An Updated Machine Learning Ensemble for Atlantic Tropical Cyclone Rapid Intensification Forecasting

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Joint Hurricane Testbed

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Background of Project

- Considerable previous work has investigated predictability of rapid intensification (RI) within Atlantic tropical cyclones (TCs)
  - RI defined as an increase of peak wind speed of 30 kt in 24 hours, current operational definition by NHC
- 2018-2019 Testbed experiments included AI-based ensemble for predicting Atlantic RI using SHIPS-RII predictors and GFS predictors
- Could the AI ensemble be improved using better features from GFS/FNL data in combination with SHIPS-RII predictors?

2019 Testbed Example Output

** MSU experimental Atlantic RI AI ensemble prediction: AL52019 Dorian 08/27/19 0

Global probability for RI (30kt/24h) 13.2%

This AI ensemble run is NOT EXPECTING RI (RI prob <= 21%)

Individual Ensemble Forecasts

Ens Name	RI/no RI	RI prob
SVM1	RI	57.9%
SVM2	no RI	16.4%
SVM3	no RI	7.3%
SVM4	no RI	3.8%
SVM5	no RI	3.1%
SVM6	no RI	15.5%
SVM7	no RI	7.0%
SVM8	no RI	4.2%
SVM9	no RI	3.2%

(RI AI ensemble predictor table for 30 KT OR MORE MAXIMUM WIND INCREASE IN NEXT

Predictor	Value	RI Predictor Range	Scaled Value
TLAT	13.3	8.9 to 34.3	-1.31
SHRG	10.3	4.8 to 31.9	-1.37
BTMAX	-56.2	-84.9 to 4.1	-0.68
KPC9_VVEL200_7	-4.25e-09	-1.84E-08 to 1.84E-08	0.08
KPC8_T600_7	3.77e-05	-2.29E-04 to 1.35E-04	1.25
VMFX	7.9	0.99 to 12.7	0.80
RHMD	45	38.0 to 84.0	-1.00
RI_COUNT	0	0.0 to 8.0	-0.60
V500	3.6	0.6 to 11.1	-0.43
RI_FLAG	0	0.0 to 1.0	-0.70
KPC9_VVEL200_9	-1.16e-04	-1.29E-04 to 1.13E-04	-1.17
KPC4_VVEL200_9	1.90e-06	-1.10E-04 to 4.09E-05	0.90
KPC1_VVEL200_9	3.63e-05	-3.92E-05 to 5.20E-05	0.40
KPC4_T600_7	1.49e-06	-3.87E-05 to 9.58E-05	0.34

Preliminary Verification Skill, 2017 – 2019 seasons (old ensemble)

- Verification skills from old model did not align with the training phase BSS values (which were roughly 0.4)
  - 2017: 0.042
  - 2018: 0.034
  - 2019: -0.08

