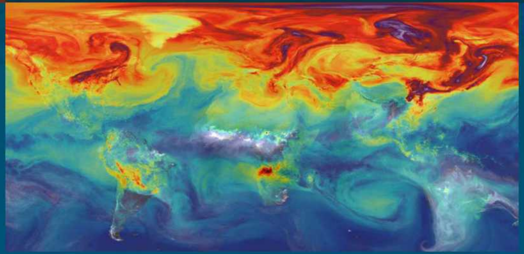
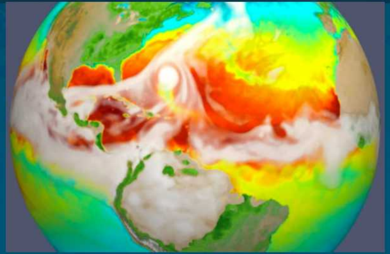
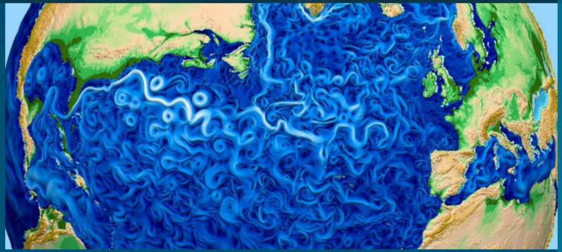
SAND2020-5922C

Machine Learning to Compare Arctic Simulations With Observed Data







J. Jake Nichol, Matthew Peterson, Kara Peterson, David Stracuzzi, G. Matthew Fricke

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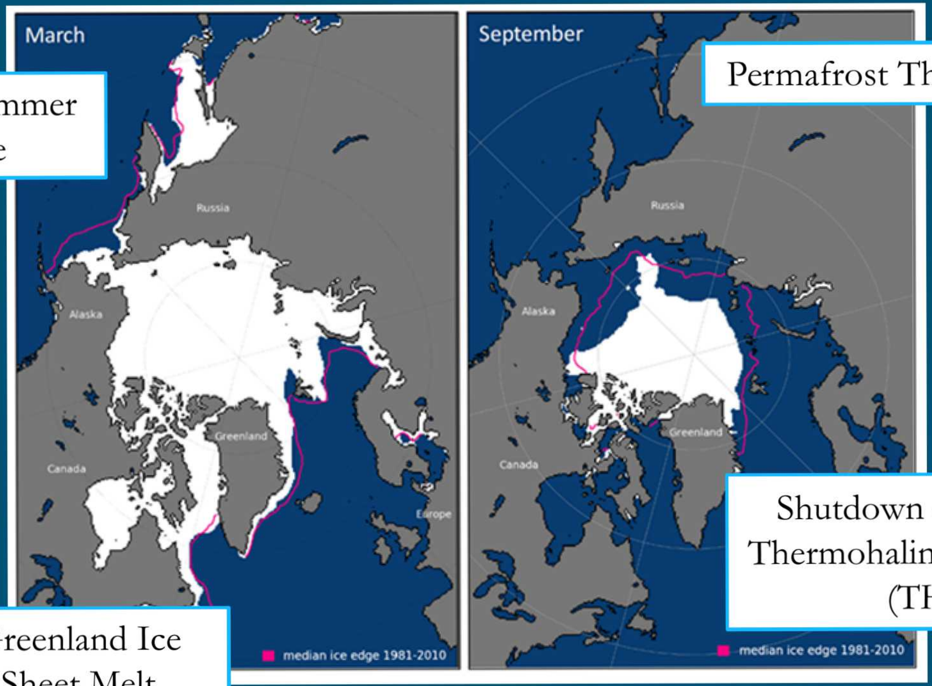
Problem: Arctic sea ice minimums impact the full Earth system

Loss of Summer Sea Ice

Impacts:
Mid-latitude weather changes; ocean current alterations



Permafrost Thaw

Impacts:
Significant greenhouse gas release; changes in hydrology; increased erosion

Greenland Ice Sheet Melt

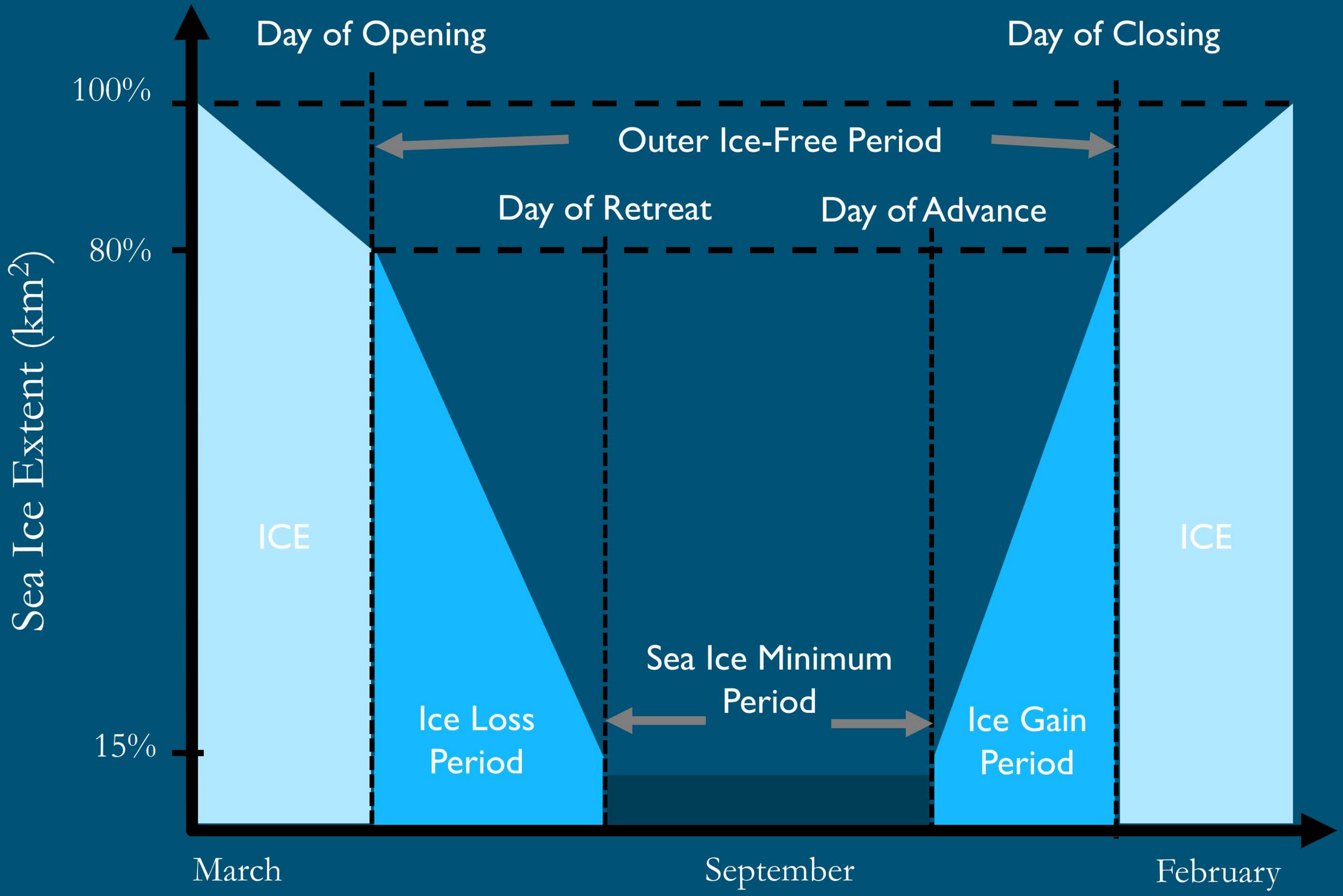
Impacts:
Sea level rise; ocean current alterations

Shutdown of Atlantic Thermohaline Circulation (THC)

Impacts:
Regional cooling; significant weather shifts in the N. hemisphere

Photograph Credit: D. Perovich et al., NOAA, *Arctic Report Card: Update for 2018*

Problem: predicting the minimum extent (km^2) each year



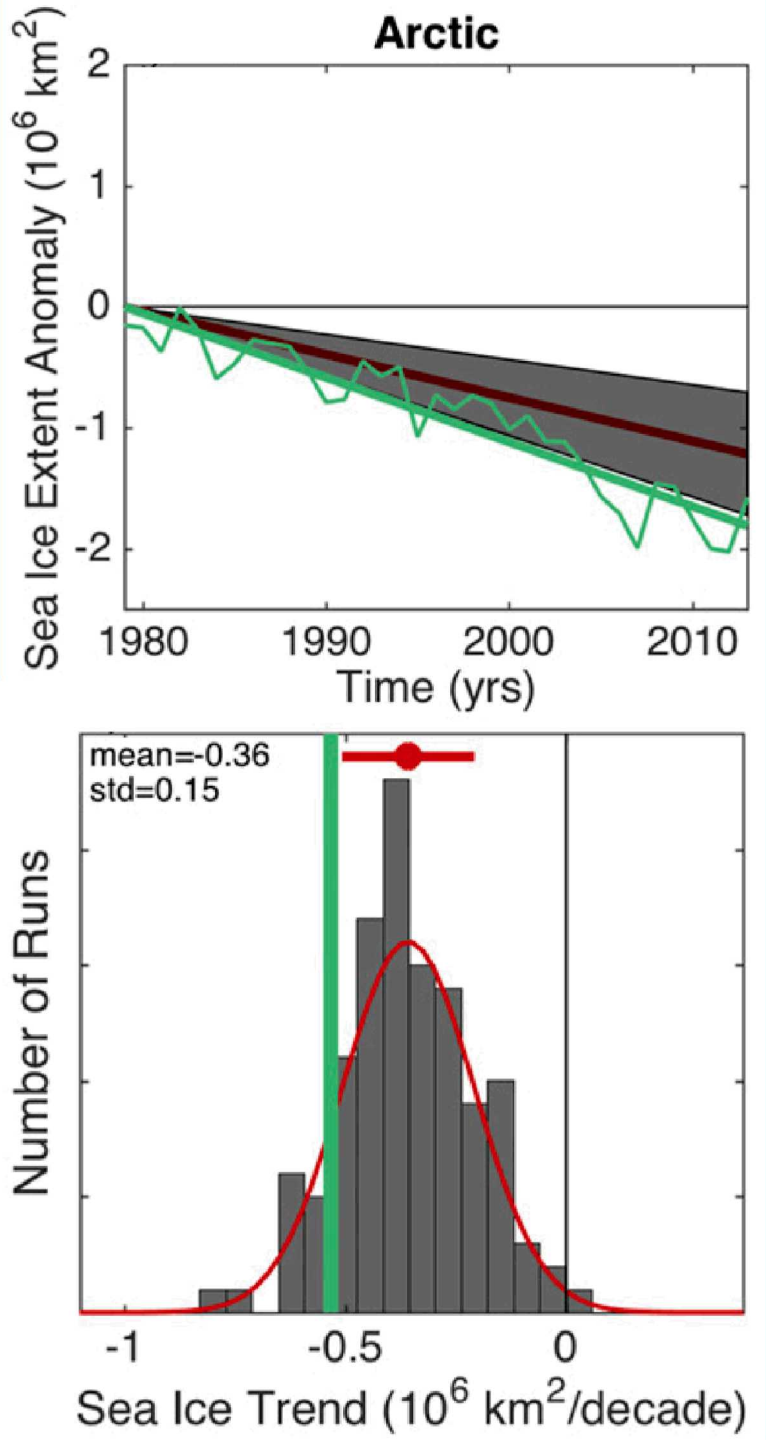
Problem: most CMIP5 models underestimate sea ice decline

