Interactive comment on “Anthropogenic Influence on the Rhine water temperatures “by Alex Zavarsky and Lars Duester

Anonymous Referee #1Received and published: 26 November 2019

Introduction:
We would like to sincerely thank both reviewers for the comments and thoughts about our work and this manuscript. We think that the input significantly improved the manuscript.

*Based on the reviewers comments and by reviewing the code once again transposed numbers were found in the coding. By correcting the calculation method ACC*w provides the lowest RMSE and largest NCS in three out of four station. At the same time we were able to further decrease the RMSE for the ACC*w calculation method. The reasons for the ACC*w resulting in lower RMSE compared to ACC or w only, is now described in detail in the methods section. Overall, the results (correlations, RMSE, NCS, ∆RBTcalc) changed only so slightly, that the scientific conclusion and the key messages were not influenced. This also visible in the attached track changes version of the manuscript.*

GENERAL COMMENTS

The manuscript presents a study of short term and long term changes in river temperature and investigates the influence of natural and anthropogenic drivers of these changes which is interesting and generally within the scope of HESS. River temperatures at various monitoring locations along the river Rhine as well as industrial production and nuclear power plant activities are analyzed. The authors further develop a novel approach of calculating a catchment-wide average air temperature which is used in the linear regression relationship between air and river temperature. Overall, the scientific approach and the methods appear to be valid. However, there are some points which need further clarification:

(1) The relationships between river temperature and its drivers are investigated using multiple linear regressions separating the so-called Rhine base temperature (i.e. the river temperature without influences of air temperature and discharge) and air temperature and discharge influences on river temperature. More information on the multiple linear regressions for each location is required for the reader to be able to evaluate the robustness of this approach

*Comment: The RMSE and the NCS information is provided for every measurement station. In addition, the data is now included in the supplement. We used the year 2001 as a test year and regressed Tw using Tc and Q just for this year. Then the 2001 regression coefficients were used to calculate a modelled Tw for the years 2000 to 2018. The RMSE and NCS show better results compared to the long term regression, which is sensible for a shorter regression period. The RMSE and NCS for each year from 2000 to 2018 follow the same pattern among the calculation methods. This means that the ACC*w method is always the best at three stations and the methods without time lag always show a larger RMSE than the ones with time lag*

(2) The computation of the catchment-wide average air temperature is based on the air temperature in each grid cell of the catchment area and the hydrological distance to the river

temperature monitoring station assuming a constant flow speed. It would be interesting on what basis the constant flow speed has been derived and how the flow speed varies in space and time and what is the justification of combining a rather complex averaging method of air temperature with a constant flow speed. In order to show the benefits of this rather complex method, benchmarking with simple approaches (e.g. Catchment average air temperature in combination with constant lag time, as in Pohle et al., 2019) is suggested.

Comment: In our model, the flow speed does not vary in space and time. Generally, the flow speed in the shipping channel is between 1 m/s and 2 m/s. This is supported by ADCP round robin tests (https://www.bafg.de/DE/05_Wissen/02_Veranst/2007/10-09-07_bericht.pdf?__blob=publicationFile) which showed a average flow speed of 1.2 m/s. Using the Koblenz data as reference we tried several flow speeds to minimize the RMSE of the model. We found a minimum of RMSE at 0.4 m/s. This is in the extended-range flow speeds. We expected a higher correlation at lower flow speeds than actually measured in the Rhine as we do not model standing water bodies. To us a flow speed with a magnitude difference would be questionable, but the one used is within reasonable limits.

(3) A data filter is used to compare river temperature and gross domestic product. It would be interesting how the filter parameters have been chosen and how sensitive the results are to different values of these filter parameters.

Comment: We used a Butterworth band-pass filter instead of a running mean filter because the filter function of a butterworth is much easier to understand and it simply cuts all variations that are outside of the pass area.
In this manuscript everything with a periodicity of 20 years (0.05 y^{-1}) or longer is cut off. The reason is to eliminate long term trends, because the aim is to compare RBT to the GDP change.
The lower limit is 0.9 years (1.1 y^{-1}). Fast variations (faster than a year) of the RBT could influence the correlation vs a data-set (here the GDP) which is provided on a yearly basis. Therefore we smoothing is needed.

(4) As short-term and long-term changes of river temperature and its drivers are presented, it would be interesting to know if the data also show statistically significant trends and change points. The introduction section would benefit from more information and references to recently published literature. Also, the results need to be discussed with reference to related work and including appropriate reference to studies on river temperature. To that end, the authors are suggested to further familiarize with recently published studies on factors influencing river temperature (e.g. Garner et al., 2017; Lisi et al., 2015), river temperature modelling (e.g. Ketabchy et al., 2019; Wondzell et al., 2019; Zhu et al., 2019) as well as short-term and long-term changes in river temperature and its drivers (e.g. Basarin et al., 2016; Caldwell et al., 2015; Isaak et al., 2018; Pohle et al.,2019).The manuscript is overall well-written and structured. The results section includes many statements which would be better suited in the methods section. Further, I suggest adding a separate discussion section.

Comment: Thank you for pointing out additional literature. We added the rescaled adjusted partial sums to the manuscript. We checked trends of Tw and Ta at the four measurement stations and differences are visible. These differences are in accordance with our hypothesis that the progress of Tw at Worms, Koblenz and Mainz cannot be fully explained by the trend of Ta.

SPECIFIC COMMENTS

Page 1 – line 22 probably it is better to use “physical based” than “physical”. Also, please check whether “deterministically” is the right term – probably it is referred to statistical models?

Comment: Thank you, we changed the wording.

Page 2 – line 6/7 Is the statement by Markovic true for all rivers? (Their paper refers to Elbe & Danube.)

Comment: We added the information that their study is based on Elbe and Danube data. As these two rivers are more or less comparable in size and catchment area to the Rhine, we think and also show that consistent results are given.

Page 2 – line 20 The equation is very specific and may be better suited in the “methods “part.

Comment: Thank you for the comment, but the fundamental idea of our hypothesis is to use the regression coefficients as explanation for changes in Tw. Therefore we need a simple linear Ta→Tw model. We want to present this idea and thought process in the Introduction. This is also done because we want to explain why we do not use hybrid, exponential models.

Page 2 – line 21 Suggestion to define coefficients already directly below the equation.

Comment: Thank you, we changed it.

Page 2 – line 25/26 Is this statement universal or only valid for the rivers studied in the cited papers – in that case please name these rivers.

Comment: We reorganized the references and specified to which subject the references addressed.

Page 3 – line 3 what is the original temporal resolution of the datasets? What were the procedures for quality control and have there been missing values?

Comment: The original resolution is 10 min. We added a line to missing values and resolution in Sec. 2.1. The quality control is done by the sources. They initially verify the data-set. Additionally, the data-set was screened by us for suspicious features.

Page 4 – Fig. 1 Please revise the map: make the river Rhine more visible, include monitoring stations and NPPs. Do the time lags refer to hydrological distance or to the grid? How have 0.733 m/s been derived? How robust is this number – I would assume spatial & temporal variability of flow speed.

Comment: We revised Fig. 1 which is now Fig. 2. The NPPs and measurement stations are now also included. We also describe in Sec. 2.7 how we obtained the flow speed and compare it to measured flow speeds.

Page 5 – tab. 2 How exactly have these values been derived?

Comment: We changed the table caption and added a few sentences in the "weighing coefficients" subsection, answering the question.

Page 7 – line 10 Sentence not needed.

Comment: We removed this sentence.

Page 7 – line 13-15 Suggest moving sentence to "methods" section.

Comment: These lines briefly explain Fig. 3. Hence, the authors think it should better remain in the Results section.

Page 8 – Fig. 3, tab. 3 Suggest adding 2nd figure column for air temperature. Merge figure and table (i.e. add slope values to the table). Please check robustness of number of digits of slopes, also state whether slopes are statistically significant.

Comment: We reduced the number of digits and added R^2 values and a significance statement. We also added Ta in the figure and the RAPS index for trend analysis.

Page 8 – line 3 Which difference? It is stated that Ta warming rates are not really different.
Comments: We added "from each other" to clarify this sentence.

Page 9 – line 3/4 Please be more specific what is meant with "average European river"

Comment: We removed this part.

Page 9 – line 9/10 Move to "methods" section.

Comment: This is a brief reminder and explanation for Tab. 5. We prefer to keep it there.

Page 9 & 10 Combine tab. 4 & 5 and highlight the best model for each criterion & location

Comment: We combined the tables and highlighted the best model.

Page 11 - tab. 6 what does "GW" stand for? Omit "the table shows"

Comment: Thank you, we replaced GW with "ΔHi [GW]". We removed "the table shows".

Page 11 – line 16 What is meant with "on average constant" – what time step does the average refer to?

Comment: The sentence was completely revised. P 16 Line 289.

Page 11 – line 25 Why has this particular company (BASF) been chosen?

Comment: It is close to the measurement station Worms and also provides significant heat input. We added this information to the manuscript.

Page 12 – line 2 Provide test statistics for significance or reword.

Comment: We omitted the word significant.

Page 14 – line 2 Linear models have also been applied elsewhere. However, it is unclear from this sentence how a linear relationship between air and river temperature implies universal applicability of the method presented in this paper. Furthermore, Morrill et al. found a better fit of non-linear models which might be even more pronounced outside of the tropics (i.e. conditions when air temperature, unlike river temperature, goes far below 0∘C)

Comment: The scope of this paper is not only finding a better (lower RMSE) way to model Tw, but to apply coefficients of a linear regression to better explain trend in Tw. more precise (etc.) models might be available, but most of them don't allow to distinct between anthropogenic, meteorological and hydrological impacts. If they allow this distinction, they are very labor-, time-, staff- and computing capacity intensive. This is not the case for the model proposed by us.
Morrill et al. found suitable linear relationships between Ta and Tw for rivers around the world. This was a prerequisite for our analysis.

Page 15 – line 8 for reproducibility, please also name the data providers.

Comment: The data providers are mentioned in the methods section.

TECHNICAL CORRECTIONS

Page 1 – line 2/3 Sentence unclear – please revise.

Comment: Changed.

Page 1 – line 15 What does "their" refer to?

Comment: It refers to: energy intensive industries such as power plants, oil refineries, paper or steel mills. Changed to: "Its availability is a basic requirement for the facilitie's location (Förster and Lilliestam, 2010).

Page 2 – line 8 Please revise sentence structure.

Comment: We revised the sentence.

Page 2 – line 16 Please correct spelling to "assess"

Comment: Thanks we changed it.

Page 2 – line 24 Is the Markovic reference at the correct position of the sentence?

Comment: We changed the position.

Page 3 – tab. 1 Move table into methods section.

Comment: It is in the methods section. The final formatting is applied by Copernicus.

Page 3 – line 13 Please correct to “European Centre for Medium-Range Weather Forecast”.

Comment: Sorry, an awkward mistake. We changed it.

Page 3 – line 23 Hydrological distance between what? Noun missing.

Comment: Corrected.

Page 4 – line 12 Please consider moving reference to end of sentence.

Comment: We moved them.

Page 6 – line 3 “2019” instead of “20019”

Comment: We corrected it.

Page 7 – line 2 Better “reunification” as “unification” refers to 1871.

Comment: Typo, corrected.

Page 9 – line 9&10 Nash-Sutcliffe (“e” missing”).

Comment: We added an e.

Page 12 – Fig. 5 Y-Axis missing for Worms.

Comment: We added the axis.

Page 12 – line 3 Remove duplicate “by a”.

Comment: Thanks, corrected.

Page 13 – line 2 Check spelling of “Mineralölraffinerie“ and use the official name “Oberrhein” instead of “Karlsruhe”.

Comment: We changed that.

Page 13 – line 2 Use Author (Year) citation format.

Comment: That’s the formatting prescribed by Copernicus.

Page 14 – line 2 Remove given name from reference.

Comment: Changed.

Page 14 – line 10 Sentence unclear – “and” missing?

Comment: We corrected it.

Page 14 – line 15 Use Author (Year) citation format. Suggest to use “physical-based

Comment: That’s the formatting prescribed by Copernicus.

