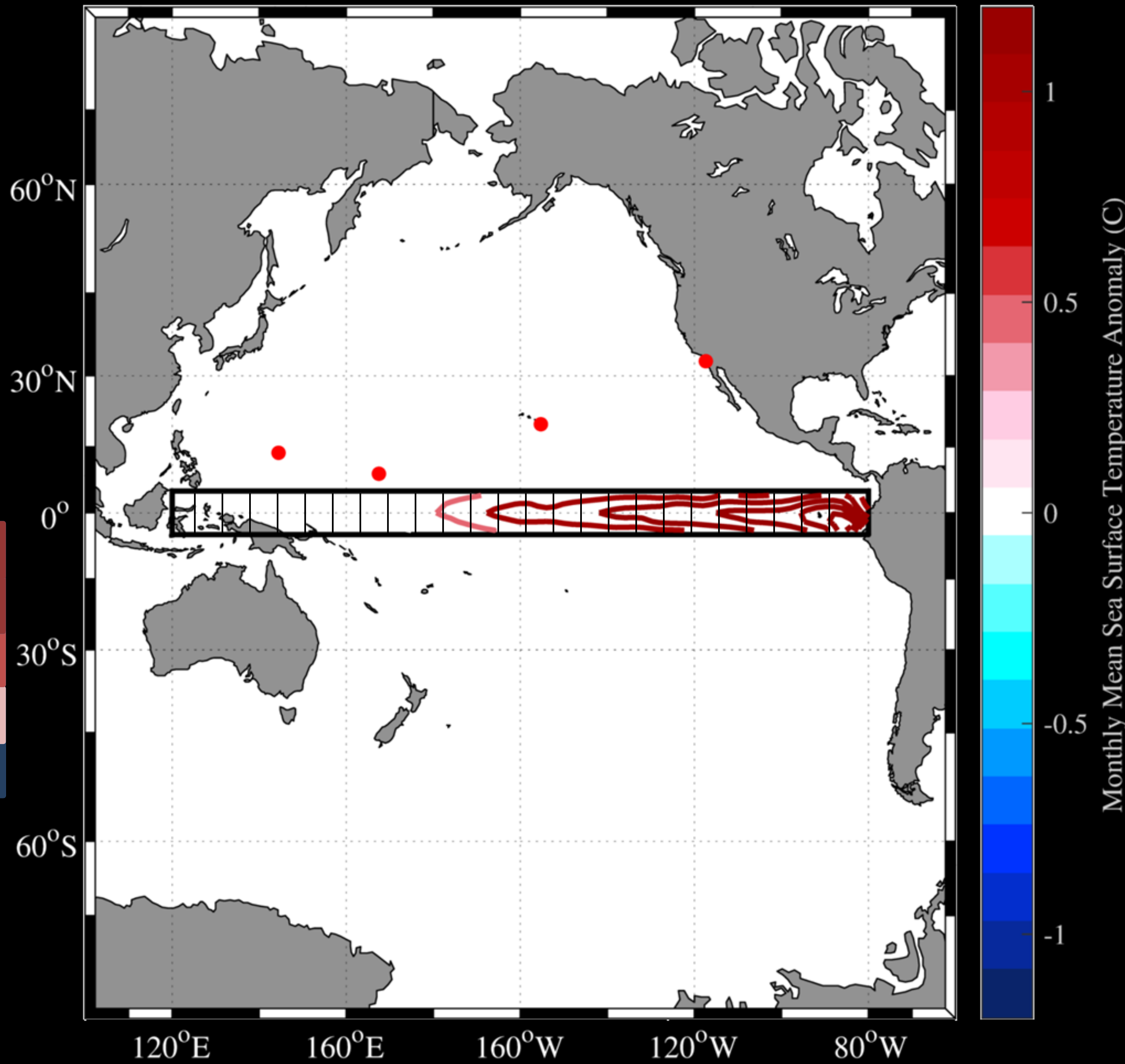
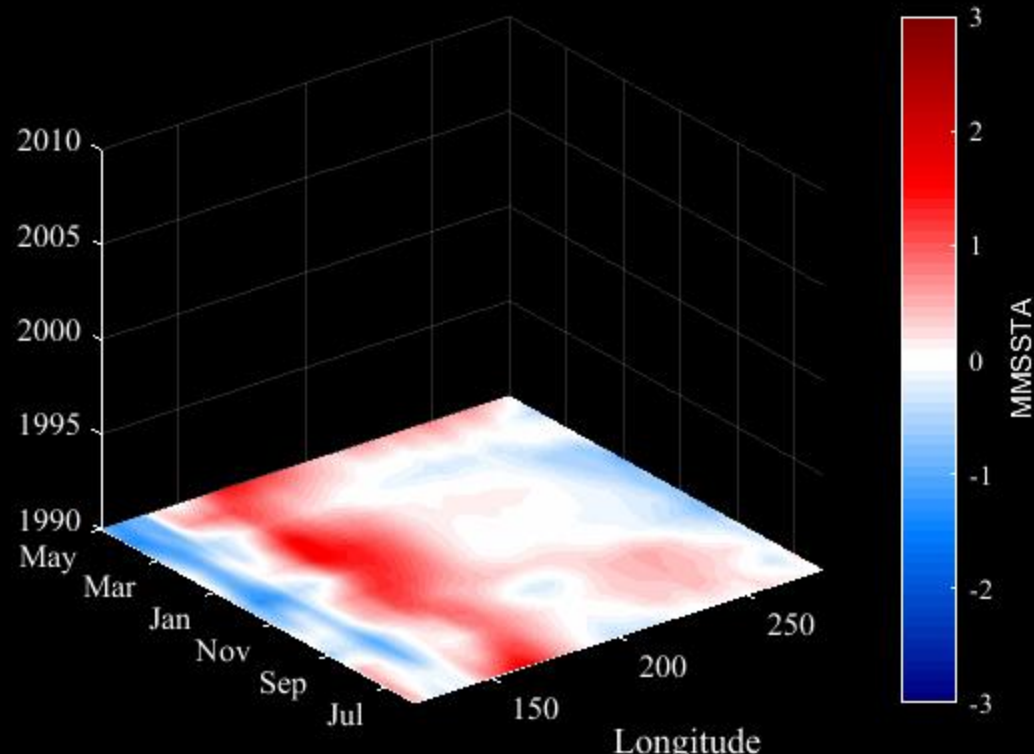


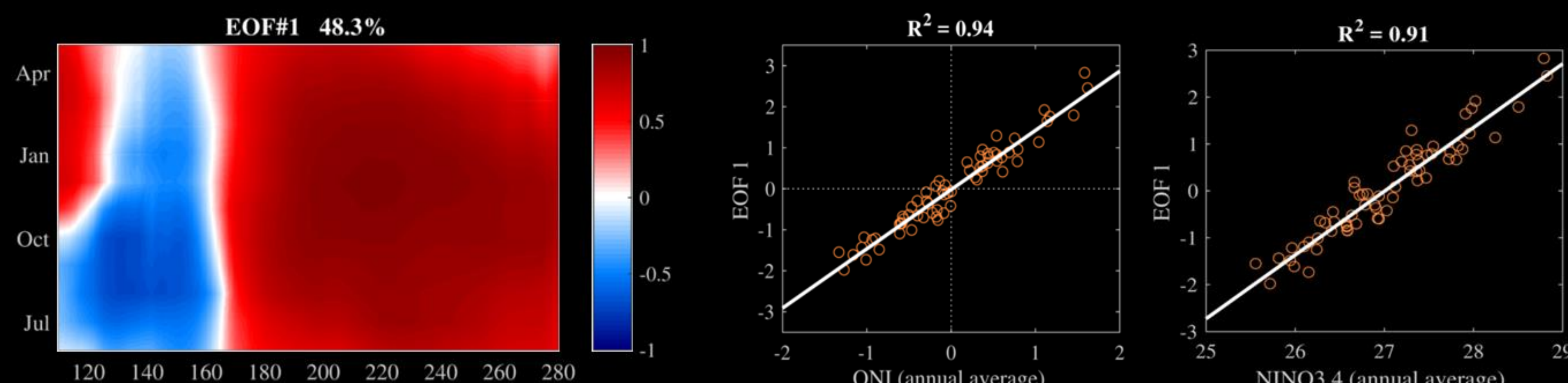


ERSSTv4 (NOAA): 1880-present

Creating Annual Predictor: **X^a**

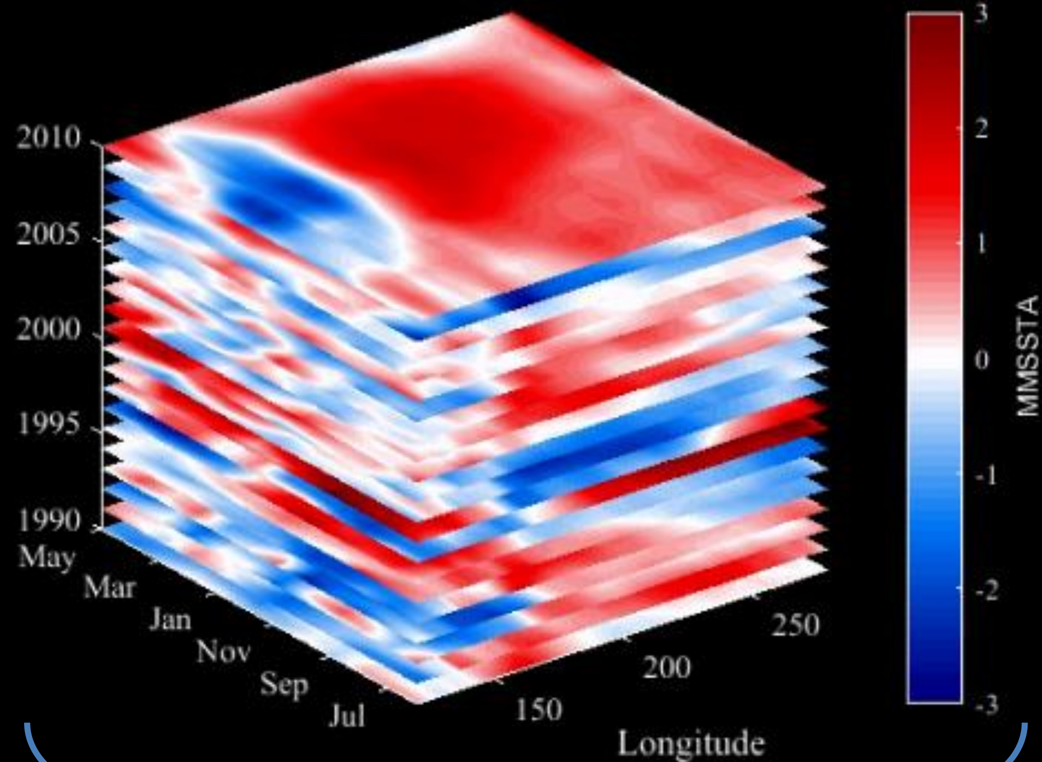


Principle Component Analysis: Identify dominant modes of variability in "Hovmoller" space

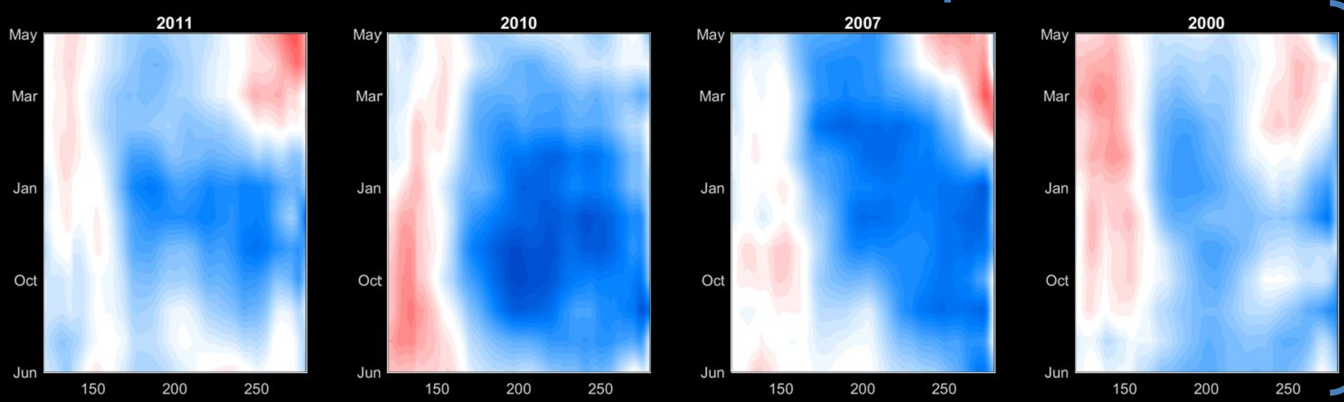


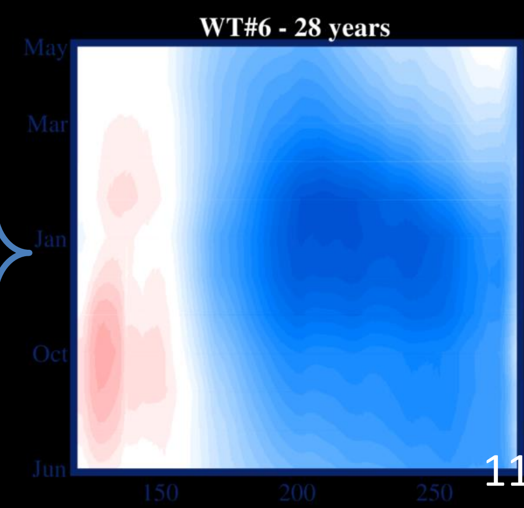
Creating Annual Predictor: $\mathbf{X}^a$

ERSSTv4 (NOAA)
1880-present

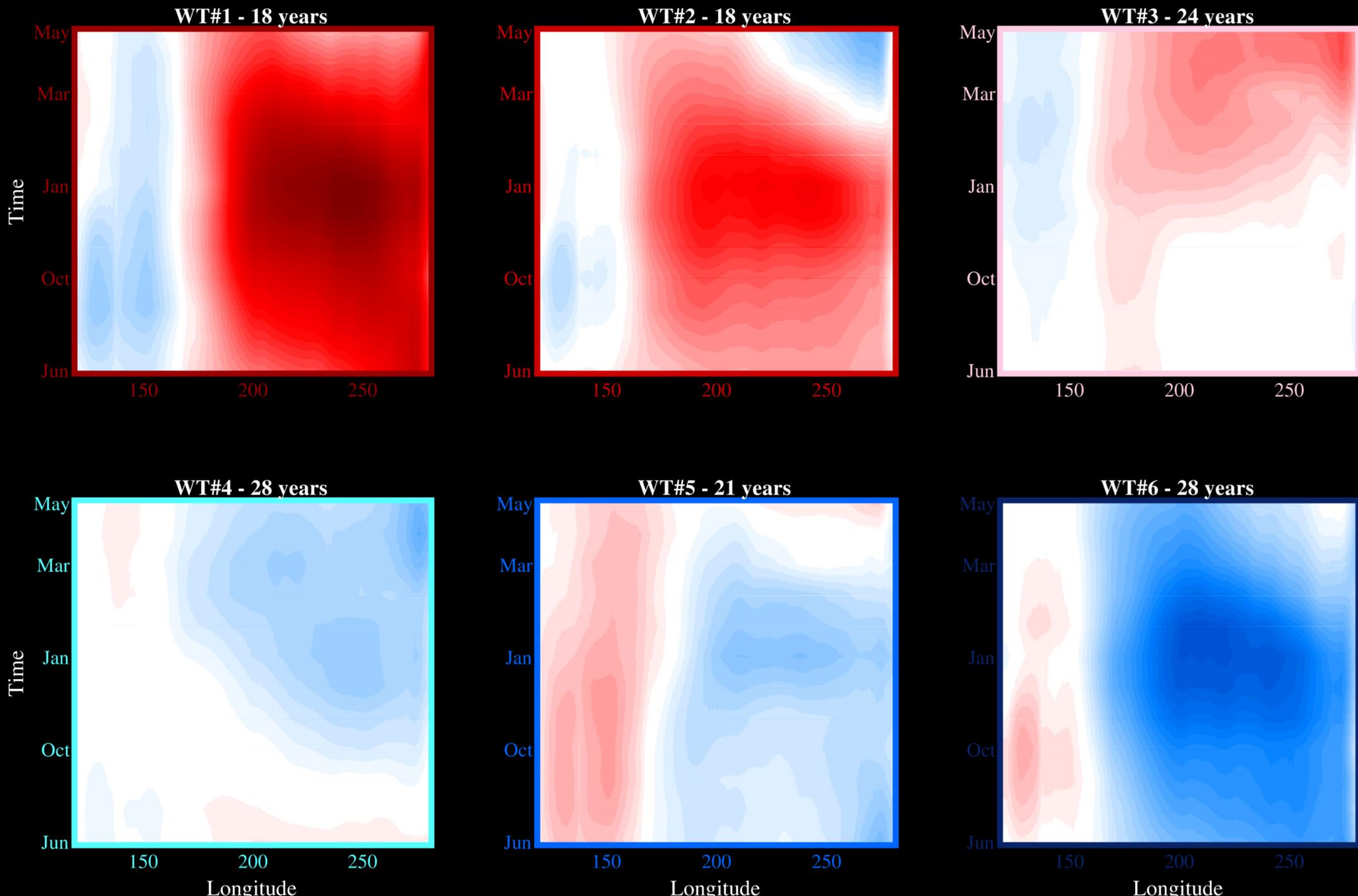


<u>Clustering in PC-space</u>: Identify representative patterns by K-mean clustering of $PC_{1,2,3}$



