Climate Change in der Schweiz -Hydrologie (CCHydro)

Feasibility study:

Stream temperature evolution in Switzerland under climate change scenarios

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Preface

The present report summarizes a feasibility study with the goal of evaluating the potential of an extensive research on developing tools and models to predict stream temperatures under climate change forcing in Switzerland. The study opens a new module in the ongoing project *Climate Change in der Schweiz – Hydrologie, CCHydro* initiated and coordinated by the Bundesamt für Umwelt. A future principal research project in the context of CCHydro on the development of a stream temperature prediction model will be based on a climate change scenario for air temperature and precipitation until the year 2050 and will provide a flexible tool for detailed climate change impact studies related to stream temperature changes with all associated consequences for riparian vegetation, aquatic fauna, industrial use of stream water and water resource management in general.

The presentation and discussion of previous work related to the topic constitutes a fundamental part of this report. Results and findings of past stream temperature research are taken as the basis for any further or new development in this direction. Various existing data sources possibly useful and essential for the realization of the principal research project are briefly described in a section. Some of these data have already been used in a preliminary analysis to gauge the potential of a simple regression approach. The report concludes with a summary presenting judgements and recommendations concerning the feasibility of a focused research project, and elaborates also on the role, resources and possibilities of the Laboratory of Environmental Fluid Mechanics and Hydrology, EFLUM.

Lausanne, March 2010

Introduction

Stream temperatures are the result of complex interaction of energy and mass balance components. Since stream temperature is also a key quantity in several important terms of the energy balance there is feedback and bidirectional dependencies which can be complex and non-linear. The energy and mass balances are also strongly influenced by numerous geomorphological factors; the most prominent of them are listed below. Figure 1 shows important processes and quantities influencing the energy and mass balance of the water in a stream segment. Considering all variables necessary to describe each of the quantities in Figure 1 immediately leads to a system of high level complexity.



Figure 1: Schematic of mass (blue) and energy (red) balance components together with atmospheric (green) and geometric (orange) variables. Q denotes water flux, subscripts 'gw' and 'i' stand for groundwater and infiltration, respectively, v is the water advection velocity, P is the precipitation, E is the evaporation, S is the net shortwave radiation, L is the net longwave radiation, H is the sensible heat flux, C is the conductive heat flux, Ta is the air temperature, RH is the relative humidity of air, u is the wind speed, Tw is the water temperature, A is the cross sectional area of the considered stream segment, and dx is the length of the segment.

Factors influencing stream temperature

- <u>topography</u>: upland shading, riparian vegetation, stream orientation, latitude, altitude, bedrock
- <u>atmospheric conditions</u>: solar radiation, air temperature, wind speed, humidity, precipitation, evaporation, melting
- <u>stream discharge</u>: friction (streambed), volume of water, slope/water falls, turbulence, inflow/outflow
- <u>streambed</u>: conduction, groundwater input, radiation absorption properties

Heat exchange

While the mechanisms and processes of heat exchange between the stream water and the adjacent media (atmosphere and streambed) can be very diverse, only two geometric interfaces exist for heat exchange: the water surface and the streambed.

Heat exchange at the air/water surface interface appears to be the dominant surface since roughly 80% of the total energy exchange occurs across this interface (Caissie, 2006), while solar radiation (net shortwave radiation) is by far the most significant component, followed by net longwave radiation, the heat flux associated with evaporative and condensation processes, and the convective heat transfer. Heat input by precipitation was quantified as a rather small contribution compared to other components.

Heat exchange at the streambed/water interface makes up for the remaining 20% and is a function of geothermal heating through thermal conduction, absorption of solar radiation, and advective heat transfer through groundwater contribution and hyporheic exchange (Caissie, 2006).

Literature Review

The existing literature on the topic presents three fundamental typologies of models that can be described as follows

- 1. **Regression** models use only air temperature as an input parameter. The applied regression model is usually complex with multiple regression coefficients since the relationship is nonlinear and may even display hysteresis. The regression models usually perform better at weekly and monthly scales as compared to daily or hourly intervals.
- 2. **Stochastic** or **statistical** models require as input data at least air temperature and discharge; they use time-series analysis or classical regression analysis, and are typically preferred for daily time steps.
- 3. **Deterministic** models are based on more or less accurate and complete mathematical representations of the underlying thermodynamics and physics and require strict conservation of energy and mass. Many inputs

variables are required (geometry, geology, hydrology, and meteorology) which are not always available. In those cases simplified formulations reducing the model complexity are applied or/and parameterizations of physical processes are necessary.

In the following, the three model types are discussed in more detail and some examples from the literature are shown to illustrate the method and its success.