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Reviewer 2

Interactive comment on “Anthropogenic Influence on the Rhine water temperatures” by Alex Zavarsky and Lars Duester

In this study, the authors analyze the effects of Nuclear Power Plants on river water temperature of the Rhine. The authors propose a multiple linear regression model where river water temperature is simulated based on air temperature and streamflow as predictor variables. Air temperature is evaluated through an averaging procedure that accounts for the geomorphology of the hydrological catchment. The intercept of the multiple linear regression models is used as a proxy for the anthropogenic impact on river water temperature and is compared to the time series of GDP and heat input from NPPs. The presentation of the methodological approach and of the results should be improved, both in terms of clarity and quality. In my opinion the robustness of some methodological aspects is weak (e.g., the use of a constant flow velocity, the interpretation of the multiple linear regression intercept as "indicator for industrial heat input") and the discussion of the results should be expanded and deepened. The literature review on modeling of river water temperature and assessment of anthropogenic impacts should be updated and the grammar and syntax of the manuscript should be checked carefully. Please, find below some specific comments.

Introduction by the authors:
We would like to sincerely thank both reviewers for the comments and thoughts about our work and this manuscript. We think that the input significantly improved the manuscript.

*Based on the reviewers comments and by reviewing the code once again transposed numbers were found in the coding. By correcting the calculation method ACC*w provides the lowest RMSE and largest NCS in three out of four station. At the same time we were able to further decrease the RMSE for the ACC*w calculation method. The reasons for the ACC*w resulting in lower RMSE compared to ACC or w only, is now described in detail in the methods section. Overall, the results (correlations, RMSE, NCS, ∆RBTcalc) changed only so slightly, that the scientific conclusion and the key messages were not influenced. This also visible in the attached track changes version of the manuscript.*

Specific comments

Introduction:

The literature review on modeling of river water temperature should be expanded and updated including the most recent studies in this field. Besides "classical" deterministic and statistical models, there is a wide range of models based on machine learning techniques or hybrid physically-based/statistical approaches (e.g., Sahoo et al., 2009;Toffolon and Piccolroaz, 2015; Sohrabi et al., 2017), which have been emerging in the last years. Despite it is not recent, I suggest giving a look to the review paper by Benyahya et al. (2007), which provides a good overview of deterministic and statistical models used in the field of river water temperature prediction. Another useful and more recent paper is that by Gallice et al. (2015).

Comment: Another thorough literature search was undertaken and we added among other references, the references proposed the reviewers. The overview of water temperature models was extended in the introduction.

In addition, the authors should refer also to existing literature on the assessment of anthropogenic impact on river water temperature (e.g., Cai et al., 2018; Gaudard et al., 2018; Raman Vinna et al., 2018,just to cite some recent papers).

Comment: The publications were cross-checked. The input was included in the revision of the manuscript.

In general, I believe that the paragraph from P1, line 19 to P2, line 8, should be thoroughly restructured and revised, and the authors should be more precise throughout the text (e.g., at P1, line 22: I believe that the authors intend deterministic and statistical models here; at P2, lines 21-23, the sentence is unclear; at P2, lines 25-26, the comment is superfluous since in a multiple linear regression, such as the one used by the authors, these components are obviously neglected). P2, lines 7-8: I would rephrase this sentence in more general terms, because the amount of variance in river water temperature explained by air temperature and streamflow are strongly dependent on the case study (hydrological regime, season, etc.).

Comment: Thank you for the comments. We revised the whole introduction. The changes we made can be seen in the track changes version.
P2 lines 25-26: We know that our model does exclude ground heat flux and friction. If the parameters are important they would appear most likely and unfortunately in the regression coefficient a1. However, a1 is the basis of our analysis which should display the anthropogenic heat input We just want to say that we think these heaf fluxes are neglible and do not interfere with our anthropogenic heat input.
In this regard, the authors should expand the analysis of parameters a2 and a3 of their regression model. The second half of the Introduction (from P2, line 16) should be moved to the methods section and should be improved, as in its current form it does not clearly describe how the authors set up their analysis, especially concerning the definition and use of RBT as an "indicator for industrial heat input" and the time resolution of the data used in the multiple linear regression analysis.
Figure 1 This figure should be updated with the location of the monitoring station and of the NPPs. The main course of the Rhine should also be indicated.

Comment: We changed Figure 1. In the introduction we give just a basis overview of our *idea which is closely linked to the linear regression model. We moved some parts to the methods section. The detailed calculations are described in the methods section.*

Section 2.1. I agree on the comment about accuracy and precision, however I wonder if the measurements are affected by instrumental drift and, in case, if the dataset has been corrected accordingly.

Comment: The data was verified by the data provider(e.g., by recurrent validation measurments, recalibration if needed or cross-validation). The data-set was screened for suspicious features. We stated this in the manuscript.

P3, line 9: this sentence is unclear. In general, I agree that water temperature is rather homogeneous at a river section if it has a compact geometry, while it may be non-uniform if the geometry is complex.

Comment: We know that the measured water temperature, especially in complex river geometries, is an on-spot in-situ temperature and could be different from a cross-section average Tw. However, a method benefit of this analysis is that only the water temperature differences are needed. If the measured Tw changes and the cross-section Tw does, accordingly.

Section 2.2.Here the authors used a constant flow speed to evaluate the flow time required to travel from a cell of the catchment to the catchment outlet. The authors should clarify how they selected this flow speed and if it is reasonable to assume a constant value (was this velocity the same for the four outlets?). I wonder about the methodological robustness of the approach proposed by the authors since they applied the same flow velocity to all cells pertaining to the catchment, thus both to hillslope and river network cells. In this regard, I also do not fully agree on the sentence at P5, lines 21-22 since before reaching the channel network, rainfall may follow different paths (infiltration,C3runoff, etc.), thus exchanging heat with the surrounding environment and decreasing its correlation to Ta.

Comment: In our model, the flow speed does not vary in space and time. Generally, the flow speed in the shipping channel is between 1 m/s and 2 m/s. This is supported by ADCP round robin tests (https://www.bafg.de/DE/05_Wissen/02_Veranst/2007/10-09-07_bericht.pdf?__blob=publicationFile) which showed a average flow speed of 1.2 m/s. Using the Koblenz data as reference we tried several flow speeds to minimize the RMSE of the model. We found a minimum of RMSE at 0.4 m/s. This is in the extended-range flow speeds. We expected a higher correlation at lower flow speeds than actually measured in the Rhine as we do not model standing water bodies. To us a flow speed with a magnitude difference would be questionable, but the one used is within reasonable limits.

P3, line 20:

Comment: We changed the wording.

P4, line 1

Comment: We changed the wording

Section 2.3
The authors state that parameter a1 (the intercept) summarizes all effects that are not directly ascribable to Ta and Q, which "are mostly from anthropogenic sources". Personally, I do not agree that, in general, the value of a1 can be unequivocally related to anthropogenic factors.

Comment: Of course there is no proven, but this the hypothesis. We are able to strongly support this hypothesis by comparing changes in anthropogenic heat input (nuclear power plants) and short term economic changes to a1 and draw a consistent picture in the manuscript.

The authors should support this statement referring to previous literature on the topic. In this regard, a useful reading is Isaak et al (2011), where also the multiplicative interaction term has been included in the multiple linear regression model.

Comment: We reviewed all citations, thank you for the hints. If applicable we changed the manuscript. Especially, the different methods for modelling Tw are described now more detailed in the introduction.

Variablesx_0,y_0, and in eq 2 are not defined. Table 2 (and corresponding description in the main text): the authors should provide details on why they assumed a linearly deceasing weighting factor instead of other weighting functions.

*Comment: We added an explanation of x,y. We revised our model and use now ACC*w as weighting factor. The reason for a linear decrease cannot be answered within this manuscript and more research is needed.*

While the weighting factors decreases with Δt, I expect that T_w is no more correlated to T_a after some time. The authors obtain the best results using the "Time lag" model instead of the "Time lag + weight" model, saying that the furthest and oldest T_a influences on T_w are still carried as information in the water mass (P9, lines 4-5). In my opinion, the real reason is that without assuming a deceasing weighting factor the authors increase the dependence of current river water temperature on previous conditions, thus implicitly accounting for the thermal inertia of the river. This is an important aspect controlling river water temperature, which is not explicitly included in the model proposed by the authors and that can be accounted for e.g., through autocorrelation terms (e.g., Caissie et al., 2001; Toffolon and Piccolroaz, 2015).

Comment: We think that the reason for using a weighting factor decreasing is a) to put less weight on the large amount of grid-points with less ACC and b) to put less weight on temperatures with a large Δt.
Autocorrelation is an option but we decided not use it for this model.

Control scenarios I would use a different word than "scenarios" here, since these are not scenarios but different approaches to calculate T_c.

Comment: Changed.

Section 2.4 The authors should explain how they calculated the heat input by NPP to the Rhine. The section should be expanded, and the sentences harmonized to make the reading more fluid (too short sentences).

Comment: We moved the explanation of the NPP heat input to the methods section and revised it.

Figure 3 and Table 3 Figure 3 would benefit from the inclusion of the air temperature time series with the corresponding linear trends. This would be useful for better understanding the correlation between river water temperature and air temperature fluctuations, which are filtered out when using linear trends. In this regard, it would be useful to add the Pearson correlation coefficient between these two variables in Table 3.

Comment: We added air temperature to the figure. We also added the RAPS index to make trends more visible.

At P8, lines 12-15 it would be useful to compare the trends found by the authors with those of more recent studies.

Comment: We removed this section. The focus of the paper is on providing reasons for the heterogeneous Tw trends in the Rhine river, an urgent matter in regulative river heat evaluation in times of climate change.

Tables 4 and 5 Why did the authors use the "Time lag weight" approach for all other results instead of the "Time lag" approach, which performed the best? It should be clearly indicated if the RMSE and NSC refer to daily or annual values.

Comment: As mentioned before (first page of this document), the data was reanalyzed. As a consequence the tables and parts of the results were revised. The scientific conclusion was not changed.

Section 3.3 It is unclear how the authors evaluated RBT over time. Did I correctly understand that they applied the multiple linear regression model for overlapping two-year time windows shifted by one month? What was the rationale of assuming two-year time windows instead of longer periods? Are the results affected by the length of the time window used for this analysis?

Comment: Longer time windows would decrease the temporal resolution of the regression. A shorter time window increases the influence by other linear dependent influences. The two *years were chosen to address two full annual cycles. If a year was extraordinary concerning air temperature or discharge, a two year cycle would not be prone to such events.*

P10, line 2 these sentences are qualitative, and not sufficiently supported by the results.

Comment: We changed the wording. We add that we cannot meaningfully interpret the absolute value RBT.

P11, line 4: these sentences are qualitative, and not sufficiently supported by the results.

Comment: The similar trends are supported by the analysis comparing calculated ∆RBT with measured ∆RBT.

The comment on the effect of alpine lakes is not well connected to the rest of the paragraph and should be expanded with some more detailed discussion.

Comment: We just hypothesize why Basel has such an alternating RBT. However, the RBT does not show a long term trend over the whole dataset. Finding the reason is not in the scope of this paper.

Eq 10 is dimensionally not consistent.

Comment: Thank you, we missed the density. Changed.

How did the authors select the periods in Table 6?

Comment: The start of the period is the time of the maximum heat input by NPPs at the respective station. We added this information to the text.

The authors could do the same calculation in continuous, for the entire period when the data are available (e.g., using the same two-year time windows as before).

Comment: This would be a good idea. However, tha aim was to use a time windows with the largest signal to noise ratio. Therefore we picked the largest ∆HI to avoid influences by short term trends.

P11, line 16: what is the BASF company? This should be explained.

Comment: We added two sentences to explain the BASF.

Why RBT in Figures 4 and 5 are different? How sensitive are the results of the correlation analysis to the filtering of the data?

Comment: Figure 5 has filtered RBT.
We used a Butterworth band-pass filter instead of a running mean filter because the filter function of a butterworth is much easier to understand and it simply cuts all variations that are outside of the pass area.
In this manuscript everything with a periodicity of 20 years (0.05 y^{-1}) or longer is cut off. The reason is to eliminate long term trends, because the aim is to compare RBT to the GDP change.
The lower limit is 0.9 years (1.1 y^{-1}). Fast variations (faster than a year) of the RBT could influence the correlation vs a data-set (here the GDP) which is provided on a yearly basis. Therefore we smoothing is needed.

How the filtering parameters have been chosen and why 480 days has been used to shift the GDP-change time series? This number seems quite arbitrary.

Comment: It was shifted to ensure a visual match between the two data-sets (GDP and RBT). The shift can be explained by lagging and leading economic factors. This is explained in the manuscript. Mathematically the 480 days shift does not yield the largest positive correlation.

Appendices could be moved to the main text. In particular, the sentences in Appendix B should be revised because they have some syntax errors and typos. Figures A1 andA2 are inverted and the caption is the same. The analysis of parameters$a_2$and$a_3$should be deepened and moved to the main text.

Comment: We move the biggest part of the appendix into the main text, as advised.

