Responses to Referee # 3:

Accurately forecasting eddy propagation is a major challenge, requiring one not only to consider the classes of response to atmospheric forcing, but to also consider the relative impact of atmospheric forcing, updated boundary data and different ocean data types. The article of "A simple predictive model for the eddy propagation trajectory in the South China Sea" tries to build a predictive model using multiple linear regression to predict the positions of long-lifetime eddy tracks in the SCS.

Response: We greatly appreciate the reviewer for the time spending on providing the valuable comments. We made every effort to clarify our results and improve our manuscript according to the comments. Next our response to each comment will be labeled in blue.

Here, I have some concerns about the reliability and applicability of the model:

1) As presented here the MCC method, although more objective, still includes the assumption that displacements are translational. It should be acknowledged that Kamachi (1989) modified the MCC to include rotational effects. Deformational effects should also be discussed. The dependence of the predictive trajectory on the parameters used also needs to be explained clearly.

Response: Thanks for the comment. The MCC method used in this study is the same as that of Fu et al. (2006, 2009), which is a little different with that of Emery et al. (1986). In the method of Emery et al., the correlations of the image **in the subwindow** with all the neighboring ones in the whole window at the next time are computed, and the speed and direction of the maximum correlations can be estimated. While in the method of Fu et al., the correlations of the SLA **at a given location** with all the neighboring SLA at various time lags are computed, and the speed and direction of the maximum correlations can be estimated. The reason of their difference may be due to the low time-space resolution of SLA comparing with other infrared satellite images, such as AVHRR.

In the MCC method of Fu et al., the size of the time-space window for computing the correlations were determined by the time and space scales of interests. To focus on the global mesoscale eddy, the time lags were limited to less than 70 days and the dimension of the window was less than 400 km. However, the time lags should be limited to less than 42 days in the SCS, since many correlation coefficients are below the 95% confidence level at larger time lags (Zhuang et al., 2010). Besides, Chen et al. (2011) found that eddies propagate with 5.0-9.0 cm/s in the northern SCS. Thus the search radius can be generally limited as 300 km (9.0 cm/s*42 days≈300 km) to reduce incidence of spurious MCC vectors. We add several sentences in the introduction of MCC method to clarity the parameters and their setting.

2) As the core novelty in this study, the regression equations need to be clearly presented. This is important for other users or readers to independently validate or to further improve the method in real conditions.

Response: Thanks for the suggestion. The predicted zonal (meridional) displacement *DX* (*DY*) can be estimated using a multiple linear regression approach:

$$DX_j = \sum_{i=1}^{8} a_{i,j} P_{i,} \quad j = 1, 4 \tag{1}$$

$$DY_j = \sum_{i=1}^{8} b_{i,j} P_{i,} \quad j = 1, 4 \tag{2}$$

where the subscript *j* refers to the forecast interval (1-4 weeks), the subscript *i* refers to the serial number of eight normalized predictors (*P*), *a* and *b* donate normalized regression coefficients of predictors onto *DX* and *DY*, respectively. We add Section 2.3 to describe the multiple linear regression method and the regression equations with the coefficients listed in Table 3.

3) In discussing the eight predictors (Lines 211-13): "The synoptic predictors contribute less to the forecast equations comparing with persistence and climatology". Does it mean that the forecast mostly depends on the persistent inputs and climatology? And then, are the U_clim and V_clim derived from the MCC method

and the history trajectories from 1992-2013? Please clarify.

Response: Thanks for the comment. (1) Yes, the forecast mostly depends on the persistence and climatology. We suppose it may be that the week to week variations are too large so the representation of the initial U_ADT and V_ADT to the actual velocities in the 4-week window is not as good as the U_CLIM and V_CLIM. (2) The climatological eddy zonal and meridional motions (U_CLIM V_CLIM) are derived from SLA data (not historical eddy trajectories) from 1992 to 2013 using the space-time lagged MCC method. We add some sentences in the first paragraph of Section 3.2 to clarify it.

4) Another point is the accounting for the Beta effect (Lines:198-200) in the predictors (U_clim, V_clim). The associated figure and illustration verified the importance of the effect, but how to modify the predictors is not clear. Please comment.

