A New Synergetic Paradigm in Environmental Numerical Modeling: Hybrid Models Combining Deterministic and Machine Learning Components

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Acknowledgments: W. Collins, P. Rasch, J. Tribbia (all NCAR), D. Chalikov (UMD)

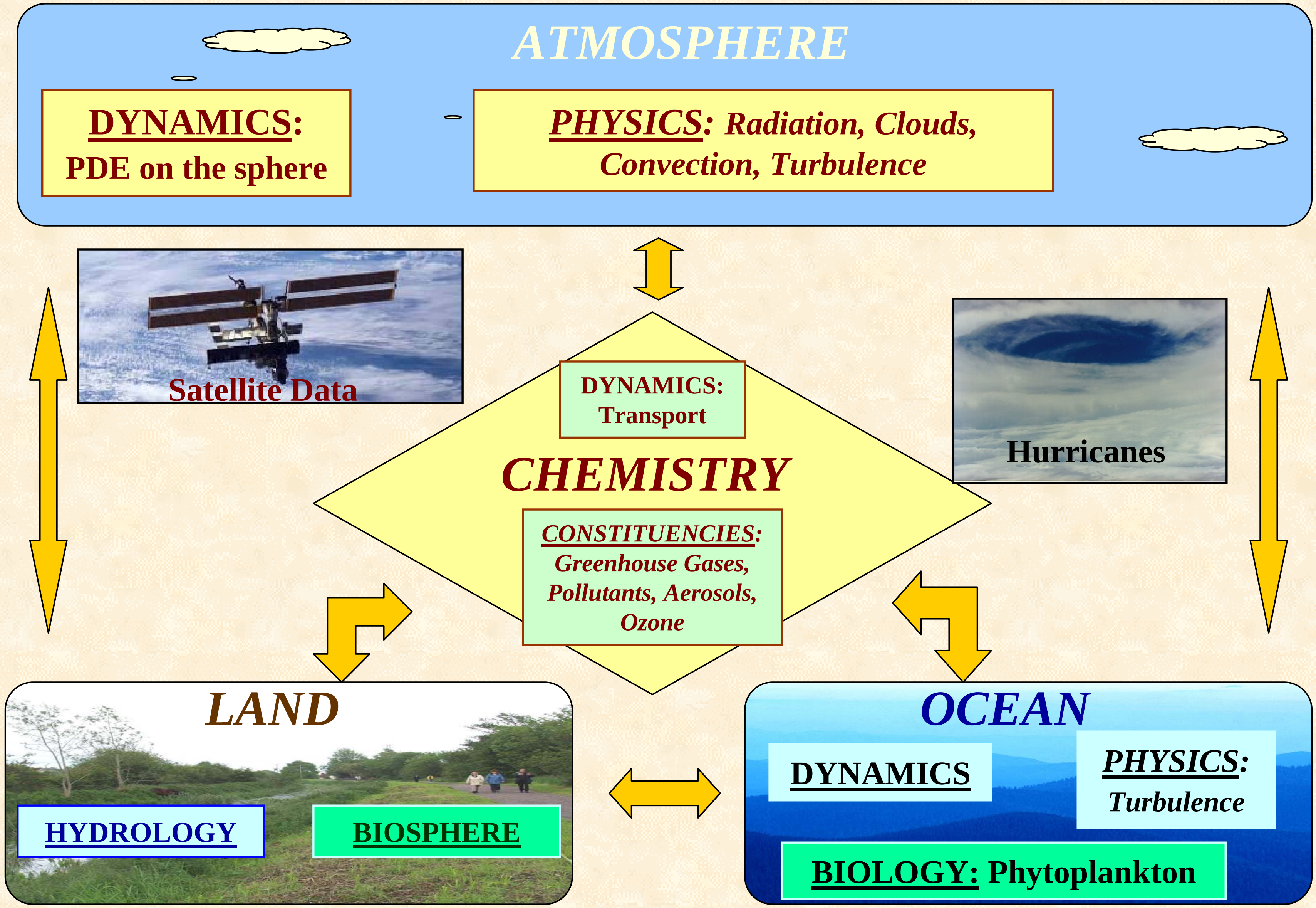
OUTLINE

- **INTRODUCTION. Motivation for the study: Complex Climate Model and its computational "Bottlenecks"**
- **APPROACH:**
  - **new hybrid model – combining <u>deterministic</u> modeling & <u>statistical</u> MLT (Machine Learning Techniques)**
  - **"*NeuroPhysics*" - NN Emulations for Model Physics Components**
- **NCAR CAM-2 Long-Wave Radiation (LWR):**
  - **Accuracy and Performance of NN Emulations**
  - **Comparison of CAM Climate Simulations: two 10 Year Parallel Runs with the Original LWR and its NN Emulation**
- **CONCLUSIONS & DISCUSSION**

Interdisciplinary Climate Model System

Climate Model - One of the Most Complex Existing Numerical Models

Interdisciplinary Complex Climate & Weather Systems



Climate Model (1)

The set of conservation laws (mass, energy, momentum, water vapor, ozone, etc.)

- ***Deterministic First Principles Models, 3-D Partial Differential Equations on the Sphere:***

$$\frac{\partial \psi}{\partial t} + D(\psi, x) = P(\psi, x)$$

  - ψ **- a 3-D prognostic/dependent variable, e.g., temperature**
  - ***x*** **- a 3-D independent variable: *x, y, z & t***
  - ***D*** **- dynamics (spectral or gridpoint)**
  - ***P*** **- physics or parameterization of physical processes (1-D vertical r.h.s. forcing)**
- ***Continuity Equation***
- ***Thermodynamic Equation***
- ***Momentum Equations***

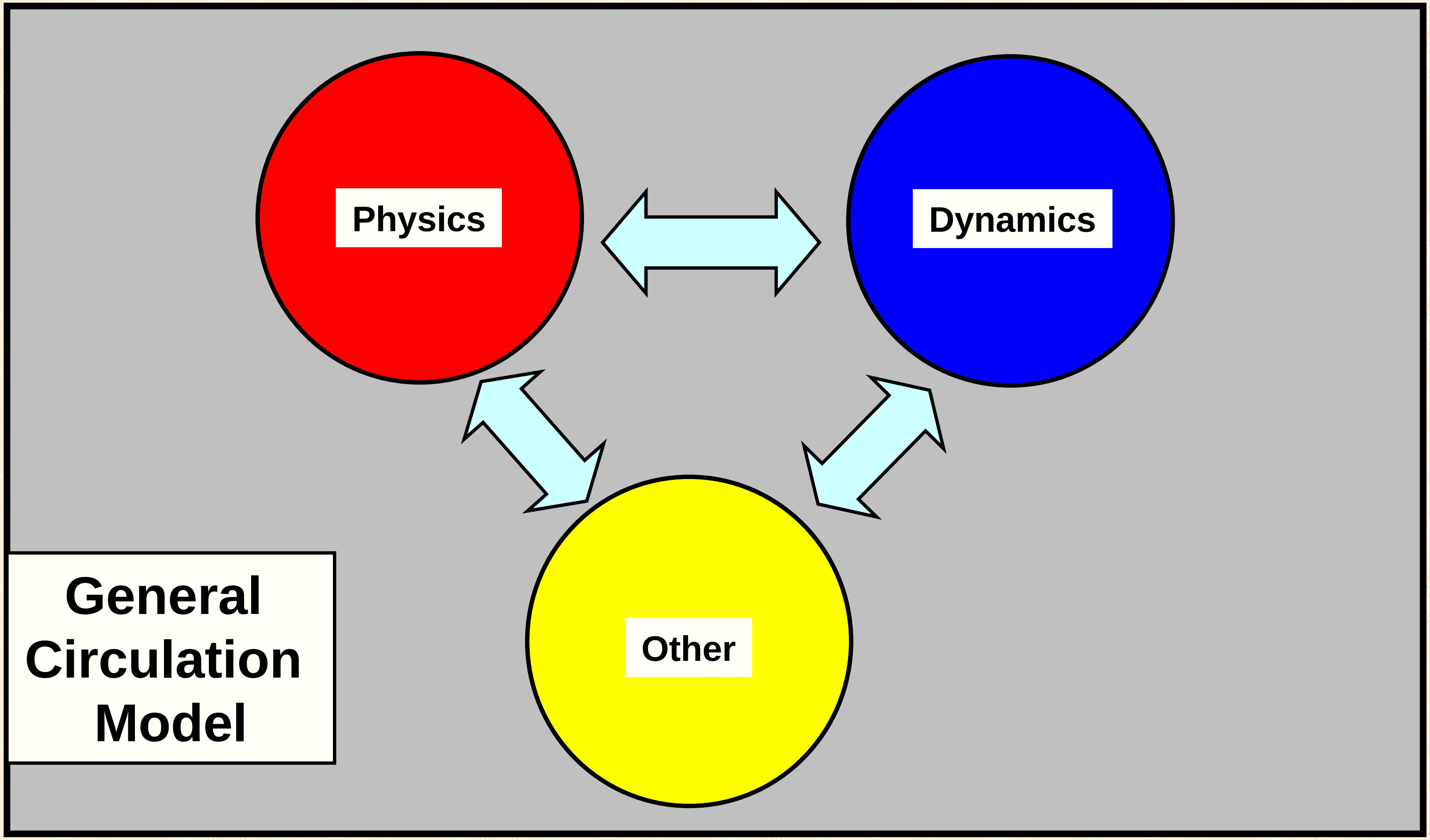
Climate Model (2)

Physics – P, currently represented by 1-D (vertical) parameterizations

- **Major components of *P* = {*R, W, C, T, S, CH*}:**
  - ***R* - radiation (long & short wave processes)**
  - ***W* – convection, and large scale precipitation processes**
  - **C - clouds**
  - ***T* – turbulence**
  - ***S* – surface model (land, ocean, ice – air interaction)**
  - ***CH* - chemistry**
- **Each component of *P* is a 1-D parameterization of complicated set of multi-scale theoretical and empirical physical process models *simplified for computational reasons***
- **P is the *most time consuming* part of climate models*!***