Technical corrections

P1, line 13: "but an" –> "but is an". Is "means of production" an appropriate term in thiscontext?

Comment: Thank you for the hint. We think means of production is appropriate.

P2, line 3 and following lines: the use of "Ta –> Tw" is informal and should be modified.

Comment: Thank you for your comment but we would like to keep it that way.

P2, line 8: "hydro-logical" –> "hydrological"

Comment: We changed it.

P2, lines 8-9: a reference is needed here.

Comment: This part has been moved and we added a reference in this sentence.

P2, line 16: is "revise" the most appropriate term here?

Comment: You are right. We use “test” now.

P2, line 20: "almost ideal" –> "ideal", "interesting", "meaningful"

Comment: Thank you, we changed it.

P4, line 13: "followed, by" –> "followed by". Please, thoroughly revise the punctuationthroughout the article (use of commas, missing close-brackets, etc).

Comment: We completely revised this part. The sentence is now rewritten.

P5, line 17: "ptovided" –> "provided"

Comment: We changed it.

P6, line 1: I would say that authors present four$T_c$calculations, not two.

Comment: We revised this part completely.

P6, line 18: "heat input by NPPsto the Rhine" –> "heat input by NPP to the Rhine"

Comment: We changed it.

P8, line 5: "(0.0350°Cy^{-1})" –> "(0.0489°Cy^{-1})"

Comment: We completely revised this table.

P10, line 15: "over the a time period" –> "over a time period"

Comment: Thank you, we changed it.

P11, line 1: "shorter timer scale but do not seem,to our" –> "shorter time scale but doC6 not seem, to our"

Comment: Thank you, we changed it.

P11, line 14: "A a discontinuity" –> "A discontinuity"

Comment: Changed.
P11, line 19: "by a by a" –> "by a"

Comment: Changed.

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Anthropogenic Influence on the Rhine water temperatures

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Abstract. River temperature is an important parameter for water quality and an important variable for physical, chemical and biological processes. River water is also used by production facilities as cooling agent. We introduce a new way of calculating a catchment-wide air temperature and regressing river temperature vs air temperatures. As a result the meteorological influence and the anthropogenic influence can be studied separately. We apply this new method at four monitoring stations (Basel, Worms, Koblenz and Cologne) along the Rhine and show that the long term trend (1979-2018) of river water temperature is, next to the increasing air temperature, mostly influenced by decreasing nuclear power production. Short term changes on time scales < 5 years are due to changes in industrial production. We found significant positive correlations for this relationship.

1 Introduction

River water temperature (T_w) greatly influences the most important physical ~~, chemical and ecological~~ and chemical processes in rivers and is a key factor for river system health (Delpla et al., 2009). T_w also defines and confines ~~ecological~~ animal habitats (Isaak et al., 2012; Durance and Ormerod, 2009) and the spread of invasive species (Wenger et al., 2011; Hari et al., 2006) and is therefore an important ecological parameter. River water is not solely important from an environmental perspective but is an important means of production. Especially for energy intensive industries such as power plants, oil refineries, paper or steel mills, river water is an important cooling agent. Its availability is a ~~reason for the choice of their~~ basic requirement for the facilities location (Förster and Lilliestam, 2010). In this context, one has to bear in mind, that given a 32 % energy efficiency, 68 % of the energy used in a facility is discharged through the cooling system into the respective stream (Förster and Lilliestam, 2010). This leads to a significant heat load even on large rivers such as the Rhine (IKSR, 2006; Lange, 2009). As a consequence, anthropogenic heat fluxes (heat discharge) can contribute significantly to the heat budget of a river. The natural influences on T_w are: [1] Meteorology, including sensible heat flux, latent heat flux, radiative heat fluxes; change in riparian vegetation [2] Source temperature, which describes the origin of the water, e.g. snow-fed, glacier-fed, groundwater-fed; [3] Hydrology, which influences the water temperature through the amount of water and the flow velocity; [4] Ground heat flux. Dependent on data availability, computing power, accuracy and the questions asked, T_w can be modeled in ~~two ways, physically or deterministically.~~ different ways. The common options are statistical models, physical based models and modeling by neural networks. Neural networks use a sample teaching data set to train artificial neurons the relationship between input (e.g. air temperature) and output (T_w) (Zhu et al., 2018). A physical T_w model (Sinokrot and Stefan, 1993) parameterizes all fluxes mentioned in [1] and [3], adds anthropogenic heat input and collects the hydrological and source boundary conditions [2] and [4]. Each modeled heat flux is then applied to the water mass, initialized with the starting and boundary conditions. However, it is difficult to get a good estimation of these parameters over ~~the catchment areaof a large river~~a larger catchment area. As a consequence, statistical models use air temperature (T_a) as a proxy for sensible, latent and radiative heat fluxes (ground heat flux can be neglected) and establish a $T_a \rightarrow T_w$ relationship through regression. T_a is rather easily available from meteorological networks or reanalysis products. This is a well established method and depending on the complexity, linear or exponential models (Stefan and Preud'homme, 1993; Mohseni et al., 1998; Koch and Grünewald, 2010) are used. Generally the exponential model has advantages due to the better simulation of extremely warm and cold ~~$T_a \rightarrow T_w$ relationships~~ T_w but lacks the clear ~~analytical~~ analytic separation of the ~~different~~ influences to T_w. Using linear models, Markovic et al. (2013) show that between 81 % ~~-90~~- 90 % of the T_w variability can be described by T_a. 9 % ~~-19~~- 19 % can be attributed to hydrological factors (e.g. discharge). The study was done for the Danube and Elbe basin using data from the 1939 to 2008. These two rivers have comparable size and catchment area to the Rhine river. Hybrid models are in between physical based and statistical models. They use physical formulation of fluxes but determine their parameters stochastically (Piccolroaz et al., 2016). Another development are spatial statistical models. They correlate various landscape variables (e.g. elevation, orientation, hill shading, river slope, channel width...) across the catchment area and try to statistically determine their influence on T_w at a certain point. These correlations can be across any distance and do not have to satisfy flow connection or direction in the river system. As a prerequisite, a detailed knowledge about the river system and its characteristics is needed (Jackson et al., 2017a, b). An improvement to spatial statistic models is to recognize rivers as a network of connected segments with a definite flow direction(Hoef et al., 2006; Hoef and Peterson, 2010; Isaak et al., 2010; Peterson and Hoef, 2010; Isaak et al., 2014). Correlation of the variables (e.g. T_a, T_w discharge, ...) which influence other T_w, is weighted on their flow connectivity and euclidean or flow distance. These models can also include time lag considerations using temporal auto correlation (Jackson et al., 2018).

1.1 Rhine

Along the Rhine, up to 12 nuclear power plants (NPP) have caused~~for decades~~ , for decades, the largest part of anthropogenic heat input ~~in the river~~(Lange, 2009). The nuclear power production increased in the 1970s and 1980s and reached a peak in the mid 1990s. After the Fukushima disaster in 2011, the German government decided to exit from nuclear power production and the first NPPs were shut down. With this political decision a clear drop on nuclear power production ~~was~~ is visible, on top of already decreasing production rates. Currently (July 2019) eight NPPs are operational in the catchment area of the Rhine using (partly) river water as cooling agent. In this publication, we hypothesize that, next to environmental factors, this long term decrease in power production together with short term economic changes have an impact on T_w of the Rhine. This impact might be heterogeonous along the river as the location of industry and NPPs is concentrated at several highly industrialized spots.

To ~~revise the hypothesis and asses~~ test this hypothesis and assess the varying impact of industry, meteorology and hydrology on the Rhine river temperatures, we ~~run a multiple regression model~~ want to combine ideas from the spatial correlation models to develop a new method of calculating a representative catchment air temperature (T_c). T_c and discharge Q is then used in a multiple linear regression $T_c \rightarrow T_w$ (Eq. 1). The model is run on a T_w time series from 1979 to 2018 measured at four Rhine stations (Basel (CH), Worms (DE), Koblenz (DE) and Cologne (DE)). The period from 1979 to 2018 experienced several changes in anthropogenic heat input to the Rhine catchment area, which makes it an ~~almost ideal~~ interesting scenario to be studied. ~~T_w is regressed with a catchment-wide air temperature T_a and river discharge Q, Eq. 1.~~

$$T_w = a_1 + a_2 \cdot T_c + a_3 \cdot Q \tag{1}$$

a_1, a_2 and a_3 are the resulting regression coefficients ~~.~~

$$\cancel{T_w = a_1 + a_2 \cdot T_a + a_3 \cdot Q}$$

which describe the magnitude of the respective fluxes (anthropogenic, meteorological and hydrological). T_c is the newly proposed catchment temperature and Q the discharge at the measurement station. The origin of water, e.g. ground water, snow melt, glacier melt, is included by ~~the catchment wide approach where T_a at~~ T_c because data from high elevations (e.g. Alps) is also included. ~~Webb et al. (2003)~~ Webb et al. (2003); Markovic et al. (2013) have shown that Q is inversely related to T_w and an important factor ~~(Markovic et al., 2013) in the $T_a \rightarrow T_w$~~ in the $T_c \rightarrow T_w$ relationship. Additionally, it functions as measure of how fast a the water mass responds to changes in T_w. Ground heat flux, ground water influx and heat generation due to friction are not included in this model because of the comparable small influence ~~(Sinokrot and Stefan, 1993; Webb and Zhang, 1997)~~ ~~.~~ (Sinokrot and Stefan (1993) for Mississippi; Caissie (2006) as review article). Other models such as hybrid models (Toffolon and Piccolroa would create lower RMSE but do not allow for a clear distinction between meteorological, hydrological and anthropogenic input.

Using the multiple regression (Eq. 1), we aim to especially investigate the change of a_1 over time, which we call the Rhine base temperature (RBT). This temperature represents the T_w without the influence of meteorology and discharge. RBT is an indicator for industrial heat input and the use of Rhine water as cooling agent. We hypothesize that its long term change is connected with the electricity production of NPPs and its short term variations is connected with overall industrial production and general economic indicators. Using different time series along the Rhine, we investigate where anthropogenic heat fluxes may influence T_w and may lead to an overall heterogeneous warming rate along the Rhine.

2 Methods

2.1 Water temperature and discharge

We use a data-set of daily averaged T_w and Q from 1979-2018 gathered from different sources (WSA, 2019; BfG, 2019; LfU, 2019; BAFU, 2019). ~~Table 1~~ The original data-sets have a 10 min sample frequency. Table (1) lists the respective stations along the Rhine (Col. 1), stream km (Col. 2), data availability (Col. 3), the important tributaries upstream (Col. 4) and the reference

name	stream km	time period	important tributary upstream	reference
Cologne	KM 690	1.1.1985-31.12.2018	Mosel	WSA (2019)
Koblenz	KM 550	1.1.1978-31.12.2018	Main	BfG (2019)
Worms	KM 443	1.1.1971-31.12.2018	Neckar	LfU (2019)
Basel	KM 170	1.1.1977-31.12.2018	Aare	BAFU (2019)

Table 1. Lists of monitoring stations used in this study. Column two provides the location as Rhine km. Column three provides the data range. The third column names the important upstream tributary and column four names the reference.

(Col. 5). T_w was measured by platinum resistivity sensors (Pt100). The accuracy of theses sensors is commonly ±0.5 ^{o}C but the precision, which describes the ability to detect temperature changes, is 0.05 ^{o}C. As we focus on the change T_w over time and do not compare the absolute temperature, the accuracy is not essential and the precision is sufficient. Errors inflicted by measuring depth and location in the river are also not influencing the calculation, regarding the aim of this study, as long as the measured T_w is a linearly dependent proxy for the average river temperature. Q is provided as daily averages in m^3~~s^{-1} by the reference (Tab. 1~~ ^{3}s^{-1} by the source in Tab. (1) and usually calculated from river stage).

The original data-sets have already been verified by the respective source but are screened by us for suspicious features. Missing data points up to one week are linearly interpolated. Longer data-outages and recurring data-outages are not experienced. The data-set is provided by state and federal operated monitoring stations which usually run backup measurement systems.

2.1.1 ~~Air temperature~~

2.2 Air temperature

T_a is retrieved from the European Centre for ~~Meridional~~ Medium-Range Weatherforcast (ECMWF) Reanalysis Model ERA5. It provides an hourly time resolution of the 2 m T_a on a $\frac{1}{4}^o$ by $\frac{1}{4}^o$ grid. The data-set is available from 1979-2018. We took the hourly T_a output and calculated a daily mean for each grid point between 1979 and 2018 to fit the time resolution of T_w.