Regression Models

(Morrill, Bales & Conklin, 2005; Mohseni, Stefan & Erickson, 1998; Webb & Nobilis, 1997; Mohseni & Stefan, 1999; Ducharne, 2008)

Air temperature is well correlated with stream temperature since it generally follows the diurnal cycle of incoming solar radiation which is the dominant variable controlling stream temperature. Water temperature varies between the equilibrium temperature (convergence toward equilibrium as water flows downstream) and the upstream water temperature, with the actual temperature depending on the travel time. It was found that weekly or monthly averages of stream and air temperature are better correlated than are daily and hourly values. This of course prevents the possibility to resolve the diurnal cycle using this method. The sensitivity of the results to the distance between the stream gauging station and the weather station where stream and air temperatures are measured is very low, and there is no significant correlation between basin size and the validity of the air-temperature/stream-temperature relationship if there are no significant topographical differences between different watersheds.

At the high and low ends of the air temperature range the water/air temperature relationship does not remain linear. As air temperature increases, the moisture holding capacity (saturation vapor pressure) of the atmosphere increases, allowing for an increased rate of evaporative cooling at the water surface; thus the water body looses more heat, and stream temperature no longer increases linearly with air temperature. Stream temperature versus air temperature typically displays an S-shape, with one asymptote near 0°C (winter) and another one at the upper bound stream temperature. However, streams in cold climatic zones (high latitude or altitude) may not show a significant change of slope at high air temperatures: air temperature does not rise high enough such that the limiting effect of evaporative cooling becomes important. In this case, a specific (simpler) regression method could be applied. Also, in cold regions the seasonal snowmelt causes data scatter at moderate temperatures. An example of a typical regression model is shown in Figure 2.

A widely used regression model (Morrill, Bales, & Conklin, 2005; Mohseni, Stefan, & Erickson, 1998; Webb & Nobilis, 1997), is given by

$$T_s = \mu + \frac{\alpha - \mu}{1 + e^{\gamma(\beta - T_a)}}$$

where

- T_s estimated stream temperature
- T_a measured air temperature

- μ minimum stream temperature
- a maximum stream temperature
- γ function of the steepest slope (θ) of the Ts function ($\gamma = 4 \tan \theta / (\alpha \mu)$)
- β air temperature at this inflection point

See Figure 3 for a graphical illustration. Variable a is calculated from the average and standard deviations of a maximum weekly stream temperature time series, and is then used in the equation to calculate the remaining parameters (iteratively while minimizing the root mean square error).



Figure 2: Linear and nonlinear correlation of weekly mean air temperature and stream temperatures for Lober River, Germany. (from Morrill, Bales, & Conklin, 2005)



Figure 3: Schematic representation of the logistic function parameters (from Mohseni, Stefan, & Erickson, 1998)

The regression model parameters are unlikely to change under warmer climate conditions because the correlation between the parameters and the mean annual or seasonal air temperature is weak. In many case studies, the *seasonal hysteresis* is present which means that a given air temperature yields different stream temperatures at different times of the year. Possible causes:

- influx of cold rain or melt water in the spring, which makes spring water temperature lower than autumn water temperature at the same air temperature
- discharge in autumn is lower than during spring resulting in different warming/cooling due to the large heat capacity of water.

Consequently, two model functions have to be fitted separately for the warming season and the cooling season to take these effects into account (Figure 4).



Figure 4: Mean weekly stream temperatures measured in the Spokane River, Washington, versus mean weekly air temperatures for the period 1978-1980. Numeric labels are the week numbers. (from Mohseni, Stefan, & Erickson, 1998)

Limitations of the model: water temperature is less sensitive to air temperature variations at sites strongly influenced by groundwater, river regulation, lake outflows and vegetation shading, all of which perturbing or biasing a regression model derived for an undisturbed (no dominant effect of the previous mentioned processes) stream system. Significant groundwater inflow decreases the slope of the S-shape of the regression model and forces the water temperature to approach a minimum temperature above 0°C. In addition, snowmelt runoff has a very important influence since it is relatively insensitive to air temperature fluctuations in regions close to the water origin.

Figure 5 presents four examples of a regression model for rivers of different parts of the United States each one representing a particular situation (Mohseni, Stefan, & Erickson, 1998). The Blanco River at Wimberley, Texas (Figure 5a), represents a warm region stream. The estimated minimum stream temperature μ is 0°C, but stream temperature is still close to 4°C when air temperature approaches 0°C. The Aroostook River near Caribou, Maine (Figure 5b), represents a cold region stream. At weekly air temperatures lower than -5°C, simulated weekly stream temperatures fall below 1°C. The model of the Spokane River downstream of the Substa Power Plant in Washington (Figure 5c) has diagnosed the hysteresis and has simulated the weekly stream temperatures by fitting two functions to the data. The presence of two a and two μ values implies jumps in simulated weekly stream temperatures at extreme air temperatures. All three data sets show the S-shaped trend.

Figure 5d displays data of an exceptional case, the Trinity River at Lewiston, California. The stream temperature data are quite scattered, and the scatter cannot be explained by hysteresis. Even with two functions fitted to the data, the model cannot simulate weekly stream temperatures at this gauging station. Note that the minimum stream temperature is relatively high and maximum stream temperature is relatively low, being a typical feature for a hypolimnetic reservoir outlet which makes the model fail in this case.



