# Forecasting Ecuador's Oil Production: Assessing the impact of halting exploitation in Block 43-ITT

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## Abstract

This project forecasts Ecuador's oil production using annual (1972–2024) and monthly (2007–2024) data, incorporating WTI prices and Block 43-ITT output. We compare several time series models—ARIMA, ETS, Holt, TBATS, neural nets, and state-space variants—identify TBATS as top performer for monthly forecasts, then simulate a shutdown of Block 43-ITT. Results show an average monthly production gap of 1,656,682 barrels (19,880,180 total) that other blocks must fill to maintain output.

## Introduction

Ecuador's economy has been heavily reliant on oil exploitation for over five decades. As is shown in (**garcia-alban_good_2021?**) a result, the oil revenue is the most important driver of the national GDP.
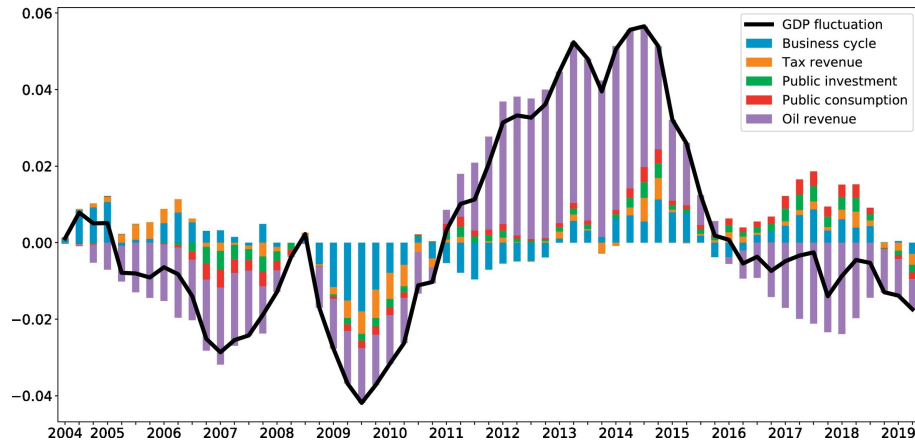


Figure 1: GDP fluctuations vs oil revenue between 2004-2019

## Motivation

- The oil well known as Block 43-ITT is located within Ecuador's Yasuní National Park—one of the most biodiverse places on Earth and home to Indigenous communities (UNESCO, 2024).

- Oil exploitation in that well began in 2016 as part of efforts to boost fiscal revenues (Banco Central del Ecuador, 2023).

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- In the 2023 national referendum, the Ecuadorian population voted to halt extraction in that well (Corte Consitutional del Ecuador, 2023).

- The decision was driven by the growing environmental and Indigenous rights movement and marked a significant shift in Ecuador's natural resource policy.

# Relevance

The government is now responsible for phasing out extraction while addressing the economic implications—especially those related to oil production levels and public revenues.Evaluating how reduced production affects overall output is critical for policy and planning future decisions on resource management.

# Objective

- This final project aims to forecast oil production in Ecuador for the forthcoming years, following the halt of extraction in Block 43-ITT, which raises questions about future national income.

1. **Quantitative Forecasting** – Produce monthly projections of national oil output through December 2027 under *baseline* and *halt* scenarios.
2. **Model Comparison** – Evaluate candidate models that accommodate seasonality, economic drivers, and structural breaks, selecting the most accurate and parsimonious specification.
3. **Decision Metrics** – Translate production deltas into fiscal terms (revenue and royalties), and present uncertainty ranges to guide policy trade-offs.

# Dataset information

- **Annual series:** Total barrels per year 1972–2024 (Government forecasts extend to 2029).
- **Monthly series:** Jan 2007–Dec 2024 total production, WTI price, Block 43-ITT output (2016–2023).

Data were cleaned and aligned in R; the annual series uses frequency 1, monthly uses frequency 12. We focus annual analysis on 2000–2023 to avoid pre-2000 volatility.

# Analysis (Methods and Models)

- **Stage A** (Annual-Level Analysis):

  - We use an annual series (1972–2024) to analyze the long-run production trend.

- **Stage B** (Monthly-Level Analysis)

  - We use monthly dataset (2007–2024) for a more detailed (higher-frequency) forecast.
  - Additional variables:
    * Monthly WTI prices
    * Monthly block-level production of Block 43 ITT.

- **Stage C** (Scenario analysis)

  The idea is that if we trust the long-run historical trend from the annual model, we can ensure that the sum our monthly forecasts matches the trend predicted by the annual model.

- **Baseline forecast:** assuming Block 43 ITT continues as historical.
- **Shutdown Scenario:** set Block 43 ITT output to zero in 2024.

The difference in total production between the baseline and shutdown forecasts is the gap that other blocks must fill to maintain the same output level.

## Stage A (Annual-Level Analysis):

We used an annual series (1972–2024) to analyze the long-run production trend.

**Annual Data**

The chart below illustrates the trajectory of Ecuador's annual oil output, which surged dramatically from the 1970s through the early 2000s. Following this period of rapid growth, production plateaued but remained substantially higher than pre-2000 levels. By the early 2020s, output had gradually declined to around 170 million barrels, possibly influenced by aging fields, constrained investment, the effects of the pandemic, or a combination of all.

The solely visualization may suggest that including data from before 2000 —when output was only a fraction of its subsequent levels— could distort our model's parameters. In contrast, restricting the sample to the period from 2000 onward, when production stabilized at its modern scale, is likely to yield a more accurate and relevant time series and forecasts. Considering this, analyzing the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) could provide valuable insights for determining the most appropriate research period, helping to identify patterns and lags in the data.
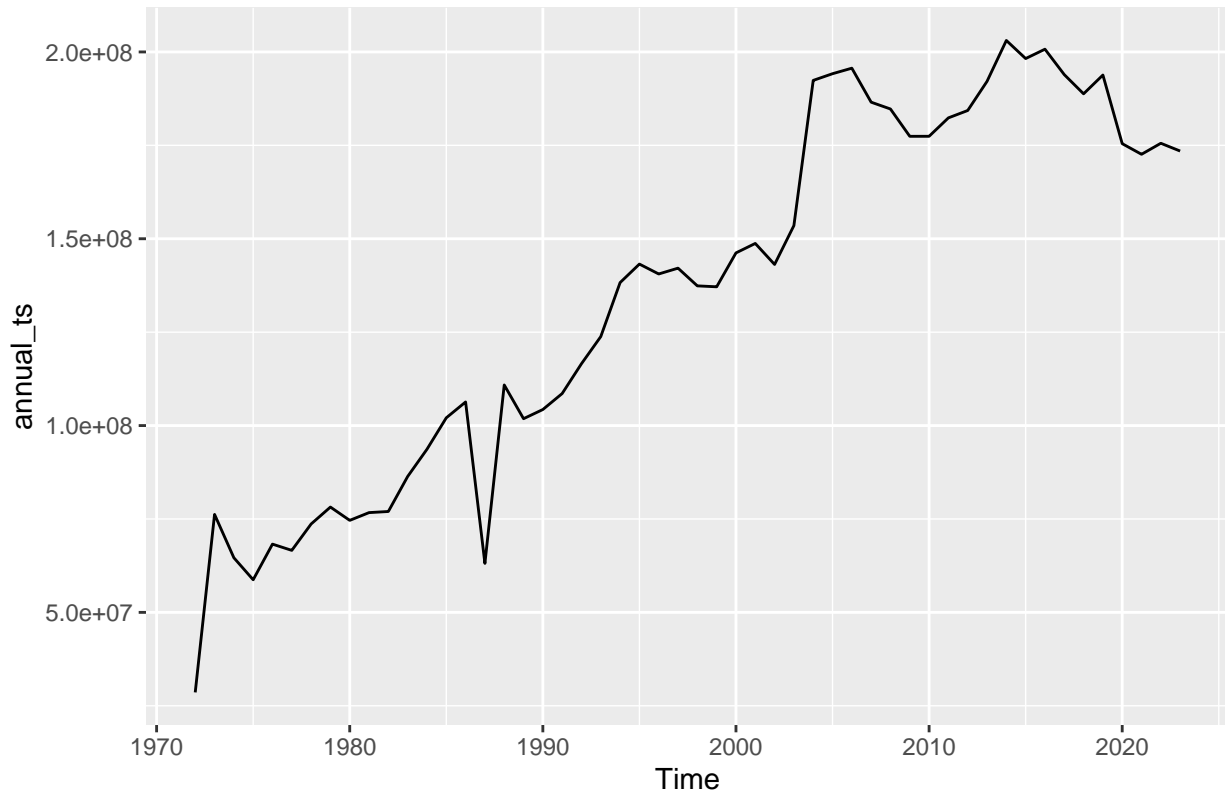
The sample ACF for the full series reveals strong autocorrelation extending up to approximately the 15 lag, beyond which the correlations sharply diminish, falling within the significance bounds for several years. This decline signals that the pre-2000 data may not exhibit meaningful memory. Similarly, the PACF presents a single significant spike at lag 1, which may suggest an AR(1) structure for the series.

From that information and given that pre-2000 output levels are an order of magnitude lower than post-2000 production and introduce disruptive long-lag noise, we confined our model to the 2000–2023 period, aiming at the model to gain precision and isolating the data's most relevant structural characteristics.
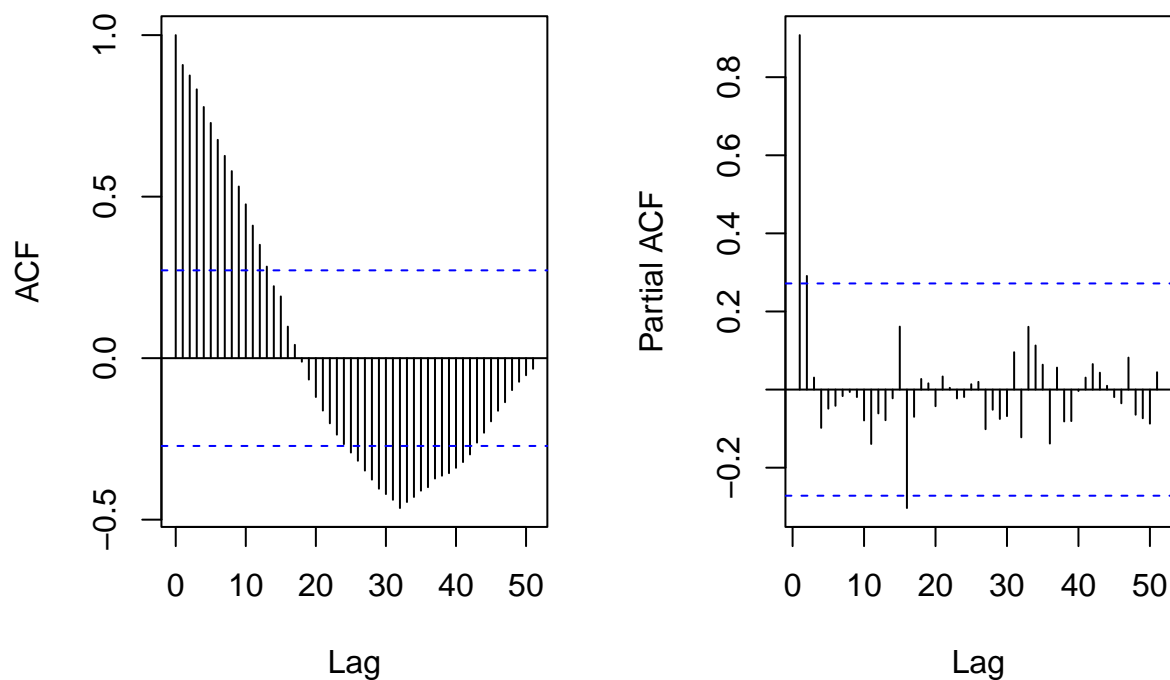


All the annual forecasting models were trained using data up to the year 2020. Because when using the pre-pandemic period, forecast performed poorly (see Annex).

**Model 1: ARIMA**

The "auto.arima" in the training time series, suggests using the ARIMA(0,1,0) model captures the general trend of Ecuador's oil production over time but demonstrates moderate accuracy when handling the data's inherent volatility (See Table 1). With a mean absolute percent error (MAPE) of 0.94 (94% error) and RMSE of approximately 2 million units, the model's performance is acceptable but not exceptional. The forecast shows relatively stable future production levels, though the wide confidence intervals (gray bands) indicate substantial uncertainty in these predictions. The Theil's U value of 0.54 suggests that while the model outperforms naive forecasting approaches, there remains considerable room for improvement in capturing the time series' complex patterns and fluctuations.

```
##      Point Forecast     Lo 80      Hi 80      Lo 95      Hi 95
## 2021      175449722 161191369 189708074 153643453 197255990
## 2022      175449722 155285366 195614077 144611001 206288442
## 2023      175449722 150753530 200145913 137680157 213219286
```

Forecasts from ARIMA(0,1,0)
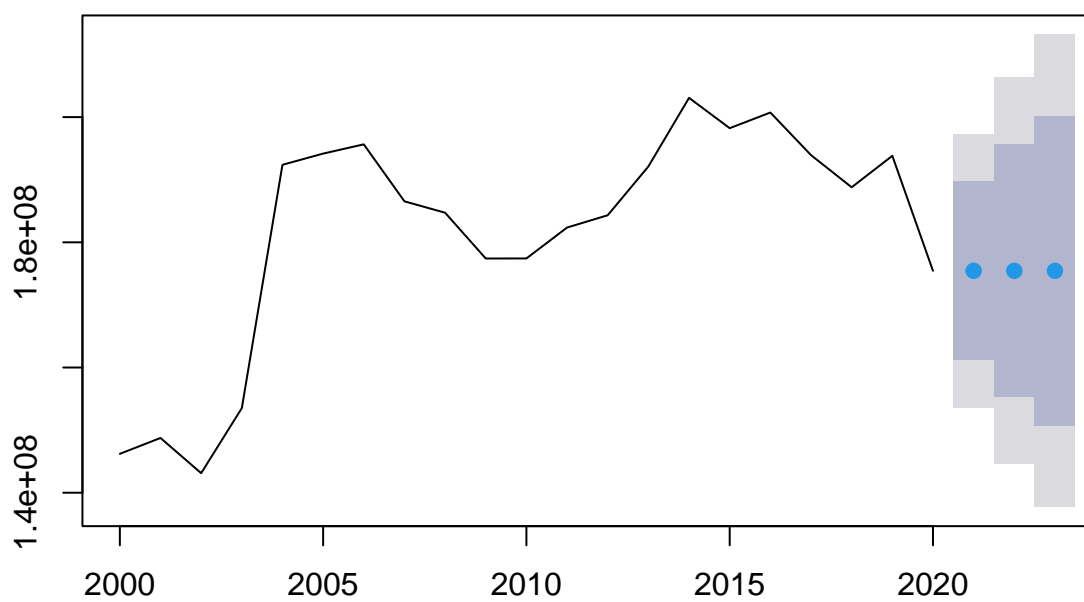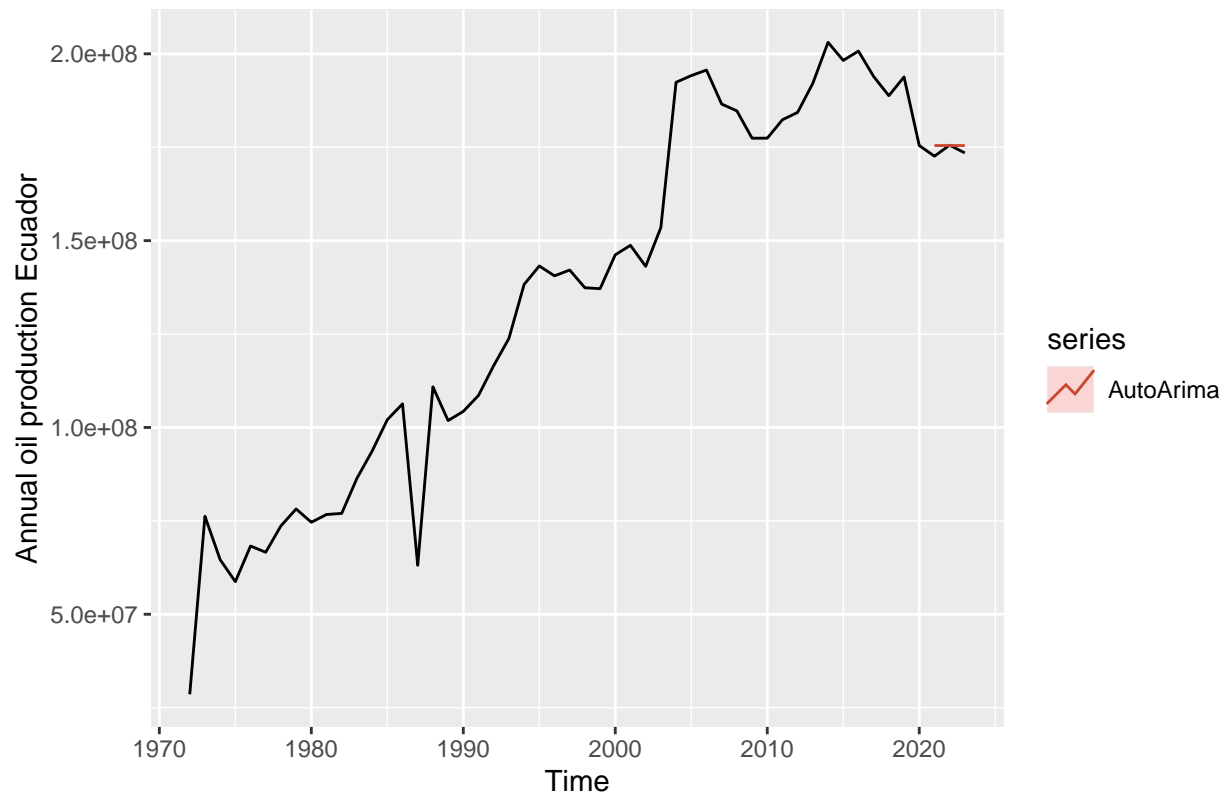
**Testing Model 2: MEAN**

The Mean model employs a much simpler approach than ARIMA, that generates a flat forecast (blue dots) at approximately 181 million barrels with a wide confidence intervals, indicating high uncertainty. Besides, its performance metrics (see Table 1) reveal significant weaknesses, with a much higher RMSE (7,781,977) compared to ARIMA and a concerning MAPE of 4.42 (442% error). Moreover, according to the model's Theil's U value of 2.77 indicates it performs worse than naive forecasting methods, essentially failing to capture any of the time series' patterns or fluctuations.

```
##      Point Forecast      Lo 80      Hi 80      Lo 95      Hi 95
## 2021      181558473 156628140 206488806 142320439 220796506
## 2022      181558473 156628140 206488806 142320439 220796506
## 2023      181558473 156628140 206488806 142320439 220796506
```

