Tropical cyclone risk modeling

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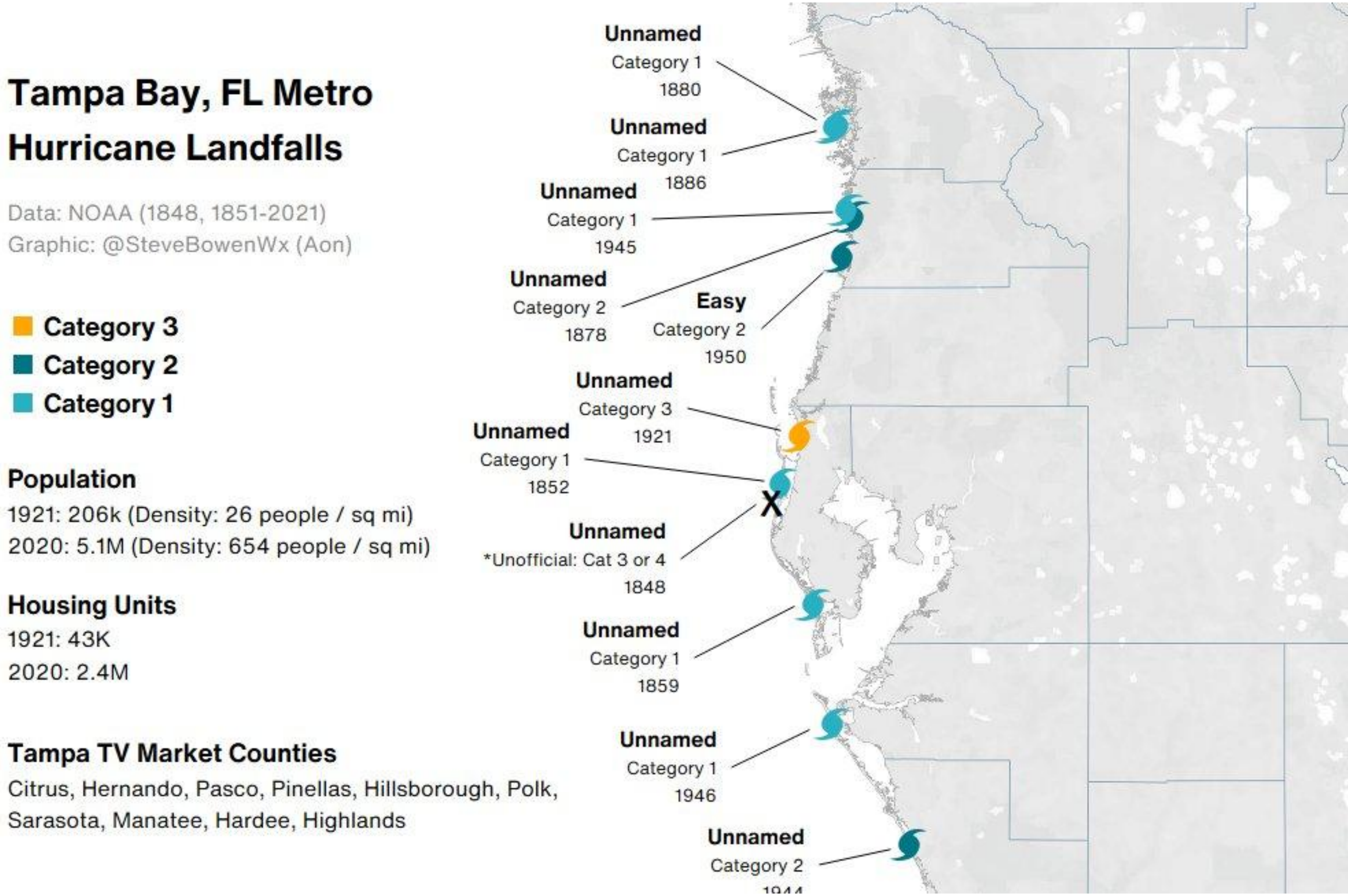
Motivation

Steve Bowen
@SteveBowenWx

Today (Oct 25) marks the 100th anniversary since the Tampa Bay area recorded a major hurricane landfall (Cat 3+).

Climatology? Luck? The region will inevitably face another event one day.

The recent population boom means a landfall today would result in MANY billions in damage.



Outline/summary

- What is risk?
  - Hazard x exposure
- How to estimate tropical cyclone risk?
  - Past observations are inadequate
  - “Models” to make more data
- What are “cat” models?
  - Risk models used by industry (esp. insurance)
- CHAZ: the Columbia tropical cyclone hazard model
  - Physics-informed, data-driven
  - Tropical cyclone genesis
  - Example: Climate change delta
  - Example: Wellbeing
  - XGboost wind model

Tropical cyclone risk is large

- The general term for hurricanes and typhoons is *tropical cyclone*
- Considered among the costliest natural hazards
- TCs are an example of a relatively rare (in any particular location), high-impact, extreme weather event

Top 10 Costliest Hurricanes In The United States

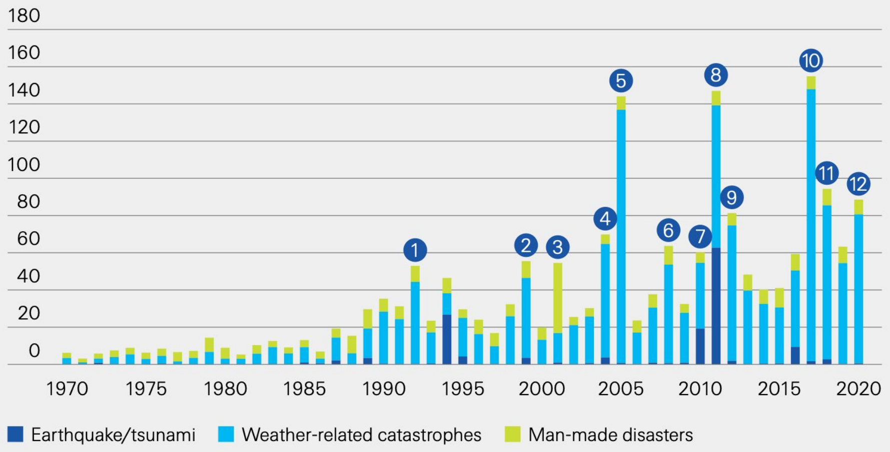
($ millions)

			Estimated insured loss	
Rank	Year	Hurricane	Dollars when occurred	In 2020 dollars (2)
1	2005	Hurricane Katrina	$65,000	$86,570
2	2012	Hurricane Sandy	30,000	33,930
3	2017	Hurricane Harvey	30,000	31,960
4	2017	Hurricane Irma	29,900	31,850
5	2017	Hurricane Maria	29,670	31,270
6	1992	Hurricane Andrew	16,000	29,700
7	2008	Hurricane Ike	18,200	21,760
8	2005	Hurricane Wilma	10,670	14,010
9	2018	Hurricane Michael	13,250	13,710
10	2004	Hurricane Ivan	8,720	12,060

https://www.iii.org/fact-statistic/facts-statistics-hurricanes

Figure 15
Insured catastrophe losses, 1970–2020, in USD billion at 2020 prices

1. 1992: Hurricane Andrew
2. 1999: Winter Storm Lothar
3. 2001: 9/11 attacks
4. 2004: Hurricanes Ivan, Charley, Frances
5. 2005: Hurricanes Katrina, Rita, Wilma
6. 2008: Hurricanes Ike, Gustav
7. 2010: Chile, New Zealand earthquakes
8. 2011: Japan. NZ earthquakes, Thailand flood
9. 2012: Hurricane Sandy
10. 2017: Hurricanes Harvey, Irma, Maria
11. 2018: Camp Fire, Typhoon Jebi
12. 2020: Hurricane Laura, wildfires



Source: Swiss Re Institute

https://www.swissre.com/institute/research/sigma-research/sigma-2021-01.html

Who cares about risk?

- People who own things
- People who insure those things
- Insurance companies often have both sources of risk
  - Liabilities (policies)
  - Assets (with which to pay claims)
- Reinsurance industry
  - Insurance for insurance companies against <u>catastrophic</u> events
  - Hurricane Andrew (1992): at least 11 insurance companies insolvent
- Governments/public sector
- Non-governmental organizations

(Things include financial instruments: cat bonds, ILS, etc.)

What are some types of risk?

- Natural
  - Earthquake
  - Hurricane □
  - Tsunami
  - Severe convective storms (tornado & hail)
  - Wildfire
  - Flood
- Human
  - Cyber
  - Terrorism
  - Pandemic

that can be insured?

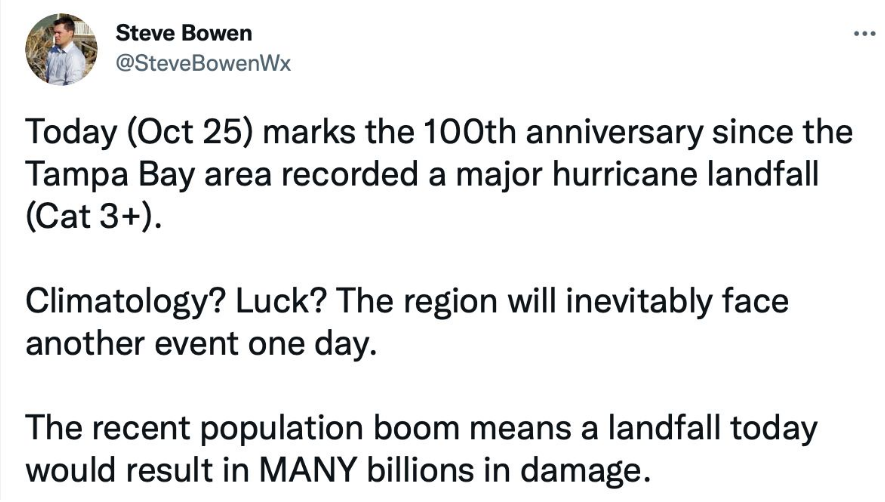
Risk = hazard (x vulnerability) x exposure

- Risk = loss
  - Economic or well-being (hard to measure)
  - Insured loss (easier to measure, hard to access, incomplete)
- Hazard (or peril) e.g., hurricane □
  - Cause of loss or damage
  - Extent and intensity
- Vulnerability
  - Damage = f(hazard) e.g., type of construction, building code
- Exposure
  - Being in harm's way (house near the coast)

Not exactly economic risk? = uncertainty, has upside and downside

Is historical data enough to estimate risk*?

- Typically 10 to years of claims data available
  - Not enough to estimate 1-in-200-year loss
- Changes in exposure
  - New building, urbanization
- Changes in vulnerability
  - Building standards
- Changes in the hazard
  - Climate change
  - Sea level rise
- Annual average number of TCs
  - Global ~90
  - Atlantic ~11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Climatology? Luck? The region will inevitably face another event one day.

The recent population boom means a landfall today would result in MANY billions in damage.

*from rare, high-impact, catastrophic events

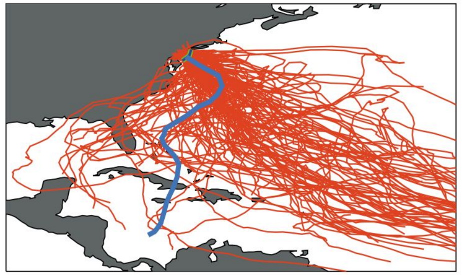
Example: What was the probability of hurricane with a Sandy-like angle?

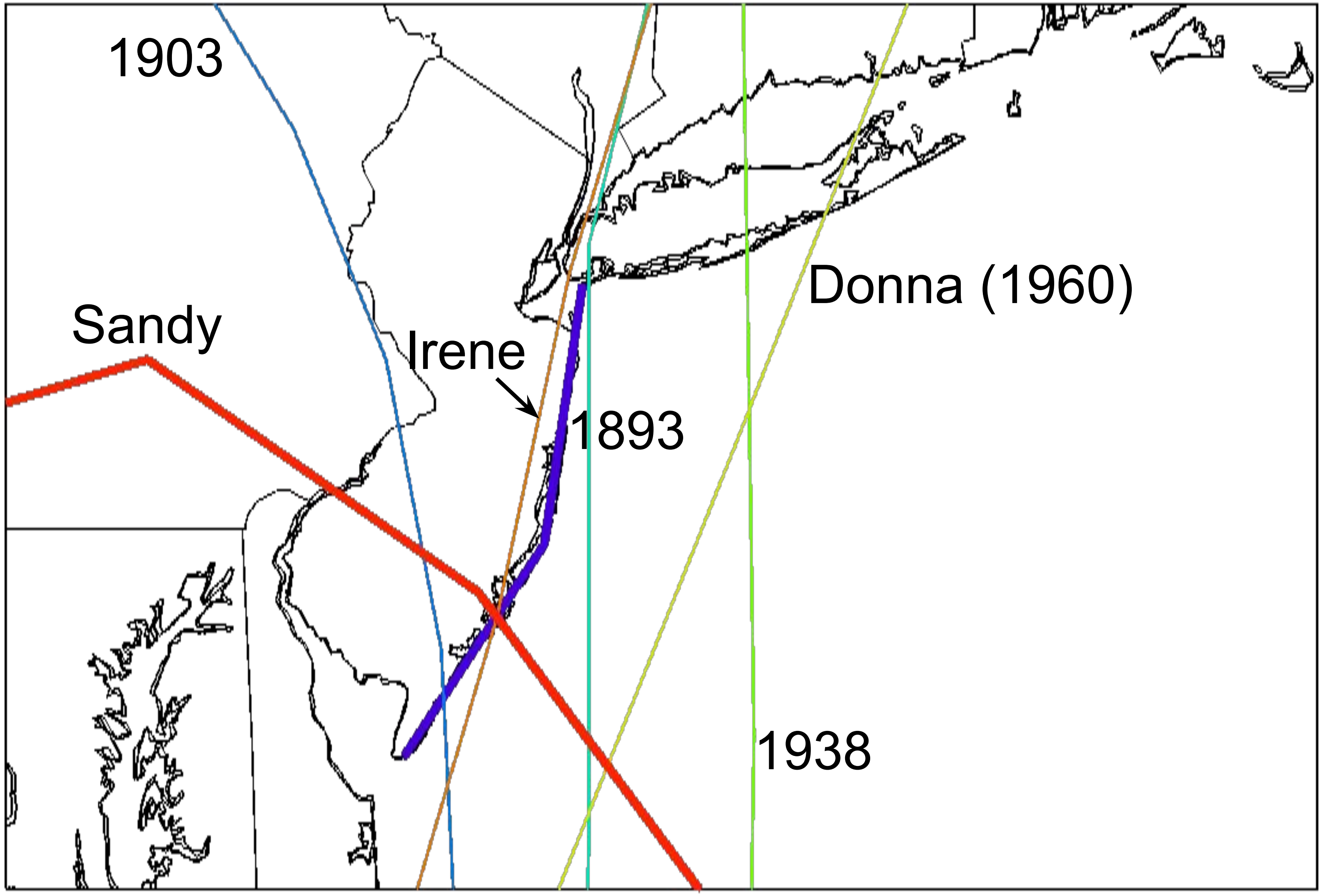
Before Sandy? Zero?

