



1 **A simple predictive model for the eddy propagation**
2 **trajectory in the South China Sea**

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19 **Abstract** A novel predictive model is built for eddy propagation trajectory using the
20 multiple linear regression method. This simple model has related various oceanic
21 parameters to eddy propagation position changes in the South China Sea (SCS). These
22 oceanic parameters mainly represent the effects of planetary β and mean flow
23 advection on the eddy propagation. The performance of the proposed model is
24 examined in the SCS based on twenty years of satellite altimeter data, and
25 demonstrates its significant forecast skills over a 4-week forecast window comparing
26 to the traditional persistence method. It is also found that the model forecast accuracy
27 is sensitive to eddy polarity and forecast season.

28



29 **1. Introduction**

30 Mesoscale eddies are coherent rotating structures that are ubiquitous over most of the
31 world's oceans (Chelton et al., 2007). They play an important role in the transport of
32 momentum, heat, mass and chemical and biological tracers, thereby become critical
33 for issues such as general circulation, water mass distribution, ocean biology and
34 climate change (Wang et al., 2012; Dong et al., 2014; Zhang et al., 2014; Ma et al.,
35 2016; Li et al., 2017). Therefore, forecasting the eddy propagation positions
36 accurately is not only important scientifically but also important practically for
37 problems such as ocean observing systems designing, fishing planning, and
38 underwater acoustic detecting.

39
40 Traditionally, ocean dynamical models were used as the tool of predicting the
41 evolution of ocean eddies (Robinson et al., 1984). To make a useful forecast,
42 accurately updated boundary data, satellite and in situ observation data for
43 assimilation must be available, and a fair degree of computer power is needed
44 (Rienecker et al., 1987; Oey et al., 2005). These restrictions preclude the all-pervading
45 operational use of dynamical models when these initial data and computer power are
46 not feasible due to some reasons.

47
48 In this paper, we used a simple statistical method to predict the eddy positions 1-4
49 weeks in advance using only the past positions of the eddy and its surrounding fields.
50 Our “test block” of ocean is the South China Sea (SCS). It is a semi-enclosed sea
51 under the dramatic influence of the East Asian Monsoon and Kuroshio intrusion (Liu
52 and Xie, 1999; Shaw, 1991). Due to the variable external forcing and complex
53 topography, mesoscale eddies show obvious geographic distributions and various
54 characteristics (Wang et al., 2003; Xiu et al., 2010), but the common character is the
55 overall westward tendency of eddy trajectories no matter of the eddy polarity (Fig. 1).
56 We will first analyze the dynamics of the common westward movement of eddies in
57 the SCS, then develop a simple predictive model of eddy trajectories, and finally



58 discuss the impact of eddy polarity and season on the model forecast accuracy.

59 **2. Data and Methods**

60 **2.1 Data**

61 The sea level anomalies (SLA) are from the Archiving, Validation and Interpretation
62 of Satellite Oceanographic data (AVISO, <ftp://ftp.aviso.oceanobs.com/>) (Ducet et al.,
63 2000). The product merges the measurements of TOPEX/Poseidon, European Remote
64 Sensing Satellite (ERS-1/2), Geosat Follow-on, Jason-1/2, and Envisat, and spans the
65 period from October 14, 1992 to August 7, 2013. Its temporal resolution is weekly,
66 and its spatial resolution is 0.25° latitude by 0.25° longitude. To estimate the
67 large-scale geostrophic currents, we use the absolute dynamic topography (ADT),
68 which consists of the SLAs and a mean dynamic topography (MDT). The method for
69 calculating the MDT was introduced by Rio and Hernandez (2004), and the data is
70 also distributed by AVISO.

71

72 The monthly climatology of observed ocean temperature and salinity from U.S. Navy
73 Generalized Digital Environment Model (GDEM-Version 3.0) is used to calculate the
74 phase speed of nondispersive baroclinic Rossby waves in the SCS. It has a horizontal
75 resolution of 0.25° latitude by 0.25° longitude, and 78 standard depths from 0 to 6600
76 m with the vertical resolution varying from 2 m at the surface to 200 m below 1600 m
77 (Canes, 2009).

78

79 The SCS eddy trajectory data is derived from the 3rd release of the global eddy dataset
80 (<http://cioss.coas.oregonstate.edu/eddies/>). The eddy positions within their trajectories
81 are recorded at 7-day time intervals. A detailed description of the eddy trajectory
82 dataset can be found in Chelton et al. (2011). To forecast the eddy trajectory 1-4
83 weeks in advance using the last position of the eddy, only eddies with a lifetime of 5
84 weeks or longer are retained in this study.



85 2.2 Maximum Cross-Correlation Method

86 The maximum cross-correlation (MCC) method is a space-time lagged technique,
87 which can estimate the surface motions from time-sequential remote sensing images.
88 It has been successfully used to track clouds from geosynchronous satellite data
89 (Leese et al., 1971), to compute sea-ice motion (Ninnis et al., 1986) and advective
90 surface velocities (Emery et al., 1986) from sequential infrared satellite images, and to
91 determine the propagation velocities of ocean eddies from satellite altimeter data (Fu,
92 2006; Zhuang et al., 2010).