**Forecasts from Mean**
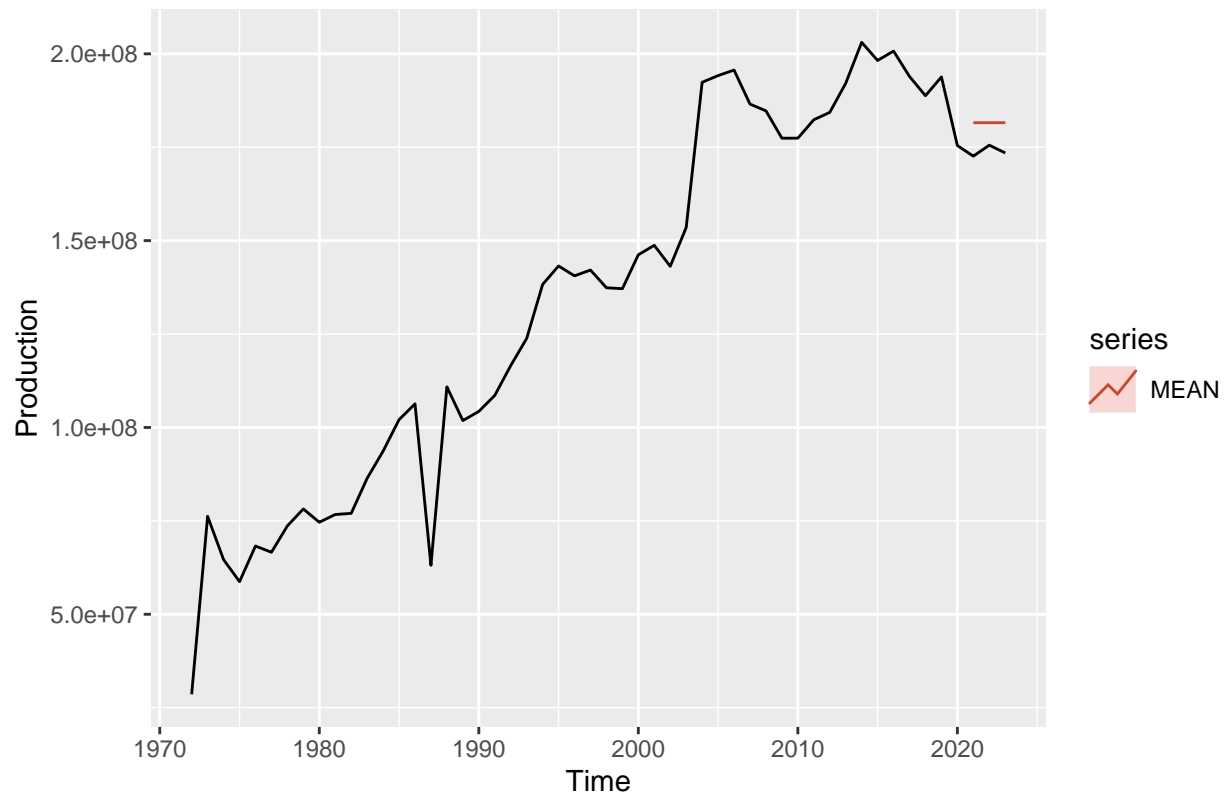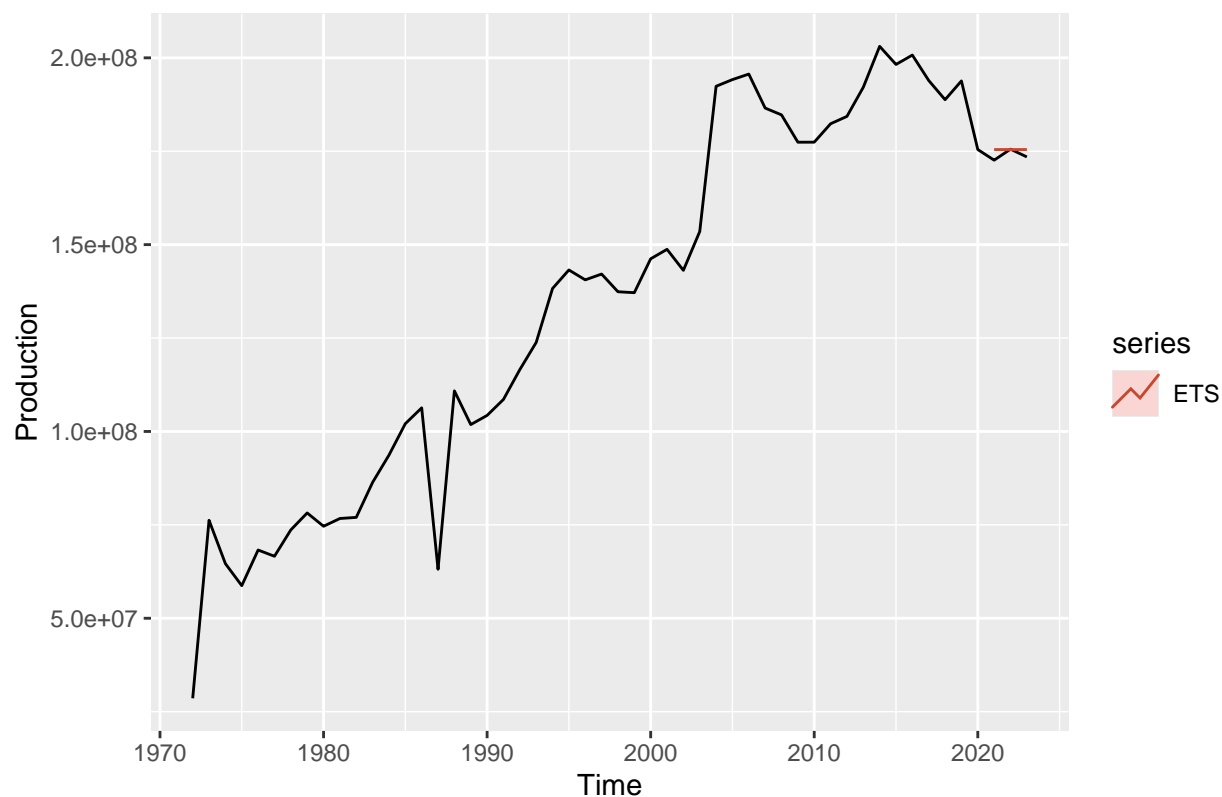
**Testing Model 3: ETS**

The ETS model effectively "locks in" the most recent observed level (approximately 175 million barrels) and extrapolates it forward, producing a flat forecast line characterized by moderately narrow confidence bands. This tighter band of uncertainty, compared to the mean model's wider fan, reflects ETS's ability to adapt to the stable, modern production regime rather than being swayed by earlier, lower historical levels.

In-sample (see Table 1), the model under-forecasts by an average of 1.6 million barrels (ME), achieving a MAPE below 1 percent (around 0.95%). A Theil's U statistic of 0.54 confirms that it outperforms a naive "no-change" forecast. However, the pronounced negative autocorrelation at lag 1 indicates that the ETS model struggles to capture some of the smoother, year-over-year momentum inherent in the data.

```
##      Point Forecast      Lo 80      Hi 80      Lo 95      Hi 95
## 2021      175451620  158940493  191962746  150200030  200703209
## 2022      175451620  152102567  198800672  139742325  211160914
## 2023      175451620  146855480  204047760  131717598  219185642
```

Forecasts from ETS(A,N,N)
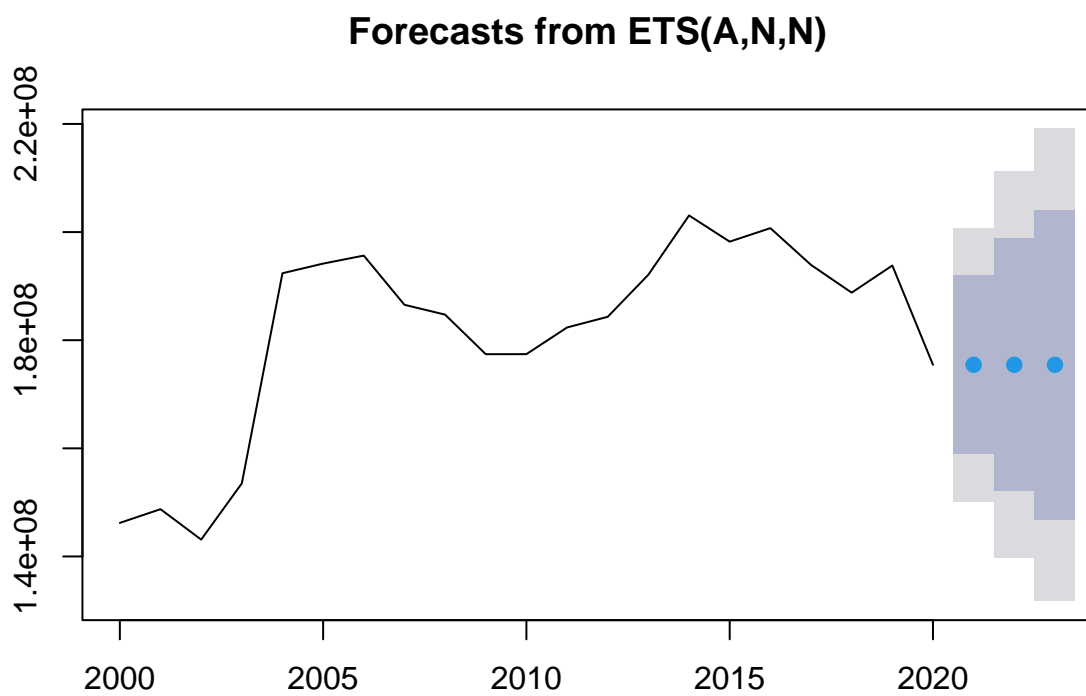
**Testing Model 4: HOLT**

Holt's method augments simple exponential smoothing with a linear trend, and its forecast barely moves from the last observed level (around 175 million barrels), producing an almost flat-looking line with even wider uncertainty bands than ETS. It stands out that its Theil's U is 1.09, which would suggests it actually performs worse than a naïve method.

```
##      Point Forecast      Lo 80      Hi 80      Lo 95      Hi 95
## 2021      176061114 159675163 192447065 151000965 201121263
## 2022      176670451 152596519 200744383 139852550 213488352
## 2023      177279788 146679865 207879711 130481244 224078332
```

# Forecasts from Holt's method

Table 1: Table 1. Forecast Accuracy for Annual Data

|  | ME | RMSE | MAE | MPE | MAPE | ACF1 | Theil's U |
|---|---|---|---|---|---|---|---|
| ARIMA | -1574422 | 2001707 | 1640694 | -0.91057 | 0.94832 | -0.61118 | 0.54238 |
| MEAN | -7683173 | 7781977 | 7683173 | -4.42404 | 4.42404 | -0.61118 | 2.77997 |
| ETS | -1576320 | 2003200 | 1641327 | -0.91166 | 0.94870 | -0.61118 | 0.54288 |
| HOLT | -2795151 | 3038681 | 2795151 | -1.61209 | 1.61209 | -0.65735 | 1.08959 |
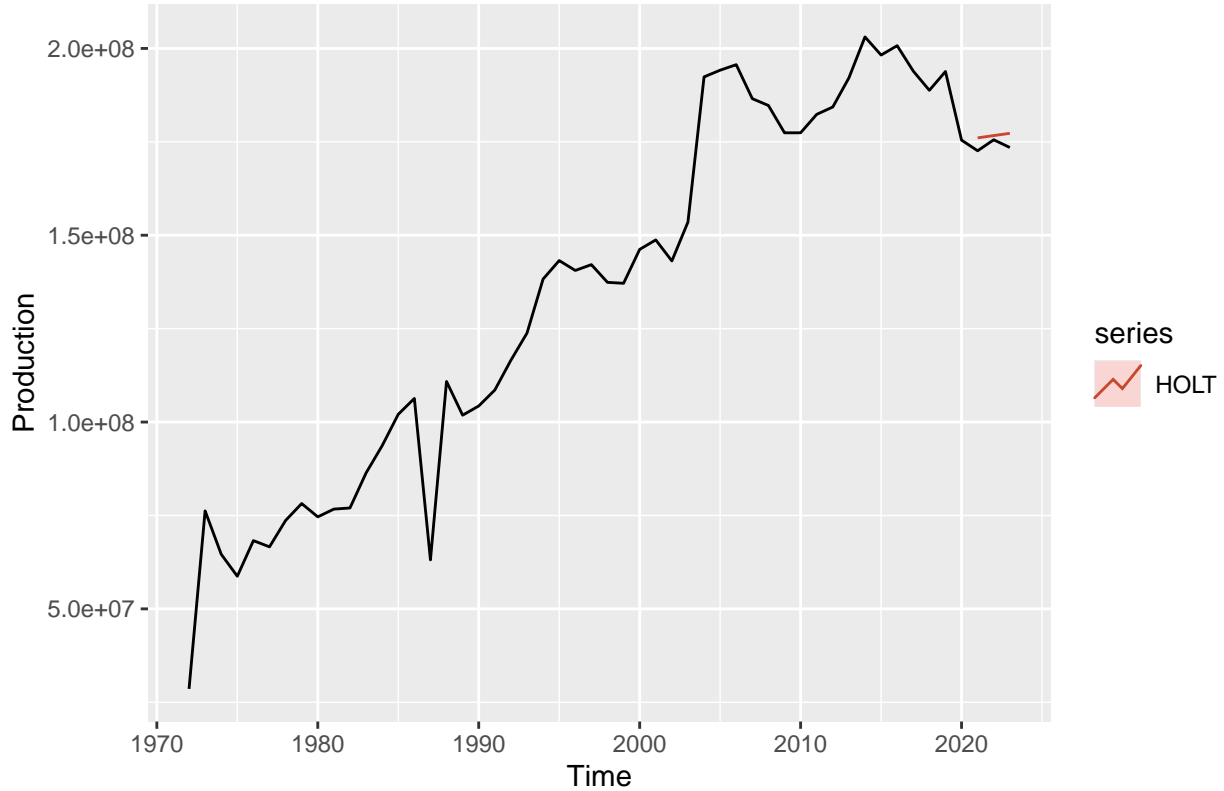


**Compare performance metrics of all models for the annual analysis**

The following table compares the mentioned models accuracy, and shows how ARIMA beats the rest of the models, while ETS is the second best model

```
## The best model by RMSE is: ARIMA
```

```
## The best model by MAPE is: ARIMA
```

Thus, we combined the two best models in aiming to have a more accurate model. By feeding the ETS errors into a simple AR(1), this hybrid forecast (red shading) sits almost exactly on today's production level (around 175 million barrels) and produces the tightest uncertainty "cone" of all models. In back-testing against 2021–2023 actuals (see Table 2), it under-forecasted by only 0.66 million barrels on average (ME around –0.66 m), cutting its RMSE from ~2.0 m (pure ETS or ARIMA) down to 1.17 m and halving the

Table 2: Table 2. Forecast Accuracy for Annual Data

|  | ME | RMSE | MAE | MPE | MAPE | ACF1 | Theil's U |
|---|---|---|---|---|---|---|---|
| ARIMA | -1574422.0 | 2001707 | 1640693.8 | -0.91057 | 0.94832 | -0.61118 | 0.54238 |
| MEAN | -7683173.0 | 7781977 | 7683173.0 | -4.42404 | 4.42404 | -0.61118 | 2.77997 |
| ETS | -1576320.2 | 2003200 | 1641326.5 | -0.91166 | 0.94870 | -0.61118 | 0.54288 |
| HOLT | -2795151.5 | 3038681 | 2795151.5 | -1.61209 | 1.61209 | -0.65735 | 1.08959 |
| Hybrid ETS & AR(1) | -657903.9 | 1171499 | 932078.9 | -0.38062 | 0.53680 | -0.40555 | 0.54320 |

MAPE to 0.54 %. The dramatic drop in MAE (to 0.93 m) and MAPE shows that capturing the year-to-year autocorrelation in the residuals yields materially more accurate point forecasts, while the narrower fan reflects increased confidence in the short-term outlook.

```
## [1] "ets_fc$lower.80%" "ets_fc$lower.95%"
```

```
##   Year  Forecast       Lo80       Hi80       Lo95       Hi95
## 1 2021 173051133 140553653 205548612 123350527 222751738
## 2 2022 175137867 135666488 214609245 114771603 235504131
## 3 2023 175410611 130689832 220131390 107016082 243805140
```

## Hybrid ETS(.,.,.) + AR(1) Forecast
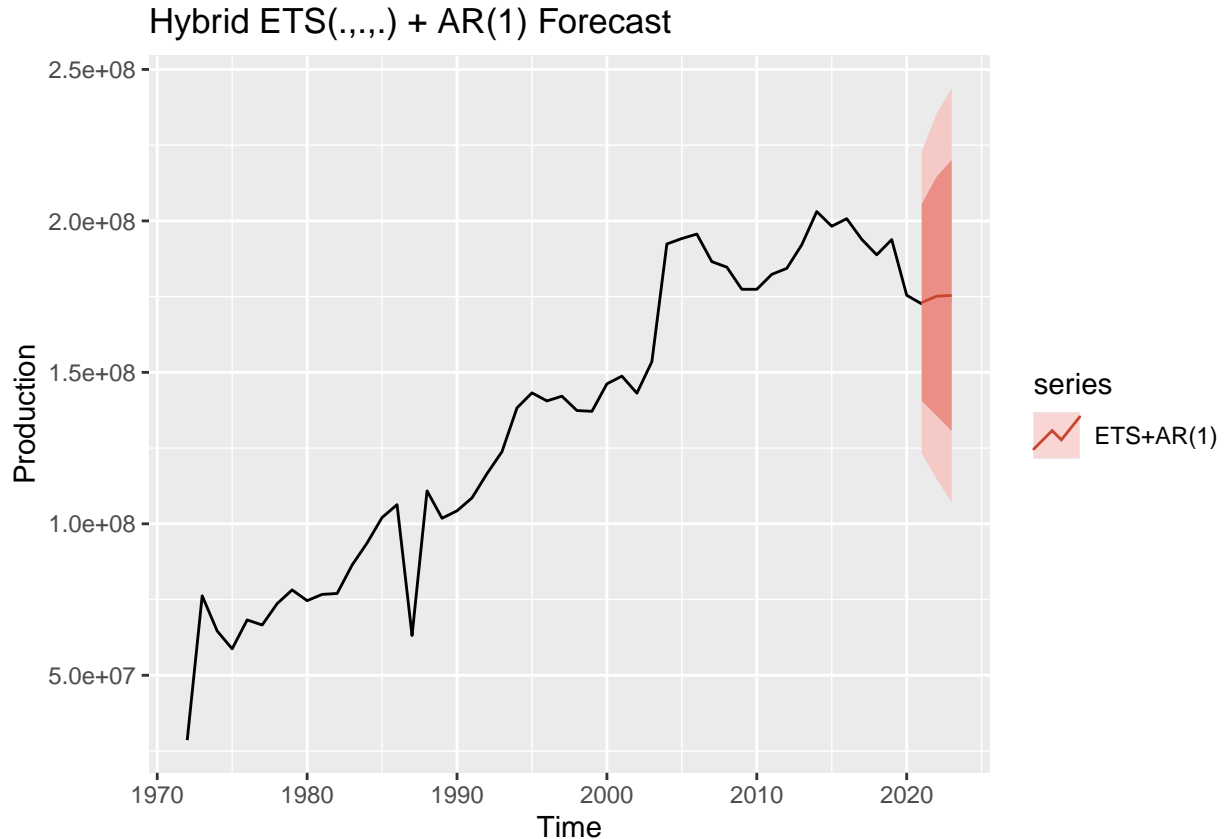


```
##                  ME    RMSE      MAE        MPE       MAPE       ACF1
## ARIMA     -1574422.0 2001707 1640693.8 -0.9105732 0.9483243 -0.6111825
## MEAN      -7683173.0 7781977 7683173.0 -4.4240445 4.4240445 -0.6111825
## ETS       -1576320.2 2003200 1641326.5 -0.9116649 0.9486952 -0.6111825
```

```
## HOLT                  -2795151.5 3038681 2795151.5 -1.6120878 1.6120878 -0.6573494
## Hybrid ETS & AR(1)  -657903.9 1171499  932078.9 -0.3806204 0.5368018 -0.4055451
##                       Theil's U
## ARIMA                 0.5423828
## MEAN                  2.7799717
## ETS                   0.5428761
## HOLT                  1.0895856
## Hybrid ETS & AR(1) 0.5432020
```

```
## The best model by RMSE is: Hybrid ETS & AR(1)
```

```
## The best model by MAPE is: Hybrid ETS & AR(1)
```

Now we use the hybrid model for our data from 2000 to 2023. This model captured the long-term level and then added an AR(1) on its one-step residuals to restore the small year-to-year momentum that pure ETS missed. The outcome is a flat forecast of about 173 million barrels per year from 2024 through 2027, with an 80 % confidence band narrowing to roughly 128–219 million and a 95 % band of 103–244 million barrels.

```
## [1] "80%" "95%"
```

```
## [1] "80%" "95%"
```

```
##   Year  Forecast      Lo80      Hi80      Lo95      Hi95
## 1 2024 173209118 142864921 203553314 126801674 219616561
## 2 2025 173441171 136598394 210283947 117095006 229787335
## 3 2026 173470963 131733639 215208287 109639234 237302692
## 4 2027 173474788 127612784 219336792 103334906 243614670
```



Hybrid ETS(.,.,.) + AR(1) Forecast: 2000–2026
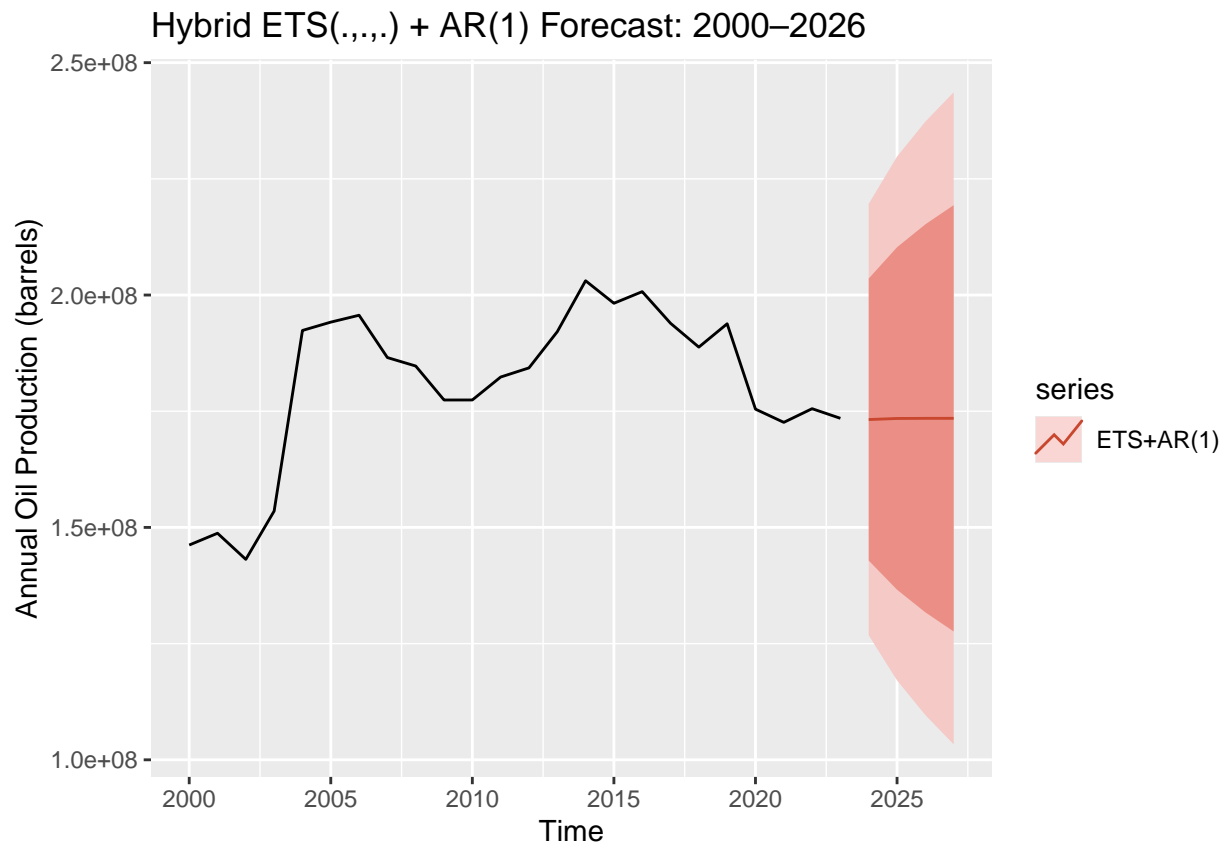
The residuals fluctuate randomly around zero with no obvious drift or changing variance, and—aside from a single large error in the mid-2000s—stay within about ±20 million barrels. Moreover, the ACF shows all lags inside the 95 % confidence bounds (lag 4 is barely crossing the bounds, but we would say there is no meaningful serial correlation). The histogram of errors looks symmetric (with slightly tails from that outlier). In brief, they behave like white noise, suggesting our hybrid ETS+AR(1) captured the main dynamics of Ecuador's oil-production series.