2.3 ~~Catchment Area~~Nuclear Power Plants

The annual electrical power production by NPPs is available from the International Atomic Energy Agency (IAEA) Power Reactor Information System (IAEA, 2019). At most 12 NPPs (1986-1988) were online in the Rhine catchment area. Separate blocks of one NPP are combined. In July 2019 eight were operational. All shutdowns were done in Germany.

From estimates by Lange (2009) and based on personal communication from different sources, the heat input by NPPs to the Rhine is calculated for each monitoring station, Fig. (1). The NPPs in Tab. (2) are included in the heat input calculation through a conversion factor which converts electrical produced power to heat input. NPPs with an exclusive river water cooling system have a conversion factor of three, which is based on the power efficiency of electricity generation. Other factors are estimated depending on the cooling system used and personal communication.

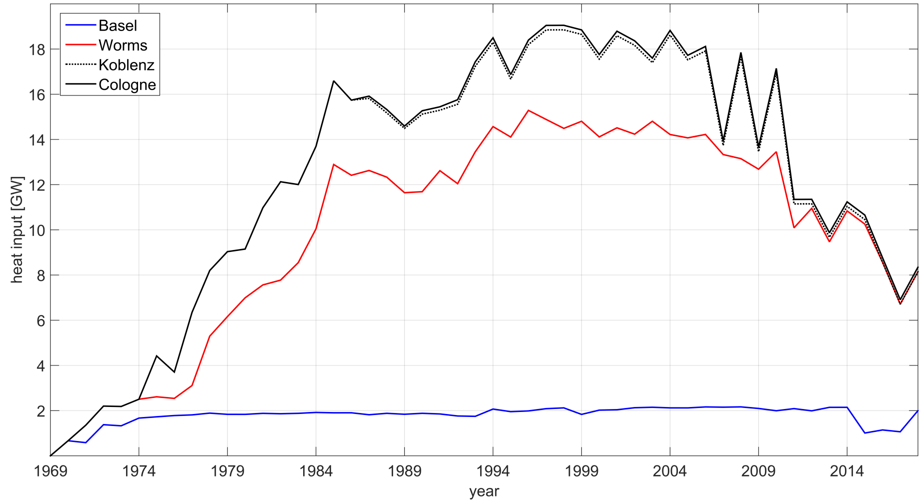

Figure 1. Using the PRIS (IAEA, 2019) database we estimated the heat input by NPPs from 1969 to 2018. This figure shows the total upstream heat input of each monitoring station.

name	country	river	conversion factor	const. heat input
Beznau I+II	CH	Aaare	3	N/A
Biblis I+II	DE	Rhine	2	N/A
Cattenom I-IV	DE	Mosel	N/A	200 MW
Fessenheim I+II	FR	Rhine	3	N/A
Goesgen	CH	Aare	N/A	50 MW
Grafenrheinfeld	DE	Main	N/A	200 MW
Leibstatt	CH	Rhine	N/A	50 MW
Muehleberg	CH	Aare	3	N/A
Neckarwestheim I+II	DE	Neckar	1	N/A
Obrigheim	DE	Neckar	3	N/A
Philippsburg I+II	DE	Rhine	1	N/A

Table 2. NPPs included in this manuscript. The coversion factor describes the conversion from electrical power generation to heat input. If cooling towers are installed a constant heat input is used based on Lange (2009).

2.3.1 Calculated temperature change

We calculate the expected change in RBT (ΔRBT) based on a change in heat input (ΔHI) by NPPs using the average discharge $\bar{Q}$, the heat capacity of water c_p and the water density ρ, Eq. (2).

$$\Delta RBT = \frac{\Delta HI}{c_p \cdot \bar{Q} \cdot \rho} \quad (2)$$

This approach follows the idea that the heat input of NPPs is essential for the heat budget of the river and significantly alters RBT as other important influences, such as meteorology (a_2) and hydrology (a_3), are excluded by applying the multiple linear regression.

2.4 Gross Domestic Product

The gross domestic product (GDP) for the adjacent German federal states is obtained from VGdL (2019a, b). Due to changes in the calculation method of the GDP before and after the German reunification (1991), two separate data-sets are used. For this study only the GDP-change of the secondary sector (construction and production) is used.

The RBT, if compared to the GDP, is filtered using a 10^{th} order butterworth bandpass filter. The sampling rate of the GDP is $1\ y^{-1}$. We use $1.1\ y^{-1}$ as higher and $0.05\ y^{-1}$ as lower cutoff frequencies for RBT. This means that signals with a periodicity larger than 20 y and lower than 0.9 y are excluded. The reasoning is to make the RBT data comparable to the yearly data of the GDP-change. The low frequency cutoff is canceling long term trends as a GDP-change is only related to the previous year. The high frequency cutoff is used to dampen fast alternating RBT signals in comparison to the slow sampled GDP data.

2.5 Rescaled adjusted partial sums

Rescaled adjusted partial sums (RAPS) is used to visualize trends in time series which may not be clearly visible in the time series itself. Equation (3) shows the calculation of the RAPS index (X) using a time series Y.

$$X_k = \sum_{i=1}^{i=k} \frac{Y_i - \overline{Y}}{\sigma_Y} \tag{3}$$

$\overline{Y}$ is the average over the total time series, σ is the standard deviation of the whole time series, Y_i is the ith data-point in Y. A change in the slope of the RAPS index only indicates a change in the slope of the original time-series. A negative RAPS slope does not indicate a negative slope in the original time series. Garbrecht and Fernandez (1994); Basarin et al. (2016) used this method to investigate trends in hydrological time series.

2.6 Catchment area

The catchment area ~~was~~ is calculated using the Hydrosheds database (Lehner et al., 2008). The $\frac{1}{125}^o$ by $\frac{1}{125}^o$ gridded data-set provides information, at each grid point, to which cell the water of a grid cell is drained. Selecting a starting location, e.g. Koblenz at 50.350 ^{o}N and 7.602 ^{o}E it is possible to iteratively ~~calculate~~ identify all grid points draining into this location. These grid points represent the catchment area of this location, in this ~~case~~ example Koblenz. By counting the iteration steps, the distance a water drop travels to reach the monitoring station Koblenz is determined. This ~~was~~ is done for each station. Additionally, the accumulation number ACC ~~was calculated~~is obtained from the data-set. It defines how many cells in total are draining into a particular cell and is a measure for the size of a river. Finally, a grid, which defines the catchment area, the ACC and the hydrological distance ~~between was~~ is established spanning the whole catchment area. Figure ~~2~~ (2) shows the catchment area, the ~~distance calculations~~ hydrological distance and the calculated flow time to the Koblenz monitoring station.

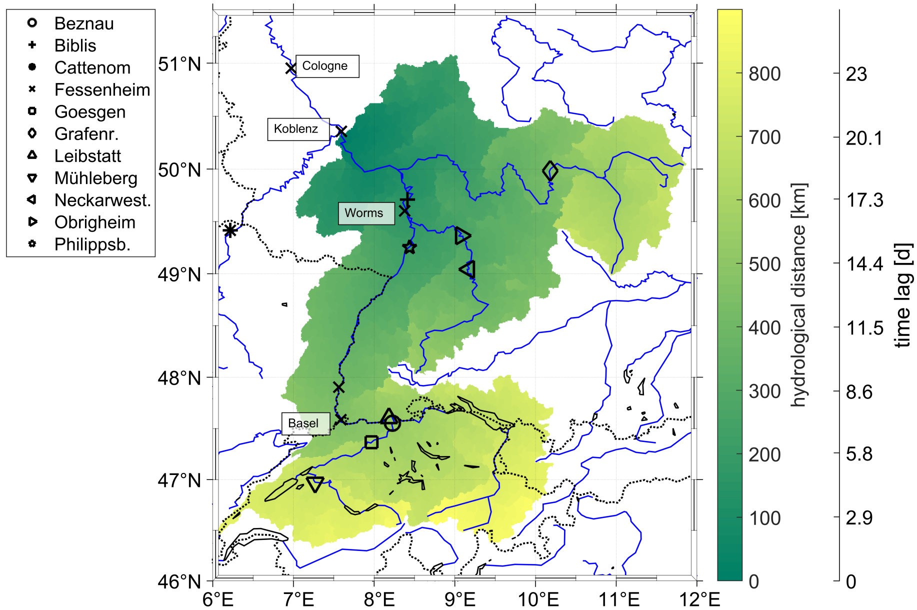

Figure 2. Catchment area of the Koblenz monitoring station. The colors show the hydrological distance between the monitoring station and each grid point of the catchment area. The second y-axis shows the time, in our model, it takes to flow from a grid point to the monitoring station based on the hydrological distance. The flow speed is ~~0.733~~0.4 ms^{-1} and in this study constant in space and time. The Xs with the name-tag Basel, Worms, Koblenz and Cologne mark the monitoring stations. The other markers show the location of the NPPs. For names refer to the legend.

Accumulation

ACC is an estimate for the river size. Grid points of large rivers which are fed by many grid points have a large ACC. Figure 3 shows the distribution of the ACC. Each grid points is given the the number of grid points discharging into this very grid point. Large rivers, such as the Rhine, Main, Neckar are easily visible.

2.7 Multiple regression

We use a multiple linear regression to separate the ~~meteorological, hydrological and anthropogenic~~ anthropogenic (a_1), meteorological (a_2) and hydrological (a_3) contributions to the river water temperature. T_w is regressed with ~~T_a~~ T_c and river discharge Q. Their regression coefficients a_2 (~~T_a~~ T_c slope) and a_3 (Q slope) represent the magnitude of the respective influences. The offset a_1 ~~, which we call RBT,~~ (RBT) combines all other influences, which are ~~mostly from~~ controlled by anthropogenic sources. ~~Instead of using~~ The linear regression is improved by using a new method for calculating T_c. Instead of taking T_a at the monitoring station, we improve Eq. ~~1 by averaging~~ (1) by a time dependent average of T_a (x,y,t) over the whole, Eq. (4). (x,y) are spatial coordinates in the catchment area and ~~make T_a time dependent. We call this new parameter catchment temperature~~ a

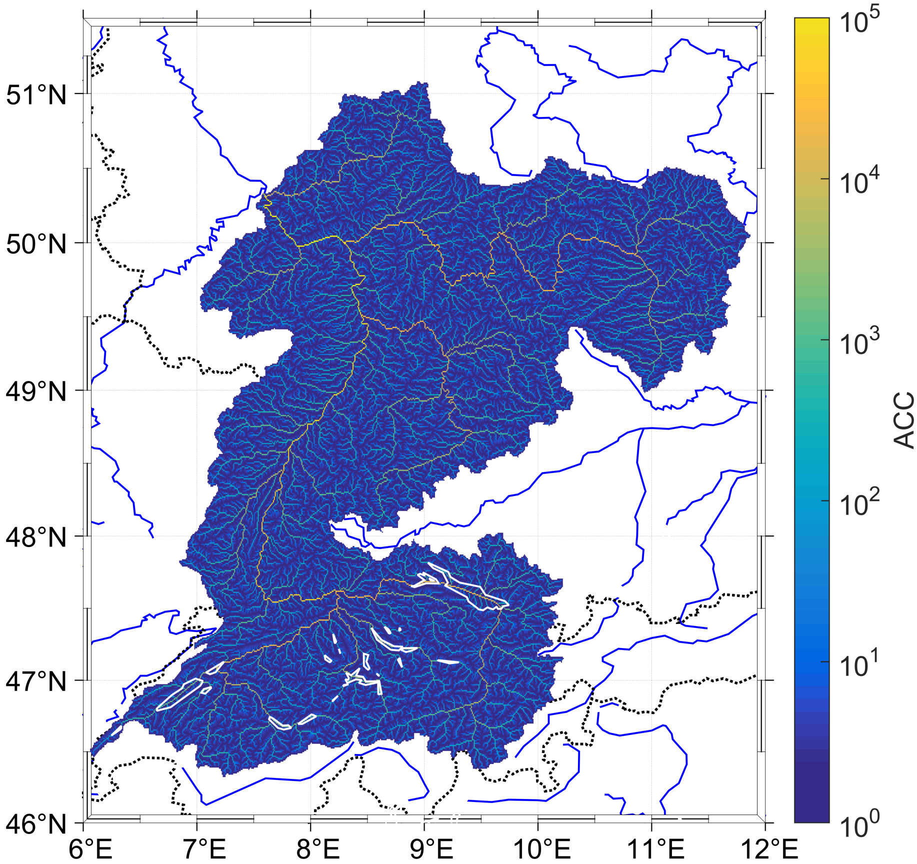

Figure 3. Catchment area of the Koblenz monitoring station. The colors show the number of grid points flowing into the specific gird point

subscript $_0$ marks the location of the measurement station.

$$T_w(t_0) = a_1 + a_2 \cdot T_c(x, y, t_0 + \Delta t(x, y)) + a_3 \cdot Q(x_0, y_0, t) \quad (4)$$

The new representative catchment temperature is called T_c. ~~T_c is defined by the location (x,y) and a time lag (~~The difference between the measurement time t_0 and the reading of T_a is called time lag Δt~~).~~ (x,y) and depends on the hydrological distance between the measurement point and the reading.