Response: Actually, the climatological eddy zonal and meridional motions (U_CLIM V_CLIM) derived from the MCC method consist of the effects of beta and the mean flow advection. We have tried to decompose U_CLIM and V_CLIM into these factors and incorporate them into the regression model, but found no improvement of the forecast skill. We add several sentences in Section 3.2 to explain it.

5) The current predictive model needs full independent validation. Page 4 Line 82- 84: "To forecast the eddy trajectory 1-4 weeks in advance using the last position of the eddy, only eddies with a lifetime of 5 weeks or longer are retained in this study". It clearly shows the eddy tracks in 2009-2013 used for evaluation here have been artificially filtered, and together with the above point 3 I think the model limit is only used for long-life eddy and the current results can be regarded as hindcast rather than prediction. So I suggest the authors consider using the current regression model to validate the new trajectories after 2013.

Response: Thanks for the comment. Given the accuracy of satellite altimeter product and to avoid sporadic eddy events, eddy which lifetime is not shorter than 4 weeks is

considered in the eddy detection and tracking (e.g., Chelton et al., 2011; Chen et al., 2011; Wang et al., 2003). Thus the 3rd release of the global eddy dataset used in this study discarded the eddies with lifetime shorter than 4 weeks by Chelton et al. (2011). To forecast the eddy trajectory 4 weeks in advance using the last position of the eddy, only eddies with a lifetime of 5 weeks or longer are retained. Table R1 lists the 1-3 week forecast results of the original eddy tracks with lifetime not shorter than 4 weeks and the filtered eddy tracks with lifetime not shorter than 5 weeks, which shows the forecast results are comparable and verify our predictive model is stable.

Table R1. Comparison of forecast distance errors (km) between the original eddy tracks with lifetime not shorter than 4 weeks and the filtered eddy tracks with lifetime not shorter than 5 weeks.

Forecast weeks	Original tracks	Filtered tracks
1	38.7	38.1
2	66.9	64.8
3	88.3	86.6

Other specific comments:

1) Before applying the MCC analysis to the images prepared, certain parameters describing the statistical method need to be set, like subwindow size, search window size as well as cross-correlation coefficient. Can you comment on their impacts, and their settings?

In the MCC method of Fu et al., the size of the time-space window for computing the correlations were determined by the time and space scales of interests. To focus on the global mesoscale eddy, the time lags were limited to less than 70 days and the dimension of the window was less than 400 km. However, the time lags should be limited to less than 42 days in the SCS, since many correlation coefficients are below the 95% confidence level at larger time lags (Zhuang et al., 2010). Besides, Chen et al. (2011) found that eddies propagate with 5.0-9.0 cm/s in the northern SCS. Thus the search dimension can be generally limited as 300 km (9.0 cm/s*42 days ≈ 300 km) to

reduce incidence of spurious MCC vectors. We add several sentences in the introduction of MCC method to clarity the parameters and their setting.

2) Here all SLA data and eddy dataset have a time resolution of 7 days. In fact, the new version based on the DT-2014 daily "two-sat merged" sea level anomaly (MSLA) fields (formerly referred to as the REF dataset) posted online by AVISO for the 22-year period January 1993–April 2015. So using the daily dataset could be more interesting, and some new knowledge can be expected.

Response: Thanks for the comment. Since the maximum westward propagation speed is about 20 cm/s in the subtropics (Chelton et al., 2011), the propagation distance in one day is about 17.3 km, which is less than one grid dimension (25 km) of AVISO SLA. This may cause some uncertainties in the forecasting using the daily dataset. Therefore, the weekly SLA data is still used in the eddy forecasting exercises (Oey et al., 2005; Zeng et al., 2015, and Xu et al., 2018).

3) Chen et al. (2011) also find that "Eddy propagation in the western basin to the east of Vietnam is quite random, with no uniform propagate direction". Do you find a southern limit to the trajectory predictive model?

