

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.

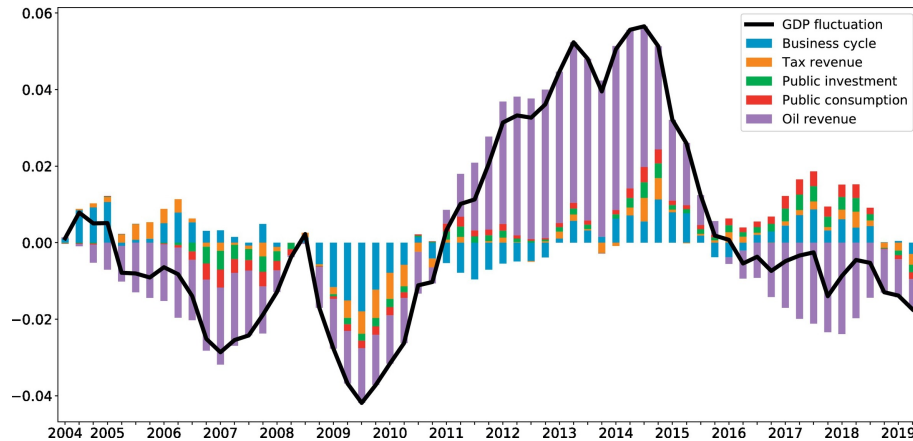


Figure 1: GDP fluctuations vs oil revenue between 2004-2019

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).

- 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 of 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.

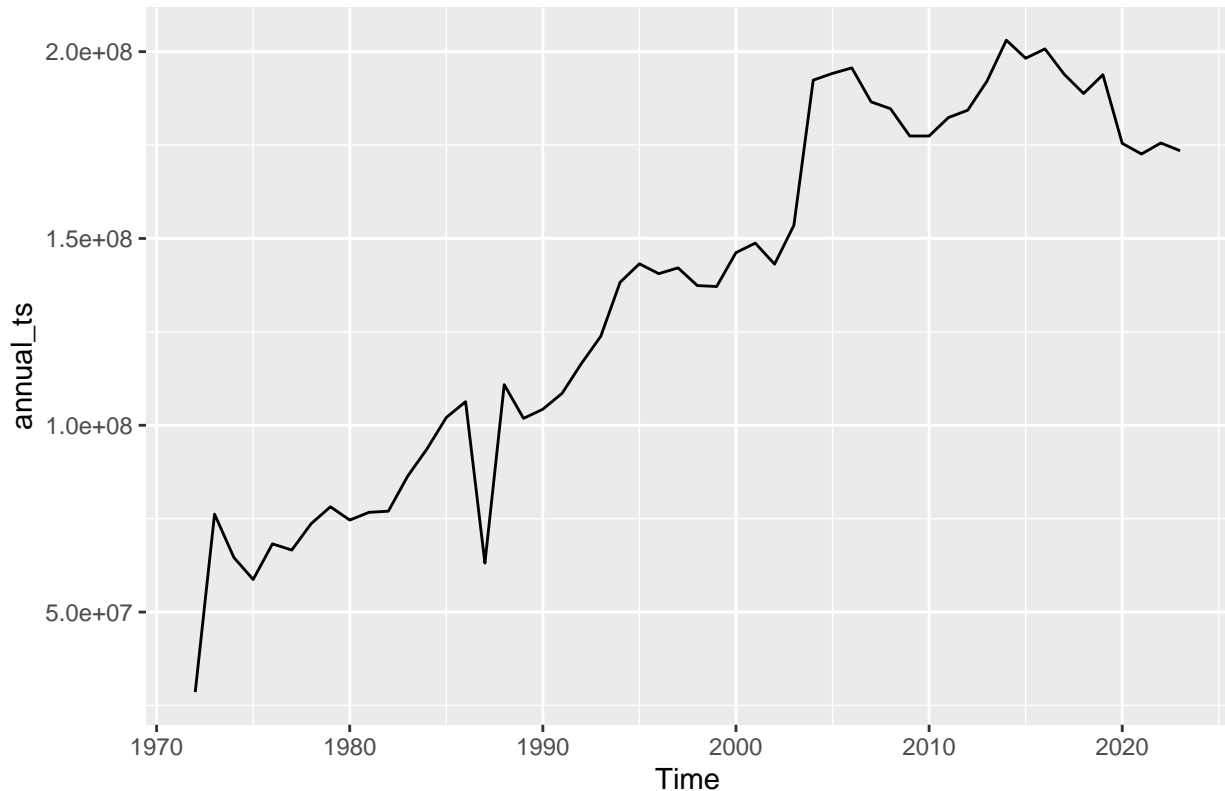
The difference in total production between the baseline and shutdown forecasts is the gap that other blocks must fill to maintain the same output level.

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.

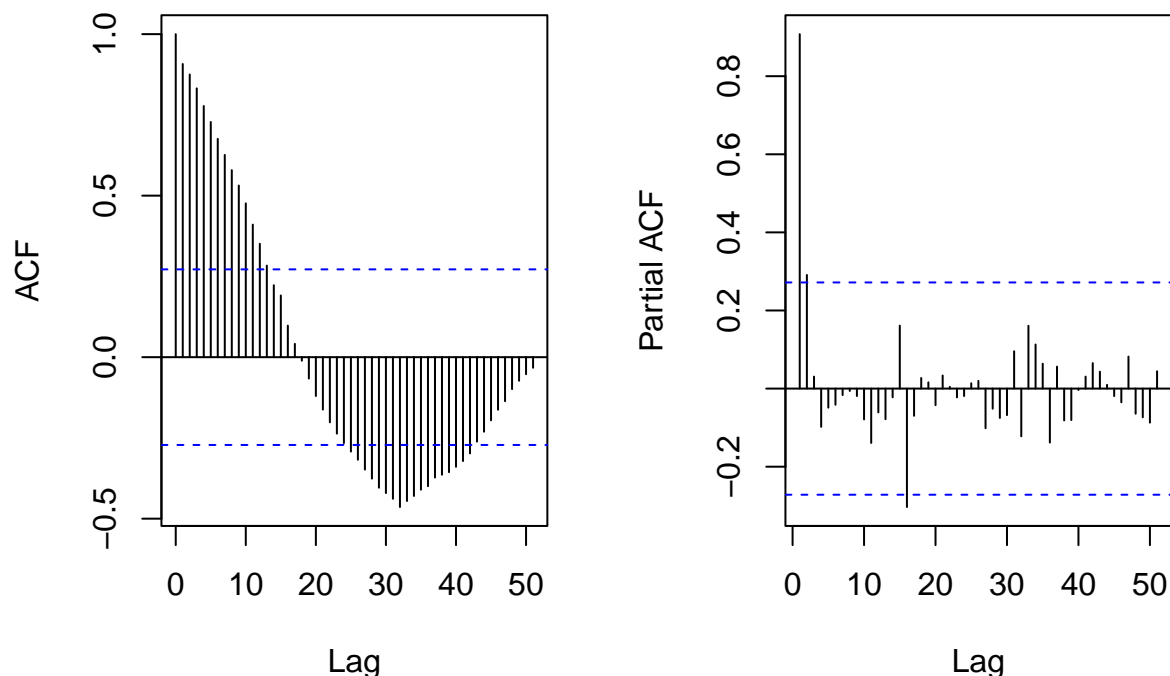
The solely visualization may suggest that including data from before 2000 —when output was only a fraction of its subsequent levels— could distort our model’s parameters. In contrast, restricting the sample to the period from 2000 onward, when production stabilized at its modern scale, is likely to yield 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.

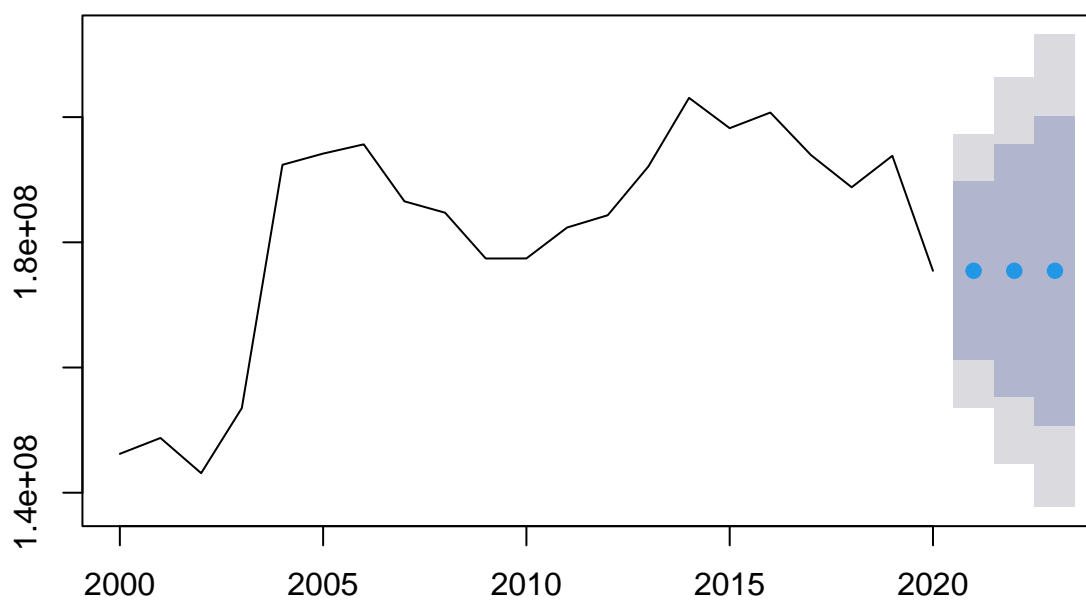


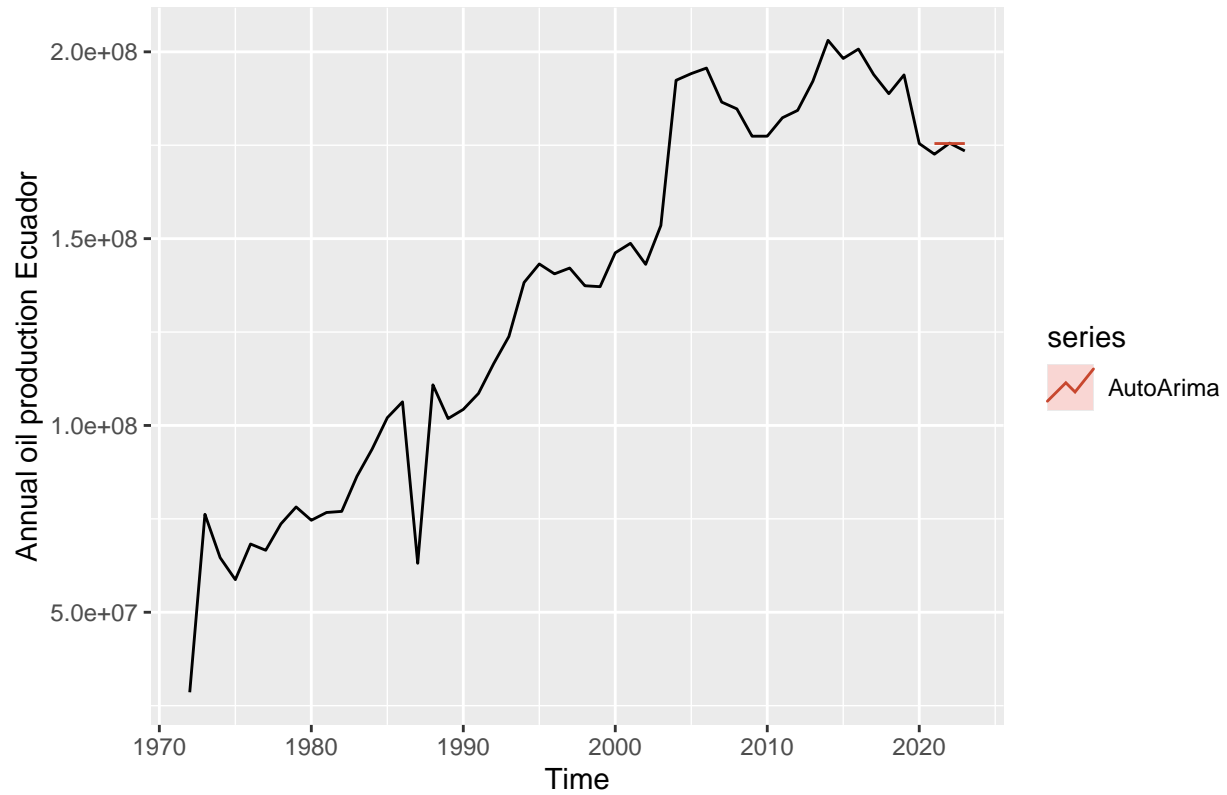
All the annual forecasting models were trained using data up to the year 2020. Because when using the pre-pandemic period, forecast performed poorly (see Annex).

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)



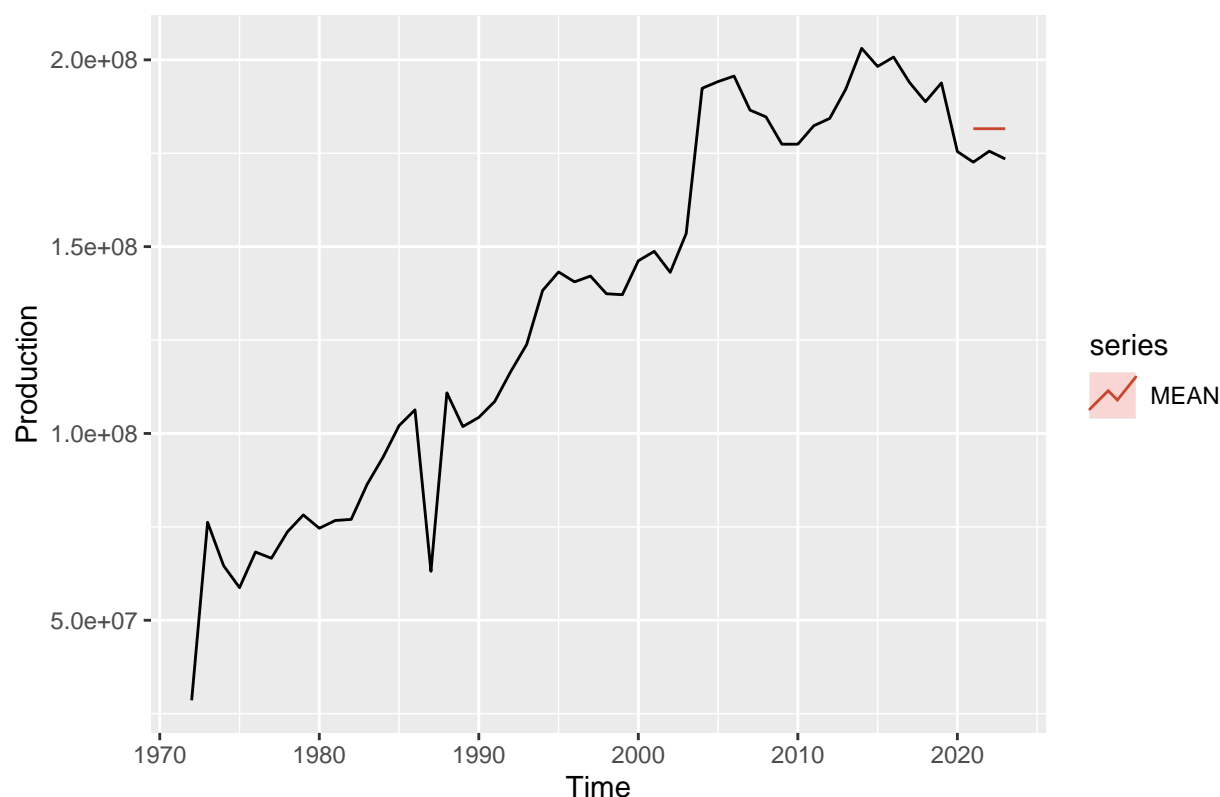


Testing Model 2: MEAN The Mean model employs a much simpler approach than ARIMA, that generates a flat forecast (blue dots) at approximately 181 million barrels with a wide confidence intervals, indicating high uncertainty. Besides, its performance metrics (see Table 1) reveal significant weaknesses, 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

