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# Policy Implications of Forecasting Water Consumption in the Province of Sultan Kudarat: A Box-Jenkins Approach

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**ABSTRACT:** Accurate water consumption forecasts are crucial for effective water resource management, ensuring sustainable supply and planning for infrastructure development in Sultan Kudarat. The study aimed to predict future water consumption patterns in Sultan Kudarat using the Box-Jenkins methodology, a statistical technique for identifying, fitting, and checking time-series models. This approach, commonly known as ARMA (Auto-Regressive Moving Average), helps in analyzing past water consumption data to develop a robust model that can forecast future demand. The result revealed that the best fit model to forecast water consumption is ARMA (3,0,1). The forecasted consumption for 2024 reveals a slight increase in the first quarter, peaking in March, followed by a gradual and steady decline for the remainder of the year.

**Keywords:** *water consumption, identification, estimation and diagnostic checking, forecast, Auto-Regressive Moving Average,*

## I. INTRODUCTION

Access to safe water, sanitation and hygiene is the most basic human need for health and well-being. Billions of people will lack access to these basic services in 2030 unless progress quadruples. Demand for water is rising owing to rapid population growth, urbanization and increasing water needs from agriculture, industry, and energy sectors. Water availability is becoming less predictable in many places. In some regions, droughts are exacerbating water scarcity and thereby negatively impacting people's health and productivity and threatening sustainable development and biodiversity worldwide. Ensuring that everyone has access to sustainable water and sanitation services is a critical climate change mitigation strategy for the years ahead (Sustainable Development Goals, n.d.).Forecasting monthly water consumption is important for the efficient operation and management of an existing water supply system. Furthermore, water demand can be seen as a dynamic system and requires mathematical modeling (Boubaker, 2017, Salimaco, 2023).

According to the World Health Organization (WHO), 2.1 billion people lack access to safe drinking, with people in rural areas with limited infrastructure being mostly affected. Within the Philippines, this concept manifests in that 91% of the country's estimated 100.7 million population have access to basic water services, but access is highly inequitable across the country, with regional basic water services access ranging from 62% to 100% (Fehr, Sahin& Freeman, 2013). Despite its growing economy, the Philippines faces significant challenges in terms of water and sanitation access. The country is rapidly urbanizing, and its growing cities struggle to provide new residents with adequate water and sanitation services (Andrew, 2018).

The total freshwater withdrawals in the Philippines increased to 91.0 billion cubic meters (bcm) in 2022 from 89.0 bcm in 2021. Meanwhile, the total water abstraction, or the amount of water removed from its source either permanently or temporarily, increased by 2.1 percent to 226.0 bcm in 2022 from 221.3 bcm in 2021. It said the overall water use efficiency (WUE) in 2022 was P211.04 per cubic meter of water used, which increased by 5.5 percent from P200.09 per cubic meter in 2021(Philippine Statistics Authority, 2023).

At the present time hydraulic models are indispensable tools for planning and operating water distribution systems. The uncertainty in key model parameters, such as water consumption, is a significant factor that may limit network simulations, especially when those models are applied to finer spatial and temporal resolutions like water quality models. A sensitivity analysis of a water distribution system clearly shows that water demands are the parameters that most influence the hydraulic response of a water distribution network which has been motivating efforts to characterize water demands at finer spatial and temporal resolutions (Perez, Uber, Shang, Boccelli, Janke, Hartman, and Lee, 2009). Residential water demands account for approximately 70 percent of the total water uses in most distribution systems and exhibit large temporal and spatial fluctuations. Further, residential and commercial water uses are essentially stochastic due to the ever changing consumption patterns (Buchberger& Li, 2007).