A small number but not zero.

~1-in-700 years event

If only there were more data!



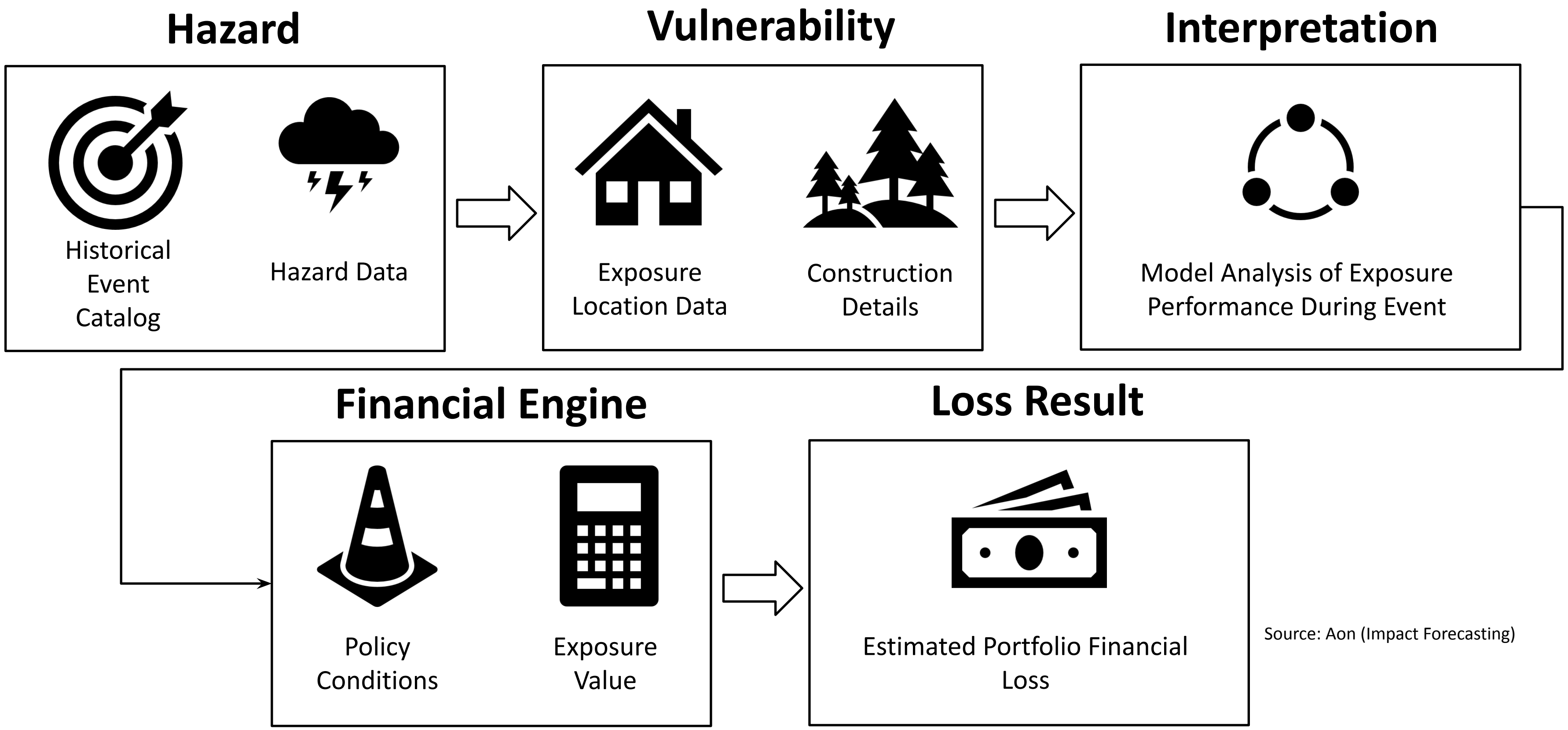


Hall and Sobel, 2013, *Geophys. Res. Lett.*

More data is needed (100’s of years) Solution: Make your own

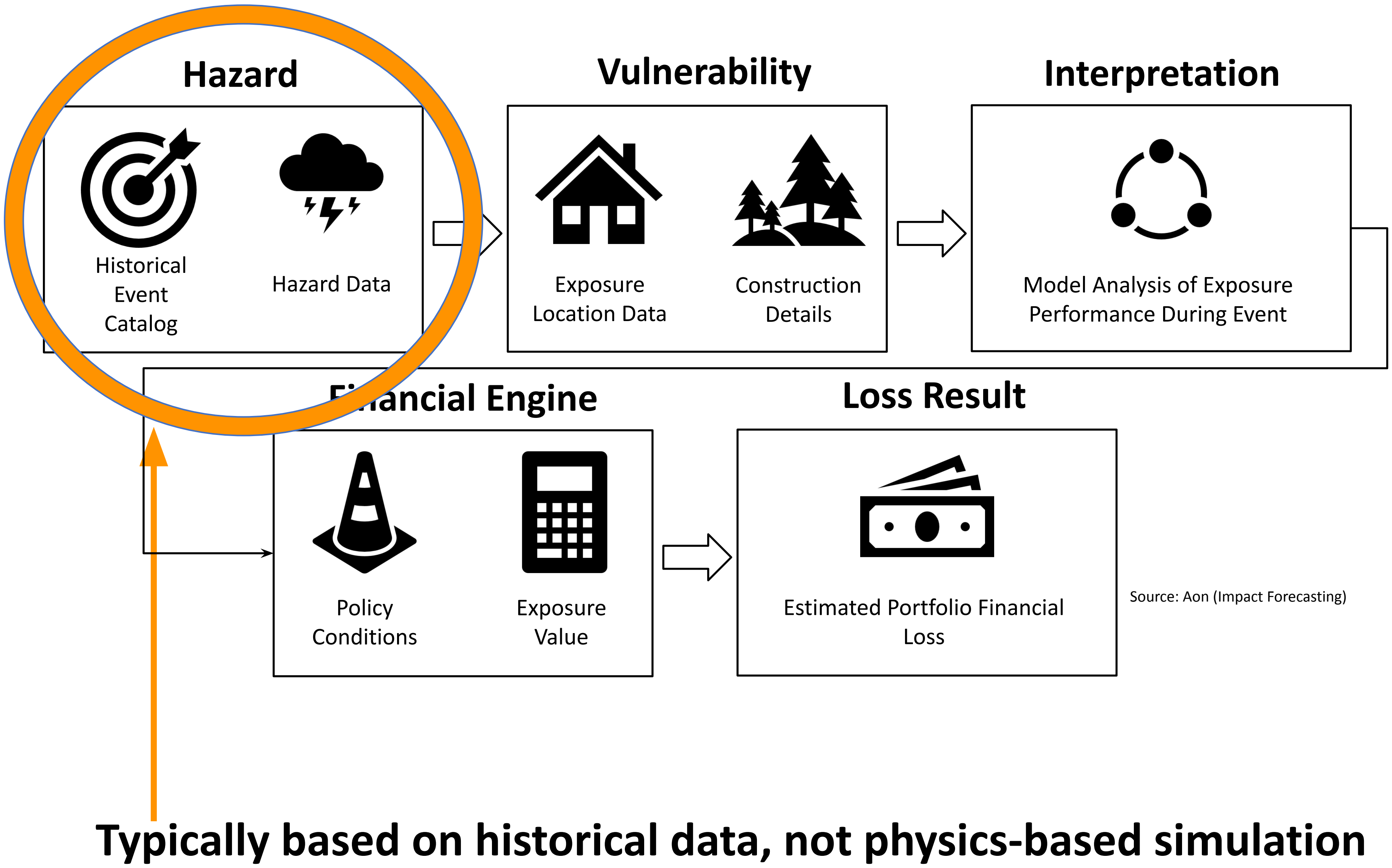
- Scientists use physics-based (PDEs) climate models
  - Pros: Physics! Include climate change & variability (ENSO). Similar to weather models. Global
  - Cons: Limited ability to represent TCs/computational cost. Systematic errors. No representation of the human impact
- Industry (insurance/reinsurance) uses cat(astrophe) models
  - Pros: Match historical events and losses. Complete: Hazard □ Loss
  - Cons: Often black boxes. Mostly statistical (stationary, no climate change). Missing in parts of the world without insurance

Catastrophe models were designed to estimate risk for the (re)insurance industry

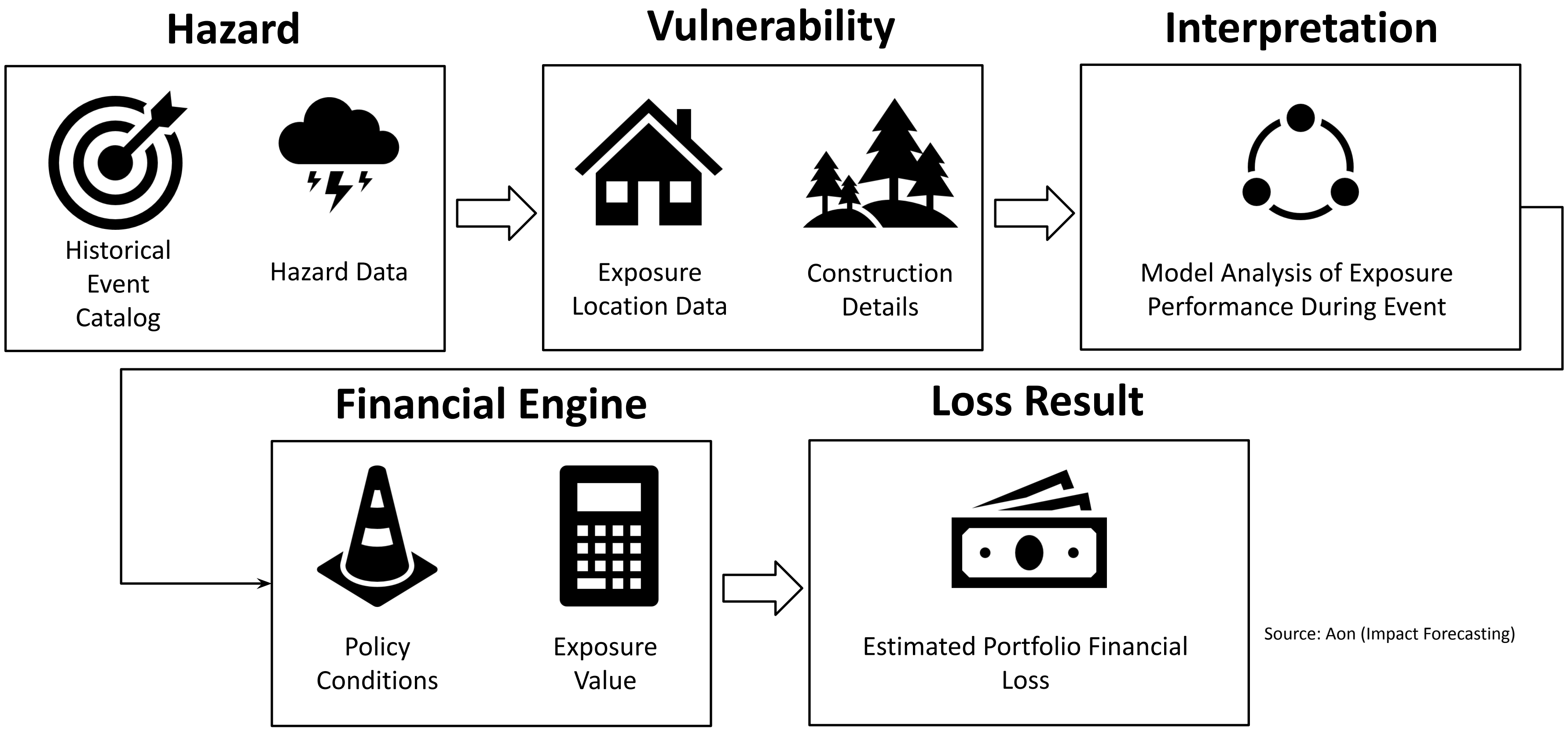


Source: Aon (Impact Forecasting)

The problem cat models solved was the shortness of the historical record --- not its unrepresentativeness due to climate change



Industry cat models are mostly a) proprietary, and b) country-specific, and weak to nonexistent for countries with little insurance



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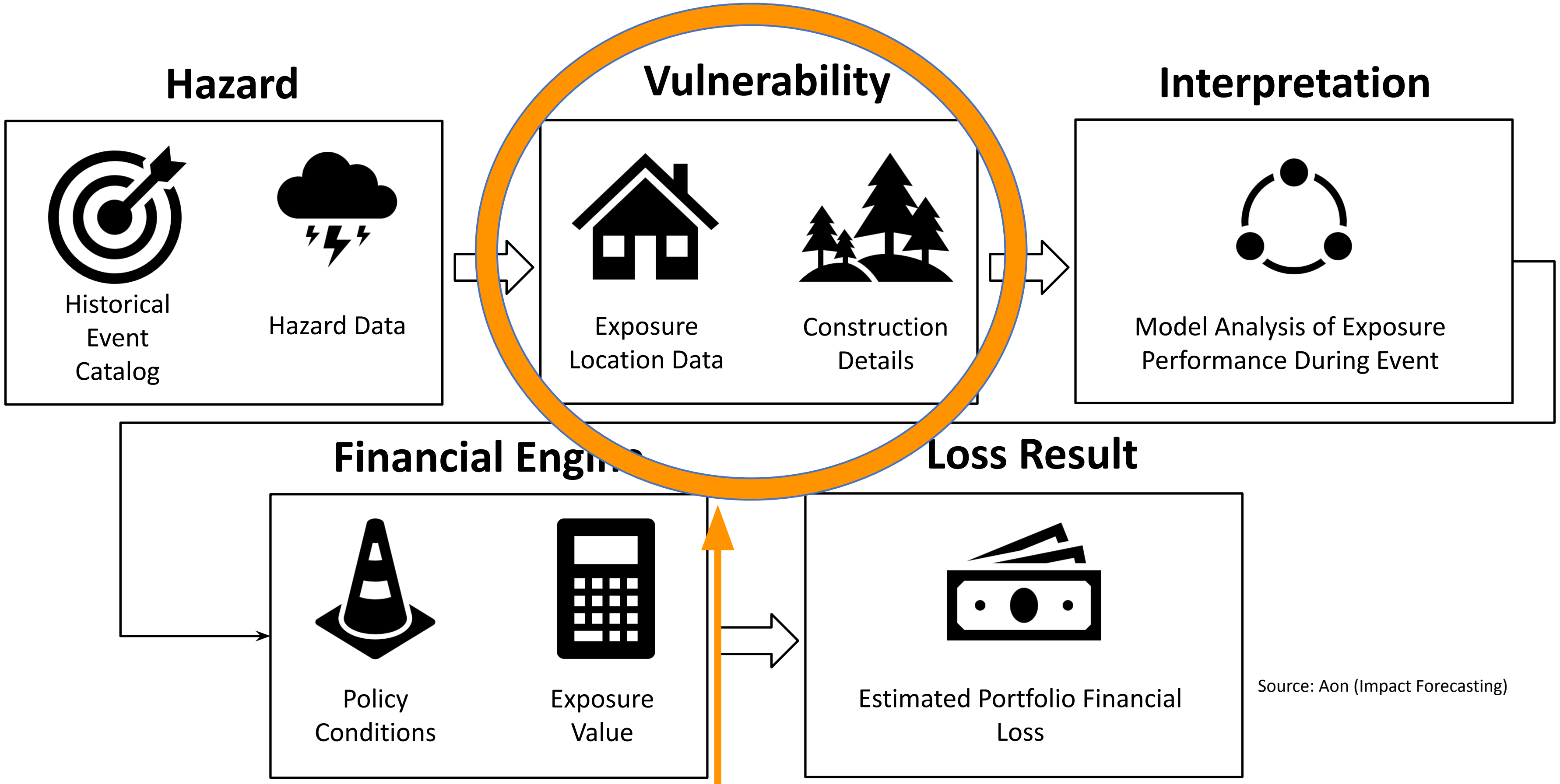


