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PREDIÇÃO DAS VAZÕES MÁXIMAS DO RESERVATÓRIO DO FUNIL (MG) POR MEIO DE UMA ABORDAGEM BAYESIANA

PREDICTION OF MAXIMUM STREAMFLOWS OF THE FUNIL RESERVOIR (MG) VIA A BAYESIAN APPROACH

PREDICCIÓN DE LOS CAUDALES MÁXIMOS DEL EMBALSE DE FUNIL (MG) MEDIANTE UN ENFOQUE BAYESIANO

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Resumo

A predição de vazões máximas é importante para o gerenciamento de reservatórios. Diante disso, este estudo teve como objetivos modelar as vazões máximas do reservatório da Usina Hidrelétrica do Funil (UHE Funil) por meio da distribuição Gumbel sob abordagem bayesiana e avaliar a influência de diferentes especificações a priori na estimação de níveis de retorno. Foram utilizados dados de vazões médias diárias de 2003 a 2025, obtidos no sistema HidroWeb da Agência Nacional de Águas e Saneamento Básico, dos quais foram extraídos os valores máximos anuais separados em períodos úmido e seco. As prioris informativas foram elicitadas a partir de séries da UHE Camargos. Na seleção dos modelos, foram utilizados registros até 2017, reservando-se os dados de Funil de 2018 a 2025 para avaliação do desempenho. Os modelos foram comparados pelo critério de informação da deviance (DIC), pelo erro médio de predição (EMP) e pela média das amplitudes dos intervalos de maior densidade a posteriori (MAHPD) de 95%. Em comparação à especificação não informativa, a

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priori informativa de menor variância reduziu o EMP de 30,93% para 26,85% no período úmido e de 27,22% para 26,31% no seco. Essa estrutura também reduziu a MAHPD dos níveis de retorno de 2, 4, 6 e 8 anos em 62,86% e 61,50%, respectivamente. No período seco, entretanto, o menor EMP foi obtido com a priori de variância duplicada, atingindo 26,14%. Os resultados indicaram que a principal contribuição das informações de Camargos foi a redução da incerteza a posteriori dos níveis de retorno, enquanto as reduções numéricas do EMP foram mais discretas, sobretudo no período seco.
Palavras-chave: Precisão; Distribuição Gumbel; Inferência bayesiana; Priori informativa; Níveis de retorno.

Abstract

Predicting maximum streamflows is important for reservoir management. Accordingly, this study aimed to model maximum streamflows at the reservoir of the Funil Hydropower Plant (Funil HPP) using the Gumbel distribution within a Bayesian framework and to assess the influence of different prior specifications on return level estimation. Daily mean streamflow data from 2003 to 2025 were obtained from the HidroWeb system of the Brazilian National Water and Sanitation Agency, from which annual maxima were extracted separately for the wet and dry periods. Informative priors were elicited from the Camargos HPP time series. Records up to 2017 were used for model selection, with the Funil data from 2018 to 2025 held out for performance evaluation. Models were compared using the deviance information criterion (DIC), mean prediction error (MPE), and mean width of the 95% highest posterior density (HPD) intervals (MHPDW). Compared with the noninformative specification, the informative prior with the smallest variance reduced MPE from 30.93% to 26.85% in the wet period and from 27.22% to 26.31% in the dry period. This specification also reduced MHPDW for the 2, 4, 6, and 8year return levels by 62.86% and 61.50%, respectively. In the dry period, however, the lowest MPE was obtained with the prior with twice the baseline variance, reaching 26.14%. The results indicated that the main contribution of the information from Camargos was a reduction in posterior uncertainty in the return levels, whereas the numerical reductions in MPE were more modest, particularly in the dry period.
Keywords: Precision; Gumbel distribution; Bayesian inference; Informative prior; Return levels.

Resumen

La predicción de caudales máximos es importante para la gestión de embalses. Por ello, este estudio tuvo como objetivos modelar los caudales máximos del embalse de la Central Hidroeléctrica de Funil (UHE Funil) mediante la distribución de Gumbel bajo un enfoque bayesiano y evaluar la influencia de diferentes especificaciones a priori en la estimación de niveles de retorno. Se utilizaron datos de caudales medios diarios de 2003 a 2025, obtenidos del sistema HidroWeb de la Agencia Nacional de Aguas y Saneamiento Básico de Brasil, de los cuales se extrajeron los valores máximos anuales por separado para los períodos húmedo y seco. Las distribuciones a priori informativas se elicitaron a

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partir de las series de la Central Hidroeléctrica de Camargos. Para la selección de los modelos, se utilizaron registros hasta 2017 y se reservaron los datos de Funil de 2018 a 2025 para evaluar el desempeño. Los modelos se compararon mediante el criterio de información de la devianza (DIC), el error medio de predicción (EMP) y la amplitud media de los intervalos de máxima densidad a posteriori (MAHPD) del 95%. En comparación con la especificación no informativa, la distribución a priori informativa de menor varianza redujo el EMP del 30,93% al 26,85% en el período húmedo y del 27,22% al 26,31% en el seco. Esta estructura también redujo la MAHPD de los niveles de retorno de 2, 4, 6 y 8 años en un 62,86% y un 61,50%, respectivamente. Sin embargo, en el período seco, el menor EMP se obtuvo con la distribución a priori cuya varianza se duplicó, alcanzando el 26,14%. Los resultados indicaron que la principal contribución de la información de Camargos fue la reducción de la incertidumbre a posteriori de los niveles de retorno, mientras que las reducciones numéricas del EMP fueron más discretas, especialmente en el período seco.

Palabras clave: Precisión; Distribución de Gumbel; Inferencia bayesiana; Distribución a priori informativa; Niveles de retorno.

1. Introduction

Water resources management is essential to economic and social development, particularly in view of the impacts of extreme hydrological events, such as droughts and floods. In this context, maximum streamflow analysis supports flood risk assessment and the planning and management of reservoirs used for electricity generation, irrigation, and water supply.