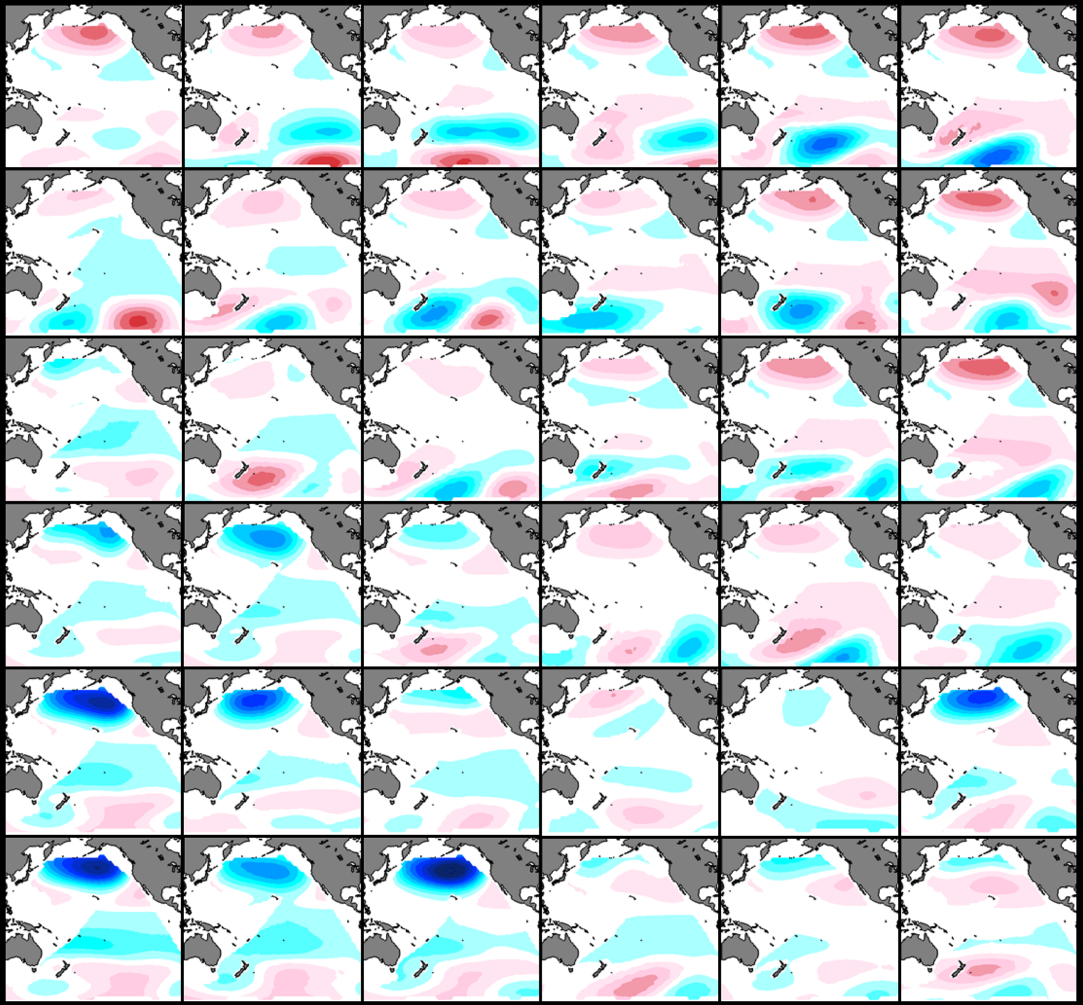


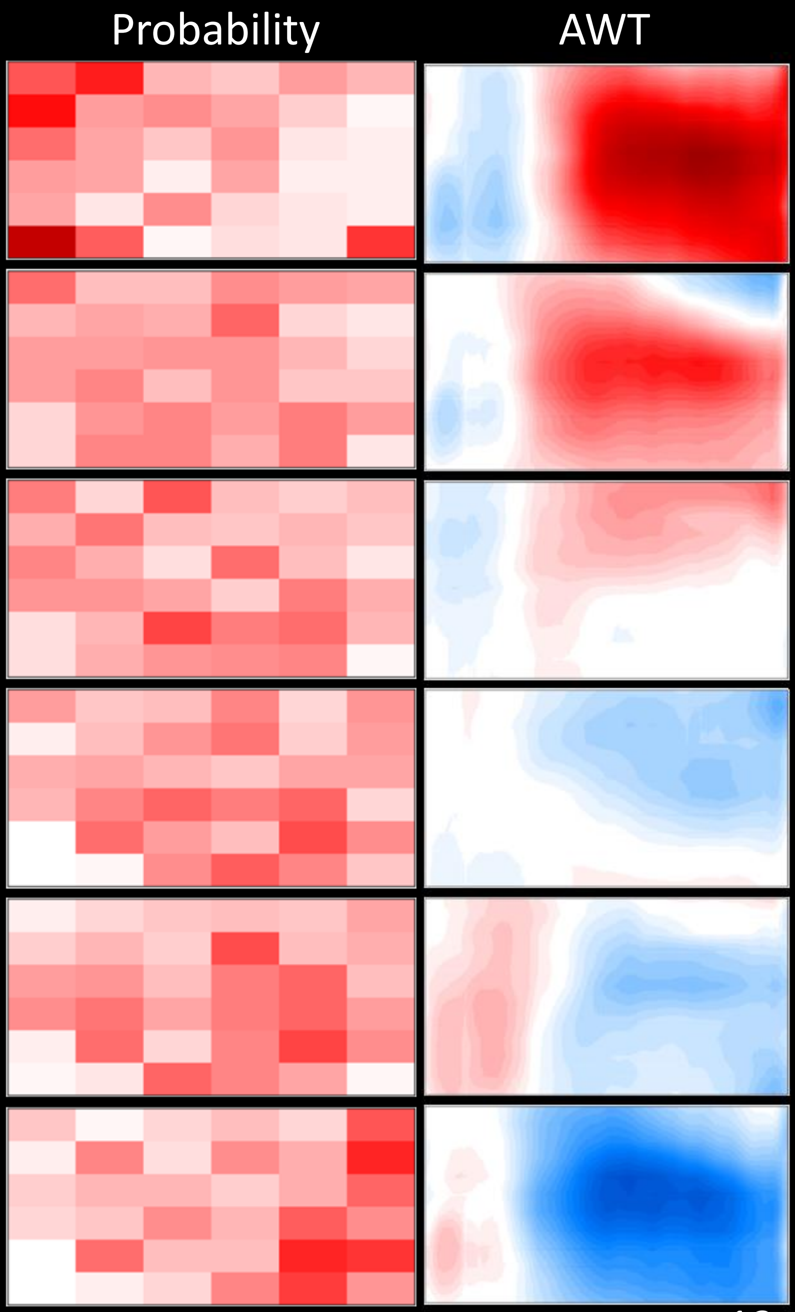
East Pacific El Nino | Modoki El Nino | Warm transition year



Cold transition year | Modoki La Nina | La Nina

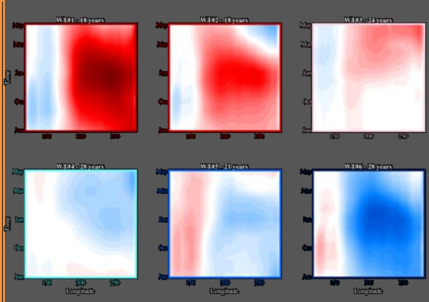
Large-scale ENSO affects the probabilities of daily meterological patterns!



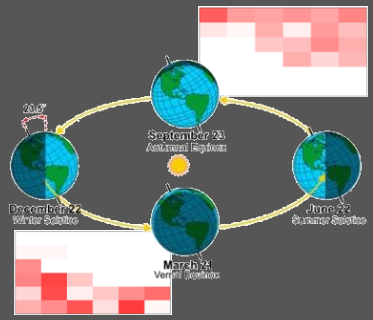


Goal: Daily Chronology model…

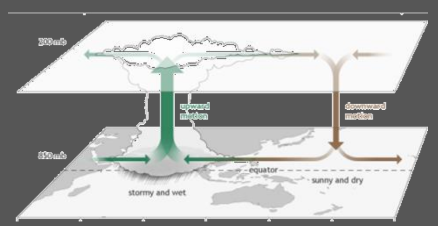
Annual Predictor



Seasonality

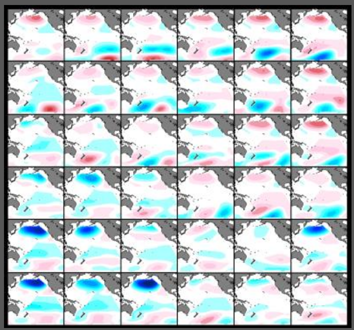


Intra-seasonal Predictor

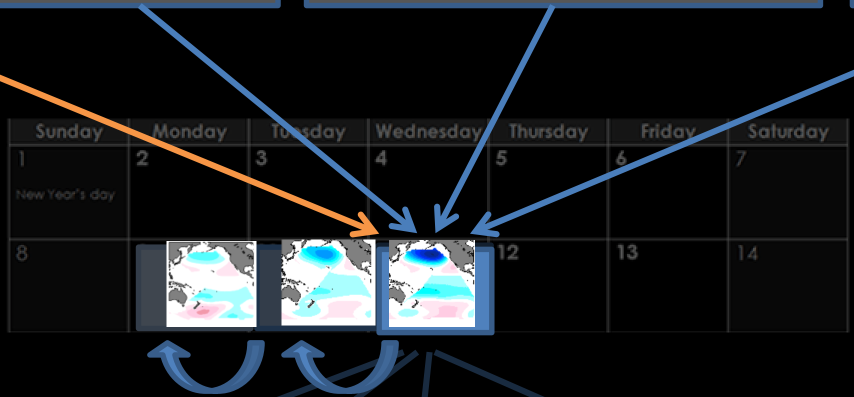


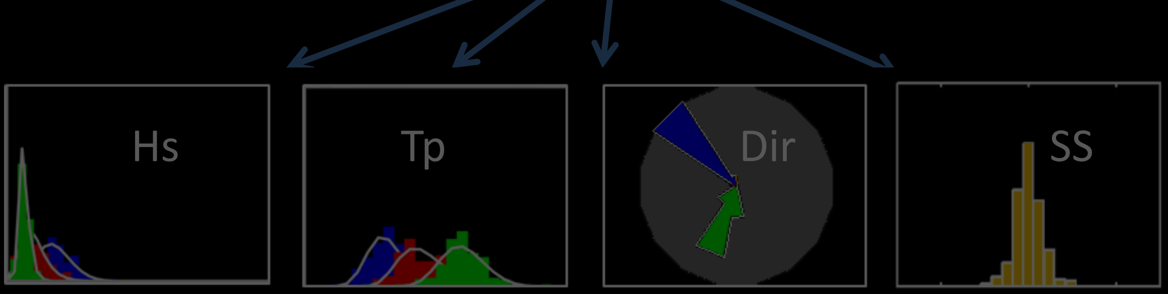
1 to 2 month
Global atmospheric circ.

Daily Predictor



… each day is assigned
a Daily Weather Type …

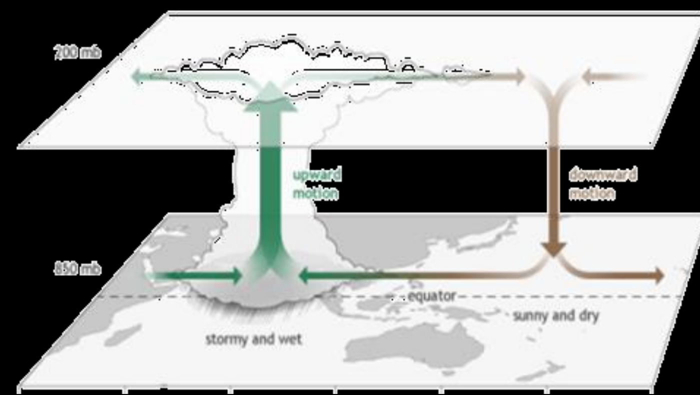


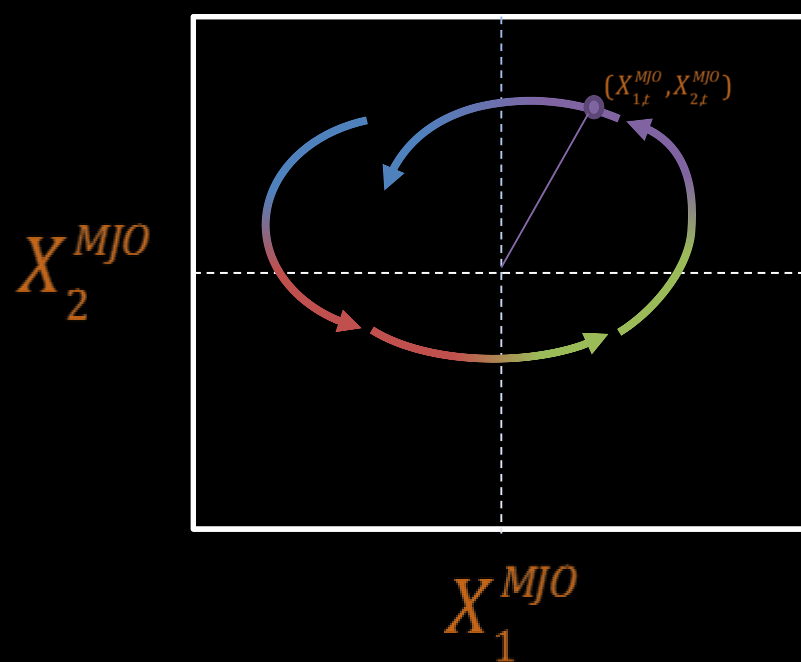


… each DWT has defined wave parameter and water level distributions, which are fed to process-based models

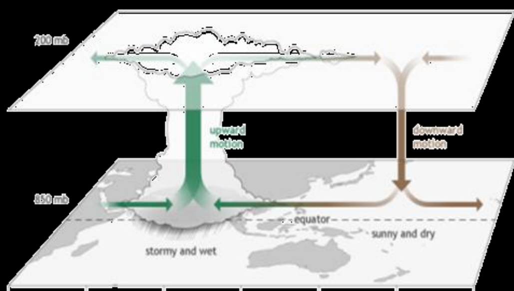
Intraseasonal Predictor: Madden Julian Oscillation

$$\mathbf{X}_t^{MJO} = \begin{cases} (X_{1,t}^{MJO}, X_{2,t}^{MJO}) \\ \varphi_t^{MJO} \in \{1,\dots,8\} \end{cases}$$

