Analyzing the radiative feedbacks using kernel and neural network methods

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Introduction

- Radiation balance: $N = F + \lambda \cdot \Delta T$
- Climate sensitivity λ^{-1} is a key factor that predicts the magnitude of global warming ΔT driven by radiative forcing F; its sign and magnitude are controlled by radiative feedbacks: $\lambda = \lambda_T + \lambda_{WV} + \lambda_C + \lambda_A$
- Method for quantifying feedback parameters λ_X

  $\lambda_X = \Delta R_X / \Delta T$ [W m^{-2} K^{-1}]

  - Partial Radiative Perturbation [Manabe & Weatherald 1988; Colman 2003]

  $\Delta R_X = R(X + \Delta X) - R(X)$, R computed by RTM

  - Kernel method [Shell et al 2008; Soden et al 2008]

  Non-cloud: $\Delta R_X = K_X \cdot \Delta X, \quad K_X = {}^{\partial R}/_{\partial X}$

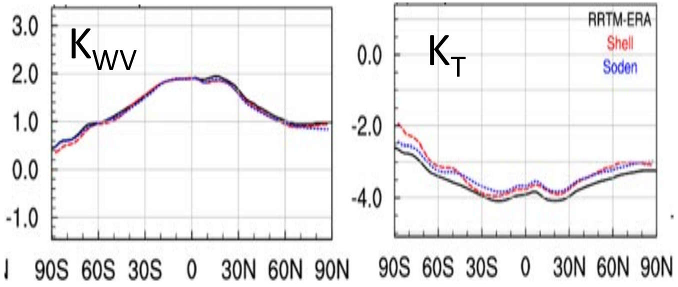
  Cloud: $\Delta R_C = \Delta R - \sum \Delta R_X$

  - Histogram method for cloud feedback [Zelinka et al 2012]: $\Delta R_C = f(H_C, \tau_C)$

A new set of kernels

[Huang, Tan and Xia, 2017]

- $R(X)$: RRTM; TOA and surface
- X: ERAi
- Global 2.5°x2.5°, 5 years' 6-hourly atmos profiles used to compute K_X, and then averaged at each grid point for every calendar month.
- TOA: in agreement



Validation for the kernels: Radiation closure test

- Radiation closure test: comparison between GCM-simulated clear-sky radiation anomaly and that reproduced by the kernels:

$$\Delta R_{total} \overset{?}{=} \sum K_X \Delta X$$

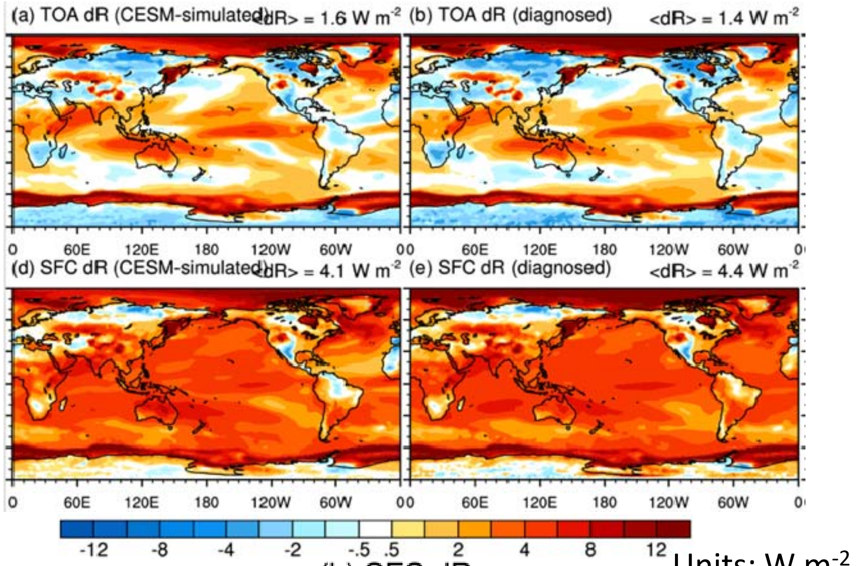
- Test 1: global warming
- Test 2: unforced internal variability