In a study [1] of Arctic sea ice predictions from the World Climate Research Programme's Coupled Model Intercomparison Project 5 (CMIP5):

- 118 simulations run using 40 models in CMIP5
- **Only 11%** of model runs agree with the observed trend

This work examines the Energy Exascale Earth System Model (E3SM)

- Not in CMIP5 but E3SM is derivative of a model in CMIP5



[1] Erica Rosenblum and Ian Eisenman. 2017. Sea ice trends in climate models only accurate in runs with biased global warming. *J. Clim.* 30, 16 (August 2017), 6265–6278. DOI:https://doi.org/10.1175/JCLI-D-16-0455.1

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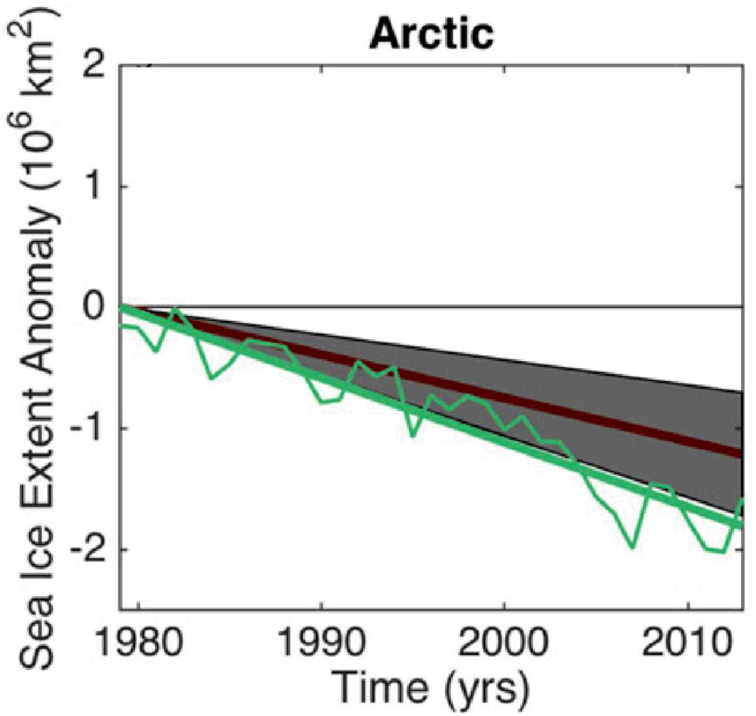

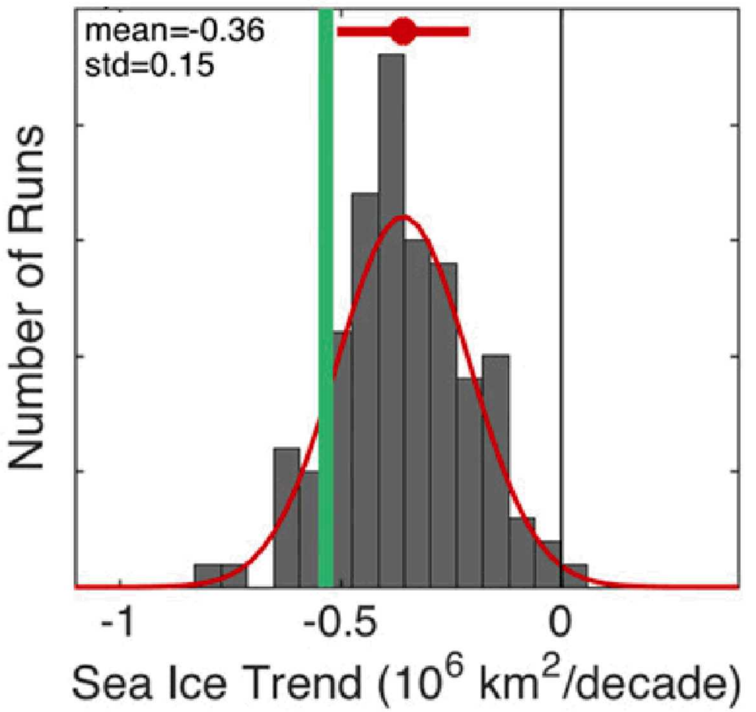

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Goals

First Steps

Identify features in June that are the most impactful for sea ice extent in September

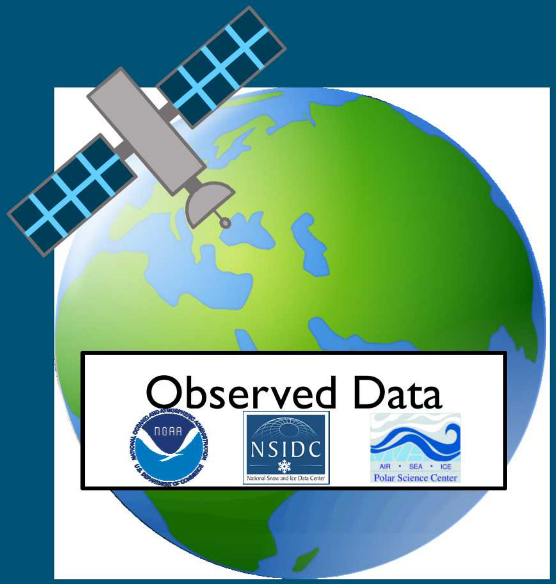
- Conduct a feature analysis on observed climate data in the Arctic
- Feature analysis can be conducted on any trained model.
- Compare results with a feature analysis on simulated data

Final Goal

Improve both physics-based and data-driven models of the Arctic climate

- Make adjustments to physics-based models to adapt for inconsistencies with observed data
- Evaluate newly tuned physics-based model for change in accuracy

Goals

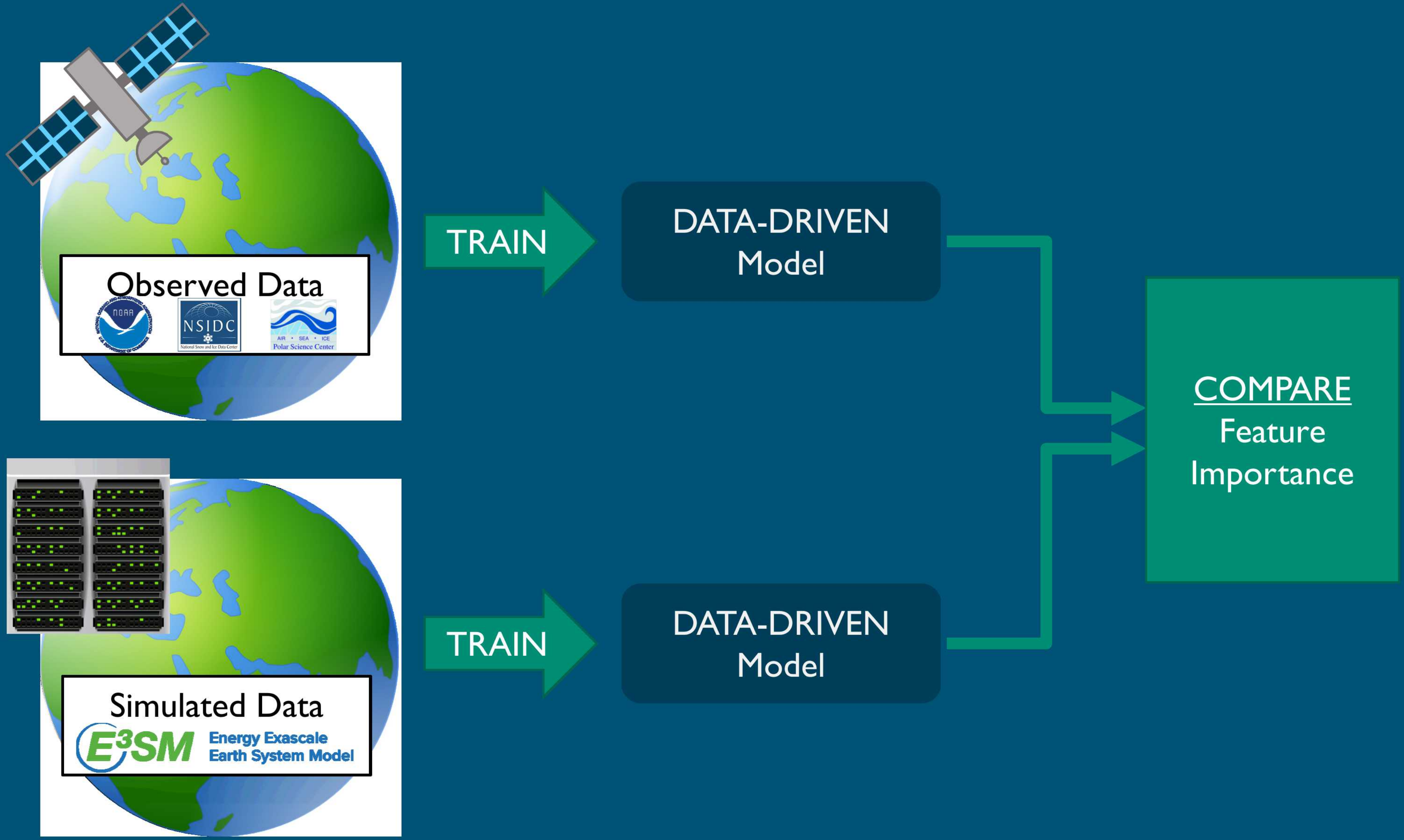


TRAIN

DATA-DRIVEN
Model

Feature
Importance

Goals


Observed Data
NSIDC
Polar Science Center
TRAIN
DATA-DRIVEN
Model
COMPARE
Feature
Importance
Simulated Data
E3SM
Energy Exascale
Earth System Model
TRAIN
DATA-DRIVEN
Model

