Blue: Authors comments

Report 1:

The manuscript has been improved substantially during the review process, as the authors considered most of the specific comments of both reviewers.
Thanks for the previous comments and the kind support.

A general comment by both reviewers was to expand the discussion of the results. However, a thorough discussion also with respect to the wider literature is still missing. Consequently, the manuscript still reads more like a case study report than a scientific article.
According to the reviewer's comments, we extended the aspect and hope to receive now an overall positive evaluation. We also added more references to previous work to put our findings in a broader context. In this manuscript we do propose a new method of regressing Tw vs Ta and, true, test this method in a case study.

A reorganization of the text so that methods and results are strictly separated (as suggested also in the previous round of reviews) is advised.
We moved the last paragraph of the introduction to the methods section. We also intensified the explanations in the method section. So, in our opinion there is a clear separation between introduction/methods/results.

Figure and table captions need to be revised so that they are distinct, concise, and self-explaining.
A thorough check of the manuscript syntax, grammar, spelling and punctuation is furthermore advised. I have included only a selection of the language issues I found in the specific comments.
As visible in the watemp_5_diff.pdf, caption- and formal revision has been undertaken.

Specific comments (page & line number according to track changes version):
Comments are also based on the watemp_4a_diff.pdf file.

P2 L25 I would assume neural network based river temperature models are statistical models.
Correct. We changed the wording accordingly and present neural networks as a subgroup of statistical models. "Artificial Neural Networks (ANN) are a subset of the statistical models and…"

P2 L37 It is not clear that this sentence refers to the Markovic paper.
Thanks. We changed it to: Using linear models, Markovic et al. (2013) show that between 81 % - 90 % of the Tw variability can be described by Ta. Furthermore, they show that 9 % - 19 % can be attributed to hydrological factors (e.g. discharge). The study was conducted for the Danube and Elbe basins using data from the 1939 to 2008. These two rivers have comparable discharge and catchment area to the Rhine river, which could mean his results are transferable to the Rhine river. These, although simple, linear models are able to clearly separate the different influences on Tw.

P2 L48 Subsection heading necessary? (There is no 1.2)
We deleted the heading.

P3 L89 Column numbers needed?
We deleted the column numbers in the text. The description of the columns is given in the caption.

Tab 1 Omit "Lists of ". Description of columns in table caption not needed

We deleted it.

Fig 1 Revise caption. E.g. "Heat input by upstream NPP…"
We changed the caption to: "Heat input by upstream NPP from 1969 to 2018 at each monitoring station."

Tab 2 caption "conversion" instead of "coversion"
Thanks for pointing out the typo.

Fig 2-4 Use distinct figure captions or merge into multi-panel figure
We changed the design and put figure 3 into a multi-panel figure as it shows a different weighing. Thanks for the comment.

Fig 2 Add "NPP" to legend and add a legend item with "x" for the monitoring stations
We added NPPs and Xs for all monitoring stations

Tab 3 Omit "This table.."
It is deleted.

P11 L 217 Revise sentence
The section was revised to:
"A catchment-wide hydrological flow model, estimating the flow speed at every grid point for every hydrological scenario, was not used. It had not been yet available for every grid point of the catchments and the focus of this study was to create a simple set-up, also transferable to other river catchments."

P12 L 246 Revise sentence – How do grid points reach monitoring stations?
We deleted the last part of the sentence as it is unnecessary. The temporal relationship is anyways explained in the next sentence using Δt:
"Tc (x0;y0; t0) was calculated by weighted (ACC _w) averaging Ta (x;y; t+_t (x;y)) over all grid points of the catchment area (x=1,...n y=1,...m) which was set by the measurement point (x0,y0). The time-lag dt was an estimate for the time it takes for a water droplet from a specific grid point (x,y) in the catchment area to the measurement location."

Fig 6 Revise caption to make it more self-explanatory. Also: Relative contribution of what? What does "using by number" mean?
We think the reviewer means Fig. 5 (in the new version it is Fig. 4). We changed the caption:
"ACC bins (x-axis) vs the relative contribution (y-axis). The grid points are binned by their ACC value. The red bars show the relative contribution (largest contribution normalized to one) by the number of grid points in this bin only. The white bars show the distribution using the number of grid points in this bin and weighing ACC _w."
The paragraph regarding this figure was also changed:
"The grid points were binned according to their ACC value. A high bin represents large rivers, a low bin their tributaries. The reason was to investigate the importance of the different ACC bins to the total Tc calculation. The ACC bin with the largest contribution in Fig. (4) was normalized to 210 one making it a relative contribution. The red bars (Fig. (4)) show the relative contribution (y-axis) of each ACC bin by the number of grid points in this bin only, no ACC _w weighing was applied. The results showed that the large number at low ACC bins (small water mass) have a larger influence compared to the rather low numbers at high ACC bins (e.g. large water masses, rivers, lakes). The difference in relative contribution is four powers of magnitude. The white bars show the relative contribution using the number of grid

points in the bin and the ACC_w weighing. 215 This distribution delivered rather equal importance to all grid points as it puts more weight on grid points covering lakes and rivers. The average difference in relative contribution is about 1 power of magnitude."

Tab 4 Linear fits to what? No need to mention column numbers in caption. What does R2 > 1.99 mean (I assume it is a typo)

We deleted the numbers in the caption. We also added that data-basis of the linear fit is described in the header. The "1.99" was a typo it should have been 0.19, Thank you, it was corrected.

Tab 5 Would it be possible to call the first column "approach" or "model" rather than "descr."?

You are right. "descr." is odd. We call it method, as we call it calculation method in the manuscript

Fig 9 Omit "the three panels show". Omit "the" before Cologne

Thanks. We changed that.

Once again many thanks for the support from reviewer 1, we appreciate the time spend on the manuscript and think that it has been improved by the comments provided.

Report 2 states

I believe that the authors improved the original version of the manuscript by clarifying some important aspects of their analysis.
Thank you for the time invested in proof reading, we to be able to further clarify and improve the manuscript with your support.

Still however I believe that there are some important issues that the authors should improve and clarify, including some requests of my previous review that were not addressed.
We added the full RMSE and NSC data for all calculated flow speeds to the supplement. The change in RBT is now continuously calculated (Fig. 6 in last Version). These are the main but not sole improvements regarding the robustness of our approach.

In general, grammar, syntax, and equation notation should be carefully checked throughout the manuscript and I suggest that the structure of some sections should be revised.
The manuscript was once again carefully proof read and also given to a third person just for proofreading.

I believe that the analysis and the quality of the manuscript can be substantially improved in several aspects, as suggested in my specific comments below.
Thank you once again for the constructive support; we addressed all points raised by you, below.

Introduction:

- Line 20: I would not mention riparian vegetation together with meteorological forcing. Rather, I would move it to point 3, after opportune adjustments. In addition, I believe that, given the focus of the study, anthropogenic effects should be explicitly mentioned in a specific point.
Even though we think that “riparian vegetation” does not fit perfectly there, we follow the reviewer advice and moved it to point [3] and mention the anthropogenic impact in the sentence before.

- Lines 26-28: please revise this sentence: it seems that fluxes and boundary conditions are two distinct entities, while in many cases boundary conditions are fluxes. This sentence confirms that riparian vegetation should be removed from point 1 (it is not a flux).
You are correct. We changed the sentence. The fluxes are now combined and the boundary and starting conditions as well, we wrote:
“A physical Tw model (Sinokrot and Stefan, 1993) usually parameterizes or estimates the meteorological and ground heat fluxes and adds anthropogenic heat input. Each modeled heat flux is then applied to the water mass, initialized with the starting and boundary conditions of source temperature and discharge. However, it is difficult to get a good estimation of these different 30 terms over a larger catchment area.”

- Line 29: does the term "parameter" refer to the fluxes mentioned in the previous sentence? If so, since fluxes are not parameters, I suggest using e.g., the word "terms".
Thank you for the hint, we changed it accordingly to “terms”.

- Line 34: I do not understand the use of the term "analytic" here.
We revised the sentence and hope it is clearer now:

“Using linear models, Markovic et al. (2013) show that between 81 % - 90 % of the Tw variability can be described by Ta. Furthermore, they show that 9 % - 19 % can be attributed to hydrological factors (e.g. discharge). The study was conducted for the Danube and Elbe basins using data from the 1939 to 2008. These two rivers have comparable discharge and catchment area to the Rhine river, which could mean his results are transferable to the Rhine river. These, although simple, linear models are able to clearly separate the different influences on Tw.”

- Line 37: please start a new paragraph after "... to the Rhine river."
We did it and we also restructured the last part of the introduction.

- Section 1.1: it is uncommon to have a subsection in the Introduction and I do not think that it is needed here, thus I strongly recommend to removing subsection 1.1. In doing so, a connection sentence between the first half of the Introduction and the second half will be required. As commented in my previous review, this second part of the Introduction reads more as a paragraph of Material and methods. I strongly recommend to fully revise the structure of this section focusing on presenting the objectives of the manuscript and an outline of the approach followed by the authors. Both points are not sufficiently addressed in the present version of the Introduction. Some specific comments are provided below:
We moved the last part of the introduction to the methods part. Anything regarding the mathematical description of the model is in the methods part. We then rewrote the remaining last part of the introduction to connect to the methods. pls. cf. the watemp_5_diff file.

*** Lines 57-59: this sentence is unclear and the link between the concept of Tc and the assessment of the impact of industry, meteorology and hydrology is confused and unsettled. The syntax should be revised (e.g., "combine ideas from")**
We restructured this part of the introduction and moved it to the methods part: The paragraph reads: “We investigated the change in anthropogenic heat input and its spatial and temporal heterogeneity along the Rhine combining 70 ideas from the spatial correlation models to develop a new method of calculating a representative catchment air temperature (Tc). Tc and discharge at the measurement station Q were used in a multiple linear regression Tc !Tw (Eq. 1). The resulting regression coefficients a1, a2 and a3 describe the magnitude of the respective influences (anthropogenic heat input, meteorological and hydrological).”

*** Lines 61-62: I would not call the period 1979 to 2018 a "scenario"**
We changed it to “case”.

*** Lines 66-67: I do not agree with this sentence: Ta does not take into account the origin of water. This is particularly evident for ground water sources. This comment should be removed from the manuscript.**
We deleted the sentence. We think it was unclear too.

*** Lines 70-72: this sentence is debatable since the hybrid model cited by the authors has been already used to evaluate the separate effects of anthropogenic and climate changes (Cai et al., 2018) and I have some concerns on affirming that a simple linear regression model (eq 1) can "allow for a clear distinction between meteorological, hydrological, and anthropogenic input".**
Maybe Cai et al., 2018 is not the best example, as they train their model Pre-Three Gorges Dam (TGD) and then apply it to the air temperature post-TGD. After that, they take the difference in simulated Tw and observed Tw. This approach provides estimates on the difference of a1 a2 and a3. These differences can be of anthropogenic origin.

Our model, if it were used on the TGD data-set, would only use the measured Tw data and interpreting the model parameters (a1), which delivers in our case the anthropogenic heat input. We would not investigate any possible anthropogenic or natural changes to the meteorological influence or the influence of discharge. We also do not use a subset of our data for training and then relate it to others but stepwise compare sub-datasets in a time series.
However, we agree with the reviewer, using a1 from the air2 stream model (Marco Toffolon and Sebastiano Piccolroaz 2015 *Environ. Res. Lett.* 10 114011) would also show the anthropogenic change. The simple air2stream mode with 3 paramteres from Toffolon et al 2015 is basically the same model that we use.
Hence, we deleted the sentence and added a thought to the introduction:
"Hybrid models can reproduce river water temperatures better than simple statistical models (linear regression) \citep{Tof2015}. The approach includes more parameters and thus, is more complex. A simple hybrid model with for example, three parameters, is comparable to a statistical model with the same number of parameters."