Response: Good suggestion. Eddy propagation in the western basin to the east of Vietnam is quite random, which cause the eddy trajectories irregular or even convoluted. As we can see, the forecast errors in the southern area (Figure R1a) are larger than those of other regions (Figure R1b).
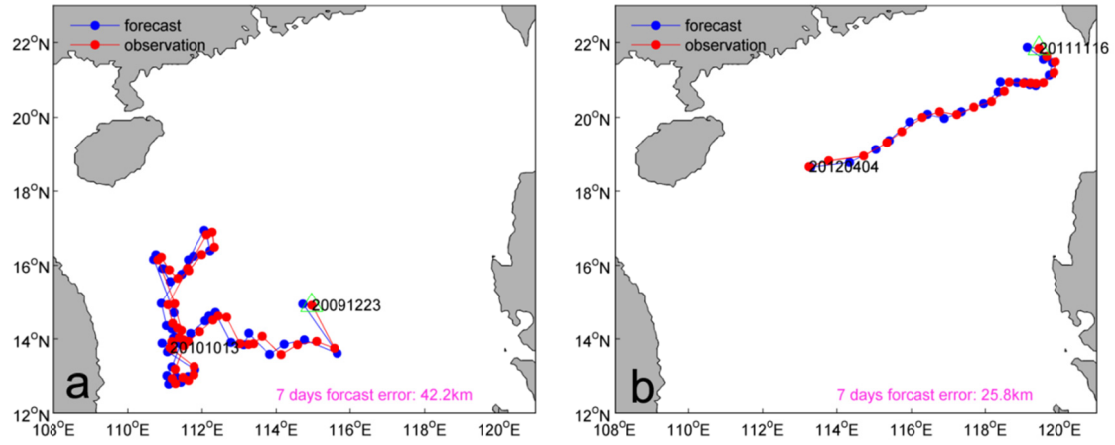
Figure R1. Eddy trajectory 1-week forecast error in (a) the western basin to the east of Vietnam and (b) the northern basin.

4) The right hand panels of Fig. 2 (c, f) showing differences should keep the NaN areas as in (a) and (d).

Response: Corrected.

5) Page 9, Line 217: "there are a total of 8 regression equations"? Could you provide the equations, to clearly distinguish the explanatory variables, response variables, and input regression data sources?

Response: Thanks for the suggestion. The predicted zonal (meridional) displacement *DX* (*DY*) can be estimated using a multiple linear regression approach:

$$DX_j = \sum_{i=1}^{8} a_{i,j} P_{i,} \quad j = 1, 4 \tag{3}$$

$$DY_j = \sum_{i=1}^{8} b_{i,j} P_{i,} \quad j = 1, 4 \tag{4}$$

where the subscript *j* refers to the forecast interval (1-4 weeks), the subscript *i* refers to the serial number of eight normalized predictors (*P*), *a* and *b* donate normalized regression coefficients of predictors onto *DX* and *DY*, respectively. To distinguish the input predictors, the forecasted variables, and the related regression equations clearly, we revise Table 2 and 3, add a new Table 1, and add Section 3.2 to describe these in the revised manuscript.

6) Figure 5 only shows one trajectory. Could you show all trajectories in the SCS during the time periods in question, in order to more thoroughly test the credibility of this method?

