HYDROPOWER TIME SERIES MODELLING FOR CLIMATE-RESILIENT ENERGY SYSTEM OPTIMIZATION

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Abstract

Achieving a carbon-neutral energy supply poses significant challenges, particularly due to climate change-driven increases in extreme weather events that affect renewable energy systems. To ensure a stable energy supply under these conditions, reliable forecasting tools are essential to assess the impact of future climate scenarios. This work presents the development of such a tool for run-of-river hydropower plants. The rainfall-runoff model of the tool was calibrated using historical precipitation and discharge data for selected plants and is applied using ERA5 weather data. Catchment areas were derived from GIS data, and hydrological processes were simulated using the GR4J model, complemented by a snow module. Simulated discharges were used as inflows and converted into hourly energy generation time series based on plant-specific characteristics and adjusted using calibration factors derived from the mean annual generation data. The resulting tool enables the generation of hydropower time series from future climate data and thus serves as input for energy system optimization models. While developed for Austrian run-of-river hydropower plants, the methodology is transferable to any other region, supporting broader analyses of renewable energy integration in interconnected energy systems.

Keywords: Hydropower, Modelling, Simulation, Hydrology, Renewable Energy, Energy System Optimization, Time Series Data

1 Introduction

Ensuring low-carbon electricity generation requires a fundamental transformation of energy systems, driven by the increasing electrification of multiple sectors and the growing share of renewable energy sources. This transformation places high demands on energy system planning and optimization, which in turn rely on reliable representations of renewable generation and its temporal variability. In particular, hydropower in Austria plays a key role due to its comparatively high contribution to electricity supply and its potential to provide system flexibility.

Energy system optimization models are widely used to support long-term planning and strategic decision-making. To produce meaningful results, these models require consistent and

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physically plausible representations of renewable energy inflows that reflect meteorological and hydrological conditions. While wind and solar generation can be directly linked to weather-driven models due to their immediate response to atmospheric conditions and the absence of significant time delays, hydropower, particularly run-of-river (RoR) plants, is often still represented using static or statistical assumptions that neglect underlying hydrological processes.

This paper builds on the author's Master's thesis [1] and presents a modelling framework designed to improve the representation of RoR hydropower in long-term energy system analyses. The focus is on Austria, where RoR hydropower accounts for approximately 40 % of annual electricity generation [2].

Despite the importance of hydropower for energy system modelling, no publicly available modelling framework was found that provides a fully integrated workflow linking meteorological data, hydrological inflows, and RoR hydropower generation in a form directly usable for ESOMs. Existing implementations addressing similar challenges were identified only as internal projects within energy supply companies and are not publicly accessible or transferable to other regions or applications [3] [4].

To address this gap, this paper presents a modelling framework developed within the *iKlimEt* project [5] and applied in the *Frauental* renewable energy module as an input for the Low-carbon Expansion Generation Optimization (*LEGO*) model [6]. The main contributions of this work are threefold:

1. **The development of a comprehensive database of Austrian RoR hydropower plants,** including all technical, spatial, and hydrological information required by the model, designed in a way that allows straightforward extension to additional countries if suitable data is available.
2. **The consistent linkage of meteorological data to hydrological inflows**, enabling the simulation of discharge time series that reflect climatic variability and catchment-specific characteristics.
3. **The conversion of simulated discharges into hydropower generation time series,** producing energy outputs that can be directly integrated into long-term energy system optimization models.

By providing a reproducible and physically consistent workflow, the presented approach is designed to enable an open implementation in the future, enhancing the representation of RoR hydropower in energy system analyses and supporting the assessment of long-term energy system transformation pathways.

