We thank the reviewer for constructive comments and provide our answers hereunder.

RC2

Råman Vinna and colleagues have used a coupled climate-hydrological-temperature model setup with different levels of representation of reality (fidelity) to simulate river temperatures in Swiss rivers, including future climate projections. They include extreme temperatures and ecological thresholds in their analysis. The topic and scope are rather similar to the Michel et al. (2022, cited in text) paper, also published in *HESS*, but they expand on it by their multi-model approach and additional analysis of thresholds, extremes, and hysteresis. The paper is well-written, clear, and comprehensive, and I did not have major comments, only some minor and mostly technical ones that I outline below.

Minor and technical comments:

- 24 -> “but also in rivers where…”

Corrected.

- 239: -> “inverse stratification”

Corrected.

- 261: I cannot find Table C2. I assume you meant B2?

Yes, it is B2. Corrected.

- 332: “refiling” or “refilling”?

Refilling, corrected.

- Figure 3: Change y-axis to “Water temperature”

Corrected.

- 357: -> “straightforward”

Corrected.

- 362-373: I like this definition of a severity index

Thank you, yes, it is neat to be able to compare across temporal scales and between scenarios.

- 421: “at” or “for”

Corrected.

- 450: -> “from, for example, …”

Corrected.

- The caption of Table 3 mentions yellow marking which does not occur in the table.

It should be *italic*. Table 3, B9 and B10 caption has been updated.

- 525-528: It is unclear from this sentence what vital principle is referred to..

Section reworked, on line 581 to 596 it now reads

4.1 Multi-fidelity modeling approach

> The use of semi-empirical models by definition means that some of the physical processes affecting heating is simplified under parameterization and some are directly resolved. The models air2stream and air2water resolve the effect of river depth, discharge, thermal signals from tributaries, inverse stratification in lakes during winter, and seasonal cycles. Parts of the heat balance (e.g. short and longwave radiation) is thus not allowed to change as climate change in our study. However indirectly we consider heat budget changes by using high quality air temperature and discharge projections as input. Glacier retreat is included in the hydrological models providing discharge projections to this study (eg. Muelchi et al., 2021), however for temperature this effect is only indirectly considered in air2stream and air2water through reduced water availability in summer. The effect of high altitude warming as snow and ice recede is not included. Therefore as the cooling caused by melt water recedes, it is expected that warming in high altitude rivers is larger than projected in this study. Yet the lower fidelity water temperature model approach using high-fidelity climate/hydrological model outputs as input enable the important principle of multi-model ensemble, comparison and analysis that is required for robust climate change impact assessments (Duan et al., 2019).

- 552-556: Are there 15 or 16 Alpine stations?

This study includes 16 Alpine stations. Note that station 2462 is not shown in Figures 6 and 7 since Model M_4 lacked 30 years of data.

- 585: -> “Rhône”

Corrected.

- 584-586: Could you rewrite this sentence? It is not clear whether lakes or rivers warmed faster in the cited reference.

Paragraph on line 637 to 648 rewritten to:

In terms of overall warming, the strongest warming on an annual basis emerged for stations in the Alpine thermal regime, followed, in order, by stations in the Downstream Lake, Regulated, Swiss Plateau, and Spring thermal regimes (Figure 4). The strong warming of Alpine regime stations has its origins in the strongest near-surface air temperature warming trend in summer that is occurring in southern parts of Switzerland (CH2018, 2018). The strong warming in the Downstream Lake thermal regime can be explained by the extended residence time of water in lakes compared to rivers in general (allowing longer time for waters to heat up) and to a difference in seasonal patterns, aspects that the employed air2water model explicitly considers. A previous coupled modeling study by the author showed that future lake surface waters (epilimnion) heat faster compared to river waters, with a difference in warming trends between Lake Biel and the Aare River of +0.03 °C per decade and between Lake Geneva and the Rhône River of +0.11 °C per decade (Råman Vinnå et al., 2018).

- 625: “brown trout’s” -> “brown trout”

Corrected.

- 675-676: 0.37 °C/decade over 11 decades would be a 4 °C increase. Could you double check the numbers? Moreover, the Results mention a 3.18 °C increase total and 0.36 °C/decade, so please standardise these values.

Corrected. The change is from 2020 to 2099 (8 decades) corrected in manuscript. Line 707 to 710

According to the simulations, for the high emission climate scenario (RCP8.5), average river water temperatures across Switzerland will increase by 3.2 °C (0.36 °C per decade from 2020 to 2099), while under the low emission scenario (RCP2.6) temperatures increase by only 0.9 °C.

- Discussion: One major process for river temperature in the studied systems seems to be the role of disappearing glaciers and snow cover. This is also likely an important factor for changing hysteresis patterns. The discharge models used in the paper may take this into account, but air2water/air2stream do not (e.g. L. 280). It may be valid to assume a nonlinear response of river temperature to disappearing snow/ice that may not be reflected well in the training data (especially for Alpine streams and their low number of stations with long measurement time series). It would be good to add a short paragraph to the Discussion on how this may affect the projections in this paper.

Section 4.1 line 581 to 607 now reads:

The use of semi-empirical models by definition means that some of the physical processes affecting heating is simplified under parameterization and some are directly resolved. The models air2stream and air2water resolve the effect of river depth, discharge, thermal signals from tributaries, inverse stratification in lakes during winter, and seasonal cycles. Parts of the heat balance (e.g. short and longwave radiation) is thus not allowed to change as climate change in our study. However indirectly we consider heat budget changes by using high quality air temperature and discharge projections as input. Glacier retreat is included in the hydrological models providing discharge projections to this study (eg. Muelchi et al., 2021), however for temperature this effect is only indirectly considered in air2stream and air2water through reduced water availability in summer. The effect of high altitude warming as snow and ice recede is not included. Therefore as the cooling caused by melt water recedes, it is expected that warming in high altitude rivers is larger than projected in this study. Yet the lower fidelity water temperature model approach using high-fidelity climate/hydrological model outputs as input enable the important principle of multi-model ensemble, comparison and analysis that is required for robust climate change impact assessments (Duan et al., 2019).

To expand on previous results of river water temperature projections for Switzerland (Michel et al., 2022), we employed a multi-fidelity modeling approach able to automate the generation of water temperature simulators for the different national river temperature monitoring stations of Switzerland, as summarized in Figure 1. Models of varying complexity were built from integrating high-fidelity climate and hydrological modeling outputs (i.e., downscaled climate (Table 1) and hydrological model outputs (Figure 2a), CH2018 and Hydro-CH2018) with low-fidelity river temperature models of varying degrees of parametrization i.e., air2water and air2stream (Toffolon & Piccolroaz, 2015; Piccolroaz et al., 2013). Statistical learning-based coupling of atmospheric and hydrological stations (Table 2) and classification of river stations into thermal regimes (Figure 2b & 2c) enabled optimal low-fidelity model selection (Figure 2d) and parametrization.