Radiation anomaly in a CESM 2xCO2 experiment

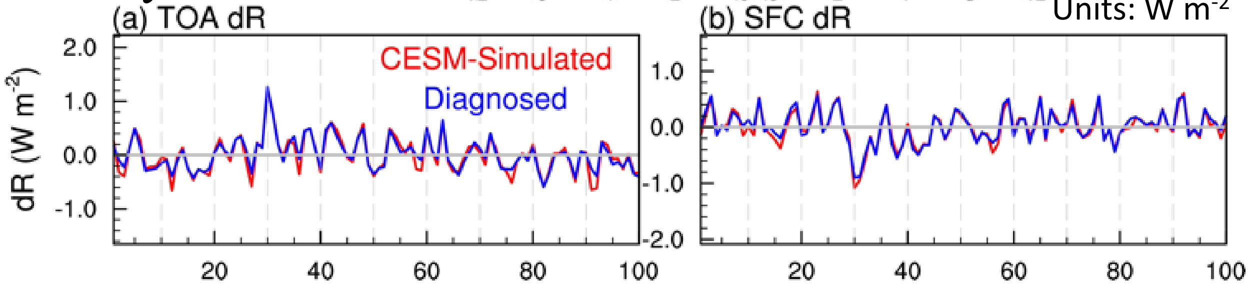
GCM-simulated Kernel-diagnosed

TOA

Surface



Units: W m^{-2}



Global mean TOA and surface radiation anomaly in a CESM 100-yr control experiment.

Limitations of the kernel method

- Previous methods: Pros & Cons

  - PRP method

$$\Delta R_X = R^{RTM}(X + \Delta X) - R^{RTM}(X)$$

Evaluated as defined;
Computationally expensive.

  - Kernel method (approximation)

$\Delta R_X = K_X \cdot \Delta X$
Computationally inexpensive;
Linearity assumption; ΔR_C as residual.

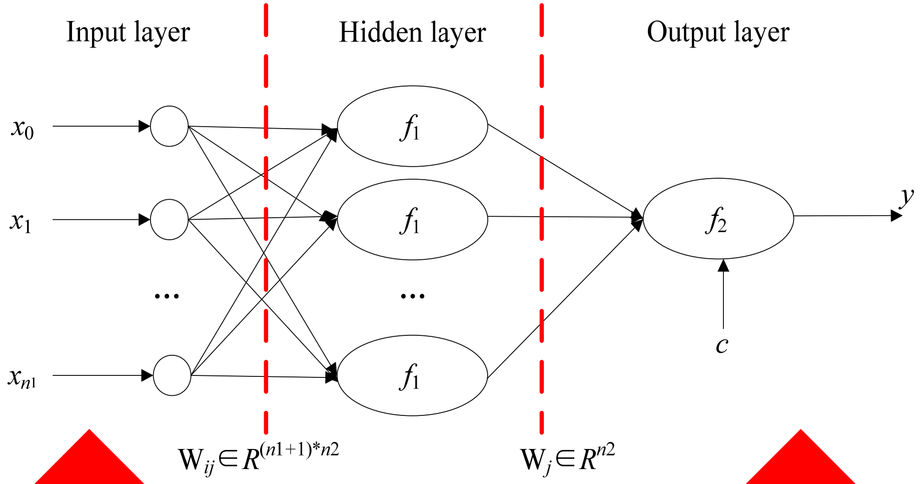
- Solution?

Predict R-X relationship with a computationally efficient, non-linear model - Neural Network (NN).

$$\Delta R_X = R^{NN}(X + \Delta X) - R^{NN}(X)$$

Soden et al (2008): "Cloud feedbacks cannot be evaluated directly from a cloud radiative kernel because of strong nonlinearities."
Shell et al (2008): "The remaining error is due to the fact that the surface albedo feedback is somewhat nonlinear, …, and the radiative kernel calculation depends on the size of the standard anomaly used. …"

