The Abdus Salam International Centre for Theoretical Physics

United Nations Educational, Scientific and Cultural Organization

IAEA International Atomic Energy Agency

2160-24

Conference on Decadal Predictability

16 - 20 August 2010

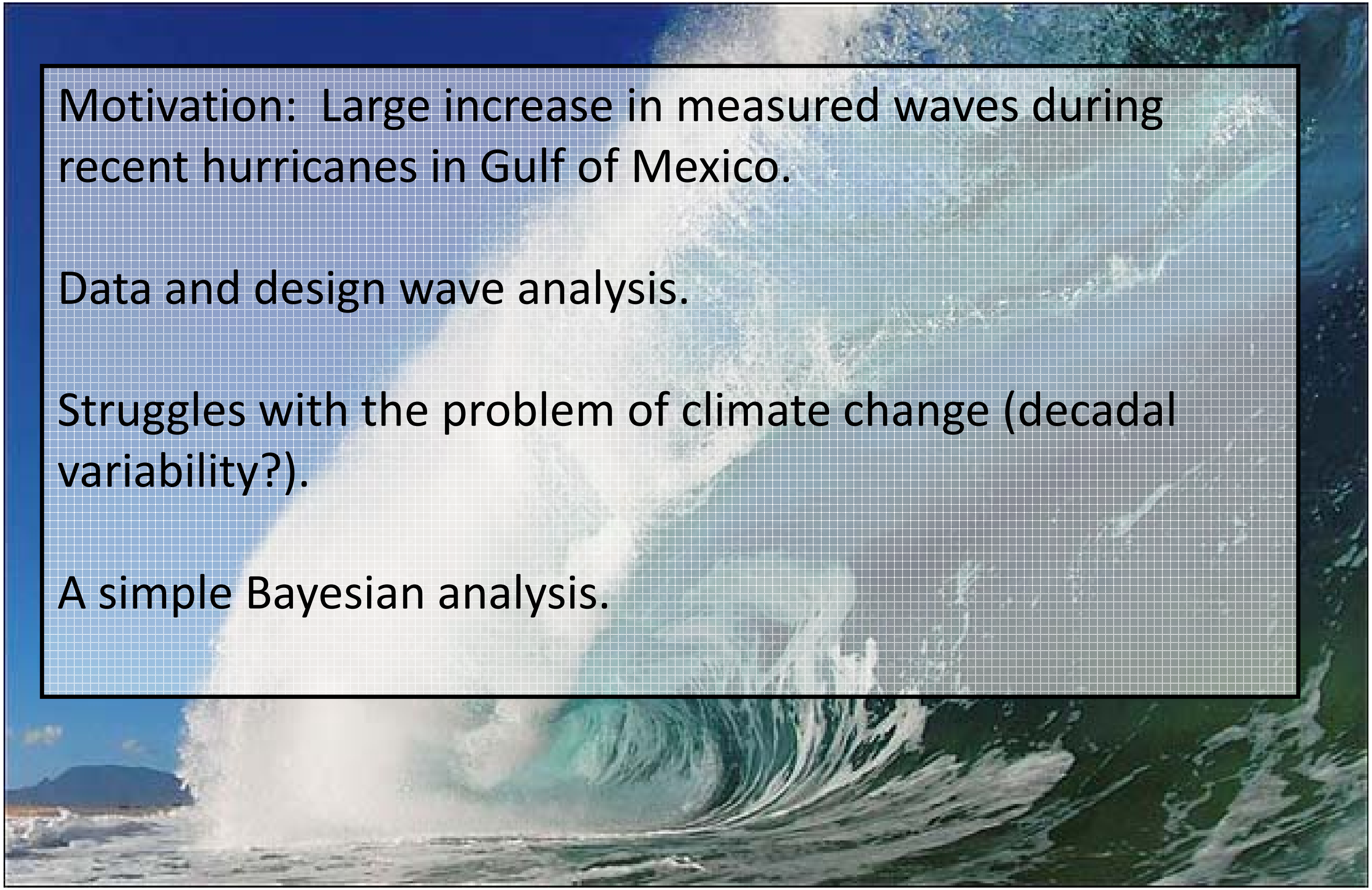
The nature and impacts of the commingled influence of Sahel precipitation and tropical Pacific sea surface temperature variability on Atlantic hurricane activity

PEARCE Bryan

University of Maine, 303 Boardman Hall
Orono 04469
Maine
U.S.A.

The nature and impacts of the commingled influence of Sahel precipitation and tropical Pacific sea surface temperature variability on Atlantic hurricane activity.

Bryan Pearce – Department of Civil Engineering
Shaleen Jain- Department of Civil Engineering
Bill Halteman – Department of Mathematics
University of Maine

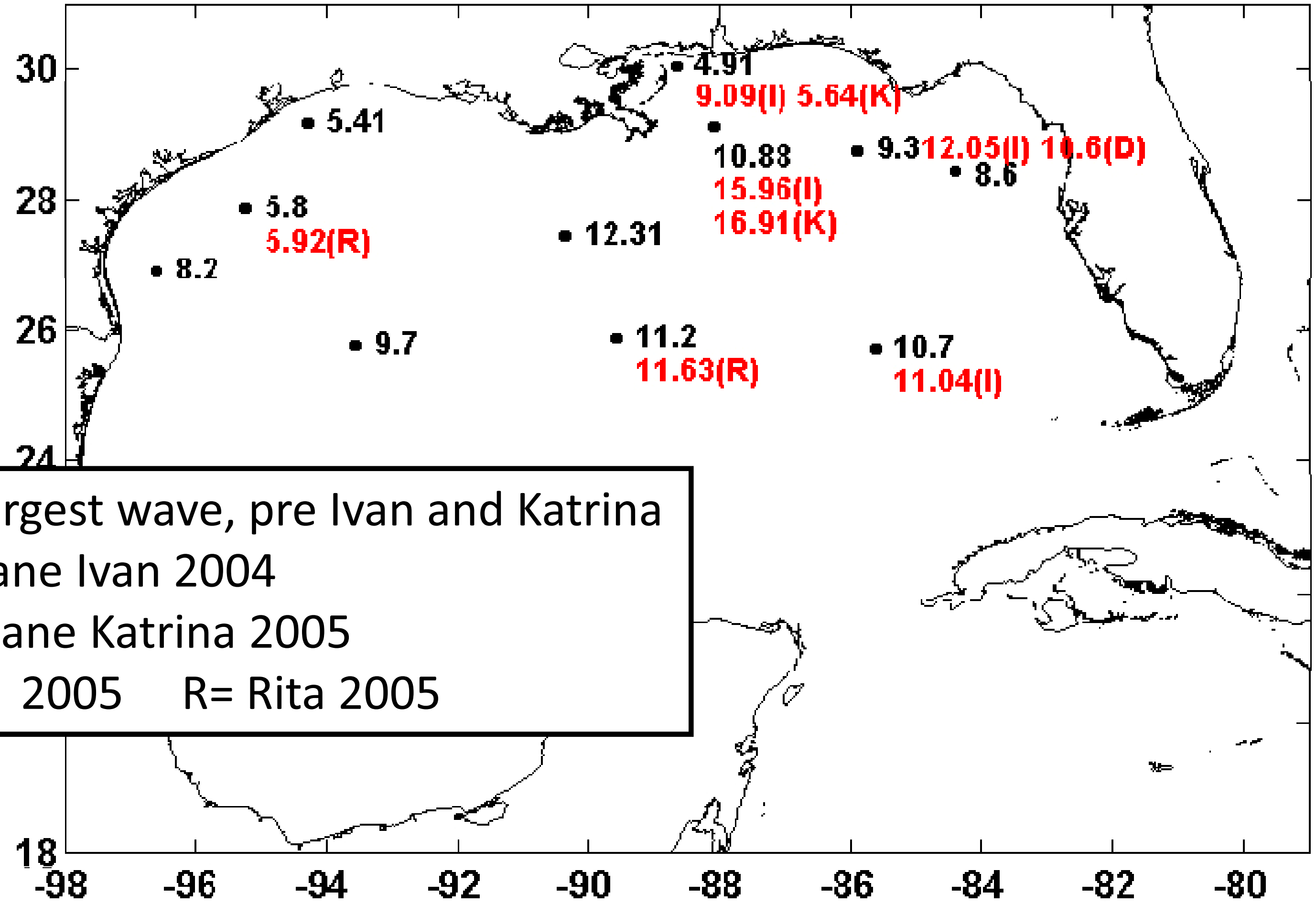


Wind Generated Waves

Platform Medusa after Hurricane IVAN, 2004

Platform Medusa after Hurricane IVAN, 2004

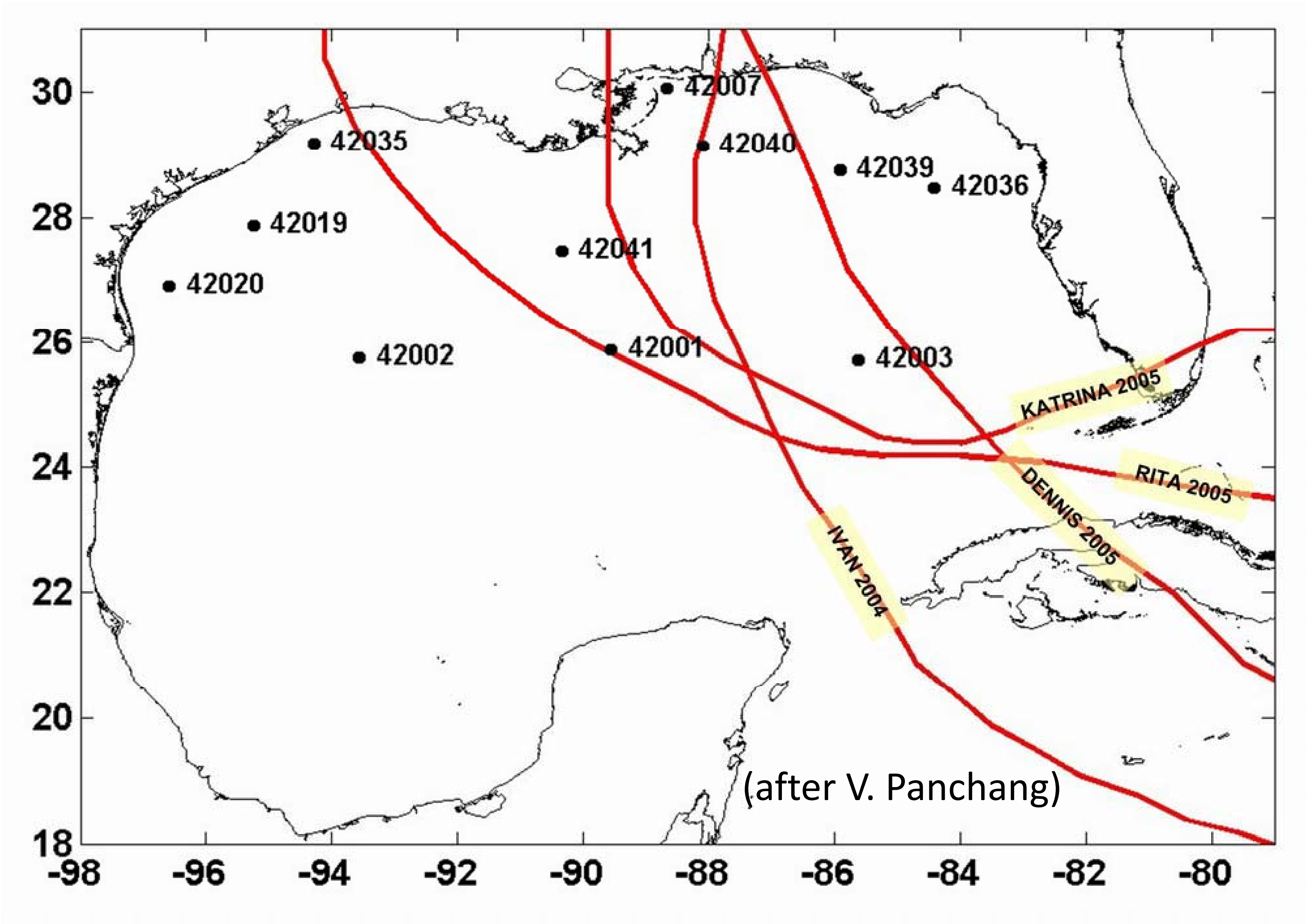
Max. Significant Wave Heights From NOAA BUOYS (after V. Panchang)