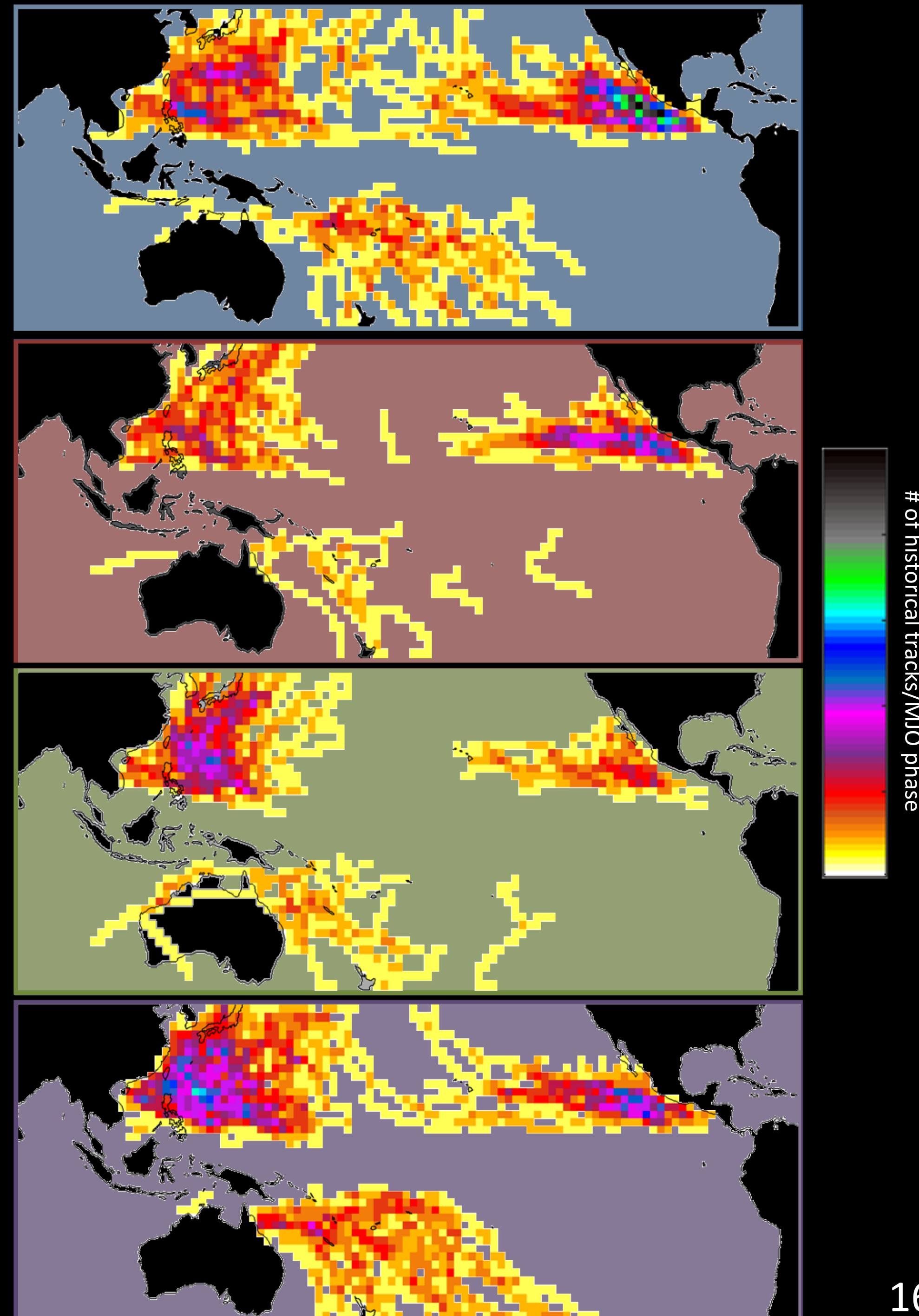




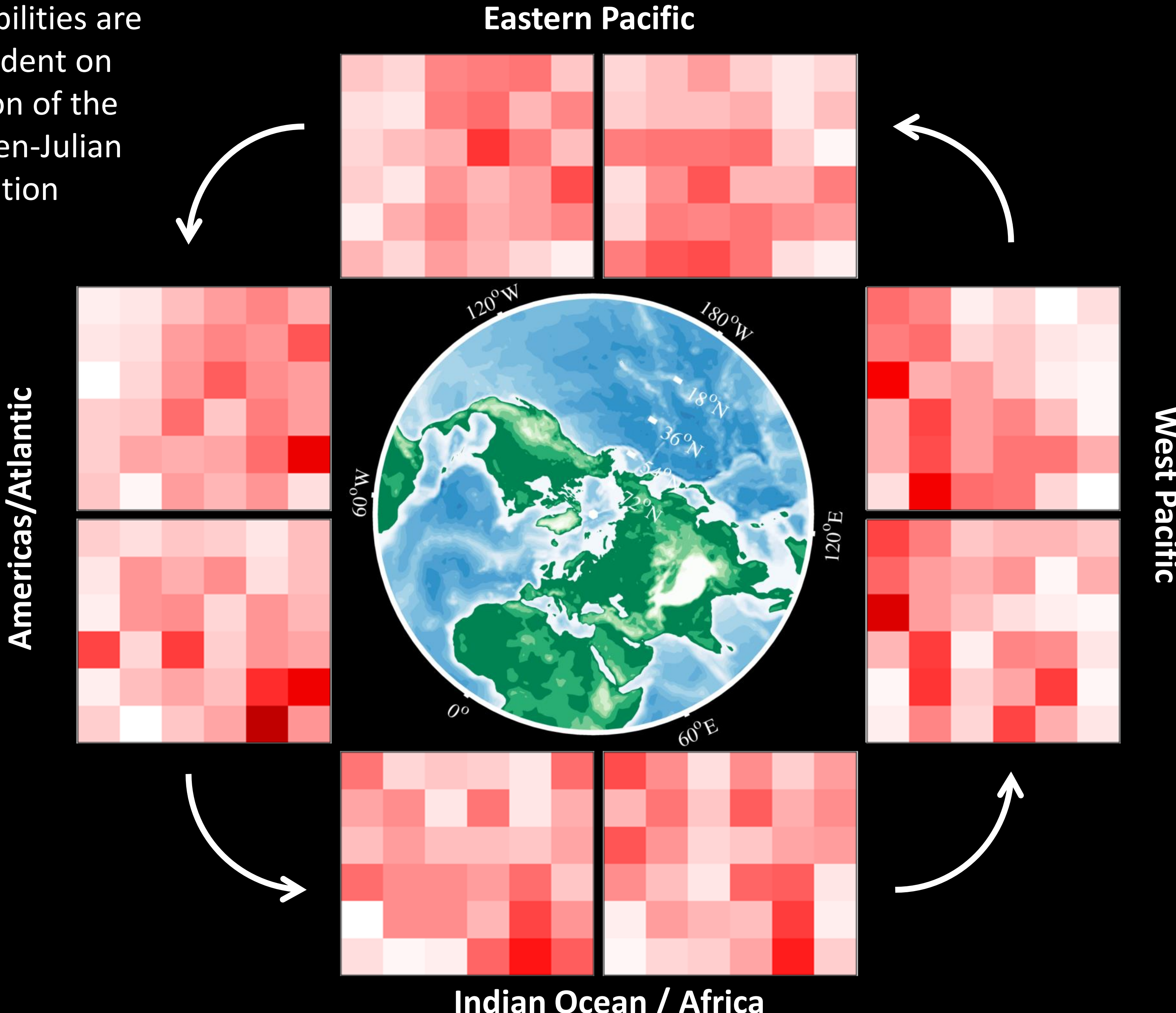
Intraseasonal Predictor:
Madden Julian Oscillation



MJO has a clear affect on Tropical Cyclone frequency and tracks…

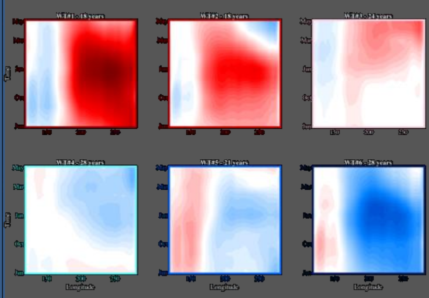


Probabilities are dependent on location of the Madden-Julian Oscillation

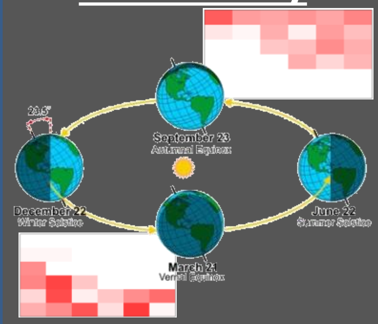


Goal: Daily Chronology model…

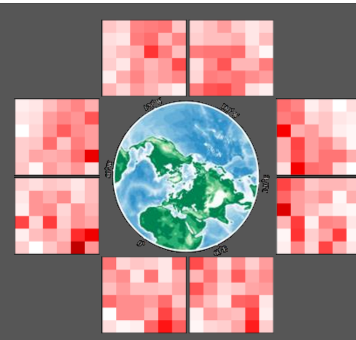
Annual Predictor



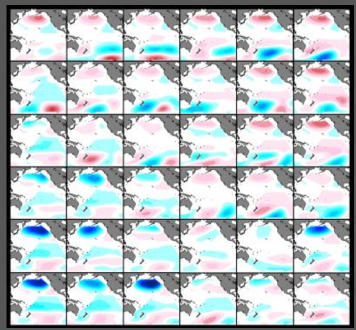
Seasonality



Intra-seasonal Predictor



Daily Predictor



… each day is assigned a Daily Weather Type …

… each DWT has defined wave parameter and water level distributions, which are fed to process-based models

Chronology Model: Climate-based Autoregressive Logistic Model

Categorical time series of DWTs for Extratropical Cyclones (ET) and Tropical Cyclones (Cat_i)

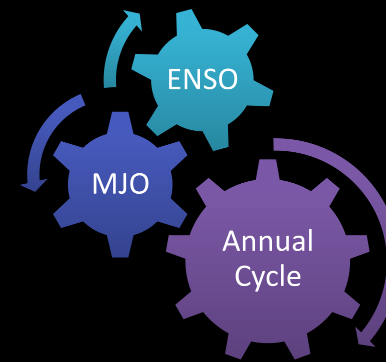
$$\Pr(DWT_t = i \mid DWT_{t-1},\dots,DWT_{t-e},\mathbf{X}_t^a,\mathbf{X}_t^m,\mathbf{X}_t^{MJO}) =$$

$$= \frac{\exp(\alpha_i + \beta_i \mathbf{X}_t + \sum_{j=1}^{e} \gamma_{ij} DWT_{t-j}^d)}{\sum_{k=1}^{n_{DWT}} \exp(\alpha_k + \beta_k \mathbf{X}_t + \sum_{j=1}^{e} \gamma_{kj} DWT_{t-j}^d)};\forall i = 1,\dots,n_{DWT}$$

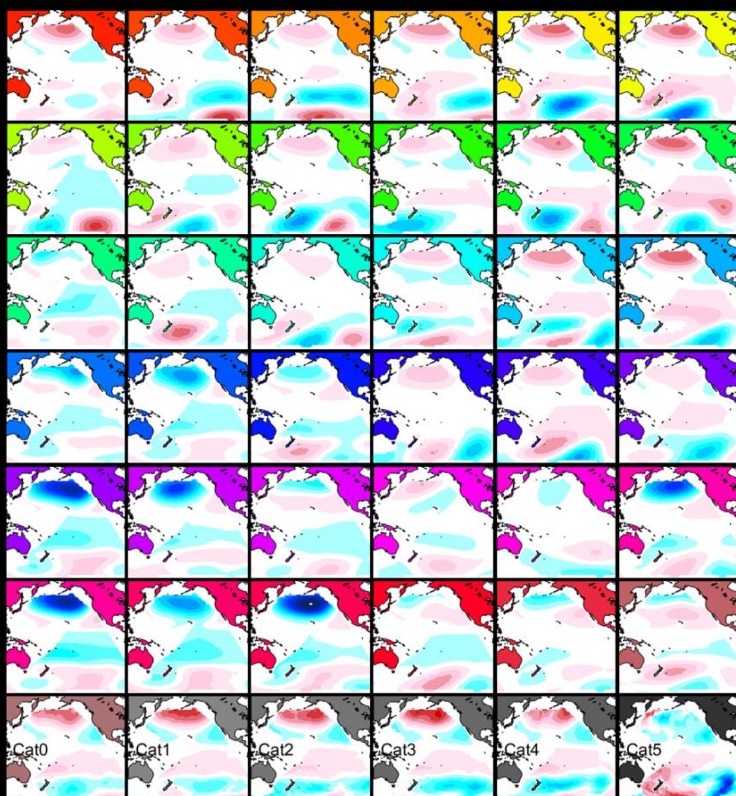
$$ET_t^d \in \{1,\dots,n_{ET}\}$$

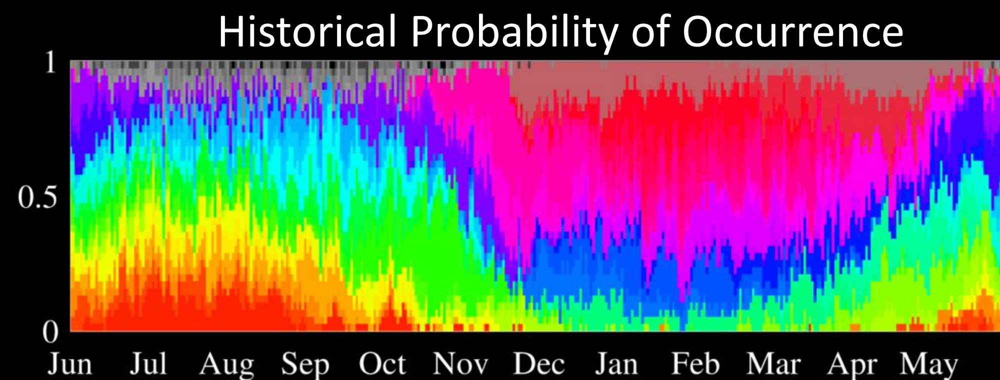
$$TC_t^d \in \{C_0,\dots,C_5\}$$

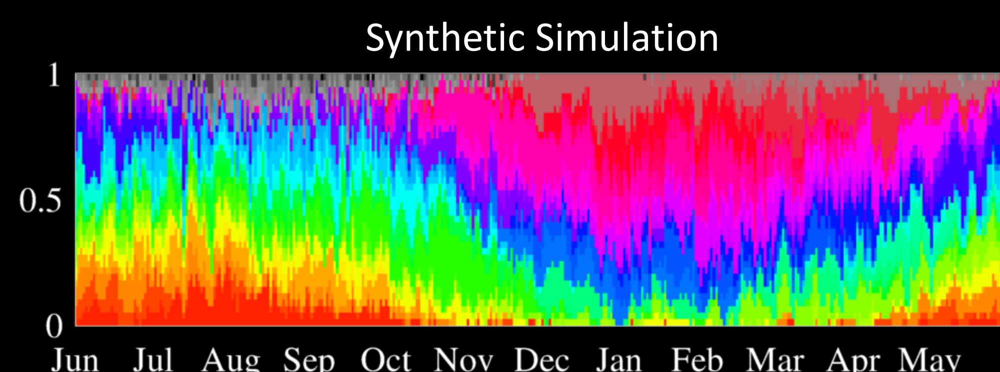
$$DWT_t = (ET_t^d \cup TC_t^d) \in \{1,\dots,n_{DWT}\}$$



$$\mathbf{X}_t = (X_{1,t}^a, X_{2,t}^a, X_{3,t}^a, \cos\frac{2\pi t}{T_a}, \sin\frac{2\pi t}{T_a}, X_{1,t}^{MJO}, X_{2,t}^{MJO})$$







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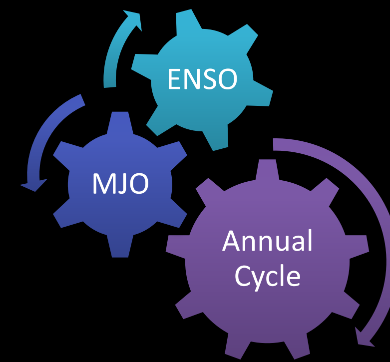
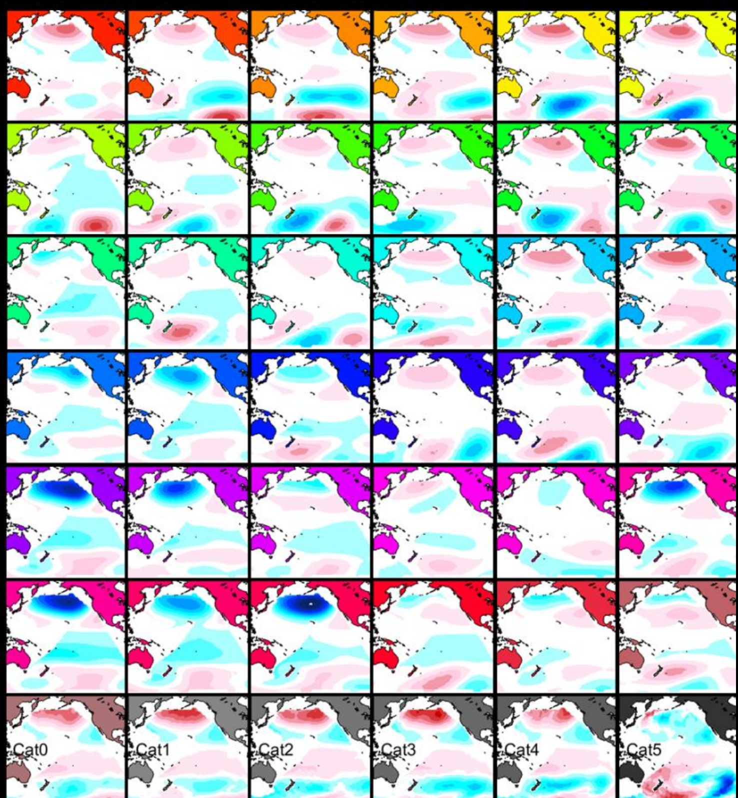
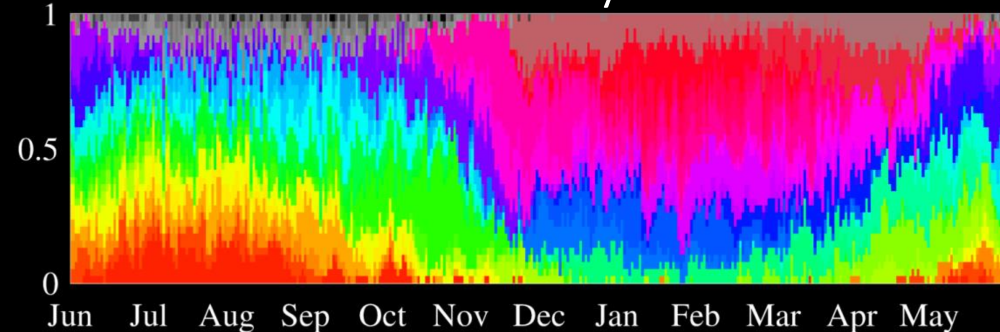


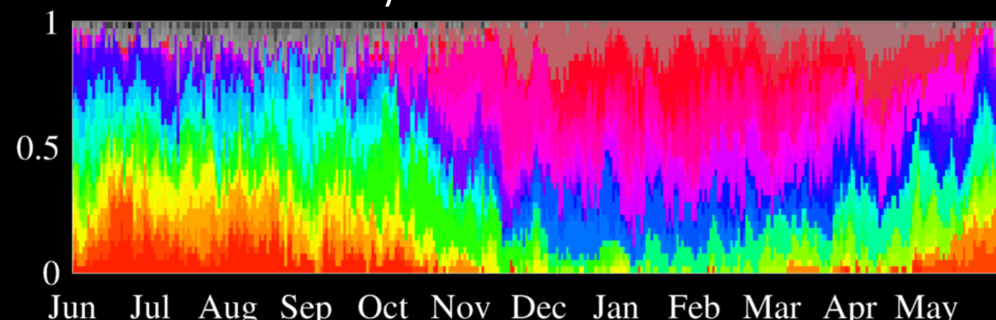
$$\mathbf{X}_t = (X_{1,t}^a, X_{2,t}^a, X_{3,t}^a, \cos\frac{2\pi t}{T_a}, \sin\frac{2\pi t}{T_a}, X_{1,t}^{MJO}, X_{2,t}^{MJO})$$



Historical Probability of Occurrence



Synthetic Simulation



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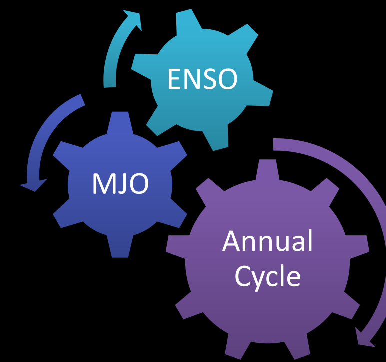

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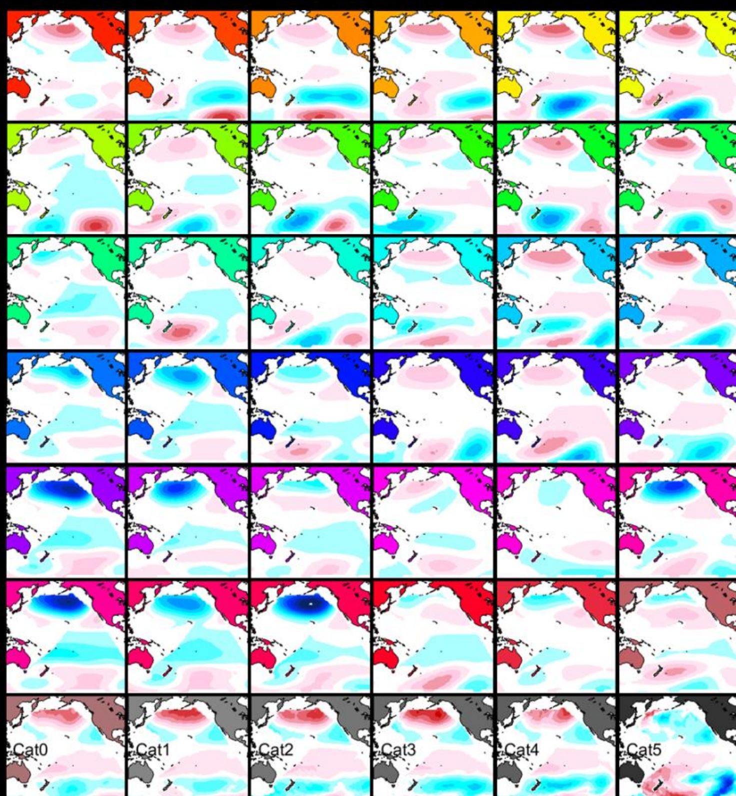