Data

6 Datasets

Observed

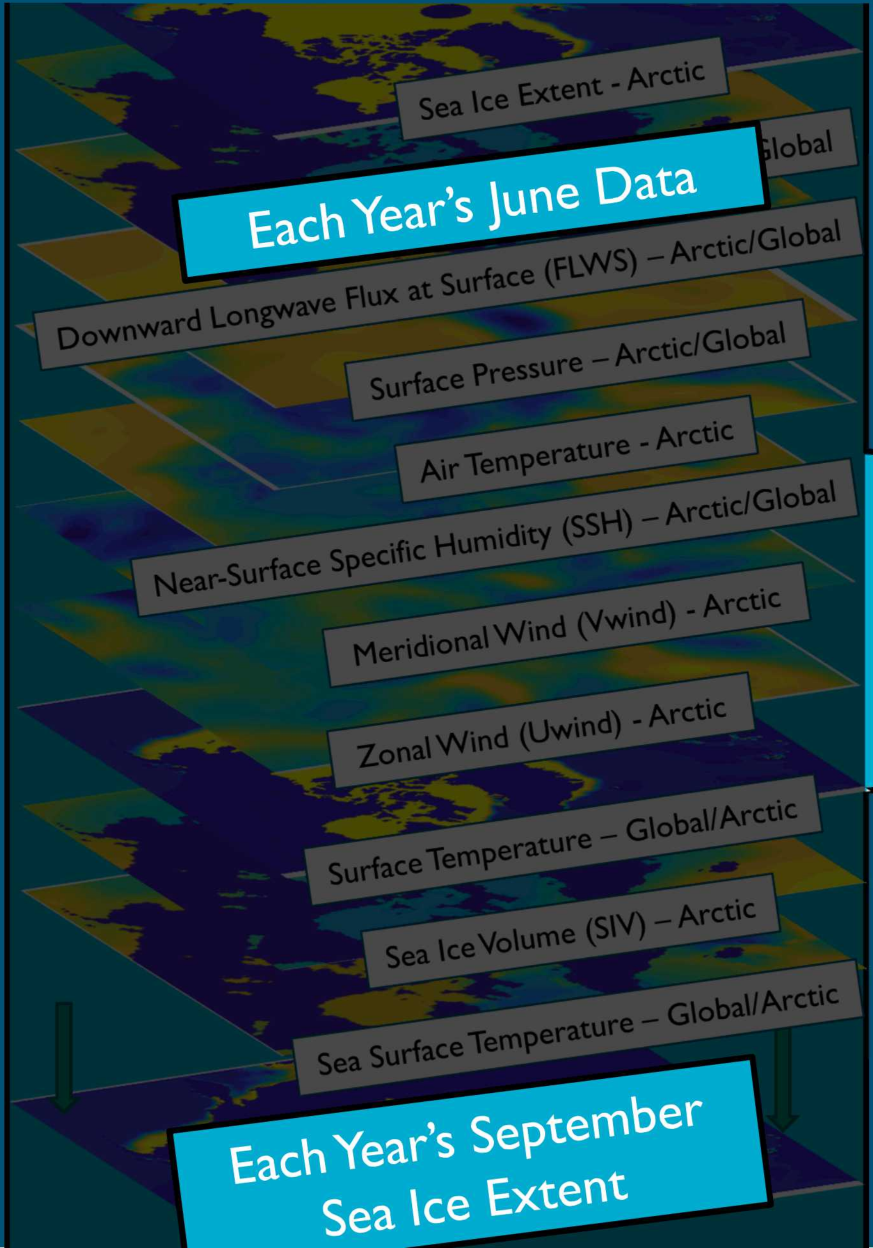
- NOAA
- NSIDC
- Polar Science Center

5 E3SM Ensembles

- Separate 165-year runs with differing initial conditions
- 165 years allows initial model chaos to settle
- Last 35 years extracted for datasets

