Atmospherically Forced Regional Ocean Simulations of the South China Sea: Scale Dependency of the Signal-to-Noise Ratio

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(Manuscript received 26 June 2019, in final form 16 October 2019)

ABSTRACT

When subjecting ocean models to atmospheric forcing, the models exhibit two types of variability—a response to the external forcing (hereafter referred to as signal) and inherently generated (internal, intrinsic, unprovoked, chaotic) variations (hereafter referred to as noise). Based on an ensemble of simulations with an identical atmospherically forced oceanic model that differ only in the initial conditions at different times, the signal-to-noise ratio of the atmospherically forced oceanic model is determined. In the large scales, the variability of the model output is mainly induced by the external forcing and the proportion of the internal variability is small, so the signal-to-noise ratio is large. For smaller scales, the influence of the external forcing weakens and the influence of the internal variability strengthens, so the signal-to-noise ratio becomes less and less. Thus, the external forcing is dominant for large scales, while most of the variability is internally generated for small scales.

1. Introduction

Based on the concept of the “stochastic climate model” (Hasselmann 1976), the trajectory of the climate system can be described as that of an inert system subject to internally generated variations. That is, a relevant part of the variability of a system is not introduced by external factors, but internally generated. The internal variability (also called intrinsic variability, unprovoked variability, chaotic variability, or noise) is ubiquitous in the climate system and its oceanic and atmospheric components; it emerges at all locations and times, at all scales (von Storch et al. 2001). The cause for the emergence of such noise is in part due to nonlinearities, but equally important is the presence of very many degrees of freedom, which transforms short term small-scale disturbances to large-scale variations—in the spectral domain, this morphs a white noise spectrum into a red noise spectrum (Hasselmann 1976).

The presence of unprovoked variability was first recognized when doing numerical experiments with global atmospheric models, for instance, on the effect of anomalous sea surface temperature distributions (Chervin et al. 1974; Laurmann and Gates 1977). The noise is not just academically interesting but of great practical significance for the practice of numerical experimentation. For determining the effect of a modification, say of anomalous sea surface temperatures or changed parameterizations of physical processes, either very long simulations or ensembles of simulations are needed, and the null hypothesis “the modification has no effect” needs to be rejected with a statistical test. Thus, the discrimination between the signal, due to the modification, and the noise, due to internal processes, is needed.

The same problem comes to the forefront when analyzing the ongoing climate variability, if it would contain a component, which is forced by anthropogenic factors, in particular elevated greenhouse gas or aerosol

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DOI: 10.1175/JPO-D-19-0144.1

presences in the atmosphere. Hasselmann coined the term “detection” for determining if a signal is present, and “attribution” for determining which external factor would plausibly be the source of the signal (Hasselmann 1979, 1993). In the climatic system, the signal-to-noise (S/N) ratio problem has been studied since the 1980s (Madden and Ramanathan 1980; Wigley and Jones 1981; Wigley and Raper 1990; Alien et al. 1994; Santer et al. 1994, 1995). Santer et al. (2011) estimated the time-scale dependency of the S/N ratio in the climatic system.

The challenge of discriminating between the signal related to some forcing of interest, and the noise, which is generated internally, has been recognized in the global modeling communities for almost 50 years—with significant consequences for numerical experimentation and evaluation of observed variations. The regional atmospheric modeling communities, however, seem to have overseen the issue for a long time. Only in the late 1990s, was the regional atmospheric modeling community confronted with the need of ensemble simulations (Ji and Vernekar 1997; Rinke and Dethloff 2000; Weisse et al. 2000). In the global ocean community, the issue came up when eddy-resolving models came into use (e.g., Jochum and Murtugudde 2004, 2005; Arbic et al. 2014; Li and Han 2015; Sérazin et al. 2015; Penduff et al. 2018).

In the regional ocean modeling community the issue went mostly unnoticed, possibly until 2016. In personal communication, we were confronted with the unsubstantiated claim that the presence of lateral boundary conditions would constrain the system, so that the emergence of noise would be suppressed. However, Büchmann and Söderkvist (2016) reported about the problem emerging in operational regional oceanography. Also, Waldman et al. (2017) addressed this issue for an analysis of Mediterranean Sea variability. Nevertheless, “noise” is rarely considered an issue for numerical experimentation, it seems. A simply designed numerical experiment demonstrated the problem for simulations with high grid resolution (Tang et al. 2019).

