Authors' responses (tc-2019-159)

Response to the comments on "Prediction of monthly Arctic sea ice concentration using satellite and reanalysis data based on convolutional neural networks" by Young Jun Kim et al.

The authors would like to thank the editor and referees for their precious time and invaluable comments. The corresponding changes and refinements are highlighted in yellow in the revised paper and are also summarized in our responses below. Authors' responses are in blue. The editor and reviewer's comments are in black. When the manuscript in cited, it is shown in italics.

Response to editor

Both referees provided positive feedback for your revised manuscript.
While referee #2 requests only one technical correction, referee #1 mentions a few issues regarding missing literature, restriction to one-month predictions and impact on sea ice extent.

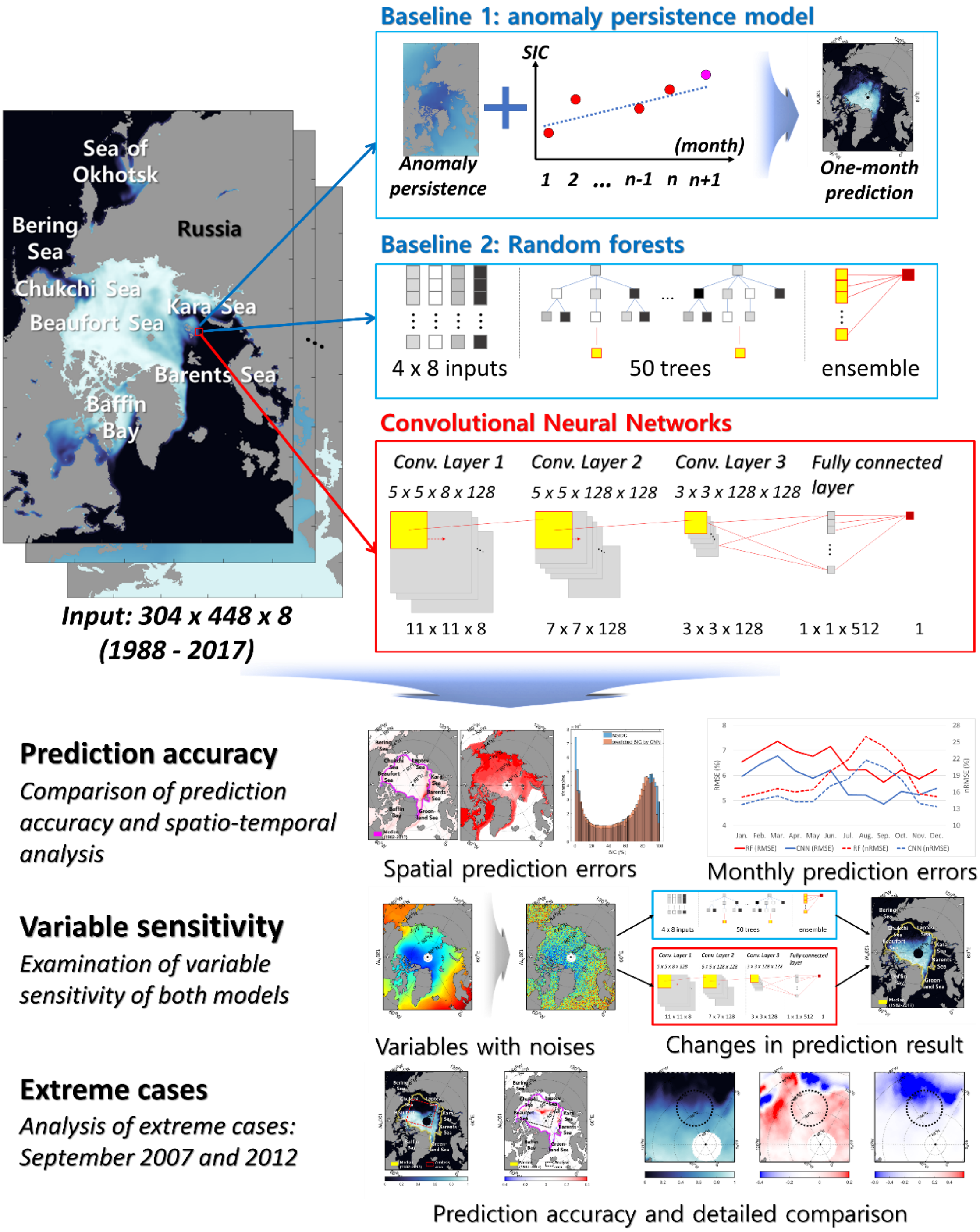
I would like you to improve Figure 1, add the missing literature and to illustrate the impact on sea ice extent. While it would be useful to extend your one-month predictions to seasonal predictions, this might be not feasible within this paper. However, please comment why you restricted your analysis to one-month predictions and whether it is possible in prinicple to extend this method for seasonal predictions.

