Using Neural Networks to Improve Atmospheric Model Physics

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Outline

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    - Convection
  - Neural Networks
- NN Emulations of Existing Model Physics:
  - Accurate and Fast NN Emulations of LWR and SWR Parameterizations
  - Validation in NCEP CFS
- New NN Parameterizations of Model Physics:
  - Stochastic NN ensemble Convection Parameterization
  - Validation in NCAR CAM
- Conclusions

GCM Background

Global Climate/Circulation Model (GCM)

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)
  - *P* - physics or parameterization of physical processes (1-D vertical r.h.s. forcing)
- *Continuity Equation*
- *Thermodynamic Equation*
- *Momentum Equations*

GCM (2)

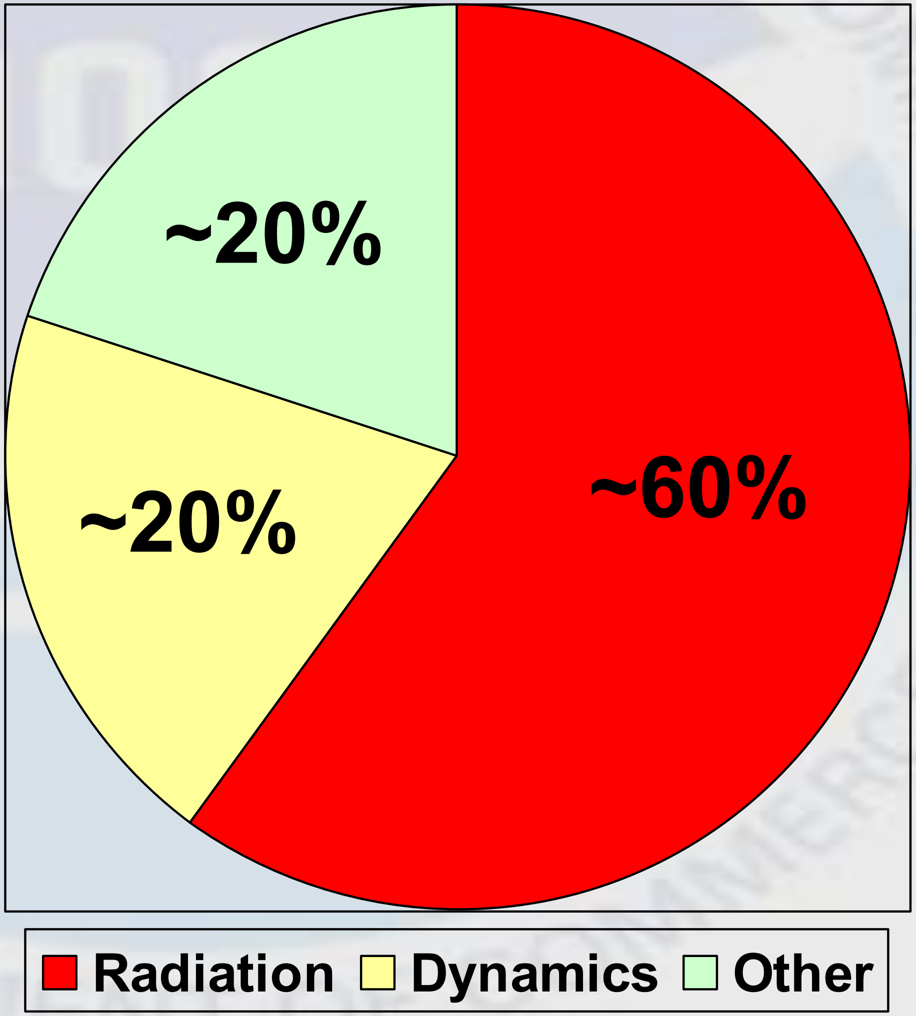
Physics – P, currently represented by 1-D (vertical) parameterizations

- Major components of ***P* = {*R, W, C, T, S, CH*}**:
  - ***R*** - radiation (long & short wave processes): AER Inc. rrtm, ncep0, and ncep1
  - ***W*** – convection, large scale precipitation processes & clouds
  - ***T*** – turbulence
  - ***S*** – land, ocean, ice – air interaction
  - ***CH*** – chemistry (aerosols)
- Components of *P* are 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 and uncertain* part of climate/weather models!**
- **W is one of the most uncertain parts of physics**

Distribution of NCEP CFS Calculation Time

NCEP CFS T126L64

Radiation is calculated every hour; however, the integration step is 10 min.



NN Background

Mapping and NNs

- **MAPPING** (continuous or almost continuous) is a relationship between two vectors: a vector of input parameters, *X*, and a vector of output parameters, *Z*,

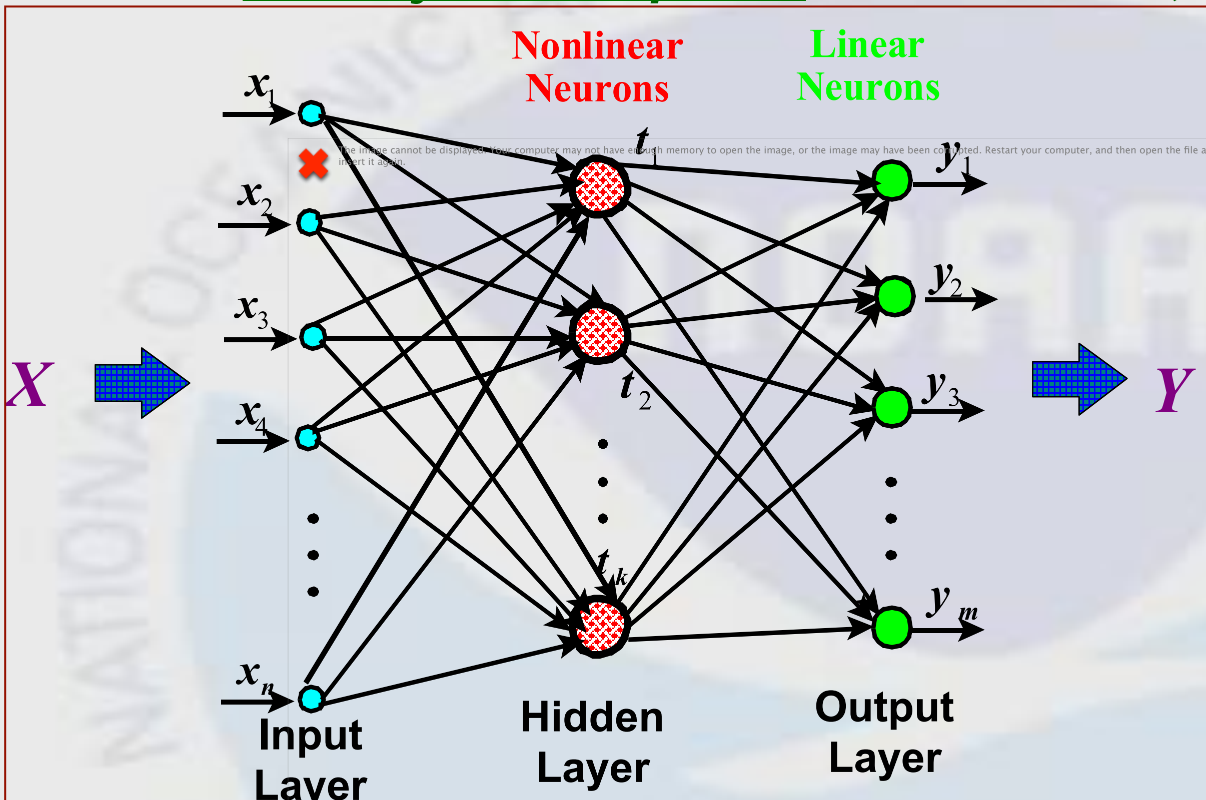
$$Z = F(X); \quad X \in \Re^n \; and \; Z \in \Re^m$$

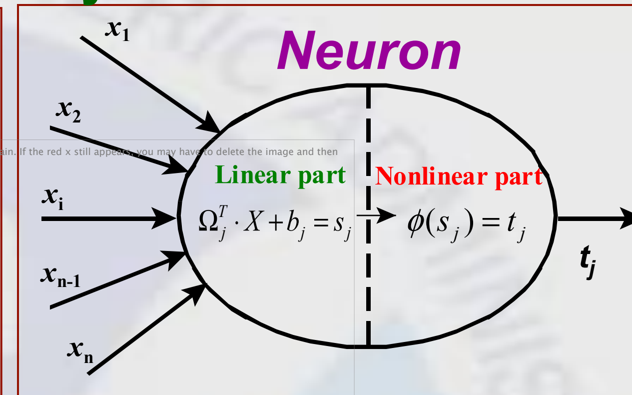
- NN is a generic approximation for **any** continuous or almost continuous mapping given by a set of its input/output records:

$$\text{SET} = \{X_i, Z_i\}_{i = 1, \dots, N}$$

NN - Continuous Input to Output Mapping

Multilayer Perceptron: Feed Forward, Fully Connected





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

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

Y = F$_{NN}$(X)

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

Jacobian !

