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METHODOLOGY FOR TARGET FORECASTING OF WATER LEVEL IN HYDROELECTRIC PLANT RESERVOIRS UNDER CONDITIONS OF LOW INFLOW

César A. Yajure Ramírez

Universidad Central de Venezuela.

https://orcid.org/0000-0002-3813-7606

Email: cyajure@gmail.com

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ABSTRACT

The “El Niño” phenomenon brings periods of drought to northern South America that negatively impact the level of hydroelectric plant reservoirs, which could reduce their energy production. In order to avoid reaching the minimum operating level before the end of the drought period, this research proposes a methodology based on data science for the target forecast of the level of hydroelectric plant reservoirs in low flow conditions. The goal is that the minimum operating level of the reservoir be reached on the estimated end date of the drought period, that is, March 31, 2024. It is applied to the data of the reservoir of a hydroelectric plant located in the northwest of South America, for which three sequential forecast horizons are used, allowing the models to be evaluated as these periods pass, using the metrics: MAPE, RMSE, and MAE. To meet the goal, the predictive sampling method of the Prophet forecasting technique is used. The results indicate that the technique is a useful additional tool for the plant dispatcher, with values for the performance metrics during the third forecast horizon of 0.045%, 48 cm, and 62 cm, for the MAPE, the MAE, and the RMSE, respectively.

I. INTRODUCTION

The “El Niño” phenomenon brings with it diverse climatic conditions for Latin America. According to the UN World Food Program [1], the countries of the Central American Dry Corridor (Nicaragua, El Salvador, Guatemala and Honduras) and northern South America experience drier conditions than usual in the presence of this phenomenon, with a probable reduction in precipitation. Thus, since mid-2023, Venezuela has been experiencing a drought due to this phenomenon that was enhanced by climate change [2]. These conditions imply a period of drought that can extend longer than normal, usually ending in the month of April, to ending approximately at the end of May, making it necessary to administer the reservoirs in general, in a restrictive manner. In the case of hydroelectric generation plants, this involves a decrease in energy production for the population, and therefore a possible increase in electricity rationing. Consequently, in periods in which low or no precipitation is expected, and consequently, low or no inflow to the hydroelectric plant reservoirs, a point in time must be estimated at which conditions are likely to change in a favorable manner, and dispatch these hydroelectric plants in such a way as not to reach the minimum operating level in the period with low or no inflow flow.

Due to the above, it is necessary to make a forecast of the level of the reservoirs with a goal to be achieved at the end of the critical drought period. In this sense, the objective of this research is to present a methodology based on data science to develop target forecasting of hydroelectric plant reservoirs under conditions of low or no inflow. The Prophet forecasting tool is applied through the use of the Python programming language.

Previous research related to the topic of study of this work was reviewed, finding that none of them have a forecasting approach with a goal in conditions of low inflow. For example, Li et al. [3] investigate the performance of four different deep learning models in predicting the water level in the dam area of the "Three Gorges" reservoir of the hydropower plant located in China. The models considered were: Long Short-Term Memory (LSTM) network, bidirectional LSTM network, convolution LSTM network, and the attention and convolution LSTM network. The performance metrics used were: determination coefficient (R^2), mean absolute error (MAE), the square root of the mean square error (RMSE), and the mean absolute percentage error (MAPE). They found that the attention-convolution LSTM network performed the best, with an R^2 of 0.994, a MAPE of 0.0032, a MAE of 0.5296, and an RMSE of 0.6748. Likewise, Sapitang et al. [4] carry out the forecast of the level change in a reservoir located in Malaysia, considering forecast horizons from one day to seven days, and two scenarios. They evaluate the performance of four models: decision tree regression, random forest regression, Bayesian linear regression, and artificial neural network regression. The metrics used to evaluate the models were: R^2, MAE, RMSE, RAE, and relative squared error (RSE). They conclude that the Bayesian linear regression model outperforms the other models, with an R^2 between 0.998952 and 0.99992. Similarly, Tsao et al. [5] present a methodology for forecasting the water level of a reservoir with a horizon of 48 hours, and using fuzzy neural networks in a multi-stage architecture. They apply the methodology in the Techi hydroelectric plant located in Taiwan. They conclude that with this methodology the energy efficiency of the system is improved, in addition to improving the effectiveness of the plant.

