Analyzing Aerosol Indirect Effect (AIE) on Deep Convective Clouds (DCCs) over the Global Oceans by Using AI Based Techniques

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Outline

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Background

- DCCs play an important role in the hydrological and energy cycles associated with atmospheric circulations as well as in regional and local weather and climate systems.
- Due to complicated dynamical, thermodynamic, and microphysical processes in the formation and development of DCCs, the global aerosol indirect effects (AIE) on DCCs are extremely complex and widely debated, and is still the most actively studied subject of aerosol cloud interactions (ACIs).
- Observational and modeling studies of aerosol effects on DCCs are performed more actively on regional and local spatial scales as well as on cloud and sub-cloud scales with short temporal coverage, which is critical for identifying the mechanisms and processes for the interactions of aerosols and DCCs.
- The study of global long-term effects of aerosols on DCCs from a climatological (or long-term mean) perspective are mainly based on global model simulations with limited validations due to lack of global coherent long-term observations of aerosols and DCCs. As a result, large uncertainties still exist in the climate simulations of ACIs for DCCs in global climate models.

Objective

- We would like to use nearly 40-years NOAA satellite climate data records (CDRs) of aerosol and cloud along with NCEP meteorological reanalysis to study the aerosol effects on DCCs over the global oceans from a climatological perspective considering that the climate of the atmosphere represents its mean state for a given relatively long time period.
- Specifically, we would like to identify potential signatures or imprints of the aerosol effect on DCCs over the global oceans from the long-term mean values of cloud variables by disentangling the aerosol effect from the covariance of meteorological condition with the help of AI techniques.

Satellite CDRs and Reanalysis Product Used

1. NOAA AVHRR + HIRS PATMOS-x Cloud CDRs (v6.0):

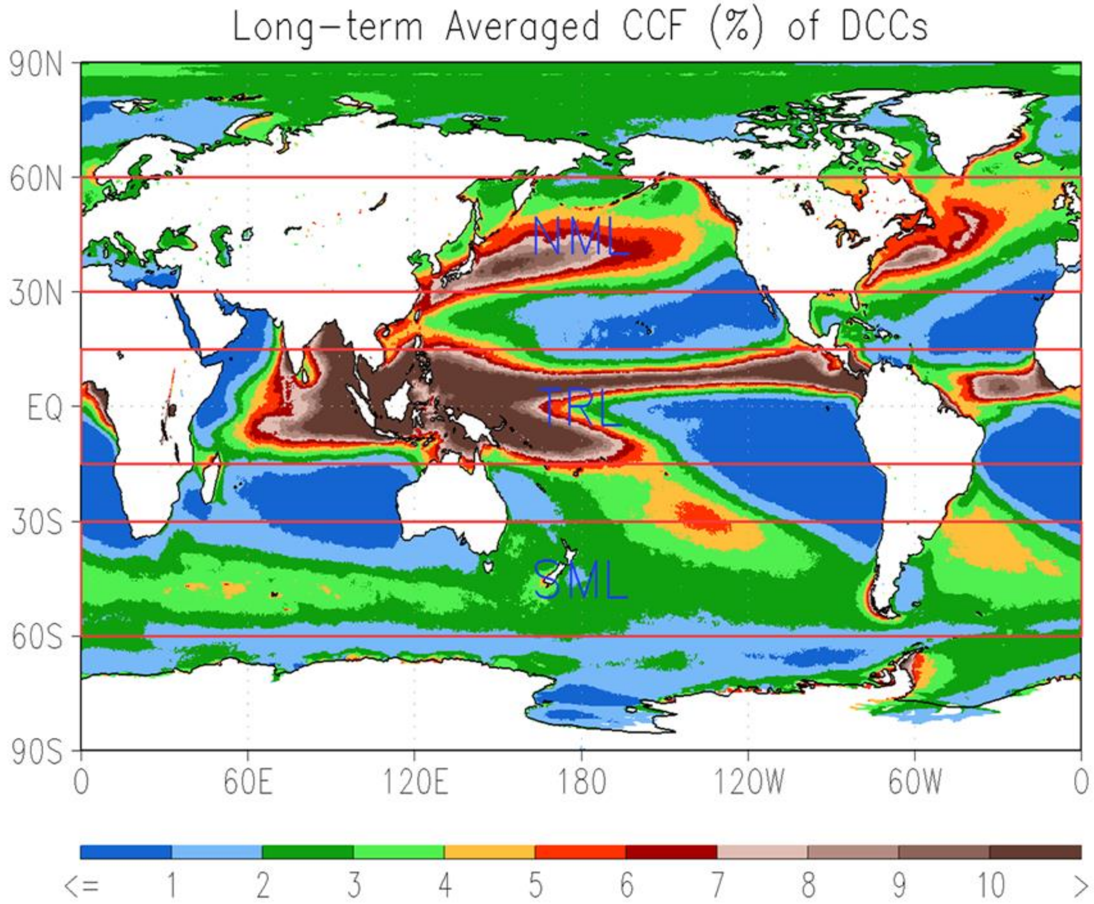
- **Level-2b Products:** 0.1º x 0.1º equal angle daily orbital grid. Global coverage from 1981-present.
- **6 Cloud Variables:**
    - *3 microphysical variables: CPER, COD, IWP*
    - *3 macrophysical variables: CCF, CTH, CTT*

Determine DCC for orbital grids:

- Ice cloud
- CTT < 245K, CTH > 6km, and COD > 23

Thirty-eight years (1982–2019) of daily orbital DCC products of 6 cloud variables are averaged to obtain their monthly, annual, and long-term mean values and used in this study.

Studied Regions (NML, TRL, SML)



2. NOAA AVHRR Satellite AOT CDR (v4.0):

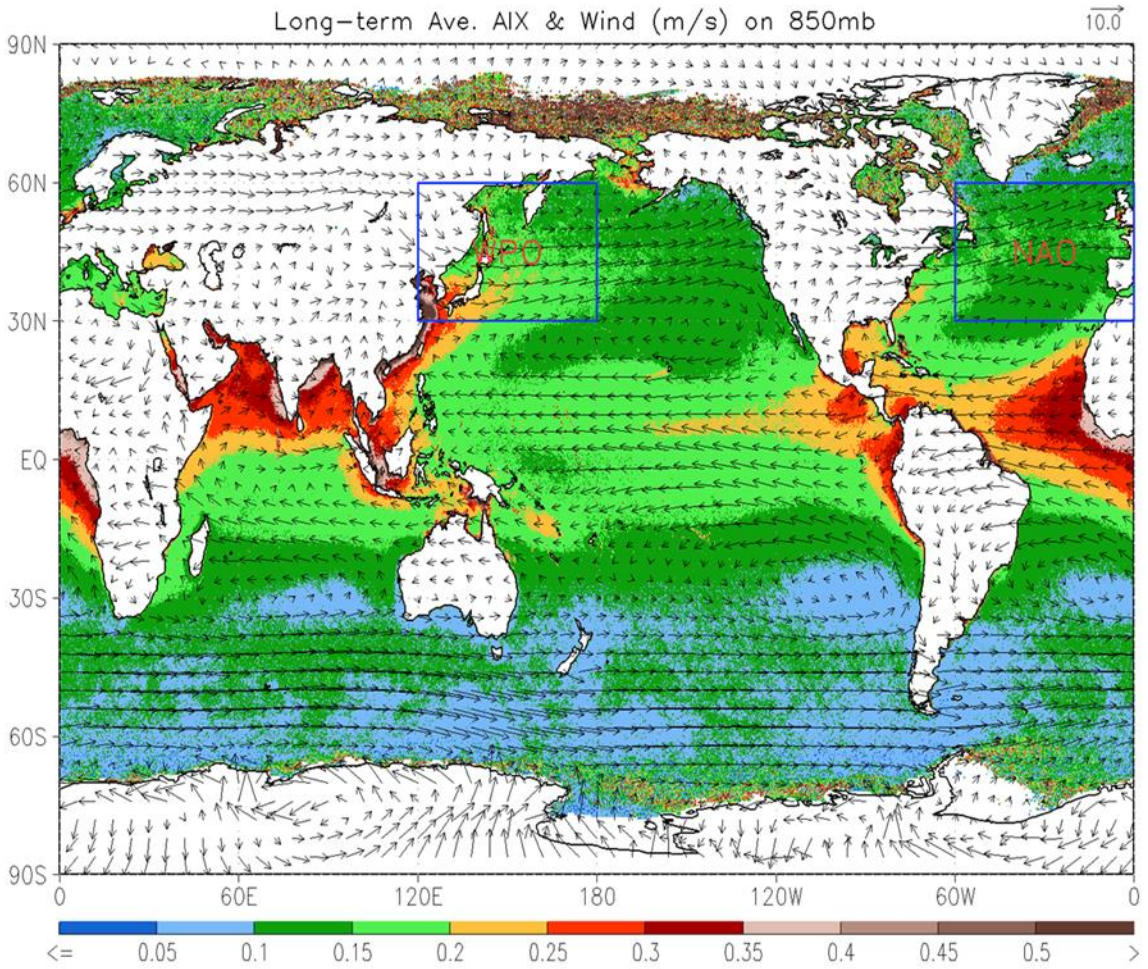
- AOT at λ_1 = 0.63μm (τ_1) & λ_2=0.86μm (τ_2)
- Spatial/temporal resolution: 0.1^o x 0.1^o/daily & monthly
- Spatial/temporal coverage: global ocean/1982-present

Derive the Daily Aerosol Index (AIX):

- AIX = τ_1 x α , α = -ln(τ_1/τ_2)/ln(λ_1/λ_2)
- AIX is a better proxy for column aerosol concentration than AOT.

Thirty-eight years (1982–2019) of daily products of AVHRR AIX are averaged to obtain monthly, annual, and long-term mean values and used in this study.