Figure 5: Weekly observed (dots) and model (lines) stream temperatures versus weekly air temperatures at (a) Blanco River at Wimberley, Texas, and Austin, Texas, for the period 1978-1979 (56 weekly data points); (b) Aroostook River at Caribou, Maine, and Caribou, Maine, for the period 1977-1980 (152 weekly data points); (c) Spokane River, Washington, and at Spokane, Washington, for the period 1978-1980 (156 weekly data points) and (d) Trinity River at Lewiston, California, for the period 1977-1980 (156 weekly data points). (from Mohseni, Stefan, & Erickson, 1998)

Webb & Nobilis (1997) show in their study how predicted stream temperatures obtained from a regression model mached actually observed stream temperature over a period of several years (Figure 6).



Figure 6: Observed and predicted monthly mean water temperatures for the study catchment in the period 1991-1993, using ensemble (A) and monthly (B) air-water temperature regression relationships. (from Webb & Nobilis, 1997)

Stochastic Models

(Ahmadi-Nedushan, et al., 2007; Caissie, El-Jabi, & St-Hilaire, 1998)

Stochastic models take into account the autocorrelation structure of stream water temperature and can also account for the correlation with external variables. The input parameters are the daily mean air temperature and the daily mean discharge (daily mean stream temperatures are required to calibrate the model).

The temperature is split into two components: seasonal and residuals. The seasonal component of stream water and air temperature is established by fitting a periodic sinusoidal function to these time series. The residuals are calculated for both water and air temperature time series by subtracting the seasonal components from the corresponding time series. Different stochastic models were used to model the water temperature residuals, where the second-order Markov process provided the best results for this application. Figure 7 illustrates the performance of the approach for the selected example.



Figure 7: Results of the stream water temperature modeling using a second-order Markov process approach. The bold line represents measured temperatures and the thin line those predicted by the model. (from Caissie, El-Jabi, & St-Hilaire, 1998)

Deterministic Models

Several physically based models for stream temperature simulation exist and exhibit more or less complete consideration of geometrical, hydrological, meteorological and geomorphological variables. Different unsteady, onedimensional advective/dispersive heat transport equations, with heat exchange through the water/air interface and water/streambed, have been already developed. As the net heat transfer is a function of the unknown water temperature, deterministic models require either an implicit discretization, or, since usually not possible, an iterative numerical scheme. Often, a one-dimensional modeling concept is used, averaging the values of all parameters over the channel cross section. The idea is to simulate the temperature in a stream segment with uniform conditions. In LeBlanc, Brown, & FitzGibbon, (1997) for example, the reach was divided into several sub-reaches and the temperature output of the previous sub-reach becoming the input to the next sub-reach (cf. Figure 1).

The energy balance includes: <u>radiative</u> heat fluxes (shortwave and longwave radiation), <u>evaporative</u> heat flux (phase changes), <u>conductive</u> heat flux (between water and streambed), <u>convective</u> heat flux (sensible heat exchange between water and air) and <u>advective</u> heat flux (water at different temperatures added to the stream, i.e. snowmelt, precipitation, groundwater and lateral inflow).

Different physical or empirical parameterizations have been used to calculate the various heat fluxes of the energy budget (cf. Figure 1). For example, Gaffield, Potter, & Wang, (2005) use formulations for some components of the energy balance and illustrate the difficulty that the parameterization of a quantity often results in more (unknown) model parameters. Their specific representation of solar shortwave and atmospheric longwave radiation, vegetative longwave radiation, stream water emitted longwave radiation, convection at the air/water interface, evaporation and stream bed conduction can be found in the Appendix as an example.

A different approach for describing components of the energy balance is proposed by Westhoff et al, 2007. Also here the representation of various energy balance components entails a list of new model parameters which have to be defined in an appropriate way. Figure 8 illustrates the simulated quantities for a selected time period.

A big advantage of deterministic models is that, in case appropriate forcing and input data are available, and depending on the model time step, they can resolve the diurnal cycle which may be of great interest. An example is given in Figure 9 which shows a comparison of simulated and observed daily maximum and minimum stream temperatures.



Figure 8: Heat flux components of the energy budget as modeled in a case study for a subcatchment (Maisbich, Luxemburg). (from Westhoff, et al., 2007)



Figure 9: Comparison of measured and modeled daily maximum and minimum stream temperature. (from Flint & Flint, 2008)

Concept of Equilibrium Temperature

(Caissie, Satish, & El-Jabi, 2005; Krajewski, Kraszewski, & Grenney, 1982)

Some models apply the concept of equilibrium temperature: that is the water temperature at which the sum of the heat fluxes across the air/water interface is zero, and the temperature around which the instantaneous temperature tends to oscillate. Using this concept, the water temperature (T_w) is function of:

- water temperature at the head of the reach (T₀)
- equilibrium temperature (T_e)
- thermal exchange coefficient (K)
- distance from head to a downstream point where temperature is searched (X)
- average depth of the water (D)
- average cross-sectional velocity of the river (V)

The quantities K and T_e are supposed to represent the combined effects of the average meteorological conditions. Assuming that the total heat flux (H_t) is proportional to the temperature difference between the water temperature and the equilibrium temperature, the problem of heat exchange is reduced to a Newton's law of cooling $H_t=K(T_e-T_w)$. Existing graphs of K and T_e as a function of various meteorological variables can be used to estimate K and T_e for a specific situation but afterwards these two quantities have to be determined through a calibration procedure (Krajewski, Kraszewski, & Grenney, 1982).

