Supplementary material for

On the cause-and-effect relations between aerosols, water vapor and clouds over East Asia

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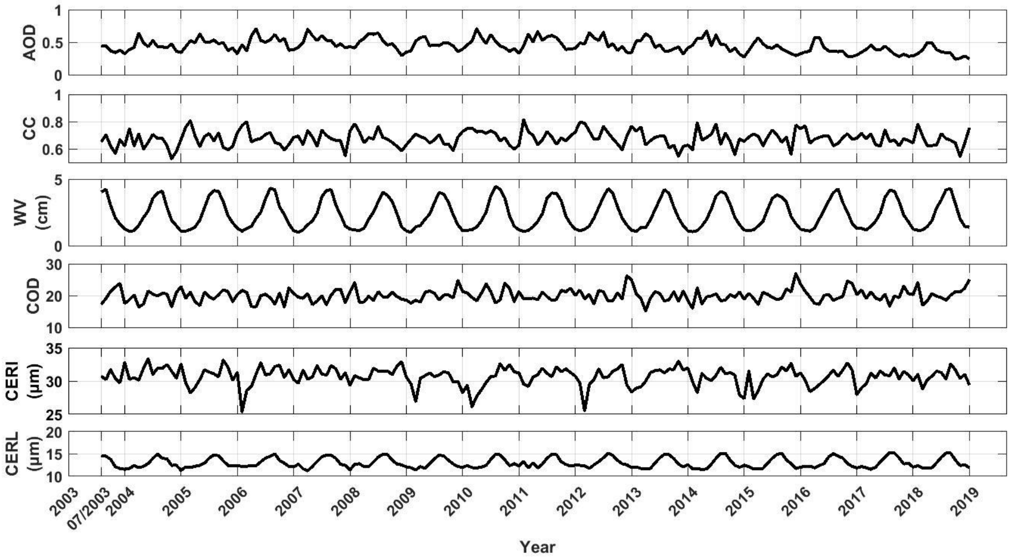

Fig. S1 Timeseries of Aerosol Optical Depth at 550 nm (AOD), Cloud Cover (CC), Water Vapor (WV), Cloud Optical Depth (COD), Cloud Effective Radius-Ice (CERI) and Cloud Effective Radius-Liquid (CERL) from MODIS/Aqua, over East Asia (EA), for the period 2003-2018

Table S1 Spearman correlation coefficient (ρ_s) between Aerosol Optical Depth at 550 nm (AOD) and Cloud Cover (CC), Water Vapor (WV), Cloud Optical Depth (COD), Cloud Effective Radius-Ice (CERI) and Cloud Effective Radius-Liquid (CERL). The asterisks (*) denote statistical significance at 95% confidence level.

X - Y	ρ_s
AOD - CC	0.210*
AOD - WV	0.132
AOD - COD	-0.373*
AOD - CERI	-0.142
AOD - CERL	-0.024

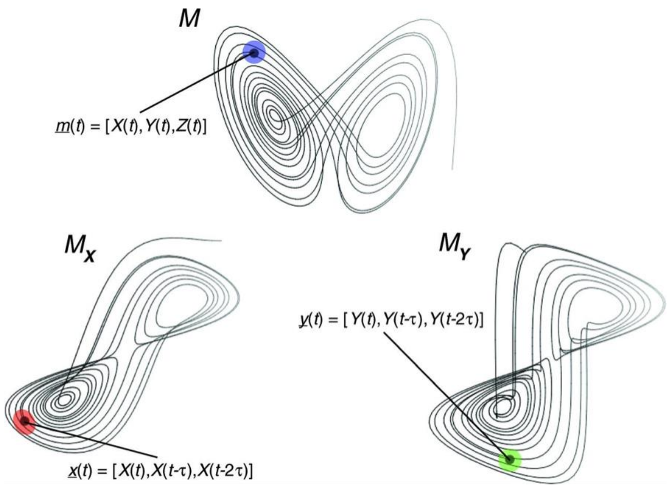

Fig. S2 Convergent cross mapping tests (CCM) for correspondence between shadow manifolds (M_x and M_y), constructed using lagged-coordinate embeddings of X and Y, respectively (lag = τ). Figure courtesy of Dr. Sugihara, adopted from Sugihara et al. (2012)