Many other factors can directly or indirectly influence water consumption. These include rainfall, temperature, demography, land use, pricing, and regulation. On the other hand, water demand can be understood through historical data and it is highly dominated by daily, weekly, and yearly seasonal cycles. The univariate time series models based on the historical data series can be quite useful for short-term demand forecasting as we accommodate various periodic and seasonal cycles in the model specifications and forecasts (Caiado, 2010). Likewise, Forecasting techniques for water availability are critical for sustainable planning in service water providers. By predicting future water supply based on factors like climate change and population growth, districts can anticipate shortages, implement conservation measures, and make informed decisions to ensure long-term sustainability of water resources.

Increasing water demand makes a restoration of the balance between demand and limited supplies necessary to avoid severe global water crisis (UNESCO, 2015). The planning and management of water resources as well as design and operation of water infrastructure remains critical to the provision of water supply services, and forms the basis for water demand forecasting (Oyebode et al., 2014). Decisions on water-related investments are critically dependent on how future water demands are to be forecasted (Almutaz et al., 2013). Water demand forecasting is therefore of strategic importance, especially in regions with limited water supplies where the role of demand management policy becomes increasingly significant.

One of the most popular uses of current univariate time series forecasting (Box et al., 1994) particularly ARMA model. ARMA explains and analyzes exchange rate behavior, applying many modeling approaches. The model's goal is to predict future securities or financial market moves by examining the differences between values in the series instead of through actual values. A systematic approach for detecting, diagnosing, checking, and employing autoregressive (p), integrated (q), and moving average (d) time series models is known as Box – Jenkins analysis. Several studies using time series forecasting water demand (Ristow, Henning, Kalbusch, Petersen, 2021; Du, Zhao, Xue, 2020; Oliveira, Steffen & Cheung, 2017; Salimaco, 2023)

Using forecasting techniques in water districts is crucial for effective planning, resource allocation, and infrastructure management. These techniques help predict future water demand, identify potential supply shortages, and optimize operational strategies. According to the American Water Works Association (AWWA), forecasting methods assist water utilities in making informed decisions to ensure reliable water supply and sustainable management practices (AWWA, 2017). By employing forecasting techniques, water districts can enhance resilience to climate variability, population growth, and other dynamic factors affecting water availability and demand.

Forecasting water consumption demand in the Philippines is the limited focus on integrating socio-economic factors, regional variations, and climate change impacts into predictive models. Existing studies often overlook the complexities of water demand drivers across different geographical and demographic contexts within the country. Therefore, there is a need for more localized and nuanced forecasting approaches that consider these factors to improve the accuracy and effectiveness of water management strategies. The main objective of this study primarily aims to identifyARMA model to forecast monthly total water consumption in the Sultan Kudarat using ARMA model. Forecasting water consumption demand is crucial for effective water management and planning. Consequently, it allows utilities to anticipate future demand patterns, optimize infrastructure investments, and ensure sufficient water supply to meet growing needs. By accurately forecasting demand, local government can implement proactive measures to maintain water availability, reduce waste, and promote sustainability.

## II. METHODS

This study is utilizing a quantitative forecasting method. This method is based on mathematical and econometrics (quantitative) models and is objective in nature which relies heavily on mathematical computations. Specifically, this piece of endeavor is anchored to the time-series models as it looks at past patterns of data and attempts to predict the future based on the underlying patterns contained within those data. The major goal of this research was to find a viable ARIMA model for forecasting the water consumption.

**Table 1**. *Data Specification*

| | |
|---|---|
| Water consumption in Sultan Kudarat province | It is the volume of water, measured in cubic meters, ($m^3$) billed to residential and commercial consumers. |

This research was planned as a developmental or time series study. The ARIMA (Auto-Regressive Integrated Moving Average) model is a widely used time series forecasting method. It is suitable for time series data that exhibit trends and/or seasonality. It is widely used in various fields such as finance, economics, meteorology, and hydrology for forecasting purposes.

The ARIMA (Auto-Regressive Integrated Moving Average) model equations involve mathematical formulations representing the autoregressive, differencing, and moving average components. These equations are the foundation of ARIMA modeling for time series forecasting (Pono, 2022).

