Improving Prediction of Large-scale Regime Transitions

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- Spatiotemporal distribution of cyclone clustering;
- Influences of atmospheric blocking and phases/amplitudes of the major teleconnection indices, ENSO and the MJO;
- Composite/case study analyses of cyclone clustering events;
- regime change predictability horizons associated with cyclone clustering events;

- Weather regime classification, transition probabilities, CFSv2 model climate;

- Weather regime classification;
- Arctic air mass generation and modification; life cycles of the MJO;
- Poleward heat and moisture transports of subtropical air masses;

- Multiscale & multi-institutional process integration -> weeks 1-4 prediction tool;

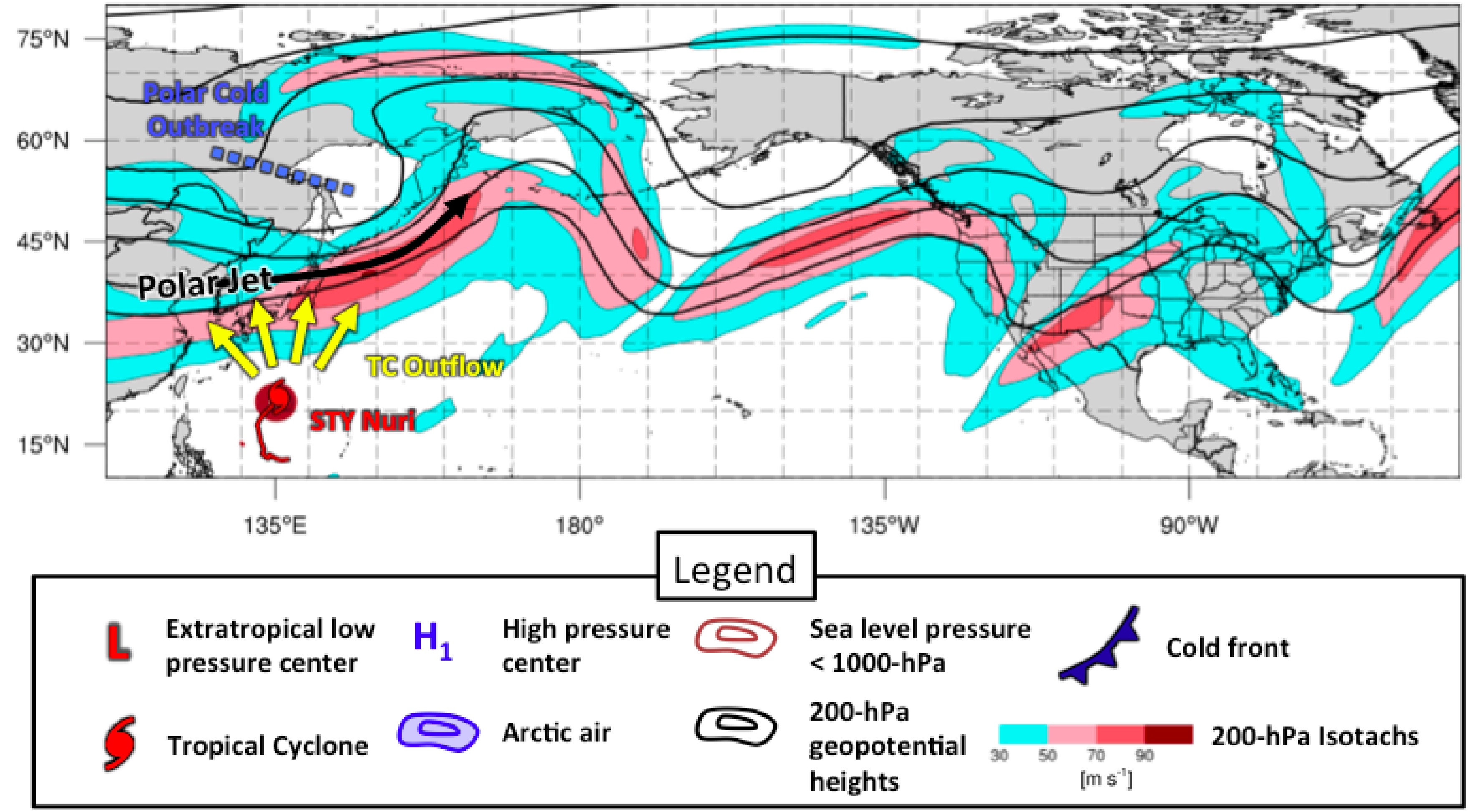
Weeks 1-4 CONUS cool season atmospheric predictability depends upon the structure, configuration, and evolution of the North Pacific jet stream (NPJ) ...

- NPJ can be perturbed on its tropical side by recurving/transitioning tropical cyclones and by longitudinally varying convection associated with the MJO.

- NPJ can be perturbed on its poleward side on synoptic time scales by midlatitude and polar disturbances that originate over the Asian continent, triggering downstream Rossby wave propagation across the North Pacific, North America, and North Atlantic.

Schematic – Synoptic Evolution November 2014

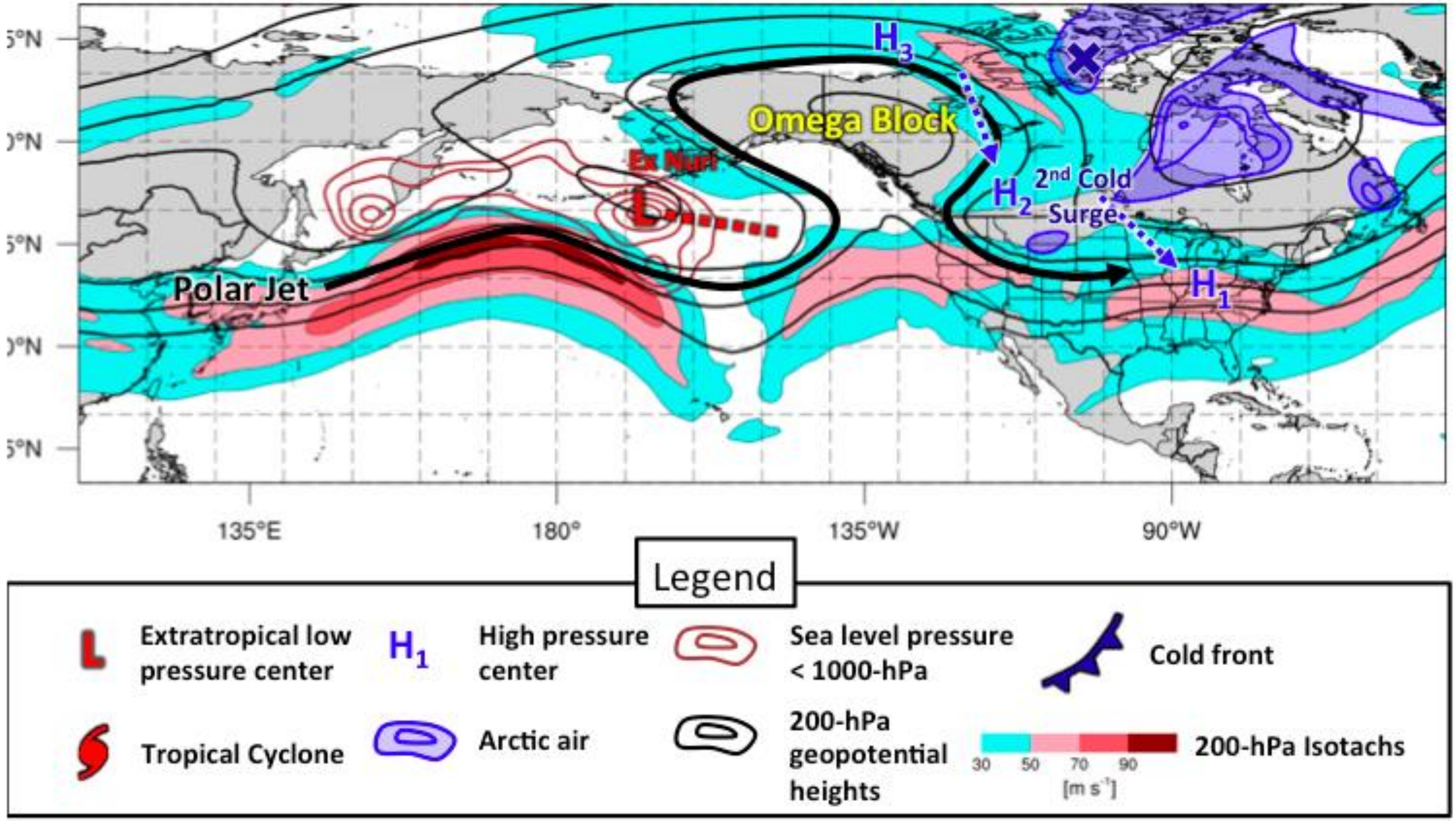
0000 UTC 4 November 2014



Schematic map of the observed large-scale flow structure across the North Pacific/North America prior to the extratropical transition of Supertyphoon Nuri at 0000 UTC 4 November 2014.