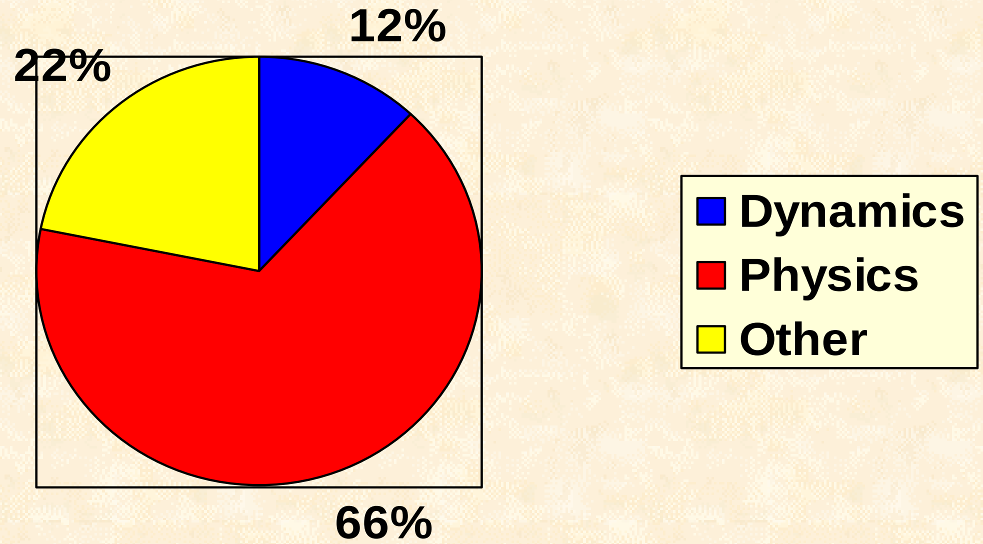
Structure of General Circulation Model

Interaction of Major Components

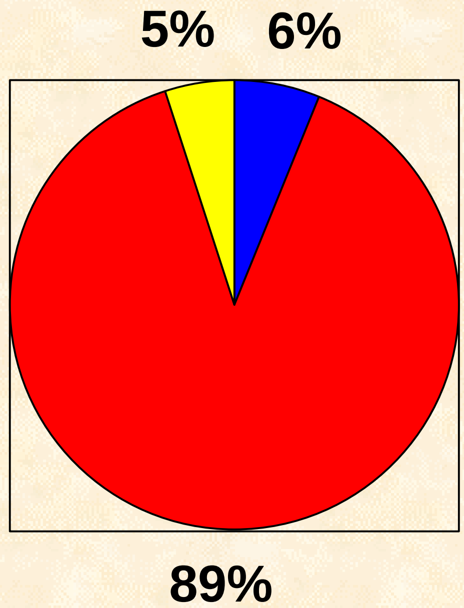


Distribution of Total Climate Model Calculation Time

Current NCAR Climate Model (T42 x L26): ~ 3° x 3.5°



Near-Term Upcoming Climate Models (estimated) : ~ 1° x 1°



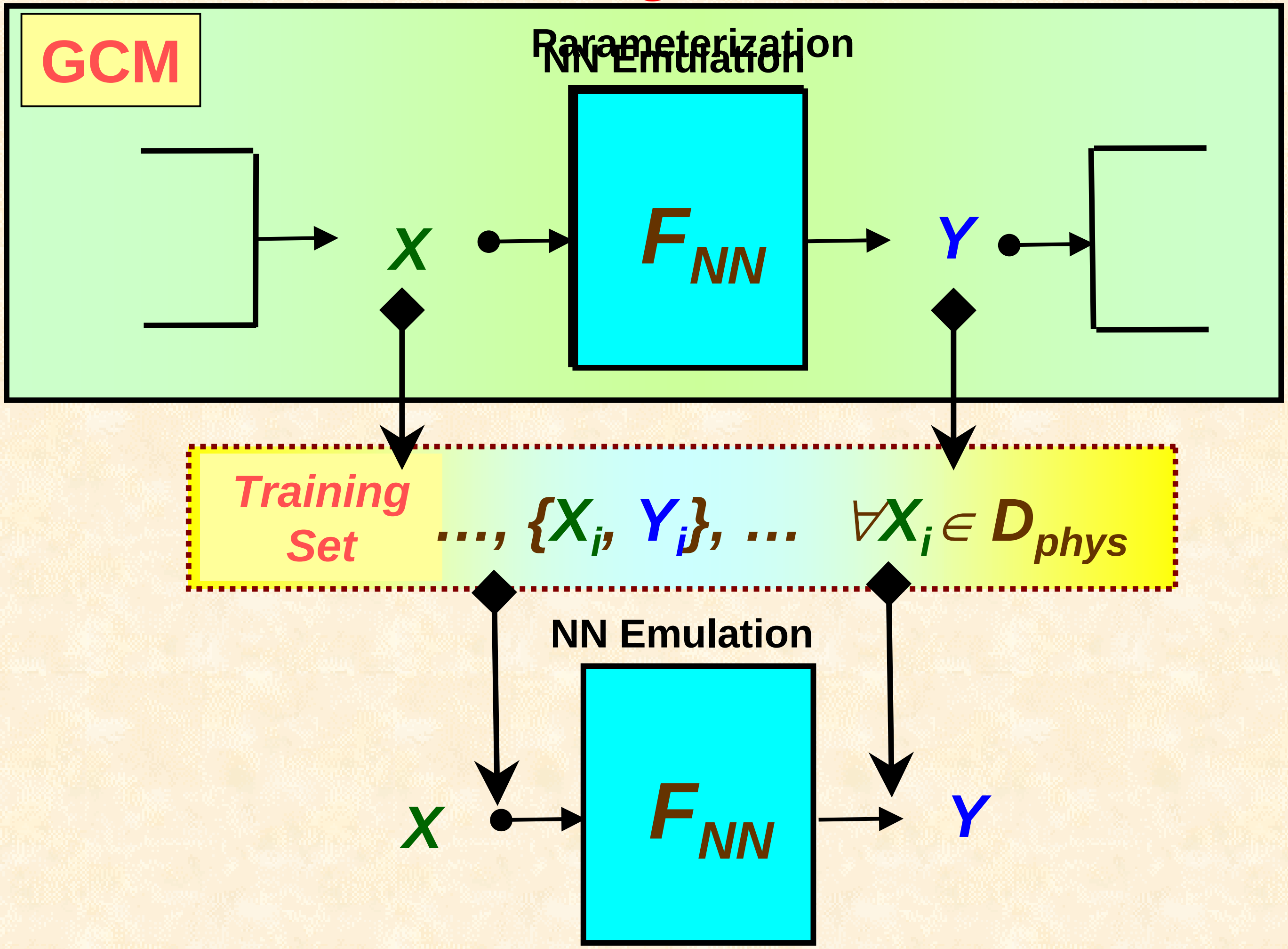
Approach

MLT/NN Emulations for Model Physics

Generic Solution – "NeuroPhysics"

Accurate and Fast NN Emulation for Parameterizations of Physics

Learning from Data



Major Advantages of NNs Relevant for Emulating Numerical Model Components:

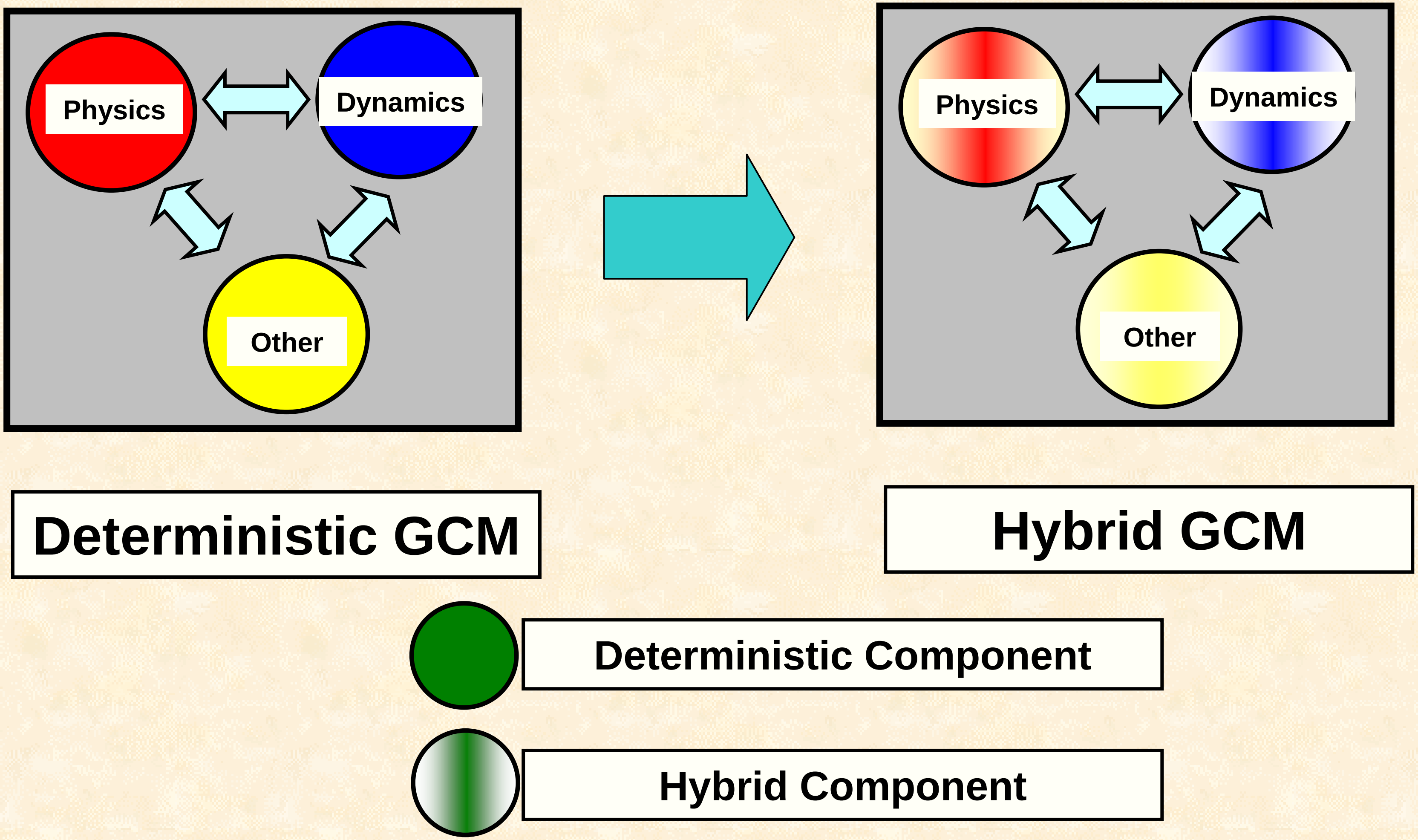
- NNs are very *generic, accurate and convenient* mathematical (statistical) models which are able to emulate numerical model components, which are complicated nonlinear input/output relationships (continuous or almost continuous mappings).
- NNs are ***robust*** with respect to random noise and fault- tolerant.
- NNs are *analytically differentiable* (training, error and sensitivity analyses): almost free Jacobian!
- NNs emulations are **accurate and fast but <u>NO FREE LUNCH</u>!**
- Training is complicated and time consuming nonlinear optimization task; <u>*however training should be done only once for a model version!*</u>
- Possibility of online adjustment
- NNs are well-suited for parallel and vector processing

Our applications >> usual applications in terms of complexity & dimensionality!

We reevaluated and adjusted all basic NN components & procedures correspondingly!

