A Hybrid Statistical Downscaling Approach Based on Nonstationary Time Series Decomposition

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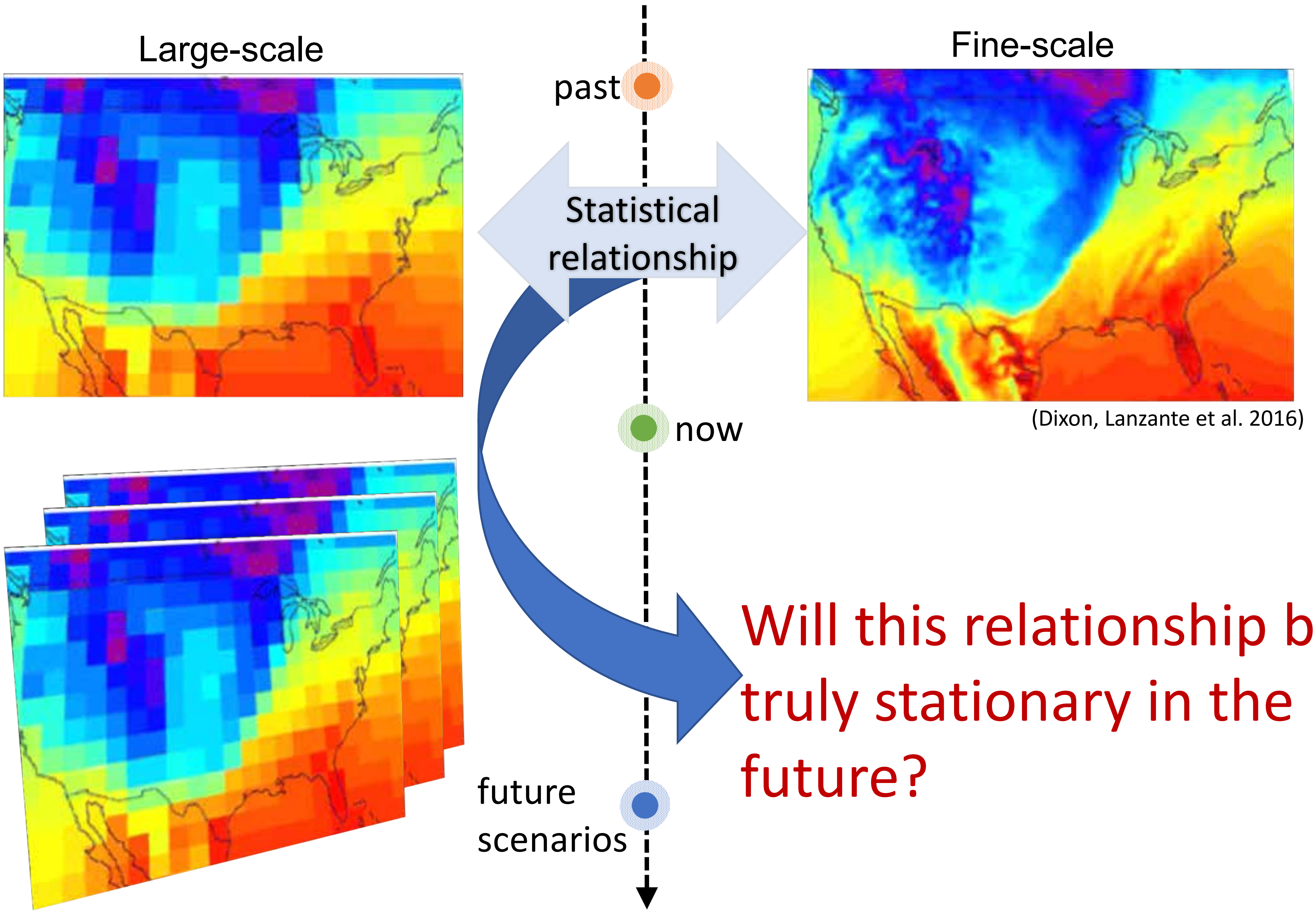
Outline