Statistical analysis of historical streamflow records allows the exceedance probabilities of specified levels to be estimated and associated with return periods of interest (Khosravi *et al.*, 2012). These estimates support the design of hydraulic structures, such as spillways, channels, dams, and drainage systems, helping to reduce the impacts of high flows and flooding (Teixeira *et al.*, 2011).

Among the models used in maximum streamflow analysis, the Gumbel distribution is widely employed to model block maxima, such as annual maxima. Its parameters can be estimated using maximum likelihood, moments, L-moments, and TL-moments, as well as Bayesian inference procedures (Seckin *et al.*, 2010; Seckin *et al.*, 2011; Jan *et al.*, 2018; Xu *et al.*, 2018; Langat *et al.*, 2019; Chagas Neta *et al.*, 2019).

The Bayesian approach provides a probabilistic framework for combining observed data with additional information, expressed through prior distributions,

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and for quantifying uncertainty in parameters and return levels (Xu *et al.*, 2018). Information from hydrologically similar sites can contribute to estimation at the site of interest (Lima *et al.*, 2016). When appropriately specified, informative prior distributions can reduce uncertainty in the estimates, especially when data availability is limited.

Furthermore, Suekame *et al.* (2020) report difficulties in modeling streamflow arising from the scarcity of data on this hydrological variable. In block maxima analysis, the sample size is reduced by selecting a single maximum value from each block of observations. In this context, the Bayesian approach allows inference without relying on asymptotic approximations and incorporates additional information through prior distributions, which may support the analysis of short time series. However, the influence of these distributions on the results may be greater in small samples, making it important to assess the sensitivity of the estimates to the adopted specifications.

Given the importance of estimating maximum streamflow return levels for reservoir management, this study aimed to evaluate Gumbel models within a Bayesian framework applied to Funil HPP, considering different prior distribution specifications for their parameters. Maximum streamflow data from Camargos HPP were used to construct the informative prior distributions. Models were compared using the deviance information criterion (DIC), mean prediction error, and mean widths of the 95% highest posterior density (HPD) intervals for the return levels.

2. Materials and Methods

2.1 Data and study area

Historical daily mean streamflow series were used from two sites in the Grande River basin in Minas Gerais, Brazil: Camargos HPP, with records from 1990 to 2025, and Funil HPP, with records from 2003 to 2025. Funil HPP is the site of interest for modeling and return level calculations, whereas information from Camargos HPP was used, after rescaling, to elicit informative prior distributions for the parameters of the Gumbel distribution applied to Funil HPP. The data were obtained from the Brazilian National Water and Sanitation Agency (ANA, 2026).

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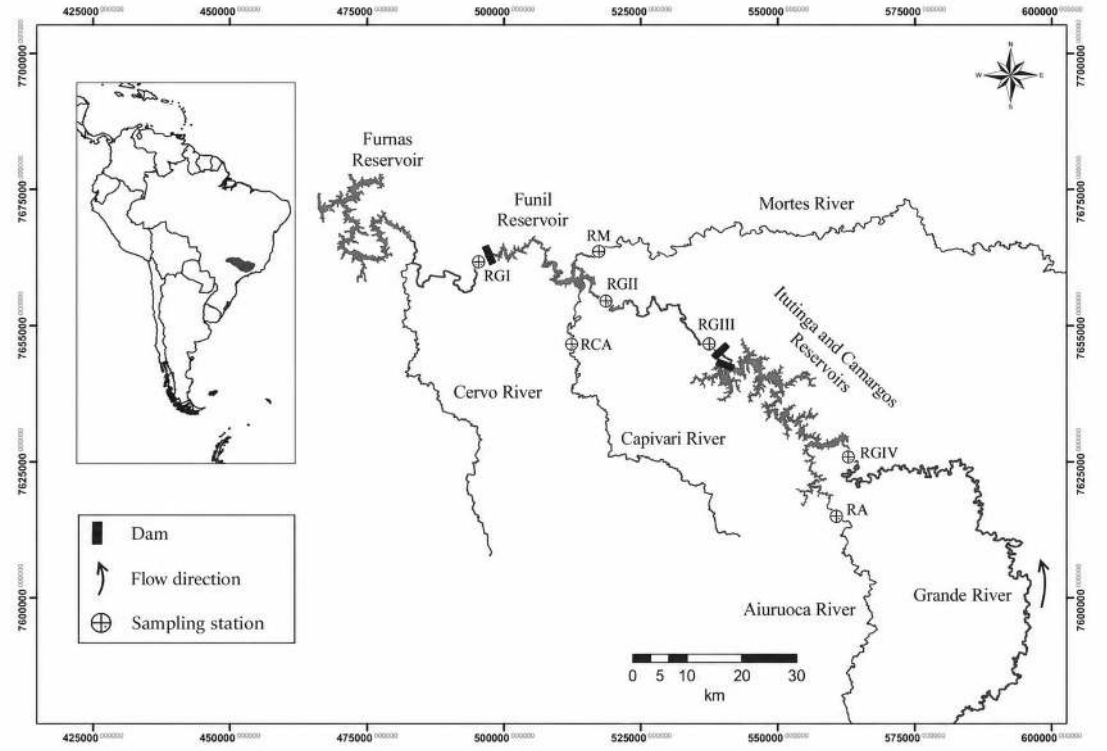
Funil HPP is located on the Grande River, between the municipalities of Lavras and Perdões, in the state of Minas Gerais (Figure 1). Funil HPP, also known as the Engenheiro José Mendes Júnior Hydropower Plant, was completed in 2002. At its maximum operating level, the reservoir covers an area of 40.49 km² in the municipalities of Lavras, Perdões, Bom Sucesso, Ijaci, and Ibituruna. Funil HPP generates enough electricity to supply a city of 500,000 inhabitants and has a reservoir with a storage capacity of 285 million cubic meters of water (Coelho and Pereira, 2011).

Figure 1: Location of Funil Reservoir.



Source: Adapted from Suzuki *et al.* (2011).