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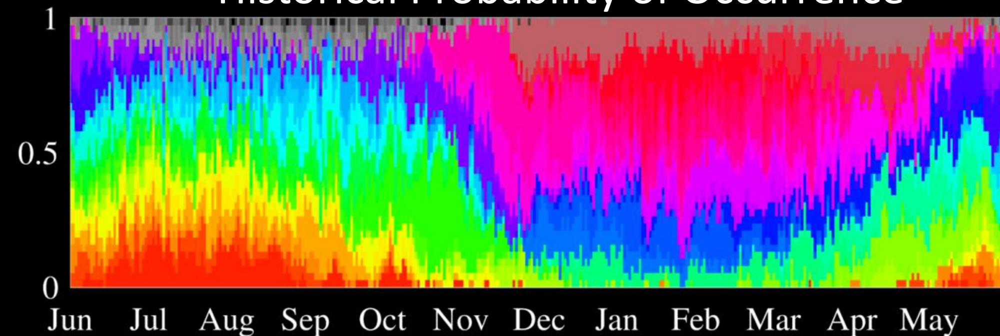

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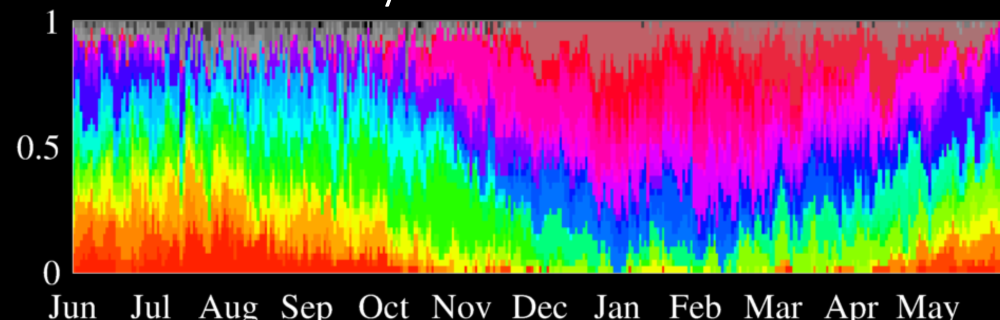

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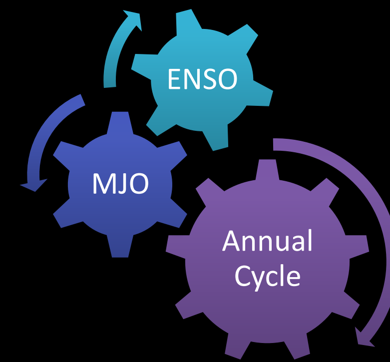

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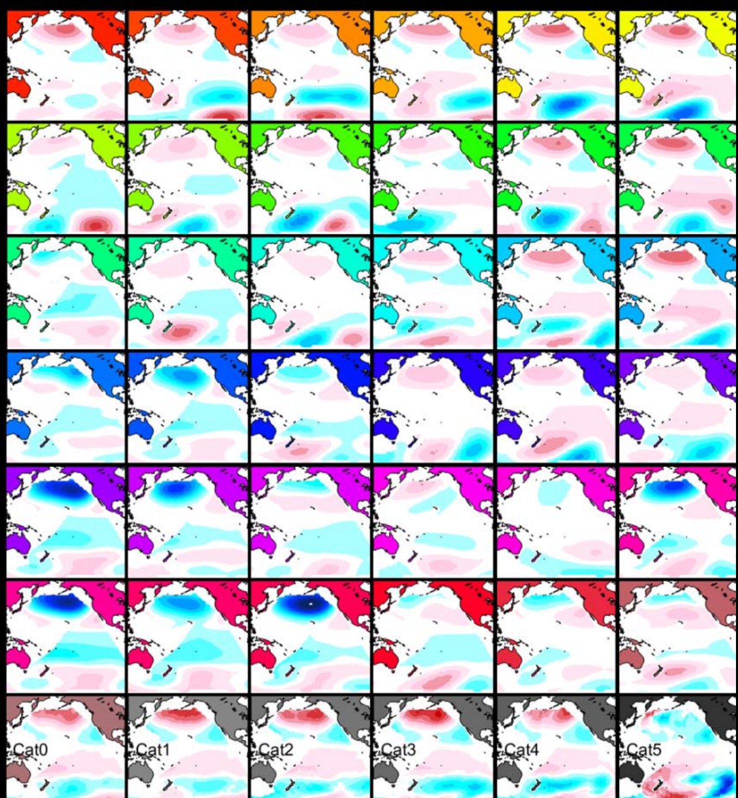

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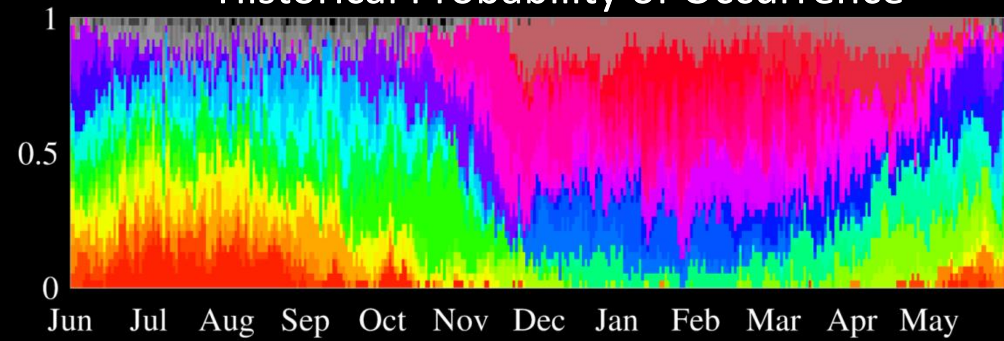
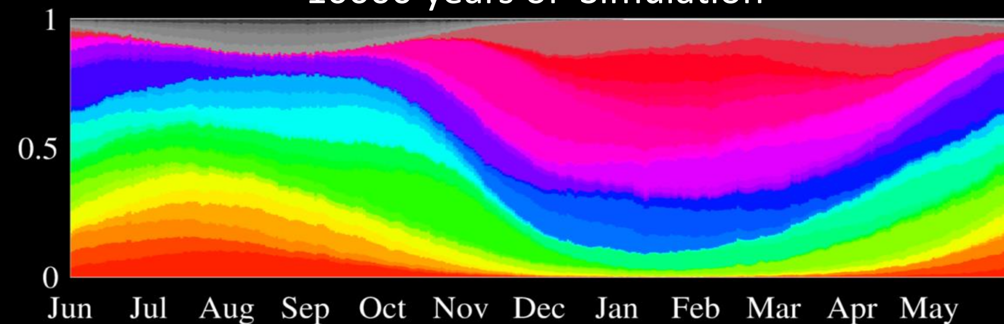
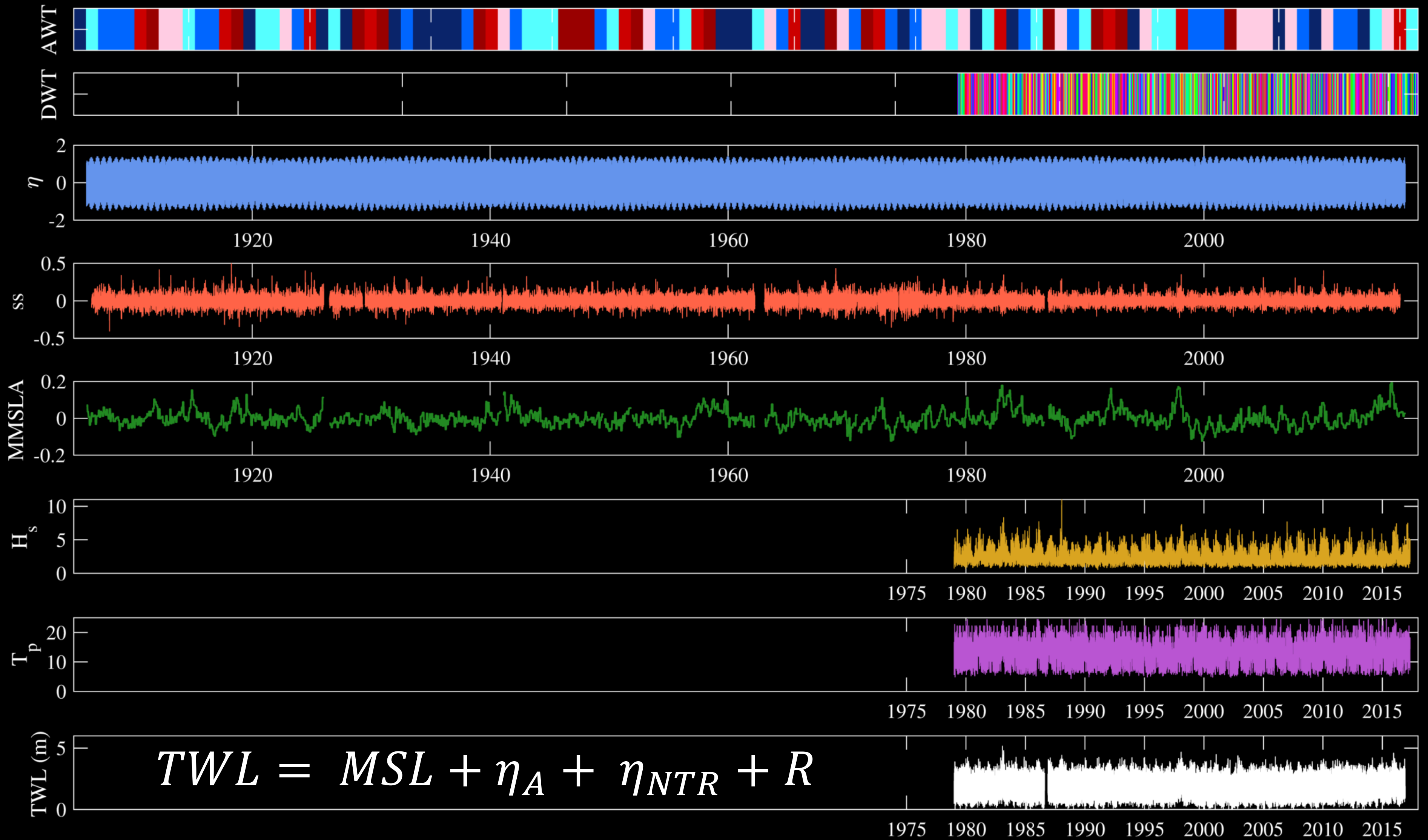


