A weakly coupled data assimilation system of a coupled physical–biological model for the northeastern South China Sea

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ABSTRACT

A weakly coupled data assimilation system was established for a coupled physical–biological model for the northeastern South China Sea (NSCS). The physical model used was the Regional Ocean Modeling System; the biological component was a seven-compartment nitrogen–phytoplankton–zooplankton–detritus ecosystem model; and the data assimilation method was Ensemble Optical Interpolation. To test the performance of the weakly coupled data assimilation system, two numerical experiments (i.e. control and assimilation runs) based on a process-oriented idealized case were conducted, and climatological SST was assimilated in the assimilation run. Only physical variables were adjusted in the weakly coupled data assimilation. The results showed that both the assimilated SST and other unassimilated physical variables had reasonable process responses. Due to the warmer SST observation, the water temperature (salinity) in the assimilation run increased (decreased) in coastal upwelling regions. Both the alongshore and bottom cross-shore currents were reduced, jointly demonstrating the weakening of the upwelling system. Meanwhile, ecosystem variables were also affected to some extent by the SST assimilation through the coupled model. For example, larger phytoplankton (chlorophyll) productivity was found in the upwelling region within the shallow layer due to the warmer waters in the assimilation run. Hence, the application of this data assimilation system could reasonably modify both physical and biological variables for the NSCS by SST assimilation.

1. Introduction

Data assimilation is a novel and versatile methodology for estimating oceanic variables or parameters (e.g. Powell et al. 2008; Yu et al. 2012; Wilkin and Hunter 2013). A data assimilation procedure can optimally extract and merge the information contained in the model results and the real data, and then provide a synthesis (Bennett 1992; Natvik and Evensen 2003; Ford et al. 2012). Because models contain uncertainties due to inadequate approximations and parameterizations, and because observations are sparse in the spatiotemporal domain, the integrated estimates are more accurate and can lead to model improvement.

Data assimilation has been applied in ocean models to improve the simulation of physical variables, such as SST, salinity, and sea level anomalies (e.g. Wang, Wang, and Xie 2003; Xiao, Wang, and Xu 2006; Xie et al. 2011; Zeng et al. 2014; Peng, Zeng, and Li 2016). The approaches described above result in improved model results and enhance our understanding of ocean physical dynamics, especially in coastal regions. In addition to its use with ocean physical fields, data assimilation has been utilized recently to improve our understanding of biological distributions and processes by estimating ecosystem variables, especially ocean chlorophyll in coupled physical–biological or physical–biogeochemical models (e.g. Lellouche, Ouberdous, and Eifler 2000; Nerger and Gregg 2007; Gregg 2008; Ford et al. 2012). However, few studies have examined the physical or both physical and biological state estimations in...
coupled models (Fiechter et al. 2011; Liu, Meier, and Eilola 2014). Nonetheless, these coupled physical–biological data assimilation systems are very important, due to the manifold interaction between physical and biological processes. Typically, ocean ecosystems are largely regulated by their physical conditions (Gan et al. 2010); therefore, improving the simulation of physical quantities by data assimilation is a priority. This is also an effective and efficient approach to improving the model representation of ocean biological variables and parameters, which are critical for coastal zone environments and fish stock management.

In this study, a weakly coupled data assimilation system (not adjusting the biological variables directly when physical variables are assimilated) was established in a coupled physical–biological model and the performance of the weakly coupled assimilation system was examined. Based on the study of Gan et al. (2009), we focused on the northeastern South China Sea (NSCS), because it contains well-documented physical processes and prominent ecosystem processes. Because Ensemble Optical Interpolation (EnOI) is a multivariate assimilation scheme, it includes approximate relationships between the assimilated variables and those that require adjustment (Zhang et al. 2013). Therefore, to assess the weakly coupled data assimilation system, we conducted an SST assimilation experiment and analyzed the relationships between the changes of the assimilated SST and other adjusted physical variables. Furthermore, the unadjusted biological variables were also analyzed to investigate the effects of improved physical quantities on ecosystems.

This paper is organized as follows: the coupled model and the data assimilation method are described in Section 2. The physical and biological process responses are analyzed in Sections 3 and 4, respectively. Section 5 provides conclusions.