The basic ARIMA model is expressed as:

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \epsilon_t - \theta_1 \epsilon_{t-1} - \theta_2 \epsilon_{t-2} - \ldots - \theta_q \epsilon_{t-q}$$

Where:

$Y_t$ is the observed value at time $t$,
$c$ is a constant,
$\phi_1, \phi_2, \ldots, \phi_p$ are the autoregressive parameters,
$\epsilon_t$ is the error term at time $t$,
$\theta_1, \theta_2, \ldots, \theta_q$ are the moving average parameters,
$p$ is the order of the autoregressive component, and
$q$ is the order of the moving average component.

The integrated part, denoted by $d$, represents differencing to achieve stationarity. It is applied as $(1-B)^d Y_t$, where $B$ is the backshift operator.When applying the ARIMA model, it's important to determine the values of p, d, and q through techniques like autocorrelation function (ACF) and partial autocorrelation function (PACF) plots, as well as model evaluation metrics like AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion).

**Estimation Process**

1. *Identification.* Identify statement reads time series that are to be used in statements, possibly differencing, and computes autocorrelations, inverse autocorrelations, partial autocorrelations, and cross correlations. Stationarity tests is performed to determine if differencing is necessary. The analysis in this usually suggests one or more ARIMA models that could be fit. Options allow to test for stationarity and tentative ARMA order identification.

2. *Estimation and diagnostic checking.* Specify the ARIMA model to fit to the variable specified in the previous identify statement, and to estimate the parameters of that model. The estimate statement also produces diagnostic statistics to help judge the adequacy of the model.

3. *Forecasting*. The forecast statement is used to forecast future values of the time series and to generate confidence intervals for these forecasts from the ARIMA model produced by the preceding estimate statement.

The study was carried out in the province of Sultan Kudarat, Philippines. The data of total water consumption from 1990 to 2023 was used as the data and instrument in this investigation. The information gathered is secondary. The Sultan Kudarat Water District provided this information on monthly total water consumption. The researcher stated that the work will be reviewed by the University's Ethics and Review Committee. Box-Jenkins This study's analysis was done with ARIMA. The procedures of identification, estimate, diagnostics, and forecasting were followed to come up with the optimal model. The ethical consideration in the study's conduct is guided by the ethical standard form, with corrections made following the panelists' judgment of plagiarism and authorship.

## III. RESULTS AND DISCUSSION

**1. Identification**

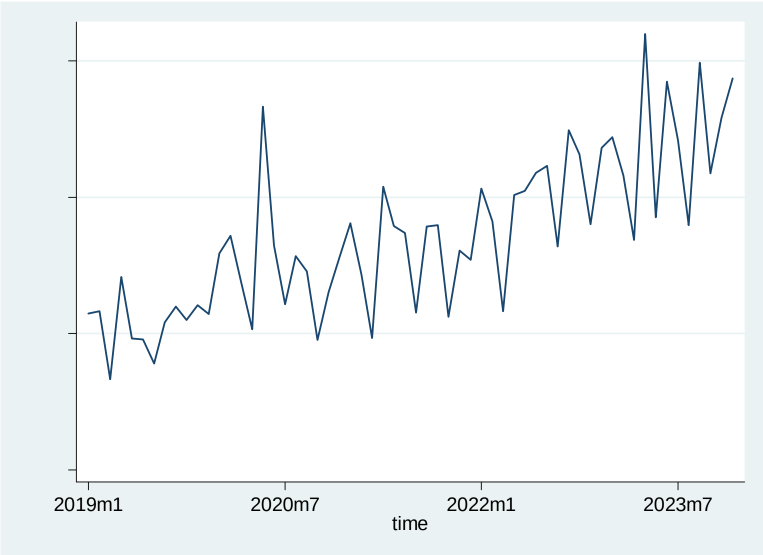


**Figure 1**. *Time Series Data of Water Consumption in sultan Kudarat*

**Table 2**. *Augmented Dickey-Fuller Test*

| | Test Statistic | 1% Critical Value | 5% Critical Value | 10% Critical Value |
|---|---|---|---|---|
| Z(t) | -4.252 | -3.567 | -2.923 | -2.596 |