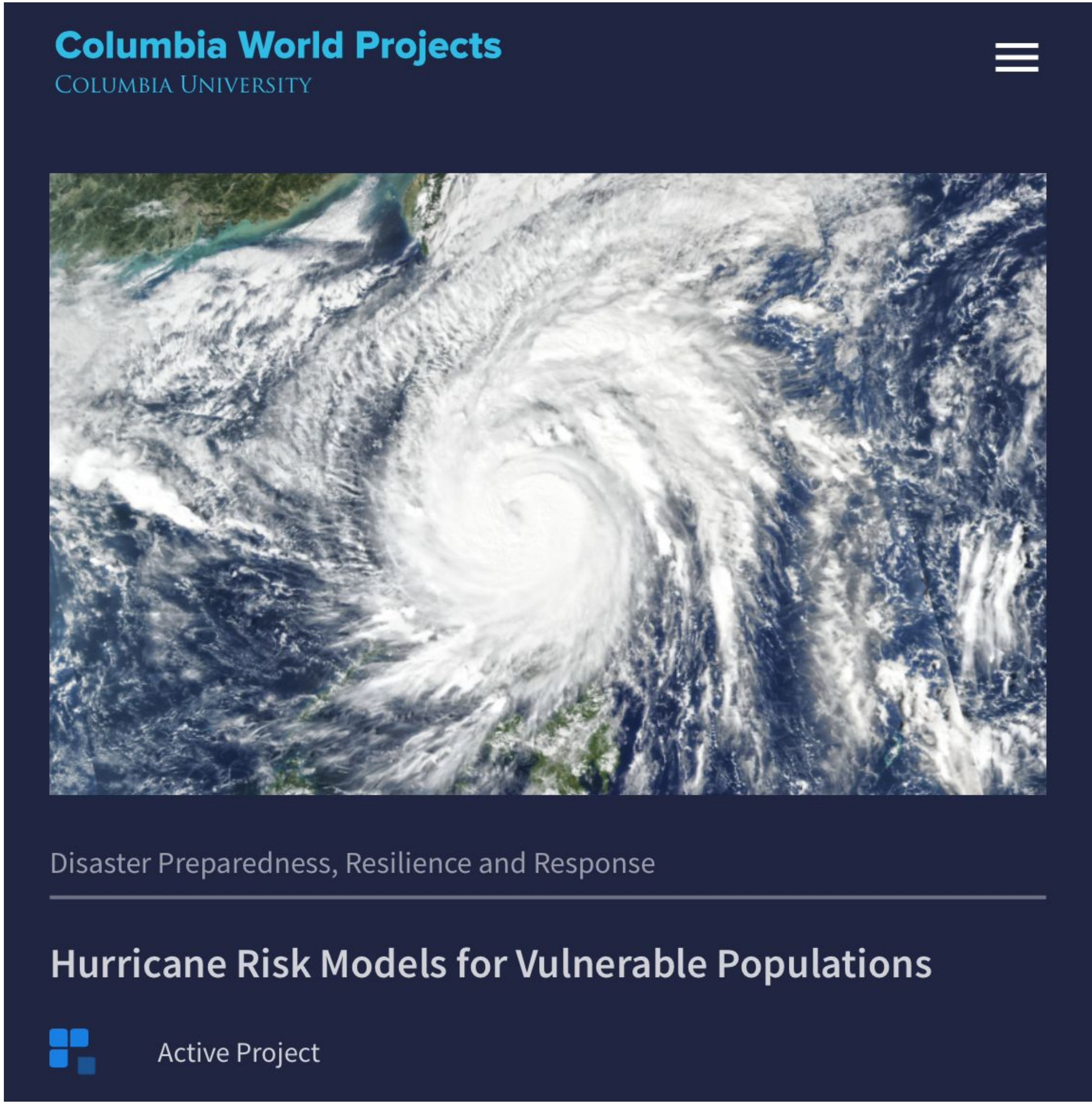
Source: Aon (Impact Forecasting)

Good public vulnerability & exposure data is hard to come by

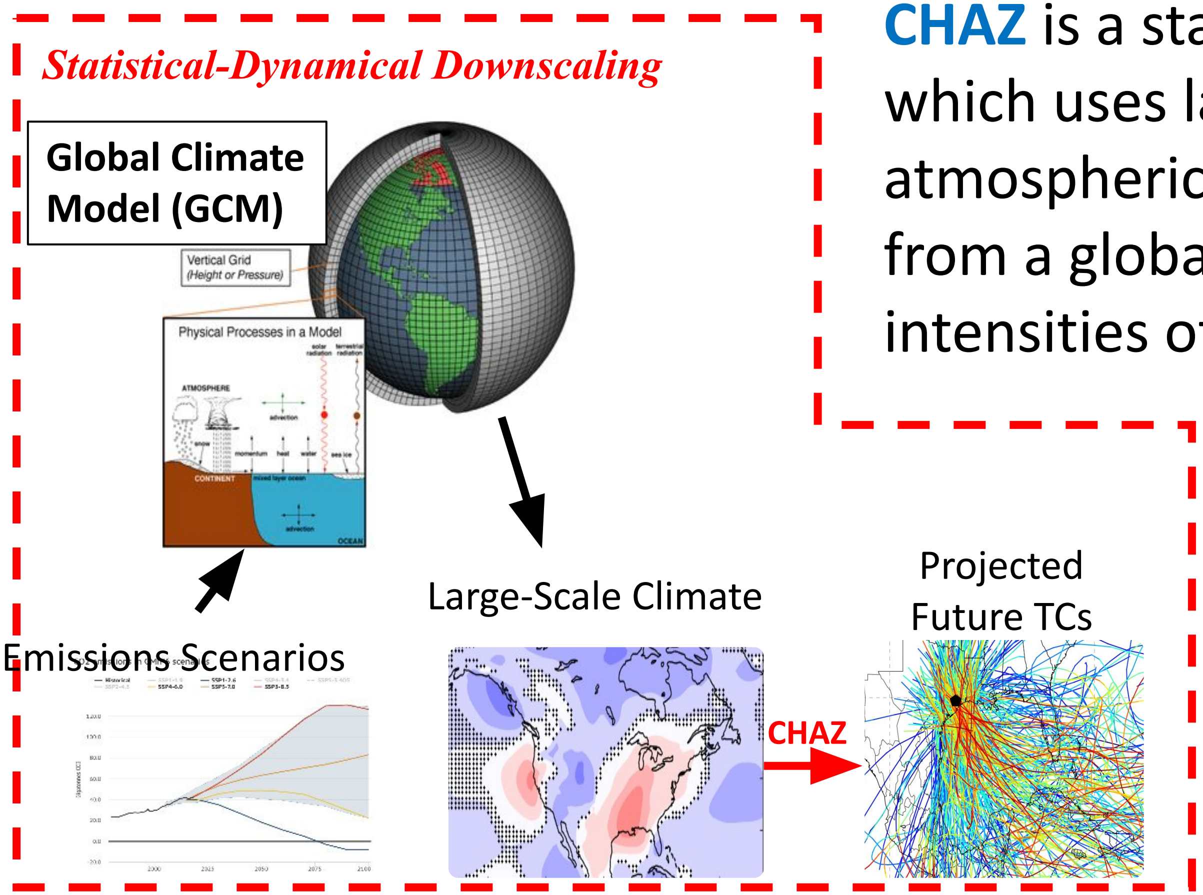
Academic catastrophe modeling

- Open source – debated in the peer-reviewed literature
- Physics informed – in order to handle climate change
- Data driven – computationally efficient
- Can address problems globally, even where the insurance industry may not have a large interest
- *Our group been building a model for tropical cyclone risk (CHAZ). The hazard component is fully functional since a couple years ago, simple representations of exposure and vulnerability are being added.*

Originally inspired by the work of K. Emanuel (2006, 2008...)!



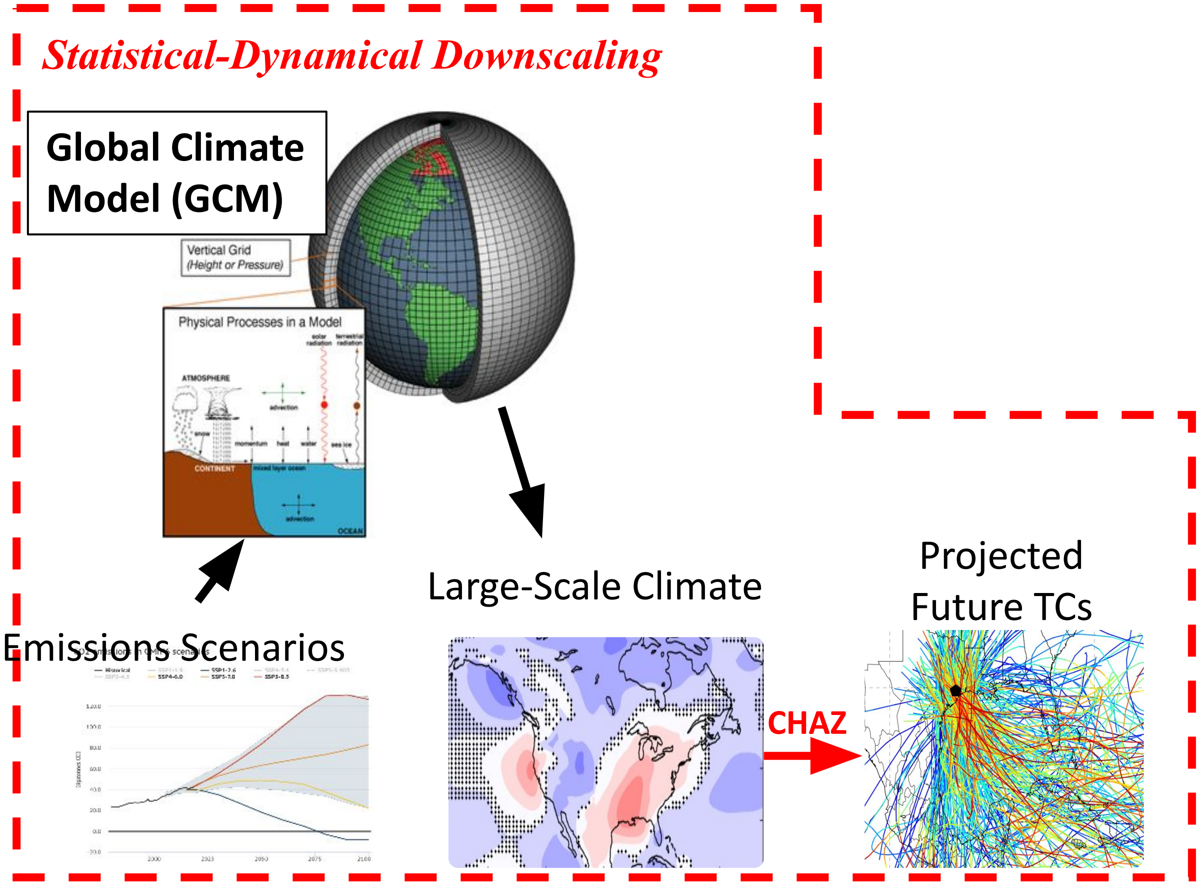
The Columbia TC hazard model: CHAZ

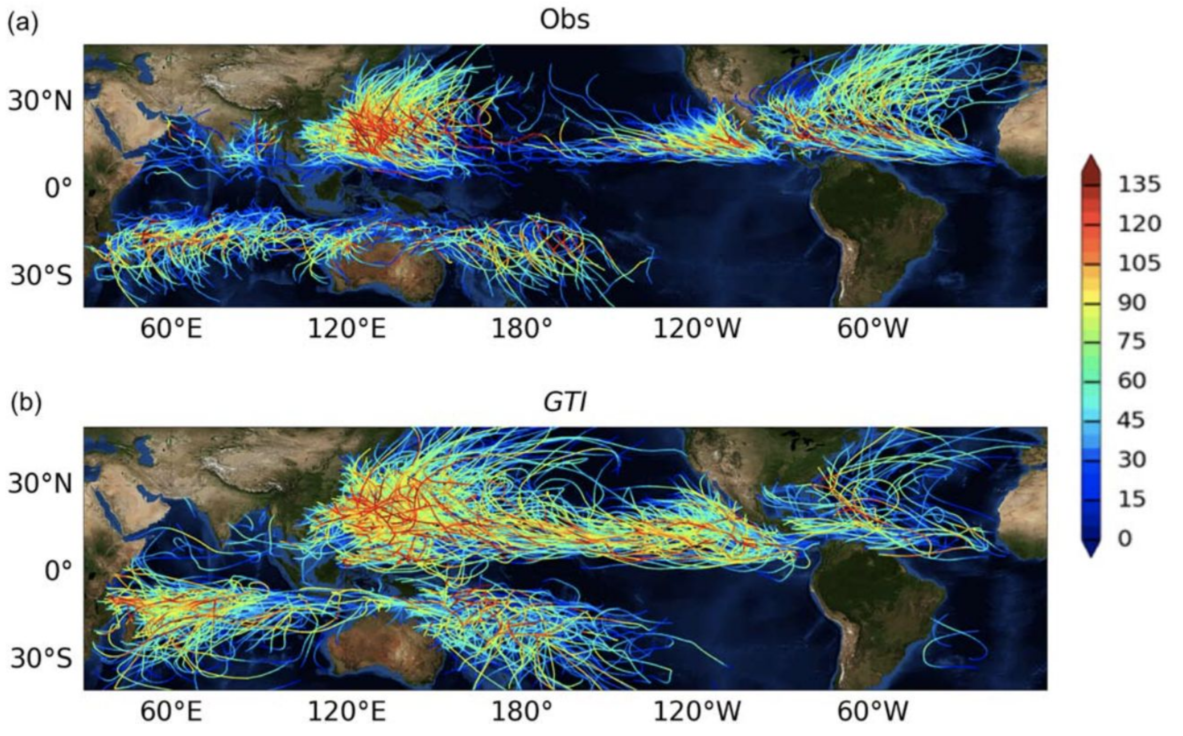


CHAZ is a statistical-dynamical downscaling model which uses large-scale conditions representing the atmospheric dynamic and thermodynamic environment from a global model to predict the genesis, tracks and intensities of synthetic TCs. (Lee et al. 2018, JAMES)