Neural Network Method



INPUT:
Atmos State
X

$$g_j = \sum_{i=1}^{n_1} w_{ij} x_i + b_j$$

$$u_j = f_1(g_j) = \frac{2}{1+e^{-2g_j}} - 1$$

$$y = \sum_{j=1}^{n_2} w_j u_j + c$$

OUTPUT:
Rad Flux
R

TOA Net Incoming Shortwave Radiation

TOA Outgoing Longwave Radiation

Outputs	Inputs
SSRC/TSRC	TCWV, SP, TCO3, FAL, Loc
SSR/TSR	TCWV, SP, TCO3, FAL, TCIW, TCLW, HCC, MCC, LCC, Loc
STRC	SKT, T10, T200, T500, TCWV, Loc
STR	SKT, T10, T200, T500, TCWV, HCC, MCC, LCC, Loc
TTRC	SKT, T10, T200, T500, Q200, Q500, Q700, Loc
TTR	SKT, T10, T200, T500, Q200, Q500, Q700, HCC, MCC, LCC, Loc

Abbreviation	Description
SSRC	Surface net solar radiation in clear sky, W/m^2
SSR	Surface net solar radiation in all sky, W/m^2
TSRC	Top net solar radiation in clear sky, W/m^2
TSR	Top net solar radiation in all sky, W/m^2
STRC	Surface net thermal radiation in clear sky, W/m^2
STR	Surface net thermal radiation in all sky, W/m^2
TTRC	Top net thermal radiation in clear sky, W/m^2
TTR	Top net thermal radiation in all sky, W/m^2
TCWV	Total column water vapor, kg/m^2
SP	Surface pressure, Pa
TCO3	Total column ozone, kg/m^2
FAL	Forecast albedo, (0,1)
TCIW	Total cloud ice water, kg/m^2
TCLW	Total cloud liquid water, kg/m^2
HCC	High cloud cover, (0,1)
MCC	Medium cloud cover, (0,1)
LCC	Low cloud cover, (0,1)
Loc	Location, including longitude, sin(longitude) and cos(latitude)
SKT	Skin temperature, K
T10	Air temperature at 10 hPa level, K
T200	Air temperature at 200 hPa level, K
T500	Air temperature at 500 hPa level, K
Q200	Specific humidity at 200 hPa level, kg/kg
Q500	Specific humidity at 500 hPa level, kg/kg
Q700	Specific humidity at 700 hPa level, kg/kg

ERA interim dataset

Validation of $R^{NN}(X)$

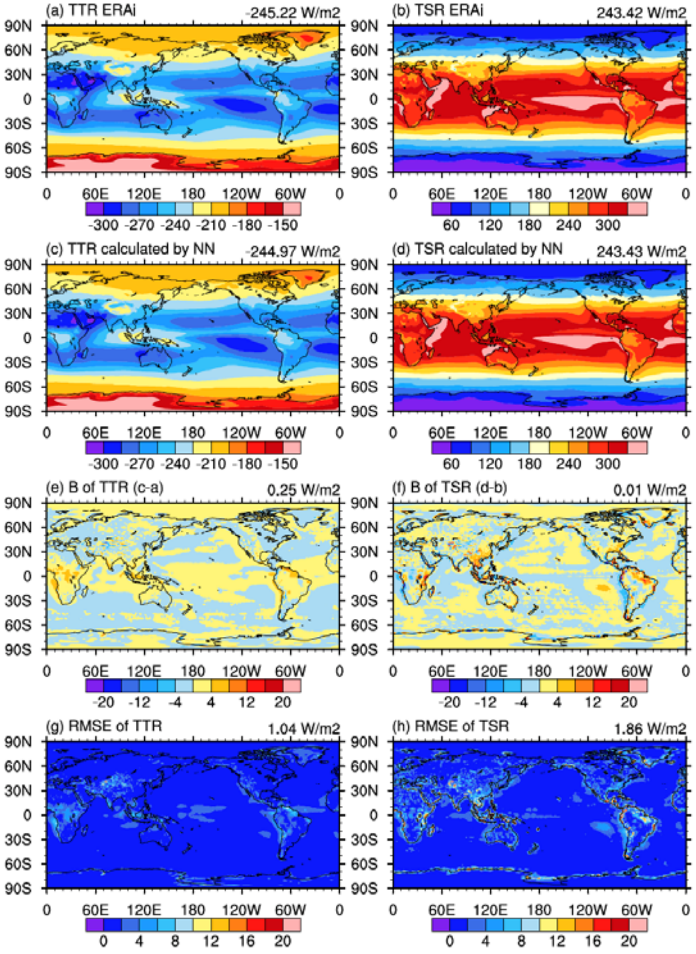
Outgoing LW Radiation | Net incoming SW Radiation

