Leveraging Exogenous Insights: A Comparative Forecast of Paddy Production in Nepal Using ARIMA and ARIMAX Models

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Abstract

Using annual time series data from 1975 to 2022, this study analyzed the ARIMA (1,1,7) and ARIMAX (1,1,7) models to improve paddy production forecasts in Nepal. The ARIMA model was initially employed to forecast paddy production. The availability of agricultural land was subsequently included as an exogenous variable in the ARIMAX model (after a significant endogeneity test) to increase precision. In contrast to the ARIMA model, which predicted paddy production of 5787.64 metric tons per hectare for the year 2022, the ARIMAX model predicted 5681.17 metric tons per hectare. Compared to the ARIMA model's MAE (0.0295), MAPE (0.797), and RMSE (0.0373), the ARIMAX model exhibited better accuracy with lower values of MAE (0.0247), MAPE (0.667), and RMSE (0.0301). The results emphasize how crucial it is to include pertinent exogenous variables to capture important dynamics influencing agricultural output. The study has important ramifications for Nepalese policymakers and agricultural planners since it suggests that the ARIMAX model can provide additional insight for policies that maximize production and optimize land usage, hence promoting food security and economic stability.

***Keywords*:** paddy production, ARIMA, ARIMAX, agricultural land, forecast accuracy

***JEL Classification*:** Q11, C53, C22, Q15, C52

Introduction

Nepal's agricultural sector, once the cornerstone of the economy, faces a fascinating metamorphosis. While the service sector ascends, agriculture's share of the Gross Domestic Product (GDP) in the country exhibits a gradual descent (25.8 percent in the fiscal year 2021/22 to 24.7 percent in the fiscal year 2022/23), with the industrial sector remaining relatively constant (Ministry of Finance [MoF], 2023). Despite this shift, agriculture retains significant importance, contributing roughly 24.7 percent to GDP in the fiscal year 2022/23. Recent data from the MoF (2023) reveals a modest 3.9 percent increase in paddy production, a staple food cherished for generations. However, Dahal et al. (2016) highlighted a persistent nemesis - droughts. These recurring events pose a significant threat to agricultural productivity, particularly rice cultivation.

Currently, Nepal's paddy import landscape is undergoing a noteworthy shift. Data from Nepal Rastra Bank (NRB_a, 2023) revealed a promising decline in paddy imports. In the fiscal year 2022/23, import of paddy reached Rs. 36,404.3 Million, marking a significant 23.1

percent decrease compared to the previous year (Rs. 47,356 Million). This trend followed a similar decline observed between the fiscal year 2020/21 and 2021/22. While rice imports still constituted a notable 2.3 percent share of total imports in 2022/23, this downward trajectory hinted at potential progress towards self-sufficiency (NRB_a, 2023).

Nepal's government is taking bold steps to empower its farmers and bolster domestic food production. According to the MoF (2023), a key strategy is the Minimum Support Price (MSP) system, which guarantees a baseline income for farmers selling essential crops like paddy (rice). This year (2022/23), the MSP for paddy, wheat, and sugarcane has seen a welcome increase compared to the previous year. The outlook for food production is promising, with an expected 3.85 percent increase across paddy/rice, wheat, and corn. This positive trend stands in contrast to a projected 2.65 percent decline in industrial crops like sugarcane and jute. Notably, paddy production has already surpassed expectations, achieving a remarkable 6.90 percent growth in fiscal year 2022/23. Further fueling this progress is the innovative Superzone Development Program. Currently operational in 16 districts across Nepal, this program strategically focuses on specific crops in designated areas. Paddy Super Zones in 4 districts, for instance, provide targeted support for paddy cultivation. Paddy yields within these programs reach an impressive 4.71 metric tons per hectare, exceeding the national average of 3.81 metric tons per hectare. Similar trends are observed for wheat, maize, and vegetables. These results paint a compelling picture of the program's effectiveness in boosting agricultural output (MoF, 2023).

As the Nepal's agricultural landscape is undergoing a significant shift, while the service sector flourishes - agriculture, particularly paddy production, remains a cornerstone of the nation's economy and food security (MoF, 2023). Recent trends paint a promising picture, with a decline in paddy imports and impressive growth in domestic production. However, the ever-present threat of droughts necessitates proactive strategies for long-term sustainability.

To affirm this, Magar (2020) stated that though the service sector is dominant in the country, Nepal's agricultural sector, particularly paddy production, remains a cornerstone of the economy. While there is a positive correlation between domestic paddy/rice production and Nepal's Gross National Income (GNI), a surprising discovery emerged - imported paddy has a stronger impact on GNI (Magar, 2020). This seemingly contradictory finding fueled the motivation for the ARIMA and ARIMAX modelling perspective of the research. Magar (2020)'s further study suggested a misconnection between domestic production and its direct contribution to the economic growth, highlighting the need to optimize domestic rice production for economic benefit. This gap in his paper fueled to analyze historical data on paddy production, by forecasting the future trends and analyze it with the impact of an exogenous variable affecting the paddy production. Also, ARIMA/X models exceled at handling the inherent uncertainties associated with agriculture with an exogenous variable in consideration, such as droughts (however, in this paper we ignore the seasonal component). All this analysis was done because, Nepal's agriculture, particularly paddy production, remains crucial despite a growing service sector (MoF, 2023).

This research aims at developing a reliable ARIMA model for forecasting Nepal's paddy production at first and an ARIMAX model considering an exogenous variable to forecast the paddy production from both of the methods and compare the forecast errors between them thereby suggesting whether the incorporation of an exogenous variable results in better forecast or not. Ultimately, these forecasts inform policymakers, agricultural stakeholders, and future research, all working to strengthen Nepal's paddy production and achieve long-term food security, indicating its original contribution.

Review of the Literature

Sivapathasundaram and Bogahawatte (2012) shed light on the critical role of accurate paddy production forecasts in Sri Lanka. While the nation has achieved self-sufficiency in rice production, a cause for celebration, the rice sector continues to be burdened by rising expenditures. Highlighting the importance of informed decision-making for planning and import policies, the authors delve into historical and future trends of paddy production using time series analysis. To achieve this, they leverage data spanning 1952 to 2010 and construct an ARIMA model, a robust method specifically designed for time series forecasting. This model not only captures long-term trends in paddy production but also offers predictions for production changes over the following three years.

