Forecasting water temperature in lakes and reservoirs using seasonal climate prediction

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Supplementary material

Hydrologic modeling

Mesoscale Hydrologic Model (mHM)

The mesoscale Hydrologic Model (mHM v5.9: http://www.ufz.de/mhm) was used to implement the hydrologic simulations in the Ter River catchment in the Sau Reservoir case study. This is an open source and spatially distributed model with grid pixel as the main hydrologic unit and a multiscale parameter regionalization approach. It has the capacity to represent the main physical processes for the temporal and spatial scales of this study (e.g, soil moisture dynamics, infiltration and surface runoff, subsurface processes, canopy interception, and snowmelt processes). Apart from being driven by meteorological variables (precipitation, temperature and potential evaporation), it also depends on land cover, leaf area index (LAI), soil, and hydrogeologic maps.

The model has three levels of resolution to represent the surface characteristics (i.e, soil, land cover, terrain), the hydrologic processes and geological formations, and the variability of the meteorological forcing. Accordingly, the model was set up using the resolutions 100, 1000 and 10000 meters, respectively. These resolutions were selected according to (i) the area of our catchment and terrain resolution, (ii) the resolution of the meteorological forcing used and (iii) the suggestions from the user manual of the model. Additionally, the Jarvis equation (Jarvis, 1989) to represent soil moisture processes and the Muskingum approach (McCarthy, 1939) to represent the routing conditions were selected.

The hydrologic model was auto-calibrated using a Shuffled Complex Evolution optimization algorithm and NSE (Nash–Sutcliffe model efficiency coefficient) as objective function $(1.0 - 0.5 * (NSE + log(NSE)))$, to calibrate high and low flows. The observed data to implement the calibration was provided by the water treatment plant company in charge of the reservoir (Ens d'Abastament Ter-Llobregat (ATL)). More details of calibration and validation results are found in Table **??**, where the NSE and Kling-Gupta efficiency (KGE) metrics are calculated.

GR4J & GR6J

To model the inflows for the Wupper Reservoir and the Mt Bold Reservoir (Onkaparinga and Echunga Creek), the *Génie Rural* (GR) models were used within the R package "*airGR*" (Coron et al., 2017). These are a range of lumped conceptual rainfall-runoff models that can be applied at varying timescales from annual to hourly (Perrin et al., 2013). These models have been demonstrated to accurately simulate hydrologic flow regimes across a variety of different catchments such as mountainous terrain (Coron et al., 2017), near-natural catchments with high precipitation (Broderick et al., 2016) and across climatic shifts (Brulebois et al., 2018).

The GR4J and GR6J models are parsimonous model which are forced by precipitation and potential evapotranspiration (PET). Catchment size is the other required variable that is used in the computation of discharge. There are four parameters that can be calibrated within GR4J: production store capacity, intercatchment exchange coefficient, routing store capacity and unit hydrograph time constant. While GR6J (Pushpalatha et al., 2011) includes the same four parameters it comes along with two extra parameters: intercatchment exchange threshold and coefficient for emptying exponential store.

To calibrate the model, first a manual screening process was performed using a predefined grid to identify a 'good parameter set'. This is then used as the initial conditions for starting a steepest descent local search algorithm. Similarly to mHM, NSE was the objective function used within the calibration algorithm. However, for the German case study, the GR6J was calibrated using KGE as an objective function in order to ensure better representation of base flows since the reservoir was otherwise prone to drying out. More details of calibration and validation results are found in Table **??**

SimplyQ

SimplyQ, used to model the inflows to Lake Vansjø (Norway), is the hydrologic module of the catchment model for phosphorus SimplyP and described in detail by Jackson-Blake et al. (2017). Briefly, SimplyQ is forced by precipitation and air temperature, and computes snow accumulation and melt, evapotranspiration, terrestrial (soil, quick-surface and groundwater flows) and in-stream hydrologic processes. Six parameters were manually calibrated: degree-day evapotranspiration, degree-day factor for snow melt, proportion of precipitation that contributes to quick flow, baseflow index, groundwater time constant and soil water time constant. As for the other models, NSE was the objective function used during calibration, more details of calibration and validation results are found in Table **??**

Lake temperature modeling

General Ocean Turbulence Model (GOTM)

The General Ocean Turbulence Model (GOTM: http://gotm.net) was used for simulating the thermal dynamics of Sau Reservoir (Spain) and Lake Vansjø (Norway). GOTM is an open source ocean model adapted to lakes, which assumes a one-dimensional water column model for studying hydrodynamic and biogeochemical processes in marine and limnic waters. It models the state-of-the-art of the main physical processes in lakes: vertical turbulent fluxes of momentum, heat, and dissolved and particulate matter. To execute, it must be forced by meteorological data (precipitation, winds, pressure, air temperature, relative humidity, cloud fraction and solar radiation) and associated river inflow data (river discharge and water temperature). Additionally, for the Spanish case study, the water level fluctuations in the lake depend also on the historical outflow controlled by the water supply company, which was supplied as an observed forcing.