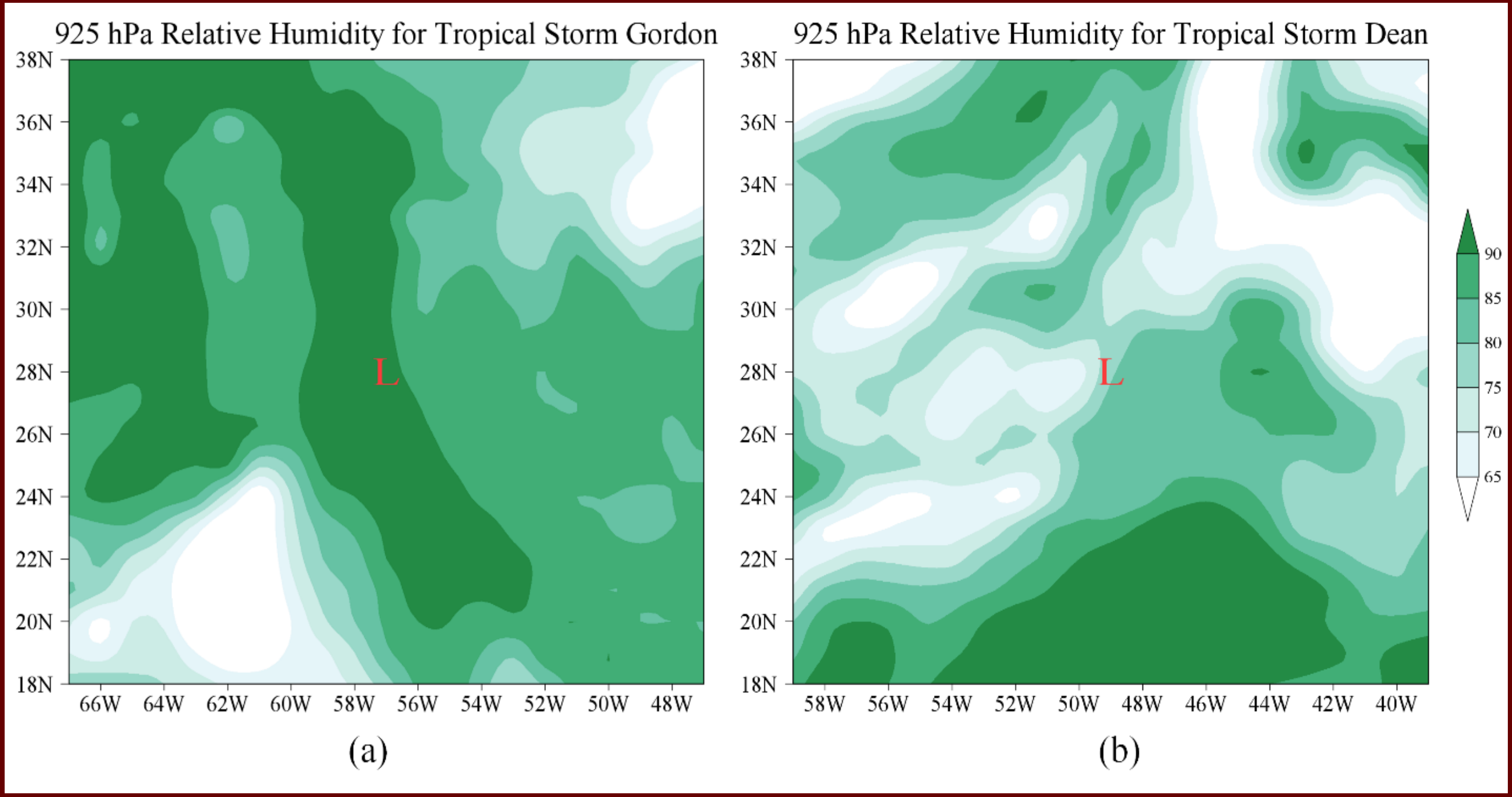
    (preliminary based on b-decks for 11 storms – through Lorenzo)
- Poor performance attributed to overfitting in the cross-validation phase when building the ensemble
- New ensemble generation has been finalized and is now being verified, as described below

Data and Methods – Updates

- RI dataset – HURDAT2
  - All Atlantic Basin TCs spanning 2004-2016 were included, a total of 3605 timesteps (observations taken every 6 hours)
  - Used HURDAT2 only to categorize RI (no real-time best-track data used for forecasts)
- Statistical Hurricane Intensification Prediction System (SHIPS) Rapid Intensification Index (RII) parameters
  - Initial set of 109 predictors from SHIPS used prior to feature selection
    - 71 SHIPS predictors
    - 17 GOES IR imagery predictors
    - 21 Precipitable water predictors
- Also employed 5 persistence predictors (6, 12, and 24-hour previous intensity change, previous RI flag, previous RI count)