Indeed, ocean models with coarse resolution, as were common in early global climate models, behaved almost deterministically, but as soon as mesoscale variability, in particular eddies, enters the dynamics, the situation changes, and the system becomes stochastic. The constraining by lateral boundary values does possibly reduce but not suppress the noise, if the considered region is not very small (cf. Schaaf et al. 2017).

First systematic studies about the emergence of noise in global ocean models have been summarized by Penduff et al. (2018). They drew mostly on the Oceanic Chaos—Impacts, Structure, Predictability (OCCIPUT) project, within which an ensemble of 50 members of 56 years (1960–2015) “global ocean/sea ice simulations

driven by the same atmospheric reanalysis, but with perturbed initial conditions” was built and examined. They showed that there is a massive presence of noise, mostly but not only on smaller spatial scales, and also at low frequencies.

The issue of noise in regional ocean simulations was addressed every now and then, such as the analysis of Jochum and Murtugudde (2004, 2005) who showed that internal variability can explain a significant part of the observed SST variability in the tropical Pacific Ocean and the western Indian Ocean. By studying the decadal sea level variations, Li and Han (2015) also indicated that ocean internal processes have considerable contribution along the Somali coast and in the western Bay of Bengal and the subtropical south Indian Ocean.

In this work, we study the presence of noise in simulations of the dynamics of the South China Sea (SCS). Plenty of previous works has shown that the main features of these dynamics of the SCS are influenced by the surface forcing and the water exchange at the boundary (e.g., Luzon Strait inflow). However, by using a three-layer nested simulation with the climatological forcing without any short-term atmospheric variability, Tang et al. (2019) demonstrated that unprovoked variability, that is, noise, is formed, and that the noise generation becomes stronger in models with higher resolution. From this observation and the results reported by Penduff et al. (2018) we derive the hypothesis that the S/N ratio depends on the spatial scale. This paper is testing and quantifying this hypothesis and finds it valid.

Before we begin our analysis, a brief discussion of the term noise is needed. This term is used differently in different scientific and engineering quarters. Noise is unprovoked variability, but the term “provoked” may depend on which “signal” is studied. In climate change simulations, the signal is related to the anthropogenic drivers, and the weather variations and their oceanic responses are part of the noise. In our simulations, described below, the signal is the response to the atmospheric forcing, so that their oceanic response is not part of the noise.

An issue is, of course, where the unprovoked variations come from. There may be many sources; in case of the SCS, it is plausible that the mesoscale eddies and their dynamics contribute (cf. Zhang et al. 2019). But various types of waves, variations in river discharge, spatially inhomogeneous radiative heating modulated by clouds may add to the small-scale and short-term cacophony of disturbances. Even unphysical interventions such as rounding errors, or miniscule differences in initial conditions, which no longer have any predictive significance, may become part of the source of noise, which then is transformed to larger and longer-living

features via the mechanism suggested in the stochastic climate model (Hasselmann 1976).

The significance of the presence of noise is that the effect of a modification in a numerical experiment may in some or maybe even most cases no longer be simply described as the plain difference between a modified simulation and a control simulation (e.g., Ådlandsvik 2008; Verri et al. 2018; Luneva et al. 2015). Instead extended simulations of ensembles of simulations may be needed, and the experiments themselves must be considered a statistical challenge. If the expected response is mostly large scale, the effect may be minor, but when limited time windows, that is, events or episodes, are considered, the effect may intermittently be strong [cf. example by Weisse et al. (2000) and Weisse and Feser (2003)]. A second significant aspect is that the noise may have an effect of mixing and transport, and on marine ecosystems. To this end, knowledge about the scale dependency of the S/N ratio is helpful—large-scale features are likely robust and less affected by random variations, while at small scales all kind of variations unrelated to the forcing may take place [e.g., an example by Chen et al. (2019) on sediment dynamics on the South China Sea].

