

The ICON-o model resolution impacts on the ocean internal variability in North Atlantic

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INTRODUCTION

- Most previous studies investigate the resolution effects from a process perspective, however, resolution effects can also be studied from a system perspective. The system aspects focus on the overall behaviors quantified by statistics.
- According to Hasselmann's concept of stochastic climate model, a stationary climate results from the joint effect of fluctuations arising from fast components, that constantly excite slow climate components, and negative feedbacks related to dissipative process that counteract on the constant excitation (Hasselmann, 1976).
- This concept can be most effectively described by an AR(1)-process.

METHODS

- We use ICON-o with similar configurations (daily climatological surface forcing) but different model resolutions (**5km, 10km, and 20km**).
- After removing the mean seasonal cycle from the model output, the residuals contain only internal generated variability.
- 65 years model output after 20 years spin-up is used for the analysis.
- A stationary AR(1)-process is $u_t = \alpha u_{t-1} + f_t$, where $\alpha \in (-1,1)$ and $\alpha = 1 + d$. d is a dissipation of u_t .
- The variance of u , which represents the internal variability, equals $\sigma^2 = \frac{\sigma_f^2}{1-\alpha^2}$, where α is expected to be related to dissipation, σ_f^2 is the variance of fluctuations, and σ^2 is the variance of internal variability.

CONCLUSIONS

- The ocean internal variability intensity is determined jointly by dissipation and fluctuating forcing.
- The balance between the dissipation and fluctuation forcing per unit variance of ocean internal variability always holds: the stronger the dissipation, the smaller the memory.
- Due to the link between the dissipation and fluctuation, increasing resolution, which allows more variability to be resolved, will ultimately lead to a change in ocean memory.

Is ocean memory the sole factor governing the intensity of internal variability?

RESULTS

AR(1)-PROCESS DOES A PERFECT JOB OF OCEAN INTERNAL VARIABILITY

- It is the prerequisite that two factors of the AR(1)-process, dissipation and fluctuating forcing, can jointly determine the intensity of ocean internal variability.

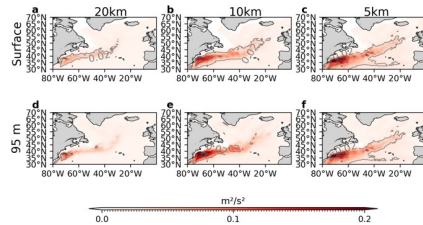


Fig. 1 The spatial distribution of the internal variance of zonal velocity (filled contour with color) for 20 km (a and d), 10 km (b and e), and 5 km (c and f) at the surface and 95m depth. The estimates directly derived from the time series are overlaid by contour lines of the variance predicted by the fitted AR(1) process to highlight their spatial relationships.

- The slope of the spectra of fluctuation term $f_{t,i}$ is almost zero at each grid point, which indicates the spectra of fluctuation term is white.

THE BALANCE BETWEEN THE DISSIPATION AND FLUCTUATING FORCING.

- The ocean memory, represented by the autocorrelation function, decreases with model resolution increases.

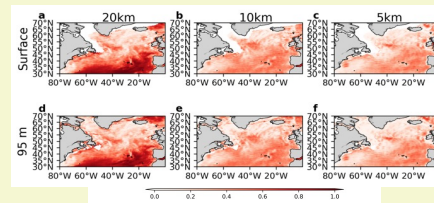


Fig. 3 Spatial distribution of α^2 (the square of the autocorrelation function) derived from the simulation of zonal velocity anomalies.

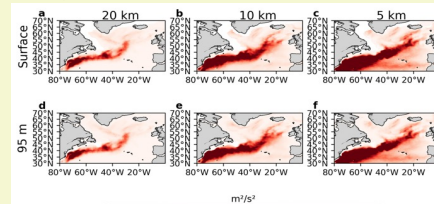


Fig. 4 The spatial distribution of the fluctuating forcing of zonal velocity anomalies.

- The results align perfectly along a single linear relationship across all resolutions, indicating that the fluctuation-dissipation balance is robust to model resolution changes.

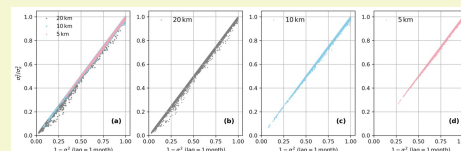


Fig. 5 The relationship between the dissipation, expressed as $1 - \alpha^2$, and the normalized variance of fluctuating forcing relative to the variance of zonal velocity anomalies at each grid point.

SCALE DEPENDENCE

- EOF to separate fields into components associated with different scales (Tang et al. 2020).
- For each of the EOFs, we determine a spatial scale using the spatial autocorrelation function (cf. Wackernagel, 1995)

$$S_j(k) = \frac{(\sum_{(m,n) \in [k]} [e_j(m, n+k) - \bar{e}_j] [e_j(m, n) - \bar{e}_j] + \sum_{(m,n) \in [k]} [e_j(m, n+k) - \bar{e}_j] [e_j(m, n) - \bar{e}_j]) / [n^{1/2} (k+1)]}{\sum_{(m,n) \in [k]} [e_j(m, n) - \bar{e}_j]^2 / [n]}$$

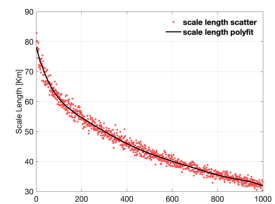


Fig. 6 The estimated scale lengths (km) of all 1000 EOFs.

- We find that the balance between the dissipation and fluctuation is still maintained after scale separation, as shown in Fig. 7.

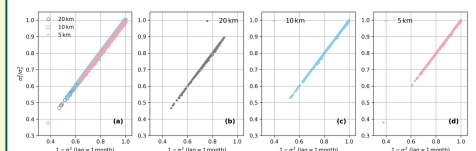


Fig. 7 The same as Fig. 6, but for first 1000 PCs.

OUTLOOK

The tidal forcing impacts on global circulation variability and on ocean internal variability.

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PUBLICATIONS

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