- The stationary hypothesis in SD
- Nonstationary Time Series Decomposition
- A Hybrid SD model: BEMD-rf
- The model performance
- Conclusion

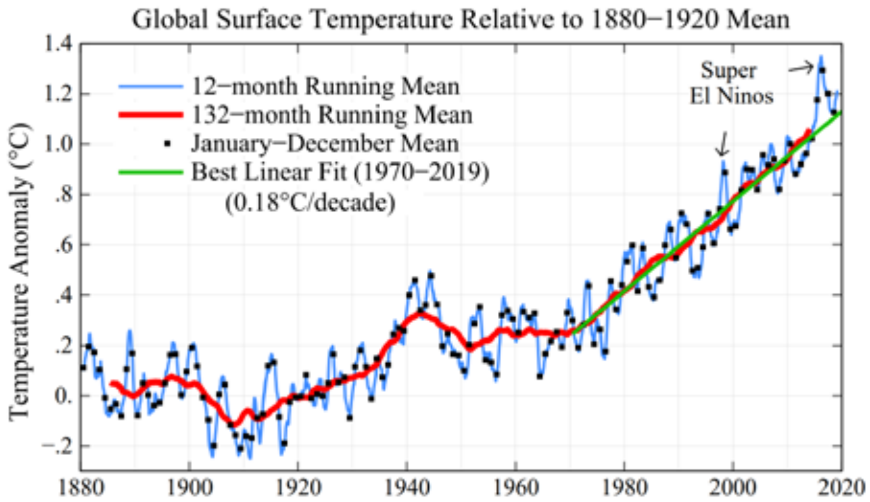
The underlying stationary hypothesis in SD



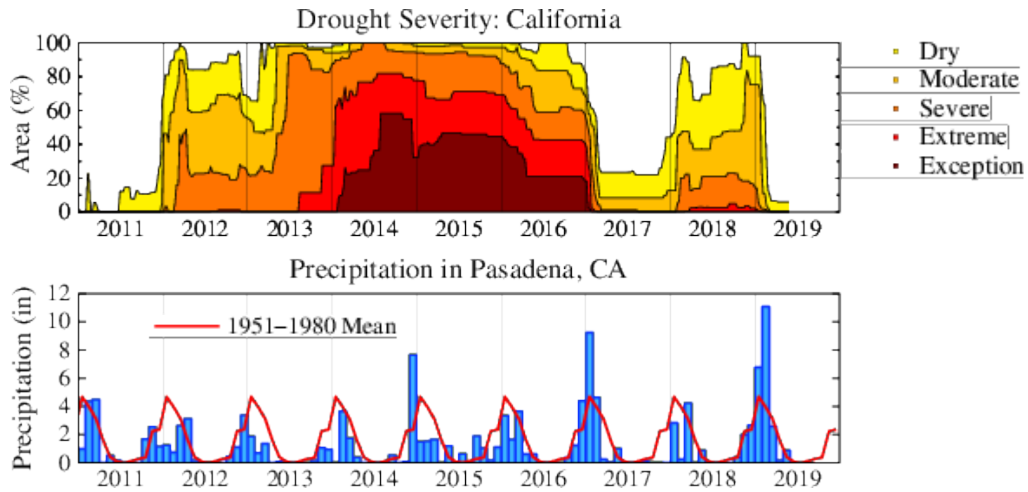
Will this relationship be truly stationary in the future?

