

Group 3 Appendix

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Introduction

The Industrial Revolution has been a boon to humanity, leading to longer life spans, increased wealth, easy access to clean water, it gave us Netflix...but with every benefit there comes a cost, and the main cost with expansion of human flourishing has been what we now call

climate change. This term encapsulates a host of changes to our environment such as rising sea levels, more extreme weather events, reduction in biodiversity, etc. The climate changing isn't particularly new, the climate is always changing. What's unique about this period in Earth's history is the rate at which everything is changing. And the consensus is that rate of change is driven by human activity dumping CO2 emissions into the atmosphere, driving up CO2 concentration in the atmosphere, causing the global temperature to rise and leading to these rapid ecosystem alterations.

Project Problem/Statement

This project was inspired by a desire to get involved in understanding the scope of the problem and hopefully finding a way to solve or mitigate it. Specifically we wanted to find a way to accurately isolate the impact of CO2 emissions on the increasing temperature trend, and by extension an individuals (defined as nation, state, city, organization etc) impact on the warming trend. The belief is that by quantifying impact, people will be better equipped to take action on changing their behavior and upgrading systems in ways that slow or reverse the warming trends.

Data Overview

```
df <- read_csv("data/global_temp.csv")  
glimpse(df, width = 45)
```

```
Rows: 2,109  
Columns: 12  
$ Year          <dbl> 1850, 1850, 1850~  
$ Month         <dbl> 1, 2, 3, 4, 5, 6~  
$ Monthly_Anomaly <dbl> -0.469, -0.660, ~  
$ Monthly_Unc    <dbl> 0.662, 0.456, 0.~  
$ Annual_Anomaly  <dbl> NA, NA, NA, NA, ~  
$ Annual_Unc     <dbl> NA, NA, NA, NA, ~  
$ FiveYear_Anomaly <dbl> NA, NA, NA, NA, ~  
$ FiveYear_Unc   <dbl> NA, NA, NA, NA, ~  
$ TenYear_Anomaly <dbl> NA, NA, NA, NA, ~  
$ TenYear_Unc    <dbl> NA, NA, NA, NA, ~  
$ TwentyYear_Anomaly <dbl> NA, NA, NA, NA, ~  
$ TwentyYear_Unc  <dbl> NA, NA, NA, NA, ~
```

```
summary(df[3:6], digits = 2)
```

Monthly_Anomaly	Monthly_Unc	Annual_Anomaly	Annual_Unc
Min. : -0.8130	Min. : 0.020	Min. : -0.5640	Min. : 0.015
1st Qu.: -0.2850	1st Qu.: 0.069	1st Qu.: -0.2780	1st Qu.: 0.037
Median : -0.0870	Median : 0.156	Median : -0.1060	Median : 0.096
Mean : 0.0069	Mean : 0.182	Mean : 0.0052	Mean : 0.110
3rd Qu.: 0.1990	3rd Qu.: 0.262	3rd Qu.: 0.1797	3rd Qu.: 0.168
Max. : 1.4490	Max. : 0.770	Max. : 1.3050	Max. : 0.360
		NA's : 11	NA's : 11

The data from Berkely Earth comes in the form of monthly anomalies. They use a baseline period (1950-1980) and record temperature observations as differences from the average temp (by month) of this period. They include the uncertainties, and 5, 10, and 20 year lag periods. For our purposes, we're only concerned with the `Monthly_Anomaly` column

Convert to Tibble and Temperatures

```
Anomaly_data <- df |> mutate(
  Month = month.abb[Month],
  Date = yearmonth(paste(Month, Year)),
  Monthly_Anomaly = replace_na(Monthly_Anomaly, mean(Monthly_Anomaly, na.rm =
    T))) |>
select(c(Date, Monthly_Anomaly)) |>
as_tsibble(index = Date)

baseline_vector <- c(
  '1' = 12.30, '2' = 12.50, '3' = 13.13, '4' = 14.06,
  '5' = 15.00, '6' = 15.66, '7' = 15.90, '8' = 15.75,
  '9' = 15.18, '10' = 14.27, '11' = 13.28, '12' = 12.57
)

converted_df <- Anomaly_data |>
mutate(
  month_char = as.character(month(Date)),
  baseline_temp = baseline_vector[month_char],
  actual_temp = baseline_temp + Monthly_Anomaly
) |>
select(c(Date, actual_temp))
```

```
converted_df |>
  head() |>
  kable()
```

Date	actual_temp
1850 Jan	11.831
1850 Feb	11.840
1850 Mar	12.703
1850 Apr	13.250
1850 May	14.625
1850 Jun	15.298

Reporting in monthly anomalies is common for publications given that the main interest is usually in the overall trend of warming. However for our purposes, since we are attempting to isolate the human effect on the warming trend, we also need to be able to accurately model temperature separate of human impact. The seasonality of global temperatures is a big part of that and using only the monthly Monthly_Anomaly measurements largely strips out that component. Both sets of data will be explored and modeled however to see which one is most useful and it may turn out that each is valuable in different capacities.

Exploratory Data Analysis of Global Anomalies

```
glimpse(df, width = 50)
```

```
Rows: 2,109
Columns: 12
$ Year      <dbl> 1850, 1850, 1850, 185~
$ Month     <dbl> 1, 2, 3, 4, 5, 6, 7, ~
$ Monthly_Anomaly <dbl> -0.469, -0.660, -0.42~
$ Monthly_Unc <dbl> 0.662, 0.456, 0.611, ~
$ Annual_Anomaly <dbl> NA, NA, NA, NA, NA, --~
$ Annual_Unc <dbl> NA, NA, NA, NA, NA, 0~
$ FiveYear_Anomaly <dbl> NA, NA, NA, NA, NA, N~
$ FiveYear_Unc <dbl> NA, NA, NA, NA, NA, N~
$ TenYear_Anomaly <dbl> NA, NA, NA, NA, NA, N~
$ TenYear_Unc <dbl> NA, NA, NA, NA, NA, N~
```

```
$ TwentyYear_Anomaly <dbl> NA, NA, NA, NA, NA, N~
$ TwentyYear_Unc      <dbl> NA, NA, NA, NA, NA, N~
```