Truth (ERAi)

NN

Mean Bias (NN-Truth)

RMSE



- Validation

Truth: ERAi data

Prediction: NN

- Error Statistics

  - LW

MB=0.16,

RMSE=1.44

  - SW

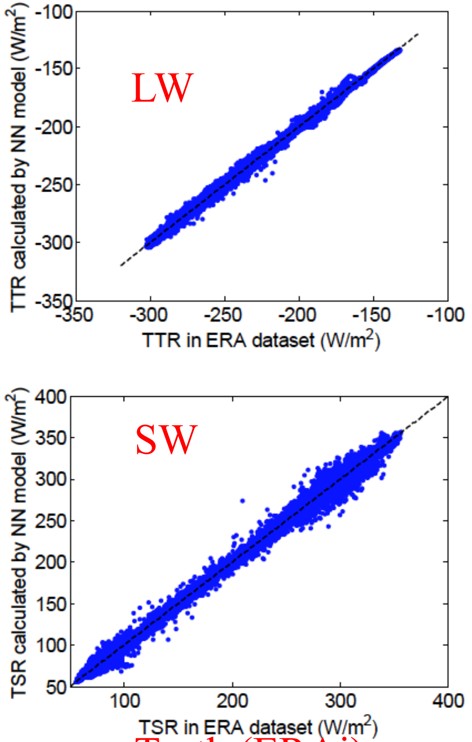
MB=0.04,

RMSE=3.10

Units: W m^{-2}

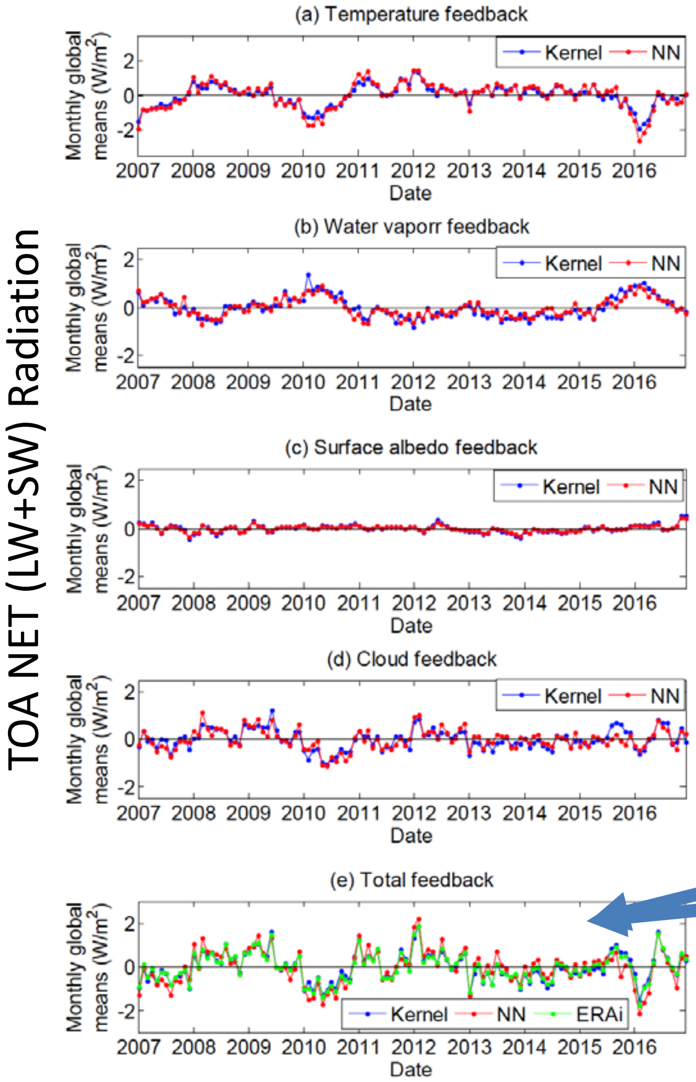
* Based on monthly values at all locations