Arif (2014) investigated the application of the Box-Jenkins ARIMA model for forecasting rice production in Bangladesh. His study focuses on identifying optimal models for the three rice cultivation seasons: Aus, Aman, and Boro. Utilizing data obtained from the Bangladesh Agricultural Ministry website, the research employs ARIMA to develop separate models for each season. The analysis identifies ARIMA(2,1,2) as the most suitable model for both Aus and Aman rice production, while ARIMA(1,1,3) proves most effective for Boro rice. The study further validates the chosen models by comparing original rice production data with the forecasted series. This comparison reveals a strong alignment, suggesting the models' effectiveness for short-term rice production forecasting in Bangladesh.

Prakash and Muniyand (2014) investigated the challenge of forecasting sugarcane production in India through a study employing secondary data encompassing 43 years (1970-71 to 2012-13), the authors leverage the ARIMA model to analyze historical trends and predict future production levels. Their investigation identifies the ARIMA(2,1,0) model as optimal for sugarcane production forecasting. While the study acknowledges potential future increases in total cropped production, it also highlights the presence of fluctuations within the country's production data. The successful application of the ARIMA model suggested its utility in projecting future sugarcane growth, which can be a valuable tool for policymakers and stakeholders within the Indian sugar industry.

GC and Yeo (2020) addressed the critical issue of food security in Nepal through their study using autoregressive integrated moving average model. The research focused into this concern within the broader context of the Sustainable Development Goals (SDGs), which aim to eradicate hunger globally by 2030. To address this challenge, the study employs the ARIMA (Autoregressive Integrated Moving Average) model by analyzing rice production and yield data from 1961 to 2017, obtained from the Food and Agriculture Organization (FAO) database. The ARIMA model forecasts a moderate increase in both rice area and yield by 2030, with average annual growth rates of 0.47 percent and 0.73 percent respectively. However, the study highlights a crucial finding: rice production is projected to increase at a decreasing rate. This suggested that even with rising production levels, Nepal may struggle to meet the ever-growing demand for rice. The authors conclude by emphasizing the importance of productivity improvements as a critical factor in ensuring food security for Nepal in the coming years.

Kumari et al. (2020) demonstrated the application of the ARIMAX model for forecasting castor production in India by incorporating rainfall as an exogenous variable. By analyzing data from 1966-67 to 2018-19, the authors identified the ARIMAX(1,1,1) model as the most effective, predicting an increase in castor production to 1547.05 thousand tons by 2020-21 and 1674.90 thousand tons by 2021-22. This model's ability to account for covariates enhances forecast accuracy and comprehensiveness, highlighting its potential utility for similar agricultural forecasts.

Mapuwei et al. (2022) investigated the declining trend of tobacco production in Zimbabwe, a nation where this crop represents the second most important cash crop after food staples. To address this concern and potentially formulate mitigating strategies, the researchers employed time series analysis on tobacco yield data spanning 1980 to 2018. Leveraging the ARIMA modeling framework, they aimed to forecast tobacco production for the period 2019-2023. The study adopted the Box-Jenkins methodology for model construction and utilized R software for data analysis. Their findings indicated that the ARIMA(1,1,0) model provided the most accurate forecasts. The predicted total yield displayed a continued decline, albeit with slight variations from the overall downward trend during the forecasted years. The authors emphasize the importance of various factors influencing future production levels, including the timely provision of agricultural inputs, farmer education and training programs, soil conservation practices, and supportive government policies.

Gaps in Research

Research on paddy production forecasting in Nepal has not extensively utilized both the ARIMA and ARIMAX models to be specific. Although previous studies have examined paddy production in Nepal and in neighboring countries, there is an opportunity to introduce new insights by applying ARIMAX models that account for an exogenous variable influencing paddy production in Nepal's distinct agricultural context. Moreover, existing forecasts typically do not extend beyond just forecasting and often overlook factors such as total agricultural land area, which are impacted by natural disasters and climate change. Addressing these gaps by comparing different forecasting models can enhance our understanding of paddy production in Nepal and provide valuable outlooks for policymakers.

Materials and Methods

Research Design

This study employs a time series inferential analysis approach with a focus on forecasting paddy production. While ARIMA and ARIMAX models are powerful statistical techniques commonly used in quantitative research for time series analysis and forecasting, it doesn't constitute a research design itself. The ARIMA model utilizes logged value of paddy production to forecast the paddy production. In the same way, an ARIMAX model assesses an exogenous variable and forecast the value of the paddy production. We assess the data's autocorrelation and partial autocorrelation to identify the appropriate ARIMA model dynamics for both the variables, that is, the paddy production and the exogenous variable. A parsimonious model selection approach was employed, followed by forecasting paddy production. To evaluate the model's robustness against potential future shocks, we conduct an inverse root test, confidence ellipse, endogeneity tests and set of comparisons of the forecast errors.

Data

The analysis utilizes annual time series data on paddy production and total agricultural land area available for paddy production (for exogenous variable) in Nepal, spanning from 1975 to 2022. The data source for paddy production is the Nepal Rastra Bank's Database on the Nepalese Economy (NRB_b, 2023). The data source for the agricultural land available in the country (*AGLAND*) is from the Database of World Bank (WB, 2023). The data *PADD* represents annual paddy production in metric tons per Hectare and *AGLAND* represents the total agricultural land area in Nepal (in square kilometers). Both the data have been taken under the log of base 10 to avoid any sorts of specific outliers.

Model Specification (ARIMA)

The ARIMA(p, d, q) model uses a combination of Autoregressive (AR) and Moving Average (MA) components to represent the underlying dynamics of paddy production data (*PADD*). These two components are represented theoretically as polynomials in the ARIMA model. The AR component considers the impact of previous *PADD* values on the current value, whereas the MA term incorporates the impact of previous forecast errors on the current prediction. The ARIMA(p, d, q) model is fitted to all data points in the *PADD* series with the goal of identifying the forecasts of paddy production. This enables more accurate projection of future output levels. The model is represented as under the reference of Enders (2017) and Chalabi et al. (2018).

$$y_t = a_0 + \sum_{i=1}^{p} a_i y_{t-i} + \sum_{i=0}^{q} \beta_i \varepsilon_{t-i} \dots\dots\dots\dots\dots\dots (1)$$

$$\Delta y_t = y_t - y_{t-1} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (2)$$

Where a_0= mean of the time series data.

p = autoregressive lags number.

a_i = the coefficients of AR.

q = lags of the MA processes.