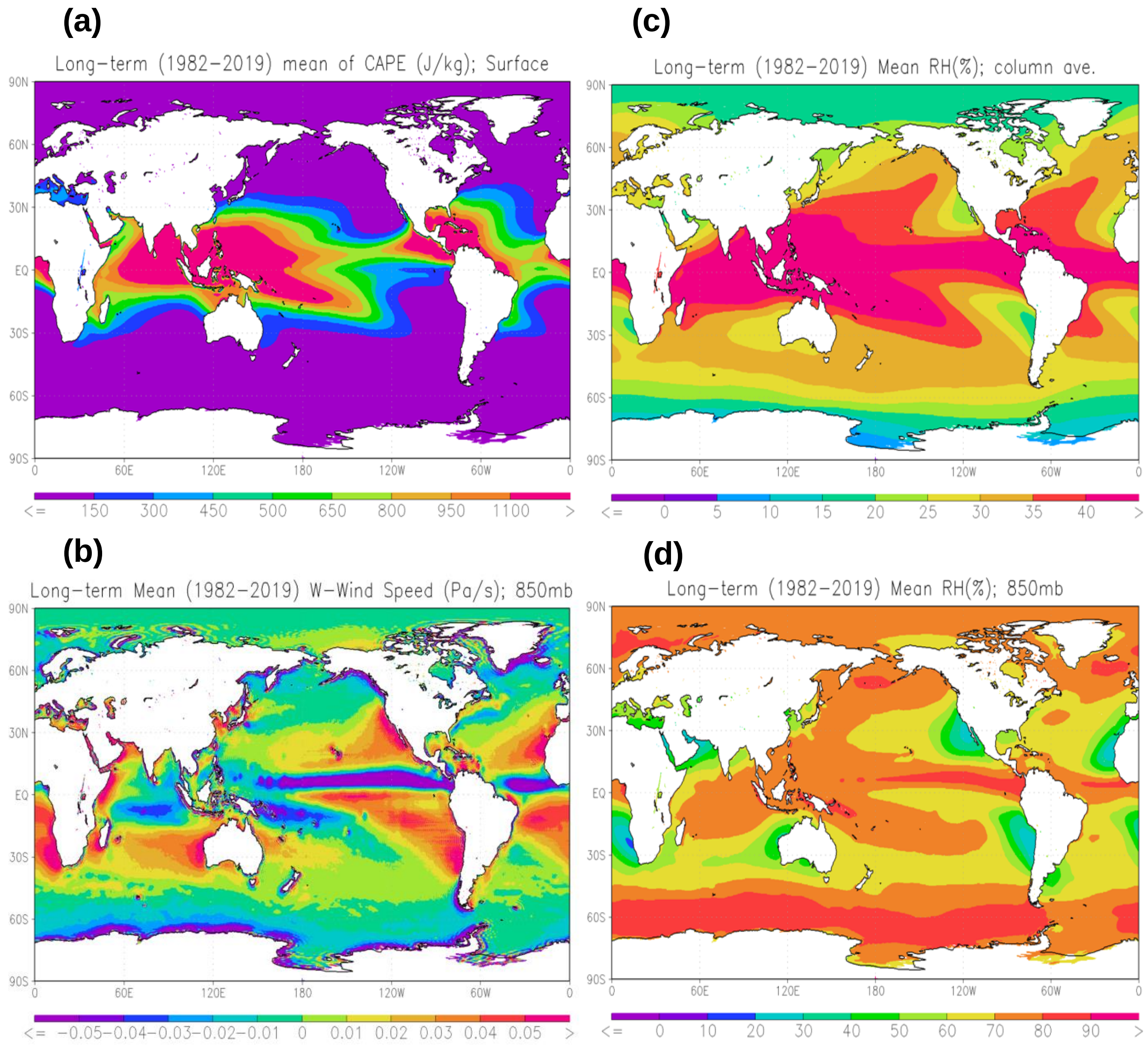
In-Depth Studied Regions (WPO, NAO)



3. NCEP CFSR Reanalysis Monthly Mean Product:

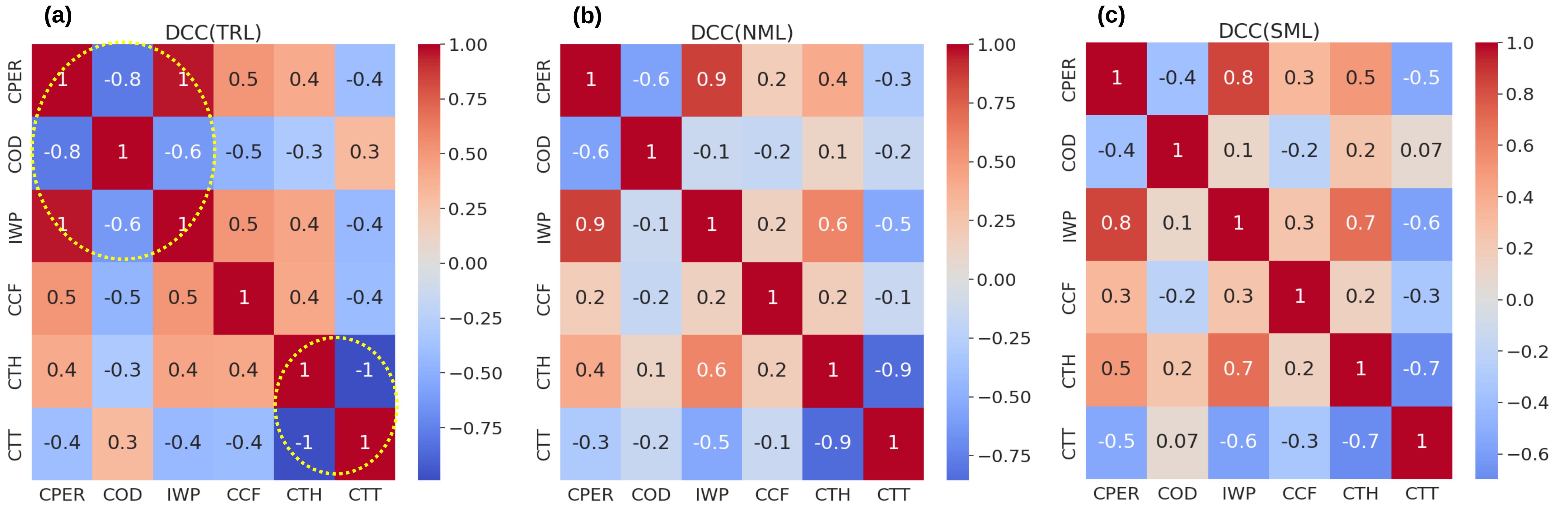
- 0.5º x 0.5º latitude/longitude global grid from 1979 to present.
- **19 Variables Selected:** CAPE(surface), PW(column), RH(column), RH(850mb), RH(400mb), RH(2m), T(850mb), T(400mb). T(2m), ω(850mb), ω(400mb), ω(sig995), U(850mb), U(400mb), U(10m), V(850mb), V(400mb), V(10m), VSHW(700mb/400mb).

Thirty-eight years (1982–2019) of 19 selected variables from monthly CFSR are interpolated to 0.1º x 0.1º and averaged to obtain annual and long-term mean values and used in this study along with their monthly values.