NN as a Universal Tool for Approximation of Continuous & Almost Continuous Mappings

Some Basic Theorems:

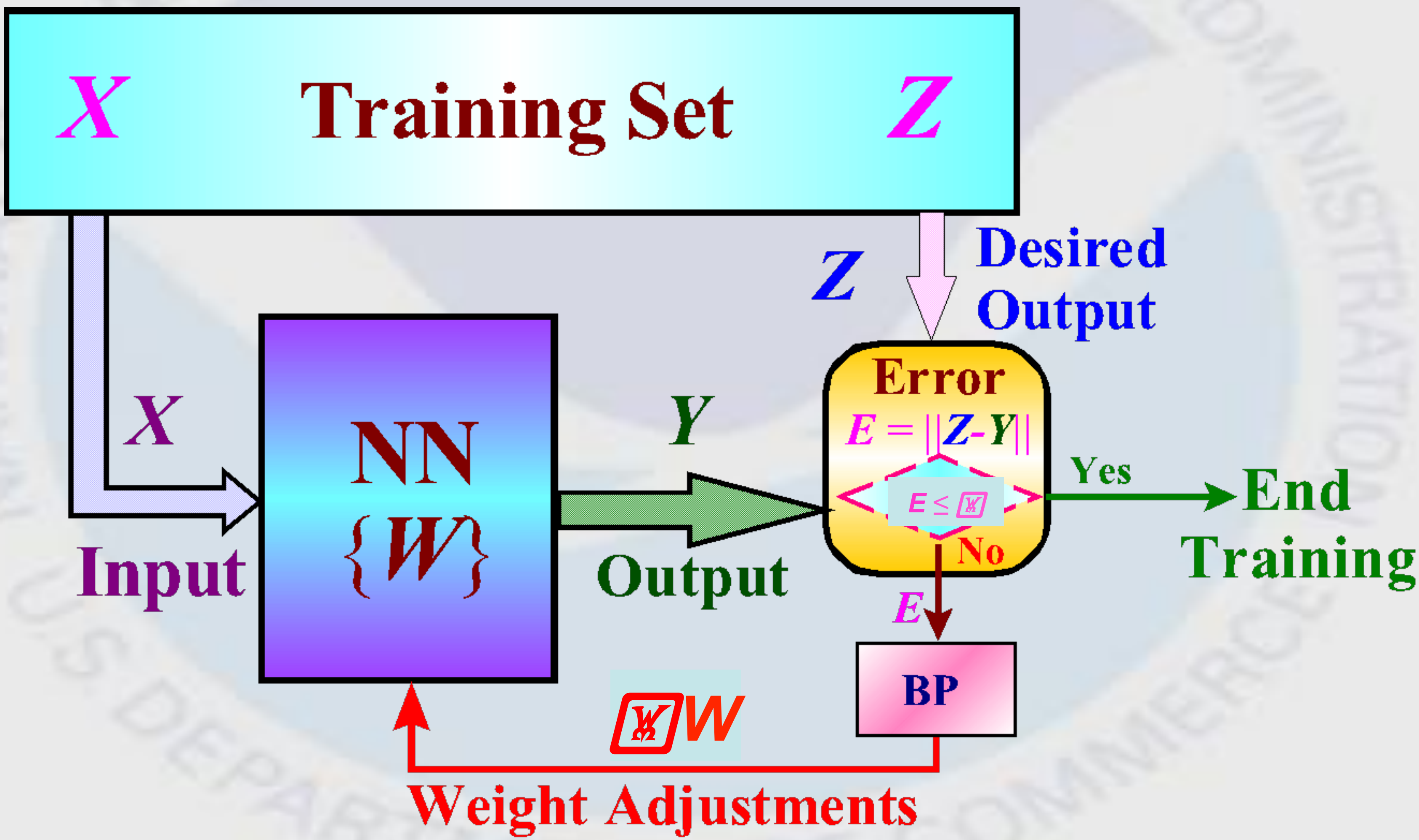
- **Any function or mapping** ***$Z = F(X)$,*** continuous on a compact subset, *can be approximately represented by* a p ($p \geq 3$) layer *NN in the sense of uniform convergence* (e.g., Chen & Chen, 1995; Blum and Li, 1991, Hornik, 1991; Funahashi, 1989, etc.)
- The **error bounds** for the uniform approximation on compact sets (Attali & Pagès, 1997):

$$\|Z - Y\| = \|F(X) - F_{NN}(X)\| \sim O(1/k)$$

k -number of neurons in the hidden layer

NN Training

One Training Iteration



Major Advantages of NNs:

- NNs are *generic, very accurate and convenient* mathematical (statistical) models which are able to emulate 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 NO FREE LUNCH!**
  - Training is complicated and time consuming nonlinear optimization task; *however, training should be done only once for a particular application!*
- NNs are well-suited for parallel and vector processing

I. NN Emulations of Model Physics

- **Major Benefit** : Significant speeding up model integration
- **Auxiliary Benefit** : Improving Model Physics

Motivation for Developing NN Emulations

- **Calculation of model radiation is always a trade-off between the accuracy and computational efficiency:**
  - NCEP and UKMO models reduce the frequency of calculations
  - ECMWF model reduces horizontal resolution of radiation calculations in climate and NWP models
  - Canadian Meteorological Service model reduces vertical resolution of radiation calculations
- **All these approaches introduce additional significant errors in model physics**

Basis for Accurate and Fast NN Emulations of Model Physics

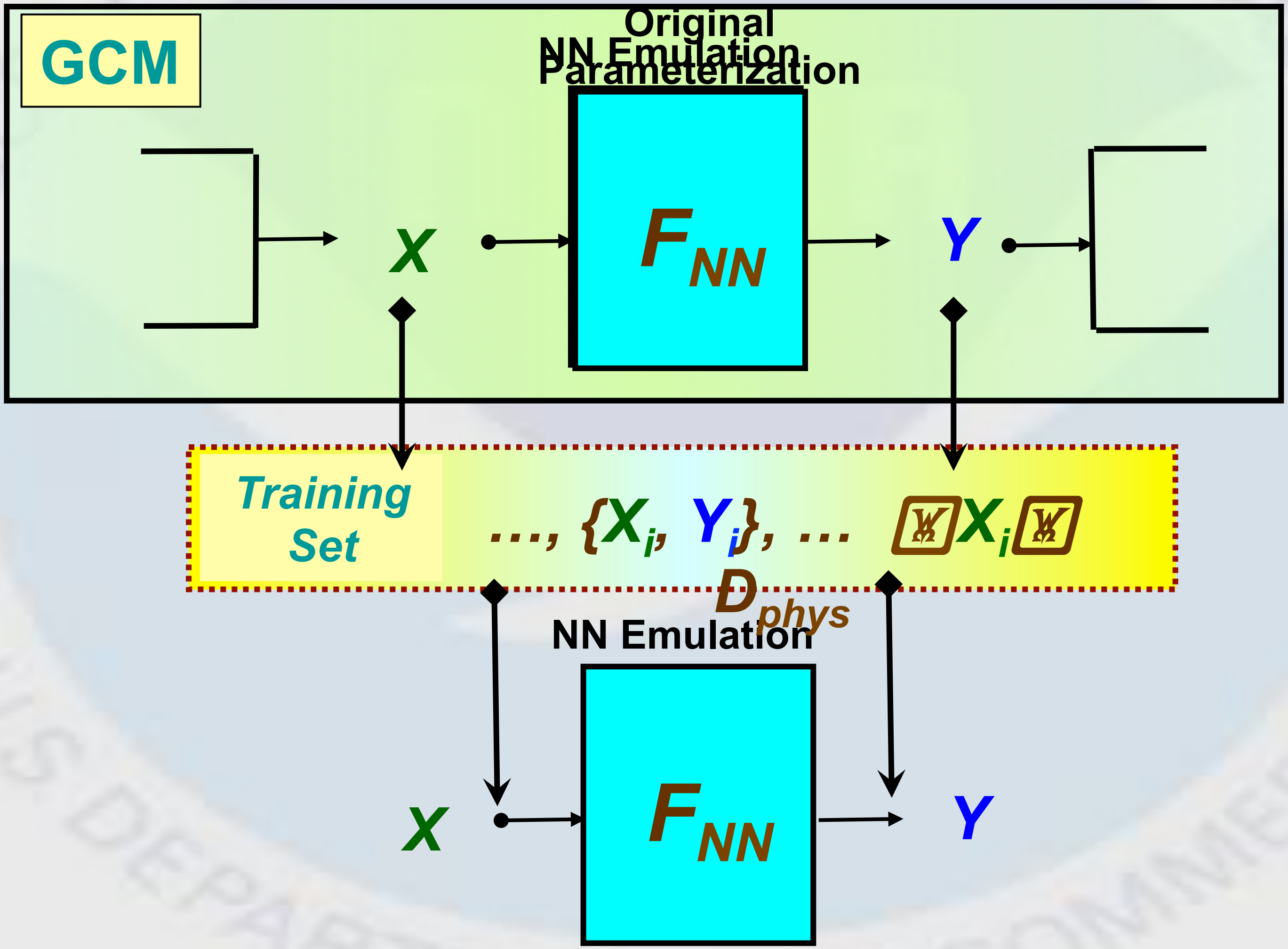
- **Any parameterization of model physics is a continuous or almost continuous mapping**