Change of Paradigm in Climate Modeling

From Deterministic to Hybrid Models



NEW METHODOLOGY HAS BEEN SUCSESSFULY APPLIED TO

- **Atmospheric Applications:**
  - **NCAR Radiation Parameterization**
  - **ECMWF Long Wave Radiation Parameterization; operational in ECMWF since 2003**
  - **Satellite Data Processing Component (SSM/I), operational NOAA/NCEP Global Data Assimilation System since 1998**
- **Oceanic Applications:**
  - **Ocean Model at NCEP: Equation of State (density and salinity of sea water)**
  - **Ocean Wind Wave Model at NCEP: Nonlinear Wave-Wave Interaction (superparameterization)**

NNs for NCAR CAM-2 Long Wave Radiation Parameterization

NN for NCAR CAM-2 Physics

CAM-2 Long Wave Radiation

- **Long Wave Radiative Transfer:**

$$F^{\downarrow}(p) = B(p_t) \cdot \varepsilon(p_t, p) + \int_{p_t}^{p} \alpha(p_t, p) \cdot dB(p')$$

$$F^{\uparrow}(p) = B(p_s) - \int_{p}^{p_s} \alpha(p, p') \cdot dB(p')$$

$$B(p) = \sigma \cdot T^4(p) \quad - \text{the Stefan} - \text{Boltzman relation}$$

- **Absorptivity & Emissivity (optical properties):**

$$\alpha(p, p') = \frac{\int_0^{\infty} \{dB_\nu(p') / dT(p')\} \cdot (1 - \tau_\nu(p, p')) \cdot d\nu}{dB(p) / dT(p)}$$

$$\varepsilon(p_t, p) = \frac{\int_0^{\infty} B_\nu(p_t) \cdot (1 - \tau_\nu(p_t, p)) \cdot d\nu}{B(p_t)}$$

$$B_\nu(p) \quad - \text{the Plank function}$$

Neural Network for NCAR LW Radiation

NN characteristics

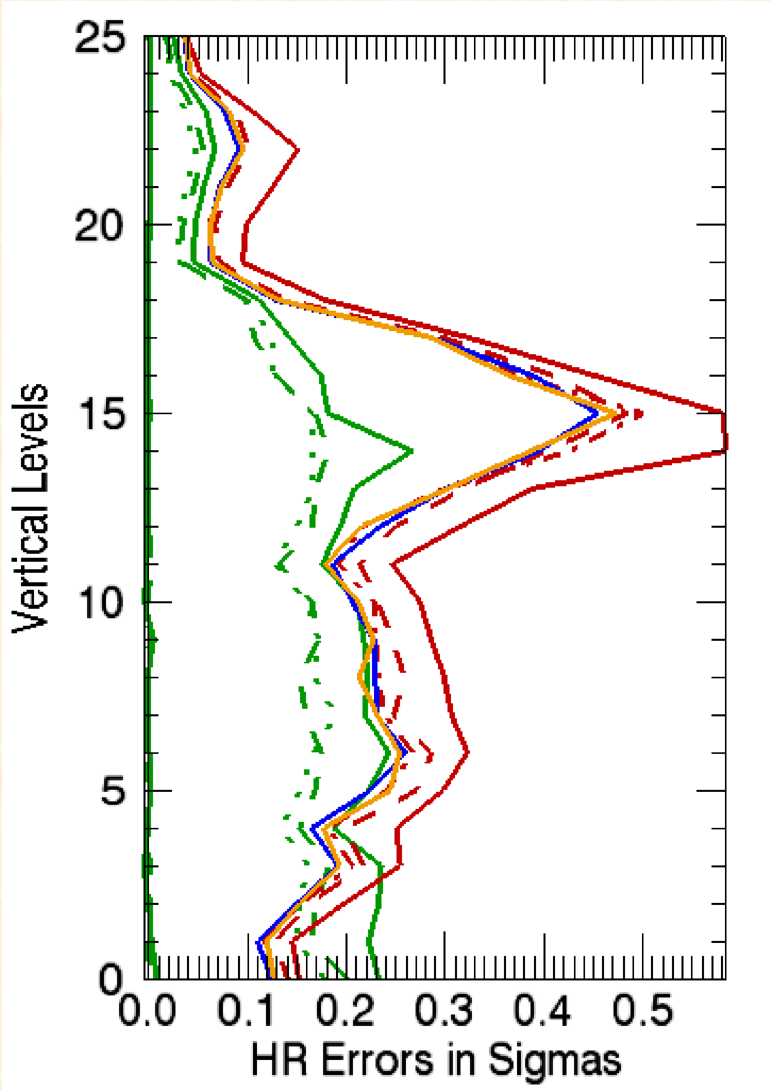
- **220 Inputs:**
  - ***Profiles:*** **temperature; humidity; ozone, methane, cfc11, cfc12, & N_2O mixing ratios, pressure, cloudiness, emissivity**
  - ***Relevant surface characteristics*****: surface pressure, upward LW flux on a surface - *flwupcgs***
- **33 Outputs:**
  - **Profile of heating rates (26)**
  - **7 LW radiation fluxes: *flns, flnt, flut, flnsc, flntc, flutc, flwds***
- **Hidden Layer: One layer with 90 to 300 neurons**
- **Training: *nonlinear optimization in the space with dimensionality of 30,000 to 100,000***
  - **Training Data Set: Subset of about 100,000 instantaneous profiles simulated by CAM-2 for the 1-st year**
  - **Training time: about 7 to 20 days (SGI workstation)**
  - **Training iterations: 2,000 to 10,000**
- **Validation on Independent Data:**
  - **Validation Data Set (independent data): about 100,000 instantaneous profiles simulated by CAM-2 for the 2-nd year**

NN Approximation Accuracy and Performance vs. Original Parameterization

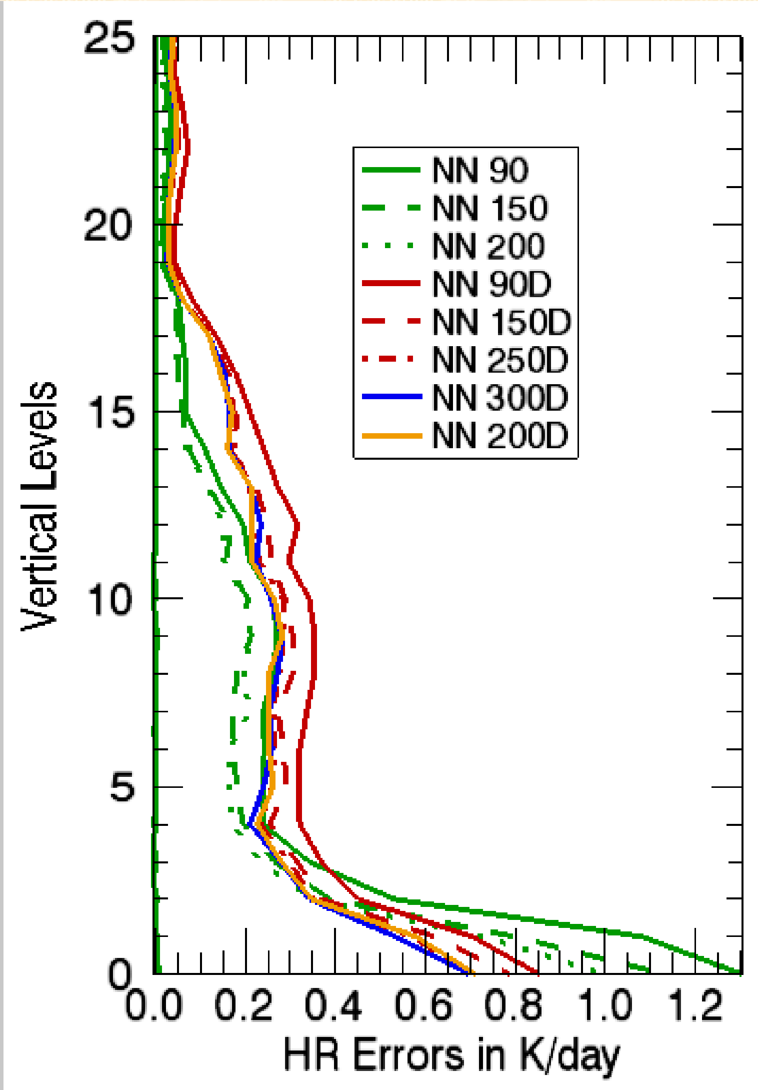
Parameter	Model	Bias	RMSE	Mean	σ	Performance
HR (°*K/day*)	NASA	$1.\ 10^{-4}$	0.32	1.52	1.46	
	NCAR	$3.\ 10^{-5}$	0.28	-1.40	1.98	~ **80** times faster
OLR (*W/m*²)	NASA	0.009	1.06	253.4	46.3	
	NCAR	0.01	1.2	240.5	46.9	