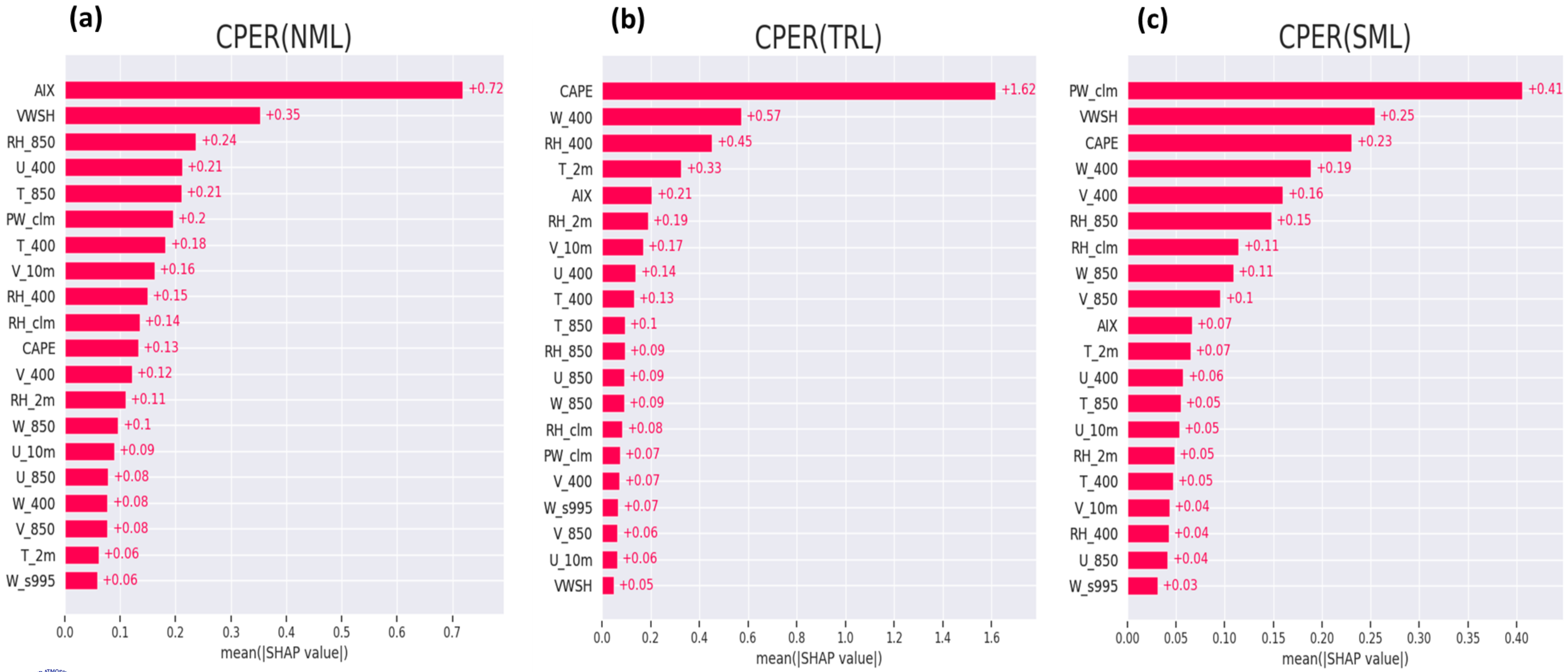


Correlation Study from XGBoost/SHAP Analysis

Nonlinear Correlation Matrix of Six DCC Variables



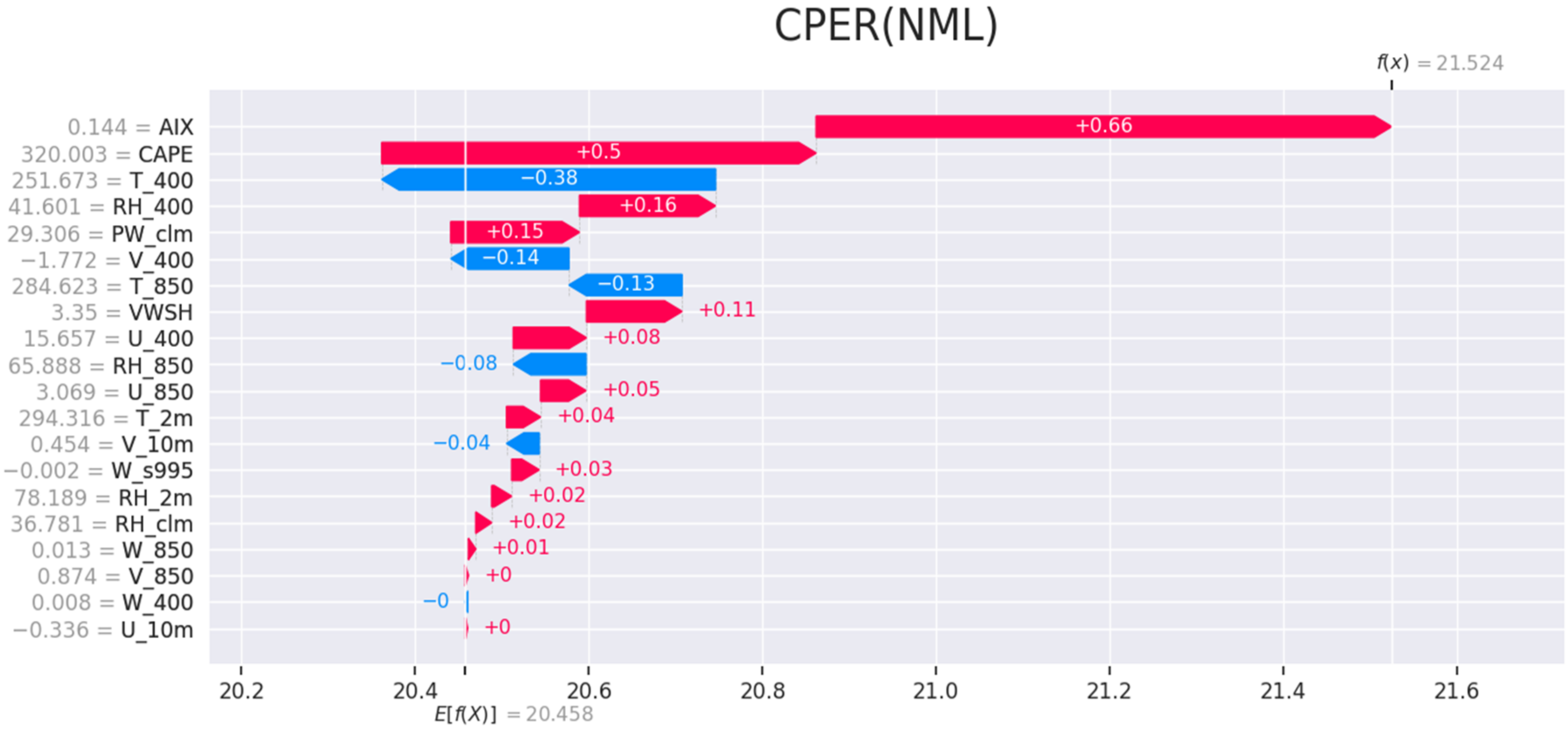
Bar Plots of Absolute SHAP Values of 20 Variables for CPER



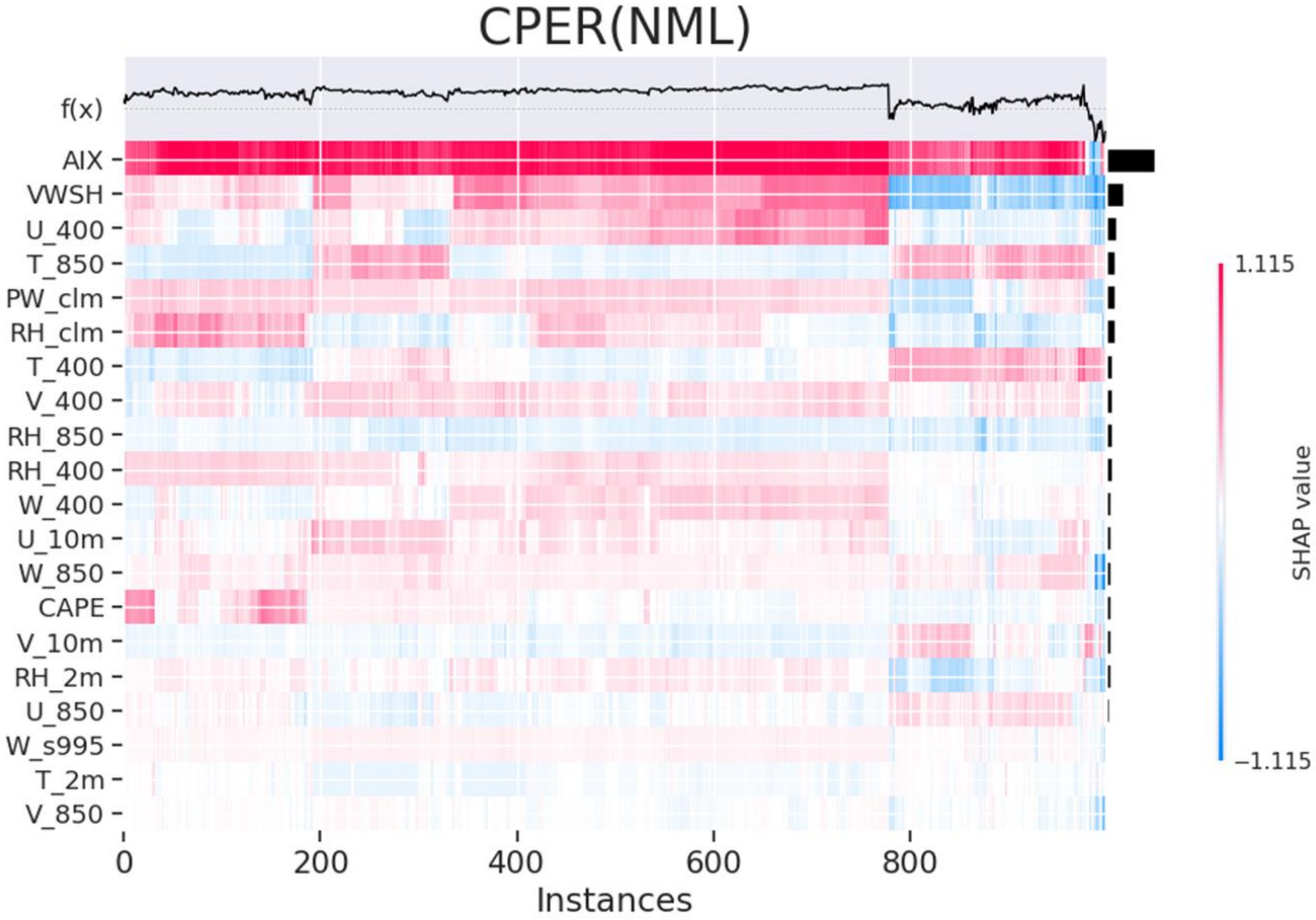
Top Three Important Aerosol and Meteorological Variables in the SHAP Analysis for the 6 Cloud Variables in the NML

Cloud Variable	1st important (SHAP value)	2nd important (SHAP value)	3rd important (SHAP value)	Notes
CPER	AIX (0.72)	VSHW (0.35)	RH_{850mb} (0.24)	AIE may easy to manifest
COD	T_{850mb} (1.04)	AIX (0.44)	RH_{400mb} (0.43)	AIE may not easy to manifest
IWP	RH_{400mb} (7.87)	VSHW (7.51)	AIX (6.20)	AIE may not easy to manifest
CCF	V_{400mb} (0.00406)	RH_{400mb} (0.00403)	U_{400mb} (0.00395)	AIE may be concealed easily
CTH	T_{400mb} (0.52)	U_{400mb} (0.11)	RH_{400mb} (0.10)	AIE may be concealed easily
CTT	T_{400mb} (0.53)	CAPE (0.44)	RH_{2m} (0.31)	AIE may be concealed easily

Waterfall Plot of SHAP Values



Heatmap of SHAP Values of 20 Variables over All the Grid Points (or Instances)