93

94 The MCC method mainly consists of two procedures (Fu, 2009): first, the
95 cross-correlations of the SLA time series (h) with others within a certain range box
96 are computed for some time lags (ΔT) in multiples of 7 days (time resolution of SLA
97 data) at each grid node location (x, y) as:

$$98 \quad C_{x,y}(\Delta x, \Delta y, \Delta T) = \overline{h(x, y, t)h(x + \Delta x, y + \Delta y, t + \Delta T)} \quad (1)$$

99 where Δx and Δy are the spatial lags and the over bar means time averaging.
100 Second, the position of the maximum correlation at each time lag (ΔT) is identified
101 and a speed can be derived from the time lag and the distance of this position from the
102 origin. Then an average speed vector (u, v) weighted by the correlation coefficients is
103 calculated from the estimates at various time lags as:

$$104 \quad (u, v) = \frac{\sum_i (\Delta x_i / \Delta T_i, \Delta y_i / \Delta T_i) C_i}{\sum_i C_i} \quad (2)$$

105 where C_i is the maximum correlation at ΔT_i , and $\Delta x_i, \Delta y_i$ are the distances
106 between the position of maximum correlation and the origin. The average velocities
107 are then assigned to the eddy movement velocities at the given grid point. To focus on
108 the mesoscale in the SCS, the time lags are limited to less than 42 days, and the
109 dimension of the search box is generally less than 300 km. To reduce incidental
110 spurious MCC vectors, the maximum speed is set to 30 cm/s, since the phase speeds
111 of baroclinic Rossby waves in the SCS are mostly lower than this threshold (Cai et al.,
112 2008).



113 3. Results

114 3.1 Dynamics of Eddy Propagation in the SCS

115 Instead of a Lagrangian description of the movement of individual eddies as reported
116 in the previous studies (e.g., Wang et al., 2003; Chen et al., 2011), the space-time
117 lagged MCC method provides an Eulerian description of the eddy propagation speed.
118 As shown in Fig. 2a and 2d, the MCC method has mapped the propagation speeds of
119 the eddies in the SCS for the winter and summer season, respectively. The
120 propagation of the eddies is generally westward in the ocean interior and southward in
121 the western boundary with the typical speed of 4-10 cm/s. The propagation direction
122 of the eddies generated southwest of Taiwan is southwestward along the 200-2000 m
123 isobaths, indicating the steering effects of the ocean's bathymetry. There are two
124 distinct differences between the winter season and the summer season: one is that the
125 eddy propagation speed in winter is relatively larger than that in summer; and the
126 other is that the influence of the western boundary current can be clearly seen near
127 16°N-18°N along the Vietnam coast in winter, creating an organized band of
128 southward eddy propagation pattern, while this cannot be found in summer. The
129 different patterns of the eddy propagation speed in winter and summer have revealed
130 several details of the mean flow in the SCS: the large-scale circulation under the
131 influence of northeasterly winter monsoon is stronger than that in the southwesterly
132 summer monsoon, and the robust western boundary current in winter becomes
133 relatively weak and unorganized in summer.

134

135 Eddies also have their own westward drift under the planetary β effect in the
136 absence of any mean flow (Nof, 1981, Cushman-Roisin, 1994). Their propagation
137 speed is approximately the phase speed of the first baroclinic Rossby waves with
138 preferences for small poleward and equatorward deflection of cyclonic and
139 anticyclonic eddies in the global ocean, respectively (Chelton et al., 2007).
140 Theoretically, the phase speed of the first baroclinic Rossby wave is $C_{R1} = -\beta R_1$,



141 where the first baroclinic Rossby radius of deformation R_1 is estimated using the
142 climatological GDEM temperature and salinity data. Figure 2b (2e) shows the
143 theoretical phase speed of nondispersive baroclinic Rossby waves calculated from
144 GDEM winter (summer) climatological temperature and salinity data. The direction
145 of the phase speed is due west and the magnitude increases from about 2 cm/s in the
146 north latitude to 12 cm/s in the south latitude.

147

148 The differences between the satellite observed propagation speed (Fig. 2a and 2d) and
149 the propagation speed induced by the β effect (Fig. 2b and 2e) in winter and
150 summer are shown in Fig. 2c and 2f, respectively, which may represent the
151 propagation speed caused by the advection of mean flow. To further illustrate the
152 advection effect of mean flow, the winter (summer) mean dynamic topography is
153 superimposed on the propagation speed caused by the mean flow. As can be seen,
154 there is a good spatial correlation (0.61 in the zonal direction and 0.52 in the
155 meridional direction, both of which are significant at the 95% confidence level)
156 between the cyclonic eddy propagation speed advected by the mean flow and the large
157 scale surface cyclonic circulation in winter, both of which are centered northwest of
158 the Luzon Island (Fig. 2c). Due to the weak cyclonic gyre in the northern SCS, the
159 spatial correspondence in summer is not as obvious as that in winter (Fig. 2f). Since
160 the propagation speed induced by the β effect is westward, this tendency is
161 reinforced by the mean flow in the north, but compensated by the mean flow in the
162 south. Because the mean flow in the south is not so strong, it is not able to reverse
163 eddy propagation from its westward motion induced by the β effect as in the
164 Antarctic Circumpolar Current region (Klocker and Marshall, 2014) no matter in
165 winter or summer.

