# Unveiling the Future of Nutrient Use Efficiency: A Journey Through Time Series Forecasting

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**ABSTRACT**

**Fertilizers play a pivotal role in global food production, but their inefficient utilization poses significant challenges for sustainability. This study explores the captivating world of nitrogen, phosphorus, and potassium (NPK) use efficiency and employs the powerful Auto Regressive Integrated Moving Average (ARIMA) model to forecast their future trends. Through a meticulous research design rooted in the renowned Box-Jenkins Methodology, we embark on an exciting journey to unravel the mysteries surrounding NPK utilization. The objectives of this study are fourfold: (1) identify the ARIMA model with the highest performance in predicting NPK utilization efficiency, (2) assess the accuracy of ARIMA models in forecasting nutrient use efficiency, (3) project NPK fertilizer use efficiency values for the years 2022, 2024, 2026, 2028, and 2030, and (4) explore the potential impacts arising from the forecasted NPK fertilizer use efficiency. Our research design embraces the predictive power of the Box-Jenkins Methodology, a time-honored approach for time series analysis and forecasting. Leveraging data from the Food and Agriculture Organization (FAO) and employing Python, we processed decades of NPK fertilizer use efficiency data. Following meticulous data preprocessing steps and statistical treatments, we unleashed the ARIMA models upon the dataset. The findings of this study are enthralling. Among the ARIMA models, we uncovered the champions in nutrient use efficiency forecasting: the ARIMA (9, 1, 0) model for nitrogen, ARIMA (13, 1, 0) for phosphorus, and ARIMA (2, 1, 2) for potassium. These models, having undergone rigorous diagnostic checks, demonstrated exceptional performance in predicting NPK utilization efficiency. Our forecasts bring valuable insights into the future of nutrient use efficiency. For nitrogen, we anticipate an upward trend, with values ranging from 56.10% to 59.30%. Phosphorus use efficiency exhibits variability but shows a general increase, ranging from 72.91% to 80.02%. These projections offer policymakers and stakeholders in the agricultural sector valuable guidance for decision-making and resource allocation in pursuit of sustainable crop production. Delving deeper, this study unravels the intricate patterns and dynamics of NPK utilization efficiency. The captivating narrative spanning decades reveals periods of high efficiency, followed by declines and resurgences, showcasing the inherent resilience of nutrient utilization in the face of changing agricultural practices. In conclusion, our study harnesses the power of ARIMA modeling and forecasting techniques to shed light on nutrient use efficiency and its potential impacts on crop production. By navigating the uncharted territories of NPK utilization, we equip policymakers, stakeholders, and researchers in the agricultural sector with valuable insights to drive sustainable and efficient crop production systems. Join us on this exhilarating journey as we unravel the future of nutrient use efficiency, empowering individuals, and organizations to make evidence-based decisions that shape a more resilient and environmentally conscious agricultural landscape.**

**KEYWORDS:***Autoregressive Integrated Moving Average (ARIMA), Box-Jenkins Methodology,Fertilizer, Fertilizer Use,Forecast, Phosphorous, PotassiumMean Absolute Percentage Error, Nitrogen,Nutrient Use Efficiency, Time-Series Analysis.*

## I. INTRODUCTION

The production of the world's food heavily relies on the use of synthetic fertilizers, as highlighted by the UN Environment Programme (UNEP, 2020). In a recent interview conducted by the World Bank Group (2022) with Ms. Alzbeta Klein, the CEO and Director of the International Fertilizer Association (IFA), it was emphasized that nitrogen, phosphorus (in the form of $P_2O_5$), and potassium (in the form of $K_2O$) - the three main fertilizer nutrients - contribute to over half of the global food production. With the projected global population of 9.1 billion by 2050 (Food and Agriculture Organization [FAO], 2009), the demand for food is expected to increase by 70%, as reported by Our World in Data. Consequently, the demand for fertilizers will also rise. However, the availability of resources to produce these vital nutrients is limited.

Obtaining nitrogen from the air involves the energy-intensive Haber-Bosch process to make it accessible to plants, while phosphate is extracted from shallow surface mines and potash is mined from deeper deposits (Fertilizers Europe, 2022). These processes are not only resource-intensive but also environmentally challenging, given the scarcity and uneven distribution of land resources worldwide. Despite these concerns, the notion that organic fertilizers are a preferable alternative or avoiding synthetic fertilizers altogether is a misconception. According to the International Fertilizer Development Center (IFDC, 2017), reverting solely to organic fertilizers would leave over 2.5 billion people hungry, indicating that synthetic fertilizers remain essential for reliable crop production. However, a significant drawback is that crops do not fully absorb the nutrients from fertilizers, leading to substantial losses that contaminate soil, water, and air (Baligar& Bennett, 1986). This poses a significant challenge to the agricultural industry in terms of achieving optimal fertilizer use efficiency, known as nutrient use efficiency (NUE).

Defined by the World Bank Group (2022), NUE reflects the balance between how much fertilizer plants can absorb and how much is wasted into the environment. Maximizing NUE while mitigating environmental harm has been a longstanding goal in agricultural science. However, due to difficulties in data collection, labor-intensive processing, and time-consuming validation, accurate and reliable information on fertilizer use and NUE is scarce (Ludemann et al., 2022). Despite the efforts of prominent agricultural organizations such as FAO, IFA, IFDC, and The Fertilizer Institute (TFI), the general public still lacks access to comprehensive information regarding fertilizer nutrient use efficiency.

While existing fertilizer forecasting often focuses on supply, demand, and consumption (Mishra et al., 2011; Padhan, 2011), there is a noticeable absence of nutrient use efficiency forecasting available to the general public. Recognizing this gap, our research aims to forecast NUE categorized by nutrients N, P, and K in cropland. To achieve this, we employ the Auto Regressive Integrated Moving Average (ARIMA) model generated through the well-established Box-Jenkins Methodology. This methodology is founded on the concept that past events influence future outcomes. Our choice of this methodology is driven by several factors: (1) Its well-studied and reliable nature, instilling confidence in its application; (2) Suitability for limited datasets; and (3) Consistent strong performance of ARIMA models compared to other widely used statistical time series methods (Ellis, 2023).

By harnessing the power of Box-Jenkins Methodology, our study aims to fill the existing knowledge gap and provide the general public with valuable insights into the future of fertilizer nutrient use efficiency. This research endeavor is driven by the understanding that accurate forecasting of NUE is crucial for sustainable agricultural practices and effective resource management.

The Box-Jenkins Methodology, renowned for its reliability and extensive research, offers a robust framework for analyzing time series data. This approach enables us to uncover meaningful patterns, trends, and relationships within the historical fertilizer use efficiency data. By incorporating autoregressive (AR), integrated (I), and moving average (MA) components, the ARIMA model derived from the Box-Jenkins Methodology allows for accurate predictions of future NUE levels for nitrogen, phosphorus, and potassium.

The significance of this research lies in its potential to guide policymakers, farmers, and other stakeholders in making informed decisions regarding fertilizer application and management. By understanding the projected trends in NUE, we can optimize fertilizer usage, minimize waste, and reduce the environmental impact associated with nutrient contamination. Moreover, this knowledge can aid in the development of strategies to meet the increasing global food demand while ensuring sustainability and resource efficiency.

Through our study, we aim to contribute to the ongoing efforts of organizations like FAO, IFA, IFDC, and TFI in disseminating knowledge and raising awareness about fertilizer nutrient use efficiency. By providing accessible and reliable information to the general public, we hope to bridge the existing information gap and promote a more informed and sustainable approach to global agriculture.