The model calibration requires observations of shortwave radiation, cloud cover, shading factor, air temperature, wind velocity, relative humidity, atmospheric pressure, the average cross-sectional velocity of the river, average depth of the river, temperature at the head of the reach, and water temperature. However, once the model is calibrated, it is possible to calculate the variation in water temperature just in function of K, T_e and D. An example (Figure 10) illustrates the success of the method.



Figure 10: Results of modeling daily mean water temperatures at Catamaran Brook from 1992 to 1999 using the equilibrium temperature model. Calibration period: 1992 to 1994, validation period: 1995 to 1999. (from Caissie, Satish, & El-Jabi, 2005)

Typical input parameters in deterministic models

(Stefan & Sinokrot, 1993; Gaffield, Potter, & Wang, 2005; Westhoff, et al., 2007; Sinokrot et al, 1995; Flint & Flint, 2008)

The following list contains important input variables required in deterministic models grouped in categories, together with information on the data source or data acquisition method.

Morphology

- cross-sectional area and surface width as a function of stream flow rate
- > From stream site visits and surveys.

Hydrology

- stream flow rate and temperature
- groundwater inflow rate and temperature (constant temperature, the same as the ground temperature (Sinokrot et al., 1995))
- tributary flow rate and temperature
- precipitation intensity and temperature (it is assumed that there is no difference between rain and air temperature (Marcé & Armengol, 2008), but in most cases this component is assumed negligible)
- From flow rate records and stage-discharge relationships, or indirectly by measuring stream flow at various locations.

Meteorology

- solar radiation (considering topographic shading, cloudiness, e.g. Flint & Flint, 2008)
- air temperature, wind speed, relative humidity
- cloud coverage
- > From weather stations or parameterized using other known variables.

Vegetation

- percentage of shading by the riparian vegetation
- Determined by model calibration

Boundary conditions

- upstream water temperature and flow rate
- From at an upstream measurement station or model output from the neighbouring upstream reach:

In addition to the above list of common forcing and model quantities, the following conditions and requirements are imperative for most of the existing deterministic models.

- The averaging period of the conditions should not be less than the travel time of the river through the reach being modelled (Stefan & Sinokrot, 1993).
- Each model must be calibrated and validated using past stream temperature measurements.
- Seasonal changes in vegetation, shading, and discharge may entail the recalculation of model parameters.

Conclusions from case studies using deterministic models

- Stream temperature is very sensitive to the distribution of groundwater input, stream width, air temperature and solar radiation (the latter being strongly dependent on shading due to the vegetation (Stefan & Sinokrot, 1993; LeBlanc, Brown, & FitzGibbon, 1997; Sinokrot et al., 1995)).
- Models developed for tributaries based on measured stream temperature data, may be used to estimate stream temperature for other ungauged tributaries. Flint & Flint, (2008) present convincing results for a very heterogeneous hydrological basin.
- Friction could be an important component for small and steep streams in cold periods and during night-time hours (Webb & Zhang, 1997).
- Bed conduction is particularly important in the case of gravel-bottomed streams (Webb & Zhang, 1997).
- Daily variations are generally small for cold headwater streams and increase for larger streams, as the streams become less dominated by groundwater and more exposed to meteorological conditions (Caissie, 2006; Gaffield, Potter, & Wang, 2005).
- Large rivers have fewer daily fluctuations in water temperature due to a larger volume of water, and are also less affected by shade compared to smaller streams (Caissie, El-Jabi, & St-Hilaire, 1998).
- During the summer, precipitation from storms may decrease stream temperature if the volume of discharge increases at a faster rate than it could be heated in a stream channel (Ahmadi-Nedushan, et al., 2007).
- The components of energy and water mass budget for a stream may vary widely in their magnitude and significance for a specific reach depending on the local characteristics of the river channel and on the local weather conditions prevailing in different seasons of the year. Especially heat budgets can vary markedly over relatively short distances of a river.

Data Situation CCHydro – Stream Temperature

For the development, testing, and validation of a stream temperature model various hydrological and meteorological quantities are necessary (see Figure 1). Such data are available from the measurement networks operated by the Federal Office for the Environment (Bundesamt für Umwelt, BAFU) and the Federal Office of Meteorology and Climatology (MeteoSwiss).