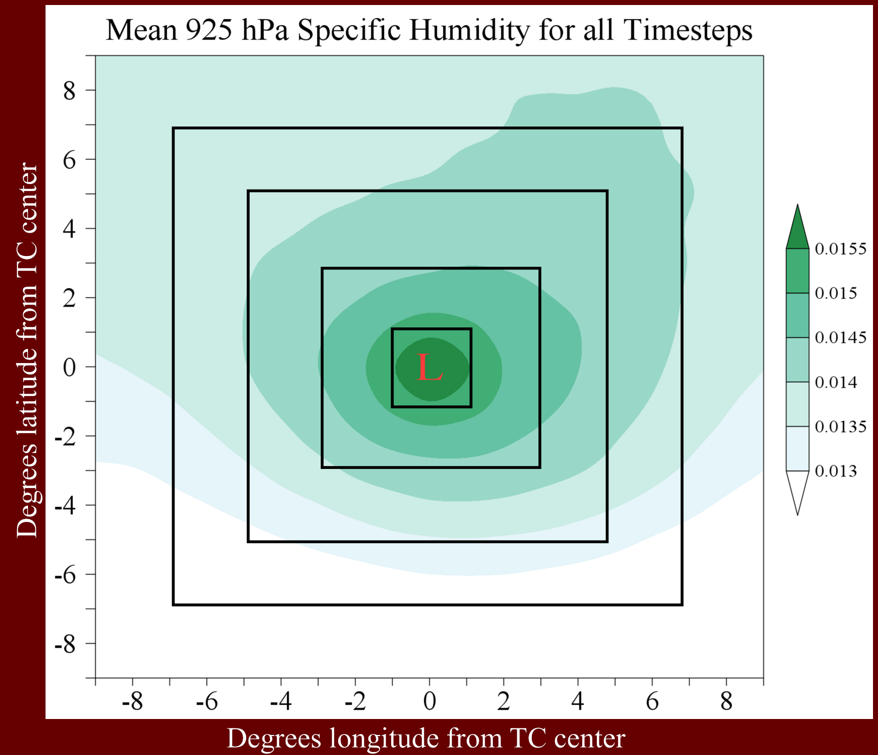
Data and Methods

- SHIPS predictors do not offer spatial insight into TC structure (e.g. 850 hPa specific humidity for two TCs with same low-level mean RH predictor value of 74)



Data and Methods

- Multiple GFS analysis grids retained for each TC timestep
  - 98 total grids
    - 6 three-dimensional variables on 11 isobaric surfaces, including temperature, *u* and *v* wind, vertical velocity, absolute vorticity, equivalent potential temperature, specific humidity
    - Static stability on 9 isobaric levels
    - 12 single-level grids, including MSLP, skin temperature, tropopause *u, v, T,* elevation, and pressure, surface-based CAPE and CIN, 850-200 hPa shear, and 200 hPa divergence



Data and Methods

- PCA and KPCA formulated on GFSA grids individually to quantify maximum separation
  - Tested 17 different kernel functions in KPCA, as well as RPCA
    - RBF kernels with separation parameter of 5, 10, 25, 50, 75, 100, 200, 500, 1000
    - Polynomial kernels with degrees from 2 to 10
  - Separation quantified by *k*-means cluster analysis with 2 clusters, quantifying RI/non-RI separation between clusters
  - Separability metric the sum of the RI percentage in RI cluster with the non-RI percentage in the non-RI cluster
  - All PC scores whose clustering yielded a separation metric exceeding the 99th percentile were retained
  - Analyses repeated for each RI category in Kaplan et al. (2015), generated unique predictors for each RI definition