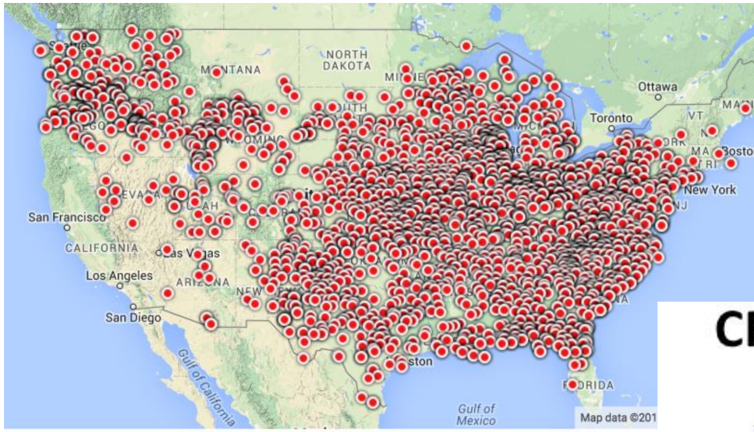
Schematic – Synoptic Evolution November 2014

1200 UTC 15 November 2014

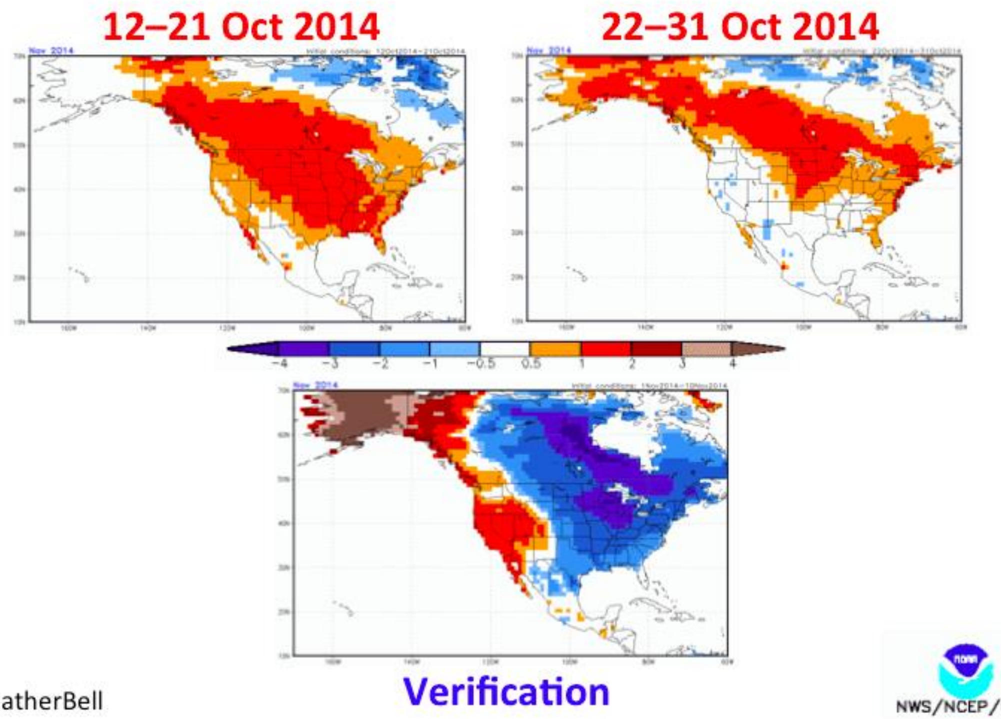


For the established high-latitude omega block at 1200 UTC 15 November 2014. H_1, H_2, and H_3 denote the locations of the anticyclones associated with three cold surges.

Minimum Temperature Records Broken: 16–22 November 2014 (N = 2677)
Source: NCDC



CFSv2 2-m Temperature Forecasts – Nov 2014



WeatherBell

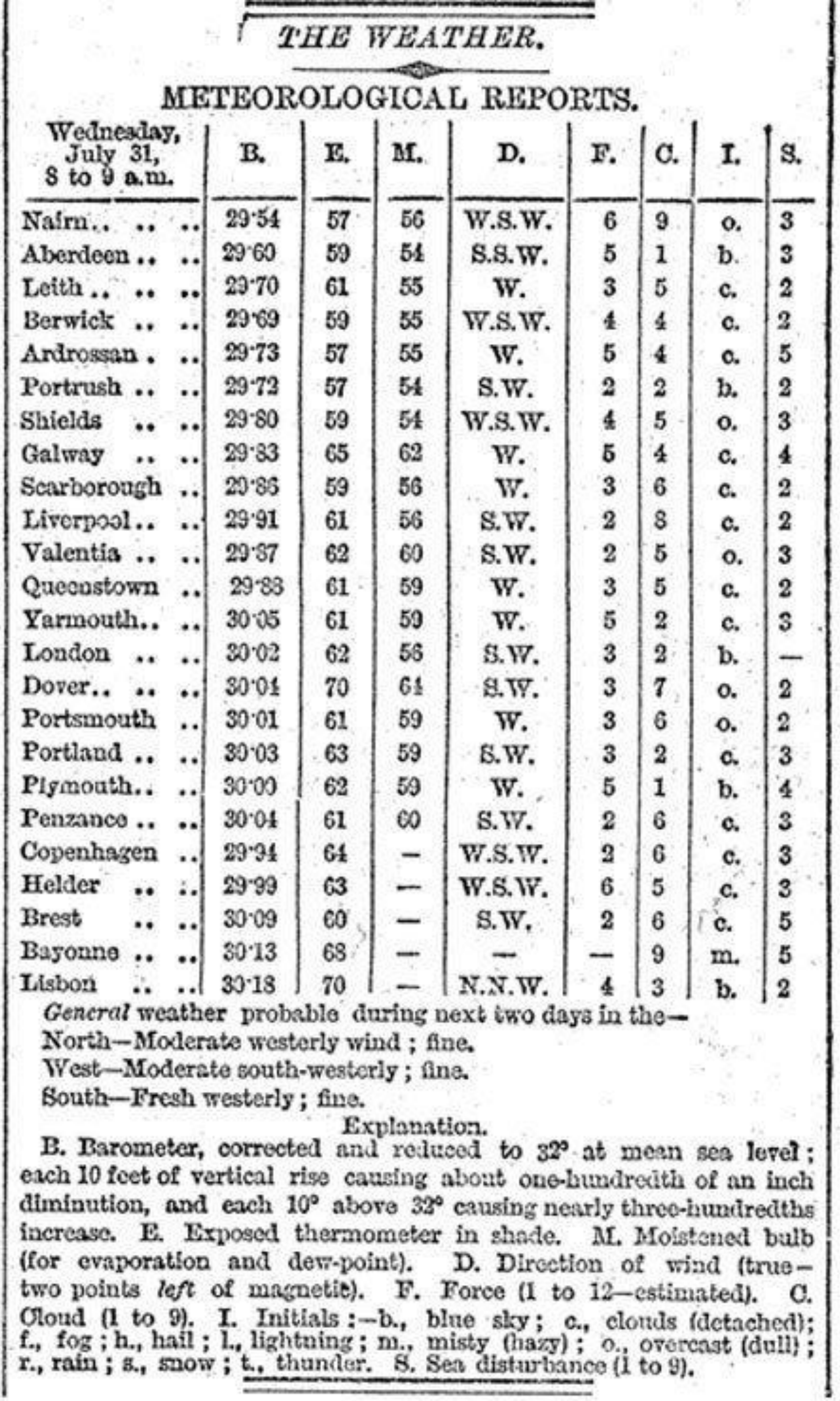
NWS/NCEP/CPC

NCEP CFSv2 2-m temperature anomaly (°C) forecasts for November 2014 made from forecasts run between 12–21 October 2014 (upper left), 22–31 October 2014 (upper right), and the corresponding observed temperature anomalies (°C) for November 2014.

PORTRAIT OF THE GENTLEMAN WHO DRAWS UP THE METEOROLOGICAL REPORTS.

"ANOTHER DEPRESSION IS COMING!"

[*Just as he was about to take his Holiday too!*



THE WEATHER.

METEOROLOGICAL REPORTS.