Chia-Ying Lee

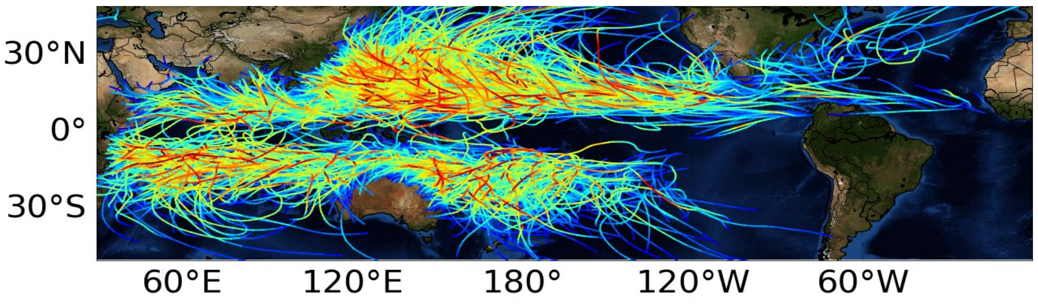
The Columbia TC hazard model: CHAZ





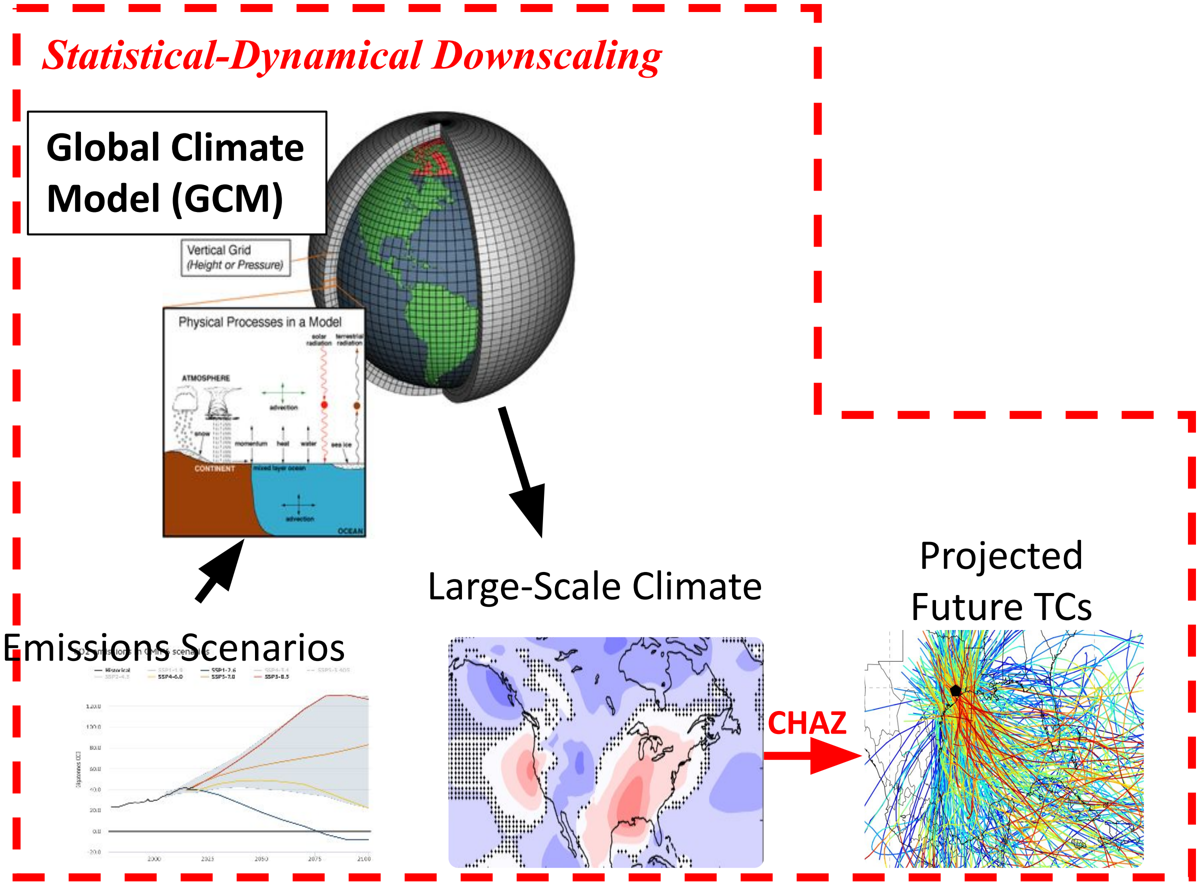
Lee et al. 2018 *JAMES*

CMIP5 climate



Lee et al. 2020 *J. Clim.*

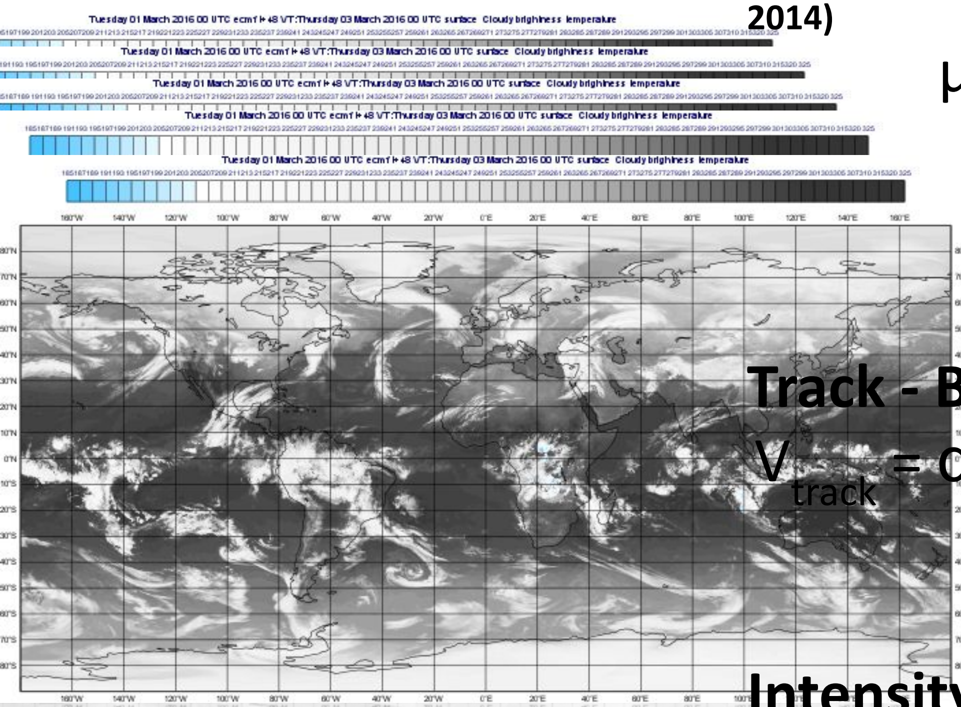
The Columbia TC hazard model: CHAZ



Three elements of the CHAZ model:

- **Genesis**: Decide where and when to seed TC precursors according to the favorability of large-scale conditions;
- **Track**: Move the seeds according to the large-scale steering flow;
- **Intensity**: Calculate storm intensity evolution using the local large-scale environmental conditions (PI, shear, water vapor content, etc.).

Three elements of the CHAZ model



ECMWF

Genesis - Tropical cyclone genesis index **(TCGI, Tippett et al. 2011, Camargo et al. 2014)**

$$\mu_{CRH} = \exp(b + b_{\eta}\eta_{850} + b_{rh}CRH + b_{PI}\,PI + b_{SHR}SHR)$$

$$\mu_{SD} = \exp(b + b_{\eta}\eta_{850} + b_{SD}SD + b_{PI}\,PI + b_{SHR}SHR)$$

Track - Beta-advection model **(Emanuel 2006)**

$V_{track} = \alpha V_{850} + (1-\alpha)V_{250} + v_{\beta}$, $\alpha=0.8$, v_{β} is a function of latitude

Intensity - Auto-regressive multiple linear regression model

$$v_{t+\Delta t} - v_t = MLR(X_t, X_{t+\Delta t}, v_t, v_{t-\Delta t}) + e_t$$

(Lee et al. 2015, 2016)

Predictors: MONTHLY wind (vorticity, shear, steering flow); temperature & moisture (PI, humidity or/and saturation deficit)

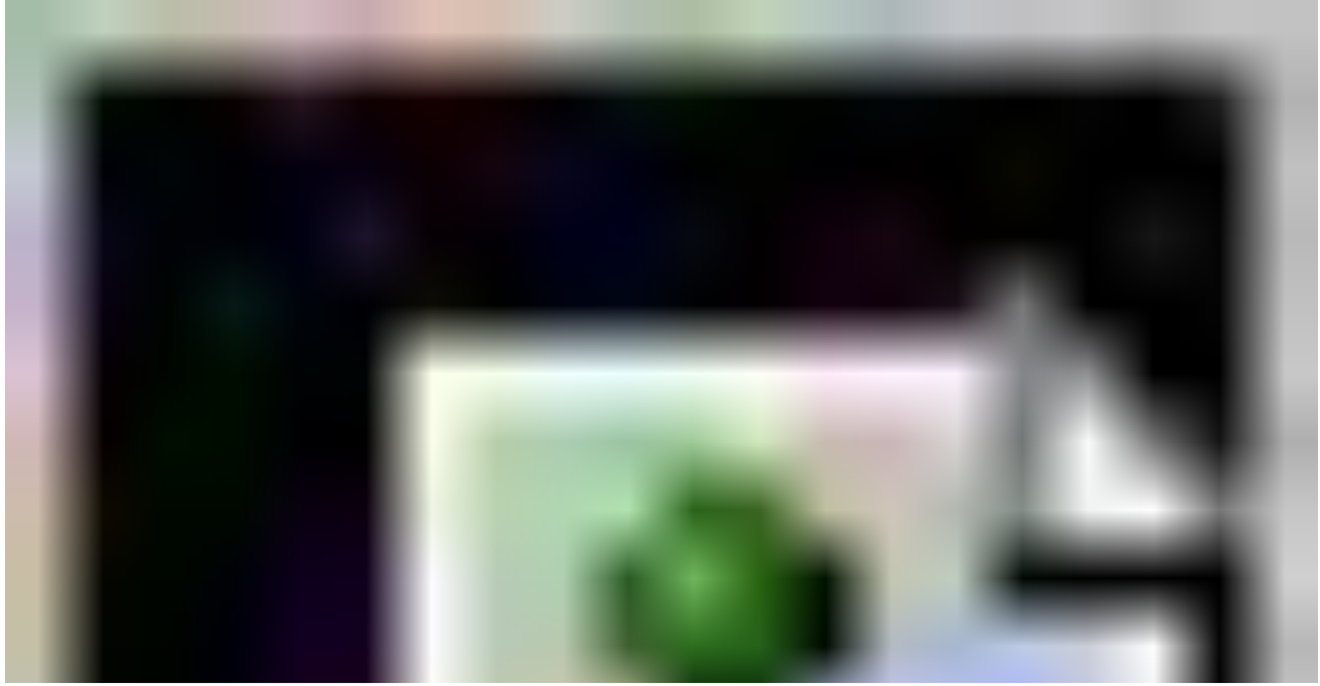
Lee et al. 2018, *JAMES*

Genesis

- Illustrates the data-driven, physics-informed approach
- A case where the physics *don’t* provide a clear answer
    - No first-principles theory for TC genesis
- Predictors that work equivalently in the current climate (in sample), diverge in the future
- Physics-based models also show uncertainty

Genesis

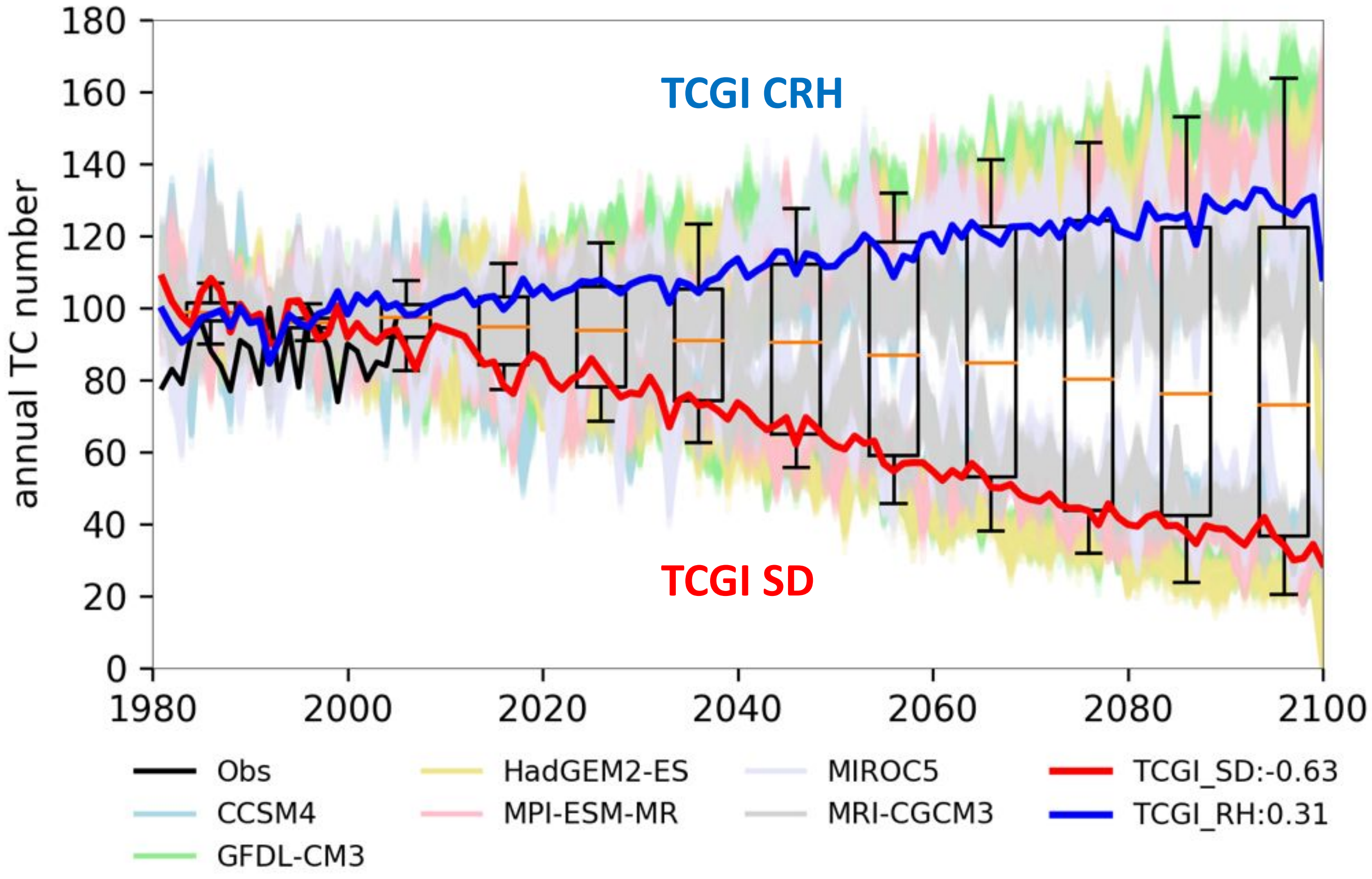
- Purely data-driven approach: Fit the rate at each location and time of the year
  - Many parameters
  - Only works in the current climate
  - Cannot tell us about variability (ENSO, etc.)
- Our approach: Use physical understanding of the factors that are favorable for genesis (SST, moisture, wind shear, vorticity)
  - Fit rate to environmental factors
  - Implicit dependence on location, time of year, climate via environment
  - Can be applied to climate projections, past climates
  - Diagnose variability (ENSO, etc.)
  - Few parameters (5!)