$$Z = F(X); \quad X \in \Re^n \ and \ Z \in \Re^m$$

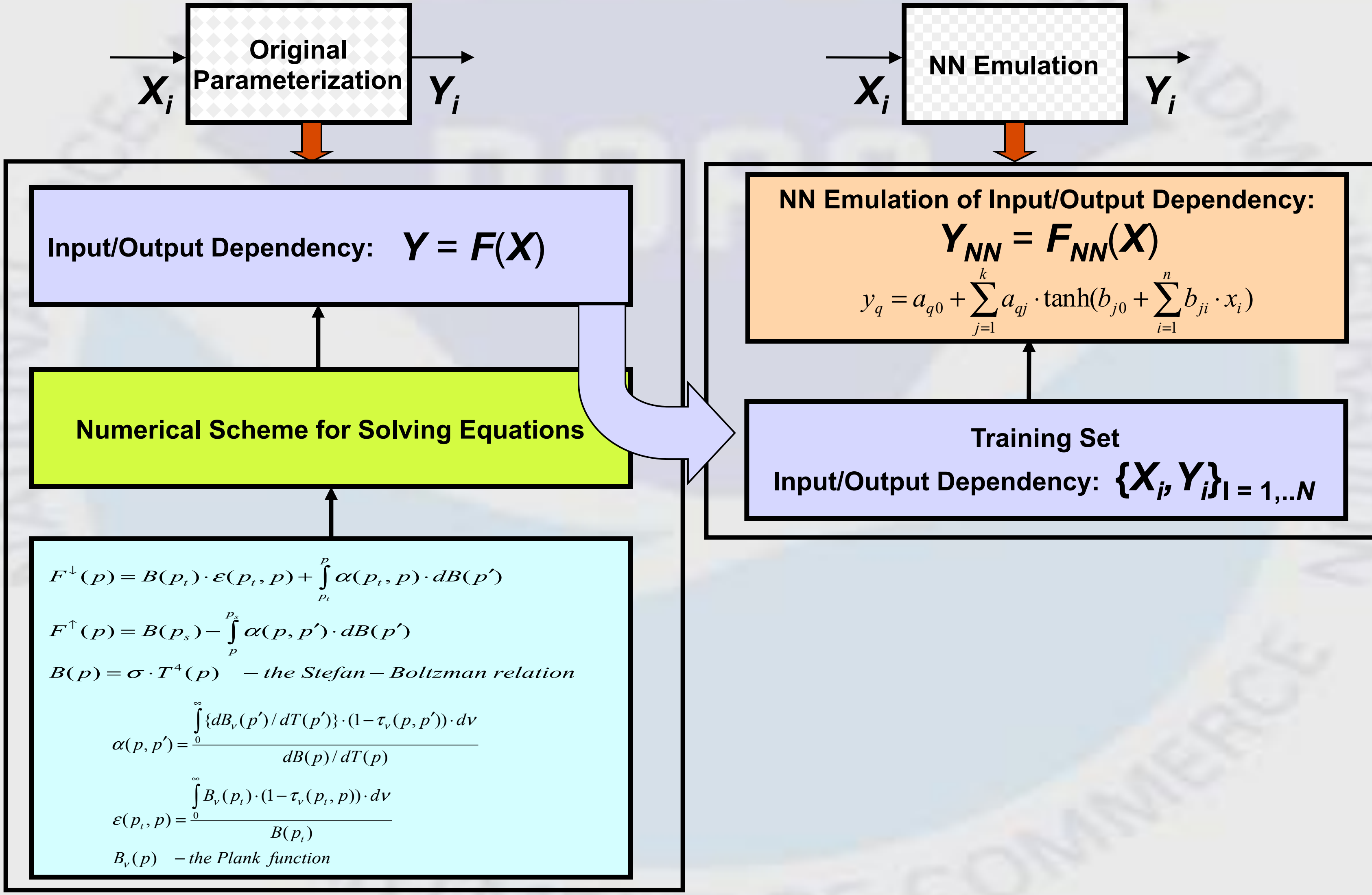
- **NN is a generic tool for emulating such mappings**

NN Emulations of Model Physics Parameterizations

Learning from Data



The Magic of NN Performance



NCEP CFS LW (SW) Radiation and NN Characteristics

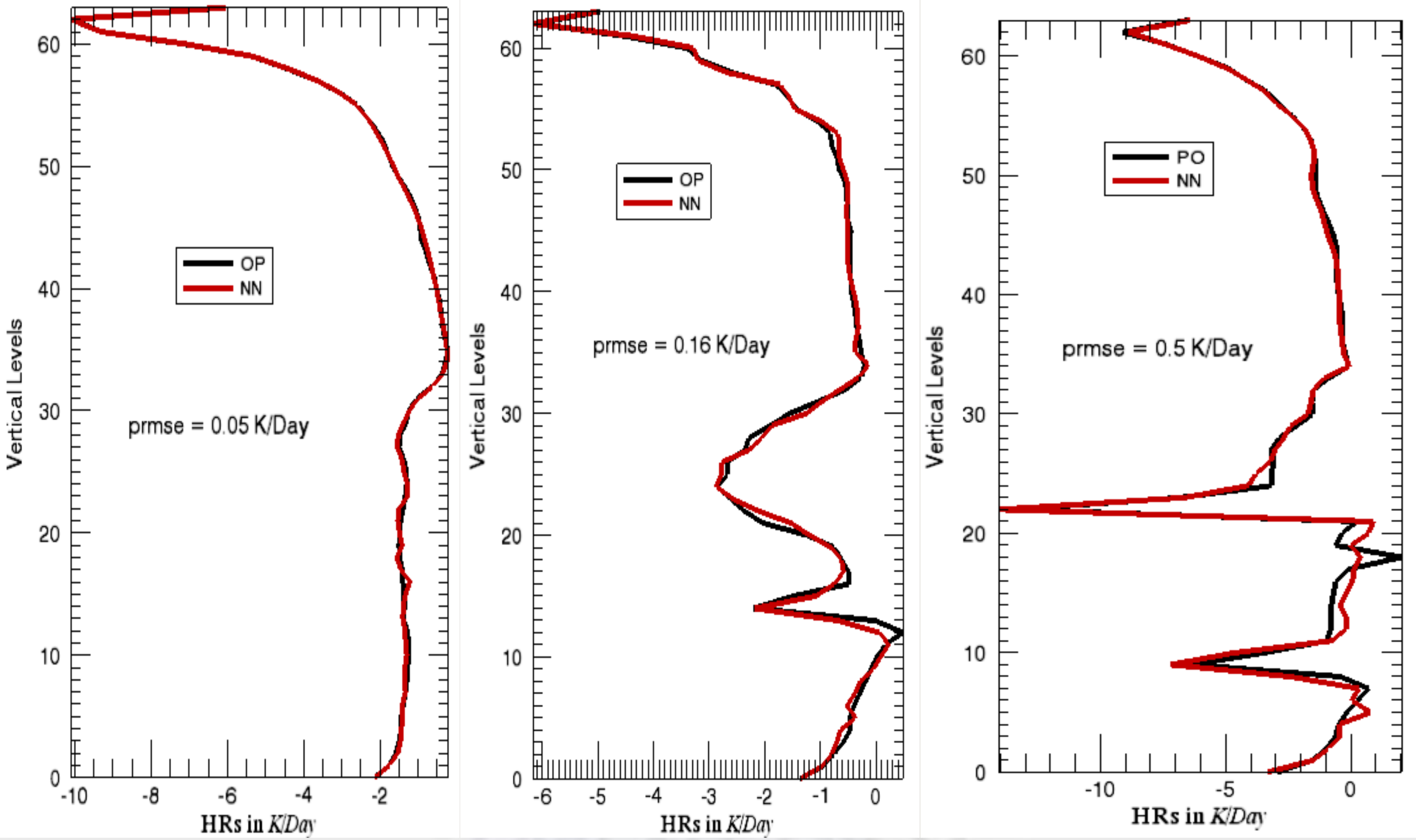
- **612 (650)** Inputs:
  - *10 Profiles:* **temperature, humidity, ozone, pressure, cloudiness, CO_2, etc**
  - *Relevant surface and scalar characteristics*
- **69 (73)** Outputs:
  - **Profile of heating rates (64)**
  - **5 (9) LW (SW) radiation fluxes**
- Hidden Layer: One layer with 50 to 300 neurons
- Training: *nonlinear optimization in the space with dimensionality of 15,000 to 100,000*
  - **Training Data Set: Subset of about 200,000 instantaneous profiles simulated by CFS for 17 years**
  - **Training time: about 1 to several days**
  - **Training iterations: 1,500 to 8,000**
- Validation on Independent Data:
  - **Validation Data Set (independent data): about 200,000 instantaneous profiles simulated by CFS**