Separating Entangled Effects of ACI by Using a BPNN Machine Learning Model

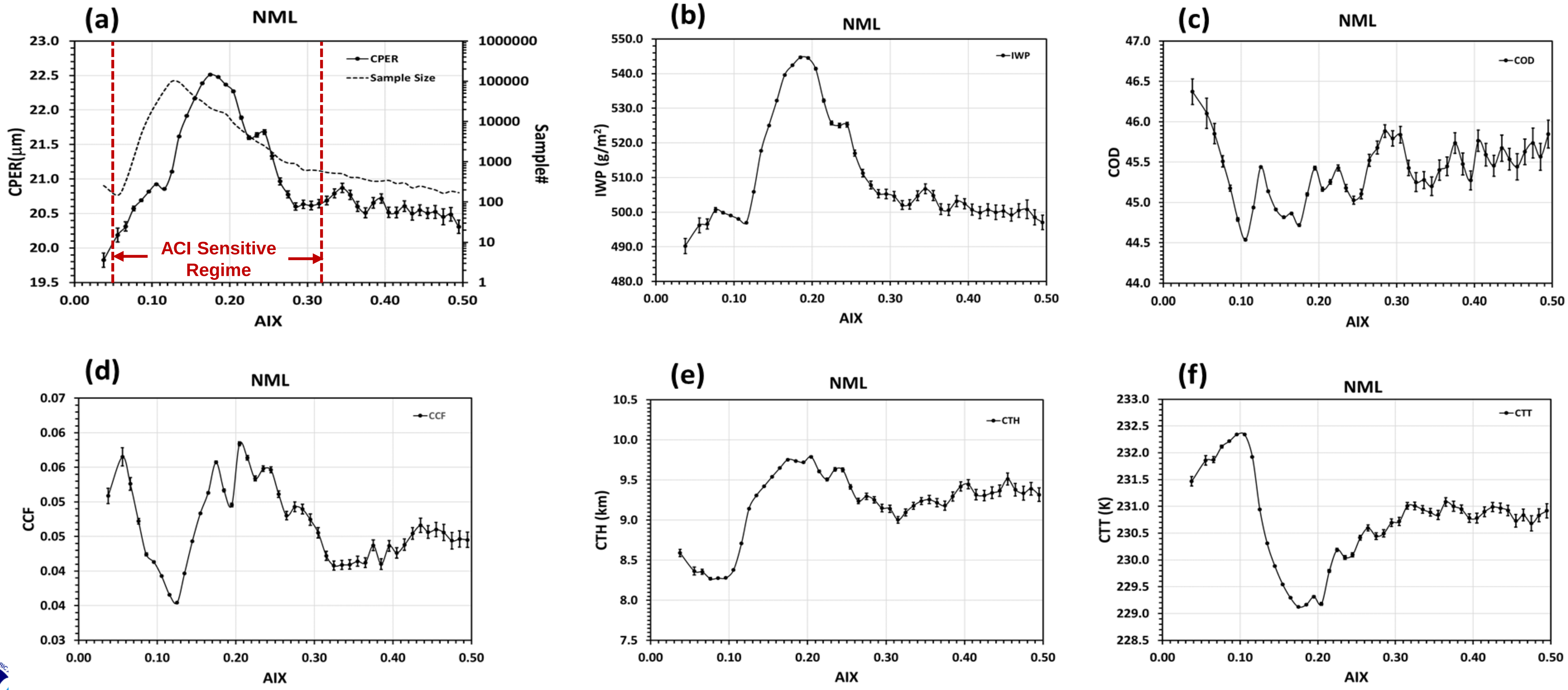
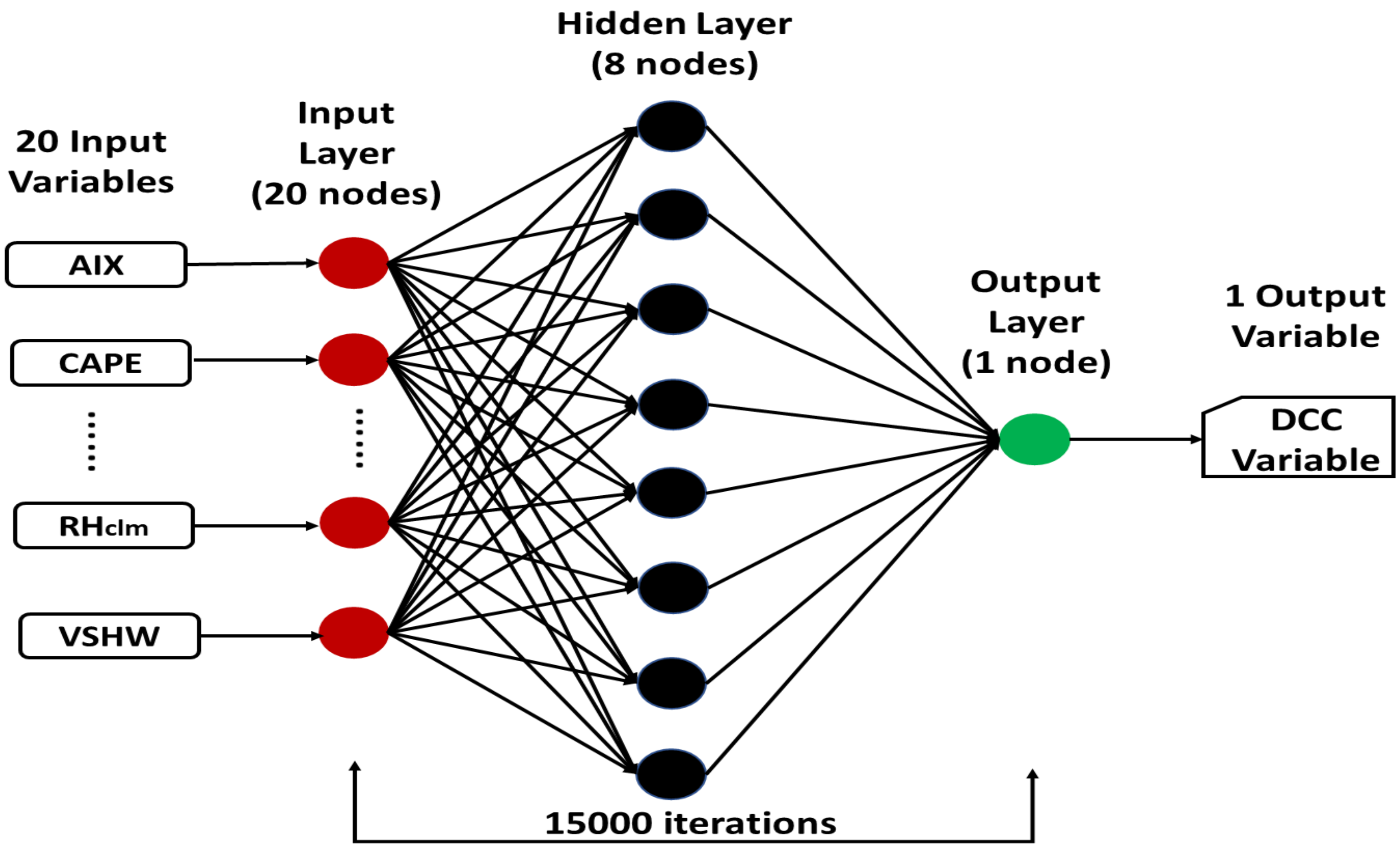
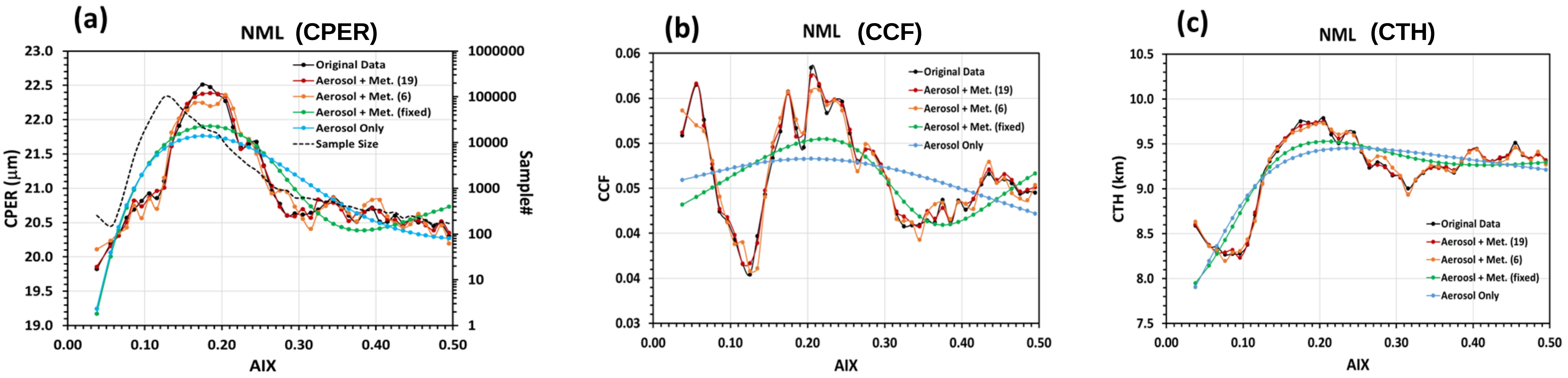


Diagram of 3-Layers Back-Propagation Neural Network (BPNN) Model



Fitting Curves from the BPNN Model with Different Input Variables



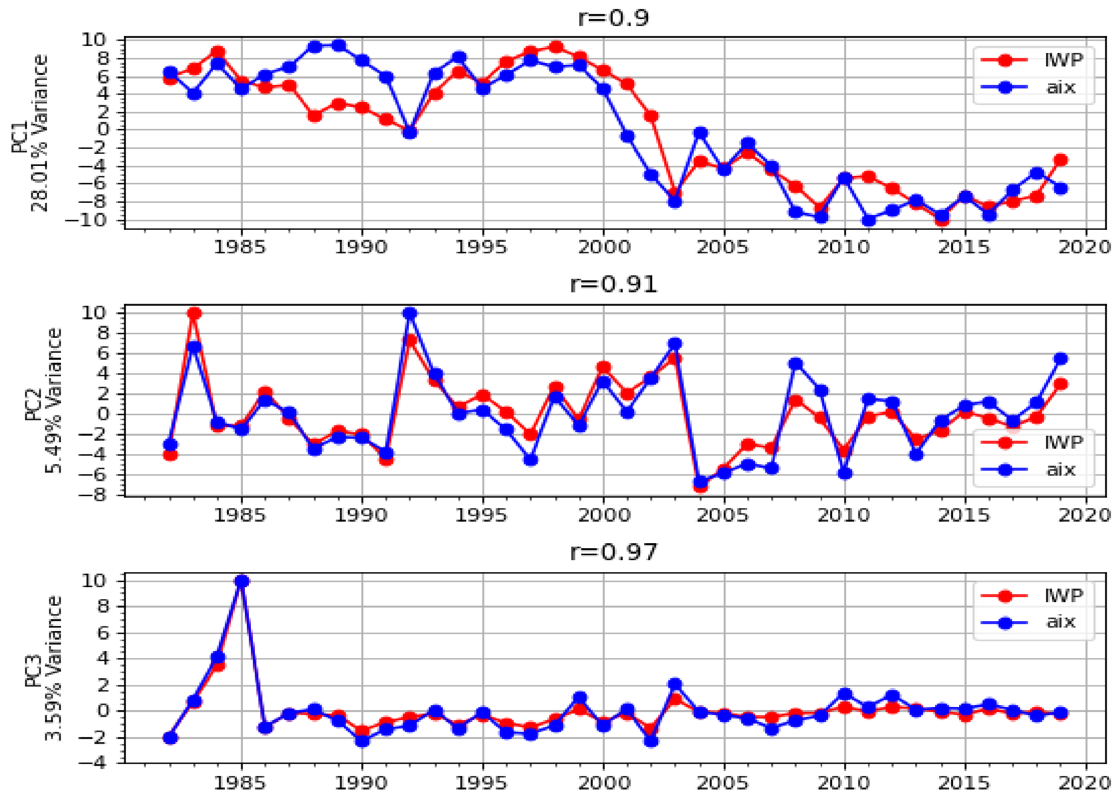
Case 1: Original statistical relationship of AIX vs 6 DCC variables.
Case 2: BPNN model fitting using AIX + 19 CFSR variables.
Case 3: Similar to Case 2 but using AIX + 6 CFSR variables (CAPE, PW, RH_{clm}, T_{850mb}, ω_{400mb}, VSHW).
Case 4: Similar to Case 2 but the values of 19 CFSR variables are fixed to their values in the 1st bin of AIX.
Case 5: Only AIX is include in fitting (the primary aerosol effect).