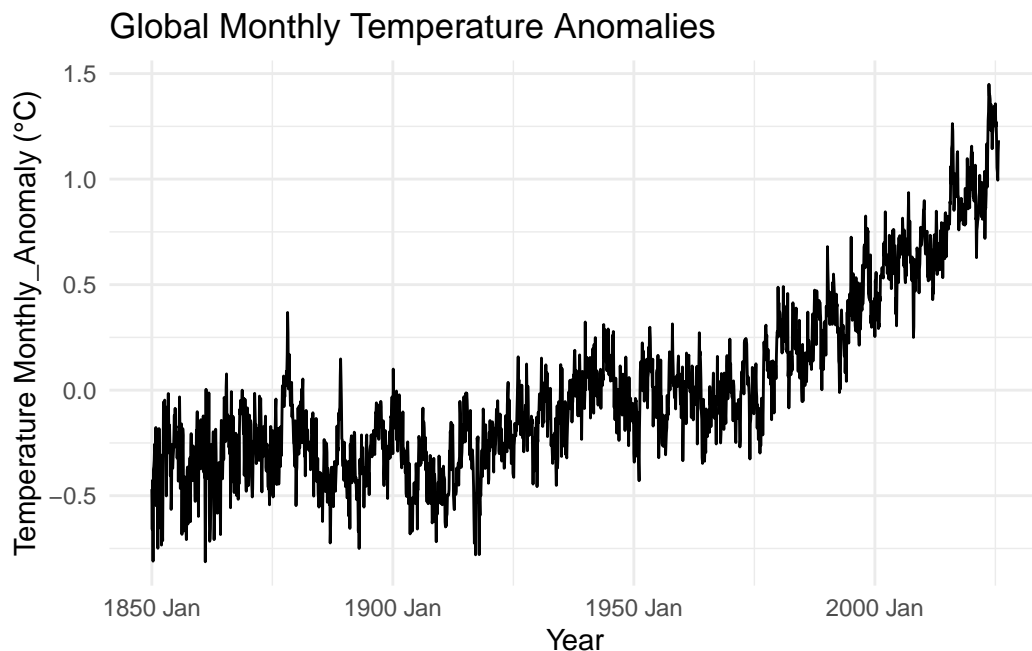
```
names(df)
```

```
[1] "Year"          "Month"          "Monthly_Anomaly"
[4] "Monthly_Unc"   "Annual_Anomaly" "Annual_Unc"
[7] "FiveYear_Anomaly" "FiveYear_Unc"   "TenYear_Anomaly"
[10] "TenYear_Unc"   "TwentyYear_Anomaly" "TwentyYear_Unc"
```

This dataset contains 2,109 monthly observations from 1850–2025, with global temperature anomalies and uncertainties, where `Monthly_Anomaly` is the primary usable series and most multi-year `Monthly_Anomaly` fields contain NA values except at the end of their smoothing windows.

```
train <- Anomaly_data|> filter(Date < yearmonth("2020 Jan"))
test  <- Anomaly_data|> filter(Date >= yearmonth("2020 Jan"))

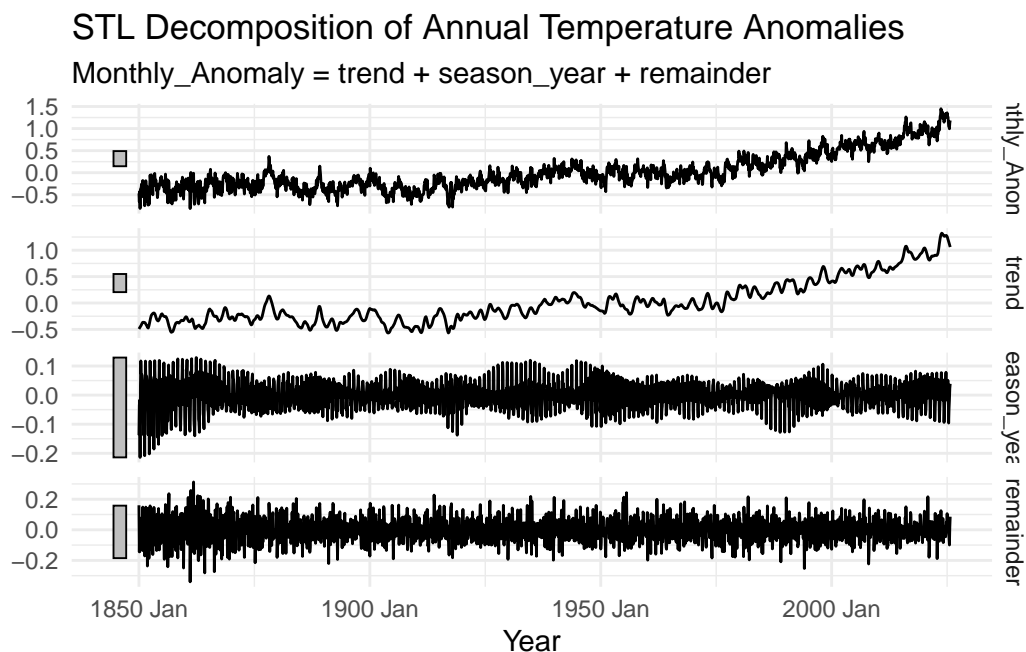
autoplot(Anomaly_data, Monthly_Anomaly) +
  labs(title = "Global Monthly Temperature Anomalies",
       x = "Year", y = "Temperature Monthly_Anomaly (°C)") +
  theme_minimal()
```



The plot shows that what was once mostly cooler-than-average (average as defined as the period between 1950 - 1980) global temperatures has transitioned into a new normal of sustained warming, particularly over the last 40 years. The sharp upward trend in recent decades signals the accelerating pace of climate change.

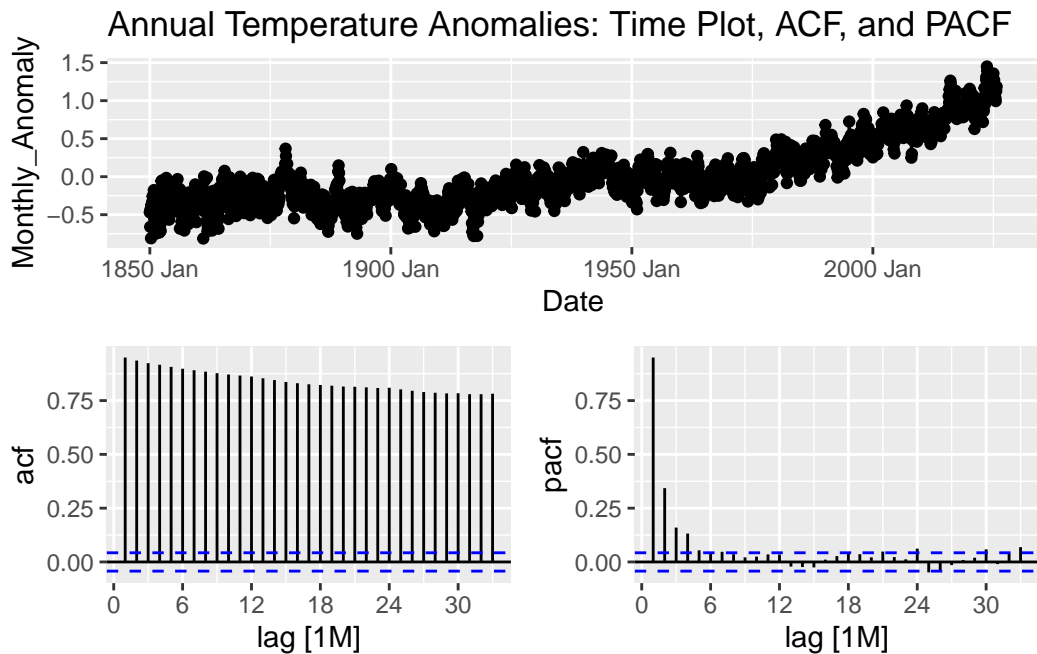
```
climate_stl <- Anomaly_data |>
  model(
    STL(Monthly_Anomaly ~ trend(window = 15))
  ) |>
  components()

autoplot(climate_stl) +
  labs(
    title = "STL Decomposition of Annual Temperature Anomalies",
    x = "Year"
  ) +
  theme_minimal()
```