Tippett, M. K., Camargo, S. J., & Sobel, A. H. (2011). A Poisson Regression Index for Tropical Cyclone Genesis and the Role of Large-Scale Vorticity in Genesis, *Journal of Climate*, *24*(9), 2335-2357.

Warming climate projection: In the future climate, the projected TC frequency either increases or decreases, depending on the choice of moisture variable

(a)



$$\exp(b + b_\eta \eta_{850} + b_{rh}RH + b_{PI}\,PI + b_{SHR}SHR)$$

$$RH = \frac{P_{H_2O}(T)}{P^*_{H_2O}\,(T)}$$

$$\exp(b + b_\eta \eta_{850} + b_{sd}SD + b_{PI}\,PI + b_{SHR}SHR)$$

$$SD = P_{H_2O}(T)\text{-}\,P^*_{H_2O}\,(T)$$

Lee et al. 2020 *J. Climate*

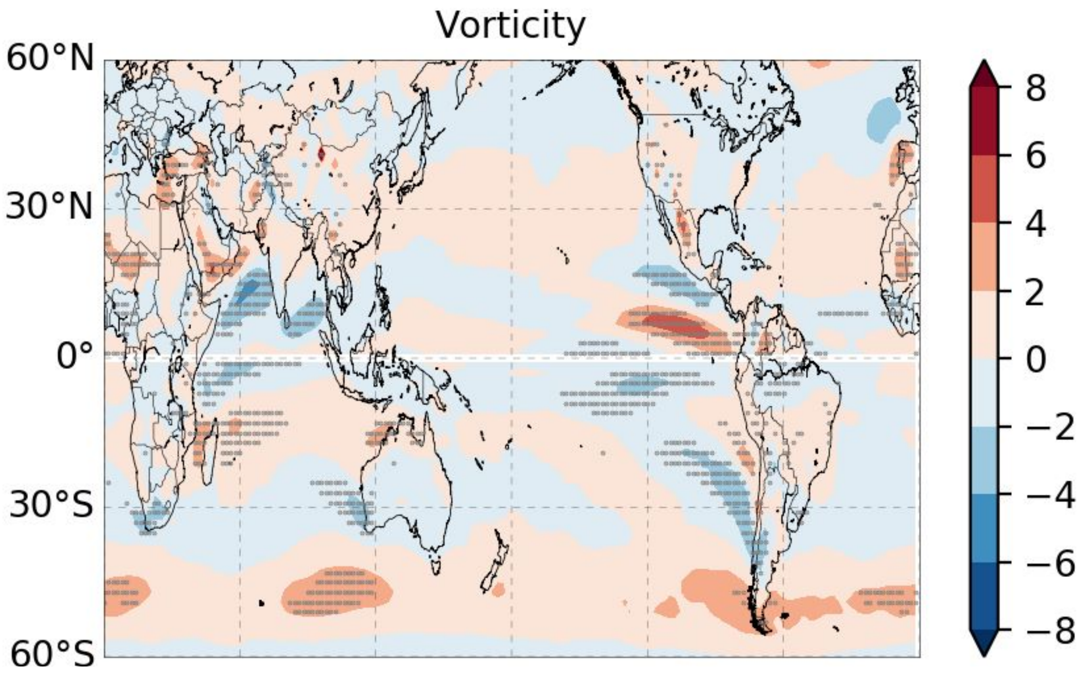
Genesis predictors

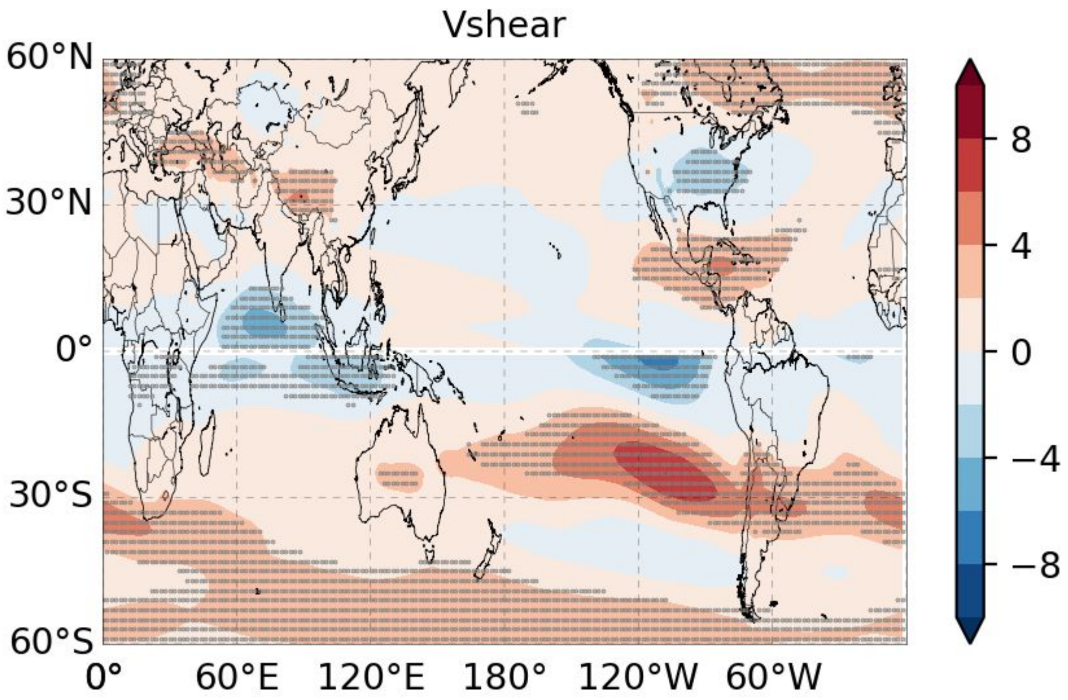
$$\exp(b + b_\eta \eta_{850} + b_{rh} RH + b_{PI}\, PI + b_{SHR} SHR)$$

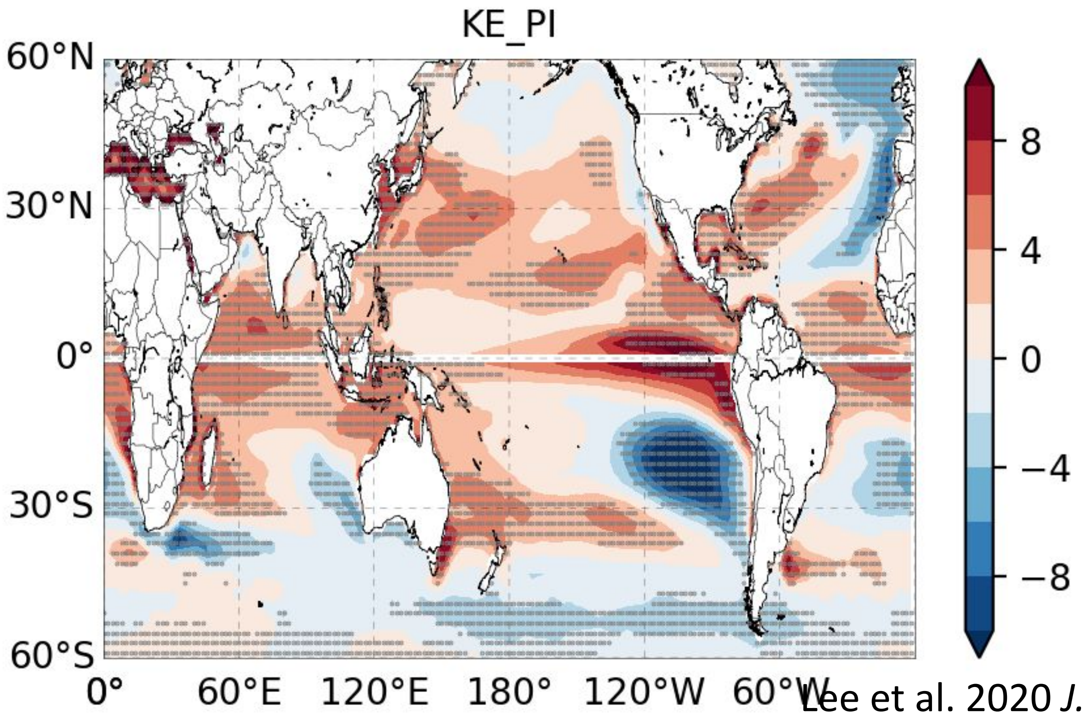
$$RH = \frac{P_{H_2O}(T)}{P^*_{H_2O}(T)}$$

$$\exp(b + b_\eta \eta_{850} + b_{sd} SD + b_{PI}\, PI + b_{SHR} SHR)$$

$$SD = P_{H_2O}(T) - P^*_{H_2O}(T)$$







Lee et al. 2020 *J. Climate*

TCGI predictors

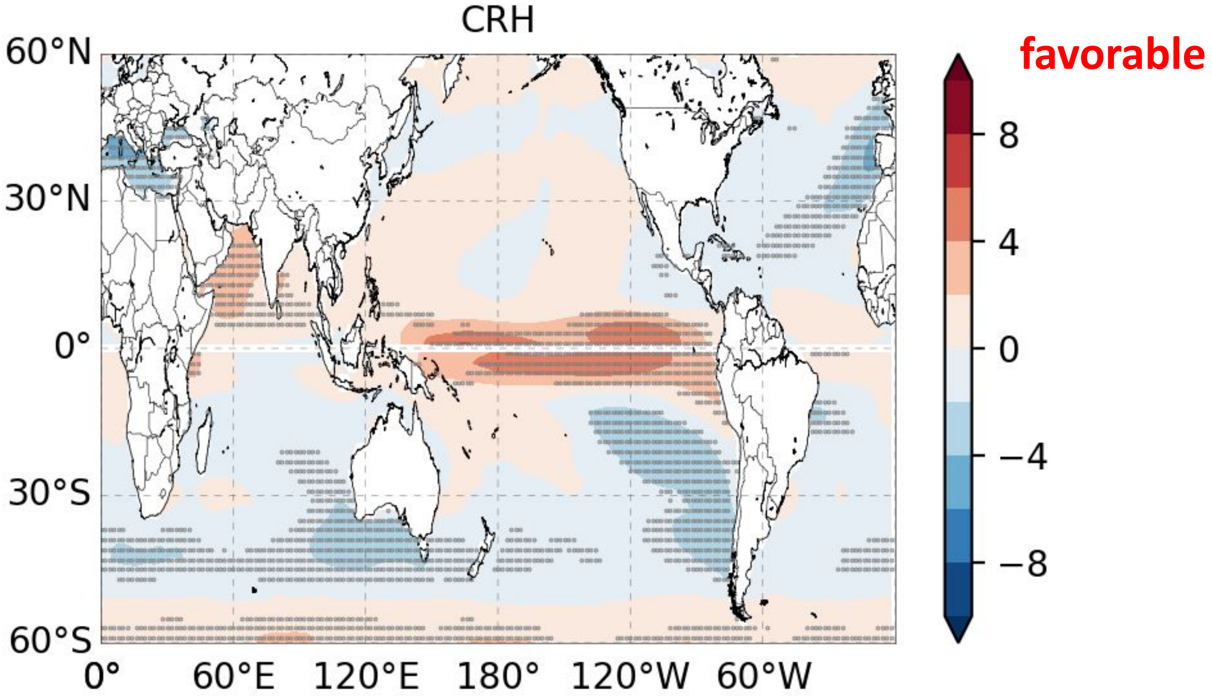
$\exp(b + b_{\eta}\eta_{850} + \underline{b_{rh}RH} + b_{PI}\,PI + b_{SHR}SHR)$

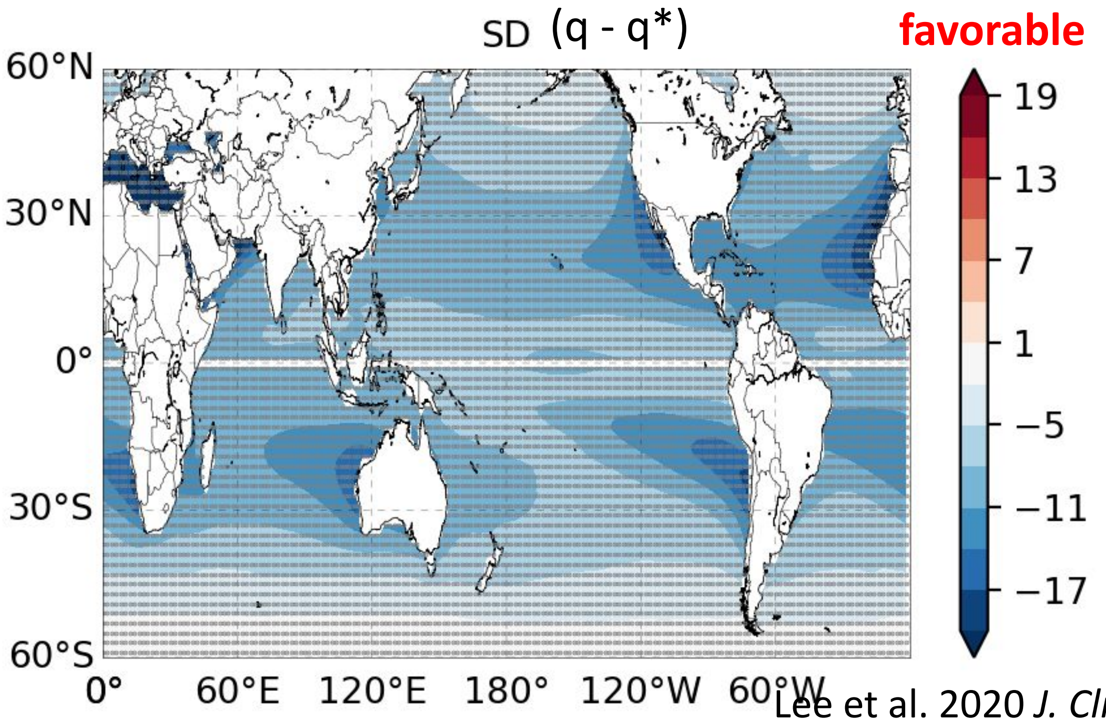
$$RH = \frac{P_{H_2O}(T)}{P^*_{H_2O}\,(T)}$$

