Authors’ response to referee 2

The work belongs to the growing number of case studies on lake response to the recent climate change. Here, the authors investigated the long-term trends in a small shallow artificial lake by applying a 3-dimensional hydrodynamic model driven by a 1960-2017 regional meteorological reanalysis dataset. The combination of the study object (shallow polymictic lake) and the approach (a full 3-d model) is particularly interesting for revealing the fine mechanisms and effects of the regional climate change. The results are presented in a clear and straightforward way, but the abovementioned potential of the study is barely unfold. Except one sentence in Conclusions, the motivation for application of a 3-d lake model is not discussed, neither its advantages and disadvantages are discussed compared with simpler 1d models. It remains unclear, why should one use such a complicated model, subject to a lot of uncertainties, just to arrive at an obvious conclusion: the lake parts shallower than the mean depth of the mixed layer do not stratify. It sounds like cracking nuts with a sledgehummer. The 3d model performance is only briefly addressed. The validation was performed only on surface (mean) temperature, which is not sufficient to trust the later model results on the stratification trends. The question about the model ability to adequately reproduce vertical thermal stratification in the lake remains open.

> **Authors’ response:** My coauthors and I would first like to thank you for these useful comments. In this document, we broke the first general comments into three sections in order to address the main comments sequentially and more clearly.
>
> We agree on the general remark that a stronger focus on 3D results is needed in order to highlight the novelty of the approach. This will be addressed in the revised draft both in the results and in the discussion section, as shown later on in this document. We can already say here, that 3D modelling is able to provide spatially distributed information in particular regarding areas favorable to the initiation of harmful algal blooms, or to biomass accumulation. Such results can be used to improve the monitoring design or provide stakeholders with new information for bloom control. Furthermore, in the perspective of a more generalized application of our approach, 3D modelling can benefit, even for small lakes, from the recent availability of fine resolution satellite images for instance for data assimilation (e.g. Allan et al., 2016).
>
> The concern on the validation of model performance probably comes from an unclear writing on our part. The model was indeed tested during validation at three depths (sub-surface, middle and bottom of the water column), where high-frequency measurements are available, and on two measuring sites. RMSE values were in all cases comprised between 0.96°C and 1.00°C and more specifically: Surf.:1.0°C, Mid.:0.96°C, Bott:0.96°C for site A, and Surf.:1.0°C, Mid.:0.96°C, Bott:0.99°C for site B. The validation of the model is now more clearly discussed in the revised draft through the results shown here in Figure 1, that also evaluates the timing and frequency of stable stratification events. Parity diagrams show very good performances for all layers. The comparison between modeled and simulated stable stratification events show how the model is able to correctly capture the timing of most stratification events. Some discrepancy however is generated by a threshold-induced effect in the definition of the temperature difference for stable stratification. This will allow to clearly state the overall robustness of our modeling set-up, and to discuss its limitations, when present.