Data and Methods

- PCA/KPCA separability results

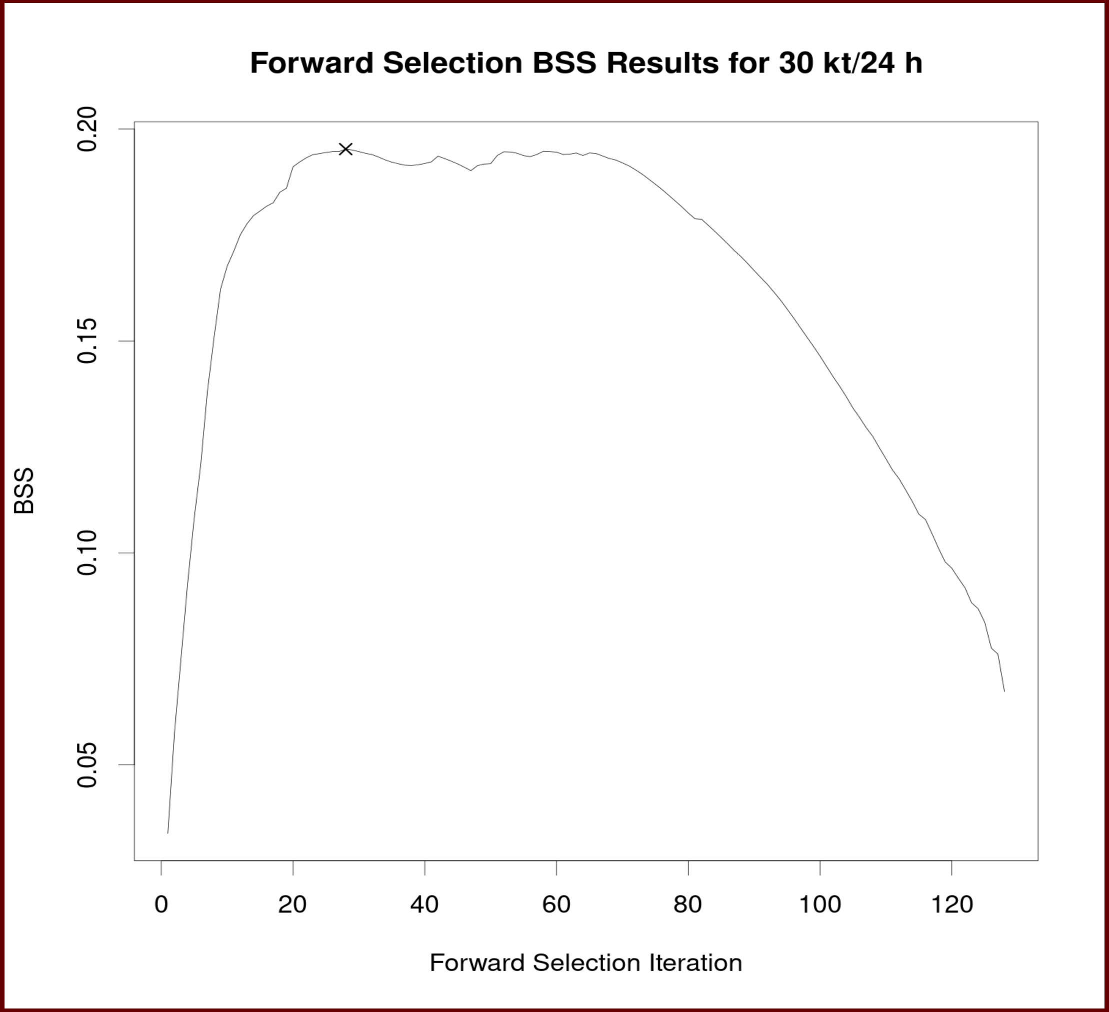
GFSA Field	Grid Size	PCA Method	PCs Kept	RI Frequency	Non-RI Frequency
30 kt/24 h					
400 hPa absolute vorticity	15° x 15°	RPCA	5	0.87	0.43
500 hPa absolute vorticity	11° x 11°	KPCA (σ=50)	6	0.74	0.55
850-200 hPa shear	11° x 11°	RPCA	2	0.87	0.42
600 hPa absolute vorticity	7° x 7°	RPCA	3	0.79	0.51

Feature Selection

- After including PCA-derived features and SHIPS predictors, used feature selection to reduce the 120+ feature sets for each RI category
- Feature selection done using forward selection on all 128 possible predictors (8256 combinations)
  - Forward selection used leave-one-season out approach to minimize overfitting issues from before
- Identified global BSS maximum on testing set, this value was used as a measure of best performance for the given predictor set
- Very computationally expensive but should find global maximum in performance for the given predictor set

Feature Selection

- Example – 30 kt/24 h



New Ensemble Members

- After establishing the feature selection procedure, building AI ensemble was next
- Tested multiple support vector machine (SVM) configurations, as well as a logistic regression model
  - Logistic regression deemed proxy for current SHIPS-RII since it gave similar performance and utilized similar predictors
- SVM configuration parameters tested; all possible permutations from set below (40 possible permutations)
  - Cost function – 0.1, 1, 10, 100
  - Values for γ in radial basis function kernel – 0.01, 0.05, 0.1, 0.25, 0.5, 0.75, 1, 2, 5, 10
- 41 total ensemble members considered