1) **The primary aerosol effect (the aerosol effect without meteorological feedbacks and covariances) explains only partially the aerosol effects & convective invigoration of marine DCCs (see green & blue lines).**
2) **The meteorological feedbacks and covariances need to be included to accurately capture the convective invigoration (see yellow & red lines).**

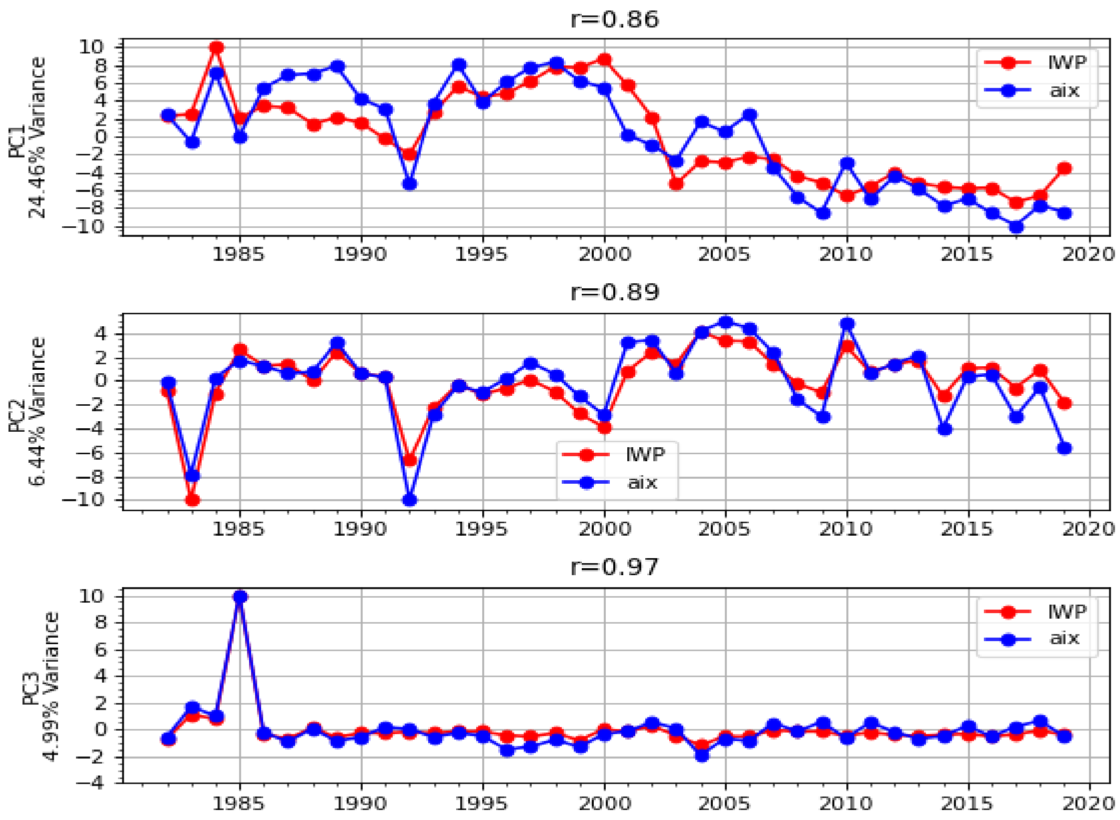
Singular Value Decomposition (SVD) Analysis of Aerosol Effect on Cloud Variables

Time Series of 3-Leading Principal Components (PCs) of SVD Analysis for IWP vs. AIX

IWP (WPO)

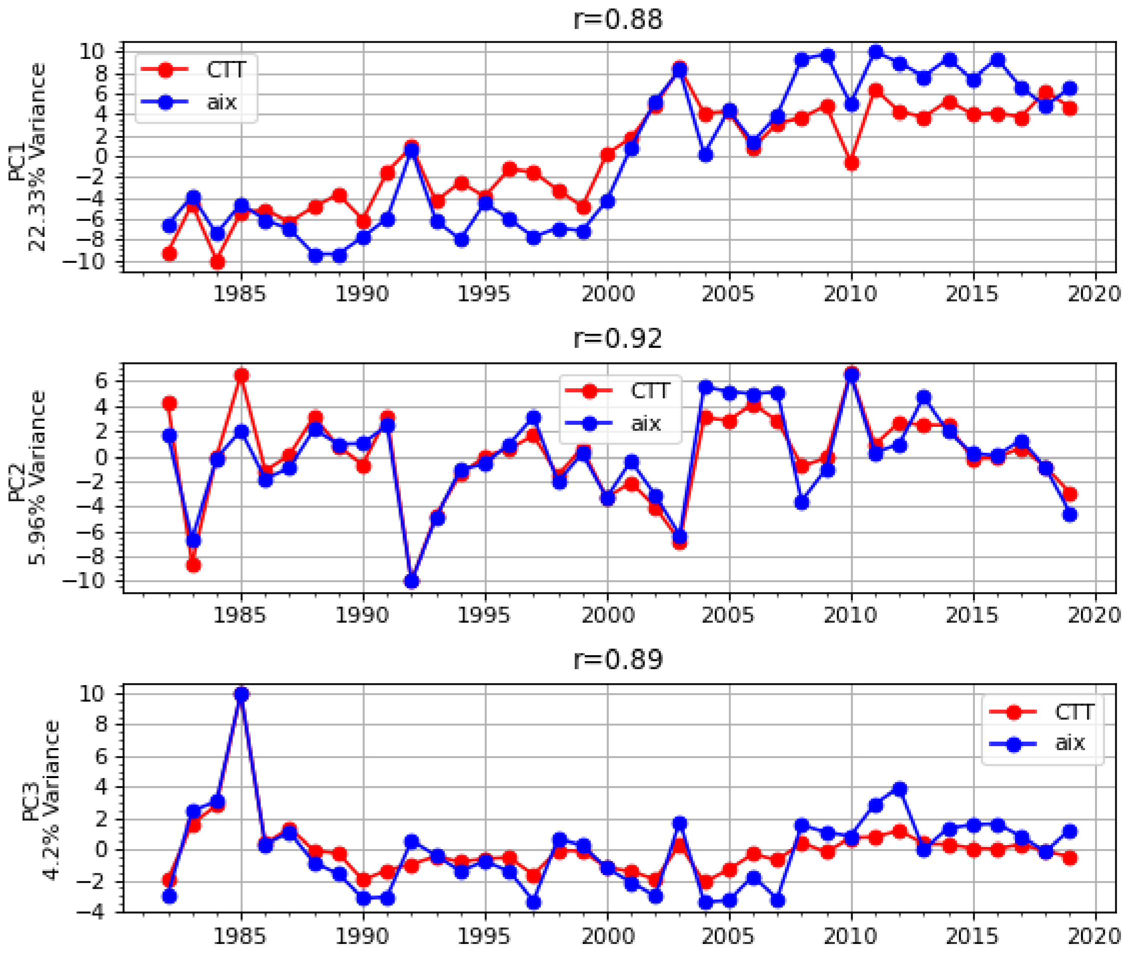


IWP (NAO)

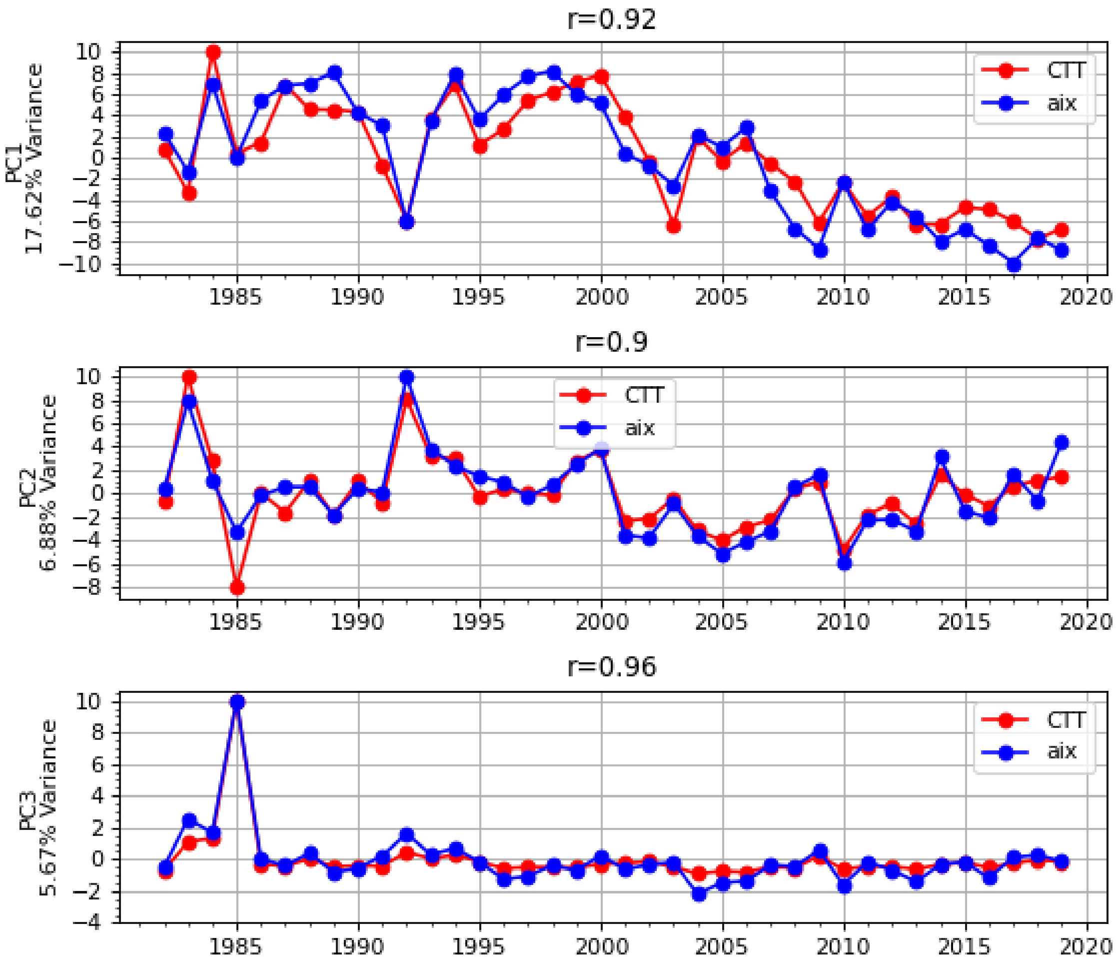


Time Series of 3-Leading Principal Components (PCs) of SVD Analysis for CTT vs. AIX

CTT (WPO)



CTT (NAO)



Summary & Conclusions

1. Long-term (1982-2019) satellite CDRs of aerosol and cloud along with CFSR reanalysis meteorological data have been used to study the aerosol effects on DCCs over the global oceans from a climatological perspective by using AI based techniques.
2. The aerosol effect on marine DCCs may be detected in NML from long-term averaged satellite aerosol and cloud observations. Specifically, CPER is more susceptible to the aerosol effect than the other cloud microphysical variables (e.g., COD).
3. The signature of aerosol effect on DCCs can be easily obscured by meteorological covariances for the cloud macrophysical variables, such as CCF and CTH.
4. IWP and CTT are more effective cloud micro- and macro-physical variables, respectively, for detecting the aerosol effect on DCCs in their leading SVD principal components.
5. BPNN analysis indicates the primary aerosol effect explains only partially the convective invigoration. The meteorological feedbacks and covariances need to be included to accurately capture the convective invigoration.
6. Our results based on the long-term averaged operational satellite observation are valuable for the evaluation and improvement of aerosol-cloud interactions in global climate models from a climatological perspective.