In present work, based on an ensemble of identical ocean model simulations which differ only in the initial conditions, the scale dependency of the S/N ratio of the atmospherically forced ocean model in the SCS is studied.

The novelty our study is, first a confirmation that noise forms in regional models in spite of the lateral boundary forcing; second, we embed the presence of noise on all spatial scales into the framework of the stochastic climate model, which implies that the noise is partly due to eddy dynamics, but also to other factor, such as wave dynamics. Indeed, for the stochastic climate model, neither nonlinearity is needed nor specific processes (such as eddies). Third, our approach of describing the complete spatial variability through empirical orthogonal functions (EOFs) circumvents problems related to complex geometries. A fourth aspect is that we emphasize the consequences for the practice of numerical experimentation, which will be significant also for ecological and morphodynamic studies on small scales.

The present paper is organized as follows. A brief introduction to the model setup is given in section 2. In section 3, the methods used for this study are introduced. The results of the estimation of the scale length and the scale dependency of the S/N ratio are presented in section 4. Conclusions are summarized in section 5.

2. Model setup

The model used in this work is the Hybrid Coordinate Ocean Model (HYCOM), which is a primitive equation

FIG. 1. The domain and bathymetry of the SCS model. There are 651 grid points in the zonal (east–west) direction and 541 in the meridional (north–south) direction. The grid includes 212 940 sea points.

ocean general circulation model and has hybrid vertical coordinates (Bleck 2002). It describes the dynamics of the SCS on a grid with 0.04° resolution (Fig. 1). The surface forcing used in this work comes from the Navy Operational Global Atmospheric Prediction System (NOGAPS) forcing products. The temporal resolution of the NOGAPS data is 3 hourly. The NOGAPS data are interpolated from a 0.5° resolution to the 0.04° SCS model resolution.

An ensemble of four simulations is generated with this model. The four simulations are identical, except for the initial condition and the integration time (see Table 1). They all cover the year 2008, and the evaluation of the simulations considers only this year.

In other studies, such as Penduff et al. (2018) and Waldman et al. (2017), larger ensembles of longer simulations are used. For our purpose, namely to demonstrate the emergence of noise in regional models, and the qualitative scale dependency of the S/N ratio, this is not needed. Indeed, the quantitative results will depend on the model used, on the region considered, on the time line (e.g., if an El Niño persists or not). These limitations do, however, not compromise our conclusions.

The simulations are initialized 1, 3, 13, and 15 months before the beginning of 2008 (Table 1). During the entire simulations the atmospheric forcing as given by NOGAPS is used. The initial conditions are taken from simulations done with the same model (HYCOM) in a nested setup, as described by Tang et al. (2019). The coarsest model (1°) is global, an intermediate model (0.2°) describes the west Pacific, and the finest the SCS model on the same 0.04° grid. These simulations were done with climatological forcing, that is, a smooth annual cycle without weather variations.

The initial condition of the first model (N1) comes from the first day of December of the 31st year of the

TABLE 1. The setup of the four simulations.

	Start time	End time	Total run time	Initial condition
N1	1 Dec 2007	31 Dec 2008	13 months	1 Dec of 31st year
N2	1 Oct 2007	31 Dec 2008	15 months	1 Oct of 31st year
N3	1 Dec 2006	31 Dec 2008	25 months	1 Dec of 30th year
N4	1 Oct 2006	31 Dec 2008	27 months	1 Oct of 30th year

climatological SCS model and is run for 13 months (including December in 2007 and the whole year of 2008). The initial condition of the second model (N2) comes from the first day of October of the 31st year of the climatological SCS model and is run for 15 months (including from October to December in 2007 and the whole year of 2008). The initial condition of the third model (N3) comes from the first day of December of the 30th year of the climatological SCS model and is run for 25 months (including December in 2006, the whole year of 2007, and the whole year of 2008). The initial condition of the fourth model (N4) comes from the first day of October of the 30th year of the climatological SCS model and is run for 27 months (including from October to December in 2006, the whole year of 2007, and the whole year of 2008). The lateral boundary conditions of all these four simulations came from the intermediate model (or west Pacific model) in Tang et al. (2019), which is forced by climatological atmospheric forcing. Across the ensemble simulations, these boundary values were identical.

