Improve CFS Week 3-4 Precipitation and 2m Temperature Forecast *with Neural Network Technique*

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Outline

- Motivation
- NN Basic
- Sanity Check
- Early Results
- Summary

Motivation

Problem:

Training Data Set

$$\{ (f_1, f_2, \ldots\ldots, f_n)_p,\ O_p \}_{p=1,2,\ldots\ldots N}$$

Where

$f_1, f_2, \ldots\ldots, f_n$ **-- predictors:** forecast daily week 3-4 total precipitation

O_p **-- predictand:** observed daily week 3-4 total precipitation

Mapping:

$$O = M(F)$$

Can Machine Learning or AI add additional value?

NN Basic

Function of Many Variables & Multiple Regression

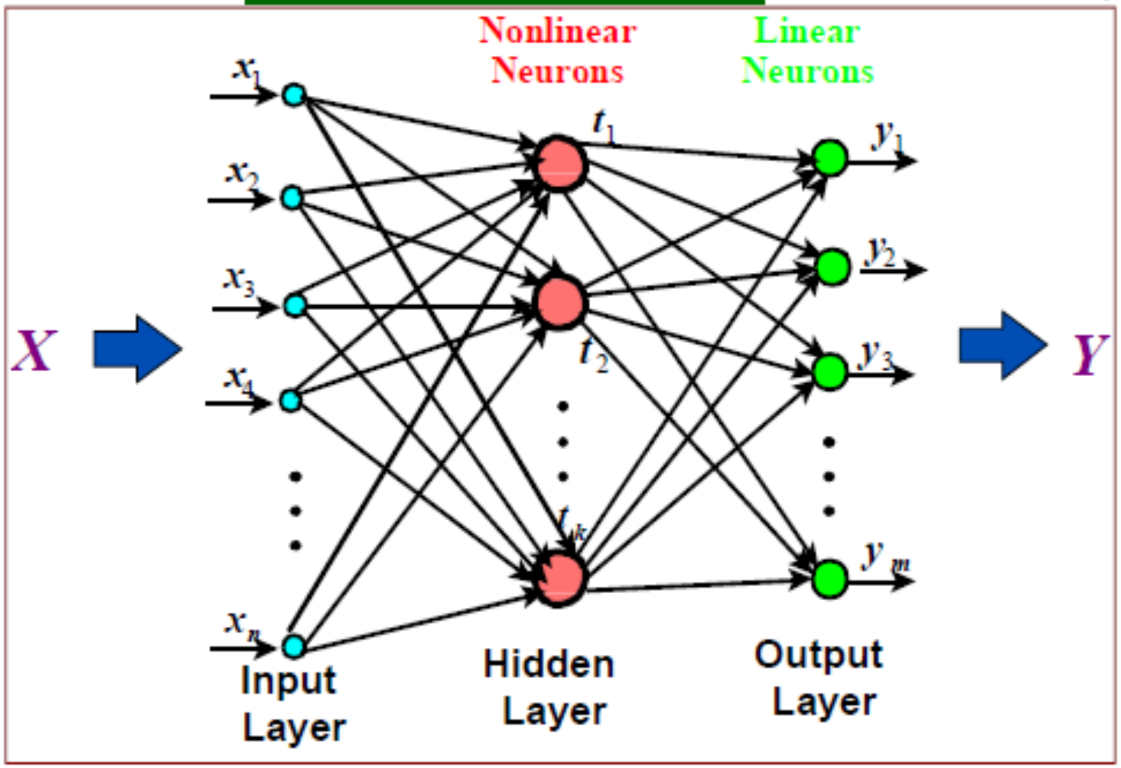
$$y = a_0 + a_1 x_1 + \cdots + a_n x_n$$ --- Multiple Linear Regression

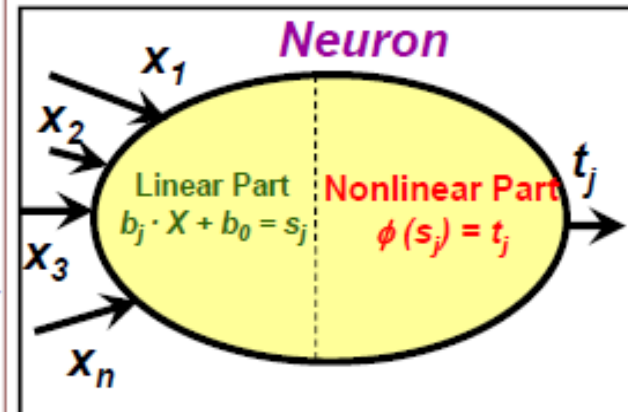
$$y = a_0 + \sum_{j=1}^{k} a_j \tanh(b_{j0} + \sum_{i=1}^{n} b_{ji} x_i)$$ --- Multiple Nonlinear Regression

NN Architectures

NN - Continuous Input to Output Mapping

Multilayer Perceptron: **Feed Forward, Fully Connected**





$$t_j = \phi(b_{j0} + \sum_{i=1}^{n} b_{ji} \cdot x_i) =$$

$$= \tanh(b_{j0} + \sum_{i=1}^{n} b_{ji} \cdot x_i)$$

$Y = F_{NN}(X)$

Jacobian !

$$\begin{cases} y_q = a_{q0} + \sum_{j=1}^{k} a_{qj} \cdot t_j = a_{q0} + \sum_{j=1}^{k} a_{qj} \cdot \phi(b_{j0} + \sum_{i=1}^{n} b_{ji} \cdot x_i) = \\ = a_{q0} + \sum_{j=1}^{k} a_{qj} \cdot \tanh(b_{j0} + \sum_{i=1}^{n} b_{ji} \cdot x_i); \quad q = 1,2,\ldots,m \end{cases}$$

From V. Krasnopolsky

NN training (1)

- For the mapping $Z = F(X)$ create a ***training set*** - set of matchups $\{X_i, Z_i\}_{i=1,\ldots,N}$, where X_i is ***input vector*** and Z_i - ***desired output vector***
- Introduce ***an error or cost function E***:

$$E(a,b) = ||Z - Y|| = \sum_{i=1}^{N} \left| Z_i - F_{NN}(X_i) \right|^2 ,$$

where $Y = F_{NN}(X)$ is neural network;