New Ensemble Members

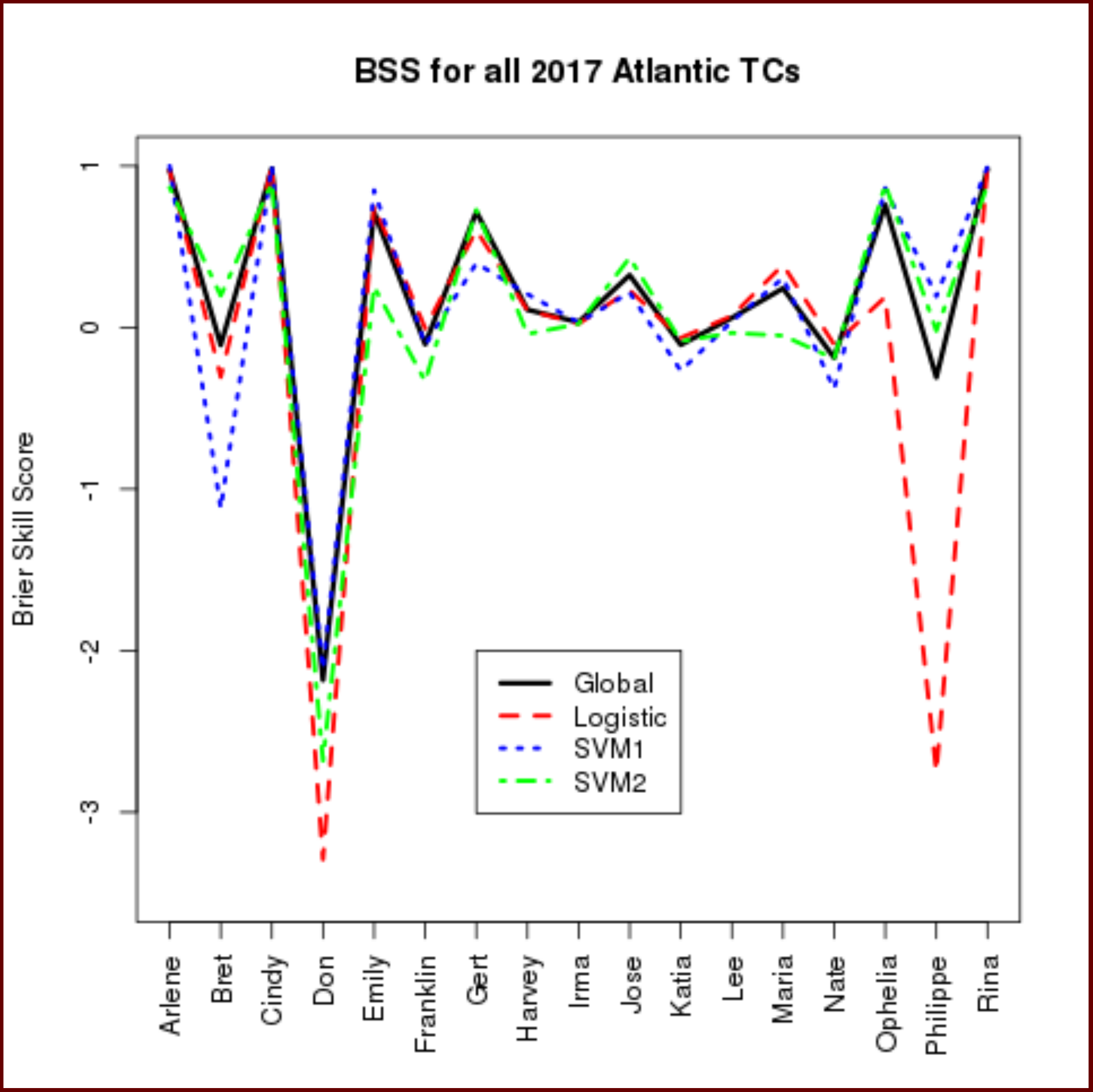
- Logistic regression performance was baseline from which ensemble members were selected
- Logistic BSS from optimal predictor (tuned for logistic model) – 0.155
- When comparing 40 SVM configurations against this value, only two members outperformed the logistic model
  - SVM – γ = 0.01, cost = 10 (called SVM1) – BSS = 0.169
  - SVM - γ = 0.1, cost = 10 (called SVM2) – BSS = 0.164
- Boost of roughly 10% over logistic model

New Predictors

- Each ensemble member retained its own unique set of predictors optimized to that member
- Predictor set sizes were still large:
  - Logistic regression – 21 predictors
  - SVM1 – 45 predictors
  - SVM2 – 36 predictors
- Common variables in all ensemble members included
  - KPC5 for 400 mb Absolute Vorticity (15 x 15 grid)
  - Generalized Shear Predictor (SHRG)
  - Percent area with brightness temperature < -10C
  - 6-hour intensity change
  - Number of previous RIs
  - Previous RI flag (1=RI, 0=no RI)