~~$T_w(t) = a_1 + a_2 \cdot T_c(x, y, t + \Delta t) + a_3 \cdot Q(x_0, y_0, t)$~~

Time lag

~~**Time lag and T_c**~~

~~Linear as well as exponential models have already introduced Δt (Stefan and Preud'homme, 1993; Webb and Nobilis, 1995, 1997) to the $T_a \to T_w$ relationship.~~ A change in ~~T_a at a location is certainly followed, by a change of T_w to restore equilibrium~~

~~conditions. The first reason~~ T_w is slower than a change in T_a. The time lag Δt describes this lagging and is commonly used in water temperature models.

A reason for the occurrence of Δt is that the water ~~masses~~mass' mixing capability, heat capacity and surface area cause a strong thermal inertia. ~~Secondly, advection is not taken into account when~~ Changing T_w through new meteorological conditions and heat fluxes take time. Therefore, linear as well as exponential models either use a fixed Δt for T_a (Eq. 5) or an average of T_a including a time span before (Eq. 6) (Stefan and Preud'homme, 1993; Webb and Nobilis, 1995, 1997; Haag and Luce, 2008; Benyaha et al. .

$$T(t_0) = T_a(x_0, y_0, t_0 + \Delta t) \tag{5}$$

$$T(t_0) = \sum_{t=t_o}^{t=\Delta t} T_a(x_0, y_0, t_0) \tag{6}$$

A second reason reason for a mismatch is advection. T_a is measured at the same location and the very same time as T_w. ~~The Rhineexhibits~~ Rivers, in this case the Rhine, exhibit current velocities which enable its water to cover significant distances on time scales larger than days. Therefore it is necessary to take ~~advection and~~ the change of T_a, in space and time, during advection into account. ~~Haag and Luce (2008) suggest to use T_a at the same location of the measurement but include the days before to extend the temporal significance. This approach is shown in Eq. ??.~~

$$T_a = w(t_0) \cdot T_a(x_0, y_0, t_0) + w(t_0 + \Delta t) \cdot T_a(x_0, y_0, t_0 + \Delta t) + w(t_0 + 2 \cdot \Delta t) \cdot T_a(x_0, y_0, t_0 + 2 \cdot \Delta t) \ldots$$

~~Time dependent weighing factors $w(t)$ are used to average $T_a(t)$ at different times before the measurement. A linearly decreasing $w(t)$ is used~~This is especially important for daily averaged T_w (Erickson and Stefan, 2000). Pohle et al. (2019) average eight days of hydroclimatic variables over the whole catchment area, Eq. (7). However, this approach ~~satisfies the idea of thermal inertial but~~ does not include ~~advection. Hence, we extend this idea of a time lagged $T_a(x_0, y_0, t_0 + \Delta t)$ from the location of~~ the ~~T_w measurement to the entire catchment area. All grid points and therefore all possible water streams in the catchment area are assigned with~~ characteristics of flow path and flow speed.

$$T(t_0) = \sum_{x=0, y=0, t=0}^{x=n, y=m, t=8} T_a(x, y, t) \tag{7}$$

We combine and extend both ideas (Eq. 5, 6 and 7) and average T_a over the whole catchment area but each grid point is linked to a specific time lag $\Delta t(x, y)$. ~~Using directional discharge maps (Sec. 2.6) and gridded temperature reanalysis data (Sec. 2.2), we propose this new 3D (x, y, t) averaging of T_a and call it the catchment temperature T_c, Eq. 9.~~

$$T_c(t) = \frac{1}{\sum w(\Delta t(x, y))} \sum_{x=1, y=1}^{x=n, y=m} w(\Delta t(x, y)) \cdot T_a(x, y, t + \Delta t(x, y))$$

Δt [d]	weighing factor	distance from measurement point [km]
0	1	0
~~-1.0588~~-1.01	~~0.9412~~0.96	~~67~~35.1
~~-2.1176~~-2.00	~~0.8824~~0.92	~~113~~69.6
~~...~~-5.02	0.81	174.6
	...	
-13.01	0.50	452.5
	...	
~~-18~~-26	0	~~1140~~904

Table 3. This table defines the weighing factors for ~~different time lags~~ the distance and ~~distances from~~ the ~~measurement point. The weight coefficient is linearly correlated to~~ resulting Δt for the ~~time lag~~monitoring station Koblenz. ~~Once the time lag~~ Δt is calculated from distance and flow speed~~(~~, Eq. (8)~~only the time lag~~. The weighing coefficient is ~~used in further calculations~~linearly correlated to the Δt.

~~$T_c(t)$ is calculated by weighted averaging $T_a(x,y,t)$ over all grid points of the catchment area (x=1,...n y=1,~~ $\Delta t(x,y)$ is dependent on a fixed flow speed v and the hydrological distance s(x,y) to the measurement point, Fig. (2). ~~..m)which arrive at the monitoring station at time t. The time lag Δ t is the time it takes for a water droplet from a specific grid point in the catchment area to the measurement location. This time can be calculated using the distance s between each grid point in the catchment area and the measurement point and an average flow speed v , Eq. 8. Δt is per definition negative. A comparison of time lag, distance and weighing factor is provided in Tab. 3.~~ The distance is obtained from the discharge map (Sec. 2.6) and calculated with v as desctribed by Eq. (8).

$$\Delta t(x,y) = -\frac{s(x,y)}{v} \qquad (8)$$

~~For reasons of simplification, we did not use a catchment wide hydrological flow model to model the flow speed at every grid point for every hydrological scenario. Therefore we use a constant flow speed of 0.733 ms^{-1}. The weighing factors $w(\Delta t(x,y))$ are shown in Tab. 3~~

Weighing coefficients

Tobler (1970) proposed that close spatial and temporal conditions tend to be higher correlated than those further away. This leads to the introduction of the weighing factor w. We use a linear decreasing weighing factor from 1 to 0 . 1 is given the grid point closest (smallest Δt) to the monitoring station and 0 the point farthest away (largest Δt). As the size of the catchment area is different for the four monitoring station, four weight coefficient tables are calculated. Table (3) shows the weighing coefficient for Koblenz, as an example.

~~Based on Eq. 9, we calculated the daily T_c for each monitoring station. This temperature represents the meteorological influence all water droplets have experienced on their way to the monitoring station.~~

~~**Control scenarios**~~

~~As control scenarios, we introduce two additional weighing coefficients and two different T_c calculations. The first scenarios (time lag) has a weighing coefficient equal to one for all grid cells, Eq. 10~~For reasons of simplification, a catchment-wide hydrological flow model is not used estimating the flow speed at every grid point for every hydrological scenario. Therefore, the flow speed of 0.4 ms^{-1} is set constant. This flow speed is determined by calculating RMSE with a step wise reduction of the flow speed from 1.5 ms^{-1} to 0.3 ms^{-1}. The lowest RMSE at Koblenz is obtained at 0.4 ms^{-1}. The weighing coefficient w is combined with ACC. ACC is used as a second coefficient which over-weighs grid points with large accumulation and therefore large water masses. This ensures a balance between the large number of low ACC grid points, which carry less water, with the influence of T_a on large water masses. Figure (4) shows the product of ACC and w over the whole catchment area of Koblenz.

$$w\left(\Delta t\left(x,y\right)\right)=1 \qquad T_c\left(t\right)=\frac{1}{n\cdot m}\sum_{x=1,y=1}^{x=n,y=m}T_a\left(x,y,t+\Delta t\left(x,y\right)\right)$$

~~The second scenario (time lag + ACC) is weighingby numbers of grid cells flowing into a particular cell.We call this the accumulation control. The ACC takes into account how much water is accumulated in a specific cell, Eq. **??**, which~~ We also calculate the number of grid points in several ACC bins. The red bars in Fig. (5) show the relative contribution of each ACC group using only their quantity without ACC*w weighing. This shows that the large amount of low ACC (small water mass) grid points would have a large influence over large ACC (e.g. large water masses, rivers, lakes) grid points. The difference is four powers of magnitude. The white bars show the relative contribution using the ACC*w weighing. This distribution gives rather equal importance to all grid points as it puts more weight on ~~large rivers.~~ grid points covering lakes and rivers. The average difference is about 1 power of magnitude.

$$w\left(x,y\right)=ACC\left(x,y\right) \qquad T_c\left(t\right)=\frac{1}{\sum ACC\left(x,y\right)}\sum_{x=1,y=1}^{x=n,y=m}ACC\left(x,y\right)\cdot T_a\left(x,y,t+\Delta t\left(x,y\right)\right)$$

~~The third scenario (no time lag) has a weighing coefficient equal to 1 and does not include a time lag, Eq. 12. It is a plain average over catchment wide T_a at the time of the measurement.~~

T_c

$$w\left(x,y\right)=1 \qquad T_c\left(t\right)=\frac{1}{n\cdot m}\sum_{x=1,y=1}^{x=n,y=m}T_a\left(x,y,t\right)$$

~~The fourth scenario (~~Combining Δt with ACC*w weighing and the gridded temperature reanalysis data of Sec. (2.2), we propose this new 3D (x,y,t) averaging of T_a ~~at station)uses a single value T_a for each time step at the respective monitoring~~

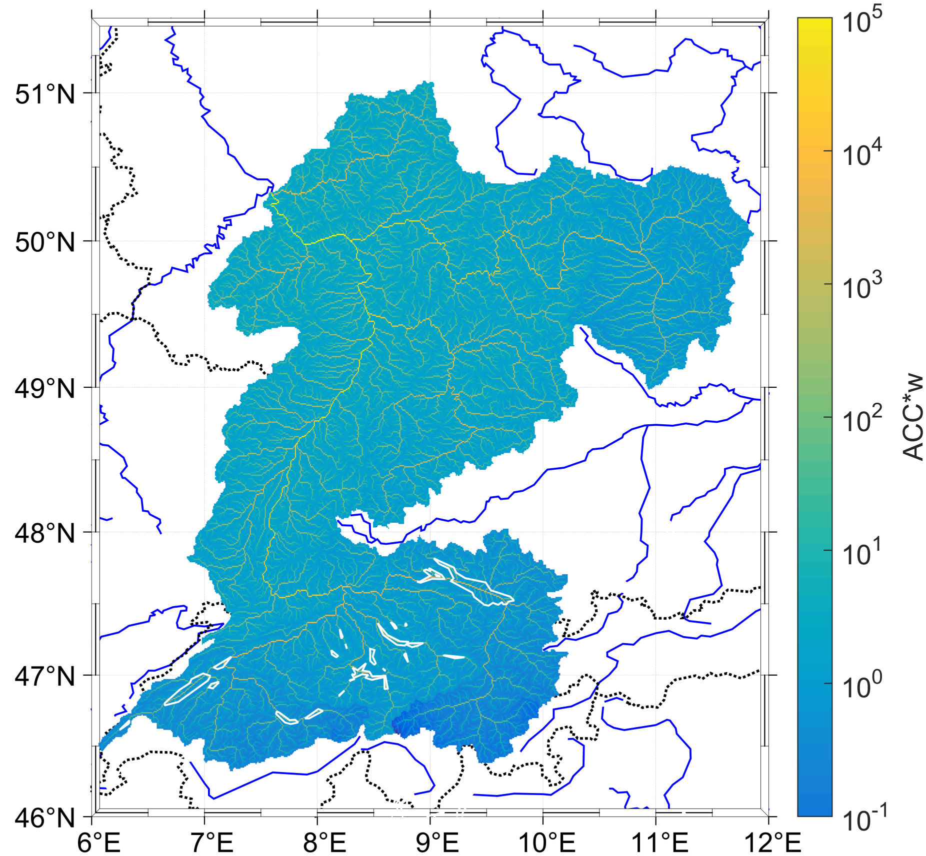

Figure 4. Catchment area of the Koblenz monitoring station. The colors show ACC multiplied with w, which is depending on the distance (Δt).