The four simulations differ only by the initial time and the initial conditions. However, the different initial conditions are fully consistent, taken from the timeline of the climatological HYCOM simulation. The time from initialization to analyzing the data is at least 1 month, a time which we consider sufficient to make sure that the details of the initial state do not matter (in the sense of predictability). But the small differences introduced by the different initial conditions will make sure that noise forms in the simulation.

We use barotropic velocity to make our case. Indeed, various variables of the ocean dynamics could be used to demonstrate our case, among them barotropic velocity or SSH. We decided on barotropic velocity because we did our demonstration of the presence of noise in the South China Sea, in Tang et al. (2019), with that variable. We found that the increase of daily variance of the barotropic streamfunction with finer model grid resolution is more obvious than when using SSH. We simply went on with the barotropic velocity because the noise in the barotropic velocity is more obvious than that in the SSH.

For demonstrating the presence of unprovoked variability, or of noise, in the set of simulations, we plot in

Figs. 2 and 3 the logarithm of the speed of barotropic velocity for the four simulations at two randomly chosen days—on the 87th day and on the 255th day of the year 2008. The figures show that the states on the same day in the four simulations are rather similar with respect to the large scales, but exhibit obvious differences on smaller scales. Thus, Figs. 2 and 3 already demonstrate the validity of our base hypothesis, but we want to do the comparison not just in terms of two cases studies, but in a more systematic manner in the remainder of this paper.

3. Methods

We need first to decompose the simulated fields in components of different scales. We do so by considering EOFs in section 3a. In section 3b we derive a measure of scale for the different EOFs, allowing for a quantitative assertion of the link of EOF rank and spatial scale, which is intuitively to be expected. In section 3c we explain how to estimate S/N ratios from the four ensemble members.

a. Decomposing according to spatial scales

The EOF analysis is a multivariate analysis technique that can be applied for the separation of different dominant patterns of variability (von Storch and Zwiers 1999). We will show below that the ranking of the EOFs is associated with a ranking of scales.

There are a total of four simulations in the year 2008 in this work. So, in order to get the scale involved for all the four model simulations, we determine the EOFs of the daily barotropic velocity across all four 2008 simulations, which is computed as

$$B(x, y, t) = \sum_{j=1}^p Q_j(t) e_j(x, y), \quad (1)$$

$$t = 1, \dots, 4 \times 366 \text{ days},$$

where B is the barotropic velocity across all four 2008 simulations, x and y denote the model's grid points in the zonal (east–west) direction and the meridional (north–south) direction, respectively, and t counts the days in the four simulations. The $e_j(x, y)$ is the j th EOF across all four 2008 simulations, the $Q_j(t)$ are the j th principal components (PCs), and j denotes the index of EOFs. Each simulation in 2008 has 366 days, so four simulations have $4 \times 366 = 1464$ days. Therefore, we can get $p = 1464$ nontrivial EOFs (i.e., with nonzero eigenvalues; see, e.g., von Storch and Zwiers 1999).

Due to the problem related to the accuracy of computing and resulting inaccuracies of determining the last EOF, the first 1463 EOFs are used for the next analysis, and the last one is discarded. The EOFs are ranked as

FIG. 2. The logarithm of the speed of barotropic velocity for the four models (a) N1, (b) N2, (c) N3, and (d) N4 on the 87th day of the year 2008.

usual, with an index sorted according to the percentage of explained variance. A visual inspection of the patterns reveals that low-indexed EOFs go with large scales, medium-indexed EOFs with medium scales, and high-indexed ones with small scales. Thus, PCs of these EOFs are associated with scales that decrease with increasing indices of the EOFs, but we will quantify this link below.

b. Estimating the scale lengths

The spatial scale lengths of EOFs are estimated by the spatial autocorrelations (Wackernagel 2013) of the EOFs derived earlier.