*** Figure 2 (the study site) should be probably cited here.**
We added an additional legend.

- As pointed out in the first revision round, I believe that the Introduction would benefit from mentioning existing literature on the assessment of anthropogenic impact on river water temperature (e.g., Cai et al., 2018; Gaudard et al., 2018; Råman Vinnå et al., 2018, just to cite some recent papers).
Included.

Section 2.1.
- Line 83-84: "reference" --> "data provider"/"data source" ?
Was changed to data-provider.

- Lines 90-92: please, check the verb tenses. The use of "by us" is not recommended.
We deleted "by us" and changed the tense. Generally, we use active voice as it is now recommended by many chief editors:
"Nature journals prefer authors to write in the active voice ("we performed the experiment...") as experience has shown that readers find concepts and results to be conveyed more clearly if written directly. We have also found that use of several adjectives to qualify one noun in highly technical language can be confusing to readers. We encourage authors to "unpackage" concepts and to present their findings and conclusions in simply constructed sentences." Nature Editor in Chief
Of course using passive voice and then adding by us is not helping to generate a fluently readable text and therefore we deleted it.

Section 2.3.
- As commented in the first revision round, the sentences in the first part of this section are too fragmentated and short.
The authors should explain in detail how they aggregated the heat input due to each NPP to obtain the overall heat input at each gauging station.
We revised the beginning and increased the readability. We added an equation explaining the heat input calculation

Section 2.4

- This section is disconnected from the previous, since the authors did not mention the use of GDP in the preceding part of the manuscript. This is something that should be mentioned in the Introduction, where the authors should properly (i.e., concisely but clearly and exhaustively) introduce objectives and approaches of their study.

In the last paragraph of the introduction we added now extra lines to explain our objectives and the use of GDP data and the data from nuclear power plants.

"Short term economic changes, observable in the change of GDP, may influence Tw on shorter time scales (<5 years). As several industrialized hotspots are present along the river, this impact might be heterogeneous. Using the nuclear power production and GDP data, we also investigated the heterogeneous anthropogenic impact on Tw along the Rhine at four monitoring stations (Basel, Worms, Koblenz, and Cologne)."

- Figure 2: I would present the catchment closed at the most downstream gauging station. In this way the entire region analyzed in the study would be presented. Please substitute the symbol used for the Fessenheim NPP as it can be confused with a gauging station.

We changed the symbol for Fessenheim. Presenting the catchment area of Cologne would indeed show the entire region but one would also loose details. So we decided that it is best decision to show Koblenz.

- Line 140: The use of subsections, subsubsections (e.g., 2.3.1) and paragraphs (e.g. Accumulation) is not harmonized. Please check it throughout the manuscript.

Every subsubsection is numbered, if there is more than one in a subsection. If not is just a separate heading without numbering was included.

- **Line 142: please revise the syntax ("... the the ..."; "... this very grid point")**

We changed the total paragraph. The part is now in section 2.6.

"Additionally, the accumulation number ACC was obtained from the data-set. It defines how many cells in total were draining into a particular cell and it is a measure for the size of a river. Finally, a grid, which defines the catchment area, the ACC and the hydrological distance was established spanning the whole catchment area. Figure (2) shows the catchment area, the hydrological distance and the calculated flow time to the Koblenz monitoring station. The ACC displays is the number of grid points which were hydrologically connected to this specific grid point. Figure 3 (top panel) shows the distribution of the ACC. Large rivers, which have a large ACC number, such as the Rhine, Main, Neckar are easily visible due to their green to yellow color."

Section 2.7

- In my view, part of subsection 1.1 (including equation 1) should be moved here. In the Introduction the authors can easily comment on their approach without showing the equation. Indeed, as commented above, in the Introduction the authors should focus on objectives and approaches used in their study in a concise and clear way.

We followed the reviewer's advice and moved the subsection 1.1. to the methods part.

More important, as commented in my previous revision, I do not agree that "The offset a1 (RBT) combines all other influences, which are controlled by anthropogenic sources". a1 accounts to much more than solely anthropogenic sources as it summarizes all contributions that are not directly linked

to Ta and Q (groundwater inflow, geothermal flux, vegetation shading, tributary heat flux, upstream heat flux, etc). Please see Segura et al (2015) for an useful overview on the physical meaning of the intercept a1. Still, the authors can suppose that if all the aforementioned conditions are kept unchanged, changes in a1 can be linked to changes in anthropogenic sources (as they comment at lines 267-270). This is conceptually and formally different. The authors should carefully avoid any misunderstanding around the meaning of a1 (adjust also Introduction, lines 265-, Conclusions and all sentences where the meaning of a1 is commented).

The reviewer comment is absolutely correct. The sentence "The offset a1 (RBT) combines all other influences, which are controlled by anthropogenic sources" is not precise and leads to misunderstanding. It was corrected, that anthropogenic changes which effect meteorology (change in shading for example) are represented in a2. Any anthropogenic changes going together with discharge would change a3. This is now clarified. We changed the wording.

We already state in the introduction of the Methods:

"Using the multiple regression (Eq. 1), we especially investigated the change of a1 over time, which we call in this study the Rhine base temperature (RBT). This temperature represents Tw without the influence of meteorology (Ta) and discharge (Q). RBT was defined to be an indicator for industrial heat input and the use of Rhine water as cooling agent, in case both are mostly independent of Ta and Q."

The overall industrial and power production would have to be dependent on Ta and Q to have an effect on a2 and a3. During extreme Q and Ta this may happen, but is very unlikely and very seldom the case. To avoid any problems with this, we always regress a two years period, because it is unlikely that over a period of two years production strongly correlates with air temperature or river discharge. This is now mentioned in the manuscript.

The lines 267-270 are now deleted.

We went over all parts where a1 is mentioned and revised the phrasing to be more consistent and to follow the suggestions. a1 is now always labeled as anthropogenic heat input, which is more precise than being the total anthropogenic influence.

- Line 50: "over the whole" --> "over the whole catchment"?

Thanks, we changed it

- Equation 4: I would have expected to see "Tc(t0-Delta t(x,y))" and "Q(x0,y0,t0)". Is this correct? As for the first point: since, as far as I understand, Tc is spatially averaged it should not depend on x and y. In addition, to predict Tw at time t0 at the closing section, Tc should be taken at time t0-Delta t(x,y) for the i-th cell located in (x,y) to account for the time delay due to water routing. Considering t0+Delta t is coherent with eq 8, where the authors define Delta t as a negative number, but this comes later in the text and in my view is misunderstandable.

We changed the equation in such a way that Tc(x0, y0, t0+Δt(x,y). Tc is now connected to x0,y0 which is the measuring point and sets the extension of the catchment area.

We also added a small explanation on the time lag being negative and hope we made it better understandable now. We also made the appropriate changes to all other equation if necessary.

Good point. Thanks.

- Equations 5 and 6: similarly to above, the time lag is not correctly accounted for: "T(x0,y0,t0) = Ta(x0,y0,t0 -Delta t)" and in the second equation the integral should be from i=t0-Delta t to i=t0. Delta t can be confused with the time lag due to routing while here it refers to the lag due to water inertia. Moreover, here and in the following equations "T" is not defined. The authors should avoid any misunderstanding, be precise in the use of notation, and carefully check all equations.

We changed the equations accordingly.

Inertia time lag vs advection time lag:
You are right there are two time lags. One is a constant (inertia) the other one depends on distance and flow speed. We state in Line 187 (newest version)
"The new _t (x;y) represents the mismatch by advection but not specifically the mismatch through thermal inertia. The thermal inertia would be independent of s(x;y) and a constant added to _t. However, we are of the opinion, that a sufficient part of the thermal inertia time-lag was included in our representation of _t (x;y)."
We also added a sentence about the inertia in relation to flow speed at
Line 203 (newest Version)
"The reason for the small flow speed (0.4 ms-1) and the even smaller ones at Basel and Worms could be the thermal inertia. As thermal inertia is not explicitly 205 represented in dt (Eq. 9) a smaller flow speed could compensate for that, especially in smaller catchment areas."

- Line 165: "reason reason". There are several other points where the syntax should be checked. I will not comment further on this, but strongly encourage the authors to thoroughly check the entire manuscript.
Thank you and we are sorry about the errors. We proof read manuscript again.

- **Lines 165-176: this part is confused. This is what has been already said in eq 4 and the reference to the 8-day lag is unclear and probably unnecessary: from the text one understands that only the routing lag has been considered, while the time lag due to thermal inertia has not. Overall, this whole section requires significant improvement and clarification**.
We agree to a certain extend. The thermal inertia is represented in our time lag, to a certain extend. We changed the paragraph starting Line 175 (newest Version). There we distinguish between thermal inertia and advection.
We also added a sentence about the inertia in relation to flow speed at
Line 203 (newest Version)
"The reason for the small flow speed (0.4 ms-1) and the even smaller ones at Basel and Worms could be the thermal inertia. As thermal inertia is not explicitly 205 represented in dt (Eq. 9) a smaller flow speed could compensate for that, especially in smaller catchment areas."

- Lines 183-186: the authors should better explain how the flow speed has been estimated. Do they mean RMSE between observed and simulated Tw using the Time lag + weight model (or just considering the Time lag, or Time lag + weight + ACC)? Is this value of flow speed confirmed also when analyzing the other gauging stations? The authors should show (at least in the supplementary material) the relationship between RMSE and flow speed for all gauging stations. Is the minimum in RMSE clear and unequivocal? Did the authors optimize independently the flow speed when testing the different definitions of Tc?
We followed the advice, added the analysis of all stations to the supporting material and hope to make it better understandable. We also added that the calculation of RMSE there was done using the whole data-set.

- Table 4: "which are statistical significant only if R2 > 1.99" there should be an error here. Please, specify that R2 refer to the linear trends. As suggested in my previous revision, I believe that the authors could add the Pearson coefficient between Ta and Tw to further (and more robustly) support their reasoning.

This is a typo. comment by reviewer1. Thanks. The correct number is 0.19. We added the Pearson coefficient to the table.

- Lines 238-241: this paragraph is chaotic. Some concepts are repeated and not necessary in this context (e.g., in Base Ta and Tw show similar behavior).
We changed the whole paragraph.

Section 3.2
- Line 246: "catchment-wide Delta t" the use of catchment-wide is probably not appropriate here as it could be understood as a constant Delta t for the entire catchment.
We deleted it.

- Line 250: see my comment relative to Lines 183-186. Here and below: NCS-->NSC
We added the calculation method of RSME and NSC to the caption and it is as well in the paragraph.

- Line 255: I would not say that a figure is the reason of the results, but that the content of the figure can explain the results.
Correct sorry, for that. We changed it.

Section 3.3
- Lines 275-276: actually RBT seems to decline some years in advance (in 1995 looking at the running mean in Fig. 7). Can the authors add a comment on this?
Correct. Beginning 1993 there was a recession and a crisis in the trade balance, which might have affected the long term trend. We think that this was a coincidental trigger for this decline.
We wrote:
"The RBT started its decline a 1-2 years before 1995, which might have been triggered by the recession in 1993 and a sharp drop in the German trade-balance."

- Table 6: here the authors do not show that the two series of Delta RBT have "similar trends" since the results in the table only depend on initial and final values (which has clear side effects and limitations). To test if the trends are similar, they should calculate Delta RBT in continuous with eq 2 and using the time series of the heat input, and compare it with the time series of RBT shown in Figure 7. This is something that I already suggested in my first review and that I strongly recommend adding to the analysis. While the authors replied that they wanted to pick the largest Delta HI to avoid influences by short term trends, I believe that analyzing the time series is needed to properly show that the two time series have comparable medium- to long-time trends (short term trends can be easily filtered e.g., with a moving average if required).
The time series of ΔRBT was added to Figure 4. We added also an analysis to the paragraph, stating that the time series of ΔRBT at Fig. 4 follows the RBT time series and the HI by NPPS. It is interesting that before 1995 an offset between RBT and ΔRBT occurs. We think that between 1985-1995 the NPP Power production stayed constant but the GDP increased by 30% during this period. So the input from industrial production seems to have contributed to this offset.