MacKinnon approximate p-value for Z(t) = 0.0005

*Ho: data of water consumption has a unit root.*

Figure 1 shows the monthly water consumption in Sultan Kudarat province. A gradual increase in water usage over the years, which may be attributed to population growth and urban development, reflecting increased residential and commercial demand.It also shows that water consumption follows a random walk, indicating stationarity. The Augmented Dickey-Fuller test supports this with a MacKinnon p-value of 0.000, leading us to reject the null hypothesis and confirm that the water consumption data is stationary.

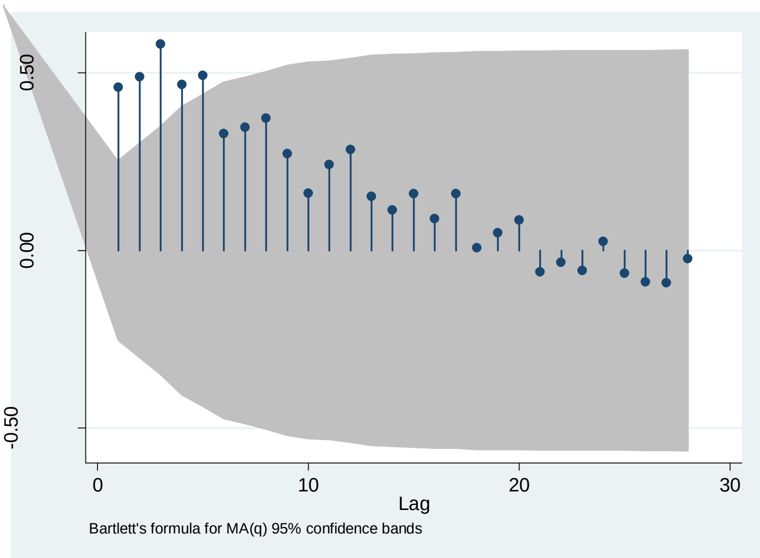


**Figure 2**. *Autocorrelation of Consumption of Water in Sultan Kudarat*

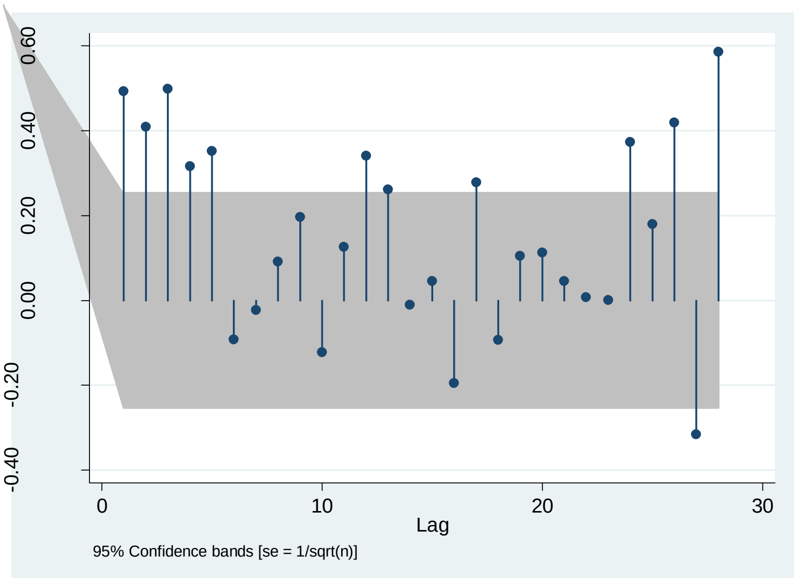


**Figure 3**. *PartialAutocorrelation of Consumption of Water in Sultan Kudarat*

In the data of water consumption, both the Autocorrelation Function and Partial Autocorrelation Function plots indicate mixed patterns, such as a slow decay in both plots, an ARMA model with both AR and MA components is necessary. ACF that shows a slow decay that cuts off showing 1 significant spike and a PACF that cuts off showing 3 significant spikes might indicate ARMA (1,0,1), ARMA (2,0,1), and ARMA (3,0,1) models.