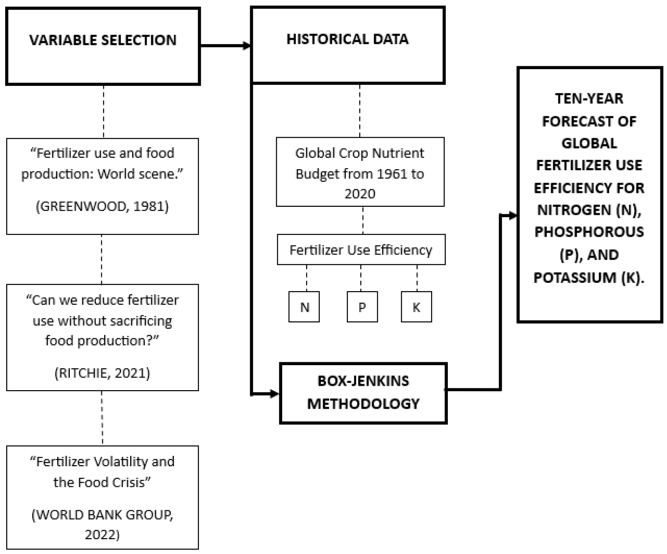
In the following sections, we will delve into the methodology employed, data sources utilized, and the process of developing the ARIMA model. Additionally, we will present the findings of our study, discussing the implications and potential applications of the predicted NUE values. Through this research, we endeavor to empower individuals and organizations to make evidence-based decisions that contribute to a more efficient and environmentally conscious agricultural landscape.

In conclusion, our study aims to utilize the Box-Jenkins Methodology to forecast global fertilizer use efficiency for nitrogen, phosphorus, and potassium. By shedding light on the future trends in NUE, we aspire to support sustainable agricultural practices, enhance resource management, and contribute to the global efforts of achieving food security while minimizing environmental impacts.

*A. Conceptual Framework*

***Figure 1.1***

***Conceptual Framework for Gross Domestic Product Using ARIMA Model***




The study's conceptual framework is depicted in Figure 1.1. During variable selection, the authors considered theories by Greenwood, Ritchie, and insights from the World Bank Group. Greenwood emphasized the importance of forecasting fertilizer use to enhance agriculture, while Ritchie concluded that crop land yield could be increased without escalating fertilizer amounts. The CEO of IFA, interviewed by the World Bank Group, emphasized the necessity of synthetic fertilizers to meet global food demand. Motivated by these factors, the authors opted to forecast NPK fertilizer use efficiency.

To establish historical context, global NUE data per nutrient from 1961 to 2020 were collected. Employing the Box-Jenkins methodology, the data were analyzed to determine the most suitable ARIMA model. Subsequently, the developed model will project global fertilizer use efficiency for each nutrient, yielding valuable insights into future trends.

*B. Statement of the Problem*

The present study endeavors to tackle a series of critical inquiries concerning the efficiency of nitrogen, phosphorus, and potassium (NPK) fertilizers. Through the utilization of Auto-Regressive Integrated Moving Average (ARIMA) models derived from the Box-Jenkins Methodology, the research aims to explore the predictive capabilities of these models in determining fertilizer use efficiency. This subsection provides an overview of the key research questions to be addressed in the course of the study.

1. Which ARIMA model demonstrates the highest performance in predicting the efficiency of nitrogen, phosphorus, and potassium utilization?
2. To what extent did the ARIMA models accurately forecast the nutrient's use efficiency?

3. What are the projected NPK fertilizer use efficiency values for the years 2022, 2024, 2026, 2028, and 2030?
4. What potential impacts may arise from the forecasted NPK fertilizer use efficiency?

Through the exploration of these core research questions, our study aims to provide significant insights into the prediction and implications of fertilizer use efficiency. The resulting findings will empower stakeholders with valuable knowledge to optimize fertilizer application, enhance agricultural practices, and foster sustainable food production, all while mitigating environmental impacts.

## II. LITERATURE REVIEW

Fertilizer use efficiency and its implications for food production and environmental sustainability have been extensively studied in the existing literature. By examining the relevant studies, we can identify common themes, contrasts, and gaps that set the stage for the present study's distinctive contribution.

One recurring theme in the literature is the cycle of food production, where fertilizers play a crucial role. Byrnes et al. (2008) highlighted how fertilizers integrate nutrients into the soil, which are then absorbed by crops. The grown crops are either consumed by humans or used as feed for livestock, and the cycle repeats with the application of fertilizers. This cyclic relationship between population growth, food demands, and fertilizer use was also noted by FAO (1978), demonstrating the interconnectedness of these factors.

The role of nitrogen (N), phosphorus (P), and potassium (K) fertilizers in crop production is another focus of the literature. Nitrogen is known to promote crop reproduction and nutrient uptake, while phosphorus is essential for seed and root formation. Potassium, along with nitrogen, enhances fruit sugar concentration, improves frost tolerance, and increases drought resistance. However, the production of nitrogen fertilizer involves significant energy usage and greenhouse gas emissions (Ghavam et al., 2021). Furthermore, the extraction and beneficiation of phosphate and potash rocks, the main resources for P and K fertilizers, pose environmental risks such as soil erosion, water contamination, and air pollution (International Plant Nutrition Institute [IPNI], 2010; Center for Biological Diversity, n.d.).

Mismanagement of fertilizers and the need for improved agricultural practices have also been highlighted in the literature. Yang et al. (2015) found widespread improper use and inconsistent application practices among farmers due to a lack of scientific information and limited support from agricultural extension agencies. The myth that "more fertilizer equals more yields" has also encouraged wasteful usage, but research in China has shown that minimizing fertilizer use is feasible without compromising crop yields (Zhang et al., 2018; Ritchie, 2021). The importance of improving nutrient use efficiency (NUE) through practices like crop diversification and implementing the 4R nutrient stewardship concept has been emphasized (Ebbisa, 2022; Fixen, 2015).

In terms of forecasting fertilizer use, the Box-Jenkins methodology, particularly the Autoregressive Integrated Moving Average (ARIMA) model, has been widely used. Greenwood (1981) emphasized the urgent need for accurate fertilizer use forecasts. Mishra et al. (2011) and Padhan (2011) employed ARIMA models to forecast the consumption, production, and productivity of NPK fertilizers in India. The ARIMA model is favored for short-term forecasting and stable data, making it a suitable choice for predicting agricultural outcomes (Scott, 2022).

**Synthesis**:

In synthesizing the reviewed literature, we recognize the critical role of fertilizers in the cycle of food production, where they supply essential nutrients to crops and contribute to increased yields. However, the environmental impacts associated with fertilizer production and mismanagement cannot be ignored. The literature emphasizes the need for improved agricultural practices to enhance nutrient use efficiency and minimize adverse effects on ecosystems.

The present study contributes to the existing literature by focusing on the prediction of fertilizer use efficiency, specifically for nitrogen, phosphorus, and potassium. By employing ARIMA models derived from the Box-Jenkins methodology, the study aims to provide accurate forecasts for each nutrient individually. This approach addresses the gap in the literature by offering granular predictions and insights into nutrient-specific efficiency.

The synthesis of the literature highlights the interconnectedness of population growth, food demands, and fertilizer use, underscoring the importance of optimizing fertilizer application for sustainable food production. It also emphasizes the significance of considering environmental risks andimplementing improved agricultural practices to minimize the negative impacts of fertilizers. The studies reviewed have shown that excessive and improper fertilizer use can lead to environmental issues such as eutrophication, salinization of freshwater sources, biodiversity loss, and pollution of land, air, and water.

To address these challenges, the literature suggests adopting the 4R nutrient stewardship concept, which emphasizes applying the right nutrient source, at the right rate, at the right time, and in the right place. Implementing precision farming techniques, diversifying crops, and promoting responsible fertilizer management can help optimize nutrient use efficiency, reduce waste, and mitigate environmental harm.

Furthermore, the literature highlights the potential of forecasting models, particularly the ARIMA model, in predicting fertilizer use and production. Accurate forecasts can aid policymakers, farmers, and stakeholders in making informed decisions regarding fertilizer management, resource allocation, and sustainable agriculture practices.

