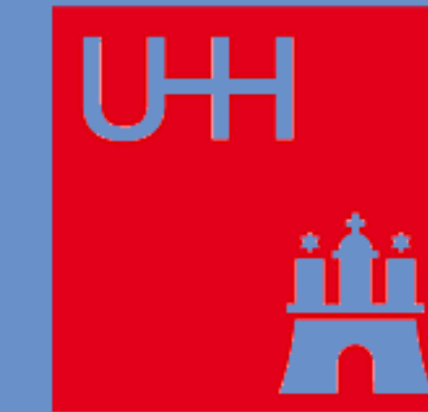


# Bias Teleconnections Due to Sea Surface Temperature Errors

Yuan-Bing Zhao, Nedjeljka Žagar, Frank Lunkeit, Richard Blender  
 Meteorological Institute, CEN, Universität Hamburg



Universität Hamburg  
 DER FORSCHUNG | DER LEHRE | DER BILDUNG



## 1. Motivation and Goal

- Climate models suffer from significant systematic errors (biases). Understanding how biases affect the simulated spatio-temporal variability is difficult since biases may have remote origins (**bias teleconnection**) [1].
- Even the atmosphere model were perfect, errors originating from the ocean lead to large biases in simulated atmospheric circulation in the coupled climate models [2].
- We quantify **atmospheric circulation biases due to errors in the sea surface temperature (SST)** and ask the following questions:
  - Which ocean region is the most “efficient” in inducing local and remote biases?
  - What are the shortcomings (across scales) in simulated atmospheric variability due to localized systematic errors in SST?

## 2. Methodology

- Century-long (1900-2010) simulations using Planet Simulator (PLASIM) and a perfect-model framework
- One reference simulation** forced with the observed SST
- 106 perturbation simulations** forced with the same SST (including interannual variation) plus regional constant SST errors with maximal amplitude of +1.5 K (Figure 1)
- Model output are **decomposed into different dynamical regimes** (balanced and unbalanced) at different scales [3].
  - Balanced regime:** Rossby modes
  - Unbalanced regime:** Kelvin modes, eastward/westward propagating inertia-gravity modes, and mixed Rossby-gravity modes
- Bias is defined as the long-term (1931-2010) mean difference between the perturbation ( $P$ ) and the reference ( $R$ ) simulations:

$$\overline{\Delta x} = \frac{1}{80} \sum_{t=1931}^{2010} [x^P(t) - x^R(t)]$$

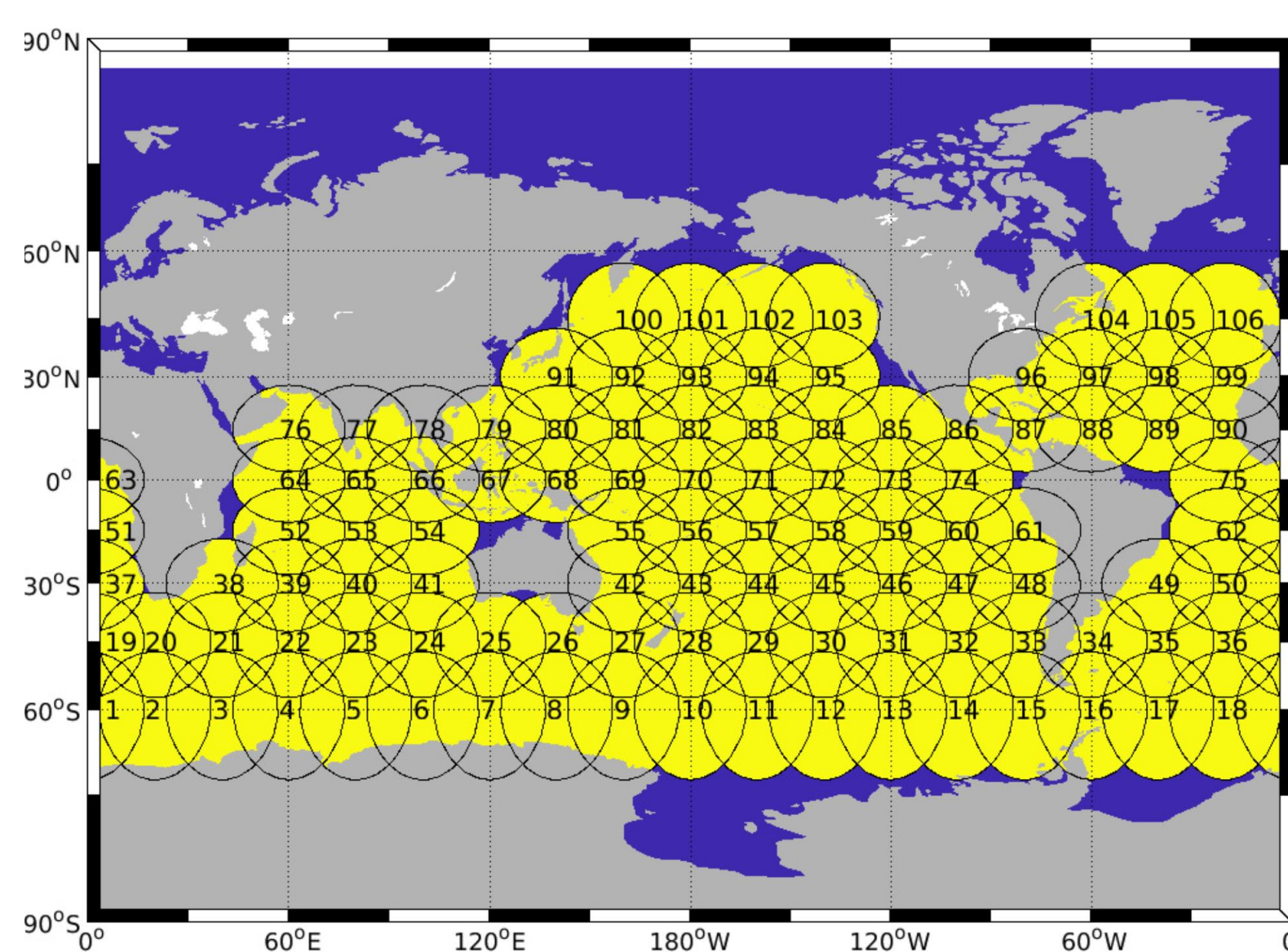


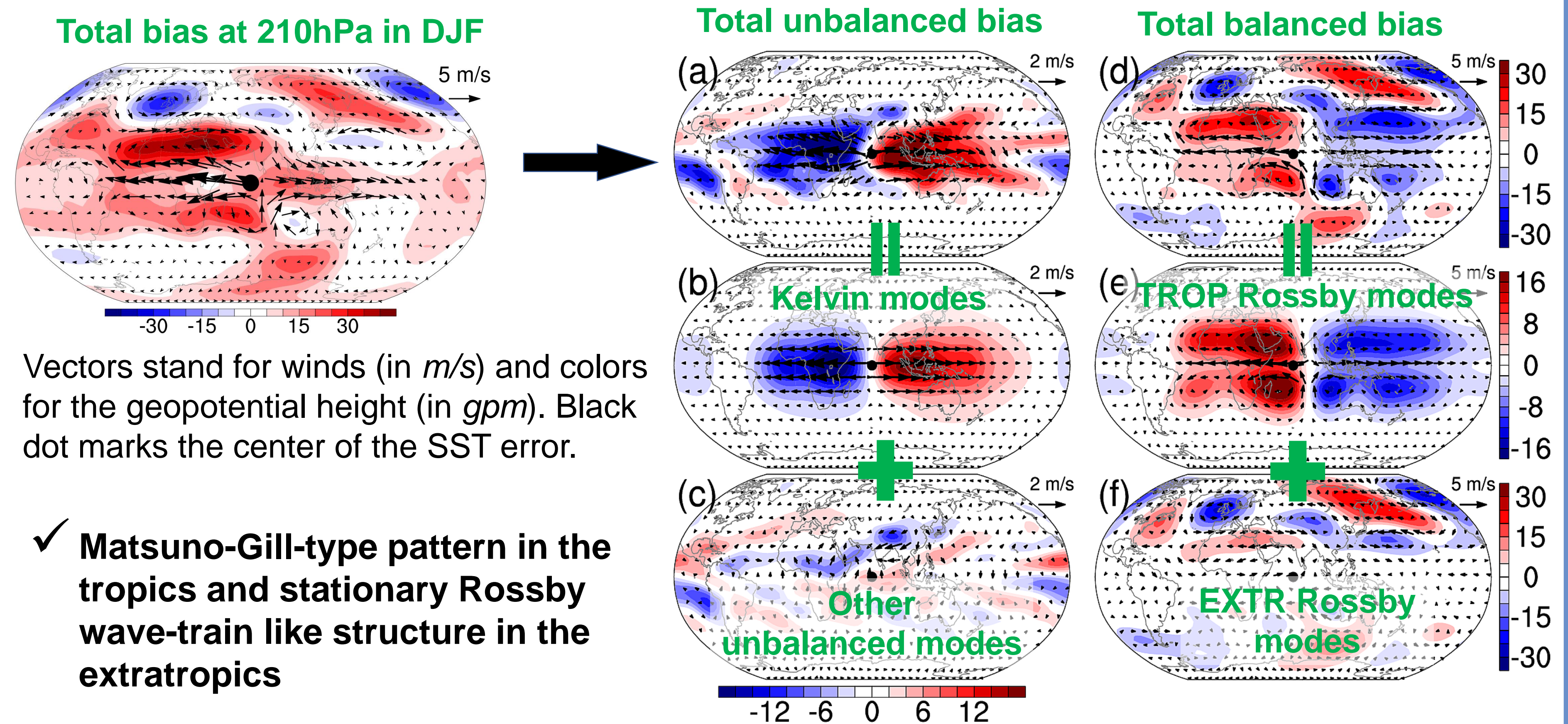
Figure 1. Schematic of the 106 perturbation experiments. Each circle denotes a region with SST errors described by a Gaussian function.