2 Methodology

The following section describes the complete workflow from data acquisition to the derivation of final energy time series and briefly outlines the key fundamentals underlying the developed tool. To get the wanted energy amounts or inflows for RoR hydropower out of weather data, there are lots of steps beforehand to achieve this goal. The tasks of the method can be roughly categorized into the following stages:

i. Building a comprehensive database comprising all fundamental information
ii. Preprocessing the meteorological input data

iii. Creating a hydropower plant database with plant-specific characteristics
iv. Calibrating and executing the hydrological model
v. Computing the resulting hydropower inflows and generation for calibration

A high-level overview of this process is shown in Figure 1.

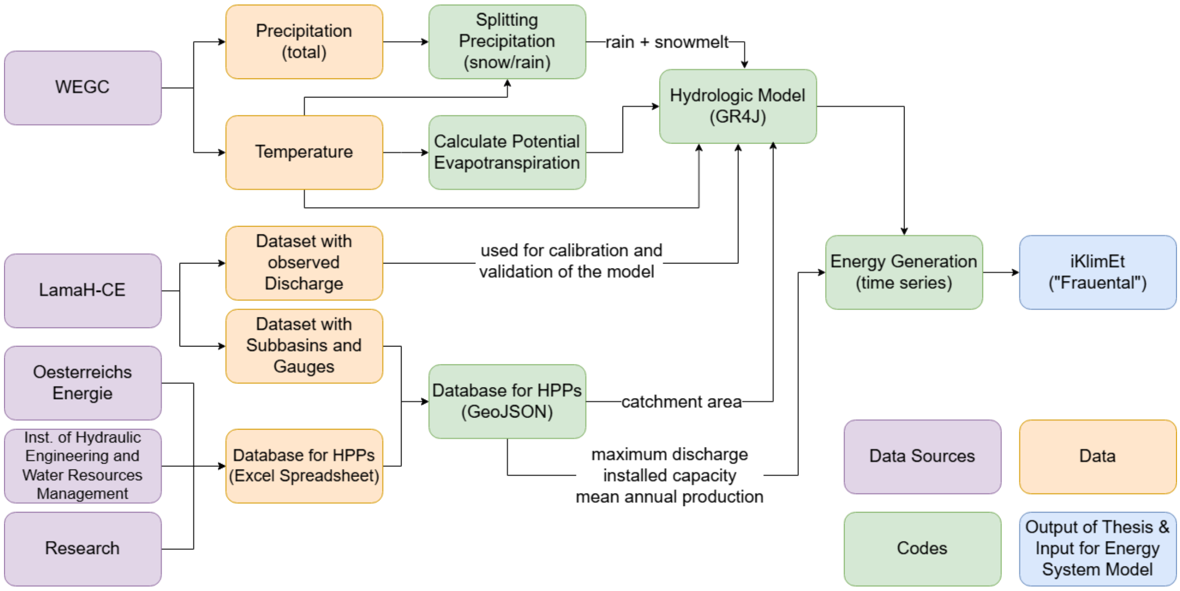

Figure 1:High-level overview of the translation process.

i. Building a comprehensive database comprising all fundamental information:

Before the actual model development can begin, an extensive data acquisition and review phase is required. This primarily concerns the meteorological input data as well as the data related to the hydropower plants. The latter includes discharge time series that is subsequently used for the calibration of the rainfall–runoff model, as well as spatial data defining the sub-basins required for the delineation of the catchment areas. For the case-study, both were used from the *LamaH-CE* dataset [7].

Discharge time series

Discharge is often strongly influenced by human activities, particularly the operation of upstream hydropower plants. RoR plants with reservoirs can substantially alter natural flow patterns through short-term storage and release driven by electric demand. These anthropogenic fluctuations affect discharge observations at gauge stations and must be considered when modelling.

To reduce the impact of this issue, the rainfall-runoff model was implemented with a daily time step. This temporal aggregation smooths short-term fluctuations and yields discharge dynamics that are closer to the natural flow conditions expected in the absence of short-term operational effects. Figure 2 compares the discharge behaviour of a hydropower plant with and without such operational regulation and highlights the strong intraday impact of storage-based flow control, thereby underlining the necessity of accounting for this effect.