The STL results highlight how the underlying warming signal has grown stronger over time, while the remainder shows noisy but relatively modest deviations from the trend. This reinforces that annual variability exists but is dwarfed by the long-term increase in global temperatures.

```
Anomaly_data |>
  gg_tsdisplay(Monthly_Anomaly, plot_type = "partial") +
  labs(
    title = "Annual Temperature Anomalies: Time Plot, ACF, and PACF"
  )
```



The climate series exhibits a persistent warming trend, and the ACF's slow decay underscores how each year's temperature is tightly linked to previous years. The PACF's immediate drop-off reinforces that this warming signal creates strong year-to-year inertia in global temperatures.

```
# KPSS
Anomaly_data |>
  features(Monthly_Anomaly, unitroot_kpss) |>
  kable(digits = 4, align = "c")
```

kpss_stat	kpss_pvalue
17.4329	0.01

The KPSS test confirms what the plots already suggest: the `Monthly_Anomaly` series isn't stationary, with the low *p*-value indicating that the warming trend dominates over random fluctuations.

```
# Non-seasonal differencing needed?
Anomaly_data |>
  features(Monthly_Anomaly, c(unitroot_ndiffs, unitroot_nsdiffs)) |>
  kable(digits = 4, align = "c")
```

ndiffs	nsdifs
1	0

```
Anomaly_data |>
  features(Monthly_Anomaly, guerrero) |>
  kable(digits = 4, align = "c")
```

lambda_guerrero
0.9662

$\lambda \approx 0.966 \rightarrow$ little to no Box–Cox transformation needed; variance is already stable. Unitroot test suggests differencing may be needed

Exploratory Data Analysis of Global Temperatures

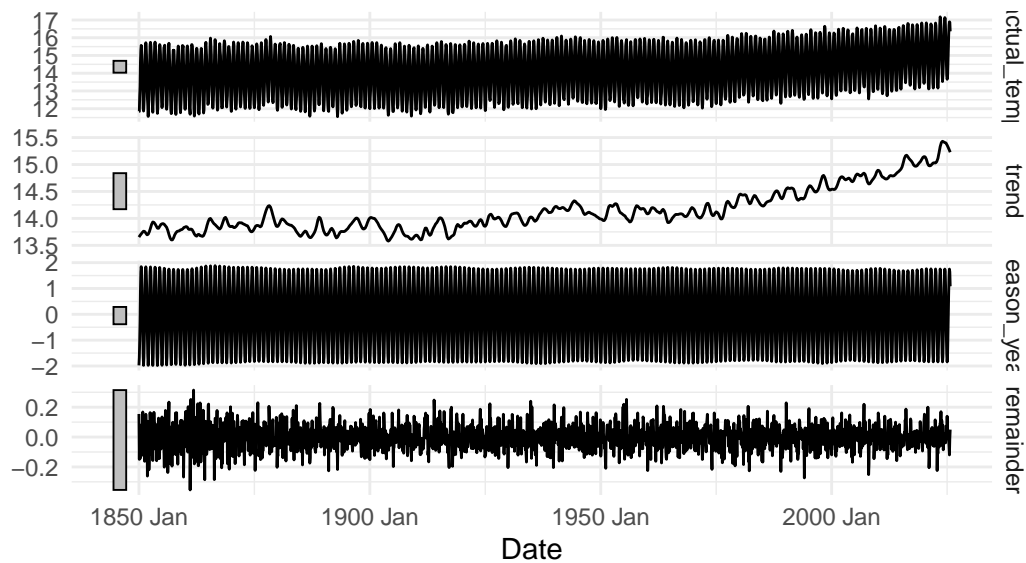
```
summary(converted_df[2])
```

```
actual_temp
Min.      :11.55
1st Qu.   :12.89
Median    :14.17
Mean      :14.14
3rd Qu.   :15.40
Max.      :17.18
```

```
converted_df |>
  model(STL(actual_temp)) |>
  components() |>
  autoplot() +
  labs(title = "STL Decomposition of Global Monthly Actual Temperatures") +
  theme_minimal()
```

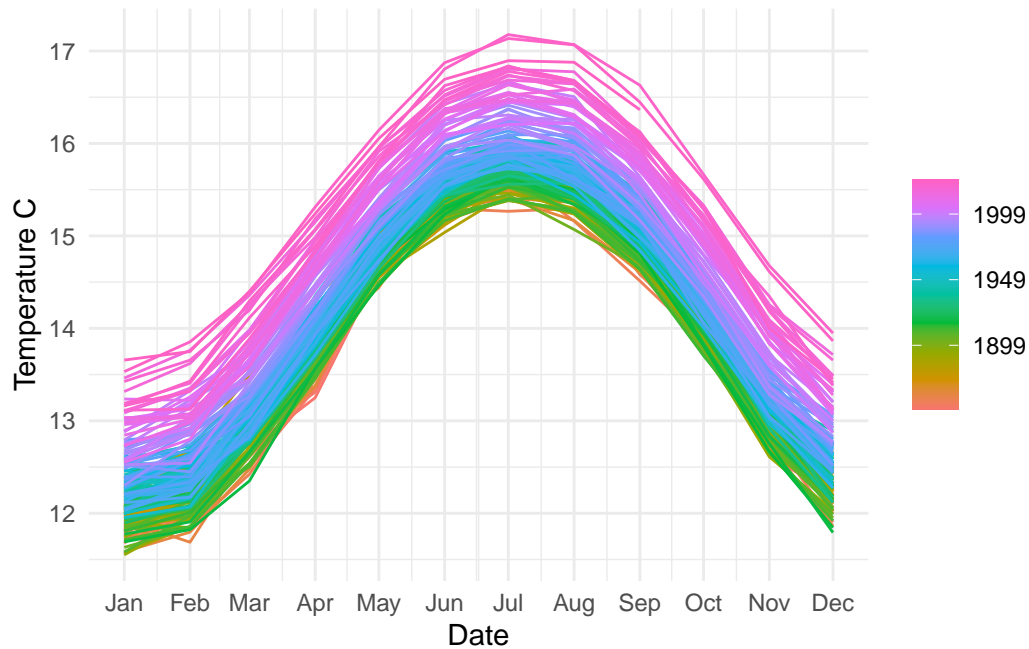
STL Decomposition of Global Monthly Actual Temperatures

$\text{actual_temp} = \text{trend} + \text{season_year} + \text{remainder}$



Decomposition of global temperatures show seasonality to mainly be constant with some compression in later years (could be a result of more precise measurements, could also be a result of warming trends flattening temperature swings each season). The main driver of the changing level is the trend which stayed fairly constant until 1920 when the trend starts to increase, then really takes off after 1980

```
converted_df |>
  ggtime::gg_season() +
  labs(y = "Temperature C") +
  theme_minimal()
```