2. Coupled model and assimilation method

2.1. Model description

The physical model was the Regional Ocean Modeling System (ROMS) (Song and Haidvogel 1994). The model domain ranged from (15.99°N, 108.17°E) to approximately (25.81°N, 119.54°E), and the central axis was directed 23° anticlockwise from true east (Figure 1(a)); a curvilinear grid with an averaged horizontal resolution of approximately 3 km was utilized. The model had 30 non-uniform vertical levels. In this process-oriented study, the only external force was surface wind, which was set to a spatially uniform southwesterly wind stress (0.025 Pa), which was representative of the typical NSCS upwelling conditions in summer. The model was initialized using horizontally uniform temperature and salinity profiles that were obtained from field measurements. The velocities and surface elevations were initialized to zero. The model domain included two open boundaries: an oblique horizontal radiation condition (Marchesiello, McWilliams, and Shchepetkin 2001) was applied on the southern boundary; open boundary conditions (OBCs) that favored wind-forced shelf circulation (Gan and Allen 2005; Gan, Allen, and Samelson 2005) were utilized along the eastern boundary. The OBCs separated the model variables at the open boundary into a forced local part and an unforced global part. The variables for the local part were obtained from an across-shore, two-dimensional submodel with reduced physics, and the variables in the global part were provided by an oblique horizontal radiation condition. The freshwater input rate from the Pearl River Estuary (PRE) was set to the typical summer value of 16 500 m³ s⁻¹; and the salinity, temperature, and NO₃ concentration of the river were set to 10 psu, 29.5 °C, and 60 mmol m⁻³, respectively.

The biological model embedded in ROMS is a Fasham-type ecosystem model (Fennel et al. 2006)—a nitrogen-based ecosystem model that describes the dynamics of seven compartments: nitrate, ammonium, chlorophyll, phytoplankton, zooplankton, large detritus, and small detritus. In this process-oriented study, most of the biological parameters applied in the biological model were taken from ROMS (Fennel et al. 2006). The initial values for the biological variables were chosen to be horizontally uniform for all parameters: nitrate and chlorophyll were observed at an offshore station (20.1°N, 115.8°E) during July 2000; the initial profiles for other parameters were obtained from a one-dimensional model after a one-year run. More details about the biological model settings and conditions used can be found in Gan et al. (2010). The main physical and biological parameters used are shown in Table 1.

2.2. Data assimilation method

The data assimilation method applied in this study was EnOI (Evensen 2003), which is based on the Ensemble Kalman Filter (EnKF). Instead of the time-varying ensemble members applied in EnKF, EnOI uses a stationary ensemble to approximate the system’s background error covariance. EnOI is also a cost-effective data assimilation method because it requires only one deterministic model run, and only one background state needs to be updated during every assimilation cycle. This method has been successfully used for a wide range of ocean applications (e.g. Counillon and Bertino 2009; Xie et al. 2011; Liu, Meier, and Axell 2013).

Assume a state vector \( x \) representing a sample (SST, salinity, or sea surface height). With \( N \) samples, we define the ensemble perturbation matrix as
Figure 1. (a) The topography (units: m) in the NSCS. The black box is the model domain. The selected cross-shelf section is marked by its grid number (338) and the location of shoreward convex isobaths exists at the head of the widened shelf about 0.5° southwest of Shanwei. (b) SST (units: °C) from the observation (MODIS SST), control run (control SST), assimilation run (assimilation SST), and the difference between the assimilation run and control run (assimilation - control) on day 40. Spatially uniform southwesterly wind stress (0.025 Pa) is shown on the MODIS SST. The 30- and 50-m isobaths are shown as black contour lines on the difference distribution.
Table 1. Main physical and biological parameters.