For explaining how this is done, we need to introduce some definitions. If $\mathbf{M}$ is a subset of gridpoints in the modeling domain, then $|\mathbf{M}|$ is the number of elements of this set. Let $\mathbf{G}$ be the set of all sea points in the modeling domain. For calculating the spatial autocorrelation at lag k of a pattern e , we form all products of $e(x, y)$ and $e(x + k\Delta, y)$, with Δ being the distance between two points in the zonal or meridional direction, if both points (x, y) and $(x + k\Delta, y)$ are in $\mathbf{G}$. Similarly, we form products of points with points neighboring in the meridional direction. Formally, when applied to the j th EOF e_j ,

$$c_j(k) = \frac{\left\{ \sum_{(x,y) \in \mathbf{G}^{kz}} [e_j(x + k\Delta, y) - \bar{e}_j][e_j(x, y) - \bar{e}_j] + \sum_{(x,y) \in \mathbf{G}^{km}} [e_j(x, y + k\Delta) - \bar{e}_j][e_j(x, y) - \bar{e}_j] \right\}}{\sum_{(x,y) \in \mathbf{G}} [e_j(x, y) - \bar{e}_j]^2 / |\mathbf{G}|} \left/ \left[|\mathbf{G}^{kz}| + |\mathbf{G}^{km}| \right] \right. \quad (2)$$

with the sets of points $\mathbf{G}^{kz} = \{(x, y) \in \mathbf{G} | (x + k\Delta, y) \in \mathbf{G}\}$, containing all sea points with a sea point k grid points to the right (z like zonal displacement). The m in set

$\mathbf{G}^{km}$ indicates that points displaced in the meridional direction are considered, and $\bar{e}_j$ is the spatial mean of the j th EOF e_j .

FIG. 3. The logarithm of the speed of barotropic velocity for the four models (a) N1, (b) N2, (c) N3, and (d) N4 on the 255th day of the year 2008.

As the length scale of the EOF e_j , we select $k^*\Delta$, with the largest k^* so that all $c_j(k)$ are larger than some threshold for all $k < k^*$. The grid mesh length is 4.0–4.4 km, and we set $\Delta = 4.2$ km.

c. Computing the S/N ratio

Because the noise is represented by the differences between the simulations in this work, the signal and noise can be computed by the ensemble mean and ensemble standard deviation between the simulations, respectively. This is first done for each PCs of the 1463 EOFs at each day of the year 2008, of which the ensemble provides four samples. Obviously, a sample of four is not large, and noteworthy random variations prevail because of the limited sampling. However, as we will see, the results are plausible and qualitatively meaningful and consistent so that an expansion of the sample size, by adding more simulations of the year 2008, would lead to some quantitative changes but not to a need of questioning the conclusions of this paper.

If $Q^i(j, t)$ is the PC at the day t of the simulation N_i of j th EOF, then the signal at the day t is estimated to be the mean at that day across the four simulations

$$\mu(j, t) = \left[\sum_{i=1,4} Q^i(j, t) \right] / 4, \quad (3)$$

and, consistently, the intensity of the noise at day t is measured by the standard deviation across the four simulations, that is, by

$$\sigma(j, t) = \sqrt{\left\{ \sum_{i=1}^4 [Q^i(j, t) - \mu(j, t)]^2 \right\} / 4}. \quad (4)$$

Then, the S/N ratio is estimated by the ratio of the standard deviation of the signal across the year ($t = 1, \dots, 366$) and of the standard deviation of the noise across the year for each of the PCs $j = 1, \dots, 1463$.

All variations in the numerator, the temporal standard deviation of the ensemble mean of the PCs, are related to the common atmospheric variations acting upon the ocean in the four different samples of the year 2008. The variations in the denominator, the temporal standard deviation of the ensemble standard deviation of the PCs, on the other hand, reflect non-synchronous variations in the different realizations of 2008, and are thus not related to the common atmospheric forcing.

FIG. 4. The joint EOFs (a)–(c) 1, (d)–(f) 5, (g)–(i) 50, and (j)–(l) 200 of the zonal u and meridional v components of the barotropic velocity. (left) The patterns of the zonal barotropic velocity u (m s^{-1}); (center) the patterns of the meridional barotropic velocity v (m s^{-1}); and (right) corresponding autocorrelation functions for EOF 1, EOF 5, EOF 50, and EOF 200.