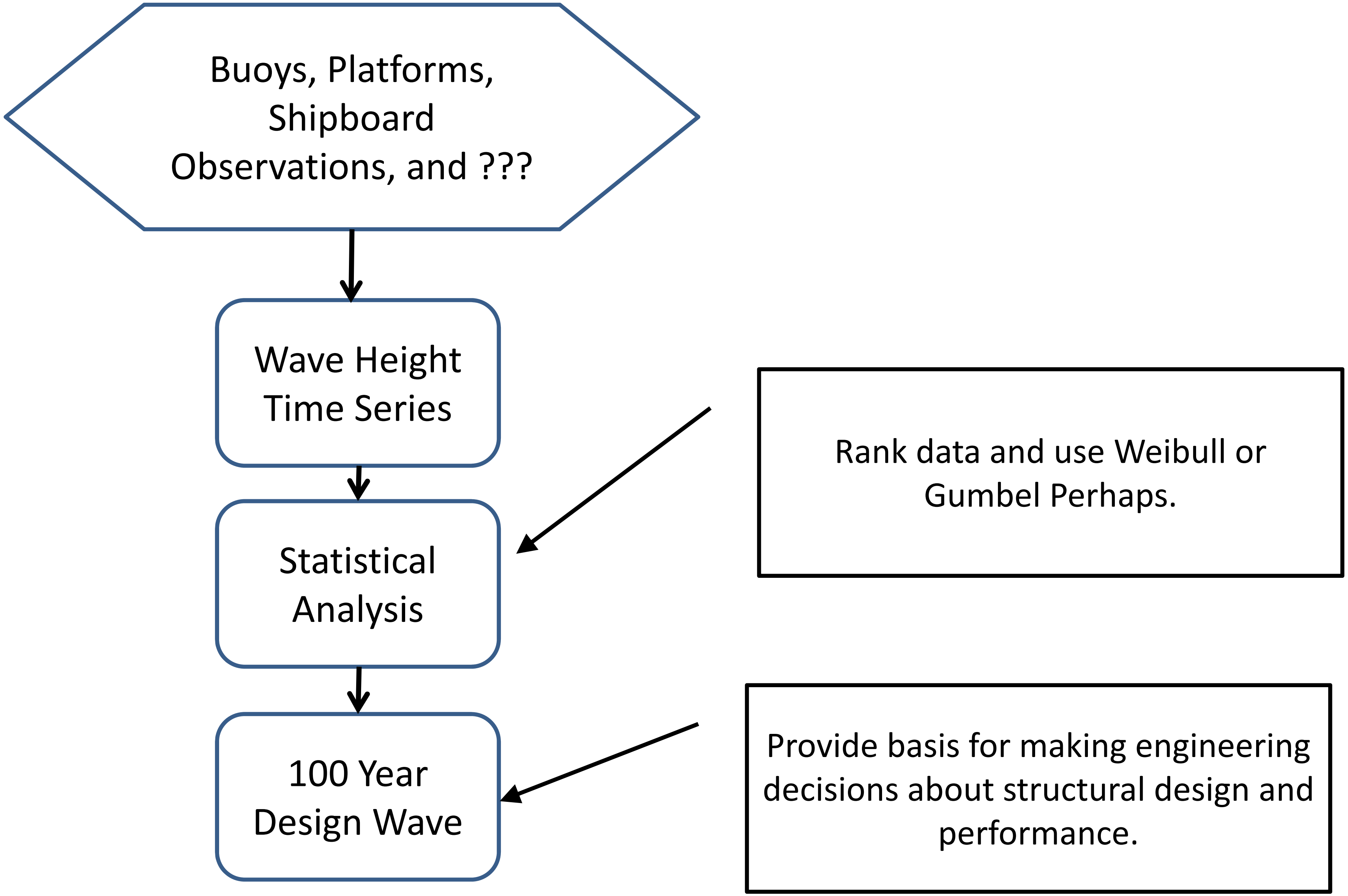
Black = Largest wave, pre Ivan and Katrina
I = Hurricane Ivan 2004
K = Hurricane Katrina 2005
D=Dennis 2005 R= Rita 2005

Note: Largest Wave is about Twice the SWH (Significant Wave Height)

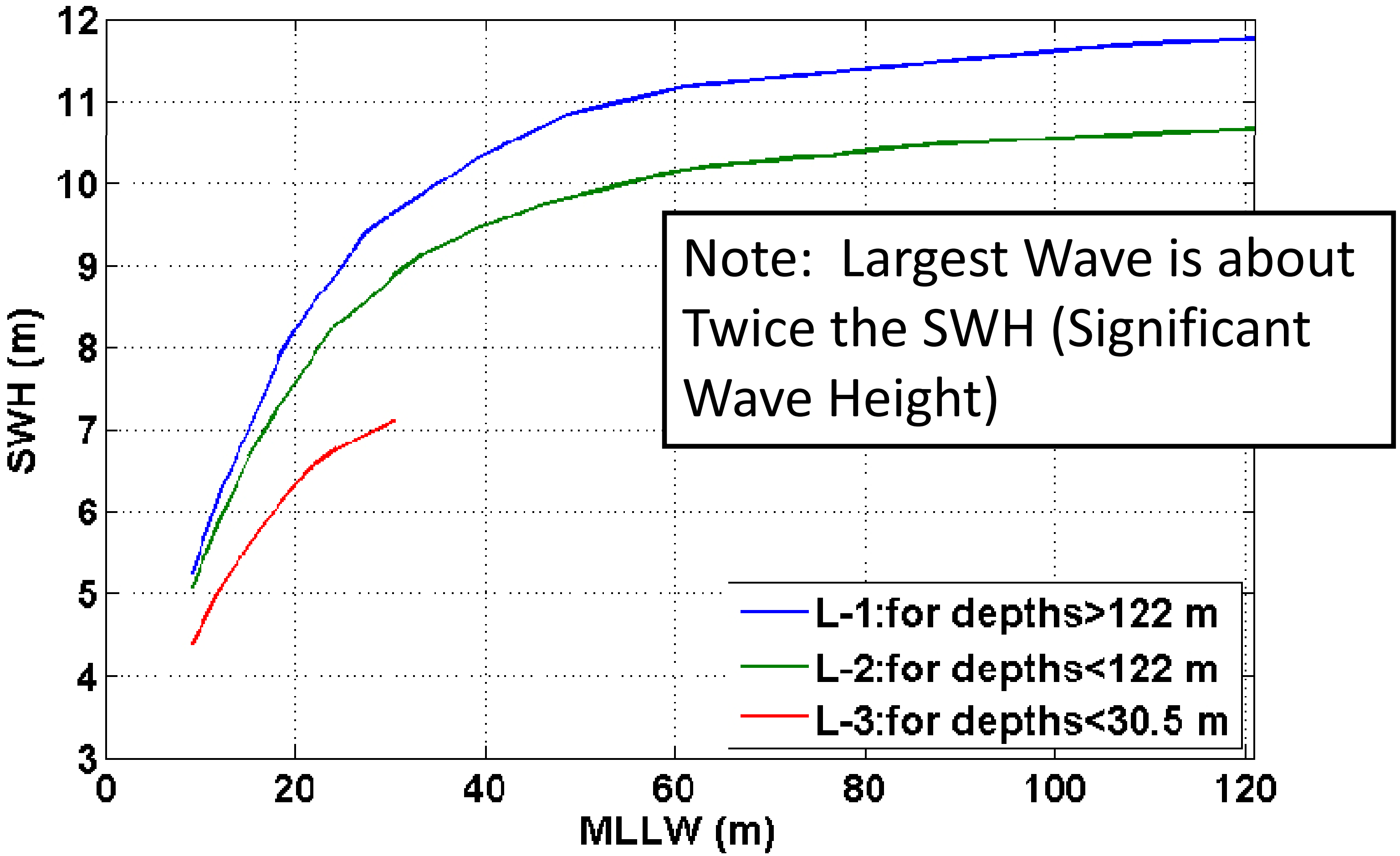
Hurricane Tracks



When the statistics were stationary. Static analysis – NO ability to update from one year to the next.

