MODELING HURRICANE TRACK DEVELOPMENT UNDER CLIMATE CHANGE

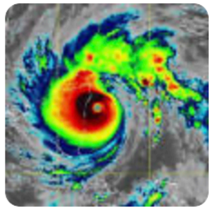
GRACE KORTUM

SML 310, PROFESSOR HANKE

HOW ARE THE IMPACTS OF HURRICANES CHANGING DUE TO CLIMATE CHANGE?

AccuWeather

Record-breaking 2020 Atlantic hurricane season officially over … but could still break more records



Generating storms at a rapid-fire pace and filled with enough plot twists to rival an M. Night Shyamalan movie, the 2020 Atlantic hurricane season started early ...

1 day ago

Yahoo News

Florida home insurance premiums set to rise amid hurricanes, lawsuits

Homeowners in Central Florida should be prepared to face higher property insurance rates next year, fueled by busy lawyers and ...

1 day ago

CNN

Hurricane season ends historic as predicted by experts back in April

Monday officially marks the final day of Atlantic hurricane season, and it has been one for the record books.

2 days ago

BBC News

In pictures: Hurricanes leave Hondurans homeless and destitute

Honduras is one of the countries in Central America to be hit not by one but two hurricanes this month. Eta arrived in Nicaragua on 3 November ...

4 days ago

The Lima neighbourhood in San Pedro Sula was quickly flooded after a levy broke during Hurricane Eta

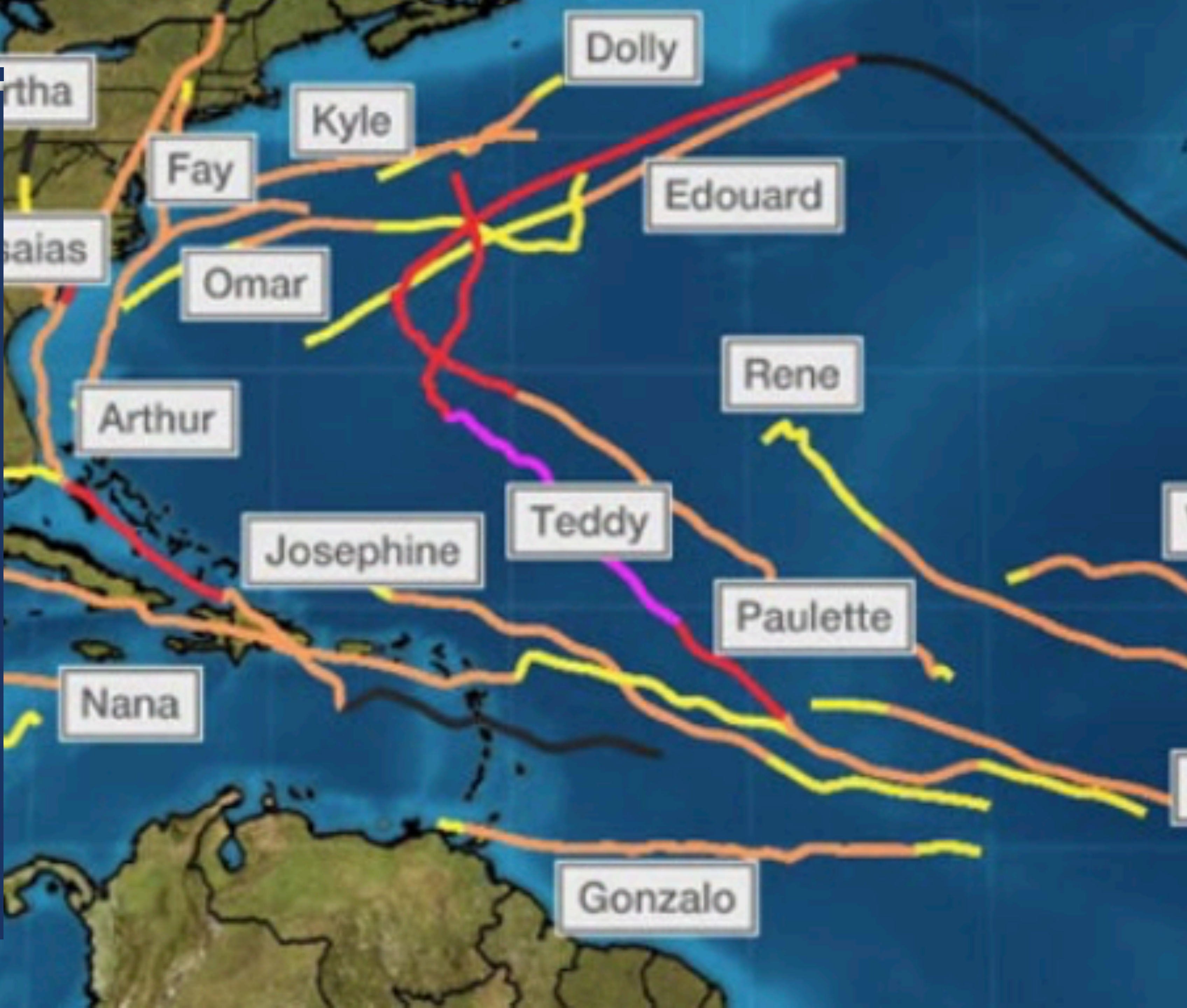
https://www.bbc.com/news/world-latin-america-55064560

HURRICANE TRACKS

LOCATION GOVERNED BY:

1. STARTING LOCATION

2. STEERING FLOW



- https://weather.com/storms/hurricane/news/2020-09-21-nine-us-landfalls-2020-hurricane-season-ties-record

SPECIFIC QUESTIONS

1. How well can a simple statistical or data science model predict hurricane movement from one time period to the next?
2. Has the way that hurricanes move been changing over time (been affected by climate change)?