## Residuals from ETS(A,N,N)
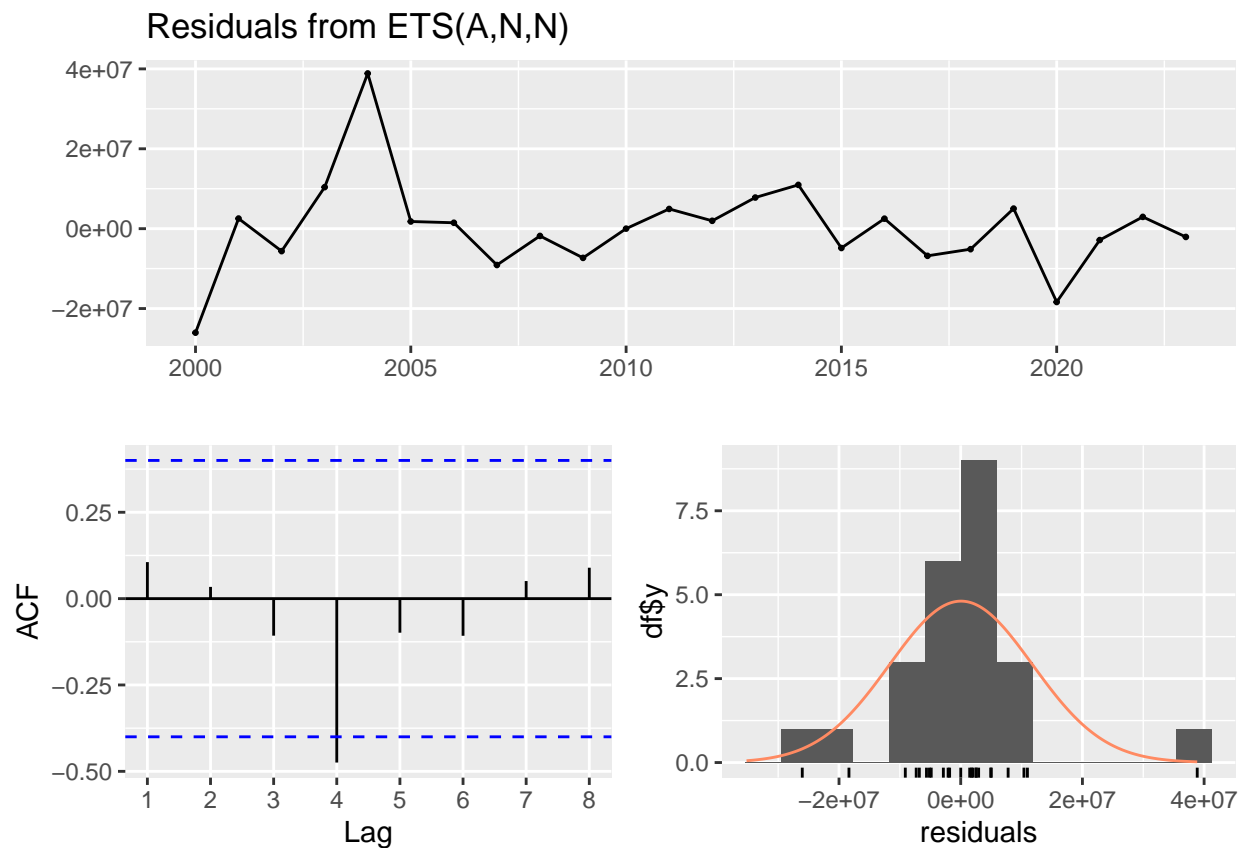


```
##
##  Ljung-Box test
##
## data:  Residuals from ETS(A,N,N)
## Q* = 8.0225, df = 5, p-value = 0.155
##
## Model df: 0.    Total lags used: 5
```

Finally, we observed that Ecuador's projected a higher production for 2026 & 2027, however, there was no information on the additional data they used for their forecasting. However it is worth noting that projections for 2026 would be historic volumes as is slightly above annual production in previous years.

## ARIMA Forecast vs. Government Expected Production (2024–2027)
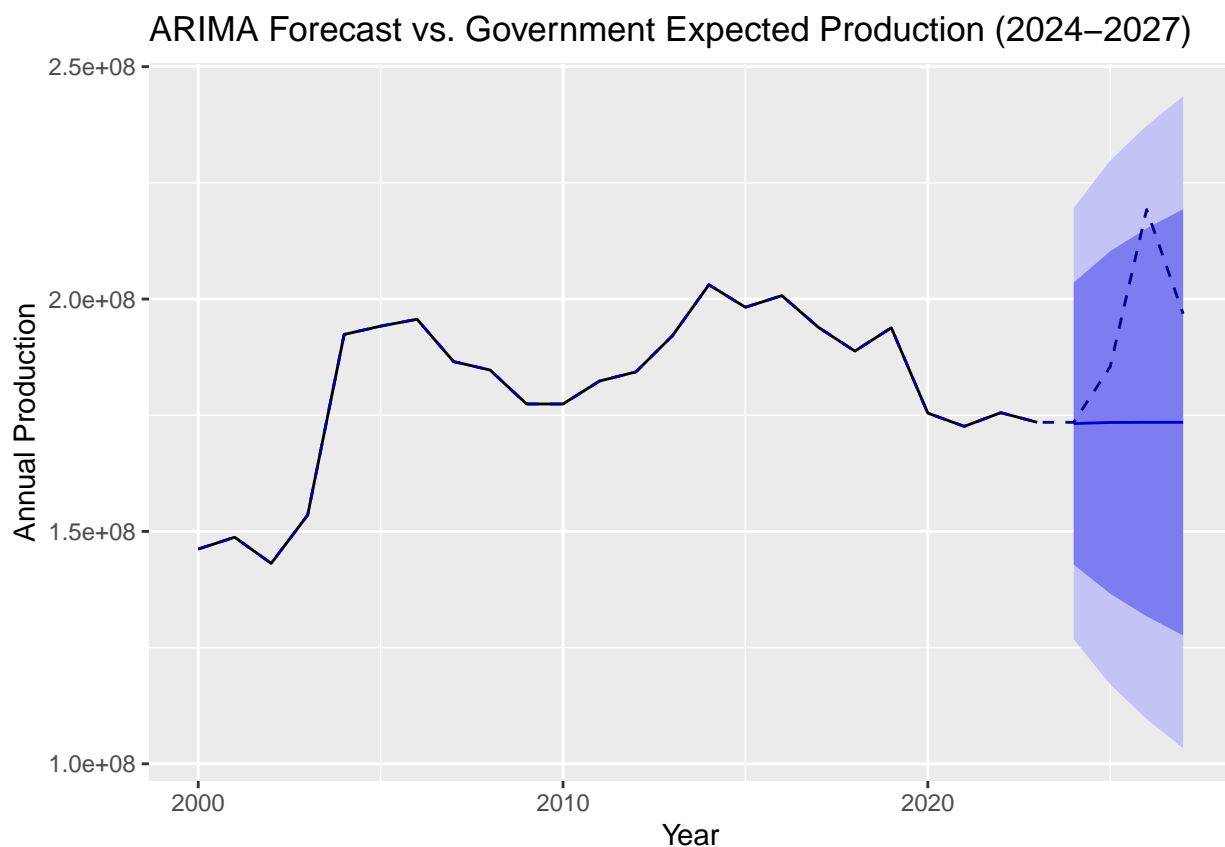


## Stage B (Month-Level Analysis):

This is a more detailed monthly analysis from 2007–2023 using monthly WTI prices and Block 43 production. The temporal split is as follows:

- **Training:** Jan 2007 – Dec 2022 (192 obs).

- **Validation:** Jan 2023 – Dec 2023 (12 obs) — used solely for model selection.

- **Test/Forecast:** Jan 2024 – Dec 2027 (48 obs) under two scenarios.

The following graphs shows oil production in Ecuador has been decreasing. Oil extraction in Block 43-ITT started in 2016 and has boosted the economy. Plot 4 shows that oil exploitation on Block 43-ITT has increased production from 2016 to 2023, reaching up to 17% of the total oil production.

National production* shows clear 12-month seasonality with shocks in 2020 (COVID-19) and 2023 (maintenance outages). *Block 43* exhibits a steady upward trajectory until 2023; *WTI* prices are markedly cyclical with abrupt drops (2009, 2014, 2020).
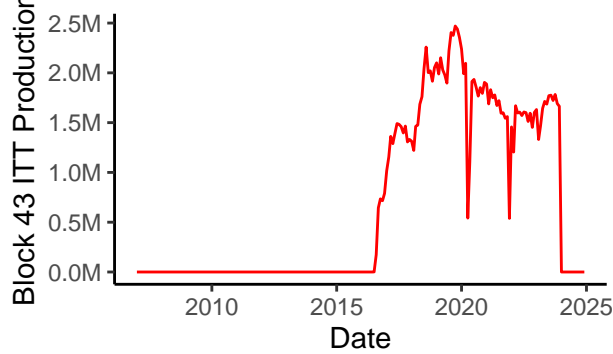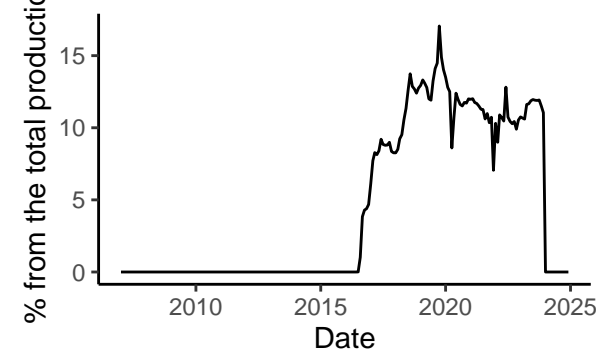
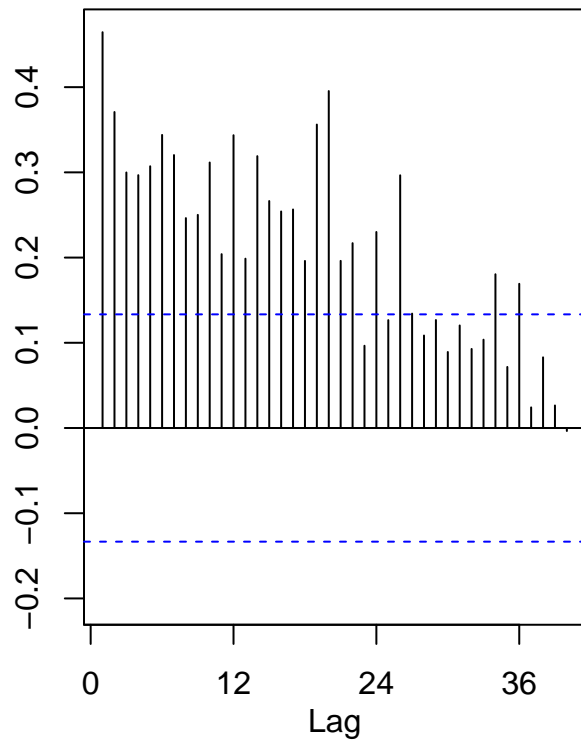Plot 1: Monthly Oil Production in Ecuador
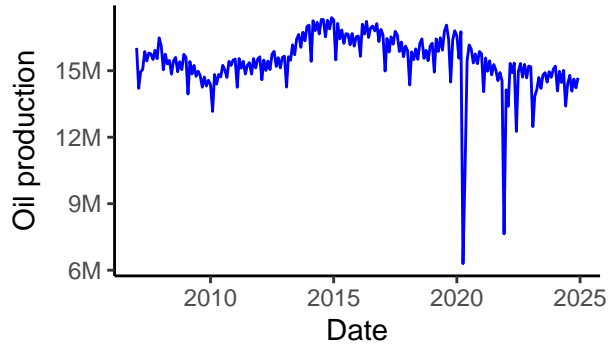
Plot 2: Monthly WTI Prices
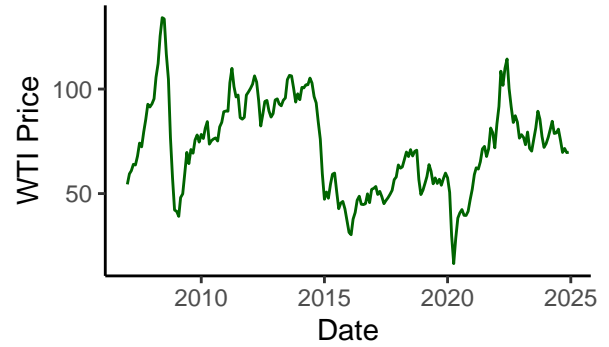
Plot 3:Monthly Block 43 ITT

Plot 4:Percentage of monthly Bloc

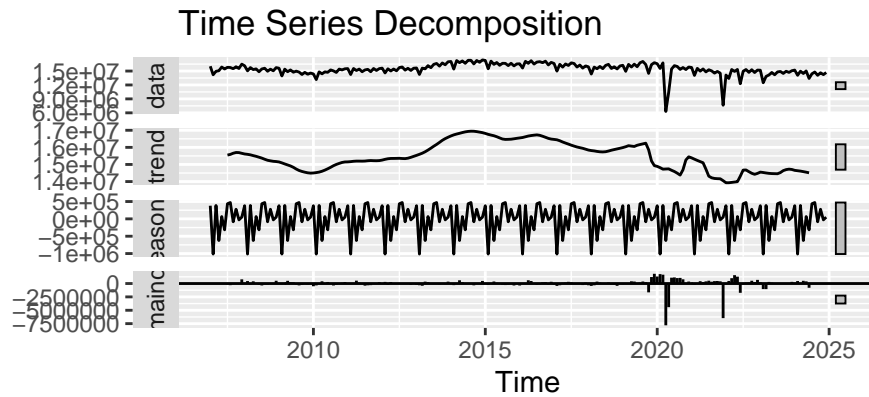## ACF of Total Production

## PACF of Total Production

## Time Series Decomposition



## Original vs. Deseasonalized Series
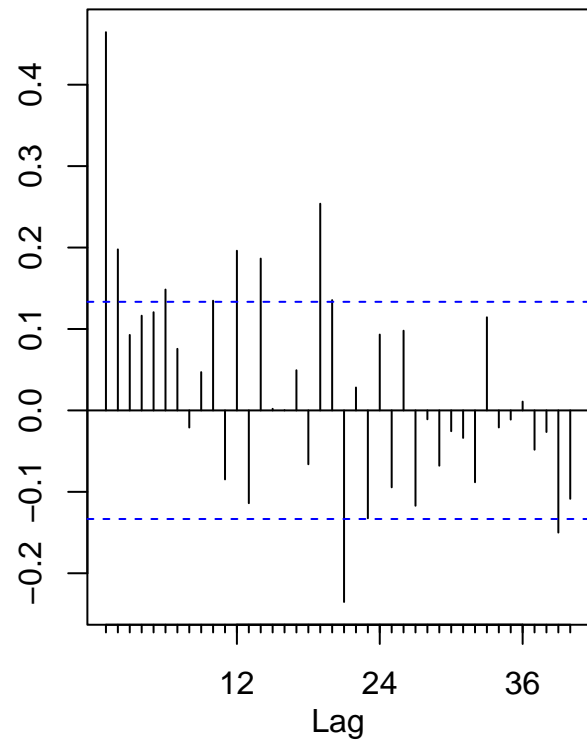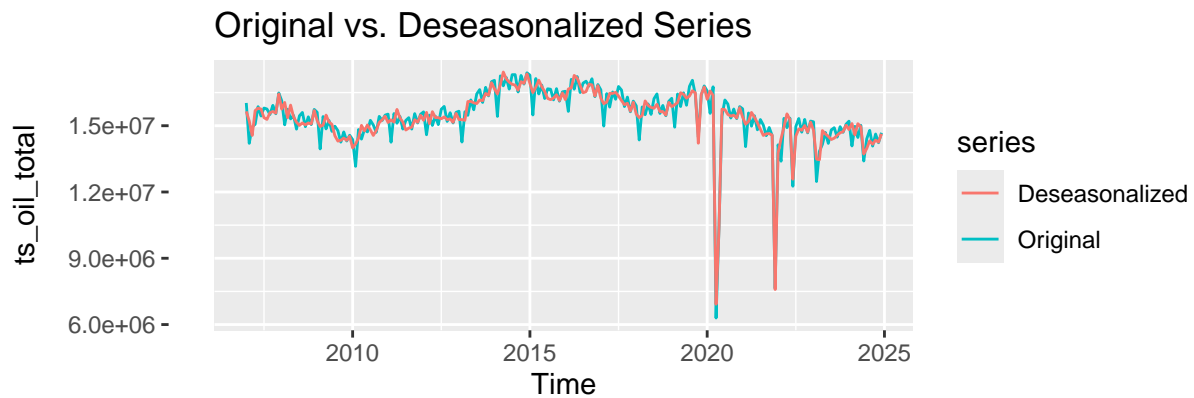


```
## 
##  Augmented Dickey-Fuller Test
## 
## data:  deseasonal_prod
## Dickey-Fuller = -2.5608, Lag order = 5, p-value = 0.3407
## alternative hypothesis: stationary
```