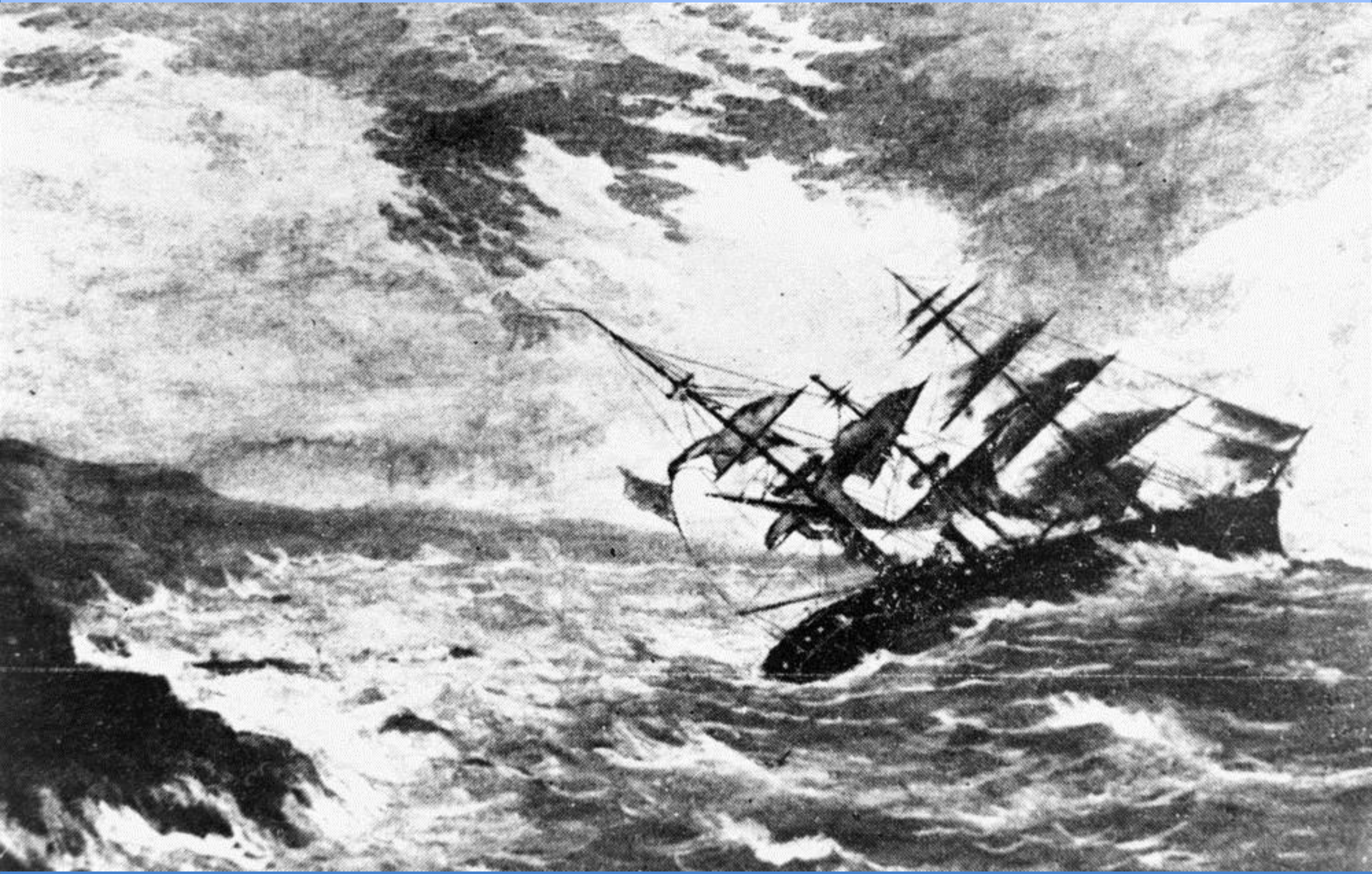
Wednesday, July 31, 8 to 9 a.m.	B.	E.	M.	D.	F.	C.	I.	S.
Nairn..	29·54	57	56	W.S.W.	6	9	o.	3
Aberdeen	29·60	59	54	S.S.W.	5	1	b.	3
Leith	29·70	61	55	W.	3	5	c.	2
Berwick	29·69	59	55	W.S.W.	4	4	c.	2
Ardrossan . ..	29·73	57	55	W.	5	4	c.	5
Portrush	29·72	57	54	S.W.	2	2	b.	2
Shields	29·80	59	54	W.S.W.	4	5	o.	3
Galway	29·83	65	62	W.	5	4	c.	4
Scarborough ..	20·86	59	56	W.	3	6	c.	2
Liverpool.. ..	29·91	61	56	S.W.	2	8	c.	2
Valentia	29·37	62	60	S.W.	2	5	o.	3
Queenstown ..	29·88	61	59	W.	3	5	c.	2
Yarmouth.. ..	30·05	61	59	W.	5	2	c.	3
London	30·02	62	56	S.W.	3	2	b.	—
Dover..	30·04	70	64	S.W.	3	7	o.	2
Portsmouth ..	30·01	61	59	W.	3	6	o.	2
Portland	30·03	63	59	S.W.	3	2	c.	3
Plymouth.. ..	30·00	62	59	W.	5	1	b.	4
Penzance	30·04	61	60	S.W.	2	6	c.	3
Copenhagen ..	29·34	64	—	W.S.W.	2	6	c.	3
Helder	29·99	63	—	W.S.W.	6	5	c.	3
Brest	30·09	60	—	S.W.	2	6	c.	5
Bayonne	30·13	68	—	—	—	9	m.	5
Lisbon	30·18	70	—	N.N.W.	4	3	b.	2

General weather probable during next two days in the—
North—Moderate westerly wind; fine.
West—Moderate south-westerly; fine.
South—Fresh westerly; fine.

Explanation.

B. Barometer, corrected and reduced to 32° at mean sea level; each 10 feet of vertical rise causing about one-hundredth of an inch diminution, and each 10° above 32° causing nearly three-hundredths increase. E. Exposed thermometer in shade. M. Moistened bulb (for evaporation and dew-point). D. Direction of wind (true—two points *left* of magnetic). F. Force (1 to 12—estimated). C. Cloud (1 to 9). I. Initials:—b., blue sky; c., clouds (detached); f., fog; h., hail; l., lightning; m., misty (hazy); o., overcast (dull); r., rain; s., snow; t., thunder. S. Sea disturbance (1 to 9).

MET OFFICE

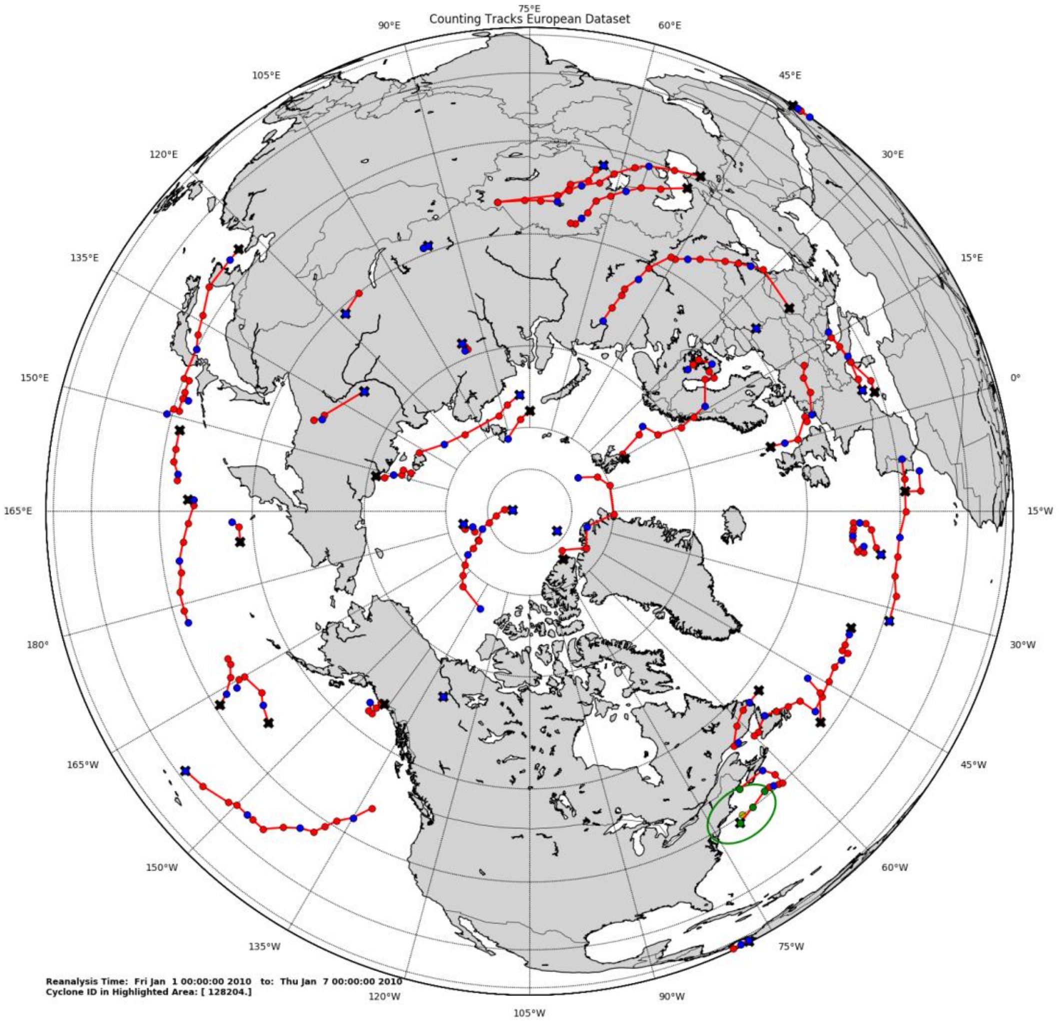


Cyclone Clustering - SUNYA

- Establish the credibility of different cyclone tracking datasets [e.g., Hodges (ERA-I, CFSR)]
- Use available cyclone tracking datasets to create cyclone clustering density maps
- Assess the sensitivity of NH cyclone clustering to the cyclone tracking dataset used

Cyclone Tracks (Examples)

- **Three Datasets Available Currently:**
- **Hodges (ERAI)**
- **Hodges (CFSR)**
- **ECMWF dataset (ERAI)**
- **These figures include data from January 1st-7th 2010**