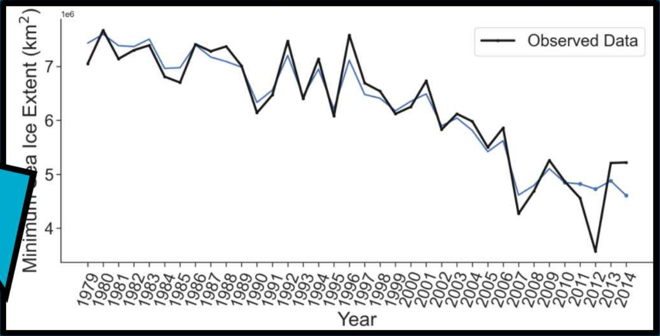
E3SM Energy Exascale Earth System Model

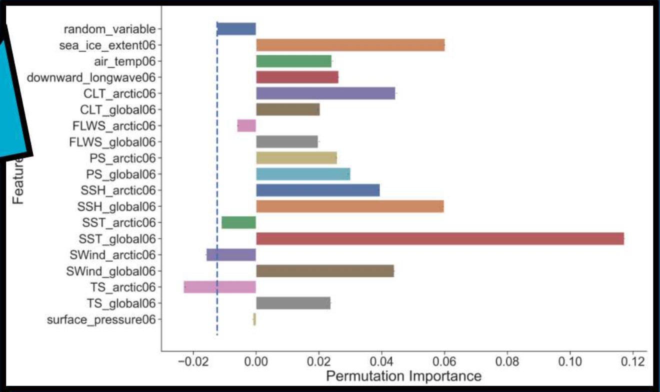
Methods



ML Model

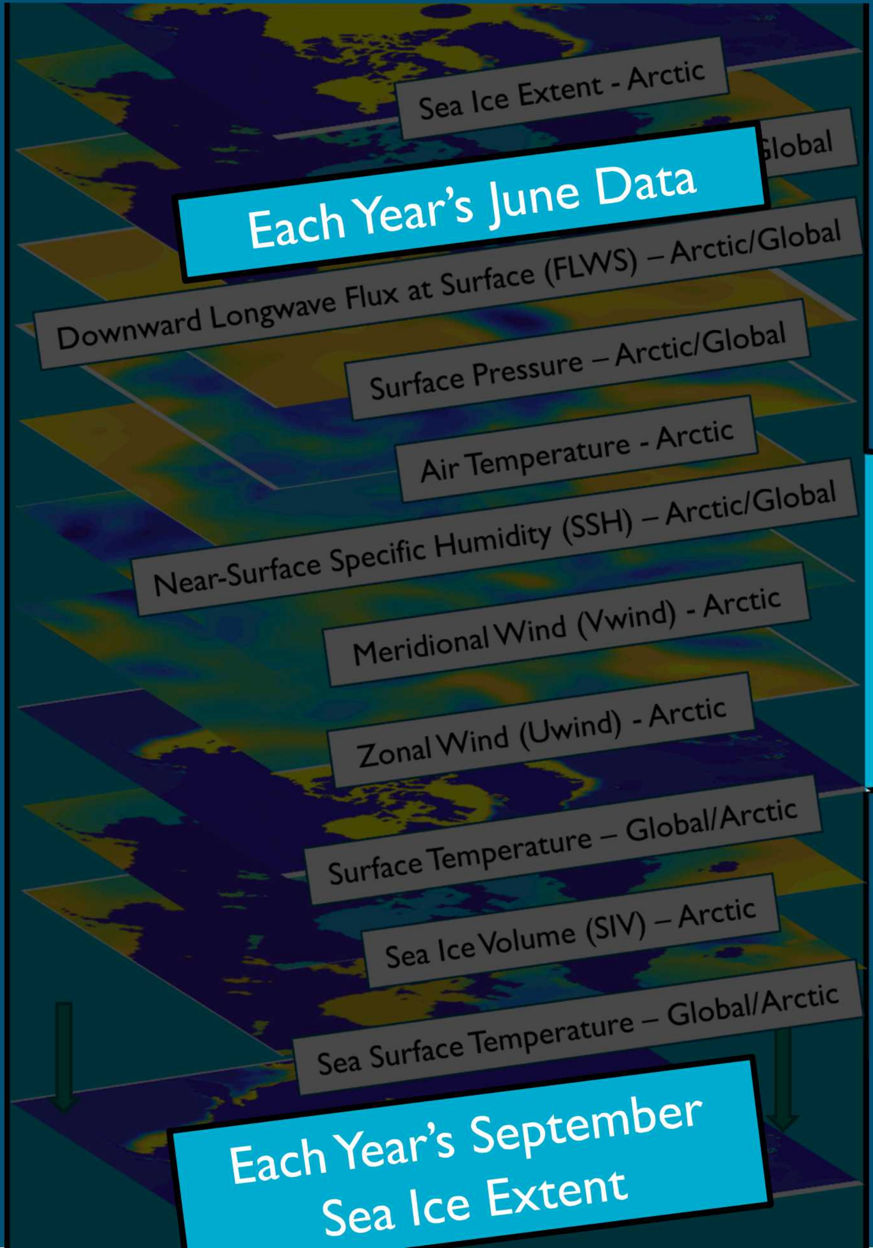
Regression





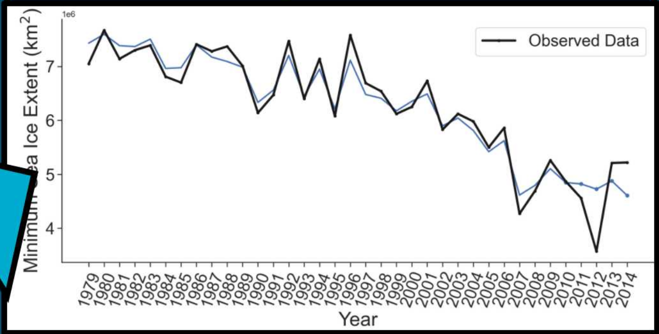
Importance

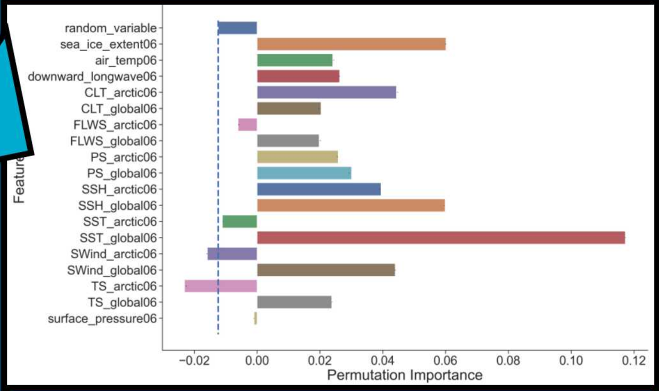
Methods



Random Forest Regression Model

Regression



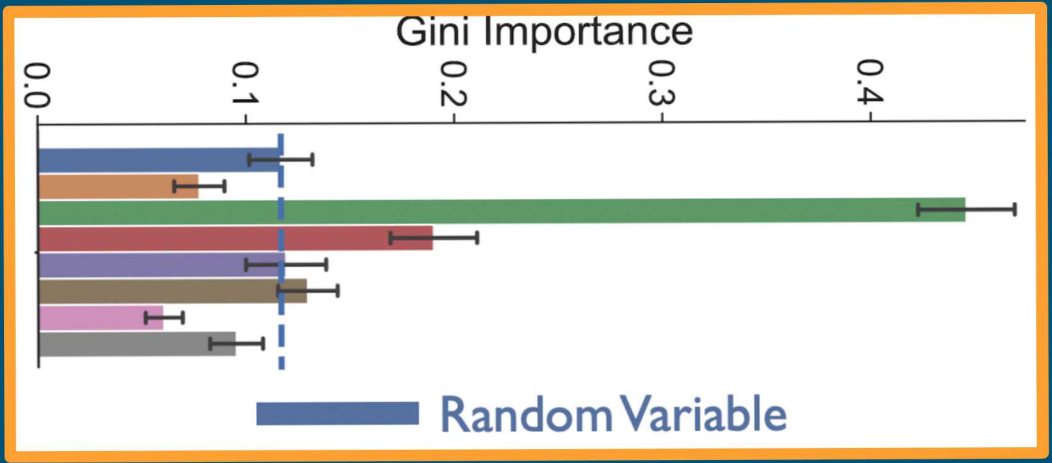


Importance

Methods: Feature Importance

Gini Importance – default for R and Python's scikit-learn

- Measures how each feature reduces variance
- Fast
- Highly biased for data with many unique values



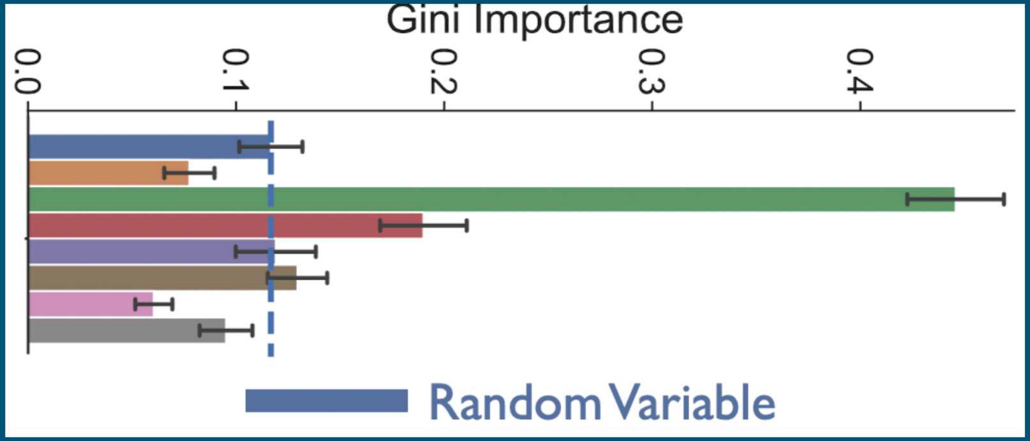
Methods: Feature Importance

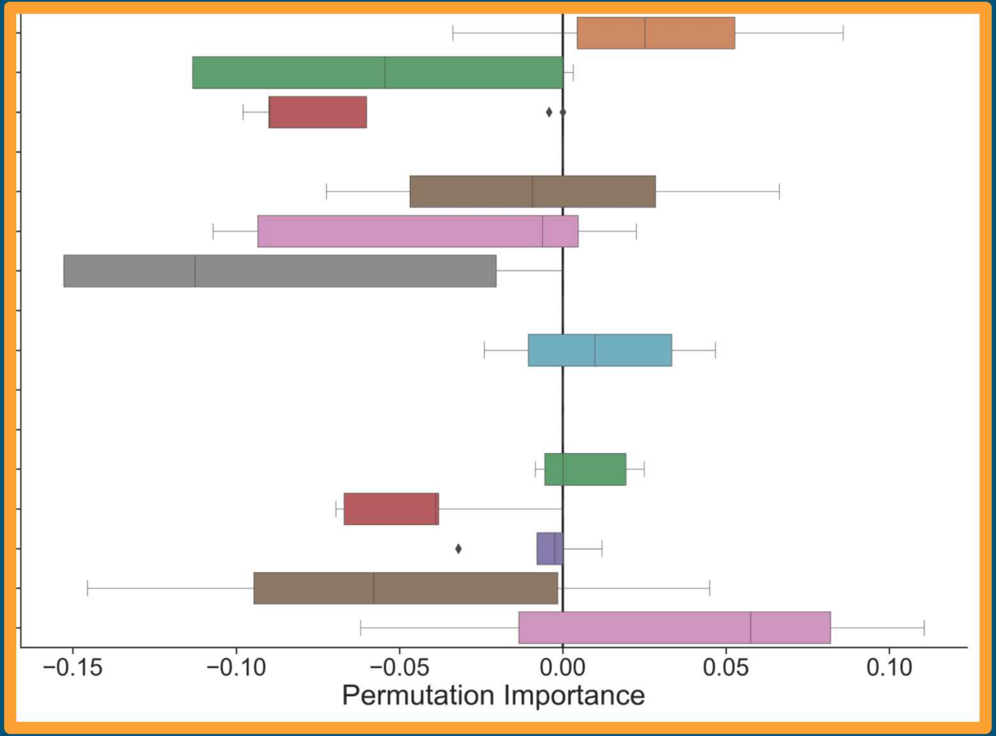
Gini Importance – default for R and Python's scikit-learn

- Measures how each feature reduces variance
- Fast
- Highly biased for data with many unique values

Permutation Importance – stochastic

- Permutes each feature and measures the changed in error
- Fast
- Results can depend on the specific permutation of each feature
- Cannot be run on training data alone





Methods: Feature Importance

Gini Importance – default for R and Python's scikit-learn
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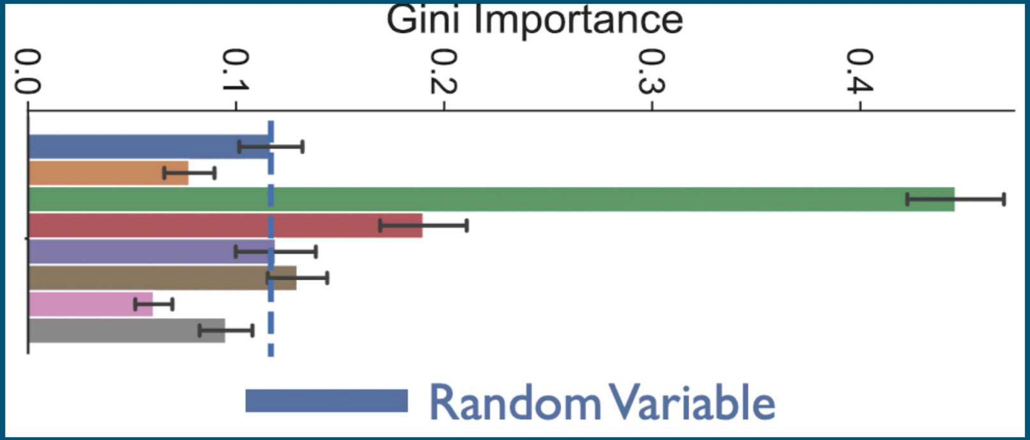