NN Prediction



Truth (ERAi)

Feedbacks: Kernel vs. NN



- Context: Interannual variation
- ΔR_X and ΔT time series: deseasoned and detrended; 2007-2016 (not used in training)
- NN very well reproduces the global mean overall feedback ΔR_{total} from the ERAi data and feedbacks ΔR_X analyzed from the kernel method.

Radiation	B			$RMSE$		
	$\sum \Delta R_X^K$	$\sum \Delta R_X^{NN}$	$\boxed{\Delta R^{NN}}$	$\sum \Delta R_X^K$	$\sum \Delta R_X^{NN}$	ΔR^{NN}
SSR	0.00	0.42	0.32	0.06	0.55	0.47
STR	0.00	-0.24	-0.23	0.15	0.29	0.27
TSR	0.00	0.39	0.27	0.05	0.49	0.41
TTR	0.00	-0.22	-0.03	0.12	0.31	0.17

Predicted with all the variables varying altogether

Feedbacks: Kernel vs. NN

- Feedback parameter: $\lambda = regress(\Delta R_X, \Delta T)$

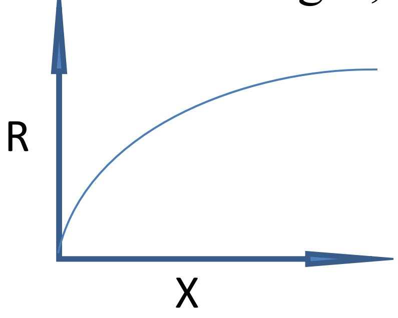
	Clear-sky				All-sky			
	Surface SSRC+STRC		TOA TSRC+TTRC		Surface SSR+STR		TOA TSR+TTR	
λ	1.47±0.50		-0.98±0.44		1.00±0.54		-1.55±0.84	
	Kernel	NN	Kernel	NN	Kernel	NN	Kernel	NN
λ_T	-1.55±0.10	-1.00±0.25	-3.92±0.39	-3.39±0.42	-1.05±0.14	-1.22±0.19	-3.83±0.44	-4.58±0.61
λ_W	2.01±0.30	1.81±0.36	2.51±0.44	2.04±0.35	1.33±0.23	1.54±0.29	2.34±0.41	2.00±0.36
λ_A	0.72±0.29	0.61±0.26	0.68±0.27	0.57±0.24	0.54±0.21	0.43±0.17	0.51±0.19	0.40±0.15
λ_C					-0.14±0.55	-0.58±0.57	-0.33±0.56	-0.59±0.56
$\sum \lambda_X$	1.17±0.43	1.43±0.55	-0.73±0.48	-0.77±0.42	0.69±0.55	0.17±0.57	-1.30±0.86	-2.78±0.92
λ_e	-0.30	-0.04	0.25	0.21	-0.30	-0.83	-0.25	1.23
λ^{NN}		1.39±0.54		-0.74±0.42		0.24±0.57		-2.37±0.91

- Good closure in clear-sky; noticeable non-closure in all-sky. Why?

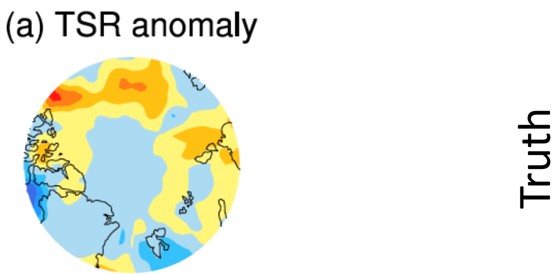
  Not strong global mean ΔR_X- ΔT relationship; inaccuracy in NN model; non-linear relationship between feedbacks!