$\exp(b + b_{\eta}\eta_{850} + \underline{b_{sd}SD} + b_{PI}\,PI + b_{SHR}SHR)$

$$SD = P_{H_2O}(T)\text{-}\ P^*_{H_2O}\,(T)$$

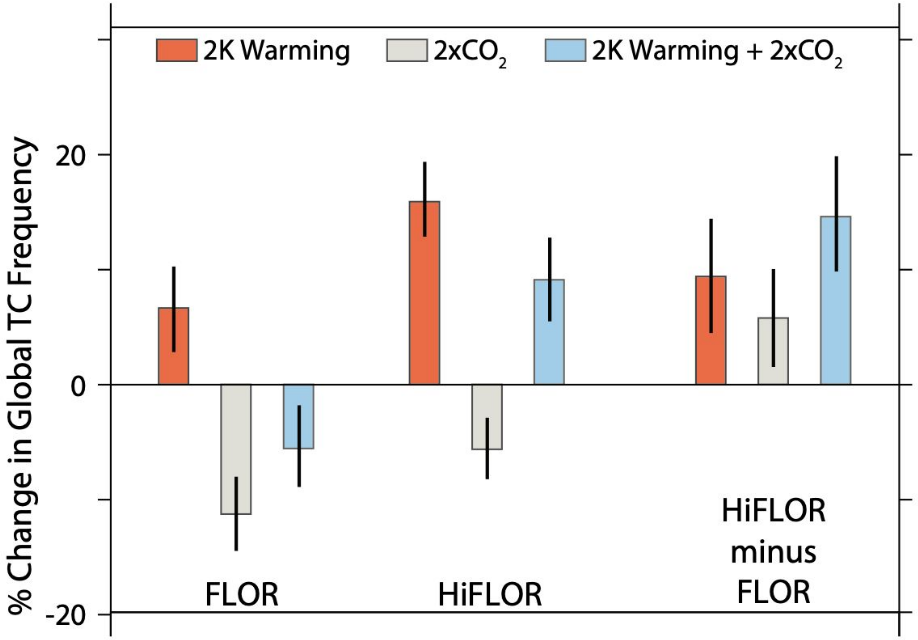
In CHAZ, how we describe the changes of moisture controls the trend in the number of the TC precursors.





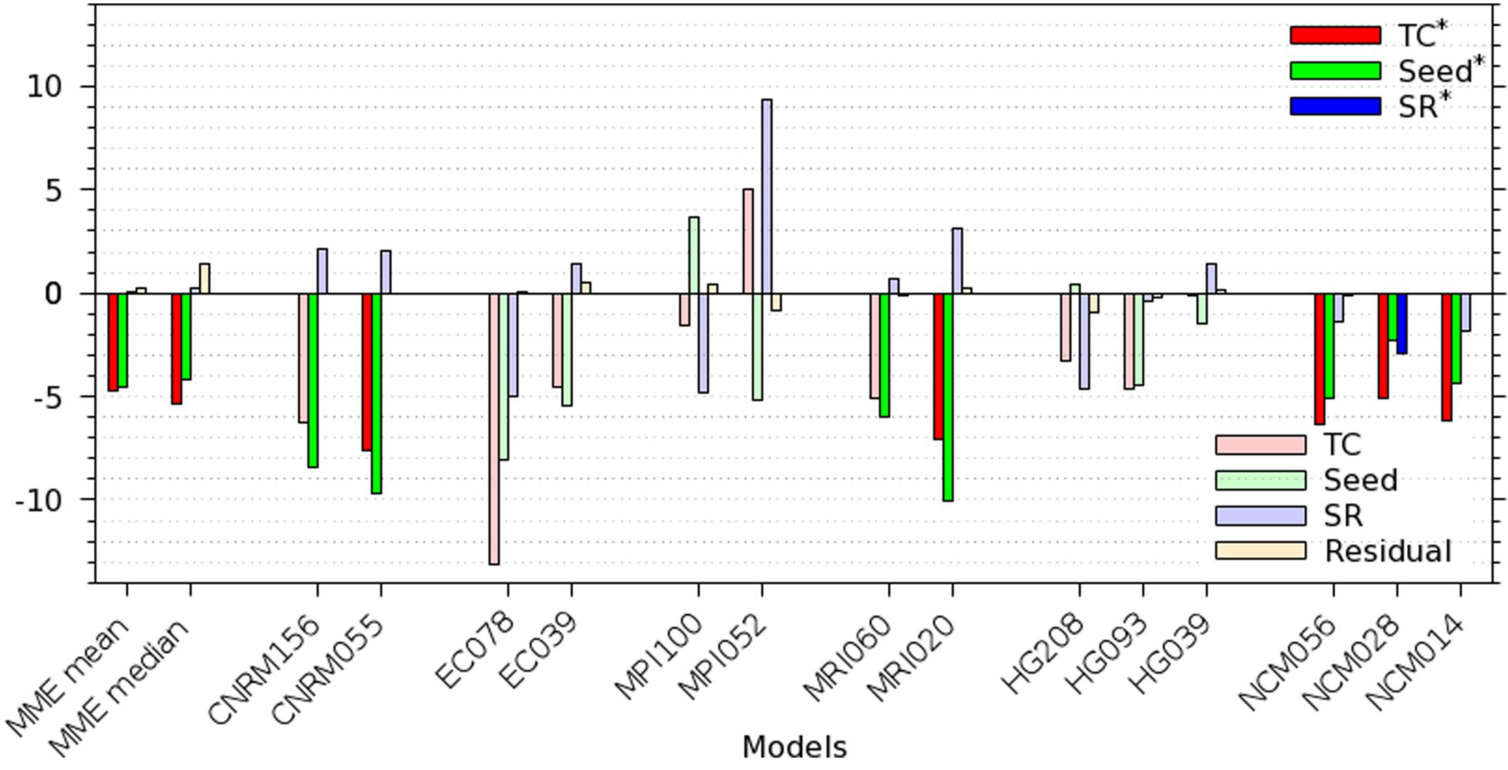
Lee et al. 2020 *J. Climate*

For different reasons, state-of-the-art GCM genesis projections show either an increase or decrease, which follow the projected changes in these models' storm precursors



Vecchi et al. 2019

Tropical cyclones, "seeds" and survival rate



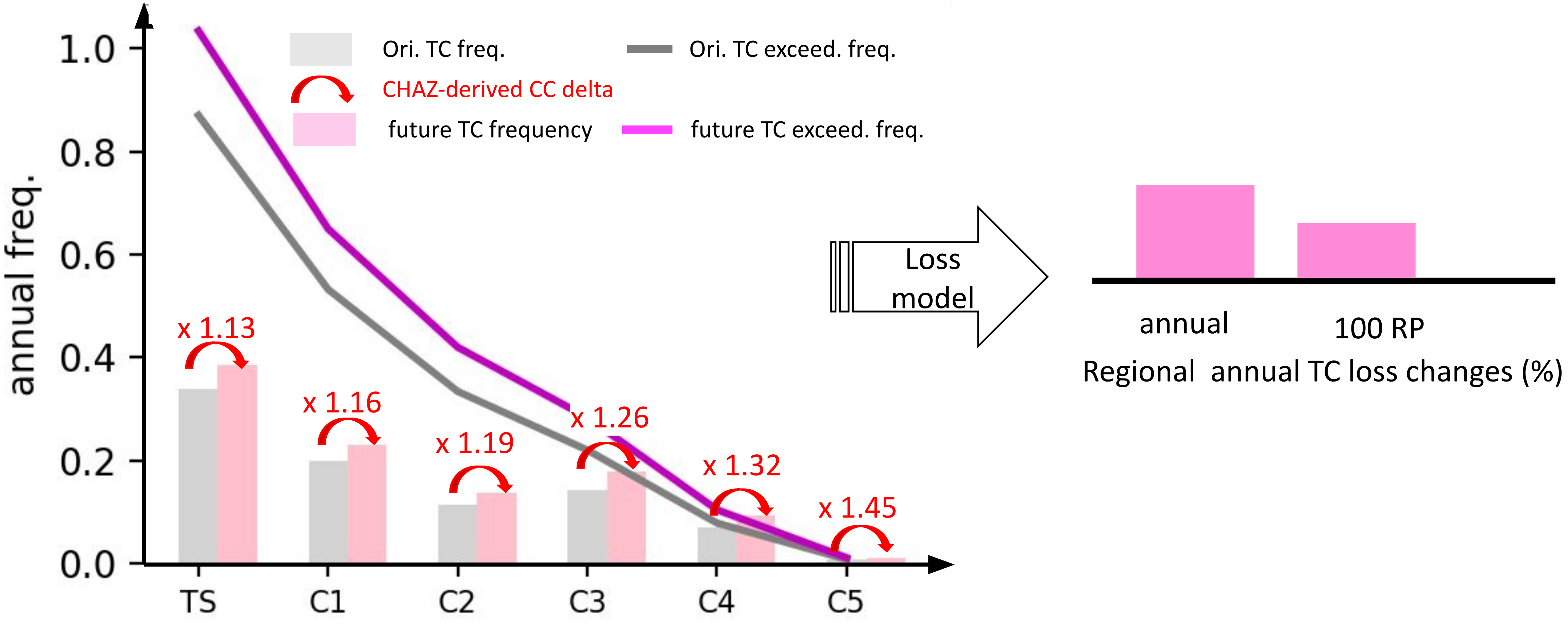
Yamada et al. 2021

Application to commercial* loss model

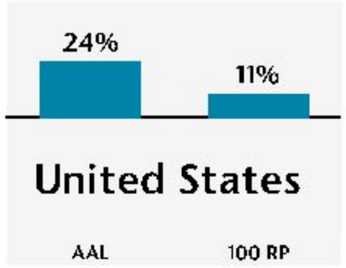
"Climate change deltas"

*"vendor"

In practice, we convert the climate-change-related increase/decrease in regional TC frequency at each intensity category, apply such differences to a commercial vendor model, and convert to losses



Modeled Loss Adjustments with increasing freq. projections



■ CRH "Favorable"

More Likely to Occur

Usage Notes

Results: Increase from the current baseline

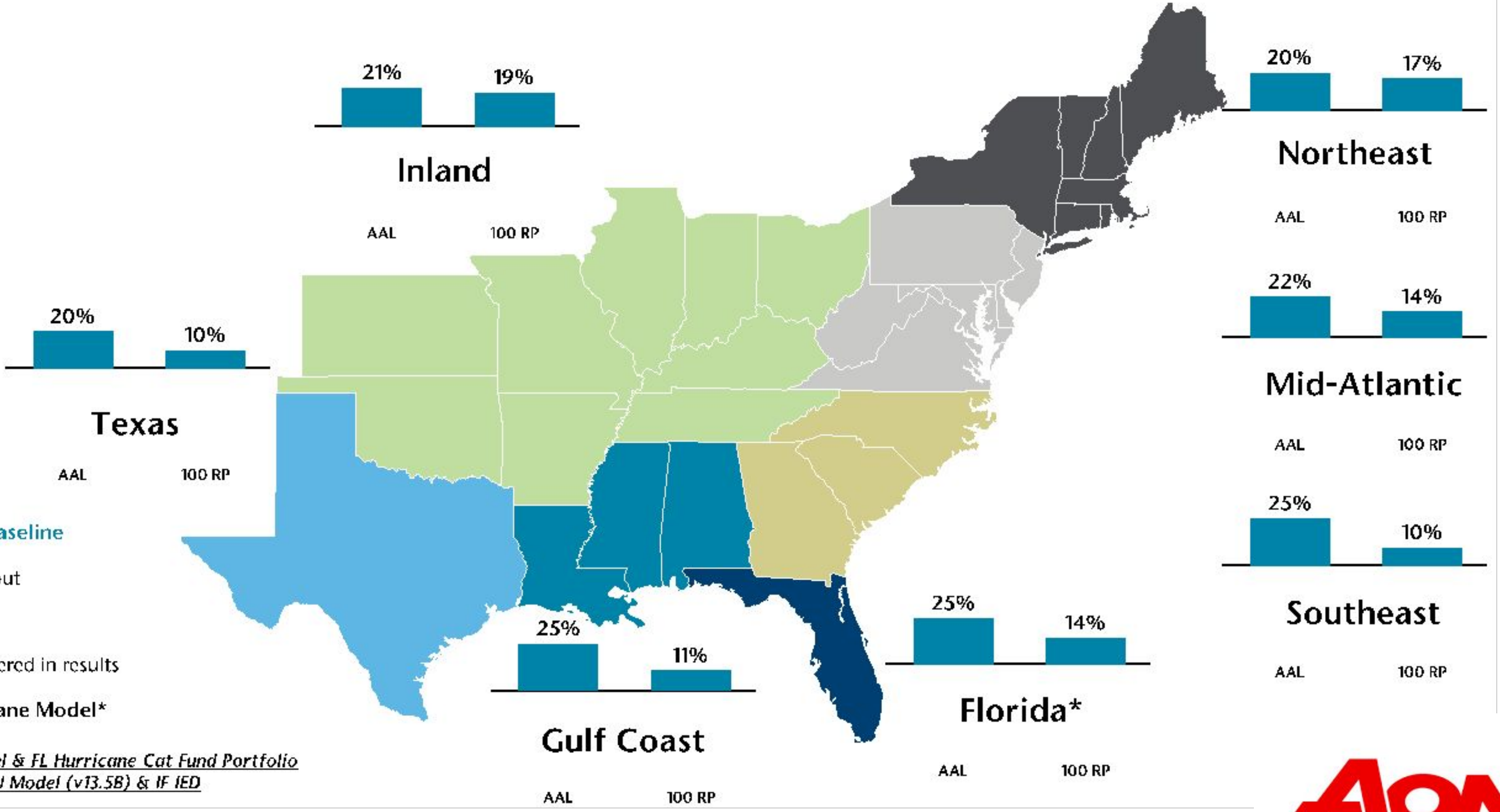
Frequency factors based on CMIP 5 output

Only accounts for changes to hazard

Current exposure & vulnerability considered in results

Results only applicable to IF Hurricane Model

^Loss results based on new IF Florida model & FL Hurricane Cat Fund Portfolio
Non-Florida loss results based on IF U.S. HU Model (v13.5B) & IF IED



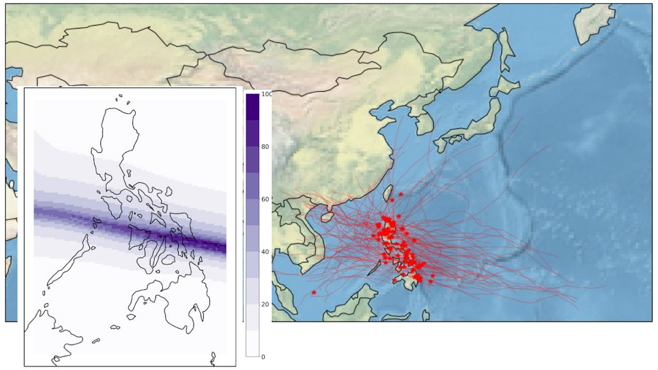
Empower Results®

From hazard assessment to wellbeing

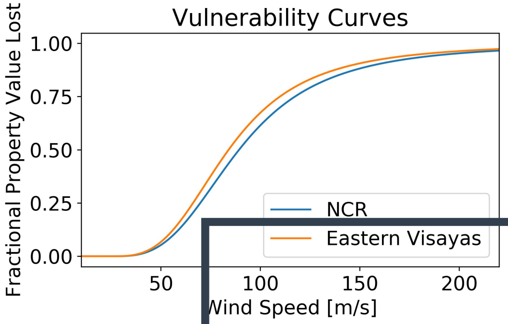
Quantify wind-related tropical cyclone risks for the wellbeing loss in the Philippines.