The present study builds upon this literature by focusing on predicting and forecasting nutrient use efficiency for nitrogen, phosphorus, and potassium individually. By employing the ARIMA model, the study aims to provide valuable insights into optimizing fertilizer application, improving agricultural practices, and ensuring sustainable food production while minimizing environmental impacts.

In conclusion, the reviewed literature underscores the need for sustainable fertilizer use to meet the increasing global food demands while minimizing environmental degradation. The present study contributes to this body of knowledge by offering granular predictions and insights into nutrient-specific efficiency. By addressing the challenges of fertilizer use and providing accurate forecasts, the study aims to equip stakeholders with the necessary knowledge to optimize fertilizer application, improve agricultural practices, and ensure sustainable food production for future generations.

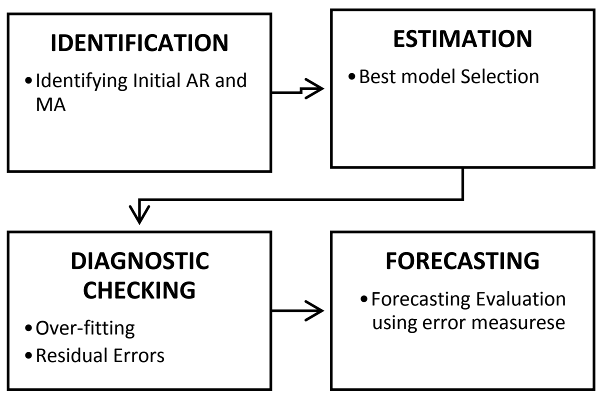
## III. METHODOLOGY

### A. ***Research Design***

The research design for this study is predictive and follows the Box-Jenkins Methodology, a widely recognized approach for time series analysis and forecasting. The univariate time series analysis approach is suitable for capturing the dynamic and interrelated nature of fertilizer use efficiency for nitrogen (N), phosphorous (P), and potassium (K). The Box-Jenkins Methodology is particularly effective when working with small datasets that have at least 50 observations. It is known to generate ARIMA models that perform well in forecasting, comparable to other commonly used techniques. The research design consists of four sections, as depicted in Figure 3.1.

***Figure 3.1***
***Box-Jenkins Methodology***

***Figure 3.1***
***Box-Jenkins Methodology***




### B. **Data Collection and Procedure**:

The data used for this research was obtained from the Food and Agriculture Organization (FAO) through their public database called FAOstat, which was recently published in November 2022. The researchers accessed the Fertilizer Nutrient Use Efficiency data for nitrogen, phosphorous, and potassium from the year 1961 to 2020. The data was processed using Python and the Box-Jenkins Method.

The calculation of Nutrient Use Efficiency (NUE) is based on the following formula:

$$NUE_{i,j,y} = \frac{CR_{i,j,y}}{\sum SF_{i,j,y} \times CF_{i,j,y}\, MAS_{i,j,y} ND_{i,j,y} BF_{i,j,y}}$$

Where:

$i$ = country

$j$ = nutrient

$y =$ year

$CR =$ crop removal

$SF =$ synthetic fertilizer

$CF =$ fraction of fertilizer applied to cropland

$MAS =$ manure applied to soil

$ND =$ nitrogen deposition

$BF =$ biological fixation

The NUE is calculated as the ratio of crop removal (CR) to the sum of inputs (synthetic fertilizers, fraction of fertilizer applied to cropland, manure applied to soils, nitrogen deposition, and biological fixation) minus outputs (crop removal).

C. **Data Preprocessing**:

Before applying the Box-Jenkins Methodology, the data underwent preprocessing steps. This involved visualizing the data through plots and dividing it into train-test sets. The stationarity of the train set was determined using Correlograms (ACF and PACF) and statistical metrics such as the Augmented-Dickey Fuller test (ADF), Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, and Phillips-Perron (PP) test. If the data was found to be non-stationary, differencing was performed, and stationarity was verified again. Once the data was stationary, the researchers proceeded with the Box-Jenkins methodology.

D. **Statistical Treatment of the Data**:

1. Augmented-Dickey Fuller test (ADF):

The ADF test is used to assess the stationarity of a time series. The null hypothesis (H0) assumes that the data is non-stationary, while the alternative hypothesis (Ha) assumes stationarity. The decision rule is based on the p-value, where if the p-value is less than 0.05, the null hypothesis is rejected, indicating that the data is stationary.

$$\Delta y_t = y_t - y_{t-1} = \alpha + \beta t + \gamma y_{t-1} + e_t$$

Hypothesis in ADF

$H_o$: The data is not stationary.

$H_a$: The data is stationary.

Decision Rule: If p-value is < 0.05, the $H_o$ is rejected. Hence, the $H_a$ is accepted.

2. Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test:

The KPSS test is another method to test for stationarity in time series data. It is based on the decomposition of a time series into a random walk component, a deterministic trend component, and a stationarity error. The null hypothesis (H0) assumes stationarity, while the alternative hypothesis (Ha) assumesnon-stationarity. The decision rule is based on the p-value, where if the p-value is greater than 0.05, the null hypothesis is accepted, indicating that the data is non-stationary.

$$x_t = r_t + \beta t + \varepsilon_1$$

Where:

$r_t$ = random walk
$\beta t$ = deterministic trend
$\varepsilon_1$ = stationarity error

Hypothesis in KPSS:

$H_o$: The data is stationary.
$H_a$: The data is not stationary.

Decision Rule: If p-value is > 0.05, the $H_o$ is accepted. Hence, the $H_a$ is rejected.

3. Phillips-Perron (PP) test:

The PP test is used to test for stationarity in time series data, similar to the ADF and KPSS tests. It also examines the presence of a unit root in the data. The null hypothesis (H0) assumes non-stationarity, while the alternative hypothesis (Ha) assumes stationarity. The decision rule is based on the p-value, where if the p-value is less than 0.05, the null hypothesis is rejected, indicating that the data is stationary.

$$\Delta y_t = (\rho - 1) y_{t-1} + u_t$$

Hypothesis in PP

$H_o$: The data is not stationary.
$H_a$: The data is stationary.

Decision Rule: If p-value is < 0.05, the $H_o$ is rejected. The $H_a$ is accepted.

4. Data Differencing:

Differencing is performed on the time series data to remove trend and seasonality, thus stabilizing the mean of the series. The order of differencing, denoted as 'm', is determined by taking the difference between consecutive values of the time series. The differenced data is then tested for stationarity using the aforementioned tests to ensure the adequacy of the differencing order.

$$d^m(t) = d^{(m-1)}(t) - d^{m-1}(t-1)\ ,$$

Where:

$m$ = order of the difference
$t$ = time series

5. Root Mean Square Error (RMSE):

RMSE is a statistical measure of the differences between the actual and predicted values in a time series forecast. It is calculated by taking the square root of the average of the squared differences between the actual and predicted values. The RMSE provides an estimate of the model's accuracy, with lower values indicating a better fit to the data.

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{(x_i - \widehat{x_i})^2}{N}}$$

where:
$i$ = variable
$N$ = number of non-missing data points
$x_i$ = actual observations
$\widehat{x_i}$ = estimated value

6. Mean Absolute Error (MAE):

MAE is another statistical measure of the differences between the actual and predicted values. It is calculated by taking the average of the absolute differences between the actual and predicted values. The MAE is less sensitive to outliers compared to RMSE, making it a useful metric for assessing forecast accuracy.

$$MAE = \frac{1}{n} \sum \frac{|x_i - \widehat{x_i}|}{x_i}$$

where:
$x_i$ = actual observations
$\widehat{x_i}$ = estimated values
$n$ = actual observations
$i$ = variable

7. Mean Absolute Percentage Error (MAPE):

MAPE is a metric used to evaluate the accuracy of a forecast by calculating the average percentage difference between the actual and predicted values. It is calculated by taking the average of the absolute percentage differences between the actual and predicted values, multiplied by 100. MAPE provides a measure of forecast accuracy relative to the magnitude of the actual values.

$$MAPE = \frac{1}{n} \sum \frac{|x_i - \widehat{x_i}|}{x_i} * 100$$

where:
$x_i$ = actual observations
$\widehat{x_i}$ = estimated values
$n$ = actual observations
$i$ = variable

The researchers analyze the RMSE, MAE, and MAPE to assess the accuracy and performance of the forecasted values, with lower error measurements indicating a closer match between the actual and predicted values. Additionally, the potential impacts of forecasted NPK fertilizer use efficiency are examined to identify any significant and uncommon inaccuracies in the forecast.