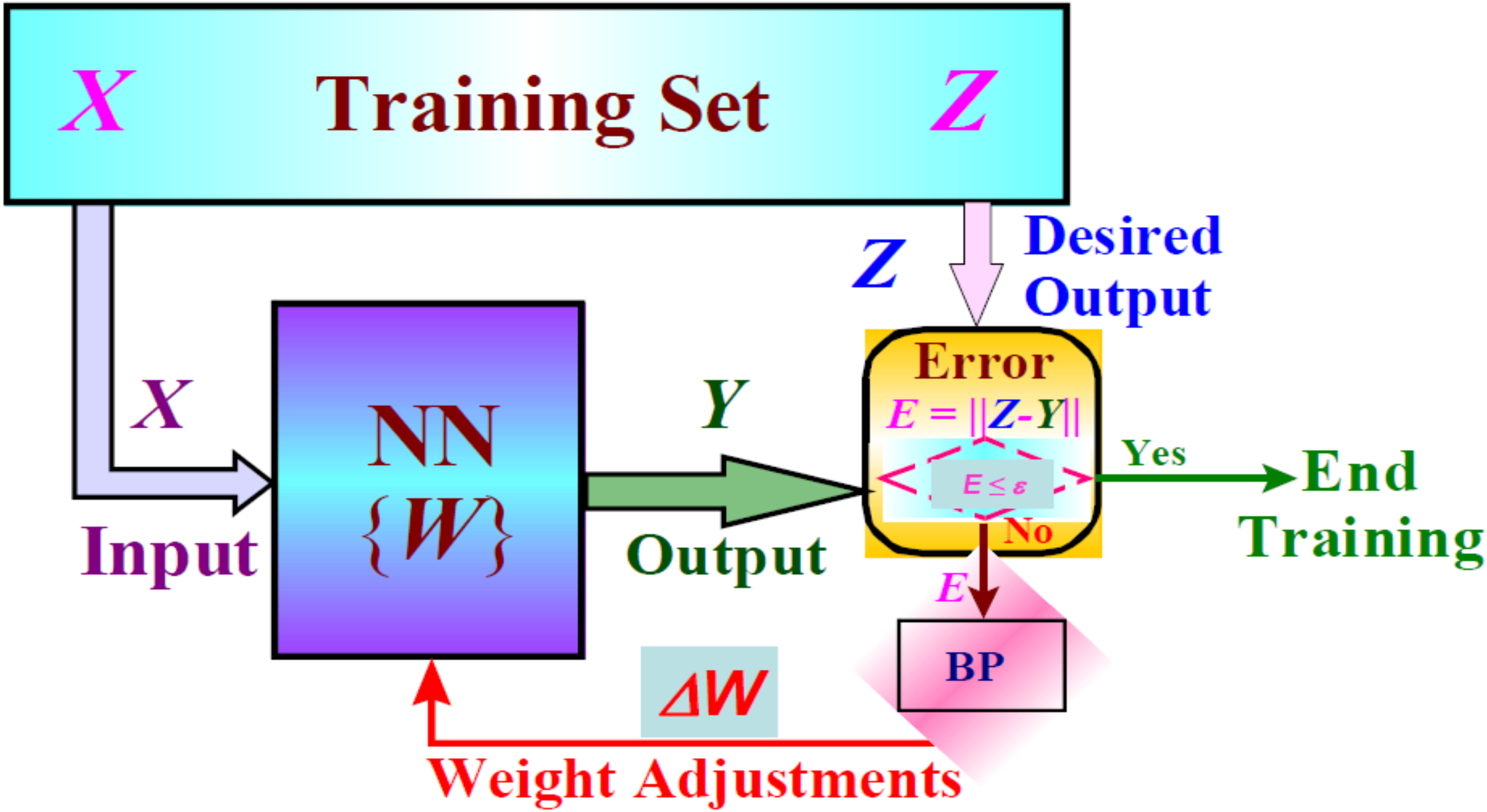
equivalent to MLH only for normal distribution of Es

- Minimize the cost function: $min\{E(a,b)\}$ and find optimal weights (a_0, b_0) – nonlinear Least Squares
- Notation: $W = \{a, b\}$ - all weights.

From V. Krasnopolsky

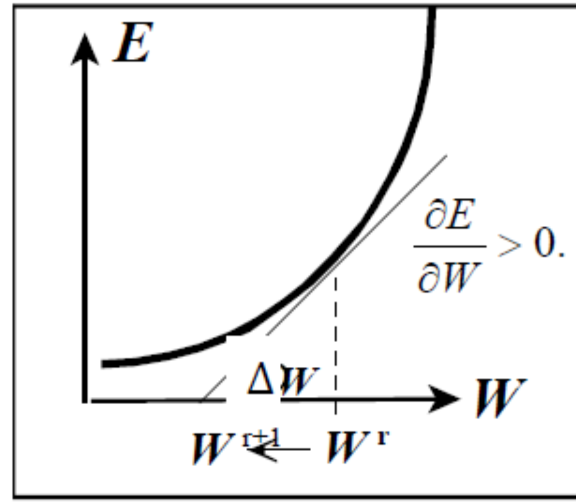
NN Training (2)

One Training Iteration



From V. Krasnopolsky

Backpropagation (BP) Training Algorithm



- **BP is a simplified steepest descent:**

$$\Delta W = -\eta \frac{\partial E}{\partial W}$$

where *W* - any weight, *E* - error function,

η - learning rate, and ΔW - weight increment

- **Derivative can be calculated analytically:**

$$\frac{\partial E}{\partial W} = -2 \sum_{i=1}^{N} [Z_i - F_{NN}(X_i)] \cdot \frac{\partial F_{NN}(X_i)}{\partial W}$$

- **Weight adjustment after r-th iteration:**

$$W^{r+1} = W^{r} + \Delta W$$

- **BP training algorithm is robust but slow**

From V. Krasnopolsky

NN Sanity Check

Mapping: *X = M(X)*

Training period: 1999-2015 17 year about 6200 daily data
Predictor: Observed daily week 3-4 total precipitation
Predictand: Observed daily week 3-4 total precipitation
Location: Tucson, AZ

NN equation:

NN (i) = b2 + w2*tanh [b1 + w1*F (i)]