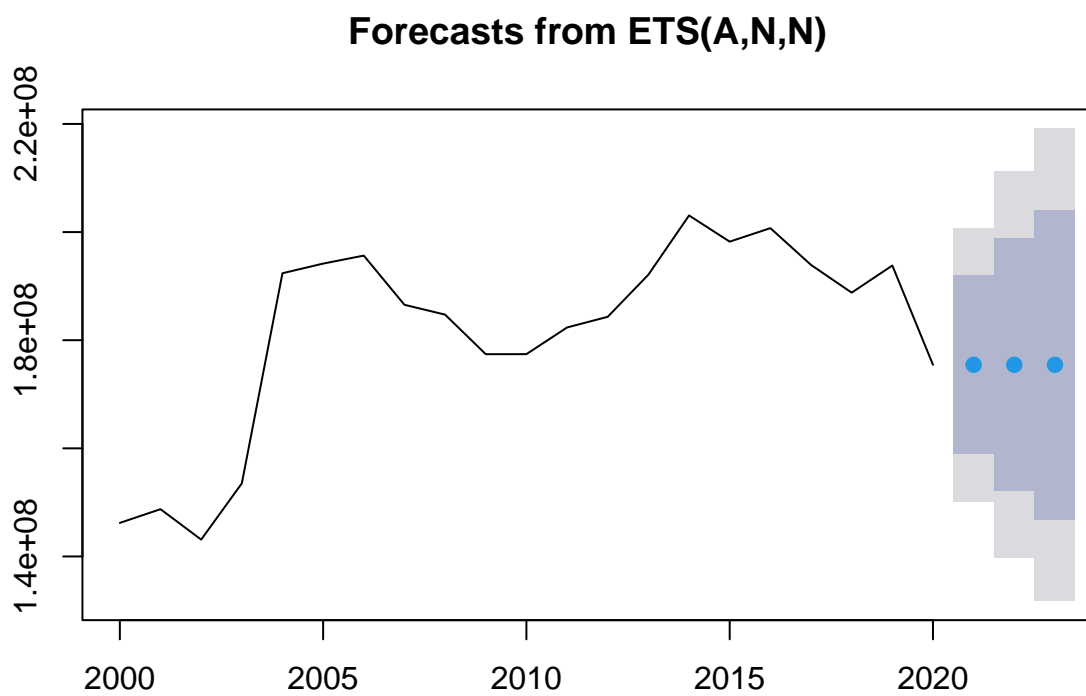


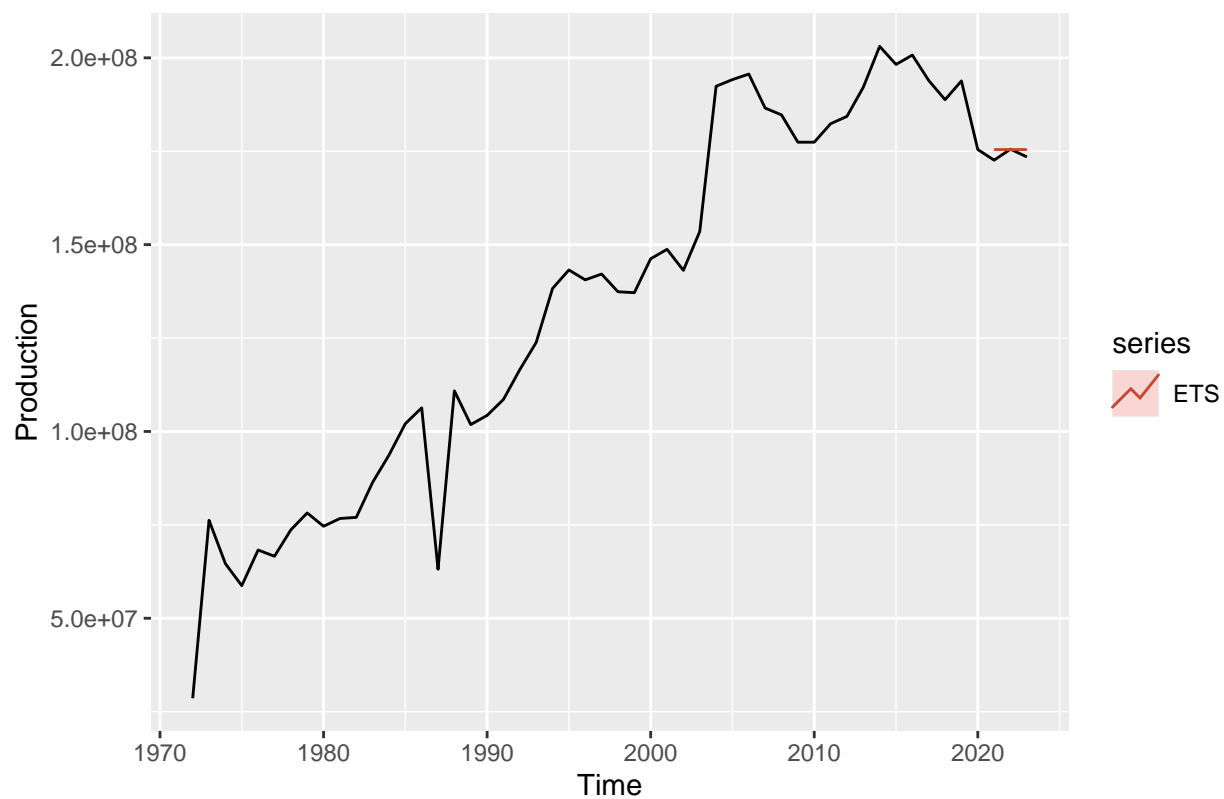


Testing Model 3: ETS The ETS model effectively “locks in” the most recent observed level (approximately 175 million barrels) and extrapolates it forward, producing a flat forecast line characterized by moderately narrow confidence bands. This tighter band of uncertainty, compared to the mean model’s 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





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 suggest it actually performs worse than a naïve method.

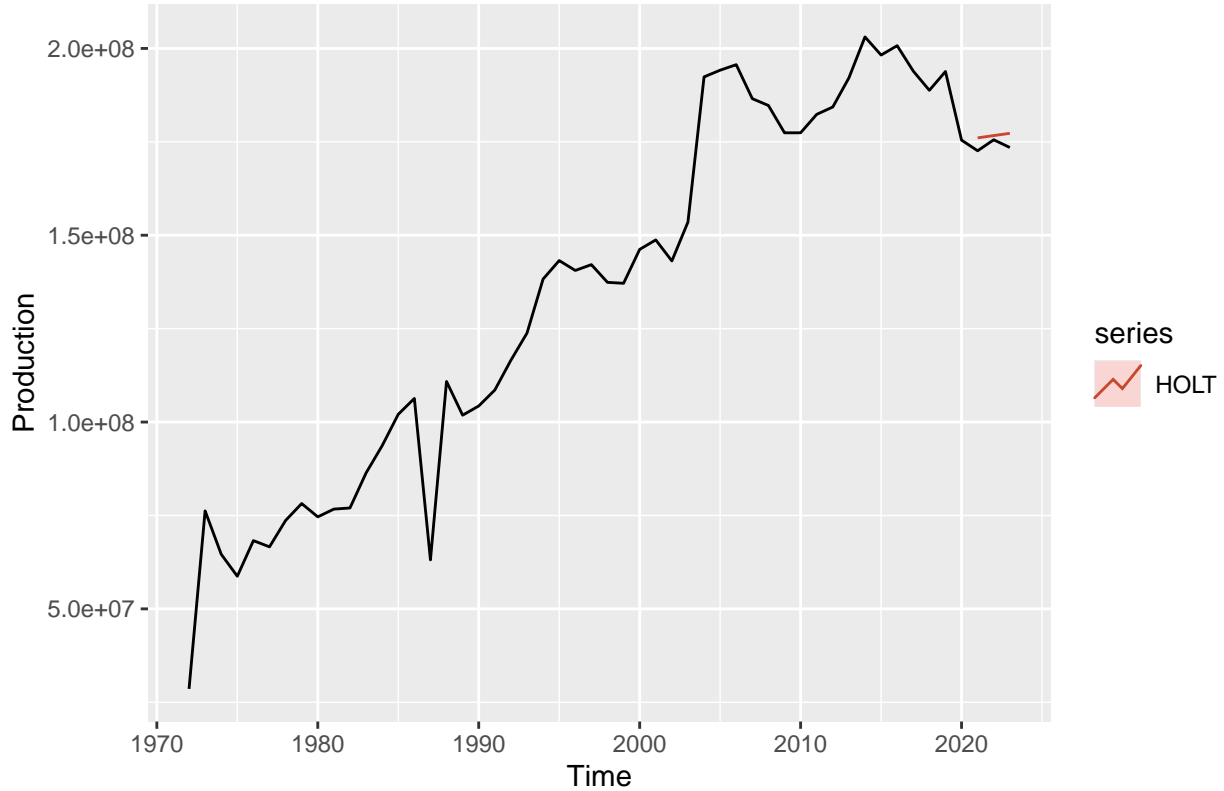
##	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
## 2021	176061114	159675163	192447065	151000965	201121263
## 2022	176670451	152596519	200744383	139852550	213488352
## 2023	177279788	146679865	207879711	130481244	224078332

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

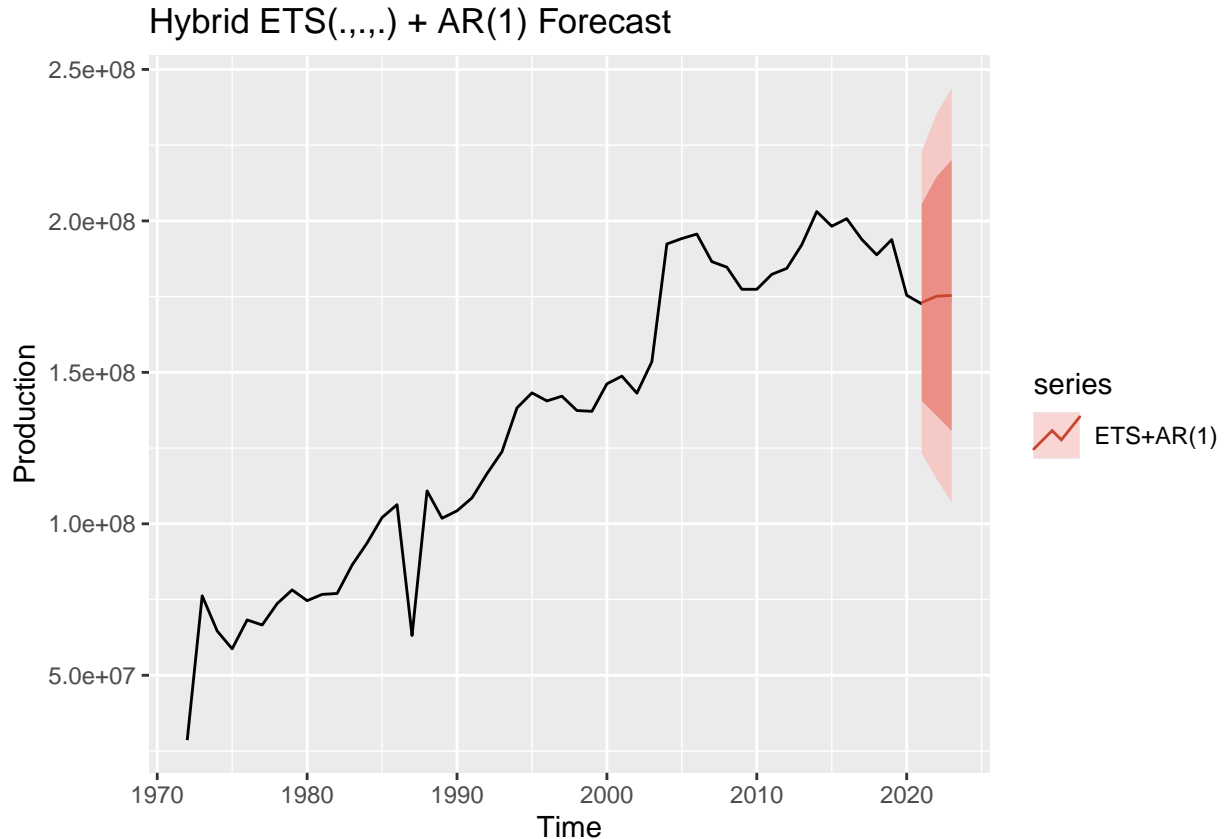
Table 2: Table 2. Forecast Accuracy for Annual Data

	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
```



```
##           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)
```

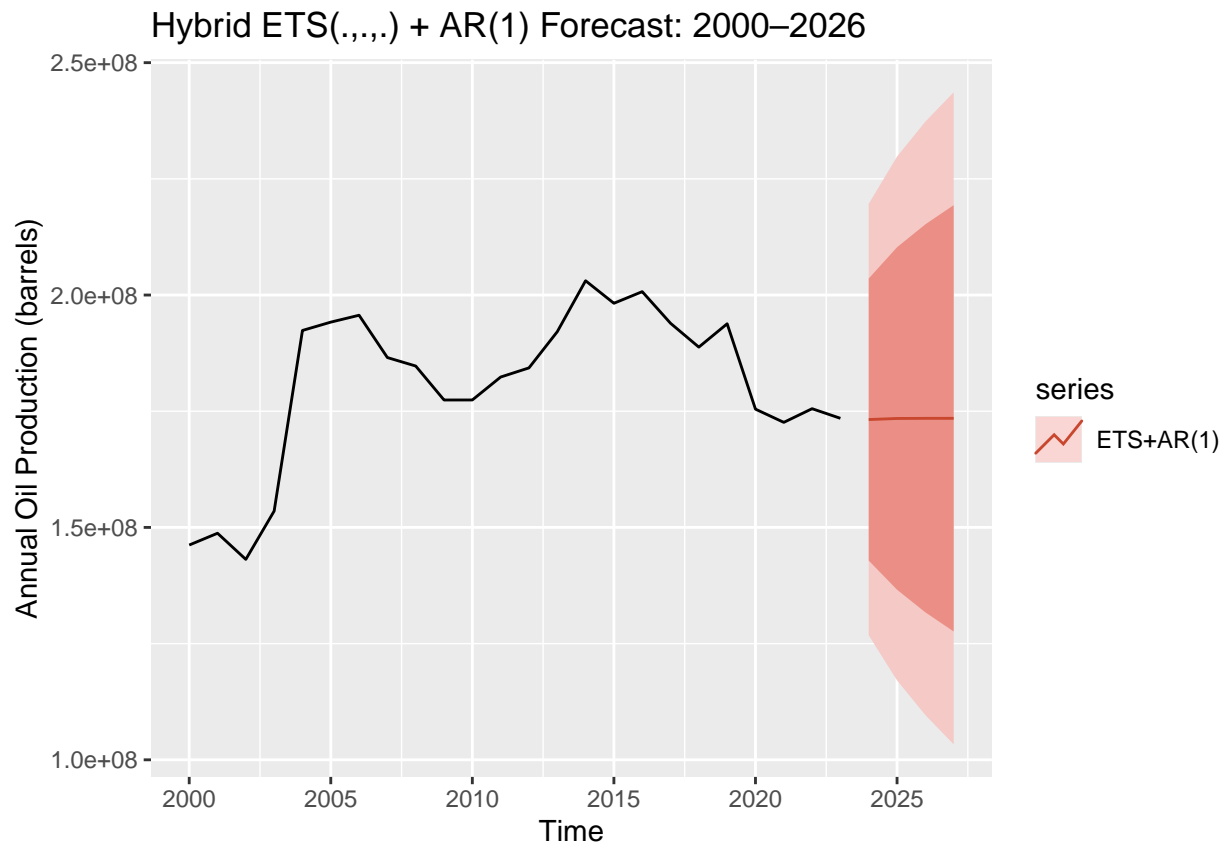
```
## The best model by MAPE is: Hybrid ETS & AR(1)
```

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.

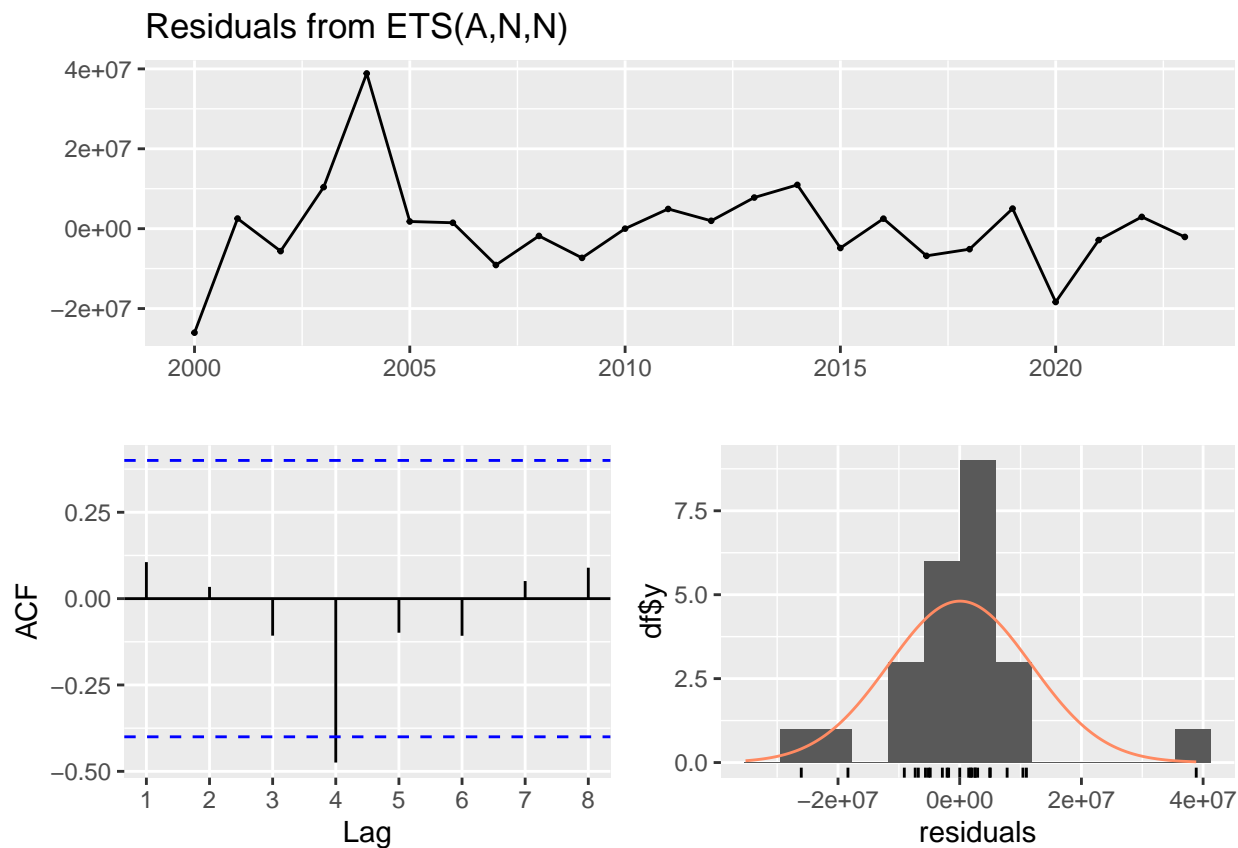
```
## [1] "80%" "95%"
```

```
## [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

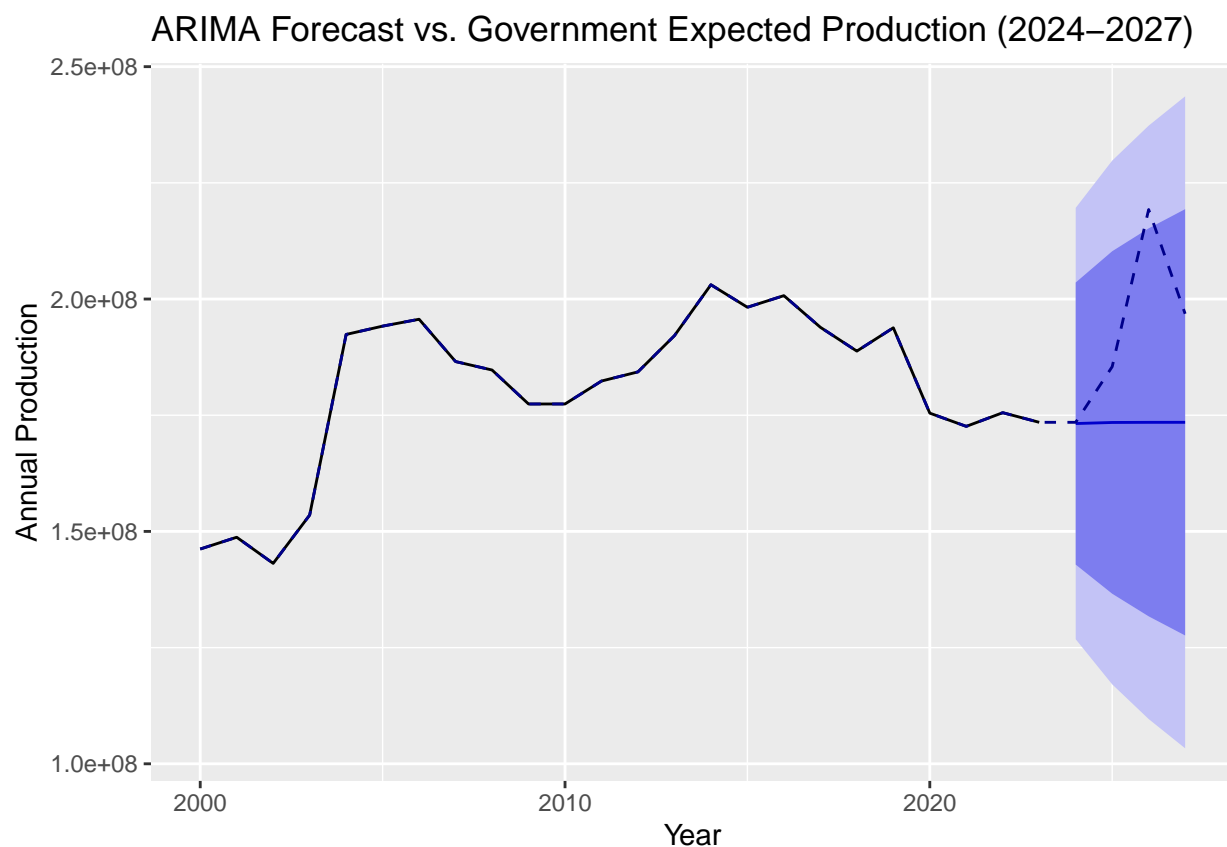


The residuals fluctuate randomly around zero with no obvious drift or changing variance, and—aside from a single large error in the mid-2000s—stay within about ± 20 million barrels. Moreover, the ACF shows all lags inside the 95 % confidence bounds (lag 4 is barely crossing the bounds, but we would say 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.



```
##
##  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: 4
```

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.