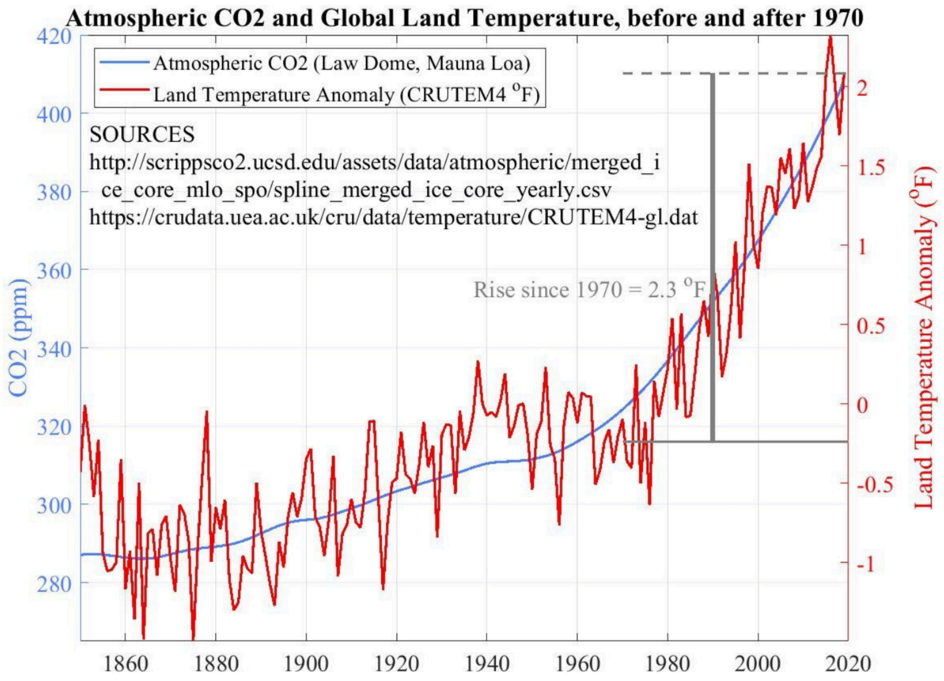
DATA CHARACTERISTICS

Ensemble members:

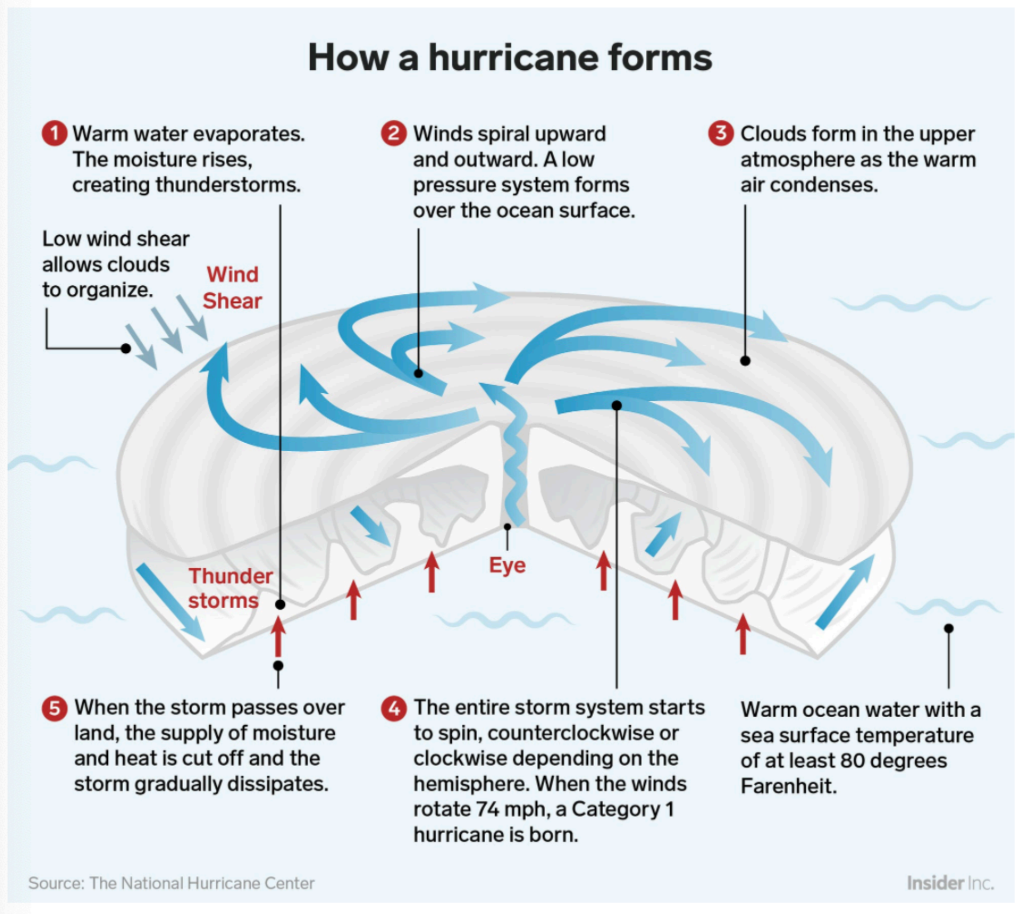
- 8 different possible states generated from a model
- Have same climate forcing but different starting conditions