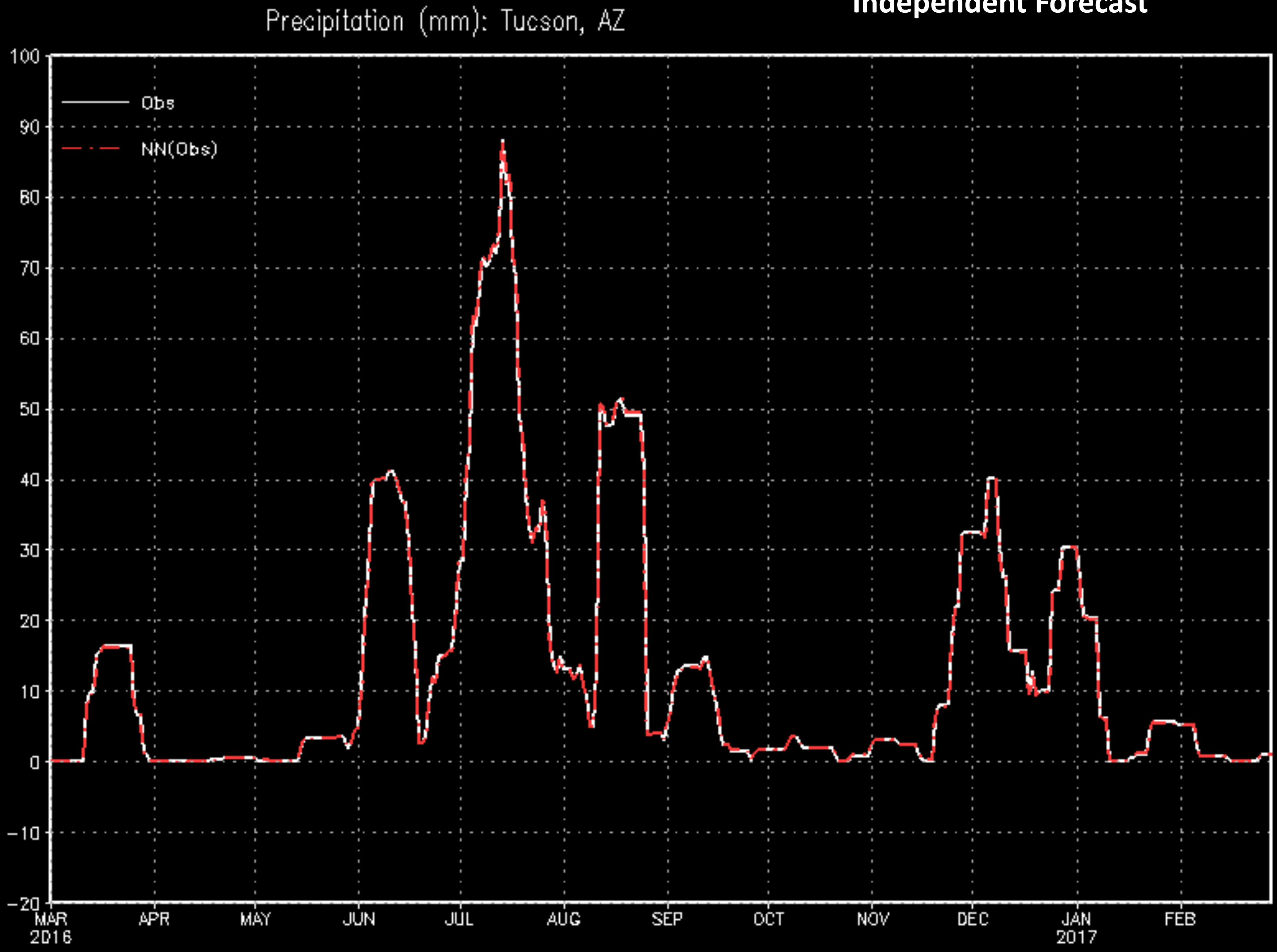
w1 = -5.4856790230e-03

w2 = -1.8592158508e+02

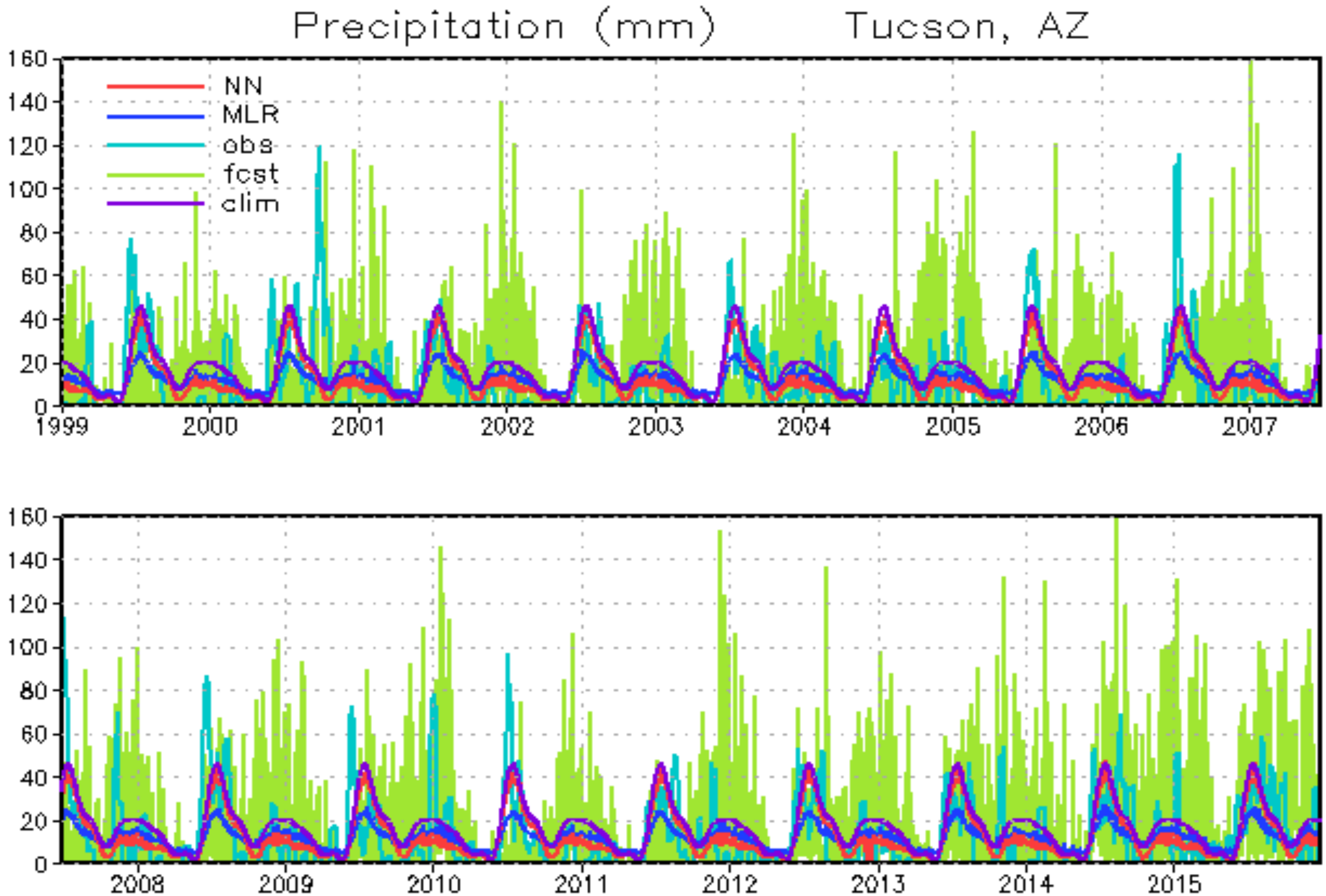
b1 = 2.3463767767e-01

b2 = 4.2932647705e+01

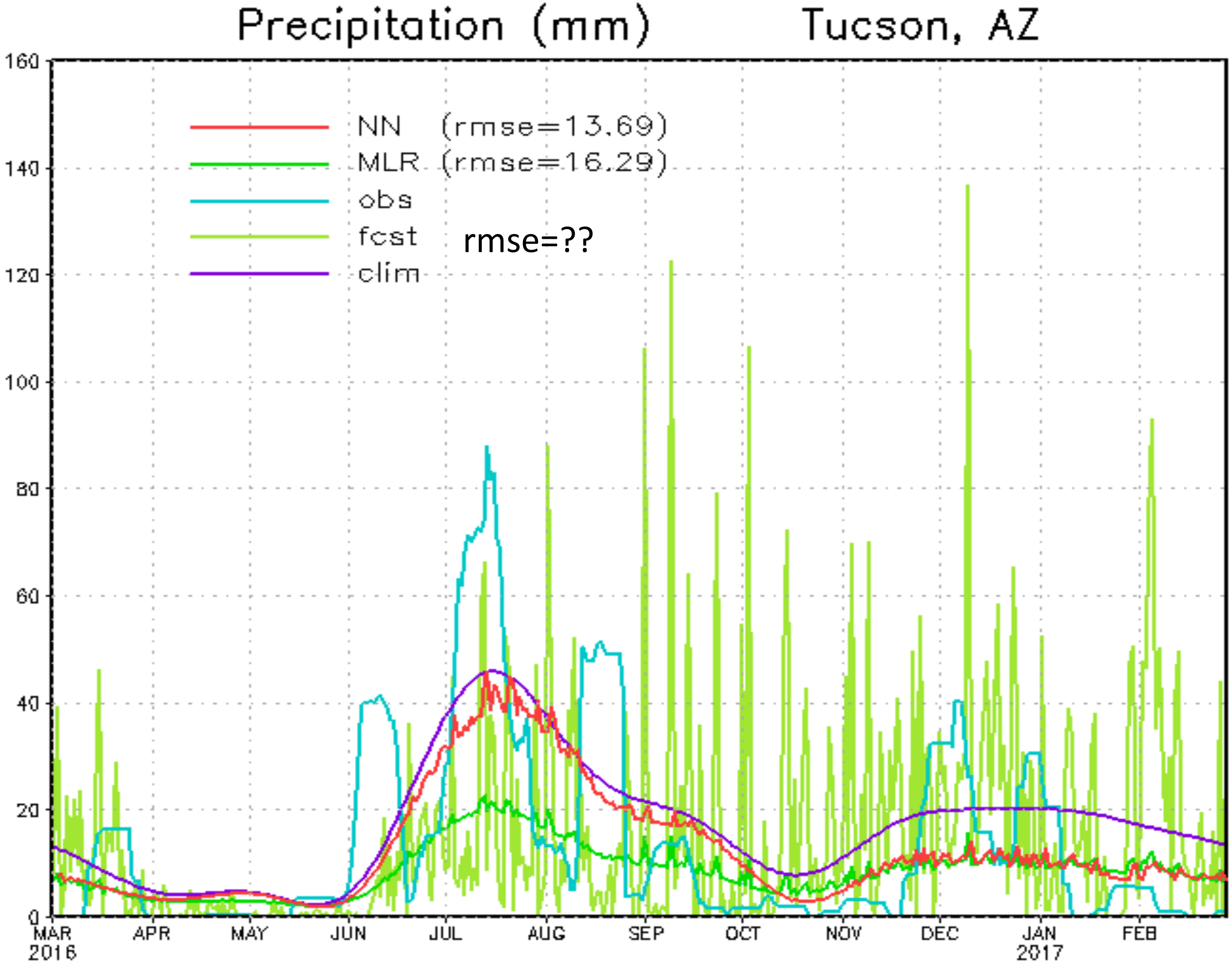
Independent Forecast



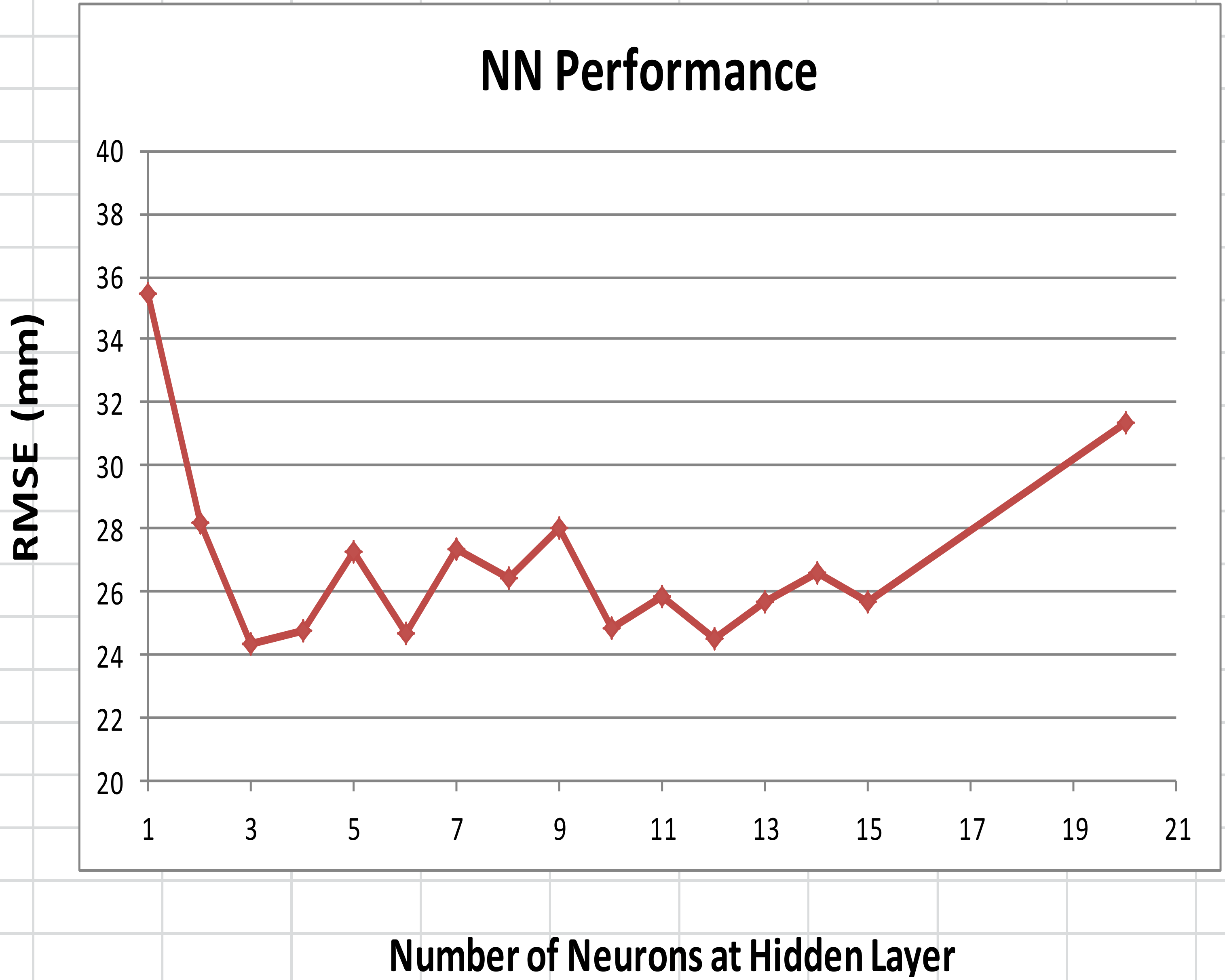