~~station~~shown in, Eq. ~~11~~(9).

$$T_c\left(t_0\right) = \frac{1}{\sum w\left(\Delta t\left(x,y\right)\right)\cdot ACC\left(x,y\right)} \sum_{x=1,y=1}^{x=n,y=m} w\left(\Delta t\left(x,y\right)\right)\cdot ACC\left(x,y\right)\cdot T_a\left(x_0,y_0,t_0+\Delta t\left(x,y\right)\right) \tag{9}$$

2.8 ~~Nuclear Power Plants~~

~~The annual electrical power production by NPPs is available from the International Atomic Energy Agency (IAEA) Power Reactor Information System (IAEA, 2019). At most 12 NPPs (1986-1988) were online in the Rhine catchment area~~ $T_c(t)$ is calculated by weighted (ACC*w) averaging $T_a(x,y,t)$ over all grid points of the catchment area (x=1,..~~Separate blocks of one NPP are combined.In July 20019 eight were operational.All shutdowns were done in Germany.From estimates by Lange (2009) and based on personal communication,the heat input by NPPs to the Rhine was calculated~~ .n y=1,...m) which reach at the monitoring station at time t_0. The time lag Δt is an estimate for the time it takes for a water droplet from a

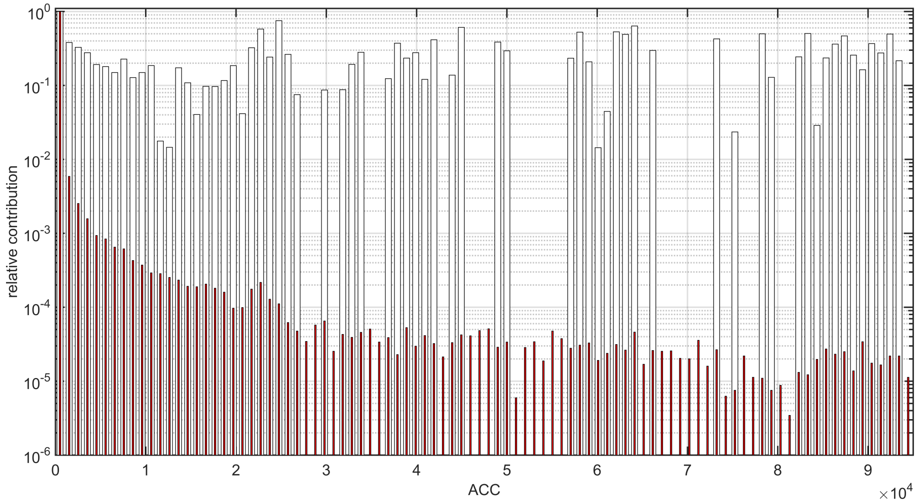

Figure 5. ACC bins (x.axis) vs the relative contribution. The red bars show the relative contribution using by number only. The white bars show the distribution using the weighing ACC*w.

specific grid point x,y in the catchment area to the measurement location. Based on Eq. (9), we calculated the daily T_c for each monitoring station~~, Fig. 1.~~

~~Using the PRIS (IAEA, 2019) database we estimated the heat input by NPPs from 1969 to 2018. This figure shows the total upstream heat input of each monitoring station.~~ . This temperature represents the meteorological influence all water droplets have experienced on their way to the monitoring station and is subsequently used in the multiple linear regression.

2.7.1 ~~Calculated temperature change~~

~~We calculate the expected change in RBT (ΔRBT) due to the change in heat input (ΔHI)by NPPS using the average discharge $\bar{Q}$ and the heat capacity of water c_p, Eq. 2~~

T_c calculation methods

We additionally use these four calculations methods, [1] w+Δt; [2] avg+Δt; [3] avg; [4] point, to compare their results of the linear regression to the calculation proposed in Eq. (9).

[1] We use only the w weight (Eq. 10) with time lag.

$$\Delta RBT\, T_c\left(t_0\right) = \frac{\Delta HI}{c_p \cdot \bar{Q}} \frac{1}{\sum w\left(\Delta t\left(x,y\right)\right)} \sum_{x=1,y=1}^{x=n,y=m} w\left(\Delta t\left(x,y\right)\right) \cdot T_a\left(x,y,t_0+\Delta t\left(x,y\right)\right) \tag{10}$$

~~This approach is based on the idea that the heat input of NPPs is essential for the heat budget of the river and significantly alters a_1 as other important influences, such as meteorology (a_2)and hydrology (a_3), are excluded.~~ [2] No weight, only time lag is used, Eq. (11).

$$T_c\left(t_0\right)=\sum_{x=1,y=1}^{x=n,y=m} T_a\left(x,y,t_0+\Delta t\left(x,y\right)\right) \tag{11}$$

2.8 ~~Gross Domestic Product~~

[3] We calculate a mean $T_a(x,y,t_0)$ over the whole catchment area at the time t_0 of the measurement, Eq. (12). Δt is not used here. ~~The gross domestic product (GDP) for the adjacent German federal states was obtained from VGdL (2019a, b). Due to changes in the calculation method of the GDP before and after the German unification (1991), two separate data-sets are used. For this study only the GDP-change of the secondary sector (construction and production)is used~~

$$w\left(x,y\right)=1 \qquad T_c\left(t\right)=\frac{1}{n\cdot m}\sum_{x=1,y=1}^{x=n,y=m} T_a\left(x,y,t_0\right) \tag{12}$$

[4] The fourth method uses $T_a(x_0,y_0,t_0)$ at the location x_0,y_0 and time t_0 of the measurement, Eq. (13). ~~The RBT, if compared to the GDP, is filtered using a 10^{th} order butterworth bandpass filter. The sampling rate was 12 y^{-1} the cutoff frequencies were 1.1 y^{-1} and 0.05 y^{-1}. This means that a signal with a periodicity larger than 20 y and lower than 0.9 y was dampened. The reason was to make the RBT data comparable to the yearly data of the GDP-change. The low frequency cutoff is canceling long term trends as a GDP-change is only related to the previous year.~~

$$T_c\left(t\right)=T_a\left(x_0,y_0,t_0\right) \tag{13}$$

3 Results

~~Using the time series of the four monitoring stations and the collected supporting data, we investigate the heterogeneity of the temperature change along the Rhine and the possible anthropogenic influence on T_w.~~

3.1 Water temperature time series

To investigate the long term change over time, we ~~fitted~~ fit a time dependent linear function to the time series of T_w and T_a (catchment average) of all four monitoring stations (Basel, Worms, Koblenz, Cologne). The same ~~was doneonly~~is also done, when all four monitoring stations ~~had~~ have an overlapping data-set (1985-2018). ~~Fig. 6~~ The left column of Fig. (6) shows the yearly averaged ~~water temperatures~~ T_w and the linear fits to the two time periods. The average T_a of the catchment area is also shown. The right column of Fig. (6) shows the RAPS index of T_a as well as T_w. The fit coefficients and the rate of warming per year are shown in Tab. ~~4. Yearly averages of water temperatures at four monitoring stations (black line). The red dashed line is a fit to the available data-set. The red dotted line is a fit to the overlapping time period. nameslope T_w whole data-setslope T_w 1985-2018slope T_a whole data-setslope T_a 1985-2018^{o}Cy^{-1}^{o}Cy^{-1}^{o}Cy^{-1}^{o}Cy^{-1}Basel0.05410.04890.05020.0497Worms0.05540.03500.0 of the linear fits to the daily temperature data. The second column is a fit to the available T_w data-set. The third column is a fit~~

name	slope T_w whole data-set~~to a study by Webb (1996) shows that the~~ [^{o}~~C warming rate for an average European river during the 20th century ($\widehat{=}$ 0.01~~ Cy^{-1}]	slope T_w [^{o}Cy^{-1}~~). Using the warming rate of this study, o~~
Basel	0.054, $R^2 = 0.66$	
Worms	0.055, $R^2 = 0.52$	
Koblenz	0.033, $R^2 = 0.31$	
Cologne	0.008, $R^2 = 0.001$	

Table 4. Slope of the linear fits to the daily temperature data. The second column is a fit to the available T_w data-set. The third column is a fit to the overlapping T_w data-set from 1985-2018. The fourth column is the rate of T_a increase in the respective catchment area during the whole data-set. The fifth column is the rate of T_a increase in the respective catchment area from 1985-2018. Next to the slope values are the R^2 values, which are statistical significant only if $R^2 > 1.99$

~~to the overlapping T_w data-set from 1985-2018. The fourth column is the rate of T_a increase in the respective catchment area during the whole data-set. The fifth column is the rate of T_a increase in the respective catchment area from 1985-2018.~~ (4). We also calculated the T_a increase in the catchment area of all monitoring stations. These slopes are shown in column four and five of Tab. ~~4~~(4).

~~Fig. 6and Tab. 4~~Figure (6) and Table (4) show that the change of T_w is heterogenous along the Rhine. The slope at Basel is approx. six times higher (0.0350 ^{o}Cy^{-1}) than the one in Cologne (0.0084 ^{o}Cy^{-1}), comparing only the overlapping data-set. However, during the same period T_a shows similar behavior at these two stations, which is an indication of similar meteorological influence. The T_w warming rate from 1985-2018 for Worms and Koblenz are in between those from Cologne and Basel. These two stations show similar T_a warming rates when comparing to Basel and Cologne. Generally, the T_a warming rates are less than 5 % different from each other. The R^2 also shows differences between the measurement stations. Basel exhibits the largest R^2 values and these are consistently high for T_a and T_w. This is in contrast to the station Cologne, where R^2 of T_w is low and insignificant. The slope of T_a at Cologne is lower than at the other stations but still significant. For T_a the RAPS indexes of all monitoring stations shows four concurrent sections (start-1987; 1987-2000; 2000-2014; 2014-end). Their borders are marked by the blue triangles in Fig. (6). The sections represent slope changes of the RAPS index and indicate trend changes in the original time-series. The T_w RAPS index for Basel shows the same pattern of sections as the T_a index. All other stations show a different RAPS T_w to RAPS T_a pattern. This means that the T_a and T_w trends of the original time-series are different at these stations. T_a can not fully describe the trends in T_w.

We hypothesize that different meteorological conditions are not the reason for this difference. Meteorological differences should be visible in the T_a warming rate of the four stations, which is not the case~~in this~~. T_a and T_w RAPS only correspond for the Basel data-set. Therefore, we applied the regression model (Eq. 4) to investigate ~~this pattern~~ the patterns of T_w in relation to T_a along the Rhine river. ~~Comparing this~~

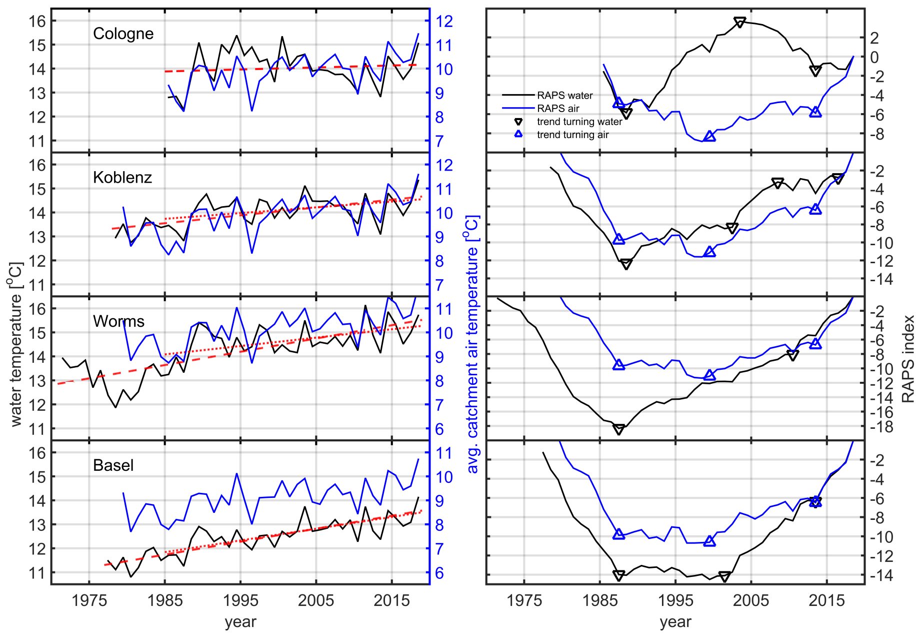

Figure 6. Left column: Yearly averages of water temperatures at four monitoring stations (black line). The red dashed line is a fit to the available data-set. The red dotted line is a fit to the overlapping time period. The blue line is the average air temperature of the catchment area. Right Column: RAPS T_w (black) and T_a (blue) indexes. The triangle markers divide the RAPS index into sections based on a slope change in the RAPS index. Each section also represent a trend change in the original T_a and T_w time-series.