166

167 To explore other possible causes of eddy propagation, Fig. 3a shows the annual mean
168 eddy propagation speed. The most striking pattern is that the eddy propagation speed



169 is accelerated markedly on the northern continental shelf of the SCS (also can be seen
170 in Fig. 2a and 2d), corresponding well to the region of negative maximum meridional
171 topographic $\beta_r = \frac{f}{H} \frac{dH}{dy}$, where H is the water depth. Their correlation is -0.40,
172 which is significant at the 95% confidence level. This relatively good correspondence
173 suggests that besides the planetary β effect and advection of mean flow, the
174 topographic β effect also contributes to the eddy propagation in some regions where
175 the bathymetry gradient cannot be neglected.

176 **3.2 Model Development**

177 To develop a simple statistical predictive model for relating various oceanic
178 parameters to eddy propagation position changes, the multiple linear regression is
179 used for developing such statistical forecast models. This method has been
180 successfully used in the forecast of tropical cyclone (TC) tracks (Neumann and
181 Randrianarison, 1976; Aberson and Sampson, 2003), hurricane intensity (Demaria and
182 Kaplan, 1994) and ENSO (Knaff and Landsea, 1997). In this study, the predictands
183 (dependent variables) are the zonal and meridional displacements at each forecast
184 time from the initial position. In choosing the potential predictors (independent
185 variables), two factors are considered. First, the candidates should have a physical
186 link (direct or indirect) with the eddy propagation. Second, the candidates must be
187 available and accessible in advance. Based on these two considerations, eight
188 potential predictors that are associated with eddy propagation are chosen (Table 1).
189 All of these are derived along the eddy trajectories.

190

191 These eight predictors can be divided into two categories: 1) those related to
192 climatology and persistence, i.e., “static predictors”, and 2) those related to the
193 changing environmental conditions, i.e., “synoptic predictors”. The static predictors
194 consist of the first six predictors, while the last two are the synoptic predictors. Since
195 the initial eddy position (LON, LAT) and the eddy motion past 1-week (U_PAST,



196 V_PAST) represent the initial conditions of the eddy, these persistence factors are
197 crucial for the next position of the eddy. The climatological eddy zonal and
198 meridional motions (U_CLIM V_CLIM) derived from the MCC method are chosen to
199 take into account the effects of β and the mean flow advection, as discussed in
200 Section 3.1. In reality, the large-scale circulation evolves during the forecast period,
201 but this effect is not taken into account in the climatology and persistence factors. To
202 help account for the time variation of the mean flow advection, the current zonal and
203 meridional absolute geostrophic flows (U_ADT, V_ADT) derived from the satellite
204 data are evaluated at the beginning of the forecast time along the eddy trajectory. The
205 relative contribution of each predictor on each forecast period is illustrated by the
206 normalized regression coefficient (Table 2). To generate the normalized coefficients,
207 both the predictors and the predictands are normalized before they are incorporated
208 into the regression model. The larger the normalized regression coefficient, the greater
209 its contribution to the individual forecast equation. Persistence factors (U_PAST,
210 V_PAST) are initially the most important predictors, while after 2 weeks the most
211 important predictors are the climatology factors (U_CLIM, V_CLIM). The synoptic
212 predictors (U_ADT, V_ADT) contribute less to the forecast equations comparing with
213 persistence and climatology. The underlying reason may be that the week to week
214 variations are too large so the representation of the initial U_ADT and V_ADT to the
215 actual velocities in the 4-week window is not as good as the U_CLIM and V_CLIM.

216

217 There are a total of 8 regression equations, i.e., both the meridional and zonal
218 directions for the weeks of 1-4. We can separate the data into two sets: one for
219 regressing and the other for forecasting. At week-1, we used 1981 (76%) eddy
220 trajectory segments (the distances between the eddy positions at 7-day time interval)
221 of 283 eddy trajectories during 1992-2008 for regressing, and 623 (24%) eddy
222 trajectory segments of 81 eddy trajectories during 2009-2013 for forecasting. The
223 other forecast experiments for 2, 3, and 4 weeks maintain the same periods for
224 regressing and forecasting. To evaluate the overall forecast ability of the model, the



225 mean forecast error is defined as the averaged distance (D) between the predicted
226 eddy positions and the satellite observed eddy positions following great circle
227 distance (Ali et al., 2007):

$$228 \quad D = R \cdot \arccos[\sin Y_o \sin Y_F + \cos Y_o \cos Y_F \cos(X_o - X_F)]$$

229 where R is the earth radius, X_o (X_F) and Y_o (Y_F) represent the observed (forecast)
230 longitude and latitude in degrees, respectively.