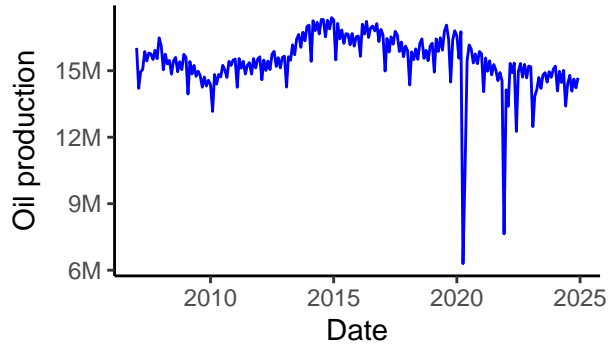


Stage B (Month-Level Analysis):

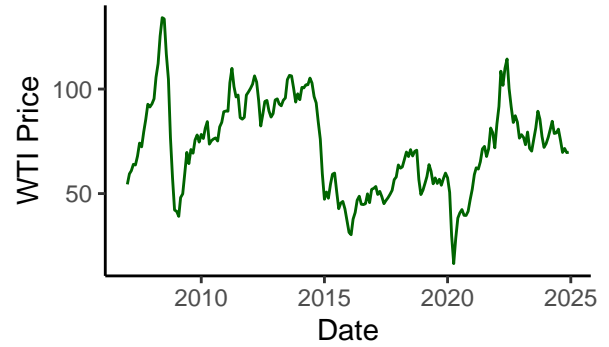
This is a more detailed monthly analysis from 2007–2023 using monthly WTI prices and Block 43 production. The following graphs shows oil production in Ecuador has been decreasing. Oil extraction in Block 43-ITT started in 2016 and has boosted the economy. Plot 4 shows that oil exploitation on Block 43-ITT 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).

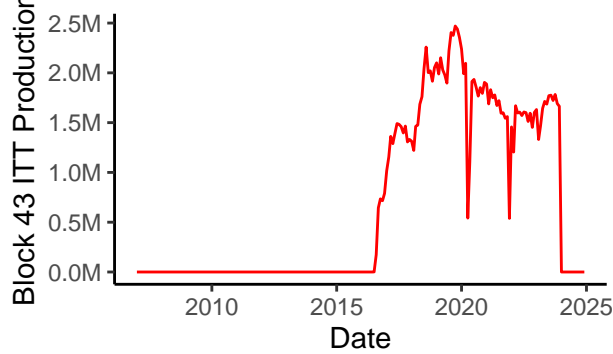
Plot 1: Monthly Oil Production in Ecuador



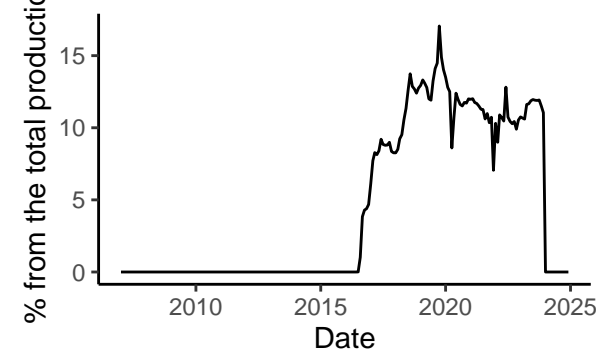
Plot 2: Monthly WTI Prices



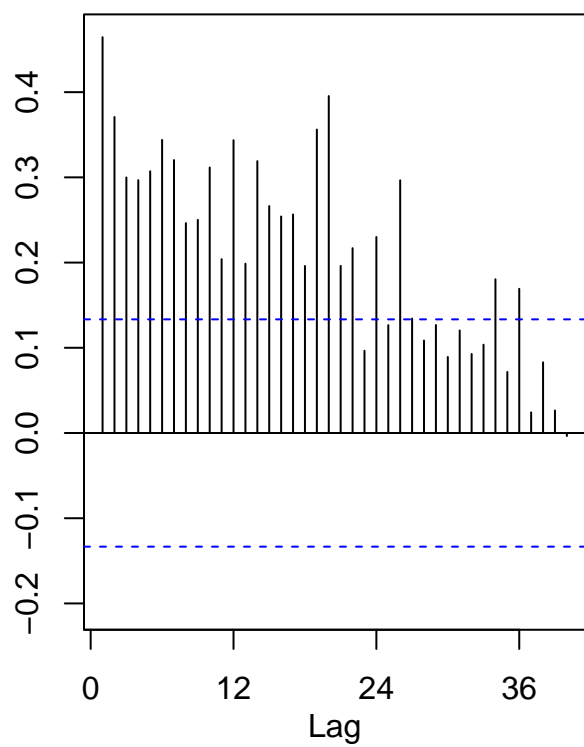
Plot 3: Monthly Block 43 ITT



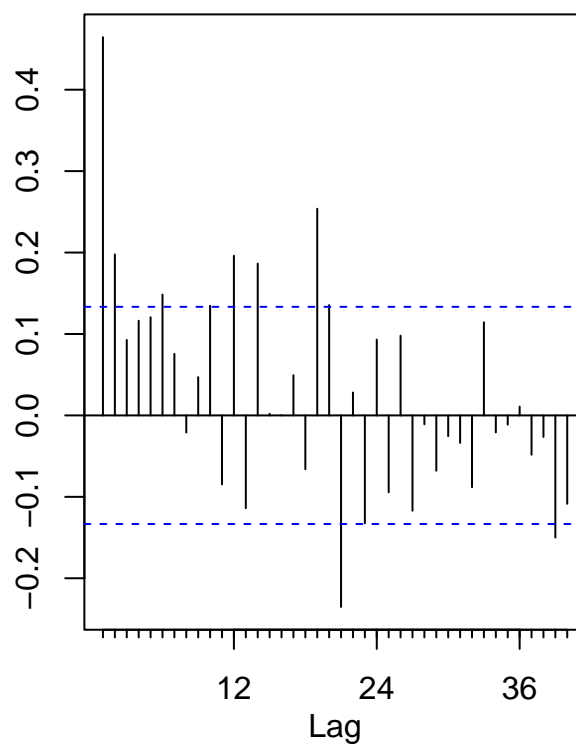
Plot 4: Percentage of monthly Block 43 ITT production

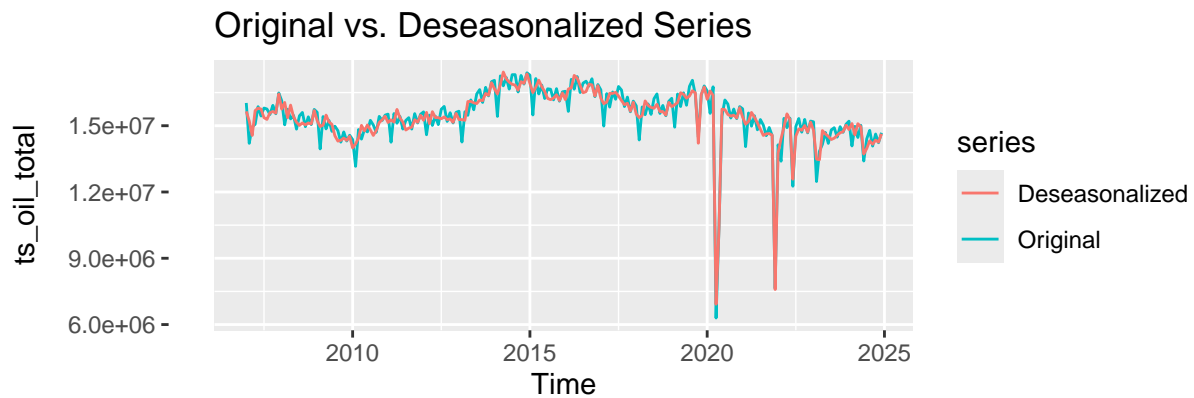
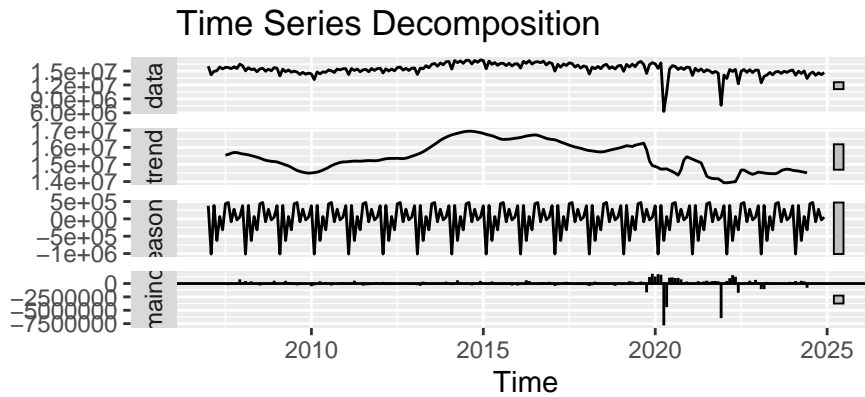


ACF of Total Production



PACF of Total Production





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

Temporal Split

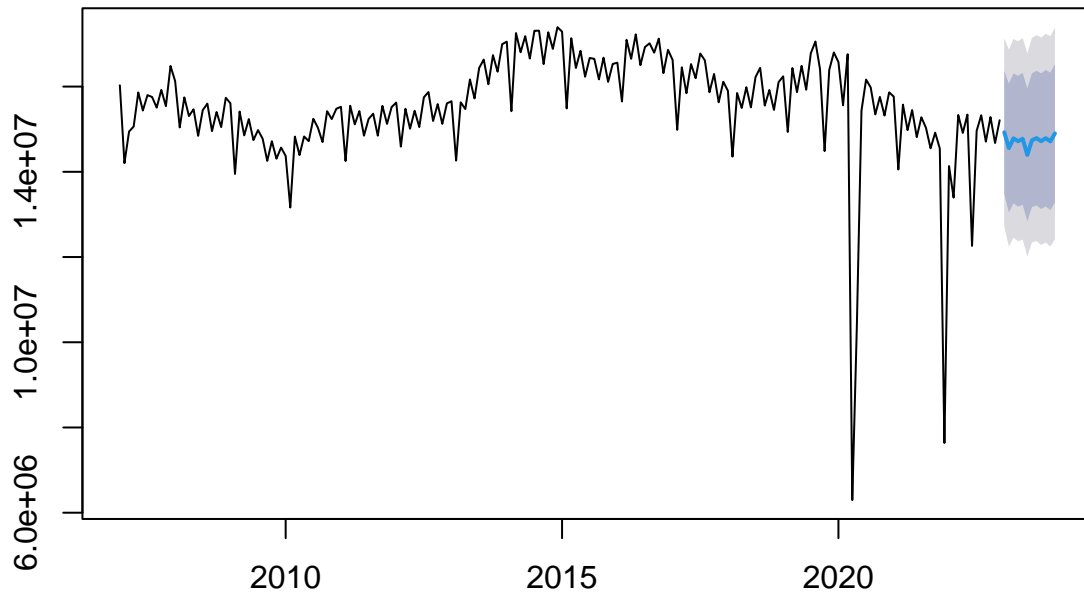
- **Training:** Jan 2007 – Dec 2022 (192 obs).
- **Validation:** Jan 2023 – Dec 2023 (12 obs) — used solely for model selection.
- **Test/Forecast:** Jan 2024 – Dec 2027 (48 obs) under two scenarios.

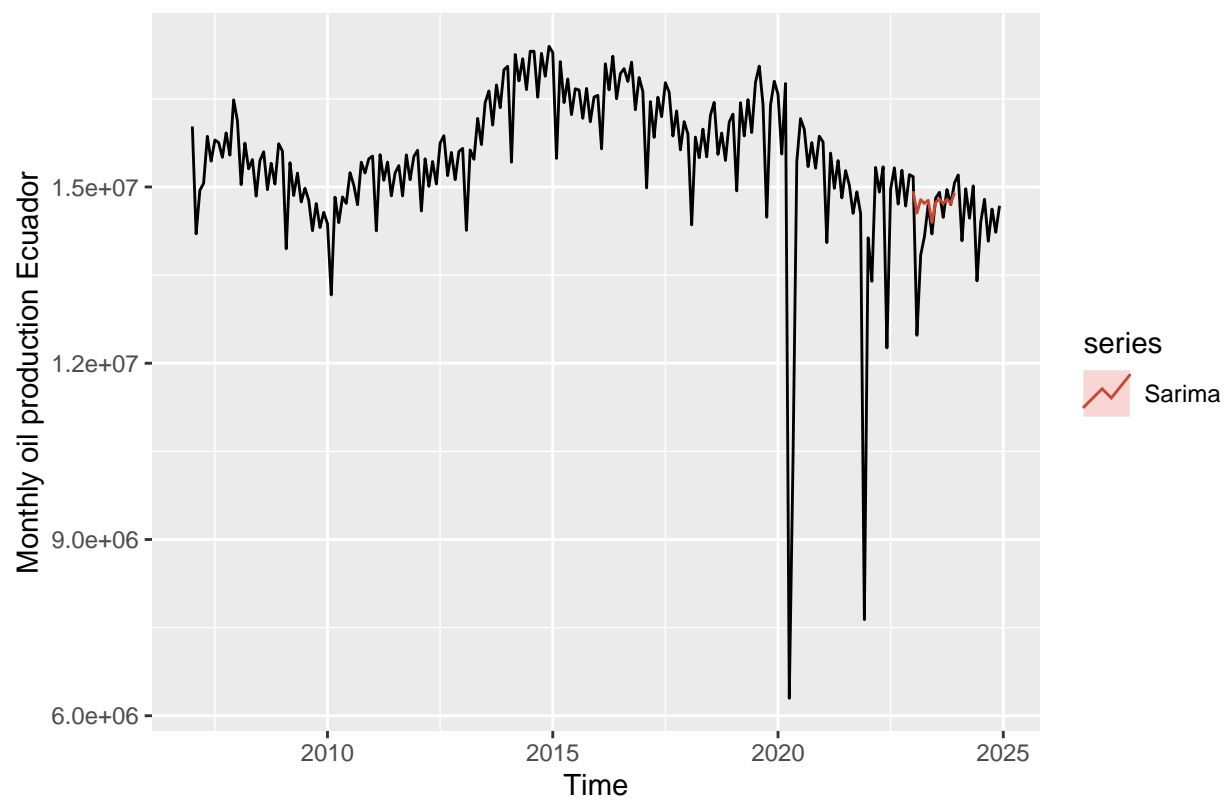
Model 1

	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

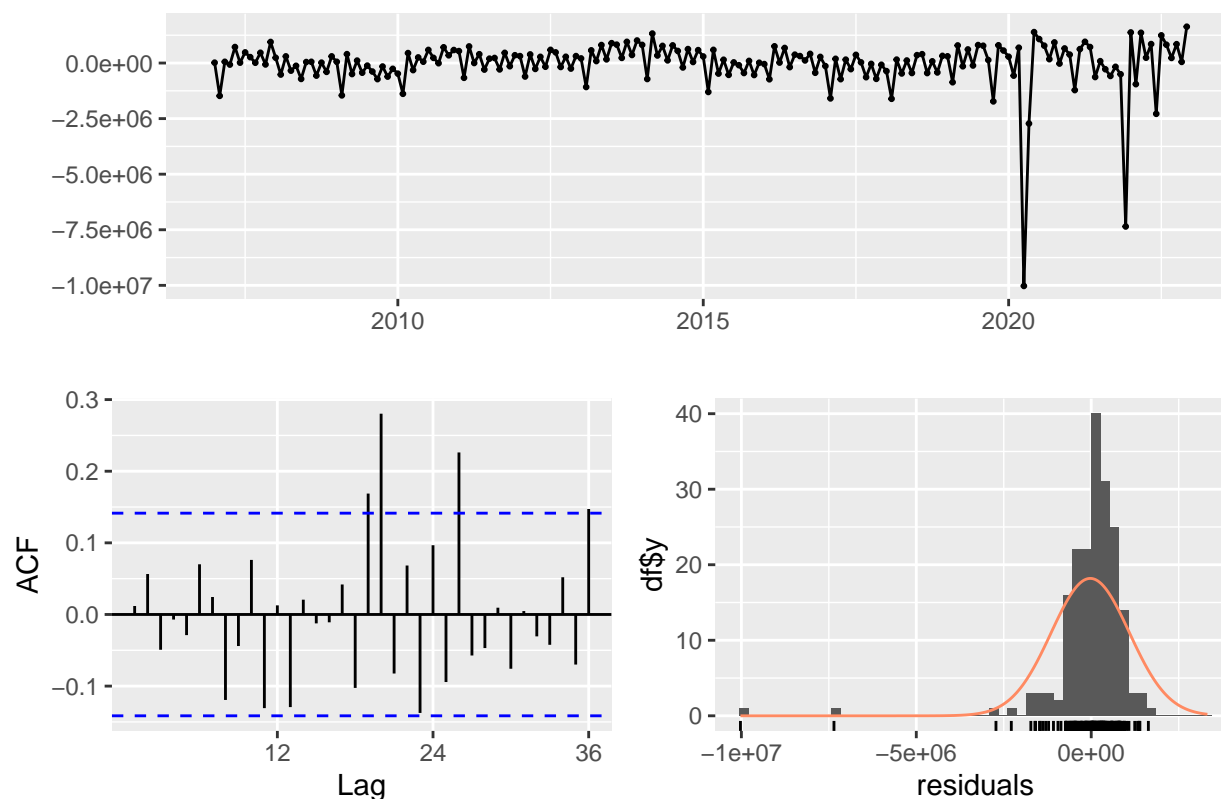
## Jul 2023	14740911	13172280	16309543	12341896	17139926
## Aug 2023	14791884	13212100	16371668	12375813	17207955
## Sep 2023	14718428	13127570	16309286	12285421	17151436
## Oct 2023	14788555	13186700	16390411	12338729	17238382
## Nov 2023	14714125	13101347	16326903	12247594	17180656
## Dec 2023	14901745	13278118	16525372	12418621	17384868