Permutation Importance – stochastic
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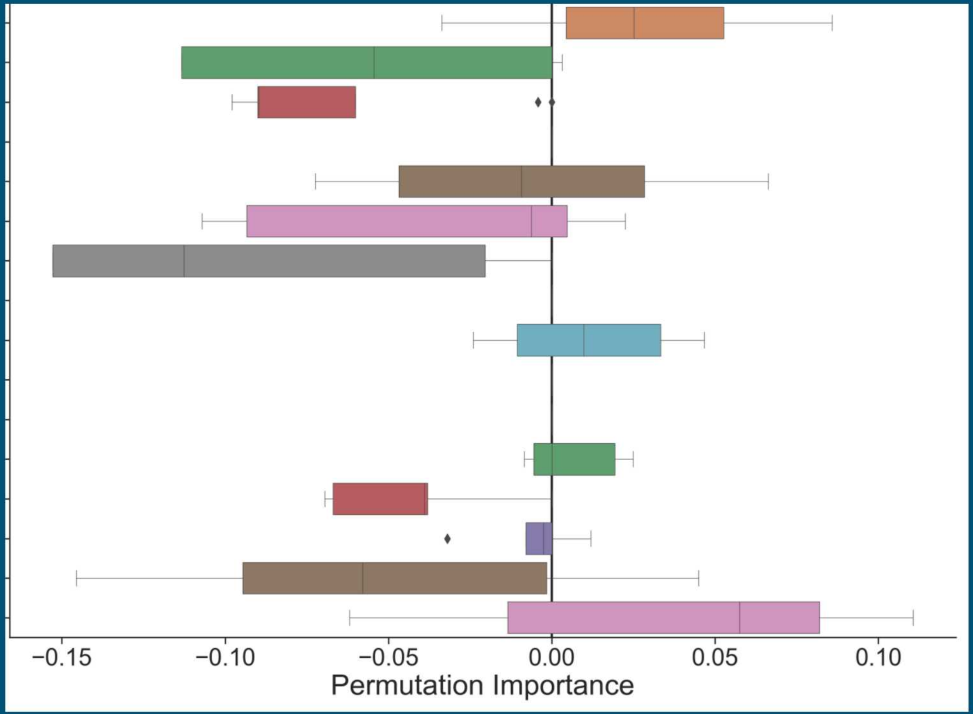
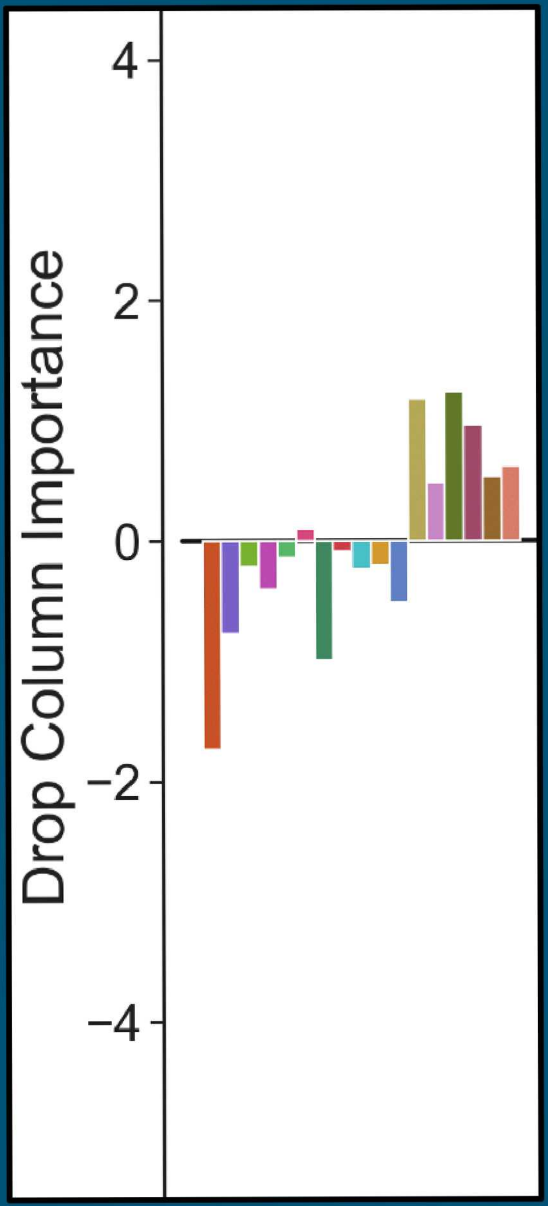


Drop-column Importance – deterministic
- Drops each feature from the data set one at a time and retrains the model each time
- Very slow
- Returns repeatable, objective results

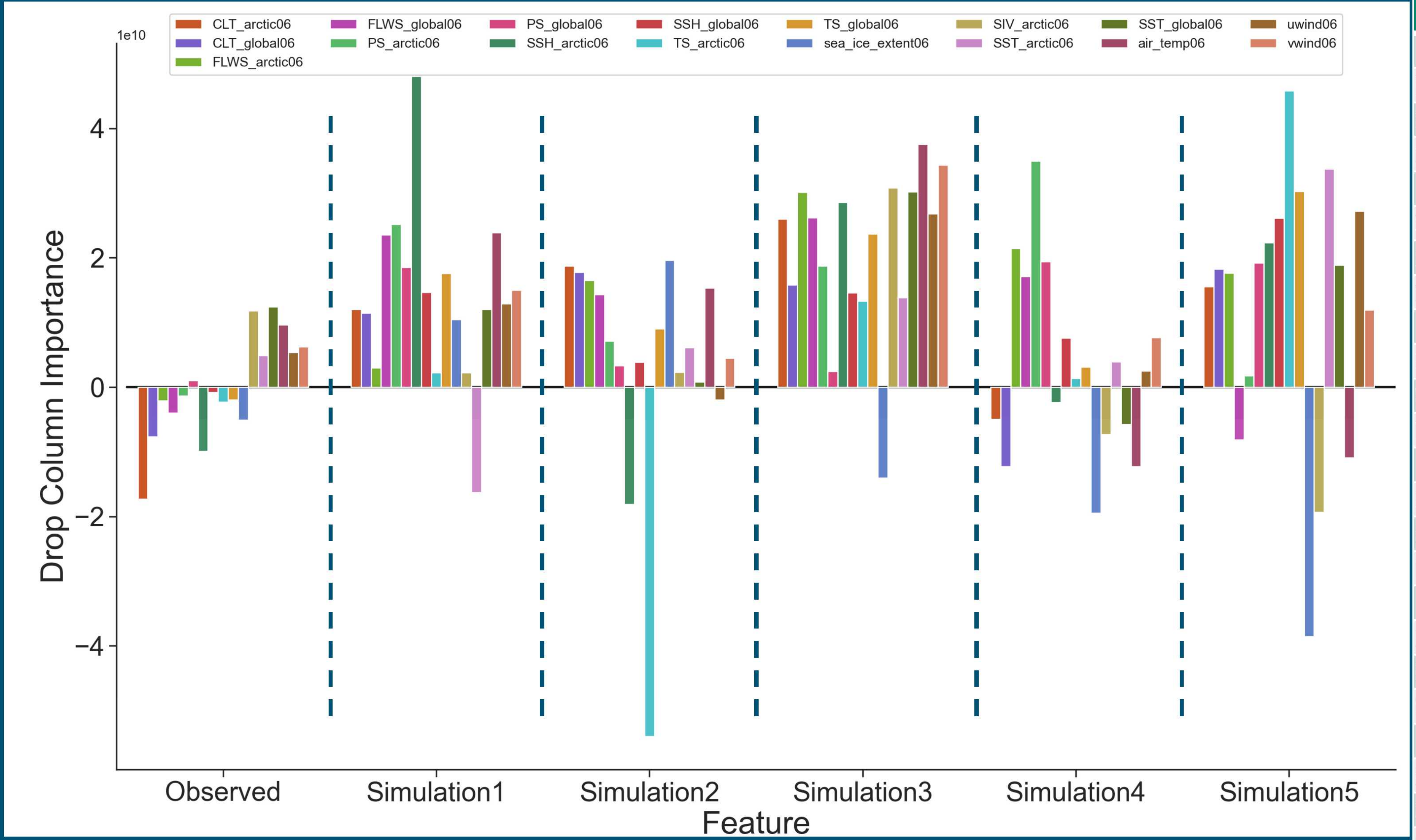
Results

- 0, 1, and 5 year forecast results
- Feature importance values for each data set
- Error metrics for each data set's regression



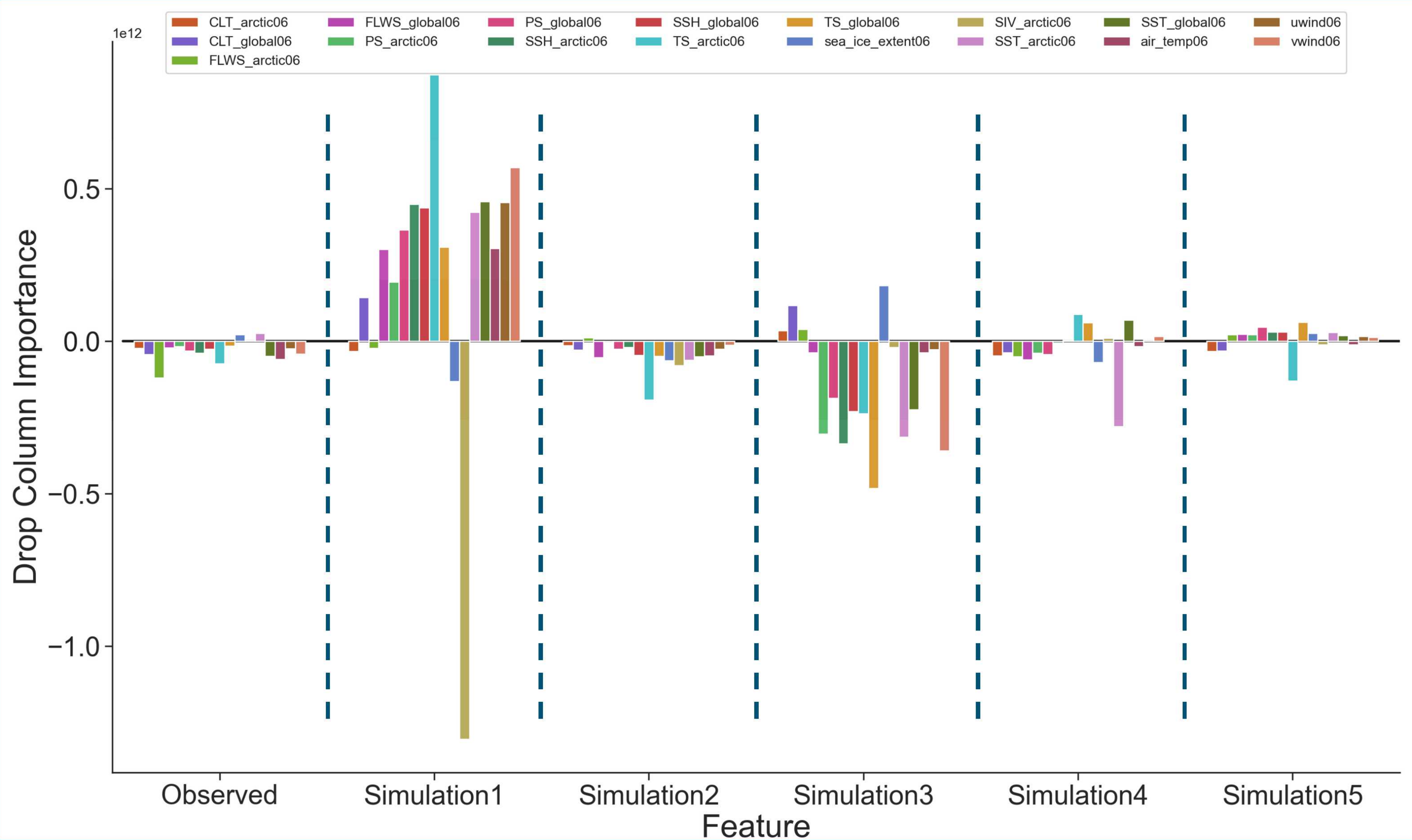
Observed	
R2: 0.9384	-0.1504
RMSE: 0.2057	0.6533
MAE: 0.1335	0.4622