231

232 Table 3 lists the number of sampling cases, root-mean-square error (RMSE) and
233 correlation coefficient between the predicted and actual longitudes (latitudes), mean
234 distance errors of our model and persistence method (no change of propagation speed
235 from the initial state, Fig. 4a) over a 4-week horizon. It shows that the developed
236 model beats the persistence method and indicates our model has some forecast skill:
237 the RMSE between the predicted and the actual longitudes (latitudes) throughout the
238 4-week horizon is 0.33-0.89 (0.30-0.73) degrees with the correlation
239 coefficients >0.93 (>0.95). As an example, Fig. 5 compares the 1-2 weeks forecast
240 performances of our model (blue) and the persistence method (green) with the
241 observation (red). Generally, the eddy trajectory predicted 1-2 weeks in advance by
242 our model coincides well with the observed trajectory with an overall average error of
243 27.6 km (week-1) and 42.5 km (week-2), and even the convoluted pattern can be
244 reproduced properly (Fig. 5 (right)) though the mean error is slightly larger than the
245 smooth case. In contrast, although the persistence forecast trajectory at week-1 is
246 relatively consistent with the observation (Fig. 5a and 5b), the persistence method
247 cannot forecast the eddy trajectories properly when the forecast horizon increases (Fig.
248 5c and 5d). This shows the superiority of our forecast model over the persistence
249 method.

250 **3.3 Sensitive Performance of Different Eddy Polarity and Season**

251 Previous studies have shown that anticyclonic eddies and cyclonic eddies in the SCS



252 have different dynamic characteristics, such as generation sites, rotation speeds and
253 propagation trajectories, and the seasonal variability of these eddies is robust (Wang et
254 al., 2006; Wang et al., 2008; Li et al., 2011). Two natural questions arise: 1) is there
255 any difference on the model forecast ability between anticyclonic eddies (Fig. 1a) and
256 cyclonic eddies (Fig. 1b)? 2) If so, is there any difference on the forecast ability for
257 one type of eddies in winter (Fig. 6a and 7a) and summer (Fig. 6b and 7b)? This
258 section will explore the different model performances on two types of eddies and
259 during different seasons in the SCS.

260

261 The period considered for regressing and predicting the anticyclonic eddy and
262 cyclonic eddy positions is the same as that used in developing the predictive model in
263 Section 3.2. The mean forecast errors of anticyclonic (cyclonic) eddies from week-1
264 to week-4 are 36.9 km (41.1 km), 62.6 km (68.1 km), 81.0 km (88.5 km), and 102.0
265 km (108.2 km), respectively (Fig. 1c). These results show that the predicted trajectory
266 errors of anticyclonic eddies are less than those of cyclonic eddies in all forecast
267 horizon, and the maximum error difference can reach 7.5 km at week-3. To investigate
268 the underlying reasons of different model performances for anticyclonic eddies and
269 cyclonic eddies, we use the persistence error ($CC' = \sqrt{AB^2 + BC^2 - 2AB \cdot BC \cdot \cos \theta}$ in
270 Fig. 4a) at week-1 as an index to measure the difficulty of trajectory forecast. The
271 underlying reason in physics is that CC' , which includes the effects of winding angle
272 (θ , measuring the trajectory curvature) and the eddy propagation distances in the
273 former and latter periods (AB and BC, measuring the eddy propagation speed), is an
274 integral characteristic of eddy trajectory. The correlation between this integrated index
275 and eddy trajectory forecast error is relatively high with $R=0.62$, which is significant
276 at the 95% confidence level and shows its ability of measuring the inherent difficulty
277 of trajectory forecast: the larger the index, the more difficult the trajectory forecast,
278 thus the larger the forecast error. Because the indices (mean persistence errors) of all
279 the anticyclonic and cyclonic eddy trajectories in the SCS are 46.6 km and 53.0 km,
280 respectively, it is not difficult to understand why the mean forecast error of



281 anticyclonic eddy trajectories is smaller than that of cyclonic eddy trajectories in the
282 SCS. The index difference between anticyclonic and cyclonic eddy trajectories is
283 caused by these different trajectory patterns (Fig. 1a and 1b), which could be due to
284 the opposing meridional drifts of anticyclonic and cyclonic eddies expected from the
285 combination of β effect and self-advection (Morrow et al., 2004).

286

287 Figure 6c (Fig. 7c) shows the mean forecast errors of anticyclonic (cyclonic) eddy
288 trajectories in winter and summer over a 4-week horizon. Because the mean
289 persistence error (42.0 km) of anticyclonic eddy trajectories in winter is smaller than
290 that (51.9 km) in summer, as expected, the mean forecast error of anticyclonic eddy
291 trajectories in winter is smaller than that in summer for all cases. This is also the case
292 for the cyclonic eddy: since the mean persistence error (54.6 km) of cyclonic eddy
293 trajectories in winter is relatively larger than that (52.8 km) in summer, the mean
294 forecast error of cyclonic eddy trajectories in winter is larger than that in summer. The
295 index difference of one type of eddy trajectories between winter and summer is also
296 caused by the different trajectory patterns. Why do the anticyclonic and cyclonic
297 eddies follow different trajectories in winter (Fig. 6a and 7a) and summer (Fig. 6b and
298 7b)? One possible dynamical reason is the different interactions between the eddies
299 and seasonal mean flows. Other underlying factors such as eddy generation
300 mechanisms and eddy-topography interactions in different seasons may also
301 contribute. This is beyond the scope of this study and needs further investigation
302 using numerical models.