The climate is changing

A rising temperature



Severe drought and precipitation



(Sato and Hansen,2019)

- A changing climate make the hypothesis less reliable
- **It is a big challenge to make SD method adapt to future non-stationary climate conditions**

Nonstationary Time Series Decomposition

- Non-stationarity is an inbuilt trait embedded in climate system at different spatial and temporal scales
- A non-stationary time series decomposition was considered from the point of time-frequency analysis
    - to separate interactions of different climate cycles
    - capture stationary weather patterns

A comparation among main time-frequency transforming

Time-frequency Transforming	Fourier	Wavelets	**Hilbert-Huang**
Basis	a priori	a priori	**adaptive**
Frequency	convolution: global, uncertainty	convolution: regional, uncertainty	differentiation: **local, certainty**
Presentation	energy-frequency	energy-time-frequency	energy-time-frequency
Nonlinear	no	no	**yes**
Non-stationary	no	yes	**yes**
Feature Extraction	no	discrete: no, continuous: yes	**yes**
Theoretical Base	theory complete	theory complete	**empirical**

* Frequency domain decomposition

Empirical Mode Decomposition(EMD, Huang et al., 1998)

a part of Hilbert-Huang transform, realizing a disintegration

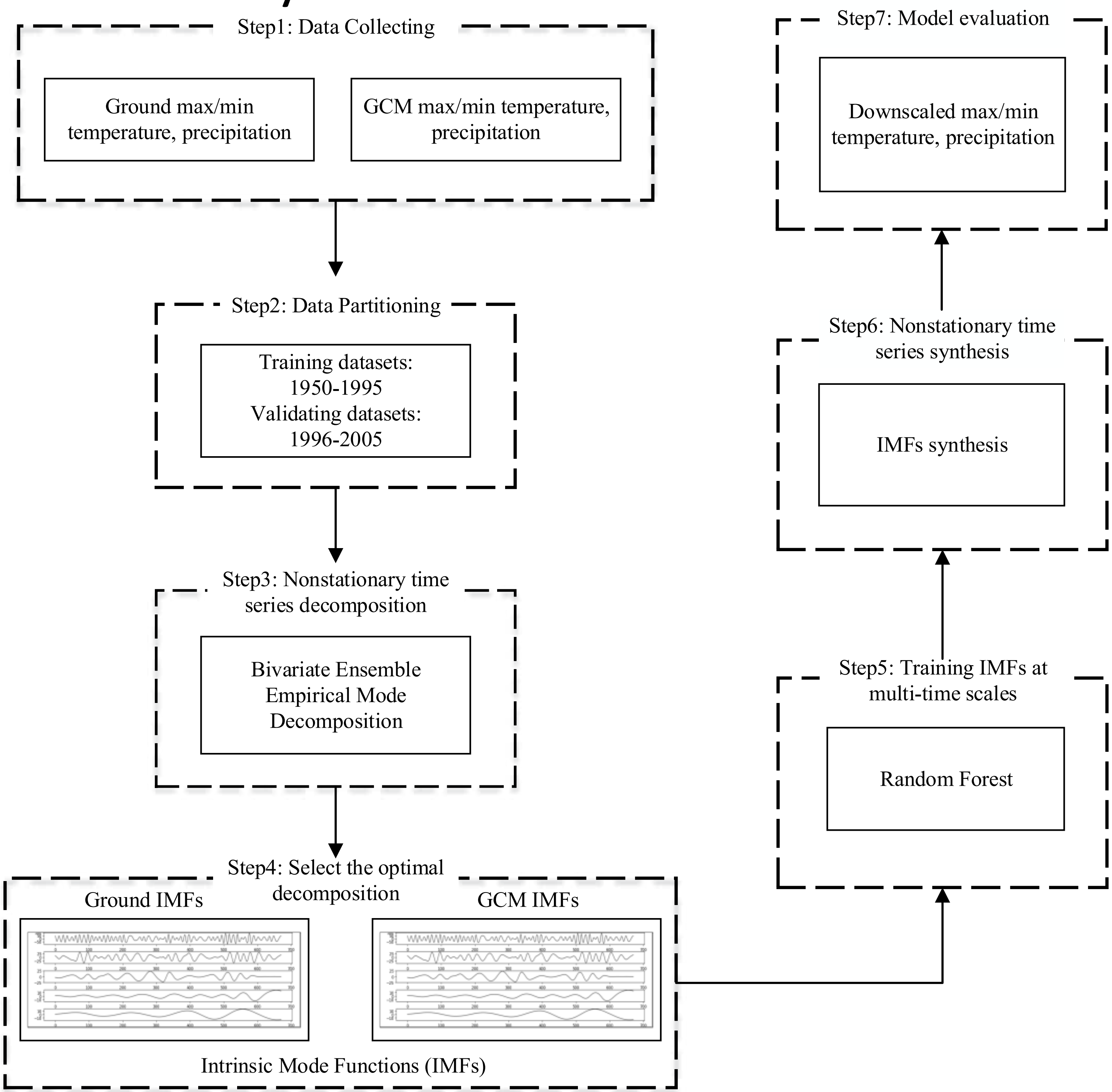
$$Y = IMF1 + \cdots + IMFn + residual$$

IMF, intrinsic mode functions

- IMFs can be seen as stationary components of original sequence in different time scales
- A residual component is a trend term

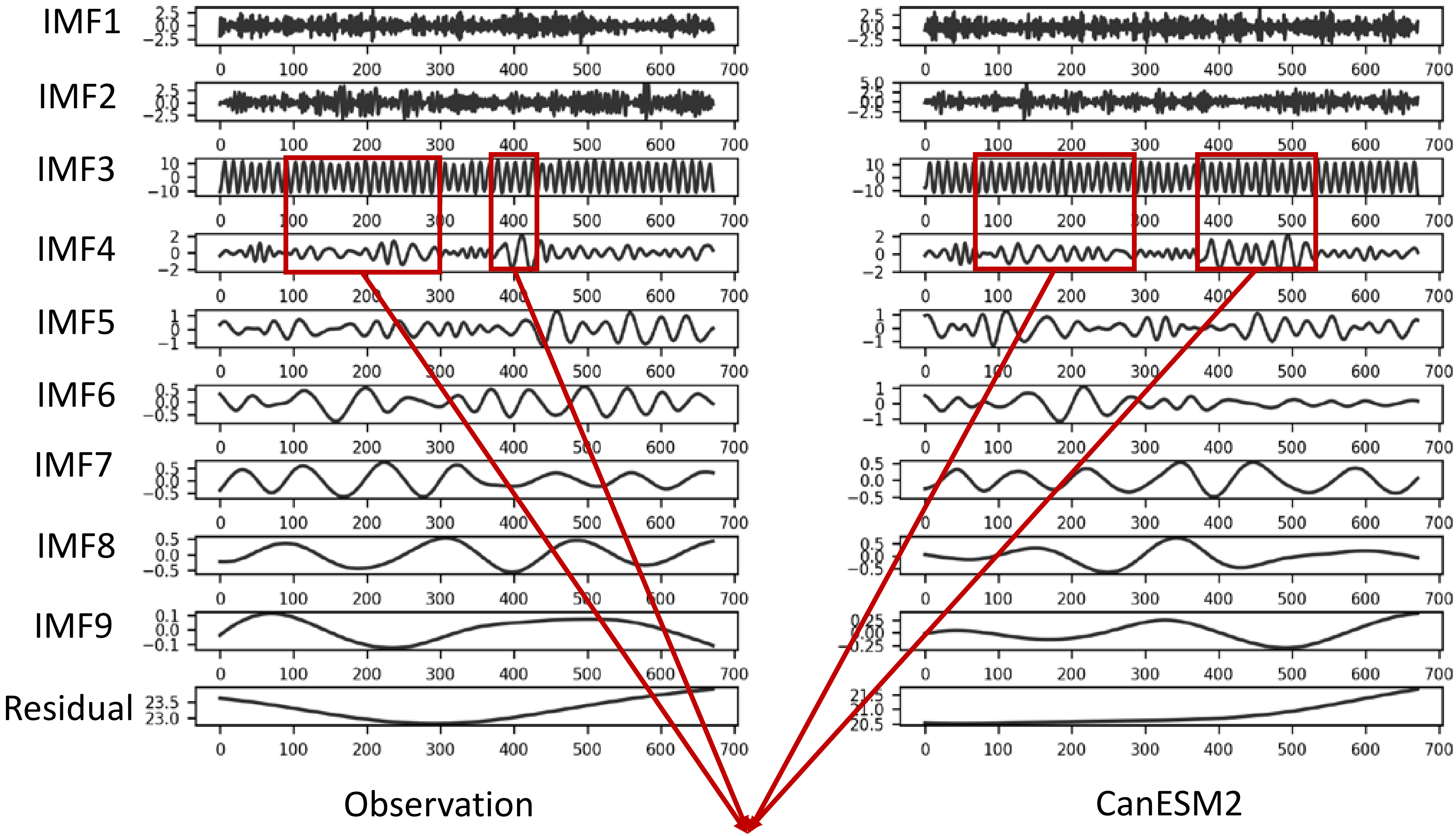
To overcome the shortcoming of EMD, losing synchronous time scales for multivariable decomposition, bivariate EMD (BEMD, Flandrin et al.,2004) was adopted.

