Responses to Referee # 2:

The submitted work proposes a regression model to forecast the trajectories of eddies in the South China Sea. The method is based on using the velocity field obtained through the Maximum Cross Correlation technique applied to sea level anomalies as capturing the combination of several dynamical components (self-propagating beta effect, advection by mean flow, etc.). The basic dynamical idea of applying the MCC to altimetry to analyze trajectories of eddies was introduced several years ago (e.g. L.L. Fu JGR, 2006). The novelty here is to go a step forward to develop a linear regression model to forecast such trajectories and assuming some dynamical elements affecting eddies propagation. The authors compare their approach against forecasting using a "persistence" approach.

Response: Thanks so much for the helpful comments. We made every effort to clarify our results and improve our manuscript according to your comments. Next our response to each comment will be labeled in blue.

From my point of view, there are not great concerns on the scientific content of the paper. The authors discuss quite adequately the main assumptions leaving for future work potential refinements of their methodology. However, the major drawback when one is trying to provide a forecast method is to analyze with major detail the robustness in the choice of parameters.

Response: During the past 20 years, mesoscale eddies in the South China Sea (SCS) have drawn much attention, and their statistical characteristics, generation mechanisms, and impact on the atmosphere and ocean have been widely studied (e.g., Wang et al., 2003; Chen et al., 2011; Li et al., 2017). However, studies on the forecast of eddies in the SCS are rare because of their complex dynamics and high nonlinearity. Just recently, Xu et al. (2018) used modern ocean dynamical model to predict two eddy cases in the northern SCS, found the eddy propagation paths can be predicted only when the eddy amplitude is larger than 8 cm. To the best of my knowledge, our work is the first attempt at forecasting the eddy propagation trajectories statistically in the SCS, and our forecasted results (forecast distance error is 86.6-106.5 km from the third to fourth week) are comparable with those of dynamical model (forecast distance error is 81-132 km from the third to fifth week). Comparing to the dynamical method, our simple statistical method don't need boundary and forcing conditions and partial differential equation discretization, thus the computation is much faster than ocean models. Also our model is independent of eddy amplitude, and the forecast distance error is comparable with that of the dynamical model. Therefore, our study may provide an alternative and fast means for an operational forecast, which is especially useful to practical applications, such as naval military operation.

There are some aspects the authors should present more carefully:

* The different choices of window search and time lag. The authors indicate the upper sizes of such values for the mesoscale in SCS (lines 107-109) but some quantitative indications on how it affects the results is necessary.

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 underlying reason of their difference may be due to the low time-space resolution of SLA comparing with other satellite images, such as AVHRR.

In the MCC method, 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.

* The regression coefficients are computed over a limited temporal interval (1992-2008). The authors should analyze the stability of these coefficients as a function of the chosen time interval and how the results depend on it.

Response: Thanks for the comment. Two sensitive forecast experiments (Table R1) in different temporal intervals were performed to further evaluate the stability and effectiveness of our model. As we can see, when the regressed temporal interval is shorter than that of this study, the number of eddy trajectories for the regressing is expected less and the forecast errors increases 0.5-3.9 km over 1-4 week forecast window. When the regressed temporal interval is longer than that of this study, the number of eddy trajectories for the regressing is expected larger and the forecast errors decreases 0.3-3.2 km over 1-4 week forecast window. The forecast errors have small fluctuation (The stand deviation (Sd) is relatively small from 0.4-3.6 over 1-4 weeks), indicating the stability and effectiveness of the results of our model.

Table R1. Settings of two sensitive forecast experiments and our study

	Regressed Time Interval	Regressed Eddy Trajectory No.	Predicted Time Interval	Predicted Eddy Trajectory No.
Exp1	1992-2006	247	2007-2013	117
Exp2	1992-2010	321	2011-2013	43
This study	1992-2008	283	2009-2013	81

Table R2. Comparison of forecast distance errors (km) of two sensitive forecast experiments and our study

	Week-1	Week-2	Week-3	Week-4
Exp1	38.6	65.6	88.2	110.4
Exp2	37.8	63.9	84.3	103.3
This study	38.1	64.8	86.6	106.5
Sd	0.4	0.9	2.0	3.6

* The regression model introduces a climatological term U_CLIM estimated from the MCC. How this climatology is built remains unclear? Is a mean over the same regression period (weekly, monthly, seasonal, ...)? How it depends on such climatology? Such questions should be clarified in a quantitative way.