On the other hand, Tucci [6] develops and applies a methodology for hourly forecasting of the water level of the reservoir of a hydroelectric plant located in the Pontecosi basin in Italy. First, it applies spatial interpolation methods to data from meteorological stations near the reservoir to determine the values of: air temperature, air humidity, precipitation, and wind speed. These variables are then used as input to a neural network to predict soil moisture concentration. Then, a nonlinear automatic exogenous input model was trained to estimate the reservoir level with different prediction horizons, using the data from the previous modules, and historical data on water level, discharge flow, and turbine flow. Estimates of the water level were generated with a horizon between 1 and 6 hours, with MAE values between 2 cm and cm, respectively. For their part, Yang et al. [7] propose a time series analysis model, based on imputation and the variable selection method, for the forecast of water levels in a reservoir located in Taiwan. They use the random forest technique, whose performance they compare with other techniques, using the metrics: correlation coefficient, RMSE, MAE, relative absolute error (RAE), and root relative squared error (RRSE). They conclude that the closest point imputation method had the best performance, as did the proposed forecasting technique. Similarly, Nguyen et al. [8] present a novel deep learning model for the prediction of water level and discharge flow of water reservoirs. To address data scarcity and improve prediction accuracy, they use an ensemble learning architecture that takes the advantages of multiple deep learning techniques. They use singular spectrum analysis to treat atypical data, and genetic algorithms to obtain the optimal values of the model's hyperparameters. They conclude that their methodology is better than current techniques according to the Nash-Sutcliffe Efficiency (NSE), mean squared error (MSE), MAE, and MAPE metrics. Specifically, they consider that NSE improves by at least 2%, and with spectral analysis this metric improves an additional 5%. Likewise, Mohammed et al. [9] propose a model based on artificial neural networks (ANN) and the marine predator algorithm to model the water levels of the Tigris River in Al-Kut, Iraq. Historical climate and water level data from the period 2011-2020 are used to build and evaluate the model, whose performance is compared with the recent particle swarm optimization based on constriction coefficients and the chaotic gravitational search algorithm (CPSOCGSA-ANN), and with the slime mold algorithm (SMA-ANN). The results show that the proposed model is the best performing one with a dispersion index of 0.0009 and a determination coefficient R^2 of 0.98. Finally, Ibañez et al. [10] study the performance of different short- and long-term forecasting, statistical and machine learning techniques for predicting the water level of the Angat Dam located in the Philippines. The six techniques compared are: naive/persistence, seasonal mean, autoregressive integrated moving average (ARIMA), gradient boosting machines, and two deep learning networks. As exogenous variables they use historical data on water levels, meteorological data, and irrigation data. The univariate neural network resulted in the best performance for the one-day horizon with a MAE and RMSE of 20 cm. For the horizons of 30 days, 90 days and 180 days, the multivariate neural network resulted in the best performance with a MAE(RMSE) of 2.9(3.3), 5.1(6.0), and 6. 7(8.1) m, respectively.

The rest of the article is distributed as follows. Section 2 presents the methodology used in the research. Then, in section 3 the results obtained are analyzed and discussed. Next, there are the conclusions derived from the research carried out. Finally, bibliographic references are presented.

II. THEORETICAL BACKGROUND

II.1 PROPHET FORECASTING TECHNIQUE

The Prophet technique developed by Facebook's data science team during 2017 is used. It was developed specifically for time series forecasting, based on an additive model where non-linear trends are easily adjusted to different types of seasonality, such as: annual, weekly, and daily, in addition to incorporating the effect of vacations and holidays. According to the team, the technique works best with time series that have strong seasonal effects and multiple seasons of historical data. It is robust with respect to missing data and changes in trend and generally handles outliers well [11].

As proposed by Taylor & Letham [12], the technique is based on a time series model composed of an element that represents the trend, another that represents regular changes, that is, seasonalities, another component that represents the effect of non-working days, and finally the error term. The model is then given by Equation (1):

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t \tag{1}$$

In (1), $y(t)$ is the time series, $g(t)$ is the trend component, $s(t)$ represents the periodic changes in the series, $h(t)$ represents the effect of holidays and vacations, and ϵ_t is the error term that represents changes that do not fit within the other components.