Errors and Variability Profiles

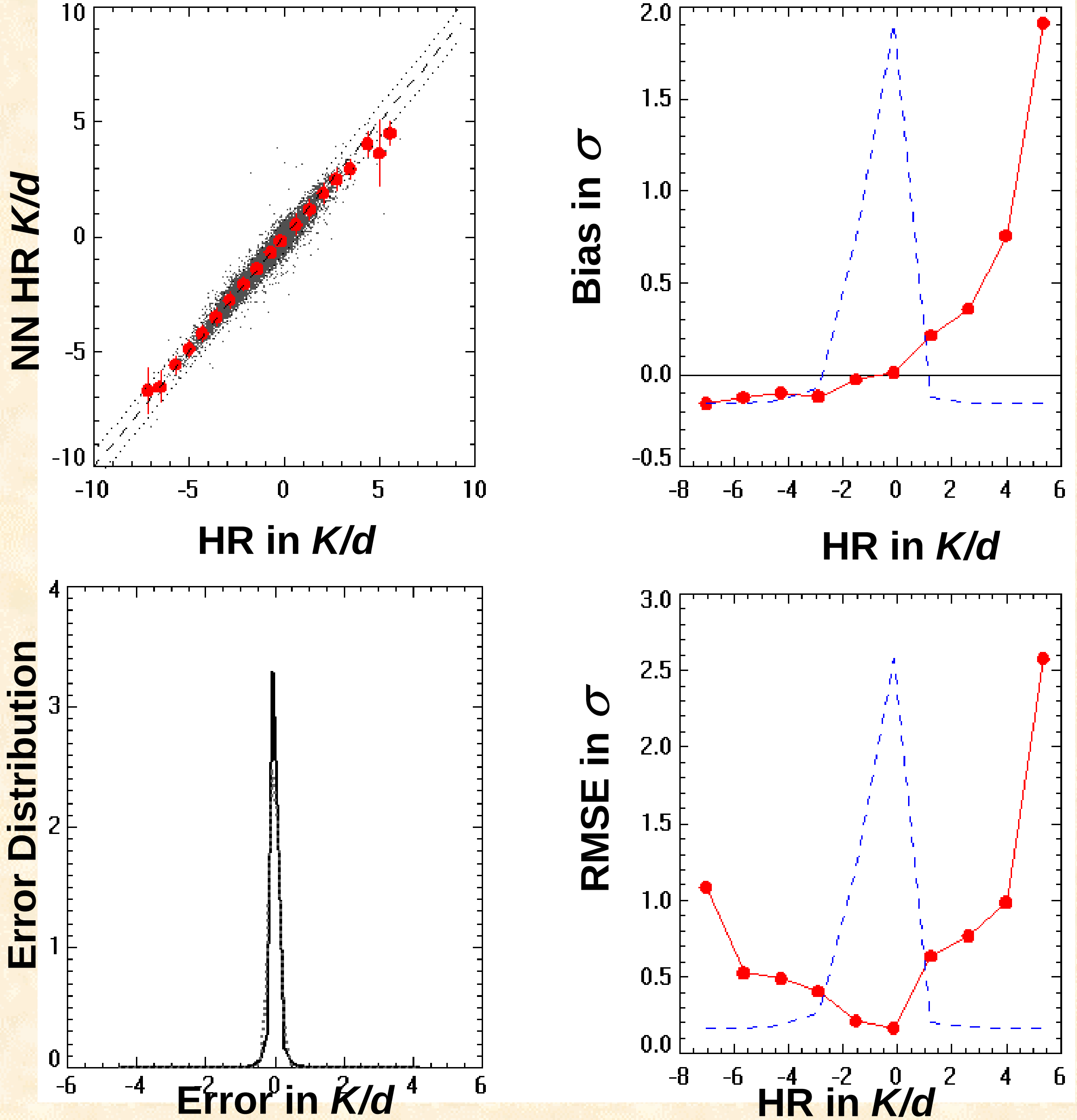
Bias and RMSE profiles in σ



Bias and RMSE Profiles in K/day



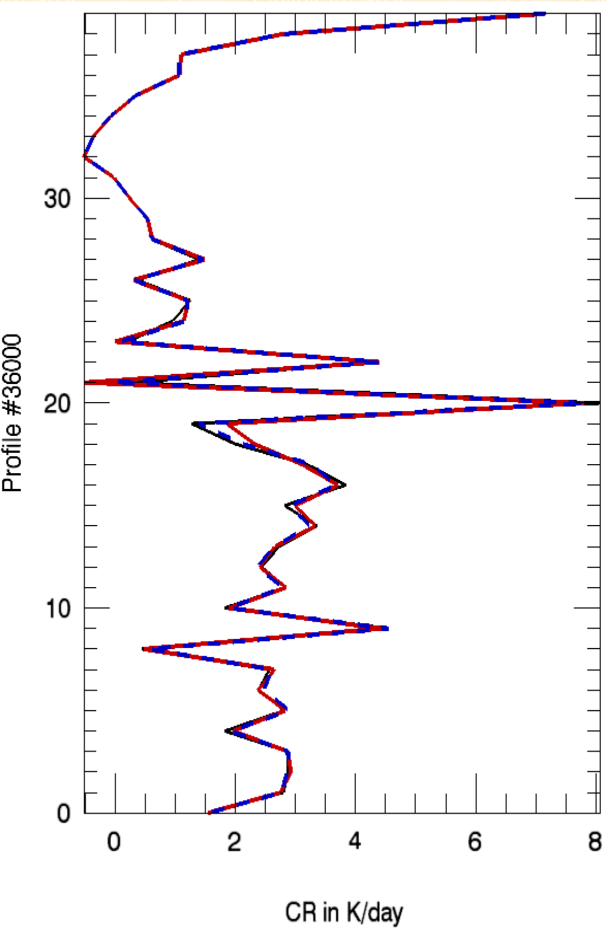
NN Approximation Accuracy: Typical

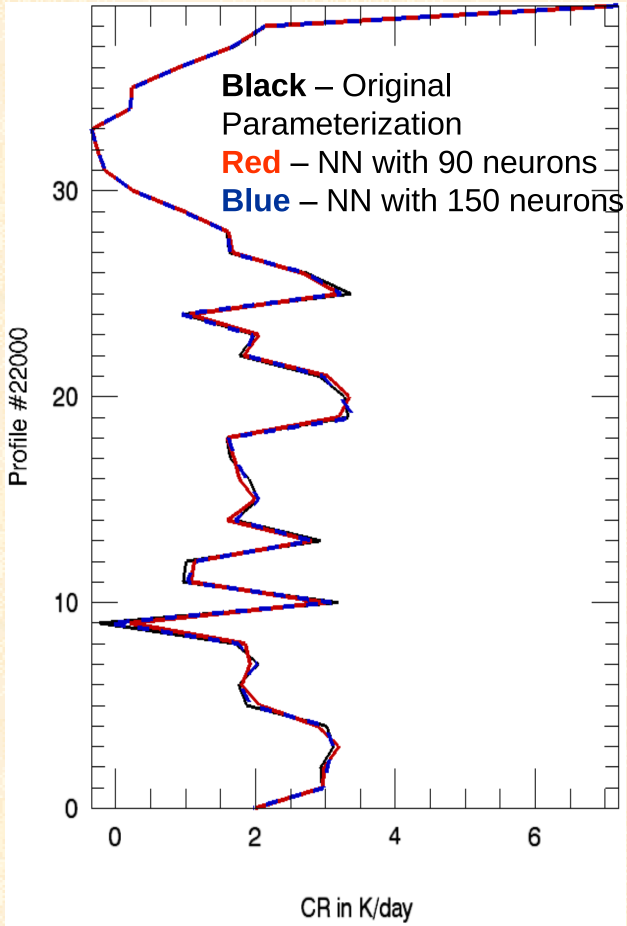


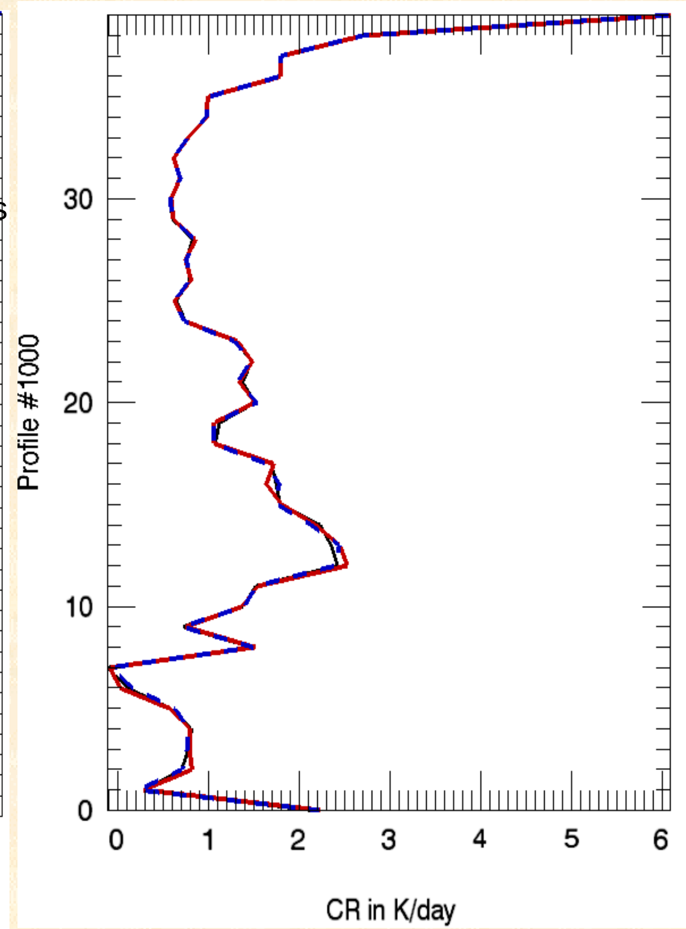
P ≅ 626 mb

Level Statistics For HRs	Orig. K/day	NN K/day
Min Val.	-7.7	-8.2
Max Val.	6.1	5.2
Mean	-0.779	-0.778
σ	0.27	0.26
Bias	-	$1.\times10^{-3}$
RMSE	-	0.145

Individual Profiles







PRMSE = 0.18 & 0.10 K/day

PRMSE = 0.11 & 0.06 K/day

PRMSE = 0.05 & 0.04 K/day

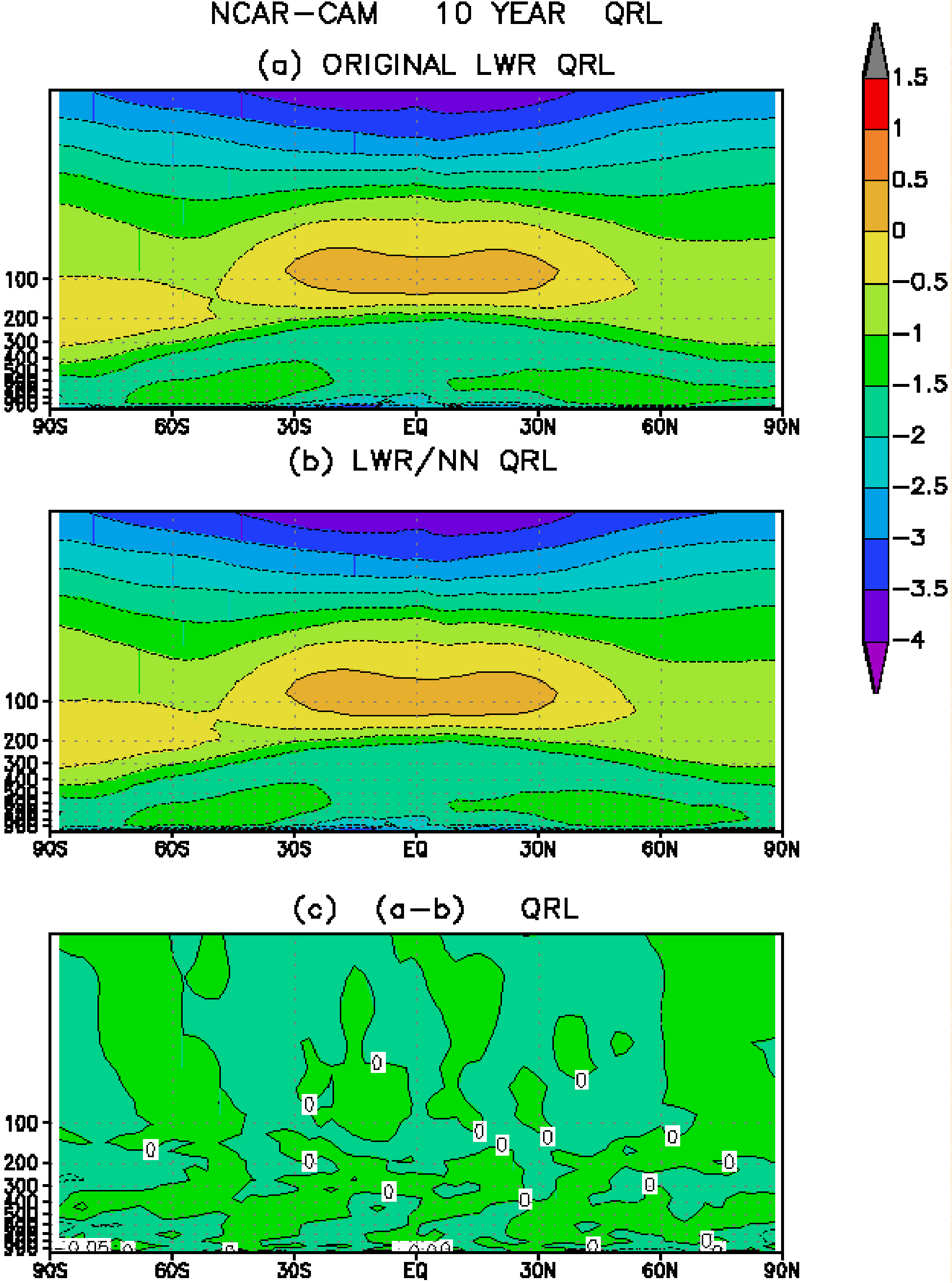
NCAR CAM-2: 10 YEAR EXPERIMENTS

- **CONTROL: the standard NCAR CAM version (available from the CCSM web site) with the original Long-Wave Radiation (LWR) (e.g. Collins, JAS, v. 58, pp. 3224-3242, 2001)**
- **LWR/NN: the hybrid version of NCAR CAM with NN emulation of the LWR (Krasnopolsky, Fox-Rabinovitz, and Chalikov, 2004, submitted; Fox-Rabinovitz, Krasnopolsky, and Chalikov, 2004 to be submitted)**

PRESERVATION of *Global Annual Means*

Parameter	Original LWR Parameterization	NN Approximation	Difference in %
Mean Sea Level Pressure (*hPa*)	1011.480	1011.481	0.0001
Surface Temperature (*°K*)	289.003	289.001	0.0007
Total Precipitation (*mm/day*)	2.275	2.273	0.09
Total Cloudiness (*fractions 0.1 to 1.*)	0.607	0.609	0.3
LWR Heating Rates (*°K/day*)	-1.698	-1.700	0.1
Outgoing LWR – OLR (*W/m^2*)	234.4	234.6	0.08
Latent Heat Flux (*W/m^2*)	82.84	82.82	0.03

