Optimizing Japanese dam reservoir inflow forecast for efficient operation

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Abstract

Despite a climate and topology favorable to hydropower (HP) generation, HP only accounts for 4% of today's Japanese primary energy consumption mix. In recent years, calls for improving the efficiency of Japanese HP towards achieving a more sustainable energy mix have emerged from prominent voices in the Ministry of Land, Infrastructure, Transport and Tourism (MILT). Among potential optimizations, data-driven dam operation policies using accurate river discharge forecasts have been advocated for. In the meantime, Machine Learning (ML) has recently made important strides in hydrological modeling, with forecast accuracy improvements demonstrated on both precipitation nowcasting and river discharge prediction. We are motivated by the convergence of these societal and technological contexts: our final goal is to provide scientific evidence and actionable insights for dam infrastructure managers and policy makers to implement more energy-efficient and flood-resistant dam operation policies on a national scale. Towards this goal this work presents a preliminary study of ML-based dam inflow forecasts on a dataset of 127 Japanese public dams we assembled. We discuss our preliminary results and lay out a path for future studies.

1 Introduction

Dam operation is a problem of control under uncertainty, in which dam operators aim to maximize multiple objectives (flood protection, HP generation, etc.) given uncertain forecasts of river discharge flowing into dam reservoirs. The more accurate river discharge forecasting is, the more efficiently (in terms of both flood protection and HP generation) dams can be operated. The uncertainty in discharge forecast can be attributed to two main factors: Uncertainty in precipitation forecast (how much rain will fall) and uncertainty in hydrological modeling (how much of the rain will flow into rivers). High levels of uncertainty and abundant alternative energy sources have lead Japanese public dam operators to adopt conservative operation strategies sub-optimal for HP production. However two factors may come to challenge this status quo: First, social and environmental pressures on fossil fuels and nuclear energy production, combined with the rapid development of intermittent renewable energy sources, are foreseen to increase the value of HP generation. Second, advances in both environmental modeling and statistical inference models are foreseen to increase the accuracy of forecast, allowing for better-informed dam operation policies. Combined, these two factors may challenge the current risk-benefit analysis of dam operation towards more efficient operation policies.

This work is part of a parent project that aims to provide both scientific evidence and actionable insights for dam infrastructure managers and policy makers to implement more energy-efficient and flood resistant dam operation policies on a national scale. In this work, we present the results of our

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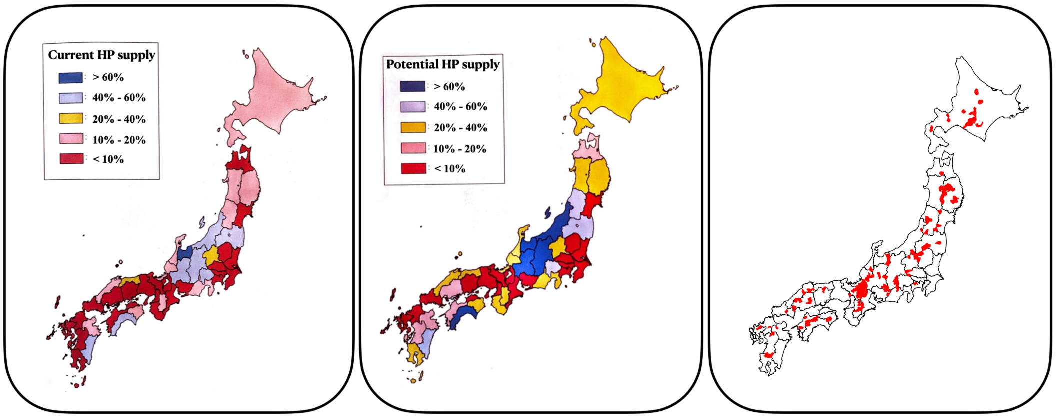


Figure 1: (Left) Current energy supply rates (Energy consumed / HP production) coming from HP (Center) Potential HP supply rate. Both figures were collected and translated from [1] (Right): Illustration of the dam locations of our dataset. Many collected dams are located in prefectures with high potential for optimization.

initial efforts, focusing on improving the accuracy of river discharge forecast inflowing to Japanese public dam reservoirs. To do so, we have assembled a dataset of public Japanese dams, which we present in Section 3, and proposed different ML discharge forecasting systems, which we evaluate in Section 4. Section 5 discusses our results and future works. Section 2 motivates our study with further background information.