Results: 0 Year Forecasts



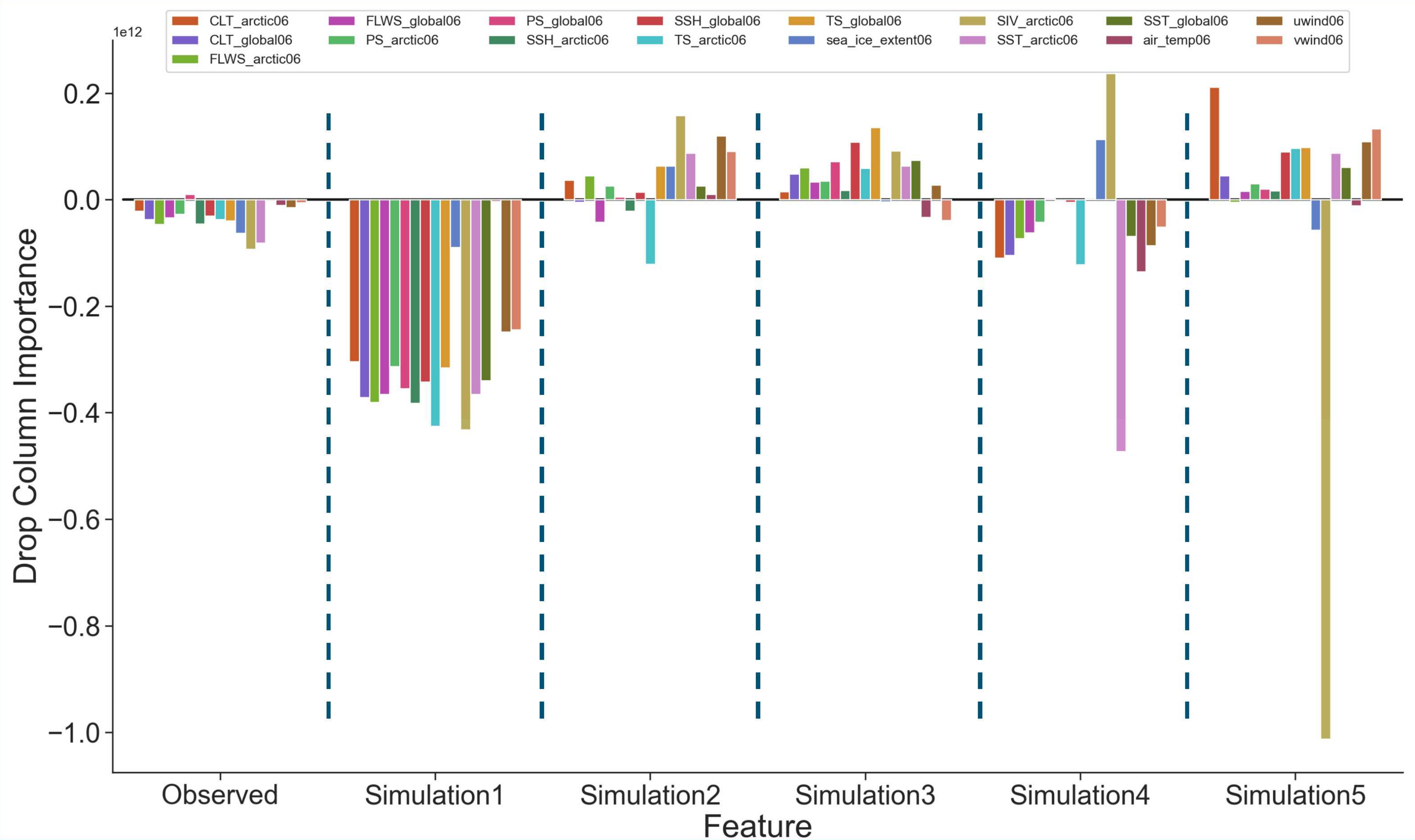
Train	Test
Observed	
R2: 0.9714	0.0000
RMSE: 0.1729	0.0000
MAE: 0.1342	0.0000
Simulation1	
R2: 0.9869	0.0000
RMSE: 0.2141	0.0000
MAE: 0.1351	0.0000
Simulation2	
R2: 0.9850	0.0000
RMSE: 0.1741	0.0000
MAE: 0.1518	0.0000
Simulation3	
R2: 0.9708	0.0000
RMSE: 0.2830	0.0000
MAE: 0.1367	0.0000
Simulation4	
R2: 0.9650	0.0000
RMSE: 0.2899	0.0000
MAE: 0.1369	0.0000
Simulation5	
R2: 0.9786	0.0000
RMSE: 0.2781	0.0000
MAE: 0.2162	0.0000

Results: 1 Year Forecasts

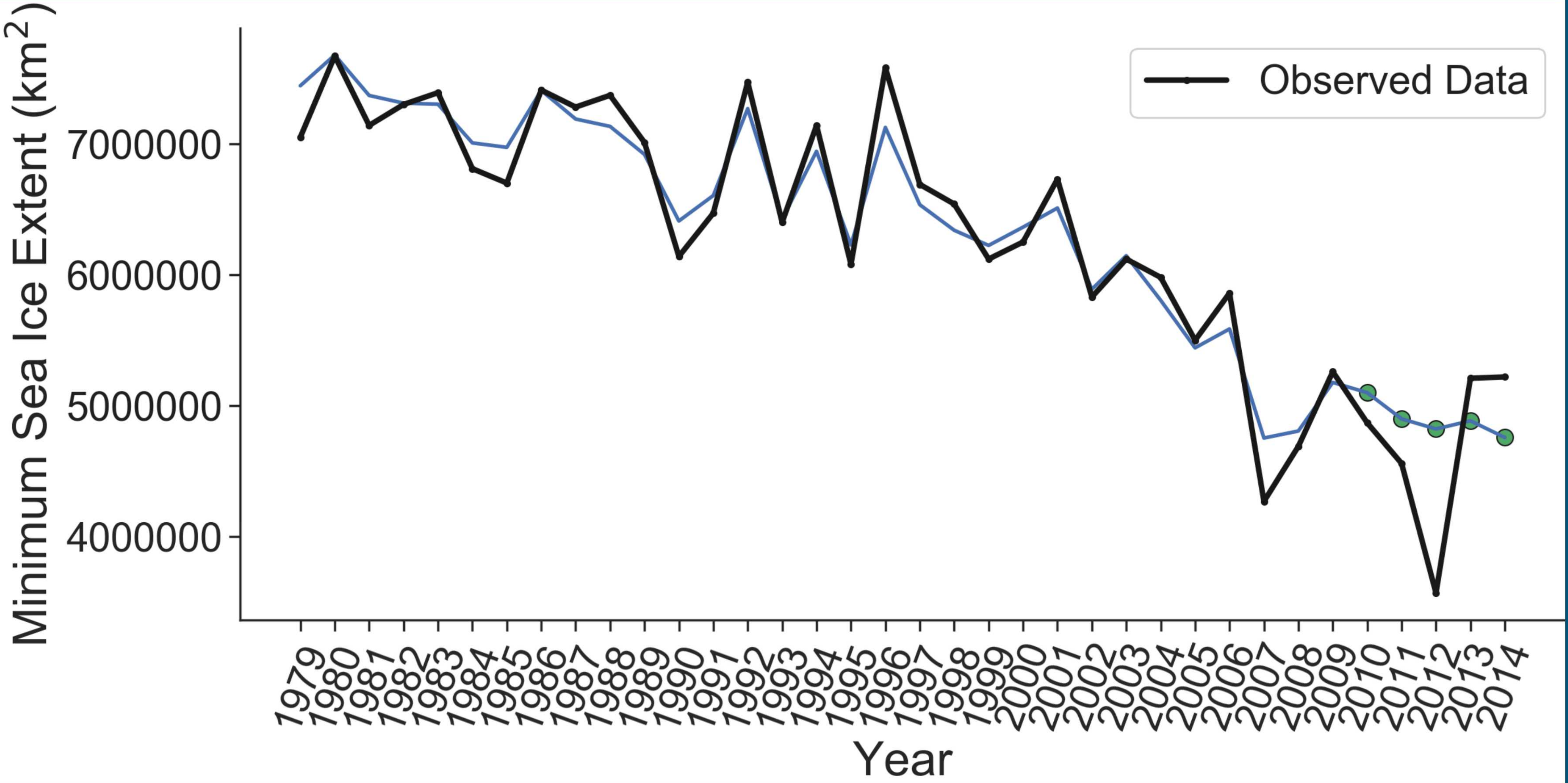


Train	Test
Observed	
R2: 0.9484	-inf
RMSE: 0.2322	0.6966
MAE: 0.1650	0.6966
Simulation1	
R2: 0.9708	-inf
RMSE: 0.3214	2.1728
MAE: 0.1665	2.1728
Simulation2	
R2: 0.9541	-inf
RMSE: 0.2930	0.2326
MAE: 0.1906	0.2326
Simulation3	
R2: 0.9578	-inf
RMSE: 0.3229	0.4385
MAE: 0.1743	0.4385
Simulation4	
R2: 0.9451	-inf
RMSE: 0.3568	0.1227
MAE: 0.2517	0.1227
Simulation5	
R2: 0.9626	-inf
RMSE: 0.3598	0.8067
MAE: 0.2440	0.8067

Results: 5 Year Forecasts



Train	Test
Observed	
R2: 0.9384	-0.1504
RMSE: 0.2057	0.6533
MAE: 0.1335	0.4622
Simulation1	
R2: 0.9805	-0.5267
RMSE: 0.2257	1.7192
MAE: 0.1359	1.4005
Simulation2	
R2: 0.9457	-10.1855
RMSE: 0.2207	1.7393
MAE: 0.1222	1.3753
Simulation3	
R2: 0.9641	-0.1832
RMSE: 0.2848	1.0340
MAE: 0.1505	0.4803
Simulation4	
R2: 0.9500	-0.8285
RMSE: 0.3412	0.8835
MAE: 0.1409	0.5806
Simulation5	
R2: 0.9692	-0.4969
RMSE: 0.2874	1.1687
MAE: 0.2384	1.0980