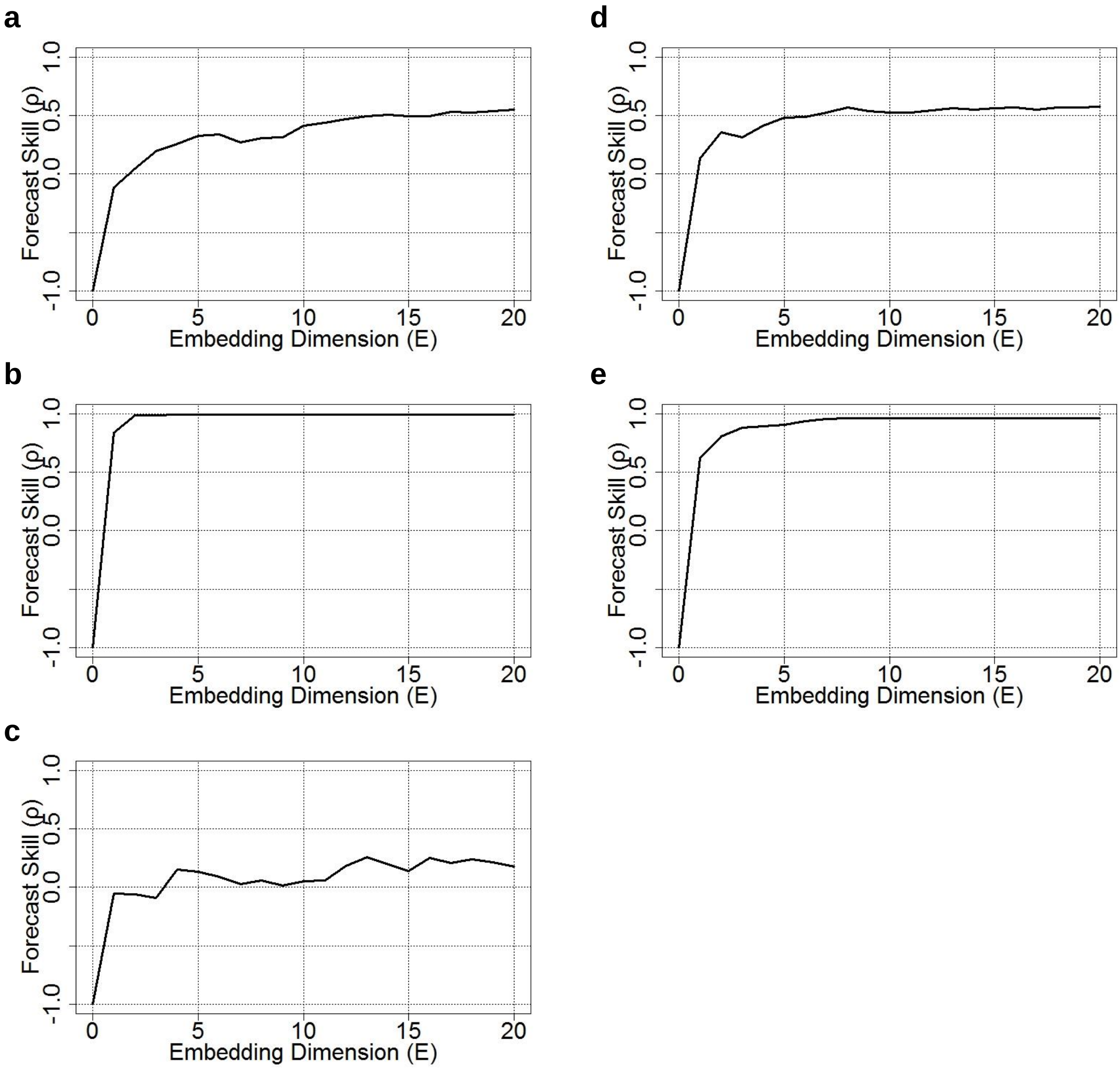

Fig. S3 Forecast skill expressed with Pearson's correlation coefficient (ρ) of the Embedding Dimension (E) for a) Cloud Cover (CC), (b) Water Vapor (WV), (c) Cloud Optical Depth (COD), (d) Cloud Effective Radius-Ice (CERI) and (e) Cloud Effective Radius-Liquid (CERL) timeseries