Response: Thanks for the comment. Since the mean flow and associated eddy propagation in the SCS have pronounced seasonal variability, we followed Zhuang et al. (2010) and divided the weekly SLA data from 1992 to 2013 into four groups according to four seasons (winter: 12-2, spring: 3-5, summer: 6-8, autumn: 9-11). Then the seasonal climatological propagation velocities (U_CLIM, V_CLIM) can be estimated in the same seasonal group using the MCC method of Fu (2006, 2009). We add several explanations in this Section 2.2 to clarity it.

Finally, the structure of the paper is decompensated with a central section ("Results") that mixes the methodological approach, the results and discussions. The "Data and Methods" section (section 2) include two subsections devoted to present datasets and to explain the MCC respectively, while the forecasting model is presented in detail in subsection 3.2 "Model Development" as part of the Results section (section 3). MCC is relevant for the system they propose but is just one of the elements of their methodology and is a well-known classical method in the context of the oceanography. Thus my suggestion is that the regression model should immediately follow the MCC description, both elements more coherently integrated in the "Data and methods" section and leaving the Results section to show the performance of the forecasting system.

Response: Thanks for the suggestion. We add a new Section 2.3: The Multiple Linear Regression Model in the "Data and methods" section to describe the regression model. Considering the importance of the selection of the predictors based on the dynamical analysis, we add a new Section 3: “Dynamics of Eddy Propagation in the NSCS and Choice of Predictors”, and leave Section 4: “Performance of the Multiple Regression Model” to show the performance of the forecasting system exclusively in the revised version.

Apart from these considerations I have the following list of small comments:

Section 2.2 and 3.1 (but also in the whole manuscript): In the text there is an abuse of the "eddy" word. Sometimes "eddy" is used in the context of deviation respect to a statistical mean while sometimes is used to refer to a dynamical coherent structure (an eddy). The MCC velocity field as applied to SLA maps is not only representative of the evolution of coherent eddies but also include many other structures as waves, filaments, fronts, etc. that may also evolve and propagate. Thus the velocity field are not necessarily the velocity of eddies understood as coherent structures alone. This must be mentioned and a careful use of the word "eddy" along the whole manuscript should be checked to avoid misinterpretations.

Response: Thank you for the comment. Yes, the MCC method cannot distinguish the various forms of mesoscale variability, such as filaments, fronts, and planetary waves. In the study of the pattern and velocity of global ocean eddies, Fu (2009) pointed out: when the space and time lags of the correlation analysis are chosen for the mesoscales, the MCC estimated velocities can represent the speed and direction of the propagation of ocean eddies. Chelton et al. (2011) compared the latitudinal variation of the mean eddy speed computed from the global eddy trajectories with that from the MCC method of Fu (2009), and found they are comparable well.

To focus on the global mesoscale eddy, Fu (2009) chose less than 70 days as the time lags and less than 400 km as the dimension of the window. In this work, 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). The search radius can be generally limited as 300 km (9.0 cm/s*42 days≈300 km, since 9 cm/s is the maximum eddy speed in the northern SCS (Chen et al. (2011))) .We add several sentences in the introduction of MCC method to explain this.

Section 3.1 (fig. 2b, e and lines148-165): Perhaps I'm wrong but I don't appreciate much differences between the winter and summer distributions of the phase speed of the first baroclinic Rossby wave. I may suppose that it is because at such latitudes the seasonal stratification does not change too much? A small comment may guide the general readers.

Response: Good comment. Yes, the difference between the winter and summer distributions of the phase speed of the first baroclinic Rossby wave is relatively small. The underlying reason is that the variation of seasonal stratification in the upper layer has little effect on the seasonal distribution of the first baroclinic Rossby deformation radius (Chelton et al, 1998, Cai et al., 2008). We add this comment and two references in the revised manuscript to guide the general readers.