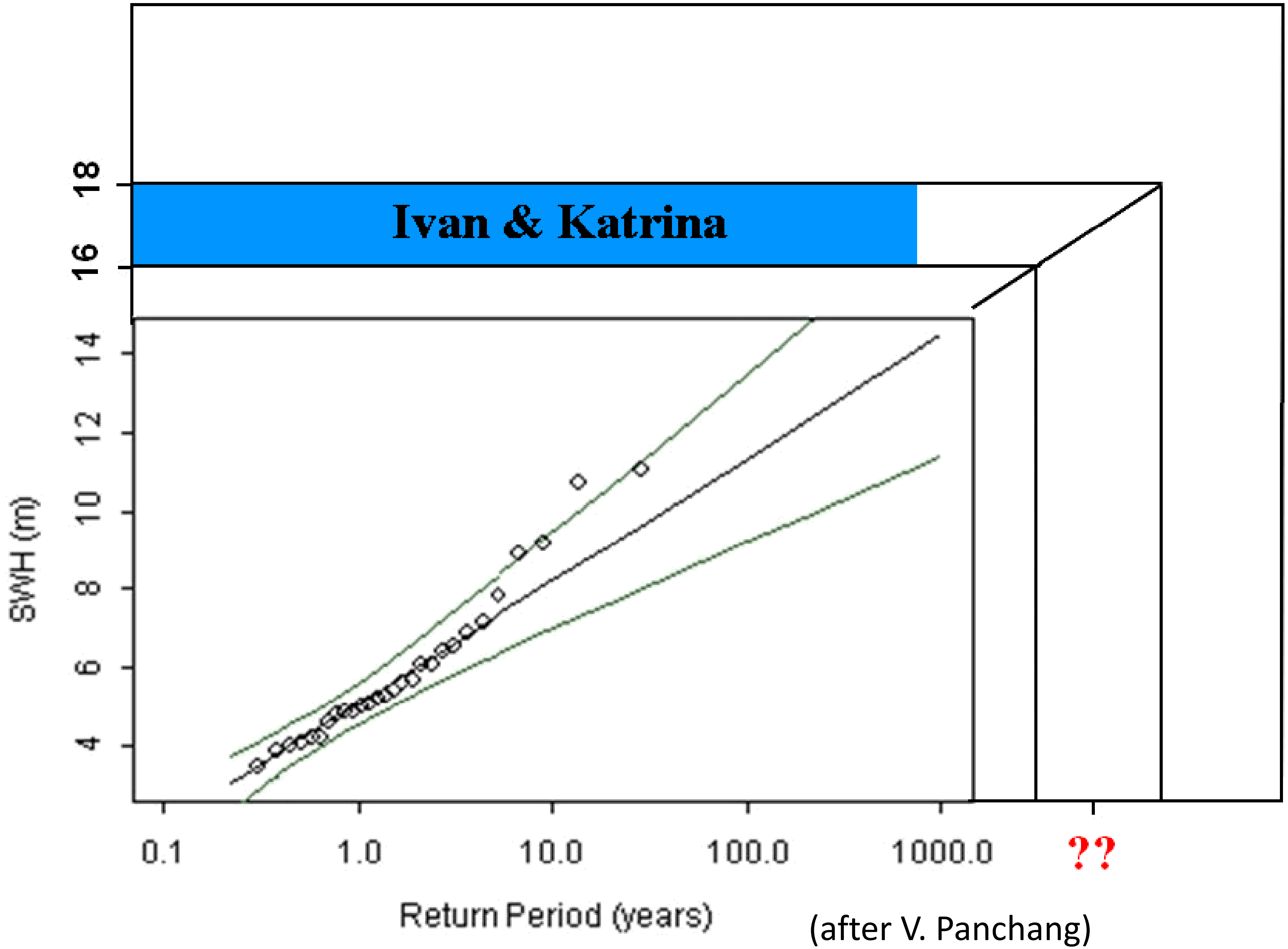


API Design Guidelines – PRE Ivan and Katrina



Gulf of Mexico, North of 27° N and west of 86° W

(after V. Panchang)

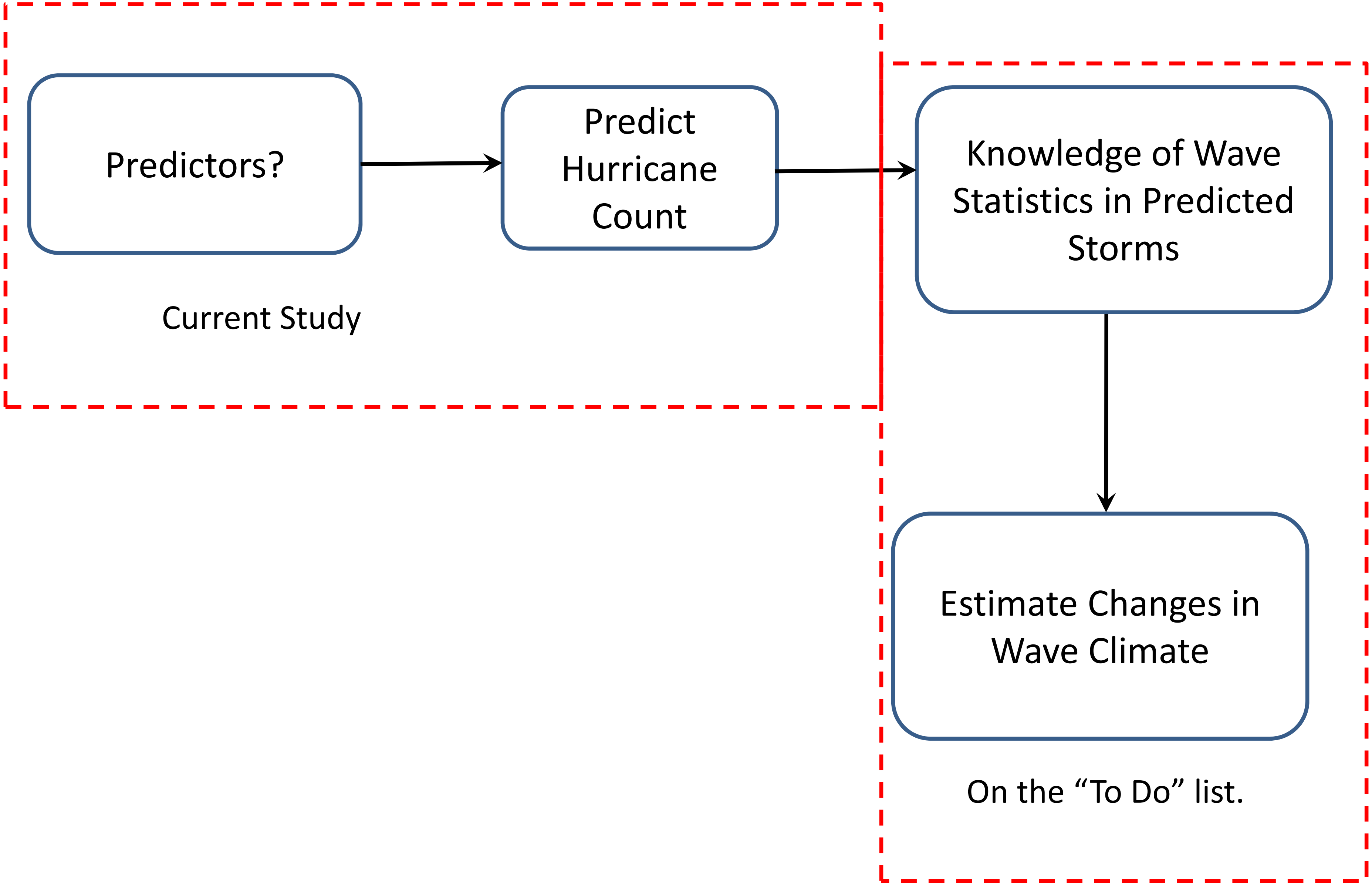


(after V. Panchang)

- Where they just unlucky or is the world changing?
- Do we focus on wave data and try to do a better analysis? Data bias for extreme events.
- How do we incorporate trends, decadal, and or inter-annual changes?????????????
- For the Gulf of Mexico, the large waves in question occur in hurricanes.
- Can we use long term (relatively) hurricane data as a proxy for wave height? And develop a heirachical model based on wave statistics in hurricanes. (Long term goal)

- Resio and Perrie(JFM-1989) – Resio et al (JGR-Oceans-2004) - Resio and Orelup 2006 (9^{th} Wave Hindcasting Conf – Vancouver)
- $$H_{MAX} \sim u^{-9/7}$$
- The maximum significant wave height in the hurricane scales approximately as the 9/7 th power of the wind speed (typically at 10 meters)
- Using U_{10} as a proxy for wave height allows us to focus on the (non?) stationarity of hurricane production without dealing with additional complexity of fluid dynamic models.

We need a plan!



Storm KATRINA is number 11 of the year 2005

****

Month	Day	Hour	Lat.	Long.	Dir.	----Speed-----		-----Wind------	
August	23	18 UTC	23.1N	75.1W	-- deg	-- mph	-- kph	35 mph	55 kph
August	24	0 UTC	23.4N	75.7W	300 deg	6 mph	11 kph	35 mph	55 kph
August	24	6 UTC	23.8N	76.2W	310 deg	6 mph	11 kph	35 mph	55 kph
August	24	12 UTC	24.5N	76.5W	340 deg	8 mph	12 kph	40 mph	65 kph
August	24	18 UTC	25.4N	76.9W	340 deg	10 mph	16 kph	45 mph	75 kph
August	25	0 UTC	26.0N	77.7W	310 deg	10 mph	16 kph	50 mph	85 kph
August	25	6 UTC	26.1N	78.4W	280 deg	6 mph	11 kph	60 mph	95 kph
August	25	12 UTC	26.2N	79.0W	280 deg	5 mph	9 kph	65 mph	100 kph
August	25	18 UTC	26.2N	79.6W	270 deg	5 mph	9 kph	70 mph	110 kph
August	26	0 UTC	25.9N	80.3W	245 deg	6 mph	11 kph	80 mph	130 kph
August	26	6 UTC	25.4N	81.3W	240 deg	11 mph	18 kph	75 mph	120 kph
August	26	12 UTC	25.1N	82.0W	245 deg	8 mph	12 kph	85 mph	140 kph
August	26	18 UTC	24.9N	82.6W	250 deg	5 mph	9 kph	100 mph	160 kph