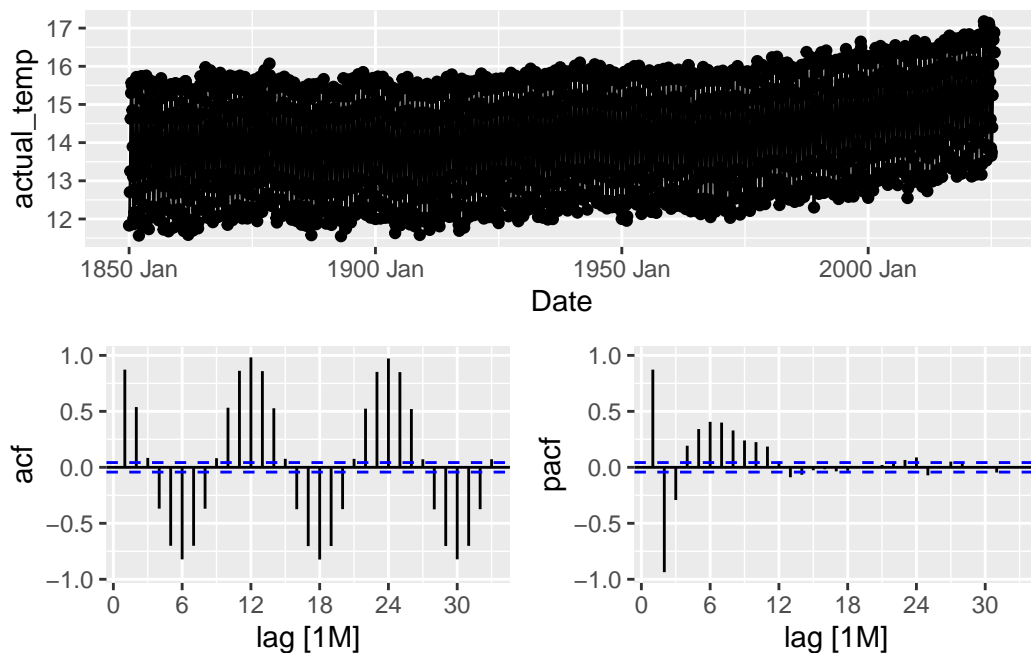
Clearer picture of the increasing trend over time, occurring across all periods

```
converted_df |>
  features(actual_temp, guerrero) |>
  kable(digits = 4, align = "c")
```

lambda_guerrero
1.4379

$\lambda \approx 1.44$, so a power transformation may be helpful

```
gg_tsdisplay(converted_df, actual_temp, plot_type = 'partial')
```



```
converted_df |>
  features(actual_temp, c(unitroot_kpss, unitroot_ndiffs, unitroot_nsdiffs))
  ↪ |>
  kable(digits = 4, align = "c")
```

kpss_stat	kpss_pvalue	ndiffs	nsdifs
8.8813	0.01	1	1

Unitroot tests suggest at least one difference and one seasonal difference. Using `gg_tsdisplay`, the seasonal autocorrelation is obvious, with the summer and winter months grouping together on opposite sides of the line. The pacf shows that the seasonal effects are strong. All of this shows the data is not stationary

Modeling / Forecasting

Monthly_Anomaly Modeling

```
# Fit ETS on the training data
```

```
fit_ets <- train |>  
model(ETS(Monthly_Anomaly))
```

```
# Print model details
```

```
report(fit_ets)
```

Series: Monthly_Anomaly

Model: ETS(A,N,A)

Smoothing parameters:

alpha = 0.4616505

gamma = 0.0001007547

Initial states:

l[0]	s[0]	s[-1]	s[-2]	s[-3]	s[-4]	s[-5]
-0.504211	-0.01987071	-0.01378345	0.03587174	-0.01243867	0.01035226	0.02029624
s[-6]	s[-7]	s[-8]	s[-9]	s[-10]	s[-11]	
0.03041389	0.01181375	-0.004461374	-0.01081024	-0.0249877	-0.02239573	

sigma^2: 0.013

AIC	AICc	BIC
6708.789	6709.026	6793.099

```
fc_ets <- fit_ets |>  
forecast(new_data = test)
```

```
fc_ets_zoom <- fc_ets|>  
filter_index("2020 Jan" ~ "2025 Dec")
```

```
autoplot(  
  fc_ets_zoom,  
  Anomaly_data |> filter_index("2020 Jan" ~ "2025 Dec")  
) +  
labs(  
  title = "Auto-ETS Forecast vs Actuals (2020-2025)",  
  subtitle = "Automatically selected ETS model",  
  x = "Year",  
  y = "Temperature Monthly_Anomaly (°C)"
```

)

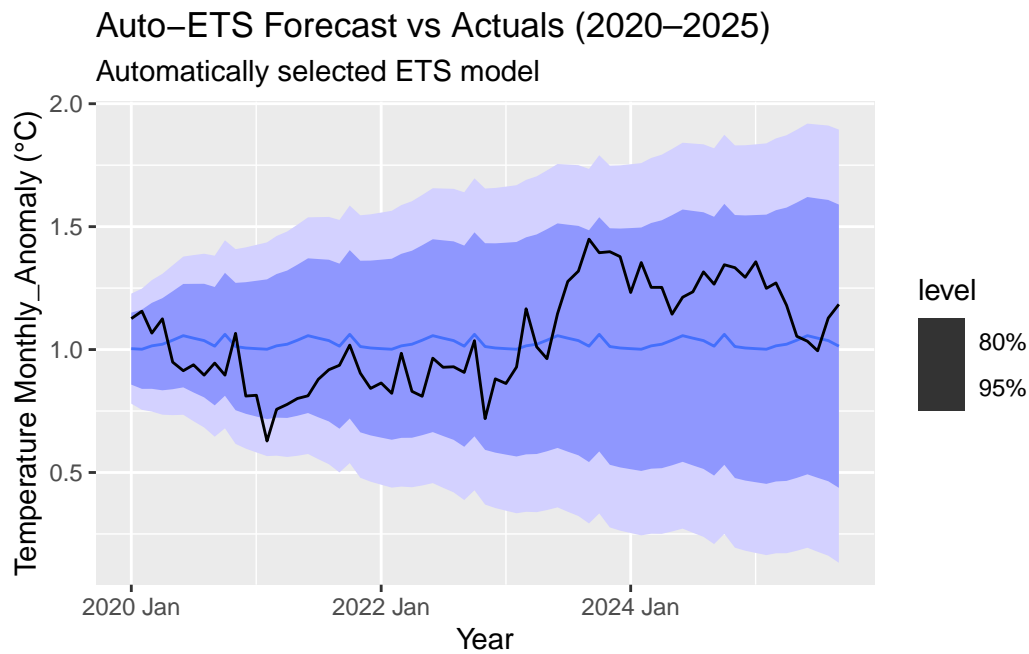


Figure 1: Auto-ETS forecast vs actuals (2020–2025).

The ETS model anticipates a relatively stable `Monthly_Anomaly` level, but the actual values frequently climb toward the upper edge of the 80% and even 95% prediction intervals. This pattern indicates that recent warming spikes are occurring faster and more intensely than the model expects based on historical structure. When observations consistently press against the top of the interval bands, it suggests the model may be underestimating both the trend strength and the volatility of contemporary climate behavior.