- Lines 285-317: as commented above, the term RBT summarizes several contributions besides anthropogenic effects. This should be properly recalled in this section, since this is the most likely reason of the differences between RBT and GBT trends (including the specific cases commented by the authors), although I agree that a significant correlation is visible in figure 9.

We added a sentence to the top paragraph of section “Short term trend”, reminding the readers, that RBT is not only influenced by industrial production (GDP) but also other sources, which we are not investigated in this paper.

As commented in my previous review, the comment on the effect of lakes is somehow disconnected from the rest of the paragraph. I perfectly understand and agree that "finding the reason [of the peculiar trend in Basel] is not in the scope of this paper", but the sentences at lines 289-293 should be better contextualized. The reasoning on stratification is fine, the fact that deep water temperature is somehow decoupled from Ta is fine as well (but only for deep lakes), however this does not explains the trend shown in Basel nor the reader knows if such lakes contribute to the Rhine through surface water (natural lakes) or deep water (hydropower reservoirs with deep intake). Better than trying to draft a possible explanation without effectively providing the proper information and hypothesis, would be to simply write that the trend in Basel cannot be explained in this analysis.

Thank you for the comment, we deleted the hypotheses.

Conclusions:

- Line 340: the term "reanalysis" and “forecast" are probably not the most appropriate here.

We remove reanalysis and forecast

- Line 342: fluxes are not parameters. I would say that fully physical models requires all meteorological data in input.

We changed it from parameters to input.

- Lines 343-348: the comment on tropical and subtropical rivers is somehow disconnected from the study presented by the authors and personally I do not believe that it is appropriate here. I do not believe that the study by Morril et al (2005) suggests that "this case study of the Rhine can be applied globally". On the contrary the comment on the possible coupling with catchment-wide hydrological models is more significant but poorly examined (please improve it, adding a comment also on the limitations of the analysis).

We deleted the sentence about tropical rivers. We do think that Morril et al 2005 gives a hint to applicability of out model. Generally for our model to work, just a linear relationship between Ta and Tw is need. The information provided by Moril et al 2005 is that they can reasonably establish a linear relationship and their RMSE is in the same range as ours and therefore we are confident, that it is possible to apply this to other rivers. We did a quick survey (not in this manuscript) of the Elbe and can reproduce the industrial development there using a1, too.

References

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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~~ introduced a new way of calculating a catchment-wide air temperature ~~and regressing river temperature vs air temperatures. As a result~~ using a time-lagged and a weighted average. Regressing the new air temperature vs river water temperature, the meteorological influence and the anthropogenic ~~influence can~~ heat input could be studied separately. ~~We apply this new method~~ The new method was tested at four monitoring stations (Basel, Worms, Koblenz and Cologne) along the ~~Rhine and show that the long term~~ river Rhine and lowered the root-mean-square error of the regression from 2.37 ^oC (simple average) to 1.02 ^oC. The analysis also showed that the long-term trend (1979-2018) of river water temperature ~~is~~was, next to the increasing air temperature, mostly influenced by decreasing nuclear power production. ~~Short term~~ Short-term changes on time scales < 5 ~~years are due to~~ y were connected with changes in industrial production. We found significant positive correlations for ~~this~~ the relationship.

1 Introduction

River water temperature (T_w) greatly influences the most important physical and chemical processes in rivers and is a key factor for river system health (Delpla et al., 2009). T_w also ~~defines and~~ confines animal habitats ~~(Isaak et al., 2012; Durance and Ormerod, 2009) and~~ (Gaudard et al., 2018; Isaak et al., 2012; Durance and Ormerod, 2009), regulates 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~~also of very significant interest for economy. Especially for energy intensive industries such as power plants, oil refineries, paper or steel mills, river water is an important ~~cooling agent~~resource. Its availability is a basic requirement for the facilities location (Förster and Lilliestam, 2010). ~~In this context, one has to bear in mind, that~~ As a cooling agent, 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)~~ effects such as industrial heat input, river regulation or stream-side land change can contribute significantly to the heat budget of a river and furthermore on T_w (Cai et al., 2018; Gaudard et al., 2018; Råman Vinnå et al., 2018). 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~~ source temperature, which describes the origin of the water, e.g. snow-fed, glacier-fed, groundwater-fed; [3] ~~Hydrology~~hydrology, which influences the water temperature through the amount of water and the flow velocity; together with the change in riparian vegetation; [4] ~~Ground~~ ground heat flux.

Dependent on data availability, computing power, accuracy and the questions asked, T_w can be modeled in different ways. The common options are statistical models ~~,~~ and 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 1and 3,~~ usually parameterizes or estimates the meteorological and ground heat fluxes and adds anthropogenic heat input~~and collects the hydrological and source boundary conditions 2and 4~~. Each modeled heat flux is then applied to the water mass, initialized with the starting and boundary conditions of source temperature and discharge. However, it is difficult to get a good estimation of these ~~parameters~~ different terms over a larger catchment area. ~~As a consequence, statistical~~ 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). Hybrid models can reproduce river water temperatures better than simple statistical models (e.g. linear regression) (Toffolon and Piccolroaz, 2015) . Their approach includes more parameters and thus, is more complex. However, a simple hybrid model with three parameters is comparable to a statistical model with the same number of parameters. 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~~ an established method and depending on the complexity, linear or exponential models ~~(Stefan and Preudhomme, 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_w but lacks the clear analytic separation of the influences~~ are used (Stefan and Preudhomme, 1993; Mohseni et al., 1998; Koch and Grünewald, 2010) . Generally exponential models delivers better results with temperature extremes. However, they lack the distinct separation between contribution to T_w from anthropogenic heat input and natural influences. Using linear models, Markovic et al. (2013) show that between 81 % - 90 % of the T_w variability can be described by T_a. Furthermore, the authors showed that 9 % - 19 % can be attributed to hydrological factors (e.g. discharge). The study was ~~done~~ conducted for the Danube and Elbe ~~basin~~ basins using data from ~~the~~ 1939 ~~to~~ - 2008. These two rivers have comparable ~~size and catchment area~~ discharges and catchment areas 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).~~ , which could mean his results are transferable. These, although simple, linear models are able to clearly separate the different influences on T_w. 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~~ aim 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~~ was 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~~ weighed on their flow connectivity and euclidean distance or flow distance. These models can also include ~~time lag~~ time-lag considerations using temporal auto correlation (Jackson et al., 2018). Artificial Neural Networks (ANN) are a subset of the statistical models and used when an incomplete understanding of most contributing processes is given (Hassoun, 1995). ANN use a sample data-set to train artificial neurons the relationship between input (e.g. air temperature) and output (T_w) (Zhu et al., 2018).

1.1 ~~Rhine~~

~~Along the Rhine, up to~~ We used a simple linear regression model (transferable to other streams) to investigate the temperature changes of the Rhine river over 40 years, which had been influenced by 12 nuclear power plants (NPP) ~~have~~ along the river Rhine. These NPPs had caused, for decades, the largest part of anthropogenic heat input (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~~ After this political decision a ~~clear~~ distinct drop on nuclear power production ~~is~~ was visible, on top of already decreasing production rates. ~~Currently (~~By July 2019 ~~) eight NPPs are~~ eight NPPs remained operational in the catchment area of the Rhine using (partly) river water as cooling agent. In this publication, we ~~hypothesize~~ hypothesized that, next to environmental factors, ~~this long term decrease in power productiontogether with short term economic changes have an~~ the long-term decrease of power production, which is coupled to a decreasing use of river water as cooling agent, has a long-term (> 10 y) impact on T_w of the Rhine. ~~This impact might be heterogeneous along the river as the location of industry and NPPs is concentrated at several highly industrialized spots.To test this hypothesis and assess the varying impact of industry, meteorology and hydrology on the Rhine river temperatures, we want to combine ideas from the~~ Short-term economic changes, observable in the change of the gross domestic product (GDP), may influence T_w on shorter time scales (< 5 y). As several industrialized hot-spots are present along the river, this impact might be spatially heterogeneous. Using the nuclear power production and GDP data, we also investigated the varying anthropogenic impact on T_w along the Rhine at four monitoring stations (Basel, Worms, Koblenz and Cologne).

2 Methods

We investigated the change in anthropogenic heat input and its spatial and temporal heterogeneity along the Rhine combining ideas from spatial correlation models to develop a new method of calculating a representative catchment air temperature (T_c). T_c and discharge ~~Q is then~~ at the measurement station Q were used in a multiple linear regression $T_c \rightarrow T_w$ (Eq. 1). The ~~model is~~ resulting regression coefficients a_1, a_2 and a_3 describe the magnitude of the respective influences (anthropogenic heat input, meteorological and hydrological).

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

Using an improved calculation method for T_c, which includes catchment-wide averaging with river-size weighing and a time-lag, the regression should deliver a better estimate for a_1, a_2 and a_3.

The model was 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~~ From 1979 to 2018 ~~experienced~~ several changes in anthropogenic heat input to the Rhine catchment area ~~, which makes~~ occurred, making it an interesting ~~scenario~~ data-set to be studied.

$$T_w = a_1 + a_2 \cdot T_c + a_3 \cdot Q$$

~~a_1, a_2 and a_3 are the resulting regression coefficients 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 T_c because data from high elevations (e.g. Alps) is also included.~~ Webb et al. (2003); Markovic et al. (2013) have shown that ~~Q~~ Q is inversely related to T_w and an important factor in the $T_c \rightarrow T_w$ relationship. Additionally, it ~~functions as~~ may function as a 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~~ were not included in this model because of the comparable small influence (Sinokrot and Stefan (1993) for the Mississippi; Caissie (2006) as review article).~~Other models such as hybrid models (Toffolon and Piccolroaz, 2015) 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~~ (1)), we especially investigated the change of a_1 over time, which we call in this study the Rhine base temperature (RBT). This temperature represents ~~the~~ T_w without the influence of meteorology ~~and discharge. RBT is~~ (T_a) and discharge (Q). RBT was defined to be 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.~~ , in case both are mostly independent of T_a and Q.

3 ~~Methods~~

2.1 Water temperature and discharge

We ~~use~~ used a data-set of daily averaged T_w and ~~Q~~ Q from 1979-2018 ~~gathered from different sources~~ provided by (WSA, 2019; BfG, 2019; LfU, 2019; BAFU, 2019). The original data-sets ~~have~~ had a 10 min sample frequency and were averaged to a daily output. 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 (Col. 5).~~ and the data-provider. 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

~~name~~station	stream km	time period	important tributary upstream	~~reference~~data-provider
~~Cologne~~Basel	KM ~~688~~171	1.1.~~1985~~.1977-31.12.2018	~~Mosel~~Aare	~~WSA (2019)~~BAFU (2019)
~~Koblenz~~Worms	KM ~~590~~443	1.1.~~1978~~.1971-31.12.2018	~~Main~~Neckar	~~BfG (2019)~~LfU (2019)
~~Worms~~Koblenz	KM ~~443~~590	1.1.~~1971~~.1978-31.12.2018	~~Neckar~~Main	~~LfU (2019)~~BfG (2019)
~~Basel~~Cologne	KM ~~171~~688	1.1.~~1977~~.1985-31.12.2018	~~Aare~~Mosel	~~BAFU (2019)~~WSA (2019)

Table 1. ~~Lists of monitoring~~ Monitoring stations used in this study ~~. Column two provides~~ from Switzerland (Basel) to the lower Rhine region (Cologne, Germany). The location as Rhine km~~. Column three provides~~ , the ~~data range. The third column names~~ time-period, the important upstream tributary and ~~column four names~~ the ~~reference~~data-source are listed.

to detect temperature changes, is 0.05 ^{o}C. As we ~~focus~~ focused on the change of T_w over time and ~~do~~ did not compare the absolute temperature, the accuracy ~~is~~ was not essential and the precision ~~is sufficient . Errors inflicted by measuring~~ of the sensors was sufficient for this study. Measurement uncertainties (e.g. depth and location ~~in the river are also~~ of the sensor) were not influencing the calculation, regarding the aim of this study, as long as the measured T_w ~~is~~ was a linearly dependent proxy for the average river temperature. ~~Q is~~ Q was provided as daily averages in m^3 s^{-1} by the source in Tab. (1) and usually calculated from ~~river stage)~~a river stage nearby.