Storm KATRINA is number 11 of the year 2005

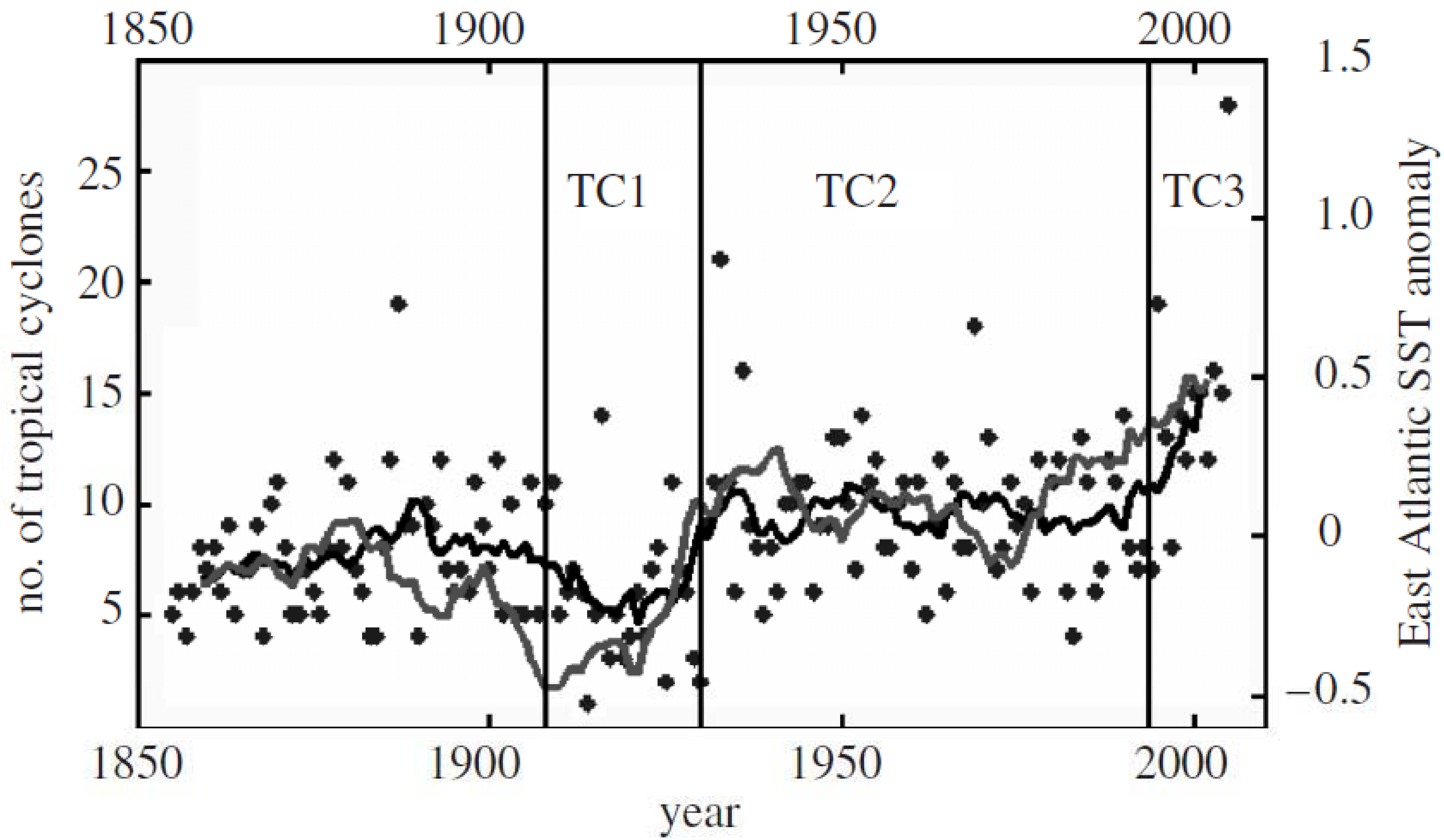
****

Month	Day	Hour	Lat.	Long.	Dir.	----Speed-----		-----Wind------		Pressure	------------Type-----------
August	23	18 UTC	23.1N	75.1W	-- deg	-- mph	-- kph	35 mph	55 kph	1008 mb	Tropical Depression
August										1007 mb	Tropical Depression
August										1007 mb	Tropical Depression
August										1006 mb	Tropical Storm
August										1003 mb	Tropical Storm
August										1000 mb	Tropical Storm
August										997 mb	Tropical Storm
August										994 mb	Tropical Storm
August										988 mb	Tropical Storm
August										983 mb	Hurricane - Category 1
August	26	6 UTC	25.4N	81.3W	240 deg	11 mph	18 kph	75 mph	120 kph	987 mb	Hurricane - Category 1
August	26	12 UTC	25.1N	82.0W	245 deg	8 mph	12 kph	85 mph	140 kph	979 mb	Hurricane - Category 1
August	26	18 UTC	24.9N	82.6W	250 deg	5 mph	9 kph	100 mph	160 kph	968 mb	Hurricane - Category 2
August	27	0 UTC	24.6N	83.3W	245 deg	8 mph	12 kph	105 mph	165 kph	959 mb	Hurricane - Category 2
August	27	6 UTC	24.4N	84.0W	255 deg	6 mph	11 kph	110 mph	175 kph	950 mb	Hurricane - Category 2
August	27	12 UTC	24.4N	84.7W	270 deg	6 mph	11 kph	115 mph	185 kph	942 mb	Major Hurricane - Category 3
August	27	18 UTC	24.5N	85.3W	280 deg	5 mph	9 kph	115 mph	185 kph	948 mb	Major Hurricane - Category 3
August	28	0 UTC	24.8N	85.9W	300 deg	6 mph	11 kph	115 mph	185 kph	941 mb	Major Hurricane - Category 3
August	28	6 UTC	25.2N	86.7W	300 deg	9 mph	14 kph	145 mph	230 kph	930 mb	Major Hurricane - Category 4

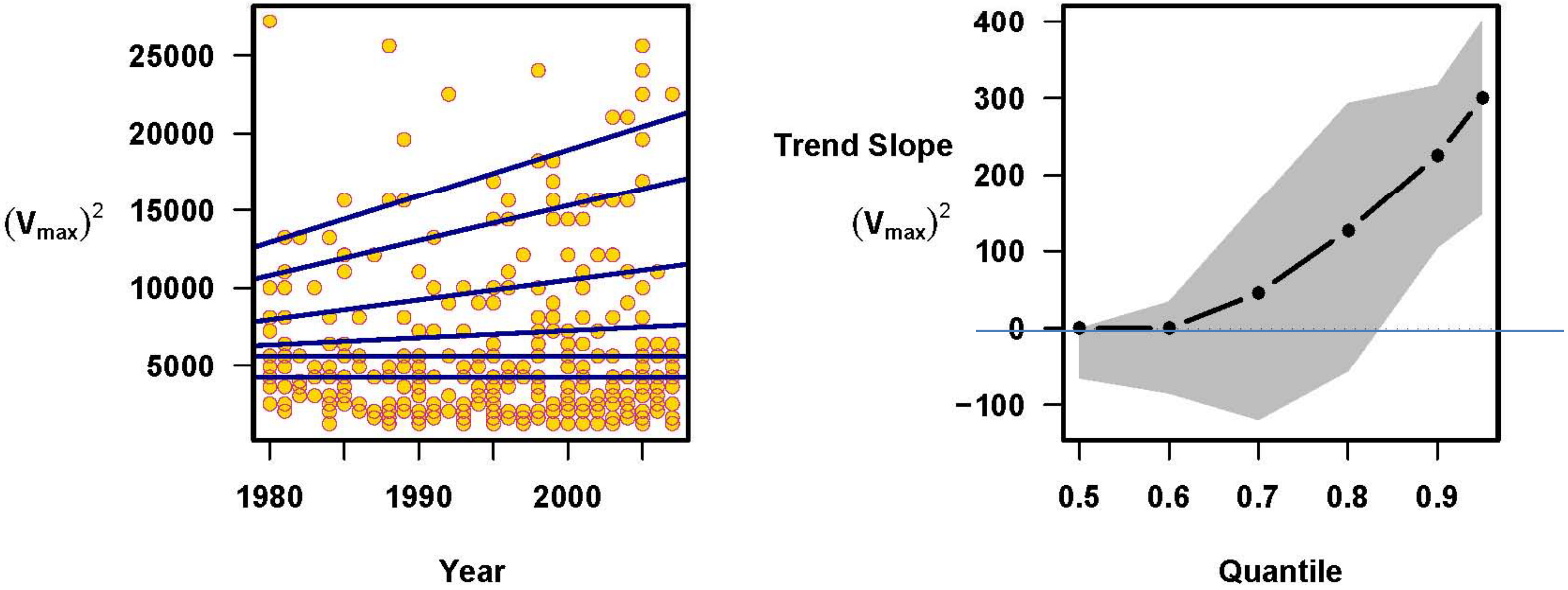
NOAA data base – HURDAT

Storms ranked , Depression, Storm , Hurricane Cat 1 to Cat 5. (Cat 5 unlimited)

HURDAT Data Set Issues – Pre and Post Satellite
Early Days – If no one saw the storm? Was it there?
Re-analysis.



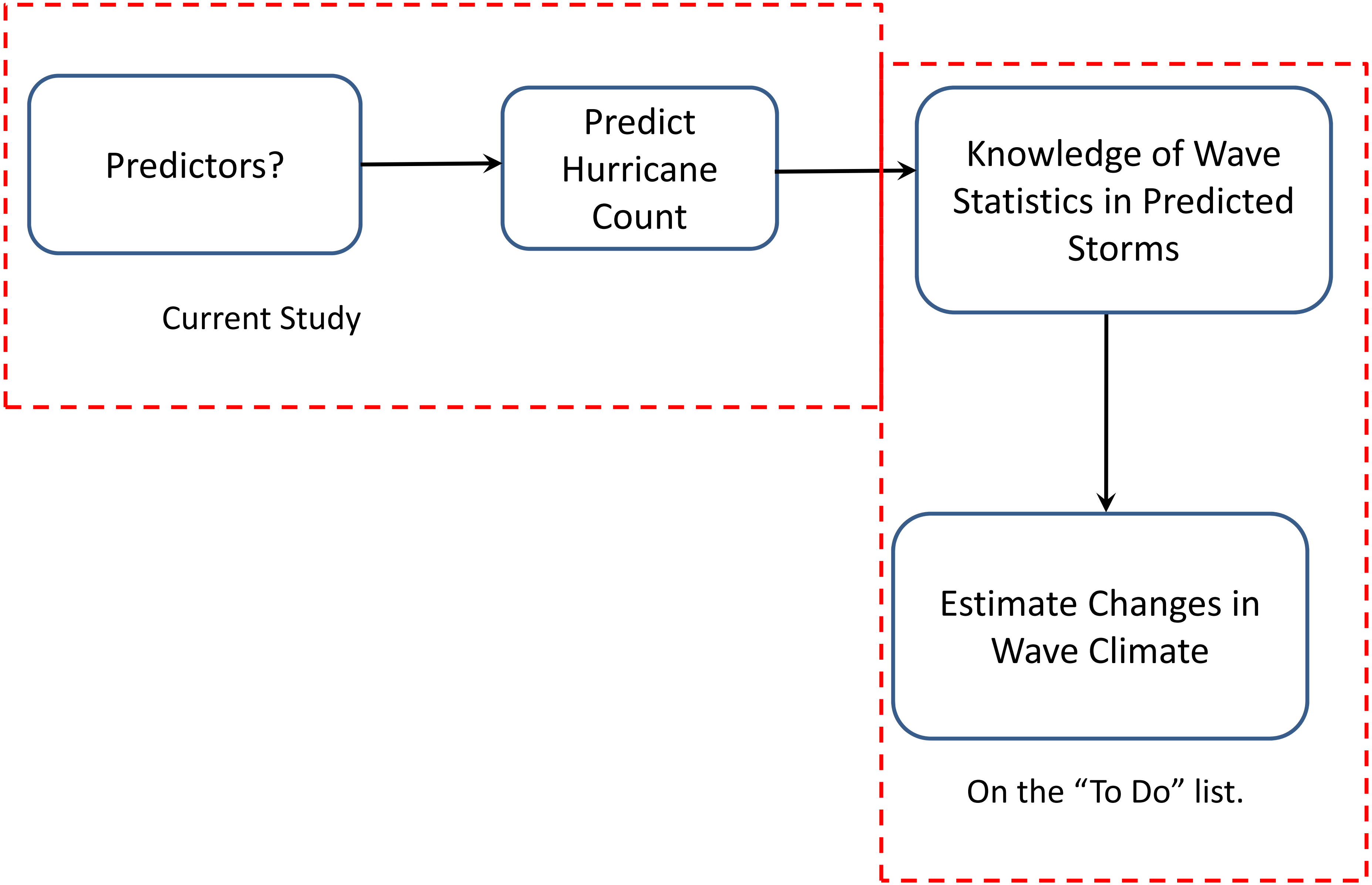
Grey – SST Anomaly   TC1, TC2, TC3 Refer to indicated time periods.
Black 9-Year Running Average   From Holland and Webster (Phil. Trans. RS. 2007)