4. Results

a. The estimation of the scale lengths

Figure 4 shows a few EOFs (viz., EOF 1, EOF 5, EOF 50, and EOF 200) of the zonal u and meridional v components of the barotropic velocity, and the corresponding spatial autocorrelation functions. From the EOF patterns, we can see that with the increase of the EOF index the spatial scale becomes less and less. Consistently the spatial autocorrelations inform that a larger EOF index is associated with a steeper decline of the autocorrelation function. This confirms our hypothesis that the index of an EOF is indicative for their spatial scale.

As mentioned before, we may define a quantitative spatial scale by choosing a critical level for determining

k^* . This choice is arbitrary but allows a consistent comparison across different patterns.

We choose 0.1 for this critical value. Figure 5 shows the resulting scale lengths for all EOFs. The scale lengths do not decline in a monotonic manner, which may be related to the fact that both, the EOFs themselves and the scales are estimated and subject to random variations. Indeed the sampling errors in EOF estimation are large for high index EOFs (North et al. 1982). But, in spite of these limitations, the estimated scale lengths are a useful tool to characterize the patterns of the EOFs.

b. The scale-conditioned S/N ratios

Using the formulas (3) and (4), we estimate the S/N ratios of the PCs of the EOFs. We consider the joint

FIG. 5. The estimated scale lengths (km) of the first 1463 EOFs.

EOFs of the zonal and meridional components of the barotropic velocity. In one case we consider the EOFs without prior subtraction of the annual cycle so that the signal is rooted in the atmospheric forcing and in the annual cycle. In the other case, we subtract the common annual cycle before doing the EOF analysis, and in this case the signal stems only from the atmospheric weather forcing. The annual cycle is fitted from the time series of the year 2008 by harmonic analysis.

Figures 6 and 7 show the scale distribution of the S/N ratio for the case with and without annual cycles. We find that with the increase of the EOF index the S/N ratio declines. Our base hypothesis is thus valid.

When looking more in detail (Fig. 6), we find three ranges of EOF indices, namely, EOFs 1–10, 11–50, and 50–1463. Within the three ranges, the S/N ratios have characteristic distributions, as illustrated by ± 3 standard deviation brackets. The first block of EOFs 1–10 has large scales, namely on average about 220 km, the

middle block of EOFs 11–50 only 110 km, and the third block of EOFs 51–1463 only 30 km. The S/N ratios in the first block decline quickly, in the middle block the decrease is weaker, and in the third block corresponding to the small scale the S/N ratio declines more slowly, and the range of the high-indexed EOFs 51–1463 is not only very small but almost constant. When the annual cycle is taken out (Fig. 7), the S/N ratios in the first block are smaller, but for the two other blocks almost unchanged.

In the same way, as for the time series of the PCs, formulas (3)–(4), we can calculate locally S/N ratios for any series of fields. We do so for the filtered fields of zonal and meridional barotropic velocity. The filtering is done by combining the EOF patterns and principal components of the three ranges mentioned above, that is, 1–10, 11–50, and 51–1463. Now, μ and σ are functions for each point (x, y) on the model grid.

Figure 8 shows the maps of the S/N ratios for the three spatial scale ranges, 1–10 (Fig. 8a), 11–50 (Fig. 8b), and 51–1463 (Fig. 8c), for the case with annual cycle; the same without annual cycle is displayed in Fig. 9.

For the large-scale component (Fig. 8a) the largest S/N ratios (>16) mainly appear to the south of Vietnam and to the west of the island of Taiwan, where the ocean is shallow. Smaller S/N ratios (<4) mainly appear in the deep ocean, north of 12°N . There are mainly three regions for S/N ratios in the large-scale component smaller than 4, which are to the east of Hainan Island, to the east of Vietnam, and to the west of Luzon Island. In Fig. 8b describing medium scales, the spatial distribution of the S/N ratio varies irregularly with the value range from 2 to 4. In Fig. 8c on small scales, the value of the S/N ratio in the shallow ocean (>2) is larger than that in the deep ocean (<2). Therefore, the results in Fig. 8 demonstrate that with an EOF index increasing or the scale becoming smaller, the S/N ratio becomes less everywhere.