Dependent Forecast (training period, 1999 – 2015)



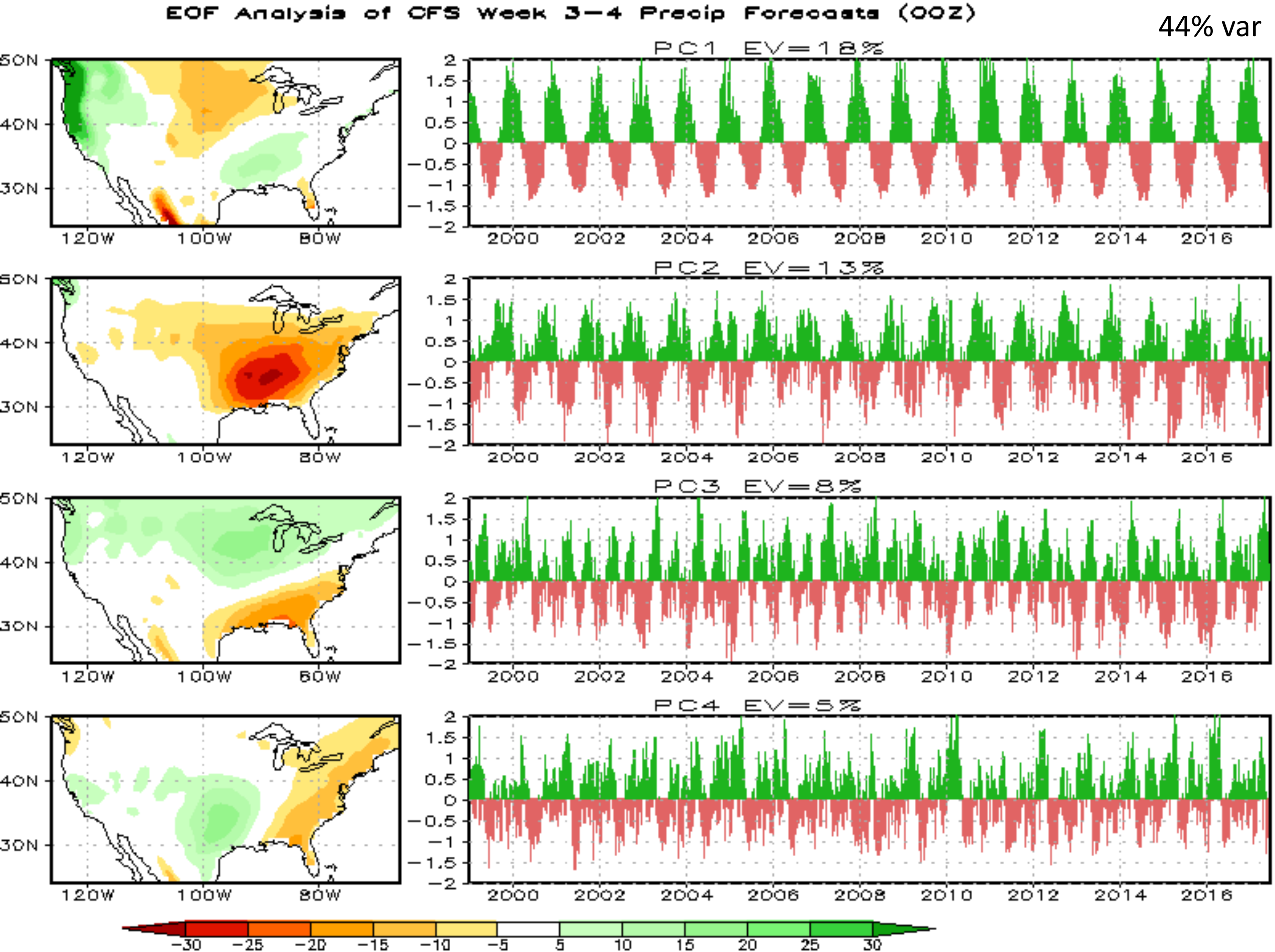
Dependent Forecast
Predictors: CFSv2 daily P_fcst (1999 - 2015), CPC daily P_obs Climatology (1981 - 2010)
Predictand: CPC daily P_obs (1999 - 2015)