The first studies on the comprehensive development of the Grande River date back to the 1950s and consisted of an inventory of the river that established the division of its available hydraulic head among potential developments. Studies for the Funil Hydropower Development (AHE Funil) date back to the 1960s and were updated in the early 1990s. During that same period (1991/1992), the environmental

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impact study and report (EIA-RIMA) were prepared as part of the project's feasibility study. The AHE Funil Consortium was established in 1997, and the installation license was granted by the State Environmental Policy Council (COPAM) in 2000. In 2002, Funil HPP was granted an operating license, and in January 2003 its first generating unit, with an installed capacity of 60 megawatts, entered commercial operation (Coelho and Pereira, 2011).

2.2 Construction and analysis of the maxima series

The block maxima method was adopted at both sites, considering the months corresponding to the wet and dry periods of each calendar year separately. The wet-period grouping comprised January through April and November through December of the same year, whereas the dry period comprised May through October. At each site, the highest daily mean streamflow in each grouping was selected for each year, yielding one maxima series for the wet period and another for the dry period. Thus, the wet period corresponds to months within the same calendar year rather than a continuous rainy season.

The analysis was conducted in two stages: model selection and return level calculation. In the first stage, historical records up to 2017 were used: the Camargos series from 1990 to 2017 provided the basis for eliciting informative priors, and the Funil series from 2003 to 2017 were used to fit the models. The Funil HPP data from 2018 to 2025 were held out for validation and were not used in calculating the rescaling factor, eliciting priors, or fitting the candidate models. In the second stage, after selecting the prior specification for each period, the full series from both sites were used to obtain maximum streamflow return levels.

The Ljung-Box test (Ljung and Box, 1978) was used to assess independence in the maximum streamflow series. The Mann-Kendall test (Mcleod, 2005) was used to assess the presence of trends in the data. A significance level of 5% was adopted for all tests.

2.3 Gumbel distribution

The Gumbel distribution was used to analyze the historical maximum

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streamflow series. The cumulative distribution function of the Gumbel distribution is given by:

$$F(x) = \exp\left[-\exp\left\{-\left(\frac{x-\alpha}{\beta}\right)\right\}\right], \quad (1)$$

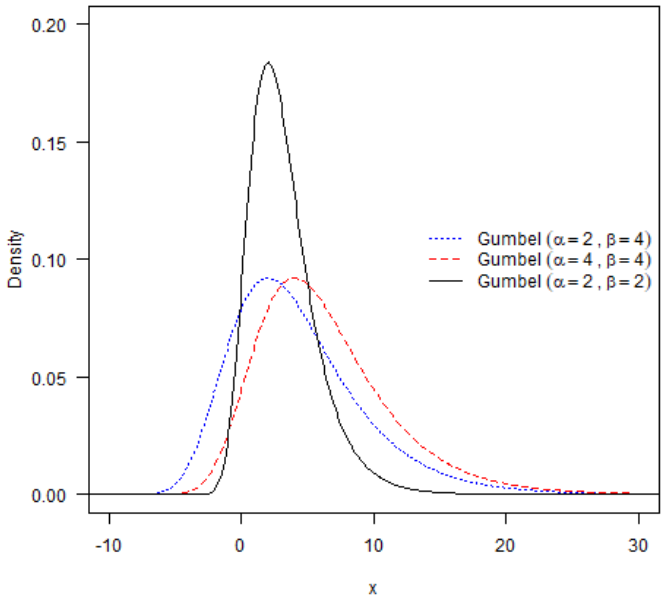
defined for $-\infty < x < \infty,$, where the parameters satisfy $-\infty < \alpha < \infty$ and $\beta > 0$. The parameters α and β denote the location (or position) and scale parameters, respectively.

Differentiating $F(x)$ in (1) with respect to x yields the Gumbel probability density function (pdf):

$$f(x) = \frac{1}{\beta}\exp\left[-\frac{x-\alpha}{\beta} - \exp\left(-\frac{x-\alpha}{\beta}\right)\right] \quad (2)$$

Figure 2 illustrates three forms of the Gumbel pdf for different parameter values.

Figure 2: Probability density function of the Gumbel distribution for $\alpha = 2$ and $\beta = 4$ (blue dotted line), $\alpha = 4$ and $\beta = 4$ (red dashed line), and $\alpha = 2$ and $\beta = 2$ (black solid line).



Source: Prepared by the authors (2026).

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Before fitting the Gumbel distribution to the Camargos series, their maximum streamflows were rescaled to make their magnitudes comparable to those observed at Funil HPP. For each period, wet and dry, each Camargos observation was divided by the ratio of the median maximum streamflow at Camargos to the median maximum streamflow at Funil:

$$R_Q = \frac{\tilde{Q}_{\max,C}}{\tilde{Q}_{\max,F}}, \tag{3}$$

where $\tilde{Q}_{\max,C}$ and $\tilde{Q}_{\max,F}$ are the median maximum streamflows at Camargos and Funil reservoirs, respectively.

During model selection, this ratio was calculated exclusively from observations available up to 2017, using the Camargos records from 1990 to 2017 and the Funil records from 2003 to 2017. The rescaled Camargos series from 1990 to 2017 were used to fit the Gumbel distribution by maximum likelihood, separately for the wet and dry periods. The 95% confidence intervals for the location and scale parameters, presented in Table 1, provided the basis for calibrating the informative prior distributions.

Table 1: 95% confidence intervals for the location and scale parameters of the Gumbel distribution, obtained for Camargos HPP from 1990 to 2017 using maximum likelihood estimation.

Parameter	Wet period		Dry period	
	LI (2.5%)	LS (97.5%)	LI (2.5%)	LS (97.5%)
α	782.85	1,093.96	221.82	292.89
β	286.03	511.23	65.21	118.08

LI: Lower limit; LS: Upper limit.

Source: Prepared by the authors (2026).