Forecasts from ARIMA(0,1,2)(0,0,1)[12]





Residuals from ARIMA(0,1,2)(0,0,1)[12]



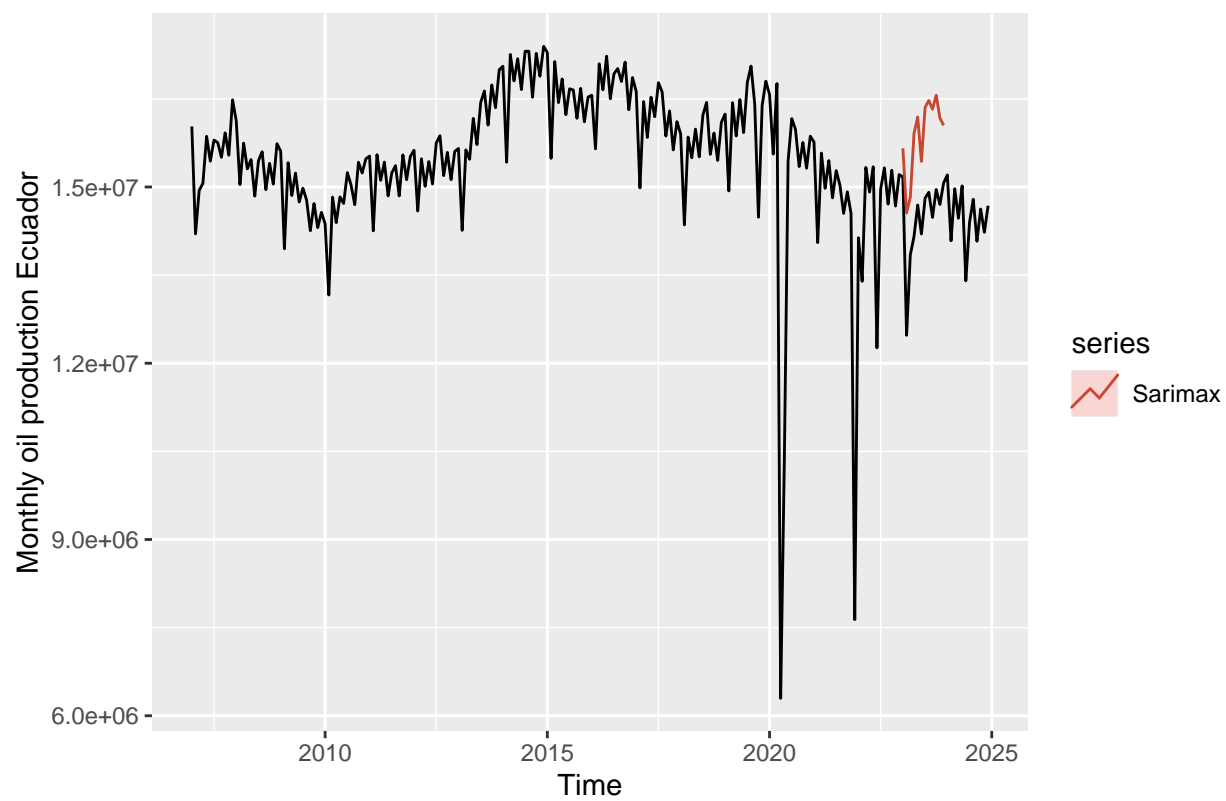
```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(0,1,2)(0,0,1)[12]
## Q* = 48.566, df = 21, p-value = 0.0005756
##
## Model df: 3.   Total lags used: 24
```

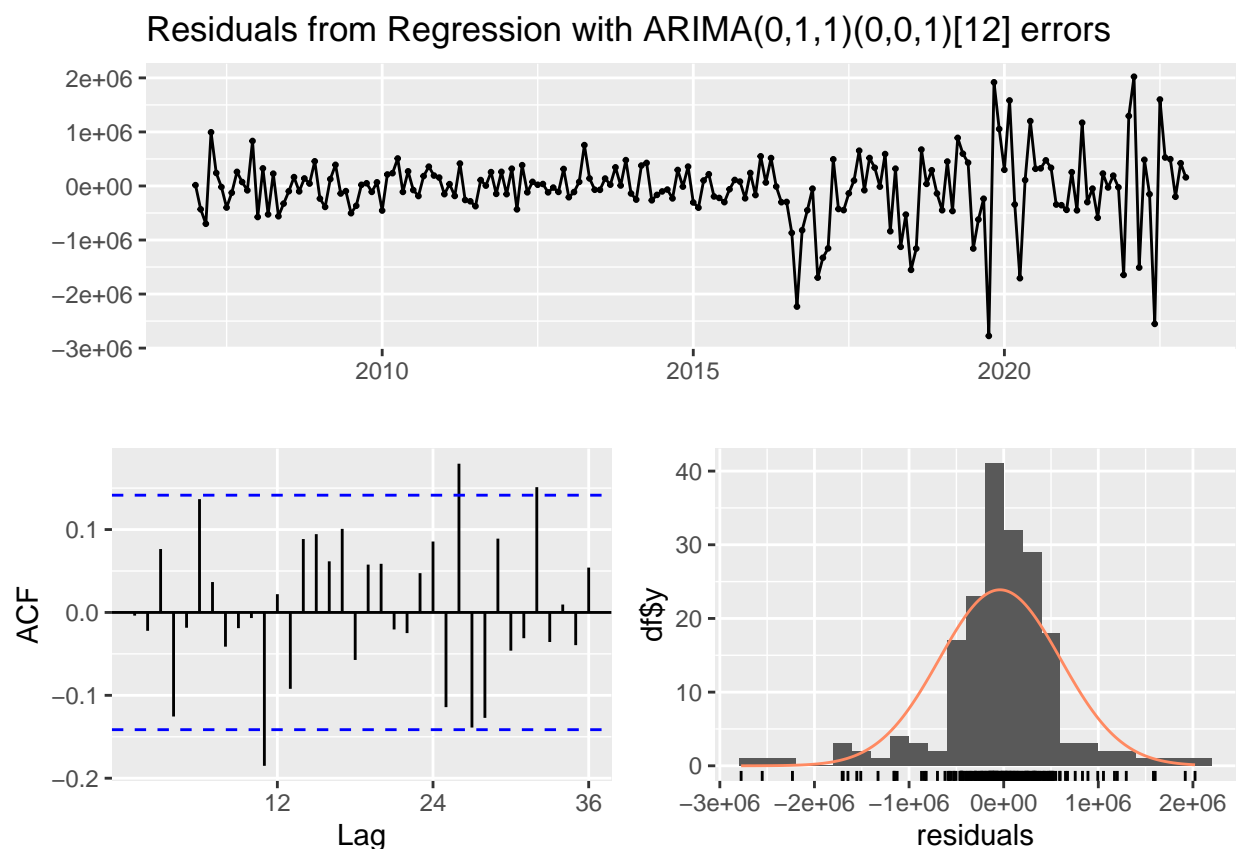
#Model 2:

	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





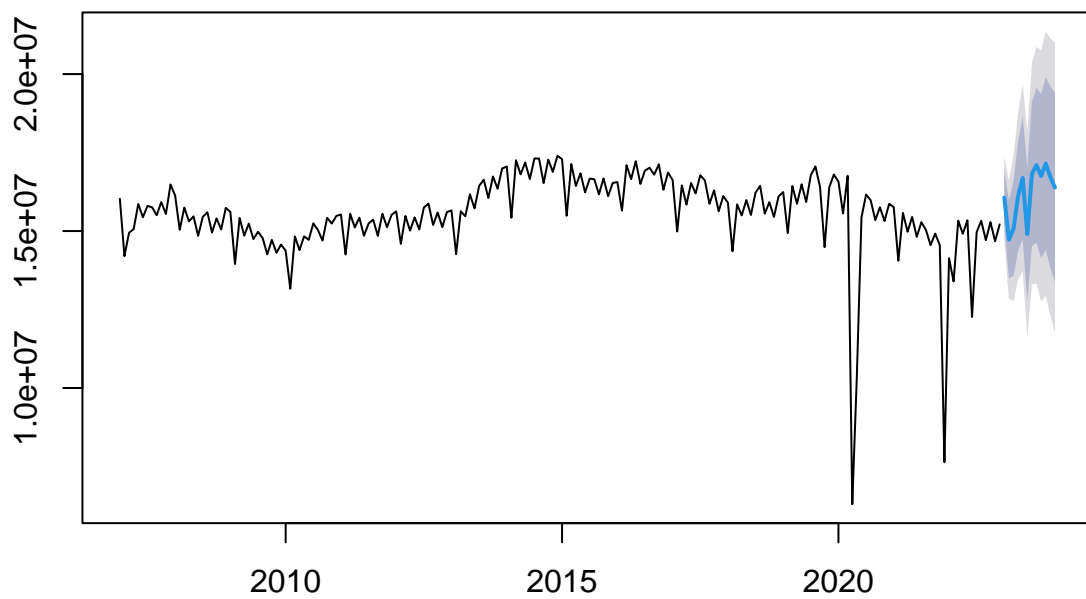


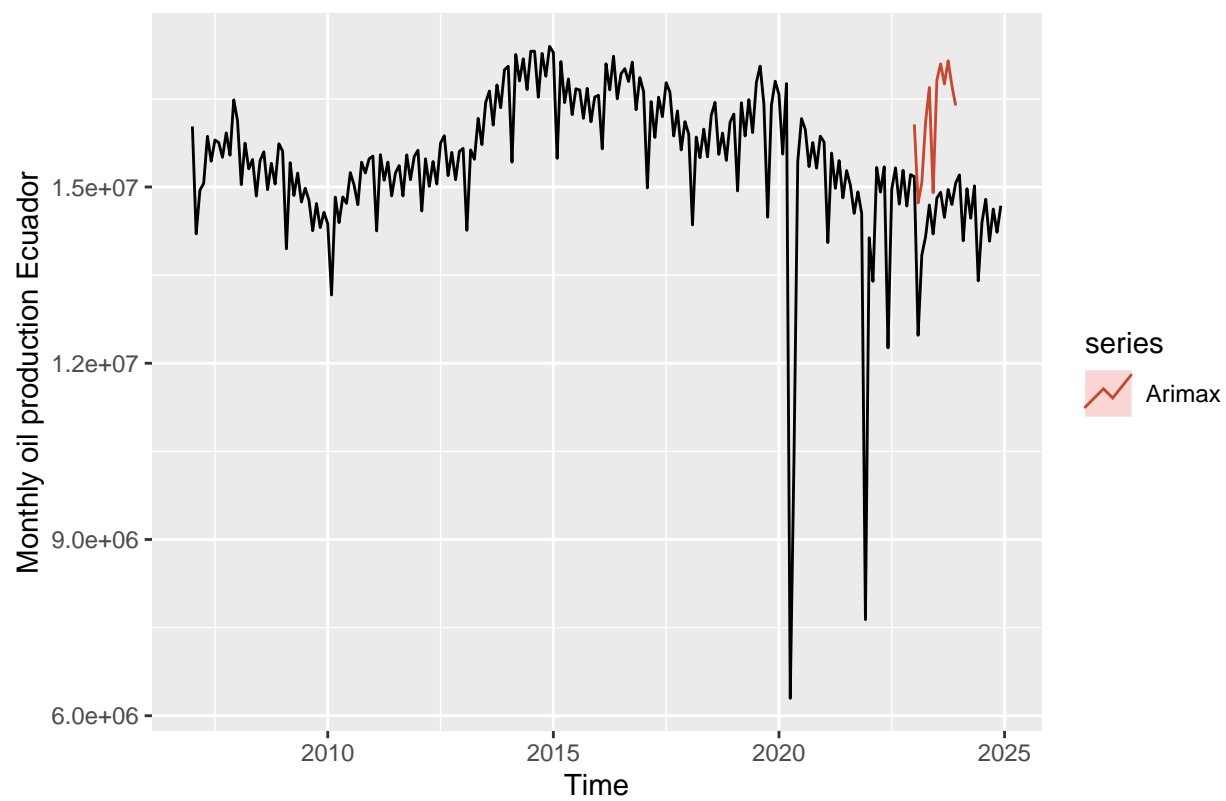
```
##
##  Ljung-Box test
##
## data:  Residuals from Regression with ARIMA(0,1,1)(0,0,1)[12] errors
## Q* = 28.794, df = 22, p-value = 0.1508
##
## Model df: 2.   Total lags used: 24
```