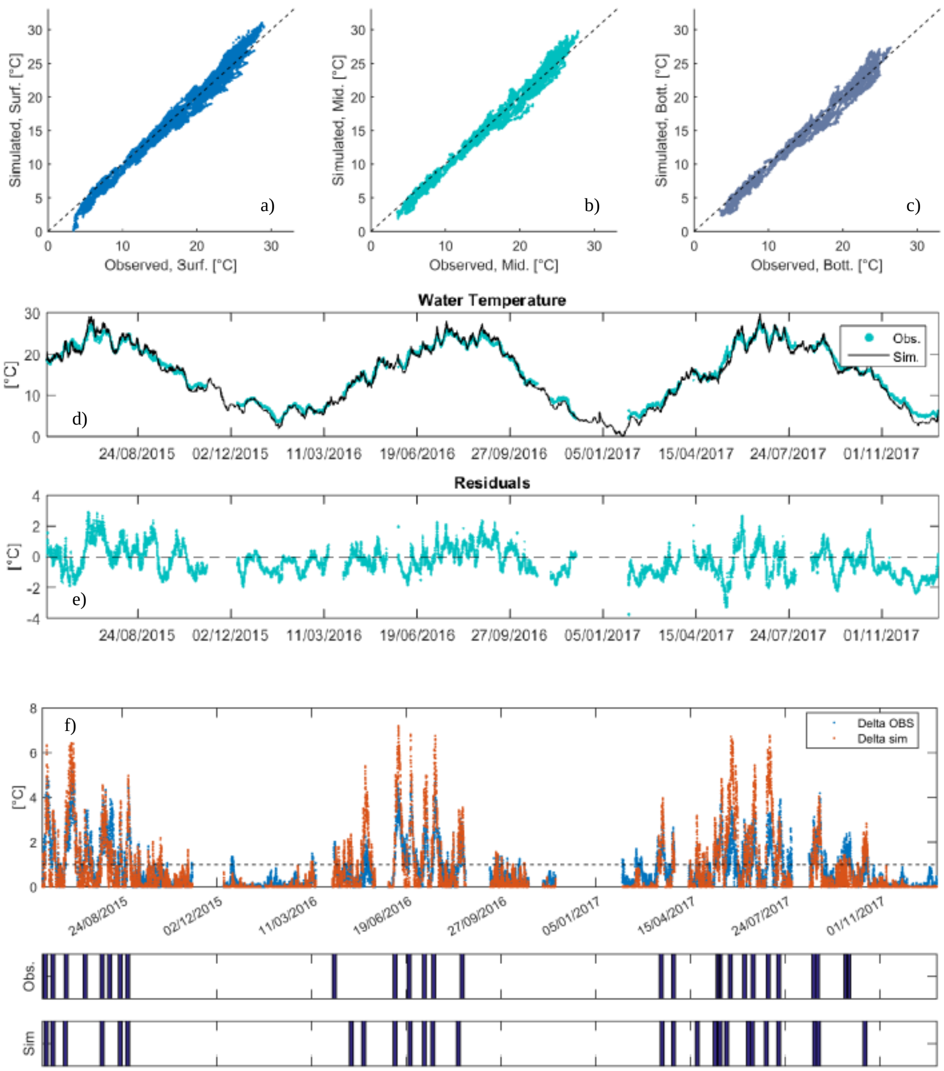

Figure 1: Model performance during validation at site A. Panels a, b and c: parity diagrams between simulations and observations for the surface, middle and bottom layers, respectively. Panels d and e: visual comparison of simulated and observed water temperature at the middle layer (d) and corresponding residuals (e). Panel f: modeled (orange) vs. observed (blue) temperature difference between surface and bottom layer and relative comparison between the timing of observed and modeled stable stratification events.

A large part of discussion is dedicated to the effect of climate change on the transient stratification development in shallow polymictic lakes. However, the stratification indices used in the analysis—Schmidt stability and the total stratification duration—are rather relevant to oligomictic (di- and monomictic) lakes. Neither duration of the longest stratification period, nor the frequency of stratification events are analyzed.

> **Authors' response:** The Schmidt stability and SSD can give relevant information also in the case of polymictic lakes, and both indices are used in various studies on shallow polymictic water bodies (e.g. Magee et al. 2017, Moras et al. 2019).
>
> We agree that an analysis of the frequency and length of stratification events is a very interesting complement to the two previously mentioned indices for a polymictic lake. The results of this analysis showed that no significant trend can be found over the long term for the annual number of stable stratification events. In contrast, a shift in the average duration of stratification events can be detected. This is shown in Figure 2, where the double cumulative curve of annual SSD and annual number of stable stratification events is plotted.

A change point analysis of the underlying linear trend shows a break point between 1988 and 1989 with a shift in the average duration of a stable stratification event from 3 to 4 days. This can be expected to influence phytoplankton growth and is discussed in the revised manuscript.