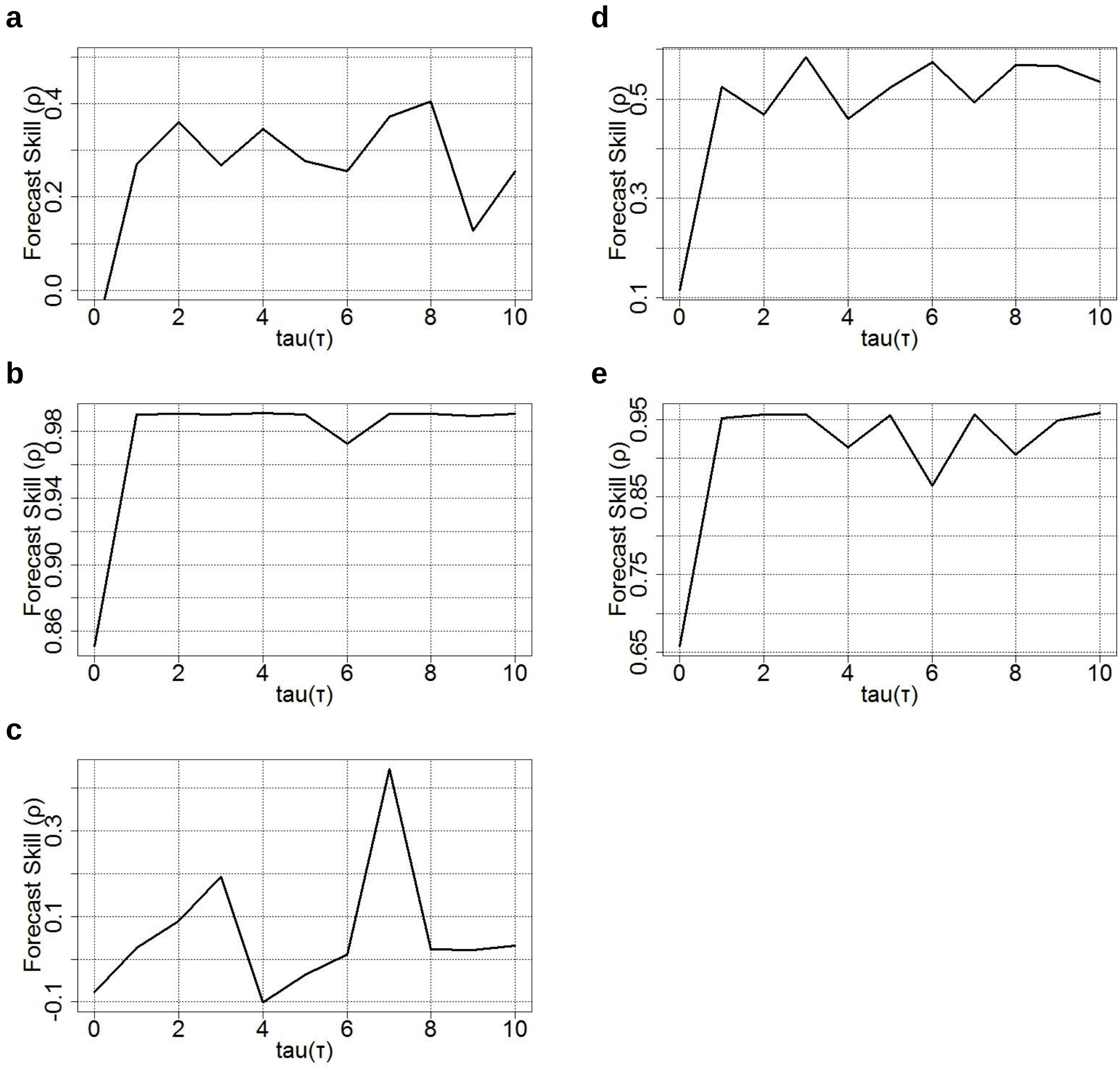

Fig. S4 Forecast skill expressed with Pearson's correlation coefficient (ρ) of the time delay embedding lag parameter (tau, τ) for embedding dimension (E) equals to 7, for a) Cloud Cover (CC), (b) Water Vapor (WV), (c) Cloud Optical Depth (COD), (d) Cloud Effective Radius-Ice (CERI) and (e) Cloud Effective Radius-Liquid (CERL) timeseries. Note that each sub-figure has different y-axis for clarity