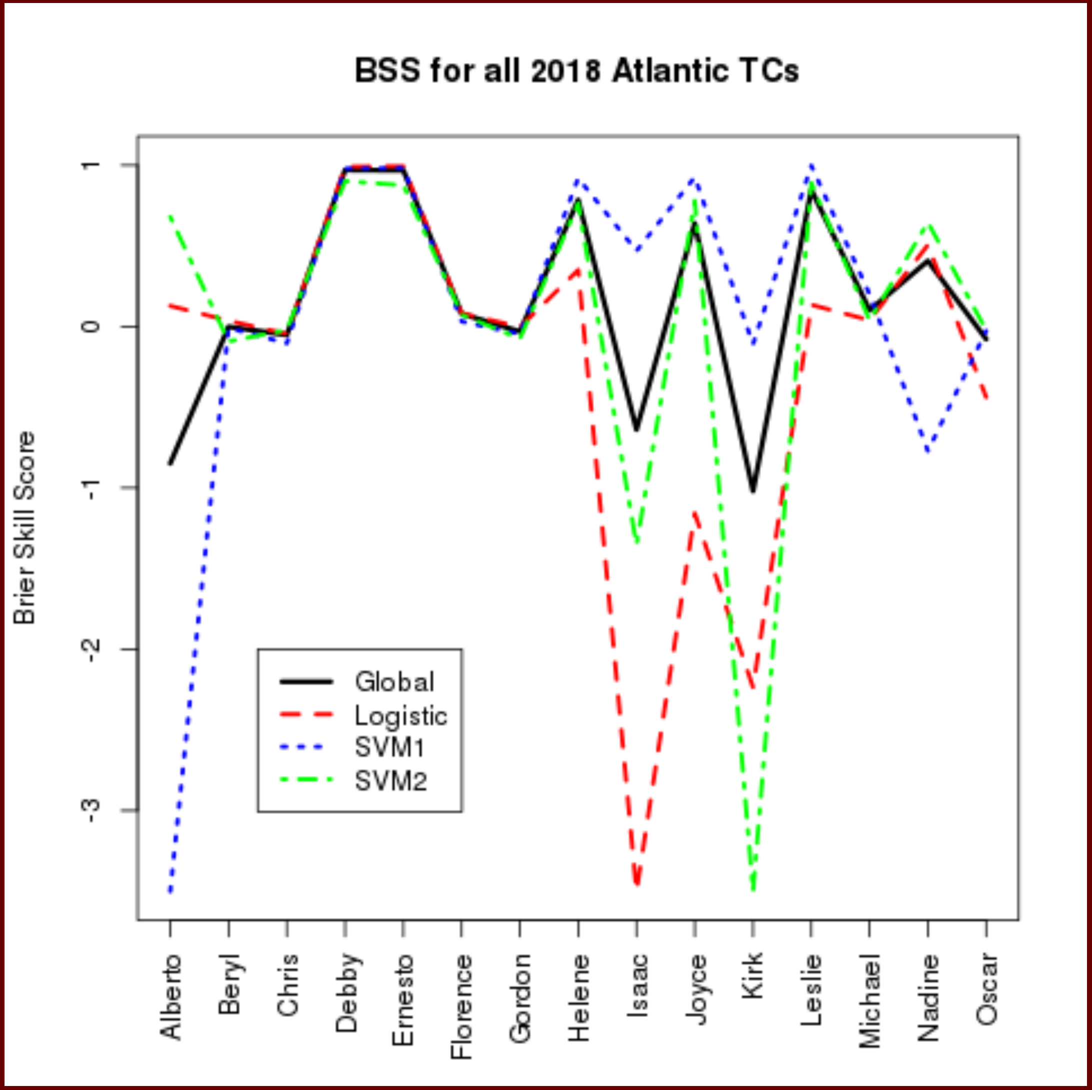
Results, New Ensemble - 2017

- All timesteps
  - Global BSS: 0.111
  - Logistic: 0.125
  - SVM1: 0.089
  - SVM2: 0.038
- Only RI timesteps
  - Global BSS: 0.123
  - Logistic: 0.152
  - SVM1: 0.141
  - SVM2: 0.041



Results, New Ensemble - 2018

- Global BSS: 0.067
  - Logistic: -0.018
  - SVM1: 0.075
  - SVM2: 0.023
- Only RI timesteps
  - Global BSS: 0.037
  - Logistic: 0.020
  - SVM1: 0.053
  - SVM2: 0.027