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

2.2 Air temperature

T_a is retrieved from the European Centre for 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 Nuclear Power Plants

The annual electrical power production (EPP) 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 .~~ and eight remained operational by July 2019. All shutdowns were ~~done~~ undertaken in Germany. In this study separate reactor blocks of the same plant NPP were combined. ~~From estimates by Lange (2009) and based on personal communication from different sources, the heat input~~ The heat input (HI) by NPPs to the Rhine ~~is~~ was 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.~~ using the conversion

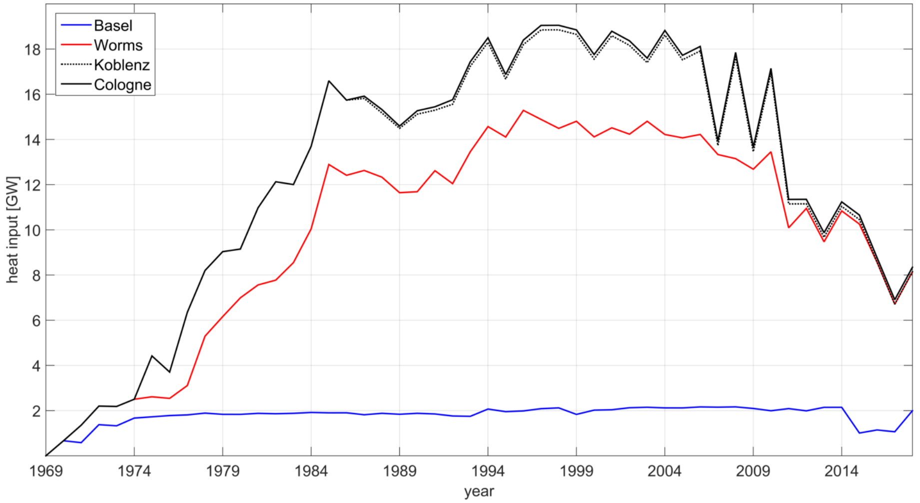

Figure 1. ~~Using the PRIS (IAEA, 2019) database we estimated the heat~~ Heat input by ~~NPPs~~ upstream NPP from 1969 to ~~2018. This figure shows the total upstream heat input of~~ 2018 at each monitoring station.

factor c and the yearly EPP, Eq. 2. NPPs with an exclusive river water cooling system have a conversion factor of three, which is based on the power efficiency of electricity generation (Lange, 2009). Other factors are estimated depending on the cooling system ~~used~~ and personal communication. If no conversion factor was available a constant HI was assumed (Lange, 2009).

$$HI[GW] = \frac{c \cdot EPP[GWh]}{365 \cdot 24[h]} \tag{2}$$

The NPPs, their conversion factor and if applicable the constant HI are shown in Tab. 2. The time series of upstream HI by NPPs for each monitoring station is shown in Fig. 1.

2.3.1 ~~Calculated temperature change~~

Calculated temperature change

We ~~calculate~~ calculated the expected change ~~in RBT (ΔRBT)~~ ΔT_w based on a change in ~~heat input~~ HI (Δ HI) by NPPs using the average discharge $\bar{Q}$, the heat capacity of water c_p and the water density ρ, Eq. (3).

$$\Delta \cancel{RBT} T_w = \frac{\Delta HI}{c_p \cdot \bar{Q} \cdot \rho} \tag{3}$$

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.~~ contribution of NPPs significantly alters the T_w and only influences the RBT fraction.

~~name~~NPP	country	river	conversion factor	const. ~~heat input~~HI
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~~study. The ~~coversion~~ conversion factor describes the conversion from ~~electrical power generation~~ EPP to ~~heat input~~HI. If cooling towers are installed a constant heat input ~~is~~ was used for the calculation based on Lange (2009).

2.4 Gross ~~Domestic Product~~domestic product

The ~~gross domestic product (GDP)~~ GDP for the adjacent German ~~federal~~ federated states is obtained from VGdL (2019a, b). Due to changes in the calculation method of the GDP before and after the German reunification (~~1991~~1990), two separate data-sets ~~are~~ were used. For this study only the GDP-change of the secondary sector (construction and production) ~~is used~~was taken into account.

The RBT, if compared to the GDP, ~~is~~ was filtered using a 10^{th} order butterworth bandpass filter. The sampling rate of the GDP ~~is~~ was 1 ~~y^{-1}. We use~~ y^{-1}. We used 1.1 ~~y^{-1}~~ y^{-1} as higher and 0.05 ~~y^{-1}~~ 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~~ were excluded from calculations and display. The reasoning ~~is~~ 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~~ was canceling long-term trends as the GDP-change ~~is~~ was only related to the previous year. The high frequency cutoff ~~is~~ was 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~~ were used to visualize trends in time series which may not be clearly visible in the ~~time series itself~~unprocessed data-set. Equation (4) shows the calculation of the RAPS index ~~(X)~~ X using a time series Y.

$$X_k = \sum_{i=1}^{i=k} \frac{Y_i - \overline{Y}}{\sigma_Y} \tag{4}$$

$\overline{Y}$ is the average over the total time series, σ is the standard deviation of the whole time series, Y_i is the ~~ith~~ 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)~~ Garbrecht and Fernandez (1994) and Basarin et al. (2016) used this method to investigate trends in hydrological time series.

2.6 Catchment area

The catchment area ~~is~~ was 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~~ By selecting a starting location, e.g. Koblenz at 50.350 ^{o} N and 7.602 ^{o} ~~E it is~~ E it was possible to iteratively identify all grid points draining into this location. These grid points represent the catchment area of this location ~~, in this example Koblenz~~(in the example from Fig. (2) Koblenz). By counting the iteration steps, the distance a water drop travels to reach the monitoring station Koblenz ~~is~~ was determined. This ~~is~~ was done for each ~~station~~of the four stations. Additionally, the accumulation number ~~ACC is~~ ACC was obtained from the data-set. It defines how many cells in total ~~are~~ were draining into a particular cell and it is a measure for the size of a river. Finally, a grid, which defines the catchment area, the ~~ACC~~ ACC and the hydrological distance ~~is~~ was established spanning the whole catchment area. Figure (2) shows the catchment area, the hydrological distance and the calculated flow time to the Koblenz monitoring station.

~~**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 ??~~ The ACC displays is the number of grid points which were hydrologically connected to this specific grid point. Figure 3 (top panel) 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, which have a large ACC number, such as the Rhine, Main, Neckar are easily visible due to their green to yellow color.

2.7 Multiple regression

~~We use a~~ A multiple linear regression was used to separate the anthropogenic ~~(~~heat input a_1~~), meteorological (~~, meteorological a_2 ~~) and hydrological (~~and hydrological a_3 ~~)~~ contributions to the river water temperature. T_w ~~is~~ was regressed with T_c and river discharge ~~Q~~Q. Their regression coefficients a_2 (T_c slope) and a_3 (~~Q~~ Q slope) represent the magnitude of the respective influences. The offset a_1 (RBT) combines all other influences ~~, which are controlled by anthropogenic sources.~~ which were not related to a change in T_c or Q. We hypothesized that the RBT is directly linked to heat input by power plants, in this study NPPs, and other industrial facilities.

~~The linear regression is improved by using a new method for calculating T_c.~~ Instead of taking T_a directly at the monitoring station, we ~~improve~~ improved Eq. (1) by a ~~time dependent~~ time-dependent and weighed average of T_a (x,y,t) over the whole catchment, Eq. (5). (x,y) ~~are~~ were spatial coordinates in the catchment area and ~~a~~ the subscript $_0$ marks the location of the

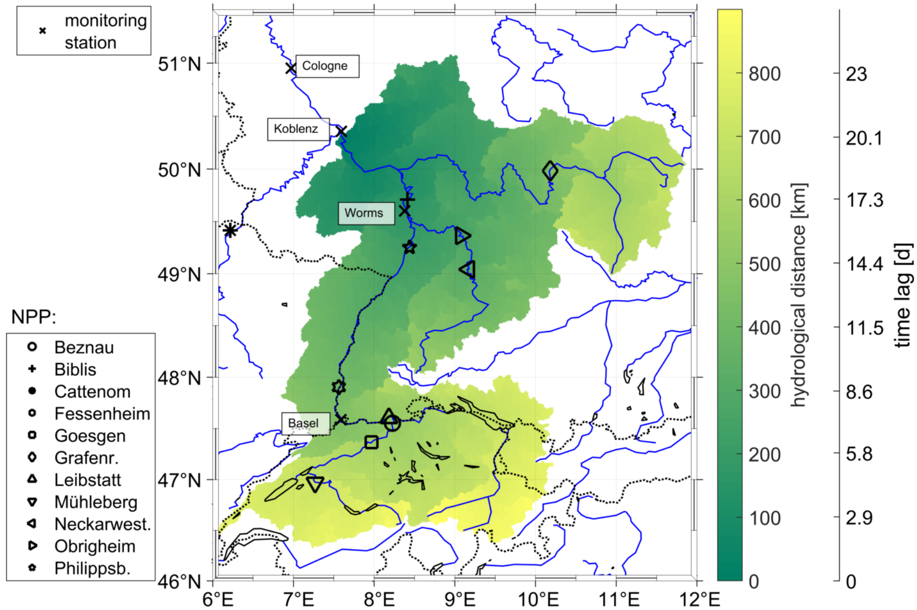

Figure 2. Catchment area of the Koblenz monitoring station as an example. The colors show the hydrological distance between the monitoring station and each grid point of the catchment area. The second y-axis shows the time it takes in days, in our ~~model~~set-up, ~~it takes~~ to flow from a certain grid point to the monitoring station based on the hydrological distance. The flow speed is 0.4 ~~ms~~m s^{-1} and ~~in this study~~ was defined to be constant in space and time. ~~The Xs with the name-tag Basel, Worms, Koblenz and Cologne mark the~~ All monitoring stations are marked by X. The other markers show the location of the NPPs.~~For names refer to the legend.~~

~~measurement~~ monitoring station.

$$T_w\left(x_0,y_0,t_0\right) = a_1 + a_2 \cdot T_c\left(x_0,y_0,t_0+\Delta t\left(x,y\right)\right) + a_3 \cdot Q\left(x_0,y_0,t_0\right) \tag{5}$$

The new representative catchment temperature ~~is called T_c.~~ was called $T_c(x_0,y_0,t_0)$. It was a weighed average of the whole catchment area (x,y) which is defined by the measurement point (x_0,y_0). The difference between the measurement time t_0 and the reading of T_a is called ~~time lag Δt(x,y)~~ time-lag $\Delta t(x,y)$ and depends on the hydrological distance between the measurement point and the reading. $\Delta t(x,y)$ is negative and points to a moment in time before the measurement.