- ➔ Thanks for the comment. We revised Figure 1 with larger font size.
- ➔ We supplemented the explanation of the limitations of the proposed CNN model. We first tested the prediction accuracy of the CNN model by changing prediction lead time from one- to three-months (Supplementary Table 1 below).
- ➔ Since there are no drastic changes in prediction accuracy among the models, we concluded that the CNN model could be extended to seasonal predictions. However, we need other supplementary variables to build a more accurate long-term prediction model like sea-ice volume and atmospheric circulation (Guemas et al., 2014).

Supplementary Table 1. Average prediction accuracies among three prediction models on the melting season (June – September) during 2000-2017 (mean absolute error, anomaly correlation coefficient, root mean square errors, normalized root mean square errors, and Nash-Sutcliffe efficiency).

	One-month	Two-month	Three-month
MAE	1.96%	2.71%	3.00%
ACC	98.09	96.51	95.71
RMSE	5.41%	7.26%	7.96%
nRMSE	19.09%	25.60%	28.26%
NSE	96.14	92.99	91.34

Lines 470 - 474: *"The proposed CNN model could be used for the longer prediction (i.e., two- or three-month prediction) in consideration of the persistent effects of input variables such as SST and T2m. Moreover, additional input variables that represent seasonal, or longer-term variabilities of the Arctic environment should be considered in the proposed models. The persistence of sea-ice volume and atmospheric circulation related variables would be suitable for the long-term sea ice forecast (Guemas et al., 2014)."*



Revised Figure 1. Study area and research flow.

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Authors' responses (tc−2019−159)

Response to anonymous referee #1

Comments:

1) Lines 40-45. should mention also these statistical models:

Wang, L., Yuan, X., & Li, C. (2019). Subseasonal forecast of Arctic sea ice concentration via statistical approaches. Climate Dynamics, 52(7), 4953–4971.

Kondrashov, D., M. D. Chekroun, and M. Ghil (2018). Data-adaptive harmonic decomposition and prediction of Arctic sea ice extent, Dynamics and Statistics of the Climate System, 3(1).

- ➔ Thanks for the comment. We have reviewed and added the suggested references regarding the statistical predictions of SIC.

Lines 50 – 59: *"A short-term forecast of SIC has been also examined using statistical approaches. Wang et al. (2019) evaluated the sub-seasonal predictability of Arctic SIC using multi-variables of sea ice, the atmosphere, and the ocean based on statistical approaches—the VAR and vector Markov models. The VAR model showed quite good predictability in the short-term with RMSE of 10%, but still resulted in high RMSEs (~20%) for longer than 4 weeks over pan-Arctic during the summer season (from June to August). Meanwhile, the Data-Adaptive Harmonic (DAH) technique, which examines a data-driven feature using cross-correlations, was demonstrated to predict Arctic SIE (Kondrashov et al., 2018). The DAH model showed a promising predictability of SIE in September, resulting in the absolute error of about 0.3 million km^2 in 2014-2016."*

2) Authors need to clarify why they have restricted their results to one-month lead time, i.e. for monthly data it is basically one-step prediction.

Can the presented method be used for predicting on longer lead times, i.e. several months ahead, such as for summertime prediction in Sea Ice Outlook (see next)? It is not clear why not, and that begs the question why results are shown for one-month only, thus creating an impression of incomplete study.