β_i = the coefficients of MA.

ε = the error called as white noise.

d = the order the integration (number of differences mentioned by the equation… (2)).

An ARIMA model acts like a sophisticated language, using three parameters (p, d, q) to describe the patterns within the historical data and predict future values. Choosing the right settings for these parameters is akin to fine-tuning to achieve a clear signal. The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) are powerful tools that help to decipher the data's language. The ACF reveals the extent to which past values (correlations) influence the current value. By analyzing the ACF plot, we can identify lags (past time steps) that have a significant impact on the present, guiding us toward the appropriate p (number of autoregressive terms) in the ARIMA model. The PACF, on the other hand, isolates the influence of a specific past value on the current one, excluding the effect of earlier lags. Examining the PACF plot helps us determine the optimal q (number of moving average terms) needed to account for past forecast errors (Enders, 2017).

Validating the Model

Once we have tentative values for p, d (achieved through differencing to ensure data stability), and q, it's crucial to assess the model's performance. This involves conducting various diagnostic checks to gauge the model's robustness. These checks ensure that the model's residuals (errors) are random and not exhibit any patterns over time. If the residuals show patterns, it signifies that the model hasn't captured all the crucial patterns in the data. In such cases, we might need to revisit our p, d, or q values, or even explore alternative models altogether. The ultimate goal is to find a model that accurately reflects the data's underlying structure and generates reliable forecasts, just like a well-tuned radio delivers a clear and consistent signal. The different stages were used to conduct an ARIMA model, as described by Box and Jenkins (1970).

Model Specification (ARIMAX)

ARIMAX model uses a technique of the ARIMA with an exogenous variable. ARIMA is a univariate forecast, however, an ARIMAX uses a bivariate forecasting mechanism with a predictor variable. The predictor variable is determined with the relevant literature pertaining to the particular research. An exogenous variable is a variable used in the ARIMAX forecast also known as extraneous and predictor variables. It is not dependent on prior values of a dependent variable but can be utilized to explicate or foretell forthcoming values of such variables (Shumway & Stoffer, 2017). The model of ARIMAX with the exogenous variable is:

$$y_t = a_0 + \sum_{i=1}^{p} a_i y_{t-i} + \sum_{i=0}^{q} \beta_i \varepsilon_{t-i} + \sum_{k=0}^{r} \xi_k x_{t-k} + \epsilon_t \ldots\ldots\ldots\ldots\ldots\ldots..(3)$$

Equation (3) aligns with Equation 2 in terms of ARIMA modelling until an exogenous variable at time $t - k$ is added in Equation 1. The r is the maximum lags of the exogenous variable included (Shumway & Stoffer, 2017). All other descriptions align with that presented in the equation (1). Equation (2) is equally prevalent in the case of ARIMAX as the exogenous variable is differenced twice to make it stationary.[1]

Determination and Validation – Exogenous Variable

The availability of agricultural land in the country has a significant impact on paddy production, but it is not the major component; rather, it appears to be an external factor (Datta, 1981). In Nepal, the amount of paddy produced and the area in which it is grown are very important. Both variables have a close relationship (MoALD, 2017). With these references, this paper attempts to use the amount of land available for agriculture in Nepal as an exogenous variable for paddy production because the total agricultural land is yearly affected by several natural calamities and erosion, as well as urbanization and the use of heavy chemical fertilizers, which degrade the fine availability of agricultural land (MoALD, 2017). With this drawing, we assumed that the total area available for agriculture in the

[1]The order of the integration is I(2) for the exogenous variable. For more information in the further methodology domain. See, Enders (2017) and Shumway and Stoffer (2017).

country (*AGLAND*) is exogenous to the paddy production. However, we tested the variable *AGLAND* with the test of endogeneity with the help of Residual Correlation (RC) LM test.[2]

Process of RC-LM Test

Initially, the original ARIMA equation was run, and the residuals were obtained as Et. The lagged values (4 lags chosen at random) of the first differenced form of *AGLAND* (all with 4 lags) were then regressed against the Et. The least squares were then conducted, and the findings were used to determine whether or not the *AGLAND* had an endogeneity issue (Wooldridge, 2010).[3]

Robustness Tests

The validity and stability of the fitted ARIMA and ARIMAX models were assessed in this study using the inverse AR root test and the confidence ellipse test. To assess forecast accuracy, we analyzed the performance of various error metrics, such as Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Root Mean Squared Error (RMSE)[4] (Box & Jenkins, 1970).

Results and Discussion

Paddy Production

Nepal has experienced an increase, in paddy production over the years as shown in the diagram despite some fluctuations. While the chart illustrates a growth in paddy output since 1975 there have been periods of both decline and growth. Various factors contribute to these production fluctuations. The primary factor is weather patterns with sufficient monsoon rainfall being crucial for paddy growth. However, droughts or excessive flooding can have an impact on yields. Moreover, long term climate changes such, as rising temperatures can also disrupt paddy cultivation. Another factor that affects production is the presence of pests and diseases that affects the paddy directly (MoALD, 2022).

The reasons behind the variations in Nepal's paddy yield are manifold. Firstly, the production of paddy is often impacted by unpredictable monsoons, droughts, and floods, all of which are consequences of climate change. Unpredictable rainfall patterns worsen by inadequate irrigation infrastructure. Production levels are also greatly influenced by the quality and availability of pesticides, fertilizers, and paddy seeds. Farmers' capacity to adopt new farming techniques and technology is hampered by socioeconomic issues, such as access to loans and agricultural extension services. Inheritance regulations cause land to become fragmented, which results in smaller, less productive farming units and lower total productivity. These are the reasons of the fluctuations of the paddy production as depicted in Figure 1 (MoALD, 2022; USAID, 2017).