~~Time lag~~

2.7.1 Time-lag

A change in T_w is slower than a change in T_a. The ~~time lag~~ 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 mass' mixing capability, heat capacity and surface area cause a strong thermal inertia. Changing T_w through new meteorological conditions and heat fluxes take time. Therefore, linear as well as exponential models ~~either use~~ include either a fixed Δt for T_a (Eq. 6) or an average of T_a including a time span before (Eq. 7) (Stefan and Preudhomme, 1993; Webb and Nobilis, 1995, 1997; Haag and Luce, 2008; Benyaha et al., 2008).

$$T_c\left(x_0,y_0,t_0\right) = T_a\left(x_0,y_0,t_0+\Delta t\right) \tag{6}$$

$$T_c\left(x_0,y_0,t_0\right) = \sum\nolimits_{\cancel{t=t_o}\ t=t_0}^{\cancel{t=\Delta t}\ t=t_0+\Delta t} T_a\left(x_0,y_0,t_0\right) \tag{7}$$

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.~~ 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 the change of T_a, in space and time, during advection into account. 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. (8). However, this approach does not include the characteristics of flow path and flow speed.

$$T_c\left(x_0,y_0,t_0\right) = \sum\nolimits_{\cancel{x=0,y=0,t=0}\ x=0,y=0,t=t_0}^{\cancel{x=n,y=m,t=8}\ x=n,y=m,t=t_0-8} T_a\left(x,y,t\right) \tag{8}$$

We ~~combine and extend both ideas~~ combined the general idea of a time-lag and averaging T_a over the whole catchment area (Eq. 6, 7 and 8)~~and average T_a over the whole catchment area but~~ , but in this study each grid point ~~is~~ was linked to a specific ~~time lag~~ time-lag $\Delta t\left(x,y\right)$~~. $\Delta t\left(x,y\right)$~~ , which is dependent on a fixed flow speed ~~v~~ v and the hydrological distance ~~s(x,y)~~ $s\left(x,y\right)$ to the measurement point, Fig. (2). The distance ~~is~~ was obtained from the discharge map (Sec. 2.6) and calculated with ~~v as described~~ v as described by Eq. (9). The new $\Delta t\left(x,y\right)$ represents the mismatch by advection but not specifically the mismatch through thermal inertia. The thermal inertia would be independent of $s\left(x,y\right)$ and a constant added to Δt. However, we are of the opinion, that a sufficient part of the thermal inertia time-lag was included in our representation of $\Delta t\left(x,y\right)$.

$$\Delta t\left(x,y\right) = -\frac{s\left(x,y\right)}{v} \tag{9}$$

~~**Weighing coefficients**~~

2.7.2 Weighing coefficients

Tobler (1970) proposed that close spatial and temporal conditions tend to be higher correlated than those further away. This ~~leads~~ led to the introduction of the weighing factor ~~w. We use a~~ w. A linear decreasing weighing factor from 1 to 0 was used. 1 ~~is given~~ marks 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~~ areas were different for the four monitoring station, four ~~weight coefficient tables are calculated.~~ weighing coefficient tables were calculated. As an example, Table (3) shows the weighing coefficient for Koblenz~~, as an example~~.

~~For reasons of simplification, a~~ A catchment-wide hydrological flow model~~is not used~~ , estimating the flow speed at every grid point for every hydrological scenario~~. Therefore, the~~ , was not used. It had not been available yet for every grid point of the

Δt [d]	weighing factor	distance from measurement point [km]
0	1	0
-1.01	0.96	35.1
-2.00	0.92	69.6
-5.02	0.81	174.6
	...	
-13.01	0.50	452.5
	...	
-26	0	904

Table 3. ~~This table defines the weighing~~ Weighing factors for the distance and the resulting Δt for the monitoring station Koblenz. Δt is calculated from distance and flow speed, Eq. (9). The weighing coefficient is linearly correlated to the Δt.

catchments and the the focus of this study was to create a simple set-up, also transferable to other river catchments. Therefore, it was decided to work using a constant flow speed of 0.4 ~~ms~~m s^{-1} ~~is set constant~~. This flow speed ~~is~~ was determined by calculating ~~RMSE~~ the RMSE (whole data-set) of the $ACC + \Delta t$ model with a step wise reduction of the flow speed from ~~1.5 ms~~1.4 m s^{-1} to 0.3 ~~ms~~m s^{-1}. The lowest RMSE was obtained at Koblenz at ~~Koblenz is obtained at~~ 0.4 ~~ms~~m s^{-1}. The ~~weighing coefficient w~~ RMSE and NSC coefficients at all flow speeds and all stations are shown in the supplement. For Basel and for Worms slower flow speeds would lower the RMSE further. We did not include this as it would create unreasonable low flow speeds. The reason for the small flow speeds, with lowest RMSE, might be the thermal inertia. As thermal inertia is not explicitly represented in Δt (Eq. 9) a smaller flow speed could compensate for that, especially in smaller catchment areas.

The weighing coefficient w is combined with ~~ACC. ACC~~ 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~~ ACC grid points, which carry less water, ~~with~~ and the influence of T_a on large water masses. Figure (~~??) shows the product of ACC and w~~ 3) (bottom panel) shows $ACC \cdot w$ over the whole catchment area of Koblenz.

~~Catchment area of the Koblenz monitoring station. The colors show ACC multiplied with w, which is depending on the distance (Δt). We also calculate the number of grid points in several ACC bins . The red bars in~~ The grid points were binned according to their ACC value. A high bin represents large rivers, a low bin their tributaries. The reason was to investigate the importance of different ACC bins to the total T_c calculation. The ACC bin with the largest contribution in Fig. (4) was normalized to one making it a relative contribution. The red bars (Fig. (4)) show the relative contribution ~~of each ACC group using onlytheir quantity without ACC*w weighing . This shows~~ (y-axis) of each ACC bin by the number of grid points in this bin only, no $ACC \cdot w$ weighing was applied. The results showed that the large ~~amount of low ACC~~ number at low ACC bins (small water mass) ~~grid points would have a large influence over large ACC~~ have a larger influence compared to the rather low numbers at high ACC bins (e.g. large water masses, rivers, lakes)~~grid points~~. The difference in relative contribution is four powers of magnitude. The white bars show the relative contribution using the ~~ACC*w~~ number of grid points in the bin and the $ACC \cdot w$

weighing. This distribution ~~gives~~ delivered rather equal importance to all grid points as it puts more weight on grid points covering lakes and rivers. The average difference ~~is about 1~~ in relative contribution is about one power of magnitude.

~~T_c~~

2.7.3 T_c

Combining Δt~~with ACC*w~~, $ACC \cdot w$ weighing and the gridded temperature reanalysis data of Sec. (2.2), we ~~propose this~~ proposed a new 3D (x,y,t) averaging of T_a shown in, Eq. (10).

$$T_c\left(x_0, y_0, t_0\right) = \frac{1}{n \cdot m} \frac{1}{\sum w\left(\Delta t\left(x,y\right)\right) \cdot ACC\left(x,y\right)} \sum_{x=1,y=1}^{x=n,y=m} w\left(\Delta t\left(x,y\right)\right) \cdot ACC\left(x,y\right) \cdot T_a\left(x,y,t_0 + \Delta t\left(x,y\right)\right) \tag{10}$$

~~$T_c\,(t)$ is calculated by weighted (ACC*w) averaging $T_a\,(x,y,t)$~~ $T_c\,(x_0,y_0,t_0)$ was calculated by weighed $(ACC \cdot w)$ averaging $T_a\,(x,y,t+\Delta t\,(x,y))$ over all grid points of the catchment area (x=1,...n y=1,...m) which ~~reach at the monitoring station at time t~~was set by the measurement point (x_0~~. The time lag~~ ,y_0). The time-lag Δt ~~is~~ was an estimate for the time it takes for a water droplet from a specific grid point (x,y) in the catchment area to the measurement location.

Based on Eq. (10), ~~we calculated~~ the daily T_c was calculated for 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.

~~T_c calculation methods~~

2.7.4 T_c calculation methods

~~We additionally use~~ Additionally, we used these four calculations methods ~~,~~ [1] ~~w+Δt~~ $w+\Delta t$; [2] avg+Δt; [3] avg; [4] point, to compare their results of the linear regression to the calculation proposed in Eq. (10).

[1] ~~We use only the w~~ w weight (Eq. 11) ~~with time lag~~and time-lag only.

$$T_c\left(x_0, y_0, t_0\right) = \frac{1}{n \cdot m} \frac{1}{\sum w\left(\Delta t\left(x,y\right)\right)} \sum_{x=1,y=1}^{x=n,y=m} w\left(\Delta t\left(x,y\right)\right) \cdot T_a\left(x,y,t_0 + \Delta t\left(x,y\right)\right) \tag{11}$$

[2] No weight, only ~~time lag is used~~time-lag, Eq. (12).

$$T_c\left(x_0, y_0, t_0\right) = \frac{1}{n \cdot m} \sum_{x=1,y=1}^{x=n,y=m} T_a\left(x,y,t_0 + \Delta t\left(x,y\right)\right) \tag{12}$$

[3]~~We calculate a mean $T_a(x,y,t_0)$~~ A mean $T_a(x_0,y_0,t_0)$ over the whole catchment area at the time t_0 of the measurement, Eq. (13). Δt ~~is not usedhere~~was not used.

$$w\left(x,y\right) = 1 \qquad T_c\left(x_0, y_0, t_0\right) = \frac{1}{n \cdot m} \sum_{x=1,y=1}^{x=n,y=m} T_a\left(x,y,t_0\right) \tag{13}$$

[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. (14).

$$T_c\left(x_0, y_0, t_0\right) = T_a\left(x_0, y_0, t_0\right) \tag{14}$$

3 Results

3.1 Water temperature time series

To investigate the ~~long term~~ long-term change over time, we ~~fit~~ fitted 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 ~~,~~ and Cologne). The same ~~is~~ was also done, when all four monitoring stations ~~have~~ had an overlapping data-set (1985-2018)~~.~~, Tab. (1). The left column of Fig. (5) ~~shows~~ presents the yearly averaged T_w and the linear fits ~~to~~ for the two time periods. The average T_a of the catchment area is also shown. ~~The~~ In the right column of Fig. (5) ~~shows~~ the RAPS index of T_a as well as T_w is shown. The fit coefficients and the rate of warming per year are ~~shown~~ displayed in Tab. (4).~~We also calculated the~~ The calculated T_a ~~increase~~ increased in the catchment area of all monitoring stations ~~. These~~ and the respective slopes are shown in column four and five of Tab. (4).

Figure (5) and Table (4) show that the change of T_w ~~is heterogenous~~ was found to be heterogeneous along the Rhine. The slope at Basel is approx. six times higher (~~0.0350~~0.049 ^{o}~~Cy~~C y^{-1}) than the one in Cologne (0.0084 ^{o}~~Cy~~C y^{-1}), comparing only the overlapping data-set. However, during the same period T_a ~~shows~~ (0.05 ^{o}C y^{-1} Basel, 0.05 ^{o}C y^{-1} Cologne) display 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~~ compared to Basel and Cologne. Generally, the T_a warming rates are less than 5 % different from each other. Arora et al. (2016) showed a mean T_w warming rate of north and north-east Germany rivers of 0.03 ^{o}C y^{-1} (1985-2000) and 0.09 ^{o}C y^{-1} (2000-2010). Regarding our time-period (1985-2010) these values are plausible. Basarin et al. (2016) found a maximum increase of T_w at the Danube at Bogojevo (1950-2012) of 0.05 ^{o}C y^{-1} which is matching the maximum increase at Basel. T_a increased by 0.02 ^{o}C y^{-1} between 1985-2010 in the study by Arora et al. (2016). We found a steeper slope at all stations. The reason could be the hiatus of global warming (Hartmann et al., 2014), which is a flattening of the T_a increase between 1998-2012. This period is fully included in the Arora et al. (2016) and our data-set but we investigated further until 2018, when the warming of T_a has already increased again (Hu and Fedorov, 2017). Michel et al. (2020) investigated T_w at 52 river gauges in Switzerland representing most of the Rhine catchment area at Basel. The authors reported an average T_w increase at the 52 stations of 0.037 ^{o}C y^{-1} (1998-2018) and 0.033 ^{o}C y^{-1} (1979-2018). T_a increased 0.039 ^{o}C y^{-1} (1998-2018) and 0.046 ^{o}C y^{-1} (1979-2018). Comparing this to our results at Basel, the T_a warming rates are similar. The difference might originate from the use of meteorological stations nearby river gauges only (Michel et al., 2020) instead of a reanalysis product. The difference of T_w warming (approx. 0.021 ^{o}C y^{-1}) could be interpreted that a lot of warming might occur in the broader vicinity before the Basel monitoring station.