303 **4. Summary and Discussion**

304 In this study we have investigated the underlying dynamics of the eddy propagation in
305 the SCS and found the propagation of SCS eddies is mainly driven by the
306 combination of the planetary β effect and mean flow. In addition, the topographic
307 β effect also has some contribution to the eddy propagation where the bathymetry
308 gradient cannot be neglected, like the steep continental shelf in the northern SCS (Fig.



309 1a).

310

311 Based on the dynamical analysis, a simple statistical predictive model for relating
312 various oceanic parameters to eddy propagation position changes is developed using
313 the multiple linear regression method. This model is made up of two predictands
314 (zonal and meridional displacements) and eight predictors (six static predictors, two
315 synoptic predictors). The six static predictors are associated with the initial position,
316 the zonal and meridional motions past 1-week, and the climatological eddy zonal and
317 meridional motion. The other two synoptic predictors account for the time variation of
318 the mean flow advection. Results showed that this simple model has significant
319 forecast skills over a 4-week forecast horizon comparing the traditional persistence
320 method. Moreover, the model performance is sensitive to eddy type and forecast
321 season: 1) the predicted trajectory errors of anticyclonic eddies are smaller than those
322 of cyclonic eddies; 2) the predicted trajectory errors of anticyclonic eddies in winter
323 are smaller than those in summer; while the contrary is the case for the cyclonic eddy.
324 The predictive model performance strongly depends on the inherent difficulty of
325 trajectory forecast.

326

327 Although the performance of the proposed predictive model is encouraging, it could
328 be refined further. Further improvement may be possible by including the effect of
329 eddy-eddy interactions on the eddy propagation, which is supposed to help induce the
330 eddy trajectory curve or loop (Early et al., 2011). Another possible improvement is to
331 replace the multiple regression method with machine learning (ML) techniques.
332 Ashkezari et al. (2016) have shown that the ML methods particularly stand out in
333 analyzing complex systems yet not fully understood, like estimating the eddy lifetime.
334 These enhancements are topics warranting future research and development.

335

336



337 *Data availability.* The SLA and MDT data can be downloaded from AVISO
338 (<ftp://ftp.aviso.oceanobs.com/>), and the SCS eddy trajectory data can be derived from
339 the 3rd release global eddy dataset (<http://cioss.coas.oregonstate.edu/eddies/>).

340

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441

442 **Figure and Table Captions**

443 **Figure 1.** The trajectories of (a) anticyclonic and (b) cyclonic eddies with lifetime ≥ 5
444 weeks in the South China Sea (SCS). The solid circle represents the ending position
445 of each trajectory. In Fig. 1a, TI: Taiwan Island, LI: Luzon Islands, VN: Vietnam. The
446 two isobaths are for 200 m and 2000 m, respectively. (c) Comparison of the mean
447 forecast errors between anticyclonic eddies (red) and cyclonic eddies (blue) over a
448 4-week window.

449

450 **Figure 2.** Winter climatology of (a) eddy propagation speed directions (vectors) and
451 magnitudes (color, cm/s), (b) The phase speed directions (vectors) and magnitudes
452 (color, cm/s) of the first baroclinic Rossby wave. (c) The speed difference (vectors)
453 between (a) and (b) superimposed on the winter mean absolute dynamic topography
454 (color, cm). (d), (e) and (f) are the same as (a), (b) and (c), respectively, but for the
455 summer.

456

457 **Figure 3.** (a) Annual mean of eddy propagation speed directions (vectors) and
458 magnitudes (color, cm/s). (b) Meridional distribution of the topographic β effect
459 (color shading).

460

461 **Figure 4.** (a) Schematic of persistence method. A, B, and C are three observed eddy
462 positions on the trajectory every 1 week interval. C' is the predictive eddy position 1
463 week in advance by persistence method, that is $BC' = AB$. Thus CC' is the persistence
464 error at week-1. (b) Scatterplot of persistence error versus forecast error of our model
465 at week-1 with best fit linear regression.

466

467 **Figure 5.** A comparison of the satellite observed trajectory (red), the predicted
468 trajectory by our model (blue) and persistence trajectory (green) at (a) week-1, (c)
469 week-2. (b), (d) are the same as (a) and (c), respectively, but for a recurved trajectory.
470 The biweekly eddy positions on each trajectory are shown by the solid circles.



471 **Figure 6.** The trajectories of anticyclonic eddies in (a) winter and (b) summer with
472 lifetime ≥ 5 weeks in the South China Sea (SCS). The solid circle represents the
473 ending position of each trajectory. (c) Comparison of their mean forecast errors over a
474 4-week window.

475

476 **Figure 7.** The same as Fig. 6, but for the cyclonic eddies.