NN Approximation Accuracy and Performance vs. Original Parameterization

(*on independent data set*)

Parameter	Model	Bias	RMSE	$RMSE_t$	$RMSE_b$	Performance
LWR (⊠ *K/day*)	NCEP CFS **AER *rrtm***	$2.\ 10^{-3}$	0.40	0.09	0.64	⊠ 12 times faster
	NCAR CAM **W.D. Collins**	$3.\ 10^{-4}$	0.28	0.06	0.86	⊠ 150 times faster
SWR (⊠ *K/day*)	NCEP CFS **AER *rrtm***	$5.\ 10^{-3}$	0.20	0.21	0.22	~45 times faster
	NCAR CAM **W.D. Collins**	$-4.\ 10^{-3}$	0.19	0.17	0.43	⊠ 20 times faster

Individual Profiles (NCEP CFS)

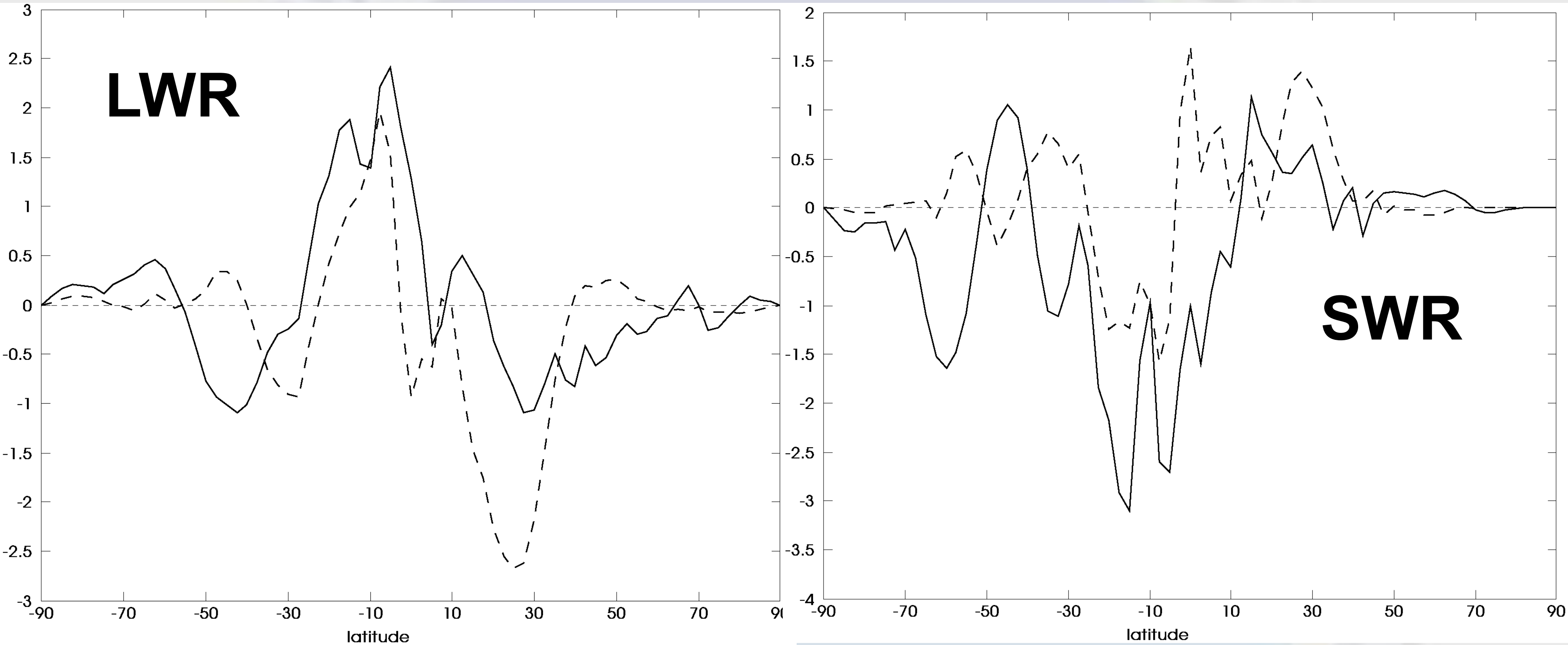


Climate Simulation
17 years:
1990 – 2006

Validation of Full NN Radiation in CFS

- The Control CFS run with the **original LWR and SWR parameterizations** is run for 17 years (1990 – 2006).
- The NN Full Radiation run: **CFS with LWR and SWR NN emulations** is run for 17 years.
- Another Control CFS Run after **updates of FORTRAN compiler and libraries**
- Validation of the NN Full Radiation run is done against the Control run. The differences/biases are less than/within observation errors and uncertainties of reanalysis
- **The differences between two controls** (“butterfly” or ”round off” differences or “model internal variability”) have been also calculated and shown for comparison.

Zonal and time mean Top of Atmosphere Upward Fluxes (Winter)