A Hybrid SD model: BEMD-rf



The model performance

- The decomposition of monthly *max temperature*



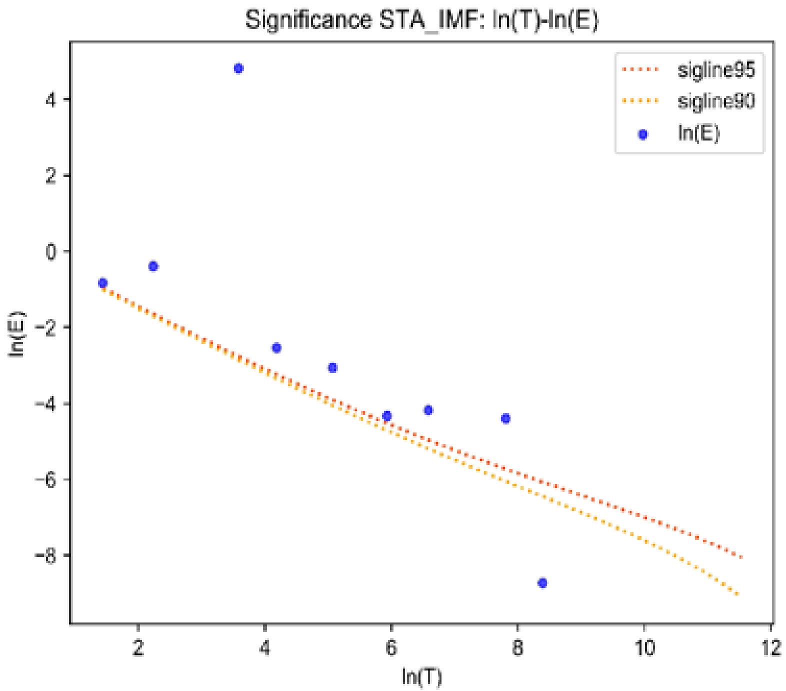
"Mode mixing"- loosing physical meaning

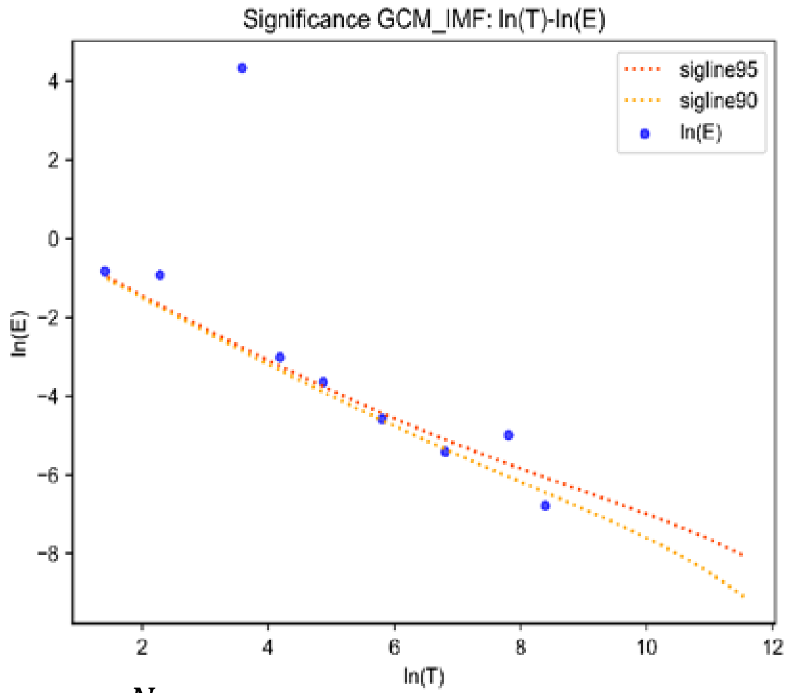
- Results of Significance Test

  To ensure the physical meaning of decomposition

  Good IMFs → with high information and less noises

  Most components passed the test

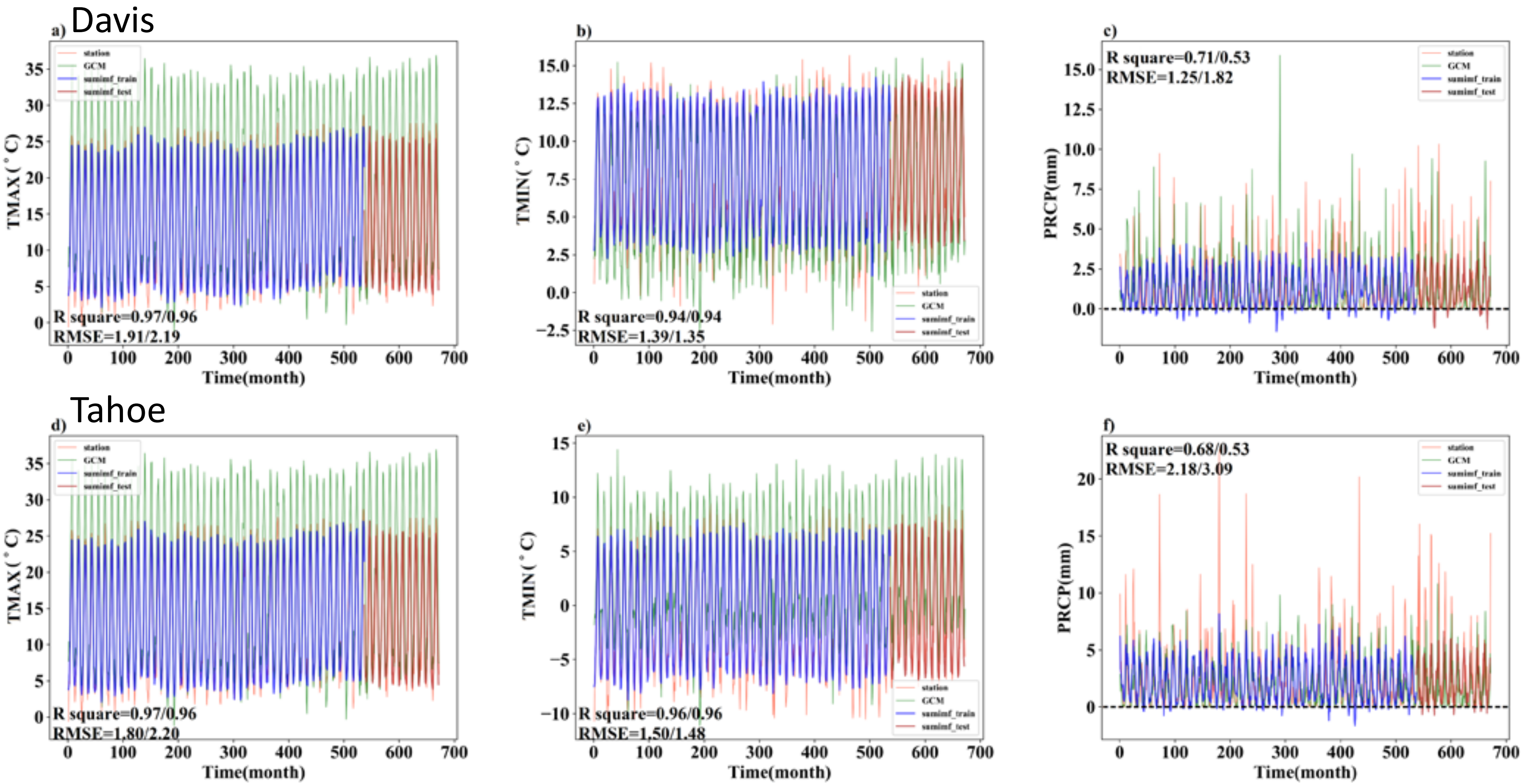




$$\ln(E) = -\ln(T) \qquad E = \frac{1}{N}\sum_{j=1}^{N}[C_n(j)]^2$$

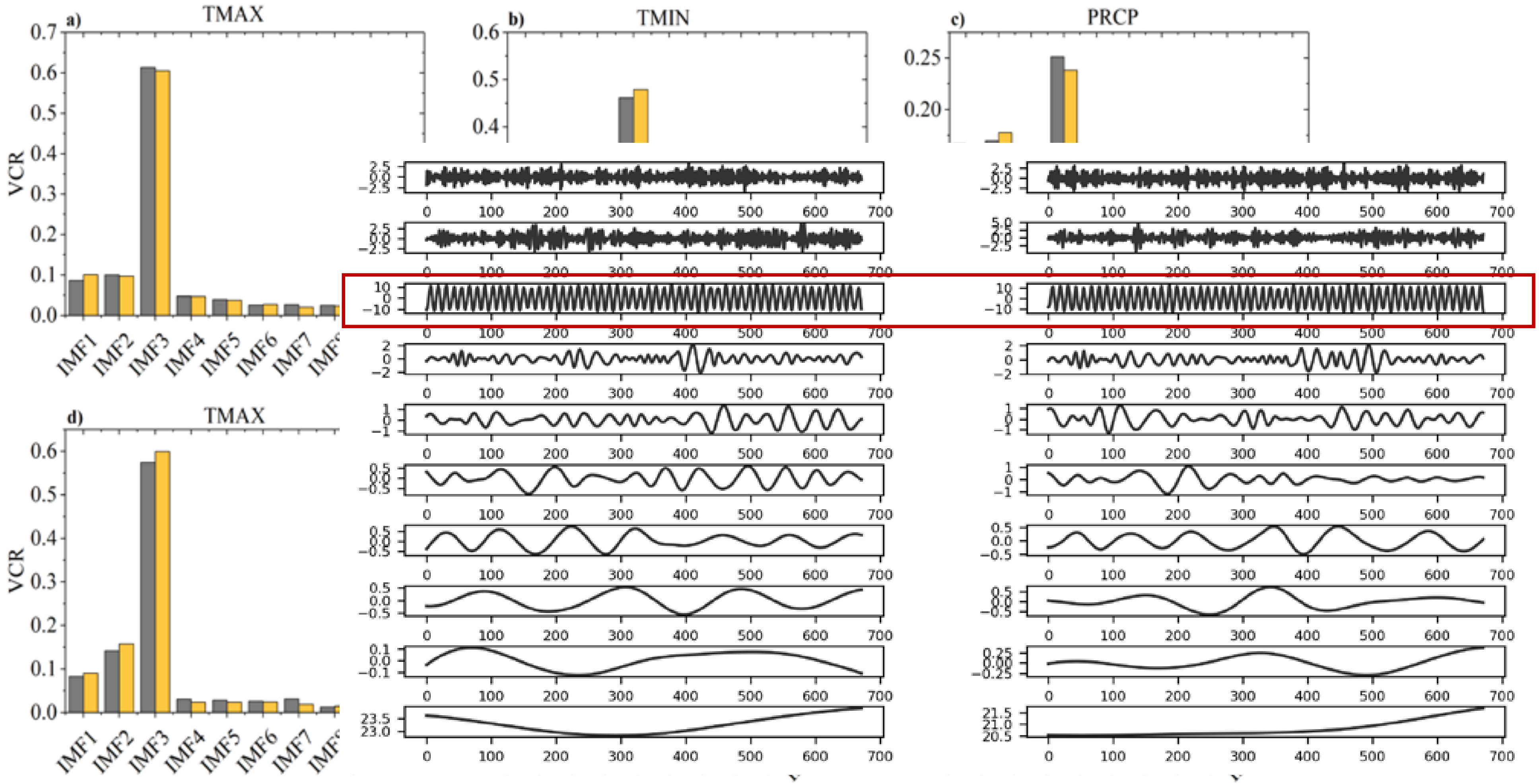
- Downscaling performance

Station CanESM2 Train Test



- The CanESM2 overestimates both the TMAX and TMIN
- The trends of downscaled TMAX and TMIN are consist with those of observation
- A poor performance for precipitation, weak ability on depicting extreme values