Section 3.2 Model Description. It is needed to introduce the opportune equations representing the linear regression model with the variables involved besides of listing them in table 2.

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

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

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

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. To distinguish the input predictors, the forecasted variables, and the related regression equations clearly, To introduce the opportune equations representing the linear regression model, we revise Table 1 and 3, add a new Table 2 and add a new Section 2.3 in the revised manuscript.

Section 3.2: If I have understood, the MCC fields introduced into U_CLIM and V_CLIM are the characteristic mean from the whole altimetric period computed at intervals of 1 week? Please may you clarify it? See the remark above.

Response: Yes, U_CLIM and V_CLIM are the characteristic mean estimated using the MCC. Since the mean flow and associated eddy propagation in the SCS have pronounced seasonal variability, we followed Zhuang et al. (2010) and divided the weekly SLA data from 1992 to 2013 into four groups according to four seasons (winter: 12-2, spring: 3-5, summer: 6-8, autumn: 9-11). Then the seasonal climatological propagation velocities (U_CLIM, V_CLIM) can be estimated from the same seasonal group at intervals of 1 week using the MCC method of Fu (2006, 2009). We add several explanations in this Section 2.2 to clarity it.

Section 3.2: The initial step in the forecasting procedure is to provide an initial starting point of a given eddy. How is this provided, manually upon a first visual inspection of maps or using some method to automatically identify coherent structures in SLA maps? Please precise.

Response: Thanks for the comment. We used the SCS eddy trajectory data derived from the 3rd release of the global eddy dataset. (http://cioss.coas.oregonstate.edu/eddies/). This eddy dataset is developed based on the weekly AVISO SLA data by Chelton et al. (2011), and contains several parameters of the detected eddies at 7-day time interval, such as: eddy positions, eddy radius, eddy amplitude. We have clarified this in the Section 2.1 in the revised manuscript.

Line 207: How the predictands and predictors are normalized? please explain.

Response: Thank you for the comment. Suppose X is the time series of one predictor (or predictand), it is normalized by:

$$X^* = \frac{X - \mu}{\sigma}$$

where, X^* is the normalized X, μ is the mean of X, and σ is the sample standard deviation. We add one sentence in the text to explain it.

Line 217: "There are a total of 8 regression equations...", please see the comments above.

Response: We add two Equations in Section 2.3 to show the opportune regression equations with the input predictors, the forecasted variables, and the related equations coefficients listed in Table 1, 2, and 3 in the revised manuscript.

Lines 232 and following and Table 3: The table caption and the description of the parameters listed in the table are not enough detailed. Why the RMSE is given in degrees? The use of parentheses in the table whether they mean latitudes, persistence or predicted may somehow confuse the reader. Please clarify it and try to make a more detailed description in the table caption which is extremely synthetic. An interesting way of presenting the differences between the persistence method and the proposed method could be to normalize distances with the Rossby radius on grid size in order to see if their differences are relevant or not.

Response: Thanks for the helpful comment. According to the comment, we make three changes in Table 5 in the revised version (Table 3 in the older version): (1) One note describing the parameters below the table is added below the table in the revised version; (2) The RMSE is given in km, which is consistent with mean distance error; (3) To make this table more clearly, the forecast results of the persistence method is removed from this table, and incorporated into the new Table 4 in the new version.

We follow the last suggestion and compare the differences between the persistence method and the proposed method by normalizing distances with the Rossby radius on each forecast grid over 4-week forecast window. As can be seen from Figure R1, their correlation decreases from 0.67 at week-1 to 0.38 at week-4. This further verifies the result 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. We add several sentences to show this point in the revised manuscript.