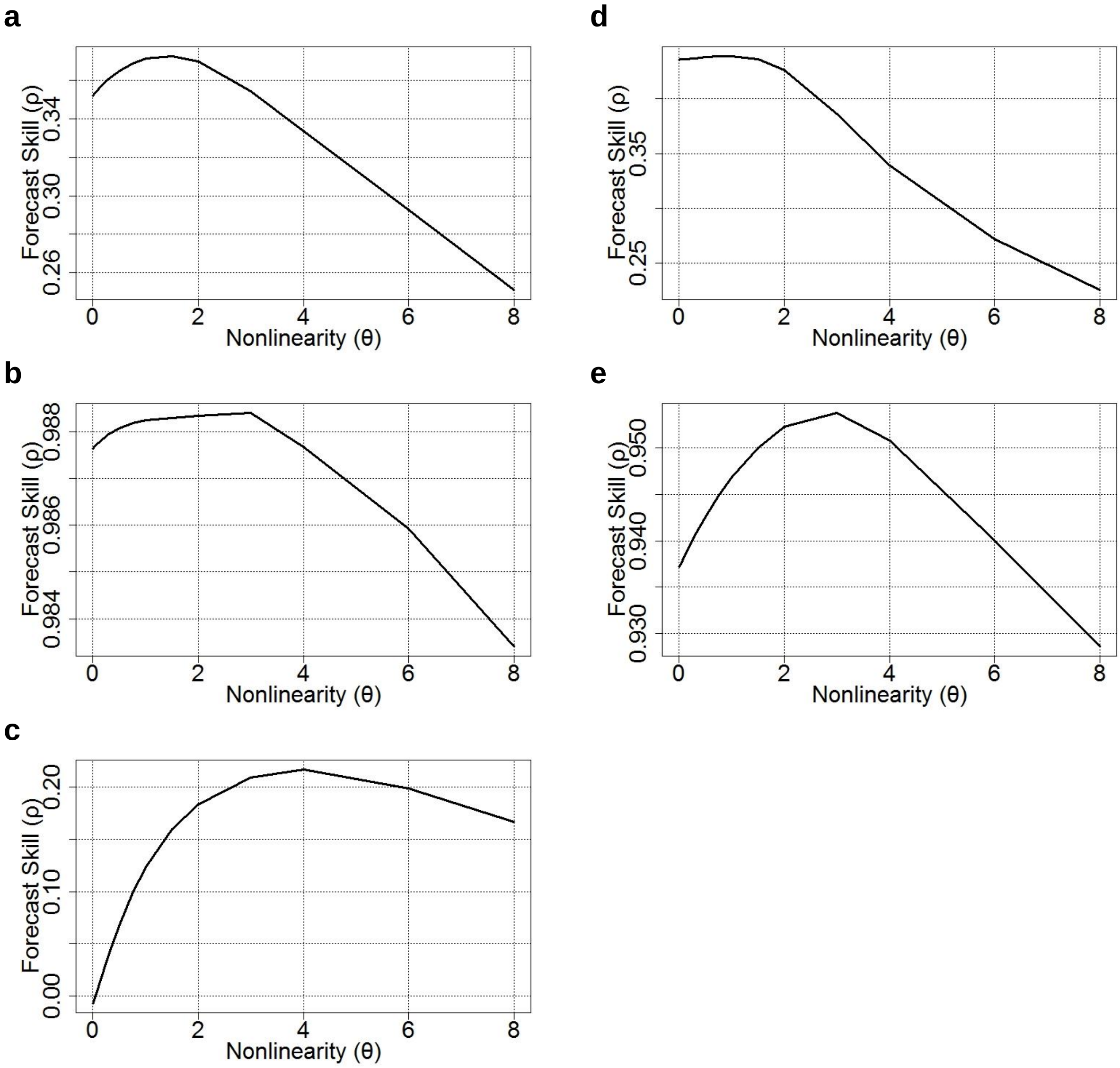

Fig. S5 Forecast skill expressed with Pearson's correlation coefficient (ρ) of the nonlinearity parameter (θ) for embedding dimension (E) equals to 7 and for time delay embedding lag parameter (τ) equals to 2, for a) Cloud Cover (CC), (b) Water Vapor (WV), (c) Cloud Optical Depth (COD), (d) Cloud Effective Radius-Ice (CERI) and (e) Cloud Effective Radius-Liquid (CERL) timeseries. Note that each sub-figure has different y-axis for clarity

Table S2 Pearson's correlation coefficient (ρ) for Aerosol Optical Depth at 550 nm (AOD), Cloud Cover (CC), Water Vapor (WV), Cloud Optical Depth (COD), Cloud Effective Radius-Ice (CERI) and Cloud Effective Radius-Liquid (CERL), using Convergent Cross Mapping (CCM) method, for embedding dimension equals to 7 (E=7) and time delay embedding lag parameter equals to 2 (τ=2). xmap denotes cross mapping which is translated as Y parameter affects X parameter.

X xmap Y	ρ
AOD xmap CC	0.501
CC xmap AOD	0.515
AOD xmap WV	0.939
WV xmap AOD	0.622
AOD xmap COD	0.373
COD xmap AOD	0.360
AOD xmap CERI	0.562
CERI xmap AOD	0.524
AOD xmap CERL	0.877
CERL xmap AOD	0.654

Table S3 Maximum absolute Pearson's correlation coefficient (|ρmax|) for Aerosol Optical Depth at 550 nm (AOD), Cloud Cover (CC), Water Vapor (WV), Cloud Optical Depth (COD), Cloud Effective Radius-Ice (CERI) and Cloud Effective Radius-Liquid (CERL), lagged for ±3 months, using cross-correlation. The asterisks (*) denote statistical significance at 95% confidence level.

	$\lvert\rho_{max}\rvert$
AOD-CC	0.427*
AOD-WV	0.623*
AOD-COD	0.413*
AOD-CERI	0.407*
AOD-CERL	0.541*