## IV. RESULTS AND DISCUSSIONS

### *A. Data Preprocessing*

#### *1) Visualizing the Data*

***Figure 4.1***
***Nitrogen Use Efficiency Over Time***

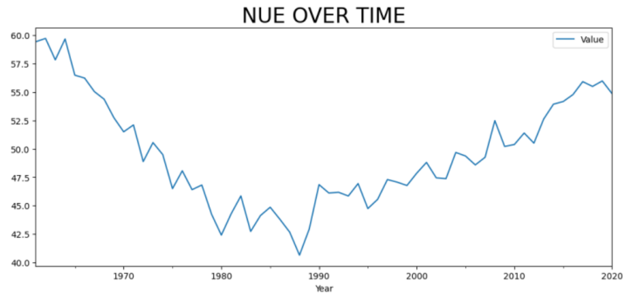



***Figure 4.2***
***Phosphorous Use Efficiency Over Time***

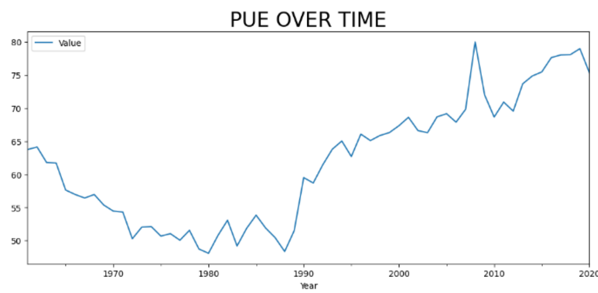
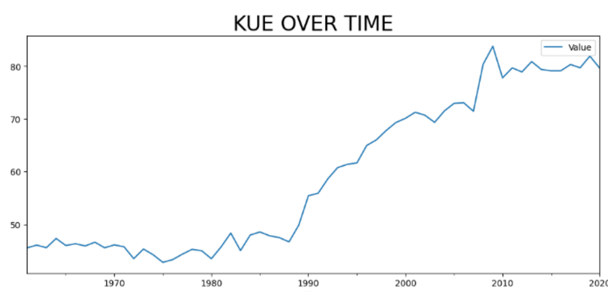



***Figure 4.3***
***Potassium Use Efficiency Over time***



The captivating figures 4.1-4.3 vividly depict the fascinating journey of nitrogen, phosphorus, and potassium utilization in crop production. These graphs unveil intriguing patterns, revealing the dynamic nature of nutrient efficiency over time. Nitrogen and phosphorus exhibit a fascinating dance, initially showcasing high efficiency, followed by a decline and eventual resurgence. On the other hand, potassium embarks on a remarkable journey, starting from humble beginnings and gradually ascending to new heights.

The astute researchers keenly observed a captivating narrative spanning several decades. During the 1970s to the late 1980s, a decline in nutrient use efficiency left them perplexed. However, like a phoenix rising from the ashes, the efficiency experienced a remarkable rebound as the 20th and 21st centuries unfolded, leaving the researchers in awe of the inherent resilience of nutrient utilization.

One particularly noteworthy revelation is the consistent range of nitrogen use efficiency, standing firm between 40% and 60%. Meanwhile, phosphorus and potassium showcase their own unique dynamics, flexing their efficiency within a range of 40% to 80%. These captivating ranges paint a vivid picture of the intricate interplay between crops and these essential nutrients, fueling the researchers' curiosity and driving them to delve deeper into the mysteries of agricultural sustainability.

These remarkable findings not only captivate the imagination but also spark intriguing questions about the underlying mechanisms that shape nutrient utilization efficiency.

*2) Train-Test Split*

***Figure 4.4***

***Train-Test Split of NUE***

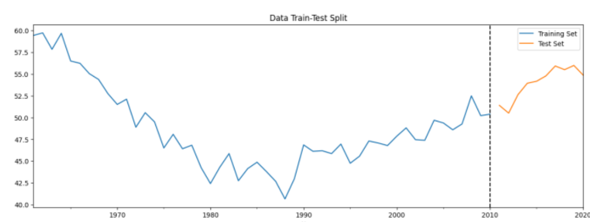


***Figure 4.5***

***Train-Test Split of PUE***

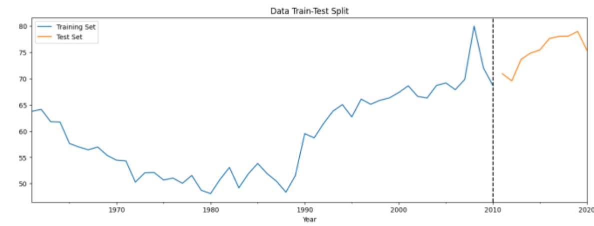
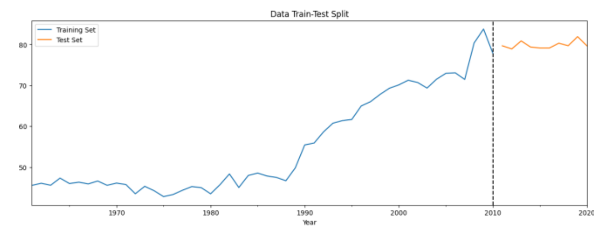



***Figure 4.6***

***Train-Test Split of KUE***




In this study, we analyzed threetime series datasets with 60 data points. To ensure accurate predictions, we divided the data into train (50 points) and test (10 points) sets. Using the renowned Box-Jenkins method, we created a model based on the train set to capture underlying patterns. This model served as the foundation for forecasting. By applying the model to the test set, we assessed its accuracy and effectiveness, gaining valuable insights into its performance and reliability.

*3) Test Stationarity*

***Table 4.1***

***Correlogram of Raw NUE, PUE, and KUE Training Set Time Series***

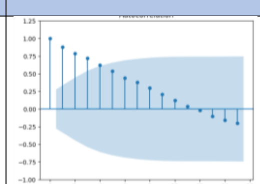
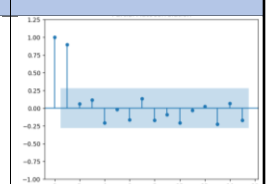
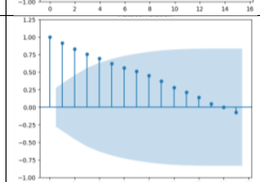
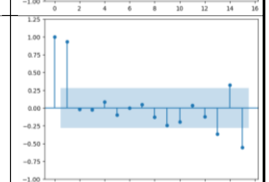
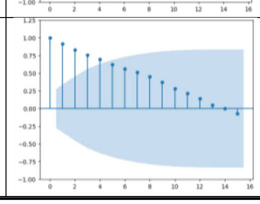
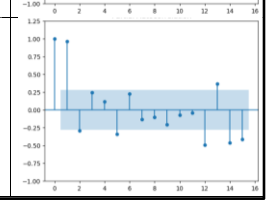
| Fertilizer Nutrient | ACF Plot | PACF Plot |
|---|---|---|
| NUE |  |  |
| PUE |  |  |
| KUE |  |  |

***Table 4.2***

***Test Stationarity of Raw NUE, PUE, and KUE Time Series Data***

| NUE | | | | |
|---|---|---|---|---|
| Test Statistics | p-value | < 0.05 | Decision | Interpretation |
| ADF | 0.414934 | FALSE | $H_o$ is accepted | Not stationary |
| KPSS | 0.048758 | TRUE | $H_o$ is rejected | Not stationary |
| PP | 0.764 | FALSE | $H_o$ is accepted | Not stationary |

| PUE | | | | |
|---|---|---|---|---|
| Test Statistics | p-value | < 0.05 | Decision | Interpretation |
| ADF | 0.940662 | FALSE | $H_o$ is accepted | Not stationary |
| KPSS | 0.018990 | TRUE | $H_o$ is rejected | Not stationary |
| PP | 0.402 | FALSE | $H_o$ is accepted | Not stationary |

| KUE | | | | |
|---|---|---|---|---|
| Test Statistics | p-value | < 0.05 | Decision | Interpretation |
| ADF | 0.998138 | FALSE | $H_o$ is accepted | Not stationary |
| KPSS | 0.010000 | TRUE | $H_o$ is rejected | Not stationary |
| PP | 0.990 | FALSE | $H_o$ is accepted | Not stationary |

In Table 4.1, for all three data sets, the lag in ACF plots gradually declined, while in the PACF plot, there was a significant spike at lag 1, followed by a subsequent descent of lags within and near the confidence interval. This behavior indicated non-stationarity, which was supported by the values of ADF, KPSS, and PP shown in Table 4.2. Therefore, data differencing was required.