**Model 1**

```
##          Point Forecast     Lo 80     Hi 80     Lo 95     Hi 95
## Jan 2023       14928191  13486338  16370045  12723067  17133316
## Feb 2023       14556697  13045060  16068334  12244847  16868546
## Mar 2023       14785338  13262131  16308544  12455794  17114881
## Apr 2023       14717948  13183259  16252637  12370844  17065052
## May 2023       14774850  13228764  16320936  12410315  17139384
## Jun 2023       14395989  12838589  15953389  12014152  16777826
## Jul 2023       14740911  13172280  16309543  12341896  17139926
## Aug 2023       14791884  13212100  16371668  12375813  17207955
## Sep 2023       14718428  13127570  16309286  12285421  17151436
## Oct 2023       14788555  13186700  16390411  12338729  17238382
## Nov 2023       14714125  13101347  16326903  12247594  17180656
## Dec 2023       14901745  13278118  16525372  12418621  17384868
```
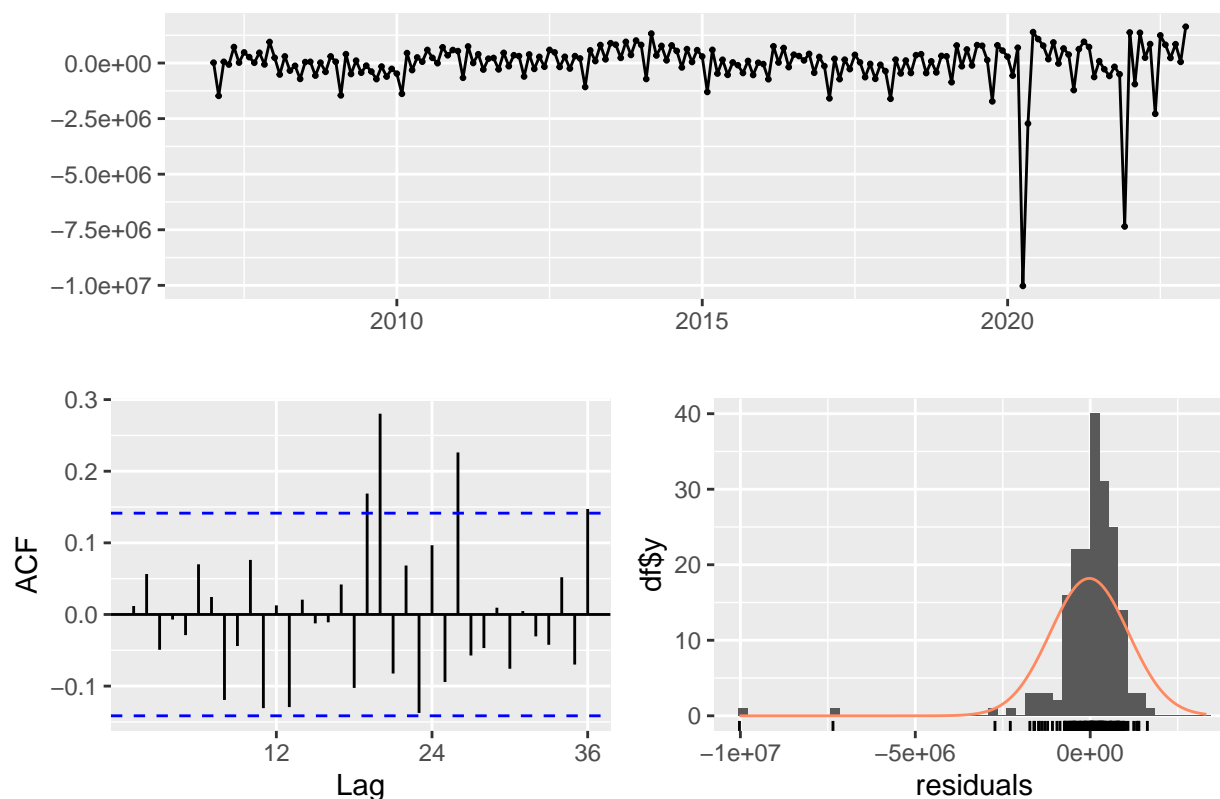
**Forecasts from ARIMA(0,1,2)(0,0,1)[12]**
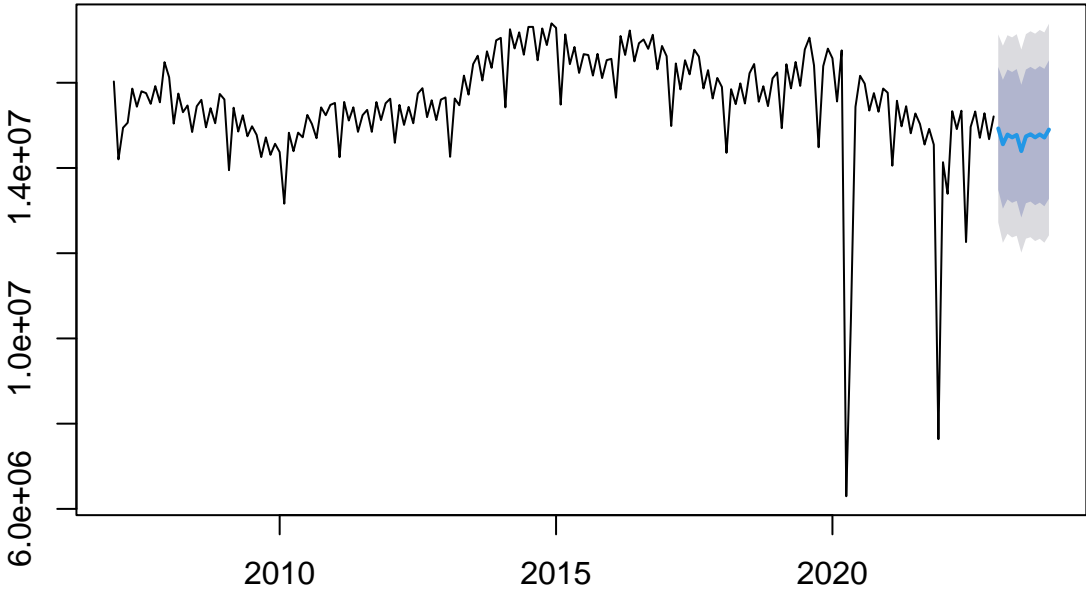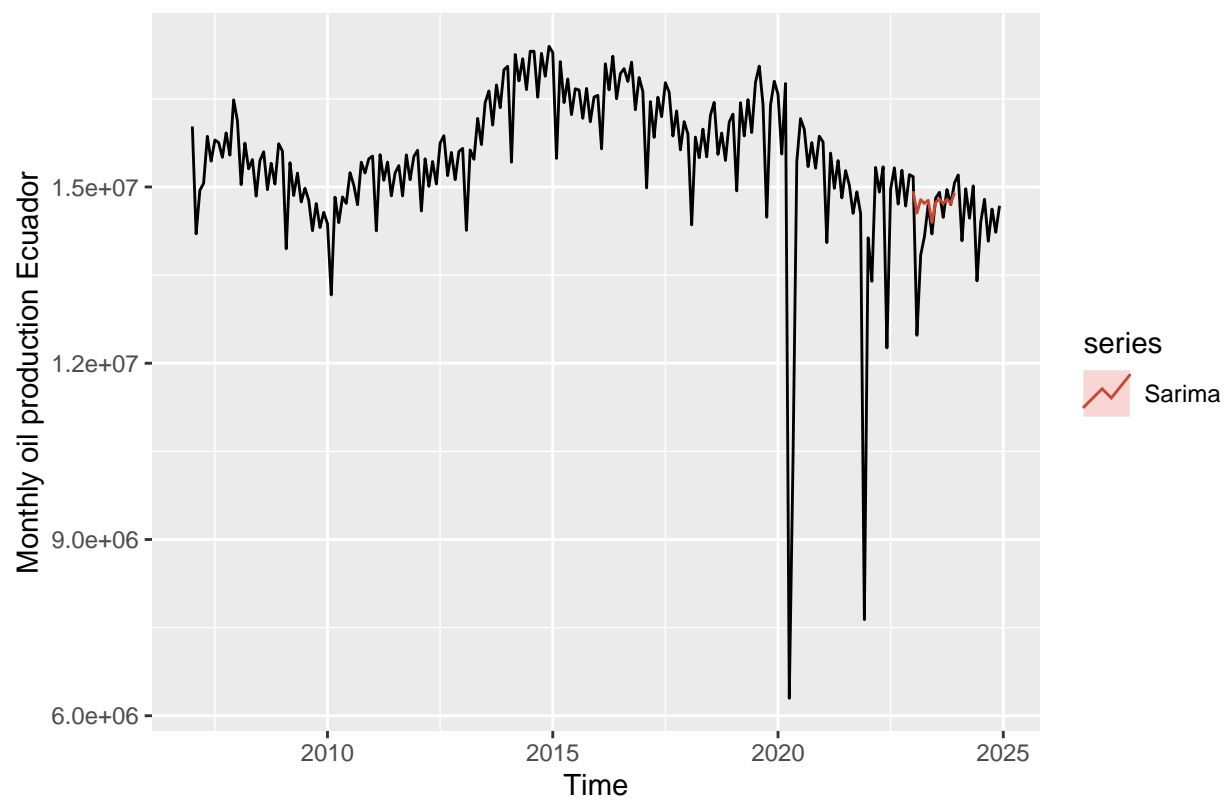
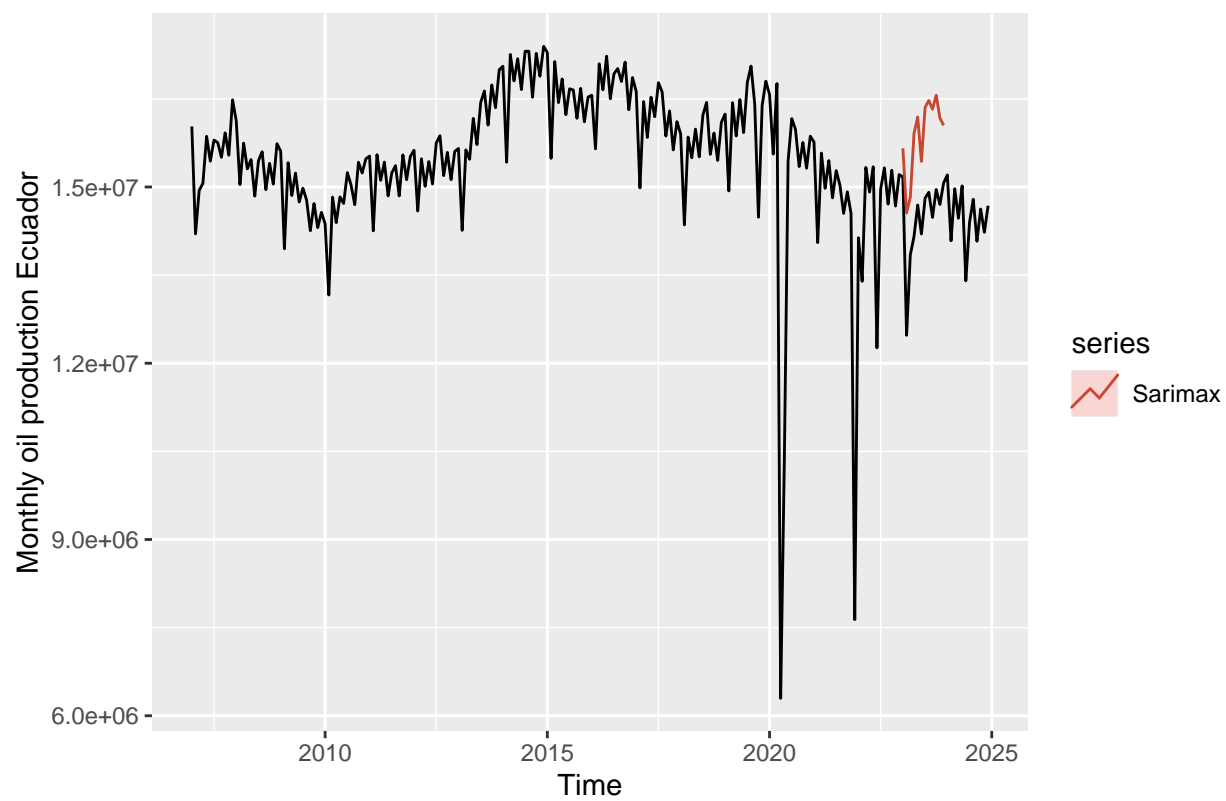## Residuals from ARIMA(0,1,2)(0,0,1)[12]



```
## 
##  Ljung-Box test
## 
## data:  Residuals from ARIMA(0,1,2)(0,0,1)[12]
## Q* = 48.566, df = 21, p-value = 0.0005756
## 
## Model df: 3.   Total lags used: 24
```
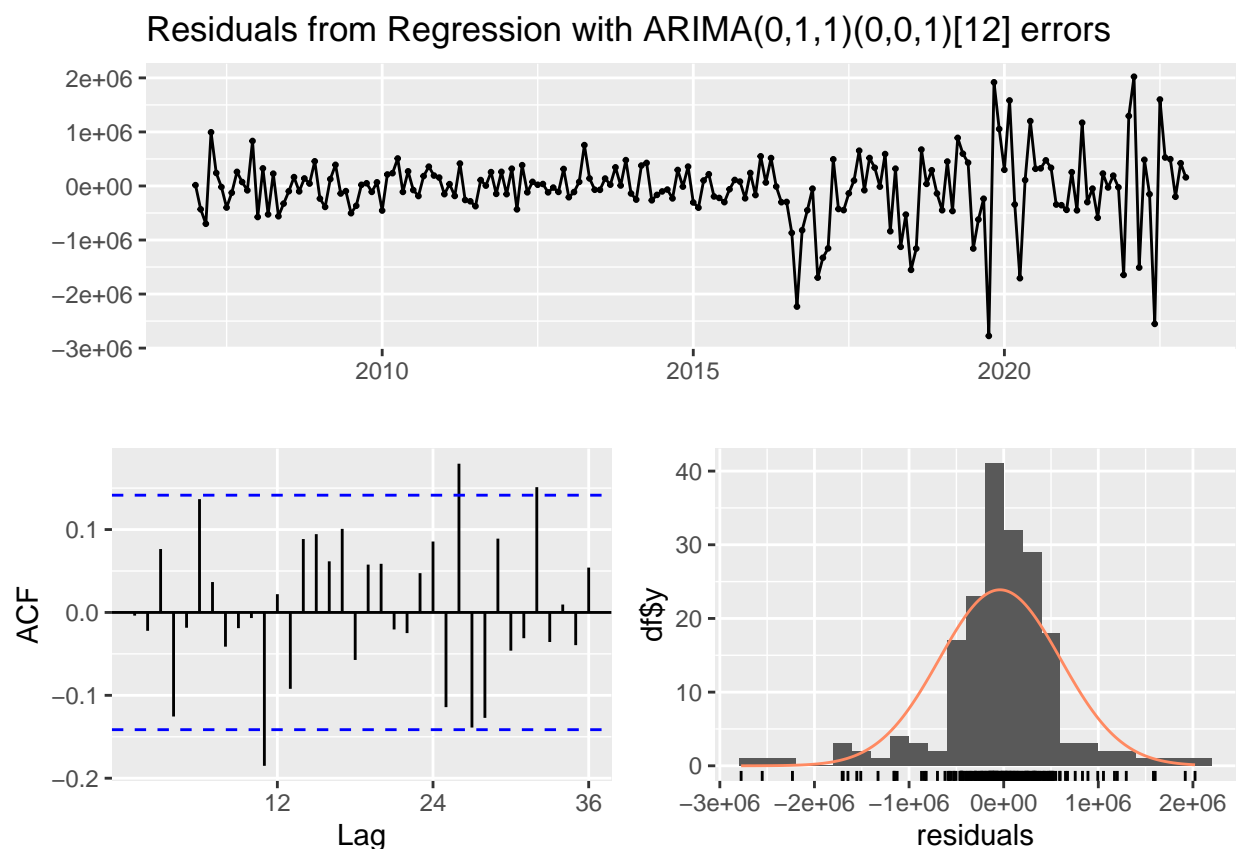
**Model 2:**

```
##          Point Forecast     Lo 80     Hi 80     Lo 95     Hi 95
## Jan 2023       15659239  14827461  16491017  14387144  16931334
## Feb 2023       14557776  13457145  15658408  12874506  16241047
## Mar 2023       14821011  13505365  16136657  12808904  16833118
## Apr 2023       15909960  14409807  17410113  13615674  18204246
## May 2023       16191741  14527412  17856071  13646369  18737114
## Jun 2023       15436036  13622331  17249742  12662213  18209859
## Jul 2023       16356481  14404799  18308162  13371641  19341320
## Aug 2023       16472308  14391780  18552836  13290415  19654201
## Sep 2023       16322671  14120824  18524518  12955236  19690105
## Oct 2023       16561109  14244287  18877931  13017836  20104383
## Nov 2023       16172619  13746264  18598974  12461829  19883409
## Dec 2023       16048412  13517260  18579565  12177349  19919476
```

## Forecasts from Regression with ARIMA(0,1,1)(0,0,1)[12] errors

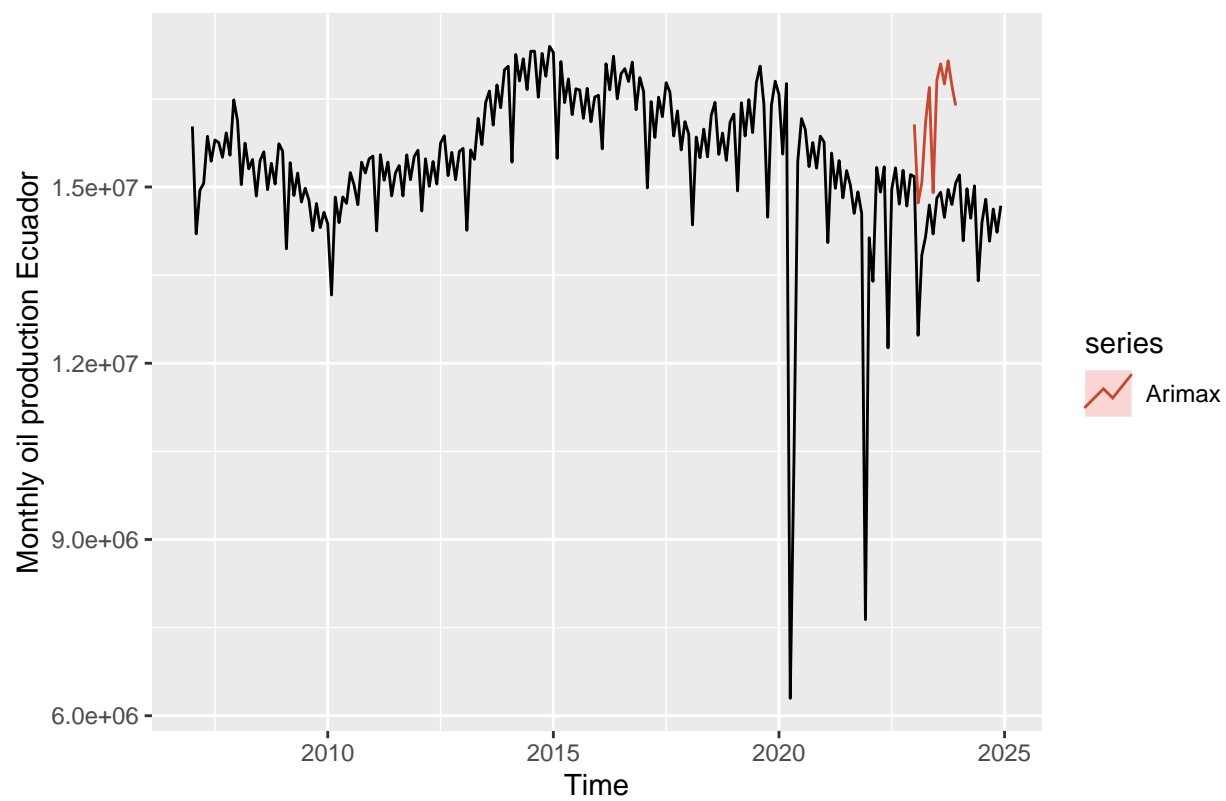## Residuals from Regression with ARIMA(0,1,1)(0,0,1)[12] errors



```
## 
##  Ljung-Box test
## 
## data:  Residuals from Regression with ARIMA(0,1,1)(0,0,1)[12] errors
## Q* = 28.794, df = 22, p-value = 0.1508
## 
## Model df: 2.   Total lags used: 24
```
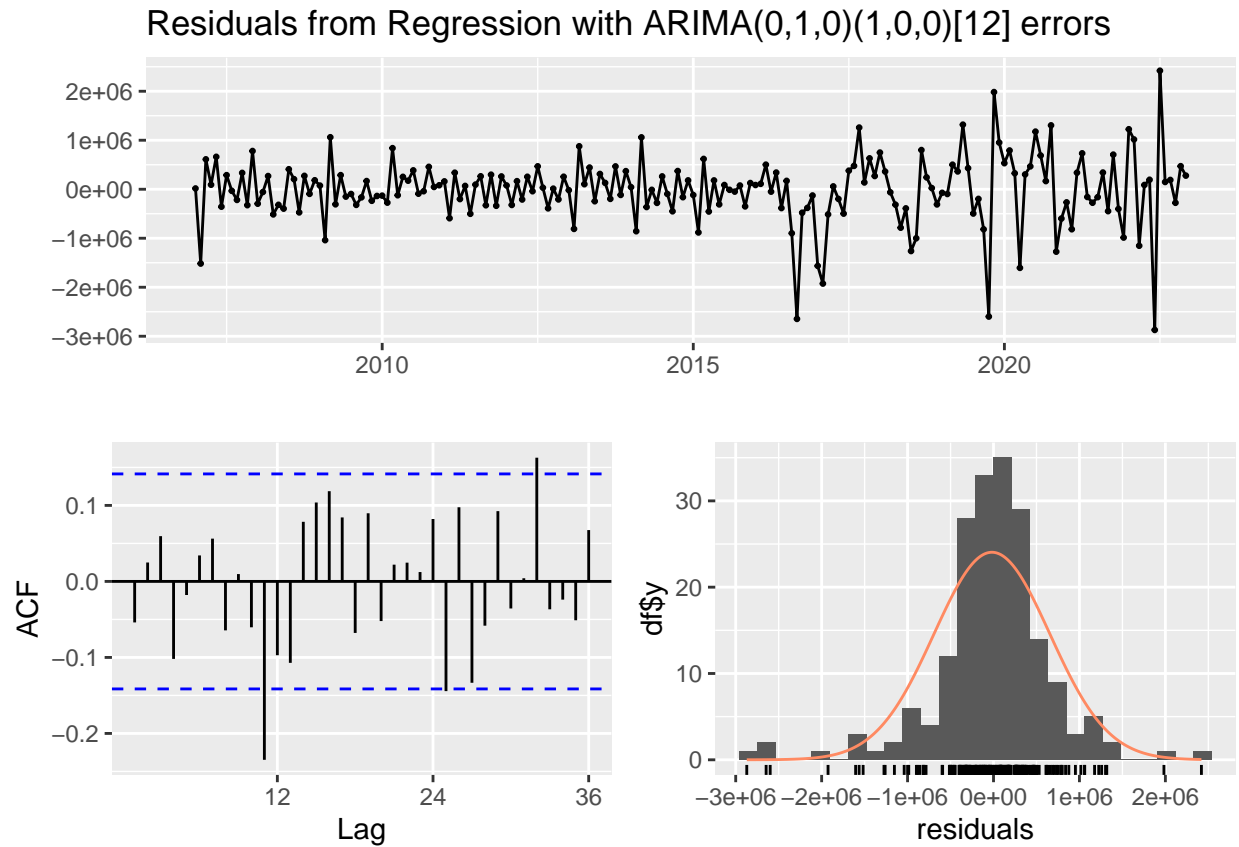
**Model 3**

```
##          Point Forecast     Lo 80     Hi 80     Lo 95     Hi 95
## Jan 2023       16065577  15194474  16936679  14733340  17397813
## Feb 2023       14728591  13496666  15960516  12844524  16612658
## Mar 2023       15077204  13568410  16585998  12769703  17384705
## Apr 2023       16106479  14364274  17848684  13442006  18770952
## May 2023       16692823  14744978  18640667  13713852  19671794
## Jun 2023       14902773  12769016  17036530  11639473  18166072
## Jul 2023       16821560  14516839  19126280  13296793  20346326
## Aug 2023       17097588  14633738  19561438  13329455  20865722
## Sep 2023       16752588  14139280  19365895  12755878  20749297
## Oct 2023       17148163  14393495  19902831  12935262  21361064
## Nov 2023       16722107  13832987  19611227  12303579  21140635
## Dec 2023       16386630  13369042  19404217  11771627  21001632
```