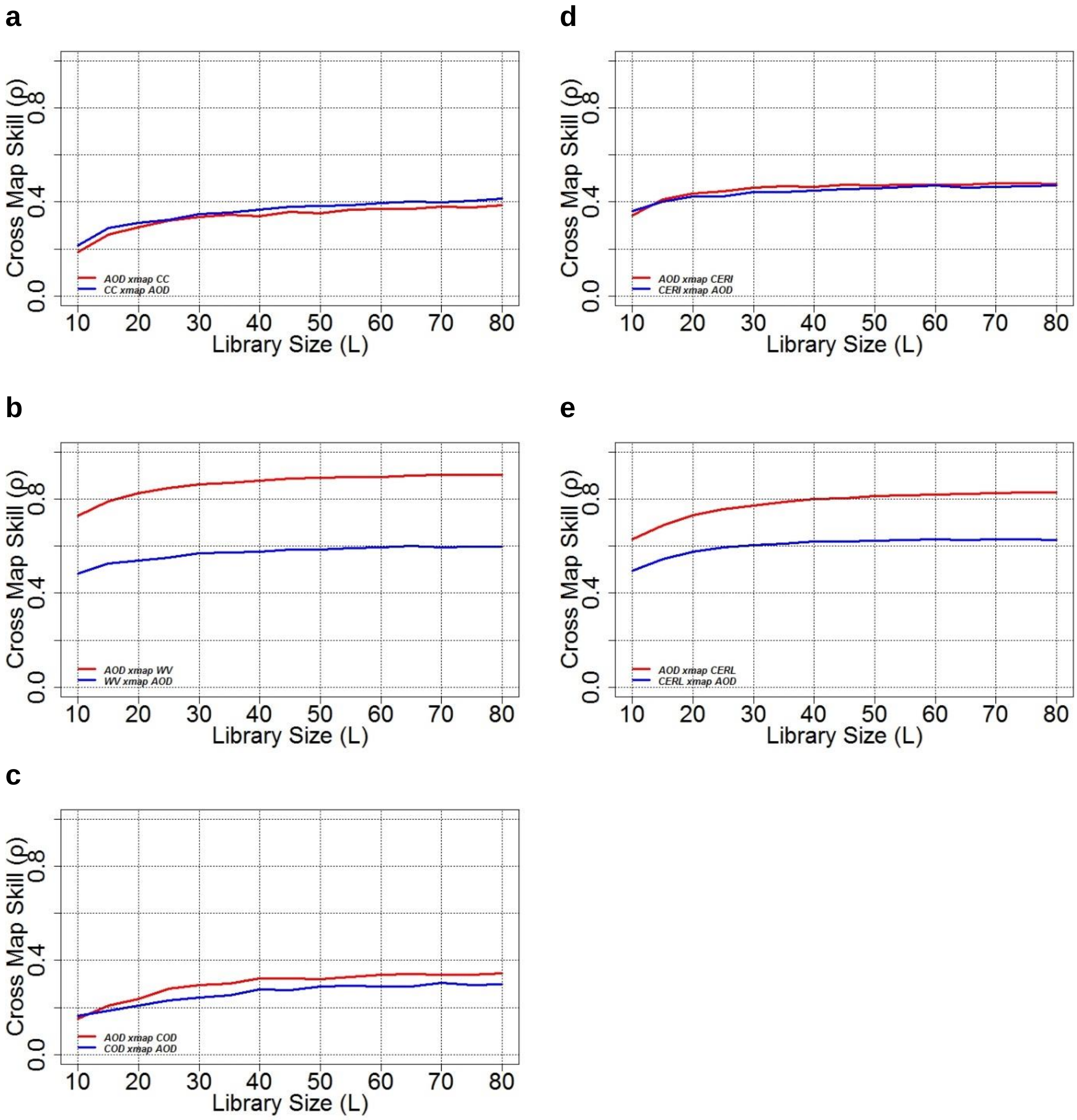

Fig. S6 Cross-map skill expressed with Pearson's correlation coefficient (ρ) as a function of library size (L) (a) for Aerosol Optical Depth at 550 nm (AOD) – Cloud Cover (CC), (b) for AOD – Water Vapor (WV), (c) for AOD – Cloud Optical Depth (COD), (d) for AOD - Cloud Effective Radius-Ice (CERI) and (e) for AOD - Cloud Effective Radius-Liquid (CERL), for embedding dimension (E) equals to 6 and for time delay embedding lag parameter (τ) equals to 2. xmap denotes cross mapping which is translated as Y parameter affects X parameter