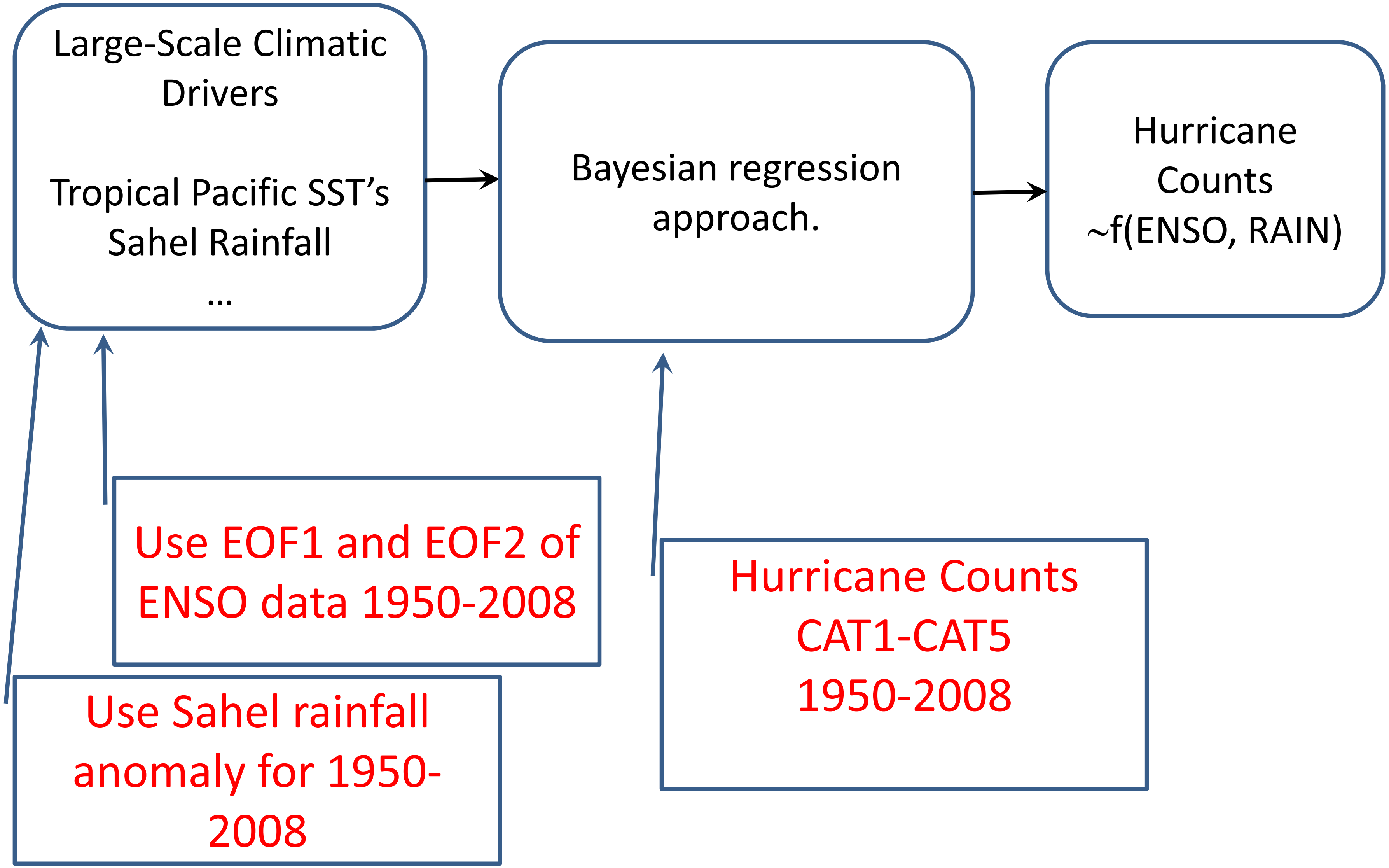


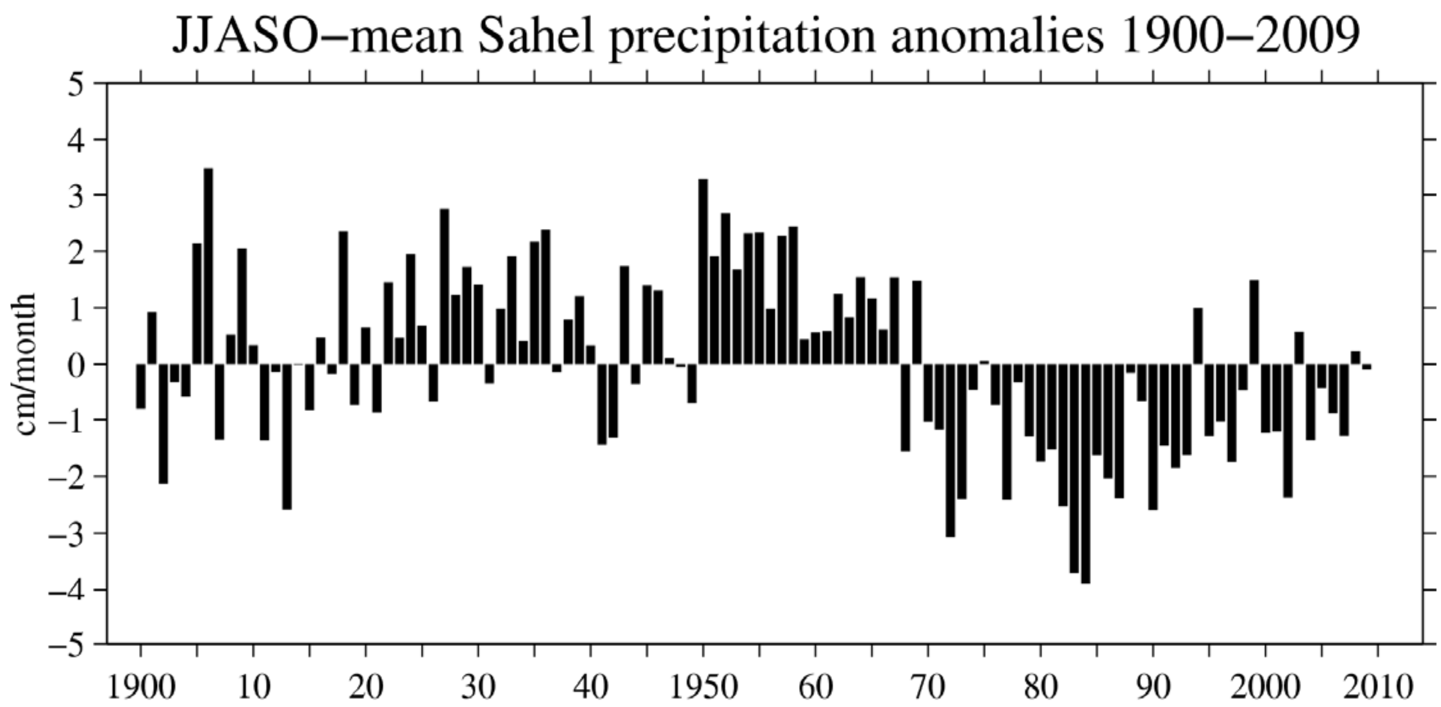
Quantile Regression of Maximum Windspeed Squared for Each Storm. 50% to 1%.

We found that we can change trend by choice of time series. Similar results by Elsner (Nature - 2008)

We need a plan!

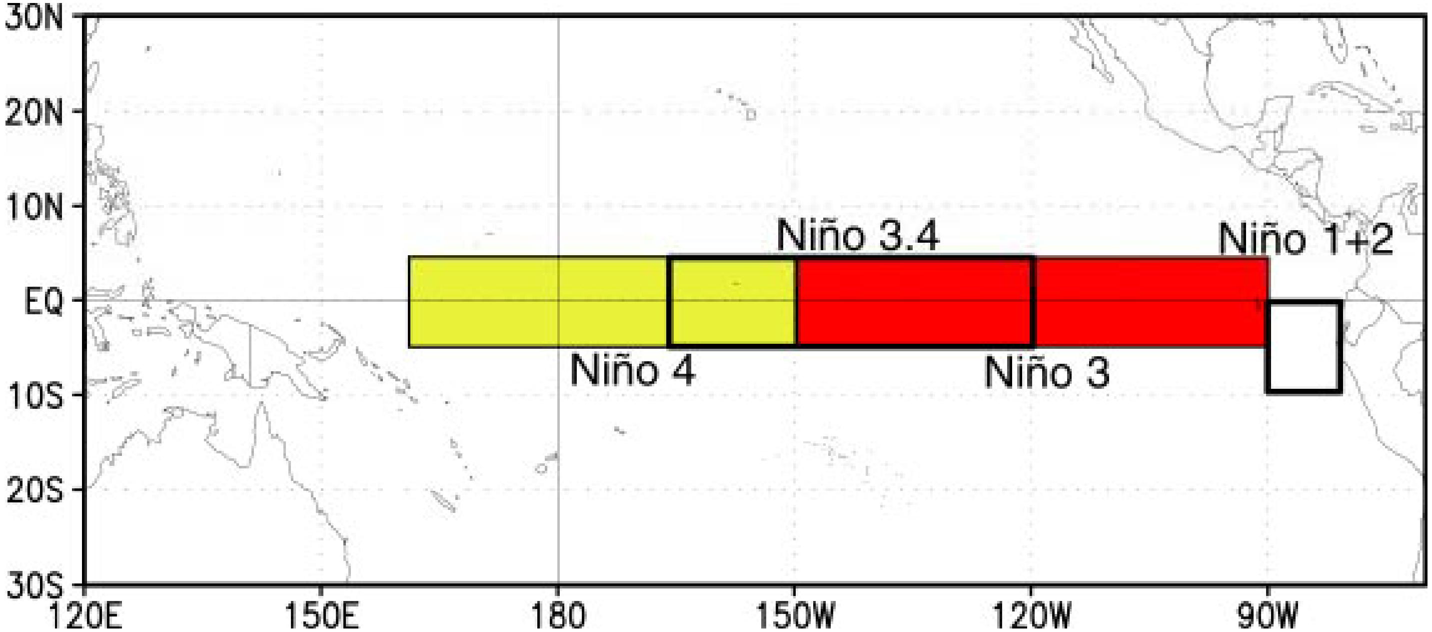



Large-Scale Climatic Drivers
Tropical Pacific SST's
Sahel Rainfall
...
Bayesian regression approach.
Hurricane Counts ~f(ENSO, RAIN)
Use EOF1 and EOF2 of ENSO data 1950-2008
Use Sahel rainfall anomaly for 1950-2008
Hurricane Counts CAT1-CAT5 1950-2008