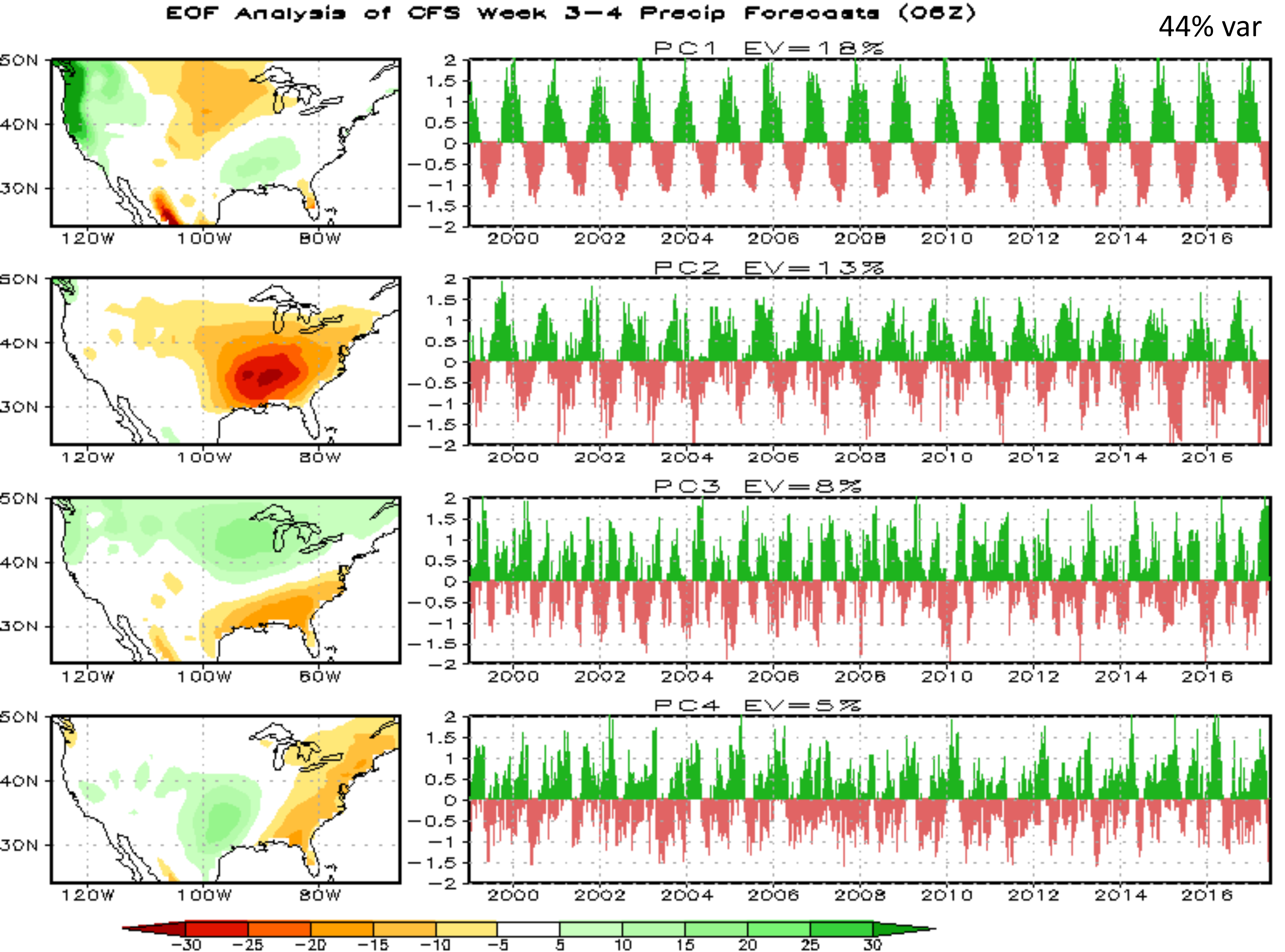
Independent Forecast


NN Performance
RMSE (mm)
40
38
36
34
32
30
28
26
24
22
20
1
3
5
7
9
11
13
15
17
19
21
Number of Neurons at Hidden Layer