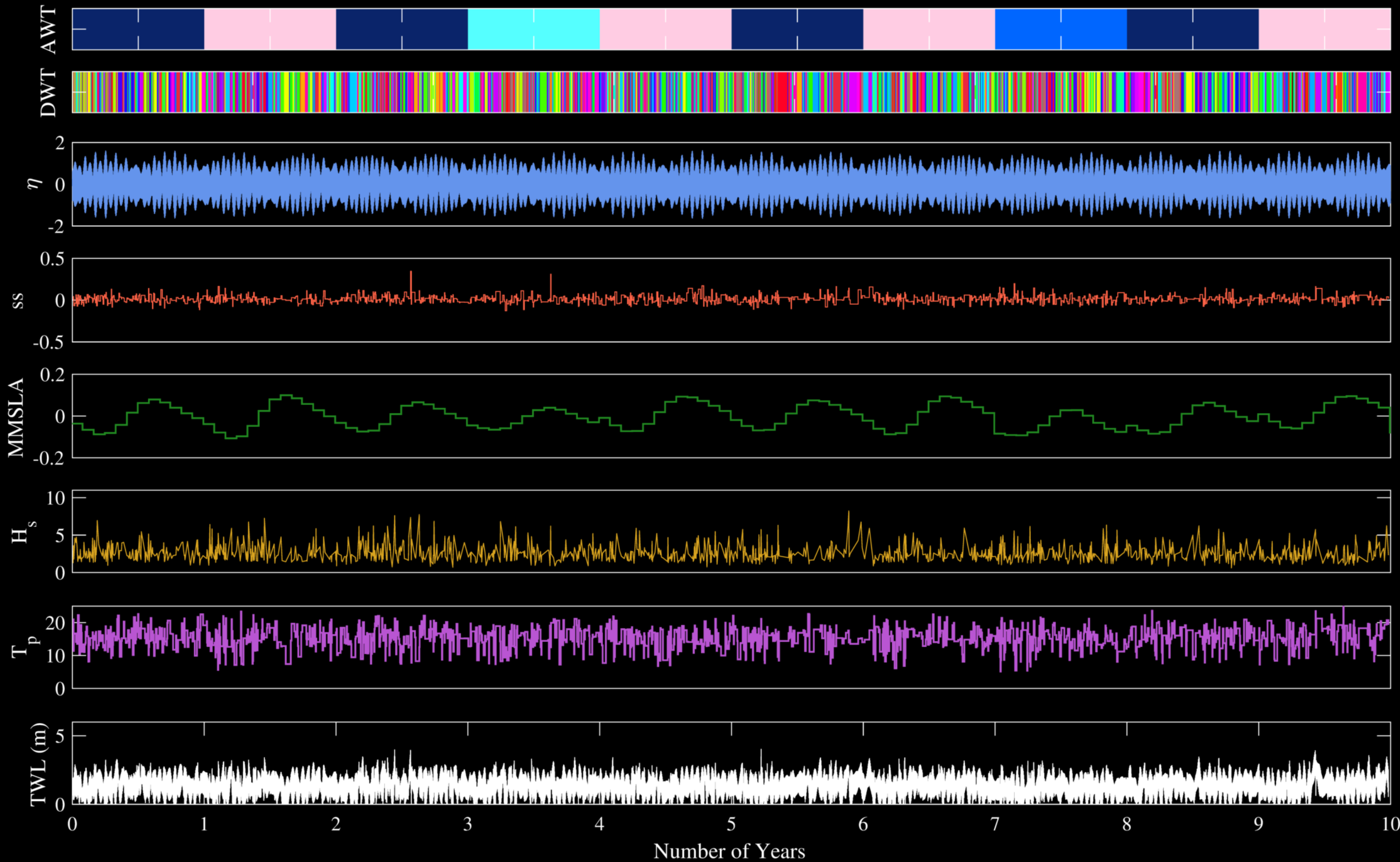
10000 years of Simulation



San Diego Observational Record



San Diego Synthetic Record



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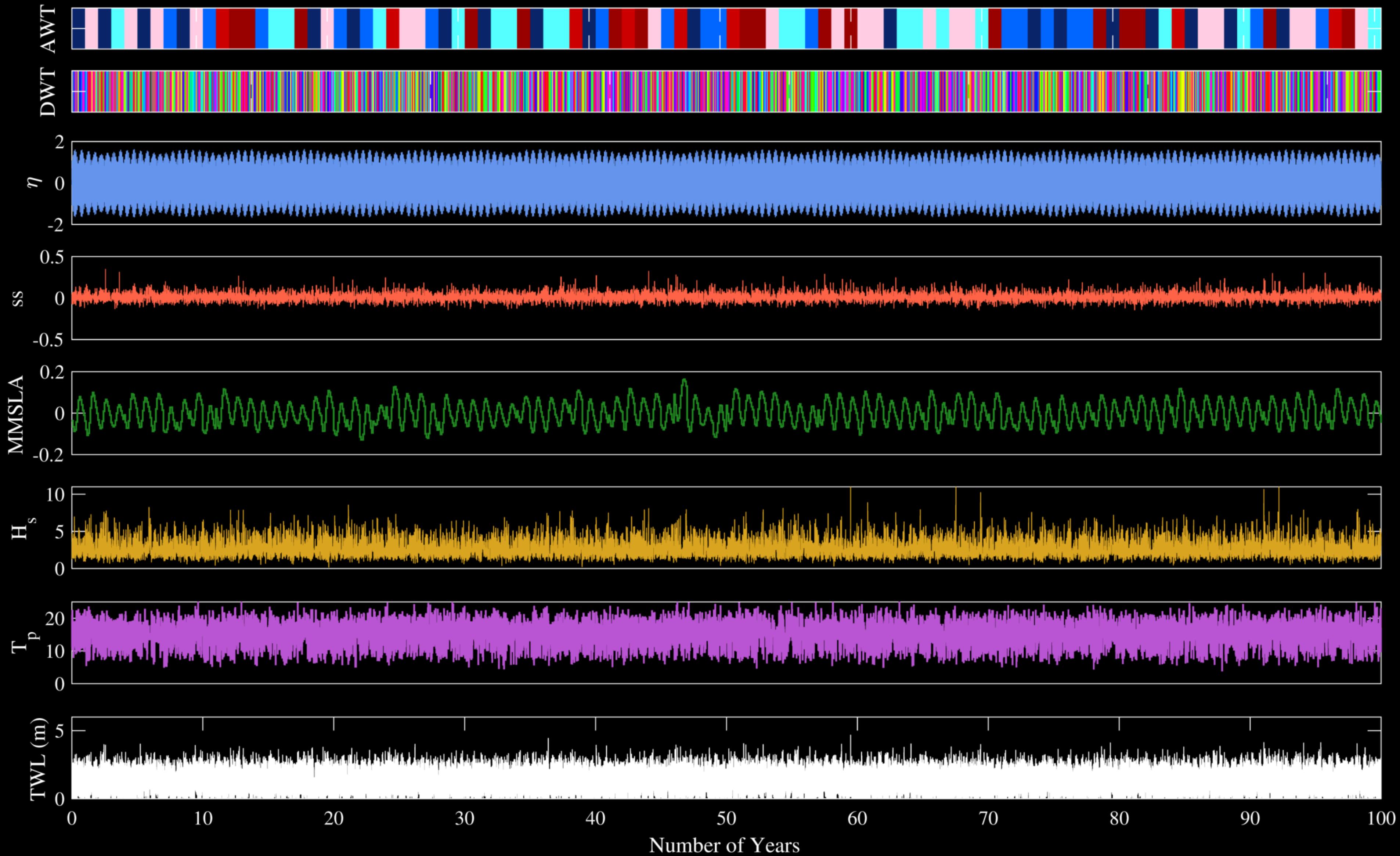
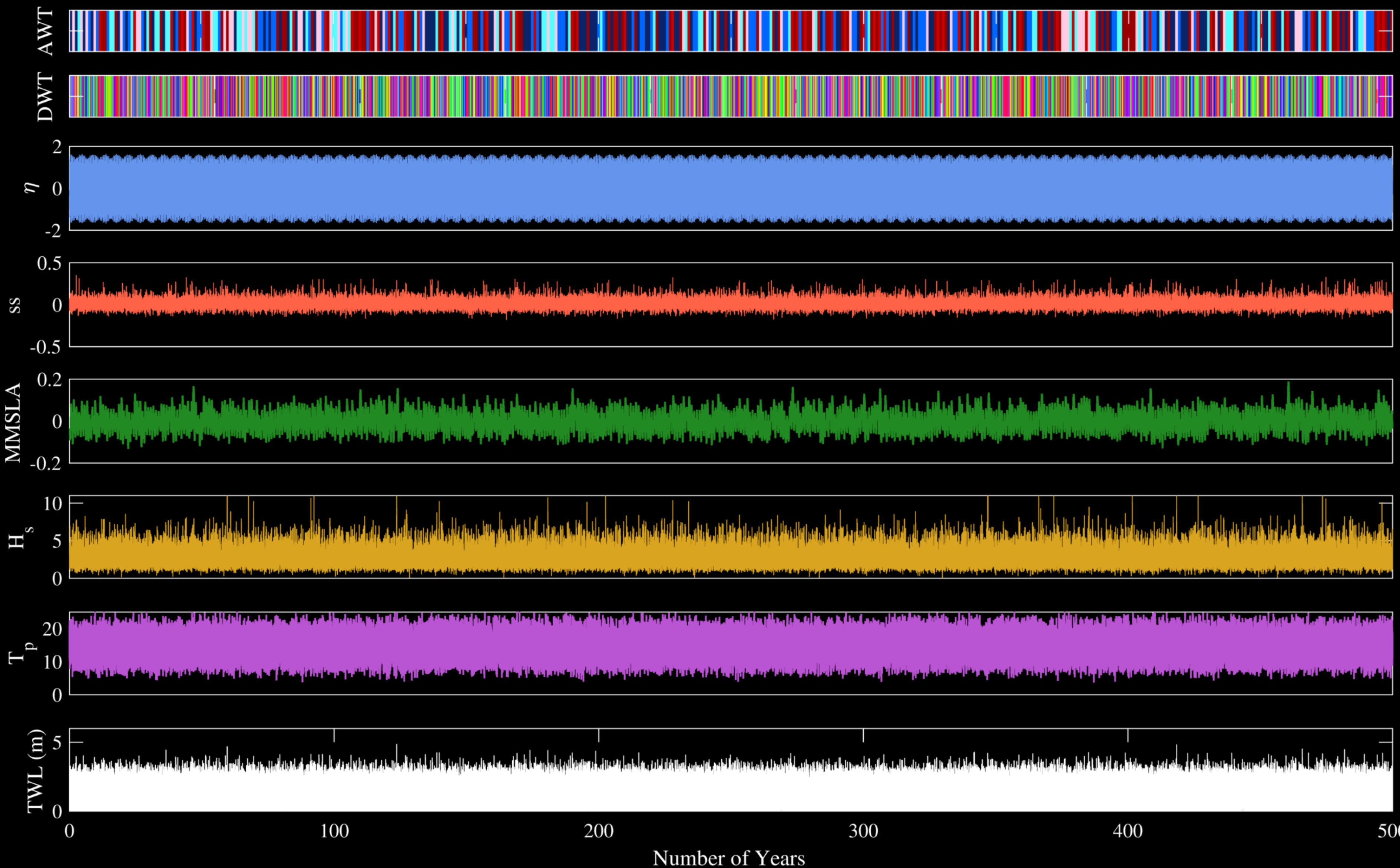
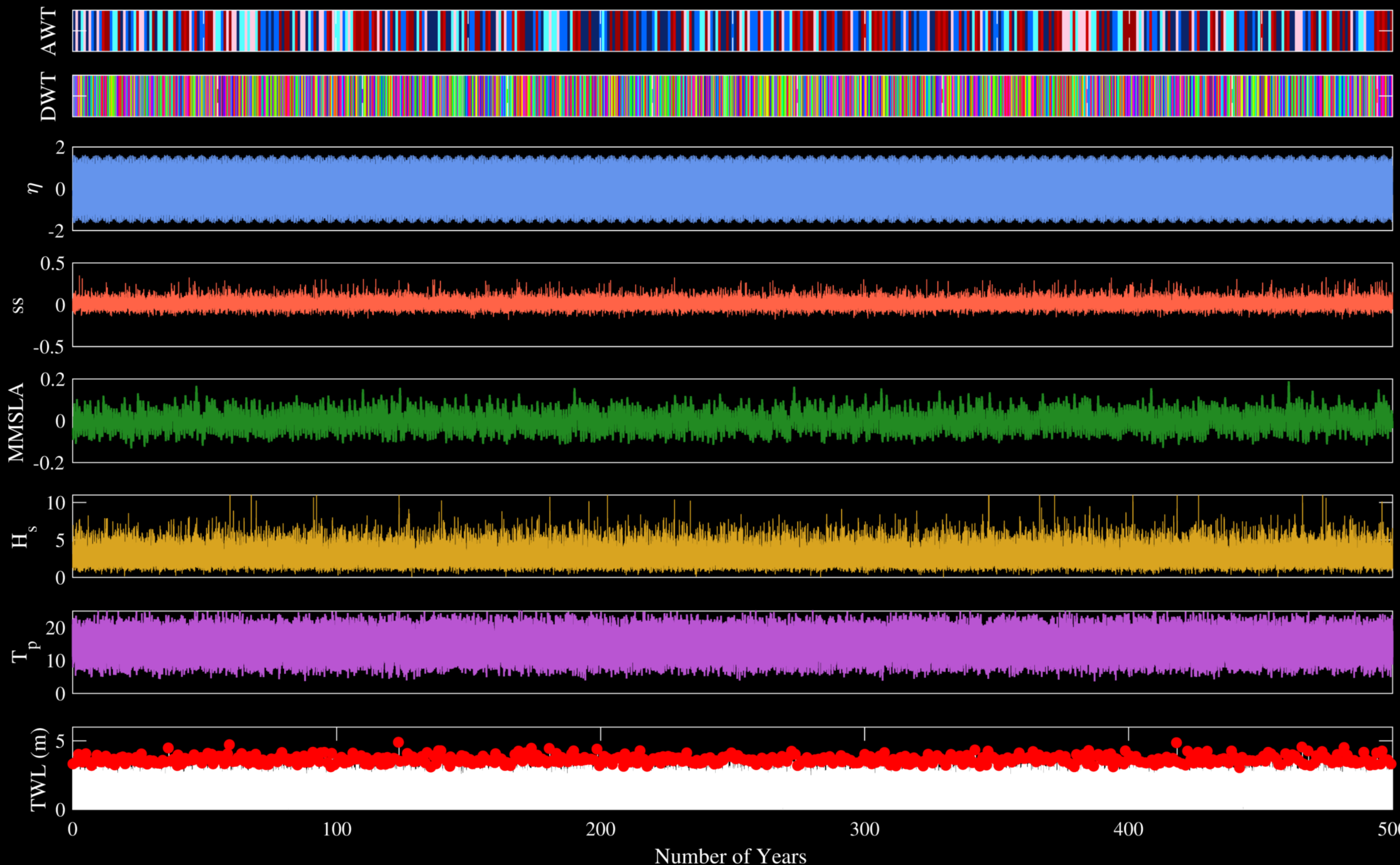


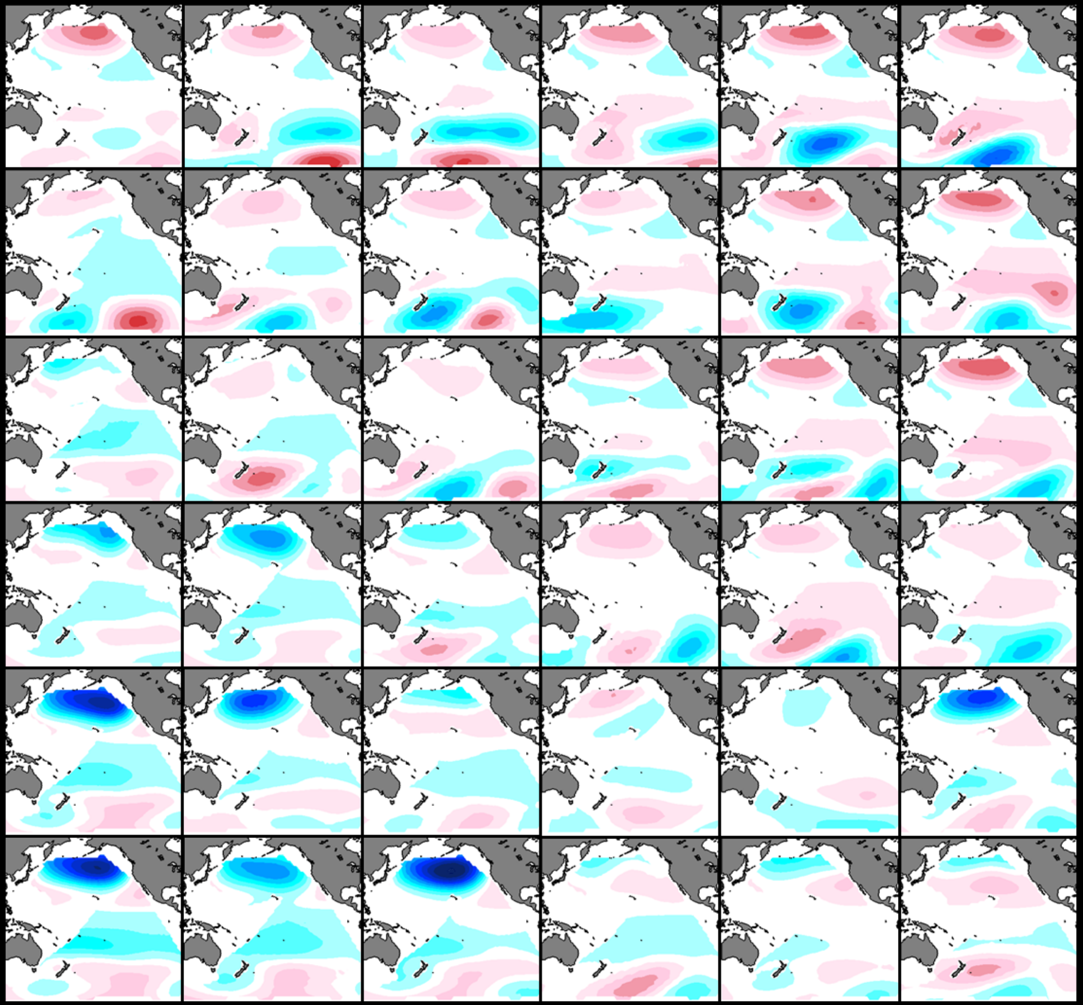
San Diego Synthetic Record

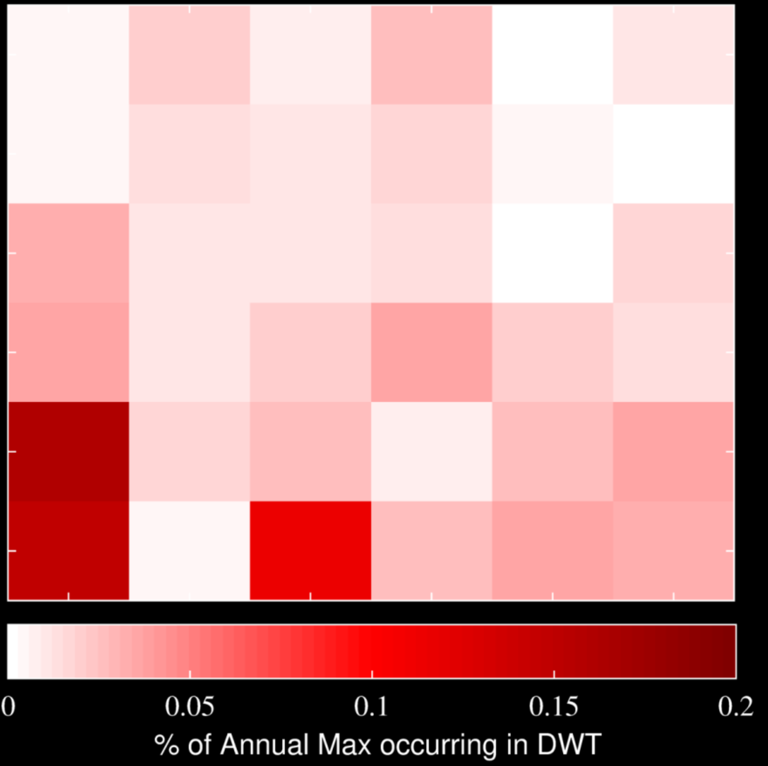


San Diego Synthetic Record

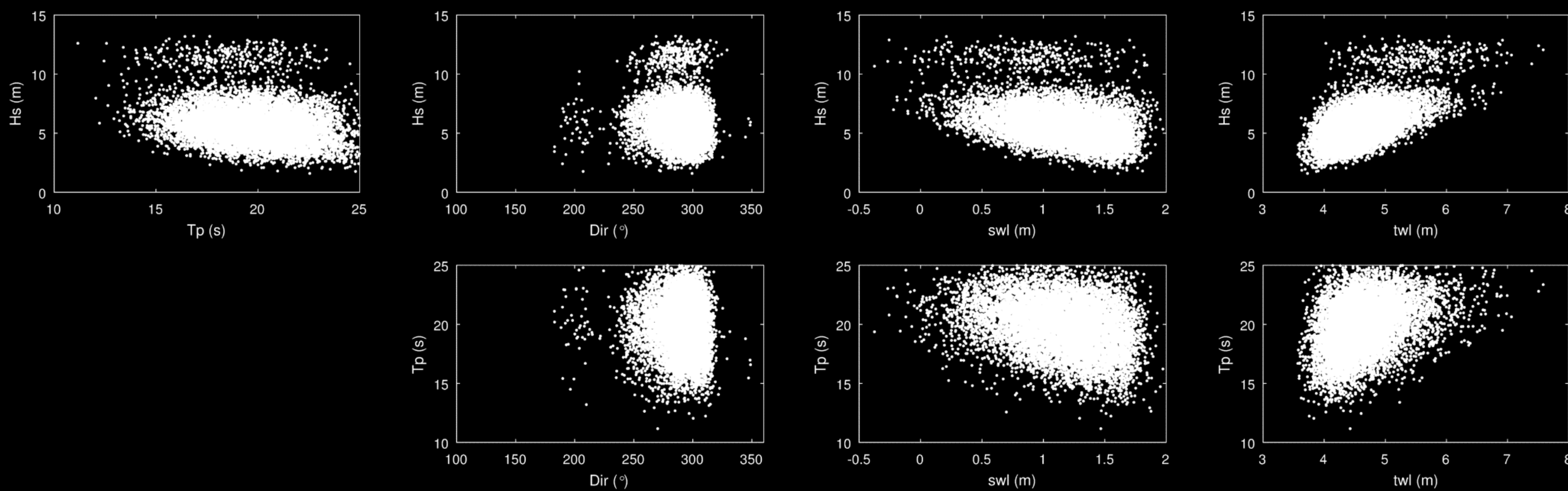


Which “climate patterns” have greatest potential for flooding?

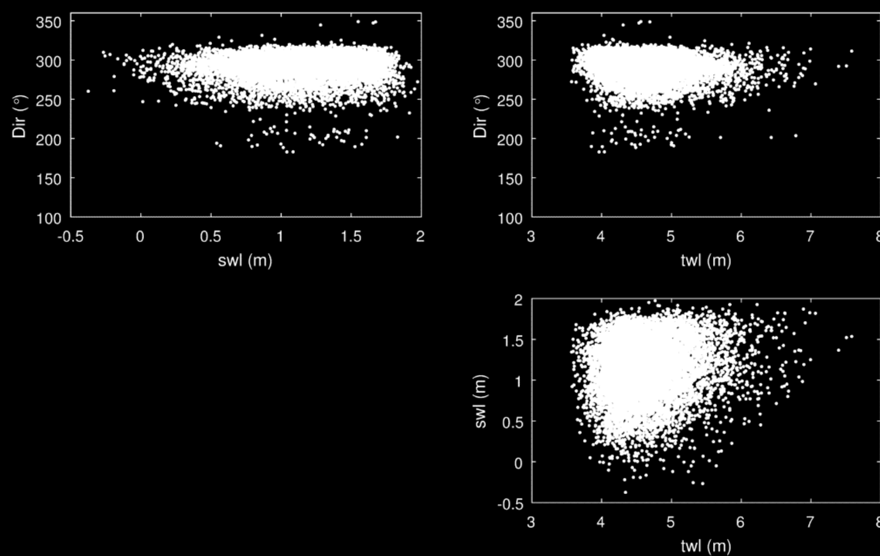




Which “compound events” have greater potential for flooding?