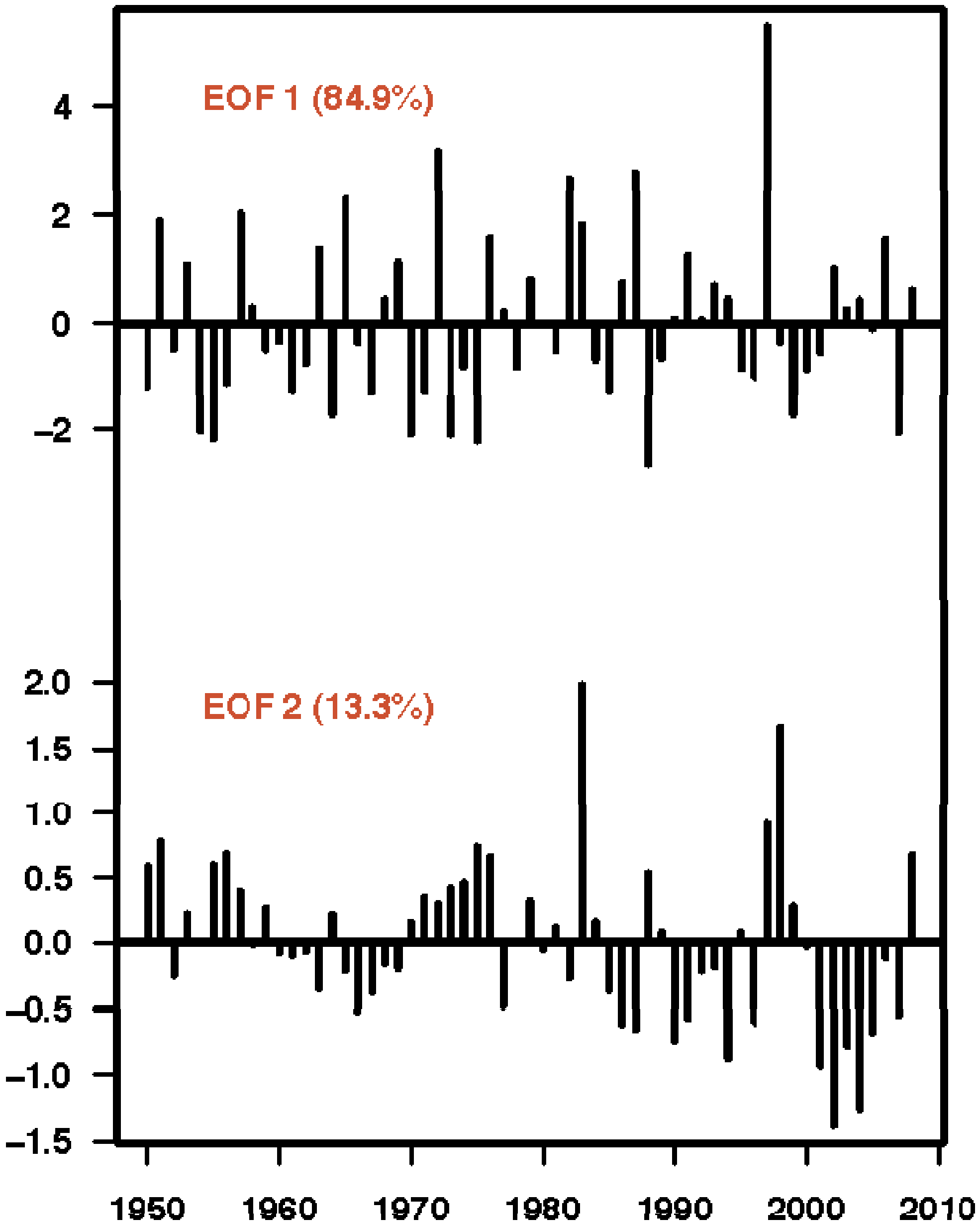


Averages over 20–10N, 20W–10E; 1900–2009 climatology
NOAA NCDC Global Historical Climatology Network data

Cumulative Jan-June Data → Antecedent Conditions at the Beginning of Hurricane Season. → Dust/Aerosol Loading. Wu & Tao (2010 – Clim Dyn) Huang et al (2010-JGR)



Used first two EOF's for combined data set.
Most of the variance. 1950-2008



Principal Components

	NINO12A	NINO3A	NINO4A	NINO34A
PC1	0.6	0.5	0.3	0.5
PC2	0.7	-0.1	-0.6	-0.5

Looking for a simple regression model.

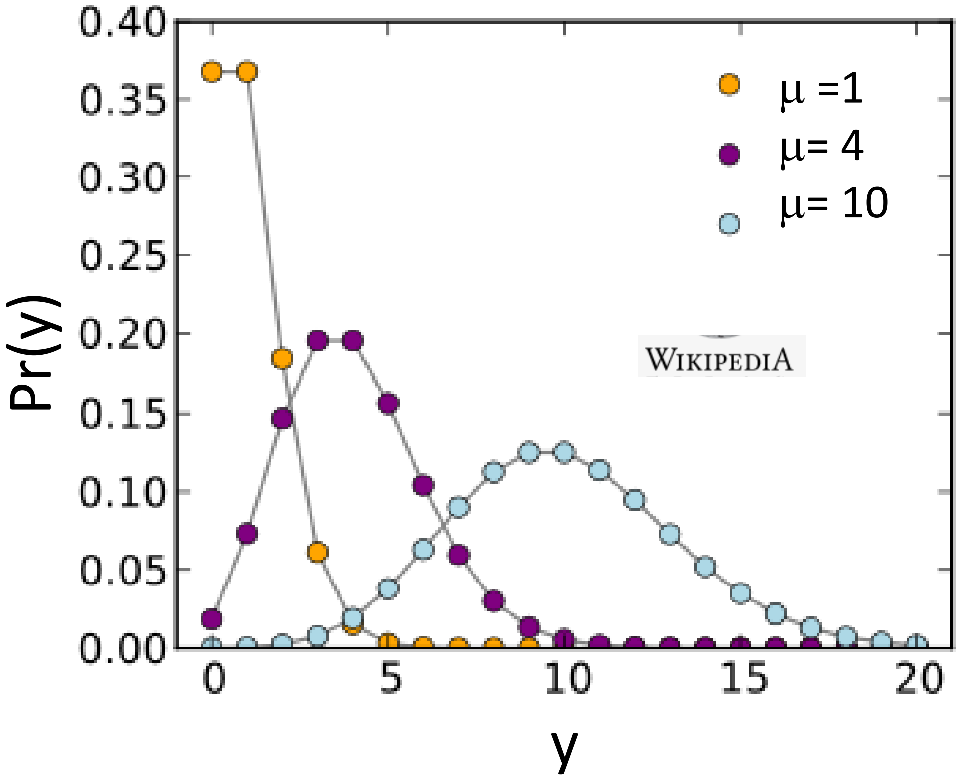
- Random variables must be non-negative integers. (Poisson)

- The Regression model must handle non-linear terms and/or categorical (binary) variables.

- Use MCMC (Markov chain Monte Carlo) (Open Bugs and/or MCMCpack in **R**)

The Poisson Distribution

$$\Pr(y \mid \mu) = \frac{e^{-\mu}\,\mu^{y}}{y!} \quad \text{for } y = 0, 1, 2, \ldots$$



- For our case the expected number of counts is the variable μ (the mean),

  E(y) = μ

- For the Poisson Distribution the Var(y) = E(y) = μ. Thus the Poisson Dist. Exhibits *equidispersion* . Of note, then, is whether the variance and means of the hurricane counts are substantially different (*overdispersion or underdispersion*).

Poisson Regression Model

$$\mu_i = E(y_i \mid \vec{x}_i) = \exp(\vec{x}_i \vec{\beta})$$

$$\mu = e^{b_0 + b_1 * EOF1 + b_2 * EOF2 + b_3 * WETDRY}$$

- μ represents the hurricane count mean
- The b's are the regression coefficients, with b_0 a constant.
- $EOF1$ and $EOF2$ are the two largest EOF's of the ENSO anomaly record and compromise about 97% of the signal.
- WETDRY is either 0 or 1 with 0 representing a dry spring and 1 a wet spring.

- A sample of the code we used in OpenBUGS is shown below. "SST1" and "SST2" refer to the ENSO EOF anomaly output, and "dry" refers to the Sahel rainfall anomaly as a 1 (dry) or 0 (wet).

- The first part represents an "uninformative prior" and variable defintion. The bottom part the regression model which, as it turns out, can be formulated, as a log or exponential. The dpois command tells OpenBUGS we wish to use a Poisson Distribution. Note that lam is equivalent to μ in the previous discussion, and represents the mean hurricane count.

- The loop from 1 to 59 represents the 59 years of data we are using in the simulation.

model (from OpenBUGS)

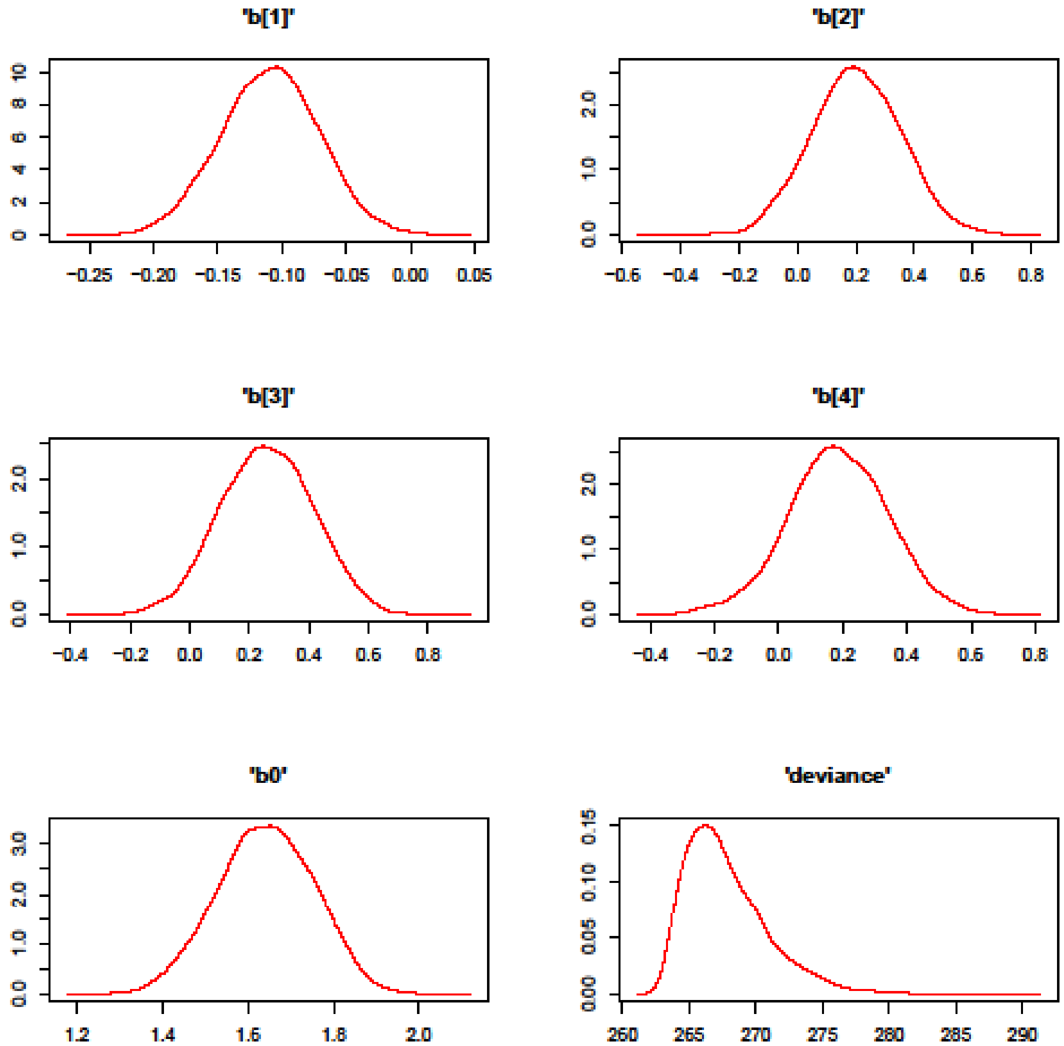
```
{ b0~dnorm(0,1.0E-6)
  for (j in 1:3) {
  b[j]~dnorm(0,1.0E-6) }
```

Uninformative Prior Distribution

```
  # specify the model for each data point.
  for (i in 1:59)
  {
  # Can write model either way.
  #log(lam[i])<-b0+b[1]*nsst1[i]+b[2]*ndry[i]+b[3]*nsst2[i]
  lam[i]<-exp((b0+b[1]*nsst1[i]+b[2]*ndry[i]+b[3]*nsst2[i]))
  major[i]~dpois(lam[i])}
 }
```