**2. Model estimation and Diagnostic Checking**

**Table 3**. *Auto-Regressive Moving Average Models*

| Criteria | Model A ARMA (1,0,1) | Model B ARMA (2,0,1) | Model C ARMA (3,0,1) | Best Fit ARMA Model |
|---|---|---|---|---|
| Log-likelihood | -683.8423 | -682.0178 | -679.3216 | Model C |
| Sigma | 21246.65 | 20559.81 | 19592.11 | Model C |
| Akaike | 1375.685 | 1374.036 | 1370.643 | Model C |
| Bayesian | 1384.062 | 1384.507 | 1393.209 | Model C |
| Model Fit | | | | Model C |

The table shows ARMA models based on ACF and PACF mixed patterns. The result revealed that ARMA (3,0,1) obtained a lowest log-likelihood of -679.3216, sigma value of 19592.11, Akaike value of 1370.643, and Bayesian value of 1393.209. the Log-likelihood function identifies a distribution that fits best with the sampled data. While it's useful, AIC and BIC punish the model for complexity, which helps make our ARIMA model parsimonious (Smigil, 2020).

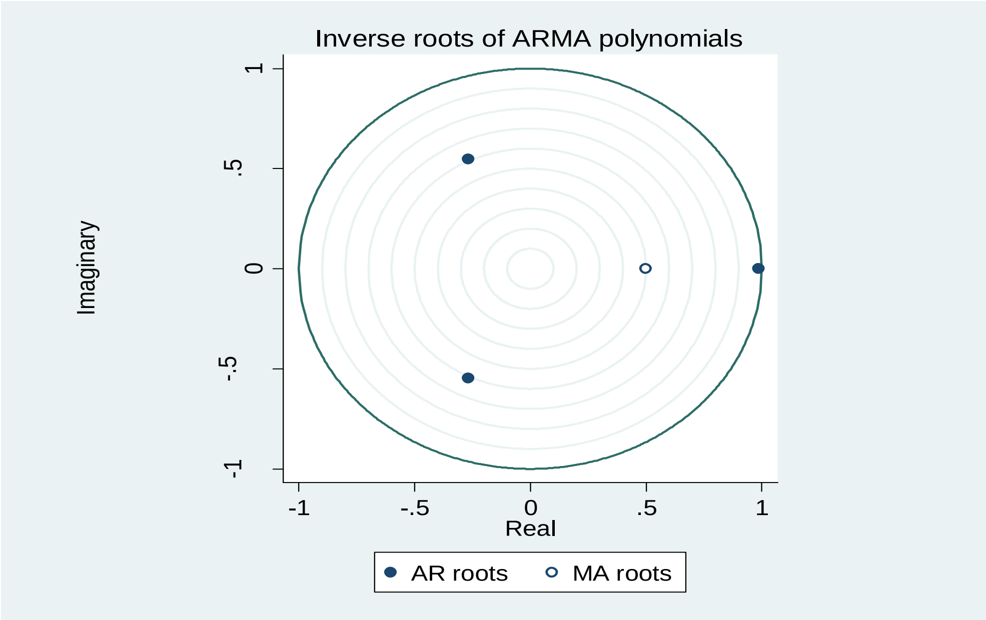


**Figure 4.***The Inverse Roots of Auto-Regressive polynomial*

**Table 4.***Portmanteau test for white noise*

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Portmanteau (Q) statistic = 26.7108

Prob> chi2(28) = 0.5340

*Ho: residuals are white noise*

The figure depicts an ARIMA (3,0,1) model, with the Auto-Regressive and Moving Average (MA) component located within the unit circle, it is therefore, exhibits characteristics of white noise. This conclusion is further reinforced by the results of the Portmanteau test, where a p-value greater than 0.05 indicates a failure to reject the null hypothesis, confirming that the model fit represents white noise.