477

478

479 **Table 1.** The Eight Predictors Used in the Predictive Model.

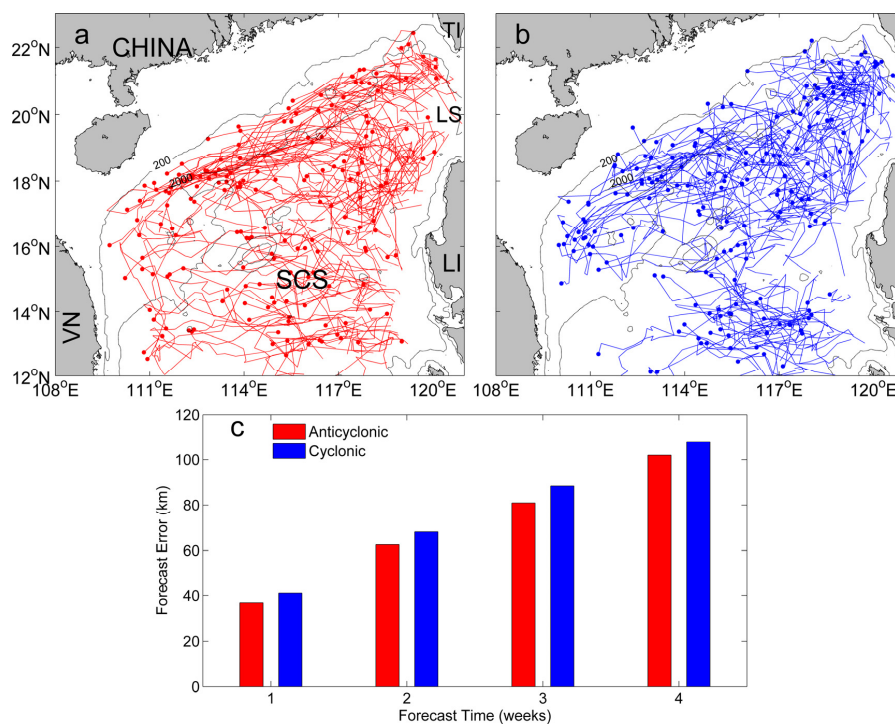
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481 **Table 2.** Normalized Regression Coefficients for Use with the Eddy Zonal
482 (Meridional) Motion Prediction Equation.

483

484 **Table 3.** Statistics of our Predictive Model for Different Forecast Time of Eddy
485 Propagation Positions in Terms of Longitudes (Latitudes).

486

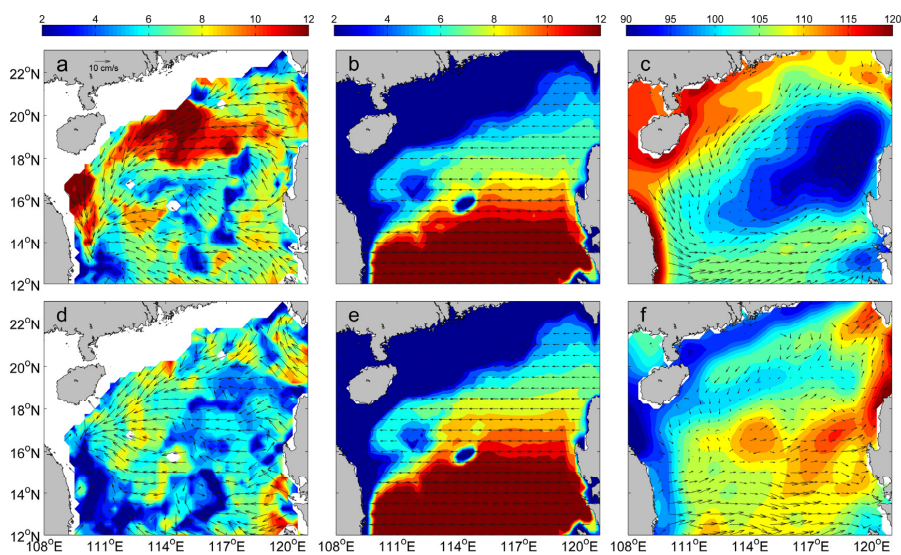


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492 two isobaths are for 200 m and 2000 m, respectively. (c) Comparison of the mean
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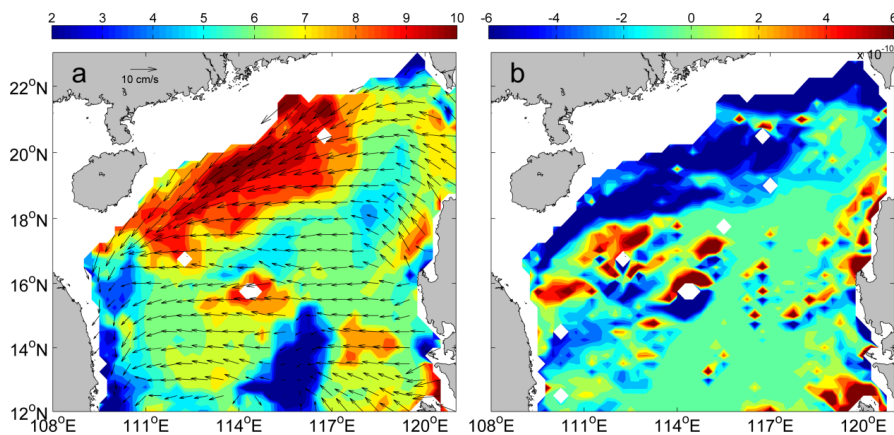