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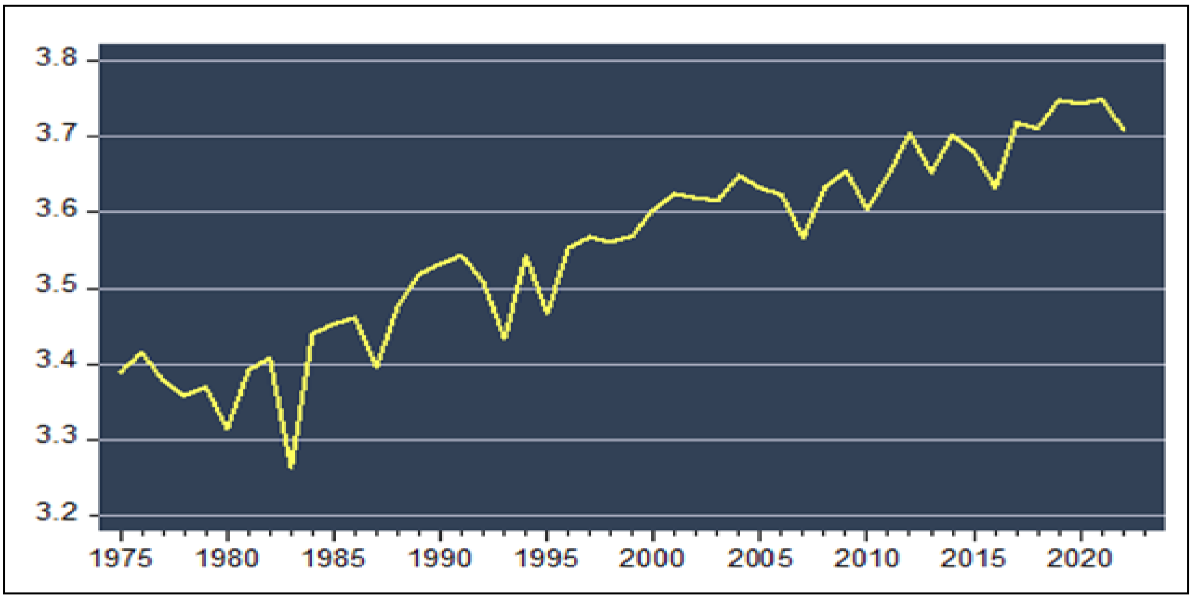
[2]The endogeneity test was required to determine that land available for agriculture (*AGLAND*) and paddy production have no significant relationship and to confirm that the variable *AGLAND* was exogenous for the *ARIMAX* model. We used the Residual Correlation LM evaluate to evaluate endogeneity using the null hypothesis (H_0: The explanatory variables are endogenously related to the error term in the *ARIMA* model). This paper omitted other endogeneity tests such as the Hausman test, the Sargan Hansen test, and the IV with SURE tests (Wooldridge, 2010).

[3] See Wooldrige (2010)'s book for the equational outlook in RC-LM Test.

[4] See Hyndman and Athanasopoulos (2018)'s book for the equational outlook of forecast errors.

Figure 1

Paddy Production in Nepal



Unit Root Tests

Before developing a Box Jenkins method, unit root tests were performed. The Augmented Dicky Fuller test determined the stationarity of the data and used in the analysis of an autoregressive model. The ADF test revealed that the *PADD* is stationary at the first I(1)[5] while *AGLAND* is stationary at I(2)[6]. This demonstrated that the data does not exhibit a steady pattern and hence is suitable for analysis using the ARIMA approach to forecast values.

Model Testing and Identification – Correlogram Test

The graph depicts the autocorrelation (ACF) and partial autocorrelation (PACF) functions for the non-differenced and differenced log-transformed paddy production series, indicated by *PADD*. These functions evaluated the stationarity of a time series. The ACF calculated the correlation between a time series and its lag variants. The ACF was plotted on the graph at lags 1-20. A lag of one indicates comparing the current value of the series to the value one period earlier. A lag of two indicates comparing the present value to the value two periods ago, and so on. The PACF is similar to the ACF, except it eliminates correlation caused by earlier lags. It assisted in identifying the lags at which the series exhibited considerable autocorrelation that was not caused by previous correlations.

The variable, paddy production, shown that it is not stationary at level in the correlogram represented below. This visualization demonstrated how this variable qualifies for ARIMA analysis, modelling the non-stationarity, and hence forecasting paddy production statistics.

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[5] The ADF test stat (constant no trend), t-stat at I(1) was -10.93 < 2.93 (.05 level of significance) which rejected the H_0 of presence of unit root in *PADD.*

[6] The ADF test stat (constant no trend), t-stat at I(2) was -6.13 < 2.93 (.05 level of significance) which rejected the H_0 of presence of unit root in *AGLAND.*

Table 1

ACF and PACF on Level and at the First Difference

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.869	0.869	38.564	0.000
		2	0.821	0.267	73.701	0.000
		3	0.774	0.086	105.68	0.000
		4	0.695	-0.130	132.03	0.000
		5	0.634	-0.042	154.47	0.000
		6	0.561	-0.083	172.44	0.000
		7	0.503	0.013	187.26	0.000
		8	0.462	0.066	200.07	0.000
		9	0.371	-0.187	208.53	0.000
		10	0.339	0.085	215.81	0.000
		11	0.261	-0.156	220.24	0.000
		12	0.251	0.234	224.43	0.000
		13	0.188	-0.192	226.85	0.000
		14	0.140	0.035	228.24	0.000
		15	0.122	-0.015	229.32	0.000
		16	0.081	-0.002	229.81	0.000
		17	0.041	-0.043	229.94	0.000
		18	0.001	-0.126	229.94	0.000
		19	-0.077	-0.150	230.44	0.000
		20	-0.097	-0.009	231.25	0.000

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.461	-0.461	10.636	0.001
		2	-0.066	-0.353	10.858	0.004
		3	0.127	-0.112	11.696	0.009
		4	-0.061	-0.084	11.896	0.018
		5	-0.026	-0.086	11.932	0.036
		6	0.085	0.024	12.338	0.055
		7	-0.134	-0.117	13.378	0.063
		8	0.052	-0.083	13.536	0.095
		9	-0.073	-0.204	13.859	0.127
		10	0.187	0.092	16.025	0.099
		11	-0.294	-0.265	21.553	0.028
		12	0.236	0.013	25.208	0.014
		13	-0.058	-0.067	25.438	0.020
		14	-0.092	-0.114	26.029	0.026
		15	0.199	0.107	28.889	0.017
		16	-0.061	0.056	29.164	0.023
		17	-0.062	0.105	29.459	0.031
		18	0.082	0.000	29.993	0.038
		19	-0.157	-0.116	32.009	0.031
		20	0.152	-0.021	33.974	0.026

After the first difference in the variable, paddy production, the data became stable; nonetheless, there are indications that some of the delays remain non-stationary. The ACF was shown with lags ranging from 1 to 20. If all of the p-values for distinct lag structures were greater than the 5 percent level of significance, the data on paddy production would be validated as stationary at the first difference while analyzing the correlogram. This analysis provides the path for further investigation into why the variable is not stationary at various lags, indicating that the ARIMA approach should be used to forecast the study's data. The proposed order of differencing is 1, thus d = 1. After this analysis, the several values of p and q are assessed. The value of p and q, both were as 1, 2, 3, and 7 respectively which led to develop the following ARIMA models (Box & Jenkins, 1970).