3.2 RBT, long and short term trends

3.3 ~~RBT, long and short term trends~~

~~We fitted~~ We fit the multiple regression model (Eq. 4), using T_c and Q to T_w of each monitoring station for the available data-set. Afterwards, we ~~recalculated~~ recalculate T_w using the regression coefficients a_1, a_2 and a_3. From the comparison between the modeled and measured T_w, we ~~calculated~~ calculate the root mean square error (RMSE) and the ~~Nash-Suteliff~~ Nash-Sutcliffe coefficient (NSC) for each monitoring station~~(Tab. ?? and ??). As a control, to~~, Tab. (5). To support the introduction of weighing coefficients ACC*w and a catchment-wide ~~time lag, we used the four scenarios~~ Δt, we compare five different calculations of T_c from Sec. ~~2. Tab. ?? and ?? show~~ (2).

Table (5) shows the RMSE and NCS values for all ~~scenarios~~correlations. The lowest ~~RSME is 1.18~~(RMSE) and highest (NSC) values are displayed bold in Tab. (5). The lowest RSME is 1.02 ^{o}C for ~~the time lag (row two~~ACC*w+Δt (row one) at the Koblenz station. At this location also the largest NCS of ~~0.96 appearsat two scenarios, time lag and time lag+weight~~0.97 appears. We optimized the flow speed for lowest RMSE at the Koblenz station. It is evident that the ~~two scenarios with time lag~~ three methods including a Δt have a lower RMSE (below ~~1.75~~2.01 ^{o}C, lowest 1.02 ^{o}C) than the two ~~scenarios without a time lag (above 2.4~~methods without a Δt (above 2.37 ^{o}C, largest 2.97 ^{o}C). The same trend holds for NCS where the ~~time~~

descr.	Basel	Worms	Koblenz	R
~~Time lag1.681.321.181.50Time lag~~ACC*w+~~ACC~~Δt	~~1.72~~1.65	~~1.37~~**1.24**	~~1.39~~**1.02**	
~~T_a at station~~(1) w+Δt	~~2.66~~**1.56**	~~2.55~~1.33	~~2.63~~1.43	~~2.85Root mean square errors $^oC$for five scenarios. The m~~
~~Time lag~~(2) avg+~~weight~~Δt	~~0.91~~1.61	~~0.95~~1.45	~~0.96~~1.70	
~~Time lag+ACC~~(3) avg	~~0.91~~2.48	~~0.95~~2.43	~~0.95~~2.37	
~~T_a at station~~(4) point	~~0.79~~2.73	2.55	2.63	

Table 5. RSME [^oC] and NSC for ~~five scenarios~~all T_c calculation method.The ~~model is~~ regressions are applied over the ~~whole~~ total data-set. The first ~~row is~~ column contains the ~~scenarios used for all other~~ calculation method number and the method short description. The best results for each monitoring station and each calculation method are bold.

~~lag scenarios are above 0.91~~ Δt methods are above 0.90 and the other two are below 0.86. We think that the use a ~~catchment wide time lag~~ catchment-wide Δt improves the quality of the multiple regression analysis and is a significant improvement to $T_a \to T_w$ based ~~modelling~~modeling. It is interesting ~~that a time (or distance) dependent weighing factor does not improve the model output. This implies that even the furthest and oldest~~ hat combining ACC with the w weighing factor provides the best estimation. Figure (5) could be the reason. Without ACC weighing small water masses (small ACC) are over represented in the contribution to T_c. Large ACC grid points represent large water masses (rivers and lakes) and the influence of T_a ~~influences on~~ on them would be otherwise underestimated.

As the ACC*w+Δt provides the smallest RMSE, this calculation method is used for all further calculations of T_c.

In the supplement we provide a calculation of the regression coefficients for the year 2001 only. These coefficients are used to calculate T_w ~~are still carried as information by a small temperature difference in the water mass.~~ for each year from 2000 to 2018. The RMSE and NCS data is consistent in magnitude with the long-term regression of this section. The RMSE at Koblenz ranges from 0.75 ^oC to 1.22 ^oC. A lower RMSE is caused by the shorter regression period. This supports the stability and validity of our regression model.

3.3 Rhine base temperature

~~From~~ Using the multiple regression in Sec. ~~3.2 we obtained~~ (3.2), we calculate the coefficients a_1-a_3~~(Eq.~~ , Eq. (4). The magnitudes of a_2 and a_3 relate to the influences by meteorology and hydrology (discharge). a_1 is the RBT, which is an indicator for the anthropogenic impact on T_w. We use the RBT to explain differences in the T_w warming rates of Tab. ~~4~~(4). To point out changes over time, we ~~regressed~~ regress a two year segment of the T_w time series and ~~used~~ use a step size of one month to create a RBT time series over the available data-set. As the absolute RBT ~~does not have a distinct meaning~~cannot be meaningfully interpreted, only the changes of RBT over time are shown in Fig. ~~7. We subtracted~~ (7). We subtract the last data point of each time series from the rest of the data and show the change of RBT vs time and a four-year running mean. The heat input by NPPs is shown as a dotted blue line with the y-axis on the right hand side.

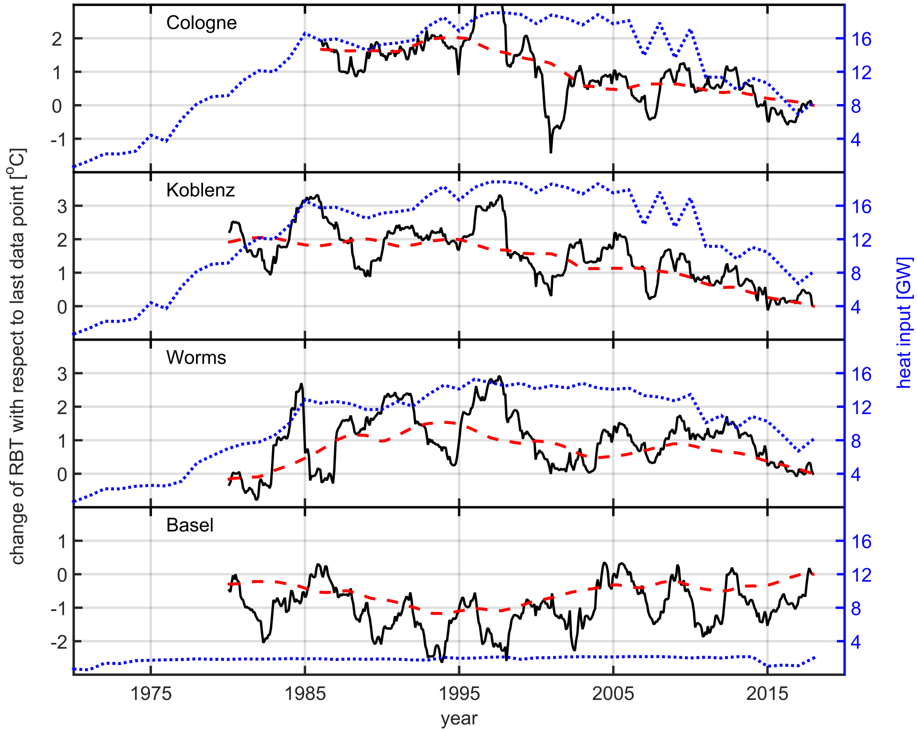

Figure 7. RBT from four monitoring stations (black solid line). The red dashed line is a four year running mean. The blue dotted line is the upstream heat input by NPPs~~(~~, Sec. (2.3).

Long term trend

In this study long term trends occur on time scales of decades. This time scale is on one hand small enough to have significance in this 40 year data-set and on the other hand covers the increase and decrease of nuclear power production.

The heat input by NPPs and the four-year running mean RBT follow a similar trend~~.~~ , Fig. (7). After the maximum of heat discharge by NPPs between 1996-1998, the heat input as well as the RBT of Worms, Koblenz and Cologne decline. At Basel the RBT as well as the heat input stay comparably constant. To investigate these similar trends we calculate ΔRBT, using Eq. ~~2~~(2), at every station and compare it to the ΔRBT from the measured T_w, Tab. ~~6.~~(6). The period for each measurement station starts at the maximum heat input by NPPs for the respective station and ends in the year 2017.

At Basel, both simulated and calculated RBT changes are negligible due to the lack of change in HI. At all other stations, the change in HI is reflected in the change of RBT. The maximum difference between simulation and calculation is ~~0.32~~0.34 ^oC. The change in nuclear power production over ~~the~~ a time period of 30 years or more can explain changes and heterogenous warming rates of T_w along the Rhine river. NPPs may also impact T_w at much shorter timer scale but do not seem, to our best knowledge, to change their power output accordingly.

name	period	ΔRBT from data-set	ΔRBT from Eq. ~~2~~(2)	Δ~~GW~~HI [GW]
Basel	2008-2017	~~-0.08~~ -0.26	0.04	0.17
Worms	1996-2017	~~1.26~~1.29	~~1.18~~1.19	7.14
Koblenz	1999-2017	~~1.55~~1.59	1.45	10.5
Cologne	1998-2017	~~1.2~~1.21	~~1.52~~1.55	10.7

Table 6. ~~The table shows the change~~ Change of RBT (column ~~3~~three) in the period given in column ~~2.~~ two. The start of the period indicates the maximum heat input of NPPs at the respective measurement station. The calculated temperature change (column ~~4~~four) and the change in HI by nuclear power plants (column ~~5~~five) are also provided. The calculations were done using Eq. (2)

Short term trend

Short term changes (< 5 y) in RBT (Fig. 7) are not influenced by the overall heat in put from NPPs, as they change production at longer time scales, but rather by local industrial conditions, which could also include fossil fuel power plants.

For Basel, we hypothesize that the varying, but ~~on average constant~~without a increasing or decreasing trend over the whole data-set, RBT is influenced by alpine lakes and natural variations. Lakes and reservoirs are to some extend decoupled from the $T_a \rightarrow T_w$ relationship (Erickson and Stefan, 2000). The upper layer (epilimnion) closely follows T_a and the temperature of the larger volume underneath is usually more stable and colder (summer) or warmer (winter). The stratification plays an important role in the outflow temperature of a lake.~~Another indication, for the weakness of the $T_a \rightarrow T_w$ model, is that the regression model has its largest RMSE (1.71 ^{o}C) at this station regarding the time lag scenarios.~~

For all other stations, we hypothesize that local production facilities and their heat input into the Rhine are responsible for the short term changes. Therefore we compare the RBT time series to economic data. ~~Fig. 8~~Figure (8) shows the comparison of RBT (black line, one year running mean) vs the changes in the GDP (blue line). A discontinuity in the GDP at 1991 is visible, due to the German reunification, when the calculation method of the GDP changed. Therefore they are plotted as separate lines. For Worms (Fig. 8, bottom panel) we added the change of turnover of the BASF company (red dashed line (AG, 1989)). ~~Its production facility~~The BASF is a chemical company. One of its largest production facility, with an estimated heat input of 500 MW to 1 GW, is located 12 km upstream (km 431) from the Worms station. We hypothesize that production and heat input changes of this factory are also visible. In 1985, although the change in GDP does not indicate a large RBT change, a ~~significant~~ RBT decrease is visible. This is backed by a turnover decrease in 1985 and 1986. After the German reunification 1991, a negative GDP change (recession) is evident. This is followed by a ~~by a~~ BASF turnover decline as well as a decrease in RBT. After that, the RBT follows the up and down movements of the GDP, so does the BASF turnover (only shown until 2000). Especially the economic events such as the burst of the dot-com bubble (early 2000s) and the mortgage crisis (2008) are visible in the RBT and the GDP, when a decrease of both parameters followed. The two events are marked with triangles in Fig. (8).