2 Background

A mountainous topology and a heavy rain climate lend Japan a high potential for hydro power generation. Historically, Japan has extensively relied on HP generation during the first half of the 20th century, favoring HP over fire-based energy for its base load supply. As the post-war period of great economic development called for increased energy consumption, fossil fuel plants were preferred to HP for their ability to quickly and efficiently answer the rapid increase in demand. Later, the oil shock has seen Japan strategically develop nuclear power generation to ensure its energy independence. Due to longer infrastructure development times, HP lost its competitiveness in times of rapidly moving energy needs, so that its operating infrastructure has been comparatively little optimized [1]. Today, nuclear incidents and international pledges to reduce carbon emissions have come to threaten the long term viability of Japan's current energy mix. While solar and wind power generation are being intensively developed, their intermittent nature does not allow them to cover for the base load and demand response capacity provided by fossil fuel plants. In this context HP generation is seen as a valuable low-carbon alternative to fossil fuels for both base load and demand response needs to complement the development of intermittent renewable energy sources. For all its benefits, several voices from the MLIT have been advocating for a more efficient use of Japanese water resources towards HP generation [1,2]. Figure 1, drawn from a 2019 report on the state and future of Japanese HP [1], shows the current rate of energy demand supplied by HP per prefecture, and contrasts it to potentially achievable supply rates, illustrating large potential benefits. Among the potential optimization, the implementation of power efficient dam operation policies powered by accurate river discharge forecasts has been identified as a high potential candidate.

Furthermore, climate change is expected to have a deep impact on surface water distribution in Japan [7], with impacting local disparities, including decreased snow melt in the northern and Japan sea regions, increased drought periods in the south, and increased flooding risks due to heavy rain events across the country. Both the destabilization of surface water distribution and the increased risks of heavy-rain related incidents call for better forecasting abilities to optimize operation processes At the same time, ML-based river discharge models have been shown to outperform traditional methods on several benchmarks[4,5,6], with notable voices calling for further development of ML approaches [3]. In the meantime, another line of work has shown ML-based precipitation nowcasting to outperform state-of-the art ensemble physical simulations Together, these works beg the question of whether

ML can provide river discharge forecast accurate enough to empower efficient dam operation policy implementations in Japan, as called for by prominent policy makers [1,2].

3 Dataset

We have assembled a dataset covering 127 public dams across Japan, as illustrated in Figure 1. For each dam, we have collected historical hourly reservoir inflow discharges provided by the MLIT, spanning from the year 1980 to 2020. Atmospheric observations (precipitation, temperatures, wind, etc.), and forecasts for the same period were collected from different sources, and interpolated to each dam's drainage area (the area). We further gathered in-situ (gauge precipitation measurements) from the MLIT and snow melt variables from land surface models, and interpolated this data to dam's drainage areas. In this paper, we focus on river discharge forecast horizons of up to 3 days, which was estimated to be the time needed for most small to medium size dams to preemptively empty their reservoirs to buffer heavy rain event discharges. After processing, each dam is represented by one catchment-aggregated time series per input variable and one for the output (discharge). Table 1 provides details on the different variables we collected for each dam. This dataset will be released, along additional Japanese river discharge measurements, following existing hydrological standard in an upcoming paper.

Data Source	Variable	Type	Unit
MLIT	Discharge	In-Situ	m^3/s
JMA	Precipitation	Forecast	mm
MLIT	Precipitation	In-Situ	mm
GSMap	Precipitation	Remote Sensing	mm
JMA	Precipitation	Assimilated Model	mm
JMA	Temperature	Assimilated Model	degrees
JMA	Wind	Assimilated Model	m/s
TE [9]	Snow melt	Model	m^3/s

Table 1: Summary of the variables in our dataset

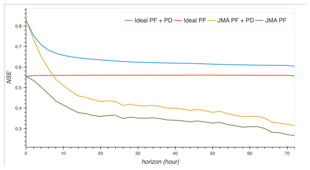
4 Experiments

We aim to maximize forecast accuracy and characterize forecast errors by quantitatively answering the questions listed below. To do so, we split our dataset into a training set ranging up to January 2018, a validation set between January and December 2018 and a test set made of data from January to December 2019. Models were trained to regress the river discharge from different variables on the training set, and evaluated on the test set. In all experiments, we train one model per dam, and report the average accuracy on the full test set (averaged accross dams). When left unspecified, the model used is a linear baseline regressor, prefered for its computational efficiency.

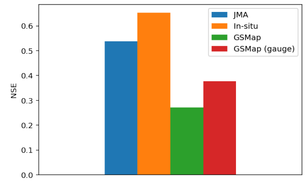
How does forecast horizon impact river discharge accuracy? Figure 2(a) illustrates the decrease of forecast accuracy with increasing forecast horizon. The yellow curve represents our best results using realistic data: in-situ measurements of past discharge (PD) and precipitations, as well as JMA's Precipitation Forecast (PF) were used as inputs to a linear model. Other curves were computed for ablation study, as discussed below.