59 Years in data set.

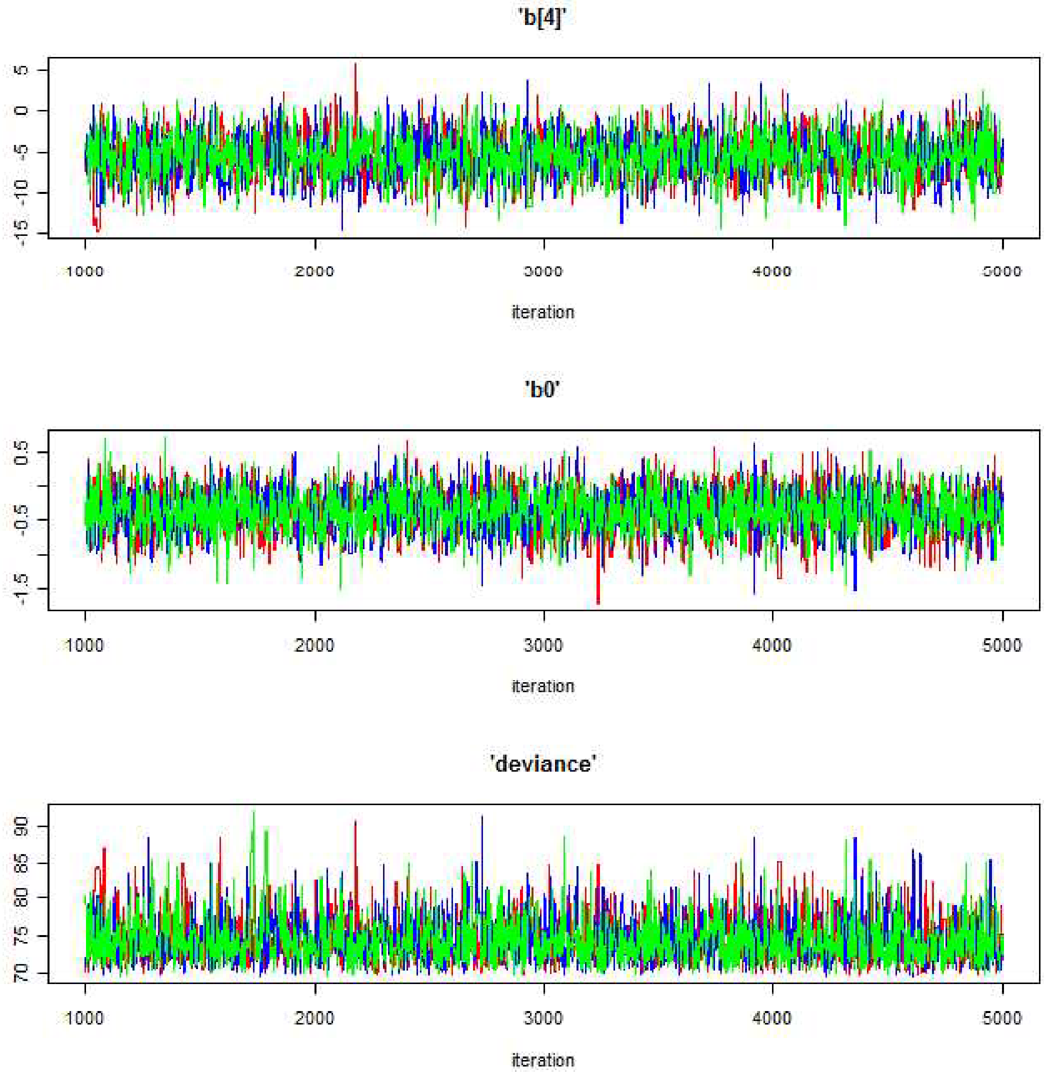
Regression model with Poisson Dist.



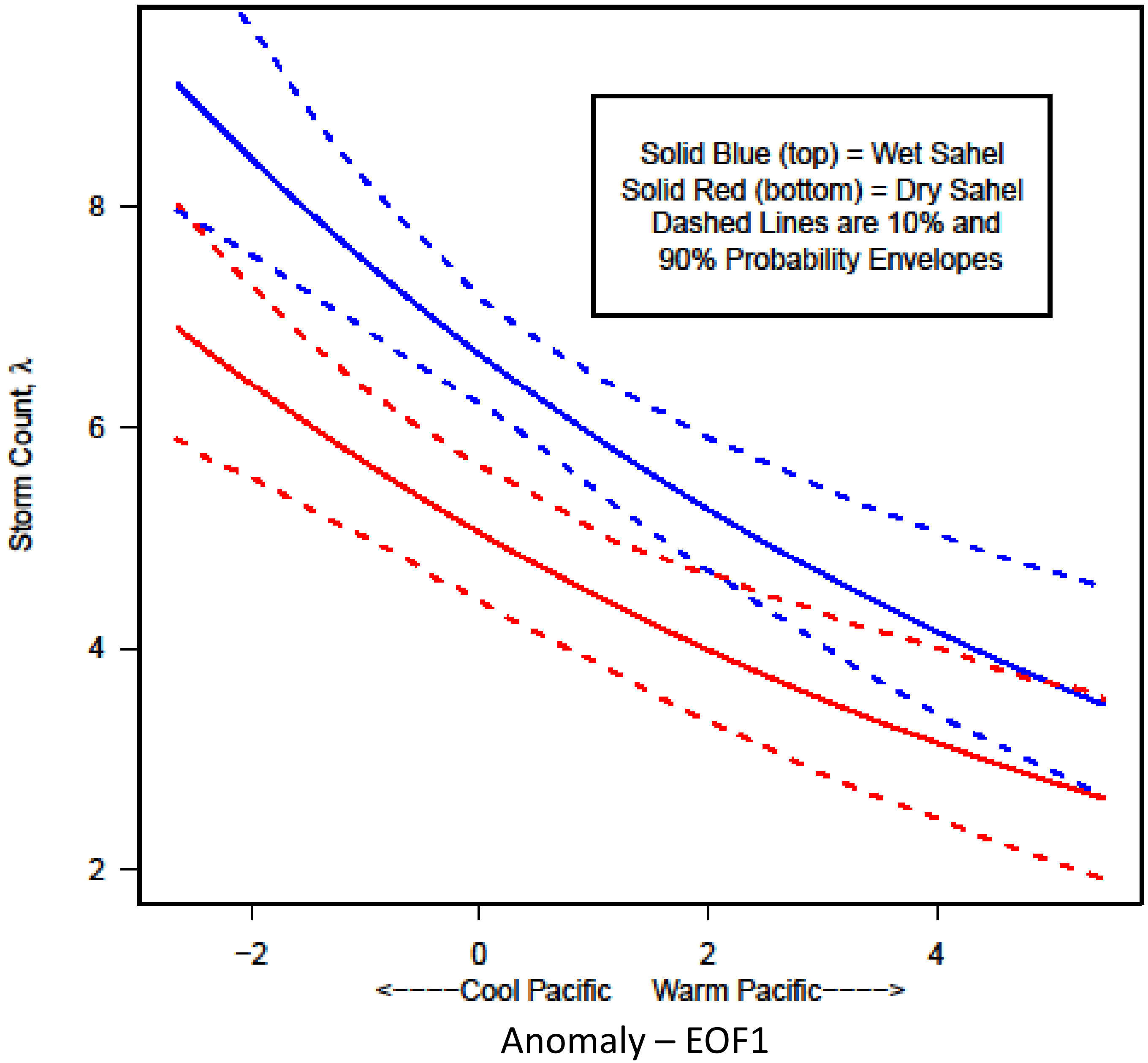
- MCMC (Markov chain Monte Carlo)
- OpenBUGS (Bayesian Analysis Using Gibb's Sampling)

The PDF of our coefficients from the MCMC simulation. We wish to see a distribution that gives us "confidence" in the results. This plot is for about 4000 trials. Increasing the number of trials by a factor of ten will smooth these curves out.

- MCMC (Markov chain Monte Carlo)

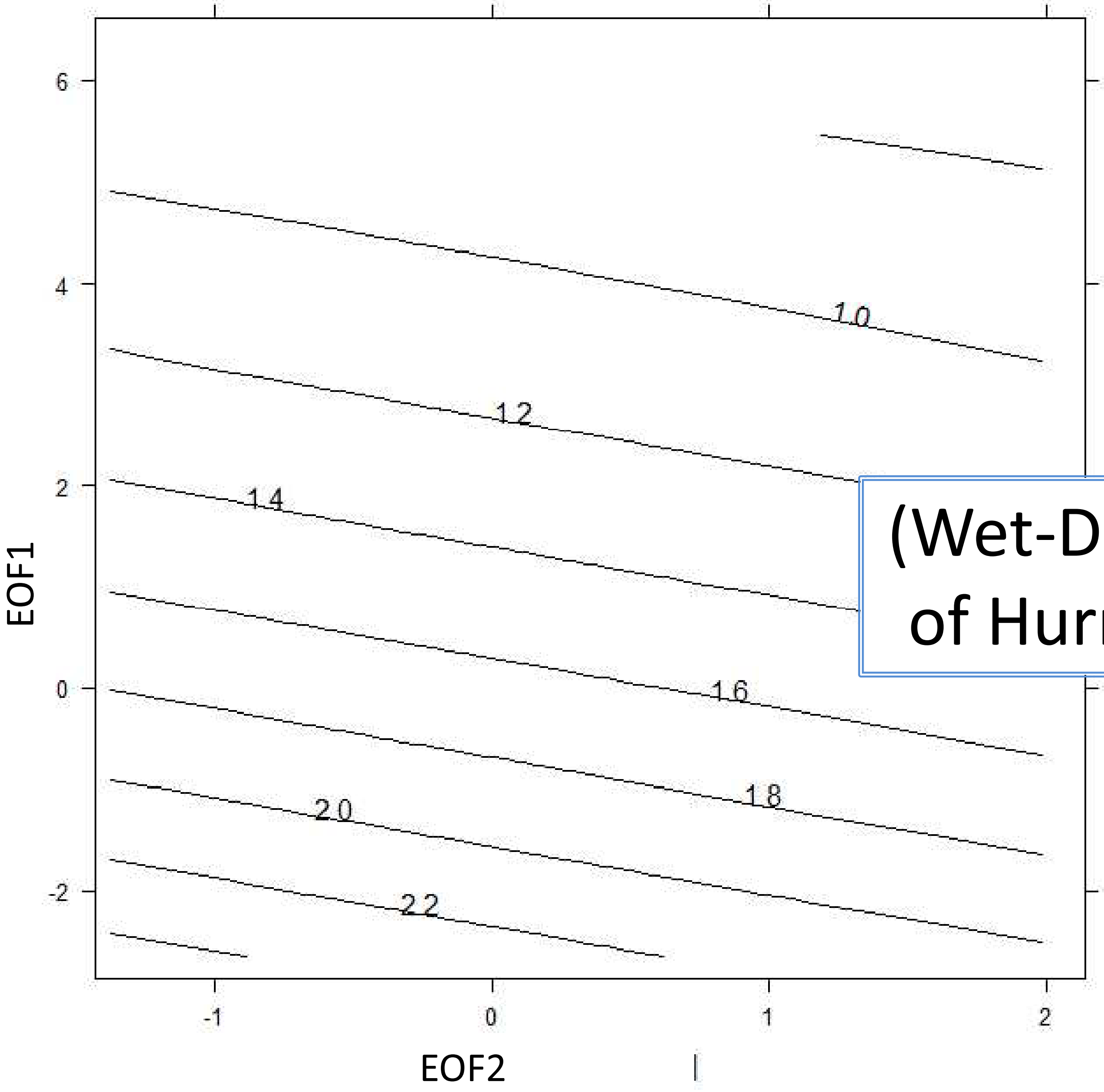


Here the three colors represent three "chains" or simultaneous simulations. The important feature is that the results are more or less random and "stable" (not increasing without bound).