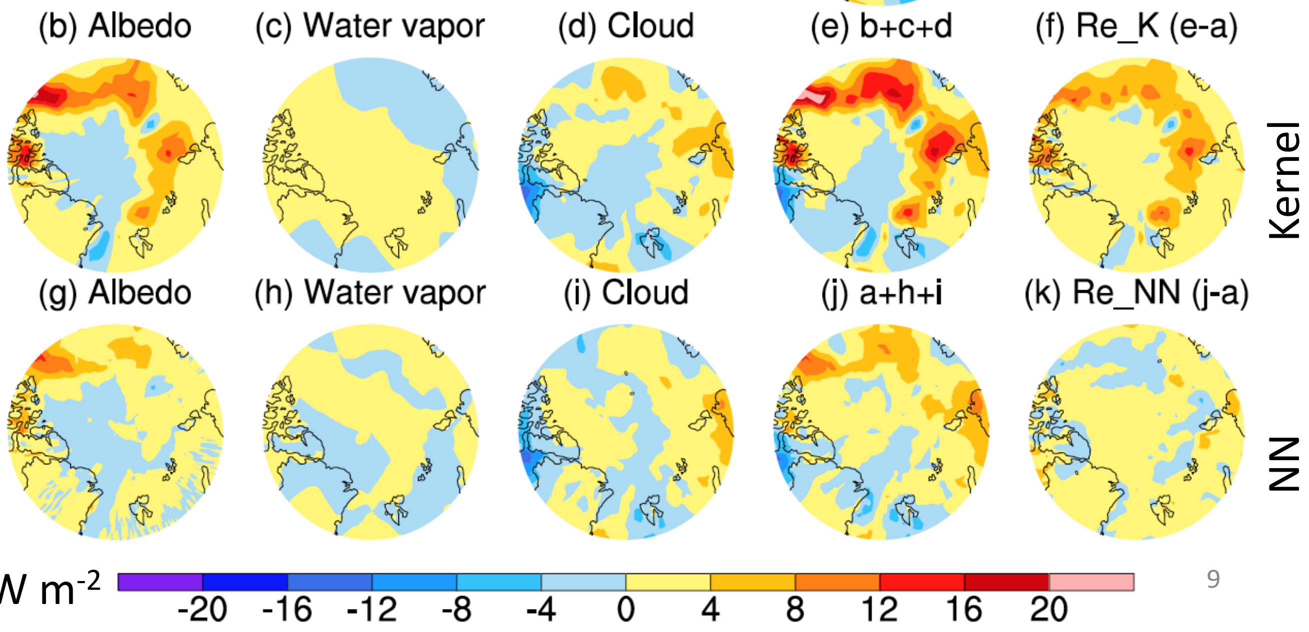
Nonlinearity in albedo feedback

- $\Delta R_X = K_X \cdot \Delta X$ Albedo kernel K_A is obtained by using small perturbation. If used to evaluated ΔR_A at large albedo changes, non-closure! [Shell et al. 2008]



- In comparison, the NN method achieves better closure.