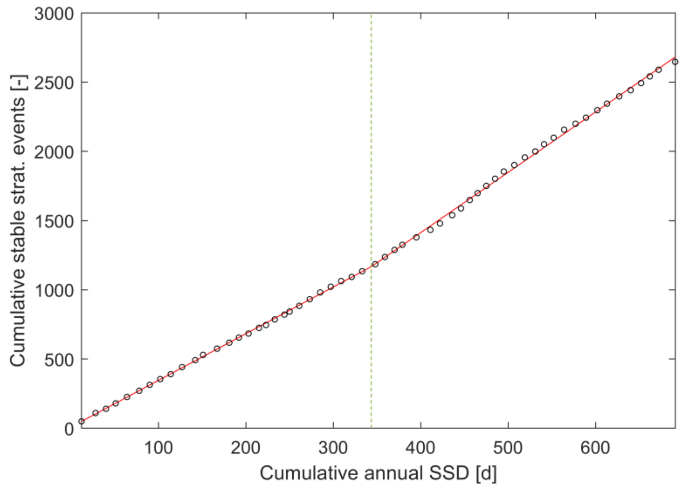

Figure 2: Double cumulative curves for the annual number of SSD (x axis) and the annual number of stable stratification events (y axis).

The indices used for the warming effect on the net biological production are also questionable: temerature as a measure of the growing season is weakly justified in lake ecosystems, especially for the climate under consideration. The "number of growing days" (NGD) in the authors' formulation is always clearly above 300, so the whole 365-days long year cycle can be a priori assumed as production-favorable in terms of temperature. Trends in GDD and NGD do not seem to be representative for any biotic processes. In particular, because high temperatures can work as a stress factor inhibiting both primary production and growth rates of higher organisms. In general, Discussion presents a lot of common knowledge but is weakly connected to the results from the study.

In summary: the study uses a promising approach and a solid dataset, but, in its current form, presents little advance on the subject under investigation. A stronger focus on the abilities of 3-d modeling for climatic lake studies and intermittent stratification dynamics of shallow polymictic lakes would strengthen this otherwise well-designed and clearly structured study.

Authors' response: Concerning the temperature based indices for aquatic environments, their application is indeed quite rare but recently growing (e.g. Dupuis and Hann, 2009, Rlaston et al., 2014, Sterner et al., 2020). In order to link the GDD and NGD not only to the overall growth of biomass but also to the growth of specific algal groups with higher optimum temperatures, two other baseline temperatures have been introduced in our analysis.

Three values were therefore tested for the base temperature in the calculation of GDD and NGD (4°C, 18°C and 25°C). These values were selected since they respectively constitute baseline temperatures for (i) overall biomass growth and species able to grow at low temperature such as diatoms (after Dupuis and Hann, 2009), (ii) most phytoplankton species, normally growing at medium / high temperatures (such as dinoflagellates or green algae), and (iii) intense growth of cyanobacteria (Paerl, 2014). These results have been analyzed over time and space and will be included in the revised draft. Such results are shown here in figure 3 for GDD, where the top 3 panels show the overall time-average of the annual values for GDD, calculated with the three different base temperatures (4°C, 18°C and 25°C from left to right), while bottom panels show the mean intensity of the monotonic trend for each cell in the domain, when statistically significant.

For T_{base}=4°C and T_{base}=18°C weak horizontal gradients (around 1% and 3%, respectively) can be found in the spatial distribution of time averaged GDD. No easily interpretable patterns can be seen in the intensity of their growing trend. Horizontal gradients grow considerably when using T_{base}=25°C, both for the overall time-average of GDD (around 4%) and for its growing trend (around 8%).

While optimal thermal conditions for cold- and medium-temperature species are quite uniform in space, and have evolved quite uniformly over time, it is not the case for species with high optimum temperatures.