The present study uses observational stream temperature data (BAFU) and air temperature data (MeteoSwiss) for some preliminary investigations. BAFU measures or measured stream temperature at 61 stations with record lengths from a few years to over 40 years in some cases. Most of these stations are operational to date and provide hourly mean values. MeteoSwiss air temperature data were measured 2m above ground and individual stations show different records lengths. Over 100 stations provide hourly and daily mean values.

Climate change scenarios (projections) from today to 2050 are available from the Institute for Atmospheric and Climate Sciences ETH (IAC). Regional Climate Model (RCM) outputs of 25km resolution from the ENSEMBLES project are subject to a climatological downscaling and statistical processing and can be interpolated on user-specified locations, typically measurement stations. The procedure applies the Delta Change Method to determine appropriate delta change factors for precipitation and air temperature using the control period of 1961-1990, and a scenario period 2021-2050. The underlying CO2 projection is the IPCC A1B scenario.

Preliminary Data Analysis

As a first step we decided to visualize the air temperature / stream temperature correlation for the available data sets for selected stations of the Swiss measurement networks. Pairs of air temperature and stream temperature measurement sites were selected such that the distance between the two sites was minimal (usually a few hundred meters to a few kilometres). Displaying large data sets in scatter plots often hides the signals or correlation to be detected. Thus, for clarity, only three years of weekly mean temperature data is shown in the following figures. This is also in agreement with the selected period length and averaging interval in several studies referenced in the regression models section. The period of plotted data differs according to the availability of data at a given pair of stations. To better visualize possible hysteresis, data points are color-coded for the warming period of the year (01.01.-30.06., blue) and for the cooling period of the year (01.07.-31.12., red). Four examples of temperature correlations are presented in Figure 11.

The first example (Venoge, upper left panel) shows a situation of a relatively small river at low altitude with generally small discharge and a certain fraction of riparian vegetation creating shading on the stream. The resulting correlation of air and stream temperature is almost linear over the total range of temperatures and the system shows no hysteresis which means that the mechanisms responsible for warming and cooling are equally important.

The next example (Aare, upper right panel) is a large stream with high discharge and a small fraction of glaciated surface area with respect to the total area at the gauging station (Unterbözberg). The air and stream temperature data display a slightly S-shaped correlation pattern with stream temperature data from the warming phase lower than during the cooling phase in the second half of the year. The volume of water (of large heat capacity) combined with glacially influenced headwaters and the buffering effect of the upstream Lake Thun are responsible for the present hysteresis.

Example three (Roseggbach, lower left panel) is typical for small Alpine streams dominated by a glacio-nival regime. The stream temperature amplitude is very small due to the large fraction of melt water input throughout the year, and stream temperatures reach zero degrees Celsius in winter time. Additionally, the S-shape is very pronounced while there is no hysteresis. All this is attributed to the dominant influence of glaciers and their melt water input.

The last example (Aar, lower right panel), is a medium sized Alpine river also with a significant fraction of glaciated area and high mean altitude of the surface area. However, the period of stream water exposure to the atmosphere is sufficient to already develop hysteresis.



Figure 11: Stream/air temperature correlations for 4 selected pairs of stations. Each plot shows weekly mean temperature data of three consecutive years, with the period depending on the availability of data at each stations pair. Blue color indicates the warming period of the year (01.01.-30.06.) and red color indicates the cooling period of the year (01.07.-31.12.). Additional information for each panel is given in Table 1.

Table 1: Station ID, basin characteristics and period corresponding to panels in Fig. 11.

Stream temperature stn:	2432
Air temperature station:	Pully
River / Large basin:	Venoge → Rhone
Period of plotted data:	Jan 2002 – Dec 2004
Surface area:	231 km2
Mean elevation:	700m
Glacier coverage:	0%
Annual mean discharge:	5 m3/s (2002)

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Stream temperature stn:	2256	Str
Air temperature station:	Samedan	Air
River / Large basin:	Rosegg → Danube	Riv
Period of plotted data:	Jan 2004 – Dec 2006	Pe
Surface area:	66 km2	Su
Mean elevation:	2716m	Me
Glacier coverage:	30%	Gla
Annual mean discharge:	2.5 m3/s (2004)	An

Stream temperature stn:	2016
Air temperature station:	Unterbözberg
River / Large basin:	Aare → Rhine
Period of plotted data:	Jan 1980 – Dec 1982
Surface area:	11726 km2
Mean elevation:	1010m
Glacier coverage:	2%
Annual mean discharge:	296 m3/s (1993)

Stream temperature stn:	2019
Air temperature station:	Meiringen
River / Large basin:	Aar \rightarrow Rhine
Period of plotted data:	Jan 1980 – Dec 1982
Surface area:	554 km2
Mean elevation:	2150m
Glacier coverage:	21%
Annual mean discharge:	35 m3/s (1992)

Summary, Conclusions and Recommendations

Based on the results of this study, the realization of a principal research project on stream temperature evolution under climate change scenario appears feasible and promising. The creation of a tool that will directly quantify the impact of climate change on an important component of the hydrological system and cycle in Switzerland will be of great value.