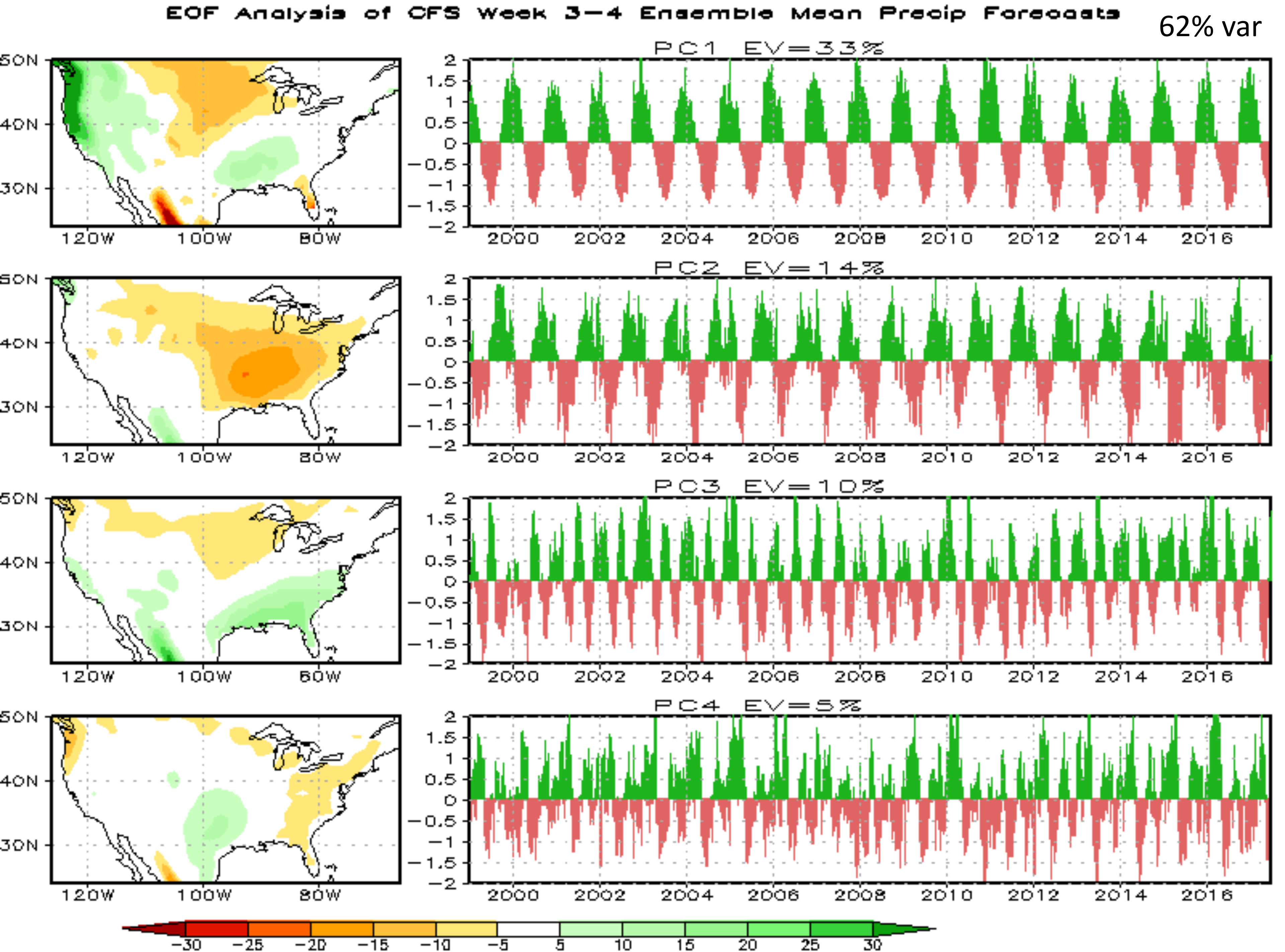
44% var



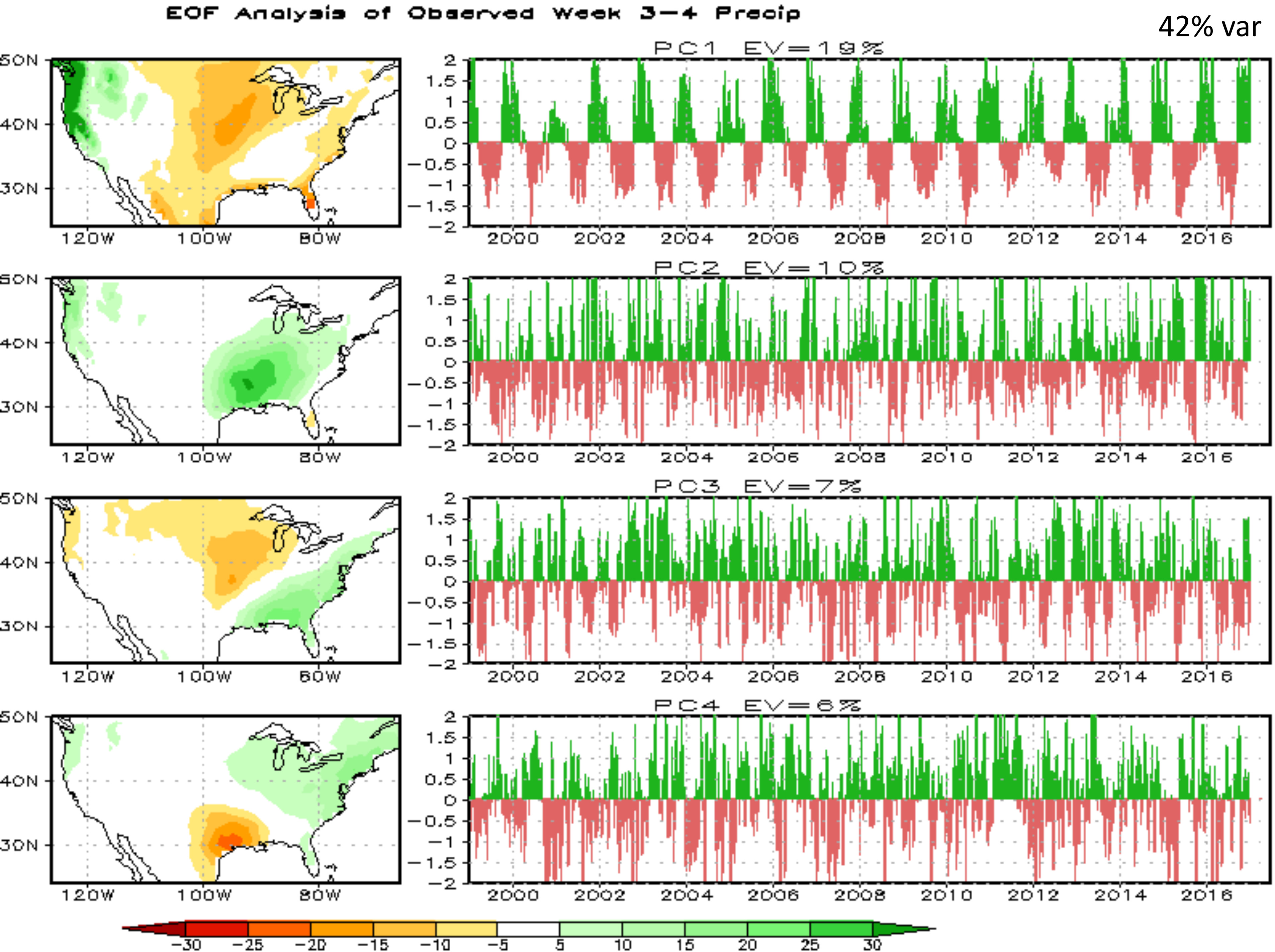
EOF Analysis of CFS Week 3-4 Precip Forecasts (00Z)
PC1 EV=18%
PC2 EV=13%
PC3 EV=8%
PC4 EV=5%
50N
40N
30N
120W
100W
80W
2
1.5
1
0.5
0
−0.5
−1
−1.5
−2
2000
2002
2004
2006
2008
2010
2012
2014
2016
−30
−25
−20
−15
−10
−5
5
10
15
20
25
30



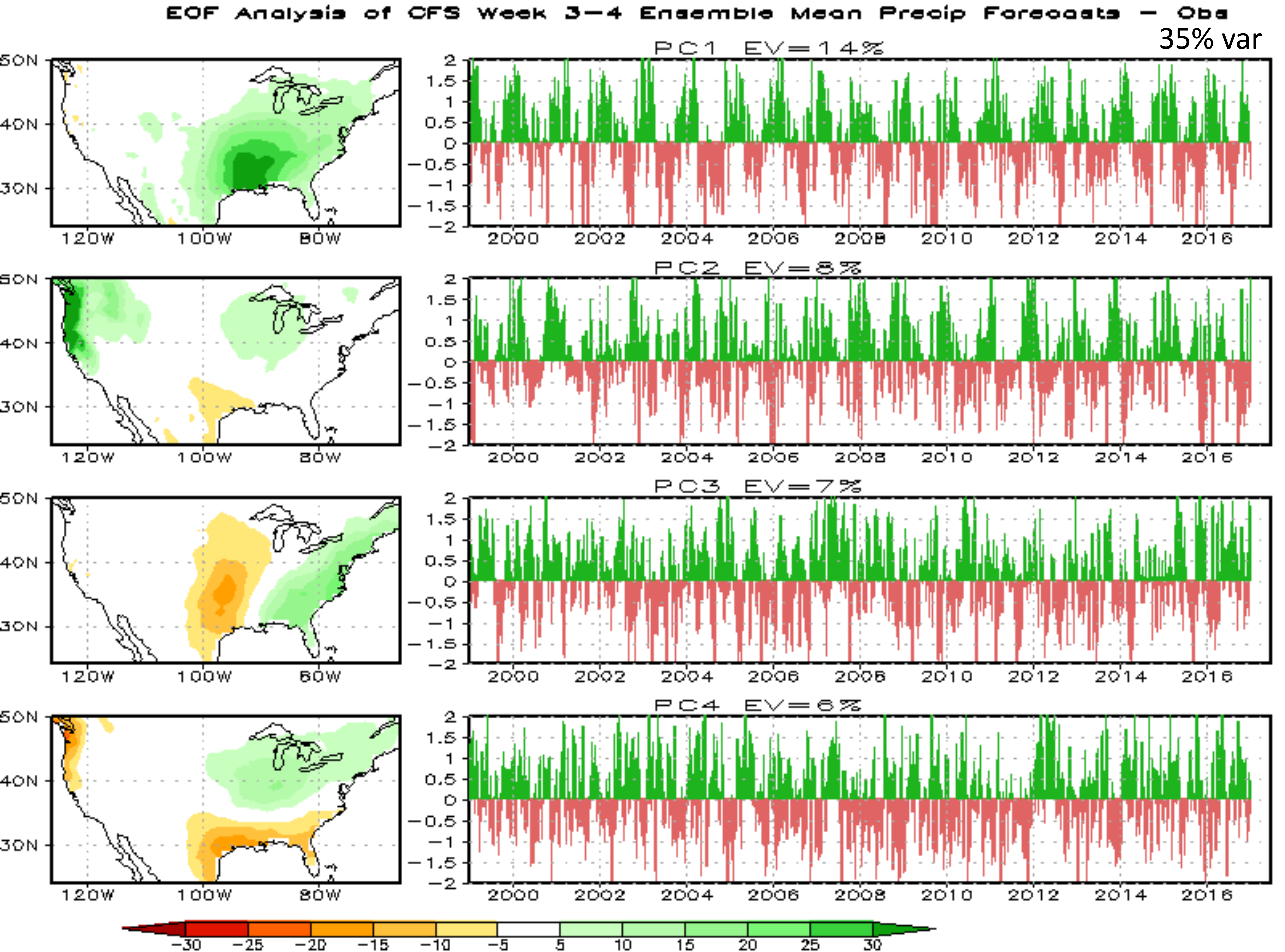
EOF Analysis of CFS Week 3-4 Precip Forecasts (06Z)
44% var
PC1 EV=18%
PC2 EV=13%
PC3 EV=8%
PC4 EV=5%
50N
40N
30N
120W
100W
80W
2000
2002
2004
2006
2008
2010
2012
2014
2016
-30 -25 -20 -15 -10 -5 5 10 15 20 25 30