Response: Thanks for the suggestion. For the sake of concise layout of the paper, we only selected two cases from all the 74 forecasted results during 2008-2013 to show the comparison. To verify the credibility of this method, the forecast distance errors of all the predicted eddy trajectories over a 4-week window are shown in Figure R2.
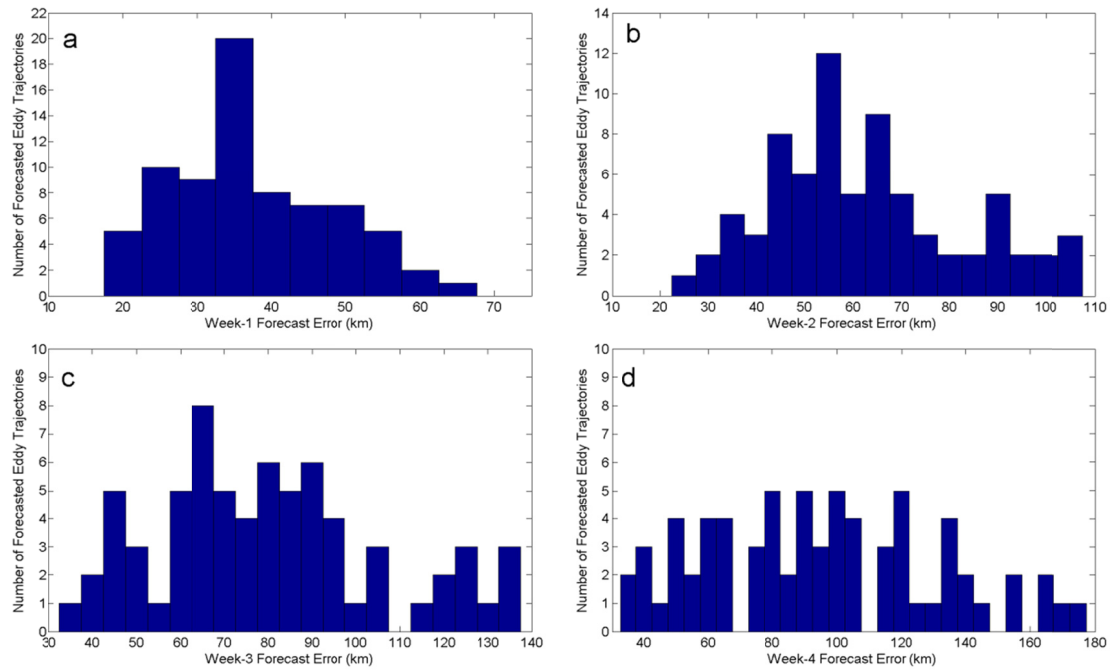
Figure R2. Histogram of the forecast distance errors of all the predicted eddy trajectories at week-1 (a), week-2 (b), week-3 (c) and week-4 (d).

7) The predictive equation should be explicitly presented in the text. Although the effects of planetary b and mean flow advection are highlighted many times, the quantitative effect on the inputs or the predictive equations still are not clear.

Response: Thanks for the suggestion. (1) In the revised manuscript, the predictive regression equations have been presented in two equations of Section 2.3, and their coefficients have been shown in Table 3 in the revised version. (2) Actually, the climatological eddy zonal and meridional motions (U_CLIM V_CLIM) derived from the MCC method consist of the effects of beta and the mean flow advection. We have

decompose U_CLIM and V_CLIM into these factors and incorporate them into the regression model, but found no improvement of the forecast skill. We add several sentences in Section 3.2 to explain it.

8) Page 5, Line 99: Have the cross-correlations been normalized by the variances of the two time series?

Response: Yes, the cross-correlations have been normalized by the variances of the two time series.

9) Page 6, Figure 2 only shows the region north of 12°N. Does it mean this study only investigates the eddy tracks in the northern SCS? If so, relevant statements, and the title, should be qualified as pertaining to the northern SCS.

Response: Yes, this study only investigates the eddy tracks in the northern SCS. We have revised the statements and title using the northern SCS (NSCS).

10) Page 9 Line 198: Are the climatological eddy motions divided into 12 months or only annual mean?

Response: The climatological eddy motions are divided into four seasons (winter: 12-2, spring: 3-5, summer: 6-8, autumn: 9-11), since the mean flow and associated eddy propagation in the SCS have seasonal variability. We add several sentences in Section 2.2 to clarity it.

11) The eddy forecast error has been discussed by Hurlburt et al. (2008). Comment upon this previous evaluation would be valuable.

E. Hurlburt, Harley & Chassignet, Eric & A. Cummings, James & Birol Kara, A & Metzger, E & F. Shriver, Jay & Smedstad, Ole & J. Wallcraft, Alan & N. Barron, Charlie. (2008). EddyResolving Global Ocean Prediction. Washington DC American Geophysical Union Geophysical Monograph Series. 353-381. 10.1029/177GM21.

Response: Thanks for the comment. Because mesoscale eddies are often associated with strong nonlinear processes and their dynamical mechanisms are quite different,

the operational forecast of eddies has been a big challenge to ocean numerical model. Much progress has been made in recent years in eddy-resolving ocean prediction. With the data assimilation and the increasing of model resolution, the model increases forecast skill. Eddy center position daily forecast errors in the northwestern Arabian Sea and Gulf of Oman is 44-68 km in $1/12^o$ global HYCOM model, and reaches to 22.5-37 km in $1/32^o$ NLOM model (Hurlburt et al., 2008). The forecast skill and predictability of dynamical models can only be increased by better assimilation schemes (initialization), sufficient data (especially the subsurface), and improving resolution (physics and computing power). We have added this reference and some comments in the Section 1 of the revised manuscript.