FIG. 6. The S/N ratios as a function of the EOF index for the case when the annual cycle is included in the EOF analysis. Small scales are situated at the right end, and large scales are at the left end. Based on the distribution of the S/N ratio, the scales (EOFs) are divided into three blocks: EOFs 1–10, EOFs 11–50, and EOFs 51–1463. The green line in each block is the mean value of the ratio values, and the red lines above and below the green line in each box are the mean value ± 3 standard deviations of the S/N ratio.

FIG. 7. The S/N ratios as a function of the EOF index for the case when the annual cycle is excluded in the EOF analysis. Small scales are situated at the right end, and large scales are at the left end. Based on the distribution of the S/N ratio, the scales (EOFs) are divided into three blocks: EOFs 1–10, EOFs 11–50, and EOFs 51–1463. The green line in each block is the mean value of the ratio values, and the red lines above and below the green line in each box are the mean value ± 3 standard deviations of the S/N ratio.

In general, the atmospherically triggered signals are best visible in the shallow parts of the SCS, whereas the internal dynamics dominate in the deep part of the SCS. This is not surprising as in the shallower parts of the ocean, the atmospheric forcing acts on a smaller water body, whereas eddies tend to form in deeper waters.

The results for the reconstructions without the annual cycle (Fig. 9) differ only for the first, large-scale range. In whole SCS the S/N ratios without the annual cycle in the large scale are smaller than that with the annual cycle. This is not surprising, since the annual cycle resides mostly in the low-indexed EOFs—and the patterns shows an obvious weakening of the maxima in Fig. 9a, south of Vietnam, where the

effect of the seasonal monsoonal change is particularly strong.

5. Conclusion and comments

With an ensemble of identical ocean model simulations that differ only in the initial conditions at the different spinup times, we test the hypothesis that the ratio of externally forced variability and of internally generated variability is strongly dependent on the spatial scale in a regional sea. This ratio is quantified with help of a signal-to-noise ratio. Here, the signal is the impact of atmospheric variability, and the noise is unprovoked variability.

By doing so, we demonstrate also that the presence of lateral boundary values is not eradicating the emergence

FIG. 8. Maps of the S/N ratio for the case that the annual cycle is included in the EOF analysis for (a) the first range of EOFs 1–10, (b) the second range of EOFs 11–50, and (c) the third range of EOFs 51–1463.

FIG. 9. Maps of the S/N ratio for the case that the annual cycle is excluded in the EOF analysis for (a) the first range of EOFs 1–10, (b) the second range of EOFs 11–50, and (c) the third range of EOFs 51–1463.

of internal variability, which we call noise. A novel aspect of our analysis is that we define the spatial scales empirically with EOFs, so that we cover all spatial variability in a sea with irregular geometry. Two significant conceptual conclusions of our study refer to the applicability of the “stochastic climate model” for framing the issue of noise, and the implications for numerical experimentation and simulation of impacts with regional laterally constrained ocean models.

That intrinsic variability, that is, unprovoked variability or in our terminology noise, emerging in global eddy-resolving models has been known for about two decades. However, the regional oceanographic community mostly overlooked the problem until recently, possibly because of a tacit assumption that the regional constraints through lateral boundary conditions would transform the stochastic system into a deterministic one also for eddy-resolving dynamics. This perception is seemingly inaccurate.

Our study deals with this regional, laterally constrained system, specifically the dynamics of the South China Sea, described on a 0.04° grid in the year 2008. We do our analysis with the daily stored barotropic velocity. The choice of the year and the variable is ad hoc.

We find our hypothesis fully confirmed for the South China Sea. For spatial scales of about 220 km and more, the signal is stronger than the noise. This is particularly so in the shallower parts of the SCS. But there is noise at these large scales, as predicted by the stochastic climate model. The ratios become comparable for scales on the order of about 110 km, whereas for spatial scales of about 30 km and less, the noise dominates. This is particularly so in the deeper parts of the ocean.

Our results concerning the emergence and scale dependency of noise are consistent with what [Penduff et al. \(2018\)](#) found in their analysis on an ensemble of global ocean/sea ice models.