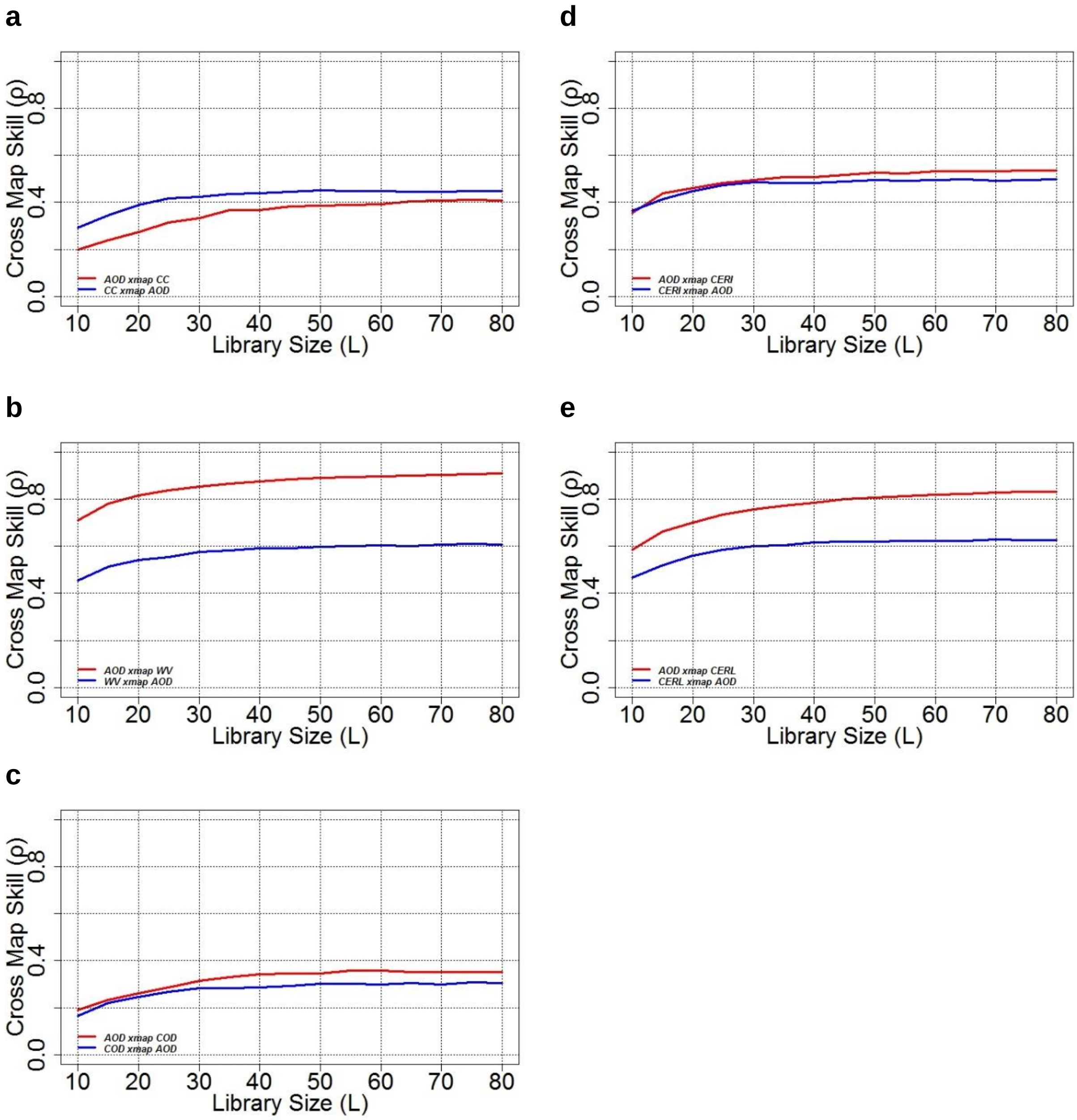

Fig. S7 Cross-map skill expressed with Pearson's correlation coefficient (ρ) as a function of library size (L) (a) for Aerosol Optical Depth at 550 nm (AOD) – Cloud Cover (CC), (b) for AOD – Water Vapor (WV), (c) for AOD – Cloud Optical Depth (COD), (d) for AOD - Cloud Effective Radius-Ice (CERI) and (e) for AOD - Cloud Effective Radius-Liquid (CERL), for embedding dimension (E) equals to 8 and for time delay embedding lag parameter (τ) equals to 2. xmap denotes cross mapping which is translated as Y parameter affects X parameter