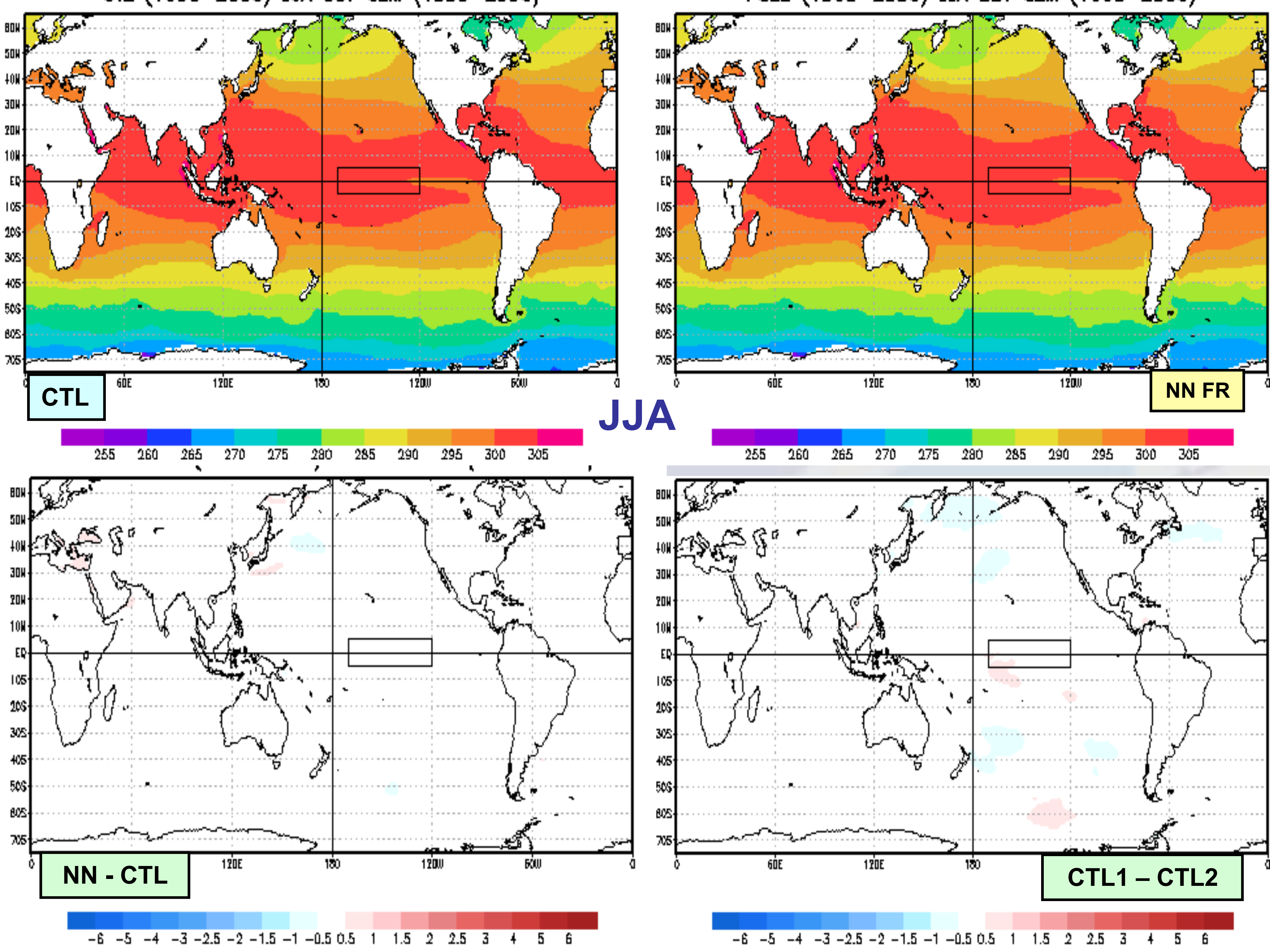


The solid line – the difference (the full radiation NN run – the control (CTL)), the dash line – the background differences (the differences between two control runs). All in W/m².

The time mean (1990-2006) SST statistics for summer

	Control Run	NN Full Radiation Run
Fields →	Control Run	NN Full Radiation Run
Differences →	NN - Control	Control1 – Control2

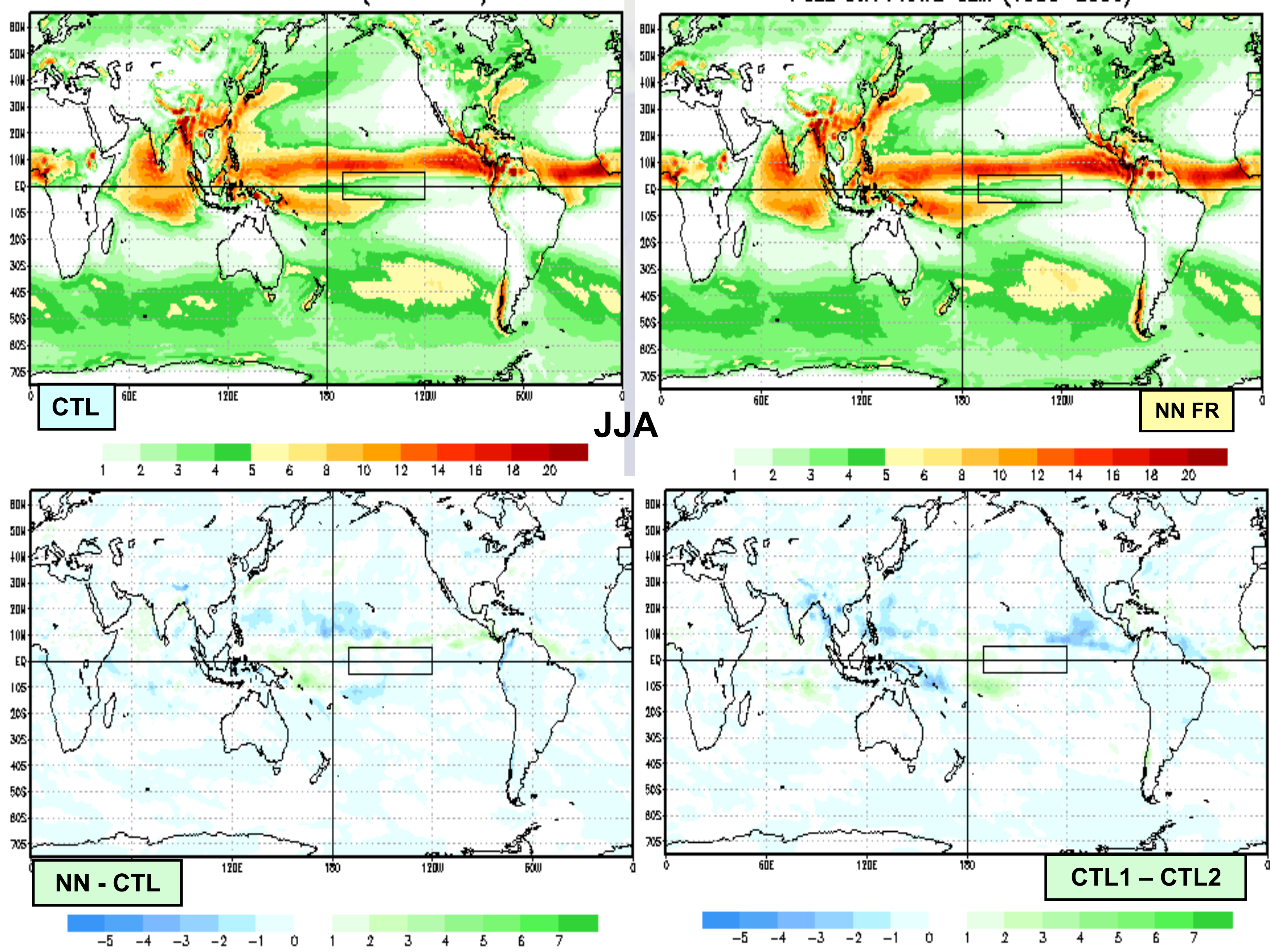
The contour intervals for the SST fields are 5º K and for the SST differences are 0.5º K.


CTL
NN FR
JJA
255 260 265 270 275 280 285 290 295 300 305
NN - CTL
CTL1 – CTL2
−6 −5 −4 −3 −2.5 −2 −1.5 −1 −0.5 0.5 1 1.5 2 2.5 3 4 5 6

The time mean (1990-2006) total precipitation rate (PRATE) statistics for summer

Fields →	Control Run	NN Full Radiation Run
Differences →	NN - Control	Control1 – Control2

The contour intervals for the PRATE fields are 1 mm/day for the 0 – 6 mm/day range and 2 mm/day for the 6 mm/day and higher; for the PRATE differences the contour intervals are 1 mm/day