Time Period:

- 1971 to 2019
- Storms measured at 6 hour intervals



EXPLANATORY VARIABLES



https://www.businessinsider.com/how-hurricanes-form-2018-9

Wind	**Sea Level Pressure**	**Latitude**	**Longitude**	**Position in storm 'XCOUNT'**	**Date and time**	**Global Mean temperature anomaly**
Magnitude of wind strength	Pressure at that location and time	Location of the measurement	Location of the measurement	For example, is it the first point, the second point, etc. that occurred in a given storm	Year, day, and hour	Global average temperature anomaly for that year. Used to represent change over time.

RELEVANT VARIABLES

AUTOREGRESSIVE TIME SERIES REGRESSION MODEL – AR(2)

$$
\begin{aligned}
lat_t = \;& \beta_1 lat_{t-2} + \beta_2 lon_{t-2} + \beta_3 wind_{t-2} + \beta_4 SLP_{t-2} \\
& + \beta_5 lat_{t-1} + \beta_6 lon_{t-1} + \beta_7 wind_{t-1} + \beta_8 SLP_{t-1} \\
& + \beta_9 MeanTemp + \beta_{10} XCOUNT \\
& + \beta_{11} lat_{t-1}\, lon_{t-1} + \beta_{12} lat_{t-1} lon_{t-2} + \beta_{13} lon_{t-1} lat_{t-2} + \beta_{14} lon_{t-2}\, lat_{t-2} \\
& + \beta_0 + \varepsilon
\end{aligned}
$$

Two time steps before

One time step before

Non AR variables

Interaction terms for lat and lon

Intercept and error

$$
\begin{aligned}
lon_t = \;& \beta_1 lat_{t-2} + \beta_2 lon_{t-2} + \beta_3 wind_{t-2} + \beta_4 SLP_{t-2} \\
& + \beta_5 lat_{t-1} + \beta_6 lon_{t-1} + \beta_7 wind_{t-1} + \beta_8 SLP_{t-1} \\
& + \beta_9 MeanTemp + \beta_{10} XCOUNT \\
& + \beta_{11} lat_{t-1}\, lon_{t-1} + \beta_{12} lat_{t-1} lon_{t-2} + \beta_{13} lon_{t-1} lat_{t-2} + \beta_{14} lon_{t-2}\, lat_{t-2} \\
& + \beta_0 + \varepsilon
\end{aligned}
$$

Two time steps before

One time step before

Non AR variables

Interaction terms for lat and lon

Intercept and error

REGRESSION RESULTS

OLS MODEL

WITH HETEROSKEDASTICITY ROBUST STANDARD ERRORS

Longitude Model

Dep. Variable:	Longitude	**R-squared:**	0.998
Model:	OLS	**Adj. R-squared:**	0.998
Method:	Least Squares	**F-statistic:**	3.423e+06
Date:	Mon, 07 Dec 2020	**Prob (F-statistic):**	0.00
Time:	10:51:17	**Log-Likelihood:**	-2.0389e+05
No. Observations:	131874	**AIC:**	4.078e+05
Df Residuals:	131857	**BIC:**	4.080e+05
Df Model:	16		

	coef	std err	z	P> |z|	[0.025	0.975]
const	-9.5426	1.244	-7.669	0.000	-11.981	-7.104
lon2	-0.9179	0.026	-35.952	0.000	-0.968	-0.868
wind2	0.0102	0.001	6.832	0.000	0.007	0.013
lat2	-1.2469	0.127	-9.804	0.000	-1.496	-0.998
SLP2	-0.0046	0.001	-4.241	0.000	-0.007	-0.002
lon	1.9355	0.026	74.527	0.000	1.885	1.986
wind	0.0054	0.001	3.802	0.000	0.003	0.008
lat	1.2426	0.126	9.895	0.000	0.996	1.489
SLP	0.0108	0.001	10.470	0.000	0.009	0.013
XCOUNT	-0.0004	0.000	-1.644	0.100	-0.001	8.19e-05
meanTemp	0.0158	0.012	1.374	0.170	-0.007	0.038
lat lon	0.0274	0.007	3.745	[illegible]	0.013	0.042
lat lat2	7.995e-06	6.85e-05	0.117	0.907	-0.000	0.000
lat lon2	-0.0319	0.007	-4.299	0.000	-0.046	-0.017
lon lat2	-0.0316	0.007	-4.220	0.000	-0.046	-0.017
lon lon2	-3.021e-05	1.53e-05	-1.968	0.049	-6.03e-05	-1.24e-07
lat2 lon2	0.0361	0.008	4.764	0.000	0.021	0.051

Omnibus:	77413.342	**Durbin-Watson:**	2.247
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	113037081.114
Skew:	1.290	**Prob(JB):**	0.00
Kurtosis:	146.406	**Cond. No.**	1.59e+07

Warnings:
[1] Standard Errors are heteroscedasticity robust (HC0)
[2] The condition number is large, 1.59e+07. This might indicate that there are strong multicollinearity or other numerical problems.