ARIMA Models Selection

The proposed ARIMA models were, viz., ARIMA(1,1,1), ARIMA(1,1,2), ARIMA(1,1,3), ARIMA(1,1,7), ARIMA(2,1,3), ARIMA(3,1,1), ARIMA(7,1,1). These models were chosen for testing under the condition that the model with the lowest AIC and SIC values, an AR and MA roots falling inside the unit circle position as well as the highest SIGMASQ and R^2 values, would be opted for forecasting PADD (Box and Jenkins, 1970).

Table 2

ARIMA Models Selection Criterion

S.N	ARIMA Models	AIC	SIC	SIGMASQ	R^2	AR and MA root position
1.	ARIMA (1,1,1)	-3.2512	-3.0937	0.0017	0.4265	Circumference of the circle
2.	ARIMA (1,1,2)	-3.2303	-3.0729	0.0017	0.4188	Circumference of the circle
3.	ARIMA (1,1,3)	-3.0246	-2.8671	0.0024	0.2279	*Inside the circle*
4.	ARIMA (1,1,7)	-3.0341	-2.8766	0.0024	0.2386	*Inside the circle*
5.	ARIMA (2,1,3)	-2.7851	-2.6276	0.0031	0.0142	*Inside the circle*
6.	ARIMA (3,1,1)	-3.2488	-3.0914	0.0017	0.4260	Circumference of the circle

Note. Author's Calculation.

In ARIMA models, inverse roots within the unit circle suggest a stable and invertible model, which is crucial for effective forecasting, implying that models 1, 2, and 3 do not meet the model selection requirements. Models 3, 4, and 5 appeared to be suitable for future forecasting operations because their AR and MA roots met the unit circle criterion (Hyndman

& Athanasopoulos, 2018). Model 4 has the lowest AIC and SIC values among models 3, 4, and 5. Though model 4 has the lowest SIGMASQ value to model 5, it exhibits the highest R^2 value. After conducting all of these analyses, the ARIMA(1,1,7) model was determined to be the best for predicting (Box & Jenkins, 1970).

ARIMA - Robustness Tests

Figure 2 depicted the inverse roots of the AR and MA polynomials from the ARIMA(1,1,7) model, which is used to forecast paddy production. The red circle indicated the AR root, while the green dots represent the MA roots, which are all drawn within a unit circle. To be stable and suitable for forecasting, all of these roots must be within the unit circle. In this figure, all roots are within the circle, showing that the model's autoregressive and moving average components are stable and invertible. This assures that the ARIMA (1,1,7) model is well-specified and capable of generating dependable and steady paddy production estimates without exhibiting non-stationary behavior (Box et al., 2015).

Figure 2

Inverse Roots Test (ARIMA)

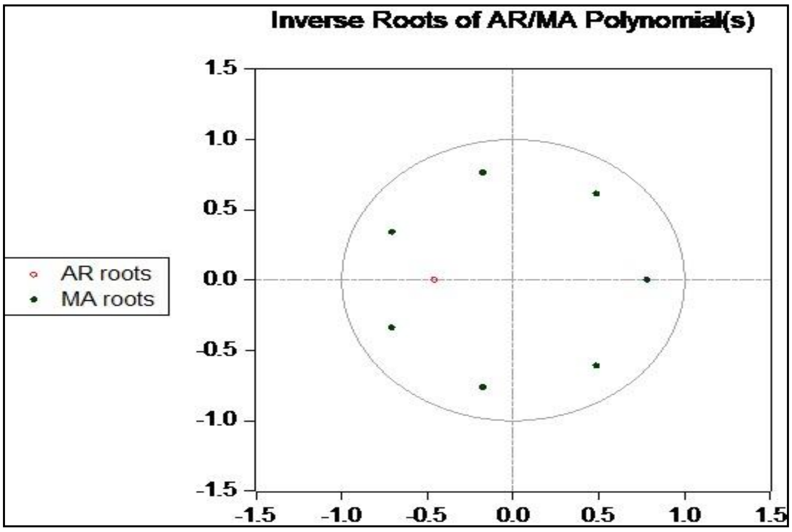
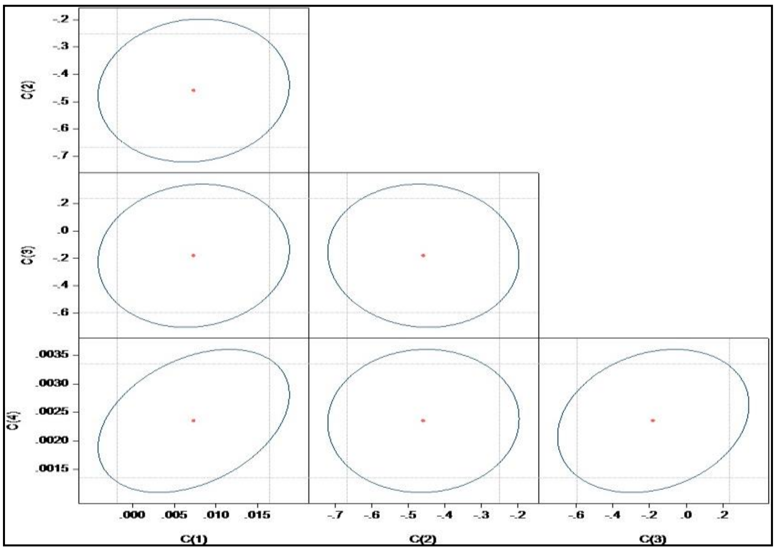


Figure 3 illustrates a confidence ellipse analysis. The overall structure of the ellipses indicates that the ARIMA (1,1,7) model's components are relatively independent, with some minor relationships. The greater association between C(4) and C(2) implies that these components may interact, affecting the model's accuracy. The absence of strong connections (as evidenced by the near-circular forms of most ellipses) shows that the model is well-specified and that the components are neither redundant or overly dependent. This ellipse suggested that the ARIMA (1,1,7) model for forecasting paddy production was built with primarily independent components and only a few weak correlations. This showed a robust model with slight difficulties with multicollinearity, while the association between C(4) and C(2) may require further investigation, however, the robustness was fine (Box et al., 2015; Hyndman & Athanasopoulos, 2018).