Bayesian analysis was performed separately for the wet- and dry-period maximum streamflow series at Funil HPP. In all models, the Gumbel likelihood was constructed exclusively from Funil HPP observations, considering different

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noninformative and informative prior specifications for the parameters. Information from the rescaled Camargos series was incorporated only through the informative priors. For each period evaluated, the noninformative priors for the Gumbel model parameters were specified as follows:

$$\alpha \sim N\left(0;10^{-7}\right) \tag{4}$$

$$\ln\beta \sim N\left(0,01;10^{-4}\right) \tag{5}$$

where $N\left(\mu_0;\tau_0\right)$ denotes the normal distribution parameterized by the mean μ_0 and precision τ_0, with τ_0 defined as the inverse of the variance. For β, a lognormal distribution was adopted whose underlying normal distribution has mean 0.01 and precision 10^{-4}, corresponding to the inverse of the variance of $\ln\beta$. The lognormal distribution ensures the constraint $\beta > 0$. These specifications were used as an alternative to the informative priors to provide broadly dispersed noninformative prior distributions.

The informative prior distributions for the parameters of the Gumbel distribution applied to Funil HPP were calibrated using the 95% confidence intervals obtained by maximum likelihood for the rescaled Camargos series, presented in Table 1.

For the wet and dry periods, normal prior distributions were adopted for the location parameter and lognormal prior distributions for the scale parameter, calibrated so that their 2.5% and 97.5% quantiles matched the corresponding confidence limits reported in Table 1 for Camargos HPP. For the location parameter α, with limits LI_α and LS_α, the prior was specified as $\alpha \sim \text{Normal}\left(\mu_0 = a; \tau_0 = \frac{1}{b^2}\right)$, where a and b are the mean and standard deviation of the prior for α, respectively. From the 95% confidence intervals for α presented in Table 1, a and b can be calculated as follows:

$$a = \frac{LI_\alpha + LS_\alpha}{2} \tag{6}$$

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$$b = \frac{LS_{\alpha} - LI_{\alpha}}{2z_{0,975}} \tag{7}$$

where $Z_{0,975}$ is the standard normal quantile, with an approximate value of 1.96.

For the scale parameter β, with limits LI_{β} and LS_{β}, the prior was specified as $\ln \beta \sim \text{Normal}\left(\mu_0 = c; \tau_0 = \frac{1}{d^2}\right)$, where c and d are the mean and standard deviation of the prior for $\ln \beta$, respectively. From the 95% confidence intervals for β presented in Table 1, c and d were calculated as follows:

$$c = \frac{\ln\left(LI_{\beta}\right) + \ln\left(LS_{\beta}\right)}{2} \tag{8}$$

$$d = \frac{\ln\left(LS_{\beta}\right) - \ln\left(LI_{\beta}\right)}{2z_{0,975}} \tag{9}$$

with $Z_{0,975} \approx 1,96$.

Thus, the information obtained at Camargos was used to specify the central 95% intervals of the prior distributions for Funil HPP, treating the rescaling ratio as fixed.

Additional informative prior specifications were proposed by multiplying the variances $\left(b^2, d^2\right)$ of the Gumbel distribution parameters by $\frac{1}{2}$, 2, and 4. The aim was to vary the strength of the prior information. Using these new values, new priors were elicited following the same criteria used for the informative priors described above. The hyperparameter values for the different proposed informative prior specifications, obtained from maximum streamflow information for Camargos Reservoir, are presented in Table 2.

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Table 2: Hyperparameter values of the informative prior distributions for the Gumbel distribution parameters based on maximum streamflows at Camargos Reservoir (1990-2017), for the wet and dry periods.

Par.	Hyp.	Wet				Dry			
		$I_{\frac{1}{2}V}$	I_{1V}	I_{2V}	I_{4V}	$I_{\frac{1}{2}V}$	I_{1V}	I_{2V}	I_{4V}
α	μ_0	938.40	938.40	938.40	938.40	257.36	257.36	257.36	257.36
	τ_0	0.00032	0.00016	0.0008	0.0004	0.00608	0.00304	0.00152	0.00076
β	μ_0	5.95	5.95	5.95	5.95	4.47	4.47	4.47	4.47
	τ_0	91.12	45.56	22.78	11.39	87.18	43.59	21.79	10.90

Par.: Parameter; Hyp.: Hyperparameter; *I*: Informative prior.

Source: Prepared by the authors (2026).

The joint posterior distributions were obtained from the respective prior distributions and the likelihood; for the Gumbel distribution, these posteriors have no analytical solution. An iterative method was therefore required to obtain the marginal distributions: the algorithm known as the Gibbs sampler, implemented in OpenBUGS. This software can be interfaced with R through the R2OpenBUGS package (Sturtz *et al.*, 2010).

Three independent Markov chain Monte Carlo (MCMC) chains were run using the R2OpenBUGS package. The settings specified 10,000 iterations per chain (n.iter), a burn-in of 2,000 (n.burnin), and thinning of 50 (n.thin). Because R2OpenBUGS applies thinning directly during the updating phase, this configuration corresponds to 500,000 total updates per chain, with the first 100,000 allocated to burn-in. Of the remaining 400,000 updates, one iteration was stored every 50 updates, yielding 8,000 samples per chain and a total of 24,000 posterior samples per parameter. Chain convergence was monitored using the coda package (Plummer *et al.*, 2006) in R (R Core Team, 2026).

The criteria used to assess convergence of the MCMC-generated posterior chains were the Raftery and Lewis (1992) diagnostic, rejecting chains with a dependence factor greater than 5; Geweke's (1992) Z statistic, rejecting chains for

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which $|Z| > 1,96$; and the Heidelberger and Welch (1983) diagnostic, adopting a significance level of 5% and rejecting chains with p-values below 5%.