The R^2 ~~also shows~~ values make differences between the ~~measurement stations~~ four monitoring stations visible. 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~~

station ~~name~~	slope T_w whole data-set [^{o}~~Cy~~C y^{-1}]	corr. $T_w \leftrightarrow T_a$ whole data-set	slope T_w 1985-2018 [^{o}~~Cy~~C y^{-1}]	corr. $T_w \leftrightarrow T_a$ 1985-2018	slope T_a whole data-set [^{o}~~Cy~~C y^{-1}]	slope T_a 1985-201 [^{o}~~Cy~~C y^{-1}]
Basel	0.054,$R^2 = 0.66$	0.867	0.049,$R^2 = 0.38$	0.874	0.050,$R^2 = 0.48$	0.050,$R^2 = 0.32$
Worms	0.055,$R^2 = 0.52$	0.690	0.035,$R^2 = 0.38$	0.729	0.050,$R^2 = 0.20$	0.048,$R^2 = 0.36$
Koblenz	0.033,$R^2 = 0.31$	0.778	0.024,$R^2 = 0.38$	0.762	0.052,$R^2 = 0.11$	0.048,$R^2 = 0.36$
Cologne	0.008,$R^2 = 0.001$	0.499	0.008,$R^2 = 0.31$	0.499	0.050,$R^2 = 0.001$	0.050,$R^2 = 0.31$

Table 4. Slope of ~~the~~ linear fits and Pearson's correlation coefficients to the daily temperature data ~~. The second column is a fit to~~ at the ~~available T_w data-set~~four monitoring stations. The ~~third column is a fit to the overlapping T_w~~ data-set ~~from 1985-2018. The fourth column used~~ is ~~the rate of T_a increase~~ described 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~~header. Next to the slope values are the R^2 values, which are ~~statistical~~ statistically significant ~~only~~ if ~~$R^2 > 1.99$~~$R^2 > 0.19$

~~low and insignificant~~was low and statistically not significant. The slope of T_a at Cologne is lower than at the other stations but still ~~significant.~~ statistically significant. The Pearson's correlation coefficients between T_a and T_w were lowest at Cologne and largest in Basel. For T_a the RAPS ~~indexes~~ index of all monitoring stations ~~shows~~ showed four concurrent sections (start-1987; 1987-2000; 2000-2014; 2014-end). Their borders are marked by the blue triangles in Fig. (5). The ~~sections~~ section between 2000-2014 could be a consequence of the hiatus of global-warming between 1998-2012 (Hartmann et al., 2014). Each section represent slope changes of the RAPS index and indicate trend changes in the original time-series. The T_w RAPS index for Basel ~~shows~~ displayed the same pattern of sections as the T_a index. All other stations ~~show a different~~ showed other RAPS T_w to RAPS T_a ~~pattern~~patterns. This means that the T_a and T_w trends of the original time-series ~~are~~ were different at these stations. T_a can not fully describe the trends in T_w.

We ~~hypothesize~~ hypothesized that different meteorological conditions ~~are~~ were not the reason for this difference. Meteorological differences should ~~be~~ have also been visible in the T_a warming rate of the four stations, which ~~is~~ was not the case. The RAPS analysis for T_a and T_w ~~RAPS only correspond for~~ only coincided within the Basel data-set. ~~Therefore, we applied the regression model (Eq. 5) to investigate the patterns of T_w in relation to T_a along the Rhine river.~~

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

~~We fit~~

3.2 Regression

We fitted the multiple regression model (Eq. 5), using T_c and ~~Q~~ Q to T_w of each monitoring station for the available data-set. Afterwards, we ~~recalculate T_w~~ recalculated $T_{w,modelled}$ using the regression coefficients a_1, a_2 and a_3. From the comparison between the ~~modeled~~ $T_{w,modelled}$ and measured T_w, ~~we calculate~~ the root mean square error (RMSE) and the Nash-Sutcliffe coefficient (NSC) for each monitoring station was derived, Tab. (5). To support the introduction of weighing coefficients ~~ACC*w and a catchment-wide~~ $ACC \cdot w$ and Δt, we ~~compare~~ compared five different calculations of T_c from Sec. (2).

	RMSE				NSC			
~~descr.~~method	Basel	Worms	Koblenz	Cologne	Basel	Worms	Koblenz	Cologne
~~ACC*w+Δt~~$ACC \cdot w + \Delta t$	1.65	**1.24**	**1.02**	~~**1.41**~~**1.31**	**0.93**	**0.96**	**0.97**	**0.95**
(1) w+Δt	**1.56**	1.33	1.43	~~1.86~~1.87	0.92	0.95	0.95	0.92
(2) avg+Δt	1.61	1.45	1.70	~~2.01~~2.08	**0.93**	0.94	0.93	0.90
(3) avg	2.48	2.43	2.37	2.97	0.82	0.84	0.86	0.79
(4) point	~~2.73~~2.67	2.55	2.63	2.85	0.78	0.82	0.82	0.80

Table 5. RSME [^oC] and NSC for all T_c calculation ~~method~~methods. ~~The~~ Different T_c calculation methods and the regressions are applied over the total data-set. The RMSE and the NSC are calculated between T_w and $T_{w,modelled}$. The first column contains the calculation method~~number and the method short description~~. The best results for each monitoring station and each calculation method are bold.

Table (5) shows the RMSE and ~~NCS~~ NSC values for all correlations. The lowest (RMSE) and highest (NSC) values ~~are~~ were displayed bold in Tab. (5). The lowest RSME ~~is~~ was found to be 1.02 ^oC for ~~ACC*w+Δt~~ $ACC \cdot w + \Delta t$ (row one) at the Koblenz station. At this location also the largest ~~NCS~~ NSC of 0.97 ~~appears. We optimized the flow speed~~ appeared. The flow speed was optimized for lowest RMSE at the Koblenz station~~. It is~~, Sec. (2.7.2). It was evident that the three methods including a Δt have a lower RMSE (below 2.01 ^oC, lowest 1.02 ^oC) than the two methods without a Δt (above 2.37 ^oC, largest 2.97 ^oC). The same trend ~~holds for NCS~~ held true for NSC where the Δt methods ~~are~~ were above 0.90 and the other two ~~are~~ were below 0.86. We think that the use of a catchment-wide Δt ~~improves~~ improved the quality of the multiple regression analysis and ~~is~~ delivered a significant improvement to the $T_a \rightarrow T_w$ based modeling. ~~It is interesting hat combining ACC with the w weighing factor provides~~ Interestingly, combining ACC and the weighing factor w provided the best estimation ~~. Figure~~ for all stations, except for Basel. The content of Fig. (4) could ~~be the reason. Without ACC~~ explain this result. Without ACC weighing small water masses (small ~~ACC) are over represented~~ ACC) may be over-represented in the contribution to T_c. Large ~~ACC~~ ACC grid points represent large water masses (rivers and lakes) and ~~the influence of T_a on them would~~ their influence on T_a may be otherwise underestimated. At Basel the fraction of low ACC grid points was relatively small compared to the other stations, as Basel is closest to the water sources and has the smallest catchment area. Therefore, the ACC weighing might have provided weaker results.

As ~~the ACC*w+Δt provides the~~ $ACC \cdot w + \Delta t$ provided the smallest RMSE, this calculation method ~~is~~ was 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~~ were then taken as a basis to calculate T_w for each year from 2000 to 2018. The RMSE and ~~NCS data is~~ NSC data was consistent in magnitude with the long-term ~~regression~~ regressions of this section. The RMSE at Koblenz ~~ranges~~ ranged from 0.75 ^oC to 1.22 ^oC. A lower RMSE ~~is~~ was caused by the shorter regression period. This supports the stability and validity of ~~our~~ the regression model.

3.3 Rhine base temperature

name	period	ΔRBT from data-set	~~ΔRBT~~ ΔT_w from Eq. (3)	ΔHI [GW]
Basel	2008-2017	-0.26	0.04	0.17
Worms	1996-2017	1.29	1.19	7.14
Koblenz	1999-2017	1.59	1.45	10.5
Cologne	1998-2017	1.21	1.55	10.7

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

~~Using the multiple regression in Sec. (3.2), we calculate the coefficients a_1-a_3, Eq. (5). 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~~ The RBT was taken to explain differences in the T_w warming rates of Tab. (4). ~~To point out changes over time, we regress a two year~~ We regressed a two-year segment of the T_w time series and ~~use~~ set a step size of one month in order to create a RBT time series over the ~~available~~ full data-set. The regression of a two-year segment should also compensate extreme events occurring during one year. These could be extreme low discharge or extreme water temperatures, to which industrial and power production had to react. As the absolute RBT cannot be meaningfully interpreted, only the changes of RBT over time are shown in Fig. (6). We ~~subtract~~ subtracted the last data point of each time series from the rest of the data and ~~show~~ showed the change of RBT~~vs time and~~ , a four-year running mean ~~. The heat input~~ and Δ RBT (Eq. 3) vs time. The HI by NPPs is shown as a dotted blue line with the y-axis on the right ~~hand side.~~ (Fig. (6)).

~~**Long term trend**~~

3.3.1 Long-term trend

In this study~~long term trends occur~~ , long-term trends were visible 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 NPPsand~~ The HI by NPPs, the four-year running mean RBT ~~follow~~ and ΔRBT followed a similar trend in this analyis, Fig. (6). After the maximum ~~of heat discharge by~~ heat discharge from NPPs between 1996-1998, the ~~heat input~~ HI as well as the RBT of Worms, Koblenz and Cologne ~~decline~~declined. The RBT started its decline 1-2 years before 1995, which might have been triggered by the recession in 1993 and a sharp drop in the German trade-balance. At Basel the RBT as well as the ~~heat input stay~~ HI remained comparably constant. ~~To investigate these similar trends we calculate ΔRBT~~Additionally, we calculated ΔT_w based on the change in HI, using Eq. (3), at every station and ~~compare~~ compared it to the ΔRBT from the ~~measured T_w~~regression model, Tab. (6). The period for each ~~measurement~~ monitoring station starts at the maximum ~~heat input~~ HI by NPPs for the respective station and ends in the year 2017.

At Basel, both simulated and calculated RBT changes ~~are~~ were negligible due to the lack of change in HI. At all other stations, the change in HI ~~is~~ was reflected in the change of RBT. The maximum difference between simulation and calculation ~~is~~ was found to be 0.34 ^oC. Before 1995 Worms, Koblenz and Cologne showed an approx. 1 ^oC offset between ΔRBT and ΔT_w (Fig. (6)). This was occuring during a time when the NPPs HI remained relatively stable but the GDP increased by 30 % between 1985-1995 (Worldbank, 2020). The change in nuclear power production over a time period of 30 years or more can explain changes and the heterogenous warming rates of T_w along the ~~Rhine river~~ river Rhine. NPPs may also impact T_w at much shorter ~~timer scale~~ time scales but do not ~~seem, to our best knowledge, to~~ change their power output accordingly.

~~**Short term trend**~~

3.3.2 Short-term trend

~~Short term~~ Short-term changes (< 5 y) in RBT (Fig. 6) are not likely to be influenced by the overall ~~heat in put~~ HI from NPPs, as ~~they change~~ these adopt production at longer time scales~~, but rather by~~ . More important are local industrial conditions, which could also include fossil fuel power plants. However, not all influences to the coefficient a_1 and subsequently to RBT originate from industrial production. Various potential influences are unknown and not within the scope of this publication. ~~For Basel, we hypothesize that the varying, but 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~~For Basel, it was not possible to satisfyingly explain the short-term variations. The Rhine and its tributaries upstream are flowing through sub-alpine lakes and, in relation to the downstream part, are not strongly industrialized. Lakes have a complicated heat budget (Råman Vinnå et al., 2018), which was not focused on in this analysis. For all other stations, we ~~hypothesize~~ hypothesized that local production facilities and their ~~heat input~~ HI into the Rhine are responsible for the ~~short term changes . Therefore we compare~~ short-term changes by comparing the RBT time series to economic data. Figure (7) 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~~ the data was plotted as separate lines. For Worms (Fig. 7, bottom panel) we added the change of turnover of the BASF company (red dashed line (AG, 1989)). ~~The~~ BASF is a ~~chemical company. One~~ major chemical company and one of its largest production facility, with an estimated ~~heat input~~ HI of 500 MW to 1 GW, is located 12 km upstream (km 431) from the Worms station. ~~We hypothesize that production and heat input~~ It was investigated if the production and HI changes of this factory ~~are~~ were also visible. In 1985, although the change in GDP ~~does~~ did not indicate a large RBT change, a RBT decrease ~~is~~ was visible. This ~~is backed~~ was indicated by a turnover decrease in 1985 and 1986. After the German reunification ~~1991~~1990, a negative GDP change (recession) ~~is~~ was evident. This ~~is~~ was followed by a BASF turnover decline as well as a decrease in RBT. After that, the RBT ~~follows~~ followed the up and down movements of the GDP ~~,~~ and 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~~ were visible in the RBT and in the GDP, when a decrease of both parameters followed. The two events are marked ~~with~~ by triangles in Fig. (7).