**3. Forecasting**

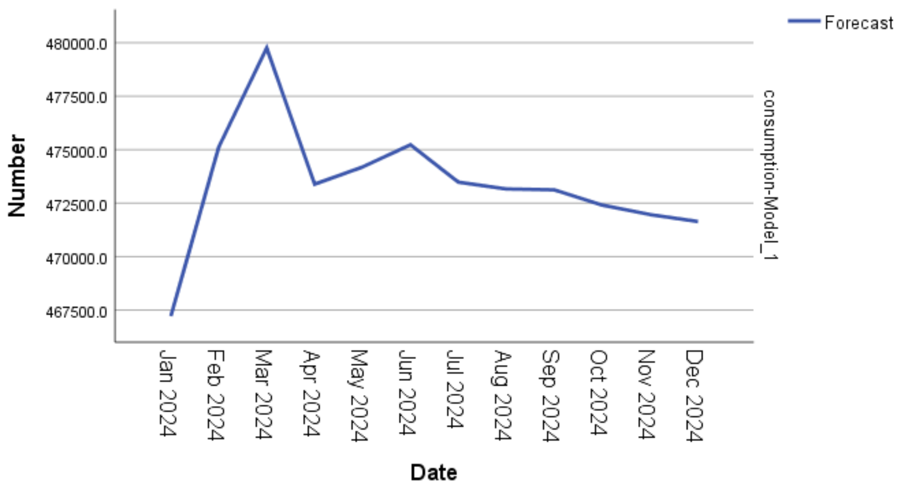


**Figure 5.***Forecast Water Consumption in the Province of Sultan Kudarat*

Figure 5 shows that there is a steady increase in water consumption, rising from 467,217.5 in January to 479,754.3 in March. Water consumption fluctuates, with minor increases and decreases. April sees a slight drop to 473,386.4, May and June experience small increases to 474,191.0 and 475,229.4 respectively, and July slightly decreases to 473,481.4. And Water consumption steadily declines, from 473,162.5 in August to 471,639.8 in December. It implies the upward trend in water consumption from January to March 2024 points to increasing demand, possibly driven by seasonal factors. The fluctuations from April to July show varying usage, potentially influenced by weather patterns or changing activities. The steady decline from August to December likely reflects reduced demand or effective conservation efforts as the year progresses.

## IV. CONCLUSION

Water usage has gradually increased over the years due to population growth and urban development, leading to higher residential and commercial demand. Analysis of the water consumption data, through ACF and PACF plots, indicates a need for an ARMA model with both AR and MA components. The ARMA (3,0,1) model emerged as the best fit, with the lowest log-likelihood, sigma value, AIC, and BIC. The ARIMA (3,0,1) model, shows the Auto-Regressive (AR) and Moving Average (MA) components within the unit circle, indicating characteristics of white noise. More so, water consumption rises from January to March 2024, fluctuates from April to July, and then steadily declines from August to December based on the ARMA (3,0,1) model forecast.

## V. RECOMMENDATION

Based on the result of the study, the researcher suggests to use ARMA (3,0,1) in forecasting water consumption. To generate a reliable forecast, the researcher suggests to follow the process of Box Jenkins methodology for ARMA model. Moreover, to address the need for clean water and meet consumer demand, water districts may consider implementing Upgrade and maintain water treatment facilities to ensure they can handle current and future demands and replace aging pipelines and distribution systems to prevent leaks and contamination. They may also develop and regularly update emergency response plans for water supply disruptions caused by natural disasters or infrastructure failures and create backup water supply systems and stockpile essential treatment materials. In addition, they may implement smart water management systems that use data analytics to optimize water distribution and identify inefficiencies and use predictive modeling to anticipate future water demand and plan accordingly.