The literature reports three model typologies, (a) regression, (b) stochastic, and (c) deterministic models, while it remains unclear in how far already developed models are geographically portable and universal. However, it is considered valuable and imperative to build on existing knowledge, that is, to use and expand on models developed to date. In our opinion, it has to be tested whether an existing model is directly applicable to the Alps. Such tests should be done as one of the first steps of the principal study.

The regression models are probably the most robust models and appear to be more or less unconditionally applicable; however they are most limited in detail. Since most of the heat exchange is a result of radiative heat transfer (shortwave radiation) the accuracy and validity of the air-water temperature regression method may be questioned. However, since the daytime air temperature is a strong function of the solar radiation, this method is certainly justified. Its previous numerous and successful application demonstrates its value and implies that it should be considered (certainly not as the only approach) in a more detailed analysis. The calculation of model coefficients will be necessary since they are specific for each stream as a function of geographic location, for instance depending on discharge, the fraction of glaciers and snow cover in the catchment, mean altitude, land use, etc. A preliminary correlation analysis using observational air and stream temperature data of several Swiss measurement stations revealed that the shape of the regression curves can vary significantly depending on the geographic situation.

Physically based models provide much more information such as the diurnal cycle for instance but need a much larger set of input variables. Many deterministic models require long periods of measured stream temperature data to perform a good model calibration. In addition, parameterizations of certain variables are very specific and might not be transferable to other geographic, geologic or climatologic regions even over small distances. The application of a stochastic approach in combination with the overall good availability of observational data may also be an interesting option and well adapted for a heterogeneous and complex terrain as in the Swiss Alps and lowlands.

Limitations arise from the inherent complexity of the natural environment of river systems and anthropogenic perturbations of these systems, as well as from the lack of specific forcing variables required for the simulations. The previous constraint can be addressed by applying appropriate scale analyses identifying the dominant variables in the system in an attempt to simplify the complexity without loosing a substantial amount of accuracy. The latter limitation is a temporary limitation with the perspective that the number of available forcing variables for specific climate scenarios may increase in the near future.

The regression method being a robust and reliable tool should be thoroughly explored for the domain of interest with all available data and test if this already

will provide a simple but useful prediction model; however we suggest go beyond this method and complement with stochastic and/or deterministic approaches. An implementation of these types of model will take more time and effort and are scientifically challenging but will probably be worthwhile since such models provide not only the possibility of predicting stream temperatures but also allow for investigating any scenario of interest and for performing sensitivity and process studies.

Competences and Potential of EFLUM-EPFL for Follow-up

The Laboratory of Environmental Fluid Mechanics and Hydrology is interested and motivated to continue with the research on stream temperature simulation under climate change scenarios. The laboratory is equipped with innovative and state-of-the-art instrumentation which could be available for case studies if this will be necessary during the course of the main project. Such measurement systems include equipment for discharge measurements, instrumentation for energy balance measurements, fiber optic distributed temperature sensing systems, wireless hydrometeorological sensor systems, and several standard acquisition systems for meteorological and hydrological measurements.

Furthermore, the laboratory has expertise in hydrological modeling of complex terrain Alpine watersheds using a 3D hydrological model (Geotop). Also, a major research line of the laboratory is concerned with energy balance studies in different climatic regions of the Alps and has a lot of expertise in this field.

In addition to competent and experienced staff of the group, the laboratory disposes of a very efficient network of local, national, and international contacts to experts in the field who could be included as partners in a future extension of the project. Some of our close partners are:

- Prof. A. Rinaldo, Laboratory of Ecohydrology, EPFL
- Prof. W. Brutsaert, Cornell University, Ithaca, USA
- Prof. N. van de Giesen, Delft University of Technology, The Netherlands
- Prof. J. Selker, Oregon State University, Corvallis, USA
- Prof. H. Stefan, University of Minnesota, Minneapolis, USA
- Prof. S. Tyler, University of Nevada, Reno, USA

Most of our expert contacts regularly spend time at EPFL for collaborations. Several PhD students and postdoctoral researchers are currently working on hydrology and climate related topics in the group. Future hires could be specifically selected with a focus on their relevant competences in the field.

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Bibliography

(For the sake of completeness, this bibliography also contains references which have been consulted for this study but are not cited in this report.)

Ahmadi-Nedushan, B., St-Hilaire, A., Ouarda, T. B., Bilodeau, L., Robichaud, E., Thiémonge, N., et al. (2007). Predicting river water temperatures using stochastic models: case study of the Moisie River (Québec, Canada). *Hydrological processes*, *21*, 21-34.

Becker, M. W., Georgian, T., Ambrose, H., Siniscalchi, J., & Fredrick, K. (2004). Estimating flow and flux of ground water discharge using water temperature and velocity. *Journal of Hydrology*, *296*, 221-233.

Bogan, T., Othmer, J., Mohseni, O., & Stefan, H. (2006). Estimating extreme stream temperatures by the standard deviate method. *Journal of Hydrology*, *317*, 173-189.