Observed Data
Minimum Sea Ice Extent (km^2)
7000000
6000000
5000000
4000000
1979
1980
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
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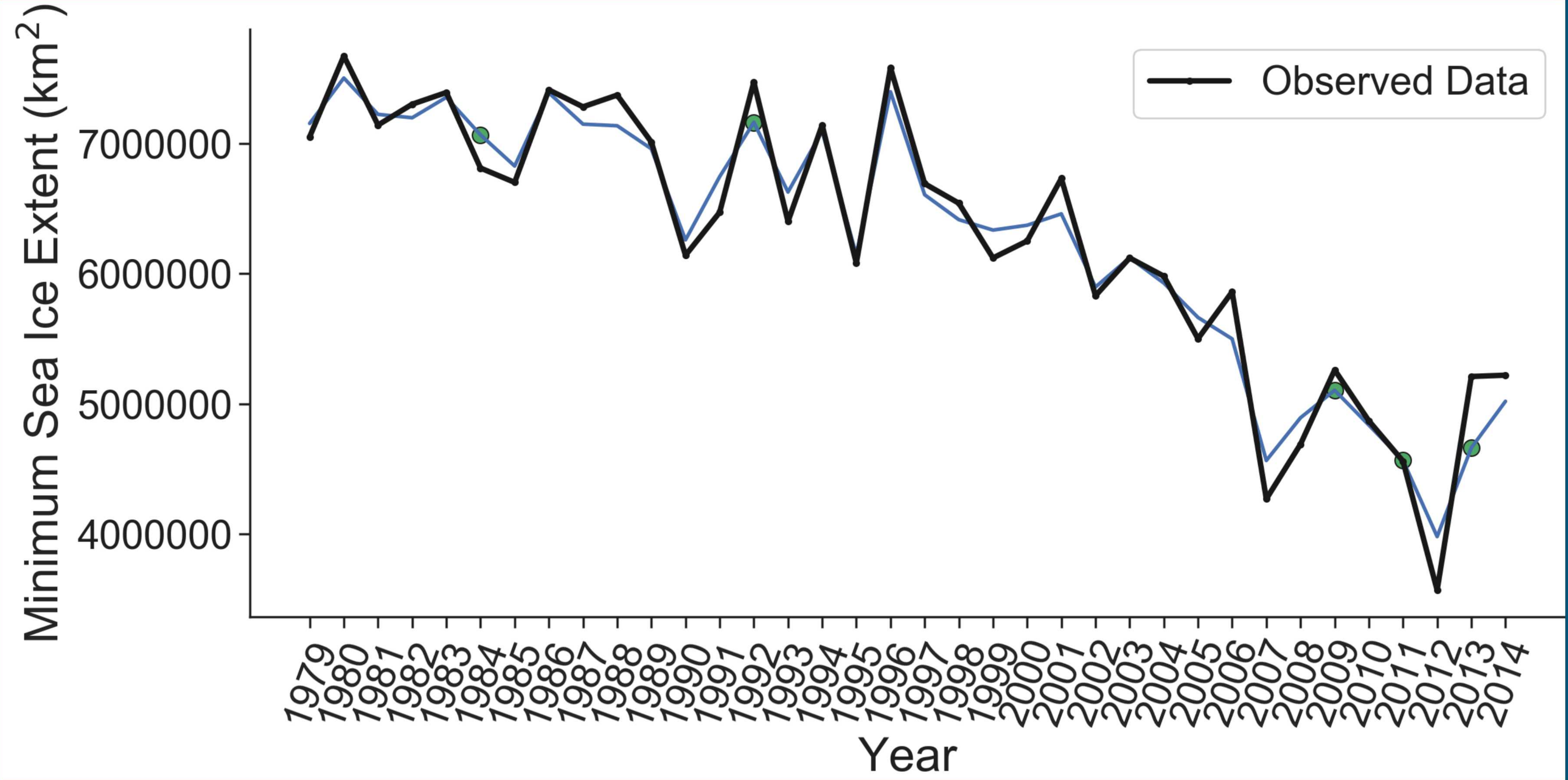
2008
2009
2010
2011
2012
2013
2014
Year


Observed Data
Minimum Sea Ice Extent (km^2)
7000000
6000000
5000000
4000000
1979
1980
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
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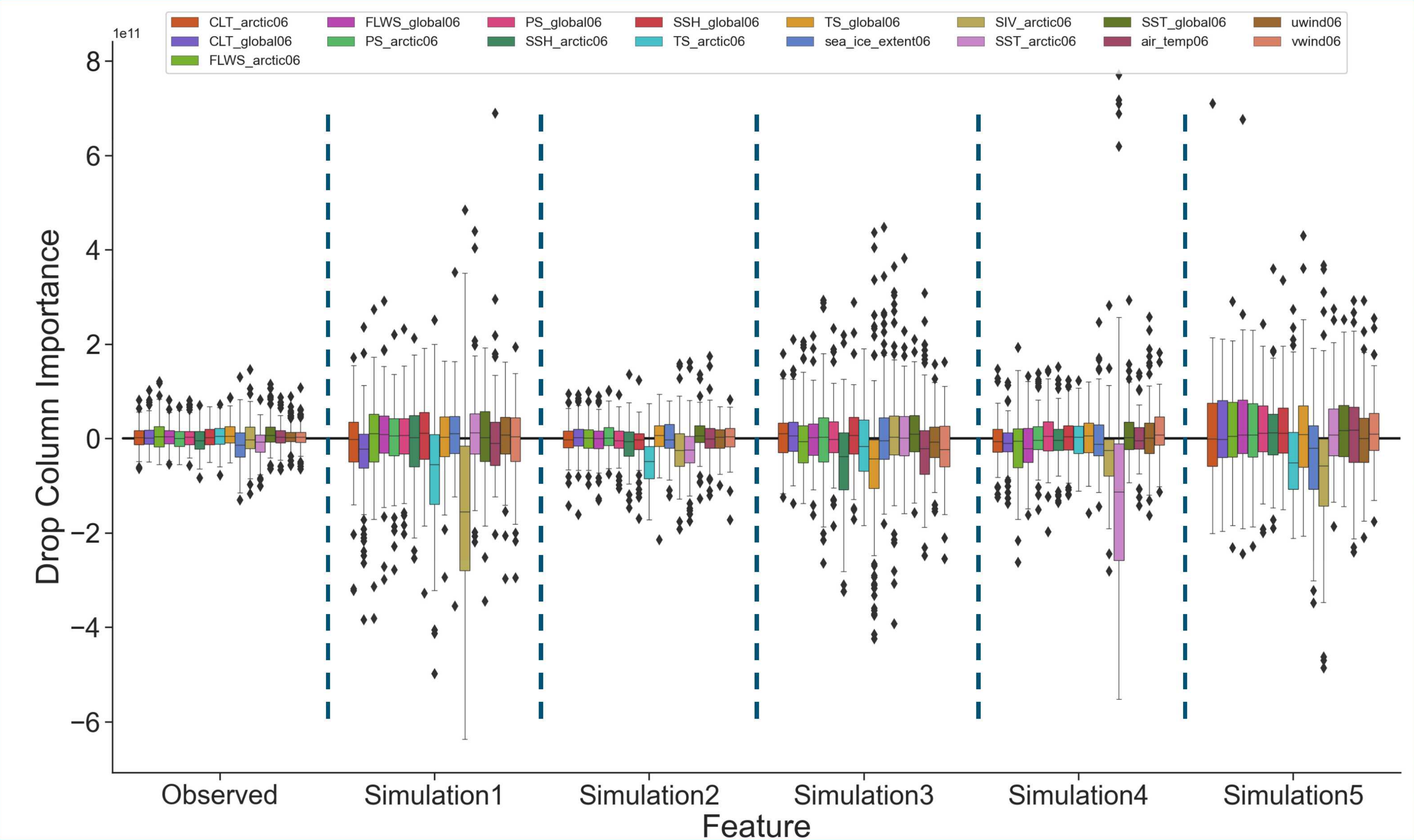
2009
2010
2011
2012
2013
2014
Year