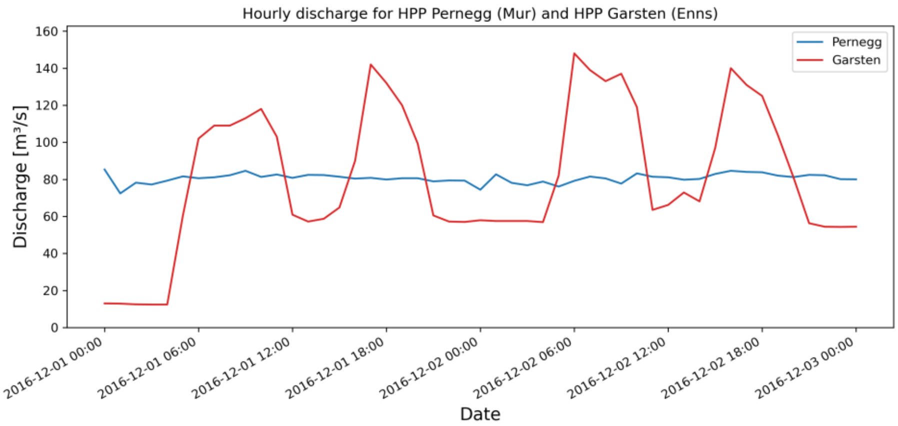

Figure 2: Comparison between RoR HPP without and with storage.[4]

For the **HPPs** themselves, the following **characteristics** are essential for the tool:

- Installed capacity (MW)
- Maximum Discharge (m³/s)
- Mean Annual Energy Output (GWh)
- Catchment Area (km²)
- Location of the HPP (latitude and longitude in degrees)

Within the framework of this work, *ERA5* reanalysis data were used as the meteorological input for calibrating and validating the model and were obtained from the Wegener Center for Climate and Global Change (WEGC). Although datasets with substantially higher spatial resolution are available, several reasons motivated the selection of *ERA5*. The data provide continuous coverage over the entire European domain and therefore fully encompass the investigated study area. More importantly, future weather scenarios will be provided in the same data format, ensuring methodological consistency and avoiding potential biases when comparing historical and future simulations.

Figure 4 illustrates the significantly higher spatial resolution of the *SPARTACUS* dataset, which is limited to historical weather observations over Austria, whereas Figure 3 shows the coarser but spatially consistent *ERA5* data used in this study.

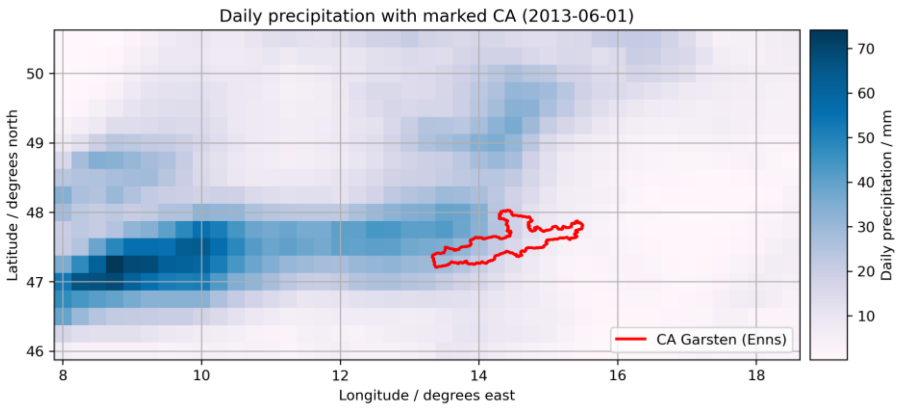

Figure 3: Precipitation grid from ERA5 data (0.25° x 0.25°)

[4] Plots were printed with hourly discharge data from the LamaH-CE dataset [7].