Before 1990, the RBT at Koblenz ~~does~~ did not follow the GDP trend and ~~shows~~ showed a rather anti-cyclic behavior, which can not be explained yet. After 1991, the RBT ~~follows~~ followed the general trend of the GDP but ~~does~~ did not seem to be strongly influenced by the short recession after the German reunification. Again, economic events such as the burst of the dot-com bubble (early 2000s) and the mortgage crisis (2008) ~~have~~ displayed an influence on the RBT.

The RBT at Cologne ~~does~~ did 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 was added 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~~ did not exceed 90 %. The increase in production ~~is~~ was clearly visible in the RBT ~~of~~ ar Cologne, where a large oil refinery is located 19 km upstream at km 671 (Rheinland refinery). The RBT at Worms and Koblenz could be influenced by the output of a refinery next to Karlsruhe at km 367 (Mineraloelraffinerie Oberrhein).

~~Correlation~~

3.3.3 Correlation

We ~~correlate~~ correlated the GDP-change ~~to~~ and the filtered RBT signal. It ~~is noticeable that we must shift the GDP-change~~ was noticeable that a 480 days shift to the past was needed to get matching trends. This means that a change in RBT or anthropogenic ~~heat input appears~~ HI appeared about 480 days earlier than in the GDP calculation. The shift could be caused by two reasons: [1] ~~We are using~~ Using the GDP difference of two consecutive years, ~~which~~ has a significance at a unspecific point of time within these two years. [2] The GDP ~~could be~~ is lagging behind the real economic situation, in this case the industrial production. Yamarone (2012) ~~claims that GDP is~~ claimed that GDP was a coincident economic indicator similar to industrial production. However, ~~he uses~~ the author used quarterly GDP calculations ~~vs our annual data~~ and in this study annual data was used. The quaterly data-set ~~could be reacting~~ may react faster to changes. A second thought ~~is that he compares~~ was that (Yamarone, 2012) compared industrial production calculations, which is an economic index, to GDP (another economic index). ~~We have basically real time data from the industrial heat input~~ In this study real-time data from industrial HI into the river was processed. This shift ~~is not done in~~ has not been done for Fig. (6) because a shift of 1.5 y on a 40-year time scale is negligible.

Table (7) shows the Spearman's rank correlation coefficients of Worms, Koblenz and Cologne ~~fo rACC*w+Δt~~ for $ACC \cdot w + \Delta t$ calculation method, which ~~produces~~ resulted in the lowest RMSE in Koblenz. All correlations ~~are positive and~~ were found to be positive and statistically significant (p<0.05). The correlation in Koblenz ~~is the~~ was highest. Fig. 8 shows the filtered RBT signal vs the GDP-change at the three monitoring stations. The RBT time-series ~~is~~ was detrended and filtered. ~~This graph depicts in detail the correlation of GDP-change and RBT.~~ Most of the time~~the change in filtered and shiftedRBT is coincident, after shifting)~~ , the variations in the RBT (filterend and shifted) were coincident with the GDP-change. The RBT peak ~~from~~

name	~~ACC*w+Δt~~ $ACC \cdot w + \Delta t$	significance
Worms	0.48	$p<0.05$
Koblenz	0.53	$p<0.05$
Cologne	0.44	$p<0.05$

Table 7. Spearman's rank correlations between RBT and GDP-Change for ~~ACC*w+Δt~~ $ACC \cdot w + \Delta t$. The last column shows the significance.

between 1995-1998 ~~is~~ was not very well represented by the GDP-change, which has already been discussed earlier in context of Fig. 7.

4 Conclusions

We ~~introduce~~ introduced a new catchment-wide air temperature T_c, which ~~decreases~~ decreased the RMSE (Tab. 5) in a $T_c \rightarrow T_w$ regression. T_c is a ~~weighted (ACC*w~~ weighed ($ACC \cdot w$) average of all T_a across the catchment 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~~ In the approach, this time-lag was used as an indicator for the point in time when a 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~~ certain point (in this study a monitoring station) and it delivered better linear $T_c \rightarrow T_w$ estimates. This improvement in the $T_c \rightarrow T_w$ relationship ~~supports the analysis , reanalysis and forecast of T_w~~ may support the analysis of processes in the heat budget of rivers. Usually T_a data is readily available and can easily be combined with ~~Q data for a~~ Q data for multiple linear regression analysis. Still a sufficient long (decade) time-series of T_w ~~is~~ was required. Nevertheless a linear relationship ~~is~~ was found to be simpler than a full physical model which requires all meteorological fluxes as ~~parameters~~ input quantities. ~~This a case study for the~~ In the prove of concept, we focused on the Rhine catchment area but in principle the model can be ~~theoretically used in~~ applied to any river system around the globe~~. Catchment area~~ , if the respective long-term data are available. However, catchment-area data and reanalysis T_a data are often globally available. Morrill et al. (2005) ~~show~~ showed a linear $T_a \rightarrow T_w$ relationship for 43 rivers with various catchment areas in the subtropics. This ~~could indicated that this case study of the Rhine~~ potentially indicates that the proposed model and procedure can be applied ~~globally. There is a lack of studies on the $T_a \rightarrow T_w$ relationship in the tropics, where precipitation and extreme events, such as monsoon, could complicate this relationship. Future calculations could~~ elsewhere. However, this still has to be verified. Future calculations may be coupled with catchment-wide hydrological models to improve the accuracy of the ~~time lag.~~ time-lag. The time-lag used in this study was based on try and error in search for the lowest RMSE. A detailed catchment wide hydrological flow model would be especially beneficial to set an upper limit for the time-lag and constrain its validity. It would also be interesting to estimate the importance of the advection time-lag vs the thermal inertia time-lag.

~~Using~~ With T_c we ~~regress~~ regressed four T_w time series (Basel, Worms, Koblenz and Cologne) along the Rhine. The offset in the this regression a_1, ~~which we call~~ was called RBT, and its change over time ~~is~~ was found to be an indicator for anthropogenic

~~heat input~~HI. The RBT ~~can be correlated with long term~~ positively correlated to long-term economic changes such as the decrease of nuclear power production as well as ~~short term~~ to short-term economic events. We ~~show that change~~ showed that changes in production rates (oil refineries or chemical industry) as well as a change in GDP ~~can~~ may influence the RBT and therefore the Rhine water temperature. ~~Adsitionally~~Additionally, the Spearman's Rank correlation between RBT and GDP is positive and significant~~which supports the connection between RBT and GDP~~, delivering another indication for the relation. This case study ~~could be on one hand~~ might deliver a tool for ~~understanding the long term~~ better understanding of long-term consequences of industrial water use and ~~on the other hand~~ it might be used as a verification tool for reported ~~heat input~~HI. Germany has a rigorous reporting system on cooling water use. However, other countries could check if industrial ~~heat input~~ HI is in accordance with legislative guidelines~~.~~, without depending on official reports. Whether the ongoing COVID-19 (2020) pandemic and its impact on the economy is also visible using the offered procedures, will need to be proven after the crisis.

Hardenbicker et al. (2016) ~~estimate~~estimated, 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~~ is plausible, according to the historical data analyzed, if the T_a increase remains constant. However, they used a constant anthropogenic ~~heat input.Different~~ HI by e.g. power plants and production industries and different warming rates along the Rhine ~~could occur by a change in anthropogenic heat input.~~ can result from changes in anthropogenic HI. Next to the global air temperature increase, the industrial use of river water is advised for the future Rhine water temperature.

The difference of the T_w warming rate between Basel and the other monitoring stations in ~~our~~ the 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~~ calls for a more integrative river water management than today.

For the ~~Rhine river we find a decreasing ,~~ river Rhine a decreasing (except for Basel~~, RBT ,~~) RBT which indicates a decreasing ~~anthropogenic heat input. However, other~~ HI, was found. Other river catchment areas with growing energy intensive industries ~~could experience a larger warming rate than it is~~ might be impacted by much larger warming rates than those caused by the general increase of T_a, experiencing all consequences for ~~the~~ physical, chemical and biological processes.

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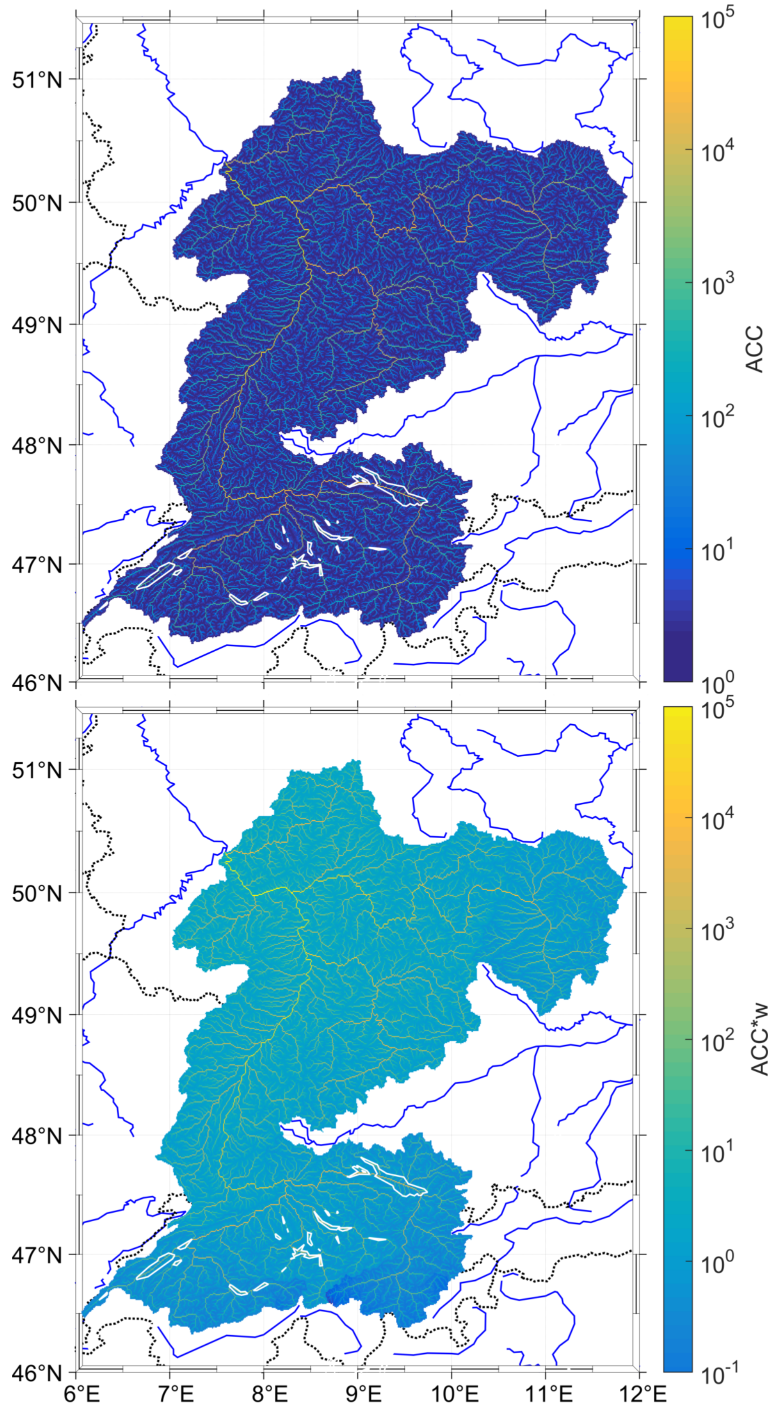

Figure 3. ~~Catchment~~ Both panels show the catchment area of the Koblenz monitoring station. ~~The colors show the number~~ Top: Number of grid points ACC flowing into ~~the~~ each specific ~~gird~~ grid point. Bottom: $ACC \cdot w$, distance and ACC weighed grid cells.