Acknowledgement

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---Thank You for Your Attention---

Questions?

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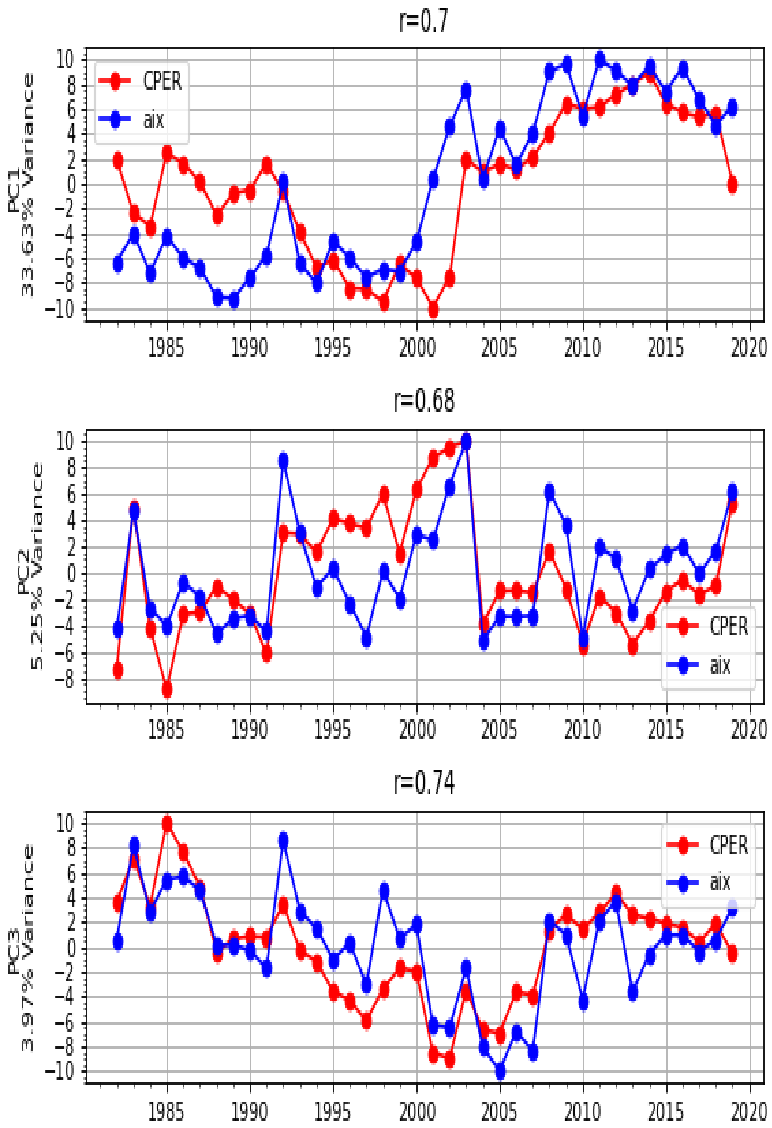
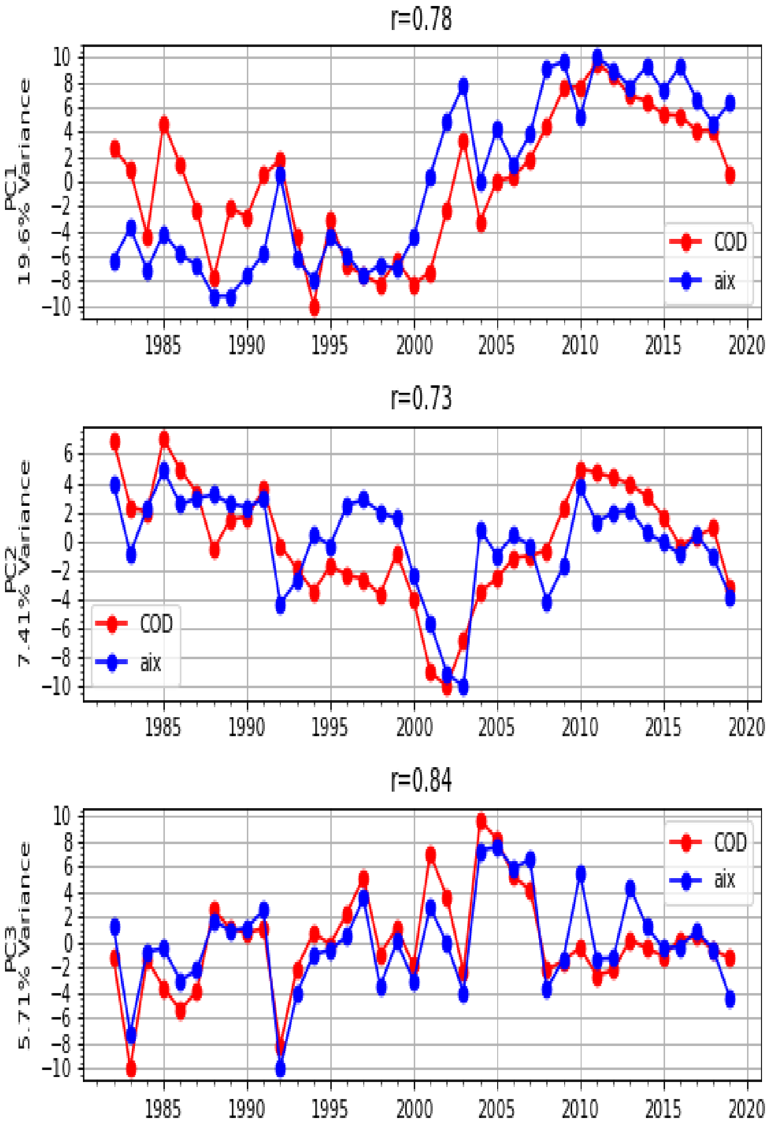
Backup Slides

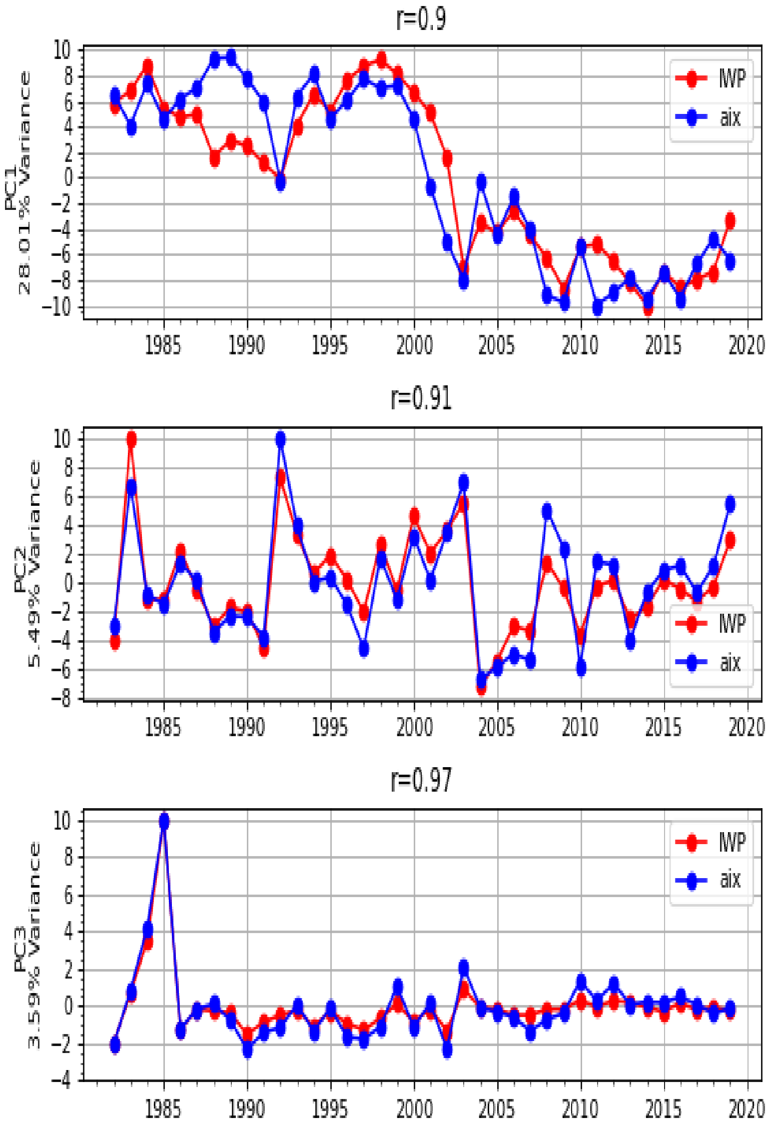
CPER (WPO)



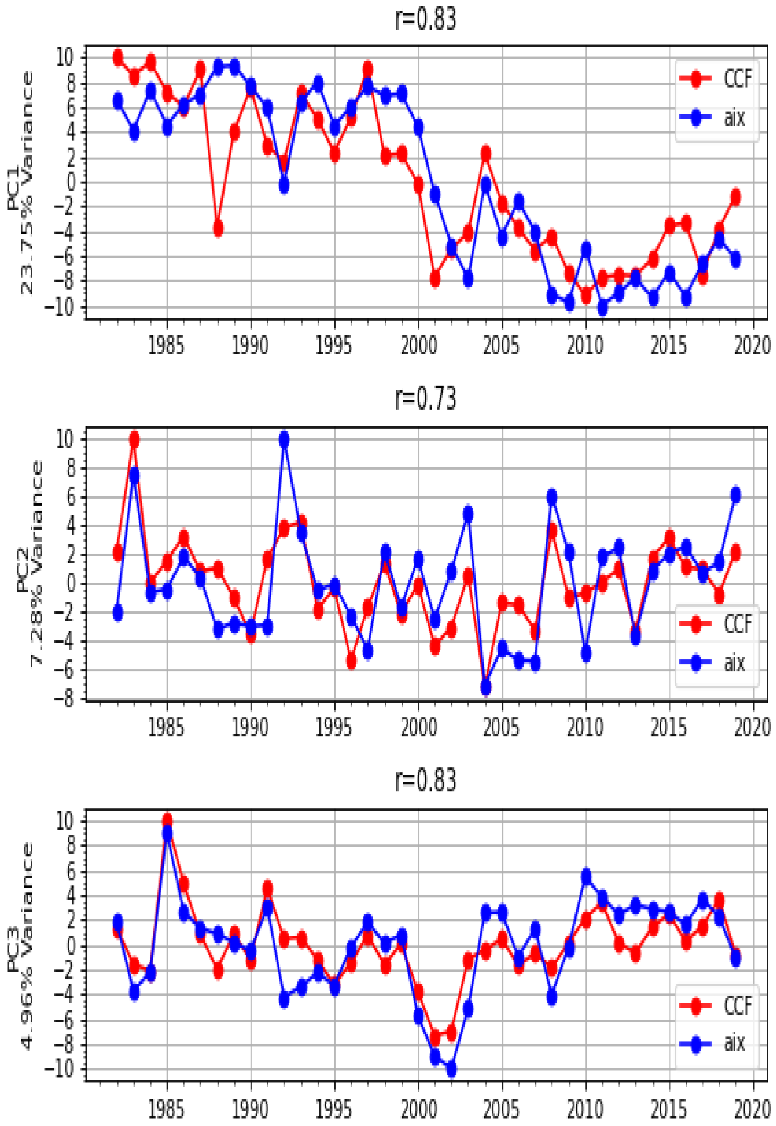
COD (WPO)