Latitude Model

Dep. Variable:	Latitude	**R-squared:**	0.998
Model:	OLS	**Adj. R-squared:**	0.998
Method:	Least Squares	**F-statistic:**	2.407e+06
Date:	Mon, 07 Dec 2020	**Prob (F-statistic):**	0.00
Time:	10:51:17	**Log-Likelihood:**	-1.2576e+05
No. Observations:	131874	**AIC:**	2.515e+05
Df Residuals:	131857	**BIC:**	2.517e+05
Df Model:	16		

	coef	std err	z	P> |z|	[0.025	0.975]
const	0.6212	0.367	1.694	0.090	-0.097	1.340
lon2	-0.1454	0.007	-21.297	0.000	-0.159	-0.132
wind2	-0.0023	0.001	-3.053	0.002	-0.004	-0.001
lat2	-0.9953	0.063	-15.900	0.000	-1.118	-0.873
SLP2	-0.0088	0.001	-15.494	0.000	-0.010	-0.008
lon	0.1400	0.007	20.301	0.000	0.127	0.154
wind	0.0103	0.001	13.777	0.000	0.009	0.012
lat	2.0024	0.062	32.254	0.000	1.881	2.124
SLP	0.0090	0.001	15.526	0.000	0.008	0.010
XCOUNT	-0.0010	0.000	-7.468	0.000	-0.001	-0.001
meanTemp	-0.0082	0.006	-1.285	0.199	-0.021	0.004
lat lon	0.0173	0.002	7.089	[illegible]	0.013	0.022
lat lat2	7.73e-05	1.6e-05	4.837	0.000	4.6e-05	0.000
lat lon2	-0.0185	0.002	-7.423	0.000	-0.023	-0.014
lon lat2	-0.0191	0.002	-7.834	0.000	-0.024	-0.014
lon lon2	1.133e-05	3.53e-06	3.211	0.001	4.41e-06	1.82e-05
lat2 lon2	0.0202	0.002	8.134	0.000	0.015	0.025

Omnibus:	34024.578	**Durbin-Watson:**	2.180
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1315745.846
Skew:	0.529	**Prob(JB):**	0.00
Kurtosis:	18.438	**Cond. No.**	1.59e+07

Warnings:
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REGRESSION RESULTS

OLS MODEL

WITH HETEROSKEDASTICITY ROBUST STANDARD ERRORS

Wind Speed Model

Dep. Variable:	Wind	**R-squared:**	0.858
Model:	OLS	**Adj. R-squared:**	0.858
Method:	Least Squares	**F-statistic:**	3.114e+04
Date:	Mon, 07 Dec 2020	**Prob (F-statistic):**	0.00
Time:	03:51:17	**Log-Likelihood:**	-3.4779e+05
No. Observations:	131874	**AIC:**	6.956e+05
Df Residuals:	131857	**BIC:**	6.958e+05
Df Model:	16		

	coef	std err	z	P> |z|	[0.025	0.975]
const	51.1967	1.682	30.442	0.000	47.900	54.493
lon2	-0.1459	0.020	-7.142	0.000	-0.186	-0.106
wind2	0.2111	0.005	42.359	0.000	0.201	0.221
lat2	-0.4397	0.147	-2.998	0.003	-0.727	-0.152
SLP2	0.1878	0.004	48.033	0.000	0.180	0.195
lon	0.3245	0.021	15.799	0.000	0.284	0.365
wind	0.5838	0.005	106.838	0.000	0.573	0.594
lat	0.1074	0.144	0.744	0.457	-0.175	0.390
SLP	-0.2559	0.004	-63.230	0.000	-0.264	-0.248
XCOUNT	-0.0070	0.001	-11.815	0.000	-0.008	-0.006
meanTemp	0.1241	0.034	3.641	0.000	0.057	0.191
lat lon	-0.0370	0.005	-8.156	0.000	-0.046	-0.028
lat lat2	-0.0010	5.95e-05	-16.533	0.000	-0.001	-0.001
lat lon2	0.0368	0.005	7.902	0.000	0.028	0.046
lon lat2	0.0336	0.005	7.445	0.000	0.025	0.042
lon lon2	-0.0003	1.61e-05	-20.980	0.000	-0.000	-0.000
lat2 lon2	-0.0323	0.005	-6.981	0.000	-0.041	-0.023

Omnibus:	11258.678	**Durbin-Watson:**	2.038
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	67584.957
Skew:	0.161	**Prob(JB):**	0.00
Kurtosis:	6.492	**Cond. No.**	1.59e+07