Bravo, H. R., Krajewski, W. F., & Holly, F. M. (1993). State Space Model for River Temperature Prediction. *Water resources research*, 29 (5), 1457-1466.

Brown, G. W. (1969). Predicting Temperatures of Small Streams. *Water Resources Research*, *5* (1), 68-75.

Caissie, D. (2006). The thermal regime of rivers: a review. *Freshwater Biology*, *51*, 1389-1406.

Caissie, D., El-Jabi, N., & St-Hilaire, A. (1998). Stochastic modelling of water temperatures in a small stream using air to water relations. *Can. J. Civ. Eng.*, *25*, 250-260.

Caissie, D., Satish, M. G., & El-Jabi, N. (2005). Predicting river water temperatures using the equilibrium temperature concept with application on Miramichi River catchments (New Brunswick, Canada). *Hydrological processes*, *19*, 2137-2159.

Chenard, J.-F., & Caissie, D. (2008). Stream temperature modelling using artificial neural networks: application on Catamaran Brook, New Brunswick, Canada. *Hydrological processes*, *22*, 3361-3372.

Constantz, J. (1998). Interaction Between Stream Temperature, Streamflow, and Groundwater Exchanges in Alpine Streams. *Water Resources Research*, *34* (7), 1609–1615.

Ducharne, A. (2008). Importance of stream temperature to climate change impact on water quality. *Hydrology and Earth System Sciences*, *12*, 797-810.

Erickson, T. R., & Stefan, H. G. (2000). Linear air/water temperature correlations for streams during open water periods. *Journal of Hydrologic Engineering : ASCE , 5*, 317-321.

Evans, E. C., McGregor, G. R., & Petts, G. E. (1998). River energy budgets with special reference to river bed processes. *Hydrological processes*, *12* (4), 575-595.

Flint, L. E., & Flint, A. L. (2008). A Basin-Scale Approach to Estimating Stream Temperatures of Tributaries to the Lower Klamath River, California. *J. Environ. Qual.*, *37*, 57-68.

Gaffield, S. J., Potter, K. W., & Wang, L. (2005). Predicting the summer temperature of small streams in southwestern Wisconsin. *Journal of the American Water Resources Association*.

Jeppesen, E., & Iversen, T. M. (1987). Two simple models for estimating daily mean water temperatures and diel variations in a Danish low gradient stream. *Oikos*, 49 (2), 149-155.

Kobayashi, D. (1985). Separation of the snowmelt hydrograph by stream temperatures. *Journal of Hydrology* , *76* (1), 155-162.

Kobayashi, D., Ishii, Y., & Kodama, Y. (1999). Stream temperature, specific conductance and runoff process in mountain watersheds. *Hydrological processes*, *13* (6), 865-876.

Krajewski, K. L., Krajewski, W. F., & Holly Jr., F. M. (1993). Power Plant River Heating. *Journal of Energy Engineering*, *119* (1).

Krajewski, W. F., Kraszewski, A. K., & Grenney, W. J. (1982). A graphical technique for river water temperature predictions. *Ecological Modelling*, *17*, 209-224.

LeBlanc, R. T., Brown, R. D., & FitzGibbon, J. E. (1997). Modeling the Effects of Land Use Change on the Water Temperature in Unregulated Urban Streams. *Journal of Environmental Management*, *49*, 445-469.

Lowry, C. S., Walker, J. F., Hunt, R. J., & Anderson, M. P. (2007). Identifying spatial variability of groundwater discharge in a wetland stream using a distributed temperature sensor. *Water Resources Research*, 43.

Malcolm, I. A., Soulsby, C., Hannah, D. M., Bacon, P. J., Youngson, A. F., & Tetzlaff, D. (2008). The influence of riparian woodland on stream temperatures: implications for the performance of juvenile salmonids. *Hydrological Processes*, *22* (7), 968-979.

Marcé, R., & Armengol, J. (2008). Modelling river water temperature using deterministic, empirical, and hybrid formulations in a Mediterranean stream. *Hydrological processes*, *22*, 3418-3430.

Mohseni, O., & Stefan, H. G. (1999). Stream temperature/air temperature relationship: a physical interpretation. *Journal of Hydrology*, *218*, 128-141.

Mohseni, O., Erickson, T. R., & Stefan, H. G. (1999). Sensitivity of stream temperatures in the United States to air temperatures projected under a global warming scenario. *Water resources research*, *35* (12), 3723-3733.

Mohseni, O., Stefan, H. G., & Erickson, T. R. (1998). A nonlinear regression model for weekly stream temperatures. *Water resources research*, *34*, 2685-2692.

Morrill, J. C., Bales, R. C., & Conklin, M. H. (2005). Estimating Stream Temperature from Air Temperature: Implications for Future Water Quality. *Journal of Environmental Engineering ASCE*, 139-146.

Nelson, K. C., & Palmer, M. A. (2007). Stream temperature surges under urbanization and climate change: data, models, and responses. *Journal of the American Water Resources Association*, *43* (2), 440-452.