We know that the noisy mesoscale variability comes mostly from the accumulation of perturbations originating from instability mechanisms, in particular eddies but also waves. But what is driving the seeding of eddy formation and of wave formation? It is seemingly mostly not external factors ([Zhang et al. 2019](#)), but a variety of random effects, related to nonlinearities or computational process details (e.g., [Ludwig and Geyer 2019](#)), when the numerical viscosity is weak.

Of course, the S/N ratio depends on the forcing, which is the source of the signal. If this is weak, the S/N ratio will become small for all scales. If the forcing is of small scales and not dominated by large scales, the situation may change. But we expect that we will find the type of S/N spectra as in [Figs. 6 and 7](#), when the forcing is mostly large scale—which is the case in atmospherically driven regional ocean simulations or in climate change simulations. More cases, with different seas, need to be studied, but in our two cases, when the annual cycle is, or is not, considered part of the signal, we see the same type of S/N spectrum, albeit with smaller values for the leading EOFs.

The scale dependency of the S/N ratio is important to supplement for our recognition of oceanic hydrological dynamics, especially the small scales. For example, for the oceanic eddies, we see the hypothesis confirmed that the generation of some oceanic eddies is mostly caused by inherently internal variability and is hardly due to the external forcing ([Zhang et al. 2019](#)). Consistently,

Chen et al. (2019) rightly failed to connect small-scale deposition dynamics in the South China Sea to large-scale forcing.

The presence of noise is not only of such academic interest but has practical consequences. Namely, the effect of a modification in a model or in a simulation, be it a change in the forcing or in a parameterization, is not given by the mean difference between a control and an experimental simulation as the signal, but must be studied with an extended dataset, be it a very long simulation or an ensemble of simulations, for identifying a robust part of the signal. This is long known in atmospheric sciences, but seemingly hardly recognized in numerical experimentation with regional ocean models.

In certain cases, some argue, for instance when tides are very strong, the noise part may become less important if not outright negligible. Indeed, the tides may be efficient in limiting the predictive skill of the knowledge about an initial state but may not eradicate the formation of noisy components. However, this needs to be tested in designed experiments. Additionally, the dynamical characters, as to which processes are mainly responsible for the formation of noise, need to be studied. Eddies are an obvious candidate, but internal wave activity or stochastic elements or stochastically varying driver discharge may have a share. Finally, one should keep in mind that the dynamics in the South China Sea may be substantially different from those in other regional seas, such as in the North Sea.

Given our results, one could assume that the stochastic character of the simulations is less important if variations that are large scale in space and slow in time are studied. But this may not always be so, as the examples of Penduff et al. (2018) demonstrate. Also, the effect of spurious signals, which are in reality an expression of the activity of noise, may become dominant if specific episodes of limited temporal extension are selected.

Our study is limited by the relatively short time window of 1 year for each member of our ensemble. Previous studies (Mikolajewicz and Maier-Reimer 1990; Arbic et al. 2014; Penduff et al. 2018) have indicated that low frequency noisy large-scale variability unprovoked by specific forcing may emerge. Indeed, the theory behind Hasselmann's (1976) stochastic climate model does not imply that noteworthy unprovoked variability would prevail only at higher frequencies. The famous experiment by Mikolajewicz and Maier-Reimer (1990) operated with a coarse grid model without mesoscale eddies, but generated strong quasi-oscillatory variability after centuries as a response to space-time white noise freshwater fluxes. It certainly would be interesting to

see if such large-scale variability, for instance, as in Mikolajewicz and Maier-Reimer (1990), would emerge in a millennial run with climatological (weather-free) forcing due to small-scale random disturbances in the ocean. However, this is beyond the scope of our present analysis.

Acknowledgments. This work is supported by the Project “Oceanic Instruments Standardization Sea Trials (OISST)”, (2016YFC1401300) of National Key Research and Development Plan, and Taishan Scholars Program. Thanks is given to German Climate Computing Center (DKRZ) and China National Super Computing Center in Jinan for providing the computing resources and Ms. Liu Xin for computing support. We thank Ralf Weisse and Zhang Wenyan from HZG and Frabk Janssen from BSH for valuable advice.

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