Results: 5 Random Test Years

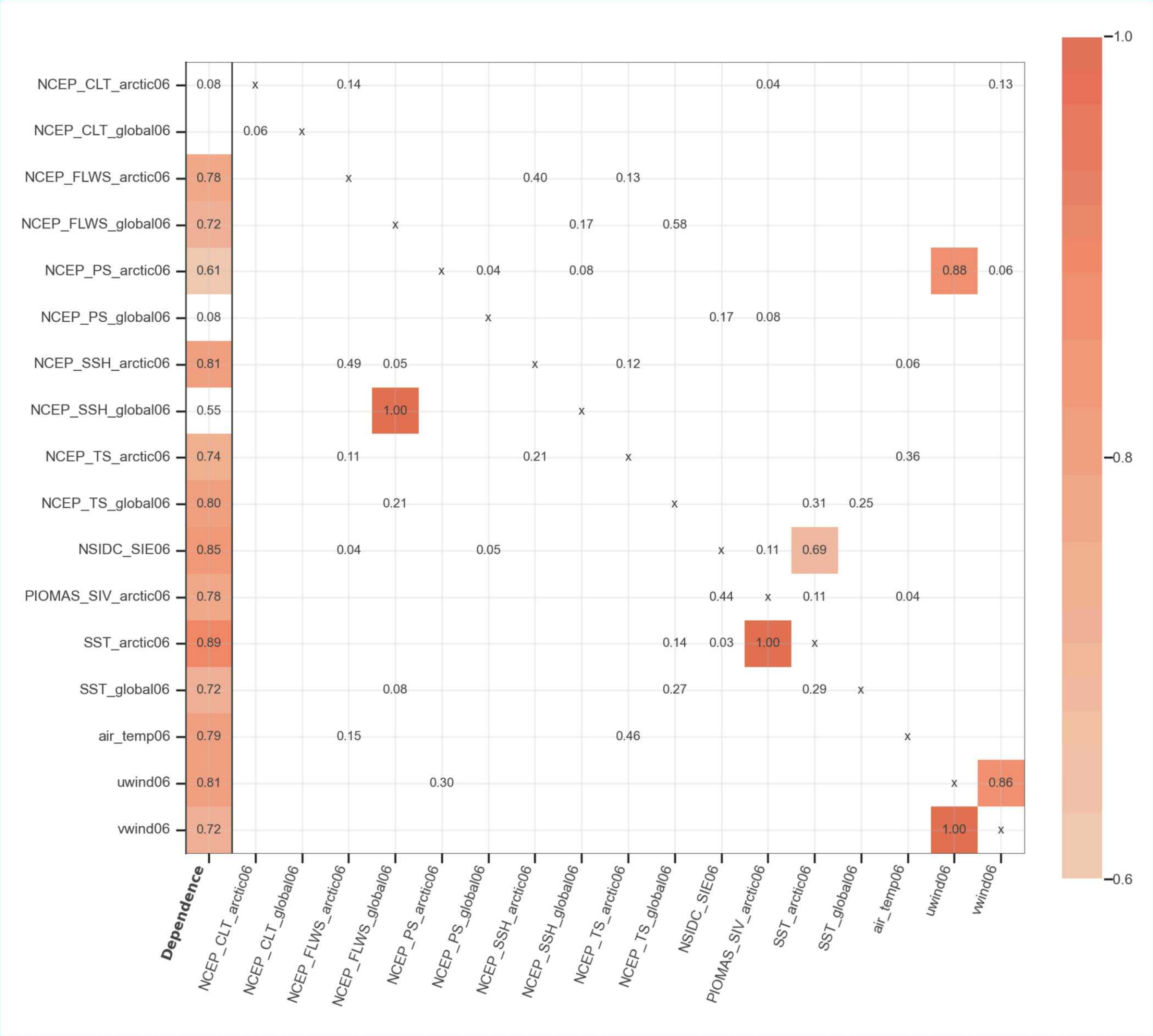


Train	Test
Observed	
R2: 0.9648	0.4939
RMSE: 0.1903	0.508
MAE: 0.1234	0.3691
Simulation1	
R2: 0.9744	0.5423
RMSE: 0.2968	0.8438
MAE: 0.1889	0.6332
Simulation2	
R2: 0.9786	0.5289
RMSE: 0.2024	0.6095
MAE: 0.1395	0.4942
Simulation3	
R2: 0.9649	0.2872
RMSE: 0.3069	0.8401
MAE: 0.1942	0.6301
Simulation4	
R2: 0.9595	0.5483
RMSE: 0.3078	0.8127
MAE: 0.1702	0.5527
Simulation5	
R2: 0.9697	0.5733
RMSE: 0.3272	0.9756
MAE: 0.2151	0.778

Next Steps

- Investigate high variance of results
  - Likelihood of multicollinearity
  - Use principal component analysis and feature selection techniques to eliminate features
- Retrieve more features from E3SM that can be measured in nature
- Obtain domain expertise to determine relevant features

Multicollinearity: Dependency Matrix



Multicollinearity: Spearman Rank Order Correlation Matrix

	NCEP_CLT_arctic06	NCEP_CLT_global06	NCEP_FLWS_arctic06	NCEP_FLWS_global06	NCEP_PS_arctic06	NCEP_PS_global06	NCEP_SSH_arctic06	NCEP_SSH_global06	NCEP_TS_arctic06	NCEP_TS_global06	NSIDC_SIE06	PIOMAS_SIV_arctic06	SST_arctic06	SST_global06	air_temp06	uwind06	vwind06
NCEP_CLT_arctic06	x	0.05	0.44	-0.04	-0.45	-0.15	0.28	-0.21	0.12	0.06	-0.28	-0.32	0.28	0.03	0.18	0.48	0.58
NCEP_CLT_global06		x	-0.10	0.24	0.02	0.09	0.03	0.10	-0.14	0.03	-0.02	0.07	0.07	-0.00	-0.14	0.08	0.18
NCEP_FLWS_arctic06			x	0.56	-0.12	-0.39	0.89	0.39	0.87	0.69	-0.77	-0.69	0.68	0.56	0.87	0.01	0.17
NCEP_FLWS_global06				x	0.15	-0.15	0.66	0.88	0.52	0.89	-0.65	-0.55	0.72	0.80	0.54	-0.20	-0.02
NCEP_PS_arctic06					x	0.11	-0.09	0.27	0.01	0.02	0.09	-0.08	-0.06	0.12	-0.12	-0.86	-0.77
NCEP_PS_global06						x	-0.45	0.10	-0.54	-0.31	0.58	0.49	-0.34	-0.30	-0.42	0.13	-0.03
NCEP_SSH_arctic06							x	0.48	0.85	0.69	-0.75	-0.64	0.63	0.53	0.85	0.03	0.14
NCEP_SSH_global06								x	0.40	0.72	-0.38	-0.33	0.44	0.65	0.44	-0.29	-0.19
NCEP_TS_arctic06									x	0.58	-0.73	-0.57	0.48	0.49	0.87	-0.16	-0.08
NCEP_TS_global06										x	-0.78	-0.70	0.85	0.89	0.63	-0.19	-0.00
NSIDC_SIE06											x	0.88	-0.87	-0.78	-0.65	0.12	-0.12
PIOMAS_SIV_arctic06												x	-0.84	-0.78	-0.54	0.25	-0.03
SST_arctic06													x	0.80	0.49	-0.12	0.16
SST_global06														x	0.46	-0.28	-0.11
air_temp06															x	0.01	0.12
uwind06																x	0.86
vwind06																	x

1.0

0.8

0.6

Conclusions

Inconsistency between data sets at all forecast intervals.

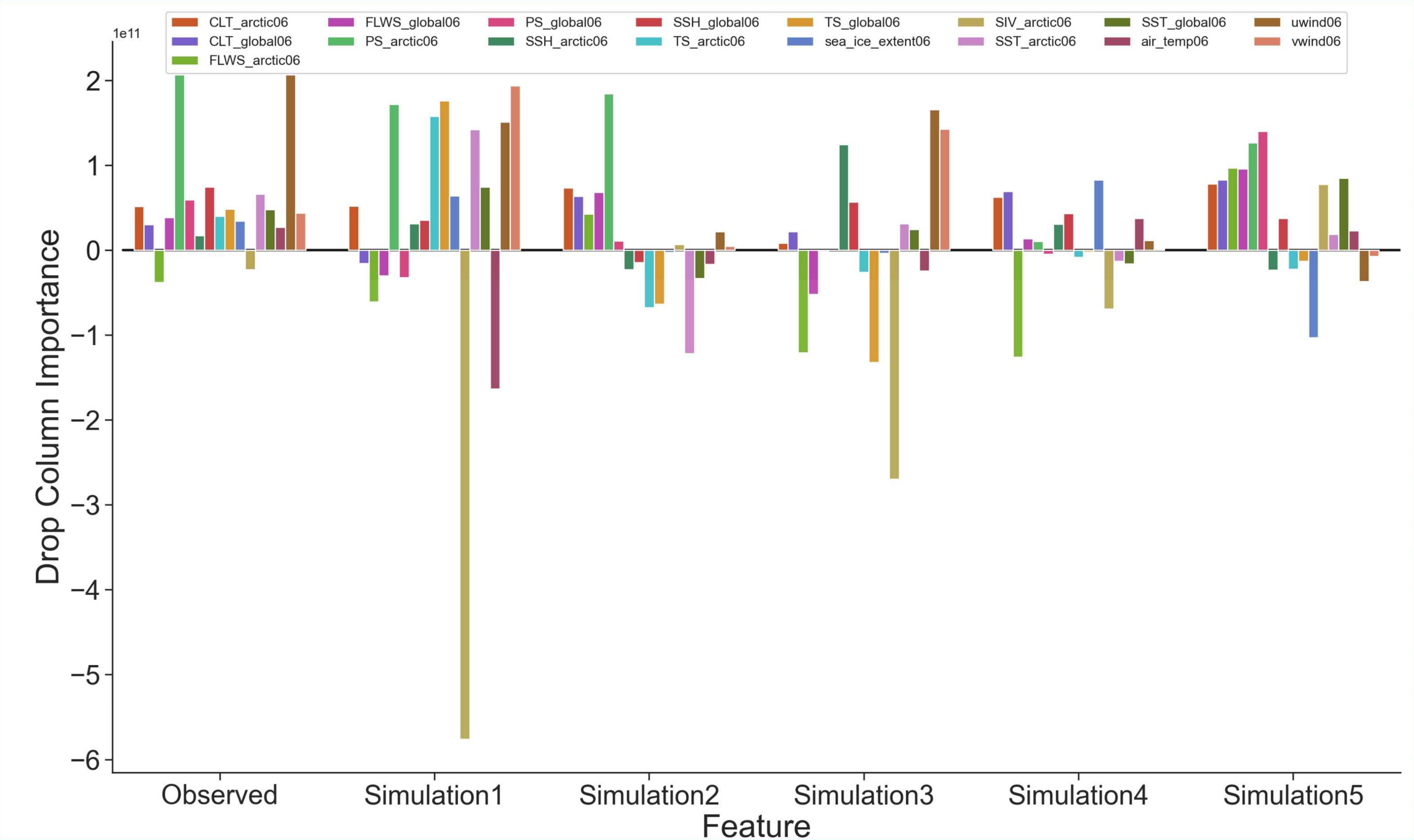
Model accuracy increases when it can train on more years but feature importance values do not become more consistent.

Choosing a random set of test years is ideal but introduces large variance in feature importance results.

Multicollinearity is likely the culprit as indicated by the correlation and dependency matrices.

Questions

Results: 10 Year Forecasts



Train	Test
Observed	
R2: 0.9051	-3.3662
RMSE: 0.1691	1.3109
MAE: 0.1280	0.9818
Simulation1	
R2: 0.9706	-4.0025
RMSE: 0.1901	2.3922
MAE: 0.1042	2.3208
Simulation2	
R2: 0.9434	-2.1010
RMSE: 0.1779	1.7757
MAE: 0.0983	1.5042
Simulation3	
R2: 0.9595	-8.0864
RMSE: 0.1758	2.5147
MAE: 0.1307	2.5485
Simulation4	
R2: 0.9217	-3.2620
RMSE: 0.2972	1.6320
MAE: 0.1637	1.2468
Simulation5	
R2: 0.9431	-5.9398
RMSE: 0.2328	2.5439
MAE: 0.1951	2.4189