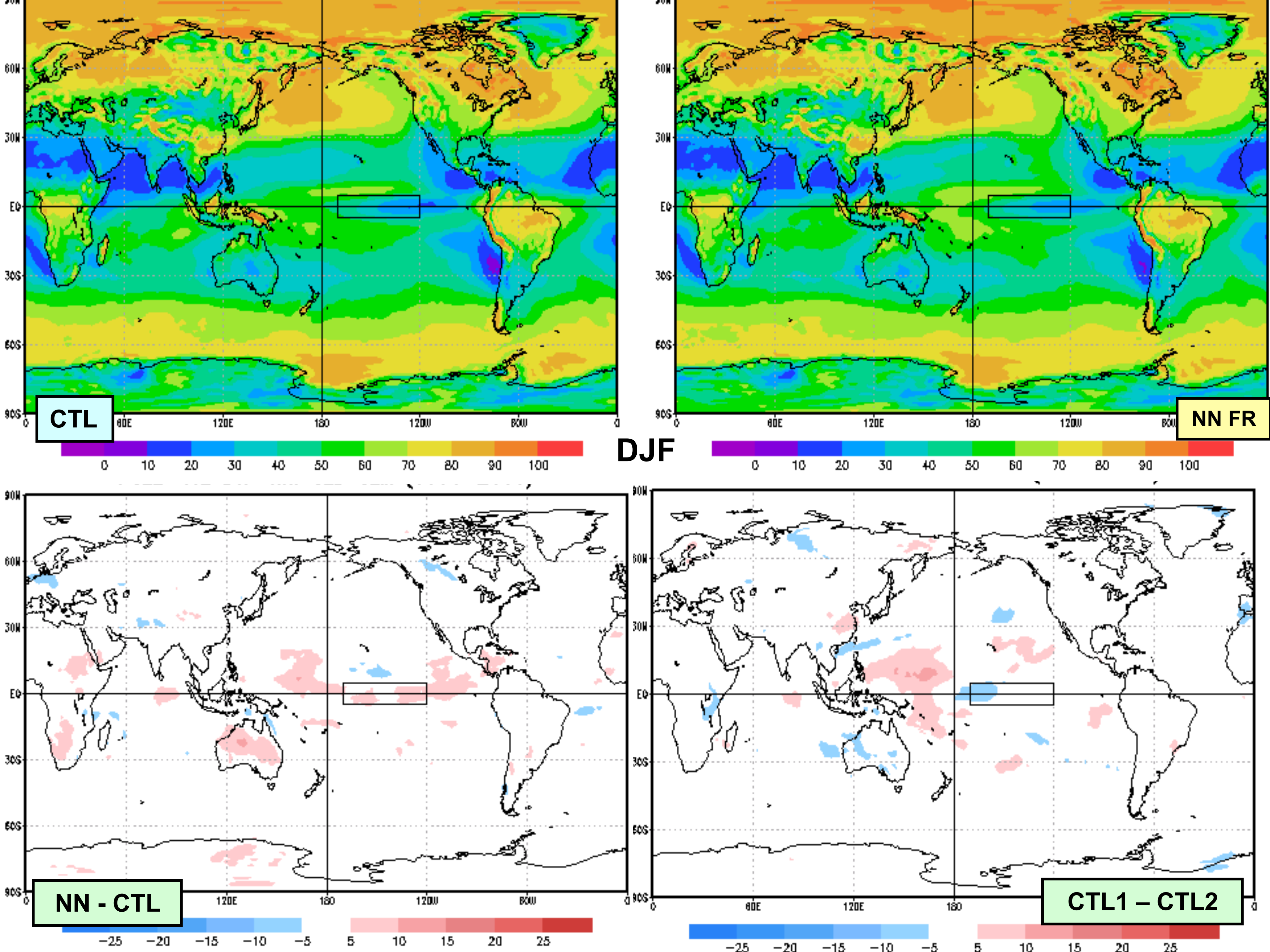


CTL
NN FR
JJA
NN - CTL
CTL1 – CTL2

The time mean (1990-2006) total) total clouds statistics for winter

Fields	Control Run	NN Full Radiation Run
Differences	NN - Control	Control1 – Control2

The contour intervals for the total clouds fields the cloud fields are 10% and for the differences – 5%.



CTL
NN FR
DJF
NN - CTL
CTL1 – CTL2
0 10 20 30 40 50 60 70 80 90 100
–25 –20 –15 –10 –5 5 10 15 20 25
90N 60N 30N EQ 30S 60S 90S
0 60E 120E 180 120W 60W 0

NN Emulations of Model Physics
Conclusions – 1

- **NN is a powerful tool for speeding up calculations of model physics through developing NN emulations**
  - **Accurate and fast NNs emulations have been successfully developed for:**
    - **NCEP LWR & SWR parameterizations**
    - **NCAR CAM LWR & SWR parameterizations**
    - **NASA LWR parameterization**
  - **The simulated diagnostic and prognostic fields are very close for the parallel climate (and seasonal prediction) runs performed with NN emulations and the original parameterizations**
- **NN emulations approach also can improve model physics allowing to use new, more advanced and complex parameterizations that are otherwise computationally prohibitive.**

II. New NN Based Parameterizations of Model Physics

- **Major Benefit** : Improving Model Physics
- **Auxiliary Benefit**: Significant speeding up model integration

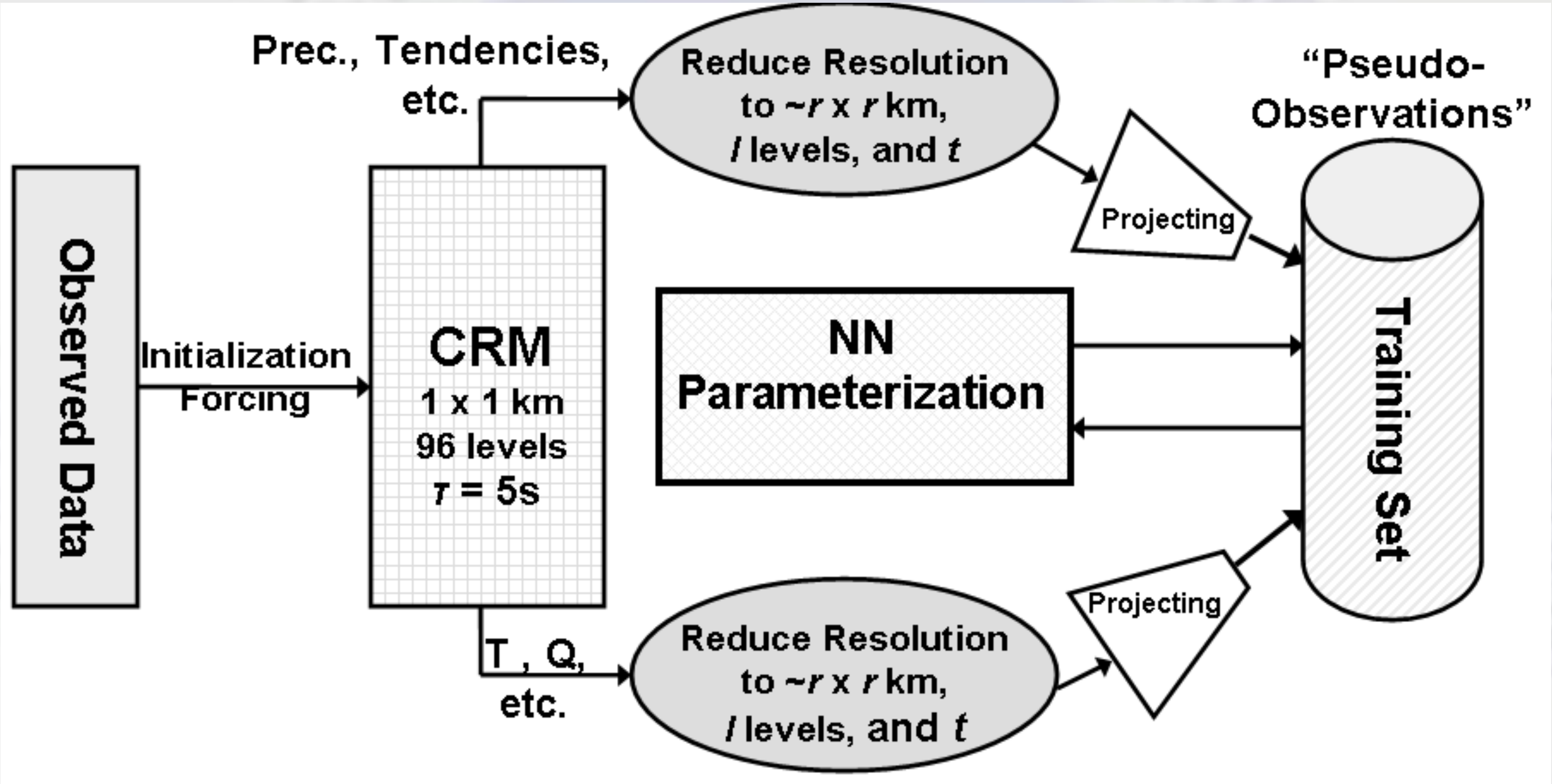
Motivations for Using NNs

- **Uncertainty in convection, large scale precipitation processes & clouds is high:**
  - **Existing parameterization are simplified**
  - **Vast range of time and space scales involved**
- **Alternative approaches are prohibitively time consuming:**
  - **Global Cloud System Resolving Models (GCSRMs or GCRM): $10^5 – 10^7$ more expensive than regular parameterizations**
  - **Multiscale Modeling Framework (MMF) or “Super-parameterization” – 2D CRM imbedded into GCM: still $10^2 – 10^3$ more expensive than parameterizations**

New NN Parameterization

- **New NN parameterizations** of model physics can be developed based on:
  - Data simulated by first principles models like CRM (e. g., Khairoutdinov and Randall 2003)).
  - Observations (e.g., ARM, TOGA COARE)
- Our approach is aimed at developing ***new more sophisticated and fast model convection schemes*** based on using NNs for **direct learning cloud physics from simulated CRM** and observed data.
- NN serves as an **interface** transferring information about sub-grid scale processes from fine scale data or models (CRM) into GCM (upscaling)

Creating Development Set for Stochastic Parameterization



- Horizontal resolution 1 km $< r \leq R$
- Vertical resolution 96 layers $< l \leq L$
- Averaging time – $\tau < t \leq T$
- **Projecting** – reducing the number of variables

Data Evolution and Emerging Uncertainties

We start with: $\boldsymbol{y} = \mathbf{M}_{\mathbf{CRM}}(\boldsymbol{x})$,
x and ***y*** are high resolution CRM simulated data (in CRM space)