*3. Differencing*

***Table 4.3***

***Correlogram of Differenced NUE, PUE, and KUE Training Set Time Series***

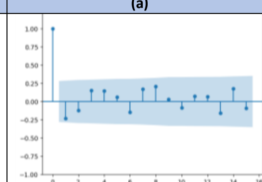
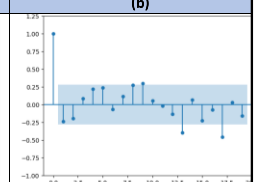
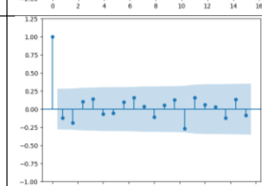
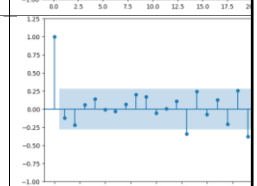
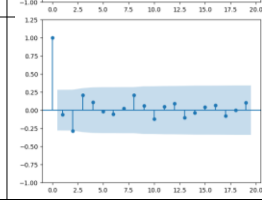
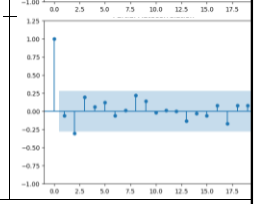
| Fertilizer Nutrient | ACF Plot (a) | PACF Plot (b) |
|---|---|---|
| NUE |  |  |
| PUE |  |  |
| KUE |  |  |

***Table 4.4***

***Test Stationarity of Differenced NUE, PUE, and KUE Time Series Data***

| NUE | | | | |
|---|---|---|---|---|
| Test Statistics | p-value | < 0.05 | Decision | Interpretation |
| ADF | 3.576678e-08 | TRUE | $H_o$ is rejected | Stationary |
| KPSS | 0.060751 | FALSE | $H_o$ is accepted | Stationary |
| PP | 0.000 | TRUE | $H_o$ is rejected | Stationary |

| PUE | | | | |
|---|---|---|---|---|
| Test Statistics | p-value | < 0.05 | Decision | Interpretation |
| ADF | 2.098772e-07 | TRUE | $H_o$ is rejected | Stationary |
| KPSS | 0.100000 | FALSE | $H_o$ is accepted | Stationary |
| PP | 0.000 | TRUE | $H_o$ is rejected | Stationary |

| KUE | | | | |
|---|---|---|---|---|
| Test Statistics | p-value | < 0.05 | Decision | Interpretation |
| ADF | 0.020425 | TRUE | $H_o$ is rejected | Stationary |
| KPSS | 0.100000 | FALSE | $H_o$ is accepted | Stationary |
| PP | 0.000 | TRUE | $H_o$ is rejected | Stationary |

The ACF and PACF plots in Table 4.3 revealed a pattern indicating that the series had been transformed to become stationary. It was observed that both NUE and PUE exhibited no significant lag in their ACF plots, whereas KUE displayed a significant lag at 2. It is important to note that lag 0 was disregarded due to the high correlation of the value with itself.Additionally, the PACF plot of NUE showed spikes at lags 9, 13, and 17, while PUE exhibited spikes at lags 13 and 17. KUE displayed a significant lag at 2.

To further assess the stationarity of the series, the researchers calculated its ADF, KPSS, and PP values, as shown in Table 4.4. The ADF and PP p-values of NPK were found to be less than 0.05, leading to the rejection of the null hypothesis, which states that the series is not stationary. However, the KPSS results for NPK were greater than 0.05, indicating acceptance of null hypothesis and confirming that the series is stationary according to the KPSS test. Therefore, the series' stationarity was confirmed based on these results.

*B) Box-Jenkins Method*

*1) Identification*

1a. NUE ARIMA Parameter Identification

In Table 4.3, NUE (a) exhibited no significant lags from 1 to 19, indicating that the parameter q was equal to 0. This implied an ARIMA model of (p, d, 0) since there was no presence of seasonality in the data.

In Table 4.3, NUE (b) displayed spikes at lags 9, 13, and 17, suggesting that p should be evaluated using these three parameters. This type of ARIMA model is referred to as an nth-order autoregressive model with one order of non-seasonal differencing and a constant term. Therefore, to select the optimal model, the initial examination would involve three models: ARIMA (9, 1, 0), ARIMA (13, 1, 0), and ARIMA (17, 1, 0).

1b. PUE ARIMA Parameter Identification

In Table 4.3, PUE (a) exhibited no significant lags from 1 to 19, indicating that the parameter q was equal to 0. This suggested an ARIMA model of (p, d, 0) since there was no presence of seasonality in the data.

In Table 4.3, PUE (b) displayed spikes at lags 13 and 19, suggesting that p should be evaluated using these parameters. This had the same nature of an ARIMA model as NUE. Therefore, to select the best possible model, two models—ARIMA (13, 1, 0) and ARIMA (19, 1, 0)—were initially examined.

1c. KUE ARIMA Parameter Identification

In Table 4.3, KUE (a) did not show any significant lags from 1 to 19, indicating that the parameter q was determined to be 0. This observation pointed towards an ARIMA model of (p, d, 0) since no seasonality was evident in the data.

In Table 4.3, KUE (b) exhibited spikes at lags 13 and 19, suggesting that the parameter p should be evaluated using these values. This indicated that KUE followed a similar pattern to NUE, and an ARIMA model with non-seasonal differencing and a constant term should be considered. Therefore, two initial models—ARIMA (13, 1, 0) and ARIMA (19, 1, 0)—were examined to determine the most suitable model.

*2) Estimation*

***Table 4.5***

***LL and Information Criterion of the Selected ARIMA models in NUE***

| NUE | | | | |
|---|---|---|---|---|
| Model | Log-Likelihood | AIC | BIC | HQIC |
| ARIMA (9, 1, 0) | -87.15244 | 194.30489 * | 213.22309* | 201.48243 * |
| ARIMA (13, 1, 0) | -84.48880 | 196.97760 | 223.46308 | 207.02615 |
| ARIMA (17, 1, 0) | - 79.84960* | 195.69919 | 229.75196 | 208.61877 |

2a. NUE Estimation Result

The ARIMA (17, 1, 0) model had the highest value in terms of log-likelihood. However, when considering the values for the three information criteria (AIC, BIC, and HQIC), ARIMA (9, 1, 0) had the lowest values. Therefore, among the selected models, ARIMA (9, 1, 0) was determined to be the most effective model.