Zonal Mean Vertical Distributions
and
Differences Between the Experiments



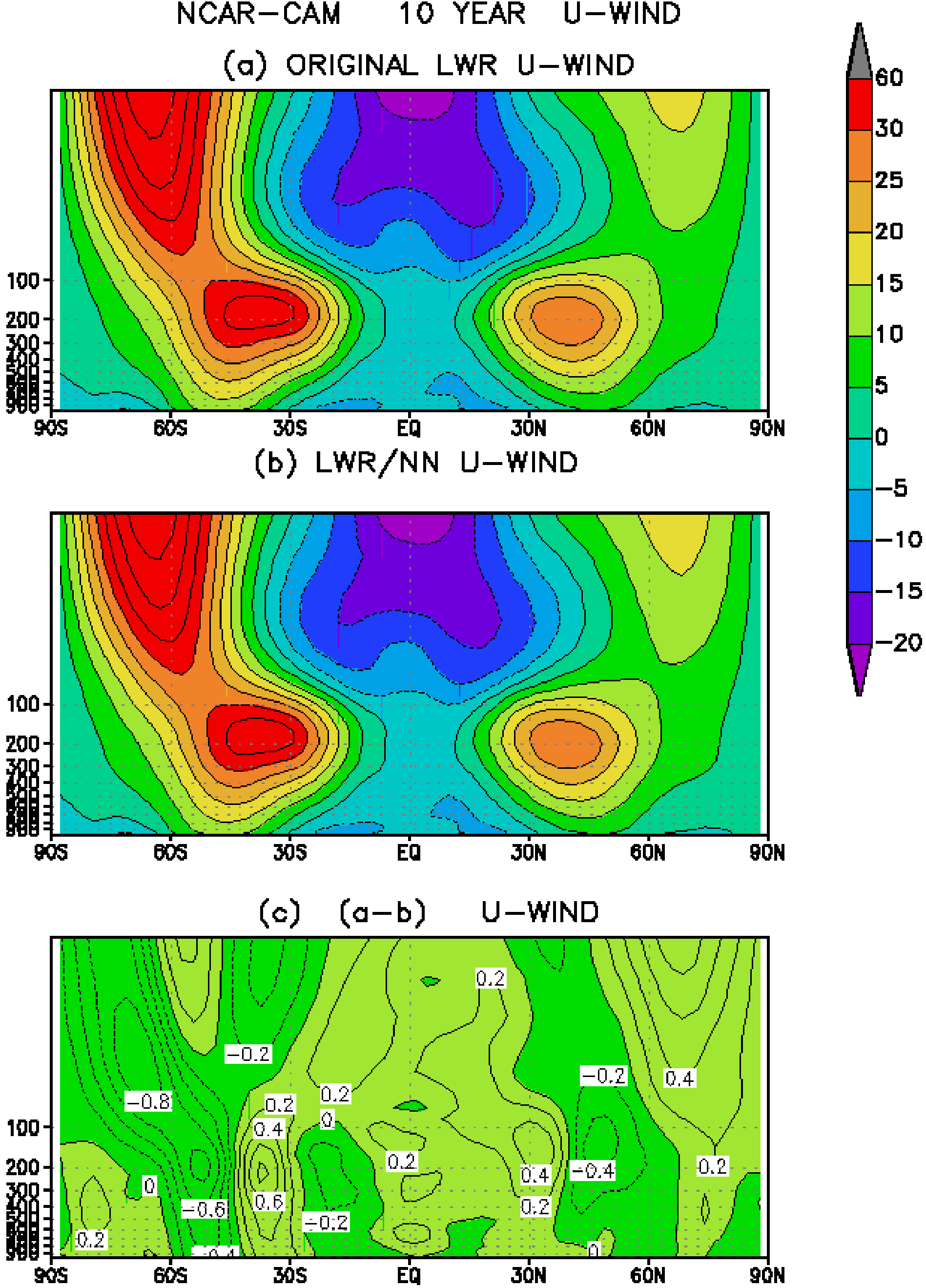
NCAR CAM-2 Zonal Mean Heating Rates 10 Year Average