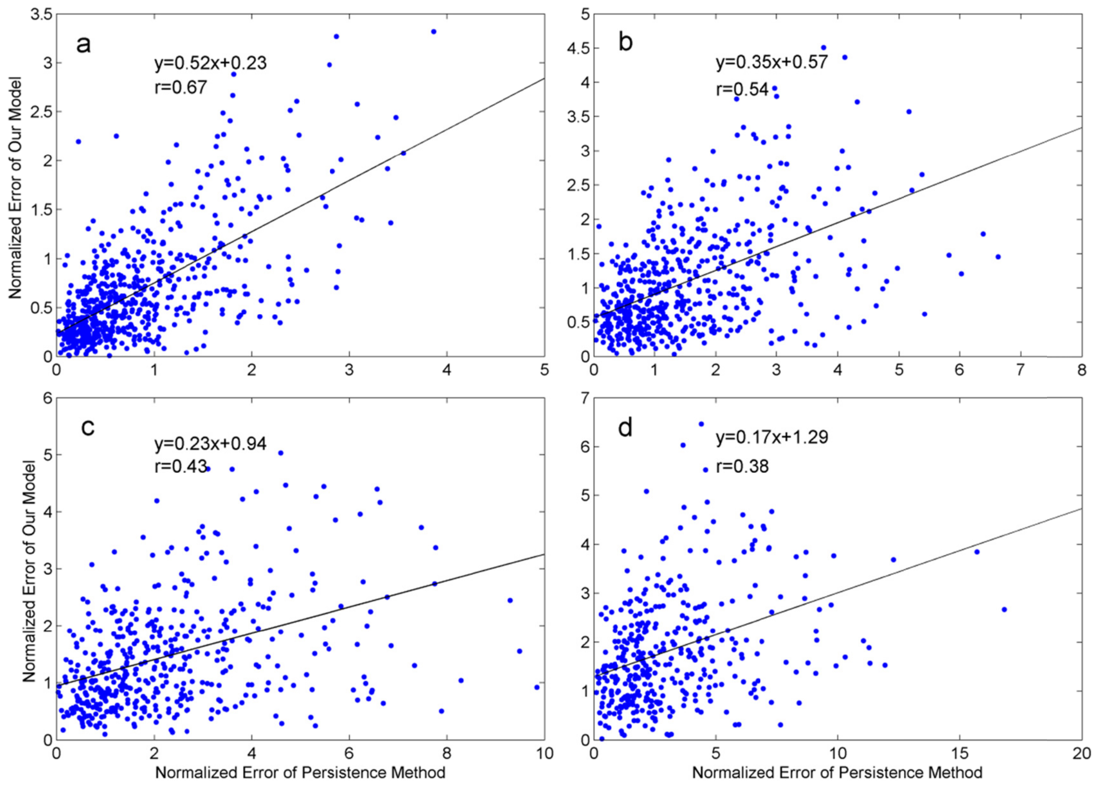

Figure R1. Scatterplot of the normalized forecast distance errors of persistence method vs. the normalized forecast distance errors of out linear regression model with best fit linear regression at week-1 (a), week-2 (b), week-3 (c) and week-4 (d).

Summary and Discussion: The authors only test the performance on seasonality and polarity but perhaps other processes as dissipation, merging or splitting which can be quite common and linked to eddy dynamical parameters as for example vorticity may affect the performance. Some comments or discussions on that should be welcome in this section but some examples on how the forecast are in such cases could also be illustrated.

Response: Thanks for the comment. Actually, in the developing process of our model, we have tried to incorporate the eddy dynamical parameters, such as eddy radius, eddy amplitude, eddy rotational speed, and eddy vorticity into our model, but sadly, no improvements have been shown. The underlying reasons may be that the propagation of eddies are related to strong nonlinear processes, which have not been fully understood and resolved.

Another possible improvement in the model forecast skill is to use artificial neural network (ANN) in developing the forecast model. ANN has been successfully used in the predicting cyclone tracks (Ali et al., 2007) and loop current variation (Zeng et al, 2015), and the salinity profile estimation from satellite surface observations (Bao et al., 2019). ANN can represent both linear and non-linear relationships learned directly from the data being modeled. It mainly contains three layers: the input layer, the hidden layer, and the output layer. To be consistent with the multiple linear regression, the input layer also includes the same eight predictors, and the output layer includes the two predictands. The hidden layer consists of two layers of neural variables. Through iterations on backward propagation of the error, the neural network learns by itself to achieve an optimum weighting function and a minimum error. The forecast errors of ANN for 1-4 weeks are listed in Table R3. We can see that some improvements (0.3-4.2 km during 1-4 weeks forecast horizon) have been shown comparing with linear regression method. We add these sentences in the Summary and Discussion Section of the revised manuscript.