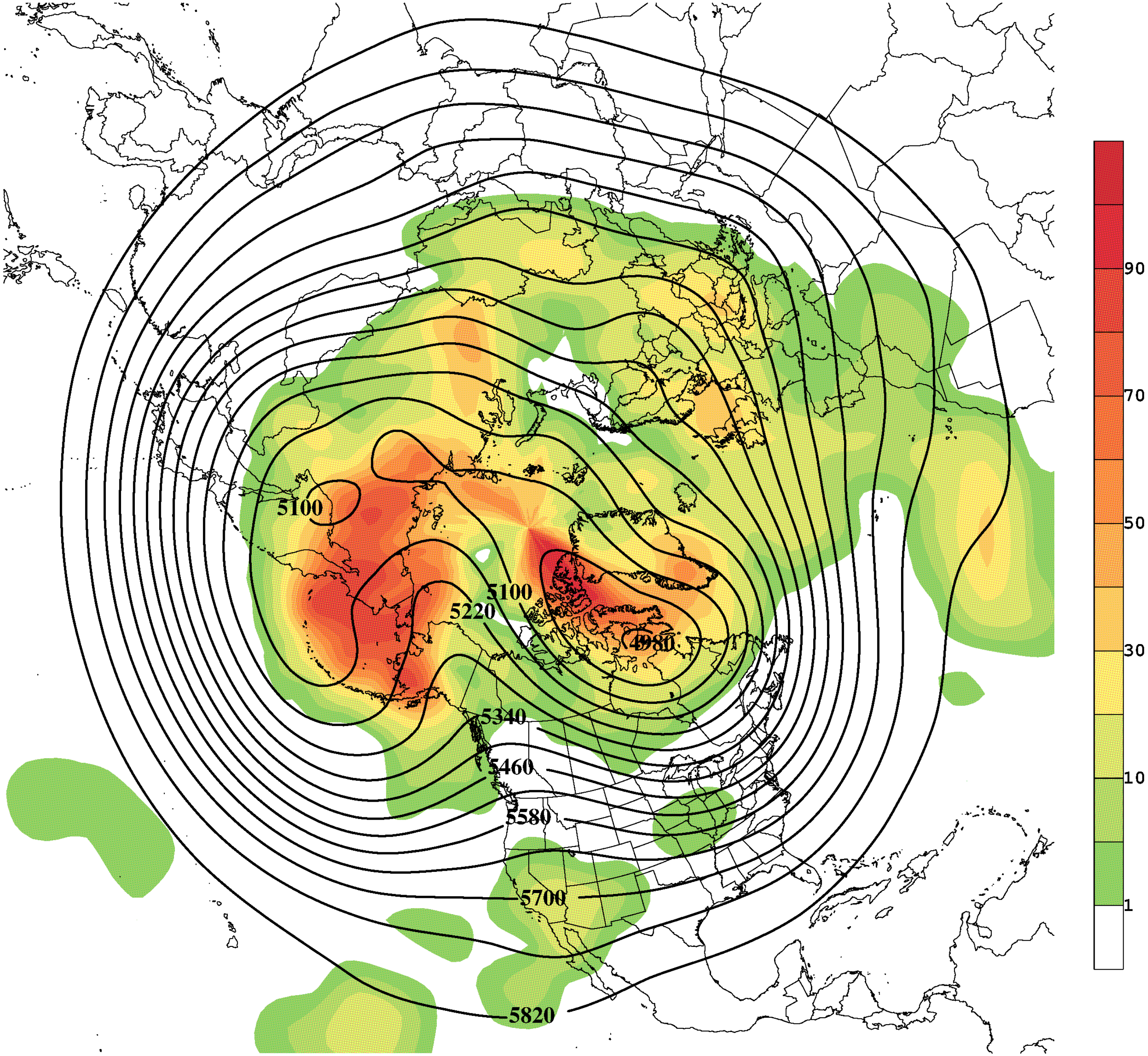


Counting Tracks European Dataset

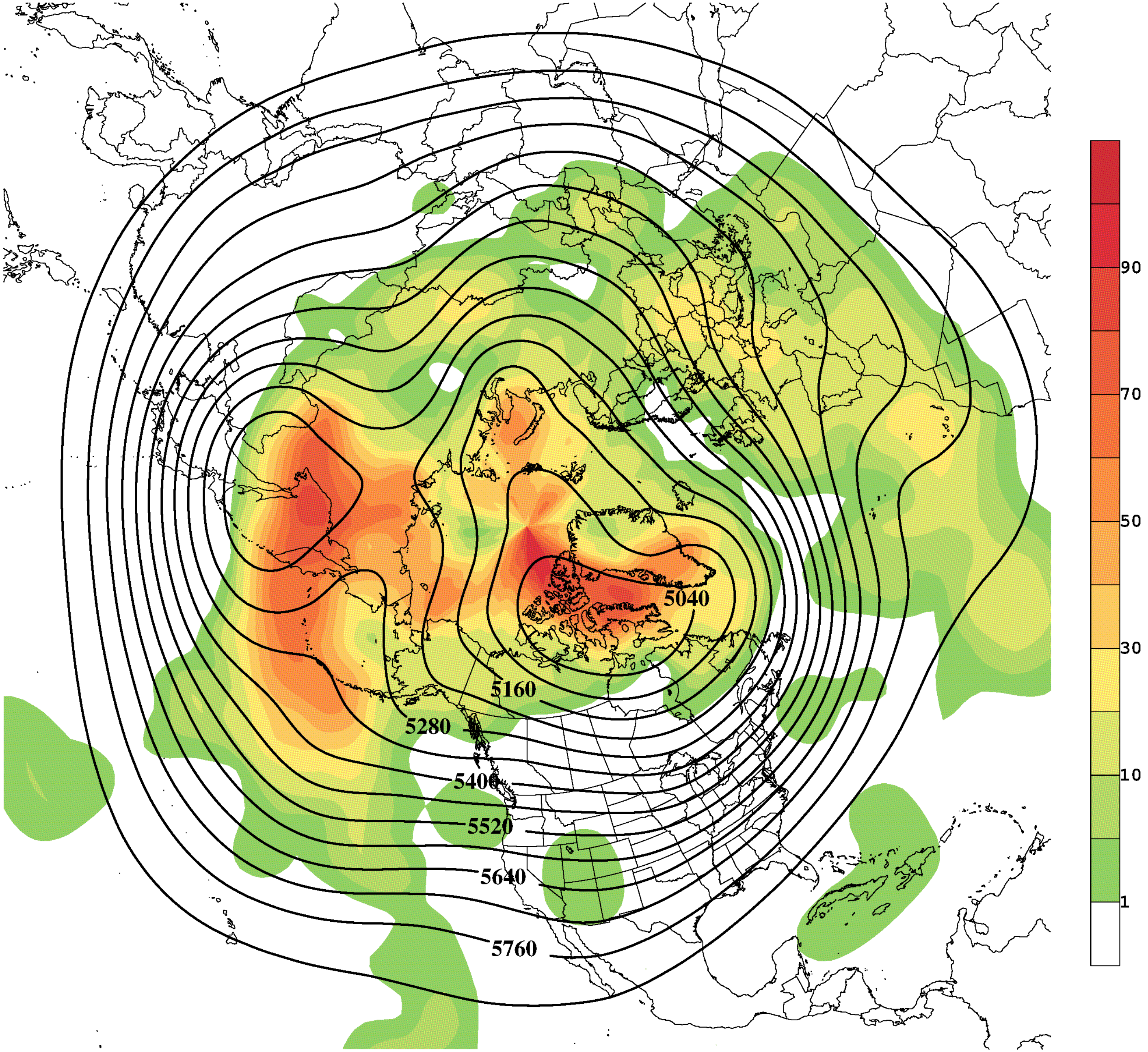
Reanalysis Time: Fri Jan 1 00:00:00 2010 to: Thu Jan 7 00:00:00 2010
Cyclone ID in Highlighted Area: [128204.]