- 10,000 annual max TWL



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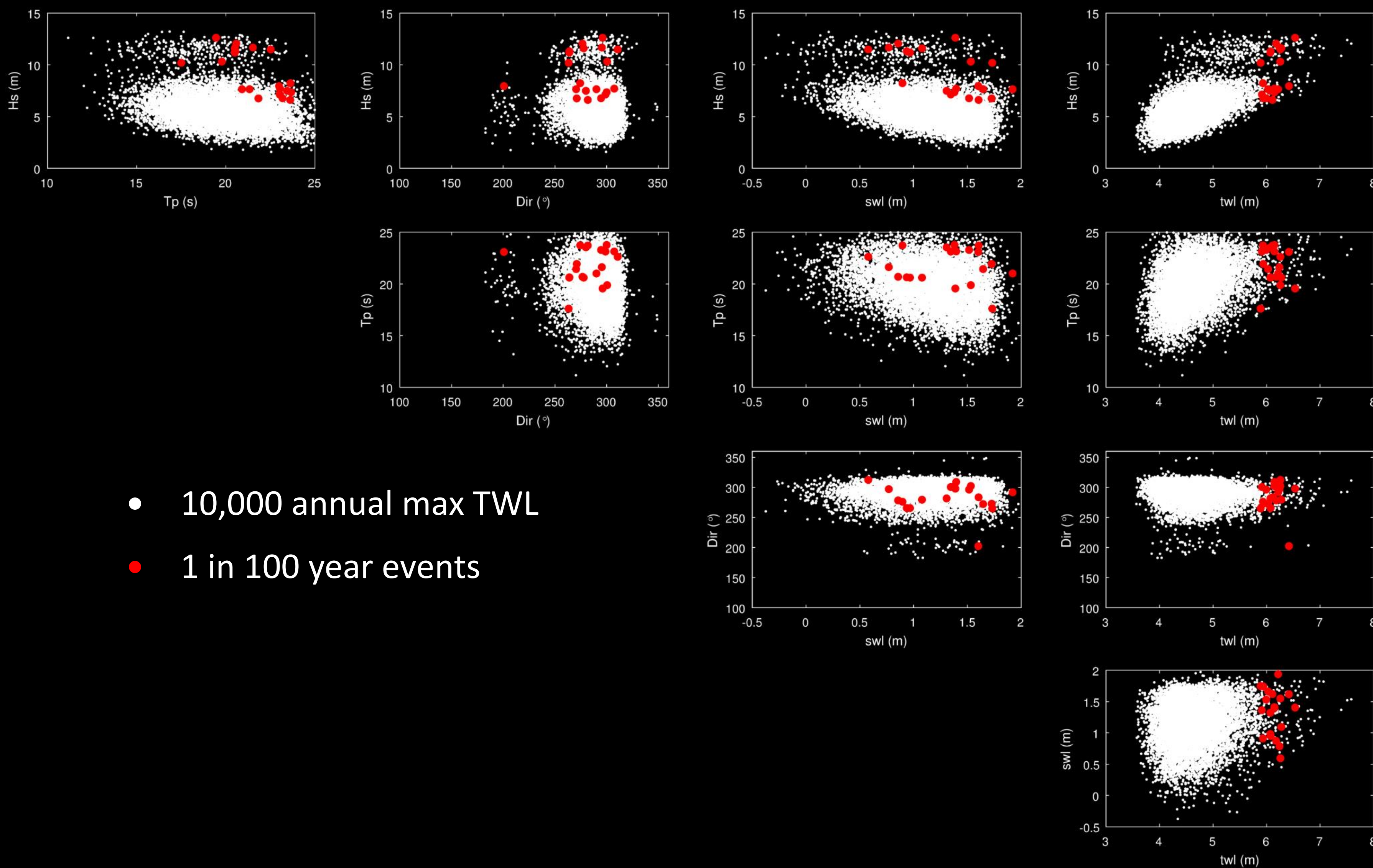


- 10,000 annual max TWL
- 1 in 100 year events

Extrapolate climate to DOD training operation questions

$$TWL = GSLR + MSL + \eta_A + \eta_{NTR} + R$$

ET3	ET3	ET6	ET6	ET6	Cat2	ET1	ET13	…	ET2	Cat4	ET7	ET7

Inputs to dynamic modeling frameworks

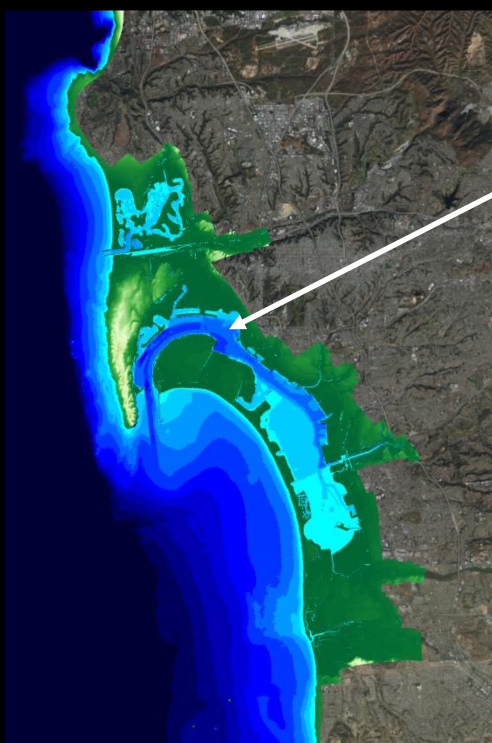
Specific engineering questions

Extrapolate climate to DOD training operation questions

$$TWL = GSLR + MSL + \eta_A + \eta_{NTR} + R$$

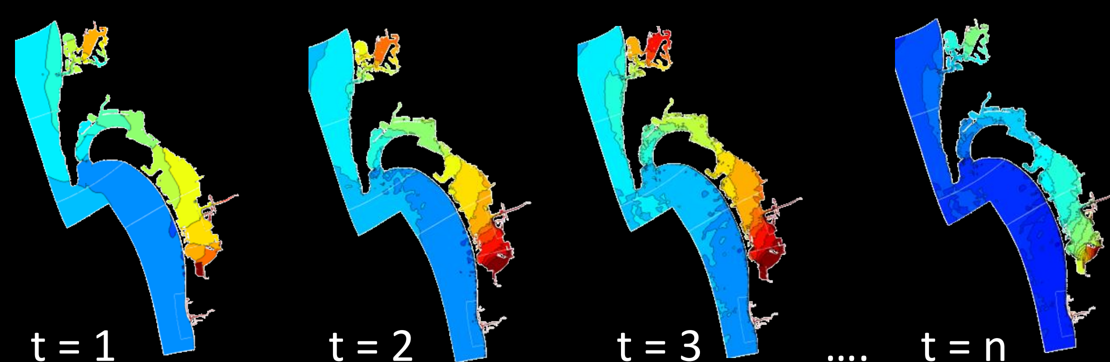
ET3 | ET3 | ET6 | ET6 | ET6 | Cat2 | ET1 | ET13 | ... | ET2 | Cat4 | ET7 | ET7

Inputs to dynamic modeling frameworks



Delft3D FLOW-WAVE (from COSMOS – Barnard et al. 2014)

Time series of inundation maps



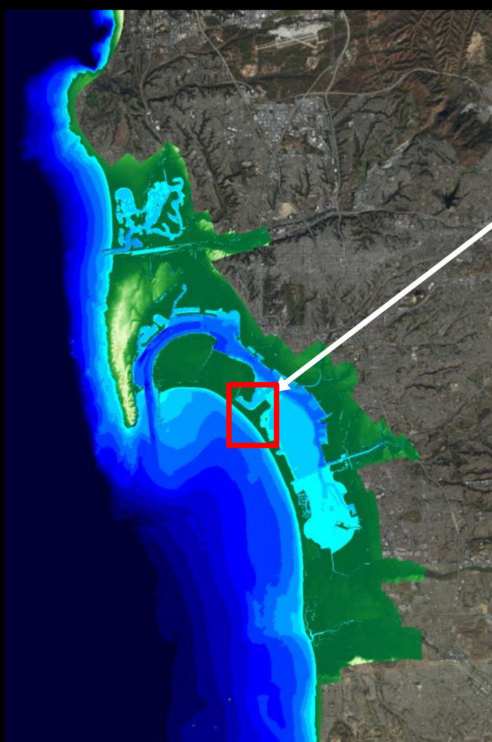
Extrapolate climate to DOD training operation questions

$$TWL = GSLR + MSL + \eta_A + \eta_{NTR} + R$$

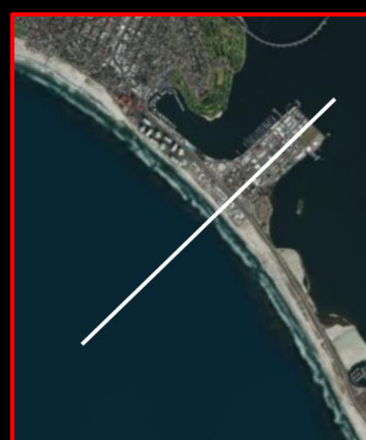
ET3	ET3	ET6	ET6	ET6	Cat2	ET1	ET13	…	ET2	Cat4	ET7	ET7

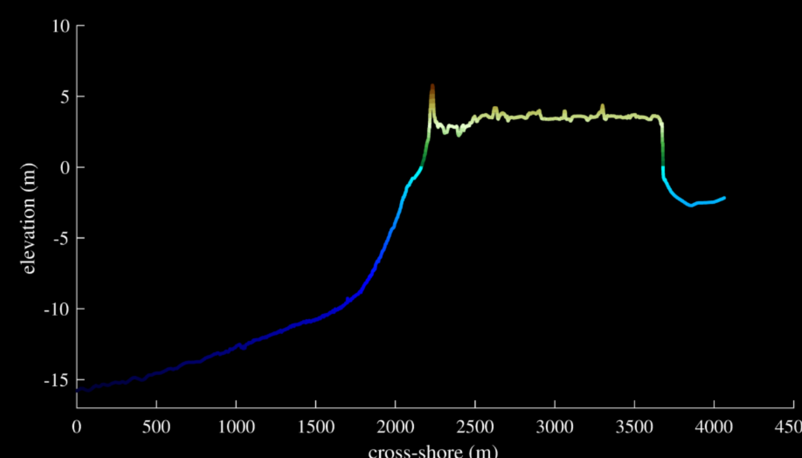
Inputs to dynamic modeling frameworks

XBeach (from COSMOS – Barnard et al. 2014)



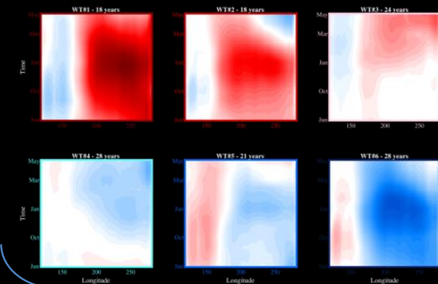
Resiliency of potential dune nourishments

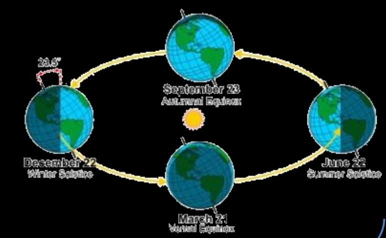


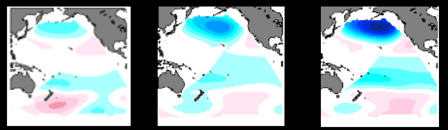


TESLA-Flood

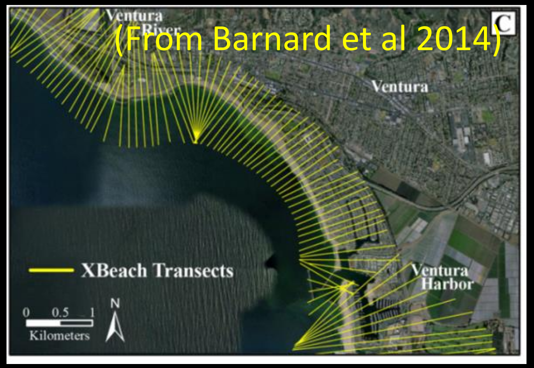
Framework for downscaling climate variability to coastal impacts
- Occurrence Probabilities
- Return Periods
- Chronological Behavior

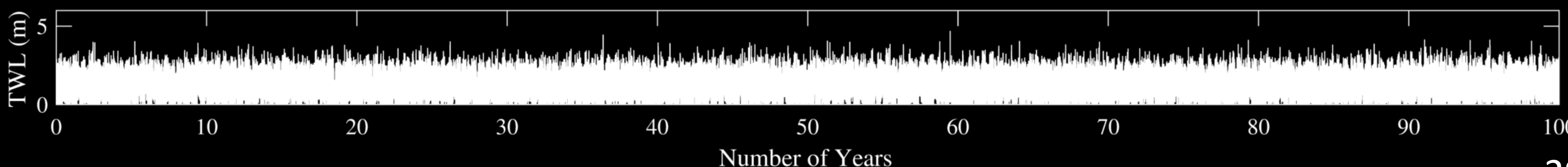




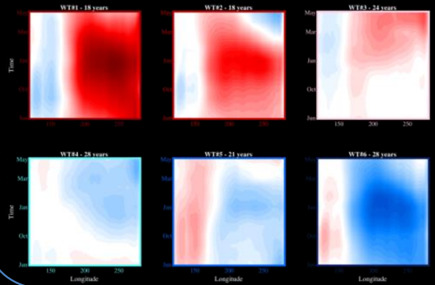


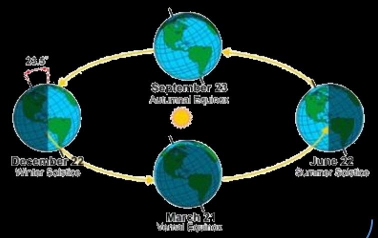
Incorporated meta-models for:
- Synthetic Tropical Cyclones
- Intra-daily Storm Hydrographs

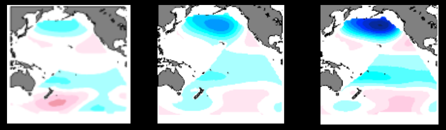




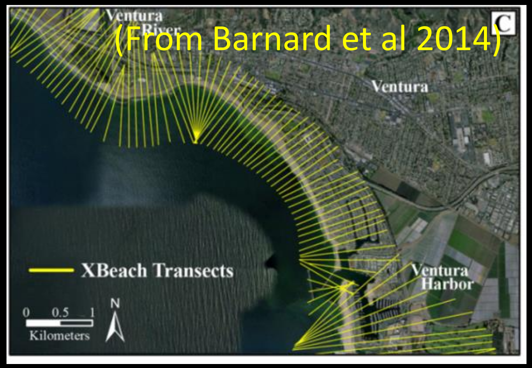
Questions

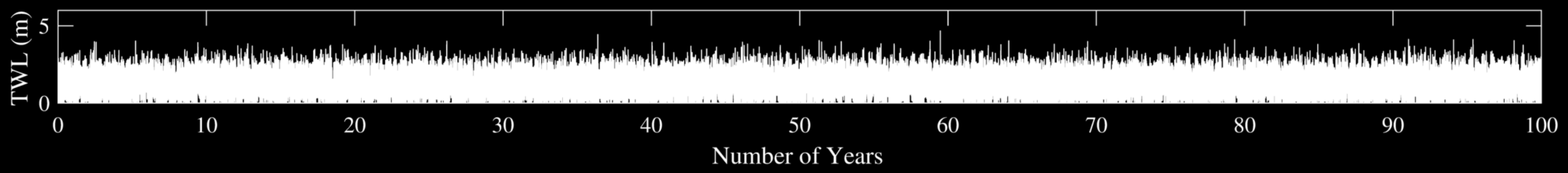



23.5°
September 23
Autumnal Equinox
December 22
Winter Solstice
June 22
Summer Solstice
March 21
Vernal Equinox

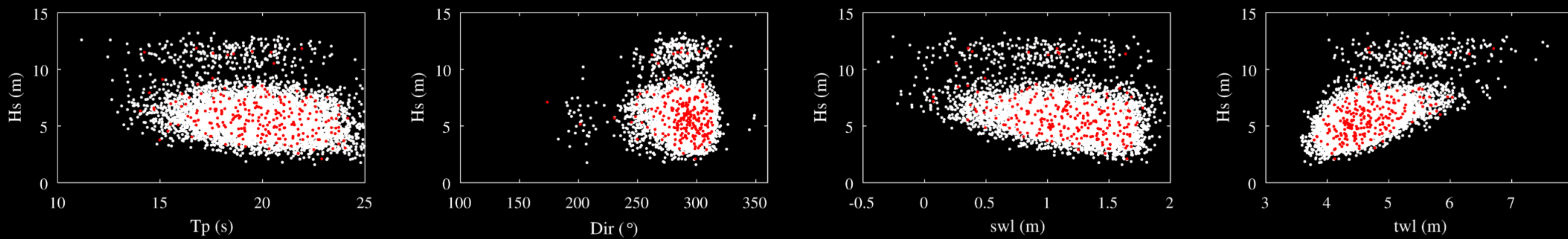


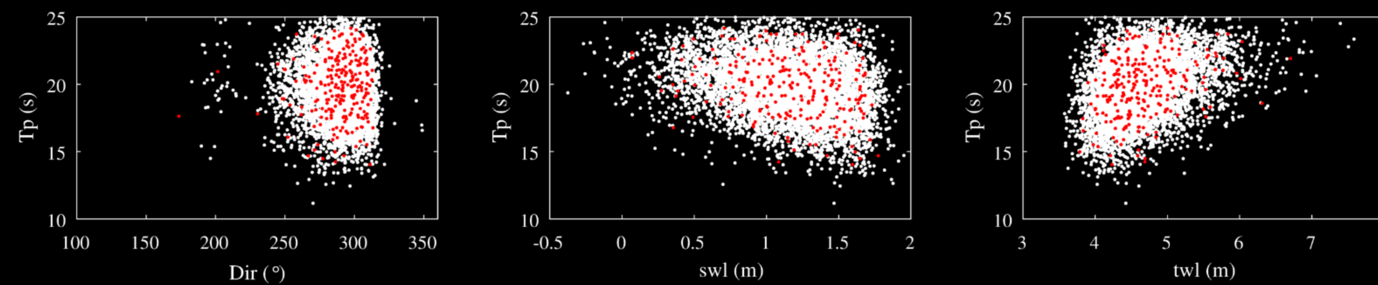

N46219

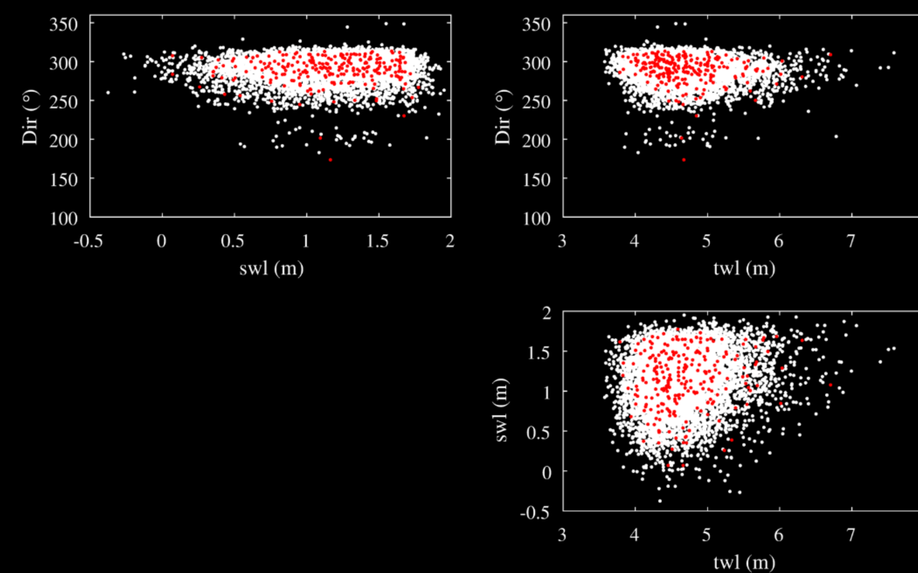

Ventura
River
(From Barnard et al 2014)
C
Ventura
XBeach Transects
Ventura
Harbor
0 0.5 1
Kilometers
N


TWL (m)
5
0
0
10
20
30
40
50
60
70
80
90
100
Number of Years

Which “compound events” have greater potential for flooding?