# Forecasts from Regression with ARIMA(0,1,0)(1,0,0)[12] errors

# Residuals from Regression with ARIMA(0,1,0)(1,0,0)[12] errors
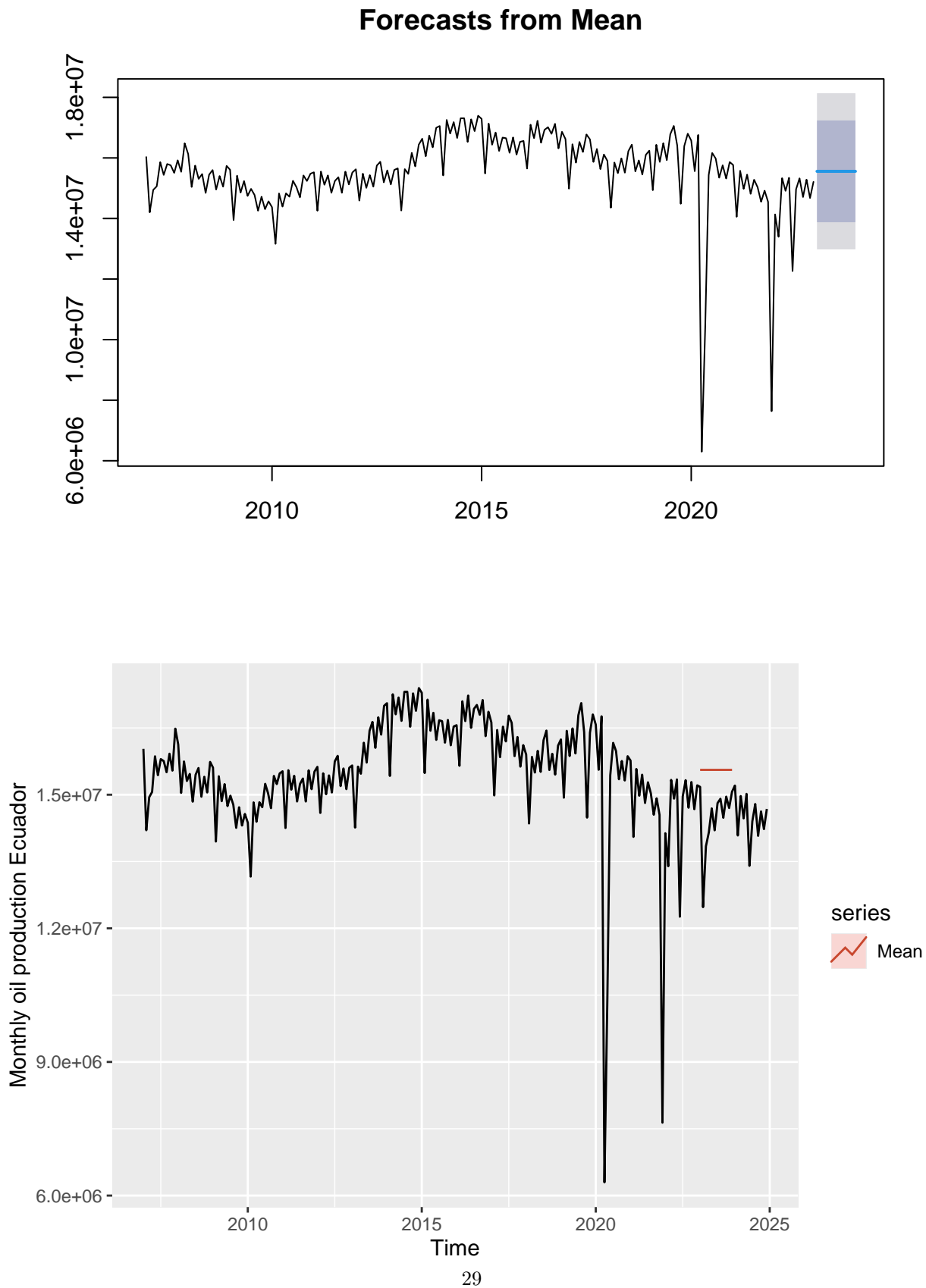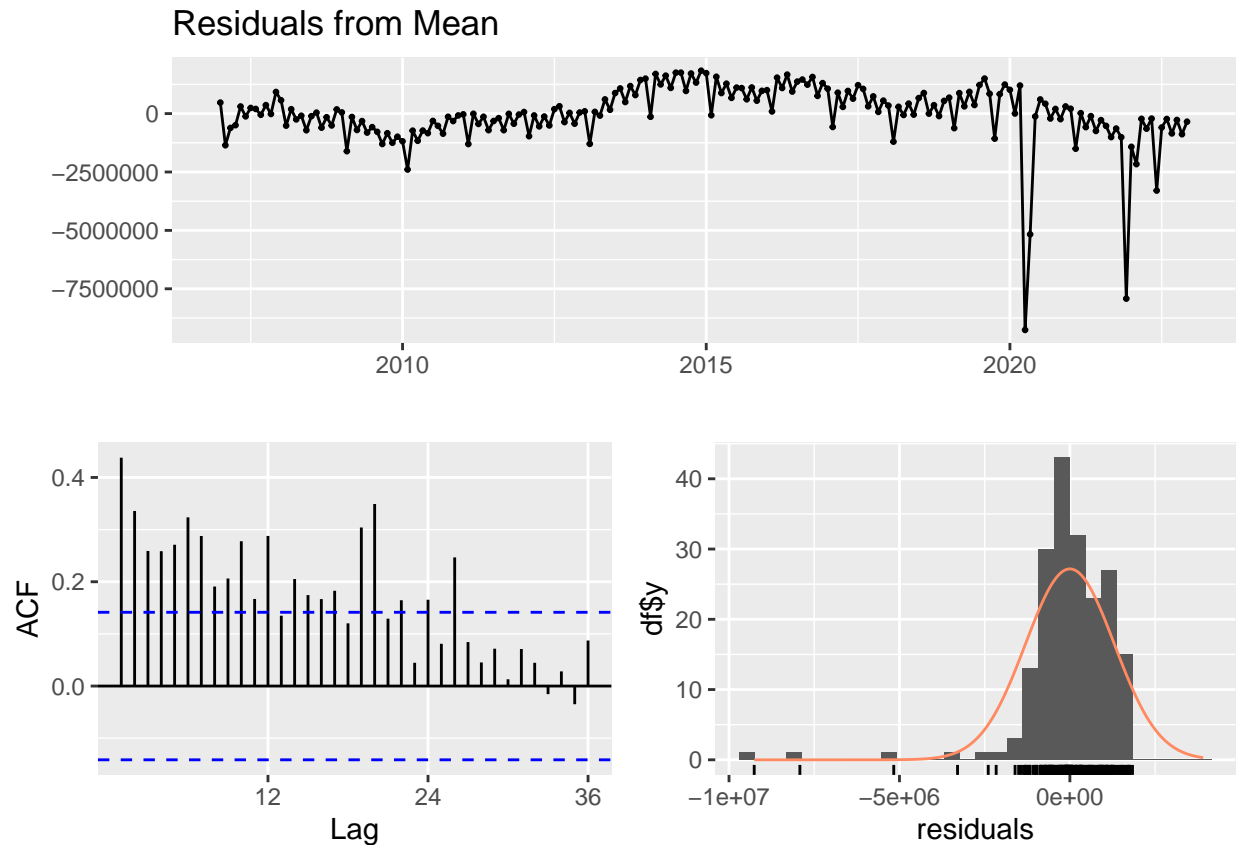


```
## 
##  Ljung-Box test
## 
## data:  Residuals from Regression with ARIMA(0,1,0)(1,0,0)[12] errors
## Q* = 34.78, df = 23, p-value = 0.05469
## 
## Model df: 1.   Total lags used: 24
```
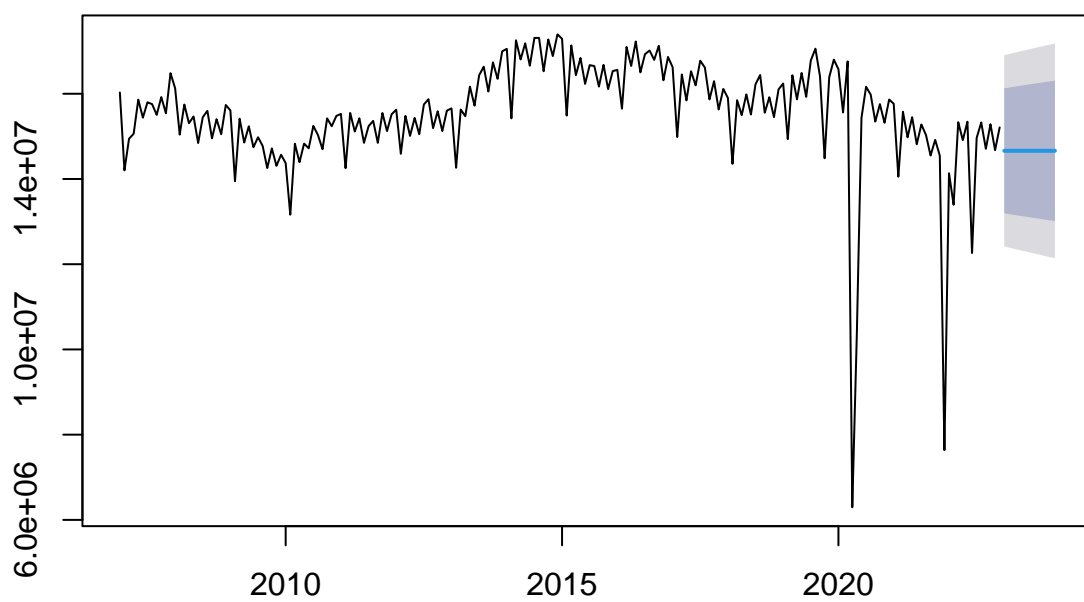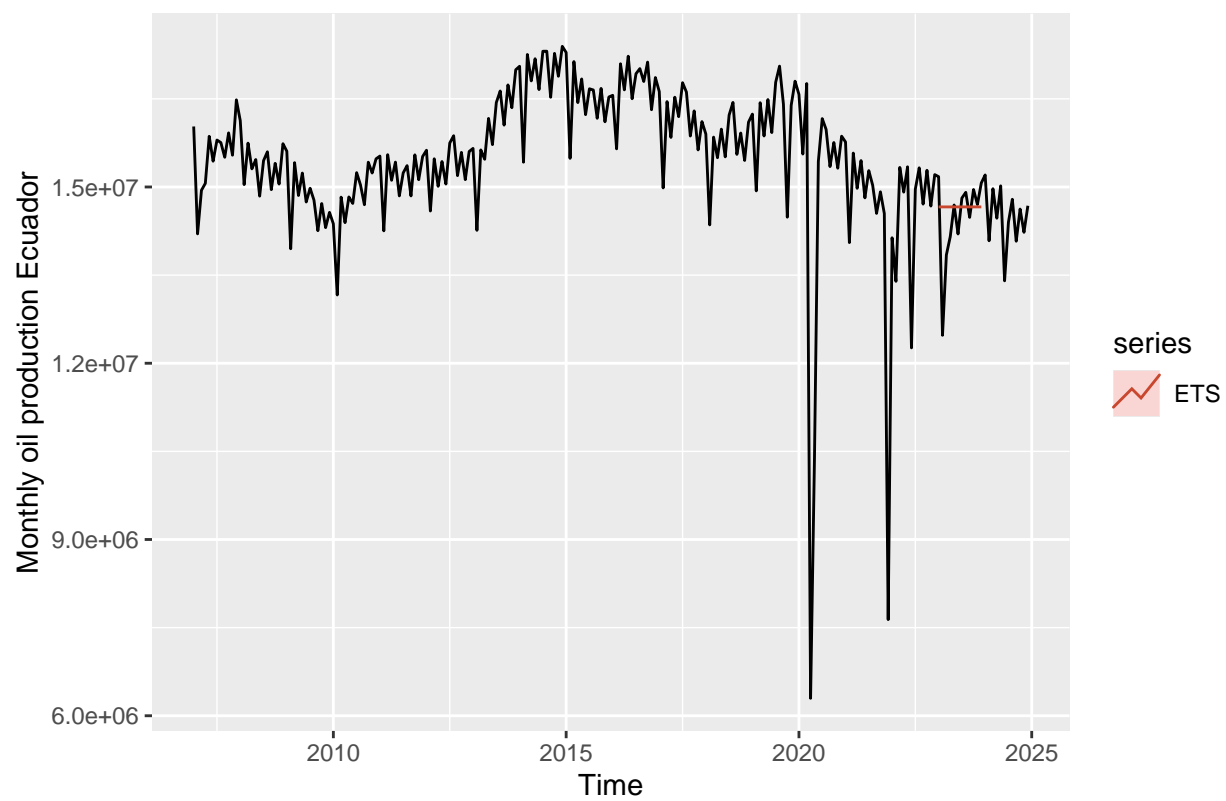
Model 4

# Forecasts from Mean

## Residuals from Mean



```
##
##  Ljung-Box test
##
## data:  Residuals from Mean
## Q* = 290.4, df = 24, p-value < 2.2e-16
##
## Model df: 0.   Total lags used: 24
```
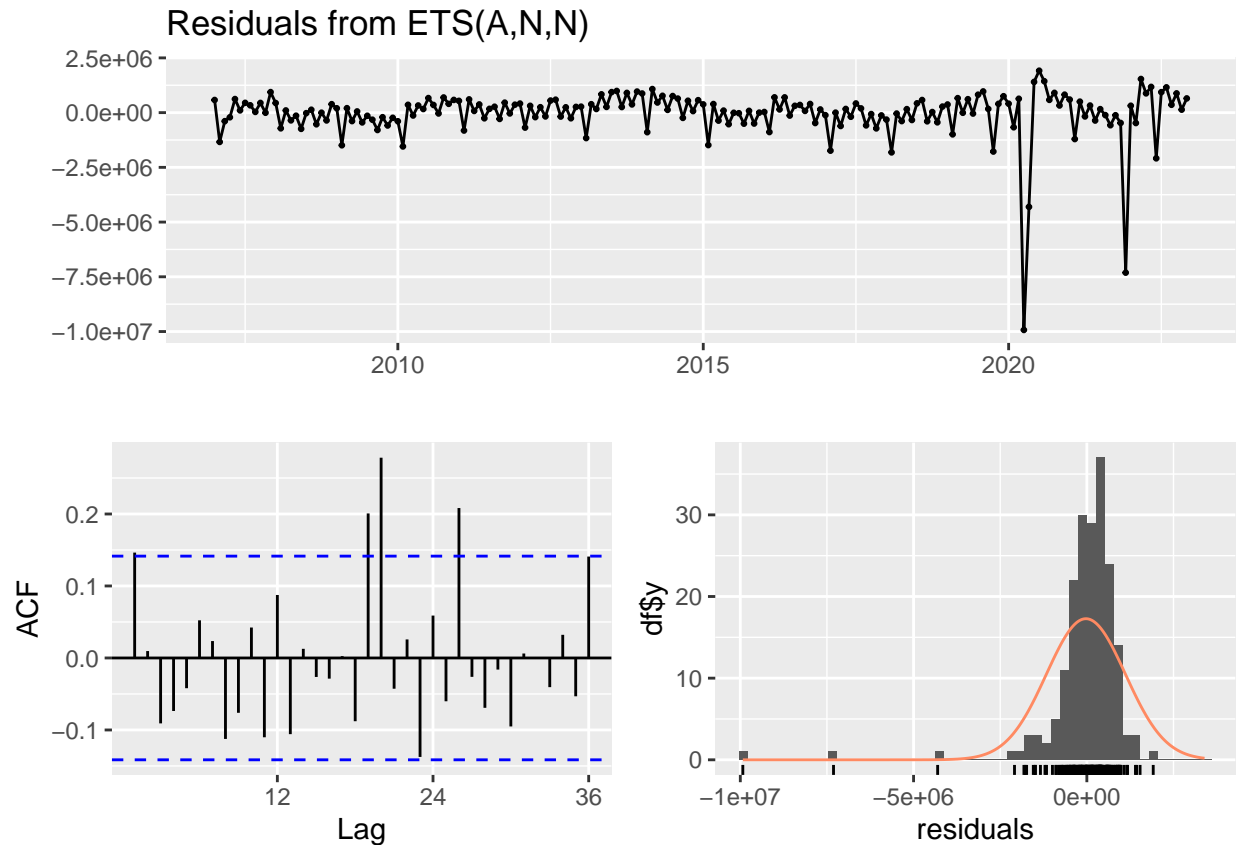
**Model 5**

```
##          Point Forecast     Lo 80     Hi 80     Lo 95     Hi 95
## Jan 2023       14661274 13194535 16128013 12418090 16904458
## Feb 2023       14661274 13177242 16145306 12391643 16930905
## Mar 2023       14661274 13160149 16162399 12365501 16957047
## Apr 2023       14661274 13143248 16179300 12339654 16982895
## May 2023       14661274 13126533 16196015 12314090 17008458
## Jun 2023       14661274 13109998 16212550 12288803 17033746
## Jul 2023       14661274 13093638 16228910 12263782 17058767
## Aug 2023       14661274 13077447 16245102 12239019 17083529
## Sep 2023       14661274 13061419 16261129 12214507 17108041
## Oct 2023       14661274 13045551 16276998 12190238 17132310
## Nov 2023       14661274 13029836 16292712 12166205 17156343
## Dec 2023       14661274 13014272 16308276 12142402 17180146
```

# Forecasts from ETS(A,N,N)
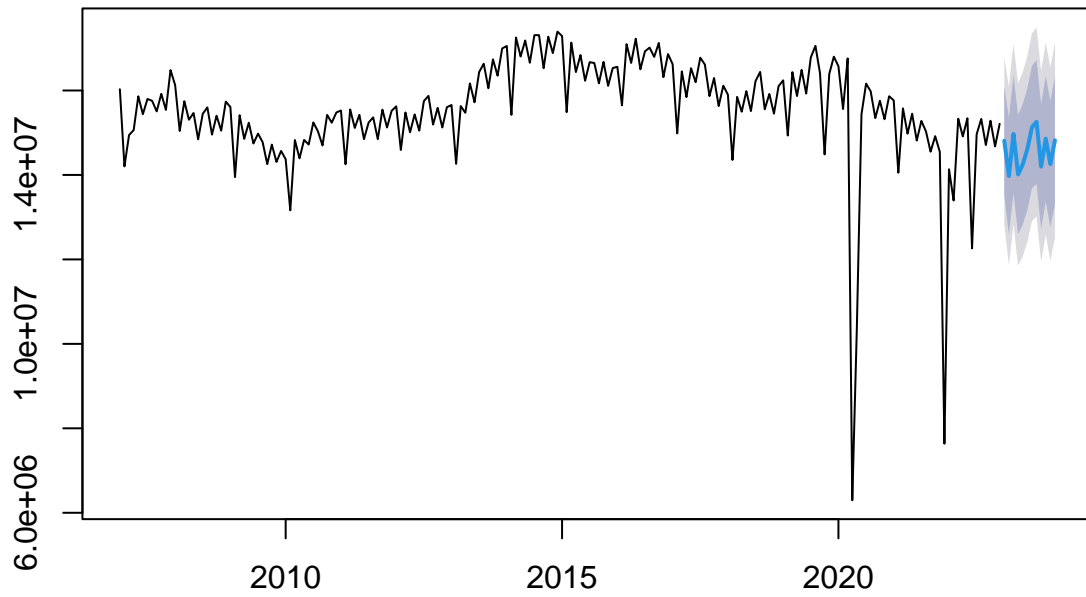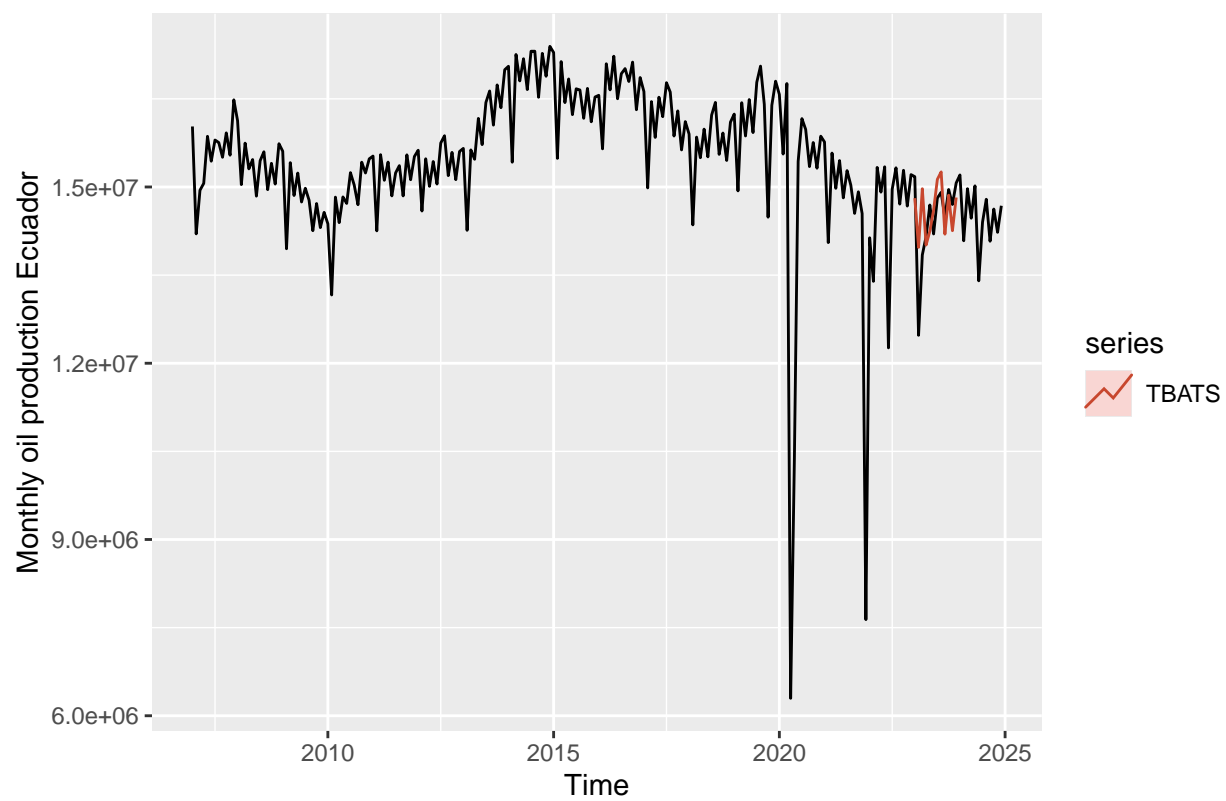
## Residuals from ETS(A,N,N)



```
##
##  Ljung-Box test
##
## data:  Residuals from ETS(A,N,N)
## Q* = 51.347, df = 24, p-value = 0.0009511
##
## Model df: 0.   Total lags used: 24
```