Norton, G. E., & Bradford, A. (2009). Comparison of two stream temperature models and evaluation of potential management alternatives for the Speed River, Southern Ontario. *Journal of Environmental Management*, *90*, 866-878.

Roth, T. R., Westhoff, M. C., Huwald, H., Huff, J. A., Rubin, J. F., Barrenetxea, G., et al. (2010). Stream Temperature Response to Three Riparian Vegetation Scenarios by Use of a Distributed Temperature Validated Model. *Environmental Science & Technology*.

Selker, J., Giesen, N. v., Westhoff, M., Luxemburg, W., & Parlange, M. B. (2006). Fiber optics opens window on stream dynamics. *Geophys. Res. Lett.* (33).

Selker, J. S., Thévenaz, L., Huwald, H., Mallet, A., Luxemburg, W., Giesen, N. v., et al. (2006). Distributed fiber-optic temperature sensing for hydrologic systems. Water Resources Research , 42.

Sinokrot, B. A., & Stefan, H. G. (1994). Stream Water-Temperature Sensitivity to Weather and Bed Parameters. *Journal of Hydraulic Engineering*, *120* (6), 722-736.

Sinokrot, B. A., Stefan, H. G., McCormick, J. H., & Eaton, J. G. (1995). Modeling of climate change effects on stream temperatures and fish habitats below dams and near groundwater inputs. *Climatic Change*, *30*, 181-200.

Sinokrot, B. A., & Stefan, H. G. (1993). Stream Temperature Dynamics: Measurements and Modeling. *Water Resources Research*, *29* (7), 2299-2312.

Stefan, H. G., & Sinokrot, B. A. (1993). Projected global climate change impact on water temperatures in five north central U.S. streams. *Climatic Change*, *24*, 353-381.

Travis, B., Mohseni, O., & Stefan, H. G. (2003). Stream temperature-equilibrium temperature relationship. *Water Resources Research* , *39* (9).

Travis, B., Stefan, H. G., & Mohseni, O. (2004). Imprints of secondary heat sources on the stream temperature/equilibrium temperature relationship. *Water Resources Research*, 40.

Webb, B. W. (1996). Trends in stream and river temperature. *Hydrological processes*, *10*, 205-226.

Webb, B. W., Clack, P. D., & Walling, D. E. (2003). Water-air temperature relationships in a Devon river system and the role of flow. *Hydrological Processes*, *17* (15), 3069-3084.

Webb, B. W., & Nobilis, F. (1997). Long-term perspective on the nature of the air-water temperature relationship: a case study. *Hydrological processes*, *11*, 137-147.

Webb, B. W., & Zhang, Y. (1997). Spatial and seasonal variability in the components of the river heat budget. *Hydrological processes*, *11*, 79-101.

Westhoff, M. C., Savenije, H. H., Luxemburg, W. M., Stelling, G. S., Van de Giesen, N. C., Selker, J. S., et al. (2007). A distributed stream temperature model using high resolution temperature observations. *Hydrology and Earth System Sciences*, *11*, 1469-1480.

Appendix

Physical or empirical parameterizations of various heat flux components of the energy budget according to (Gaffield, Potter, & Wang, 2005).

Shortwave solar radiation

 $S_s = (1-s) (1-a_s) R [W/m^2]$

- s, fraction of sky blocked by shade [-]
- a_s , albedo of water (typical value 0.06) [-]
- R, solar radiation; measured or estimated based on geographic location and time of day and year $[W/m^2]$

Atmospheric longwave radiation

 $S_a = (1-s) (1-a_L) 10.03(0.53+0.065e^{0.5}) (1+0.4m_c) \sigma (T_a+273.16)^4 [W/m^2]$

- a_L, longwave reflectivity (typical value 0.03) [-]
- e, atmospheric vapour pressure [mb]
- m_c, fractional cloud cover [-]
- T_a, air temperature [°C]
- σ, Stefan-Boltzmann constant [5.67x10⁻⁸ W/m²/C⁴]

Vegetative longwave radiation

 $S_v = s \epsilon_v \sigma (T_a + 273.16)^4 [W/m^2]$

- ϵ_v , vegetation emissivity [-]

Longwave radiation emitted by stream

 $S_w = \varepsilon_w \sigma (T+273.16)^4 [W/m^2]$

- ϵ_v , water emissivity [-]
- T, water temperature [°C]

Convection (at air/water interface)

 S_c = (0.00375+0.0014 v_w) P_a (T_a-T) [W/m²]

- v_w , wind speed [m/s]
- Pa, atmospheric pressure [mb]

Evaporation

 $S_e = (40+15v_w) (R_h 1.064^{Ta} - 1.064^{T}) [W/m^2]$

- R_h, relative humidity

Streambed conduction

 $S_b = K_T \left(\frac{T_s - T}{s} \right) [W/m^2]$

- z, depth [m]
- T_s, soil equilibrium temperature [°C]
- K_T, thermal conductivity [W/m/°C]