The model was calibrated against observed water temperature profiles using the ParSAC autocalibration tool (https://bolding-bruggeman.com/portfolio/parsac/) and the Maximum Likelihood optimization method. The parameters considered during calibration were the scale factor for short-wave solar radiation, scale factor for surface heat fluxes, scale factor for wind, minimum turbulent kinetic energy (TKE), and the light extinction coefficient. For Lake Vansjø, two additional parameters were calibrated for the ice dynamics: the ice albedo and the minimum threshold ice thickness.

The same parameters from the calibration were then used to run all time period for the water temperature data period using ERA5. The outflows are managed everyday according to the real-time changes in the water quality column in SAU reservoir and it reproduces a natural flow in the Vansjo lake. In Sau reservoir then, any difference between ERA5 inflows from mHM model (hydrologic) could lead to a dry out in the GOTM model (lake).

According to the most common statistical parameters (Nash-Sutcliffe Efficiency (NSE) and Root-Mean-Square Error (RMSE)) to evaluated calibration and validation in lake modeling (see Table **??**), the fit between modelled and observed temperatures is better when closer to surface. However, it has to be noticed that when going deeper the amount of observations decreased affecting the statistical parameters to evaluate the fitting.

General Lake Model (GLM)

The General Lake Model (GLM) is a 1-D lake model that calculates the water balance and models thermal stratification within lake water bodies

(Hipsey et al., 2019). It can be coupled to ecological and biogeochemical models through the Framework for Aquatic Biogeochemical Models (FABM) and also has an own Aquatic Ecosystems Dynamics library (AED) (Hipsey et al., 2013). It includes the impact of inflows, outflows, internal mixing, heat fluxes and ice formation. Within the model, a flexible Lagrangian layer structure is incorporated, which allows the layer thickness to change in response to inflows, outflows, internal mixing and heat and mass fluxes. It has been used to model lake hydrodynamics at regional scales (Read et al., 2014), reservoir operation (Feldbauer et al., 2020), lake management strategies (Ladwig et al., 2018), and has undergone rigorous stress testing across 32 lakes globally distributed (Bruce et al., 2018).

The model was calibrated slightly differently at Wupper Reservoir and Mt. Bold. In both cases, modelled temperatures were compared to observed temperatures but also considerable effort was made to ensure that the water balance and thus the water level simulated within the model reasonably replicated observed changes. Accurately capturing the water balance is critically important owing to the sensitivity of the heat budget to the volume of water.

For Mt. Bold Reservoir, assumptions were made in regards to the withdrawal and the Murray Bridge pipeline delivering water to the Onkaparinga. Using historically observed data, an average annual cycle was calculated for both and then replicated throughout the entire timeseries. While this assumption does not allow for inter-annual variation, it allowed for simulation of water level fluctuation each year that represented the seasonal cycle apparent within Mt. Bold. For calibration, residuals were visualized and it was identified that mixing of heat to lower depths was the largest. Using an automatic calibration for two parameters, scaling factor on the wind and scaling factor on the incoming long-wave radiation a RMSE of 1.17 degrees for the calibration period was achieved.

For Wupper Reservoir, a statistical model was developed to calculate the reservoir's outflow based on the inflow using the historical observations for each discharge simulation of the catchment model. Such an approach allows mimicking the outflow decision and approximately resembling the observed water-level to avoid the cases of dry-outs or exceedingly low volumes of water due to inflow underestimation. Moreover, this method could also help in future operational forecastings, aiming to represent a realistic water balance while respecting the reservoir's operational rules during the system run-time. The calibration function of the R package "glmtools" was used to set the values of the wind factor, light extinction coefficient, and long-wave radiation. Since the reservoir has a short residence time and is substantially affected by the inflow dynamics, the inflow parameters (i.e. streams drag coefficient, slope, and width angle) were also calibrated.

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