Figure 3

Analysis of the Confidence Ellipse (ARIMA)

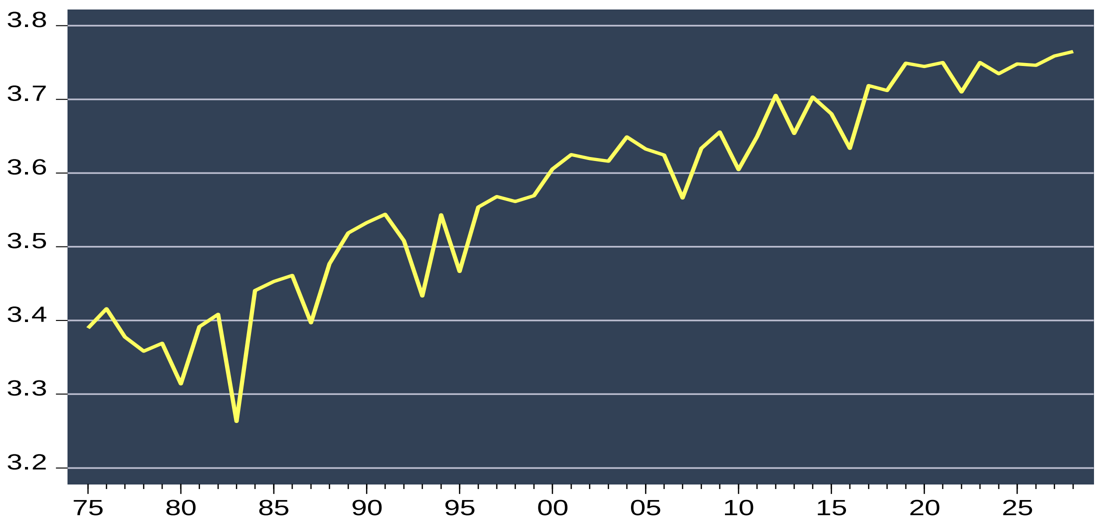


Forecasting – Out Sample (ARIMA)

Paddy production is projected to keep up till year five, from 2023 to 2027. The anticipated paddy yields for 2023, 2024, 2025, 2026, and 2027 were 5623.48, 5427.04, 5596.09, 5574.42, and 5737.15 metric tons per hectare. This forecasted figure appears to be increasing at a lowering pace from 2022 to 2026, then increasing at an increasing rate in 2027. This demonstrated the policy of import limits on paddy, which takes around 4 years to enhance paddy production in the country. This necessitates an immediate legislative response to provide farmers with financial and technical assistance for production in their own nation. This also corresponded with seed restoration and the enhancement of seed banks in the country, particularly for farmers, so that they can save seeds if weather disrupts paddy production in a given year (MoALD, 2022).

Figure 4

ARIMA Out Sample Forecast – Paddy Production



ARIMAX Model

The ARIMAX model accommodates for the inclusion of an exogenous variable in an ARIMA setup for improved forecast accuracy (Enders, 2017). After applying the exogenous variable, *AGLAND*, it was subjected to endogeneity tests, which revealed that *AGLAND* was exogenous and had no direct effect on paddy production. Therefore, its usage in ARIMAX was justified. The endogeneity test was performed using an LM test, which is shown in Table 4 (Box & Jenkins, 1970).

The endogeneity tests were conducted to ensure that the exogenous variable *AGLAND* was not endogenously related to the residuals generated from the ARIMA(1,1,7) paddy production process. The ARIMA(1,17) residuals were obtained and regressed with the four lags (chosen arbitrarily[7]) of *AGLAND*, which was regressed with the ET_PADDY - the ARIMA(1,1,7) residuals. All of the lagged coefficients had p-values greater than .05, rejecting the null hypothesis that the *AGLAND* possessed endogeneity. Following this evaluation, the exogenous variable, *AGLAND*, was determined to be appropriate for the ARIMAX(1,1,7) model setup (Shumway and Stoffer, 2017).

Table 4

LM Test for the Test of the Endogeneity (ARIMAX (1,1,7))

Dependent Variable: ET PADDY(*ARIMA(1,1,7)),* EXOG VAR: AGLAND
Method: Least Squares
Date: 05/21/23 Time: 23:03
Sample (adjusted): 1981 2022
Included observations: 42 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.002583	0.008015	0.322291	0.7491
D(D(AGLAND))	-2.409272	8.697158	-0.277018	0.7834
D(D(AGLAND(-1)))	2.778675	12.26855	0.226488	0.8221
D(D(AGLAND(-2)))	-17.27457	12.50359	-1.381568	0.1756
D(D(AGLAND(-3)))	-4.984943	12.50021	-0.398789	0.6924
D(D(AGLAND(-4)))	6.705714	12.05974	0.556042	0.5816

R-squared	0.076775	Mean dependent var	0.002912
Adjusted R-squared	-0.051451	S.D. dependent var	0.050060
S.E. of regression	0.051332	Akaike info criterion	-2.969438
Sum squared resid	0.094859	Schwarz criterion	-2.721199
Log likelihood	68.35820	Hannan-Quinn criter.	-2.878449
F-statistic	0.598745	Durbin-Watson stat	2.424844
Prob(F-statistic)	0.701080		

ARIMAX Forecast

The exogenous variable *AGLAND* was utilized as a covariate and was regressed alongside the ARIMA(1,1,7) model, with the first differenced variable of paddy production as the dependent variable, and the forecast was evaluated appropriately. Because *AGLAND* is limited to 2022, we used a year's (2022) worth of projections to compare ARIMA with ARIMAX, with a focus on forecast errors. We did this to get rid of the bias in the prediction results, as forecasting the variable *AGLAND* with ARIMA for ARIMAX(1,1,7) would result in an overfitted model and not so parsimonious model (Shumway and Stoffer, 2017). To

[7] See, Box and Jenkins (1970)

achieve this, the model described by equation 3 was run, and its robustness tests were then analyzed.