| Description                                      | Symbol | Value | Units       |
|--------------------------------------------------|--------|-------|-------------|
| Vertical mixing parameter                        |        |       |             |
| S-coordinate surface control parameter           | THETA_S| 2.5   |             |
| S-coordinate bottom control parameter            | THETA_B| 0.8   |             |
| Depth control the surface and bottom layer stretching | TLINE  | 50    | m           |
| Minimum water depth                              | h_min  | 5     | m           |
| Eastern boundary condition                       |        |       |             |
| Southern boundary condition                      |        |       |             |
| Half-saturation for phytoplankton NO₃ uptake     | Kₖ₂   | 0.5   | mmol Nm⁻³   |
| Half-saturation for phytoplankton NH₄ uptake     | Kₖ₆   | 0.5   | mmol Nm⁻³   |
| Maximum cellular chlorophyll: C ratio            | θₙ    | 0.054 | mgChl-αmgC⁻¹|
| Phytoplankton mortality rate                     | mₚ    | 0.15  | d⁻¹         |
| Zooplankton maximum grazing rate                 | gₘₐₓ  | 0.6   | d⁻¹         |
| Zooplankton basal metabolism                     | lₘᵦ   | 0.1   | d⁻¹         |
| Zooplankton specific excretion rate               | lₑₘ   | 0.1   | d⁻¹         |
| Zooplankton mortality rate                       | mₑₘ   | 0.025 | d⁻¹ (mmol Nm⁻³⁻¹) |
| Small detrital remineralization rate              | rₑₗ   | 0.03  | d⁻¹         |
| Large detritus remineralization rate             | θₑₗ   | 0.01  | d⁻¹         |

\[ A^{N×N} = [\delta x^{(1)} , \ldots , \delta x^{(N)}] , \]  

where \( \delta x^{(i)} = x^{(i)} - \bar{x} \). Therefore, the background error covariance matrix \( P^b = \alpha \frac{N}{N-1} A^T A \), and the standard analysis equation of EnOl is 

\[ x^a = x^b + P^b H^T (H P^b H^T + R)^{-1} (y - H x^b) . \]  

The analysis state can be determined by solving the following EnOl analysis equation:

\[ x^a = x^b + a A^T H^T (a H A^T H^T + (N-1) R)^{-1} (y - H x^b) , \]  

where \( a \in (0,1) \) is introduced to allow for different weights on the ensemble versus measurements (this parameter was set to 0.8 based on a set of sensitivity experiments); \( y \) is the observation vector (the observation error variances were all set to 0.5 (observation errors were assumed to be uncorrelated)); \( H \) is the observation operator that maps the model state onto the observation space; \( R \) is the error covariance for the measurements; and the superscripts a and b refer to the analysis and forecast model states, respectively. To remove unrealistic long-range correlations associated with large values of m, we adopted the localization scheme and specified a uniform radius of influence of 100 km.

### 2.3. Experimental design and assimilation procedure

This study focused on two experiments to examine the performance of the weakly coupled data assimilation system: the control run—an idealized simulation capable of representing intensified upwelling over the widened shelf in the NSCS (Gan et al. 2009); and an assimilation experiment, which assimilated the 12-year (2003–2014) averaged daily MODIS SST from 21 June to 20 July. The SST observation had a resolution of 4 km, and the error was given as 0.5 °C. For simplicity, the ensemble members were selected from model outputs in the control run. We selected the outputs every 6 h from day 20 to 50 for each assimilation cycle. The assimilation frequency was once every five days, and the number was based on a set of sensitivity experiments. In the weakly coupled data assimilation system, only ocean temperature, salinity, sea surface height and velocity were adjusted by the SST assimilation directly. To examine the ecosystem response to changes of the physical variables, the SST data assimilation had no direct influence on biological variables. The control experiment was run for 50 days, and the assimilation experiment started on day 20 and was run for 30 days. We focused on the region over the widened shelf, where the upwelling system occurs.

### 3. Improvement of the physical processes

#### 3.1. SST, salinity, and velocity

Coastal upwelling is one of the most important physical processes in the NSCS and is largely controlled by the shelf topography (Gan et al. 2009), which is characterized most obviously by a prominent eastward widened shelf (Figure 1(a)). As shown in both observation and model outputs (Figure 1(b)), driven by the spatially uniform southwesterly wind stress, dense cold waters were transported shoreward and upward and eventually outcropped near the coastal regions. Intensified upwelling was often generated to the east off Shantou. For the MODIS SST, a low temperature zone was found near the coast at approximately 118°E, which was higher in temperature than that of the control run. After SST data assimilation, SST increased, and an obvious increment (~1.5 °C) was found at 117–118°E, seaward of the intensified upwelling center and the 30-m
model integration, exhibited almost the same pattern as that described in the above analysis (not shown). The reasonable relationships between the changes in different variables demonstrate the relatively good performance of this weakly coupled assimilation system.