This suggests the existence of a region, the shallower north-eastern part of the lake, particularly favorable to the development and dominance of toxic species such as cyanobacteria. Furthermore, this spatial heterogeneity is increasing over time (see fig. 3-f). This region of the lake could also become more favorable to the initiation of cyanobacteria blooms.

Finally, this shows how observations taken at one single site as well as 1D models might only be partially representative of overall dynamics of a water body, especially for shallow water bodies with strong relative bathymetric variations.

In order to take this analysis into account, in the revised draft the relative parts in the Materials and Methods, Results and Discussion sections are appropriately modified. The results and the limitations of this approach for linking hydrodynamics and ecology (as water temperature is a key factor but not the only one influencing primary production) are further discussed in the revised draft.

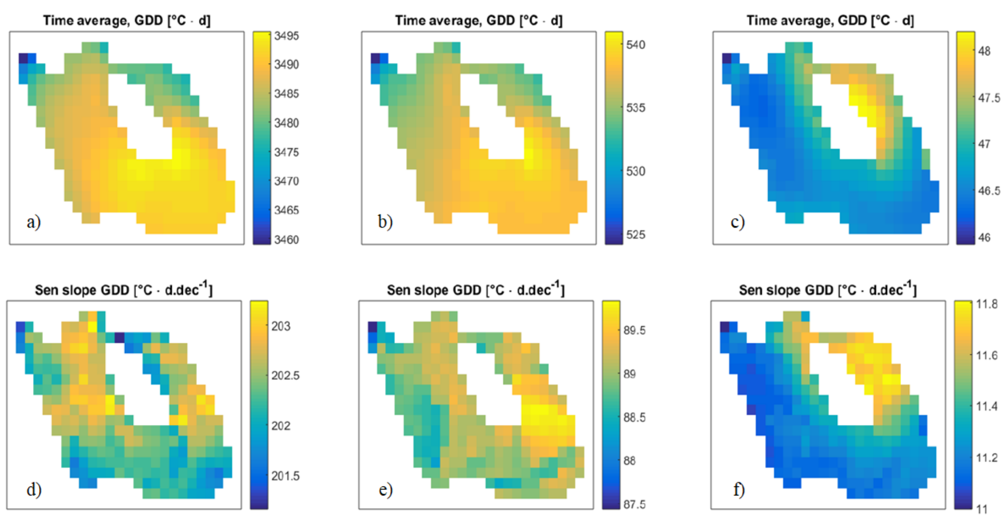

Figure 3: Spatial analysis of GDD. Different base temperatures were tested for the calculation of the GDD and the relative trends; they are represented along the three columns: first column: T_{base}=4°C, second column T_{base}=18°C, third column T_{base}=25°C. Panels a, b and c represent, for each cell in the domain, the average over the 58 years of simulation of annual values of GDD. Panels d, e and f show, for each cell in the domain, the average interannual trend calculated through the Sen slope (all Mann-Kendall tests were statistically significant).

Here are some specific remarks:

- The model uses constant cloudiness as input, which is quite strange, especialy, taking into accout significant long-term trends in solar radiation. Why the real variability of cloud cover (or long-wave atmospheric radiation) was not used? Can you estimate the resulting errors in the model output?