Temperature Modeling

```
cv_data <- converted_df |>
  stretch_tsibble(.init = 1506, .step = 60)

cv_trn <- cv_data |>
  group_by(.id) |>
  slice(1:(n() - 60)) |>
```

```

ungroup()

cv_valid <- cv_data |>
  group_by(.id) |>
  slice_tail(n = 60) |>
  ungroup()

```

Modeling on all temp data with cross validation sets created from the first roughly 125 years of data (1850 - 1930) and rolling forward by 5 years (60 months). This creates 11 cv splits covering the range of available observations

ETS

```

ets_fit <- cv_trn |>
  model(
    ets_auto = ETS(),
    additive = ETS(actual_temp ~ error("A") + trend("A") + season("A")),
    multiplicative = ETS(actual_temp ~ error("M") + trend("A") +
      ↪ season("M")),
    damped = ETS(actual_temp ~ error("A") + trend("Ad") + season("A")),
    mult_damp = ETS(actual_temp ~ error("M") + trend("Ad") + season("M")),
    log_auto = ETS(log(actual_temp)),
    box_cox_auto = ETS(box_cox(actual_temp, lambda = 1.5))
  )

```

```

ets_fit |>
  accuracy() |>
  group_by(.model) |>
  summarise(across(.cols = c(RMSE, MAE, ME), .fns = mean)) |>
  arrange(RMSE) |>
  kable(digits = 4, align = "c")

```

.model	RMSE	MAE	ME
box_cox_auto	0.1146	0.0893	5e-04
ets_auto	0.1158	0.0907	8e-04
damped	0.1158	0.0909	7e-04
additive	0.1166	0.0917	-2e-04
mult_damp	0.1195	0.0942	-1e-04

.model	RMSE	MAE	ME
log_auto	0.1198	0.0947	1e-04
multiplicative	0.1249	0.0988	-4e-04

```
# Smoothing parameters
ets_fit |>
  tidy() |>
  group_by(.model, term) |>
  summarise(across(.cols = estimate, .fns = mean)) |>
  pivot_wider(names_from = term, values_from = estimate) |>
  select(.model, alpha, beta, gamma, phi) |>
  kable(digits = 4, align = "c")
```

.model	alpha	beta	gamma	phi
additive	0.4026	0.0001	0.0285	NA
box_cox_auto	0.4386	0.0006	0.0001	0.9727
damped	0.4325	0.0002	0.0178	0.9787
ets_auto	0.4304	0.0003	0.0109	0.9800
log_auto	0.4139	0.0001	0.0343	0.9754
mult_damp	0.4469	0.0001	0.0295	0.9786
multiplicative	0.2812	0.0057	0.0755	NA

```
# Report on top performing model
ets_fit |>
  filter(.id == 10) |>
  select(log_auto) |>
  report()
```

Series: actual_temp

Model: ETS(A,A,A)

Transformation: log(actual_temp)

Smoothing parameters:

alpha = 0.408761

beta = 0.0001000166

gamma = 0.0549685

Initial states:

l[0]	b[0]	s[0]	s[-1]	s[-2]	s[-3]	s[-4]
2.615744	6.255243e-05	-0.1166191	-0.05617134	0.01551034	0.07698261	0.1148955

```

      s[-5]      s[-6]      s[-7]      s[-8]      s[-9]      s[-10]      s[-11]
0.1262374 0.111805 0.06813664 -0.001073793 -0.0717811 -0.1219244 -0.1459979

sigma^2: 1e-04

      AIC      AICc      BIC
-3724.686 -3724.375 -3629.590

```

All versions of ETS performed well on the training data with `box_cox_auto` performing the best. Auto selection chose an additive model with a damped trend. Looking the parameters, the **alpha** parameter values ranged from .2812 to .4469. This shows that the level is fairly stable and perhaps indicates that the recent warming trend is being masked by the long tail of relatively stable temperatures. This idea is bolstered by the the really small, almost 0 values of the **beta** parameter which indicates a stable trend. The **gamma** parameters are all very small as showing, suggesting that the ETS models are correctly reading that the seasonal pattern is relatively stable.

```

ets_fc <- ets_fit |>
  forecast(new_data = cv_valid)

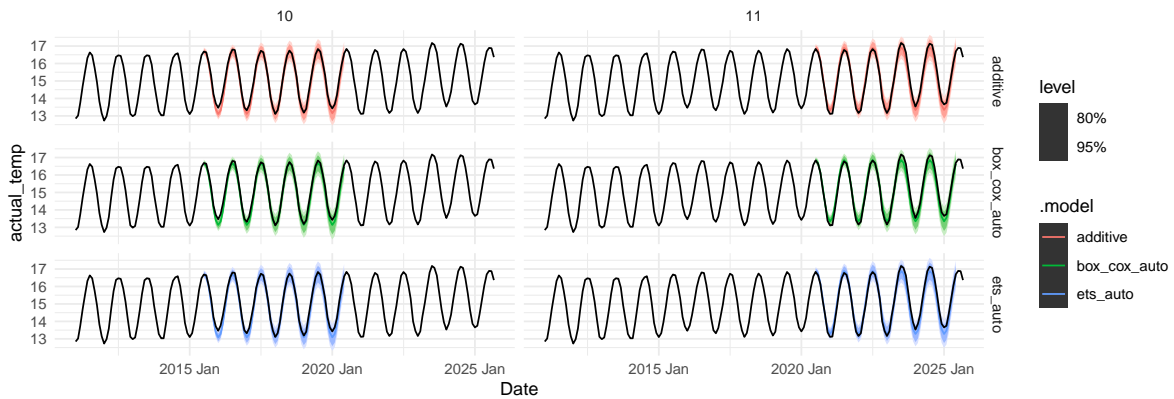
ets_fc |>
  accuracy(cv_valid) |>
  group_by(.model) |>
  summarise(across(.cols = c(RMSE, MAE, ME), .fns = mean)) |>
  arrange(RMSE) |>
  kable(digits = 4)

```

.model	RMSE	MAE	ME
additive	0.1724	0.1412	-0.0013
ets_auto	0.1726	0.1409	0.0239
box_cox_auto	0.1730	0.1409	0.0183
damped	0.1735	0.1419	0.0208
log_auto	0.1758	0.1441	0.0033
mult_damp	0.1763	0.1442	0.0261
multiplicative	0.1919	0.1627	-0.0179

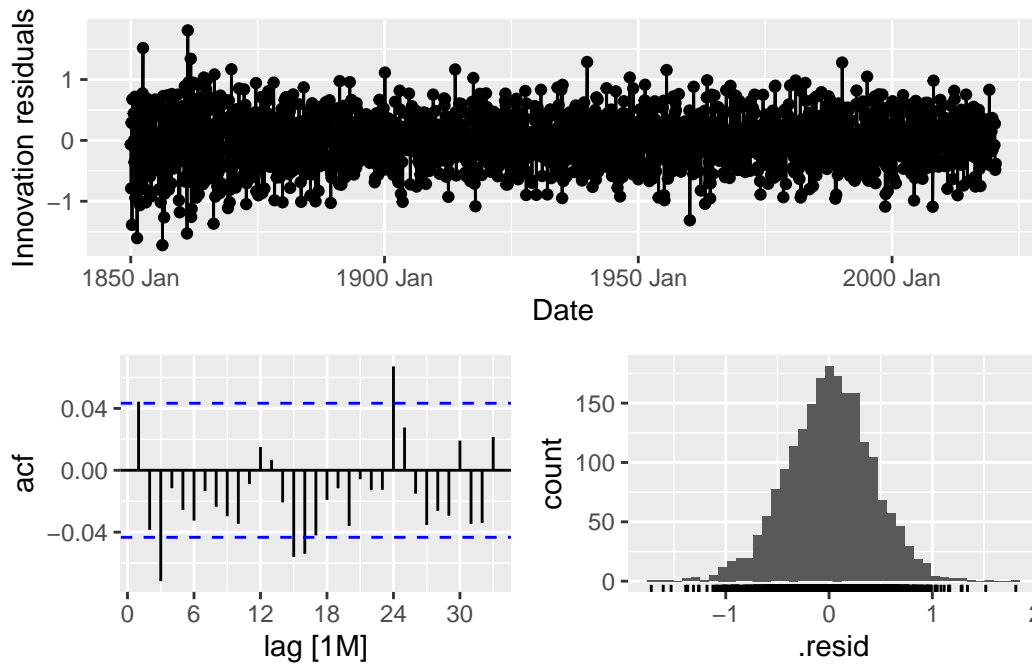
The additive model performs the best on the validation data but the out performance is negligible to `ets_auto` and `box_cox_auto`

```
ets_fc |>
  filter(.id %in% c(10, 11), .model %in% c('additive', 'box_cox_auto',
    ↪ 'ets_auto')) |>
  autoplot() +
  autolayer(converted_df |> filter(year(Date) > 2010), actual_temp) +
  facet_grid(.model ~ .id) +
  theme_minimal()
```