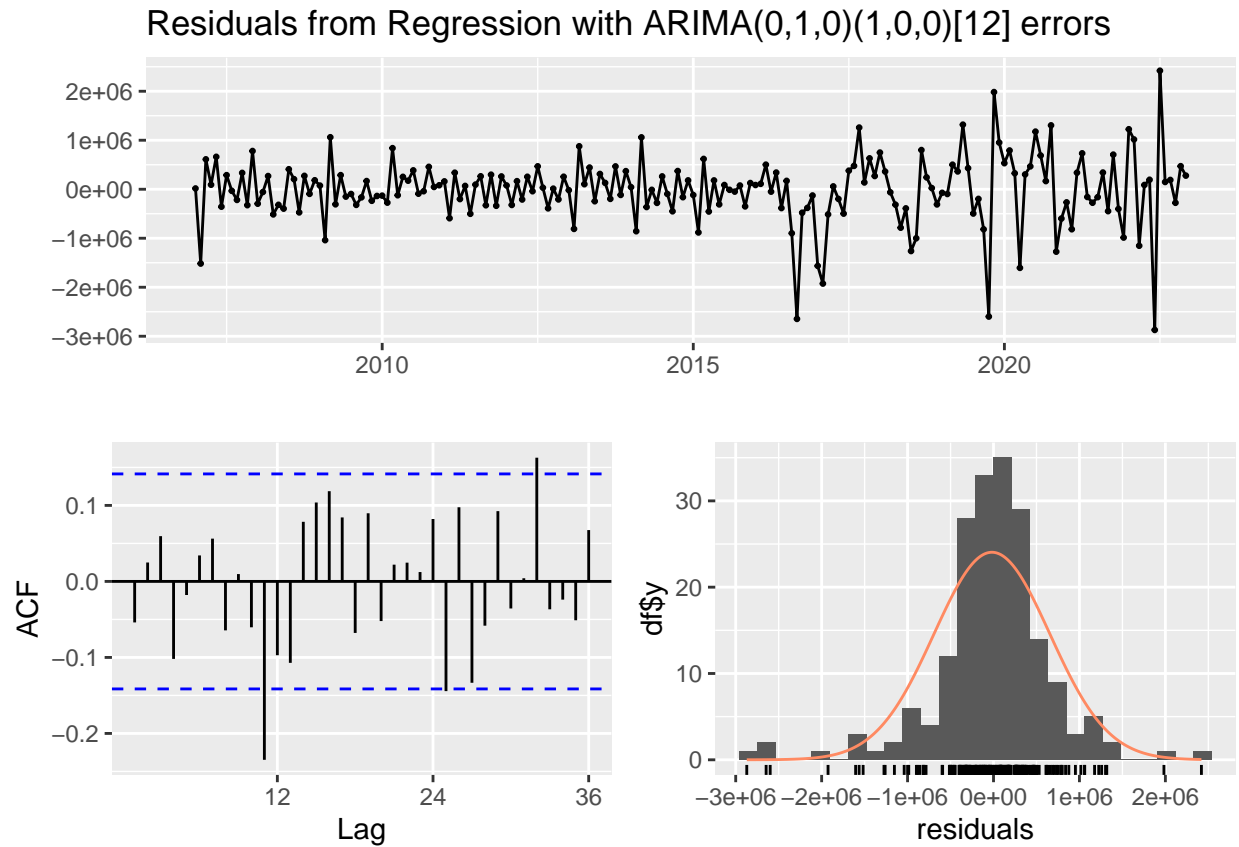
#Model 3

	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



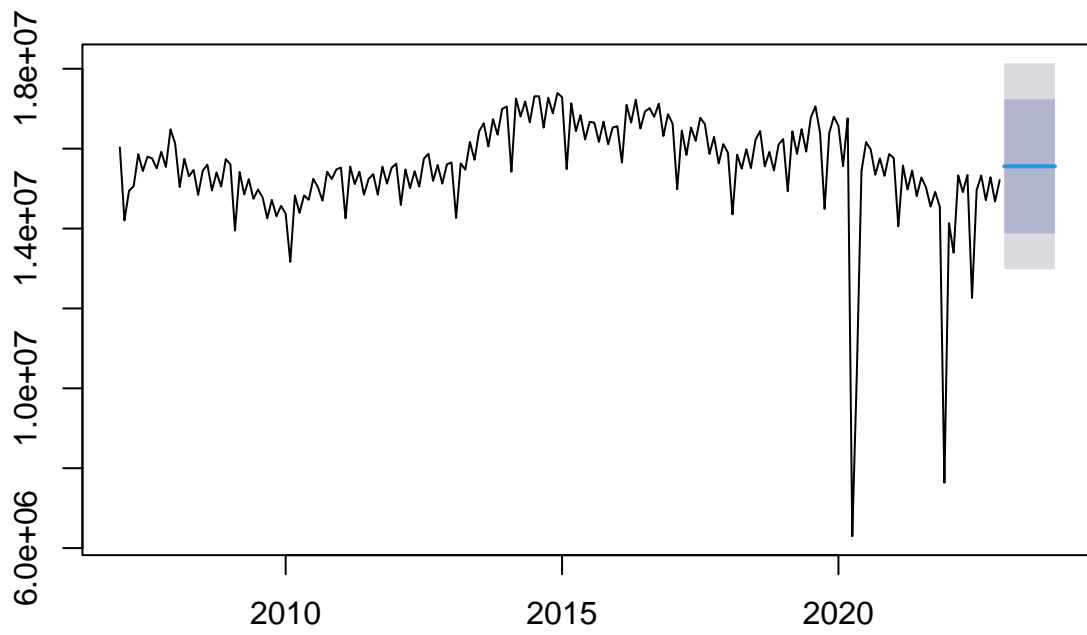


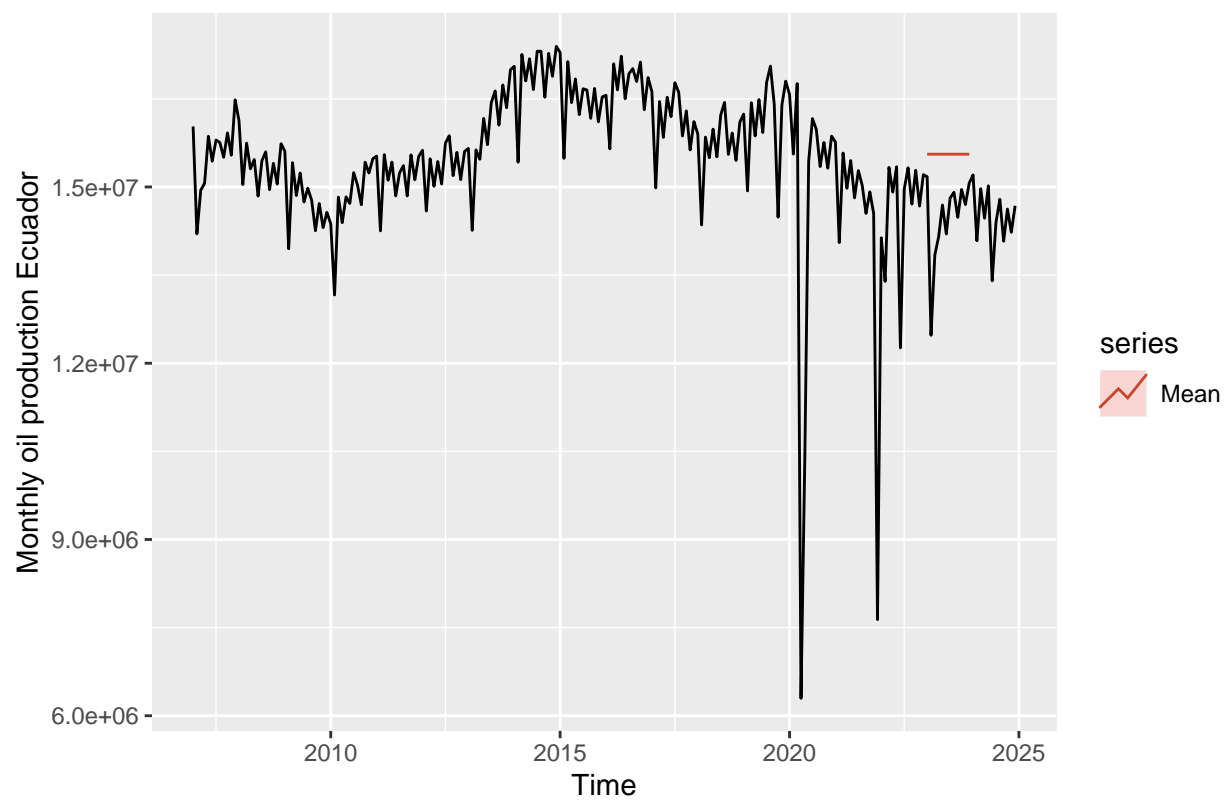


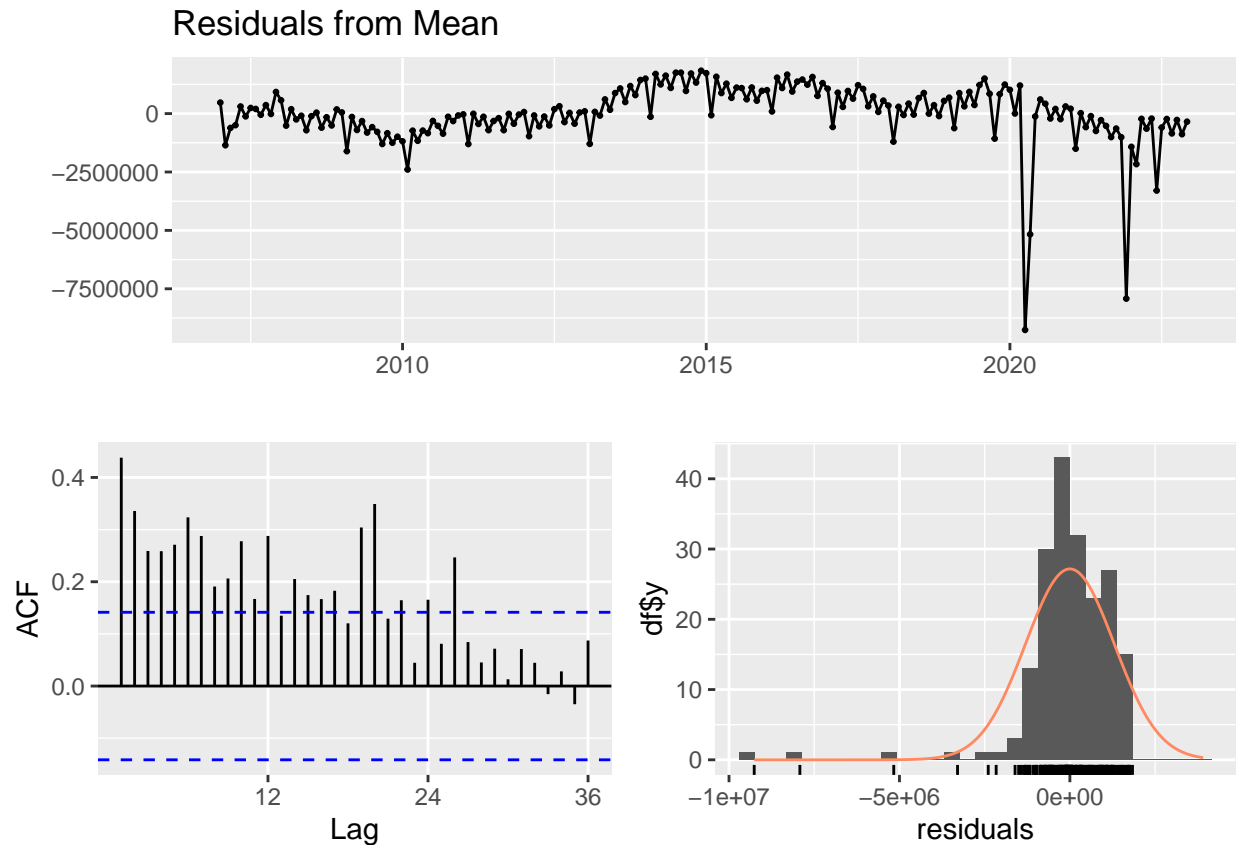
```
##
##  Ljung-Box test
##
## data:  Residuals from Regression with ARIMA(0,1,0)(1,0,0)[12] errors
## Q* = 34.78, df = 23, p-value = 0.05469
##
## Model df: 1.   Total lags used: 24

#Model 4
```

Forecasts from Mean



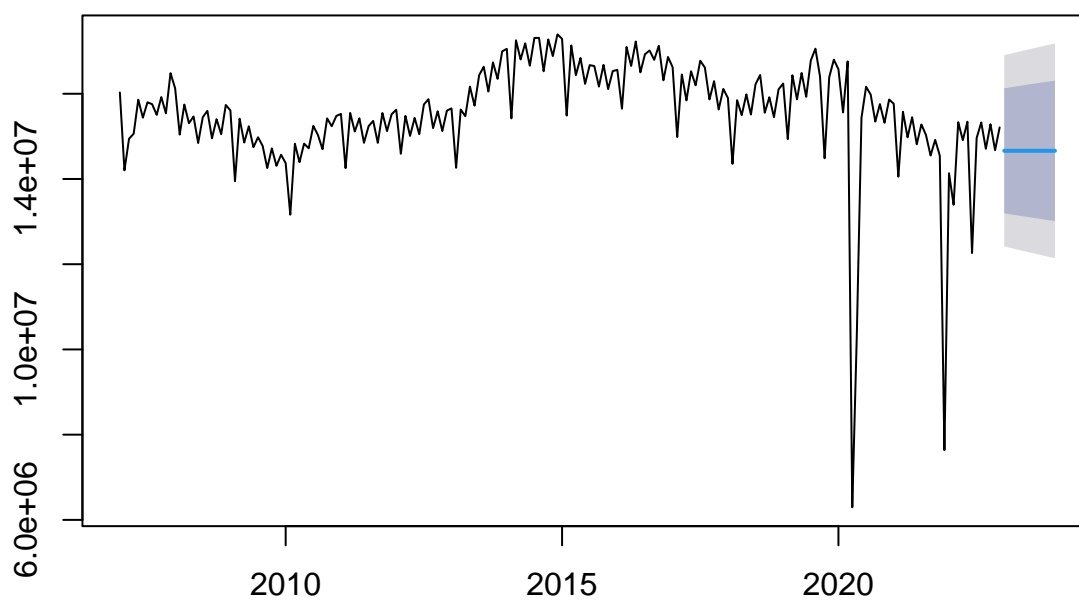


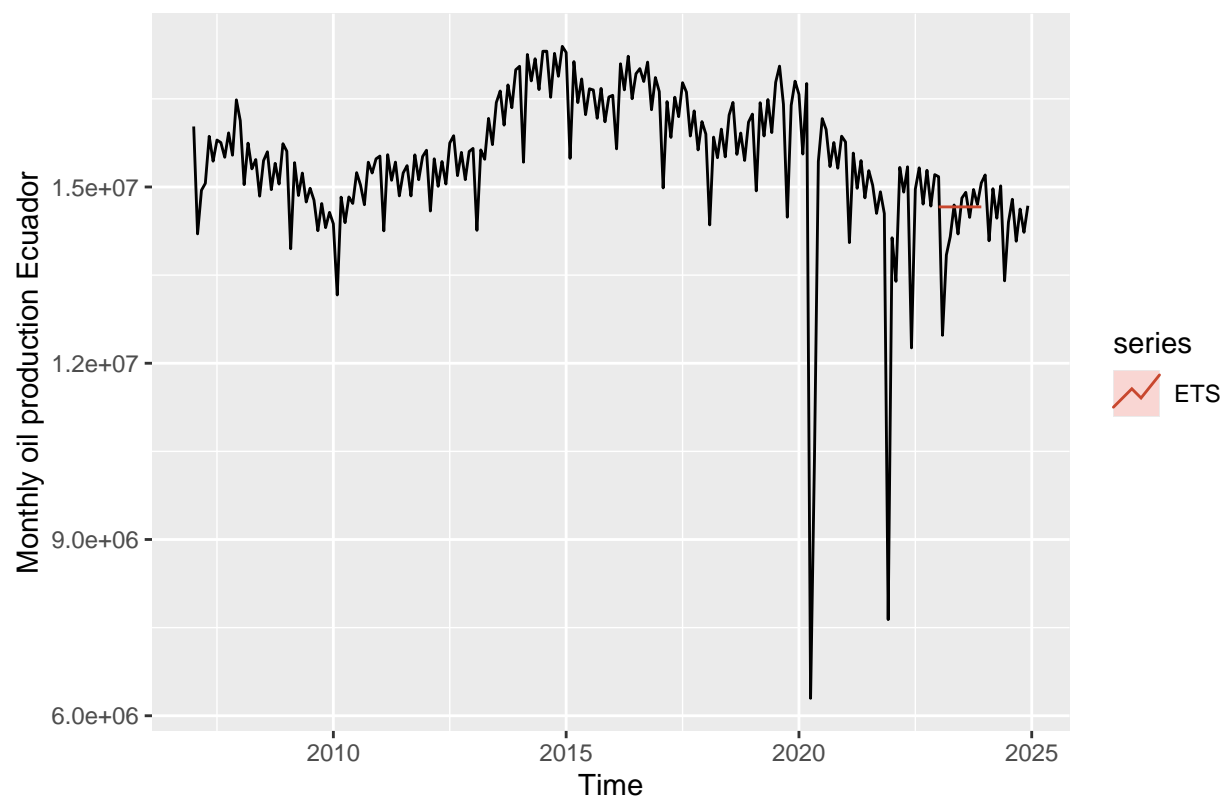


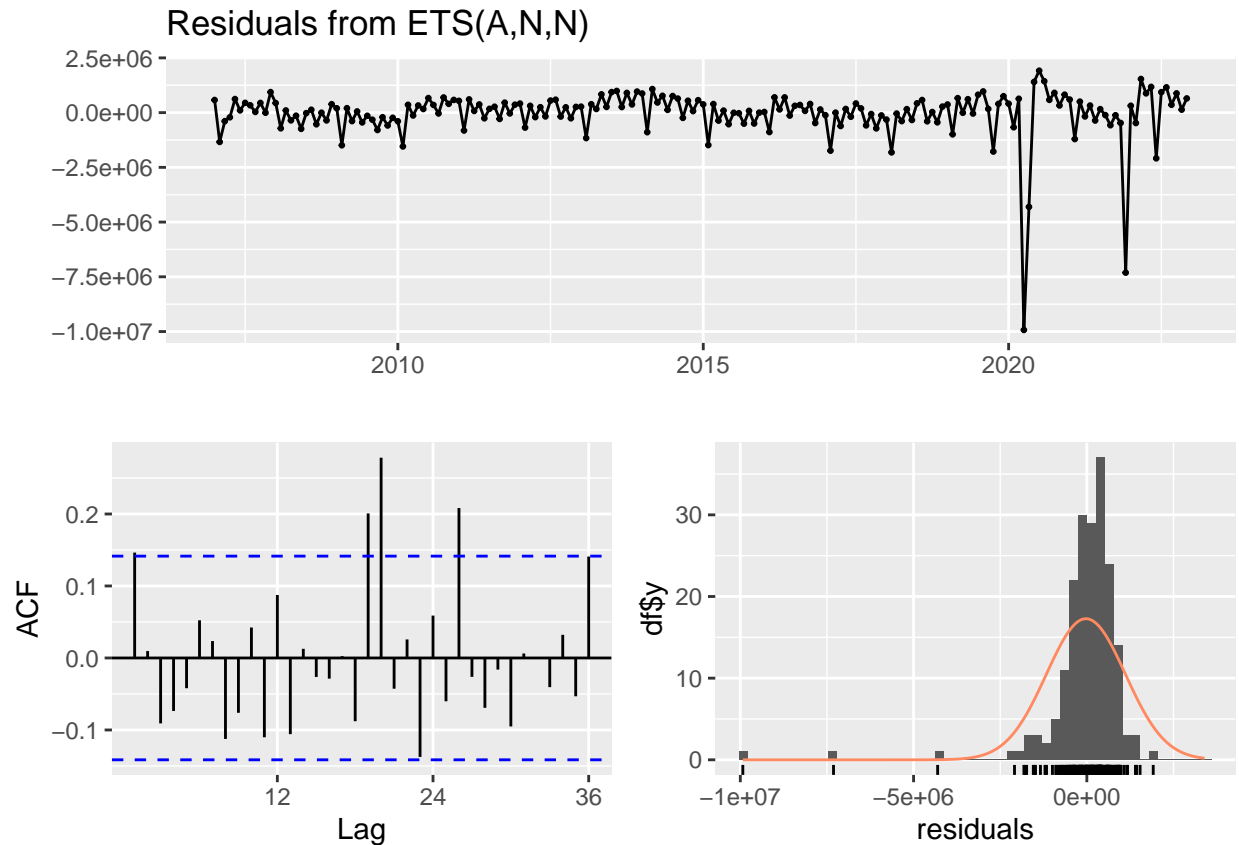
```
##
##  Ljung-Box test
##
## data:  Residuals from Mean
## Q* = 290.4, df = 24, p-value < 2.2e-16
##
## Model df: 0.   Total lags used: 24
```


	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)