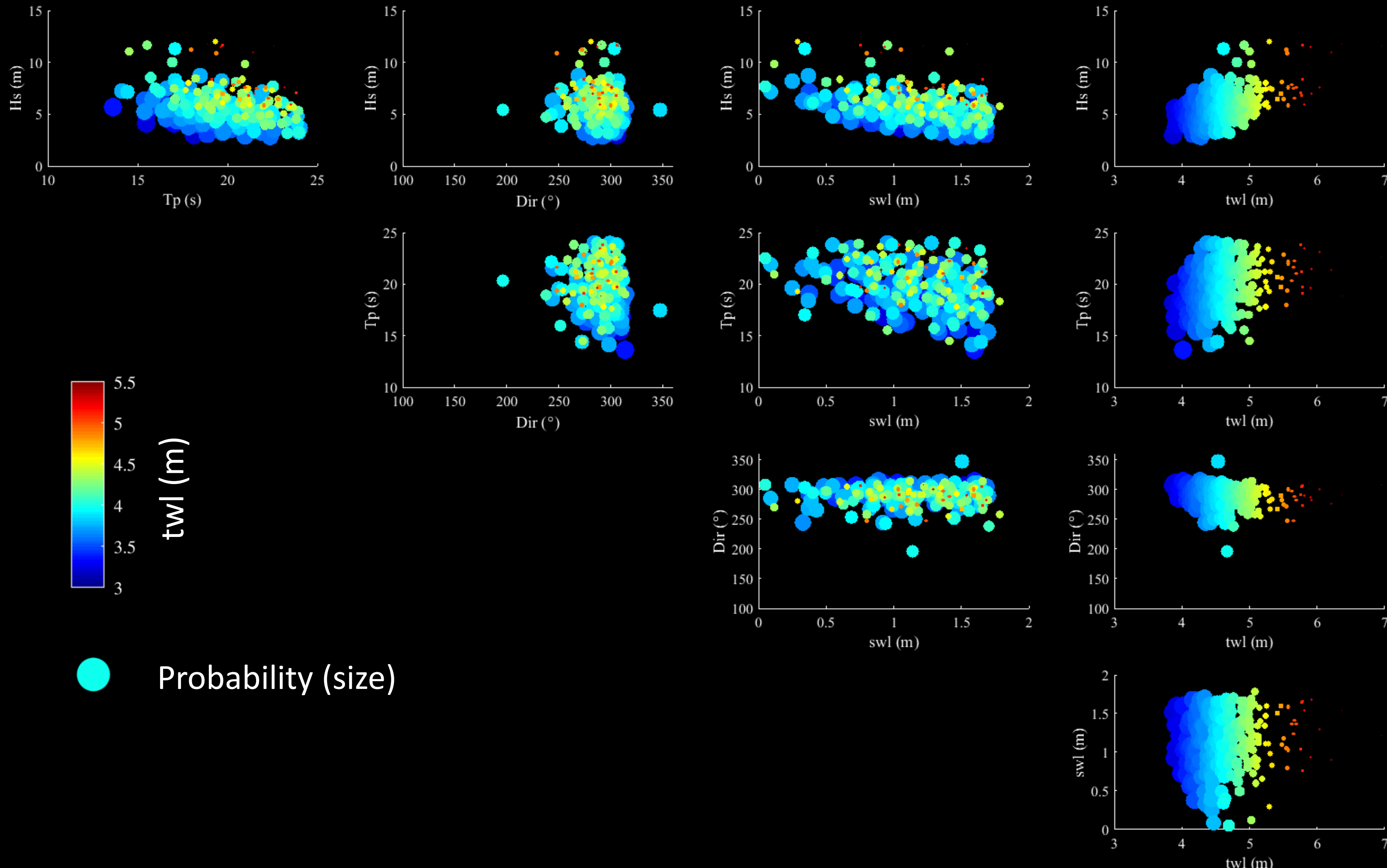






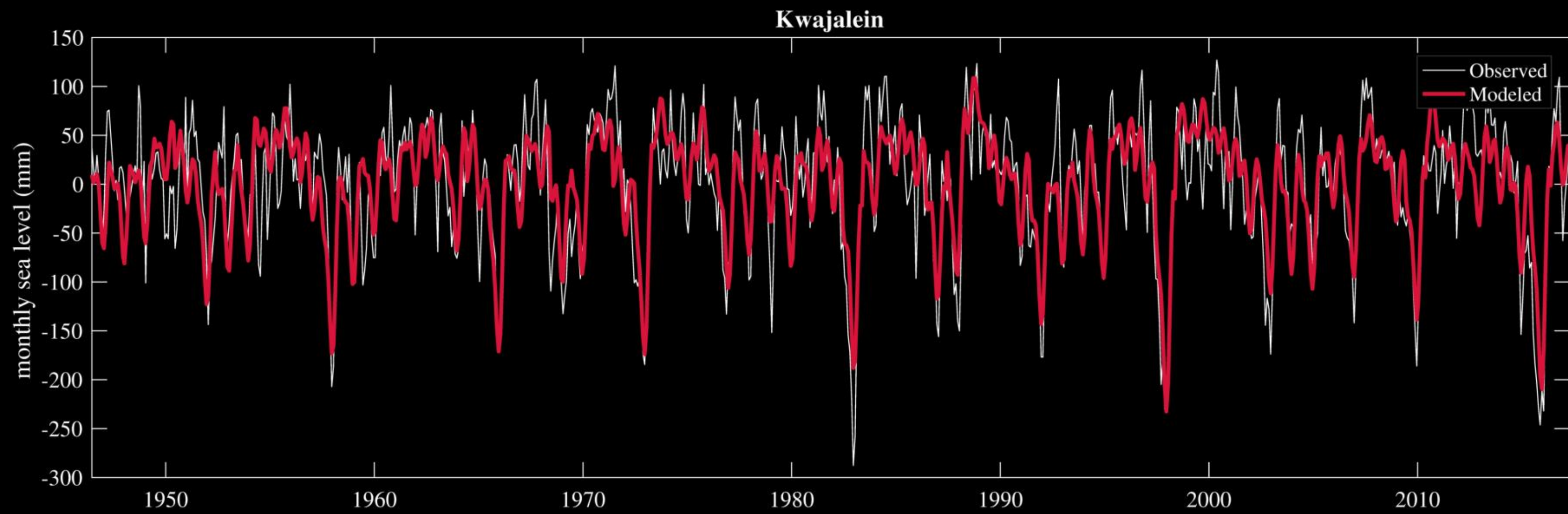
- 10,000 annual max TWL
- 250 centroids

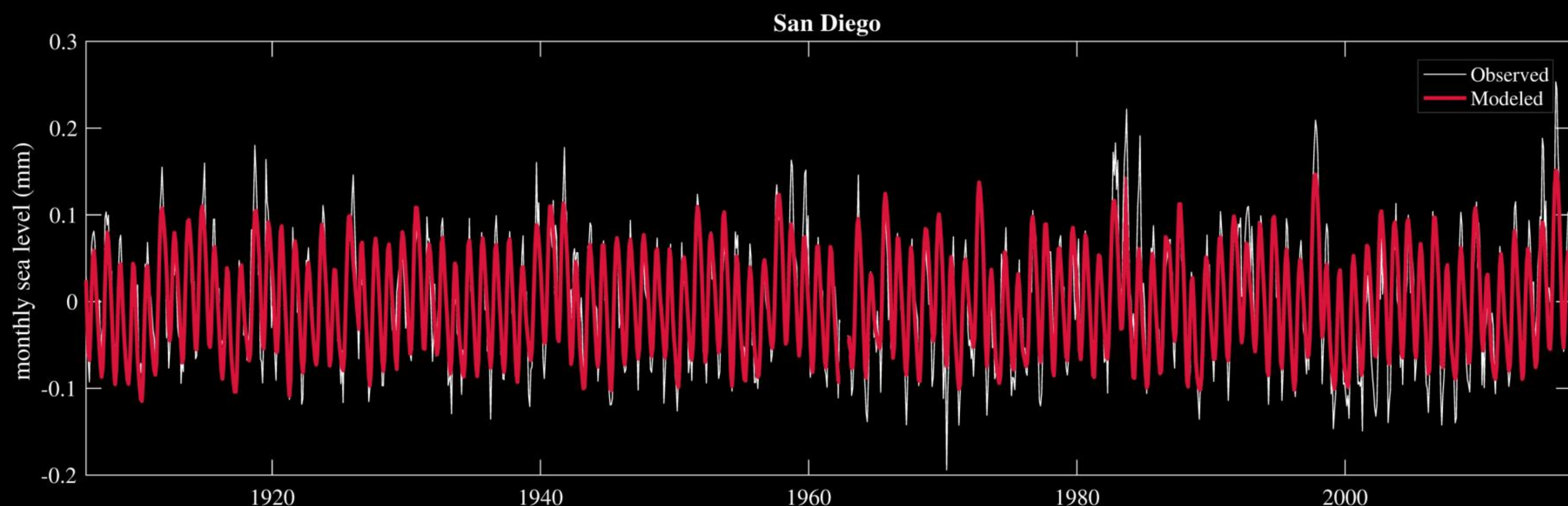
Which “compound events” have greater potential for flooding?



Regression Model for MMSL

$$MMSL(t)=a_0+a_1X_1^a(t)+a_2X_2^a(t)+a_3X_3^a(t)+\left(b_0+b_1X_1^a(t)+b_2X_2^a(t)+b_3X_3^a(t)\right)\cos\left(\frac{2\pi t}{365}\right)+\ldots$$





Correct axis

Chronology Model: Climate-based Autoregressive Logistic Model

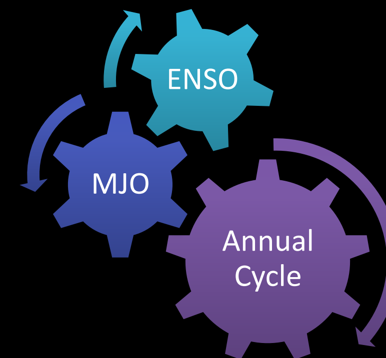
Categorical time series of DWTs for Extratropical Cyclones (ET) and Tropical Cyclones (Cat_i)

$$\Pr(DWT_t = i \mid DWT_{t-1},\ldots,DWT_{t-e},\mathbf{X}_t^a,\mathbf{X}_t^m,\mathbf{X}_t^{MJO}) = \frac{\exp(\alpha_i + \beta_i \mathbf{X}_t + \sum_{j=1}^{e} \gamma_{ij} DWT_{t-j}^d)}{\sum_{k=1}^{n_{DWT}} \exp(\alpha_k + \beta_k \mathbf{X}_t + \sum_{j=1}^{e} \gamma_{kj} DWT_{t-j}^d)}; \forall i = 1,\ldots,n_{DWT}$$

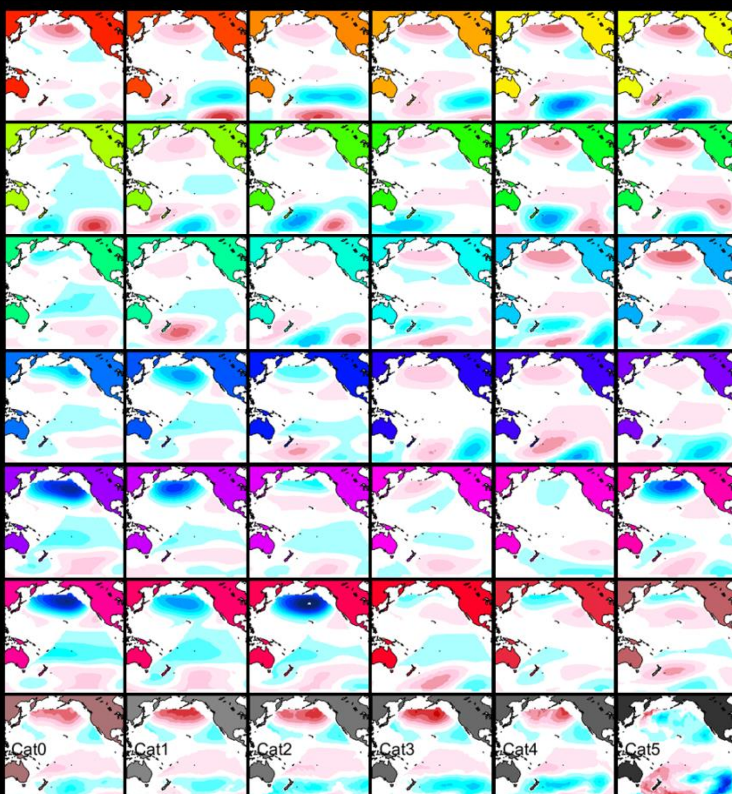
$$ET_t^d \in \{1,\ldots,n_{ET}\}$$

$$TC_t^d \in \{C_0,\ldots,C_5\}$$

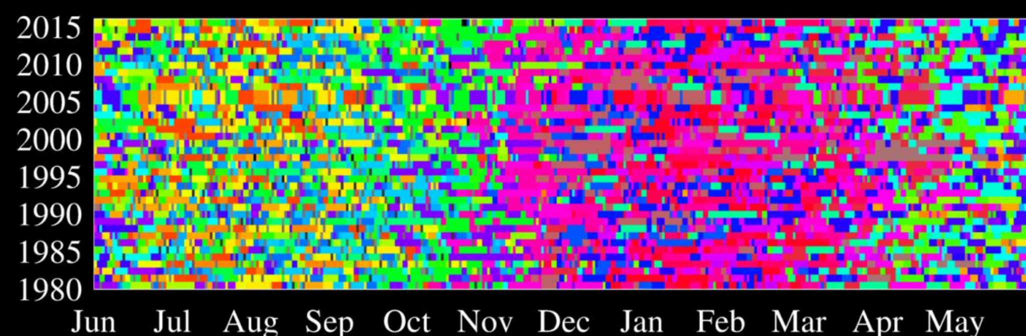
$$DWT_t = (ET_t^d \cup TC_t^d) \in \{1,\ldots,n_{DWT}\}$$



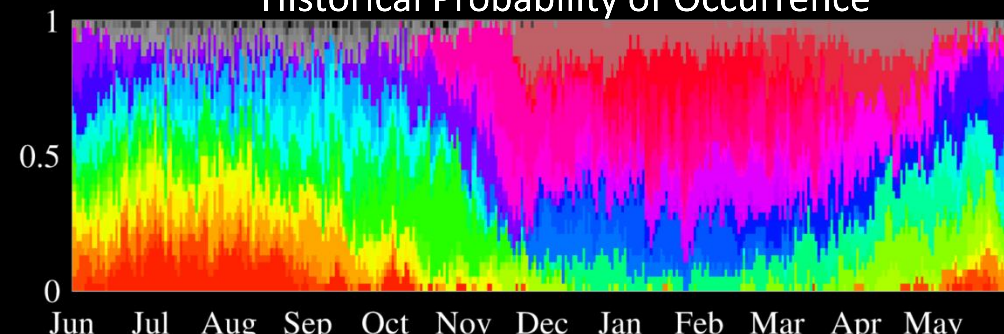
$$\mathbf{X}_t = (X_{1,t}^a, X_{2,t}^a, X_{3,t}^a, \cos\frac{2\pi t}{T_a}, \sin\frac{2\pi t}{T_a}, X_{1,t}^{MJO}, X_{2,t}^{MJO})$$