Example work flow:

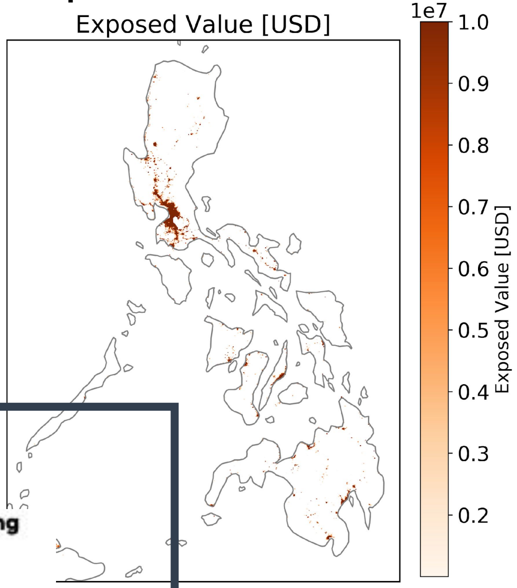
wind swaths from CHAZ tropical cyclones making landfall



vulnerability (fraction damaged for different wind speeds)



exposed value

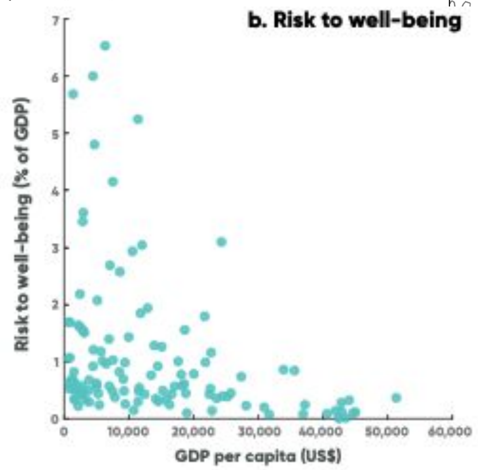


https://www.janebaldw.in

asset loss to wellbeing loss transformation

THE WORLD BANK

g losses
e damage

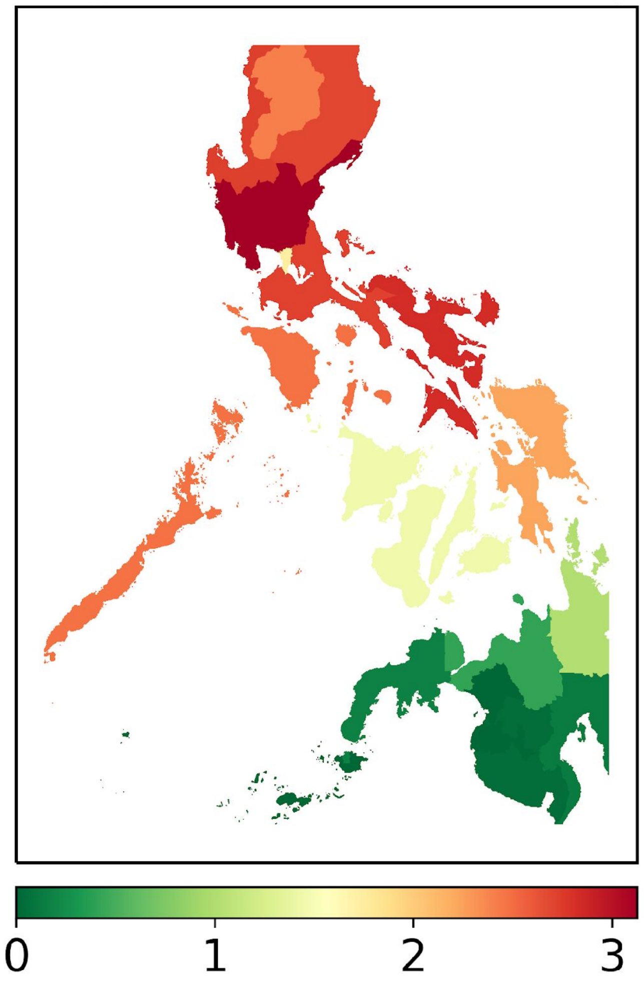


(Hallegatte et al 2016, World Bank)

Courtesy of Dr. J. Baldwin, UC Irvine (Baldwin et al., in prep)

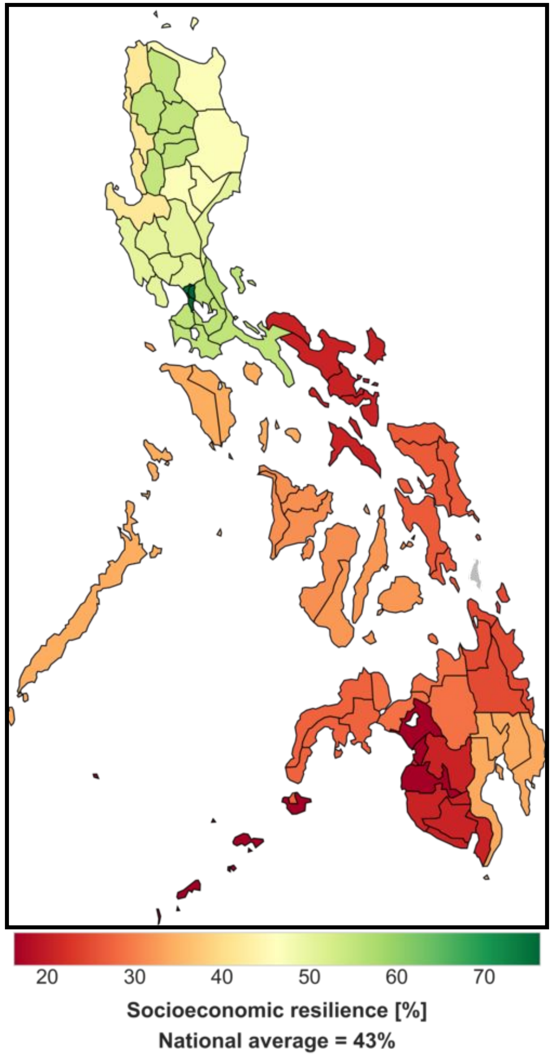
Motivating problem: how should the Philippines distribute funds to increase resilience to TCs?

Storm Density



(philippines.kosgep.org)

Socioeconomic Resilience



Perils to couple to CHAZ events

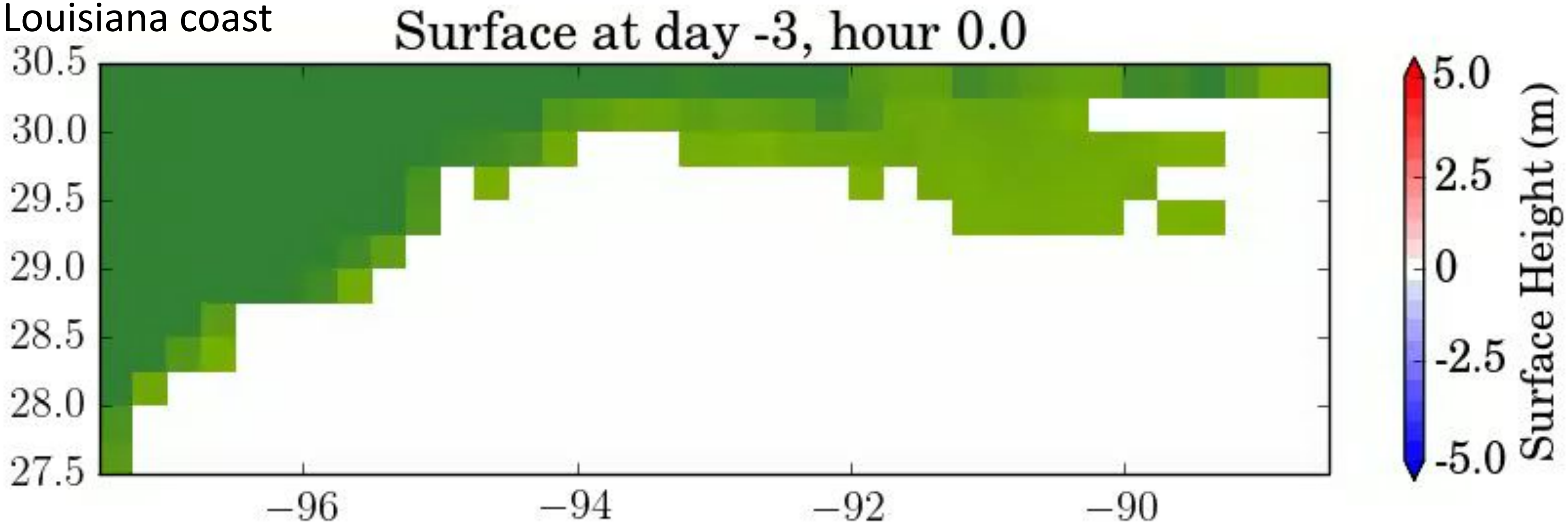
Primary

- Wind field near landfall □

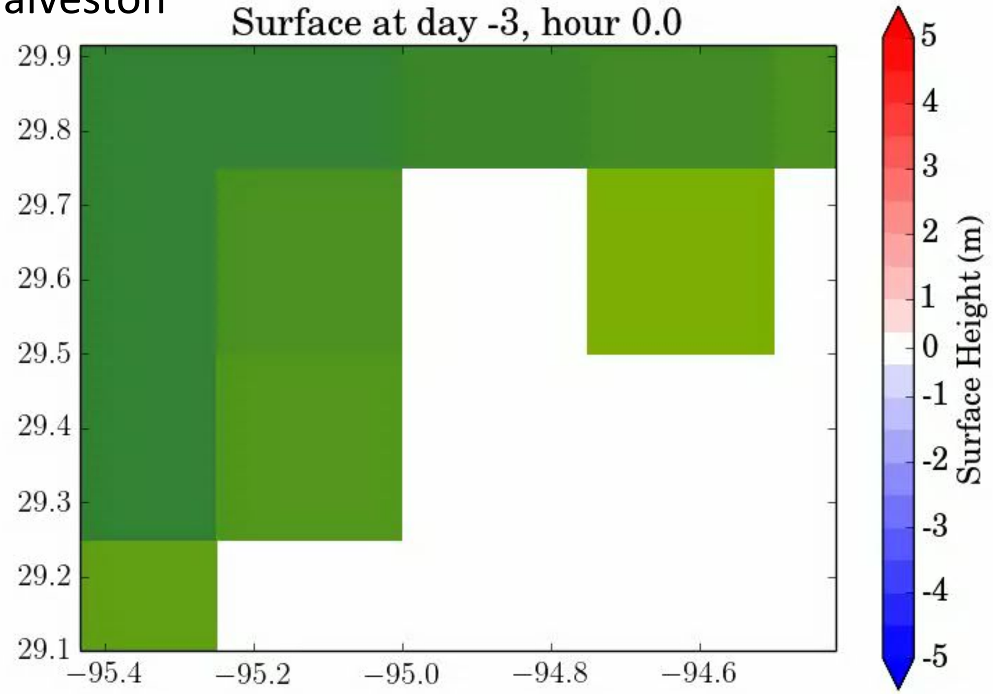
Secondary

- Coastal flooding
    - Surge driven by wind (GeoClaw, http://www.clawpack.org/geoclaw K. Mandli)
- Inland flooding
    - Rainfall
- Tornado
- Landslides

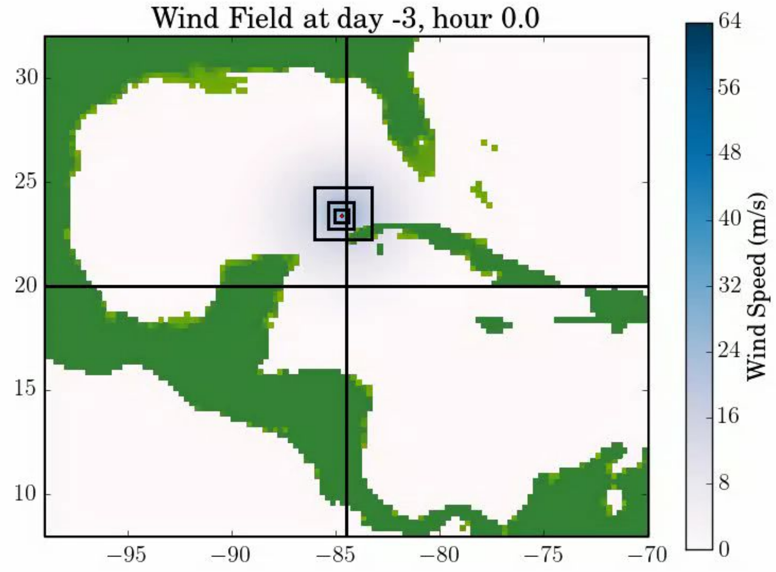
Texas Louisiana coast



Galveston



Hurricane Ike (2008)



Mandli, K. T. & Dawson, C. N. *Adaptive Mesh Refinement for Storm Surge*. Ocean Modelling 75, 36–50 (2014).