Regime classification - McGill

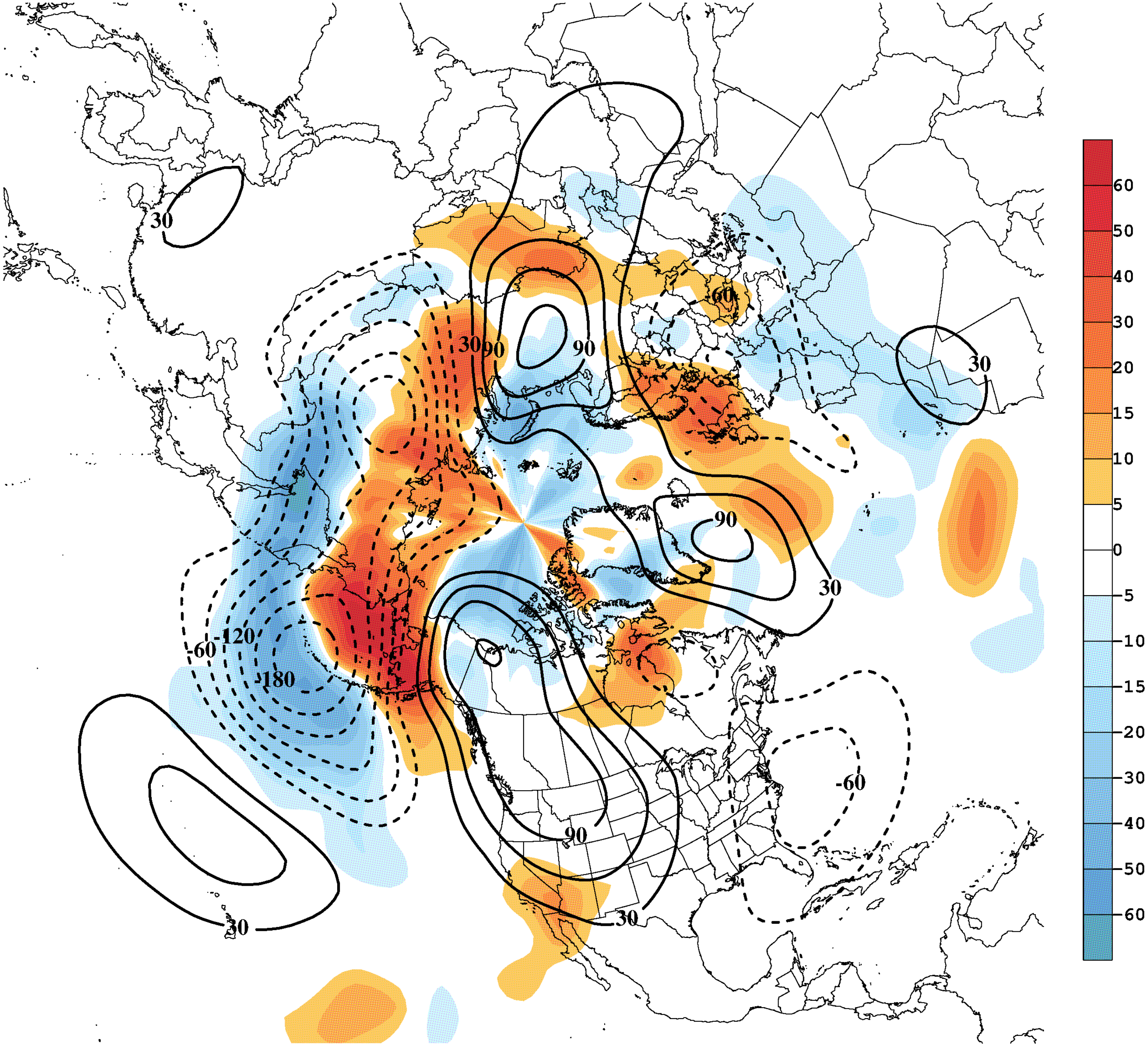
- Establish classifications using general circulation metric
- Analyze predictability and compare to other approaches



Stagnation Freq and 500 hPa HGHT for lowvar in the East Pacific for DJF



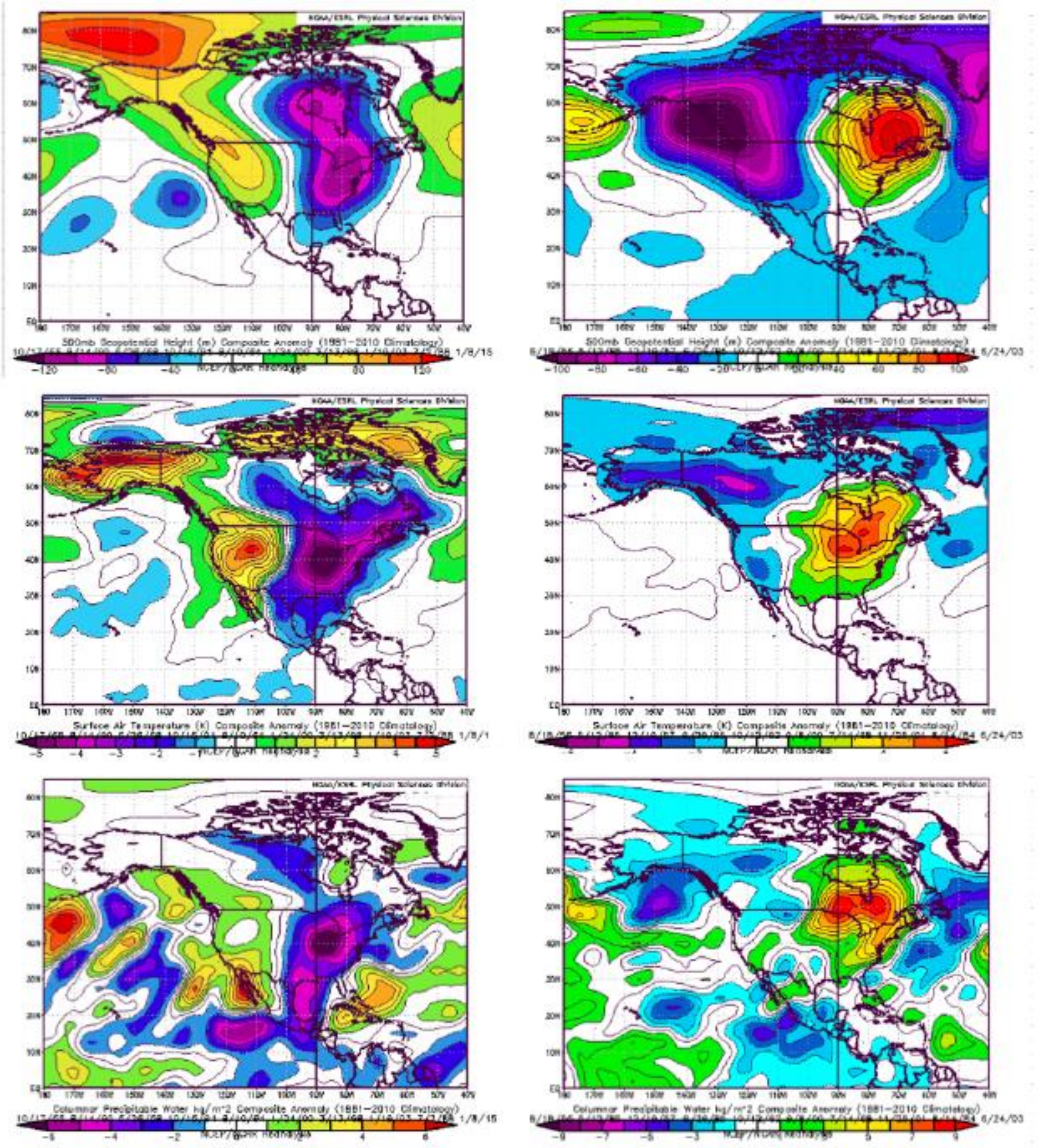
Stagnation Freq and 500 hPa HGHT for highvar in the East Pacific for DJF



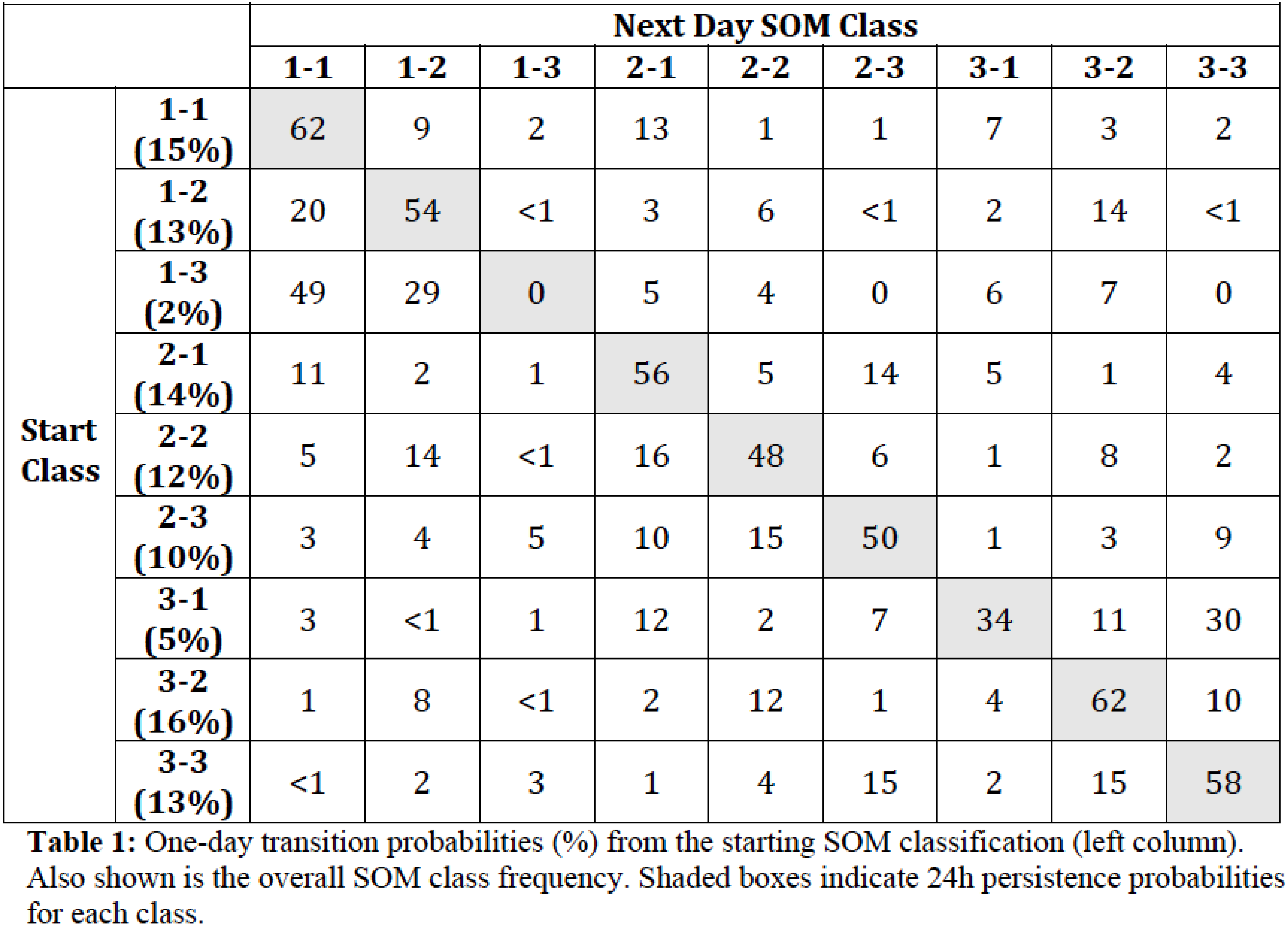
Lowvar - Highvar Stagnation Freq and 500 hPa HGHTs for East Pacific DJF