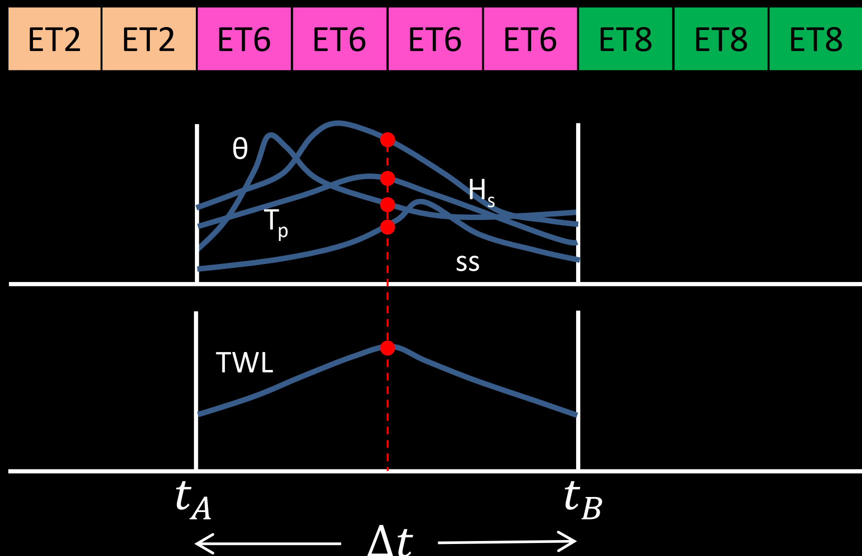
Historical Timestack of DWT



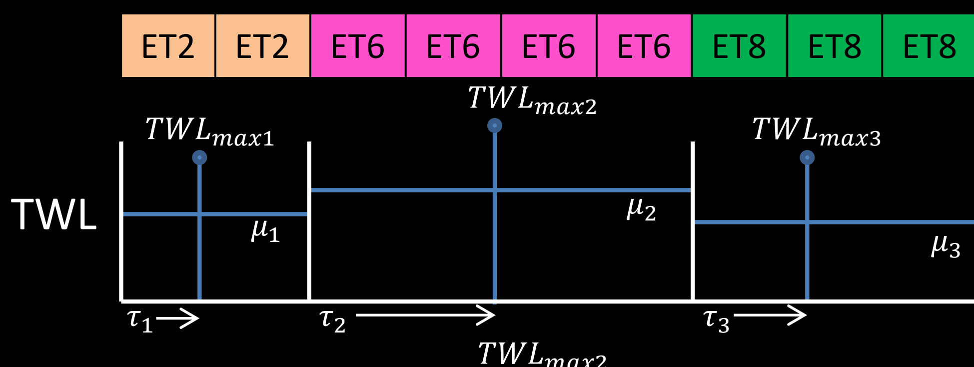
Historical Probability of Occurrence

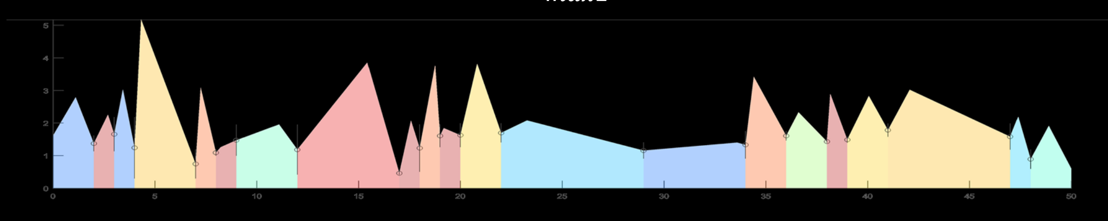


Intra-daily simulations: hydrograph approach



Response function: $TWL = R(H_s, T_p) + SS$





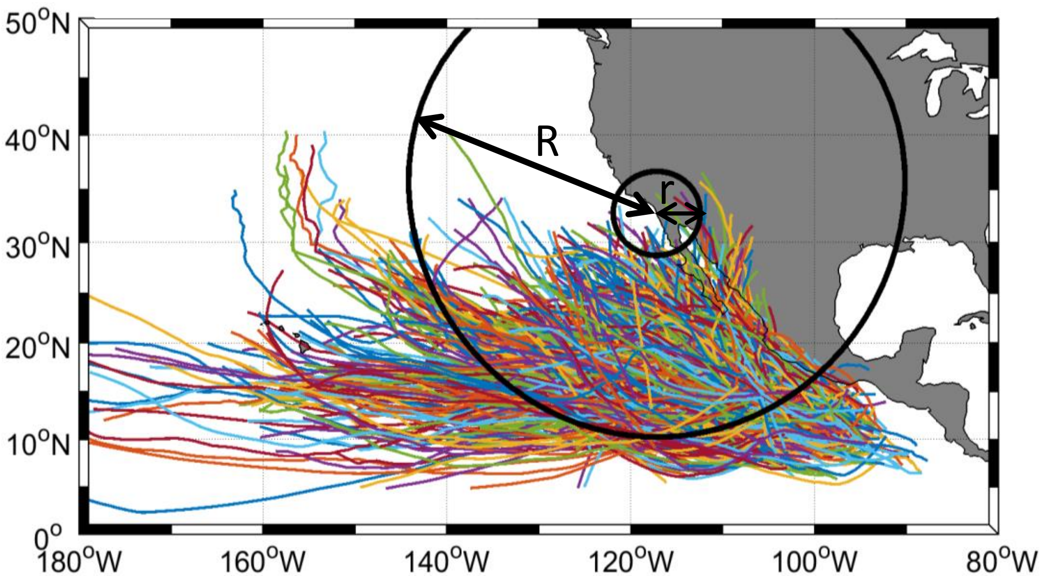
Modelling triangles:

$$DWT = \{H_s{}^{(k)}, T_p{}^{(k)}, \theta^{(k)}, SS, \tau, \mu\}$$

Timing until TWL_{max}

Average TWL during hydrograph

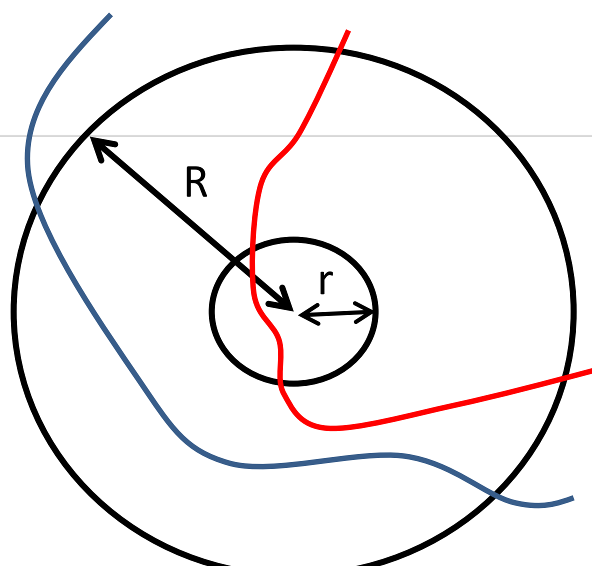
Tropical Cyclones: Potential Tracks



Use historical TC tracks to identify SLP patterns when TCs are generated/enter the region of interest

Use synthetic tracks to determine likelihood of impacting specific site

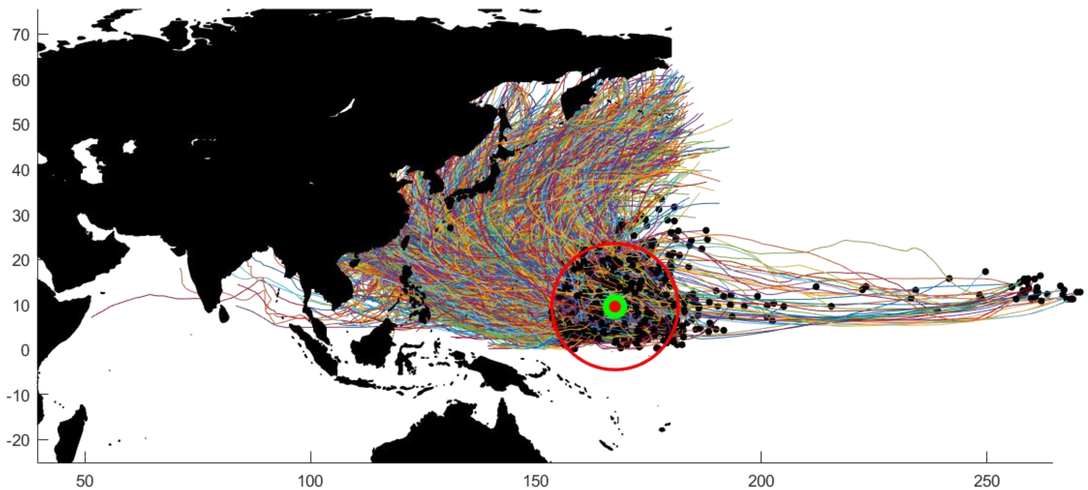
(currently using Nakajo et al. 2014 for 1 million synthetic tracks).



How do we decide if a cyclone track is close enough to turn on process-based modeling?

$$\frac{\text{\# storms local to site (r)}}{\text{\# storms in the region (R)}}$$

Tropical Cyclones: Potential Tracks



Use historical TC tracks to identify SLP patterns when TCs are generated/enter the region of interest

Use synthetic tracks to determine likelihood of impacting specific site

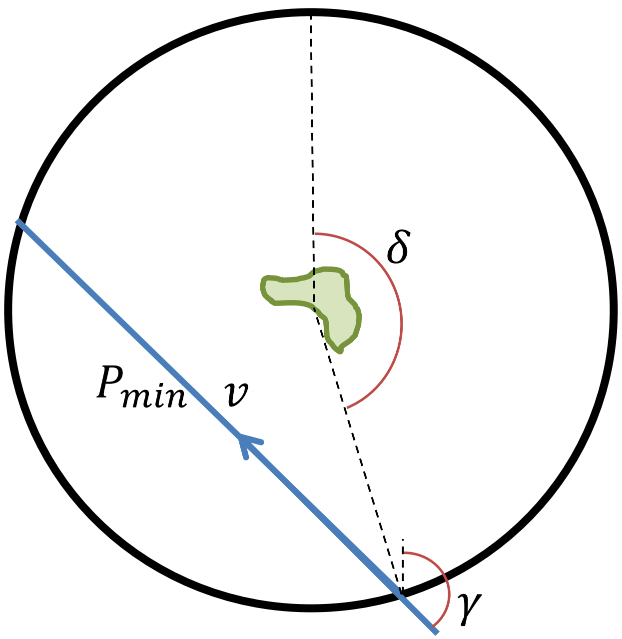
(currently using Nakajo et al. 2014 for 1 million synthetic tracks).

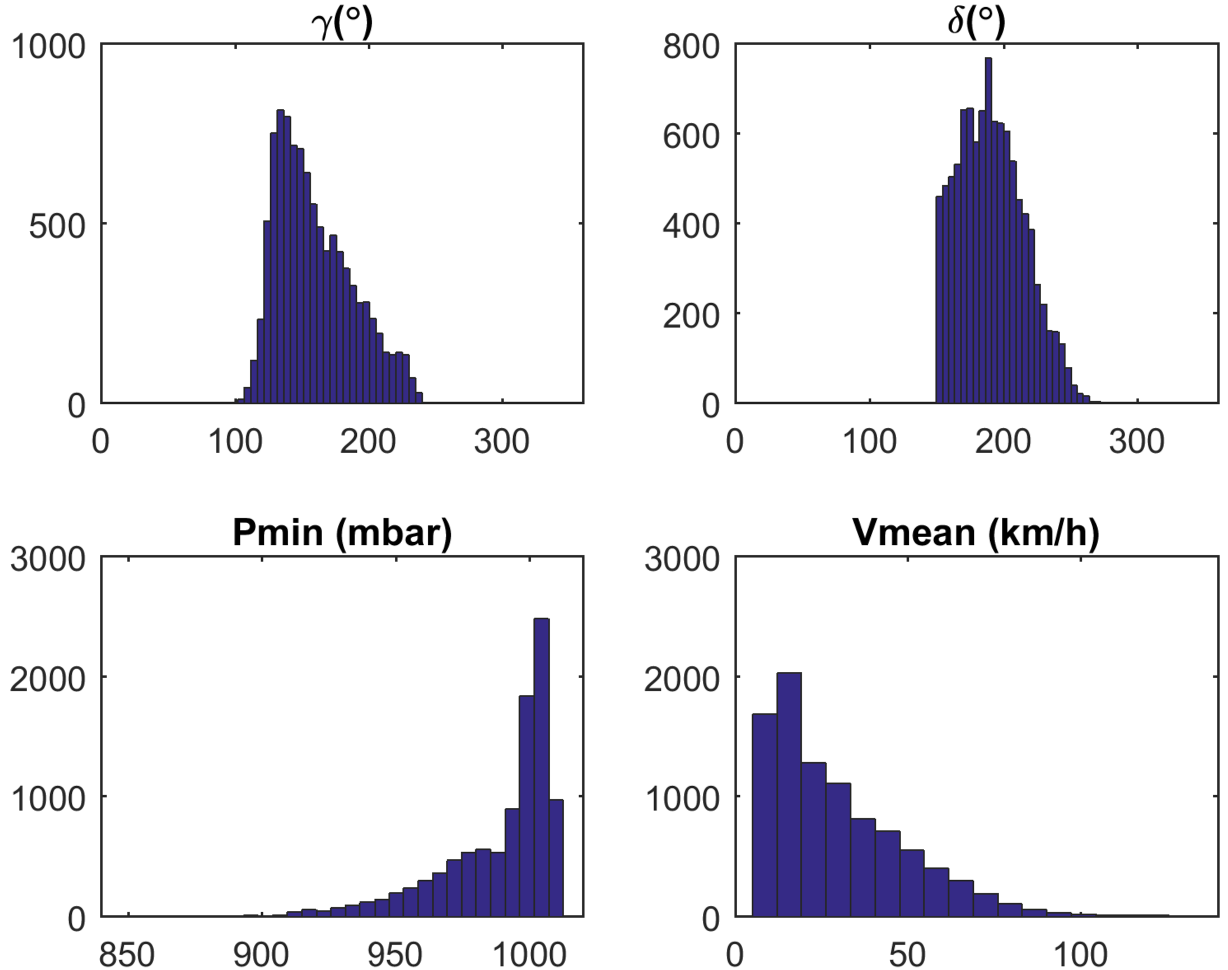
		R=14						
		C0	C1	C2	C3	C4	C5	TOTAL
r=2	C0	0.031	0.029	0.032	0.026	0.0095	0.001	0.131
	C1	0	0.018	0.071	0.118	0.152	0.027	0.387
	C2	0	0	0.005	0.016	0.115	0.056	0.192
	C3	0	0	0	0.001	0.031	0.086	0.118
	C4	0	0	0	0	0.002	0.056	0.058
	C5	0	0	0	0	0	0.122	0.122
	ENTRANCE	0.031	0.048	0.108	0.162	0.310	0.348	9.4%
	NO ENTRANCE	0.969	0.951	0.892	0.838	0.689	0.652	90.6%
TOTAL		1 (0.367)	1 (0.326)	1 (0.078)	1 (0.103)	1 (0.065)	1 (0.061)	1

<u>Breakdown by Category:</u> "if a storm is X strength in R, it could be Y strength in r"

Probability of Cyclone affecting local site

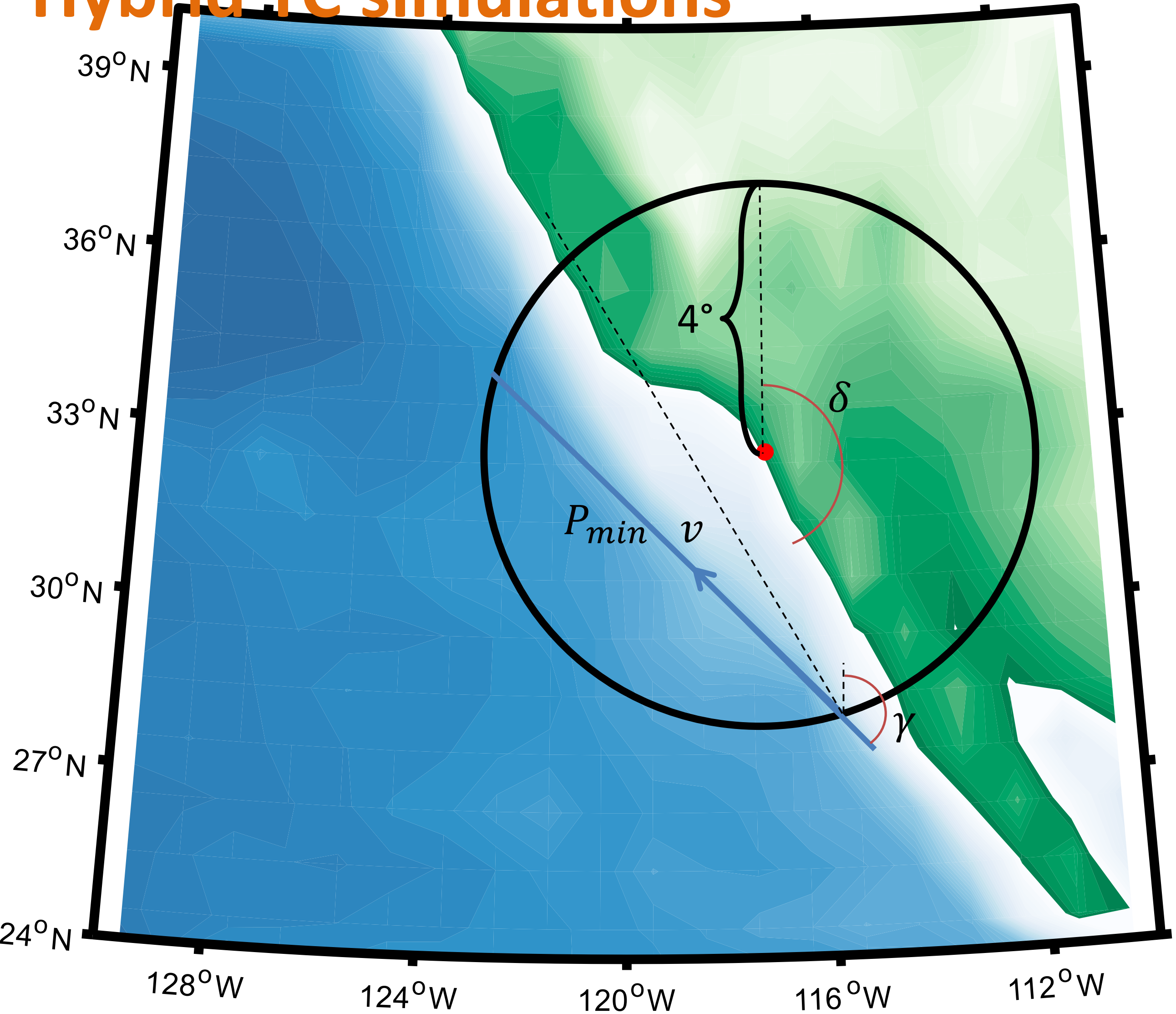
Hybrid TC simulations





A meta-model is developed from hydrodynamic modeling of the potential combinations of $\{P_{min}, v, \delta, \gamma\}$.

Hybrid TC simulations



Parameters that define a TC
- pmin, Minimum Pressure
- V, forward velocity
- δ, azimuth
- γ, angle of entrance

4 degree radius centered on San Diego (32.6717,-117.1441)

Synthetic Tracks + MDA Selection Algorithm (Camus et al, 2011)

N = 100 Synthetic Tracks