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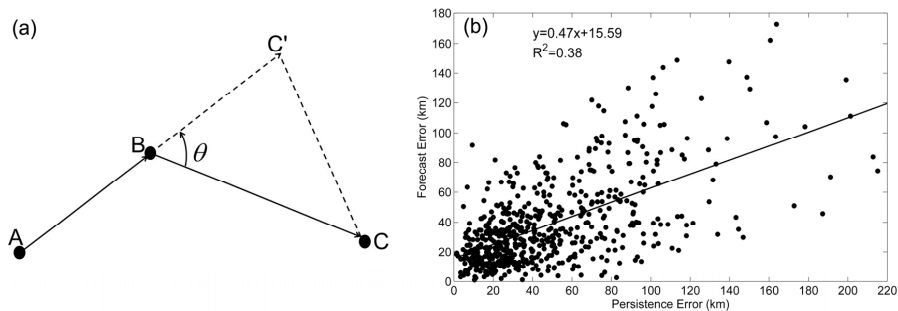


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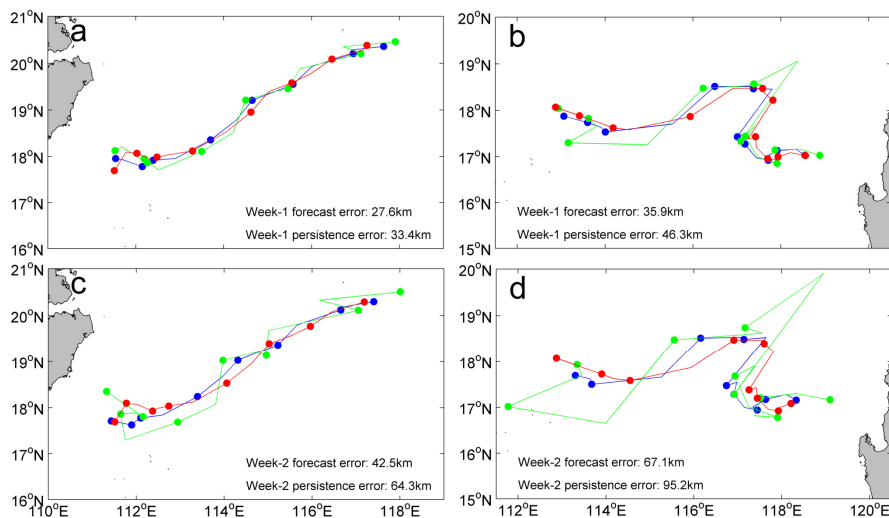


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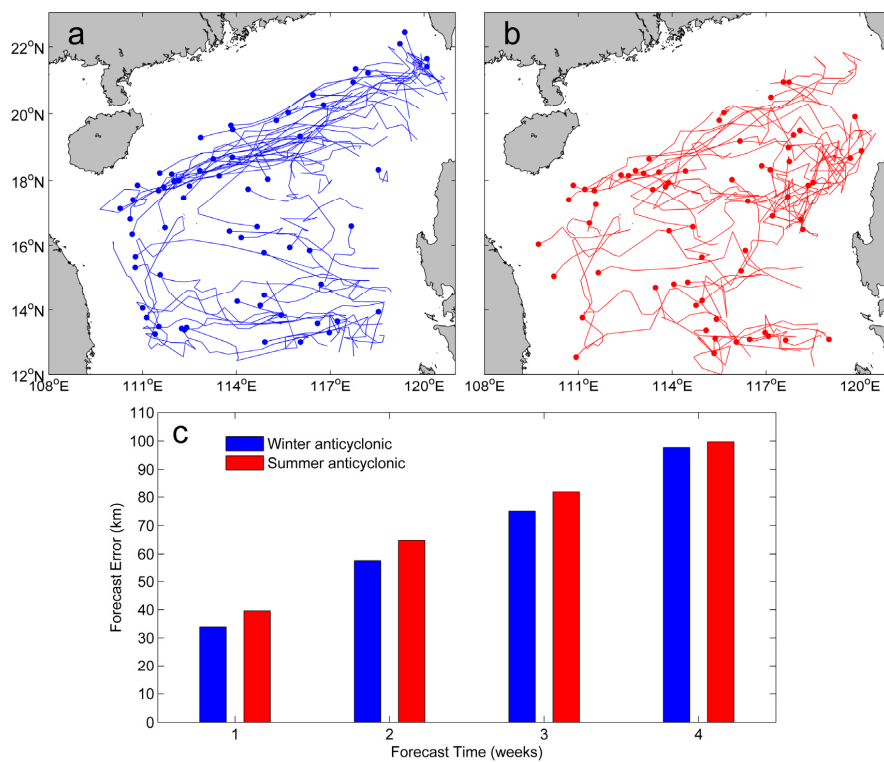