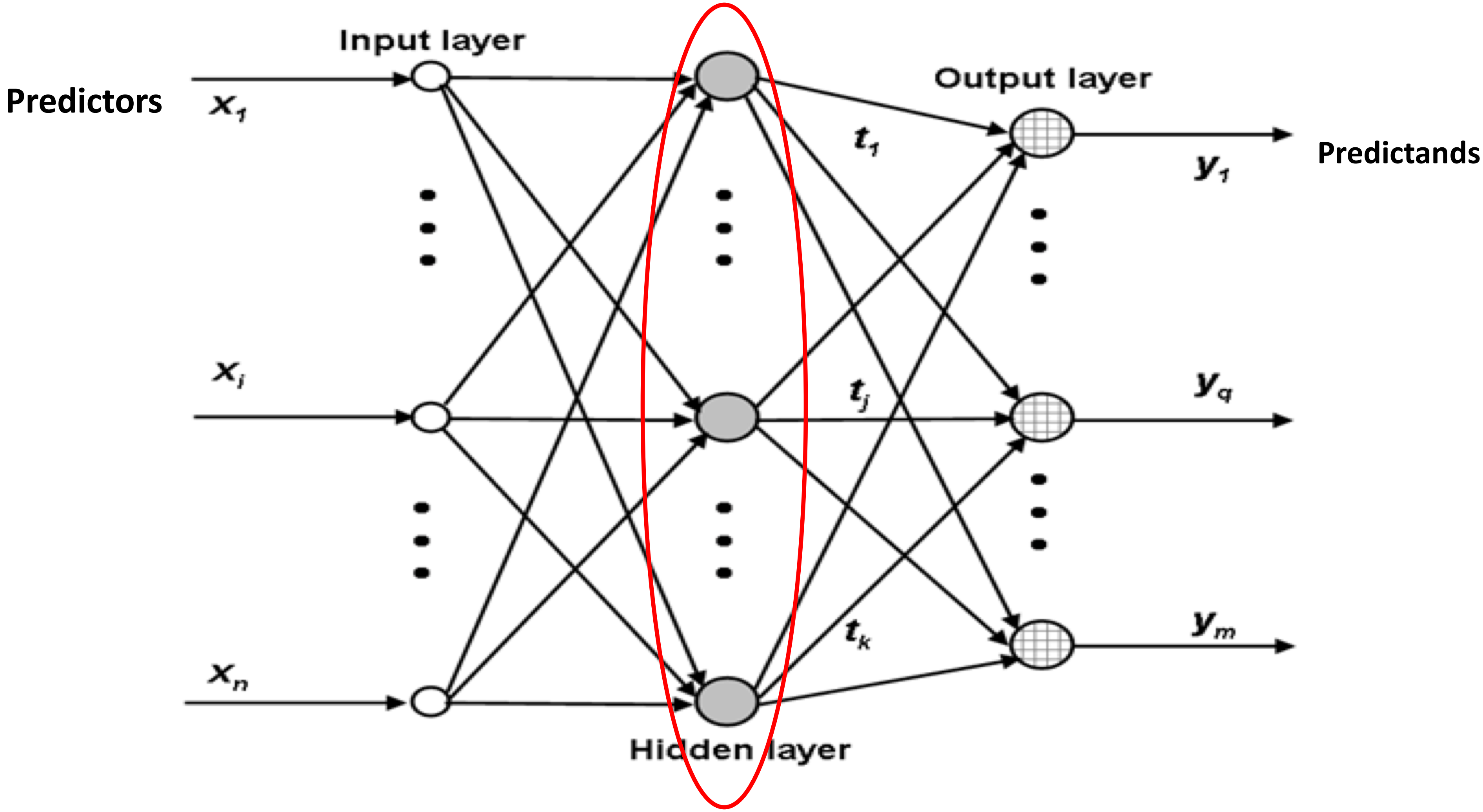
EOF Analysis of CFS Week 3-4 Ensemble Mean Precip Forecasts
62% var
PC1 EV=33%
PC2 EV=14%
PC3 EV=10%
PC4 EV=5%
50N
40N
30N
120W
100W
80W
2000
2002
2004
2006
2008
2010
2012
2014
2016
-30 -25 -20 -15 -10 -5 5 10 15 20 25 30



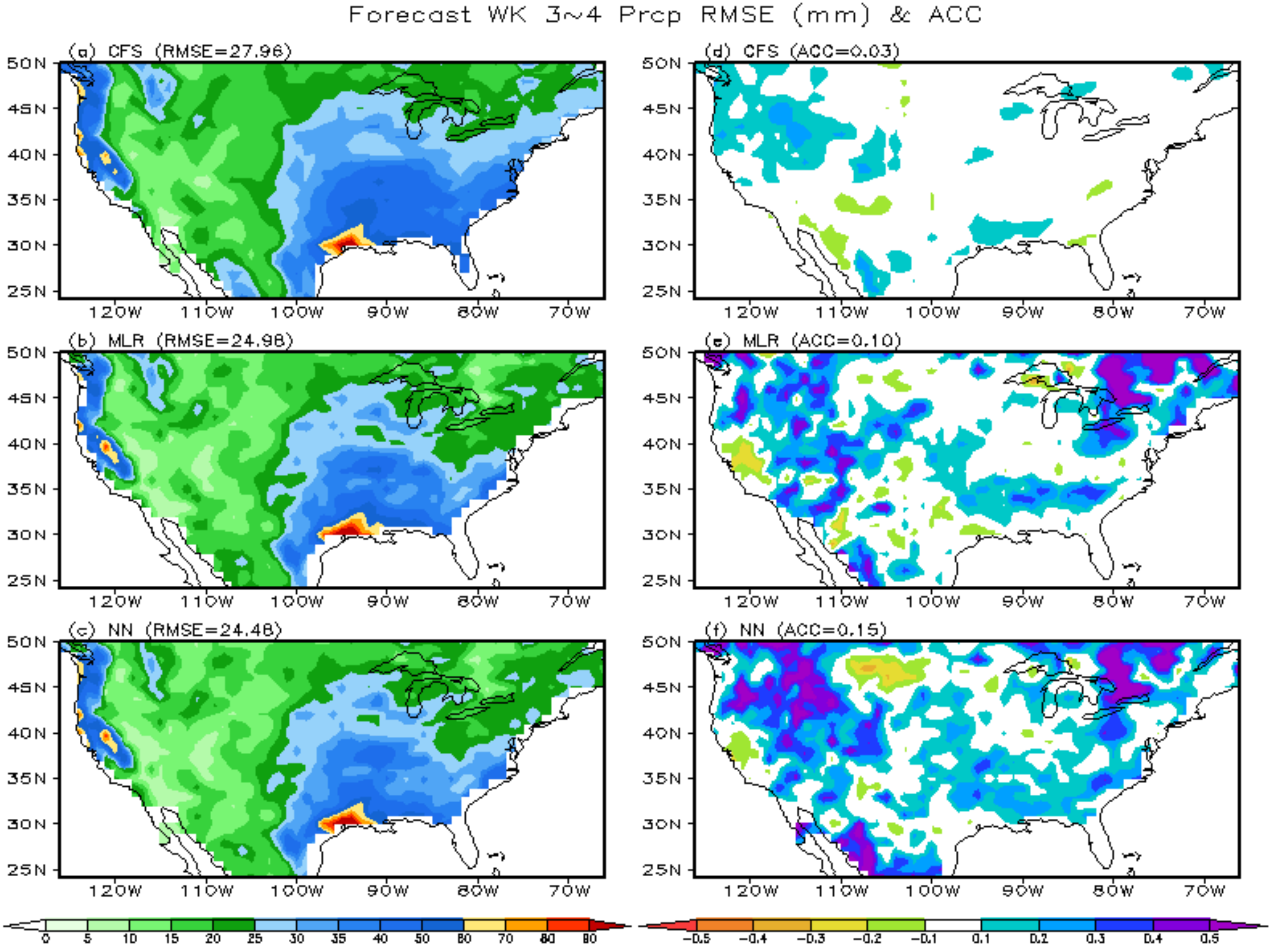
EOF Analysis of Observed Week 3-4 Precip
42% var
PC1 EV=19%
PC2 EV=10%
PC3 EV=7%
PC4 EV=6%
50N
40N
30N
120W
100W
80W
2000
2002
2004
2006
2008
2010
2012
2014
2016
-30 -25 -20 -15 -10 -5 5 10 15 20 25 30