2.4 Model evaluation

The deviance information criterion (DIC) was used to evaluate the different prior specifications used to fit the Gumbel distribution (Spiegelhalter *et al.*, 2002). Lower DIC values indicate better models. For model comparison and selection, Lunn *et al.* (2012) propose the following criterion based on the absolute difference between the DIC values of two models, denoted A and B. This criterion is given by:

$$D = \left| DIC_A - DIC_B \right|. \tag{10}$$

Thus,

i) if $D < 5$, the models are considered to produce very different inferences, and presenting only the model with the lowest DIC may be misleading.

ii) if $5 \leq D \leq 10$, the difference between the models is considered substantial, and the model with the lowest DIC is preferred.

iii) if $D \geq 10$, the model with the highest DIC can be disregarded.

When case i) applies, the best model can be selected using another comparison measure. The precision of predictions for the 2-, 4-, 6-, and 8-year return levels was also analyzed to select the best model. Model performance was assessed using the lowest mean prediction error (MPE), whereas precision was assessed using the mean width of the HPD intervals (MHPDW).

MPE was calculated as follows:

$$\text{MPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|x_i(t) - \hat{x}_i(t)|}{x_i(t)} \times 100, \tag{11}$$

where $x_i(t)$ is the observed maximum streamflow, $\hat{x}_i(t)$ is the predicted streamflow for the ith return period t, and n is the number of predictions.

MHPDW was obtained as follows:

$$\text{MHPDW} = \sum_{i=1}^{4}\frac{LSNR(t_i) - LINR(t_i)}{4}, \tag{12}$$

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where $LSNR_i(t)$ and $LINR_i(t)$ are the upper and lower limits, respectively, of the 95% HPD interval for the ith return period t (2, 4, 6, and 8 years).

The error metrics assess performance in terms of deviations between observed maximum streamflows and predicted maximum streamflow values. Accordingly, the Gumbel distribution with a given prior yielding a lower MPE was considered more suitable than those yielding higher MPE values.

To calculate DIC, MPE, and MHPDW, the wet- and dry-period maximum streamflow observations at Funil HPP were divided into two datasets. The first, covering 2003-2017, was used to estimate the parameters and calculate the likely maximum streamflows for return periods of 2, 4, 6, and 8 years. From the second dataset, covering 2018-2025, the highest observed maximum streamflow was extracted for the following time windows: 2 years (2018-2019), 4 years (2018-2021), 6 years (2018-2023), and 8 years (2018-2025), for each period.

Selection of the most suitable model for each period was based on a joint assessment of DIC, MPE, and MHPDW. Selection favored the lowest values of these indicators, without imposing a hierarchical order among them. When the criteria favored different specifications, the choice considered the trade-off between predictive performance and posterior precision of the return levels, examining the magnitude of the observed differences. The best-performing model based on these criteria for each period was fitted to the full maximum streamflow series at Funil HPP and used to calculate expected maximum streamflows for return periods of 5, 10, 20, 30, 50, and 100 years, with their respective 95% HPD intervals.

3 Computational resources

All statistical analyses were performed using R (R Core Team, 2026) and OpenBUGS (Lunn *et al.*, 2009). The R packages used were coda (Plummer *et al.*, 2006), evd (Stephenson, 2002), and R2OpenBUGS (Sturtz *et al.*, 2010).

4 Results

Table 3 presents descriptive statistics for the maximum streamflow series ($m^3 s^{-1}$) at Funil Reservoir, considering the wet and dry periods for the historical series

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from 2003 to 2017 and from 2003 to 2025 (full series). The mean and median maximum streamflows were found to be close within each period. In the wet period, mean and median maximum streamflows were approximately four times the corresponding dry-period values. This result can be explained by the characteristics of Funil HPP.

Table 3: Descriptive statistics of the maxima series (m^3s^{-1}) of daily mean streamflow at Funil Reservoir, by wet and dry period.

Period	2003 - 2017						
	Median	Mean	SD	Minimum	Maximum	Range	CV (%)
Wet	1,148.49	1,145.70	456.06	438.20	2,154.42	1,716.22	39.81
Dry	287.00	295.88	105.22	110.64	489.00	378.36	35.56
Period	2003 - 2025						
	Median	Mean	SD	Minimum	Maximum	Range	CV (%)
Wet	1,119.97	1,064.98	452.07	438.20	2,154.42	1,716.22	42.45
Dry	258.92	274.03	96.86	110.64	489.00	378.36	35.35

SD: Standard deviation; CV: Coefficient of variation, expressed as a percentage.

Source: Prepared by the authors (2026).

Funil HPP (MG) operates essentially as a run-of-river plant with daily regulation and a small reservoir of approximately 40.49 km². This hydrological characteristic means that the plant cannot store water from one month to the next to attenuate severe floods and depends on the combined inflows from the headwaters of the Grande River (where upstream plants such as Camargos and Itutinga HPPs are located), the Mortes River basin, and other small tributaries (Figure 1). Consequently, during the dry season, streamflows converge toward low values, reflecting the inflows reaching the plant from these sources.

Table 3 also shows that the measures of central tendency behaved differently in the wet and dry periods. In the wet period, the median maximum streamflow

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exceeded the mean, whereas the opposite pattern was observed in the dry period. In typical years, values of this hydrological variable rise in a controlled manner between November and April, following the gradual increase in rainfall that recharges groundwater in southern Minas Gerais.

The behavior of the wet-period measures of central tendency in both series can be explained by the severe water crisis that affected southeastern Brazil and the Grande River basin in 2014 and 2015 (Cuartas *et al.*, 2024). The historical minimum of 438.20 $m^3 s^{-1}$ was recorded in the wet period of 2014 and was lower than the highest dry-period maximum streamflow in the entire historical series, which was 489.00 $m^3 s^{-1}$. The value observed in 2015 (560.66 $m^3 s^{-1}$), although higher than that in 2014, remained very low for a rainy period, corresponding to approximately 50% of the plant's historical median streamflow in both series (1,148.49 or 1,119.97 $m^3 s^{-1}$). Southeastern Brazil also experienced two other water crises that affected rainfall patterns, in 2021 and in 2024-2025 (Cuartas *et al.*, 2024; Montecino *et al.*, 2026). Because the median is less sensitive to extreme values, the median maximum streamflow was not affected to the same extent as the mean maximum streamflow in the wet-period historical series.