- The proposed model has good generalization ability on topography

- Stationary analysis



  - IMF with high variance contribution rate are stationary
  - For other IMFs, they may be quasi-stationary

- Physical meaning of periods

			IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8	IMF9	IMF10
DAVIS	PRCP	STA_IMF	2.9	4.4	7.4	**12.4**	23.2	33.6	74.7	134.4	224	672
		GCM_IMF	2.9	4.4	7.2	**12.4**	21	39.5	56	134.4	224	336
	TMAX	STA_IMF	2.7	4.9	**12**	18.16	29.2	56	112	224	336	—
		GCM_IMF	2.7	4.9	**12**	18.16	29.2	56	112	224	336	—
	TMIN	STA_IMF	2.6	4	6.9	**12**	19.2	29	56	134.4	224	—
		GCM_IMF	2.6	4	6.7	**12**	20.4	32	74.7	134.4	224	—
TAHOE	PRCP	STA_IMF	2.7	4.2	6.2	**12.2**	21	33.6	61.1	112	224	336
		GCM_IMF	2.6	4	5.9	**12.2**	21	33.6	56	112	168	336
	TMAX	STA_IMF	2.6	5.3	**12**	20.4	33.6	61.1	134.4	168	336	—
		GCM_IMF	2.7	5.5	**12**	20.4	35.4	61.1	134.4	224	224	—
	TMIN	STA_IMF	2.6	4.4	**12**	16	26.9	51.7	74.7	168	224	672
		GCM_IMF	2.6	4.9	**12**	16.4	30.5	42	74.7	134.4	224	672

*The periods were averaged periods and not precise.

Seasonal cycle
Semiannual cycle
Annual cycle
Biennial cycle
Inter-annual cycle
Decadal cycle

- A strong annual cycle control the local weather mode.
- For the decadal cycles, they may influenced by the sea surface temperatures of tropical and mid-latitude regions.

(Joseph et al. 2000)

Conclusions

a) The interactions of different climatic cycles were separated. BEMD can decompose observations and GCM simulations into synchronized IMFs which are correspond to physical processes of climate at different time scales.

b) The decomposed stationary components can capture most variations of temperature and precipitation. The proposed BEMD-RF model outperforms the downscaling model without BEMD and can regain the observation sequences.

c) Because precipitation is more sensitive to sub-diurnal and synoptic modes than temperature and the coarse time resolution of monthly data used in this study which cannot capture a cycle with fine time scale, the downscale results of temperature are better than those of precipitation.

d) The inherent weakness including mode mixing and problem of boundary condition of interpolating envelop of BEMD can affect the decomposition results which inevitable brings errors in the proposed downscaling method.

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