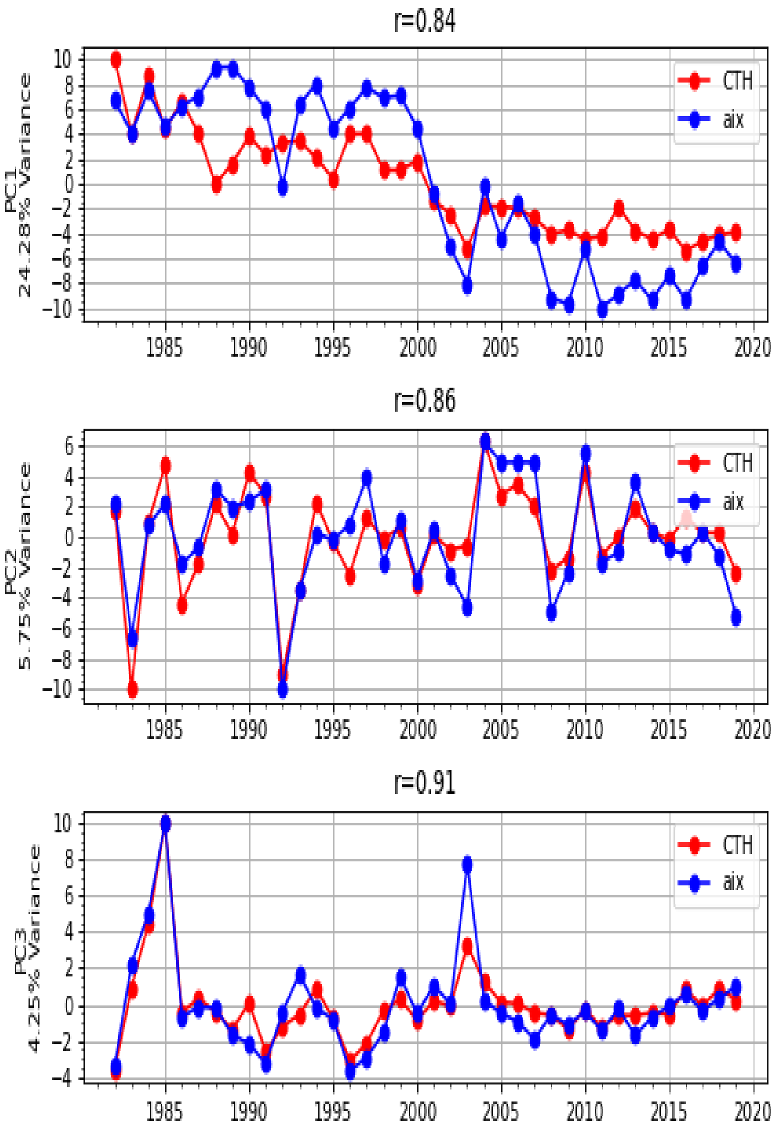
IWP (WPO)



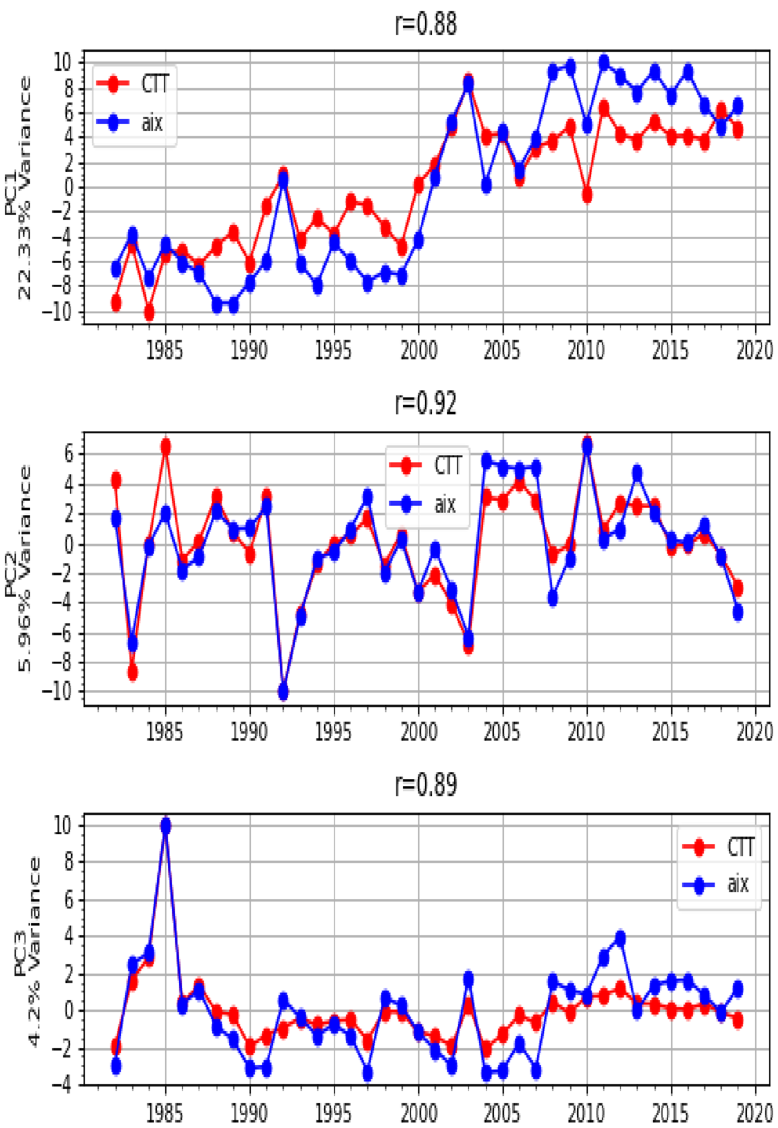
CCF (WPO)



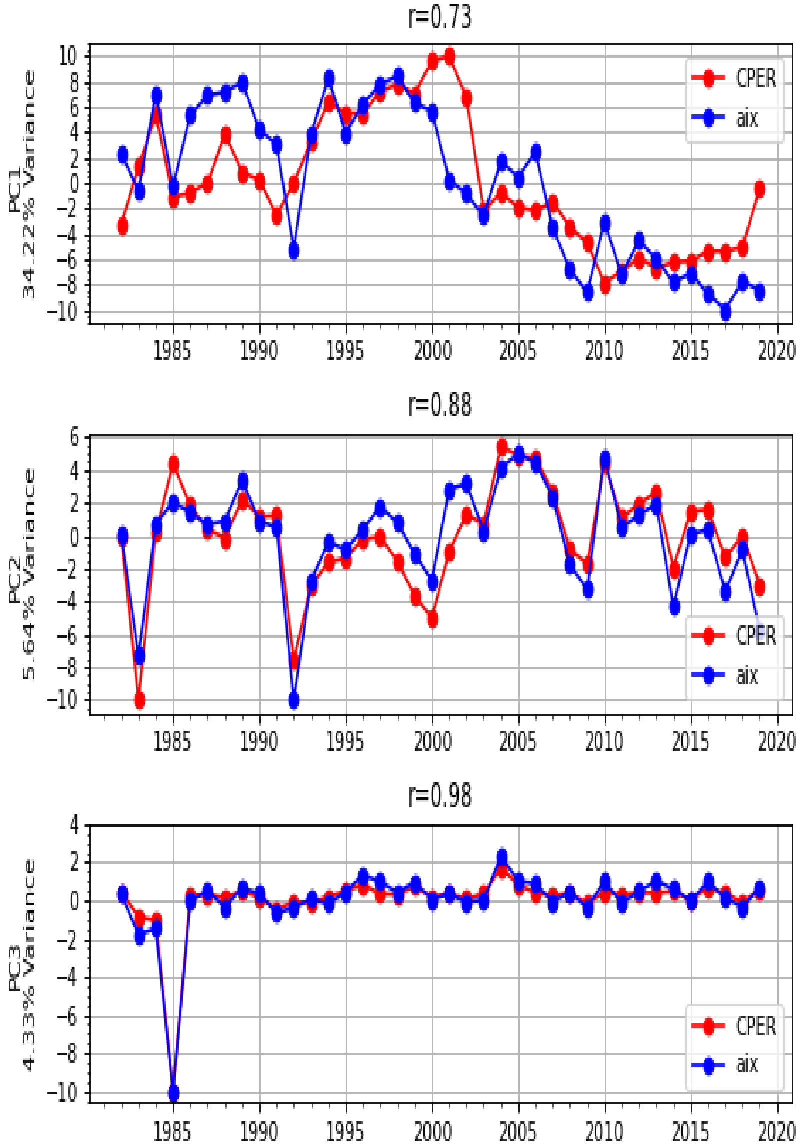
CTH (WPO)