Warnings:
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SLP Model

Dep. Variable:	SLP	**R-squared:**	0.951
Model:	OLS	**Adj. R-squared:**	0.951
Method:	Least Squares	**F-statistic:**	1.101e+05
Date:	Mon, 07 Dec 2020	**Prob (F-statistic):**	0.00
Time:	10:51:17	**Log-Likelihood:**	-3.6994e+05
No. Observations:	131874	**AIC:**	7.399e+05
Df Residuals:	131857	**BIC:**	7.401e+05
Df Model:	16		

	coef	std err	z	P> |z|	[0.025	0.975]
const	34.1887	1.830	18.683	0.000	30.602	37.775
lon2	0.0402	0.022	1.854	0.064	-0.002	0.083
wind2	0.0318	0.005	6.412	0.000	0.022	0.042
lat2	-0.4835	0.152	-3.177	0.001	-0.782	-0.185
SLP2	-0.1254	0.005	-25.239	0.000	-0.135	-0.116
lon	-0.1885	0.022	-8.709	0.000	-0.231	-0.146
wind	-0.0182	0.005	-3.473	0.001	-0.028	-0.008
lat	0.8545	0.150	5.704	0.000	0.561	1.148
SLP	1.1069	0.005	217.351	0.000	1.097	1.117
XCOUNT	0.0161	0.001	24.057	0.000	0.015	0.017
meanTemp	-0.0935	0.040	-2.311	0.021	-0.173	-0.014
lat lon	-0.0365	0.006	-6.573	0.000	-0.047	-0.026
lat lat2	0.0008	6.5e-05	12.040	0.000	0.001	0.001
lat lon2	0.0330	0.006	5.817	0.000	0.022	0.044
lon lat2	0.0369	0.006	6.543	0.000	0.026	0.048
lon lon2	0.0003	1.45e-05	20.514	0.000	0.000	0.000
lat2 lon2	-0.0345	0.006	-6.001	0.000	-0.046	-0.023

Omnibus:	17282.917	**Durbin-Watson:**	2.035
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	90602.205
Skew:	-0.529	**Prob(JB):**	0.00
Kurtosis:	6.920	**Cond. No.**	1.59e+07

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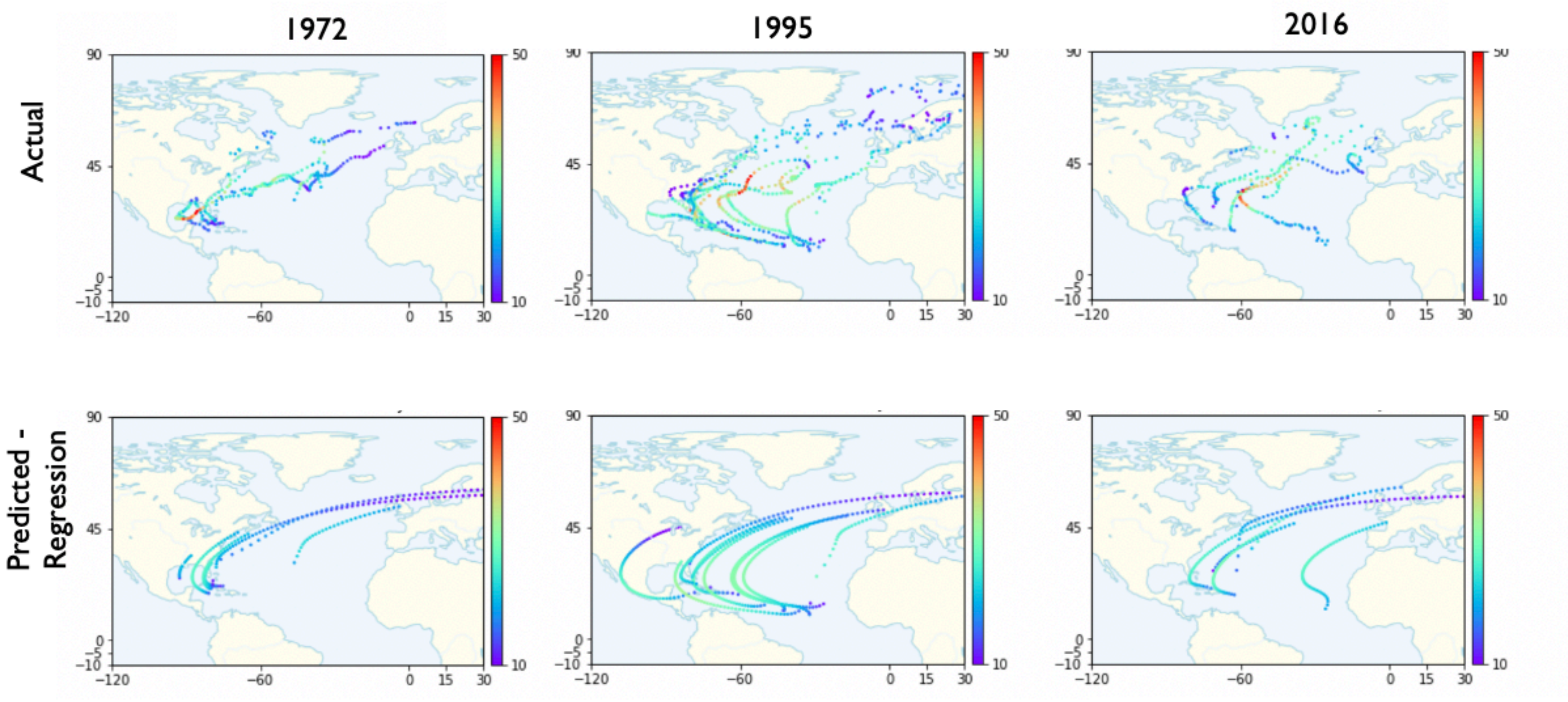
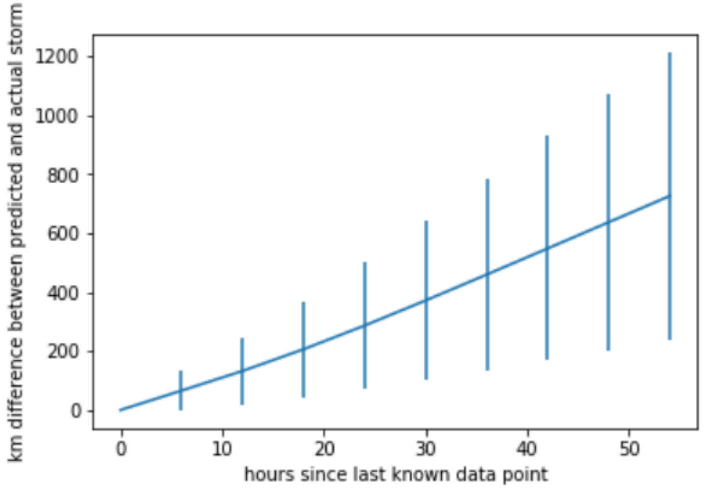
SAMPLE PREDICTED TRACKS