Regime Classificiation – UWM

- Compare weather regime classifications defined via several methods (SOM using DT and 850 hPa theta-e; SUNYA results via clustering; McGill results via GC metric) and evaluate predictabilty
- Evaluate robustness of CFSv2 model climate
- Evaluate predictive utility of regime transition probabilities



<u>Figure 3</u>: 500 hPa height (top), surface temperature (middle), and precipitable water (bottom) anomalies for SOM class 1-1 (left) and 3-3 (right).



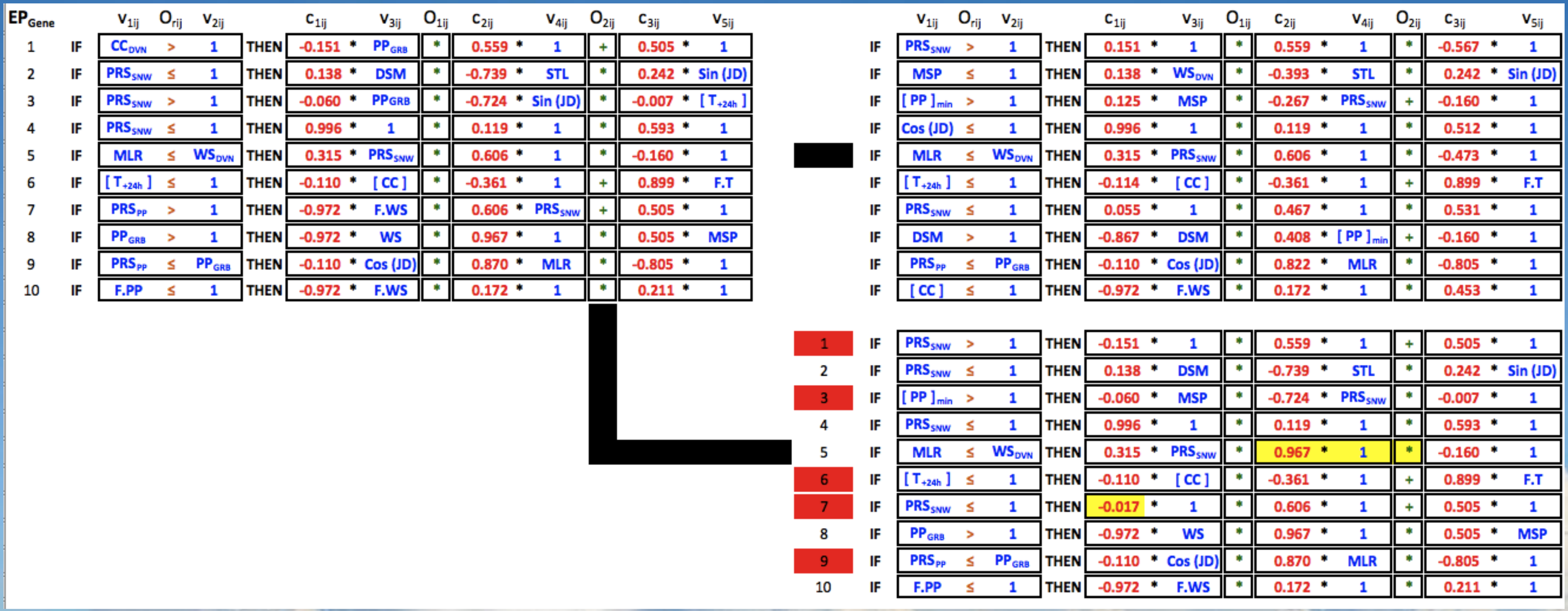
		Next Day SOM Class								
		1-1	**1-2**	**1-3**	**2-1**	**2-2**	**2-3**	**3-1**	**3-2**	**3-3**
Start Class	**1-1 (15%)**	62	9	2	13	1	1	7	3	2
	1-2 (13%)	20	54	<1	3	6	<1	2	14	<1
	1-3 (2%)	49	29	0	5	4	0	6	7	0
	2-1 (14%)	11	2	1	56	5	14	5	1	4
	2-2 (12%)	5	14	<1	16	48	6	1	8	2
	2-3 (10%)	3	4	5	10	15	50	1	3	9
	3-1 (5%)	3	<1	1	12	2	7	34	11	30
	3-2 (16%)	1	8	<1	2	12	1	4	62	10
	3-3 (13%)	<1	2	3	1	4	15	2	15	58

Table 1: One-day transition probabilities (%) from the starting SOM classification (left column). Also shown is the overall SOM class frequency. Shaded boxes indicate 24h persistence probabilities for each class.

Future work – Predictive tools

- How to integrate individual pieces of predictive information?
- Variety of spatio-temporal approaches exist

Evolutionary Programming (if-then conditionals)



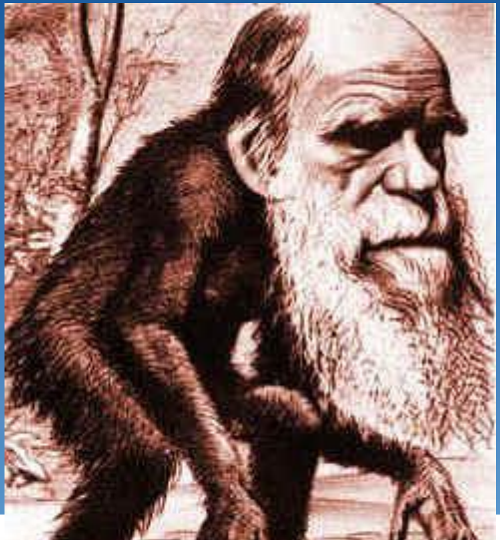
EP$_{Gene}$		v$_{1ij}$	O$_{rij}$	v$_{2ij}$		c$_{1ij}$		v$_{3ij}$	O$_{1ij}$	c$_{2ij}$		v$_{4ij}$	O$_{2ij}$	c$_{3ij}$		v$_{5ij}$
1	IF	CC$_{DVN}$	>	1	THEN	-0.151	*	PP$_{GRB}$	*	0.559	*	1	+	0.505	*	1
2	IF	PRS$_{SNW}$	≤	1	THEN	0.138	*	DSM	*	-0.739	*	STL	*	0.242	*	Sin (JD)
3	IF	PRS$_{SNW}$	>	1	THEN	-0.060	*	PPGRB	*	-0.724	*	Sin (JD)	*	-0.007	*	[T$_{+24h}$]
4	IF	PRS$_{SNW}$	≤	1	THEN	0.996	*	1	*	0.119	*	1	*	0.593	*	1
5	IF	MLR	≤	WS$_{DVN}$	THEN	0.315	*	PRS$_{SNW}$	*	0.606	*	1	*	-0.160	*	1
6	IF	[T$_{+24h}$]	≤	1	THEN	-0.110	*	[CC]	*	-0.361	*	1	+	0.899	*	F.T
7	IF	PRS$_{PP}$	>	1	THEN	-0.972	*	F.WS	*	0.606	*	PRS$_{SNW}$	+	0.505	*	1
8	IF	PP$_{GRB}$	>	1	THEN	-0.972	*	WS	*	0.967	*	1	*	0.505	*	MSP
9	IF	PRS$_{PP}$	≤	PP$_{GRB}$	THEN	-0.110	*	Cos (JD)	*	0.870	*	MLR	*	-0.805	*	1
10	IF	F.PP	≤	1	THEN	-0.972	*	F.WS	*	0.172	*	1	*	0.211	*	1

	v$_{1ij}$	O$_{rij}$	v$_{2ij}$		c$_{1ij}$		v$_{3ij}$	O$_{1ij}$	c$_{2ij}$		v$_{4ij}$	O$_{2ij}$	c$_{3ij}$		v$_{5ij}$
IF	PRS$_{SNW}$	>	1	THEN	0.151	*	1	*	0.559	*	1	*	-0.567	*	1
IF	MSP	≤	1	THEN	0.138	*	WS$_{DVN}$	*	-0.393	*	STL	*	0.242	*	Sin (JD)
IF	[PP]$_{min}$	>	1	THEN	0.125	*	MSP	*	-0.267	*	PRS$_{SNW}$	+	-0.160	*	1
IF	Cos (JD)	≤	1	THEN	0.996	*	1	*	0.119	*	1	*	0.512	*	1
IF	MLR	≤	WS$_{DVN}$	THEN	0.315	*	PRS$_{SNW}$	*	0.606	*	1	*	-0.473	*	1
IF	[T$_{+24h}$]	≤	1	THEN	-0.114	*	[CC]	*	-0.361	*	1	+	0.899	*	F.T
IF	PRS$_{SNW}$	≤	1	THEN	0.055	*	1	*	0.467	*	1	*	0.531	*	1
IF	DSM	>	1	THEN	-0.867	*	DSM	*	0.408	*	[PP]$_{min}$	+	-0.160	*	1
IF	PRS$_{PP}$	≤	PP$_{GRB}$	THEN	-0.110	*	Cos (JD)	*	0.822	*	MLR	*	-0.805	*	1
IF	[CC]	≤	1	THEN	-0.972	*	F.WS	*	0.172	*	1	*	0.453	*	1