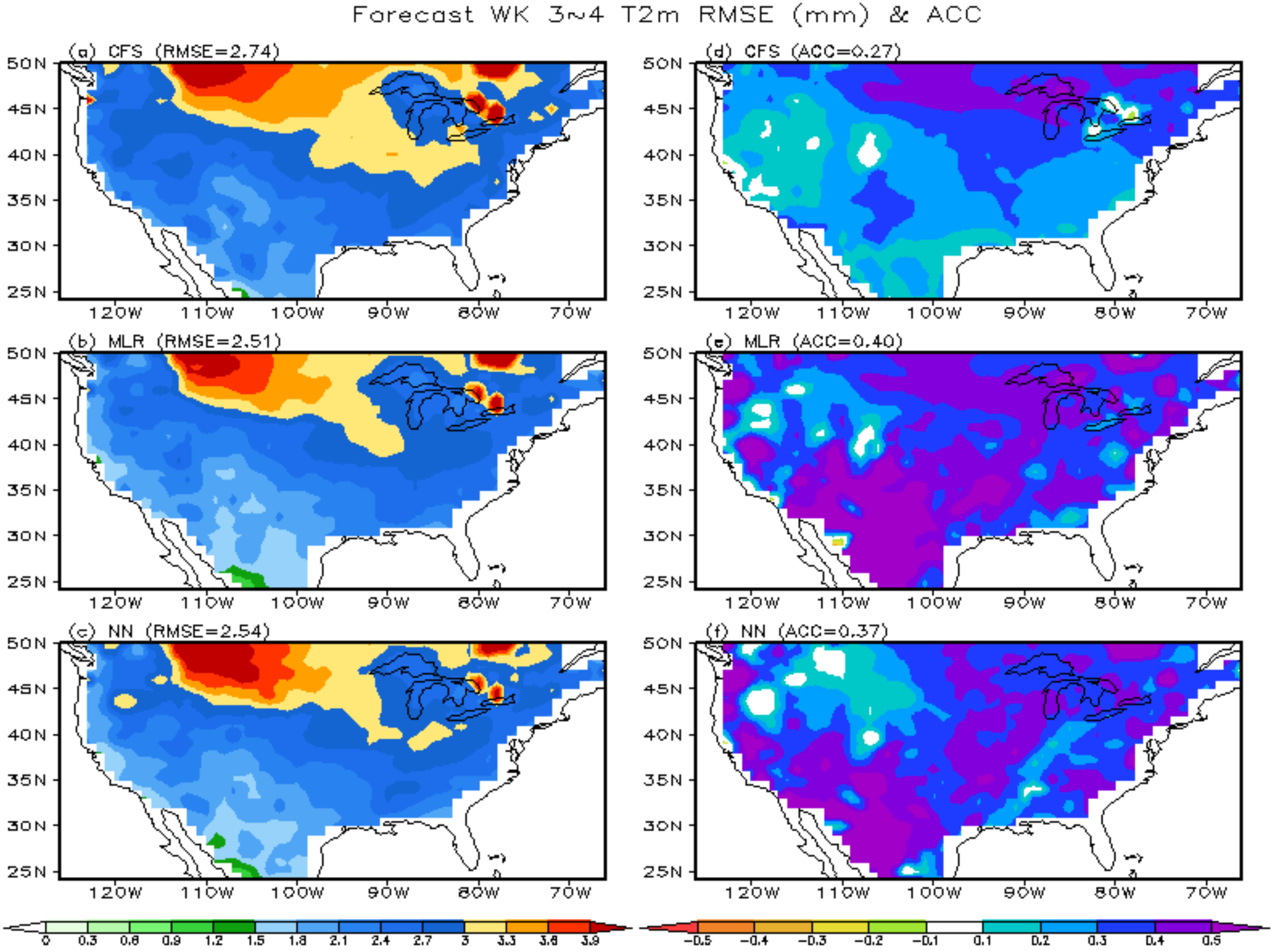


EOF Analysis of CFS Week 3-4 Ensemble Mean Precip Forecasts - Obs
35% var
PC1 EV=14%
PC2 EV=8%
PC3 EV=7%
PC4 EV=6%
50N
40N
30N
120W
100W
80W
2000
2002
2004
2006
2008
2010
2012
2014
2016
-30 -25 -20 -15 -10 -5 5 10 15 20 25 30



Predictors
Input layer
x_1
x_i
x_n
Hidden layer
t_1
t_j
t_k
Output layer
y_1
y_q
y_m
Predictands


Forecast WK 3~4 Prcp RMSE (mm) & ACC
(a) CFS (RMSE=27.96)
(b) MLR (RMSE=24.98)
(c) NN (RMSE=24.48)
(d) CFS (ACC=0.03)
(e) MLR (ACC=0.10)
(f) NN (ACC=0.15)
50N
45N
40N
35N
30N
25N
120W
110W
100W
90W
80W
70W
0 5 10 15 20 25 30 35 40 50 60 70 80 90
-0.5 -0.4 -0.3 -0.2 -0.1 0.1 0.2 0.3 0.4 0.5


Forecast WK 3~4 T2m RMSE (mm) & ACC
(a) CFS (RMSE=2.74)
(b) MLR (RMSE=2.51)
(c) NN (RMSE=2.54)
(d) CFS (ACC=0.27)
(e) MLR (ACC=0.40)
(f) NN (ACC=0.37)
50N
45N
40N
35N
30N
25N
120W
110W
100W
90W
80W
70W
0
0.3
0.6
0.9
1.2
1.5
1.8
2.1
2.4
2.7
3
3.3
3.6
3.9
-0.5
-0.4
-0.3
-0.2
-0.1
0.1
0.2
0.3
0.4
0.5

Summary

1. NN advantages: flexible nonlinear tool & easy to maintain
2. NN show some improvement on CFS week 3~4 precipitation over MLR
3. Encouraging improvement on CFS Week 3~4 precipitation achieved with unique & more beneficial NN architectures