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Appendix

**Billed in m^3 (Historical data of water consumption)**

| time | consumption | time | consumption |
|---|---|---|---|
| 1/30/2019 | 407,318.00 | 8/30/2021 | 439,192.00 |
| 2/28/2019 | 408,200.00 | 9/30/2021 | 439,687.00 |
| 3/30/2019 | 383,223.00 | 10/30/2021 | 406,207.00 |
| 4/30/2019 | 420,757.00 | 11/30/2021 | 430,498.00 |
| 5/30/2019 | 398,234.00 | 12/30/2021 | 426,986.00 |
| 6/30/2019 | 397,828.00 | 1/30/2022 | 453,164.00 |
| 7/30/2019 | 388,933.00 | 2/28/2022 | 441,055.00 |
| 8/30/2019 | 404,107.00 | 3/30/2022 | 408,153.00 |
| 9/30/2019 | 409,870.00 | 4/30/2022 | 450,853.00 |
| 10/30/2019 | 405,039.00 | 5/30/2022 | 452,238.00 |
| 11/30/2019 | 410,395.00 | 6/30/2022 | 459,003.00 |
| 12/30/2019 | 407,167.00 | 7/30/2022 | 461,511.00 |
| 1/30/2020 | 429,474.00 | 8/30/2022 | 431,874.00 |
| 2/29/2020 | 435,826.00 | 9/30/2022 | 474,546.00 |
| 3/30/2020 | 418,832.00 | 10/30/2022 | 465,701.00 |
| 4/30/2020 | 401,652.00 | 11/30/2022 | 440,097.00 |
| 5/30/2020 | 483,244.00 | 12/30/2022 | 468,159.00 |
| 6/30/2020 | 432,330.00 | 1/30/2023 | 472,024.00 |
| 7/30/2020 | 410,802.00 | 2/28/2023 | 457,985.00 |
| 8/30/2020 | 428,458.00 | 3/30/2023 | 434,382.00 |
| 9/30/2020 | 422,722.00 | 4/30/2023 | 509,778.00 |
| 10/30/2020 | 397,596.00 | 5/30/2023 | 442,710.00 |
| 11/30/2020 | 415,133.00 | 6/30/2023 | 492,429.00 |
| 12/30/2020 | 428,234.00 | 7/30/2023 | 470,893.00 |
| 1/30/2021 | 440,467.00 | 8/30/2023 | 439,758.00 |
| 2/28/2021 | 421,577.00 | 9/30/2023 | 499,383.00 |
| 3/30/2021 | 398,354.00 | 10/30/2023 | 458,846.00 |
| 4/30/2021 | 453,822.00 | 11/30/2023 | 479,136.00 |
| 5/30/2021 | 439,433.00 | 12/30/2023 | 493,612.00 |

| | | | |
|---|---|---|---|
| 6/30/2021 | 436,898.00 | 11/30/2023 | 479,136.00 |
| 7/30/2021 | 407,600.00 | 12/30/2023 | 493,612.00 |

| Forecast Consumption | |
|---|---|
| Jan 2024 | 467217.5 |
| Feb 2024 | 475129.7 |
| Mar 2024 | 479754.3 |
| Apr 2024 | 473386.4 |
| May 2024 | 474191.0 |
| Jun 2024 | 475229.4 |
| Jul 2024 | 473481.4 |
| Aug 2024 | 473162.5 |
| Sep 2024 | 473121.3 |
| Oct 2024 | 472409.0 |
| Nov 2024 | 471966.8 |
| Dec 2024 | 471639.8 |