12) In this study, the distance errors are presented by degree or km only. The relative error, relative to the eddy radius, is more important to directly understand the uncertainty.

Response: Thanks for the comment. Actually, we once considered the relative errors by normalizing the forecast distance errors with the Rossby radius on each forecast grid. Figure R3 shows the differences and correlation of relative errors between the persistence method and the proposed method over 4-week forecast window. Their correlation decreases from 0.67 at week-1 to 0.38 at week-4. This conclusion based on the relative errors is consistent with that of the comparison of forecast distance errors between the two methods: although the persistence forecast trajectory at week-1 is relatively consistent with the observation, the persistence method cannot forecast the eddy trajectories properly when the forecast horizon increases. Considering the forecast distance errors presented by degree or km have been widely accepted by operational ocean eddy forecasting (e.g., Oey et al., 2005; Zeng et al., 2015) and tropical cyclone track forecasting (e.g., Aberson et al., 2003; Ali et al., 2007), the forecast distance errors by km is still used in the evaluation of forecast performance for the convenience of common readers.
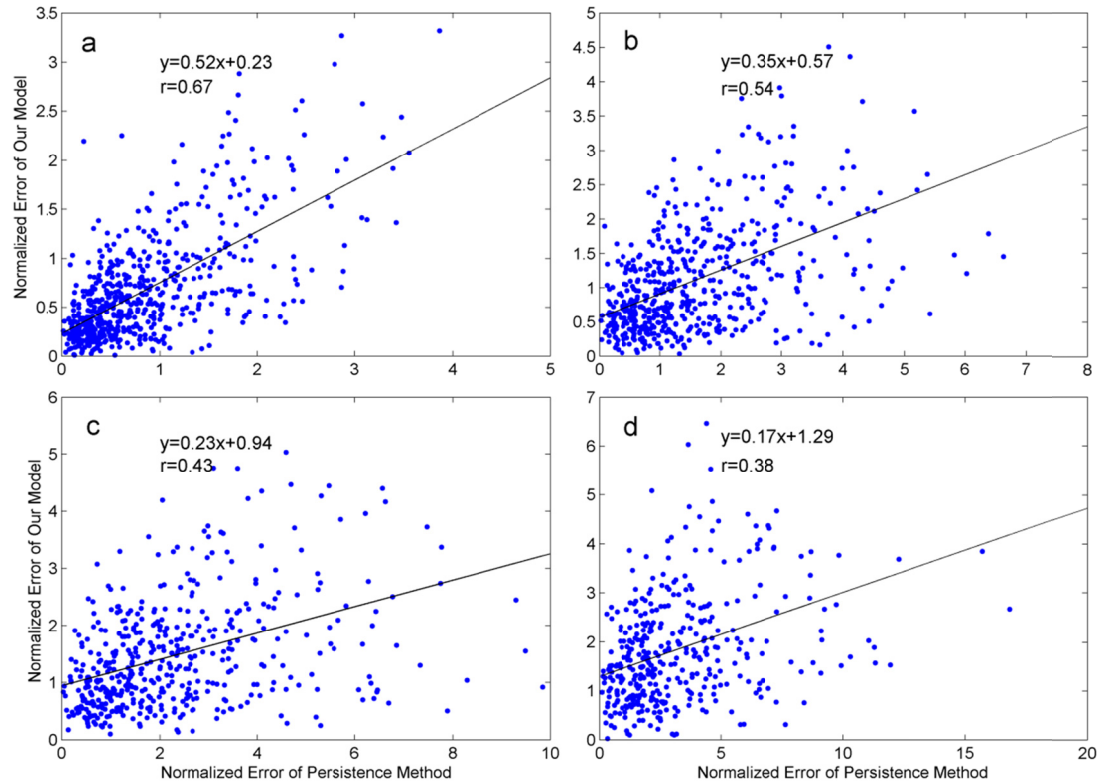
Figure R3. Scatterplot of the normalized forecast distance errors of persistence method vs. the normalized forecast distance errors of out linear regression model with best fit linear regression at week-1 (a), week-2 (b), week-3 (c) and week-4 (d).

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