Wind field near landfall

XGBoost-based hurricane wind reconstruction

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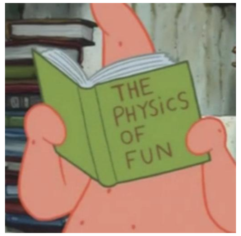


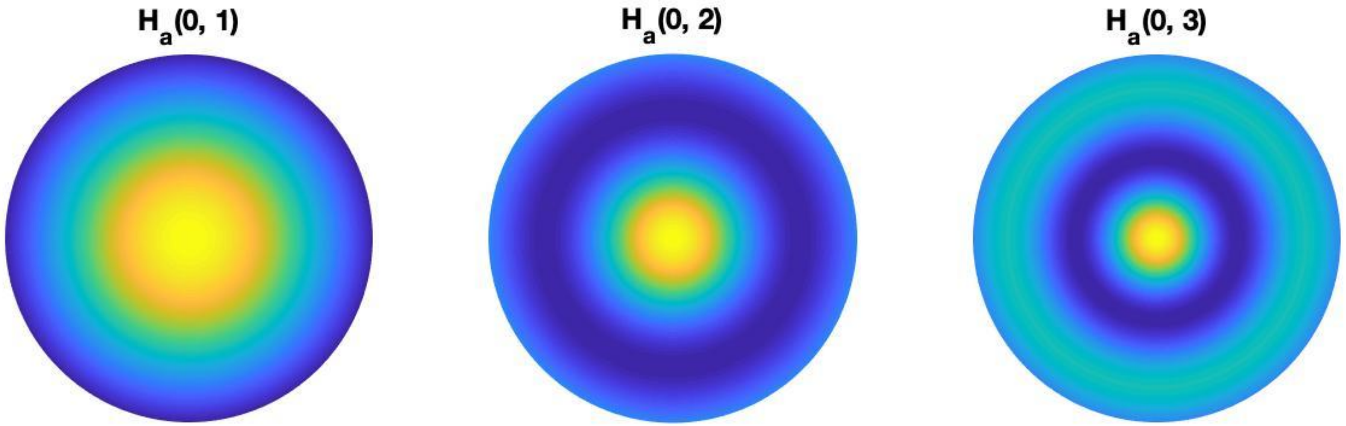
Qidong Yang

Residual field decomposition: Symmetry

$$H_a(m,n) = N_{m,n} \cdot J_m(\lambda_{m,n} r) \cdot \cos(m\theta)$$

$$H_b(m,n) = N_{m,n} \cdot J_m(\lambda_{m,n} r) \cdot \sin(m\theta)$$

$$\text{residual field} \approx \underbrace{\sum_{n=1}^{\infty} a_{0,n} \cdot H_a(0,n)}_{\text{Symmetrical residuals}} + \underbrace{\sum_{m=1}^{\infty} \sum_{n=1}^{\infty} (a_{m,n} \cdot H_a(m,n) + b_{m,n} \cdot H_b(m,n))}_{\text{Wind field asymmetries}}$$



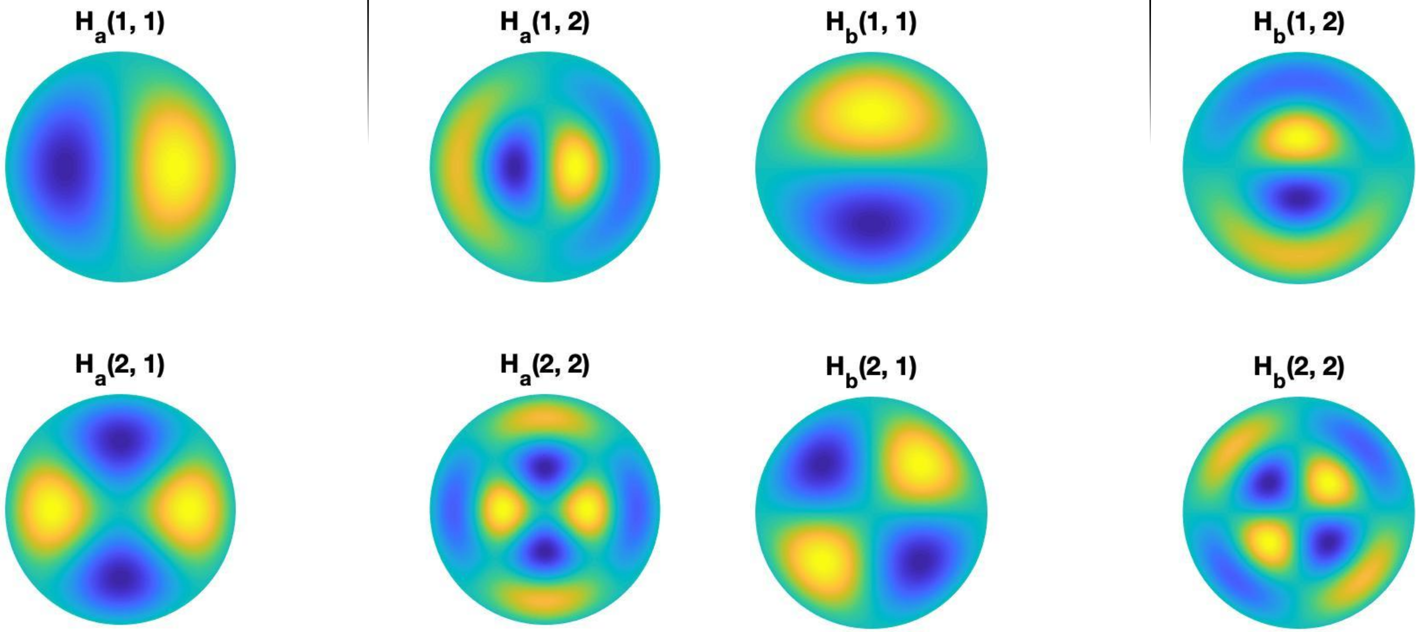
Symmetrical residual eigenfunctions

Residual field decomposition: Asymmetry

$$H_a(m,n) = N_{m,n} \cdot J_m(\lambda_{m,n} r) \cdot \cos(m\theta)$$

$$H_b(m,n) = N_{m,n} \cdot J_m(\lambda_{m,n} r) \cdot \sin(m\theta)$$

$$\text{residual field} \approx \underbrace{\sum_{n=1}^{\infty} a_{0,n} \cdot H_a(0,n)}_{\text{Symmetrical residuals}} + \underbrace{\sum_{m=1}^{\infty} \sum_{n=1}^{\infty} (a_{m,n} \cdot H_a(m,n) + b_{m,n} \cdot H_b(m,n))}_{\text{Wind field asymmetries}}$$



Wind field asymmetry eigenfunctions

Wind reconstruction procedure

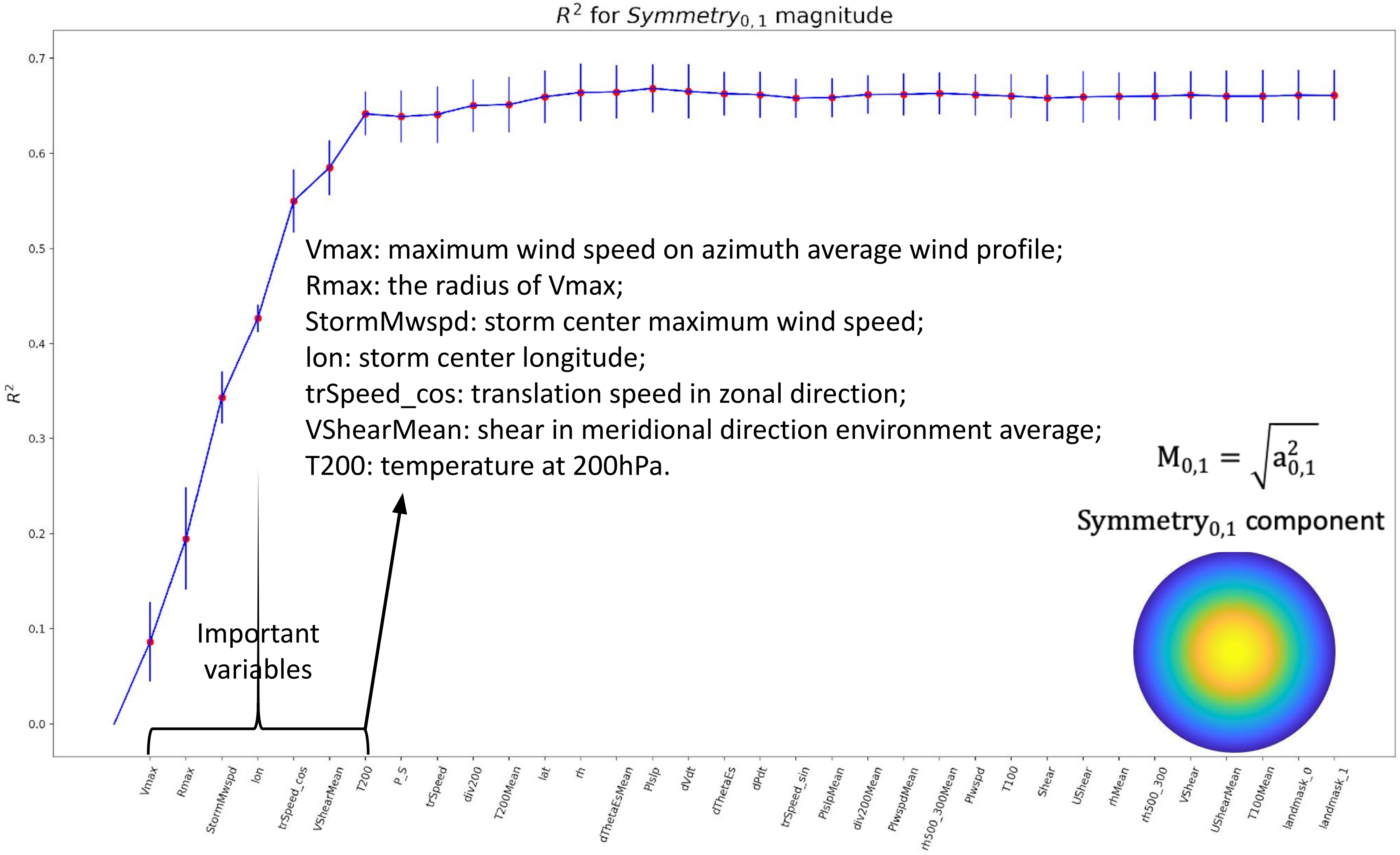
$$\text{approximated wind} \equiv \text{reference field} + \text{residual field approximation}$$

$$\equiv \text{reference field} + \sum_{n=1}^{4} a_{0,n} \cdot H_a(0,n) + \sum_{m=1}^{3} \sum_{n=1}^{4} (a_{m,n} \cdot H_a(m,n) + b_{m,n} \cdot H_b(m,n))$$

$$\text{reconstructed wind} \equiv \text{reference field} + \sum_{n=1}^{4} \hat{a}_{0,n} \cdot H_a(0,n) + \sum_{m=1}^{3} \sum_{n=1}^{4} (\hat{a}_{m,n} \cdot H_a(m,n) + \hat{b}_{m,n} \cdot H_b(m,n))$$

For each chosen factor, an XGBoost model is trained to predict it.

Important variables to $\text{symmetry}_{0,1}$ magnitude prediction

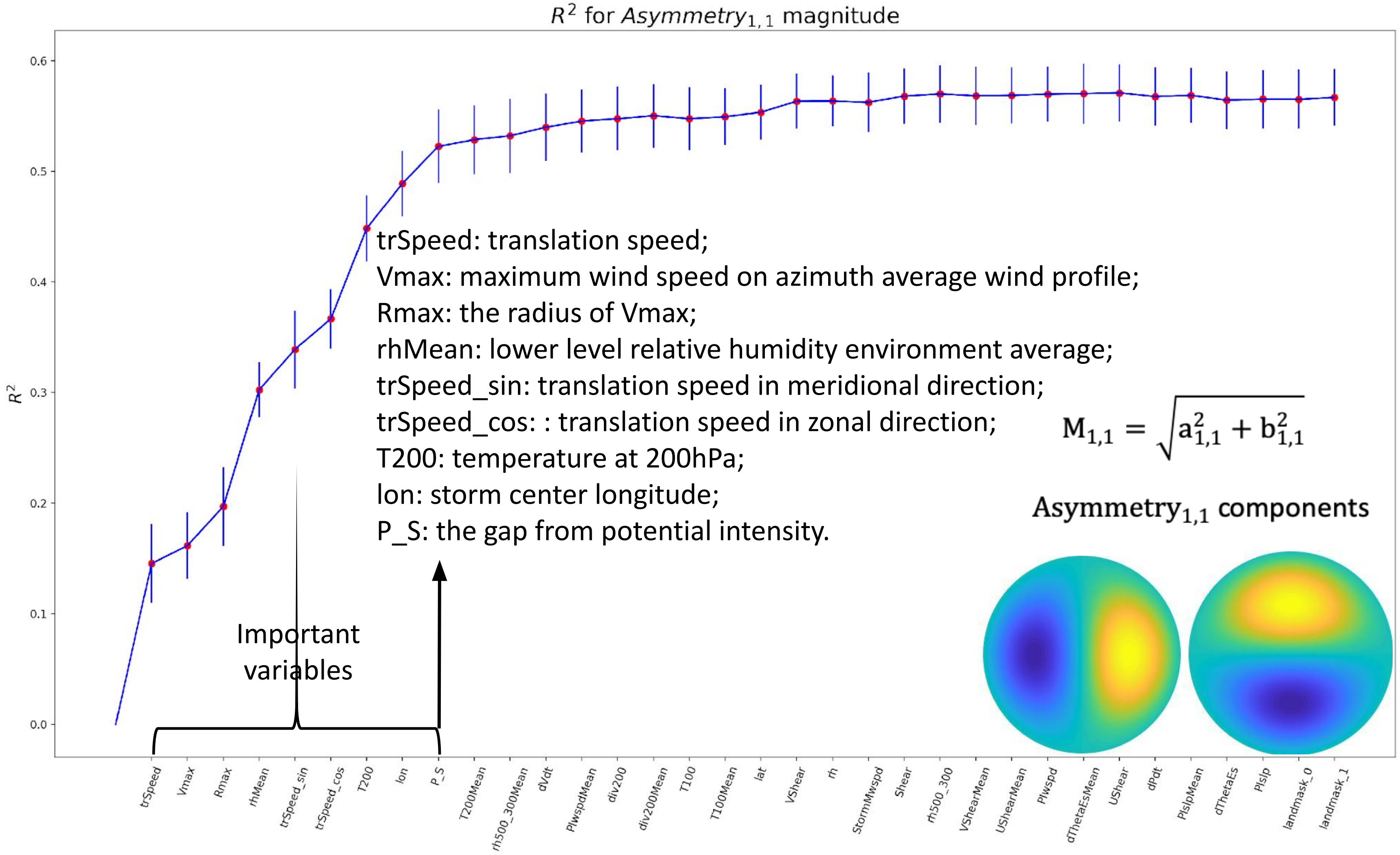


Vmax: maximum wind speed on azimuth average wind profile;
Rmax: the radius of Vmax;
StormMwspd: storm center maximum wind speed;
lon: storm center longitude;
trSpeed_cos: translation speed in zonal direction;
VShearMean: shear in meridional direction environment average;
T200: temperature at 200hPa.

$$M_{0,1} = \sqrt{a_{0,1}^2}$$

$\text{Symmetry}_{0,1}$ component

Important variables to asymmetry$_{1,1}$ magnitude prediction



trSpeed: translation speed;
Vmax: maximum wind speed on azimuth average wind profile;
Rmax: the radius of Vmax;
rhMean: lower level relative humidity environment average;
trSpeed_sin: translation speed in meridional direction;
trSpeed_cos: : translation speed in zonal direction;
T200: temperature at 200hPa;
lon: storm center longitude;
P_S: the gap from potential intensity.

$$M_{1,1} = \sqrt{a_{1,1}^2 + b_{1,1}^2}$$

Outline/summary

- What is risk?
  - Hazard x exposure
- How to estimate tropical cyclone risk?
  - Past observations are inadequate
  - “Models” to make more data
- What are “cat” models?
  - Risk models used by industry (esp. insurance)
- CHAZ: the Columbia tropical cyclone hazard model
  - Physics-informed, data-driven
  - Tropical cyclone genesis
  - Example: Climate change delta
  - Example: Wellbeing
  - XGboost wind model