SW radiation anomaly of September 2012. Units: W m^{-2}

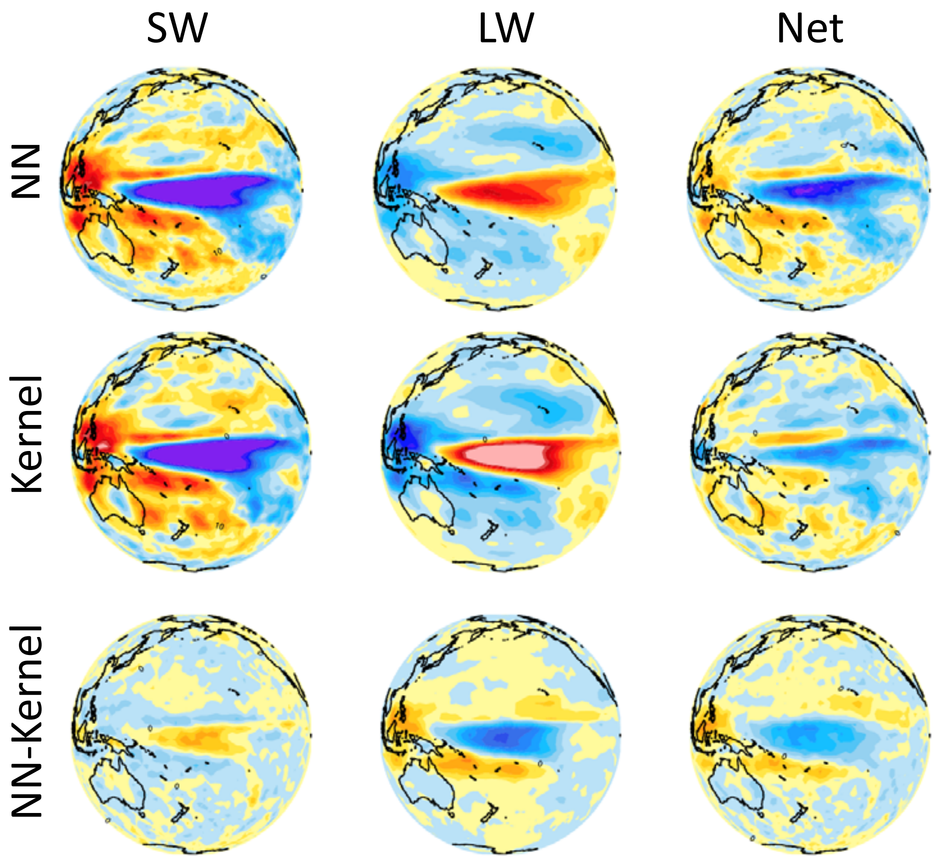
Cloud Feedback: NN vs. Kernel

Kernel: $\Delta R_C = \Delta R \quad - \sum \Delta R_X$

NN: $\Delta R_C = R^{NN}(C + \Delta C) - R^{NN}(C)$

Feedback: $\lambda_C = regress(\Delta R_C, \Delta T)$

- Similar patterns of cloud feedback from NN and kernel methods – ENSO.
- Quantitative difference – nonlinear effect between cloud and non-cloud feedbacks!



Cloud feedback. Units: W m^{-2} / K

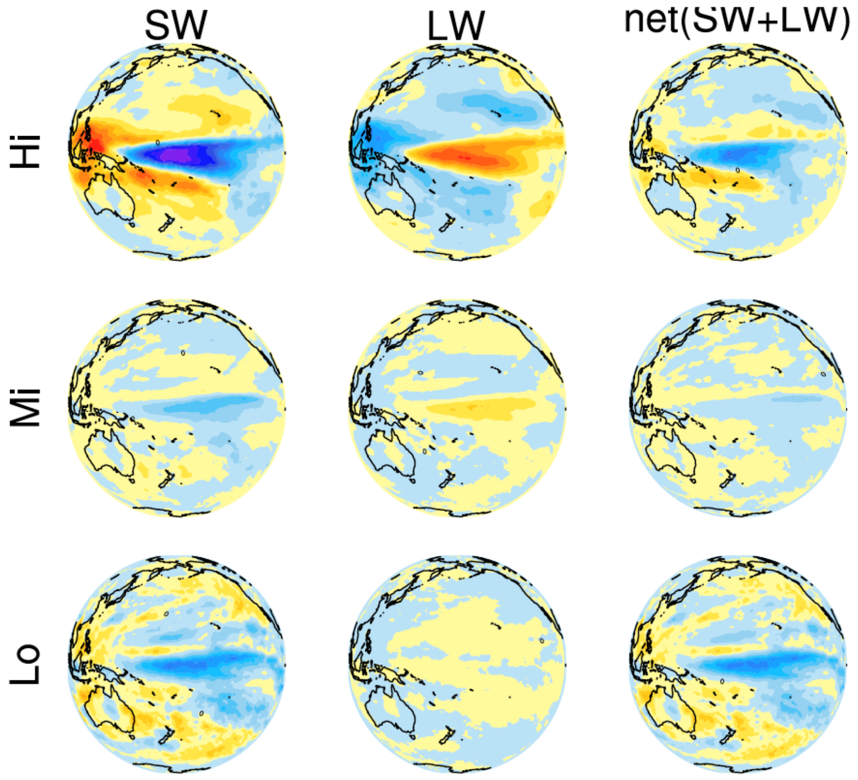
Cloud Feedback: hi/mi/lo components

- NN method can directly assess the total and component cloud feedback

E.g., high cloud (Hi):

$$\Delta R_{C\_hi} = R^{NN}(hcc + \Delta hcc, tciw + \Delta tciw) - R^{NN}(hcc, tciw)$$

- High-cloud dominates the feedback for interannual radiation variability.