### 3.2. Ocean subsurface temperature, salinity, and velocity

To show the responses in deep layers, a representative cross section was selected (Figure 1(a)): line 338 (near Shantou). In the assimilation run, where the intensified upwelling occurred, the water column down to approximately 18 m was significantly affected by the SST assimilation (Figure 3(a)). The ocean temperature increased (~1.5 °C), and the salinity decreased (~0.5 psu). Moreover, the salinity increased shoreward of the reduced center within a shallow layer (at approximately 15 m). The response of the cross-section temperature (salinity) was consistent with that of the SST (SSS).

The alongshore current split into two branches at line 338 (Figure 3(a)). The larger southern branch extended to approximately 40 m vertically in the control run and was reduced to the upper 20 m after SST assimilation. Unlike the alongshore currents ($u$), the offshore currents ($v$) were not prominent (figures not shown). The positive value of $v$ along the bottom shelf, which played a critical role in the formation of the intensified upwelling by transporting isobath. Regarding the area to the north of the Taiwan Shoals, SST decreased because of the lower observational ocean temperature.

EnOI is a multivariate assimilation scheme and can improve not only the assimilated SST but also the unassimilated variables. Forced by the southwesterly wind stress, the northeastward surface current was almost parallel to the isobaths (not shown). As shown in Figure 2, between the 30- and 50-m isobaths, large alongshore currents ($u$) occurred with distinct maxima near the head of the widened shelf (referred to as ‘shelf head’ hereafter). A comparison between the two experiments showed that the large value of $u$ at the shelf head decreased (~0.1 m s$^{-1}$) in the assimilation run. Due to the weakened eastward currents, the surface freshwater (referred to as ‘plume’ hereafter) from the PRE, which was transported downstream by the current, did not overstep 117°E. Therefore, in the farther field of the plume, sea surface salinity (SSS) in the assimilation run increased because less freshwater was transported downstream (Figure 2). Moreover, the SSS decreased by approximately −0.4 psu near the coastal regions, where the SST increased. In conclusion, due to the SST observation, SST increased in the upwelling regions in the assimilation run; this increase restrained the upwelling current, decreased the nearshore salinity, and reduced the alongshore currents. Moreover, the variable adjustments (SST, SSS, and velocity) after assimilation, without

### Figure 2.

Surface alongshore velocity ($u$) (units: m s$^{-1}$) and SSS (units: psu) from the control run, assimilation run, and the difference (assimilation – control) on day 40.
Figure 3. (a) Across-shore section of ocean temperature (units: °C), salinity (units: psu), and alongshore velocity (units: m s⁻¹) from the control run (left column), assimilation run (middle column), and the difference (assimilation – control) (right column) along line 338 on day 40. (b) Top row: the cross-isobath volume transport (units: m² s⁻¹) normal to the 30- and 50-m isobaths (left column), and the difference (assimilation – control) (right column) in the middle layer on day 40. Bottom row: as in the top row but for the PGF (units: m s⁻²) along the 30- and 50-m isobaths. The middle layer is averaged for the middle 10 m at a depth of 30 m, and 30 m at a depth of 50 m, respectively.
analyzed. The volume transport was seaward (shoreward) in the upper (bottom) layer, and were both normal to the 30- and 50-m isobaths (not shown), reflecting the two branches of the upwelling circulation. However, in the middle layer, there was very large shoreward transport that was normal to the 50-m isobath west of 116°E, which accounted for the intensified upwelling (Figure 3(b)).

To further examine the response of the intensified upwelling currents, the volume cross-isobath transport and the pressure gradient force (PGF) on day 40 were analyzed. The volume transport was seaward (shoreward) in the upper (bottom) layer, and were both normal to the 30- and 50-m isobaths (not shown), reflecting the two branches of the upwelling circulation. However, in the middle layer, there was very large shoreward transport that was normal to the 50-m isobath west of 116°E, which accounted for the intensified upwelling (Figure 3(b)).