Visualizing the top 3 models illustrates how ETS models do just fine at predicting the fall and spring months, but consistently undershoot the seasonal peaks and exhibit wide prediction intervals around those areas. ETS models have trouble capturing the increasing trend

```
ets_fit |>
  select(box_cox_auto) |>
  tail(n = 1) |>
  ggtime::gg_tsresiduals()
```



Using box cox and checking the residuals of the model fitted on the most data, the residuals show a mostly normal distribution. Slight skew to the right. There are autocorrelations at lag 3 and lag 24. We can confirm that the residuals aren't white noise with a Ljung-Box test. There are certainly factors that influence temperature that ETS isn't capturing

```
ets_fit |>
  augment() |>
  filter(.model == "box_cox_auto") |>
  features(.innov, ljung_box, lag = 24) |>
  summarize(across(.cols = lb_pvalue, .fns = mean)) |>
  kable(digits = 4, align = "c")
```

lb_pvalue
0.0041

TSLM

```
tslm_fit <- cv_trn |>
  model(
```

```

tslm_auto = TSLM(actual_temp),
tslm_trend = TSLM(actual_temp ~ trend()),
tslm_trend_season = TSLM(actual_temp ~ trend() + season()),
tslm_fourier = TSLM(actual_temp ~ trend() + fourier(K = 2)),
tslm_log = TSLM(log(actual_temp) ~ trend() + season()),
tslm_box_cox = TSLM(box_cox(actual_temp, lambda = 1.5) ~ trend() +
  ↪ season()),
tslm_piecewise = TSLM(actual_temp ~ trend(knots = c(1920, 1975)) +
  ↪ season())
)

```

Testing Fourier terms for a simpler model as opposed to using season dummy variables, and piece-wise to capture changes in the trend at those points in the data.

```

tslm_fit |>
  accuracy() |>
  group_by(.model) |>
  summarise(across(.cols = c(RMSE, MAE, ME), .fns = mean)) |>
  arrange(RMSE) |>
  kable(digits = 4)

```

.model	RMSE	MAE	ME
tslm_piecewise	0.1861	0.1492	0.0000
tslm_trend_season	0.1861	0.1492	0.0000
tslm_box_cox	0.1861	0.1493	-0.0006
tslm_log	0.1874	0.1501	0.0013
tslm_fourier	0.1880	0.1508	0.0000
tslm_trend	1.3262	1.1887	0.0000
tslm_auto	1.3409	1.1979	0.0000

```

tslm_fit |>
  select(tslm_trend_season) |>
  tail(n = 1) |>
  report()

```

Series: actual_temp

Model: TSLM

Residuals:

Min	1Q	Median	3Q	Max
-0.63061	-0.15153	-0.01237	0.14543	0.79855

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.172e+01	1.870e-02	626.999	<2e-16 ***
trend()	5.171e-04	8.187e-06	63.157	<2e-16 ***
season()year2	2.096e-01	2.365e-02	8.861	<2e-16 ***
season()year3	8.370e-01	2.365e-02	35.387	<2e-16 ***
season()year4	1.779e+00	2.365e-02	75.227	<2e-16 ***
season()year5	2.735e+00	2.365e-02	115.630	<2e-16 ***
season()year6	3.411e+00	2.365e-02	144.184	<2e-16 ***
season()year7	3.636e+00	2.369e-02	153.494	<2e-16 ***
season()year8	3.479e+00	2.369e-02	146.845	<2e-16 ***
season()year9	2.890e+00	2.369e-02	122.000	<2e-16 ***
season()year10	2.024e+00	2.369e-02	85.447	<2e-16 ***
season()year11	9.840e-01	2.369e-02	41.538	<2e-16 ***
season()year12	2.759e-01	2.369e-02	11.645	<2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2187 on 2033 degrees of freedom

Multiple R-squared: 0.9743, Adjusted R-squared: 0.9742

F-statistic: 6435 on 12 and 2033 DF, p-value: < 2.22e-16

The `trend_season`, `box_cox` and `piecewise` models all perform the same on the training data. Looking at the model report for the `trend_season` model we can see that all parameters are significant.

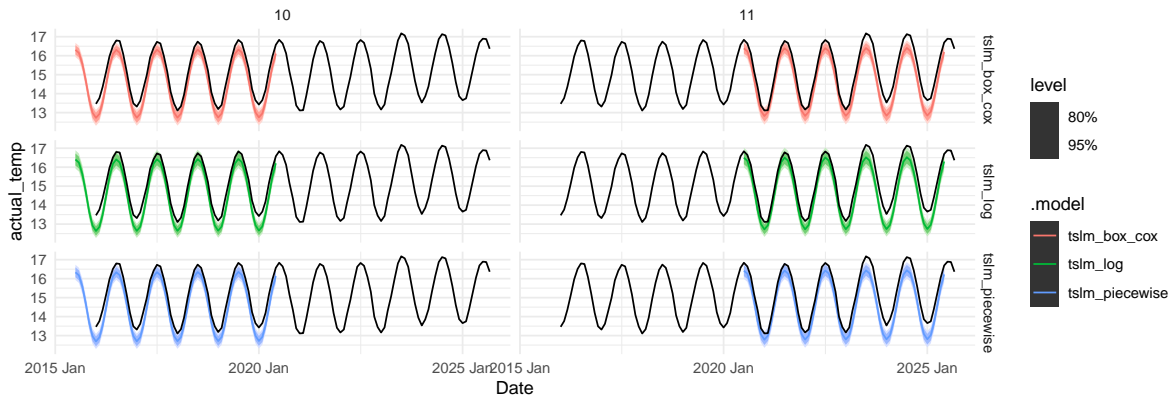
```
tslm_fc <- tslm_fit |>
  forecast(new_data = cv_valid)

tslm_fc |>
  accuracy(cv_valid) |>
  group_by(.model) |>
  summarise(across(.cols = c(RMSE, MAE, ME), .fns = mean)) |>
  arrange(MAE) |>
  kable(digits = 4)
```

.model	RMSE	MAE	ME
tslm_log	0.3198	0.2881	0.2660
tslm_piecewise	0.3212	0.2933	0.2724
tslm_trend_season	0.3212	0.2933	0.2724
tslm_fourier	0.3222	0.2939	0.2723
tslm_box_cox	0.3212	0.2940	0.2731
tslm_trend	1.3361	1.1945	0.2735
tslm_auto	1.4553	1.2584	0.6108

TSLM log performs the best on the validation data but significantly under-perform ETS models

```
tslm_fc |>
  filter(.id %in% c(10, 11), .model %in% c('tslm_log', 'tslm_piecewise',
    ↪ 'tslm_box_cox')) |>
  autoplot() +
  autolayer(converted_df |> filter(year(Date) > 2015), actual_temp) +
  facet_grid(.model ~ .id) +
  theme_minimal()
```



It's pretty clear from the visuals that TSLM models are failing even harder than the ETS models at capturing the warming trend.