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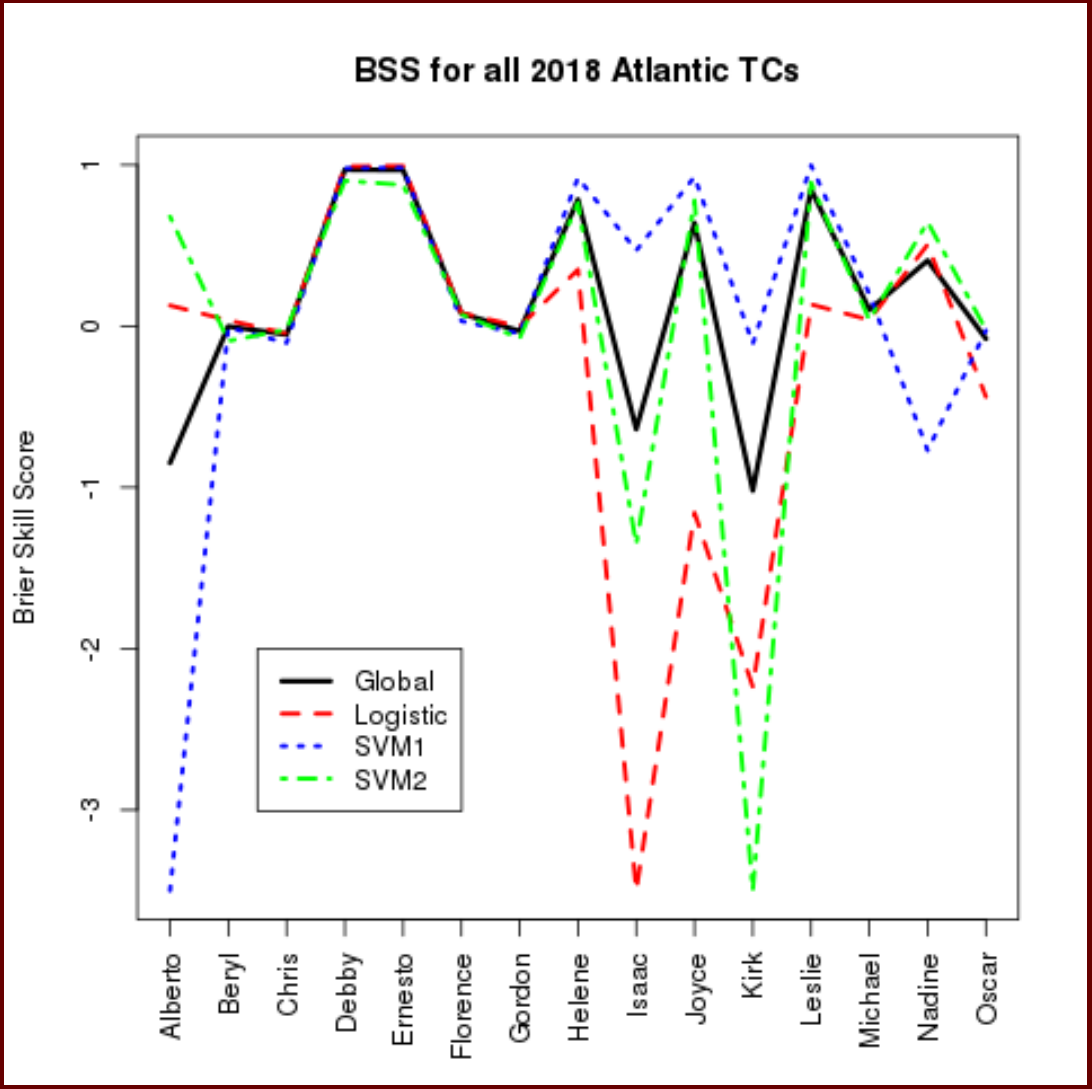