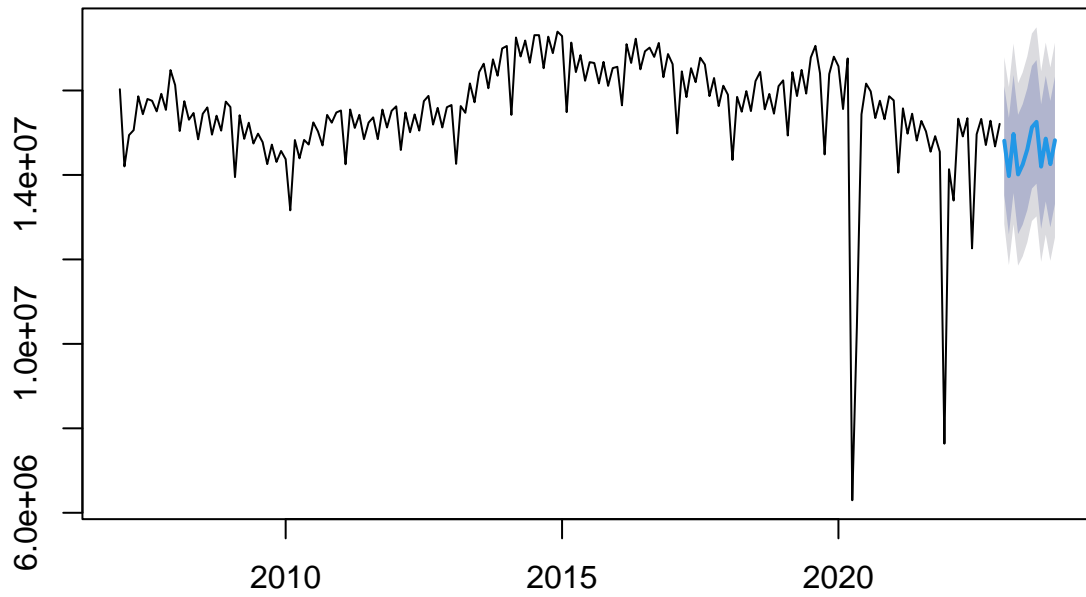


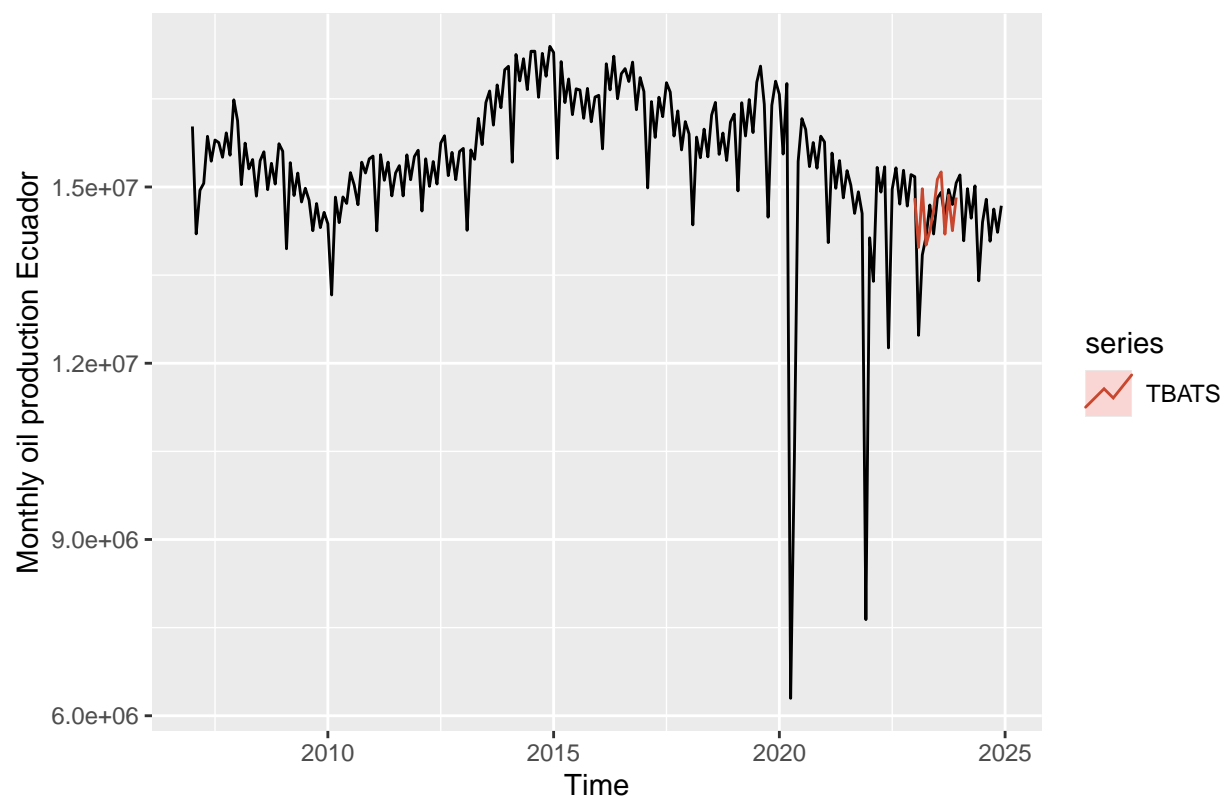


```
##
##  Ljung-Box test
##
## data:  Residuals from ETS(A,N,N)
## Q* = 51.347, df = 24, p-value = 0.0009511
##
## Model df: 0.   Total lags used: 24

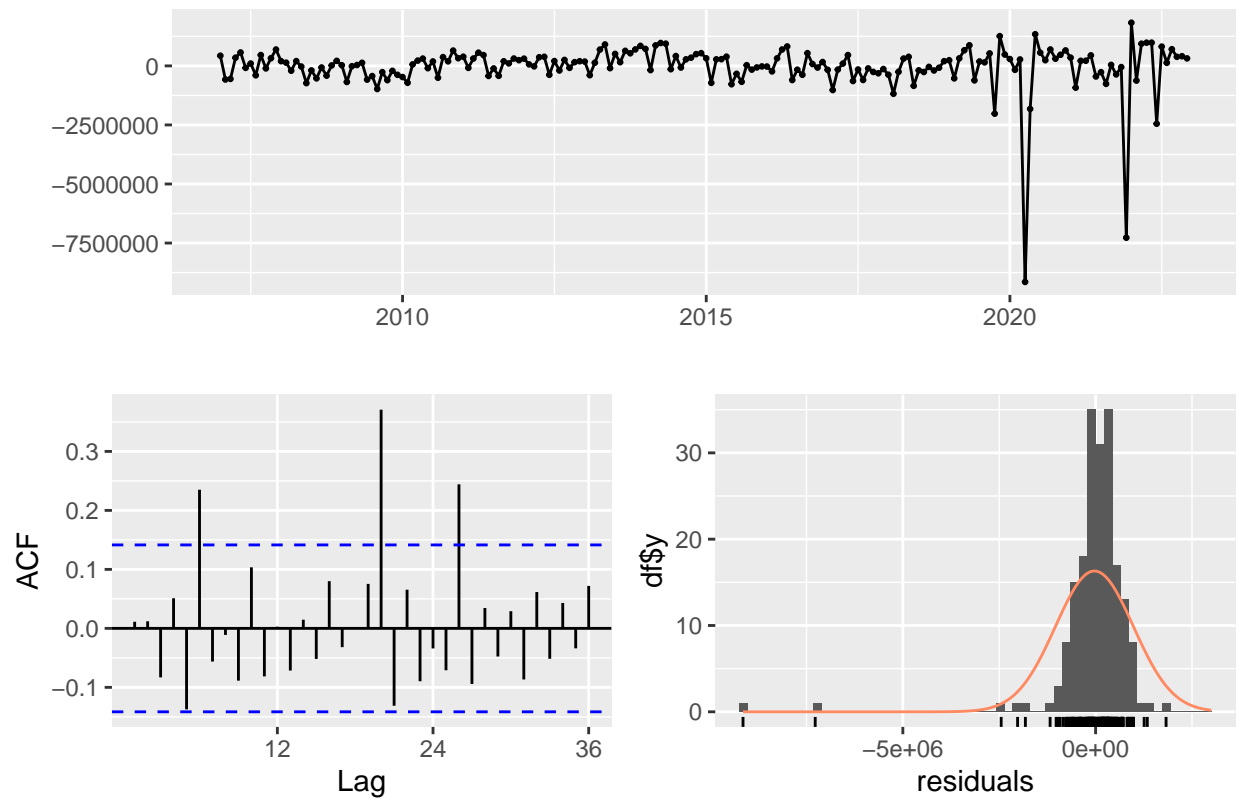
##      Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## Jan 2023      14810030 13517782 16102277 12833708 16786352
## Feb 2023      13972931 12595158 15350705 11865808 16080055
## Mar 2023      14970236 13573103 16367369 12833506 17106966
## Apr 2023      14012209 12600357 15424061 11852968 16171451
## 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>})





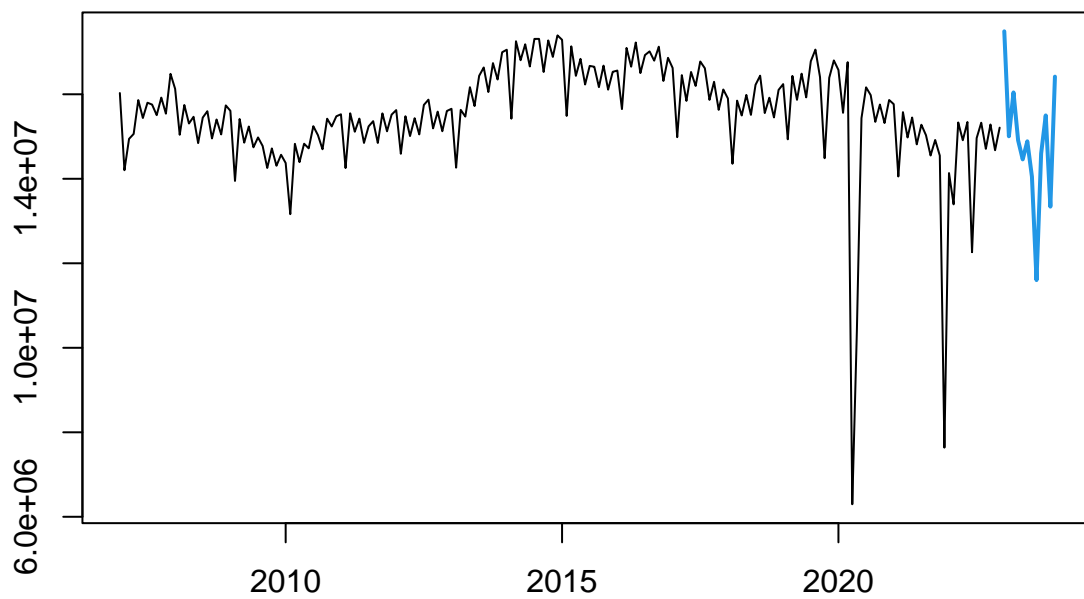
Residuals from TBATS

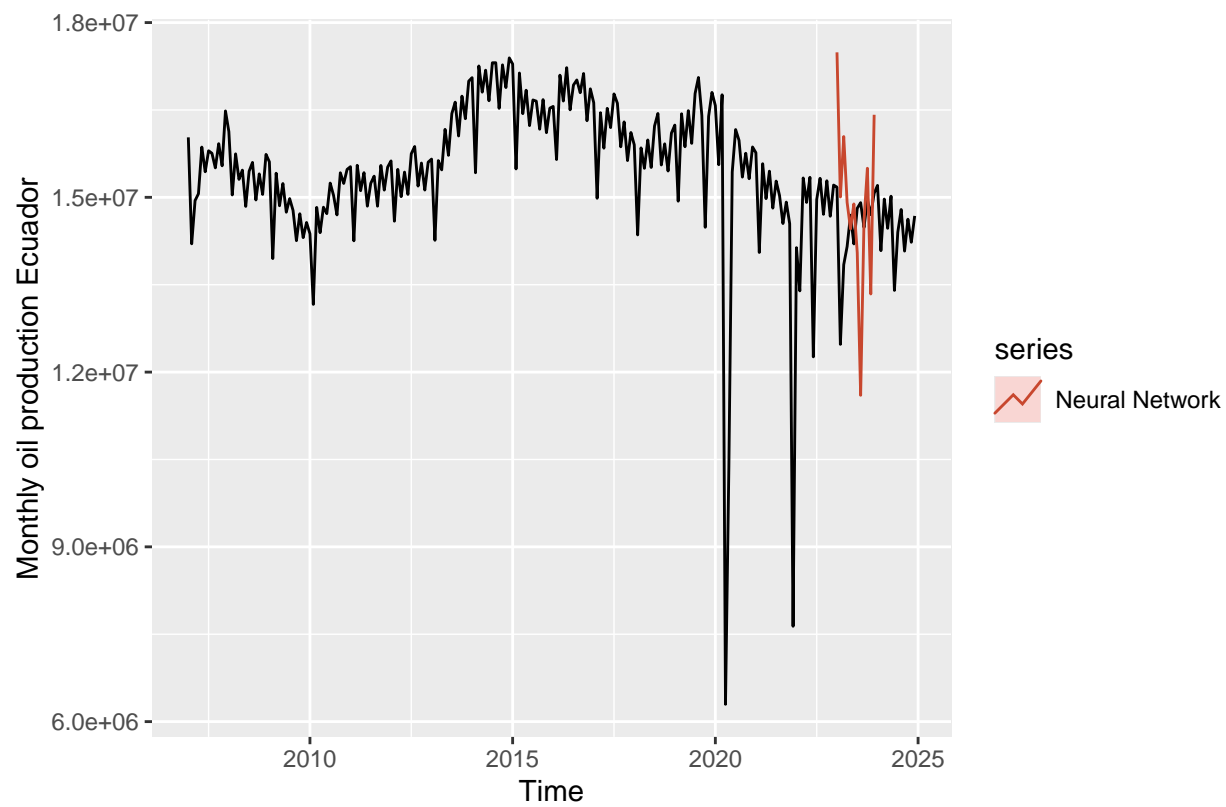


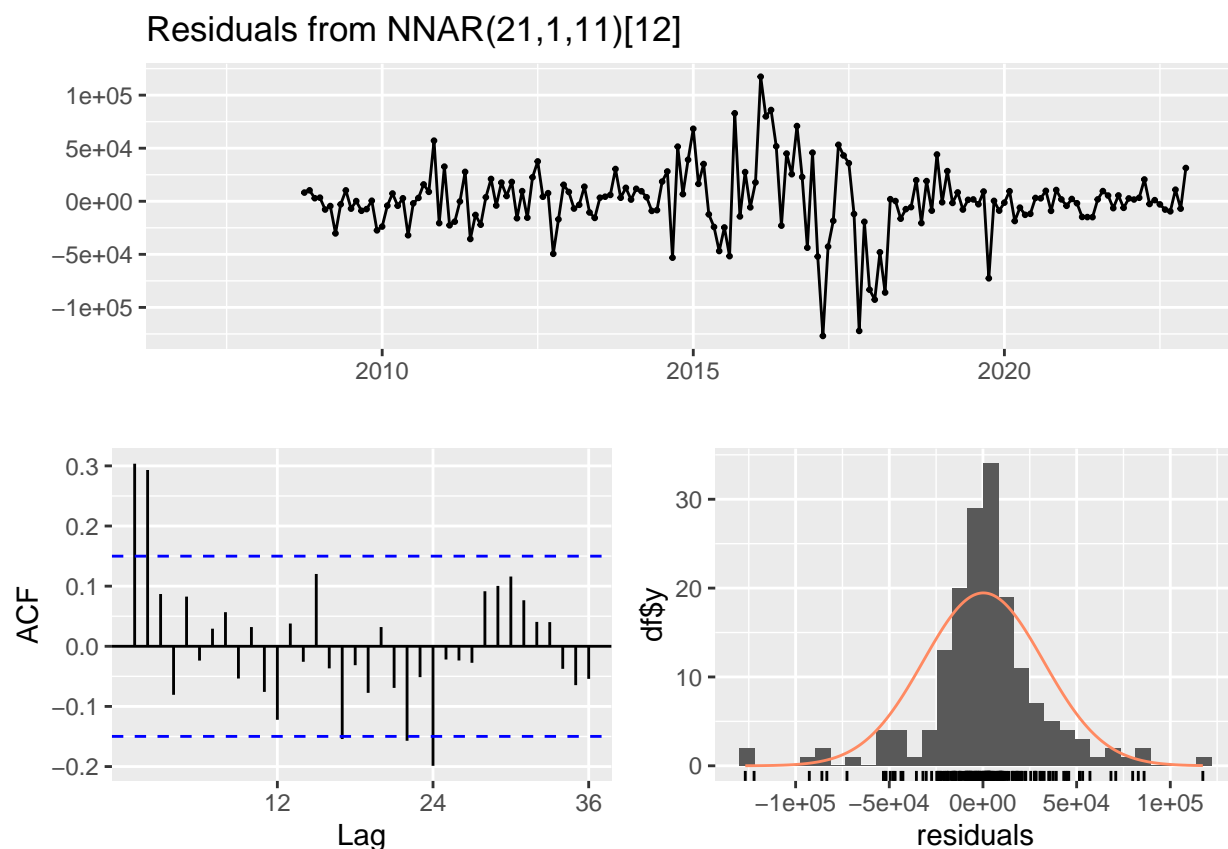
```
##
##  Ljung-Box test
##
## data:  Residuals from TBATS
## Q* = 63.515, df = 24, p-value = 2.005e-05
##
## Model df: 0.   Total lags used: 24
```

```
##           Jan      Feb      Mar      Apr      May      Jun      Jul      Aug
## 2023 17489161 15006059 16043593 14912486 14458560 14886443 14049703 11602147
##           Sep      Oct      Nov      Dec
## 2023 14596051 15499157 13341143 16417171
```

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



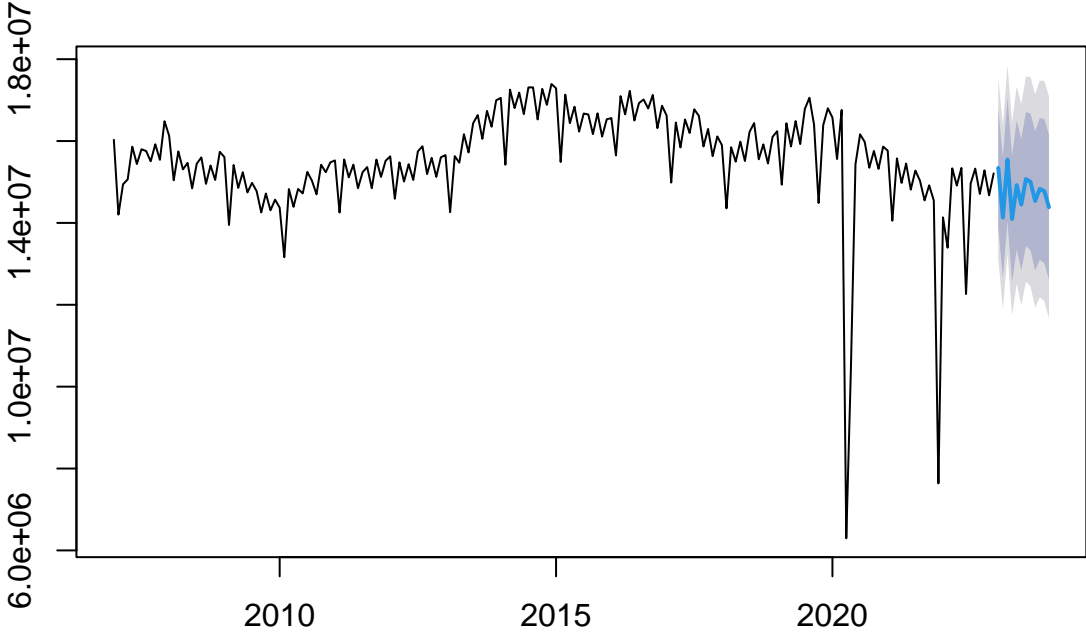


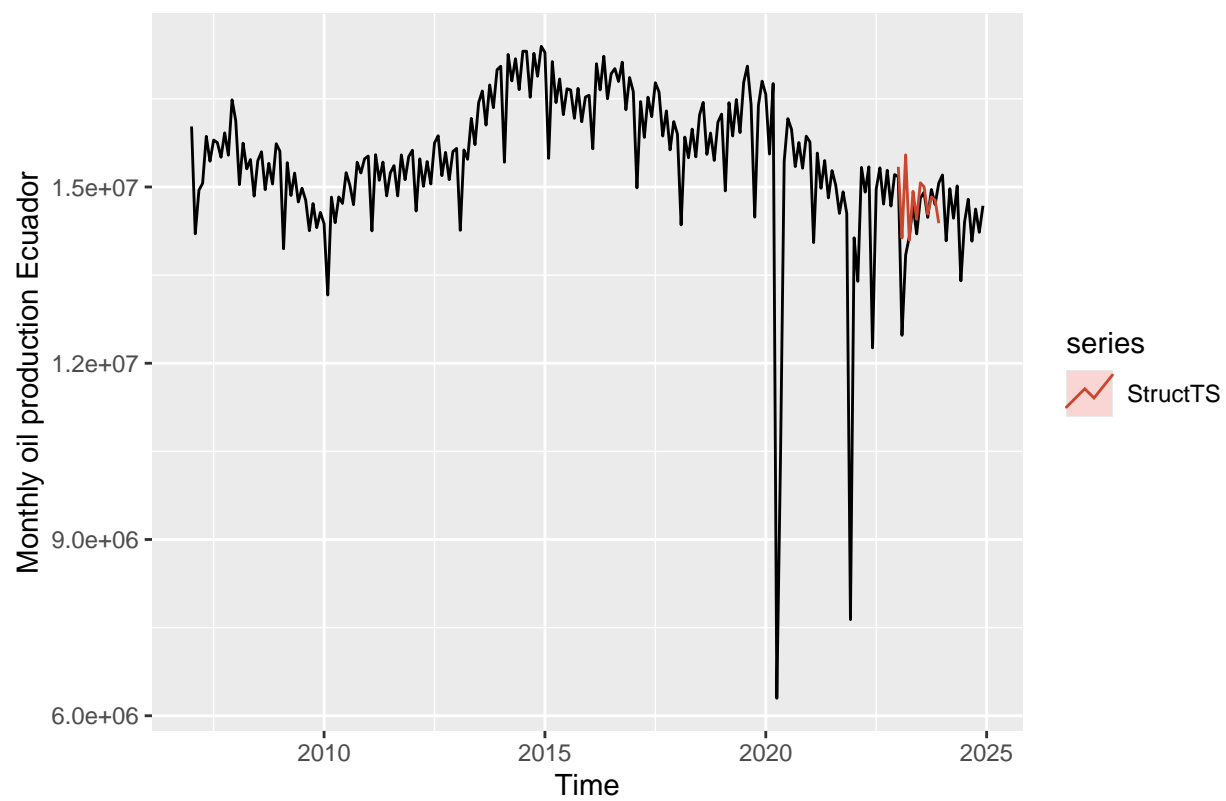