***Table 4.6***

***LL and Information Criterion of the Selected ARIMA models in PUE***

| PUE | | | | |
|---|---|---|---|---|
| Model | Log-Likelihood | AIC | BIC | HQIC |
| ARIMA (13, 1, 0) | -114.47693 | 256.95387* | 283.43935* | 267.00242* |
| ARIMA (19, 1, 0) | -112.59001* | 257.18003 | 287.449151 | 268.66409 |

2b. PUE Estimation Result

Among the chosen models, ARIMA (19, 1, 0) had the highest value in terms of log-likelihood. However, when considering the values of the three information criteria (AIC, BIC, and HQIC), ARIMA (13, 1, 0) had the lowest values. Therefore, the most effective model among the selected ones was determined to be ARIMA (13, 1, 0).

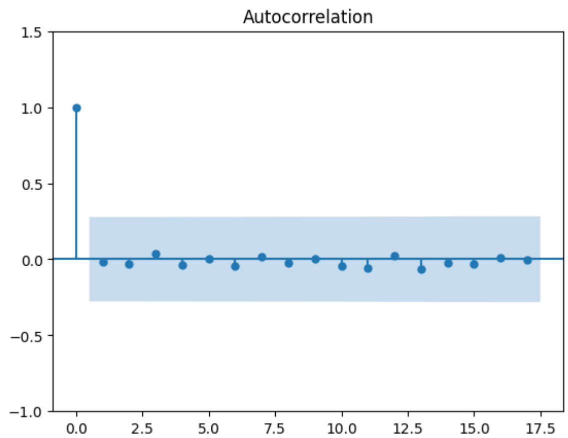
***Table 4.6***

***LL and Information Criterion of the Selected ARIMA models in PUE***

| KUE | | | | |
|---|---|---|---|---|
| Model | Log-Likelihood | AIC | BIC | HQIC |
| ARIMA (2, 1, 2) | -108.87191 | 227.74383 | 237.20293 | 231.33260 |

***Figure 4.1***

***ACF plot of ARIMA (2, 1, 2) Residual***




2c. KUE Estimation Result

No other model was comparable to ARIMA (2, 1, 2). To ensure that this model accounted for all significant lags, the researchers examined the ACF plot of residuals in ARIMA (2, 1, 2). It was observed that all the lags fell within the 95% confidence interval, indicating that the model adequately captured the important lags. Therefore, ARIMA (2, 1, 2) was determined to be the optimal model that could not be further improved.

*3) Diagnostic Checking*

***Table 4.7***

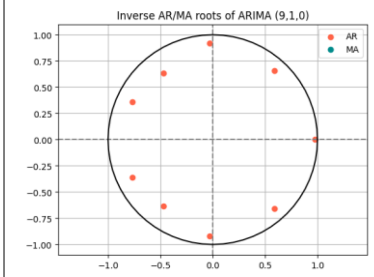
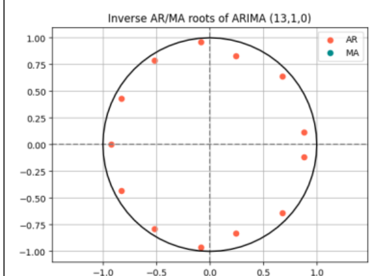
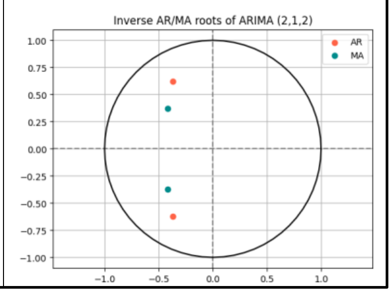
***Ljung-Box Test Result of NPK's best ARIMA models***

| Nutrient | Ljung-Box Test (p-value) |
|---|---|
| NUE | 0.942953 |
| PUE | 0.985116 |
| KUE | 0.664578 |

The researchers performed overfitting testing using the Ljung-Box test. For NUE, the ARIMA (9, 1, 0) model yielded a p-value of 0.94295. The ARIMA (13, 1, 0) model for PUE yielded a p-value of 0.985116. Lastly, the ARIMA (2, 1, 2) model for KUE yielded a p-value of 0.664578. All of these p-values were found to be greater than 0.05. Therefore, there was sufficient evidence to conclude that the models did not exhibit a significant lack of fit.

***Table 4.8***

***AR/MA Structure of the ARIMA model***

| Fertilizer Nutrient | AR/MA Structure |
|---|---|
| NUE |   |
| PUE |   |
| KUE |   |

For the ARIMA (9, 1, 0) model of NUE, the ARIMA (13, 1, 0) model of PUE, and the ARIMA (2, 1, 2) model of KUE, all the roots were found to be inside the unit circle, as indicated in Table 4.13. This suggests that the models were both stationary and invertible. Therefore, based on the diagnostic checking results, it can be concluded that the models were suitable for forecasting purposes.

*4) Forecasting*

4a. Out-of-Sample Forecasts

***Figure 4.2***

***Out-of-Sample Forecasting NUE using ARIMA (9, 1, 0) [2011-2020]***

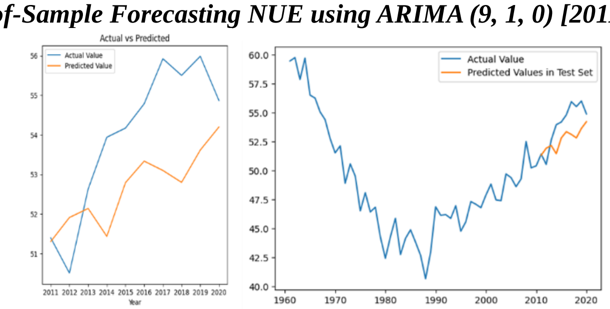



***Figure 4.3***

***Out-of-Sample Forecasting PUE using ARIMA (13, 1, 0) [2011-2020]***

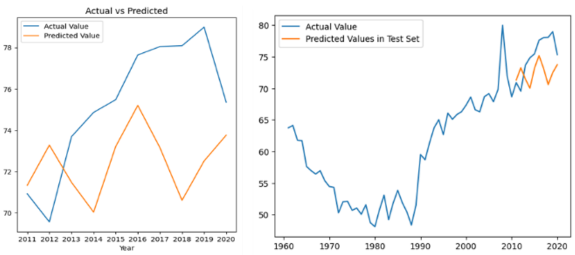



***Figure 4.4***

***Out-of-Sample Forecasting KUE using ARIMA (2, 1, 2) [2011-2020]***

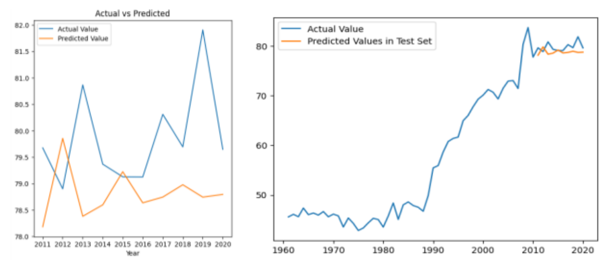



***Table 4.8***

***Error Measures of NUE: ARIMA (9,1,0)***

| Error Measures | Result |
|---|---|
| MAE | 1.58844 |
| MAPE | 0.03011 |
| RMSE | 1.83930 |

***Table 4.9***

***Error Measures of PUE: ARIMA (13,1,0)***

| Error Measures | Result |
|---|---|
| MAE | 3.63252 |
| MAPE | 0.05036 |
| RMSE | 4.21537 |

***Table 4.10***

***Error Measures of KUE: ARIMA (2,1,2)***

| Error Measures | Result |
|---|---|
| MAE | 1.25869 |
| MAPE | 0.01599 |
| RMSE | 1.54457 |

In the realm of nitrogen use efficiency (NUE) forecasting, the ARIMA (9, 1, 0) model emerged as the champion. It demonstrated superior performance by producing predicted values with an average error margin of either 1.84% lower or 1.84% higher than the actual values. The root mean square error (RMSE) of this model stood at 1.84, further affirming its accuracy. Moreover, the mean absolute error (MAE) of 1.59 showcased a consistent error magnitude in comparison to RMSE. The mean absolute percentage error (MAPE) of 0.03011 indicated a modest 3.01% error, highlighting an impressive 96.99% accuracy in predicting NUE.