1	IF	PRS$_{SNW}$	>	1	THEN	-0.151	*	1	*	0.559	*	1	+	0.505	*	1
2	IF	PRS$_{SNW}$	≤	1	THEN	0.138	*	DSM	*	-0.739	*	STL	*	0.242	*	Sin (JD)
3	IF	[PP]$_{min}$	>	1	THEN	-0.060	*	MSP	*	-0.724	*	PRS$_{SNW}$	*	-0.007	*	1
4	IF	PRS$_{SNW}$	≤	1	THEN	0.996	*	1	*	0.119	*	1	*	0.593	*	1
5	IF	MLR	≤	WS$_{DVN}$	THEN	0.315	*	PRS$_{SNW}$	*	0.967	*	1	*	-0.160	*	1
6	IF	[T$_{+24h}$]	≤	1	THEN	-0.110	*	[CC]	*	-0.361	*	1	+	0.899	*	F.T
7	IF	PRS$_{SNW}$	≤	1	THEN	-0.017	*	1	*	0.606	*	1	+	0.505	*	1
8	IF	PP$_{GRB}$	>	1	THEN	-0.972	*	WS	*	0.967	*	1	*	0.505	*	MSP
9	IF	PRS$_{PP}$	≤	PP$_{GRB}$	THEN	-0.110	*	Cos (JD)	*	0.870	*	MLR	*	-0.805	*	1
10	IF	F.PP	≤	1	THEN	-0.972	*	F.WS	*	0.172	*	1	*	0.211	*	1

Figure 1. Sample EP algorithm structure (from temperature forecasting). The ten EP-genes each contain five variables (blue), one relational operator (orange), two mathematical operators (green), and three coefficients (red). Here, a father (top left) and mother (top right) produce a child algorithm (bottom right) through crossover. The modified lines of the child (compared to the father) are indicated in red, and mutated components of EP-genes 5 and 7 are shown in yellow.

Adaptive capability essential …



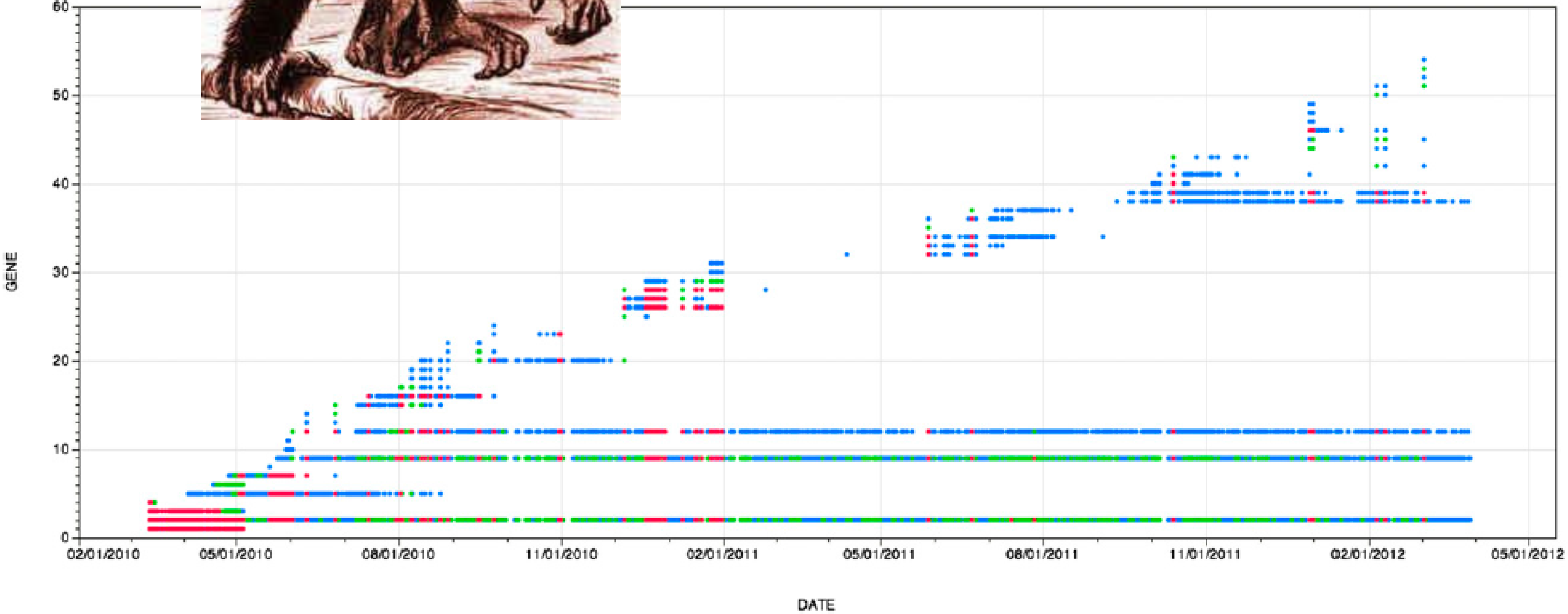
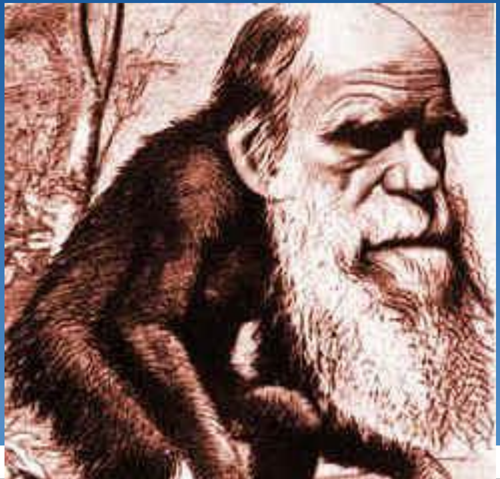


FIG. 2. Time series of the frequency of the most common EP-genes over the test period (counts: blue from 1000 to 2000, green from 2000 to 3000, red > 3000). See Table 4 for identification of the specific EP-genes and their functional translation. Note that EP-genes whose maximum occurrence at any forecast time was less than 1000 are not shown.



