<u>Response to Reviewer # 2's comments:</u>

1. ***Comment:*** *My In "Introduction", the reasons why the streamflow over the previous three days could be considered as a surrogate for antecedent soil moisture conditions need to be further clarified in the revised manuscript.*
   Response: We have added few references to support that antecedent streamflow conditions can be considered as surrogates for initial conditions of the catchments. We added in lines 93-94: "Furthermore, several studies have utilized antecedent streamflows as surrogates of initial catchment conditions (e.g. Chiew and McMohan, 2002; Piechota et al., 2001; Wang et al., 2009)."

2. ***Comment:*** *The 2th paragraph of Introduction, sentence "Developing daily streamflow forecasts over a large region using semi-distributed models require intensive spatial data (e.g. topography, land cover, soils) and computational resources, hence, we employed the KNearest Neighbor (K-NN) semi-parametric approach to develop daily streamflow forecasts contingent on updated climate forecasts." This sentence needs to be rewritten in a clearer way to highlight the reason that K-NN resampling approach was applied in this study.*
   Response: We have updated the text in lines 84-91 to clarify this as: "Developing daily streamflow forecasts over a large region using semi-distributed models require intensive spatial data (e.g. topography, land cover, soils) and computational resources, hence, we employed a semi-parametric approach in this study. In particular, we employed the K Nearest Neighbor (K-NN) semi-parametric scheme to develop daily streamflow forecasts contingent on updated climate forecasts since it can capture nonlinear relationships that are typically observed in daily streamflow data (Salas and Lee, 2010). The K-NN scheme has been widely used in hydrologic studies (Rajagopalan and Lall 1999; Prairie et al. 2006; Sharif and Burn 2006)."

3. ***Comment:*** *In "2.2 Weather forecasts database": please present the mechanism of the method for forecasting precipitation.*
   Response: We added further details in lines 129-139 as: "The GFS forecasts model has 28 sigma (pressure) levels and a T62 spatial resolution (~200 km grid size), which represents physical processes to estimate atmospheric forcings such as winds, temperature, precipitation, geopotential heights at different pressure levels (Hamill et al., 2006). 15 ensemble forecasts are obtained by initializing different atmospheric states of the GFS model every day. The control run is initialized by the National Center for Environmental Prediction (NCEP)-National Center for Atmospheric Research (NCAR) reanalysis data (Kalnay et al., 1996) while the other 14 ensemble members use a set of seven bred pairs of initial conditions (Toth and Kalnay, 1997), which are re-centered each day on the reanalysis initial condition. In this study, we make use of daily precipitation reforecasts from the GFS model consists of 15 ensemble members, up to 15 days in advance, starting from 1979 to till date."

4. *Comment: In "3. Stream and total nitrogen forecasting models", three models were proposed for forecasting precipitation, streamflow and nutrient loading, respectively. Do the model scales match? I suggest more descriptions on how these forecasting model scales match each other be presented.*
   Response: The time scales of the models match, but the spatial scales don't match. Hence, we considered a statistical model for developing streamflow forecast. We added the following sentence to address this concern: "The LODEST model can be employed with the observed or predicted daily streamflow time series at any given site. Streamflow forecast developed using large-scale precipitation forecasts and previous 3-day average streamflow using the non-parametric model is forced with the LOADEST model to develop nutrient forecasts."

5. *Comment: In "3.2 K-Nearest Neighbor (K-NN) resampling approach", there should be more description on the specific mechanism of K-NN resampling approach.*
   Response: Lines 194-223 describe the mechanism of the K-NN resampling approach. We revised the beginning to the paragraph to reflect this as: In the K-NN scheme, we used the Mahalanobis distance instead of the Euclidean distance, since the selected predictors – PCs of the principal components and the streamflow over the past observations- could be correlated."

6. *Comment: In "4.1 Skill in forecasting daily streamflow", I would suggest that the obtained conditional distribution of flows for 18 watersheds should be presented.*
   Response: It will be too many plots/data to show the conditional distribution of flows obtained for each forecasting day for all the 18 watersheds. However, we added Figure 9 to quantify the role of different predictors such as previous 3-day average streamflow prior to forecasting day and 1-day ahead precipitation forecasts in improving the skill in forecasting TN loadings for all the 18 sites. Figure 9 clearly indicates that the combination of both daily streamflow previous 3-days and 1-day ahead precipitation forecasts as predictors result in improved correlation and reduced RMSE in estimating daily TN loadings at all the sites.

7. *Comment: The contents of "5. Summary and conclusions" section should be enhanced according to the actual results. Please emphasize innovations and important conclusions.*
   Response: We have extended the discussion as well as the summary and conclusions to incorporate the results from the addition of Figures 9 and 10 along with substantiation of results from t

8. *Comment: Sections There are several typographical and grammatical errors that need to be corrected, for example: (a) Page 15628: "But, availability of data on total nitrogen is limited with concentration is typically measured on a non-continuous basis."*
   Response: We have updated the sentence.

9. *Comment: (b) Page 15628: "Similarly, considerable progress has been made in developing daily streamflow forecasts using both statistical models that consider both parametric and semi-distributed models."*

Response: We revised the sentence as: "Similarly, considerable progress has been made in developing daily streamflow forecasts using statistical models, e.g. parametric models (Rajagopalan and Lall 1999; Anderson et al., 2002; Salas and Lee, 2010), and semi-distributed watershed models (e.g., Clark and Hay, 2004; Mcenery et al., 2005, Georgakakos et al., 2010)."

10. *Comment: (c) Page 15630: "The WQN database comprises of water quality data from USGS monitoring networks from both large watersheds (National Stream Quality Accounting Network, NASQAN) and minimally developed watersheds (Hydrologic Benchmark Network, HBN)."*

Response: The sentence has been corrected as: "The WQN database comprises of water quality data from the USGS monitoring networks for large watersheds (National Stream Quality Accounting Network, NASQAN) as well as watersheds that are minimally developed (Hydrologic Benchmark Network, HBN)."

11. *Comment: (d) Page 15635: "These errors primarily occur due to the inability of the model to predict high values, which resulted in very high residuals."*

Response: This has been corrected as: "These errors primarily occur due to the inability of the model to predict high values, as indicated by very high residuals."

Comment: (e) Page 15639:"It is important to note that all the skill reported in Figs. 3–6 consider the ability to predicting exactly for those days with WQN observations."

Response: This has been corrected as: "It is important to note that all the skill reported in Figures 3-6 consider the ability to predicting those days when the WQN observations are available.

Thanks for the detailed comments!