Are discharge forecast errors most impacted by precipitation forecast errors (how much rain will fall) or hydrological errors (how much of the fallen rain will flow into the dam)? In Figure 2(a), we simulated a perfect precipitation forecast by using future in-situ precipitation observations, and used this data instead of JMA's precipitation forecast to draw the blue and red curve. We can see that the model maintains high accuracy throughout the horizon window, suggesting that most long-horizon errors are dominated by uncertainty in the precipitation forecast, as quantified by the difference between the yellow and blue curve. Using past disharge as inputs improves greatly forecast accuracy on short-term horizon, but have more limited effect on longer time horizon, as illustrated by the difference between the blue and red curve. The decrease in accuracy observed in the blue curve can thus be attributed to hydrological errors.

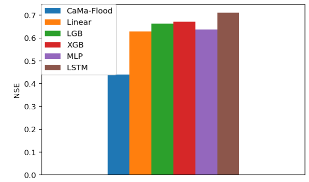
What variables are most predictive of river discharge? Figure 2(b) highlights the importance of quality precipitation estimates, by showing results on a 24 hours horizon forecast using different precipitation observations. In-situ observations provide large improvements over both remote sensing estimates and assimilated model simulations. Temperature seems to provide little predictive power, as shown in Figure 3(c) Snowmelt was also found to have an important impact for dams in the north



(a) Impact of forecast horizon



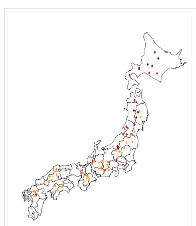
(b) Impact of precipitation data



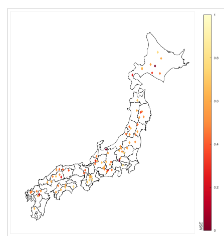
(c) Impact of hydrology model

Figure 2: Impact of different modeling on discharge forecast accuracy

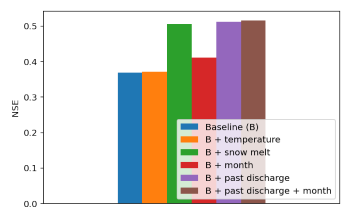
and along the Japan sea. We study the impact of providing snow melt information (simulation data provided by the Today Earth model [9]) as input to the model and compare forecast accuracy with and without snowmelt data in Figure 3. Large accuracy gains can be observed in heavy snowfall regions (North and Japan sea). We also find that using past discharge observations with conditioning of the model on the current month allow to recover similar accuracy, which suggests that snowmelt-induced discharges may be smooth enough to be infered from past discharge observations and seasonality only. It remains to be seen whether this strategy may work for longer horizon times.



(a) Without snow melt



(b) With snow melt



(c) Impact of additional data

Figure 3: Illustration of the impact of snow melt modeling on discharge forecast accuracy

What hydrological models are most accurate for river Japanese dams discharge modeling? We compare the accuracy of different ML models to that of a global hydrology model [8] on a one hour horizon forecast, and show that ML models outperform the hydrology model. This may be due to ML model relying extensively on high-precision local data, while the global model does not. In addition, it can be seen that more expressive models outperform the baseline linear models. This trend was only observed for high precision precipitation estimates, while the difference between ML models was found to be minimal when using noisy precipitation estimates.

5 Conclusion and Future Work

Motivated by calls from Japanese policy makers to optimize HP generation, we have assembled a dataset and developed models to forecast river discharge flowing into public dam reservoirs. We found that locally trained ML-based models outperform physics-based global hydrology models. We have identified precipitation observation and forecast accuracy as the critical factor of discharge forecast accuracy, and quantified the impact of snow melt modeling. Advanced ML models do improve river discharge accuracy, but only in the case of accurate enough precipitation forecast and observations. In the low precipitation accuracy regime, a simple linear baseline performs on par with more sophisticated models. The sharp decrease in accuracy observed for time horizons within 24 hours, and the observed importance of accurate precipitation forecast suggest that improvement in precipitation nowcasting may bring impacting improvements to short term river discharge forecasting. In future work, we thus plan to integrate recent deep learning based nowcasting systems to our study.

Despite the encouraging answers and perspectives we have managed to gather, many important questions remain. Maybe the most fundamental question remaining towards our final goal is: how do forecast errors impact the efficiency of dam operations, and what forecast accuracy is required to enable data-driven energy efficient policies? We have summarized our preliminary efforts to answer this question in a companion paper submitted to this workshop, in which we propose to use Reinforcement Learning as an operational metric for river discharge forecast accuracy assessment. Finally, an important axis of our study will be to integrate reliable uncertainty estimates of pour forecasts.

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