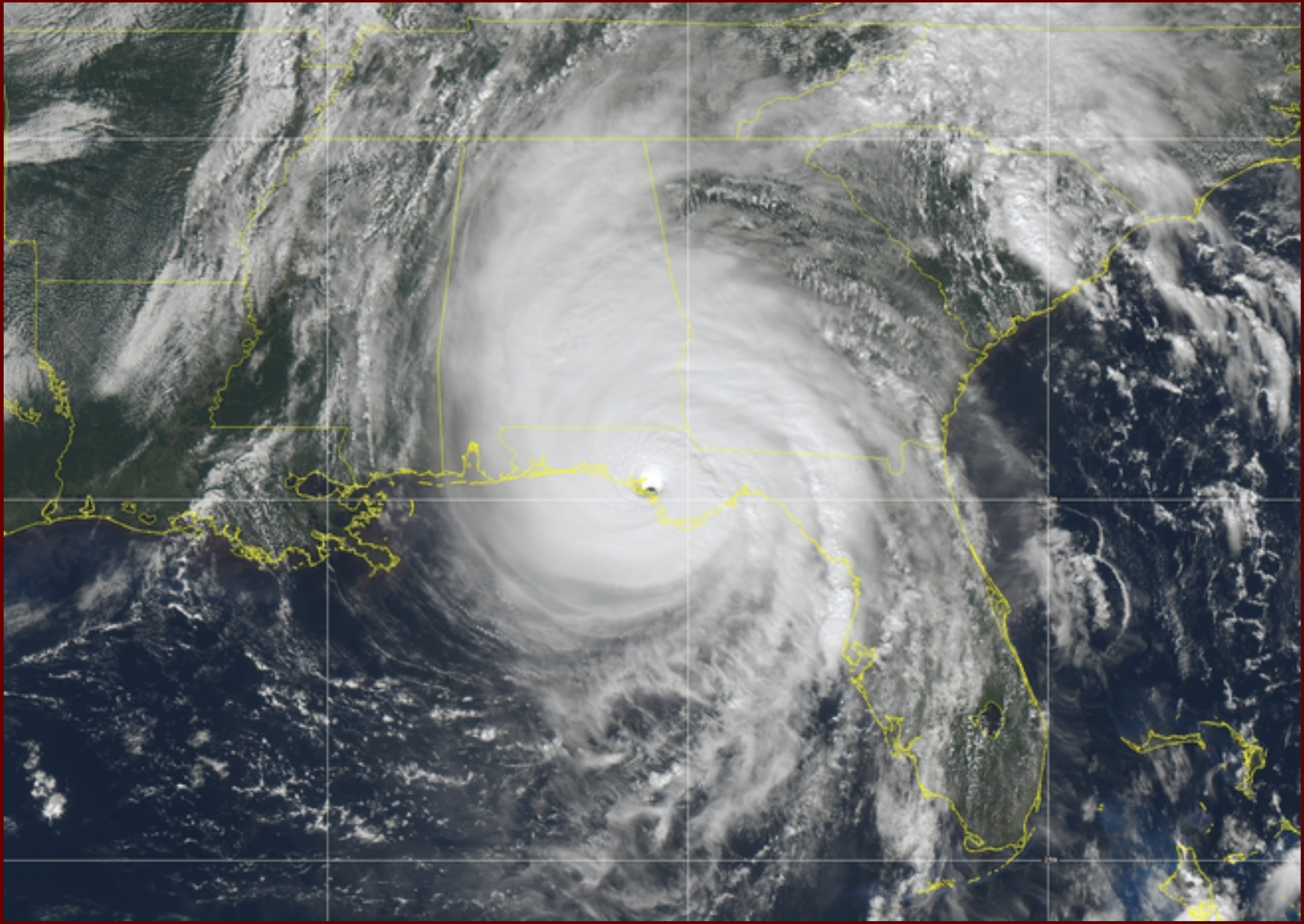
Results

- Individual member performance poorer than global results for 2017-2018. Importantly, results are less variable in global model, which is good for forecast applications
- All years results
  - Global BSS: 0.097
  - Logistic: 0.078
  - SVM1: 0.085
  - SVM2: 0.033

Conclusions

- Updated cross-validation routine providing realistic BSS values during model training phase, boosting results over logistic regression by about 10%
- GFS predictors included in all three retained ensemble members
  - Mid-level vorticity clearly has importance in identifying RI environments
- 2017-2018 results were improved on many storms that were difficult to forecast, though some poor performing storms remain
  - Should improve with additional years of data and more training of ensemble
- Working now on identifying relationships between predictors and forecasts for interpretation

Questions?



Results, New Ensemble - 2019

- Global BSS: -0.059
  - Logistic: -0.051
  - SVM1: -0.132
  - SVM2: -0.125
- Only RI timesteps
  - Global BSS: 0.003
  - Logistic: 0.078
  - SVM1: -0.088
  - SVM2: -0.013