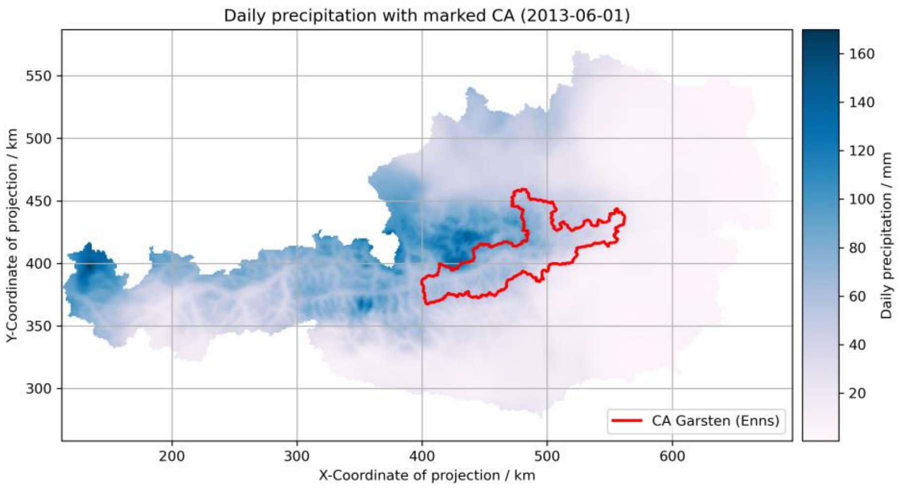

Figure 4: Precipitation grid from SPARTACUS data[5] (1 km x 1 km)

ii. Preprocessing the meteorological input data

During the preprocessing of the meteorological data, a spatial subset was extracted for the investigated study area, and all variables were converted into the units required by the hydrological model. To improve computational efficiency, the merged dataset was stored and processed in a chunked format to reduce calculation time later.

At this stage, the snow module was also implemented. Hourly meteorological variables were aggregated to daily values, and potential evapotranspiration was calculated and included as an additional model input.

Snow Module

Considering the impact of snow, the **Degree-Day Model** was used. It is a temperature-index method based on the empirical relationship between air temperature and the rate of snowmelt. It assumes that snow begins to melt when the daily air temperature exceeds a certain threshold. The melt rate is proportional to the excess temperature, expressed as: [8]

$$M = \begin{cases} DDF \cdot (T - T_{\text{threshold}}) & \text{for } T > T_{\text{threshold}} \\ 0 & \text{otherwise} \end{cases}$$

where:

- M is the daily snowmelt (mm/day),
- DDF is the degree-day factor (mm/°C/day),
- T is the mean daily air temperature (°C),
- $T_{threshold}$ is the melting threshold temperature, typically set around 0 °C.

[5] GeoSphere Austria Data Hub: https://data.hub.geosphere.at/dataset/.

Estimating Potential Evapotranspiration (PET)

Potential evapotranspiration (PET) represents the climatic demand for water vapor from a well-watered reference surface under given atmospheric conditions and serves as a required input variable for the hydrological model. It was estimated using the Hamon method [9], which represents a relatively simple empirical approach with low data requirements. The method is based on mean air temperature and the maximum possible daily sunshine duration, combined with a dimensionless calibration or correction factor. The sunshine duration is determined as a function of latitude and the day of the year, making the approach suitable for large-scale applications and data-scarce conditions.

iii. Creating a hydropower plant database with plant-specific characteristics

Next, the hydropower plant (HPP) database was established by delineating the catchment areas based on the geographic coordinates of the individual plants. For cases in which the automated catchment delineation was not successful, the results were manually corrected by assigning the appropriate HYDROID of the corresponding sub-basin.

In the same step, the optimal gauge station was assigned to each HPP. This was achieved by comparing the delineated catchment area of each plant with the catchment area of the available gauge stations. The resulting deviation between these areas was subsequently used as a correction factor for adjusting the simulated inflows.

In contrast to the database used in the initial step, which consisted of a simple spreadsheet, this information was used to construct a geospatial database based on GeoJSON files. All numerical parameters and spatial information were stored as attributes within these GeoJSON datasets.