Figure 4. (a) Surface phytoplankton (units: mmol m⁻³) and nutrients (NO₃; units: mmol m⁻³) from the control run, assimilation run, and the difference (assimilation – control) on day 40. (b) Across-shore section of phytoplankton (units: mmol m⁻³) and nutrients (NO₃; units: mmol m⁻³) from the control run (left column), assimilation run (middle column), and the difference (assimilation – control) (right column) along line 338 on day 40.
In the assimilation run, this maximum shoreward transport decreased. Moreover, a prominent decrease in the shoreward transport that was normal to the 50-m isobath was found at 115°E, transforming the volume flux from the shoreward transport seen in the control run to seaward transport in the assimilation run. The response of the volume transport that was normal to the 30-m isobaths was not obvious.

Gan et al. (2009) found that the variation of the cross-isobath volume transport was controlled primarily by variations of the along-isobath PGF and Coriolis force in the middle layer. In Figure 3(b), the PGF is negative (positive) along 50 m (30 m) over the shelf head (115–116°E). This quasi-barotropic westward (eastward) PGF geostrophically strengthened the shoreward (seaward) currents over the middle (inner) shelf. As shown by the difference (Figure 3(b)), the largest westward PGF along the 50-m isobath west of 116°E became smaller in the assimilation run, and this led to a reduction in shoreward transport. Furthermore, an obvious decrease in westward PGF was found near 115°E. Along the 30-m isobath, two moderate decreases in the eastward PGF were found near 115°E and 116°E, respectively. The decreased westward (eastward) PGF reduced the shoreward (seaward) volume transport over the shelf head—a finding that further indicated the weakening of the cross-shelf upwelling circulation after SST assimilation.

4. Improvement of the biological processes

Based on the results presented in Section 3, the adjusted physical variables had reasonable responses to the SST assimilation. All processes showed that the intensified upwelling was weakened due to the assimilation of the warmer observational SST. Coastal upwelling can modulate the biological productivity of coastal waters markedly by transporting deep water with its high concentration of nutrients to the euphotic zone (Gan et al. 2010). Therefore, it is of interest to further examine how the assimilation process affected the biological system through the coupled model.

The assimilation experiment suggested that the surface phytoplankton (chlorophyll; not shown) concentration increased in the upwelling region shoreward of the 30-m isobath (Figure 4(a)), due to the higher water temperature, which was the critical factor for phytoplankton productivity. However, because the weakened upwelling current caused a lack of nutrient-rich deep water in the surface layer, especially seaward of the 30-m isobath, the phytoplankton (chlorophyll) concentration decreased in this region. The change in NO₃ concentration was not obvious and exhibited almost the same pattern as the

5. Conclusion

A weakly coupled data assimilation system was established in a coupled physical–biological model for the NSCS. The reasonable responses found for both the assimilated SST and the unassimilated variables indicated that this weakly data assimilation system performed well.

At depths above ~18 m, temperatures were increased in the coastal upwelled waters due to the assimilation of a higher SST into the coupled model and a decrease in the transport of cold deep water to the upper layer. Salinity decreased where the warmer water occurred. Both the alongshore and offshore currents were reduced, illustrating a weakening of the upwelling circulation. This can be further demonstrated by the decreased cross-isobath volume transport that was normal to the 50-m isobath and the alongshore westward PGF along the 50-m isobath over the shelf head. All of these process responses of the physical variables acted in a coordinated way.

The biological response to the SST assimilation was largely affected by that of the physical variables through the coupled model. In the assimilation run, phytoplankton (chlorophyll) productivity was increased in the warmer waters. Due to the decreased shoreward current, the nutrient concentration decreased along the upwelling current. The assimilation of the SST adjusted the physical variables directly and then affected the ecosystem variables through the coupled model.

This study was a preliminary examination of the weakly coupled data assimilation system based on a process-oriented approach. The experiments had their limitations (e.g., in terms of the biological variables, which require improvement), and thus further effort is required to improve the assimilation system. However, the assimilation of physical observations into such a coupled model opens the door to real case studies in the future, and the assimilation of biological observations.
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