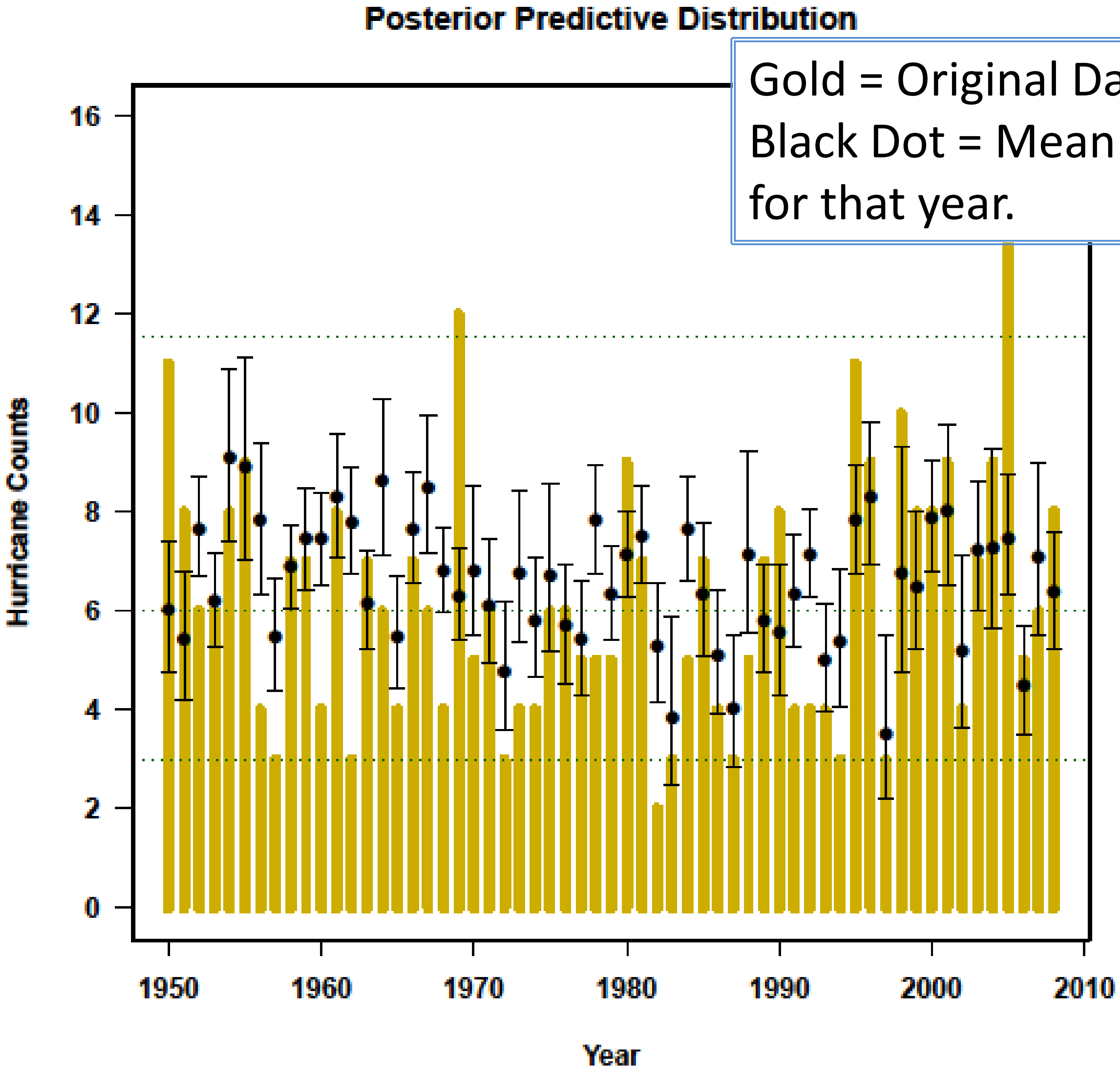


Solid Blue (top) = Wet Sahel
Solid Red (bottom) = Dry Sahel
Dashed Lines are 10% and
90% Probability Envelopes
Storm Count, λ
8
6
4
2
−2
0
2
4
<----Cool Pacific
Warm Pacific---->
Anomaly – EOF1

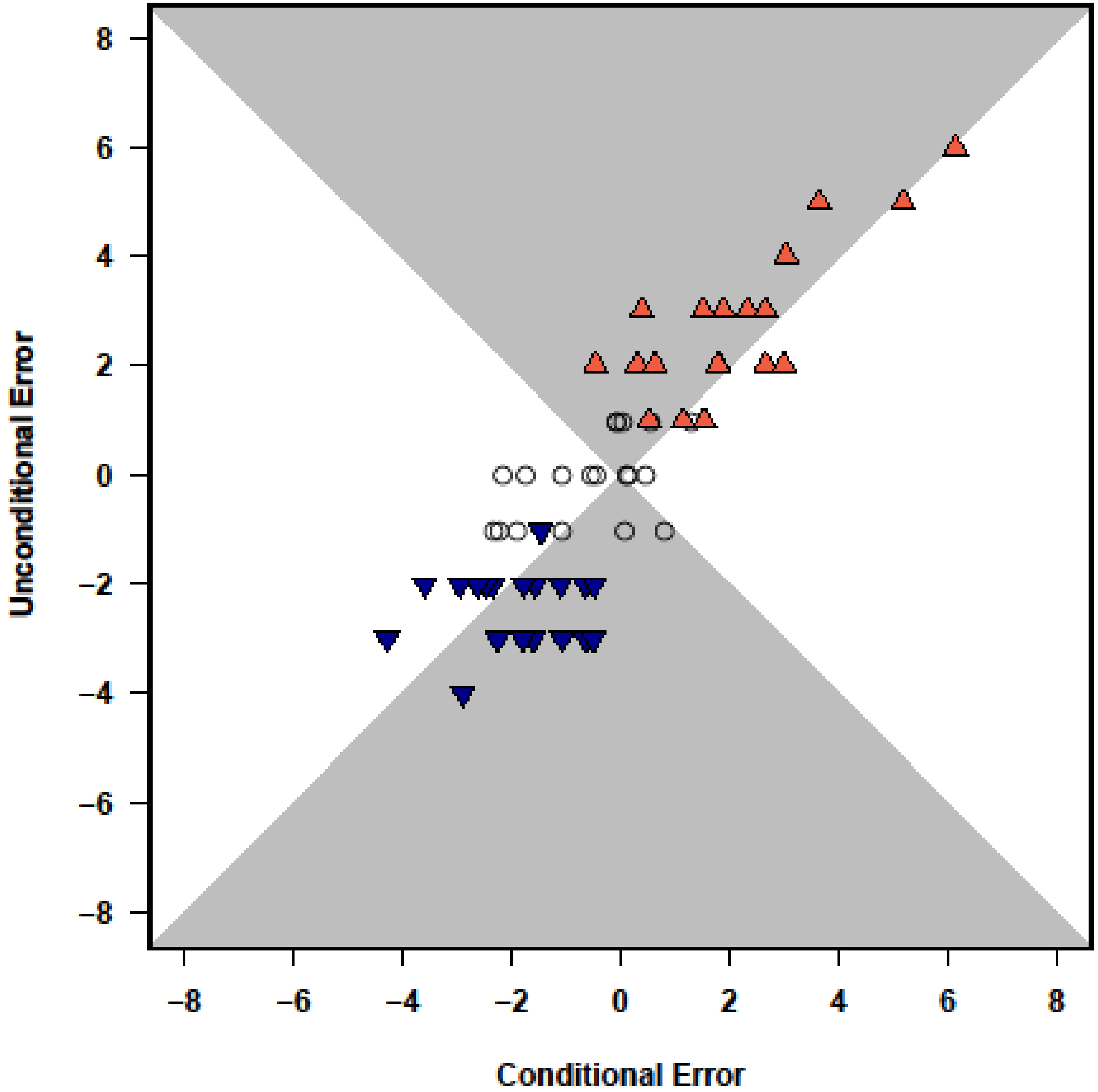
(Wet-Dry) Difference of Hurricane Counts

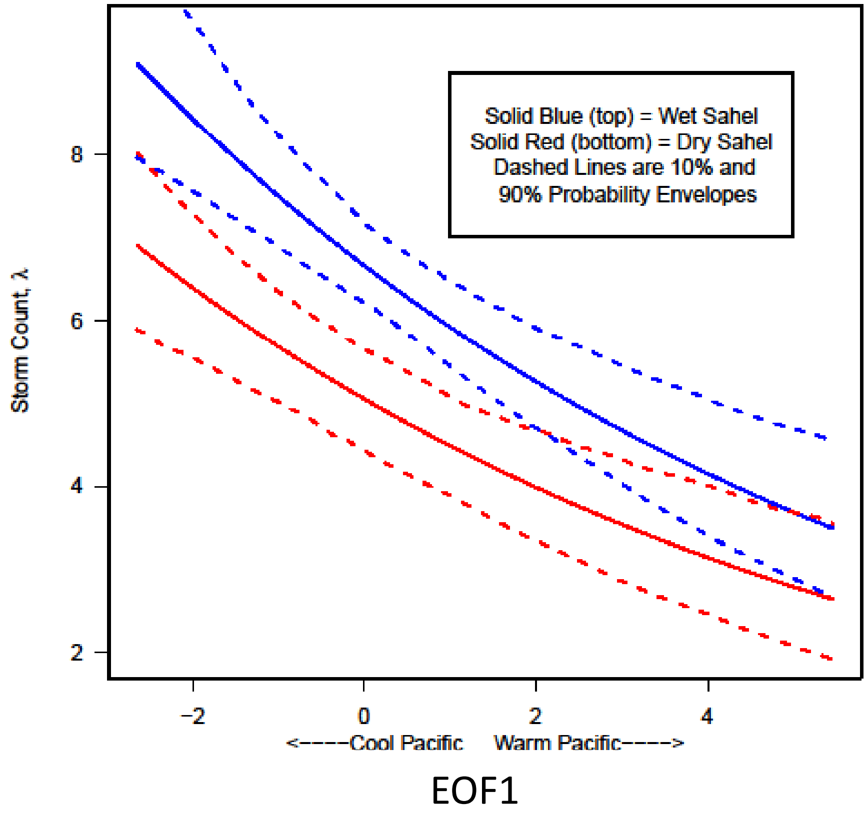


Gold = Original Data
Black Dot = Mean MCMC estimates for that year.



- MCMC (Markov chain Monte Carlo) Posterior Prediction





Where are we?

Empirical Correlation of Hurricane Counts with SRI and ENSO Anomaly.

A Number of Articles address the causality. (Dust, Wind Shear, and … .

So far we have not seen this empirical analysis including the SRI.

With pacific sst's and SRI predictions you could make a stab at hurricane count estimates.

To Do List.
NegBin. Try count predictions using ENSO predictions. Hurricane wave statistics.

The nature and impacts of the commingled influence of Sahel precipitation and tropical Pacific sea surface temperature variability on Atlantic hurricane activity.

Bryan Pearce – Department of Civil Engineering
Shaleen Jain- Department of Civil Engineering
Bill Halteman – Department of Mathematics
University of Maine