With respect to the trend component, the technique implements two types: growth saturation model, and a piecewise linear model. As for seasonality, it is modeled with periodic time functions, specifically with standard Fourier series, such as the one presented in Equation (2).

$$s(t) = \sum_{n=1}^{N} \left(a_n \cdot cos\left(\frac{2\pi nt}{P}\right) + b_n \cdot sen\left(\frac{2\pi nt}{P}\right)\right) \quad (2)$$

In this case, P is period of the series, which will depend on the type of seasonality, and N is the number of terms in the series.

Taylor & Letham indicate that P is the regular period that they expect the time series to have, being equal to 7 for data with weekly seasonality and 365.25 for data with annual seasonality. From the above it is deduced that the technique works by default with data with daily resolution. Likewise, they propose that higher values of N apply to seasonal patterns that change more rapidly, and in their studies, they have found that a value of 10 is useful for annual seasonalities, and 3 for monthly seasonalities. According to Peixeiro [13], the technique defines by default an additive seasonality, but there is also the option of establishing a multiplicative seasonality.

One of the characteristics that differentiates this technique from some other time series analysis techniques is the management of non-working days, allowing the inclusion in the model of a list with holidays and vacations that are within the historical data period, but also within the forecast horizon. It has been used in multiple applications, for example, Sharma et al. [14] use it for the prediction of stock values in the Indian stock market, Žunić et al. [15] apply this technique to forecast successful sales, Oo and Phyu [16] use the technique to develop temperature forecasting, among other applications.

II.2 FORECAST MODEL PERFORMANCE METRICS

In order to evaluate the performance of forecasting models and make comparisons between them, a series of metrics are used. Among the standard statistical measures to evaluate models are: MAE, RMSE, and MAPE. The error being the difference between the real value and the predicted value [17]. The first two metrics considered give results in physical units, while the third of them (MAPE) is given as a percentage with respect to the real value of the predicted variable. When comparing RMSE and MAE metrics, it should be noted that the former is convenient when errors are normally distributed, while the latter is recommended for use with Laplacian errors [18]. Likewise, Naser [19] states that MAPE is negatively affected when a predicted value (or several) is much larger or much smaller than the corresponding real value. Next, the mathematical equations used to calculate these metrics are presented.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |Y_i - F_i| \quad (3)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (Y_i - F_i)^2} \quad (4)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \left|\left(\frac{Y_i - F_i}{Y_i}\right) \times 100\right| \quad (5)$$

It is true that Y_i is the ith real value of the variable to be forecast, F_i is the ith predicted value, and n is the number of records or historical data available.

III. MATERIALS AND METHODS

With the purpose of achieve the stated objective, a methodology was used based on the stages of a data science project, which include: establishing objectives, obtaining data, pre-processing of data, exploratory analysis of data, modeling of the data, and finally, the decision-making stage [20]. An outline of the applied methodology is presented in Figure 1.

The objective would then be to develop the forecast of the level of the reservoir of a hydroelectric plant, subject to conditions of low inflow due to climatic phenomena, with the goal of avoiding reaching the minimum operating level of the reservoir. The data used corresponds to the historical values of the reservoir level, and the energy produced, during the period 2015-2023. It is important to mention that the climatic phenomenon considered was “El Niño”, which has been present since the fourth quarter of 2023, and has accentuated the drought period in countries with a coast on the Caribbean Sea. This phenomenon was previously present during 2016. The preprocessing of the data consisted of the application of the techniques present in [21]. Specifically, the possible existence of missing and/or atypical data was verified, imputing with appropriate techniques when necessary. Likewise, the possible existence of duplicate data was verified, and new data columns were generated from the existing ones. In the next stage, an exploratory analysis of the data was carried out, using statistical and/or graphic techniques. Subsequently, the data was modeled by applying supervised machine learning algorithms, specifically, forecasting techniques. With the results obtained from the exploratory analysis and data modeling, we proceeded to the decision-making stage.