Adaptive capability essential …

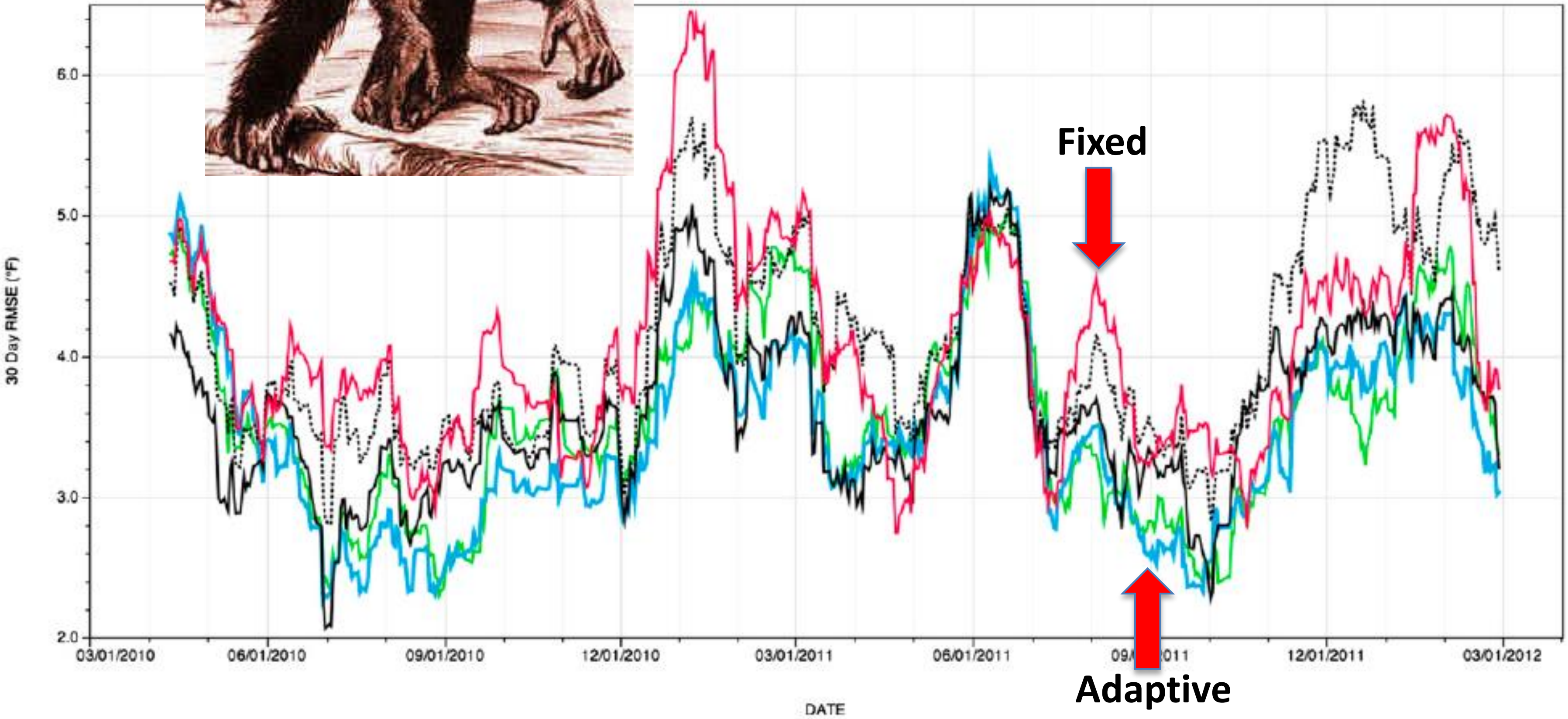
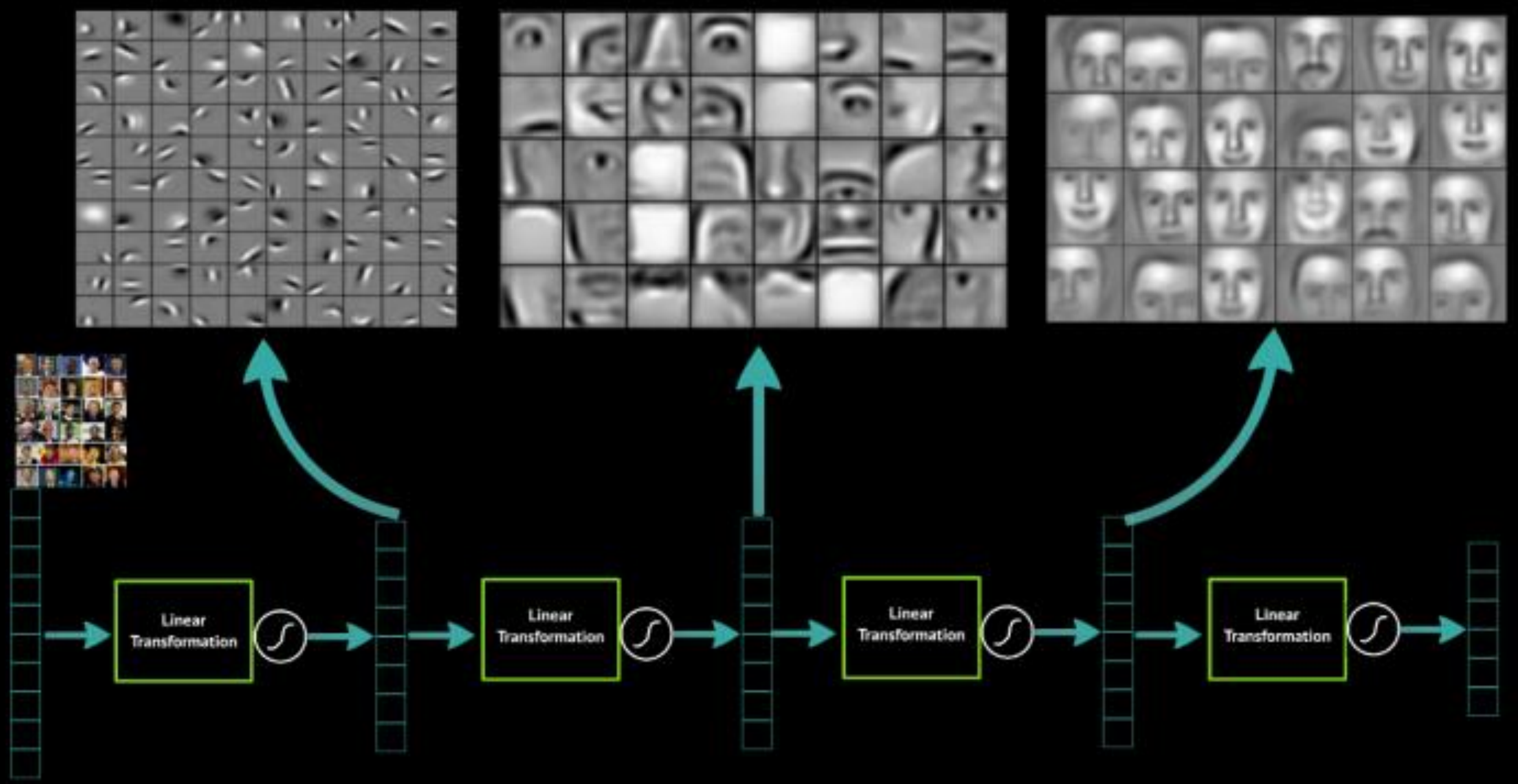


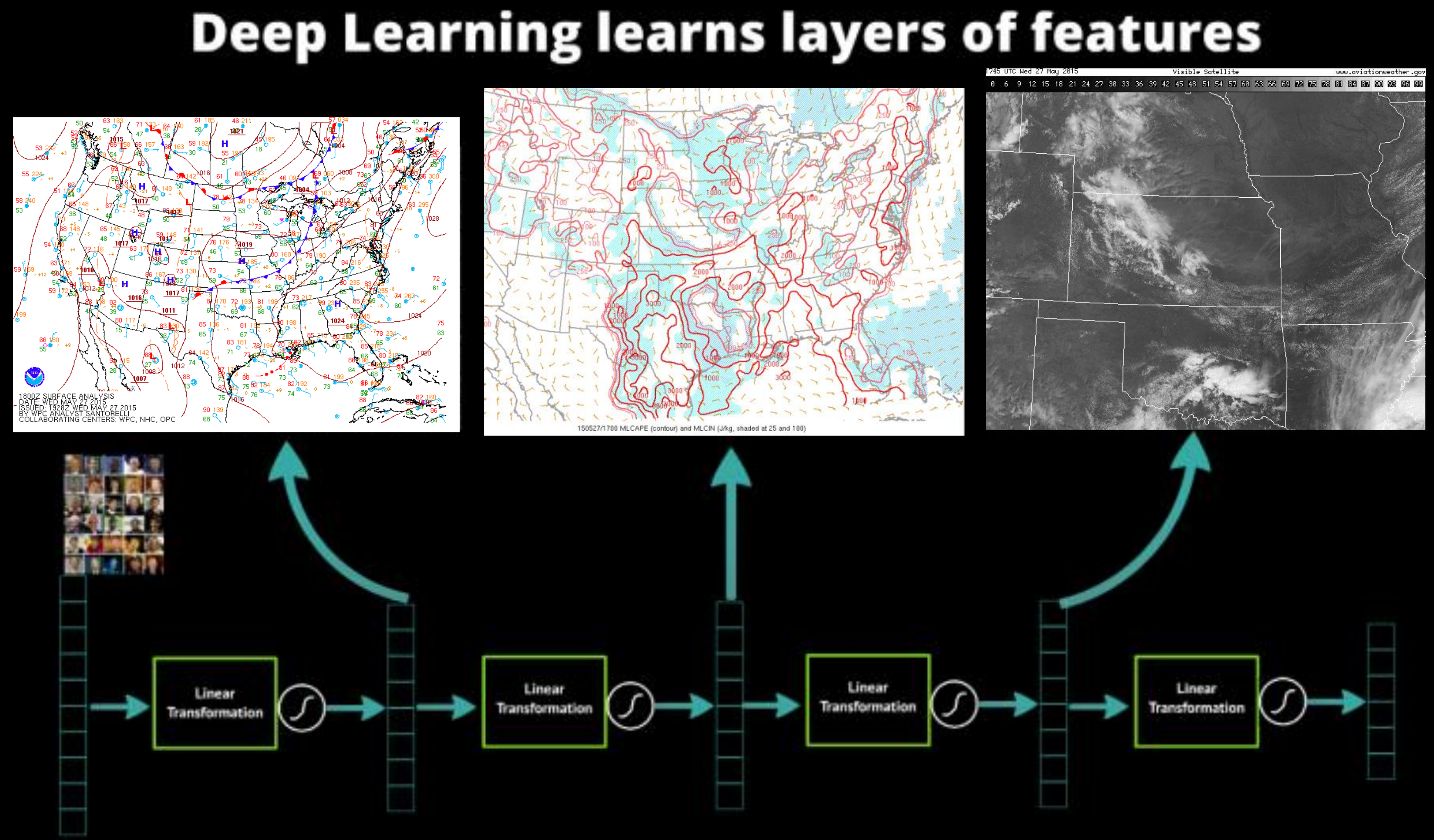
FIG. 1. Time series of the 30-day moving average of the RMSE (°F) for the fixed (red), BMC (green), and mixed-mode adaptive (blue) EP. Also shown are the 60-h GFS (dotted black) and the 36-h GFS ensemble MOS (solid black).

Convolutional Neural Nets

Deep Learning learns layers of features



Convolutional Neural Nets



Deep Learning learns layers of features