```
##
##  Ljung-Box test
##
## data:  Residuals from NNAR(21,1,11)[12]
## Q* = 64.029, df = 24, p-value = 1.688e-05
##
## Model df: 0.   Total lags used: 24
```

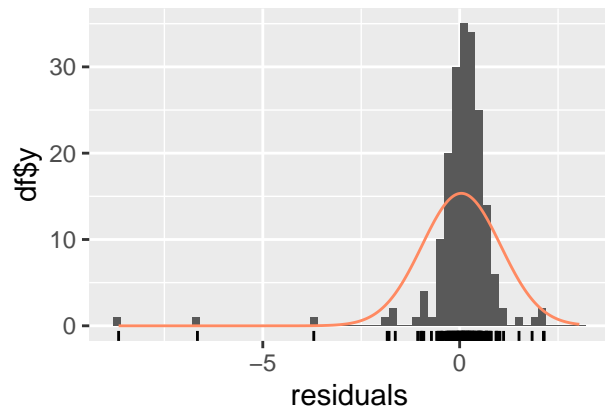
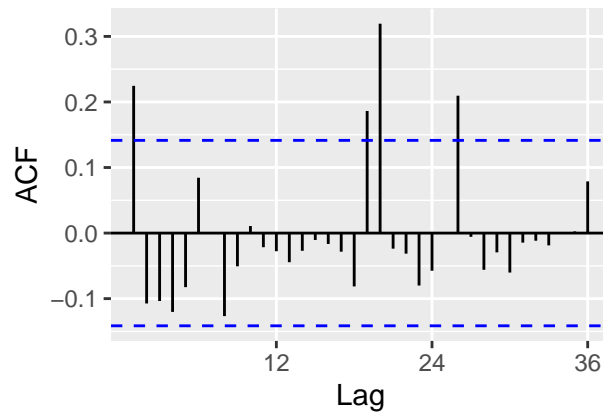
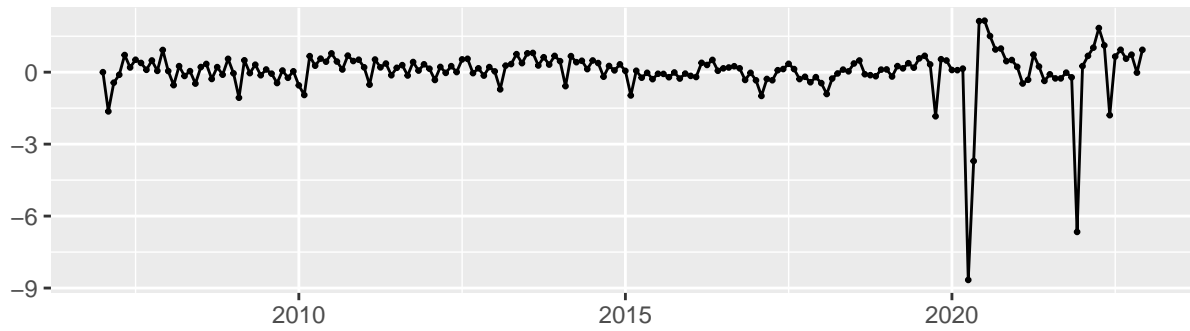
	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
## Jan 2023	15343823	13899091	16788556	13134296	17553351
## Feb 2023	14132564	12661291	15603838	11882446	16382683
## Mar 2023	15546772	14041285	17052258	13244328	17849215
## Apr 2023	14094481	12554828	15634135	11739785	16449178
## May 2023	14924654	13351495	16497813	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

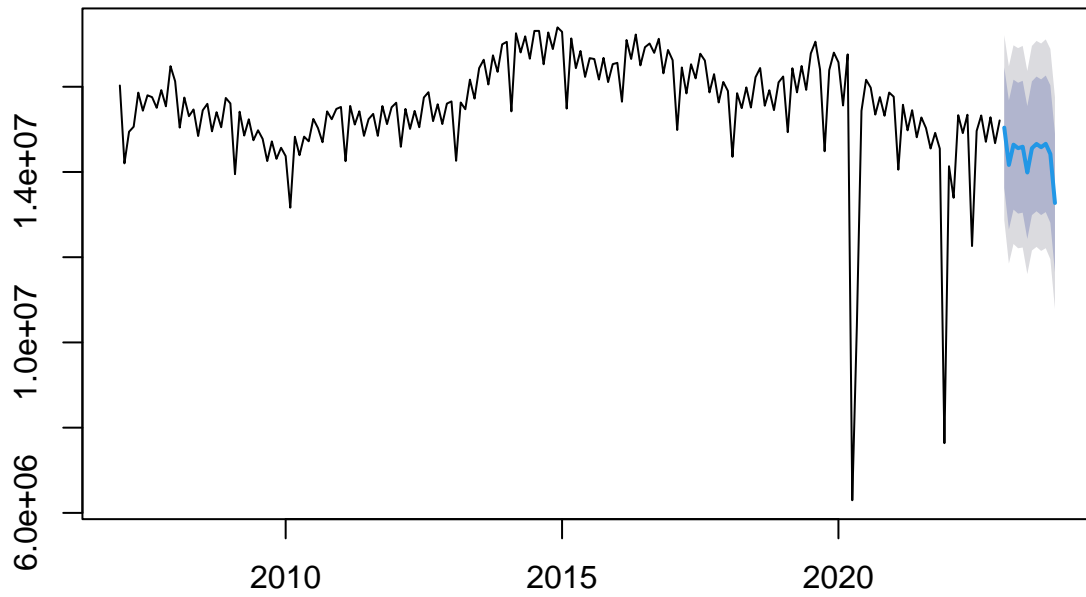


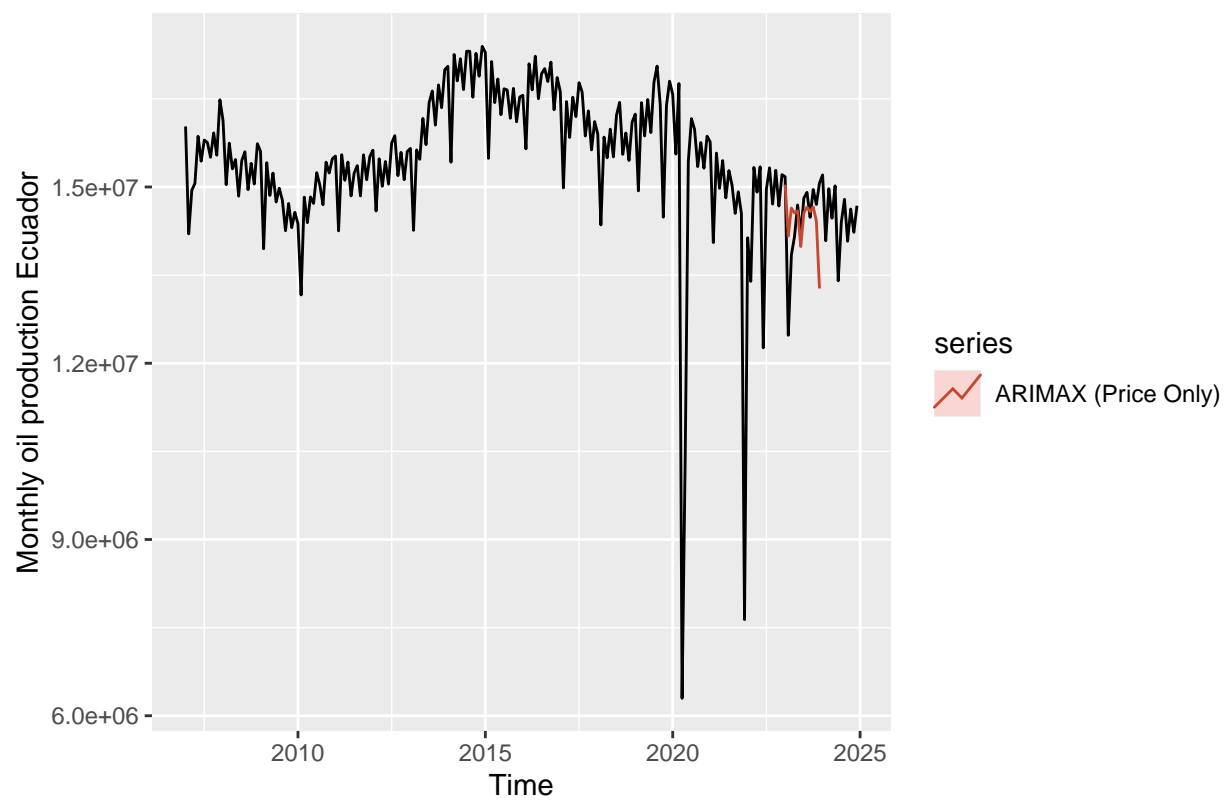
```
##
##  Ljung-Box test
##
## data:  Residuals from StructTS
## Q* = 58.197, df = 24, p-value = 0.0001143
##
## Model df: 0.   Total lags used: 24
```

#Model 9

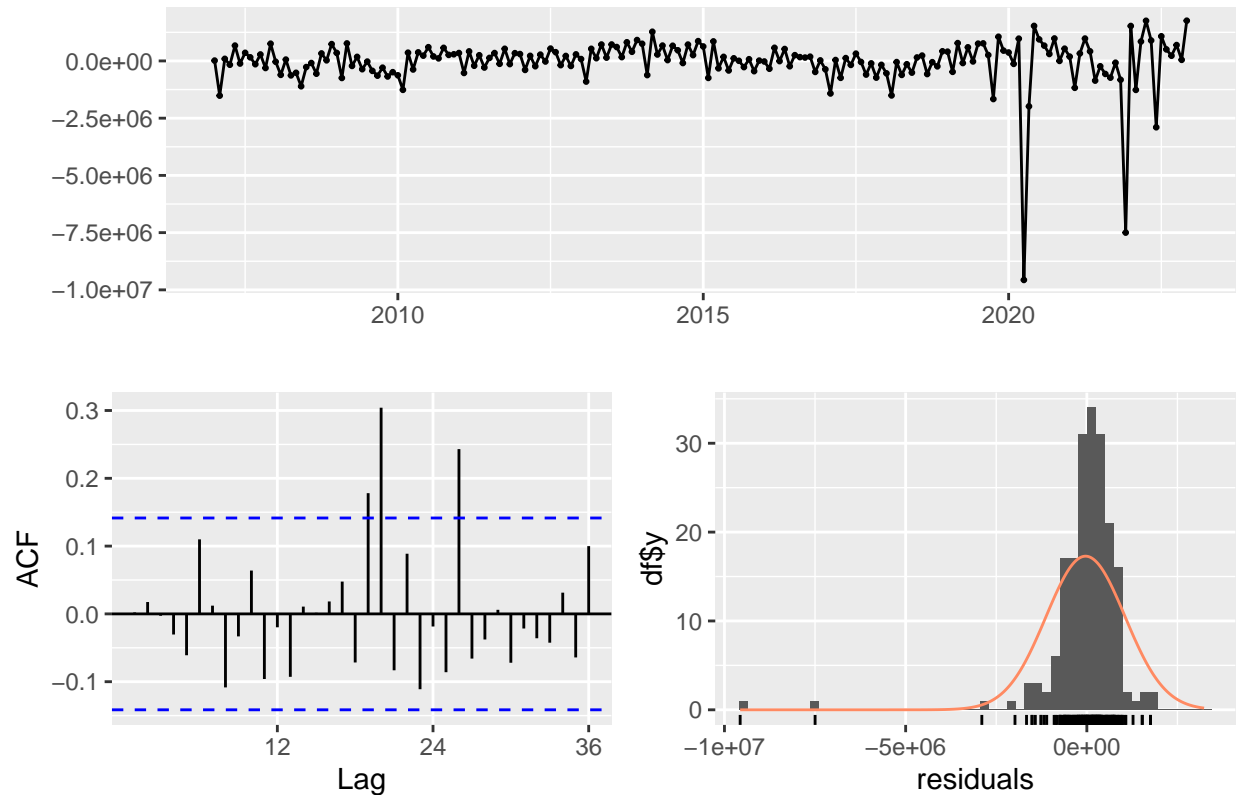
	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
## Jan 2023	15040482	13623432	16457533	12873291	17207674
## Feb 2023	14164622	12652105	15677139	11851427	16477817
## Mar 2023	14641464	13117464	16165464	12310707	16972221
## Apr 2023	14558761	13023363	16094158	12210573	16906949
## May 2023	14592767	13046056	16139478	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

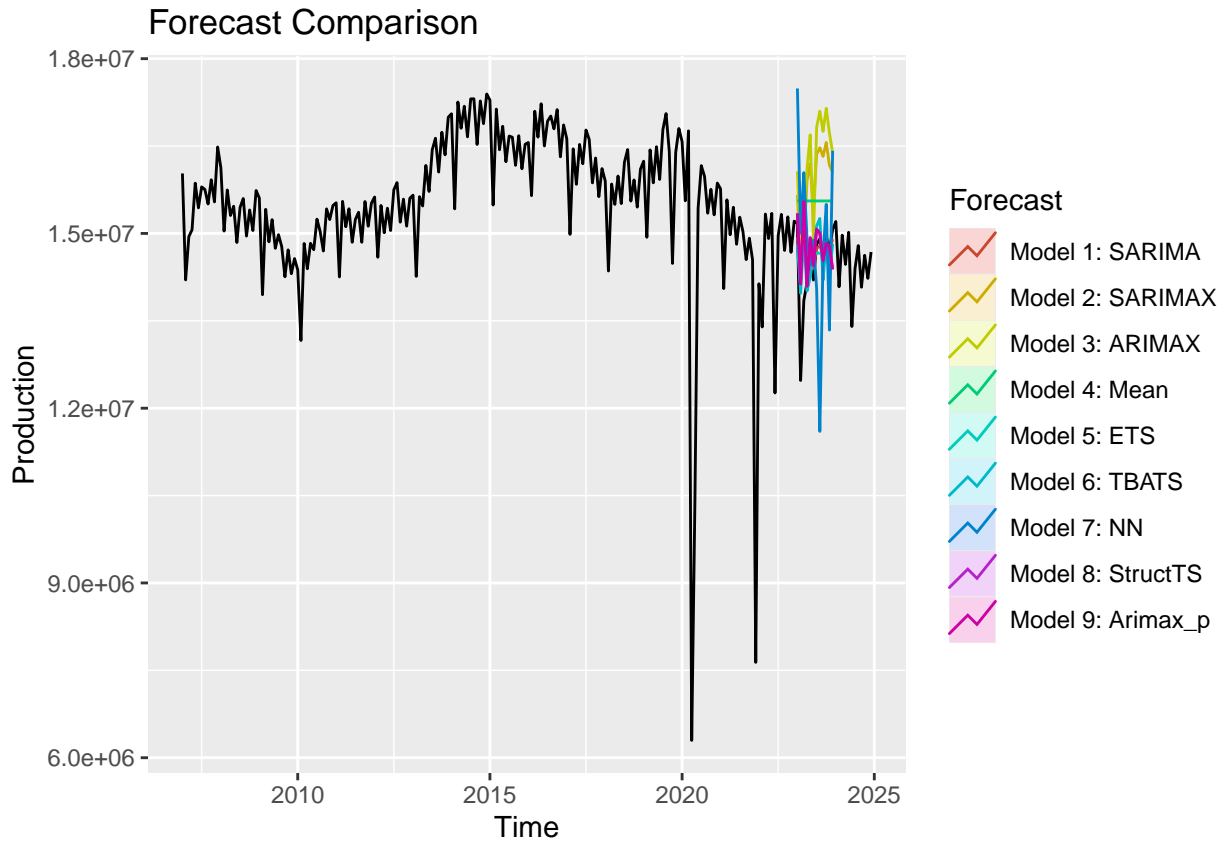
##           ME      RMSE      MAE      MPE      MAPE      ACF1
## SARIMA    -278293.15  693303.0  406561.4  -2.16415262  3.017604  0.17326075
## SARIMAX   -1419518.45  1476086.4  1419518.5  -9.82953050  9.829530  0.27825205
## ARIMAX    -1752244.91  1832260.0  1752244.9 -12.18567542  12.185675 -0.20539000
## 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        -402211.02  1663009.2  1346293.7  -3.06459219  9.427811  0.35929623
## 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
## ETS       0.7520508
## TBATS     0.6598076
```

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	-402211.02	1663009.2	1346293.7	-3.06459219	9.427811	0.35929623	1.6216843
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

```
## NN          1.6216843
## StructTS    0.8107510
## Arimax_p    0.8122824
```