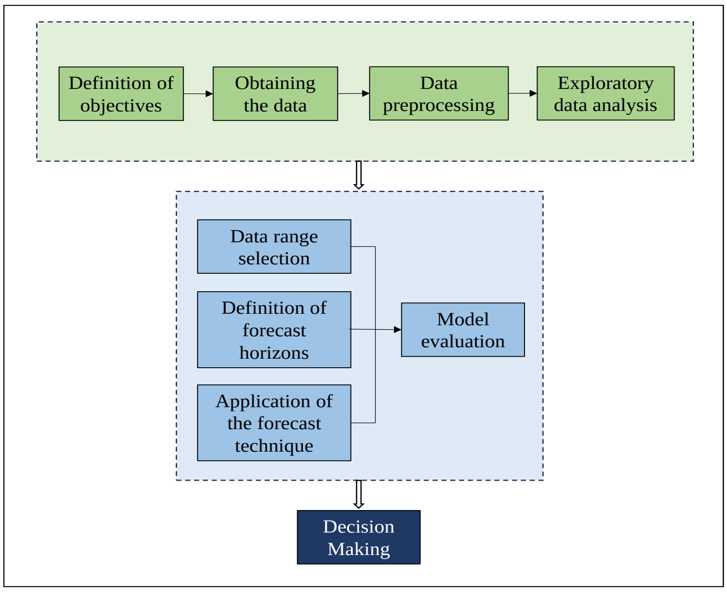

Figure 1: Outline of the applied methodology.
Source: Authors, (2024).

In the data modeling stage, the Prophet technique is applied using the Python programming language, setting the goal that by 03/31/2024 the reservoir under study does not reach its minimum level, in accordance with the forecast obtained. To achieve this, the predictive sampling method of the forecasting technique is used, and the sample that meets the programmed goal is selected. There is a first forecast horizon of 91 days between 01/01/2024 and 03/31/2024. After the month of January had passed, the actual data for that month were incorporated into the historical data, and the technique was applied again with a forecast horizon of 60 days between 02/01/2024 and 03/31/2024. Similarly, after the month of

February had passed, the historical data were readjusted, and the technique was used again, but this time with a horizon of 31 days between 03/01/2024 and 03/31/2024. For each of these forecast horizons, performance metrics were calculated by comparing the forecast obtained with the actual values of the elevations.

III.1 DATA PREPROCESSING

The data correspond to the daily values in meters, for the period 2015-2023, of the water level of a reservoir whose contents are used for the production of energy through a hydroelectric plant located in the northwest of South America. Likewise, the data set has the daily energy values, in Gigawatt-hours (GWh), produced by the plant. The data set was checked to ensure the absence of missing data and duplicate data. Likewise, it was verified that there is no presence of atypical data in both the water level and energy data. Next, the data from the water level column were used to generate the values of the variation in centimeters of water level.

IV. RESULTS AND DISCUSSIONS
IV.1 EXPLORATORY DATA ANALYSIS

Firstly, the temporal graph of the daily water level is created for the period 2015-2023, in order to observe the behavior that this variable has had. This graph is presented in Figure 2, from which it is observed that the level reached its maximum values during the years 2021 and 2022, and presents an annual seasonality. Likewise, it is also noted that the minimum value was reached during the first half of 2020.

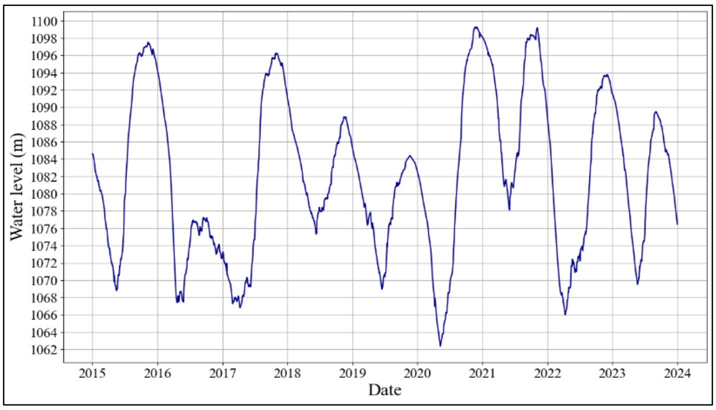

Figure 2: Daily level of the reservoir.
Source: Authors, (2024).

Additionally, it is noted that, at the beginning of the year 2016, in which the El Niño phenomenon was also present, the elevation was around 1094 m, while, at the beginning of the year 2024, this was slightly higher than 1076 m. A downward trend can be seen in the curve starting in 2020.