Regarding variability between the historical series, the standard deviation was higher for the 2003-2017 series than for the full series. However, because mean maximum streamflows differ between periods, variability in the historical series should preferably be compared using the coefficient of variation (Ferreira, 2009). In the dry period, relative variability was nearly identical in the two series: 35.56% for 2003-2017 and 35.35% for 2003-2025. In contrast, relative variability increased in the wet period. Extending the analysis from 2017 to 2025 shows how the water crisis that affected southeastern Brazil and the Grande River basin over the past decade, particularly in 2021, influenced the relative variability of the data. The wet-period coefficient of variation increased from 39.81% to 42.45%, indicating that recent years made maximum streamflow behavior slightly more unpredictable.

In a study on maximum streamflow prediction at Furnas Reservoir, Costa *et al.* (2022) divided the series into two periods: wet (November-April) and dry (May-October). Using the coefficient of variation, the authors found greater variability in the

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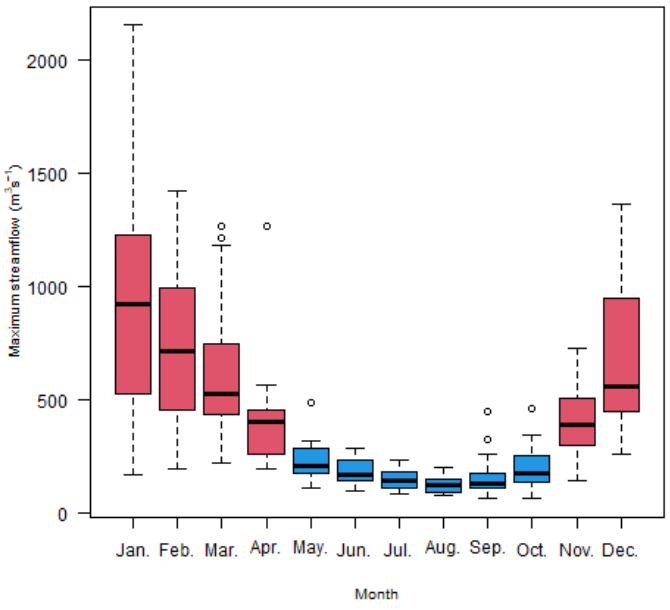
dry period at Furnas Reservoir. Using the same months to define the wet and dry periods, Brito *et al.* (2016) obtained a different result with streamflow data from several plants on the Grande River. The authors observed lower streamflow variability in the dry period than in the wet period. However, the hydrological variable analyzed in that study was mean streamflow.

A boxplot is a useful graphical representation for assessing the central location, dispersion, and presence of potentially outlying observations in a dataset. Figure 3 shows a seasonal pattern in maximum streamflows at Funil HPP from 2003 to 2025, with generally higher medians from November to April than from May to October. Lima *et al.* (2011) studied multilayer perceptron (MLP) artificial neural networks to determine the best configuration for streamflow forecasting in the Grande River basin at the Camargos, Itutinga, Funil Grande, and Furnas plants. The authors found that mean and standard deviation values during the high-flow months (November-March) were significantly higher than during the dry months (June-September). They indicated that this difference may impair forecasting during the high-flow months because of the higher coefficient of variation.

Figure 3: Boxplots of monthly maximum streamflows at Funil HPP (2003-2025).



Source: Prepared by the authors (2026).

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Also in Figure 3, the extent of the boxes and whiskers generally indicates greater absolute dispersion in maximum streamflows between November and April, particularly in January, February, and December. This feature highlights larger differences, in m³/s, among the values observed in those months. Points beyond the whiskers occur in both the wet and dry periods, indicating potentially outlying observations relative to each month's distribution. Their occurrence, however, should not be interpreted alone as explaining the greater dispersion in the wet period.

Table 4 presents the results of the independence and trend tests for the wet- and dry-period maximum streamflow series at Funil Reservoir. In both periods, there was insufficient evidence to reject the hypotheses of independence (p-value > 0.05) and absence of a trend (p-value > 0.05) in the historical maximum streamflow series at Funil HPP. Because no evidence of statistically significant serial autocorrelation or trends was found, the Gumbel distribution was fitted to the data using Bayesian inference for parameter estimation in the periods studied.

Table 4: Results (p-values) of the independence (Ljung-Box) and trend (Mann-Kendall) tests for the maximum streamflow series (m^3s^{-1}) at Funil Reservoir.

Period	2003-2017		2003-2025	
	Ljung-Box	Mann-Kendall	Ljung-Box	Mann-Kendall
Wet	0.1642	0.2763	0.1496	0.2452
Dry	0.2571	0.1659	0.1090	0.0813

Source: Prepared by the authors (2026).

For Bayesian inference on the parameters under evaluation, as well as for decision-making, it is important that the chains generated by the posterior stochastic process have converged (Rossi, 2011). Table 5 presents the posterior means and standard deviations of the Gumbel parameters α and β, together with the results of the posterior chain convergence diagnostics. The results indicate no evidence of nonconvergence of the posterior chains. Under Geweke's diagnostic, the absolute values were below 1.96, indicating no signs of nonconvergence. For the Raftery and Lewis diagnostic, the dependence factor values were close to 1. This indicates low

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dependence between iterations according to this diagnostic. Analysis of the Heidelberger and Welch diagnostic indicated that the chains were stationary (p-value > 0.05).

Table 5: Posterior means and standard deviations with 95% HPD intervals for the Gumbel distribution parameters, and results of the Geweke, Raftery and Lewis (R-L), and Heidelberger and Welch (H-W) convergence diagnostics used to evaluate the posterior chains.