When it came to phosphorus use efficiency (PUE) forecasting, the ARIMA (13, 1, 0) model took center stage as the optimal choice. Its RMSE value of 4.22 implied that the mean error of predicted values could deviate by either 4.22% higher or 4.22% lower than the actual value. The narrow gap between MAE (3.63) and RMSE signified a consistent error magnitude. The MAPE value of 0.05036 represented a 5.04% error in the model, accompanied by an impressive 94.96% accuracy in predicting PUE.

Lastly, for potassium use efficiency (KUE) prediction, the ARIMA (2, 1, 2) model showcased its prowess. It generated predicted values with a mean error of either 1.54% lower or 1.54% higher than the actual values, supported by an RMSE value of 1.54. Similar to the previous models, the small gap between MAE (1.26) and RMSE indicated a consistent error magnitude. The MAPE value of 0.01599 unveiled a mere 1.60% error, boasting a remarkable 98.4% accuracy in predicting KUE.

4b. 10-year Forecasts

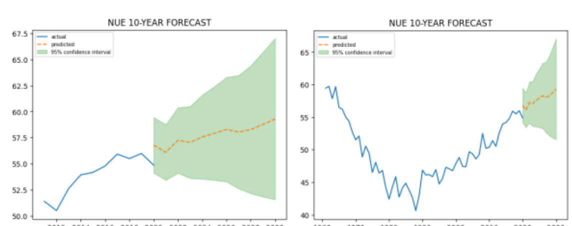
***Table 4.11***

***Forecast NUE 10 Years***

| YEAR | PREDICTED VALUE |
|---|---|
| 2021 | 56.098368 |
| 2022 | 57.256243 |
| 2023 | 57.056663 |
| 2024 | 57.569261 |
| 2025 | 57.923225 |
| 2026 | 58.290852 |
| 2027 | 58.049129 |
| 2028 | 58.284793 |
| 2029 | 58.773920 |
| 2030 | 59.303083 |

***Figure 4.5***

***Forecast NUE 10 Years***




Take a captivating journey through time guided by Figure 4.5, which revealed a 10-year forecast of nitrogen use efficiency (NUE). Witnessed the revealing of Table 4.11, where the forecasted NUE values for the years from 2021 to 2030 were displayed. The sequence of numbers presented were: 56.10%, 57.26%, 57.06%, 57.57%, 57.92%, 58.29%, 58.05%, 58.28%, 58.77%, and 59.30%. Noticed the ebb and flow of these values, uncovering a range from 56% to

59% that showcased variability. Amidst this variation, a clear narrative emerged—a consistent upward trend that depicted progress and improvement.

***Table 4.12***

***Forecast PUE 10 Years***

| YEAR | PREDICTED VALUE |
|---|---|
| 2021 | 72.911839 |
| 2022 | 78.432509 |
| 2023 | 80.018246 |
| 2024 | 78.664999 |
| 2025 | 79.758342 |
| 2026 | 78.649305 |
| 2027 | 78.729954 |
| 2028 | 78.412658 |
| 2029 | 76.876856 |
| 2030 | 77.642714 |

***Figure 4.6***

***Forecast PUE 10 Years***

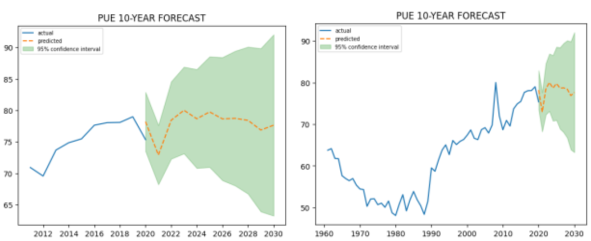



Figure 4.6 displayed the 10-year forecast of PUE. Table 4.12 unveiled the projected PUE values for the years 2021 to 2030, which were 72.91%, 78.43%, 80.02%, 78.66%, 79.76%, 78.65%, 78.73%, 78.41%, 76.88%, and 77.64%, respectively. In 2023, the highest PUE was observed, but it gradually declined by 3.14% in 2029. The forecast concluded with a PUE of 77.64%, representing a slight increase of 0.76% compared to the preceding year. Throughout the 10-year forecast period, there were fluctuations, yet the overall trend exhibited a significant positive increase of 4.73%.

***Table 4.13***

***Forecast KUE 10 Years***

| YEAR | PREDICTED VALUE |
|---|---|
| 2021 | 80.003433 |
| 2022 | 80.218201 |
| 2023 | 80.327877 |
| 2024 | 80.360208 |
| 2025 | 80.337085 |
| 2026 | 80.275606 |
| 2027 | 80.188979 |
| 2028 | 80.087267 |
| 2029 | 79.978015 |
| 2030 | 79.866769 |

***Figure 4.7***

***Forecast KUE 10 Years***

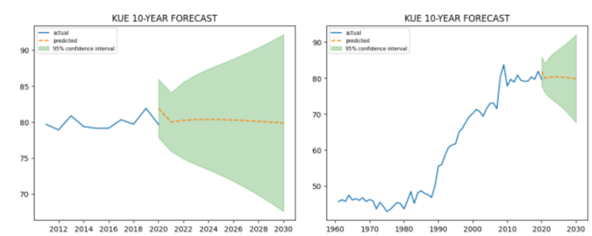



Figure 4.7 unveiled a mesmerizing glimpse into the future, offering a captivating 10-year forecast of KUE. As the curtains rose, Table 4.13 gracefully revealed the anticipated values of KUE for the forthcoming years spanning from 2021 to 2030. Like a harmonious melody, the numbers danced before our eyes: 80.00%, 80.22%, 80.33%, 80.36%, 80.34%, 80.26%, 80.19%, 80.09%, 79.98%, and 79.87%. Throughout this enchanting forecast, a striking theme emerged—consistency and stability were the protagonists of this narrative. These values gracefully hovered around the illustrious 80% mark, painting a picture of unwavering equilibrium and unwavering potential. It was as if time itself had embraced the notion of harmony, allowing the forecasted KUE values to remain steadfast in their commitment to excellence.

## VI. CONCLUSION

In the realm of agricultural enlightenment, the research findings illuminated the intricate dance of nitrogen, phosphorus, and potassium in the world of crop production. Like a captivating tale spanning across decades, the narrative unveiled periods of soaring efficiency, followed by subtle declines and glorious resurgences, showcasing the indomitable spirit of nutrient utilization amidst the ever-evolving landscape of agricultural practices.

In this grand production, the ARIMA modeling approach took the stage, proving its prowess in predicting nutrient use efficiency. With meticulous precision, specific models were tailored for each nutrient, each with its own unique performance. The ARIMA (9, 1, 0) model emerged as the star, shining brightly in predicting nitrogen use efficiency (NUE). Not far behind, the ARIMA (13, 1, 0) model claimed its well-deserved spotlight for phosphorus use efficiency (PUE), while the ARIMA (2, 1, 2) model dazzled the audience with its optimal portrayal of potassium use efficiency (KUE). To ensure their suitability for forecasting, these models underwent rigorous diagnostic checks, leaving no room for imperfection.

As the curtains of prediction rose, the forecasts bestowed upon us valuable glimpses into the future of nutrient use efficiency. The years 2022, 2024, 2026, 2028, and 2030 came alive with projected values, painting a vivid picture of possibilities. Nitrogen use efficiency (NUE) emerged as the protagonist of progress, embarking on an upward journey, its trajectory spanning from 56.10% to 59.30%. Phosphorus use efficiency (PUE), ever the shape-shifter, showcased its variability while embracing a general rise, ranging from 72.91% to 80.02%. These revelations, like treasures of wisdom, stand ready to guide policymakers and stakeholders, illuminating their path towards informed decisions and resource allocation for a sustainable harvest.