On the other hand, Table 1 presents the descriptive statistical indicators of the level, the variation of the level, and the electrical energy produced by the plant. It can be seen that there are a total of 3287 records, corresponding to each of the days in the period 2015-2023.

Table 1: Descriptive analysis of the data.

Indicator	**Level (m)**	**Variation (cm)**	**Energy (GWh)**
Records	3287	3287	3287
Mean	1082,05	-0,25	2,88
Std Dev	9,38	21,11	1,15
Min	1062,36	-131,00	0,00
P_{25}	1074,31	-12,00	2,20
Median	1081,44	-3,00	2,97
P_{75}	1089,45	8,00	3,60
Max	1099,28	132,00	6,77

Source: Authors, (2024).

It can be seen that the level varied from a minimum of 1062.36 m to a maximum of 1099.28 m. Regarding the energy produced, it varied from 0 to 6.77 GWh. The level had a minimum variation of -131 cm, that is, a maximum drop of 131 cm, and a maximum variation of 132 cm, that is, a maximum rise of 132 cm.

Likewise, Figure 3 presents a graph with the average value in centimeters of the variation in the reservoir level for the period 2015-2023. It can be seen that the fall in the level of the reservoir occurs between the month of November and the month of May, coinciding with the historical period of drought in the area where the reservoir is located, with its greatest average fall during the month of March and the minimum fall during the month of May, the month in which the rainy period historically begins.

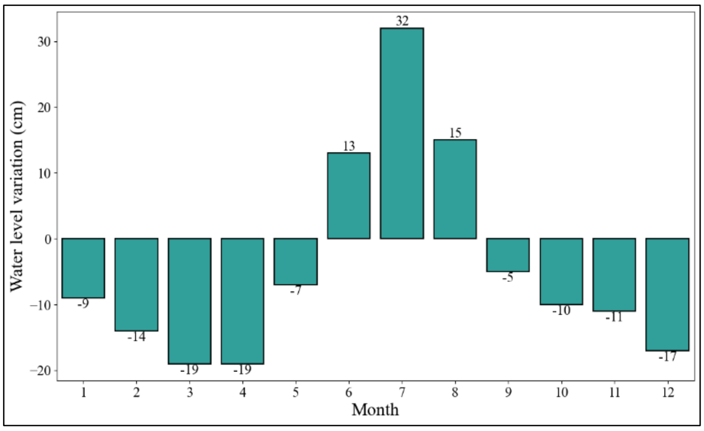

Figure 3: Average monthly level variation 2015-2023.
Source: Authors, (2024).

It can also be seen that, in the period between the month of June and the month of October, the level has its greatest increases, coinciding with the rainy period, with a maximum value for the month of July, and a minimum value for the month of July. month of October.

IV.2 DATA MODELING

To estimate the water level using the Prophet technique, daily data for the period 2021-2023 was used. This amount of data is sufficient since all seasonalities that the data could have are covered. As a goal of the forecast, it was established that the minimum level of the reservoir, which is 1066 meters, would not be reached until March 31, 2024, the date on which the recovery of the reservoirs was expected to begin, and also put other electricity generation plants were in operation, thus allowing the reservoir to recover its optimal level. Three start dates were considered for the forecast horizon: 01/01/2024, 02/01/2024, and 03/01/2024, allowing values to be added to the historical data as the deadline approached.

To generate the forecast model, a file was considered with the non-working days associated with the historical period of the data, and the period of the forecast horizon. Regarding the seasonality of the data, we worked with the default values of the technique, that is, considering the existence of annual and weekly seasonalities. The technique's m.predictive_samples(future) method was used, which allows obtaining up to 1000 water level forecast samples for the given forecast horizon. To select the sample that represents the forecast, a series of filters are applied: that the elevation is not lower than the minimum value before the deadline, and that the elevation for the deadline is the closest to 1066.

First forecast horizon goes from 01/01/2024 to 03/31/2024, with a water level at the beginning of the period of 1076.21 m. After applying the Prophet technique, there are 1000 forecast samples. After applying the filters, the required forecast is obtained, for which the water level for March 31 is 1066.84 m. At the end of the forecast horizon, the real values of the elevation are available, so the MAPE, MAE, and RMSE metrics were calculated, in order to evaluate the performance of the forecast. The results of the metrics are presented in Table 2. In the research by Ibañez et al. (2021) also works with a horizon of around 90 days, obtaining an RMSE of 6.0 meters and a MAE of 5.1 meters.