- ➔ We supplemented the explanation of the limitations of the proposed CNN model. We first tested the prediction accuracy of the CNN model by changing prediction lead time from one- to three-months (Supplementary Table 1 below).
- ➔ Since there are no drastic changes in prediction accuracy among the models, we concluded that the CNN model could be extended to seasonal predictions. However, we need other supplementary variables to build a more accurate long-term prediction model like sea-ice volume and atmospheric circulation (Guemas et al., 2014).

Supplementary Table 2. Average prediction accuracies among three prediction models on the melting season (June – September) during 2000-2017 (mean absolute error, anomaly correlation coefficient, root mean square errors, normalized root mean square errors, and Nash-Sutcliffe efficiency).

	One-month	Two-month	Three-month
MAE	1.96%	2.71%	3.00%
ACC	98.09	96.51	95.71
RMSE	5.41%	7.26%	7.96%
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Lines 470 - 474: *"The proposed CNN model could be used for the longer prediction (i.e., two- or three-month prediction) in consideration of the persistent effects of input variables such as SST and T2m. Moreover, additional input variables that represent seasonal, or longer-term variabilities of the Arctic environment should be considered in the proposed models. The persistence of sea-ice volume and atmospheric circulation related variables would be suitable for the long-term sea ice forecast (Guemas et al., 2014)."*

3) It would be very helpful to illustrate how prediction of SIC translates into the one for sea ice extent (SIE), and in particular for summertime prediction of September minimum of pan-Arctic SIE which is the main focus of Sea Ice Outlook community effort (Stroeve et al. 2014). Adding and showing results for one-month prediction (i.e. from August) and observed September pan-Arctic SIE, as well as skill in comparison with RF and baseline prediction model, would be illuminating.

- ➔ We analyzed the SIE in September 2017 by comparing three models and added Figure 5 to figure out the spatial distributions of sea ice. In addition, we evaluated the proposed prediction models by comparing other SIO contributions reported in August 2017.

Lines 233 – 240: *"The Sea Ice Outlook (SIO) open community has investigated the pan-Arctic sea ice especially in the September SIE since 2008 (Stroeve et al., 2014; Chi and Kim, 2017). They have shared the predicted September SIE from June, July, and August based on a heuristic, statistical, dynamical, and mixed approaches. Chi and Kim (2017) have pointed out the difficulties of sea ice prediction because the prediction errors have increased since 2012. To figure out September minimum SIE which is the main focus of the SIO community (Stroeve et al., 2014), we compared the predicted SIEs based on the three models evaluated in this study, together with the other 37 SIO contributions for the September SIE predictions reported in August 2017. In the present study, the SIE was identified as an area of SIC > 15% (Chi and Kim, 2017)."*

Lines 325 – 340: *"The spatial comparison of the predicted September SIEs in 2017 between the reference (NSIDC) and three approaches used in this study is shown in Figure 5. The observed SIE in Sep. 2017 was 4.80 million km2 which was reported by the Sea Ice Prediction Network (http://www.arcus.org/sipn). The SIE in Sep. 13, 2017 was the eighth-lowest in the satellite record since 1981 (NSIDC, 2017). The SIEs predicted by the anomaly persistence, RF and CNN models were 4.37, 4.95, and 4.88 million km2, respectively. While the anomaly persistence model under-estimated the SIE, the other two models slightly over-estimated. The anomaly persistence model considered the decreasing trends of sea ice somewhat excessively. The CNN-based model showed the lowest prediction error compared to the Sea Ice Prediction Network reference data (0.09 million km2). In terms of spatial distributions, the anomaly persistence model showed the excessive retreat of sea ice in the Beaufort and Laptev Sea (Fig. 5a). However, the RF and CNN models showed slightly wide SIE in the Chukchi and Barents Sea (Figs. 5b and c). The over-estimated SIE might be because of the July storm across the central Arctic Ocean through the Barents Sea (West and Blockley, 2017). The accuracy of one-month SIE prediction based on three approaches was compared to the other 37 SIO contributions for Sep. 2017 (Fig. 5d). Since the SIO reports contain only quantitative SIE values, it was not possible to compare their spatial distributions. With regard to the SIE values, the statistical approaches showed quite accurate prediction results based on Arctic sea ice thickness distributions and ice velocity data (UTokyo) and non-parametric statistical model (Slater/Barrett NSIDC). The CNN prediction result showed relatively accurate prediction accuracy."*