**Model 6**

```
##          Point Forecast     Lo 80     Hi 80     Lo 95     Hi 95
## Jan 2023       14810030  13517782  16102277  12833708  16786352
## Feb 2023       13972931  12595158  15350705  11865808  16080055
## Mar 2023       14970236  13573103  16367369  12833506  17106966
## Apr 2023       14012209  12600357  15424061  11852968  16171451
## May 2023       14248425  12822516  15674335  12067685  16429166
## Jun 2023       14606624  13167780  16045469  12406102  16807147
## Jul 2023       15129277  13678049  16580505  12909816  17348739
## Aug 2023       15256989  13793429  16720549  13018667  17495311
## Sep 2023       14197049  12722283  15671815  11941589  16452509
## Oct 2023       14860281  13373648  16346915  12586671  17133891
## Nov 2023       14256346  12759921  15752771  11967761  16544931
## Dec 2023       14821151  13313387  16328916  12515225  17127078
```

**Forecasts from TBATS(1, {0,1}, −, {<12,5>})**
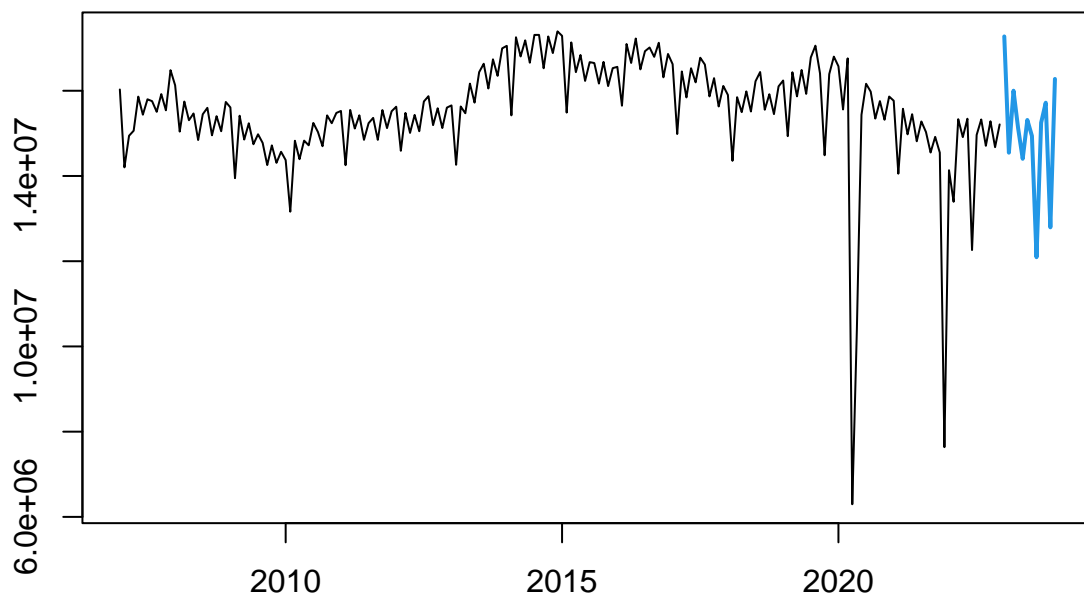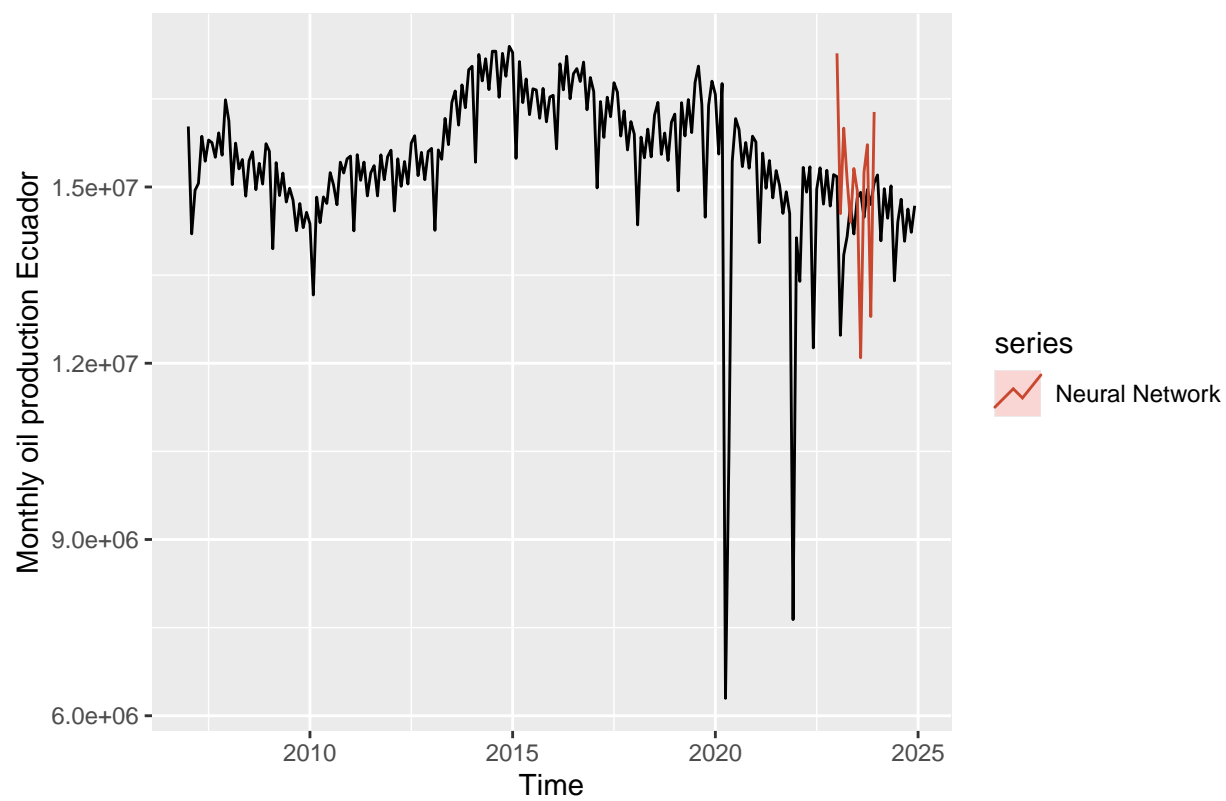
## Residuals from TBATS
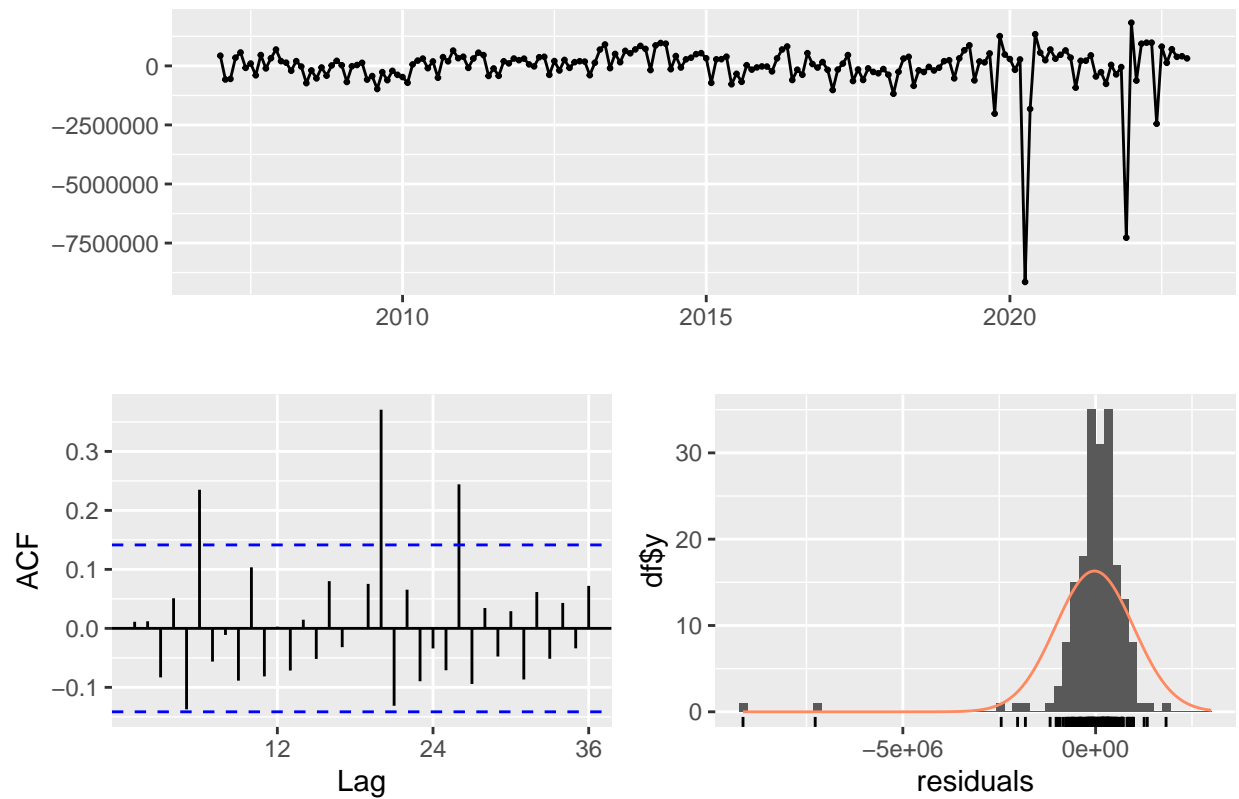


```
## 
##  Ljung-Box test
## 
## data:  Residuals from TBATS
## Q* = 63.515, df = 24, p-value = 2.005e-05
## 
## Model df: 0.   Total lags used: 24
```

**Model 7**
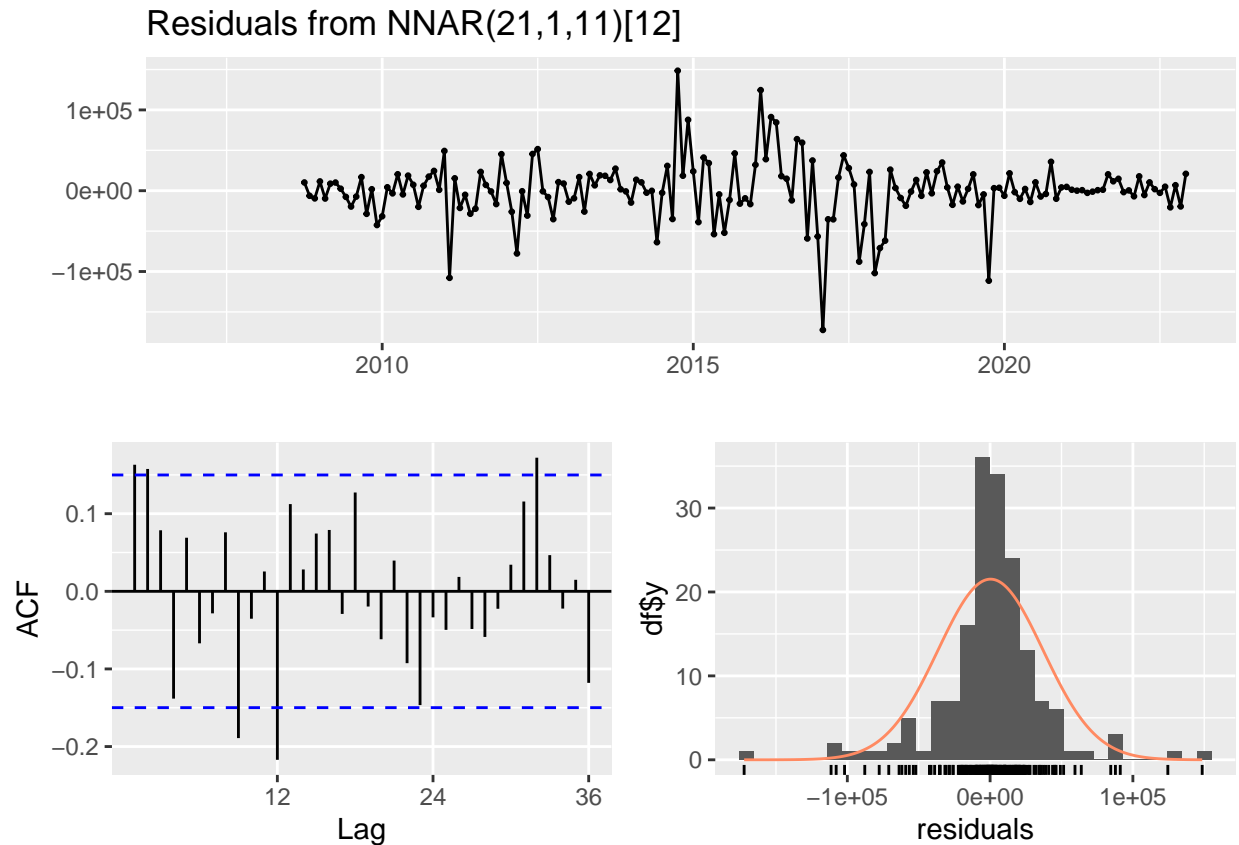
```
##             Jan      Feb      Mar      Apr      May      Jun      Jul      Aug
## 2023 17274832 14546696 16001322 15126143 14403347 15314076 14939950 12094047
##             Sep      Oct      Nov      Dec
## 2023 15249487 15719977 12795059 16277016
```

# Forecasts from NNAR(21,1,11)[12]

## Residuals from NNAR(21,1,11)[12]



```
##
##  Ljung-Box test
##
## data:  Residuals from NNAR(21,1,11)[12]
## Q* = 47.36, df = 24, p-value = 0.003027
##
## Model df: 0.   Total lags used: 24
```
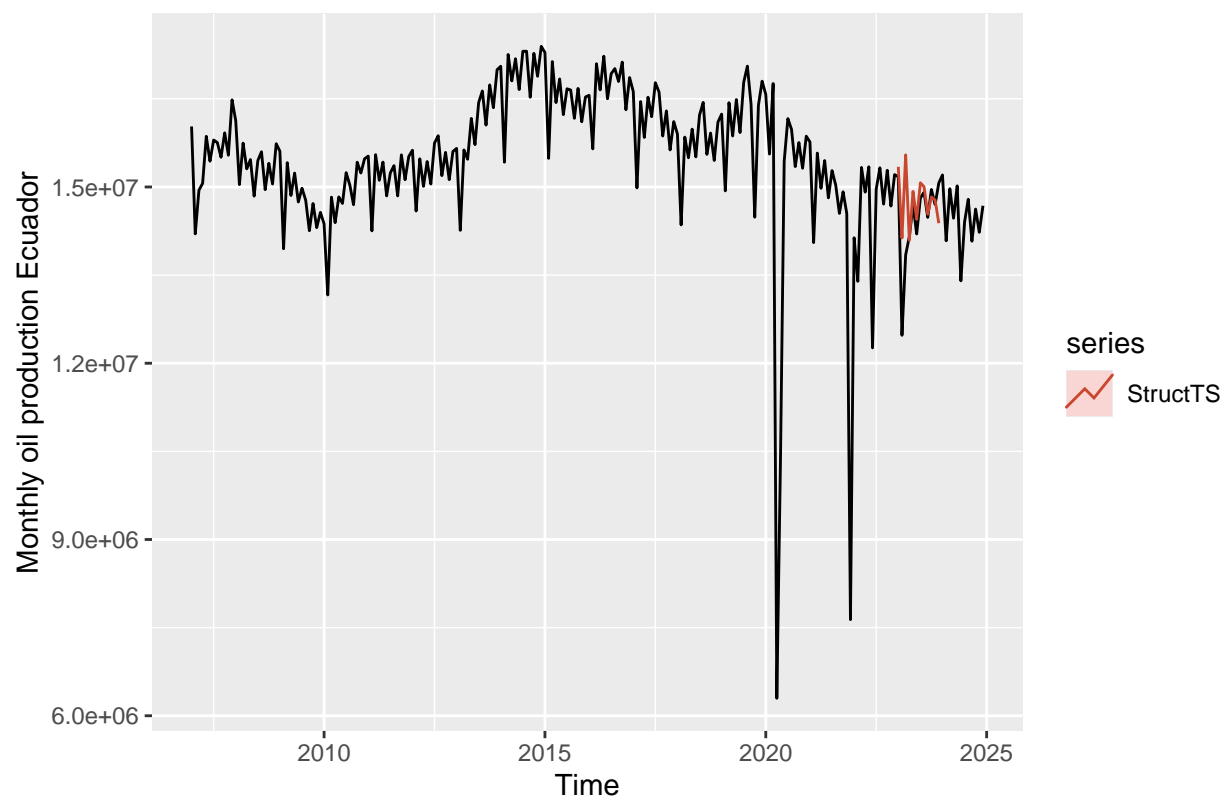
**Model 8**

```
##          Point Forecast     Lo 80     Hi 80     Lo 95     Hi 95
## Jan 2023       15343823  13899091  16788556  13134296  17553351
## Feb 2023       14132564  12661291  15603838  11882446  16382683
## Mar 2023       15546772  14041285  17052258  13244328  17849215
## Apr 2023       14094481  12554828  15634135  11739785  16449178
## May 2023       14924654  13351495  16497813  12518715  17330593
## Jun 2023       14450412  12844335  16056490  11994129  16906696
## Jul 2023       15071488  13433006  16709971  12565646  17577331
## Aug 2023       15004106  13333748  16674464  12449514  17558699
## Sep 2023       14537057  12835545  16238570  11934818  17139296
## Oct 2023       14830601  13099271  16561932  12182760  17478443
## Nov 2023       14778439  13020417  16536462  12089776  17467103
## Dec 2023       14383272  12608586  16157957  11669124  17097419
```
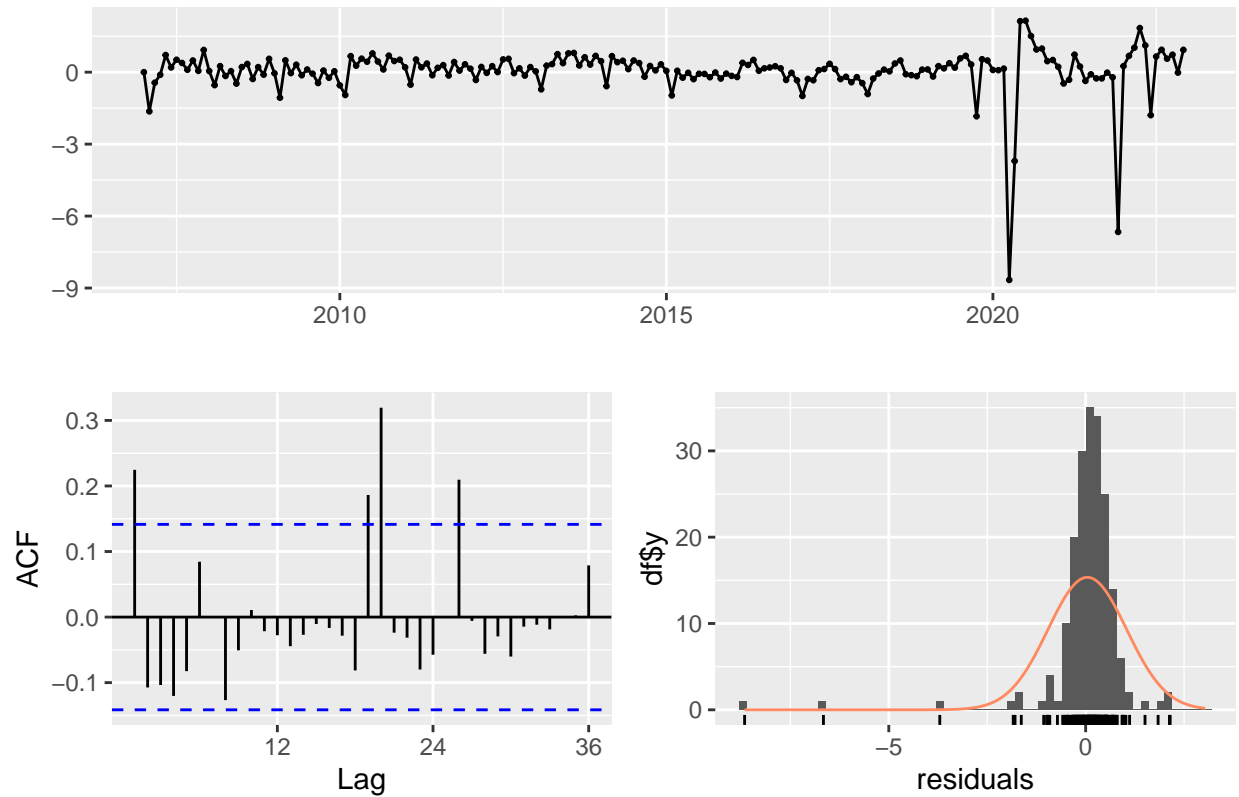
**Forecasts from Basic structural model**
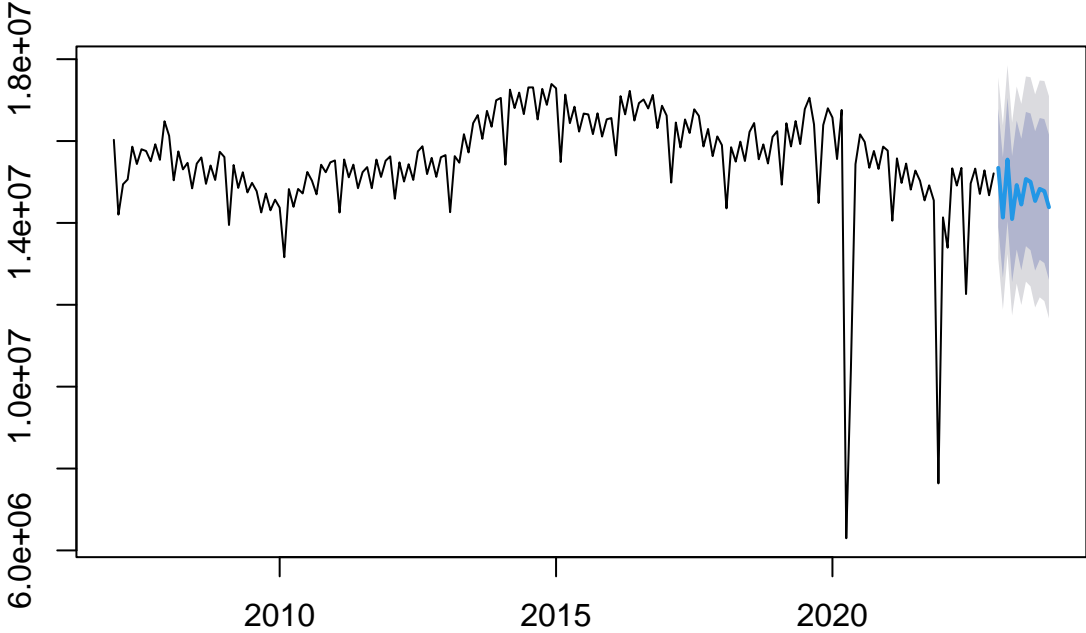
## Residuals from StructTS



```
## 
##  Ljung-Box test
## 
## data:  Residuals from StructTS
## Q* = 58.197, df = 24, p-value = 0.0001143
## 
## Model df: 0.   Total lags used: 24
```