## 4. Conclusions

- The SST errors in the tropical Indo-west Pacific region are most efficient in producing local and remote atmospheric biases.
- Likewise, SST errors in the tropical oceans have strong impacts on the simulated atmospheric spatial and temporal variability in both local and remote regions.
- Regarding the spatial variance, SST errors in the tropical Indian Ocean (TIO) increase (decrease) it in local (remote) regions. The SST errors in Maritime Continent and west Pacific increase spatial variance in local and remote regions. In other oceans the SST errors generally decrease the spatial variance.
- As for the interannual variance (IAV), SST errors in TIO and tropical Pacific Oceans (TPO) have opposite effects on it. TIO SST errors generally decrease the IAV, whereas TPO SST errors increase the IAV.

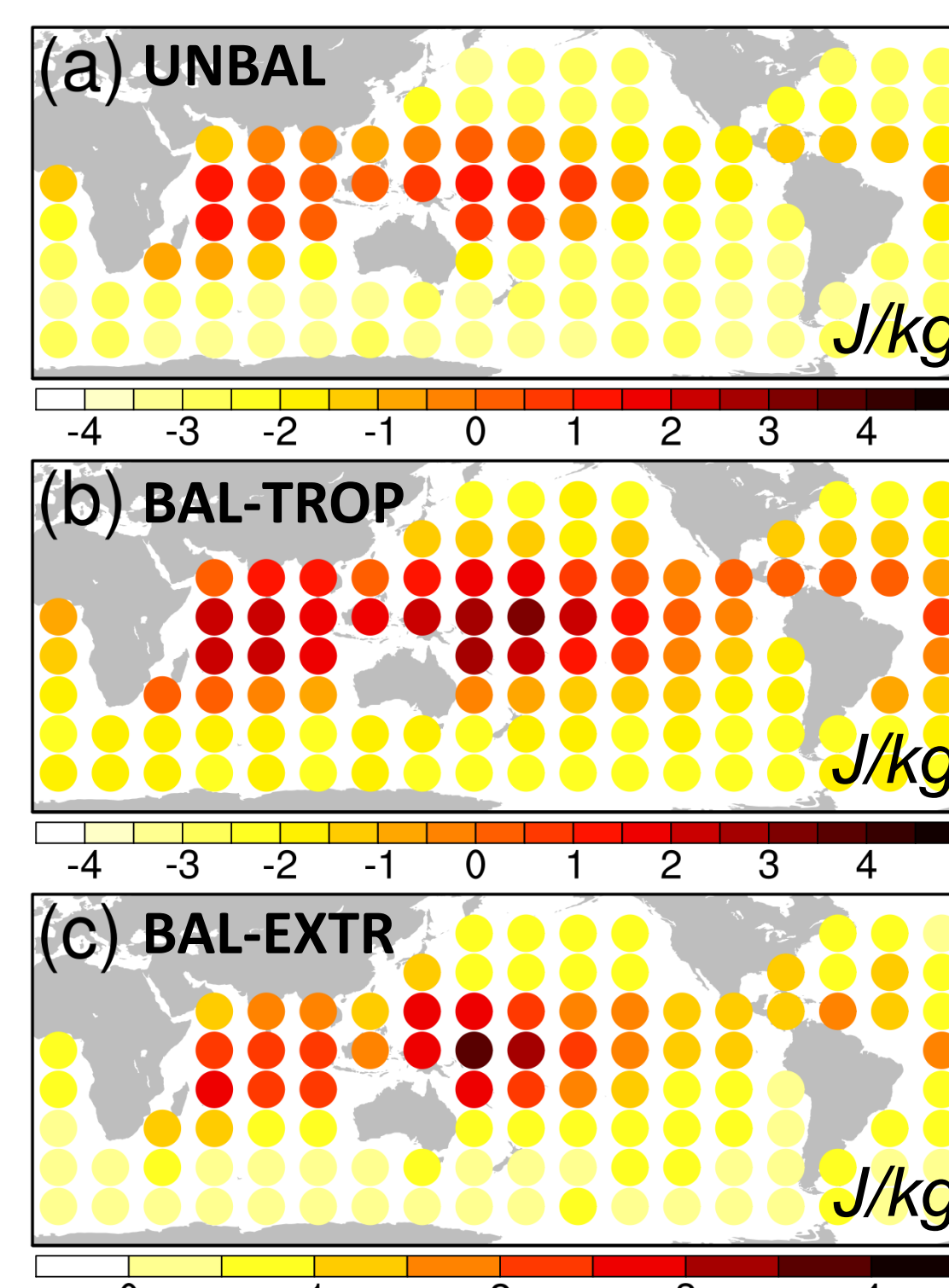
## 3. Results

### 3.1 Regime decomposition of the circulation bias (Experiment 65: Indian Ocean SST errors)

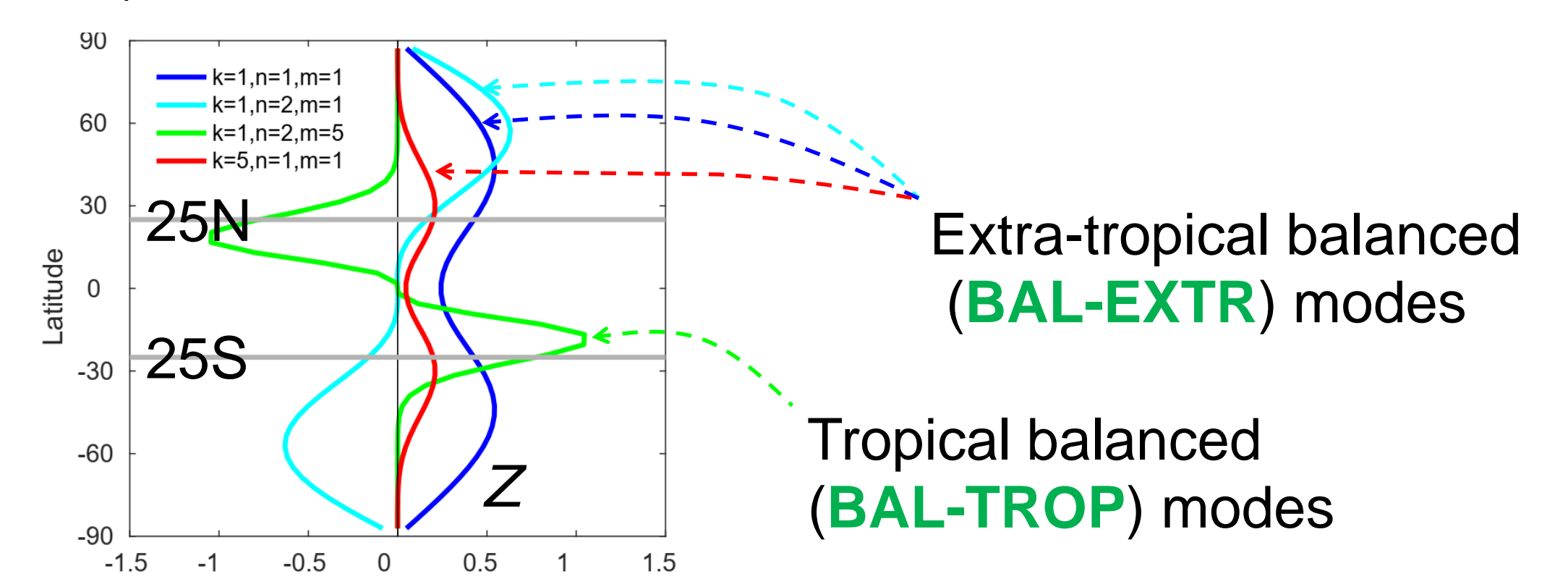


### Summary of the 106 experiments

### 3.2 Strength of the DJF circulation bias



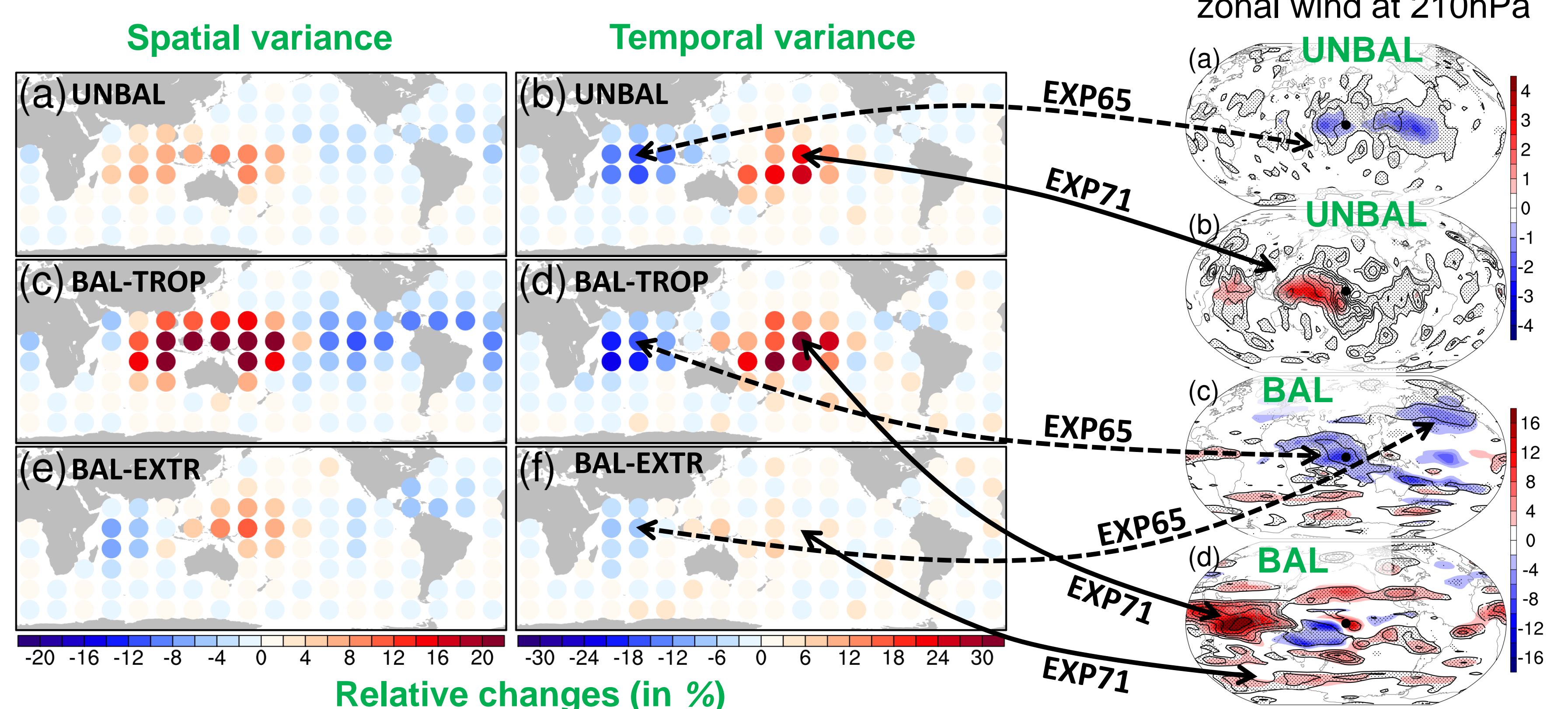
Each point denotes the **globally integrated bias variance** ( $\log[B]$ ) induced by SST errors centred at that point (see Figure 1).



The distinguishing of the **tropical** and **extratropical balanced modes** is based on their meridional structures. Any mode that has its Z maximum (or minimum) located between 25°S and 25°N is called the tropical mode, otherwise it is the extratropical mode.

- ✓ **SST errors in the Indo-west Pacific region are most efficient in producing local and remote atmospheric biases.**

### 3.3 Changes of the spatio-temporal variance



- ✓ **SST errors in the tropical oceans have strong impact on the simulated spatio-temporal variability in both local and remote regions.**
- ✓ **The responses of the spatial and temporal variances to SST errors are different, and their local and remote responses also have some difference.**

## References

- [1] Wang, C., et al. (2014): A global perspective on CMIP5 climate model biases, *Nature Clim Change*.
- [2] Žagar N., et al. (2020): An assessment of scale-dependent variability and bias in global prediction models, *Clim Dyn*.
- [3] MODES webpage: <https://modes.cen.uni-hamburg.de/>