(a)– Original LWR Parameterization

(b)- NN Approximation

(c)- Difference (a) – (b), contour = 0.05 °*K/day*

all in °*K/day*



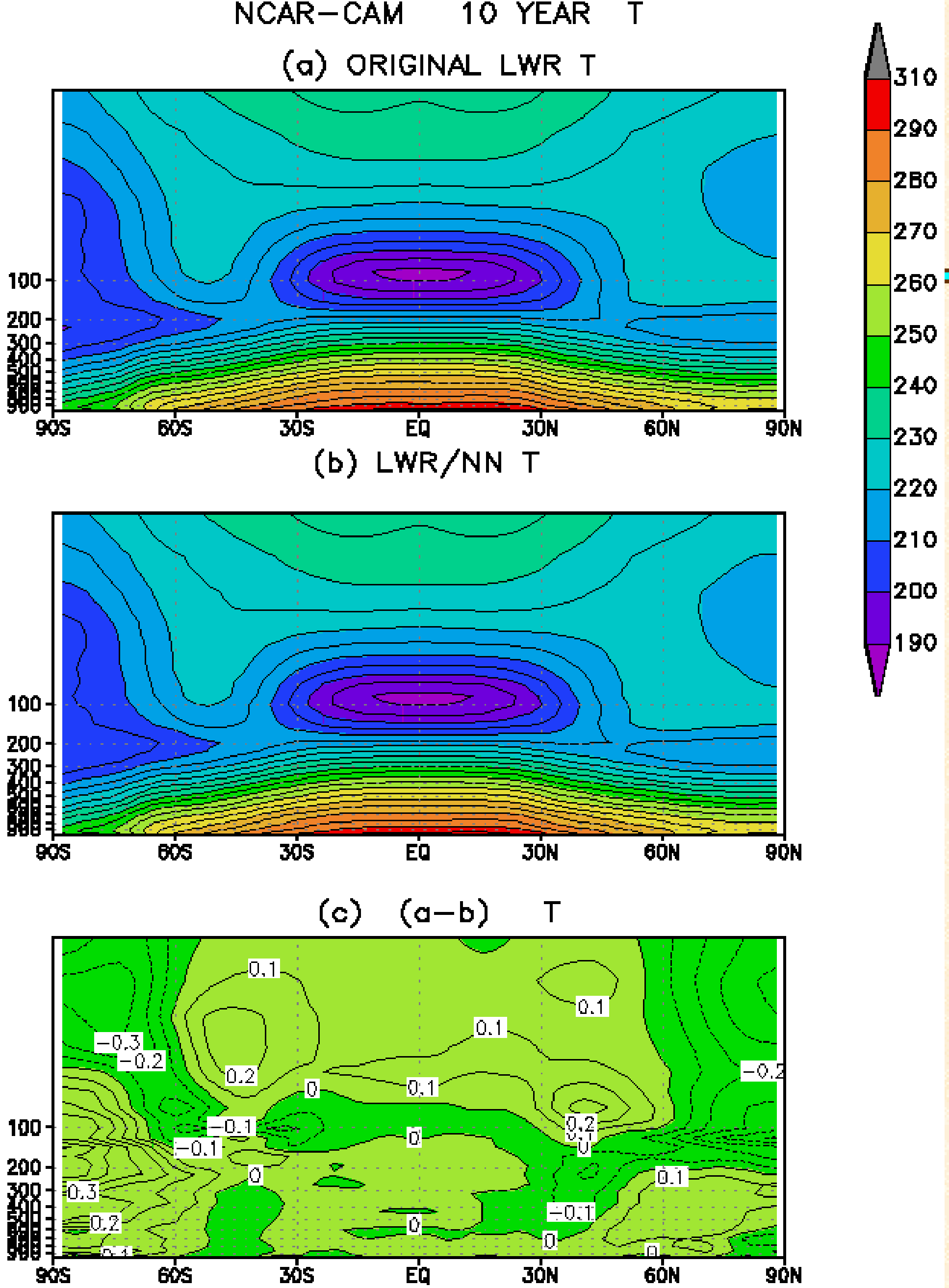
NCAR CAM-2 Zonal Mean U 10 Year Average

(a)– Original LWR Parameterization

(b)- NN Approximation

(c)- Difference (a) – (b), contour 0.2 *m/sec*

all in *m/sec*



NCAR CAM-2 Zonal Mean Temperature 10 Year Average

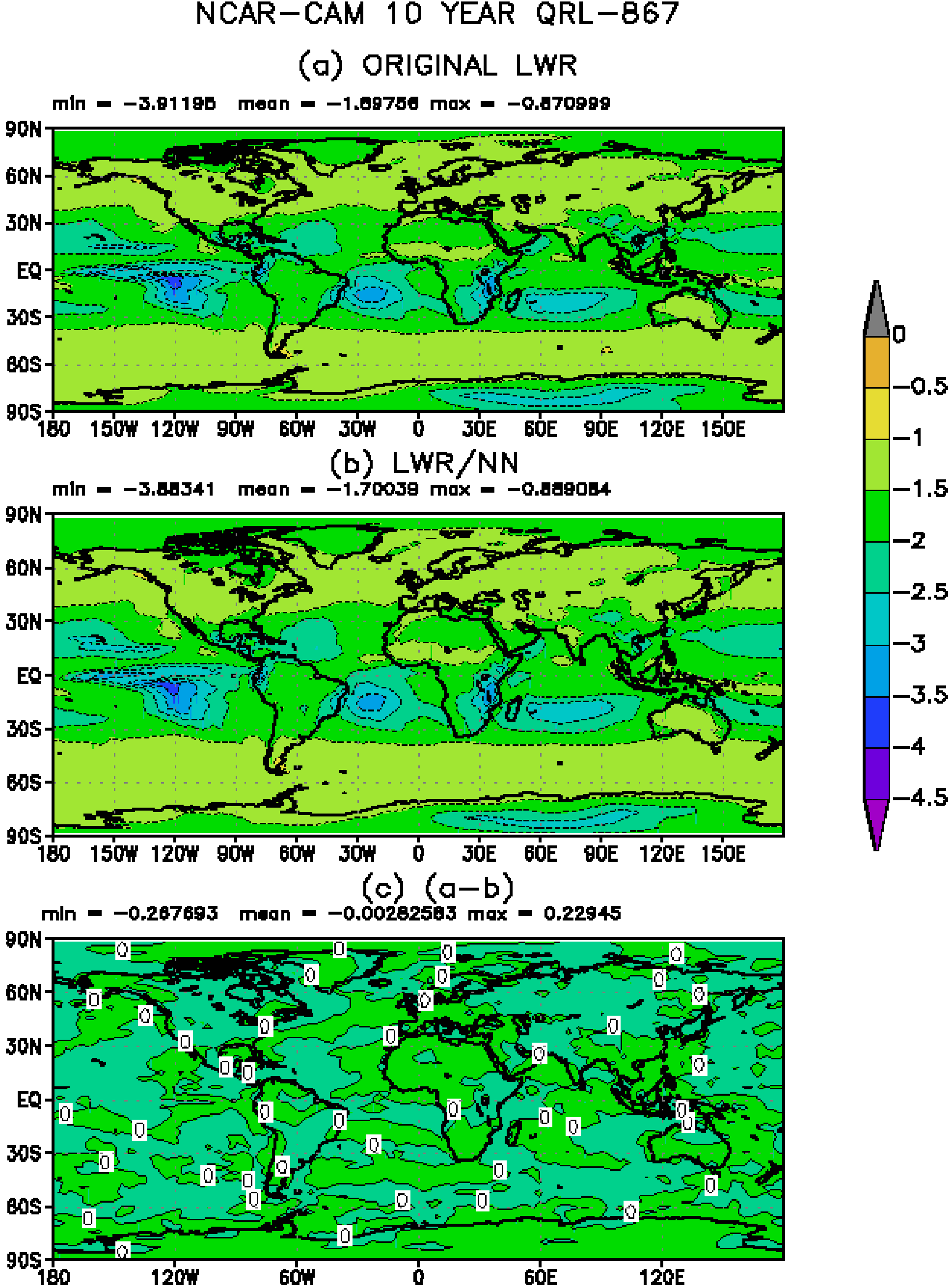
(a)– Original LWR Parameterization

(b)- NN Approximation

(c)- Difference (a) – (b), contour 0.1 °K

all in °K

Horizontal Distributions of Model Diagnostics



NCAR CAM-2 LWR Heating Rates (near 850 hPa) 10 Year Average

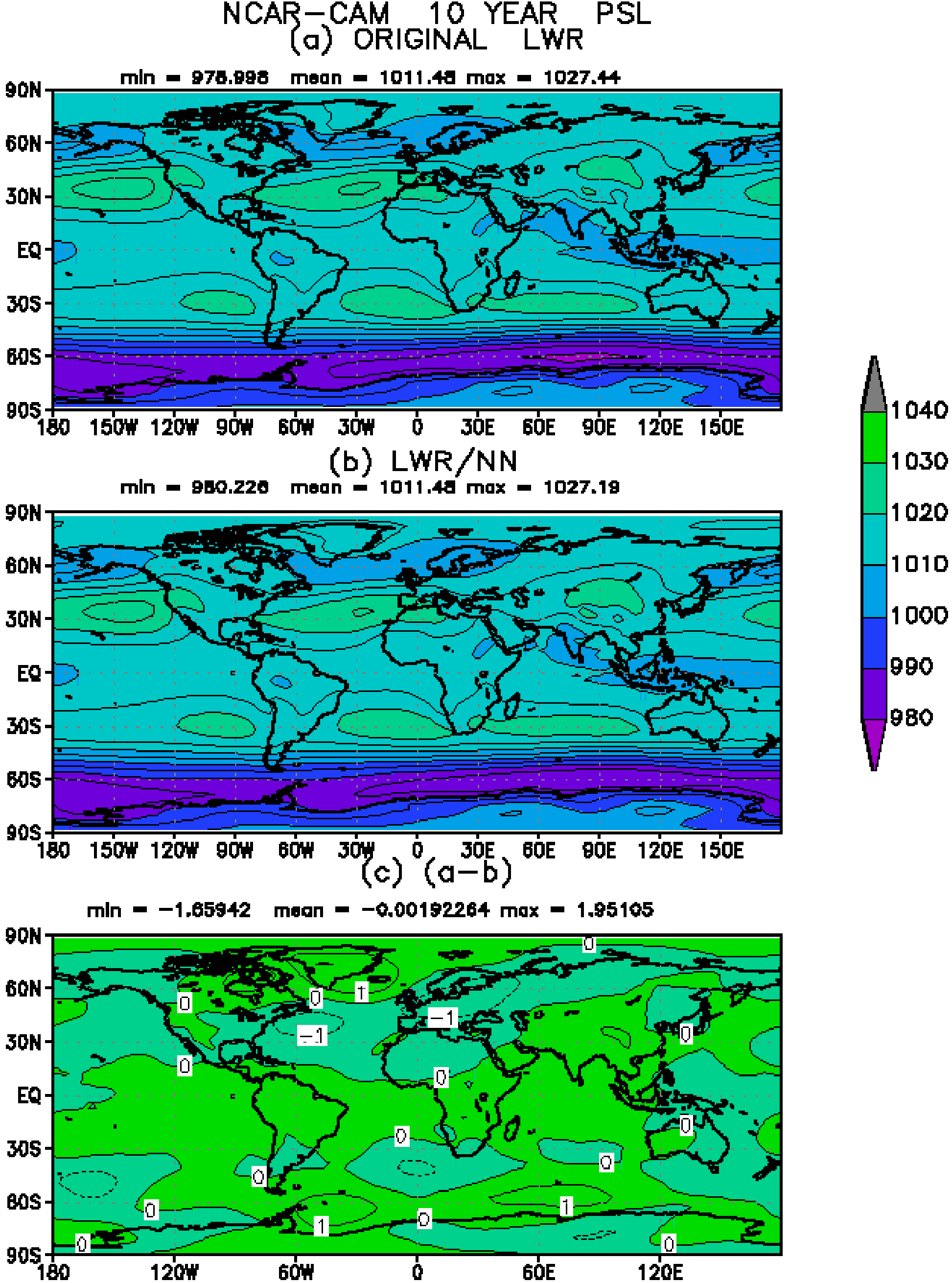
(a)– Original LWR Parameterization

(b)- NN Approximation

(c)- Difference (a) – (b)

all in *K/day*

	Mean	Min	Max
(a)	-1.7	-3.9	-0.87
(b)	-1.7	- 3.9	-0.89
(c)	-0. 003	-0. 27	0.23



NCAR CAM-2 Sea Level Pressure 10 Year Average

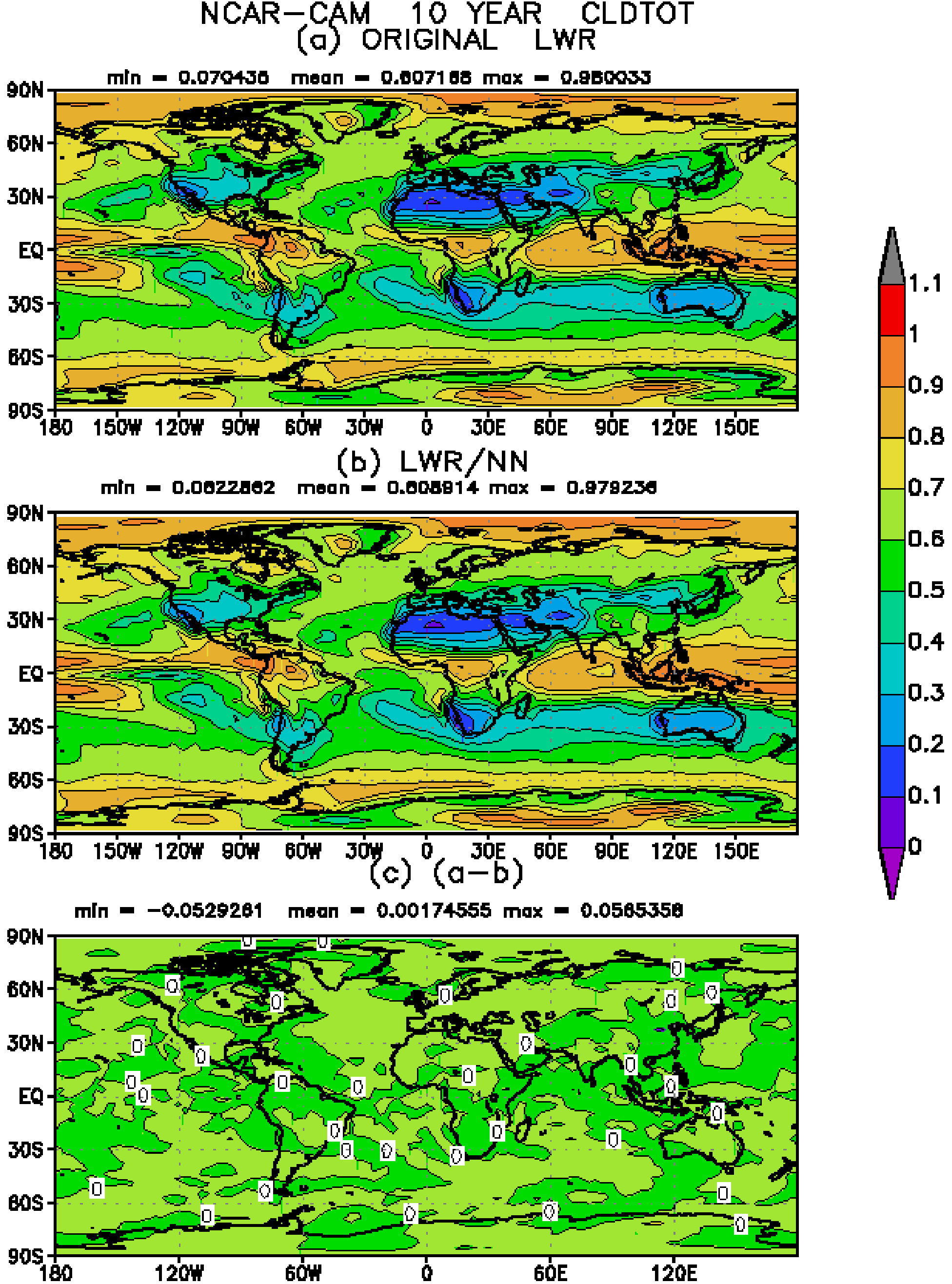
(a)– Original LWR Parameterization

(b)- NN Approximation

(c)- Difference (a) – (b),

all in *hPa*

	Mean	Min	Max
(a)	**1011.48**	**979.00**	**1027.44**
(b)	**1011.48**	**980.23**	**1027.19**
(c)	**-0.002**	**-1.66**	**1.95**