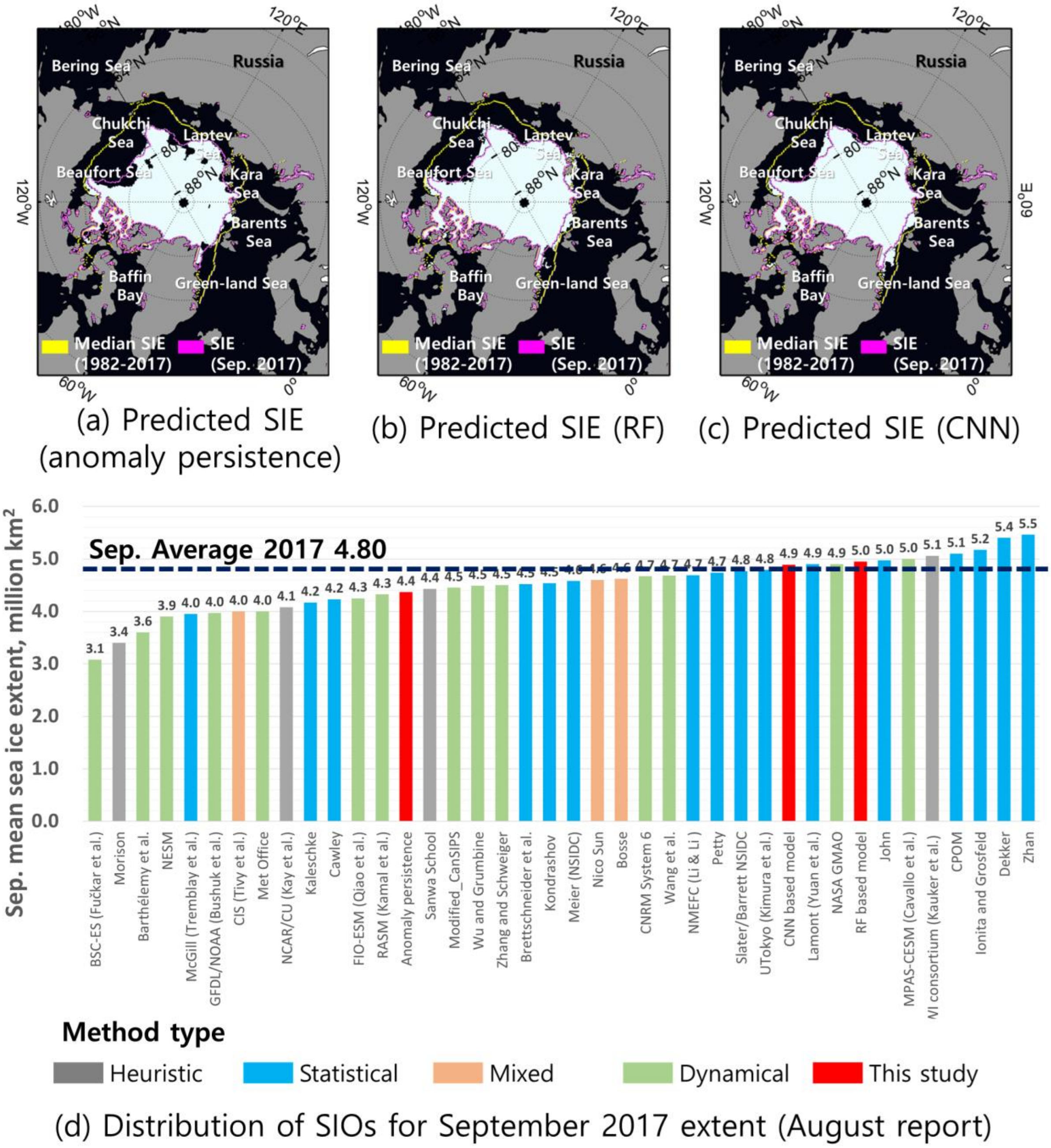


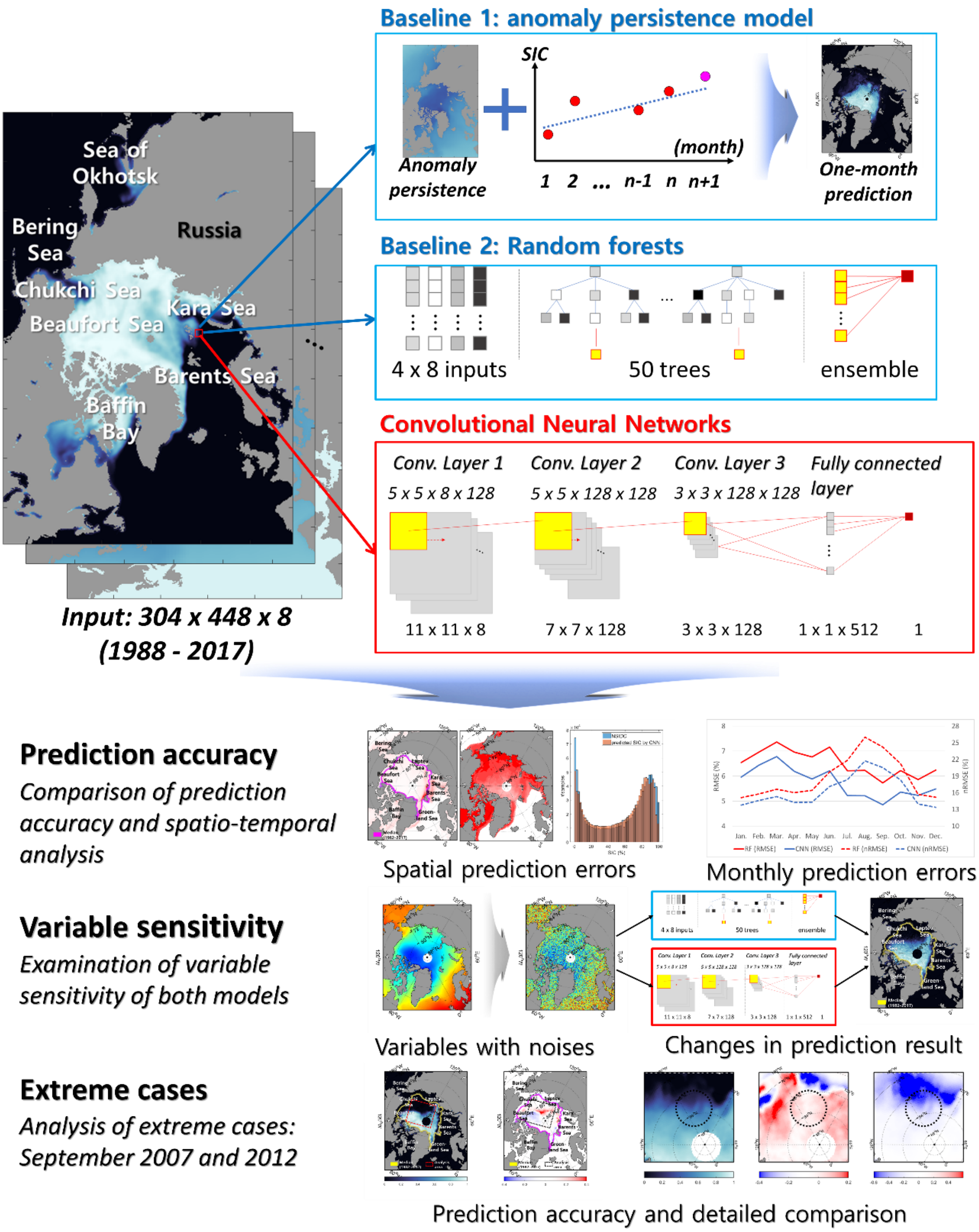
Figure 2. The predicted SIEs using the anomaly persistence (a), RF (b), and CNN (c) for Sep. 2017. Distribution of SIO values for Sep. 2017 SIEs reported in Aug. 2017. (d).

Response to anonymous referee #2

A comment:

1) Accept after revision of figures as suggested.

➔ We revised Figure 1 with a larger font.



Revised Figure 3. Study area and research flow.