Catchment Area

Catchments are typically determined by natural topography, but hydropower systems may also include artificial expansion through interbasin transfers or, in the case of diversion plants, reduced contributing areas that terminate at an upstream intake or dam. Figure 5 shows the catchment area of the HPP Graz on the Mur River, highlighted in yellow.

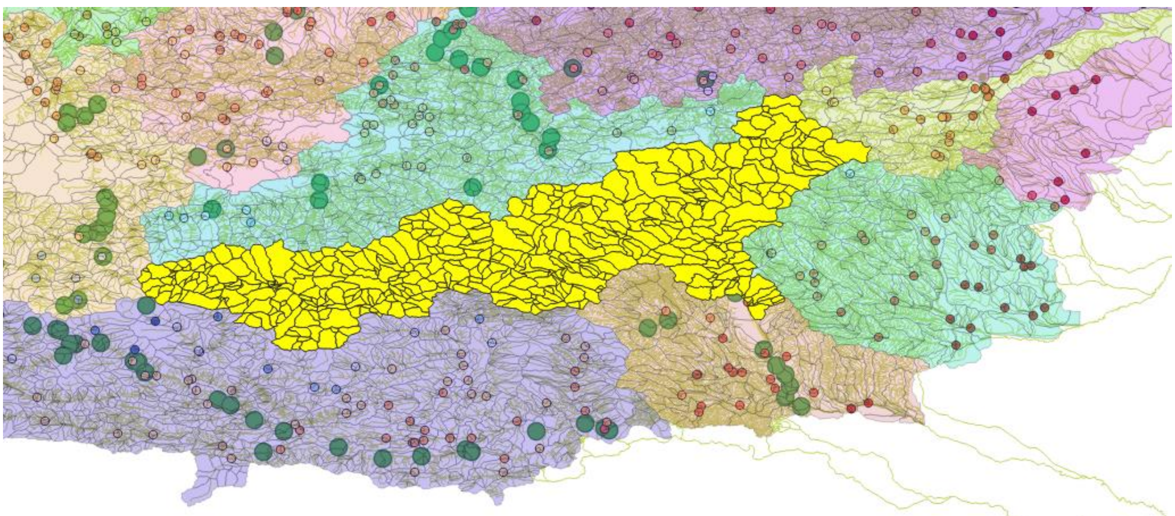

Figure 5: Yellow marked catchment area of the HPP Graz (subbasins from LamaH-CE).

iv. Calibrating and executing the hydrological model

Before the hydrological model could be calibrated for each hydropower plant, several additional data preparation steps were required. The previously pre-processed meteorological data had to be further adapted to the model requirements. First, the spatial resolution of the *ERA5* dataset was bilinearly resampled, as the original resolution was too coarse to allow direct clipping to the often relatively small catchment areas.

Subsequently, the meteorological variables were clipped to the individual catchment areas and spatially aggregated. Finally, all processed data were converted into a data format compatible with the applied hydrological model, thereby enabling the calibration procedure.

Hydrologic modelling enables the simulation and prediction of hydrological processes such as runoff generation, streamflow, evapotranspiration, and storage dynamics. Hydrologic models range from conceptual to fully distributed, physics-based simulations. The choice of model depends on data availability, the scale of analysis, and the purpose of the study. For this work, the ***GR4J*** model [10] was used. It is a lumped, conceptual rainfall-runoff model and has four parameters:

- **X1 – Production store capacity [15, 1200] mm:** Controls the size of the soil moisture storage tank, influencing how much rainfall is transformed into infiltration versus runoff.
- **X2 – Groundwater exchange coefficient [-4, 4] mm/day:** Allows for net gains or losses to groundwater, simulating inter-basin transfers or deep percolation.
- **X3 – Routing store capacity [20,400] mm:** Defines the capacity of a linear routing reservoir that delays the outflow, impacting flow attenuation and response time.
- **X4 – Time base of unit hydrograph [1, 5] mm:** Controls the time distribution of effective rainfall, effectively shaping the hydrograph.