Cloud feedback. Units: W m^{-2} / K

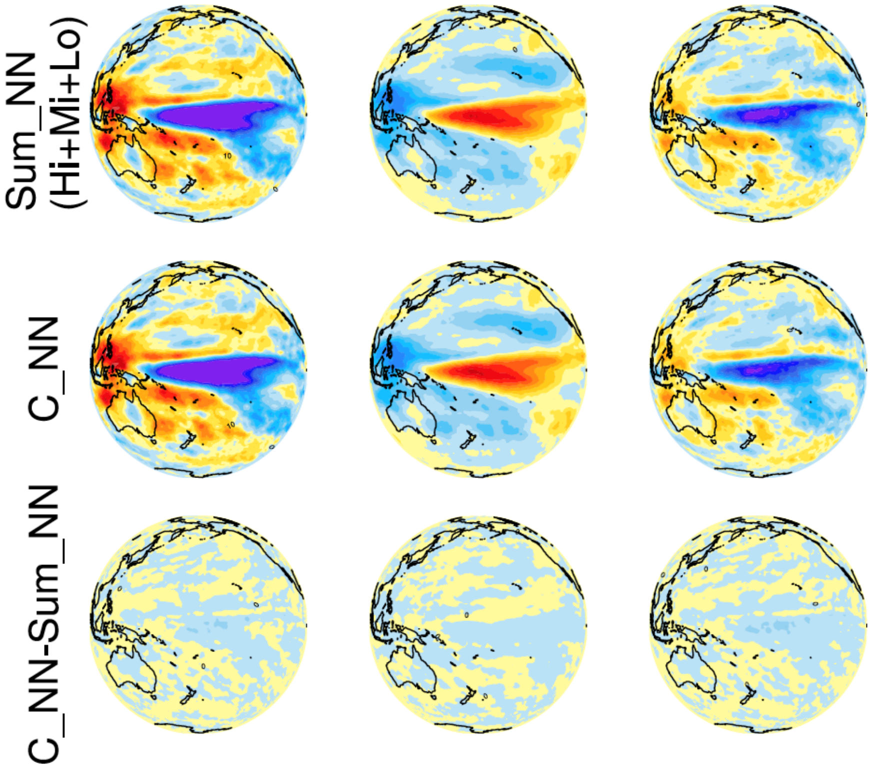
Cloud Feedback: hi/mi/lo components

- NN method can directly assess the total and component cloud feedback

E.g., high cloud (Hi):

$$\Delta R_{C\_hi} = R^{NN}(hcc + \Delta hcc, tciw + \Delta tciw) - R^{NN}(hcc, tciw)$$

- Sum of components reproduces total cloud feedback – nonlinear coupling between the hi/mi/lo components very small!



Cloud feedback. Units: W m^{-2} / K

Conclusions

- A new set of kernels now available for TOA and surface radiative feedback analysis
- NN is a viable method for feedback analysis, with advantages:
  - Accounts for nonlinearity, e.g., closure issue in the surface albedo feedback related to large Arctic sea ice melt
  - Directly measures cloud feedback, which has strong nonlinear coupling with non-cloud feedbacks
  - So far, proof-of-the-concept. Can be further improved, e.g., Global model vs. latitudinal/local models; selection of predictive variables

- References

1. Huang, Y., Y. Xia and X. Tan, (2017), On the pattern of CO_2 radiative forcing and poleward energy transport, J. Geophys. Res.-Atmos., 122, 10,578–10,593.
2. Zhu, T., Y. Huang and H. Wei, (submitted), Estimating climate feedbacks using neural network, J. Geophys. Res.-Atmos.