Period	*Prior*	Par.	*Posterior mean*	$HPD_{95\%}$		Posterior standard deviation	Convergence diagnostics		
				LI	*LS*		|Geweke|	R-L	H-W
Wet	*NI*	α	923.94	681.89	1.1170,00	123.06	0.89	0.97	0.3310
		β	442.273	298.80	671.90	96.04	1.58	1.01	0.3130
	$I_{\frac{1}{2}V}$	α	932.54	836.10	1,029.00	49.25	0.59	1.00	0.7700
		β	391.01	326.20	467.10	35.55	0.54	1.02	0.2850
	I_{1V}	α	929.72	803.90	1,054.00	63.17	0.81	0.99	0.6250
		β	397.57	316.19	498.20	46.13	1.20	1.02	0.4010
	I_{2V}	α	926.31	773.60	1,079.02	77.75	0.82	1.02	0.9860
		β	405.33	306.00	533.70	57.95	0.77	1.02	0.1420
	I_{4V}	α	926.05	742.69	1,111.00	92.90	1.10	1.03	0.3980
		β	417.63	304.20	573.10	68.93	0.39	0.98	0.3700
Dry	*NI*	α	246.17	191.90	302.70	27.62	0.12	0.98	0.7550
		β	98.91	66.48	150.00	21.75	0.34	1.00	0.3010
	$I_{\frac{1}{2}V}$	α	254.45	232.50	276.50	11.13	1.52	0.99	0.8148
		β	89.62	74.72	106.90	8.28	1.34	1.03	0.3304
	I_{1V}	α	252.77	224.80	280.80	14.34	0.49	0.99	0.2740
		β	90.85	72.18	114.10	10.68	0.37	0.98	0.7950
	I_{2V}	α	250.68	215.50	285.70	17.74	0.45	0.98	0.4300
		β	92.44	69.96	121.50	13.17	0.71	0.97	0.5410
	I_{4V}	α	248.95	208.90	290.50	20.76	0.02	0.98	0.4683
		β	94.08	68.67	129.40	15.52	0.15	1.00	0.0895

NI: Noninformative prior; *I*: Informative prior; Par.: Parameter; LI: Lower limit; LS: Upper limit.
Source: Prepared by the authors (2026).

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Table 6 presents the evaluation criteria for the different prior specifications adopted for inference on the Gumbel distribution parameters. In both periods, the lowest DIC values were obtained using prior $I_{\frac{1}{2}V}$. The largest DIC differences were 2.90, in both cases involving the noninformative prior. Although the model with prior $I_{\frac{1}{2}V}$ yielded lower DIC values, small differences should be interpreted with caution (Lunn *et al.*, 2012; Song and Ferrer, 2012). Accordingly, selection of the prior specification should also consider MPE and MHPDW. Comparing the models in terms of MPE shows that, in the wet period, MPE ranged from 26.85% for $I_{\frac{1}{2}V}$ to 30.93% for the noninformative prior, corresponding to a difference of 4.08 percentage points. In the dry period, values ranged from 26.14% for I_{2V} to 27.22% for the noninformative prior, a difference of 1.08 percentage points.

Small differences in MPE should not, on their own, be interpreted as evidence of substantial improvement or deterioration in model performance. Evaluation should consider sampling uncertainty in the indicators (Ritter and Muñoz-Carpena, 2013; Clark *et al.*, 2021) and their relevance to the intended application (Harmel *et al.*, 2014). This means that a small MPE difference may simply reflect characteristics of the sample and that, in each case, a small error reduction may be relevant to one decision and of little importance to another. In hydropower reservoir operation, the relationship between predictive quality and operational benefits depends on system characteristics and management objectives (Anghileri *et al.*, 2019).

Costa *et al.* (2022) mention that other studies have reported prediction errors of approximately 20% when predicting mean and maximum streamflows (Gomes *et al.*, 2010; Lima *et al.*, 2011; Pinto *et al.*, 2015; Brito *et al.*, 2016; Costa *et al.*, 2019). The authors emphasize that the prediction errors reported in their study were considerably lower than those found in the literature, all below 18%. In the present study, the largest prediction errors were observed in the wet period. According to Brito *et al.* (2016), seasonal variation in the series from November to April is influenced by differences in variability and measures of central tendency, which are greater in the wet period, resulting in larger forecasting errors during this period.

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Table 6: Deviance information criterion (DIC), mean prediction error (MPE), and mean width of the HPD intervals (MHPDW) for the 2-, 4-, 6-, and 8-year return levels, for predictions obtained under different prior specifications for the Gumbel distribution parameters, fitted to the maximum streamflow series (m^3s^{-1}) at Funil Reservoir (2003-2017).

Prior	Wet period			Prior	Dry period		
	DIC	MPE (%)	MHPDW ($m^3\ s^{-1}$)		*DIC*	MPE (%)	MHPDW ($m^3\ s^{-1}$)
NI	230.00	30.93	778.35	*NI*	185.20	27.22	173.32
$I_{\frac{1}{2}V}$	227.10	26.85	289.12	$I_{\frac{1}{2}V}$	182.30	26.31	66.72
I_{1V}	227.60	27.06	378.00	I_{1V}	182.80	26.22	87.20
I_{2V}	228.20	27.50	478.00	I_{2V}	183.40	26.14	109.72
I_{4V}	228.80	28.69	570.40	I_{4V}	183.90	26.21	129.05

NI: Noninformative prior; I: Informative prior.
Source: Prepared by the authors (2026).

In addition to lower MPE values, the models with informative prior specifications also yielded lower MHPDW values (narrower intervals) in both the wet and dry periods (Table 6), indicating greater precision and lower uncertainty than the models with noninformative priors. In the wet period, changing from the model with a noninformative prior (NI) to the model with informative prior $I_{\frac{1}{2}}$ reduced MHPDW from 778.35 $m^3\ s^{-1}$ to 289.12 $m^3\ s^{-1}$. This represents a 62.86% reduction in the mean width of the HPD intervals for maximum streamflow return levels. A similar pattern occurred in the dry period. The model with informative prior $I_{\frac{1}{2}}$ yielded a 61.50% reduction in the mean width of the HPD intervals for predicted maximum streamflows, with an MHPDW of 66.72 $m^3\ s^{-1}$ compared with 173.32 $m^3\ s^{-1}$ for the model with a noninformative prior (NI).