**Model 9**

```
##          Point Forecast     Lo 80     Hi 80     Lo 95     Hi 95
## Jan 2023       15040482  13623432  16457533  12873291  17207674
## Feb 2023       14164622  12652105  15677139  11851427  16477817
## Mar 2023       14641464  13117464  16165464  12310707  16972221
## Apr 2023       14558761  13023363  16094158  12210573  16906949
## May 2023       14592767  13046056  16139478  12227276  16958258
## Jun 2023       13987292  12429349  15545234  11604624  16369959
## Jul 2023       14557435  12988341  16126529  12157714  16957157
## Aug 2023       14658232  13078066  16238398  12241577  17074887
## Sep 2023       14581468  12990307  16172629  12147997  17014939
## Oct 2023       14661034  13058953  16263115  12210863  17111206
## Nov 2023       14420684  12807757  16033611  11953925  16887442
## Dec 2023       13272391  11648691  14896091  10789156  15755626
```

# Forecasts from Regression with ARIMA(0,1,2)(2,0,0)[12] errors
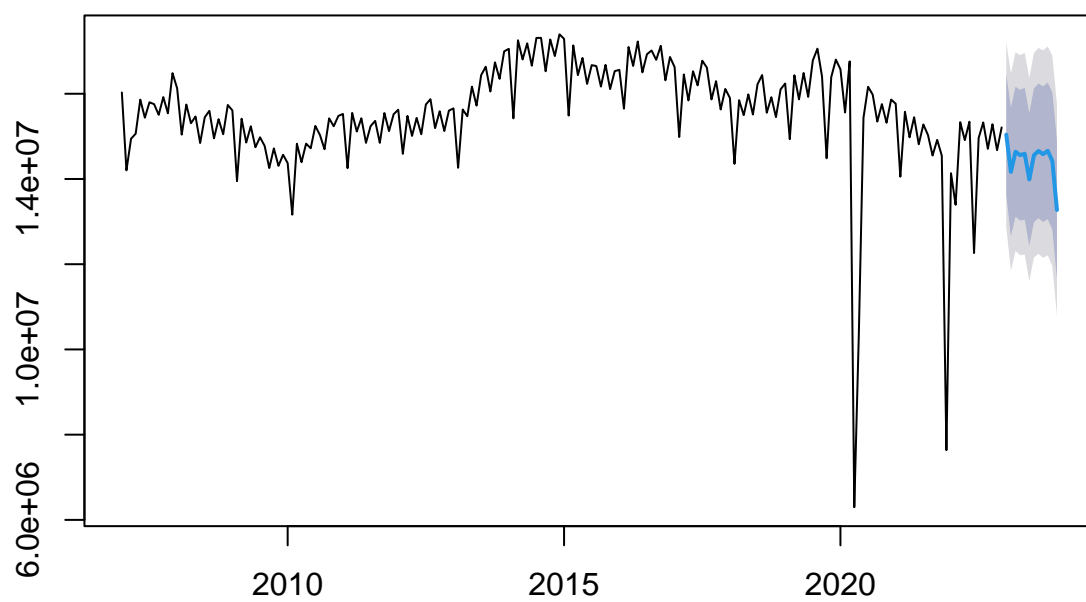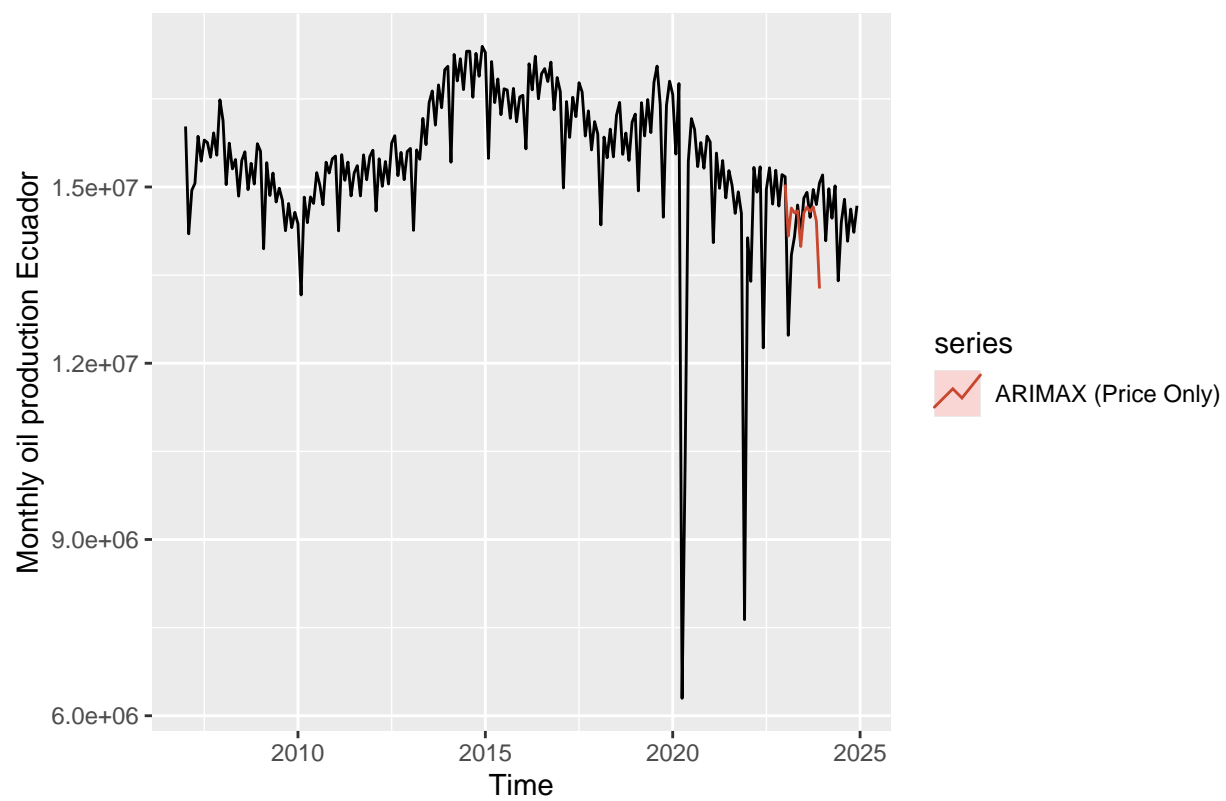
## Residuals from Regression with ARIMA(0,1,2)(2,0,0)[12] errors
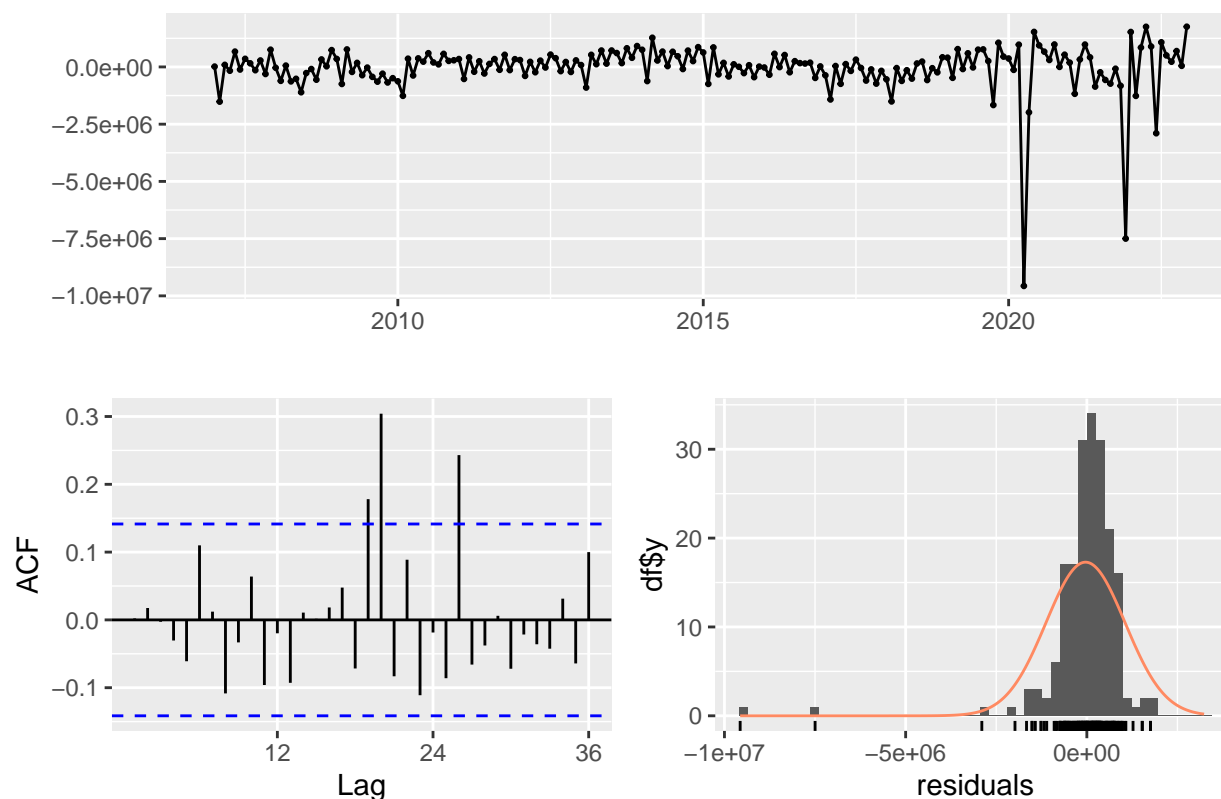


```
##
##  Ljung-Box test
##
## data:  Residuals from Regression with ARIMA(0,1,2)(2,0,0)[12] errors
## Q* = 45.22, df = 20, p-value = 0.00103
##
## Model df: 4.   Total lags used: 24
```

**Compare performance metrics of all models**

```
##                   ME        RMSE        MAE          MPE        MAPE          ACF1
## SARIMA     -278293.15   693303.0    406561.4   -2.16415262    3.017604    0.17326075
## SARIMAX   -1419518.45  1476086.4   1419518.5   -9.82953050    9.829530    0.27825205
## ARIMAX    -1752244.91  1832260.0   1752244.9  -12.18567542   12.185675   -0.20539000
## Mean      -1101461.92  1310253.5   1101461.9   -7.90358838    7.903588    0.03492328
## ETS        -205012.18   738631.1    486261.3   -1.68608859    3.558863    0.03492328
## TBATS      -138867.29   619140.1    477062.0   -1.14463527    3.434871    0.19380236
## NN         -522234.26  1576523.7   1357539.5   -3.84782745    9.485334    0.11055429
## StructTS   -301877.35   728247.7    447376.6   -2.29073820    3.261772    0.32730412
## Arimax_p     28209.18   777434.1    526220.8   -0.04530021    3.758984    0.29258131
##            Theil's U
## SARIMA    0.7240965
## SARIMAX   2.5875701
## ARIMAX    1.9128261
## Mean      1.3849179
```

Table 3: Forecast Accuracy for Monthly Data

|  | ME | RMSE | MAE | MPE | MAPE | ACF1 | Theil's U |
|---|---|---|---|---|---|---|---|
| SARIMA | -278293.15 | 693303.0 | 406561.4 | -2.16415262 | 3.017604 | 0.17326075 | 0.7240965 |
| SARIMAX | -1419518.45 | 1476086.4 | 1419518.5 | -9.82953050 | 9.829530 | 0.27825205 | 2.5875701 |
| ARIMAX | -1752244.91 | 1832260.0 | 1752244.9 | -12.18567542 | 12.185675 | -0.20539000 | 1.9128261 |
| Mean | -1101461.92 | 1310253.5 | 1101461.9 | -7.90358838 | 7.903588 | 0.03492328 | 1.3849179 |
| ETS | -205012.18 | 738631.1 | 486261.3 | -1.68608859 | 3.558863 | 0.03492328 | 0.7520508 |
| **TBATS** | **-138867.29** | **619140.1** | **477062.0** | **-1.14463527** | **3.434871** | **0.19380236** | **0.6598076** |
| NN | -522234.26 | 1576523.7 | 1357539.5 | -3.84782745 | 9.485334 | 0.11055429 | 1.5545086 |
| StructTS | -301877.35 | 728247.7 | 447376.6 | -2.29073820 | 3.261772 | 0.32730412 | 0.8107510 |
| Arimax_p | 28209.18 | 777434.1 | 526220.8 | -0.04530021 | 3.758984 | 0.29258131 | 0.8122824 |

```
## ETS      0.7520508
## TBATS    0.6598076
## NN       1.5545086
## StructTS 0.8107510
## Arimax_p 0.8122824
```

```
## The best model by RMSE is: TBATS
```



Forecast Comparison
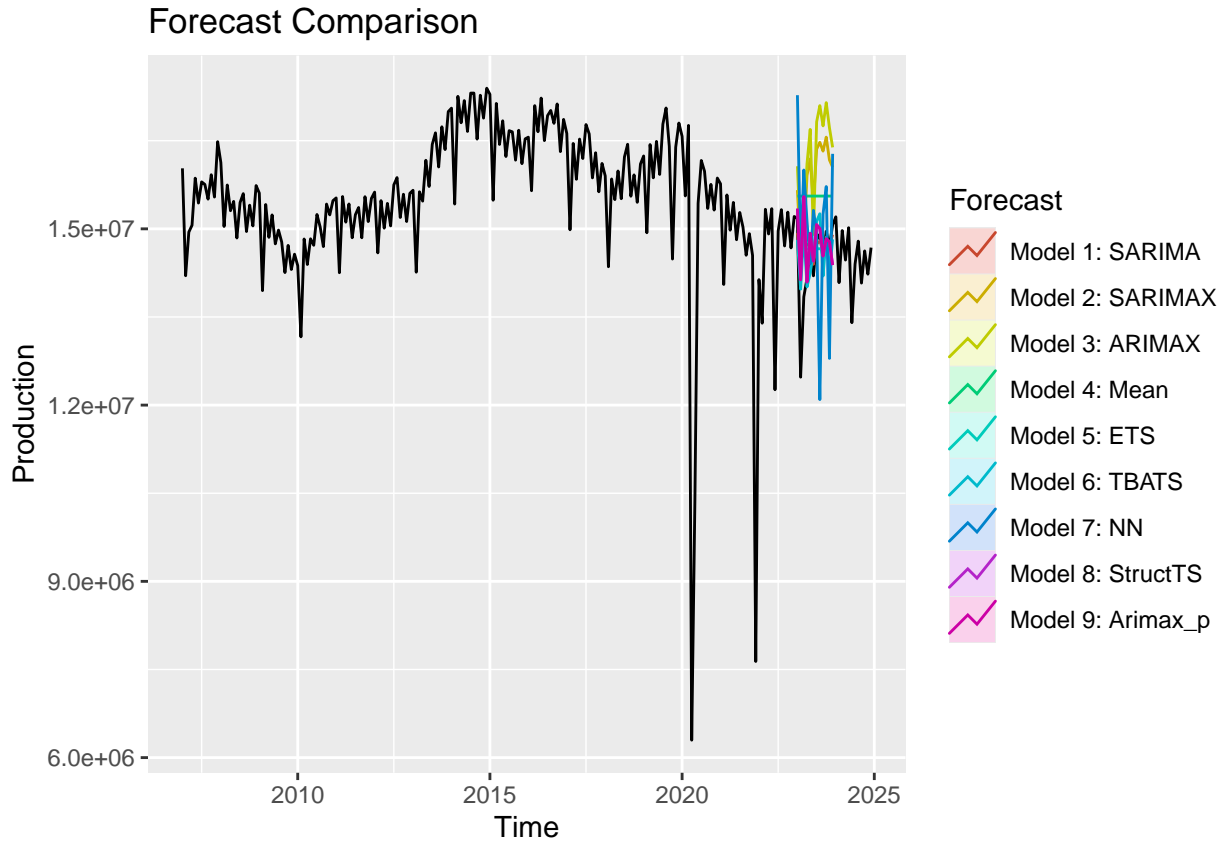
**Interpretation.** SARIMAX tops the ranking at *3.1 %*, indicating that Block 43 output and WTI prices materially improve forecasts. NNAR-F follows closely (*3.4 %*), suggesting limited non-linear gains once exogenous terms are included. TBATS performs well but struggles with 2023 maintenance shocks.