ARIMA

```
trn_data <- converted_df |>
  slice(1:(n() - 60))

valid_data <- converted_df |>
  slice_tail(n = 60)
```

ARIMA models take too long to converge on CV splits and often time out, so testing them first on normal splits

```
arima_fit <- trn_data |>
  model(
    arima_auto = ARIMA(actual_temp),
    arima_box = ARIMA(box_cox(actual_temp, lambda = 1.5)),
    arima_log = ARIMA(log(actual_temp))
  )

arima_fit |>
  accuracy() |>
  select(.model, RMSE, MAE, ME) |>
  arrange(RMSE) |>
  kable(digits = 4)
```

.model	RMSE	MAE	ME
arima_box	0.1191	0.0931	-4e-04
arima_auto	0.1192	0.0932	0e+00
arima_log	0.1318	0.1027	2e-04

ARIMA box_cox and auto performed the same on the training data

```
arima_fit |>
  select(arima_box) |>
  report()
```

```
Series: actual_temp
Model: ARIMA(1,0,0)(0,1,1)[12] w/ drift
Transformation: box_cox(actual_temp, lambda = 1.5)
```

```
Coefficients:
      ar1      sma1  constant
```

```

      0.7088 -0.8825  0.0079
s.e.  0.0176  0.0126  0.0012

```

```

sigma^2 estimated as 0.1955:  log likelihood=-1235.64
AIC=2479.28   AICc=2479.3   BIC=2501.76

```

```

arima_fit |>
  select(arima_auto) |>
  report()

```

```

Series: actual_temp
Model: ARIMA(1,0,0)(0,1,1)[12] w/ drift

```

```

Coefficients:
      ar1      sma1  constant
      0.7053 -0.8840    0.0021
s.e.  0.0176  0.0126    0.0003

```

```

sigma^2 estimated as 0.01431:  log likelihood=1426.97
AIC=-2845.94   AICc=-2845.92   BIC=-2823.47

```

Surprisingly the ARIMA models only selected a seasonal differencing instead of both a seasonal and non-seasonal. 1 non-seasonal AR component was selected and 1 seasonal moving average. So the auto selected models are using the previous observation and the previous seasons forecast error to make its predictions.

```

arima_fc <- arima_fit |>
  forecast(new_data = valid_data)

arima_fc |>
  accuracy(valid_data) |>
  group_by(.model) |>
  summarise(across(.cols = c(RMSE, MAE, ME), .fns = mean)) |>
  arrange(RMSE) |>
  kable(digits = 4)

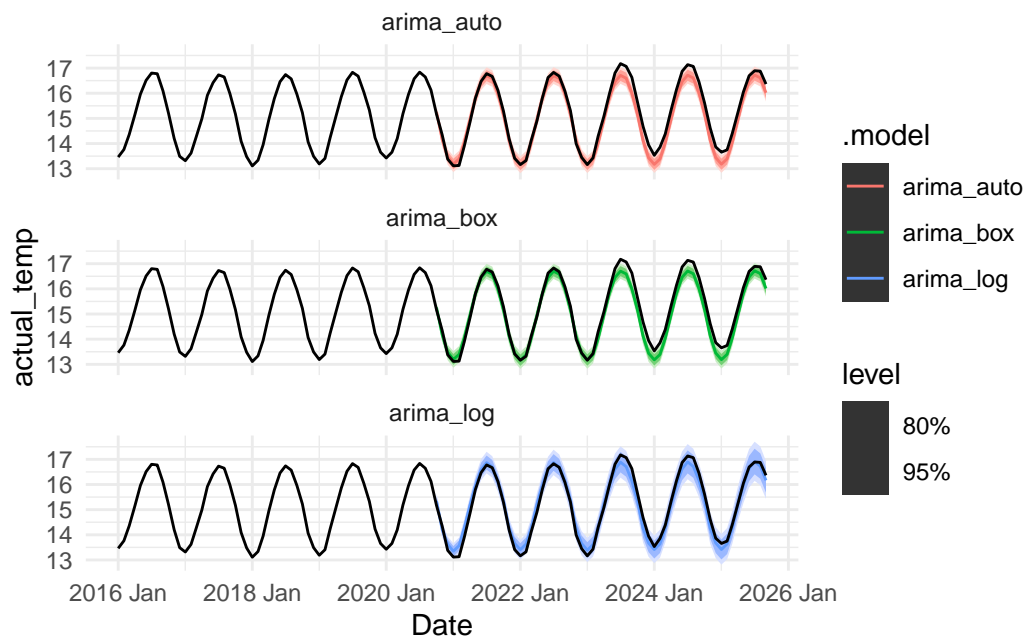
```

.model	RMSE	MAE	ME
arima_log	0.2174	0.1823	0.0214
arima_box	0.2929	0.2365	0.2020

.model	RMSE	MAE	ME
arima_auto	0.2929	0.2357	0.2035

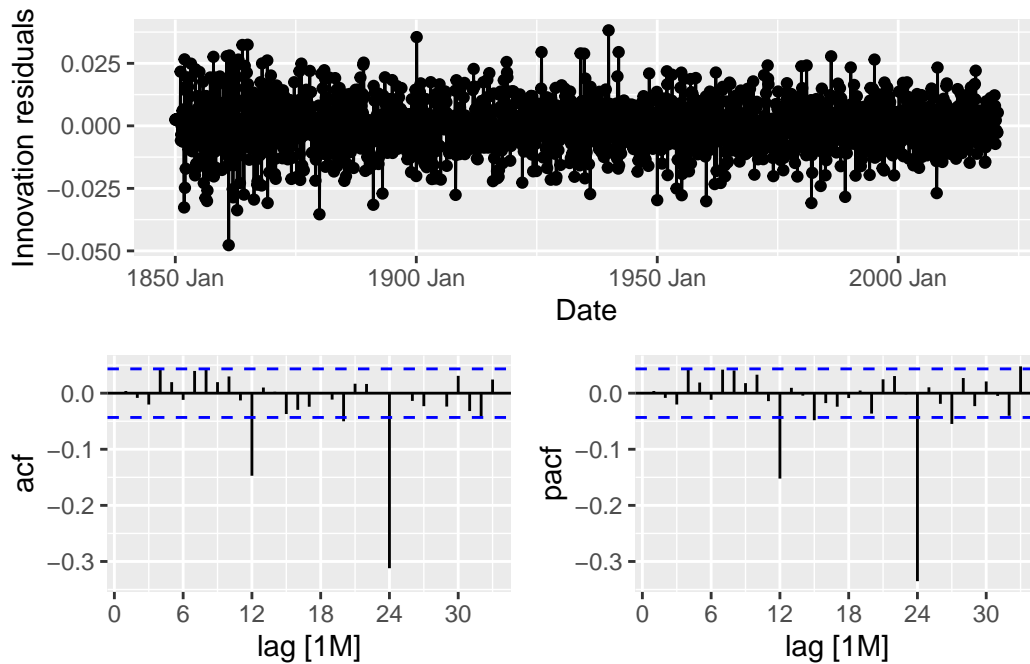
Arima log does best on the validation data by a large margin.

```
arima_fc |>
  autoplot() +
  autolayer(converted_df |> filter(year(Date) > 2015), actual_temp) +
  facet_wrap(~ .model, ncol = 1) +
  theme_minimal()
```