> **Authors' response:** We agree that it would be preferable to use cloudiness measurements. Cloud cover measurements were available from the closest meteorological station, 24 km away, but not for the 8x8 km SAFRAN reanalysis cell, contrary to other meteorological variables.
>
> The model was tested during calibration and validation using two different modules for heat exchange, the Ocean model with time series of cloud cover, and the Murakami model which is implemented with a constant cloud cover in Delft3D. Overall, water temperature was slightly better modeled by the Murakami model with a specifically calibrated value for cloud cover. For instance, for the year 2016, RMSE at site A was around 1.1°C for all three depths with the Ocean heat exchange model, while it was around 0.8°C for the Murakami heat exchange model.
>
> This can be explained on the first hand by the high uncertainty that affects ground-based cloud cover observations (Silva and Souza-Echer, 2015, Zelinka et al., 2017) and by some gaps found in the series, and on the second hand by the different source of these data from the other meteorological input. Furthermore, a preliminary analysis that we carried out on 19 years (from 2000 to 2018) of cloud cover data from the closest meteorological station, showed an overall very low seasonality in the series, (with 7 oktas (87%) being the most probable value for all seasons and 65% being the overall mean value) and no interannual trend. The absence of strong climatic trends for the area of interest in terms of cloud cover is confirmed by Pfeifroth et al. (2018).
>
> We therefore decided to use the constant calibrated value of sky cloudiness in order to achieve the best results in terms of simulated water temperature against our set of hourly averaged water temperature observations. In any case, this led to very good model performances during both calibration and validation.
>
> Finally, we think that the calibration of the parameter to a value of 80% does not introduce considerable biases in our work, even in the long term study, also given the non-negligible uncertainty that affects cloud cover observations.

- Also, a constant water transparency is used in the long-term model runs, despite the data indicate a strong transparency variability on seasonal scales. How this assumption affected the model predictions on stratification patterns? Will the time-variable Secchi depth change the modeling results?

> **Authors' response:** We chose a constant and calibrated value of the Secchi depth for two main reasons. First of all, no Secchi depth records were available for the long term simulation (before Spring 2015). Furthermore, the Secchi depth in the study site can vary suddenly between 0.8 m and the whole water column depth according to short term (one or two weeks) phytoplankton bloom events that occur between February and October. Because of the lack of long term data and the difficulty in defining a clear seasonal pattern for Secchi depth, we decided to test if a constant value would be sufficient to get good performances. We therefore performed a calibration and then used the calibrated value as a constant input of the model. As we obtained very good performances during both calibration and validation, we decided to keep it constant for this study.
>
> However, it is indeed a strong simplification that is further discussed in the revised draft.

- I do not believe that the trends in solar radiation and wind are monotonic (Fig. 3bc). A change point detection analysis should be performed here (e.g. B.K. and Tsay, R.S., 2002. Bayesian methods for change-point detection in long-range dependent processes. Journal of Time Series Analysis, 23(6), pp.687-705., or any other similar approach) with subsequent piecewise trend estimation.

Authors' response: Thank you for this remark. Just like you, we had thought of applying piecewise trend estimation on this two variables, but as the overall monotonic trends were significant, we did not do it in the initial version of the article. To follow your suggestion, we carried out a change point analysis using the Matlab function "findchangepts" (Matlab 2020b). It showed for both solar radiation and wind speed the existence of a change point at the end of the 1980s (1988 and 1987, respectively), as shown here in Figure 4. This fact was only qualitatively addressed in the submitted version, but is more clearly discussed in the revised draft.

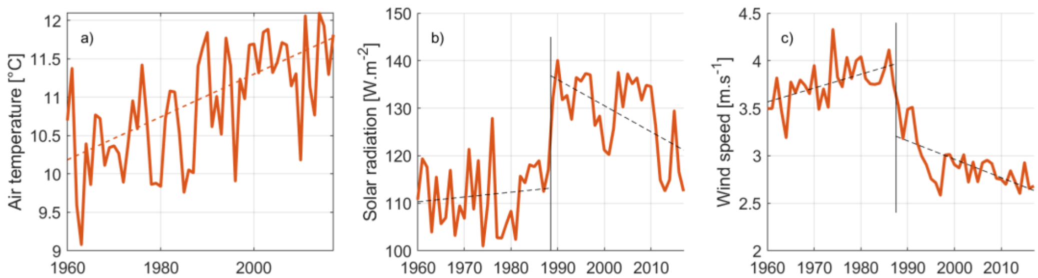

Figure 4: Mean annual averages for air temperature, solar radiation and wind speed, with change point detection.

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