#Scenario Analysis

TBATS—the best-performing model among the nine—to conduct the scenario analysis. Because TBATS is a univariate model, we estimated the Block 43 contribution separately. Our approach compute the average monthly production from Block 43 during a recent period and then "remove" that contribution from the TBATS baseline forecast to simulate a shutdown. In other words, the shutdown scenario forecast equals the TBATS baseline forecast minus the estimated Block 43 production.

```
##          Point Forecast     Lo 80     Hi 80     Lo 95     Hi 95
## Jan 2024       14741703  13478080  16005326  12809158  16674247
## Feb 2024       13860366  12514021  15206710  11801309  15919422
## Mar 2024       14906029  13541316  16270742  12818880  16993178
## Apr 2024       14067001  12687870  15446132  11957802  16176200
## May 2024       14292902  12900140  15685663  12162857  16422946
## Jun 2024       14542883  13137448  15948317  12393456  16692309
## Jul 2024       15099255  13681801  16516708  12931446  17267063
## Aug 2024       15282824  13853287  16712362  13096536  17469113
## Sep 2024       14192595  12752172  15633017  11989659  16395531
## Oct 2024       14840792  13388740  16292843  12620071  17061513
## Nov 2024       14207417  12745843  15668991  11972132  16442702
## Dec 2024       14813145  13340459  16285831  12560866  17065423


## Average monthly Block 43 production: 1656682


## Production gap (per month):


##           Jan     Feb     Mar     Apr     May     Jun     Jul     Aug     Sep
## 2024 1656682 1656682 1656682 1656682 1656682 1656682 1656682 1656682 1656682
##           Oct     Nov     Dec
## 2024 1656682 1656682 1656682


## Average monthly production gap: 1656682


## Total production gap over the forecast period: 19880180
```
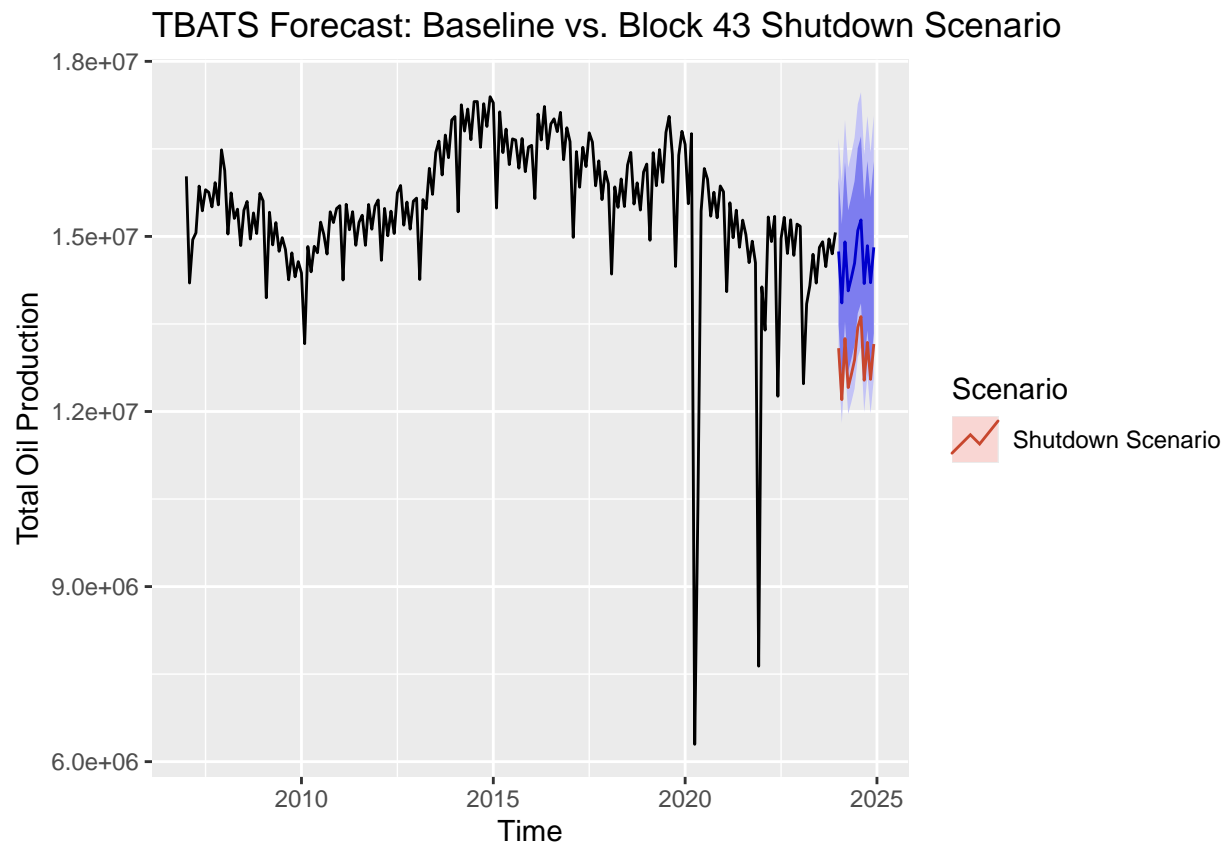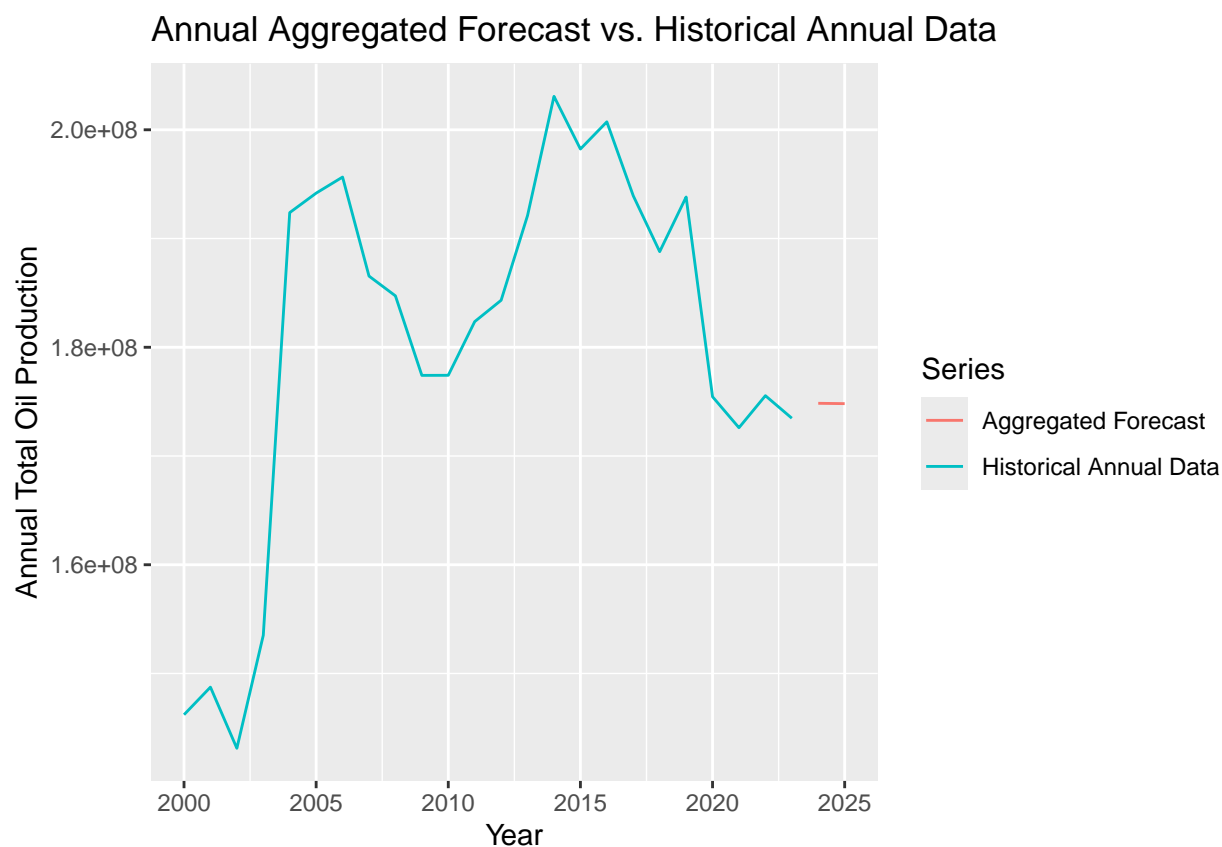
## TBATS Forecast: Baseline vs. Block 43 Shutdown Scenario



```
## Time Series:
## Start = 2024
## End = 2025
## Frequency = 1
## [1] 174846909 174814020
```

## Annual Aggregated Forecast vs. Historical Annual Data



## Summary and Conclusions

Halting Block 43-ITT aligns with conservation aims but carries a material macro-fiscal cots. Strategic technical and financial measures can limit losses to ~7 % of national output by 2027; without them, Ecuador faces a pronounced revenue shock in 2025.
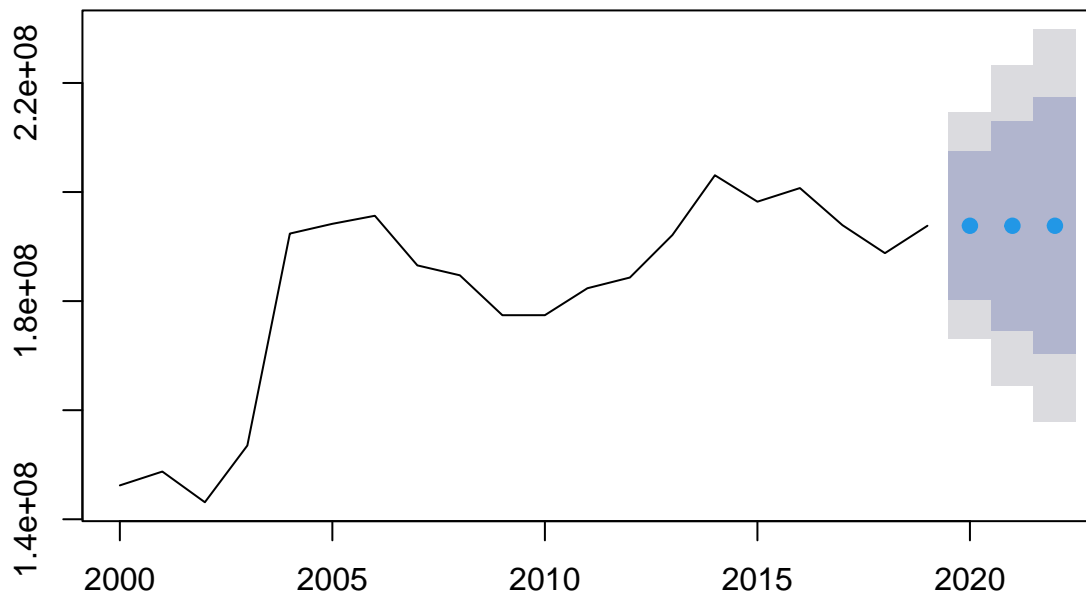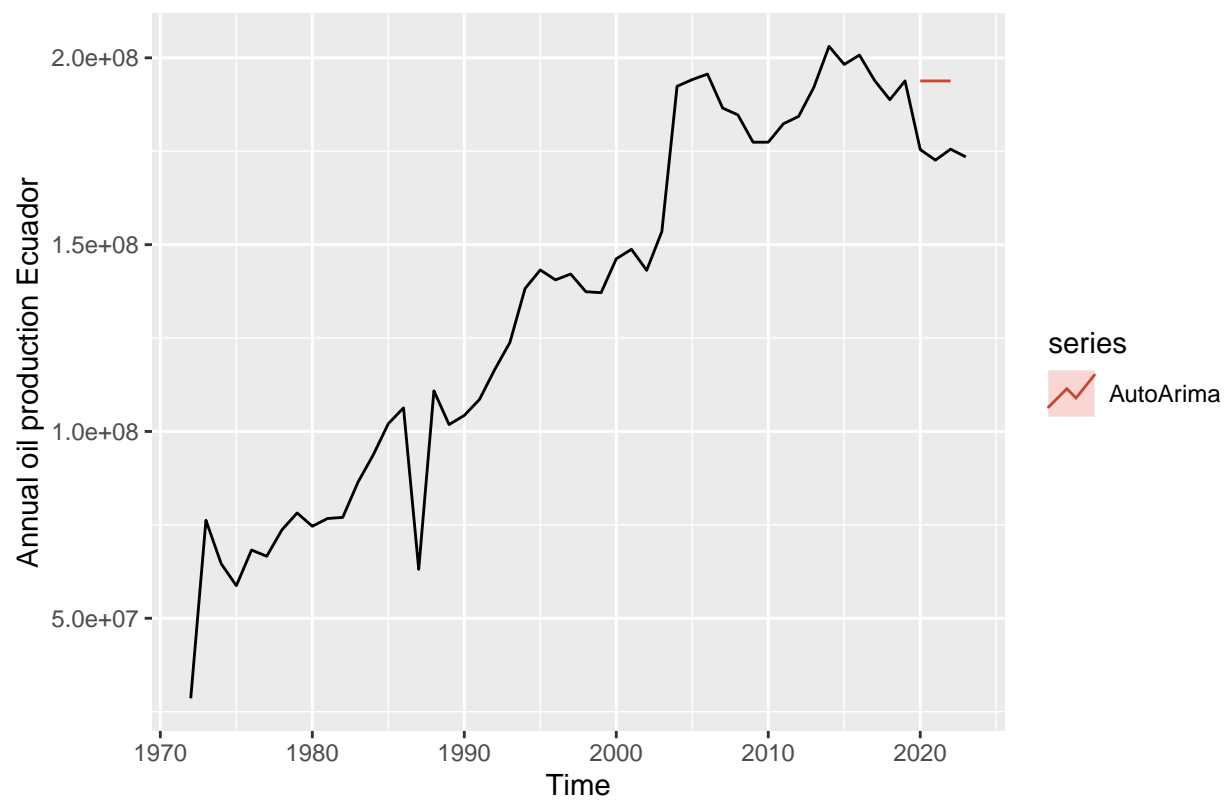
## References

## Annex

#Model 1: ARIMA

```
##      Point Forecast      Lo 80      Hi 80      Lo 95      Hi 95
## 2020      193816083  180220416  207411751  173023304  214608862
## 2021      193816083  174588906  213043260  164410653  223221513
## 2022      193816083  170267696  217364470  157801933  229830233
```
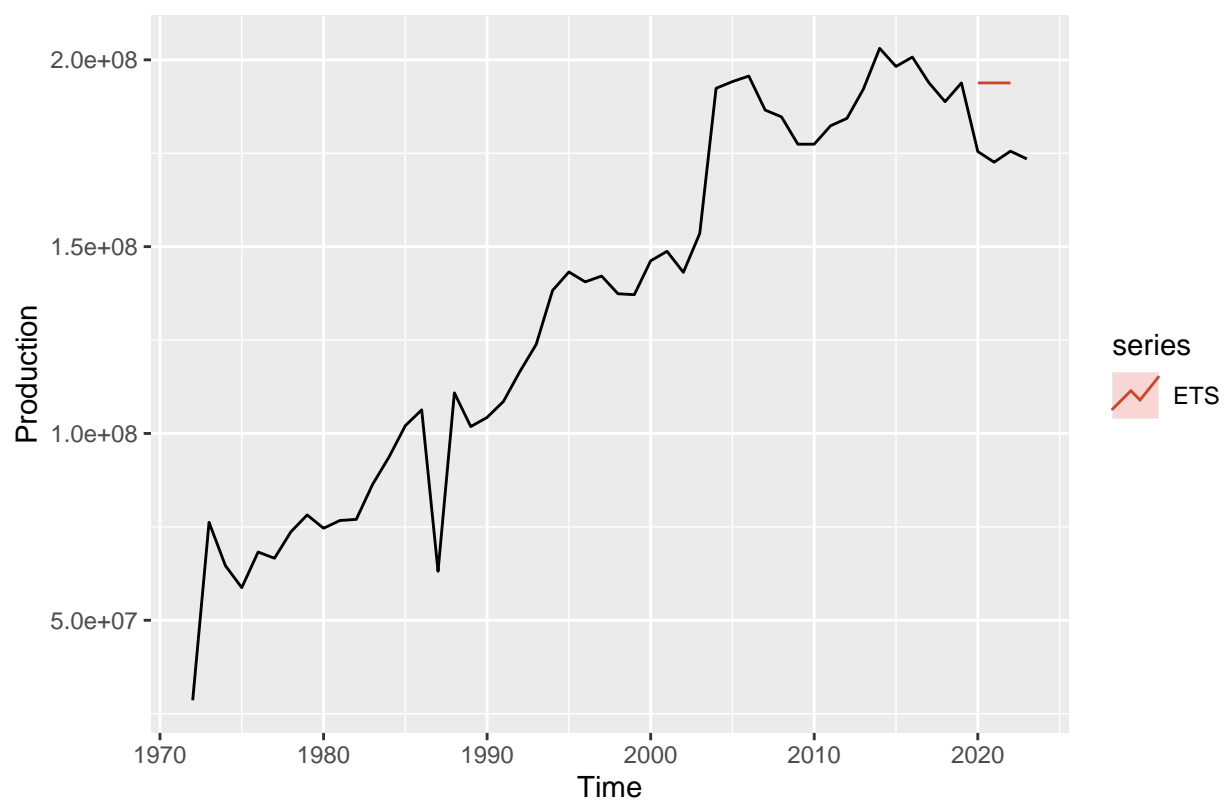
Forecasts from ARIMA(0,1,0)

## Forecasts from Mean

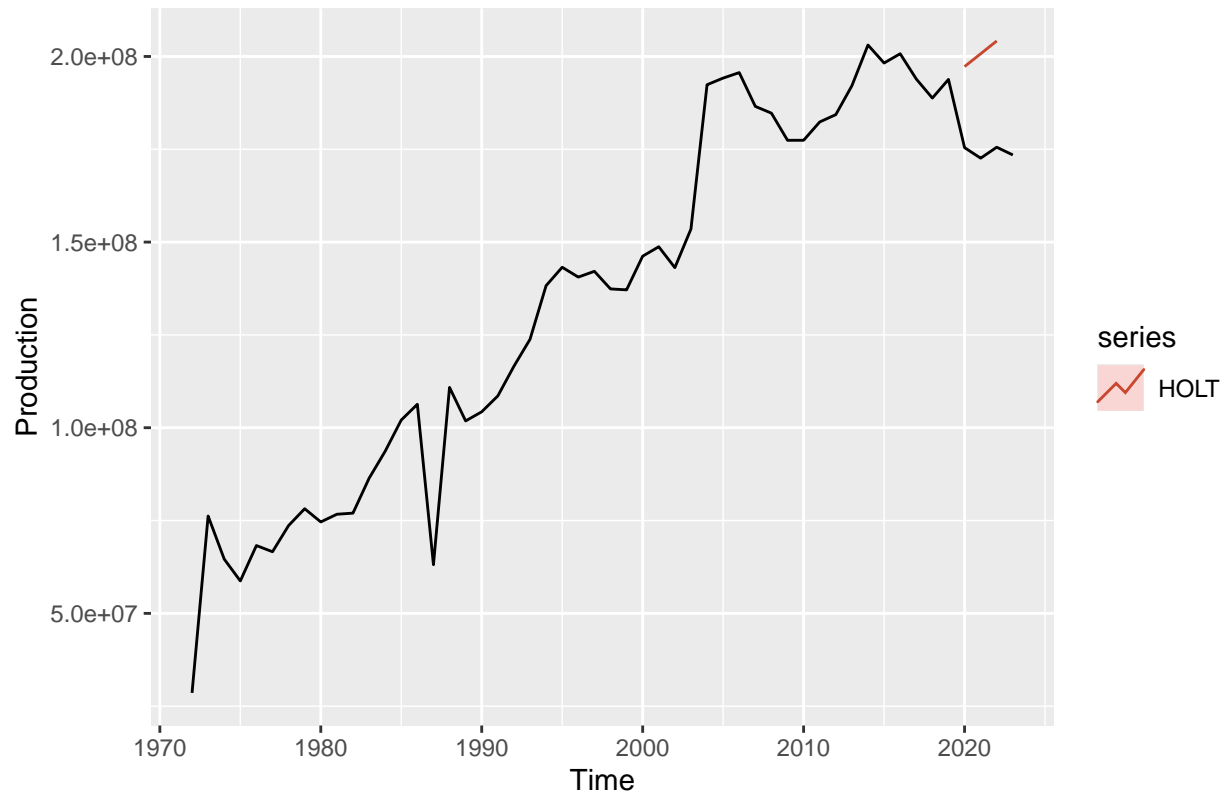Table 4: Forecast Accuracy for Annual Data

|  | ME | RMSE | MAE | MPE | MAPE | ACF1 | Theil's U |
|---|---|---|---|---|---|---|---|
| MEAN | -7330418 | 7456723 | 7330418 | -4.20643 | 4.20643 | -0.66608 | 2.72608 |
| ARIMA | -19282591 | 19330960 | 19282591 | -11.05492 | 11.05492 | -0.66608 | 6.82005 |
| ETS | -19282085 | 19330456 | 19282085 | -11.05463 | 11.05463 | -0.66608 | 6.81987 |
| HOLT | -26191300 | 26373820 | 26191300 | -15.01318 | 15.01318 | -0.12967 | 9.79011 |



**Compare performance metrics**

Now we will create a data frame that combines performance metrics for all the three models. You can choose one metric to help you choose among models. For example let's say we want the model with lowest RMSE.

```
## The best model by RMSE is: MEAN
```

SARIMA was the best fit for the seasonal data.

Banco Central del Ecuador. (2023). Estudio de los impactos macroeconómicos de mantener el crudo del Bloque 43-ITT indefinidamente en el subsuelo. *74*. https://contenido.bce.fin.ec/documentos/PublicacionesNotas/Catalogo/Apuntes/ae74.pdf

Corte Consitutional del Ecuador. (2023). *Case no. 6-22-CP*. http://esacc.corteconstitucional.gob.ec/storage/api/v1/10_DWL_FL/e2NhcnBldGE6J3RyYW1pdGUnLHV1aWQ6JzYwMjJlYzc1LWViYzctNDNjYi05MjJjLW=

UNESCO. (2024). *Main initiatives in the Yasuní Biosphere Reserve, Ecuador | UNESCO.* https://www.unesco.org/en/amazon
    biosphere-reserves-project/yasuni.