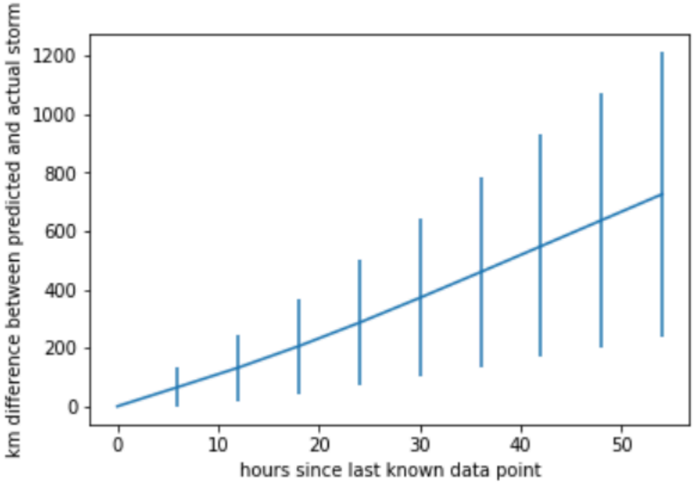


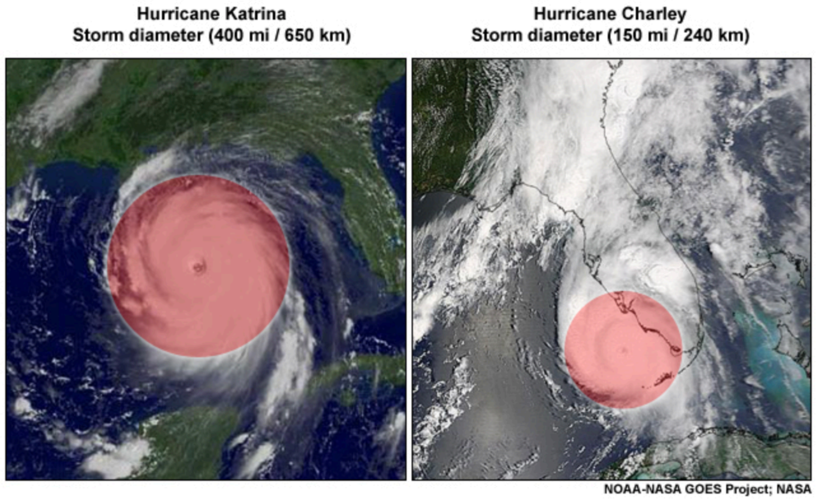
MODEL PREDICTIVE ACCURACY

Including mean global temperature variable



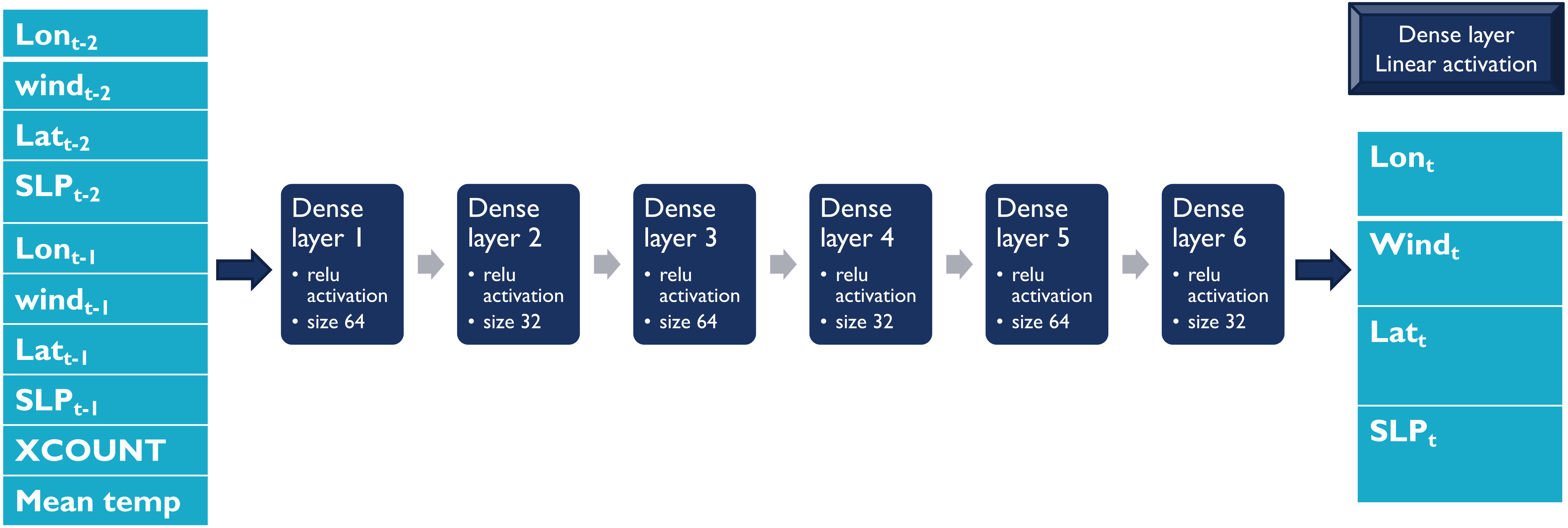
excluding mean global temperature variable