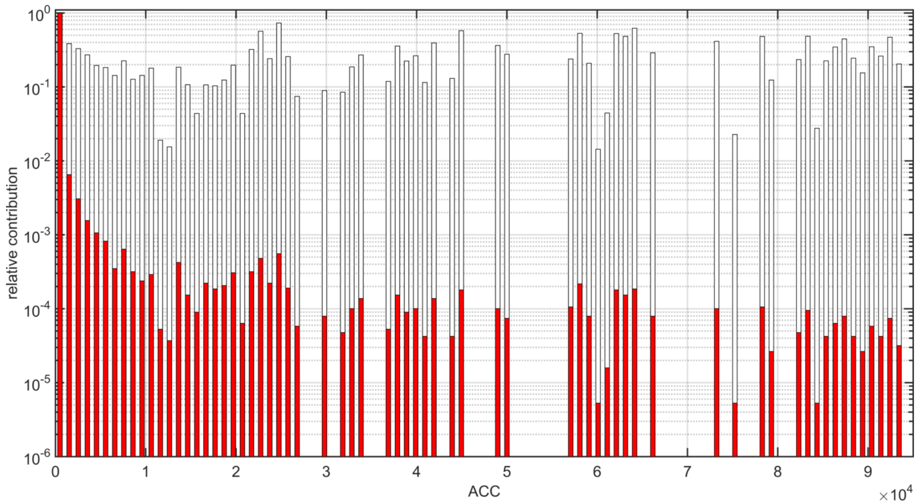

Figure 4. ~~ACC~~ ACC bins (~~x.axis~~x-axis) vs the relative contribution (y-axis). The grid points are binned by their ACC value. The red bars show the relative contribution ~~using~~ (largest contribution normalized to one) by the number of grid points in this bin only. The white bars show the distribution using the number of grid points in this bin and weighing ~~ACC*w~~$ACC \cdot w$.

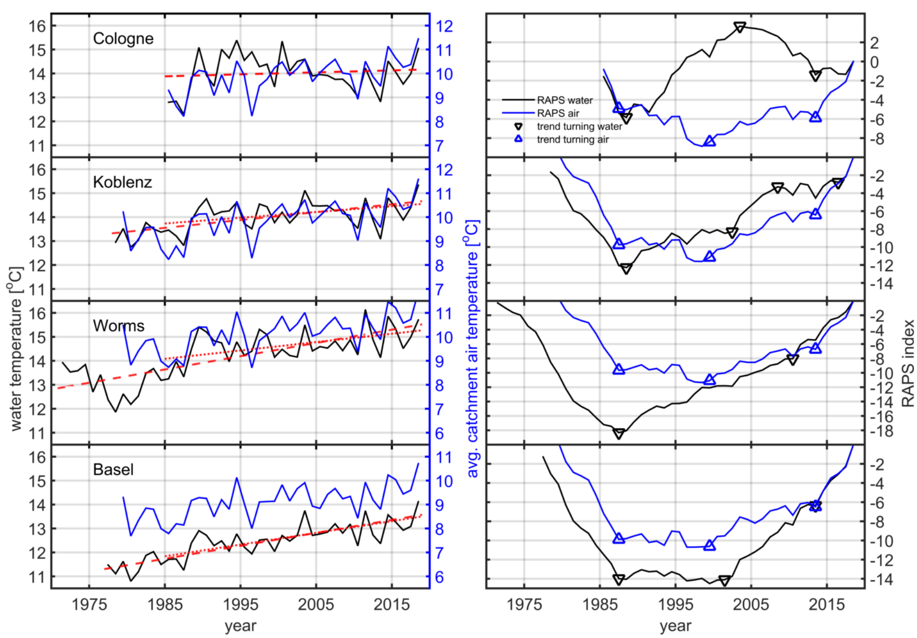

Figure 5. Left column: Yearly averages of water temperatures at the four monitoring stations (black line). The ~~red dashed~~ red-dashed line is a fit to the available data-set. The ~~red dotted~~ red-dotted line is a fit to the overlapping time period (1985-2018). The blue line is the yearly average 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~~ trend-change in the original T_a and T_w time-series.

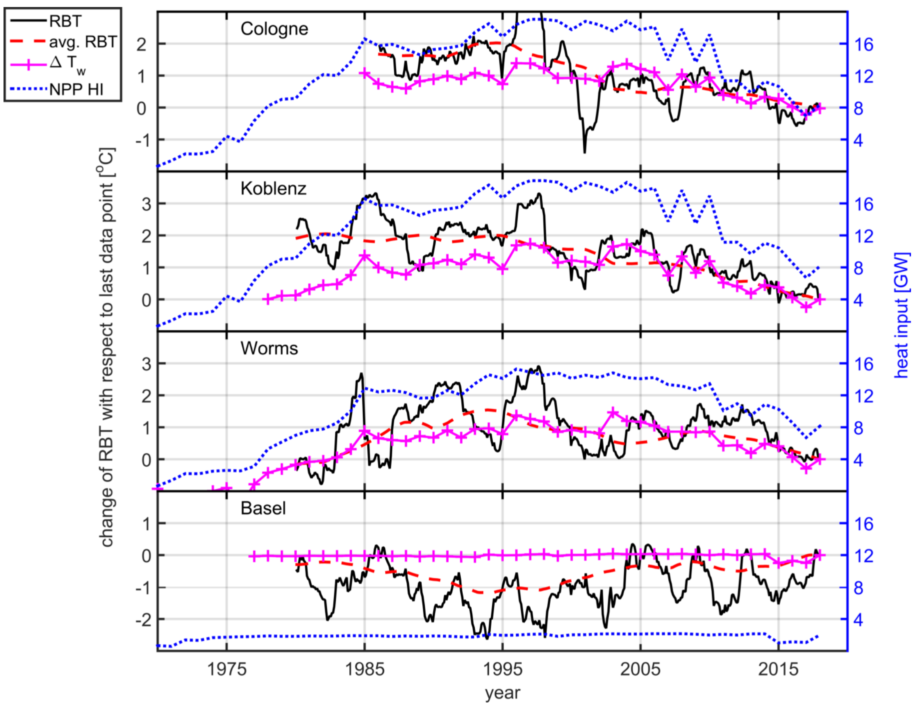

Figure 6. RBT from four monitoring stations (black solid line). The red dashed line is ~~a four year~~ the RBT four-year running mean. The magenta line with the + markers shows the ΔRBT relative to the last year. The blue dotted line is the upstream ~~heat input~~ HI by NPPs, Sec. (2.3).

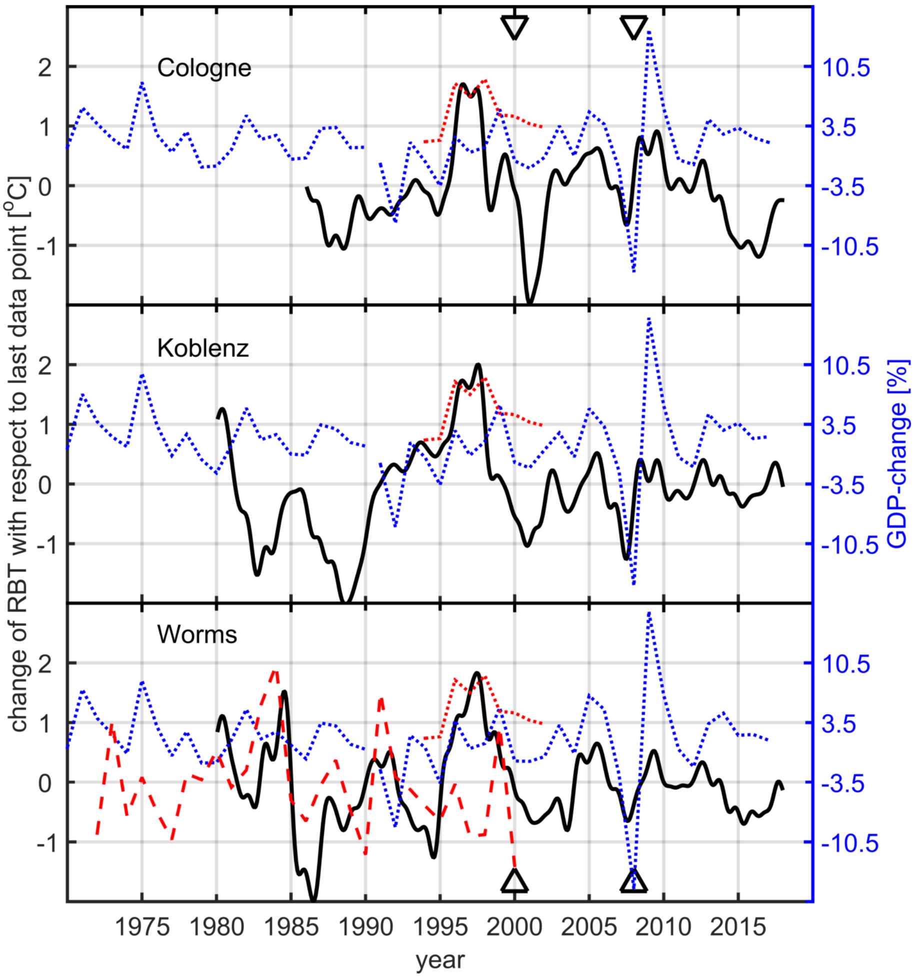

Figure 7. The change of RBT (black solid line) at three monitoring stations (Colgone, Koblenz, Worms). The blue dashed line is the GDP-change of the adjacent federal states. To explain trends during two time periods the red dashed line, which is the turnover of the BASF company, and the red dotted line, production rate of the oil refineries, ~~are~~ were added. The triangles mark the years 2000 (burst of the dot-com bubble) and 2008 (mortgage crisis).

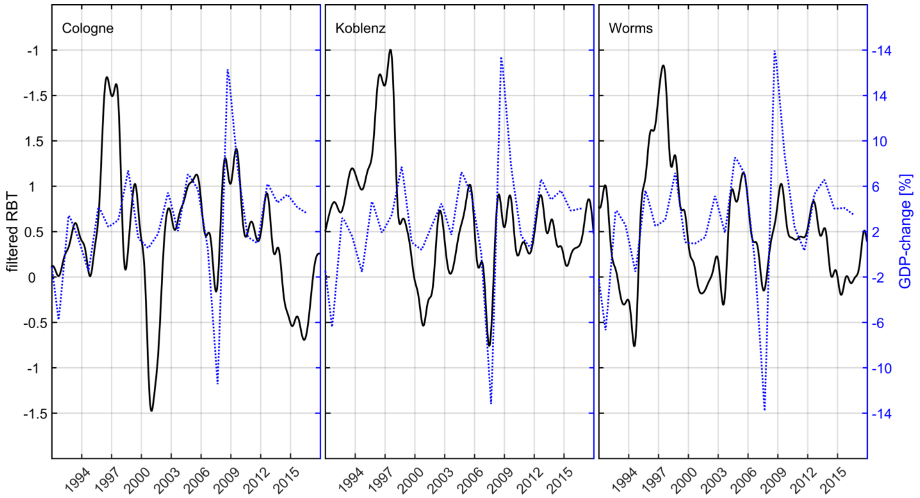

Figure 8. ~~The three panels show the detrended~~ Detrended and filtered RBT signal (black solid) and the GDP change (blue dashed) at ~~the~~ Cologne, Koblenz and Worms.