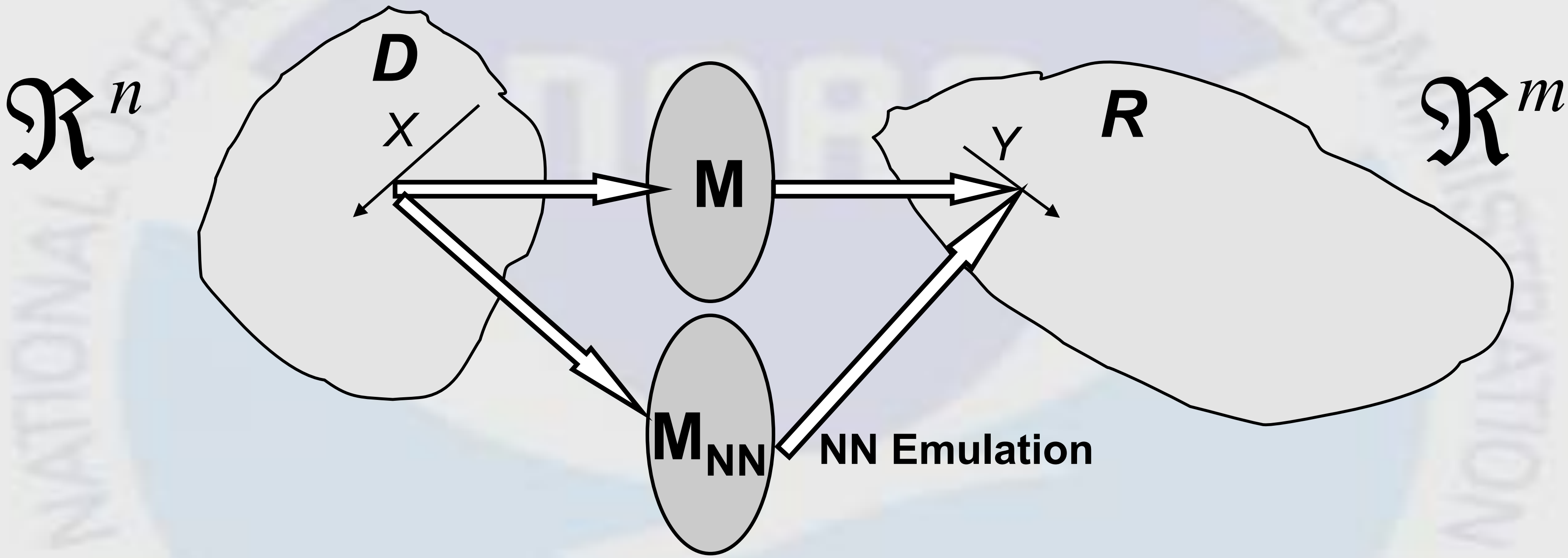
We (1) reduce resolution to *r*, *l*, and *t;* (2) reduce the number of variables (project). Thus, we get "pseudo-observations" ***X*** and ***Y*** (in GCM space)

$$\boldsymbol{Y} = \mathbf{M}_{\mathbf{GCM}}(\boldsymbol{X}) + \boldsymbol{\varepsilon}$$

ε is **uncertainty and**
$\mathbf{M}_{\mathbf{GCM}}(\boldsymbol{X})$ ***is a <u>stochastic mapping</u>***

Mapping & NN Emulation

Exact Mapping: $\boldsymbol{Y} = \mathbf{M}(\boldsymbol{X})$



Mapping with uncertainty (stochastic):

$$\boldsymbol{Y} = \mathbf{M}(\boldsymbol{X}) + \boldsymbol{\varepsilon}$$

Requires an ensemble of emulating NNs:

$$\boldsymbol{Y} = \mathbf{M}^{i}_{NN}(\boldsymbol{X}),\ i = 1,2,\ \ldots$$

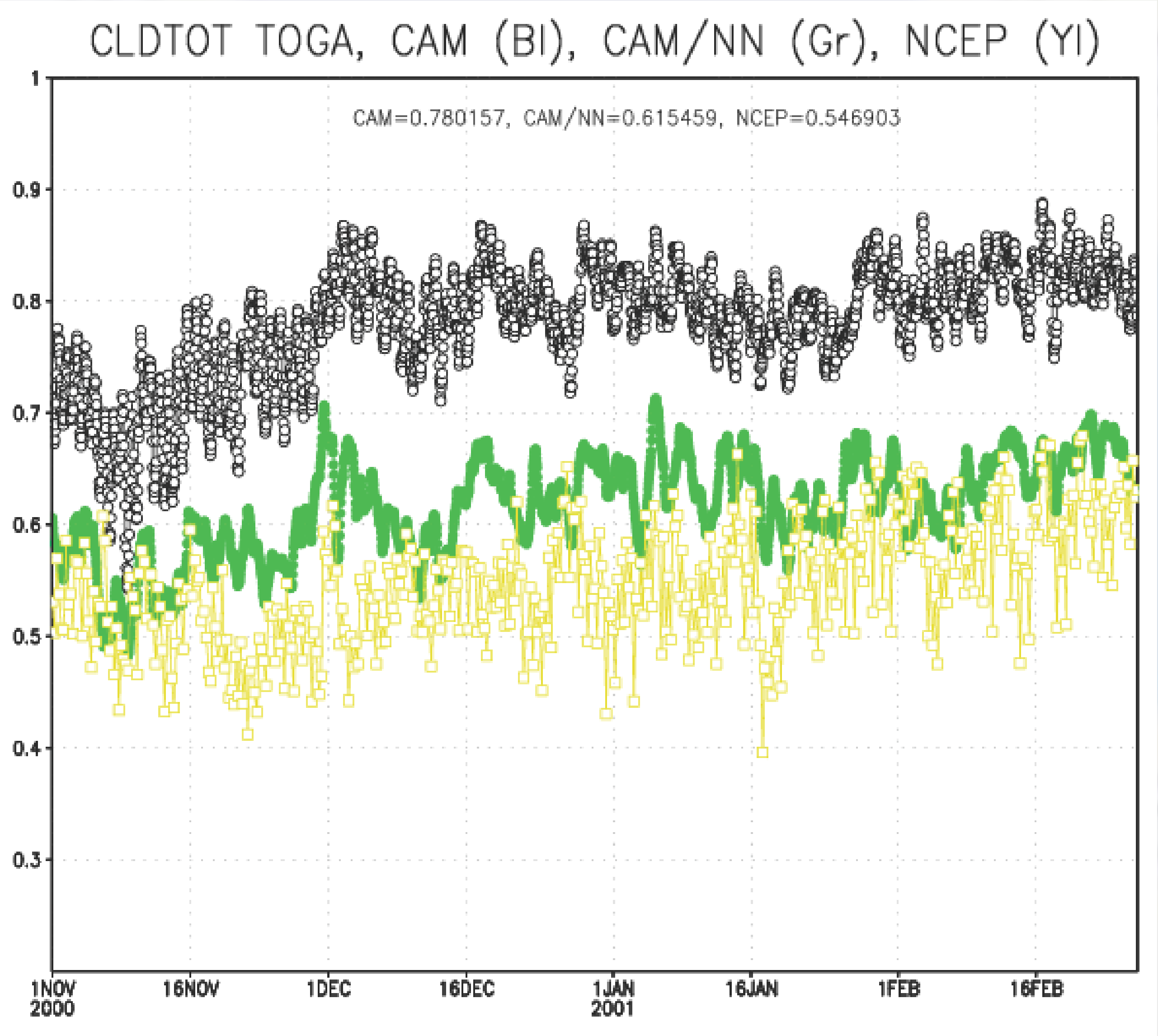
NN Convection Parameterization

- **Data (for CRM initialization and forcing):** TOGA-COARE
- **CRM:** SAM CRM (Khairoutdinov and Randall, 2003).
  - Hourly data: over 120 days for TOGA-COARE
  - Resolution: 1 km over the domain of 256 x 256 km
  - 96 vertical layers (0 – 28 km)
- **"Pseudo-observations"**
  - **Resolution of (averaged CRM data) over TOGA COARE location**:
    - Horizontal: 256 x 256 km (close to NCAR CAM)
    - Vertical: 26 vertical layers (as in NCAR CAM)
  - **a limited training data set (120 days, over one location) used for the initial development of NN convection**
- **NN inputs:** temperature and water vapor profiles;
- **NN outputs:** the tendencies of T and q, or "apparent heat source" (Q1C), "apparent moist sink" (Q2), precipitation & cloud fractions (CLD)
- **Ensemble of NNs has been trained (10 NN members)**