The use of informative prior distributions derived from Camargos HPP data resulted in lower DIC and MPE values and narrower intervals for the return levels at

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Funil HPP than the models with noninformative priors. In the wet period, the model with informative prior $I_{\frac{1}{2}V}$ yielded the lowest values for all three selection criteria. In the dry period, although the Gumbel distribution with prior I_{2V} yielded the lowest MPE (26.14%), the model with the smallest-variance prior $I_{\frac{1}{2}V}$ yielded an MPE of 26.31%, a difference of 0.17 percentage points. The latter also yielded the lowest DIC (182.30) and MHPDW (66.72 m³ s⁻¹), indicating greater posterior precision of the return levels.

Considering the three criteria jointly, the models with informative priors $I_{\frac{1}{2}}$ were adopted for both the wet and dry periods to predict maximum streamflow return levels at Funil HPP. Figures 4a (wet period) and 4b (dry period) show the expected maximum streamflows at Funil HPP for return periods of 5, 10, 20, 30, 50, and 100 years, obtained using Gumbel models with noninformative (blue) and informative $I_{\frac{1}{2}}$ (orange) prior distributions. Based on the results from the model with informative prior $I_{\frac{1}{2}}$, one interpretation of Figure 4a is as follows: for the 100-year return period in the wet period, a maximum streamflow exceeding 2,539.90 m³ s⁻¹ is expected to occur, on average, once every 100 years. The lower and upper limits of the 95% highest posterior density (HPD) interval for this prediction are 2,265.00 m³ s⁻¹ and 2,833.00 m³ s⁻¹, respectively.

Figures 4a and 4b show that interval widths increase with the return period, particularly for models with noninformative prior distributions. Thus, predictions for longer return periods are accompanied by a loss of precision in each prediction. For projects requiring return periods (in years) far longer than the number of years in the historical record, this may initially be an objection to using this information.

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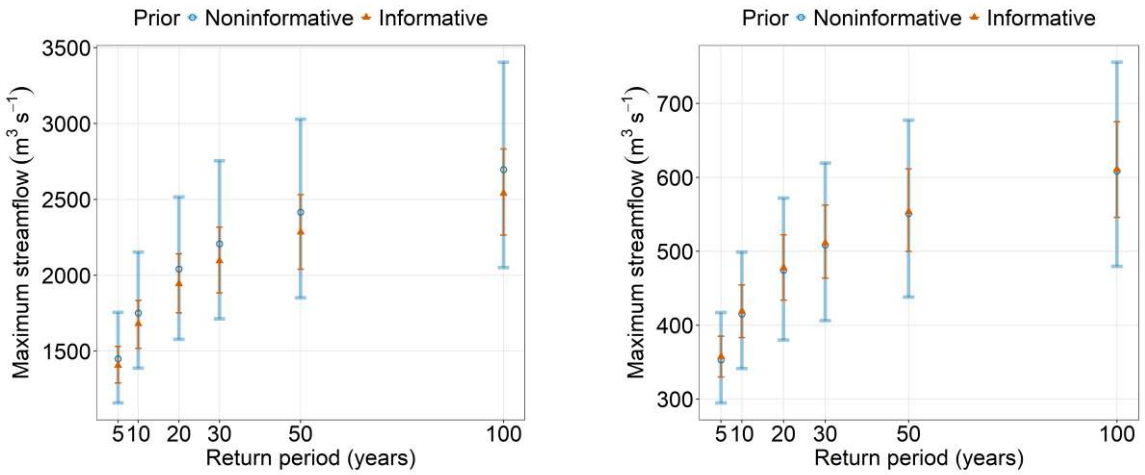
Figure 4: Expected maximum streamflows (m^3s^{-1}) at Funil Reservoir, MG, with their respective 95% HPD intervals, for return periods of 5, 10, 20, 30, 50, and 100 years.



(a) Wet period (b) Dry period

Source: Prepared by the authors (2026

However, incorporating information from Camargos HPP through informative priors in the maximum streamflow analysis at Funil HPP produced substantially narrower and, consequently, more precise intervals. The need for, and importance of, information to support decisions by water resources managers should be emphasized, with a view to sound reservoir management for electricity generation, irrigation, water supply, and other purposes. When only a few years of observations are available and predictions are needed for long return periods, the Bayesian methodology offers the advantage of increased prediction precision (Seidou *et al.*, 2006; Beijo *et al.*, 2009; Lima *et al.*, 2016).

5 Conclusions

The tests applied did not indicate evidence of serial autocorrelation or trends in the maximum streamflow series at Funil HPP at the 5% significance level, in either the wet or dry period.

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The use of information from Camargos HPP through informative priors resulted in lower mean prediction errors than the specification with noninformative priors. In the wet period, informative prior $I_{\frac{1}{2}V}$ yielded the lowest MPE, reducing it from 30.93% to 26.85%, a difference of 4.08 percentage points. In the dry period, this prior reduced MPE from 27.22% to 26.31%, whereas the lowest value, 26.14%, was obtained with the prior with twice the baseline variance. Thus, the numerical influence of the prior specification on MPE was more pronounced in the wet period.

The most substantial result was the reduction in the mean width of the 95% HPD intervals for the return levels. During model selection, informative prior $I_{\frac{1}{2}V}$ reduced MHPDW for the 2-, 4-, 6-, and 8-year return levels by 62.86% in the wet period and 61.50% in the dry period, relative to the specification with noninformative priors. Adoption of this specification in both periods was based on the set of criteria evaluated, particularly the narrower intervals, although it did not minimize MPE in the dry period.

The results indicated that information from Camargos increased the posterior precision of maximum streamflow return levels at Funil HPP, conditional on the Gumbel distribution, the specified priors, and the adopted rescaling. This gain, conditional on the model and the prior distributions adopted, may contribute to water resources planning when the available historical series is short and the return periods of interest exceed its length.

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