Before 1990, the RBT at Koblenz does not follow the GDP trend and shows a rather anti-cyclic behavior, which can not be explained yet. After 1991, the RBT follows the general trend of the GDP but does not seem to be strongly influenced by the

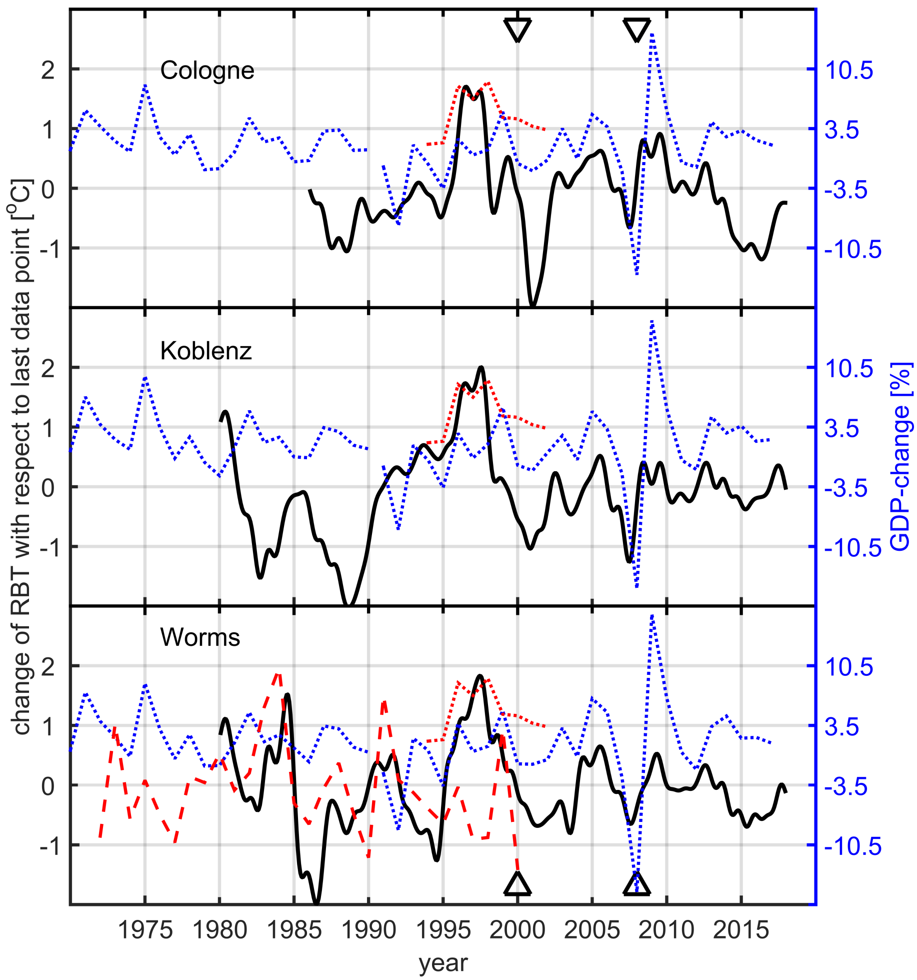

Figure 8. The change of RBT (black solid line) at three monitoring stations (Colgone, Koblenz, Worms). The blue dashed line is the GDP-change of the adjacent federal states. To explain trends during two time periods the red dashed line, which is the turnover of the BASF company, and the red dotted line, production rate of the oil refineries, are added. The triangles mark the years 2000 (burst of the dot-com bubble) and 2008 (mortgage crisis).

recession after the German ~~unification~~reunification. Again, economic events such as the burst of the dot-com bubble (early 2000s) and the mortgage crisis (2008) have influence on the RBT.

The RBT at Cologne does not seem to be strongly influenced by the recession connected to the German reunification, but after 1999 the RBT follows the up and down trends of the GDP.

For all monitoring stations, we added a red dashed line between 1995 and 1999. This dashed line indicates the production rate of German oil refineries (MWV, 2003). From 1995 to 1999 German refineries ran at full capacity level (100%). Usually the capacity levels do not exceed 90%. The increase in production is clearly visible in the RBT of Cologne, where a large oil

name	~~time-lag~~ ACC*w+~~weigh~~Δt	~~time-lag~~significance
Worms	~~0.42~~0.48	~~0.47~~p<0.05
Koblenz	~~0.52~~0.53	~~0.44~~p<0.05
Cologne	0.44	~~0.39~~p<0.05

Table 7. Spearman's rank correlations between RBT and GDP-Change for ~~two scenarios~~ACC*w+Δt. The last column shows the significance.

refinery is located 19 km upstream at km 671 (Rheinland refinery). RBT at Worms and Koblenz could be influenced by the output of ~~the~~ a refinery next to Karlsruhe at km 367 (~~Mineraloelraffinierie Karlsruhe~~Mineraloelraffinerie Oberrhein).

Correlation

We correlate the GDP-change to the filtered RBT signal. It is noticeable that we ~~shifted~~ must shift the GDP-change 480 days to the past to get matching trends. This means that a change in RBT or anthropogenic heat input appears 480 days earlier than in the GDP calculation. The shift could be caused by two reasons: [1] We are using the GDP difference of two consecutive years, which has a significance at a point of time within these two years. [2] The GDP could be lagging behind the real economic situation, in this case the industrial production. ~~(Yamarone, 2012)~~ Yamarone (2012) claims that GDP is a coincident economic indicator similar to industrial production. However, he uses quarterly GDP calculations vs our annual data. The quaterly data-set could be reacting faster to changes. A second thought is that he compares industrial production calculations, which is an economic index, to GDP (another economic index). We have basically real time data from the industrial heat input into the river. This shift ~~was~~ is not done in ~~Sec. 3.3~~ Fig. (7) because a shift of 1.5 y on a 40-year time scale is negligible.

~~Tab. 7~~Table (7) shows the Spearman's rank correlation coefficients of Worms, Koblenz and Cologne ~~for the time-lag and the time-lag~~ fo rACC*w+~~weight scenarios~~Δt calculation method, which produces the lowest RMSE in Koblenz. All correlations are positive and significant (p<0.05). The correlation ~~of the RBT data-set with weighing is slightly higher (except for Worms) than those from equally weighted T_a. The correlation~~ in Koblenz is the highest. Fig. 9 shows the filtered RBT signal vs the GDP-change at the three monitoring stations. The RBT time-series is detrended and filtered. This graph depicts in detail the correlation of GDP-change and RBT. Most of the time the change in filtered and shifted RBT is coincident, after shifting) with the GDP-change. The RBT peak from 1995-1998 is not very well represented by the GDP-change, which has already been discussed in context of Fig. 8.

4 Conclusions

We introduce a new catchment-wide air temperature T_c, which decreases the RMSE (Tab. ~~?? and ??~~5) in a ~~$T_a \rightarrow T_w$~~ $T_c \rightarrow T_w$ regression. T_c is ~~an~~ a weighted (ACC*w) average of all T_a across the catchment ~~including the improvement by using a the time lag~~ area including the use of Δt for each grid point according to the hydrological distance and flow speed. This time lag is an indicator when a measured water droplet was at a certain grid cell in the catchment area. As a result, one can get a better estimate which T_a a water droplet experienced on its way to a monitoring station and better linear ~~$T_a \rightarrow T_w$ estimates. An~~

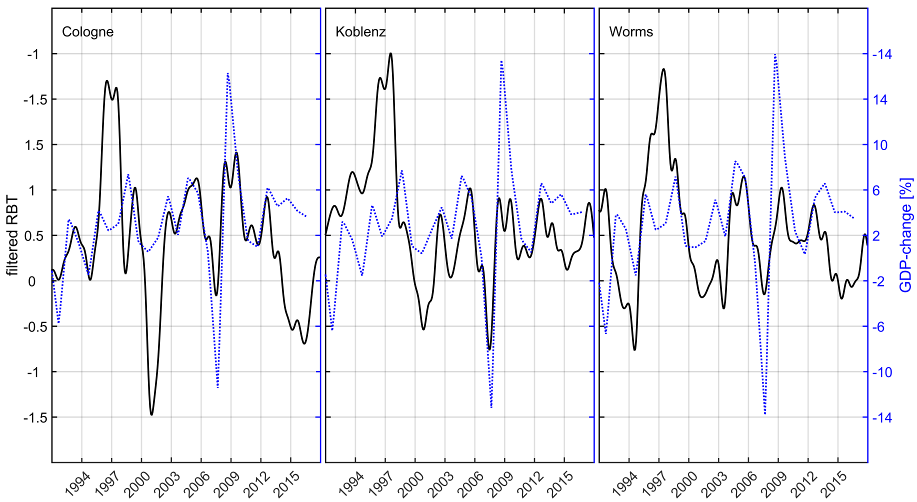

Figure 9. The three panels show the detrended and filtered RBT signal (black solid) and the GDP change (blue dashed) at the Cologne, Koblenz and Worms.

$T_c \to T_w$ estimates. This improvement in the ~~$T_a \to T_w$ relationship makes~~ $T_c \to T_w$ relationship supports the analysis, reanalysis and forecast of T_w~~easier as~~. Usually T_a data is readily available and can easily be combined with Q data for a multiple linear regression. Still a sufficient long time-series of T_w is required. ~~The~~ Nevertheless a linear relationship is simpler than a full physical model which ~~needs~~ requires all meteorological fluxes as parameters.

This a case study for the Rhine catchment area but the model can be theoretically used in any river system around the globe. Catchment area data and reanalysis T_a data are globally available. Morrill et al. (2005) show a linear $T_a \to T_w$ relationship for 43 rivers with various catchment areas in the subtropics. This could indicated that this case study of the Rhine can be applied globally. There is a lack of studies on the $T_a \to T_w$ relationship in the tropics, where precipitation and extreme ~~evens~~events, such as monsoon, could complicate this relationship. Future calculations could be coupled with ~~catchment wide~~ catchment-wide hydrological models to improve the accuracy of the time lag.

Using T_c we regress four T_w time series (Basel, Worms, Koblenz and Cologne) along the Rhine. The offset in the this regression a_1, which we call RBT, and its change over time is an indicator for anthropogenic heat input. The RBT can be correlated with long term economic changes such as the decrease of nuclear power production as well as short term economic events. We ~~showed~~ show that change in production rates (oil refineries ~~),~~ or chemical industry) as well as a change in GDP can influence the RBT and therefore the Rhine water temperature. ~~Also a statistical correlation~~ Adsitionally, the Spearman's Rank correlation is positive and significant which supports the connection between RBT and GDP. This case study could be on one hand a tool for understanding the long term consequences of industrial water use and on the other hand a verification tool for reported heat input. Germany has a rigorous reporting system on cooling water use. However, other countries could check if industrial heat input is in accordance with legislative guidelines.

~~(Hardenbicker et al., 2016)~~ Hardenbicker et al. (2016) estimate, using a physical model (QSim), that between the reference period of 1961-1990 and the near future 2021-2050 the mean annual T_w of the Rhine could increase by 0.6 ^{o}C-1.4 ^{o}C. This trend can be supported by our historical data, however they use a constant anthropogenic heat input. ~~Differences~~ Different warming rates along the Rhine ~~might be introduced~~ could occur by a change in anthropogenic heat input. The difference of the T_w warming rate between Basel and the other monitoring stations in our time-series data can be explained by the change in nuclear power production and the influence of general industrial production. This could mean that with rising T_a and the linear correlation between $T_a \rightarrow T_w$, industrial production and power production have to be more closely connected with river water temperature management. For the Rhine river we find a decreasing, except for Basel, RBT, which indicates a decreasing anthropogenic heat input. However, other river catchment areas with growing energy intensive industries could experience a larger warming rate than it is caused by the general increase of T_a experiencing all consequences for the physical, chemical and biological processes.

5 ~~Regression coefficients~~

~~In Sec. **??** regression coefficients a_{1-3} were calculated by regressing T_w by T_c and Q. The regression was done on a two-year window with a step size of one month. Fig. **??** shows the evolution of the regression coefficients at all four monitoring stations for the Time-lag+ weight scenario, as an example. Fig. **??** shows a_2 (meteorology) in relation to both environmental influences $a_2 + a3$. The y-axis percentage gives an indication, how much influence a_2 has on the variations of T_w. The remaining percentage to 100 % can be attributed to a_3 (hydrology). The relative contribution of a_2 to the variation in T_w at the four monitoring stations.~~ ~~The relative contribution of a_2 to the variation in T_w at the four monitoring stations.~~

5 ~~Nuclear Power Plants and Output~~

~~Following NPPs were included in the heat input calculation(Tab. 2).~~

~~namecountryriverconversion factorconst. heat inputBeznau I+IICHAaare3N/ABiblis I+IIDERhine2N/ACattenom I-IVDEMoselN/A200 MWFessenheim I+IIFRRhine3N/AGoesgenCHAareN/A50 MWGrafenrheinfeldDEMainN/A200 MWLeibstattCHRhineN/A50 MWMuehlebergCHAare3N/ANeckarwestheim I+IIDENeckar1N/AObrigheimDENeckar3N/APhilippsburg I+IIDERhine1N/A~~

~~NPPs included in this manuscript. The coversion factor describes the conversion from electrical power generation to heat input. If cooling towers are installed a constant heat input was used based on Lange (2009).~~ ~~The conversion factor is used to convert electrical produced power to heat input. NPPs with an exclusive river water cooling system have a conversion factor of three, which is based on the power efficiency of electricity generation. Other factors are estimated depending on the used cooling system.~~

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