Validation of NN convection in NCAR CAM

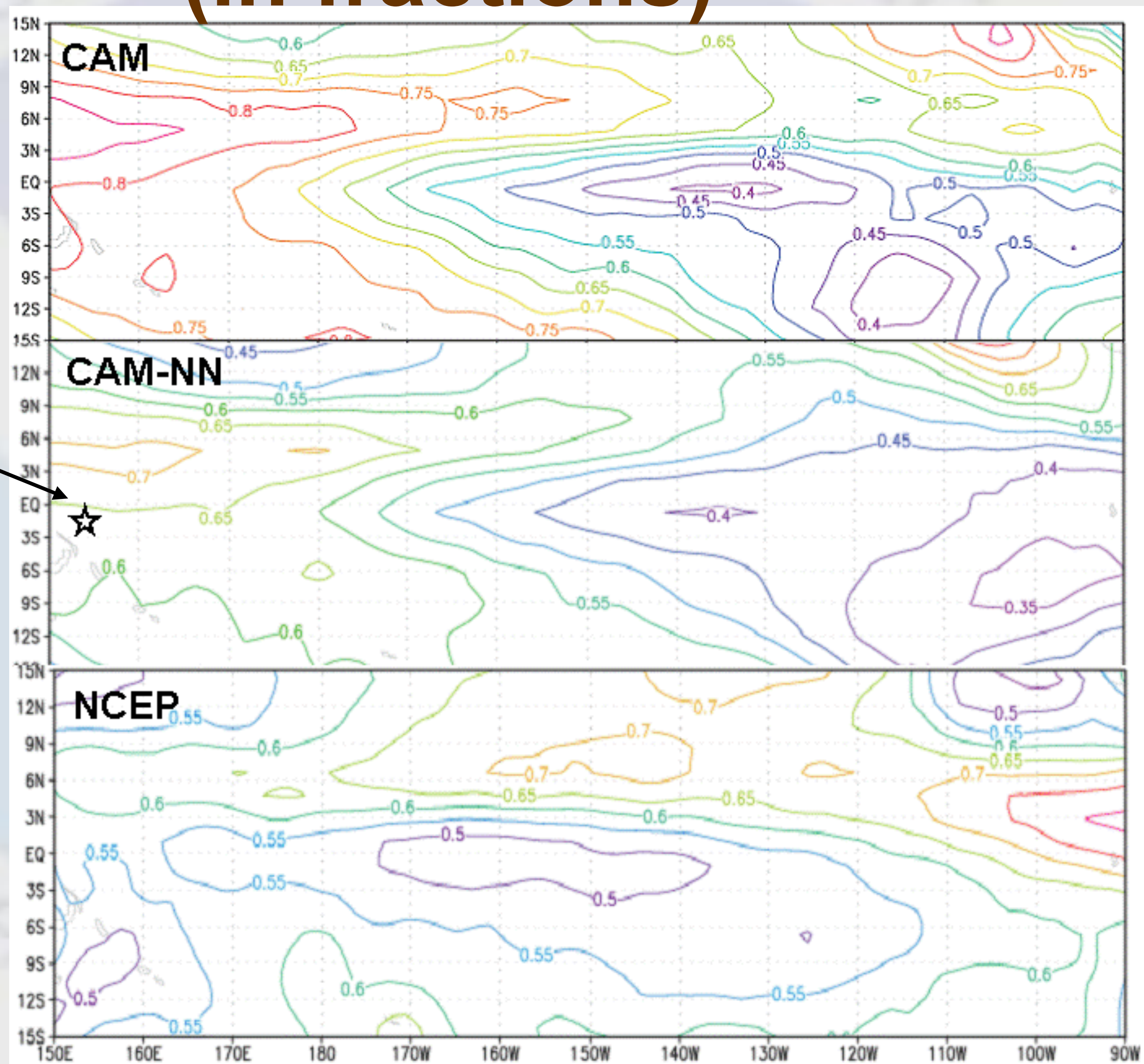
- NN convection was introduced in CAM and run during a 10-year period (1990 – 2001, excluding TOGA COARE winter) in a diagnostic mode and analyzed for winters, NDJF:
  - Over a TOGA COARE location
  - Over the 120° x 30° area in the Tropical Pacific
- At each time step in at each grid point all 10 NN ensemble members were applied and averaged.
- Results are compared with a parallel CAM run and with the NCEP reanalysis

Decadal mean total cloudiness (in fractions) for the TOGA-COARE location



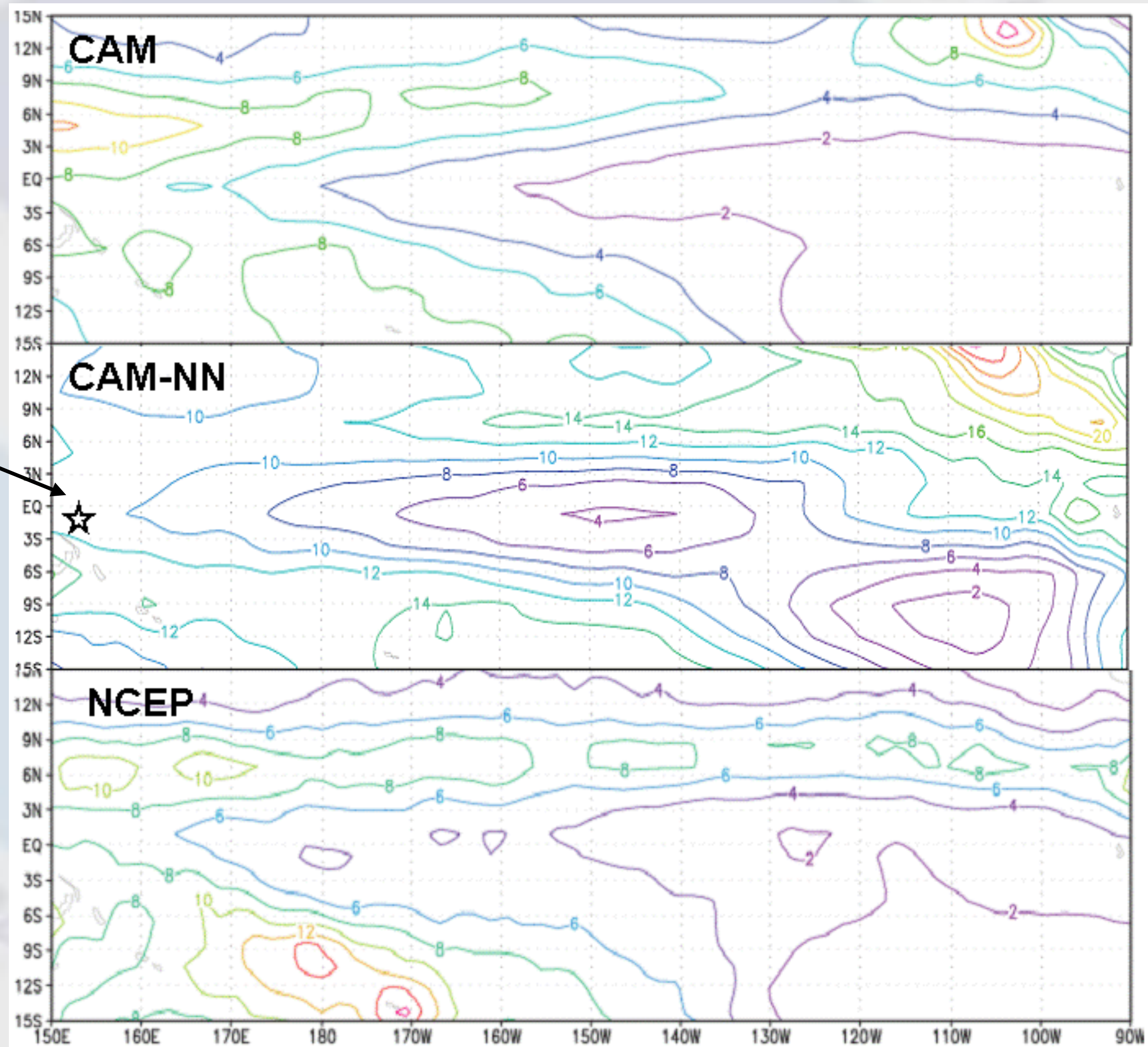
Decadal mean cloudiness distribution (in fractions)

TOGA COARE location



Decadal mean precipitation distribution (in mm/day)

TOGA COARE location



Conclusions: new NN parameterizations

- Approach has been conceptually formulated:
  - "Pseudo-observations"
  - Stochastic parameterization/mapping
  - NN ensemble as a tool for approximating stochastic mapping
  - Correcting biases between CRM and GCM
- A prototype NN convection parameterization has been developed and tested in NCAR CAM
- Further plans:
  - Validate NN convection in the prognostic mode
  - Simulate data using CRM forced by CAM
    - Broader/global geographical representation
    - Broader/all seasons range of regimes
    - Longer period of integration
  - **GOAL:** Develop a new NN convection parameterization for global applications in GCMs.