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



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

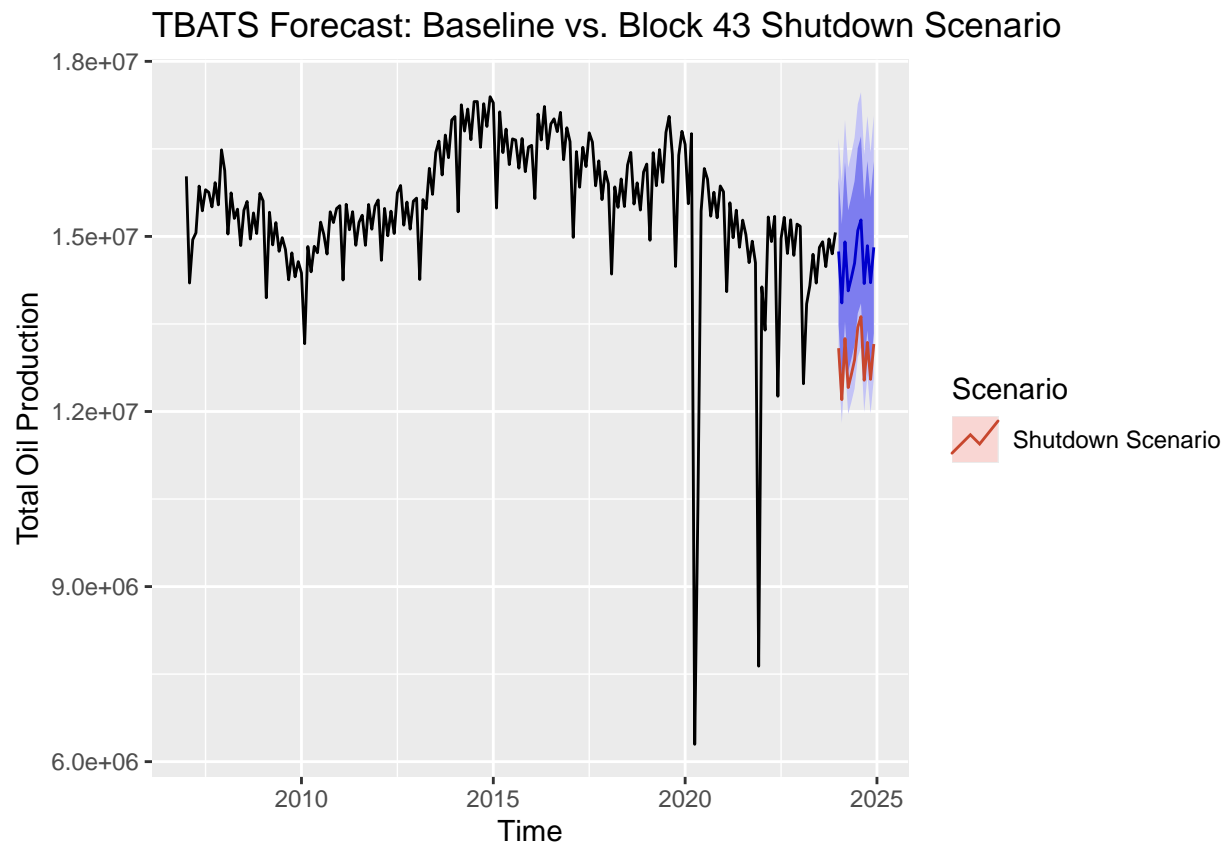
Average monthly Block 43 production: 1656682

Production gap (per month):

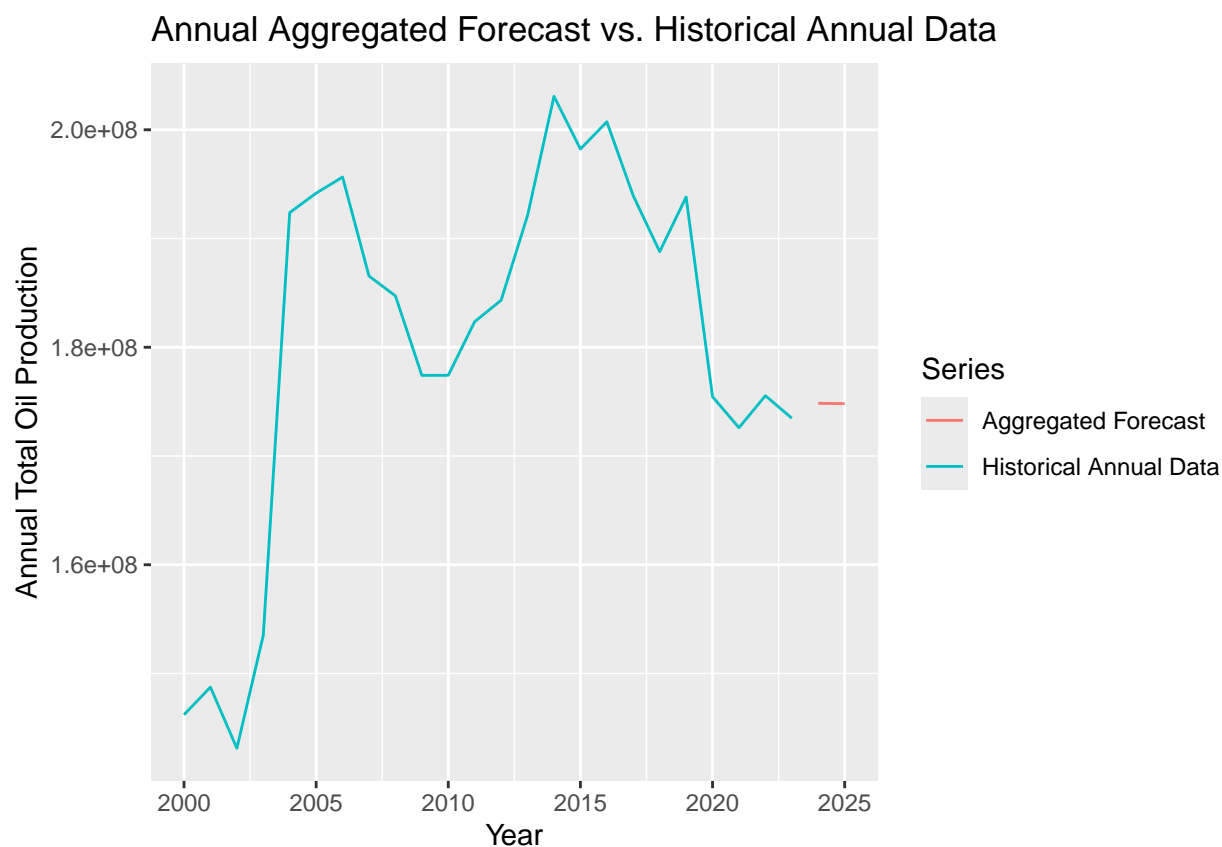
##	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
## 2024	1656682	1656682	1656682	1656682	1656682	1656682	1656682	1656682	1656682
##	Oct	Nov	Dec						
## 2024	1656682	1656682	1656682						

Average monthly production gap: 1656682

Total production gap over the forecast period: 19880180



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



Summary and Conclusions

Halting Block 43-ITT aligns with conservation aims but carries a material macro-fiscal costs. 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

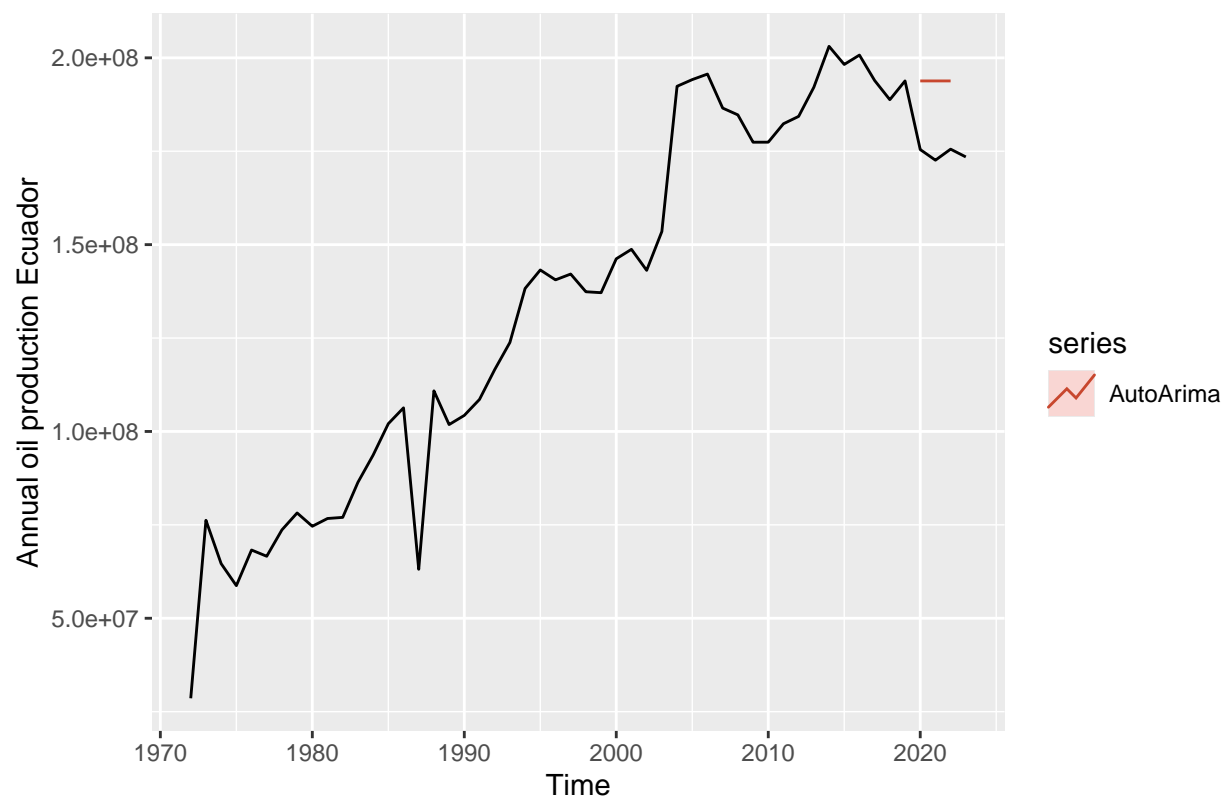
Annex

#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

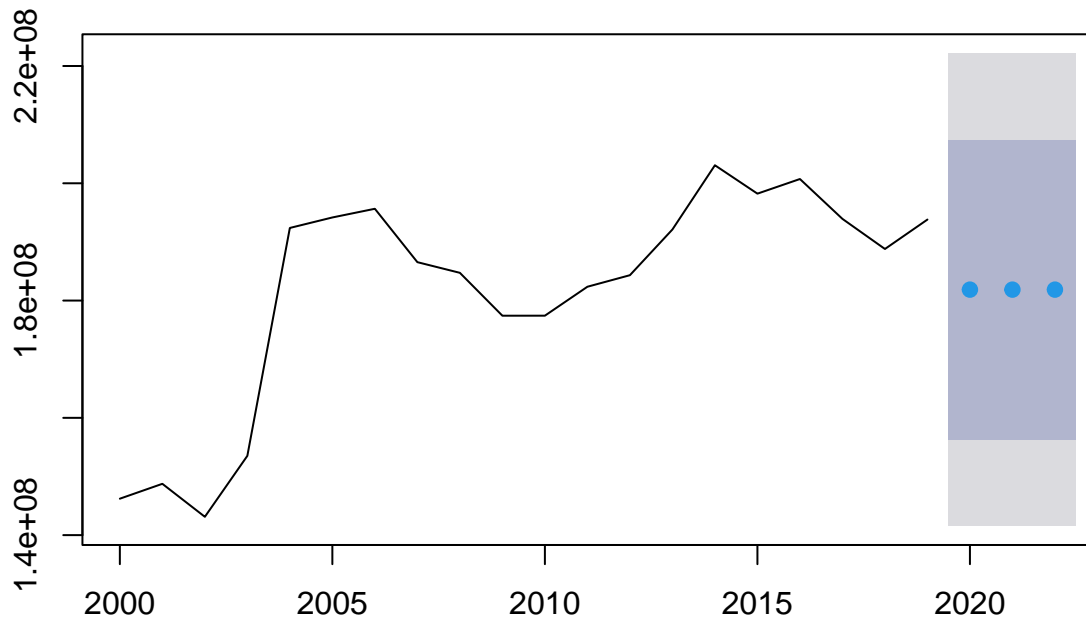
Forecasts from ARIMA(0,1,0)





Testing Model 2: MEAN_seas

Forecasts from Mean



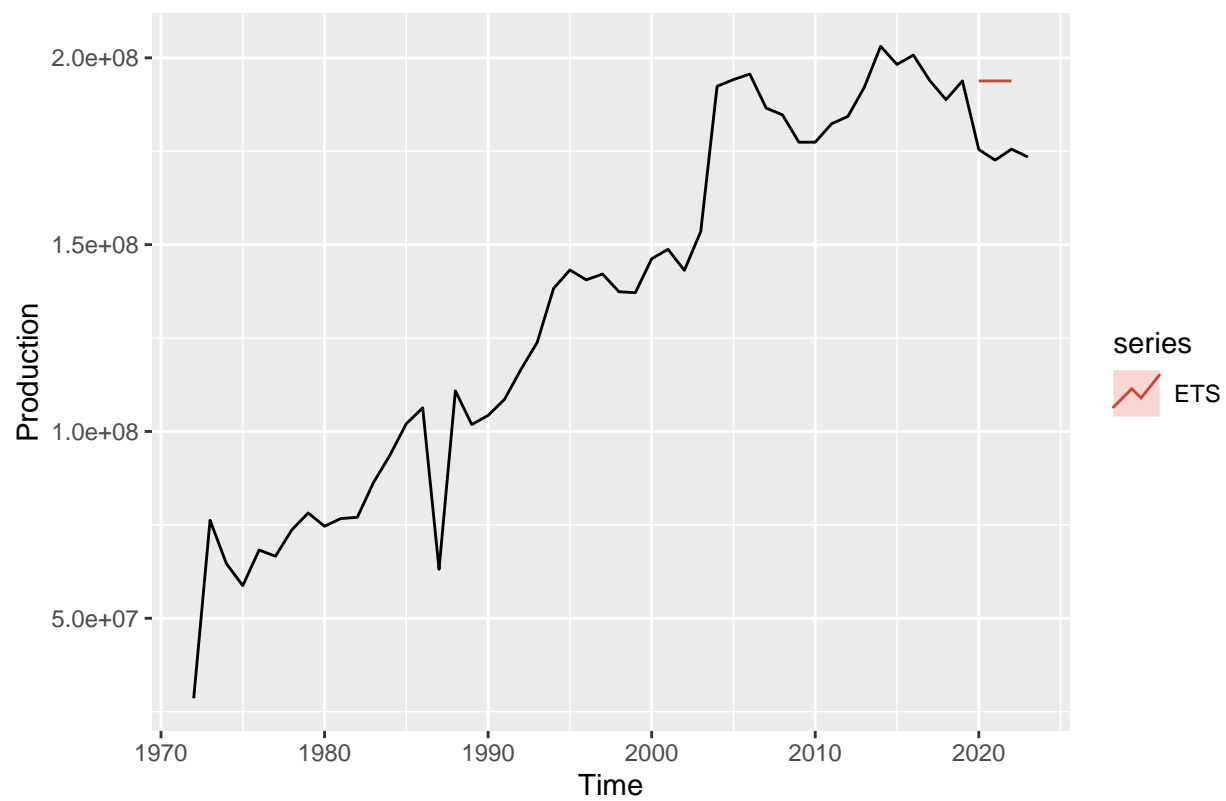
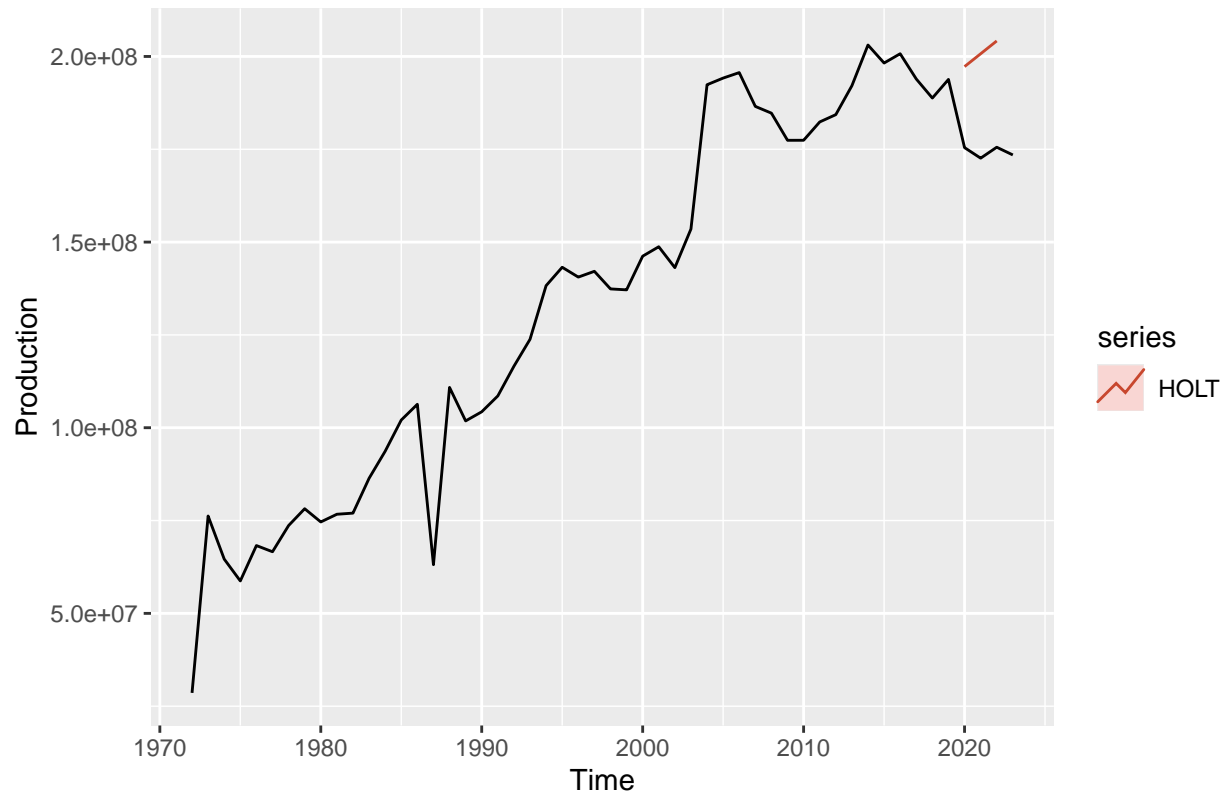


Table 4: Forecast Accuracy for Annual Data

	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 Constitucional del Ecuador. (2023). *Case no. 6-22-CP*. http://esacc.corteconstitucional.gob.ec/storage/api/v1/10_DWL_FL/e2NhcNBlDGE6J3RyYW1pdGUhLVV1aWQ6JzYwMjJlYzclLWViYzctNDNjYi05MjJjLW

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