The numbers in brackets denote the selected calibration intervals, within which an optimal parameter set is determined for each HPP.

The performance of a hydrological model is typically assessed using statistical efficiency metrics that quantify the agreement between simulated and observed streamflow data. Among the many available metrics, two commonly used in rainfall-runoff modelling are the **Nash-Sutcliffe Efficiency (NSE)** and the **Kling-Gupta Efficiency (KGE)** [11].

- A KGE or NSE value of 1 indicates perfect agreement between simulated and observed discharge.
- An NSE value of 0 or a KGE value of approximately −0.41 represents performance equivalent to the mean-flow predictor [12].
- Values below these thresholds indicate performance worse than the mean flow.

v. Computing the resulting hydropower inflows and generation for calibration

In the final processing step, hydropower generation was calculated based on the ratio of the simulated discharge to the maximum discharge, multiplied by the installed capacity of each plant. In addition, the resulting energy production was calibrated by a correction factor which results from comparing the simulated annual values for selected years with the officially reported mean annual generation.

3 Results

After model setup and calibration, the HPPs were validated. Figure 6 illustrates a sample HPP for 2016, showing observed and simulated inflows (top) and the corresponding power generation (bottom).

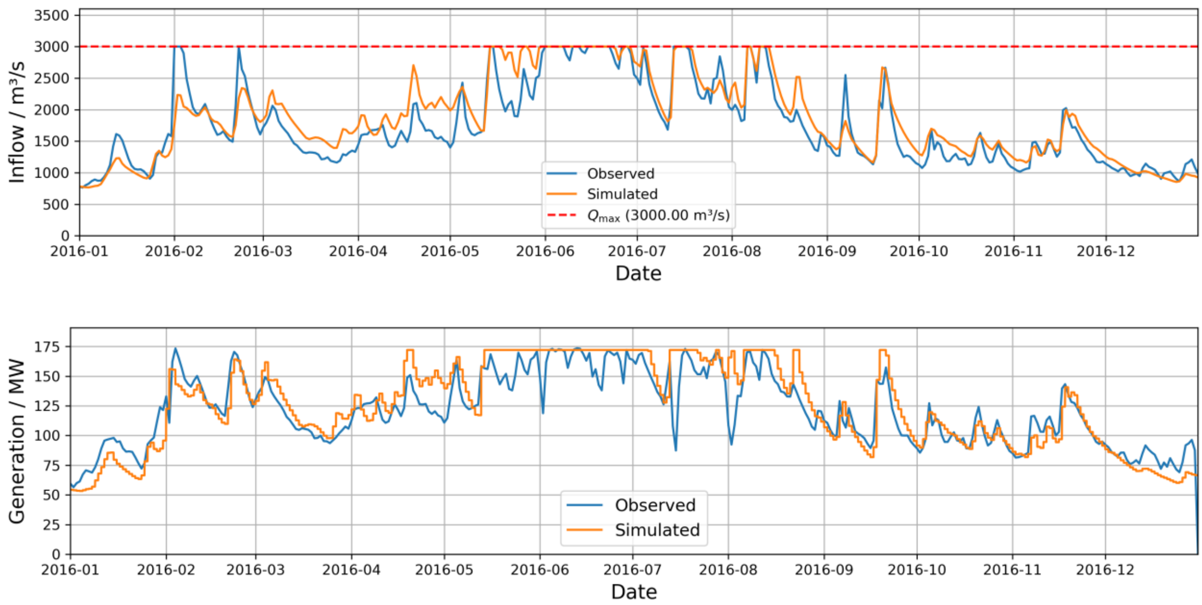

Figure 6: Simulated versus observed inflow (top) and generation (bottom).

The correlation between the time series is strong, indicating high-quality hydrological efficiency metrics. This metrics result is shown in Figure 7 and Figure 8. On the left there is shown the NSE and on the right the NSE dependent on the installed capacity.