$$PADD_t - PADD_{t-1} = AR(PADD_{t-1} - PADD_{t-2}) + MA_1\varepsilon_{t-1} + MA_2\varepsilon_{t-2} + \cdots + MA_7\varepsilon_{t-7} + CAGLAND(AGLAND_t - 2AGLAND_{t-1} + AGLAND_{t-2}) + \epsilon_t \quad \text{.....................(3)}$$

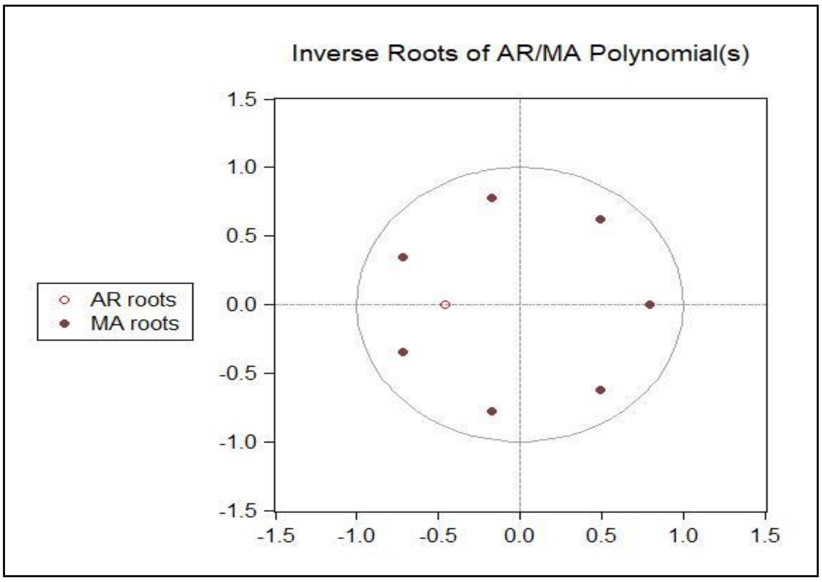
The *CAGLAND* was the coefficient for the second differenced *AGLAND*. When Equation (3) was run to test of the normal distribution, the Jarque Bera test was assessed. The JB value was 2.34 and it was statistically significant as well (being p-value of JB stat – 0.31>.05) (Box and Jenkins, 1970).

ARIMAX – Robustness Tests

The inverse root and confidence ellipse were analyzed for the robustness test of the ARIMAX(1,1,7) model. Figure 4 represented the AR roots. The model performed better once exogenous variable *AGLAND*, was employed. The inverse root plot indicated that every root lies inside the unit circle, reinforcing the model's stationarity and invertibility. When seen as a whole, these charts show how resilient the ARIMAX model is, producing reliable and consistent projections in spite of the data's intrinsic fluctuation (Box and Jenkins, 1970; Box et al., 2015).

Figure 5

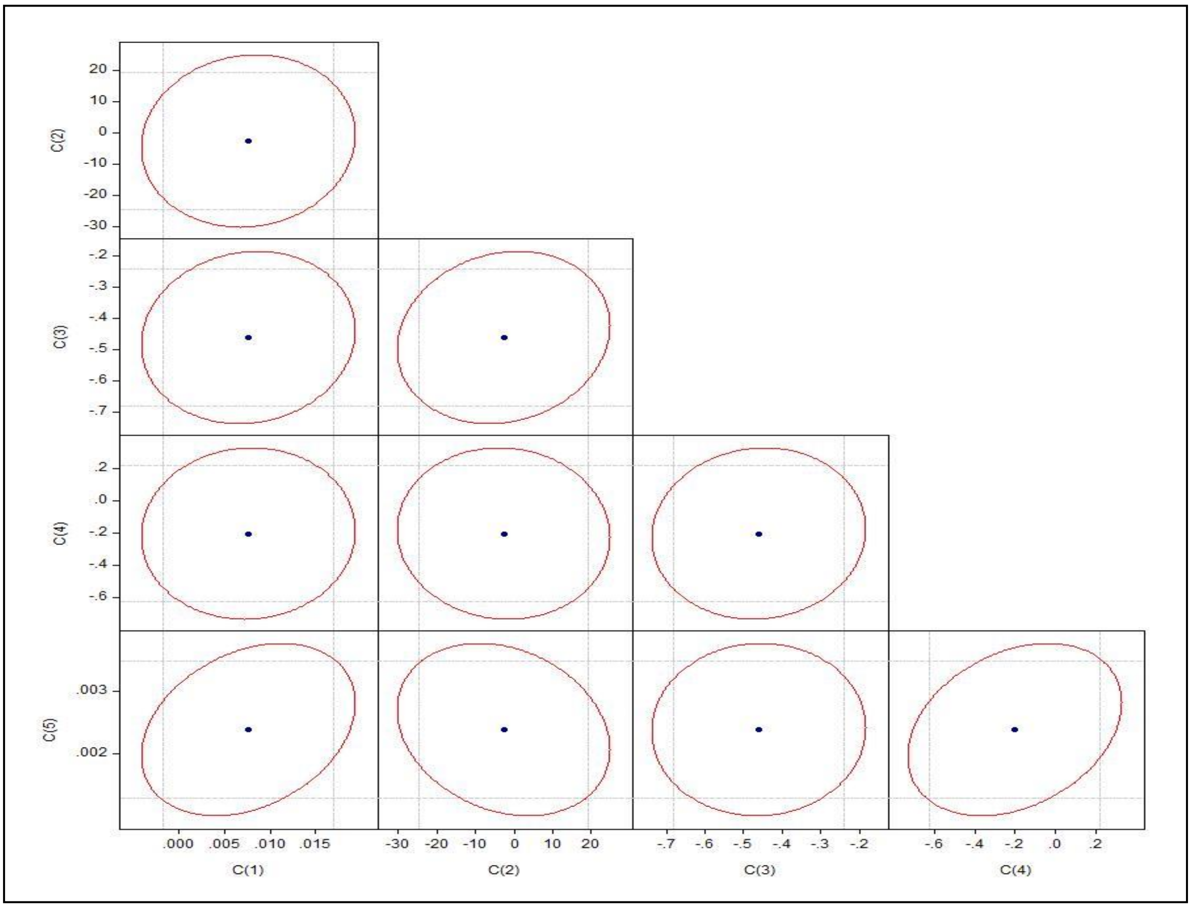
Inverse Roots Test (ARIMAX)



After this the confidence ellipse was analyzed. Figure 5 analyzes the confidence ellipse. *AGLAND* is an exogenous variable used to anticipate paddy production. The confidence ellipse plot shows how robust the ARIMAX(1,1,7) model is in this regard. An ARIMA(1,1,7) model was used at first, but the addition of *AGLAND* improved the model's capacity for explanation. A pair of coefficients was represented by each subplot, and the ellipses show the 95 percent confidence interval for the true values of the parameters. The estimated parameter values were represented by the blue dots in the ellipses' centers. The parameter estimates appear to be stable and not unduly sensitive to slight variations in the data or model assumptions, as indicated by the red ellipses that closely encircle the blue dots without being too stretched or distorted. This stability suggests that despite the inherent unpredictability in the data, the ARIMAX(1,1,7) model is robust and consistently produces accurate estimates (Box et al., 2015).