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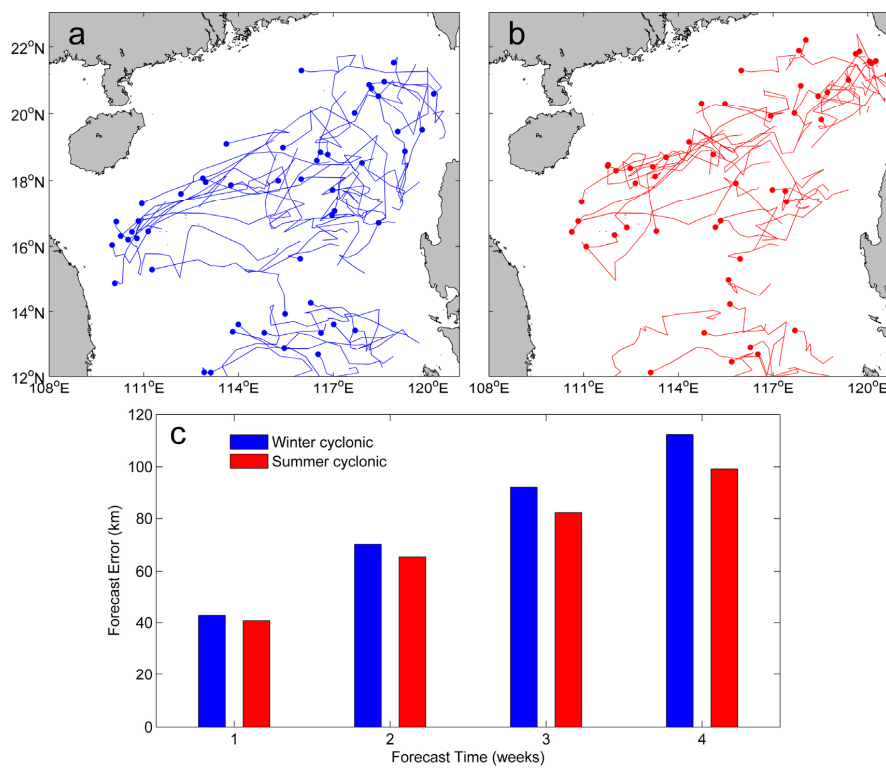


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532



533

534

535 **Figure 7.** The same as Fig. 6, but for the cyclonic eddies.

536



537 **Table 1.** The Eight Predictors Used in the Predictive Model

538

NO	Predictor	Description
1	LON	Initial longitude
2	LAT	Initial latitude
3	U_PAST	Eddy zonal motion past 1-week
4	V_PAST	Eddy meridional motion past 1-week
5	U_CLIM	Climatological eddy zonal motion from MCC
6	V_CLIM	Climatological eddy meridional motion from MCC
7	U_ADT	Initial zonal absolute geostrophic flow
8	V_ADT	Initial meridional absolute geostrophic flow

539



540 **Table 2.** Normalized Regression Coefficients for Use with the Eddy Zonal (Meridional) Motion

541 Prediction Equation

542

NO	Predictor	1 week	2 weeks	3 weeks	4 weeks
1	LON	-0.10 (0.03)	-0.14 (0.04)	-0.18 (0.05)	-0.24 (0.06)
2	LAT	0.10 (0.02)	0.13 (0.01)	0.16 (0.00)	0.18 (-0.03)
3	U_PAST	0.26 (0.00)	0.21 (0.03)	0.19 (0.07)	0.18 (0.09)
4	V_PAST	-0.02 (0.19)	-0.01 (0.10)	0.01 (0.08)	0.00 (0.08)
5	U_CLIM	0.14 (0.09)	0.19 (0.13)	0.23 (0.16)	0.26 (0.16)
6	V_CLIM	0.05 (0.17)	0.07 (0.23)	0.09 (0.26)	0.16 (0.27)
7	U_ADT	-0.05 (0.02)	-0.07 (0.02)	-0.07 (0.02)	-0.07 (0.03)
8	V_ADT	-0.03 (-0.07)	-0.01 (-0.08)	0.02 (-0.09)	0.04 (-0.09)



543 **Table 3.** Statistics of our Predictive Model for Different Forecast Time of Eddy Propagation Positions in Terms of Longitudes (Latitudes)
544

Forecast weeks	Total (Predicted) Number of Points	RMSE, degrees	Correlation Coefficient	Mean Distance Error, km	Mean Distance Error From Persistence, km
1	2604 (623)	0.33 (0.30)	0.99 (0.99)	38.1	47.6
2	2310(549)	0.55 (0.47)	0.97 (0.98)	64.8	95.2
3	2016 (475)	0.72 (0.61)	0.95 (0.97)	86.6	135.0
4	1722 (401)	0.89 (0.73)	0.93 (0.95)	106.5	180.5

545