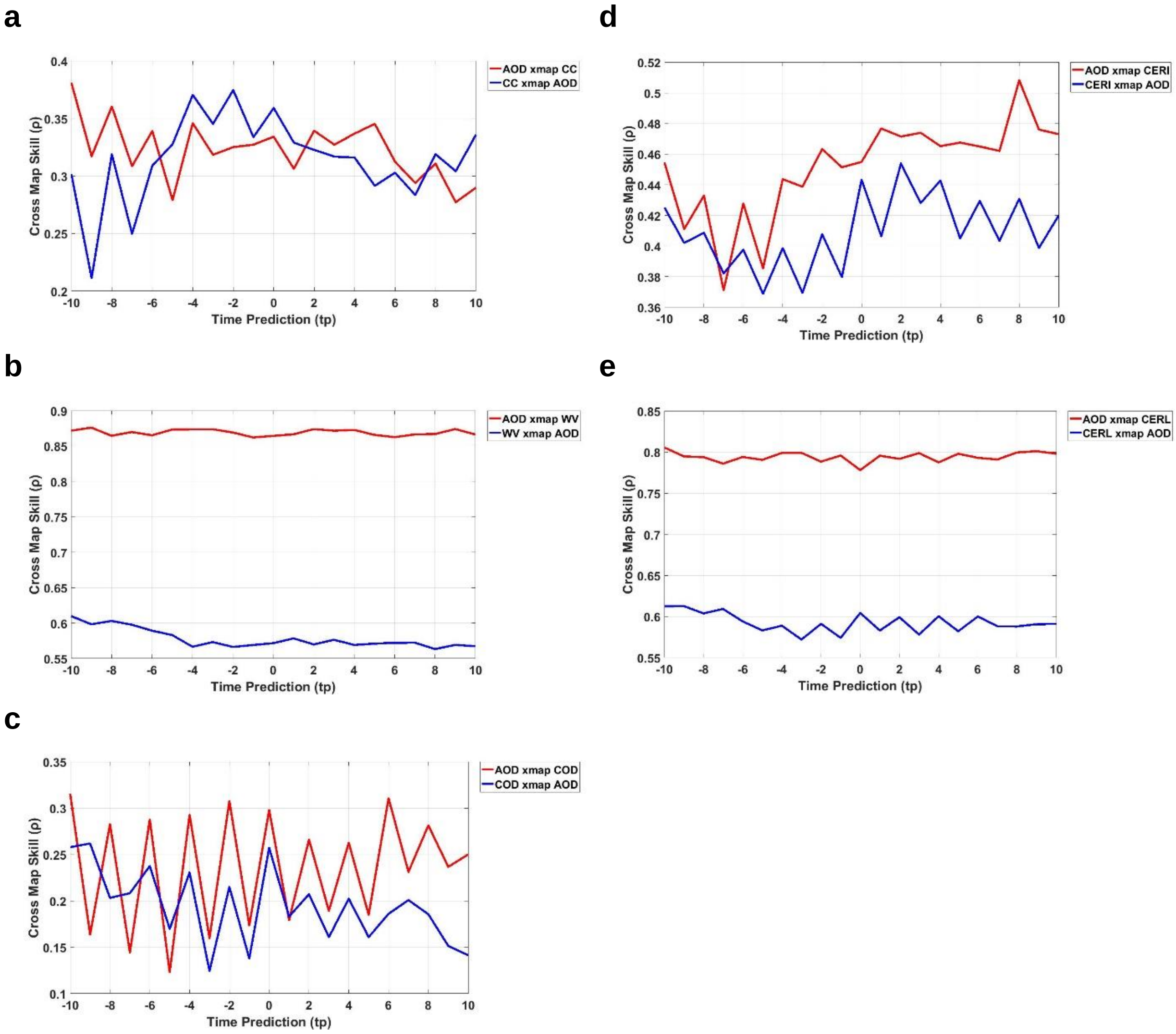

Fig. S8 Cross-map skill expressed with Pearson's correlation coefficient (ρ) as a function of Convergent Cross Mapping's (CCM) time delay prediction parameter (tp) (a) for Aerosol Optical Depth at 550 nm (AOD) – Cloud Cover (CC), (b) for AOD – Water Vapor (WV), (c) for AOD – Cloud Optical Depth (COD), (d) for AOD - Cloud Effective Radius-Ice (CERI) and (e) for AOD - Cloud Effective Radius-Liquid (CERL), for embedding dimension (E) equals to 6 and for time delay embedding lag parameter (τ) equals to 2. xmap denotes cross mapping which is translated as Y parameter affects X parameter. Note that each sub-figure has different y-axis for clarity