With this research, the doors swing open, inviting further exploration into the enigmatic mechanisms that shape the efficiency of nutrient utilization. A captivating range awaits, with nitrogen's secrets concealed within the enchanting bounds of 40% to 60%, while phosphorus and potassium's mysteries dance amidst the broader scope of 40% to 80%. By delving into these depths, the understanding gained shall lay the foundation for targeted strategies, empowering the agricultural realm to optimize sustainability and unlock the true potential of nutrient use efficiency.

In its totality, this study stands as a beacon of knowledge, shedding light on the symphony of nutrient utilization efficiency and its profound impact on the stage of crop production. Through the artistry of ARIMA modeling and the magic of forecasting, the researchers have gifted valuable insights to policymakers, stakeholders, and fellow scholars in the agricultural realm. Together, we embark on a harmonious journey, pursuing the noble quest for sustainable and efficient crop production systems.

## VIII. IMPLICATIONS

The implications of the study are highly intriguing and have significant implications for agricultural practices and sustainability. Here are some particularly interesting implications:

**Enhancing Nutrient Use Efficiency**: The research findings highlight the complex patterns and dynamics of nutrient utilization in crop production. Understanding these intricate relationships can help agricultural practitioners develop targeted strategies to improve nutrient use efficiency. By optimizing the utilization of nitrogen, phosphorus, and potassium, farmers can minimize waste and reduce the environmental impact of fertilizer application.

**Resilience of Nutrient Utilization:** The captivating narrative of periods of high efficiency, declines, and resurgences in nutrient use efficiency showcases the inherent resilience of crop plants and nutrient utilization systems. This resilience suggests that even in the face of changing agricultural practices and environmental conditions, there is a capacity for adaptation and recovery. Harnessing this resilience can be valuable for sustainable agricultural systems, as it demonstrates the potential for crops to maintain productivity while minimizing resource inputs.

**ARIMA Modeling for Forecasting**: The effectiveness of ARIMA modeling in predicting nutrient use efficiency provides a powerful tool for policymakers, stakeholders, and researchers in the agricultural sector. Accurate forecasting enables better decision-making, resource allocation, and policy formulation. By leveraging ARIMA models specific to each nutrient, stakeholders can make informed choices about nutrient management practices and optimize fertilizer use to maximize crop productivity while minimizing environmental impacts.

**Future Trends and Policy Development**: The forecasted values for nutrient use efficiency offer valuable insights into the expected trends in the coming years. Policymakers can utilize this information to develop long-term strategies and policies that promote sustainable agricultural practices. By understanding the projected increases in phosphorus use efficiency and the upward trend in nitrogen use efficiency, policymakers can support initiatives that encourage responsible fertilizer use and minimize nutrient losses to the environment.

**Mechanisms of Nutrient Utilization**: The research emphasizes the need for further exploration into the underlying mechanisms that shape nutrient utilization efficiency. Understanding the factors influencing nutrient uptake, utilization, and cycling in plants can lead to breakthroughs in crop breeding, agronomic practices, and fertilizer formulations. This deeper understanding can pave the way for innovative solutions that enhance nutrient use efficiency, reduce fertilizer dependency, and promote sustainable agricultural systems.

**Resource Optimization**: By accurately forecasting nutrient use efficiency (NUE) for nitrogen, phosphorus, and potassium, policymakers and farmers can optimize fertilizer application and minimize waste. This can lead to cost savings in agricultural production by reducing unnecessary fertilizer use while maintaining or even increasing crop yields.

**Sustainable Agriculture**: Maximizing NUE is crucial for sustainable agricultural practices. The study's findings can guide the development of targeted strategies to enhance nutrient use efficiency, thereby reducing the environmental impact associated with nutrient contamination. This aligns with the goals of sustainable agriculture, which aim to balance economic viability, environmental stewardship, and social responsibility.

**Food Production and Food Security**: With the projected global population expected to reach 9.1 billion by 2050, the demand for food is expected to increase significantly. The study's insights into future trends in nutrient use efficiency can help policymakers and stakeholders make informed decisions to meet the growing food demand. By optimizing fertilizer use and minimizing waste, agricultural productivity can be enhanced, contributing to improved food security at the global level.

**Resource Efficiency**: The study's findings can inform resource allocation decisions in the agricultural sector. By understanding the projected NUE values, policymakers can allocate resources more efficiently, ensuring that limited resources such as synthetic fertilizers are used effectively. This can lead to more sustainable use of resources and reduce the reliance on resource-intensive processes like the Haber-Bosch process for nitrogen production.

**Economic Impact**: Optimizing nutrient use efficiency can have positive economic implications. By reducing the amount of fertilizer needed while maintaining or increasing crop yields, farmers can potentially reduce their input costs and improve their profitability. This can contribute to the overall economic development of the agricultural sector.

**Environmental Sustainability**: Efficient fertilizer use has direct implications for environmental sustainability. Excessive or inefficient use of fertilizers can lead to nutrient runoff, contaminating water bodies and causing ecological imbalances. By improving nutrient use efficiency, the study's results can help mitigate these environmental impacts and promote sustainable agricultural practices.

Overall, the study's results have wide-ranging implications for economics and food security, including resource optimization, sustainable agriculture, enhanced food production, resource efficiency, economic impact, and environmental sustainability. By providing insights into nutrient use efficiency and its projected trends, the study can support decision-making processes and contribute to a more efficient and environmentally conscious agricultural landscape, and sustainable crop production systems that maximize productivity while minimizing environmental impacts.

## VII. FUTURE RESEARCH

The findings of this study present several opportunities for future research in the field of nutrient utilization and agricultural sustainability. Here are some potential avenues for further investigation:

1. **Mechanisms of Nutrient Utilization**: The study highlights the need for a deeper understanding of the underlying mechanisms that shape nutrient utilization efficiency. Future research could focus on elucidating the physiological, genetic, and environmental factors that influence the uptake, transport, and utilization of nitrogen, phosphorus, and potassium in crops. This knowledge could help identify key targets for crop improvement and inform the development of innovative agricultural practices.

2. **Fine-Tuning Forecasting Models**: While the ARIMA models employed in this study proved effective for predicting nutrient use efficiency, there is room for refinement and exploration of alternative modeling approaches. Future research could investigate the use of other time series forecasting methods, such as exponential smoothing, state-space models, or machine learning techniques, to improve the accuracy and robustness of nutrient use efficiency predictions.

3. **Long-Term Monitoring and Validation**: To validate the forecasted values and assess the accuracy of the models over an extended period, long-term monitoring of nutrient use efficiency in crop production systems is essential. Conducting field experiments and collecting data over multiple years would provide valuable insights into the actual trends and variability of nutrient use efficiency, further validating the forecasting models and enhancing their reliability.

4. **Integration of Additional Factors**: The study primarily focused on the historical trends and dynamics of nutrient use efficiency. Future research could explore the integration of additional factors that influence nutrient utilization, such as climate change, soil properties, cropping systems, and management practices. Understanding the interactions between these factors and

nutrient use efficiency would provide a more comprehensive understanding of the complexities involved and enable the development of holistic strategies for sustainable nutrient management.

5. **Comparative Analysis**: Conducting comparative analyses across different regions, crops, and management practices could provide valuable insights into the factors that drive variations in nutrient use efficiency. By studying systems with contrasting nutrient management strategies and environmental conditions, researchers can identify successful practices and share best management approaches that optimize nutrient use efficiency across diverse agricultural landscapes.

6. **Economic and Environmental Implications**: Further research could explore the economic and environmental implications of improving nutrient use efficiency in crop production. Assessing the cost-effectiveness of different strategies, analyzing the trade-offs between productivity and environmental impacts, and quantifying the potential reductions in fertilizer use and nutrient losses would contribute to the development of sustainable agricultural systems.

By pursuing these avenues of research, scientists can deepen our understanding of nutrient utilization efficiency, refine forecasting models, validate predictions, explore additional factors, and assess the broader implications of improving nutrient use efficiency. Such knowledge will support evidence-based decision-making and promote the development of sustainable and efficient crop production systems.

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