Table R3. Comparison of forecast distance errors (km) of three methods

Forecast weeks	Persistence	Linear Regression	ANN
1	47.6	38.1	37.8
2	95.2	64.8	64.1
3	135.0	86.6	84.7
4	180.5	106.5	102.3

Figures:

In fig 1 the subplot C is part of the results and I recommend to move it to the results section.

Response: Good suggestion. We move subplot C in Figure 1 to the results section as new Figure 6 in the revised version.

Fig 2 is very small in size and hard to appreciate the velocity fields.

Response: Thanks for the comment. We redraw Figure 2 with the 2*3 subplots to enlarge each panel and make the velocity fields more distinguishable.

References:

Ali, M. M., Kishtawal, C. M., and Jain, S.: Predicting cyclone tracks in the north Indian Ocean: An artificial neural network approach, Geophys. Res. Lett., 34, L04603, http://doi.org/10.1029/2006GL028353, 2007.

Bao, S., Zhang, R. Wang, H., et al.: Salinity profile estimation in the Pacific Ocean from satellite Surface salinity observations, J. Atmos. Oceanic. Technol., 36, 53-68, 2019.

Cai, S., Long, X., Wu, R., and Wang, S.: Geographical and monthly variability of the first baroclinic rossby radius of deformation in the south china sea, J. Mar. Syst., 74, 711-720, 2008.

Chelton, D. B., Schlax, M. G., and Samelson, R. M.: Global observations of nonlinear mesoscale eddies, Prog. Oceanogr., 91, 167-216, 2011.

Chelton, D., DeSzoeke, R., and Schlax, M.: Geographical variability of the first baroclinic rossby radius of deformation, J. Phys. Oceanogr., 28, 433-460, 1998.

Chen, G., Hou, Y., and Chu, X.: Mesoscale eddies in the South China Sea: Mean properties, spatiotemporal variability, and impact on thermohaline structure, J. Geophys. Res., 116, C06018, http://doi.org/10.1029/2010JC006716, 2011.

Emery, W. J., Thomas, A. C., Collins, M. J., Crawford, W. R., and Mackas, D. L.: An objective method for computing advective surface velocities from sequential infrared satellite images, J. Geophys. Res., 91, 12865–12878, http://doi.org/ 10.1029/JC091iC11p12865, 1986.

Fu, L.-L.: Pathways of eddies in the South Atlantic Ocean revealed from satellite altimeter observations, Geophys. Res. Lett., 33, L14610, http://doi.org/10.1029/2006GL026245, 2006.

Fu, L.-L.: Pattern and speed of propagation of the global ocean eddy variability, J. Geophys. Res., 114, C11017, http://doi.org/10.1029/2009JC005349, 2009.

Li, J., Zhang, R., and Jin, B.: Eddy characteristics in the northern South China Sea as inferred from Lagrangian drifter data, Ocean Sci., 7, 1575-1599, 2011.

Wang, G., Su, J., and Chu, P. C.: Mesoscale eddies in the South China Sea observed with altimeter data, Geophys. Res. Lett., 30, 2121, http://doi.org/10.1029/2003GL018532, 21, 2003.

Xu, D., Zhuang, W., Yan, Y.: Could the mesoscale eddies be reproduced and predicted in the northern South China Sea: case studies, Ocean Sci. Discuss., http://doi.org/10.5194/os-2018-74, 2018.

Zeng, X., Li, Y., and He, R.: Predictability of the loop current variation and eddy shedding process in the Gulf of Mexico using an artificial neural network approach, J. Atmos. Oceanic. Technol., 32, 1098-1111, 2015.

Zhuang W., Du, Y., Wang, D., Xie, Q., and Xie, S.-P.: Pathways of mesoscale variability in the South China Sea, Chin. J. Oceanol. Limnol., 28, 1055-1067, 2010.