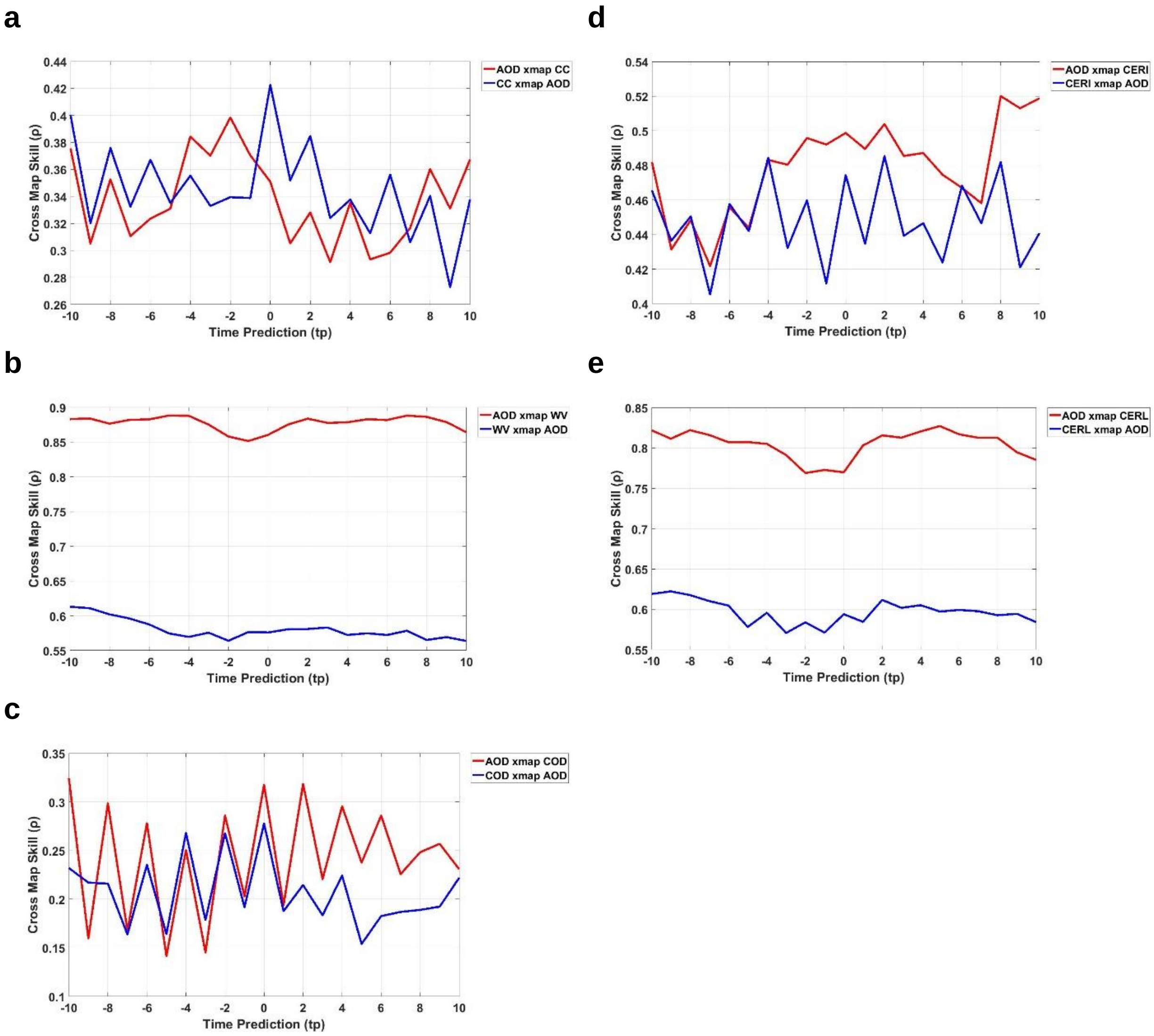

Fig. S9 Cross-map skill expressed with Pearson's correlation coefficient (ρ) as a function of Convergent Cross Mapping's (CCM) time delay prediction parameter (tp) (a) for Aerosol Optical Depth at 550 nm (AOD) – Cloud Cover (CC), (b) for AOD – Water Vapor (WV), (c) for AOD – Cloud Optical Depth (COD), (d) for AOD - Cloud Effective Radius-Ice (CERI) and (e) for AOD - Cloud Effective Radius-Liquid (CERL), for embedding dimension (E) equals to 8 and for time delay embedding lag parameter (τ) equals to 2. xmap denotes cross mapping which is translated as Y parameter affects X parameter. Note that each sub-figure has different y-axis for clarity

Notes on the S-map test for nonlinear dynamics

To determine whether a time series reflects linear or nonlinear processes we compare the out-of-sample forecast skill of a linear model versus an equivalent nonlinear model. To do this, we apply a two-step procedure: 1) we use simplex-projection to identify the best embedding dimension (Sugihara and May 1990), and 2) we use this embedding in the S-map procedure to assess the nonlinearity of the time series (Sugihara 1994).

S-maps are an extension of standard linear autoregressive models in which the coefficients depend on the location of the predictee $\boldsymbol{Y_t}$ in an E-dimensional embedding. New coefficients are recalculated (from the library of a predictant set $\boldsymbol{x}$) by singular value decomposition (SVD) for each new prediction. In this calculation, the weight given to each vector in the library depends on how close that vector $\boldsymbol{x_t}$ is to the predictee $\boldsymbol{Y_t}$. The extent of this weighting is determined by the parameter θ.

As above, we generate an E-dimensional embedding from points in the library using lagged coordinates to obtain an embedded time series with vectors $\boldsymbol{x_t} \in \mathbb{R}^{E+1}$, where $x_t(0) = 1$ is the constant term in the solution of Equation (S2) below. Let the time series observation in the prediction set T_p time steps forward be $Y_{t+Tp}(1) = Y(t)$.

Then the forecast for Y_t is $\hat{Y}_t = \sum_{j=0}^{E} C_t(j) X_t(j)$ (S1)

For our analysis, we chose $T_P = 1$. For each E-dimensional predictee vector $\boldsymbol{y_t}$, $\boldsymbol{C}$ is solved by SVD using the library set as follows:

$$\boldsymbol{B} = \boldsymbol{AC}, \qquad \text{(S2)}$$

where $B_i = w(\| \boldsymbol{x}_i - \boldsymbol{y}_t \|) y_i$, $A_{ij} = w(\| \boldsymbol{x}_i - \boldsymbol{y}_t \|) x_i(j)$, and $w(d) = e^{-\theta d_{it}/\bar{d}}$, $\theta \geq 0$, d_{it} is the distance between $\boldsymbol{y_t}$ and the i^{th} neighbor vector $\boldsymbol{x_i}$ in the library embedding, and the scale vector, $\bar{d}$, is the average distance between neighbors in the library. Note that $\boldsymbol{A}$ has dimension $n \times (E+1)$, where n = size of the library. Again, a different map is generated for each forecast, with the weightings in each map depending on the location of the predictee in the E-dimensional state space. This weighting procedure is governed by the tuning parameter θ, where $\theta = 0$ gives a global linear map, and increasing values of θ give increasingly local or nonlinear mappings. When $\theta = 0$, all vectors are more or less weighted equally so a single (global) linear map can be used for all predictions. In the case where $\theta > 0$, vectors closest to the predictee in state-space are weighted more heavily in the SVD solution. Such forecasts emphasize local information in the library set, and are therefore nonlinear.

References

Sugihara G, May R, Ye H, et al (2012) Detecting Causality in Complex Ecosystems. Science (80-) 338:496–500. https://doi.org/10.1126/science.1227079

Sugihara G, May RM (1990) Nonlinear forecasting as a way of distinguishing chaos from measurement error in time series. Nature 344:734–741. https://doi.org/10.1038/344734a0