NCAR CAM-2 Total Cloudiness 10 Year Average

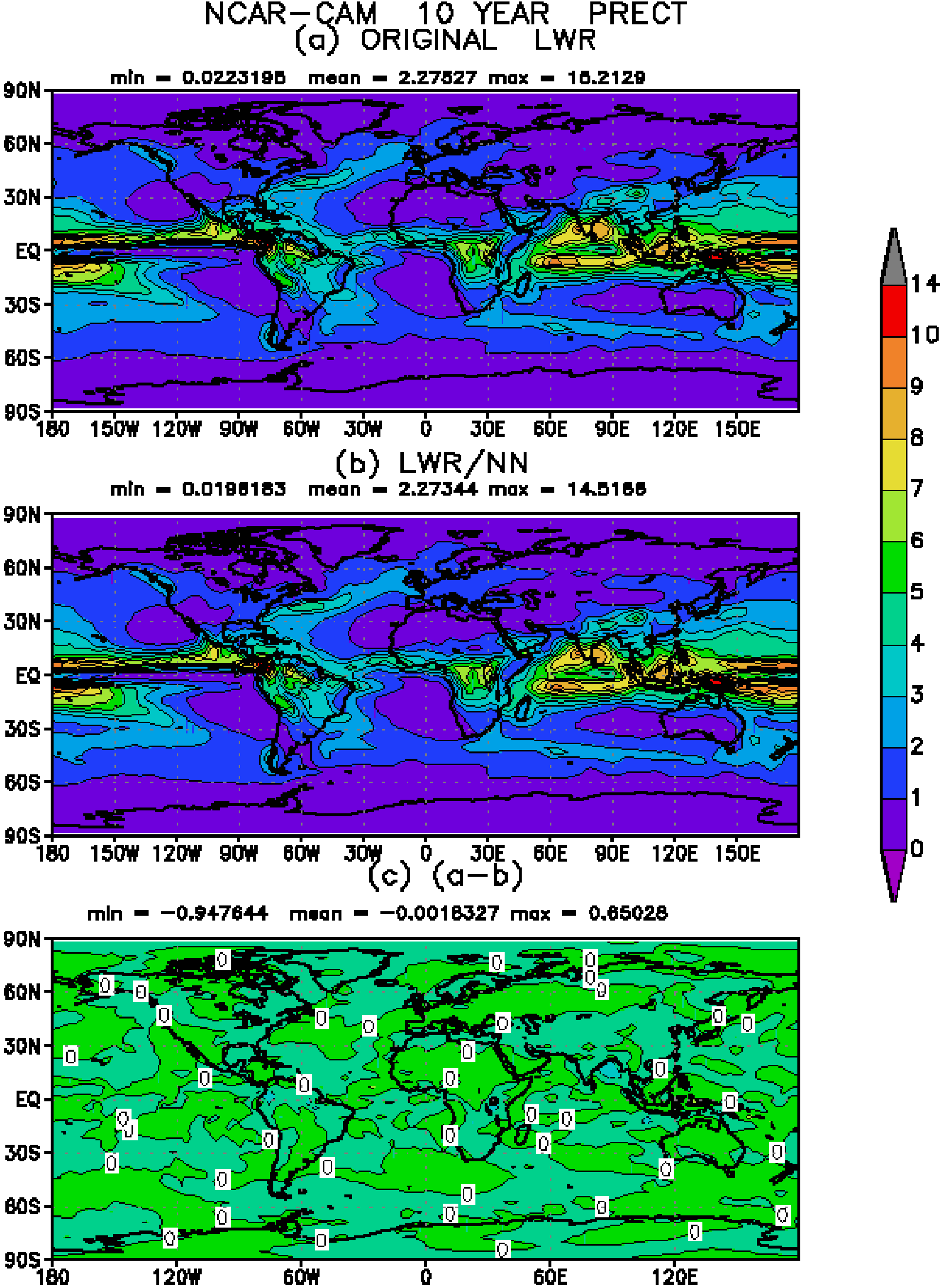
(a)– Original LWR Parameterization

(b)- NN Approximation

(c)- Difference (a) – (b),

all *in fractions*

	Mean	Min	Max
(a)	0.607	0.07	0.98
(b)	0.608	0.06	0.98
(c)	0.002	-0.05	0.05



NCAR CAM-2 Total Precipitation 10 Year Average

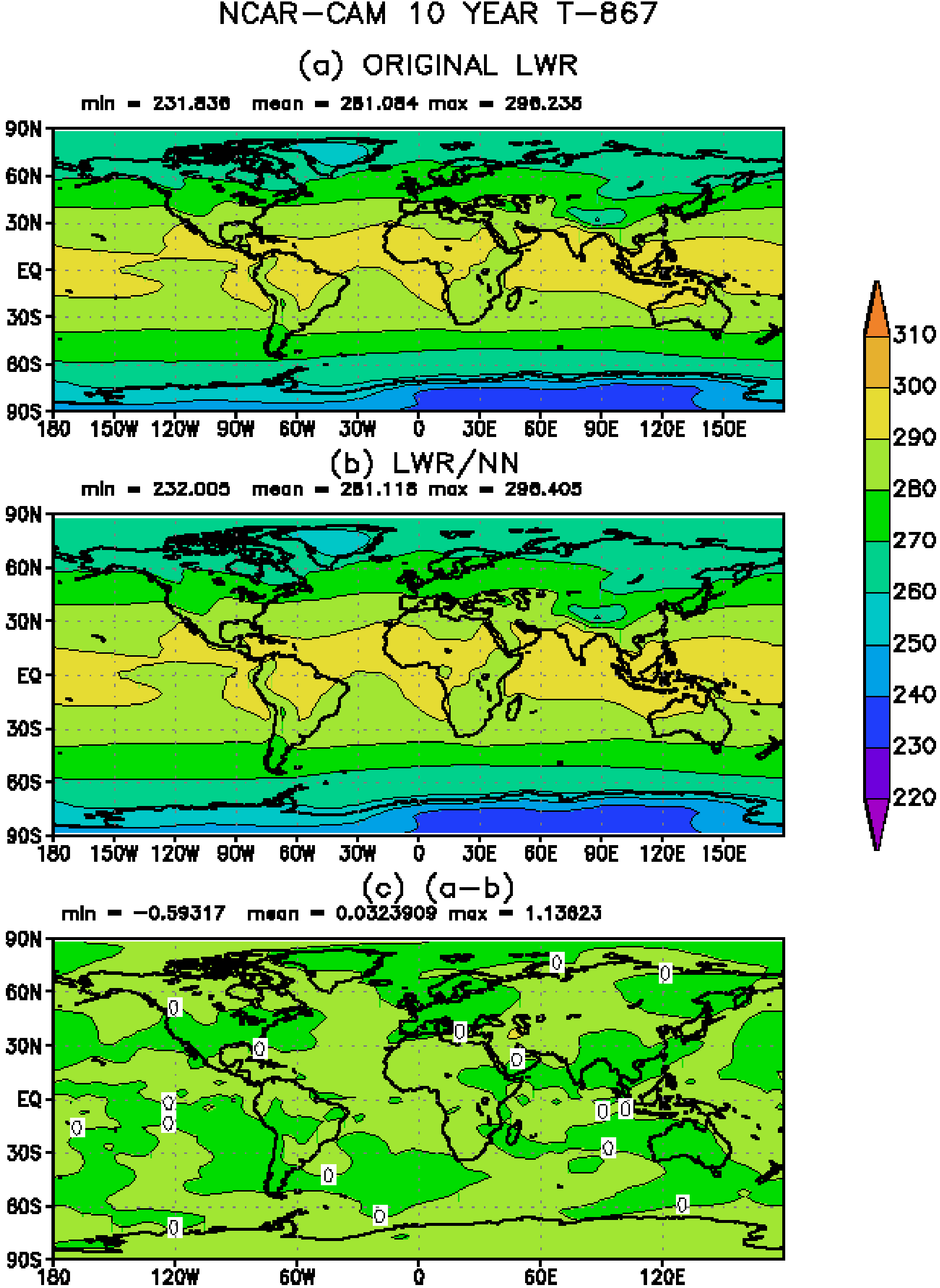
(a)– Original LWR Parameterization

(b)- NN Approximation

(c)- Difference (a) – (b), all in *mm/day*

	Mean	Min	Max
(a)	2.275	0.022	15.213
(b)	2.273	0.02	14.52
(c)	0.002	0.94	0.65

Horizontal Distributions of Model Prognostics



NCAR CAM-2 Temperature (near 850 hPa) 10 Year Average

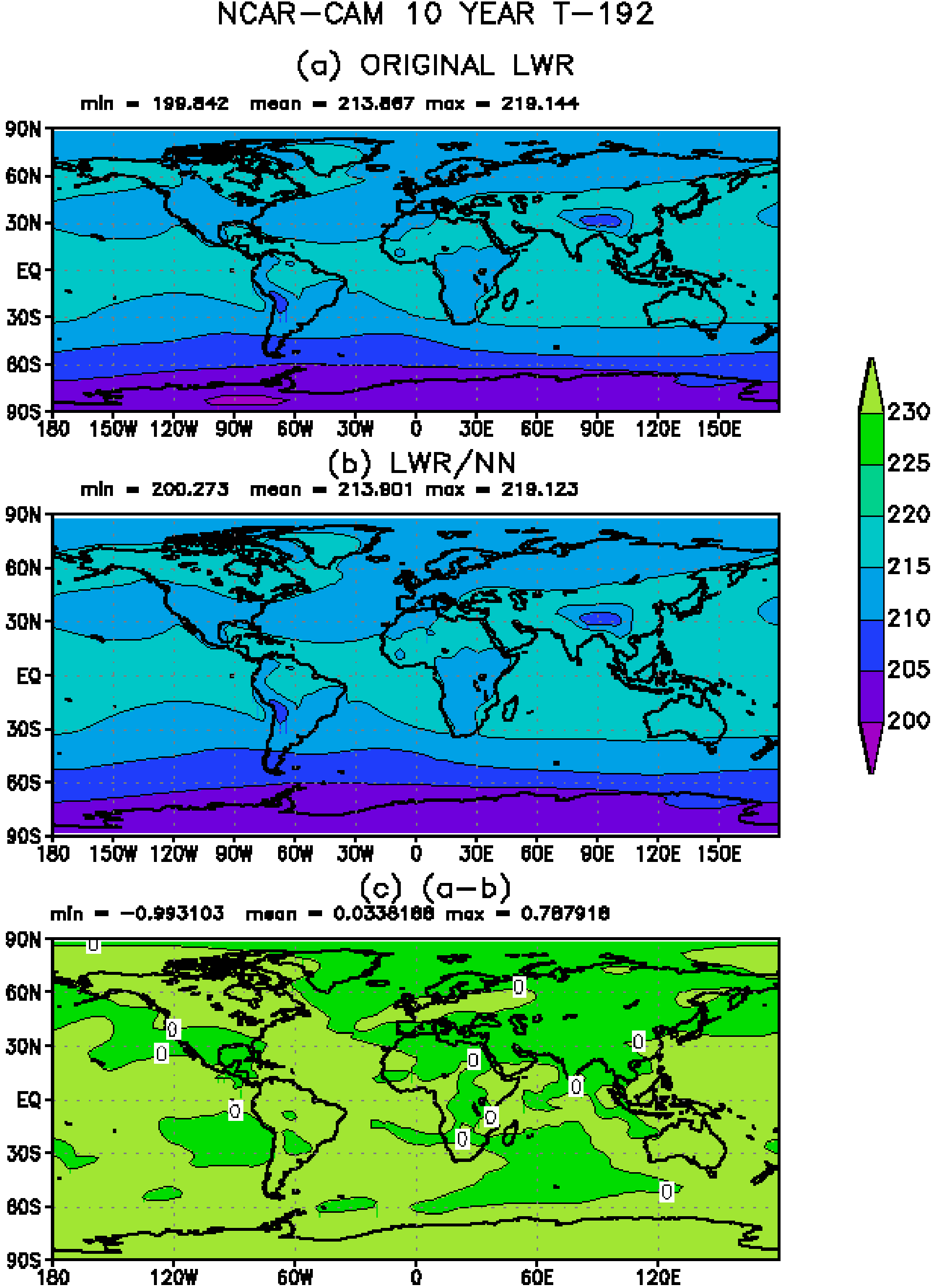
(a)– Original LWR Parameterization

(b)- NN Approximation

(c)- Difference (a) – (b)