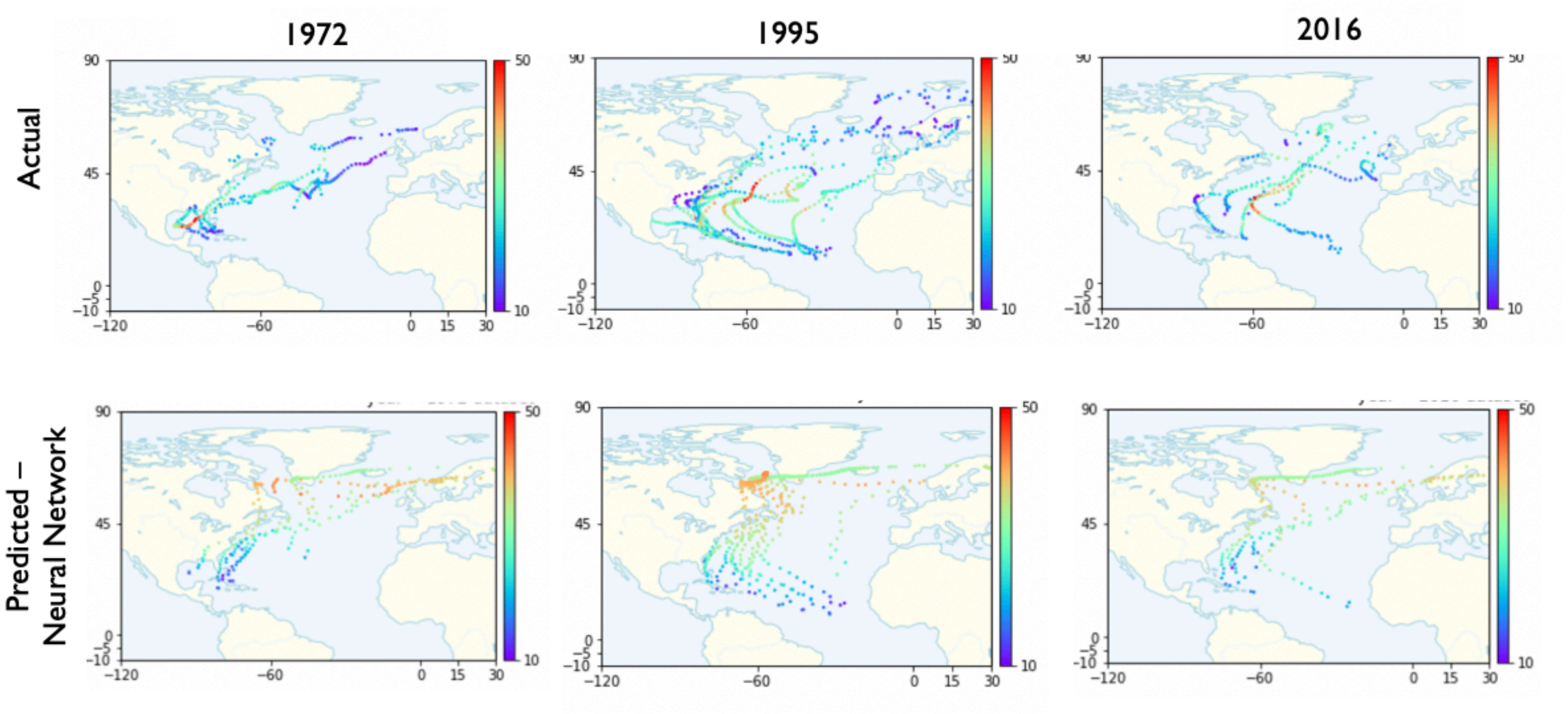


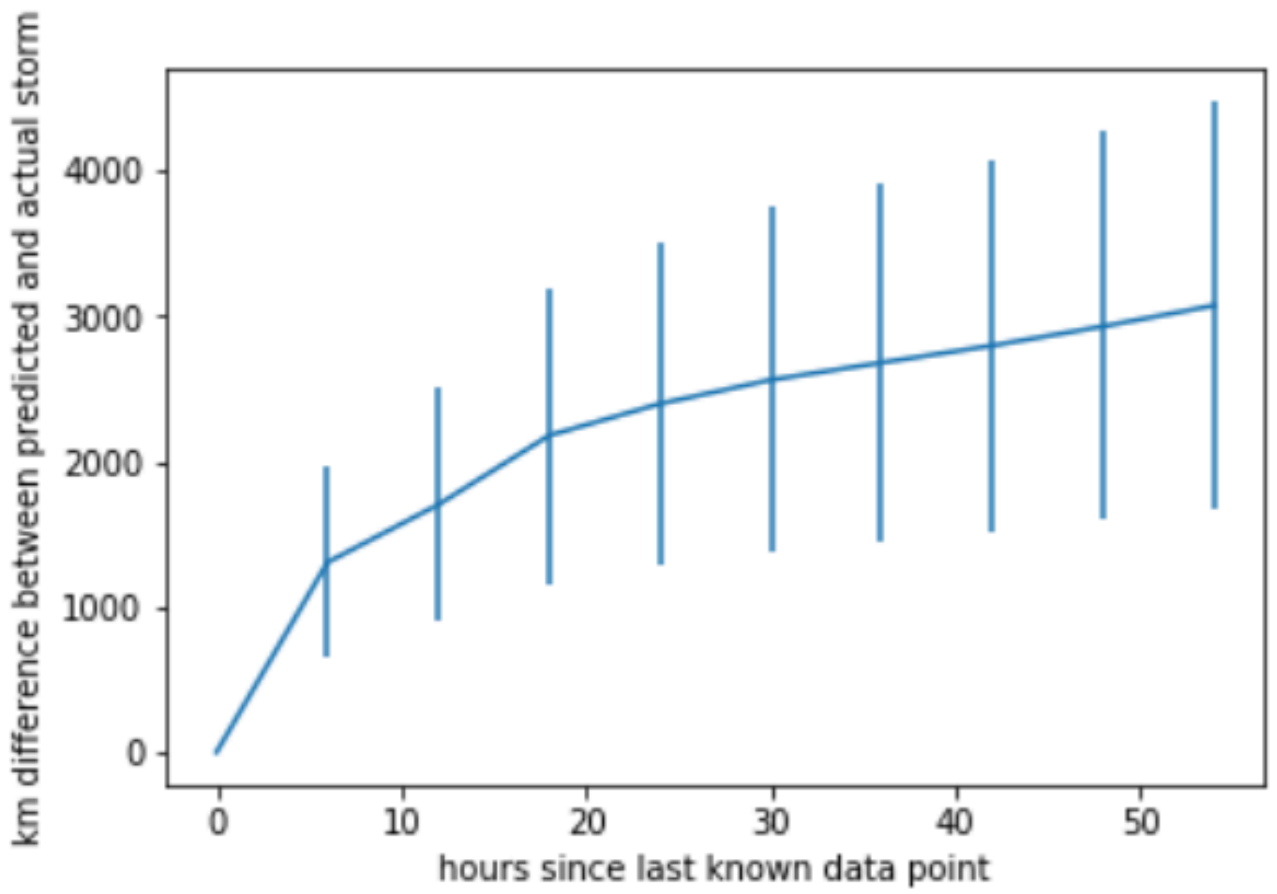
http://stream1.cmatc.cn/pub/comet/Environment/CommunityHurricanePreparedness2ndEdition/comet/hurrican/chp/print_2.htm

NEURAL NETWORK MODEL



NEURAL NETWORK MODEL





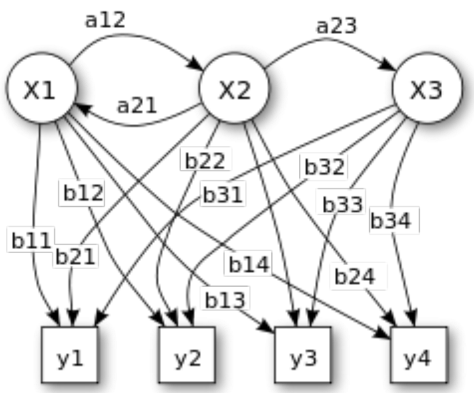
MODEL PREDICTIVE ACCURACY

CONCLUSIONS

A simple regression model yields reasonable predictions as much a day in advance

In this model, climate change, as represented by mean global temperature, did not have a significant impact on steering flow of the hurricanes.

FUTURE STEPS



https://en.wikipedia.org/wiki/Hidden_Markov_model

- Feature selection using lasso regression
- Including more predictor variables or time steps
- Refining neural network model and assessing its predictive power
- Considering a Markov chain probabilistic model

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