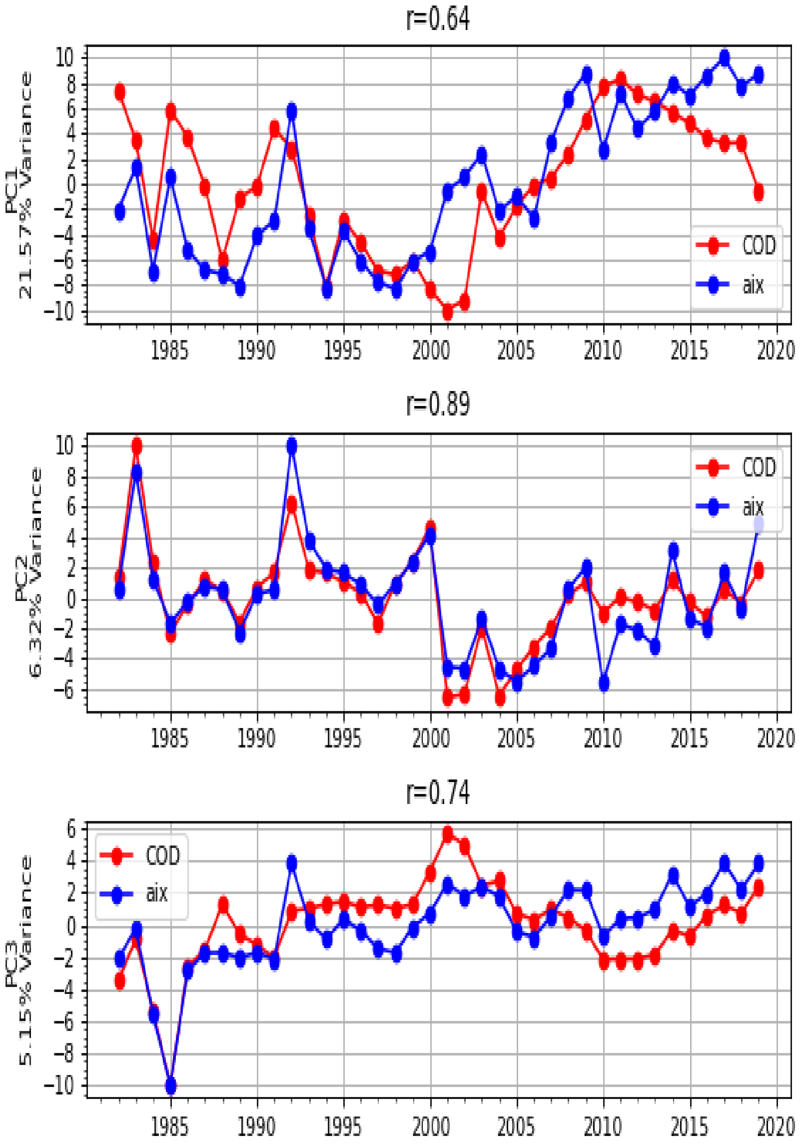
CTT (WPO)



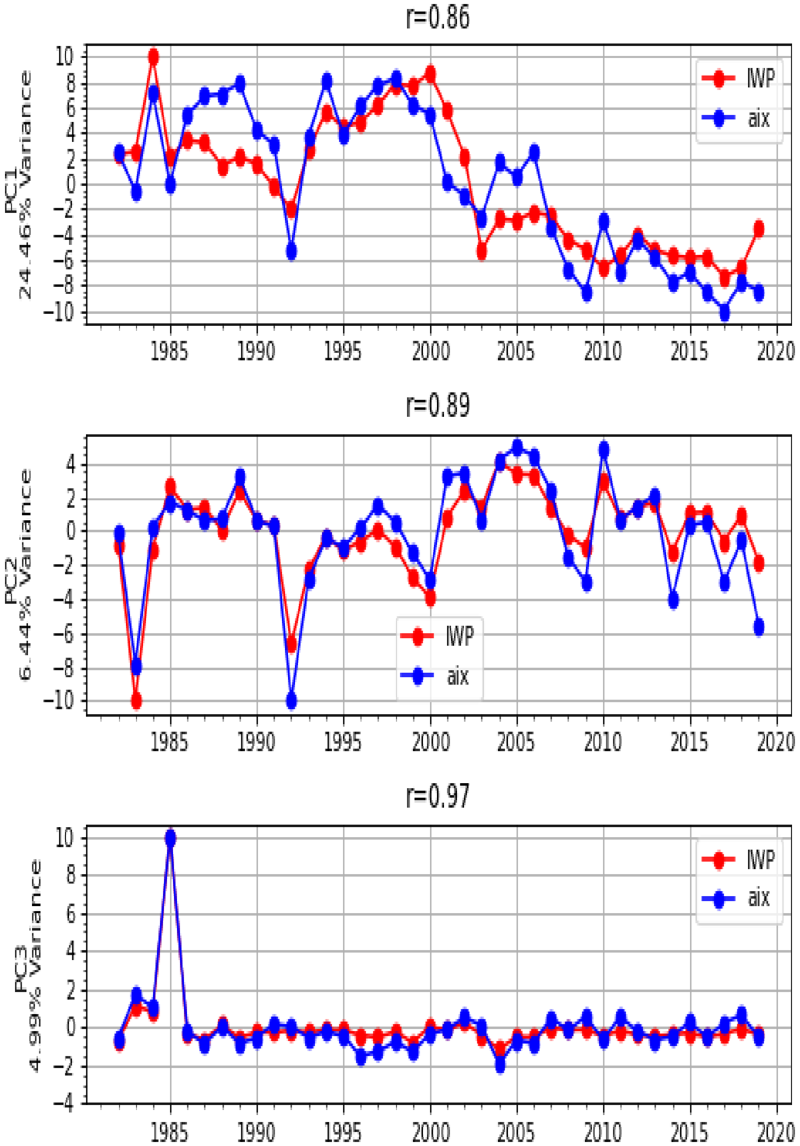
CPER (NAO)



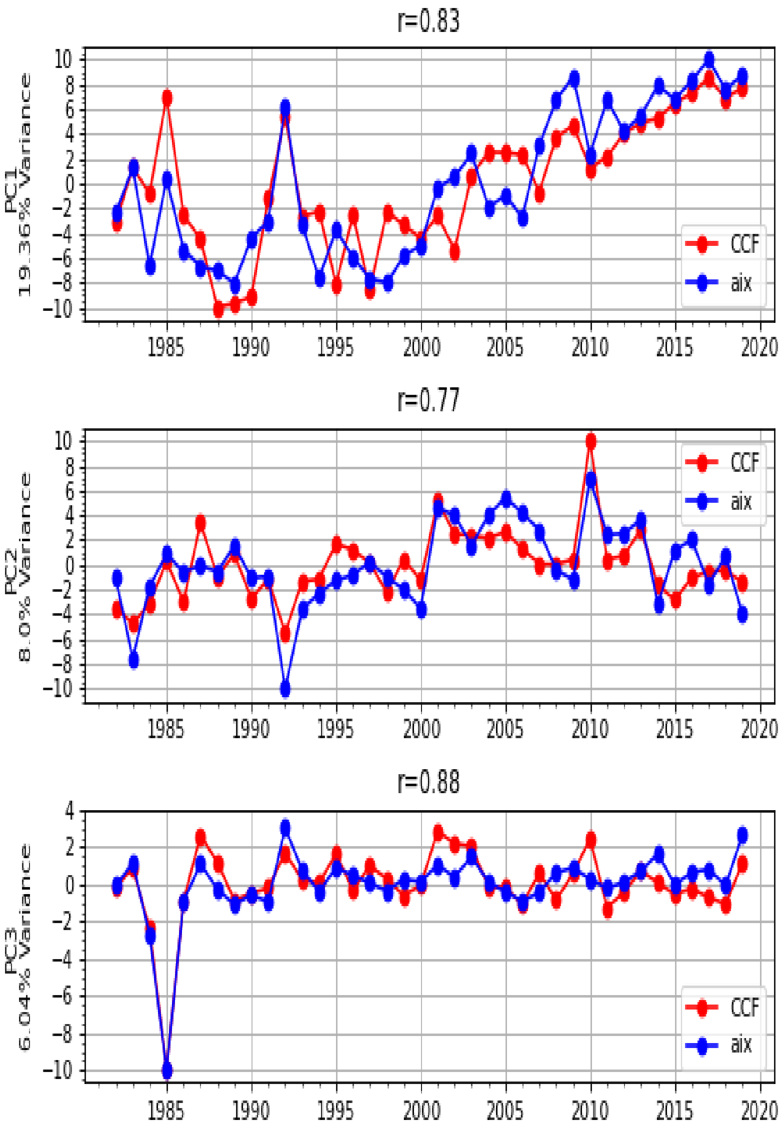
COD (NAO)



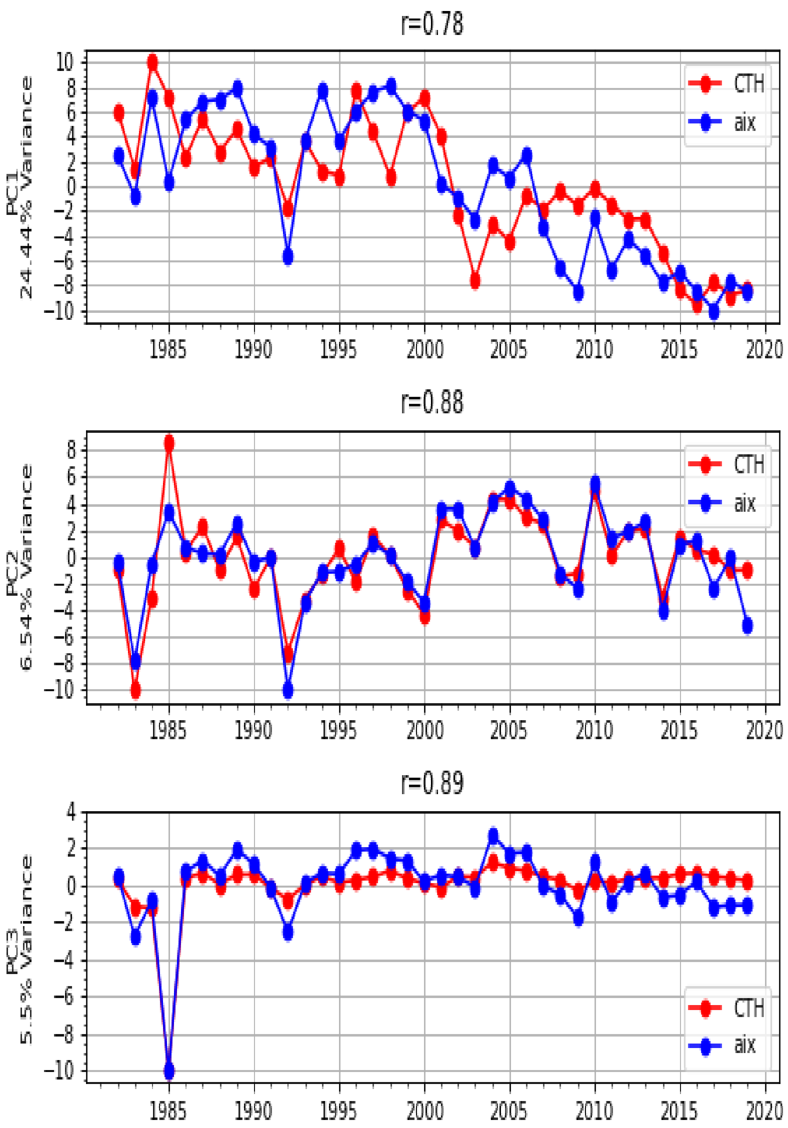
IWP (NAO)



CCF (NAO)



CTH (NAO)



CTT (NAO)