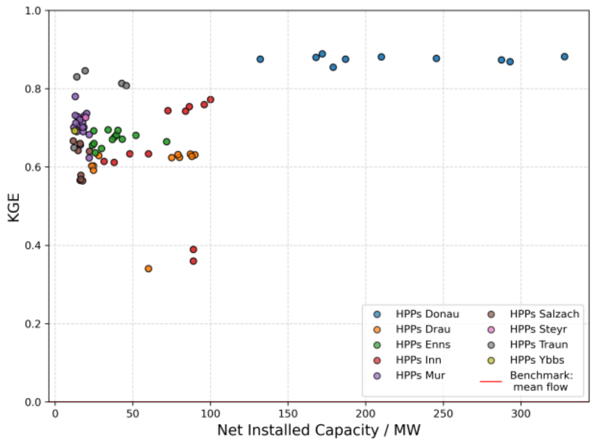

Figure 7: NSE versus Net installed capacity

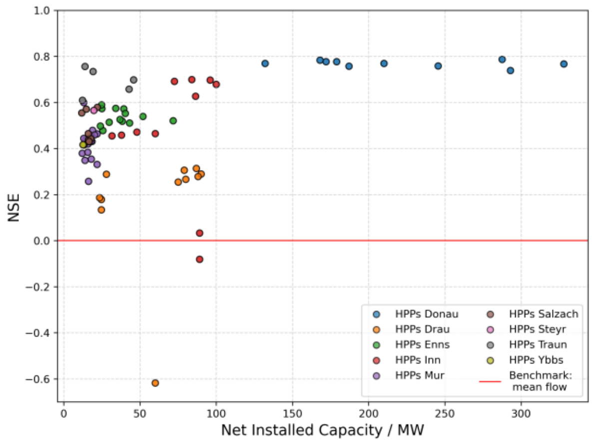

Figure 8: KGE vs. Net installed capacity

4 Conclusions

After successful implementation, the developed tool performs reliably and produces plausible results. It is therefore applicable for future weather scenarios and can be integrated into the renewable energy module *Frauental* within the *iKlimEt* project to enhance the existing energy system optimization framework. An important outcome is that the reliability of the hydrological model generally increases with catchment size, which is largely related to a higher share of hydropower in the overall energy system and represents a very encouraging result.

A substantial part of the effort into this tool was devoted to collecting and preparing the necessary input data in a format suitable for model application. Although further improvements are certainly possible, achieving a fully operational tool with stable and consistent results already constitutes a major accomplishment. The primary objective of establishing a robust and extensible modelling framework has therefore been successfully achieved.

One key limitation affecting model accuracy is the coarse spatial resolution of the *ERA5* weather data, whose grid cells are in some cases comparable in size to entire catchment areas. Although the mean NSE remains below 0.50, which would normally be considered unsatisfactory [13], this metric is of limited relevance in the present application. Deviations in peak flows strongly affect the NSE, but are less critical for hydropower production, as only discharge up to the maximum turbine capacity is relevant.

Consequently, mean flow is used as the benchmark, corresponding to a KGE value greater than −0.41, which is fulfilled for all hydropower plants included in the model. Overall, the results are satisfactory for nearly all plants, and the hydropower time series which can be simulated, provide a solid basis for practical applications in energy planning and forecasting.

Finally, several possibilities are presented that could be used to further extend and improve the model in future work:

- Dynamic snowmelt factors: calibrating the factors based on the temperature.
- Integrating additional meteorological variables beyond precipitation and temperature to further improve the representation of potential evapotranspiration and snowmelt.
- Alternative calibration strategies: e.g. multi-objective calibration of KGE components
- Improved evapotranspiration estimation: more complex method or regionally optimized constant C in the Hamon method
- Expanding the model across Europe by incorporating additional hydropower plants
- Implementing flood shutdowns of HPP, where the plants generate no electricity when the discharge exceeds a certain value

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