After the month of January had passed, the water level forecast was repeated, now with a forecast horizon from 02/01/2024 to 03/31/2024, with a elevation at the beginning of the period of 1072.84 m, That is, during the month of January the level fell 3.37 m. Again, when applying the technique, 1000 samples are obtained. After applying the filters, the required forecast is obtained, for which the level for deadline is 1066.94 m. The results of the calculated metrics are presented in Table 2.

After the month of February had passed, the water level forecast was repeated, now with a forecast horizon from 03/01/2024 to 03/31/2024, with a water level at the beginning of the period of 1069.70 m, from which it is deduced that the level fell 3.14 m. Again, when applying the technique, 1000 samples are obtained. After applying the filters, the required forecast is obtained, for which the level for March 31 is 1066.30 m. The results of the calculated metrics are presented in Table 2. For the case of the 30-day horizon, in Ibañez et al. (2021) obtained an RMSE of 3.3 meters and a MAE of 2.9 meters.

Table 2: Model performance metrics.

Horizons	MAPE (%)	MAE (cm)	RMSE (cm)
First	0,083	88	101
Second	0,078	83	95
Third	0,045	48	62

Source: Authors, (2024).

Figure 4 presents the results obtained along with the real values of the reservoir level for the study period. It can be seen that the forecast of the third horizon was the closest to the real values of the reservoir level, which at the end of said period was slightly below the goal.

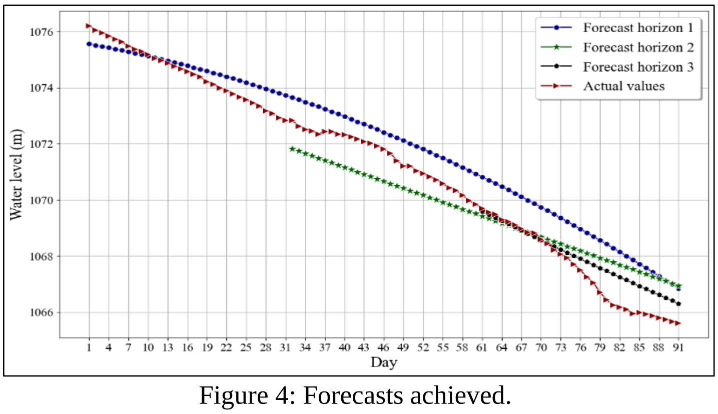

Figure 4: Forecasts achieved.
Source: Authors, (2024).

V. CONCLUSIONS

A forecasting methodology was developed with a goal for estimating the level of a reservoir with low inflow, providing the dispatcher with an additional tool for the operation of the hydroelectric plant, preventing the minimum operating level from being reached. The methodology was applied to data from a reservoir located in northwest South America. From the historical values of the water level, it was determined that the average fall for the month of January was 12 meters, as for the month of February, while for the month of March the average fall was 16 meters. These values contrast with those corresponding to the first quarter of 2024, with a drop of 3.37 meters for the month of January, for the month of February it was 3.14 meters, and for the month of March it was 4.13 meters. The shortest forecast horizon was the one with the lowest values of the performance metrics, with a MAPE of 0.045%, a MAE of 48 cm, and an RMSE of 62 cm. Likewise, the longest forecast horizon presented the highest values of the metrics with a MAPE of 0.083%, a MAE of 88 cm, and an RMSE of 101 cm. The values corresponding to the intermediate horizon were similar to those of the complete horizon. The values of the MAPE metric are significantly low as they are less than 1%, which is due to the fact that the elevations are in the order of thousands of meters, while the variations for the studied reservoir are in the order of centimeters.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: César A. Yajure Ramírez.
Methodology: César A. Yajure Ramírez.
Investigation: César A. Yajure Ramírez
Discussion of results: César A. Yajure Ramírez
Writing – Original Draft: César A. Yajure Ramírez
Writing – Review and Editing: César A. Yajure Ramírez
Resources: César A. Yajure Ramírez
Supervision: César A. Yajure Ramírez
Approval of the final text: César A. Yajure Ramírez

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