Figure 6

Confidence Ellipse (ARIMAX)



Forecasting Comparisons (In sample) ARIMA vs. ARIMAX

The in-sample forecasts of Nepal's paddy production for the year 2022 indicate clear distinctions between the ARIMA and ARIMAX models. With *AGLAND* considered as an exogenous variable, the ARIMAX model predicts a little lower paddy production of 5681.17 metric tonnes per hectare than the ARIMA model, which predicted 5787.64 metric tonnes per hectare in the year 2022. The ARIMA model's MAE of 0.0295, MAPE of 0.797, and RMSE of 0.0373 were higher than the accuracy values for the ARIMAX model, which are 0.0247, 0.667, and 0.0301, respectively. Better model performance and forecasting accuracy were indicated by lower values of these parameters. The ARIMA model overlooked certain important dynamics and limits of paddy production, which the additional variable most likely represented. The ability to cultivate paddy is directly influenced by the availability of agricultural land, and modifications or constraints in this regard may have a substantial effect on output levels. The ARIMAX model takes these real-world conditions into account by incorporating *AGLAND*, which may result in a more conservative and possibly more realistic forecast. This shows that the lower production estimate in the ARIMAX model may have been caused by elements like land restrictions or less-than-ideal use of available land (Box et al., 2015; Hyndman & Athanasopoulos, 2018).

The inclusion of the exogenous variable, *AGLAND*, appears to enhance the model's ability to capture the underlying factors affecting paddy production, leading to more precise predictions. The lower MAE, MAPE, and RMSE values for the ARIMAX model indicate that it has fewer errors and better fits the historical data compared to the ARIMA model. Therefore, we can conclude that the ARIMAX model, which integrates additional relevant information about agricultural land availability, offers a superior forecasting capability for paddy production in Nepal (Shumway and Stoffer, 2017).

Conclusion and Further Scope

Conclusions

The results lead one to infer that significant insights concerning the significance of adding exogenous variables, such as agricultural land availability, are revealed by comparing the ARIMA and ARIMAX models for forecasting paddy production in Nepal. In comparison to the ARIMA model, the ARIMAX model—which incorporated *AGLAND*—provided a more accurate and lower estimate for 2022, indicating a more realistic scenario given Nepal's land limits. This implied that the availability and use of agricultural land have a substantial impact on paddy production, in addition to past production trends. The results of this study are consistent with those of Hyndman and Athanasopoulos (2018), who stressed the need to include pertinent external elements in forecasting models to increase their accuracy and dependability. Integrating such variables becomes even more important in the context of Nepal, where land resources are scarce and agriculture is a major economic driver. Agricultural land is an exogenous variable that is especially crucial in the context of Nepal, because it employed a large number of people and contributed significantly to GDP. Due to factors including restricted access to better seeds, technology, and market possibilities, climate vulnerabilities, Nepal's agricultural output suffers, which hurts rural economies and increases food insecurity (USAID, 2017). A more sophisticated understanding of the variables affecting productivity was shown in the ARIMAX approach, which incorporated agricultural land availability into the forecasting model. Initiatives like the Food and Nutrition Security Enhancement Project (FANSEP), which emphasized the need for enhanced agricultural techniques and resilience, promote this strategy (MoALD, 2022).

The ARIMAX model's improved forecasting accuracy for paddy production indicated how useful it is for strategic planning and policy-making in Nepal. Considering how important agriculture is to Nepal's economy and food security, using models that include important exogenous variables can aid in the development of more effective plans to boost output and alleviate food insecurity. As shown by numerous international and local agricultural projects, the results seem to highlight the potential of such models to support initiatives meant to improve agricultural productivity and resilience in vulnerable areas.

Further Scope

Future studies on paddy production predictions may consider more exogenous variables including the amount of precipitation, the state of the weather, the availability of seeds, and many more. Additionally, it might use SARIMA/SARIMAX models and include the Seasonal Component Assessment. Furthermore, for more accurate forecasting mechanisms, researchers in the future may choose to employ, panel data, deep learning techniques with neural networks, and large volumes of data.

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Appendix

Level Data for Variable of Interest

Year	Paddy Production ('000 metric tons)	Agricultural land (in square kms.)
1975	2452	40090
1976	2605	40250
1977	2386	40400
1978	2282	40550
1979	2339	40700
1980	2060	40850
1981	2464	41030
1982	2560	41066
1983	1833	41102
1984	2757	41138
1985	2837	41164
1986	2892	41320
1987	2494	41346
1988	2999	41382
1989	3302	41408
1990	3409	41444
1991	3498	41470
1992	3223	41582
1993	2712	41694
1994	3493	41806

Year	Paddy Production ('000 metric tons)	Agricultural land (in square kms.)
1995	2928	41918
1996	3579	42030
1997	3699	42142
1998	3641	42254
1999	3710	42366
2000	4030	42491
2001	4216	42590
2002	4165	42410
2003	4132	42270
2004	4456	42180
2005	4290	42020
2006	4209	41850
2007	3681	41660
2008	4299	41520
2009	4524	41400
2010	4024	41260
2011	4460	41266
2012	5072.0	41210
2013	4504.0	41210
2014	5047.0	41210
2015	4788.61	41210
2016	4299.08	41210
2017	5230.33	41210
2018	5151.92	41210
2019	5610.01	41210
2020	5550.88	41210
2021	5621.71	41210
2022	5130.62	41600

Note. NRB (2023_b) and WB (2023)