all in °K

	Mean	Min	Max
(a)	281.1	231.84	298.24
(b)	281.1	232.0	296.4
(c)	-0.03	-0.6	1.1



NCAR CAM-2 Temperature (near 200 hPa) 10 Year Average

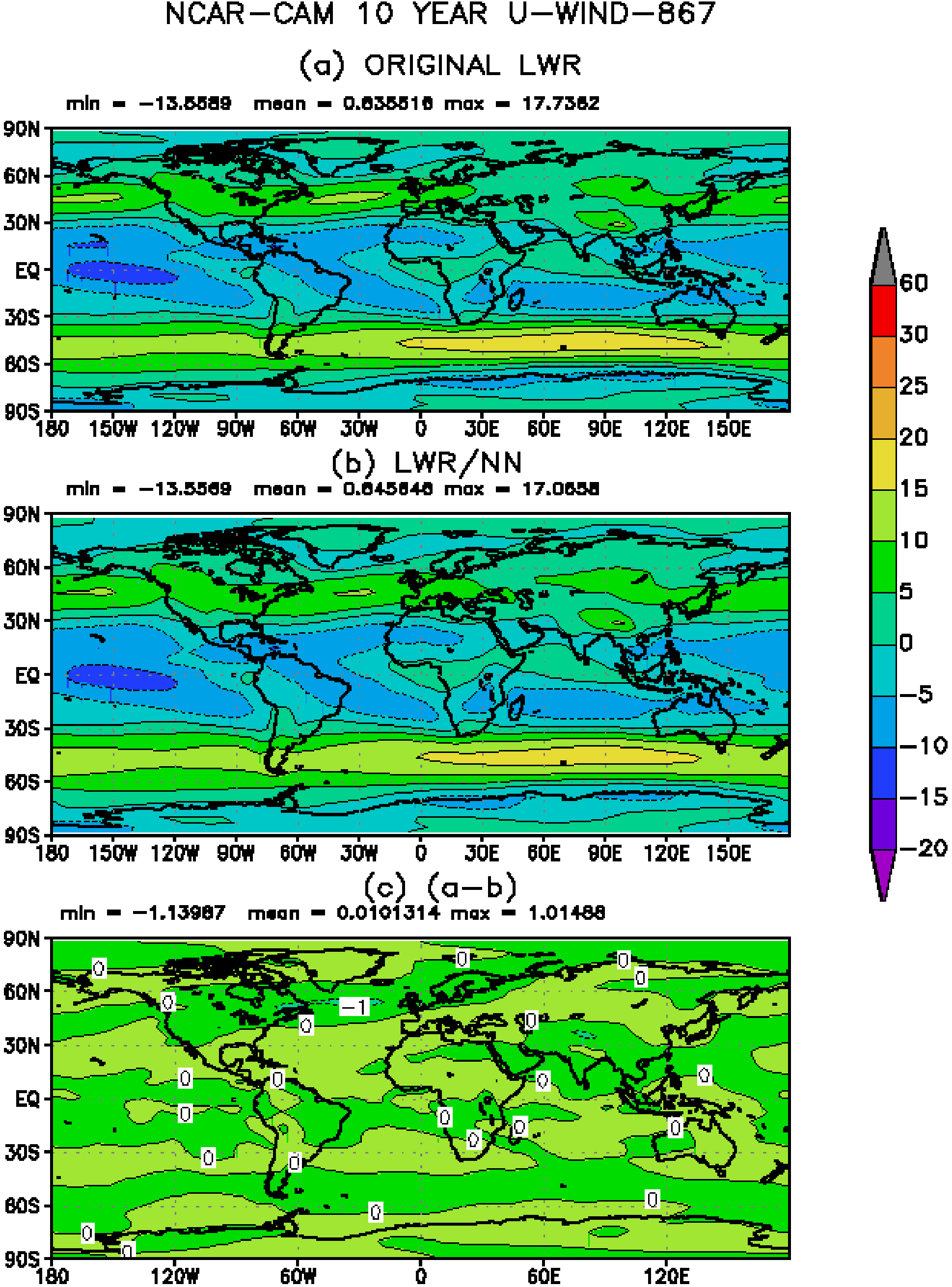
(a)– Original LWR Parameterization

(b)- NN Approximation

(c)- Difference (a) – (b)

all in °K

	Mean	Min	Max
(a)	**213.87**	**199.8**	**219.14**
(b)	**213.90**	**200.3**	**219.12**
(c)	**0.03**	**-0.99**	**0.79**



NCAR CAM-2 U (near 850 hPa) 10 Year Average

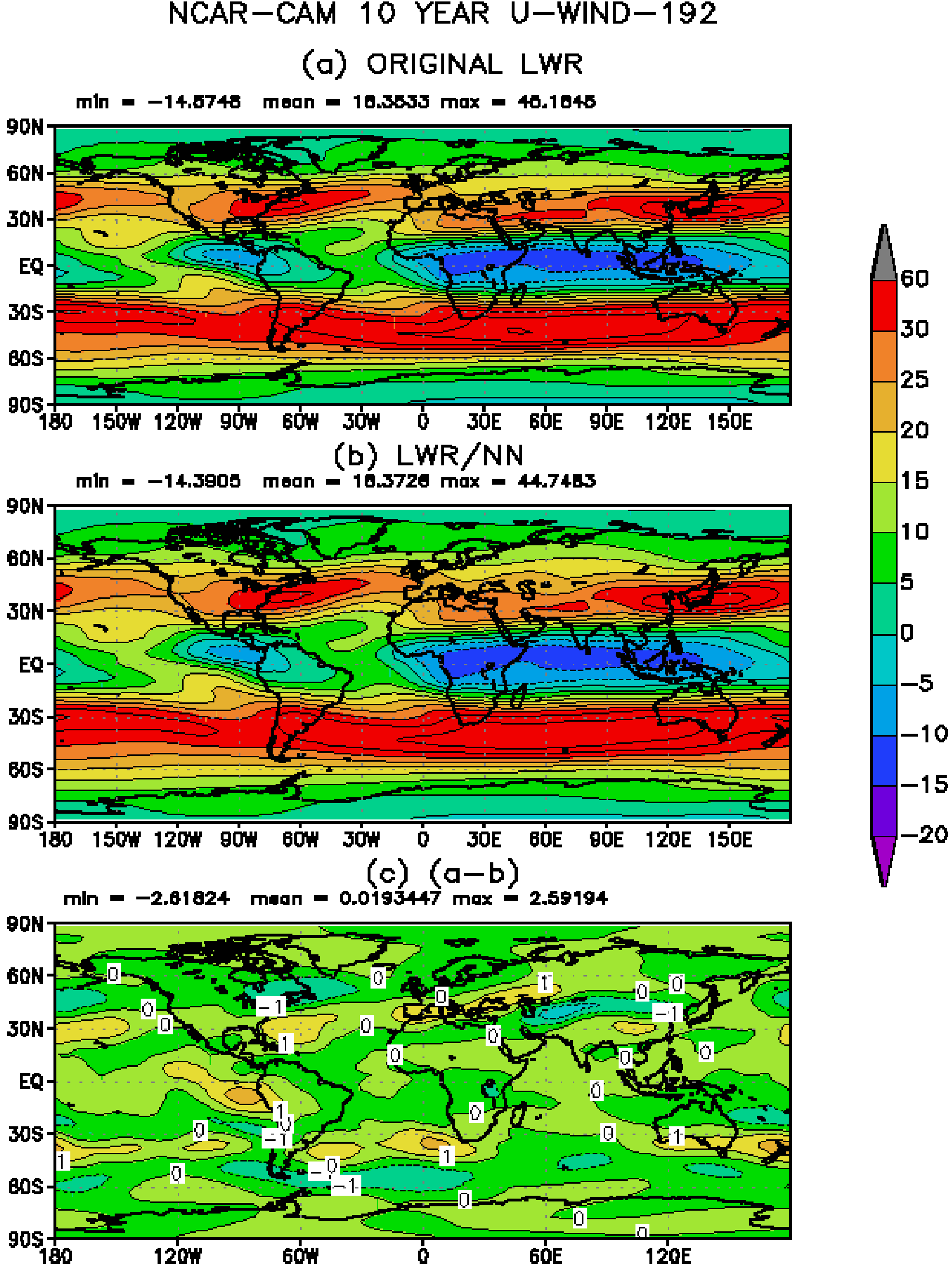
(a)– Original LWR Parameterization

(b)- NN Approximation

(c)- Difference (a) – (b)

all in *m/sec*

	Mean	Min	Max
(a)	0.64	-13.56	17.74
(b)	0.65	-13.56	17.1
(c)	-0.01	-1.14	1.01



NCAR CAM-2 U (near 200 hPa) 10 Year Average

(a)– Original LWR Parameterization

(b)- NN Approximation

(c)- Difference (a) – (b)

all in *m/sec*

	Mean	Min	Max
(a)	16.35	-14.57	45.16
(b)	16.37	-14.39	44.75
(c)	-0.02	-2.62	2.59

CONCLUSIONS:

- **The proof of concept:** Application of MLT/ NN for fast and accurate emulation of model physics components has been successfully demonstrated for the NCAR CAM LWR parameterization **and other applications**.
- NN emulation of the NCAR CAM LWR is ***80 times faster*** and **very close** to the original LWR parameterization (for other applications up to **10^5 faster**). Speed-up only in the high/adequate accuracy context.
- The simulated diagnostic and prognostic fields are **very close** for the parallel NCAR CAM climate runs with NN emulation and the original LWR parameterization
- The **conservation properties** are **very well preserved**
- **A solid scientific foundation is laid** for development of MLT/NN emulations for other NCAR CAM physics components or a complete set of MLT/"Neuro-Physics". Such a **focused effort** will result in development of a **Hybrid CAM.**

Computational gains can be used for:

- **More frequent** calculation of model physics for temporal consistence with model dynamics
- Introducing **more sophisticated physics**
- Introducing **higher model resolution**
- Using **larger ensembles**
- Improving **turnaround** for model runs
- **Speed-up** must be considered only in the high/adequate **accuracy** context!

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Special Session on NN Applications to Earth Sciences

Deadline: January 31, 2005

If you'd like to participate, email to: **Vladimir.Krasnopolsky@noaa.gov**

DEVELOPED APPROACH HAS BEEN PUBLISHED IN:

- **Fox-Rabinovitz, Krasnopolsky, and Chalikov, 2004: “Decadal climate simulations using NN emulations for long wave radiation parameterization”, to be submitted**
- **Krasnopolsky V.M., M.S. Fox-Rabinovitz, and D.V. Chalikov, 2004: “New Approach to Calculation of Atmospheric Model Physics: Accurate and Fast Neural Network Emulation of Long Wave Radiation in a Climate Model”, submitted**
- **Krasnopolsky V.M. and M.S. Fox-Rabinovitz, 2004: “A New Synergetic Paradigm in Environmental Numerical Modeling: Hybrid Environmental Numerical Models Consisting of Deterministic and Machine Learning Components”, submitted**
- **Tolman, H., V. Krasnopolsky, D. Chalikov 2004, “Neural network approximations for nonlinear interactions in wind wave spectra: direct mapping for wind seas in deep water”, *Ocean Modelling*, 2004, in press**
- **Krasnopolsky V. M. and H. Schiller, 2003: "Some Neural Network Applications in Environmental Sciences. Part I: Forward and Inverse Problems in Geophysical Remote Measurements", *Neural Networks*, v. 16, 321-334**
- **Krasnopolsky V. M. and F. Chevallier, 2003: "Some Neural Network Applications in Environmental Sciences. Part II: Advancing Computational Efficiency of Environmental Numerical Models", *Neural Networks*, v .16, 335- 348**
- **Krasnopolsky, V. and F. Chevallier, 2001,”Some neural network applications in environmental sciences: Advancing computational efficiency of environmental numerical models”, *ECMWF Technical Memorandum No. 359***
- **Krasnopolsky, V., D. Chalikov, H. Tolman, 2002, “A neural network technique to improve computational efficiency of numerical oceanic models”, *Ocean Modelling*, v.4, 363-383**
- **Krasnopolsky, V.M., W.H. Gemmill, and L.C. Breaker, 1999: "A multi-parameter empirical ocean algorithm for SSM/I retrievals", *Canadian Journal of Remote Sensing,*, Vol. 25, No. 5, pp. 486-503**
- **Krasnopolsky, V. M., 1997: "A neural network-based forward model for direct assimilation of SSM/I brightness temperatures", Technical Note, OMB Contribution No. 140, NOAA/NCEP/EMC, January 1997.**
- **Krasnopolsky, V., L.C. Breaker, and W.H. Gemmill 1995: A neural network as a nonlinear transfer function model for retrieving surface wind speeds from the special sensor microwave imager, *J. Geophys. Res*, 100, pp. 11,033-11,045**

NN Approximation Accuracy and Performance vs. Original Parameterization

Comparisons with ECMWF NN[1)]

Parameter	Model	Bias	RMSE	Mean	σ	Performance
HR (°*K/day*)	NASA	0.2	0.45			~ 8 **times faster**
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OLR (*W/m*^{2})	ECMWF	0.8	1.9			
	NCAR	0.01	1.2	240.5	46.9	

[1)]**ECMWF NN approximation consists of the battery of *40 NNs***

Operational at ECMWF since October 2003