We see that the ARIMA log model does slightly better at capturing the peaks than the other two, but all still don't quite capture the increasing trend.

```
arima_fit |>
  select(arima_log) |>
  ggtime::gg_tsresiduals(plot_type = 'partial')
```



```

arima_fit |>
  augment() |>
  filter(.model == "arima_box") |>
  features(.innov, ljung_box, lag = 24) |>
  kable(digits = 4, align = "c")

```

.model	lb_stat	lb_pvalue
arima_box	229.746	0

Residuals aren't even close to stationary. With ARIMA we can experiment with other parameter values

```

arima_fit <- trn_data |>
  model(
    arima_diff = ARIMA(actual_temp ~ pdq(d = 1)),
    arima_box_diff = ARIMA(box_cox(actual_temp, lambda = 1.5) ~ pdq(d = 1)),
    arima_box_ar_two = ARIMA(box_cox(actual_temp, lambda = 1.5) ~ pdq(p =
      ↪ 2)),
    arima_custom = ARIMA(actual_temp ~ 0 + pdq(3, 1, 2) + PDQ(1, 1, 2))
  )

```

```

arima_fc <- arima_fit |>
  forecast(new_data = valid_data)

arima_fc |>
  accuracy(valid_data) |>
  group_by(.model) |>
  summarise(across(.cols = c(RMSE, MAE, ME), .fns = mean)) |>
  arrange(RMSE) |>
  kable(digits = 4)

```

.model	RMSE	MAE	ME
arima_custom	0.2110	0.1714	0.0801
arima_diff	0.2169	0.1814	-0.1230
arima_box_diff	0.2183	0.1818	-0.1199
arima_box_ar_two	0.2212	0.1851	0.0201

Adding non-seasonal differencing, another AR term and a seasonal MA term to deal with the autocorrelation at lag 24 helped improved model results on the validation data

```

arima_fit |>
  augment() |>
  filter(.model == "arima_custom") |>
  features(.innov, ljung_box, lag = 24) |>
  kable(digits = 4, align = "c")

```

.model	lb_stat	lb_pvalue
arima_custom	21.0759	0.6342

A high p-value tells us that the residuals are now resembling white noise

Compare Best Models

```

compare_fit <- cv_trn |>
  model(
    ETS = ETS(actual_temp ~ error("A") + trend("A") + season("A")),

```

```

    TSLM = TSLM(log(actual_temp) ~ trend() + season()),
    ARIMA = ARIMA(actual_temp ~ 0 + pdq(3, 1, 2) + PDQ(1, 1, 2))
  )

compare_fc <- compare_fit |>
  forecast(new_data = cv_valid)

compare_fc |>
  accuracy(cv_valid) |>
  filter(.id != 6) |>
  group_by(.model) |>
  summarise(across(.cols = c(RMSE, MAE, ME), .fns = mean)) |>
  arrange(RMSE) |>
  kable(digits = 4)

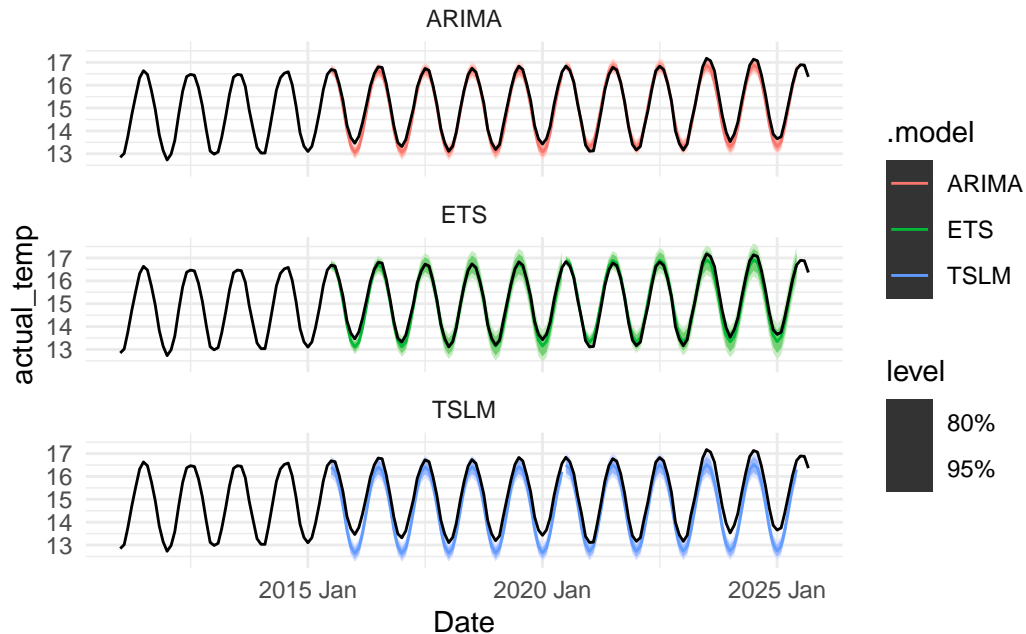
```

.model	RMSE	MAE	ME
ARIMA	0.1634	0.1323	0.0482
ETS	0.1748	0.1429	-0.0004
TSLM	0.3191	0.2880	0.2637

```

compare_fc |>
  filter(.id %in% c(10, 11)) |>
  autoplot() +
  autolayer(converted_df |> filter(year(Date) > 2010), actual_temp) +
  facet_wrap(~ .model, ncol = 1) +
  theme_minimal()

```



The metrics based on RMSE show that ARIMA does slightly better than ETS and both do much better than TSLM. Comparing ARIMA to ETS visually, we see much more uncertainty in the ETS predictions. Both models still seem to under shoot the peaks which is a strong indicator that other factors are at play that will need to be considered. In addition, looking at the `mable` for the arima models shows a null result on split 6 so there may be some instability in the chosen parameters

```
compare_fit |>
  select(ARIMA)
```

```
# A mable: 11 x 2
# Key:      .id [11]
  .id      ARIMA
  <int>    <model>
1      1 <ARIMA(3,1,2)(1,1,2)[12]>
2      2 <ARIMA(3,1,2)(1,1,2)[12]>
3      3 <ARIMA(3,1,2)(1,1,2)[12]>
4      4 <ARIMA(3,1,2)(1,1,2)[12]>
5      5 <ARIMA(3,1,2)(1,1,2)[12]>
6      6 <NULL model>
7      7 <ARIMA(3,1,2)(1,1,2)[12]>
8      8 <ARIMA(3,1,2)(1,1,2)[12]>
9      9 <ARIMA(3,1,2)(1,1,2)[12]>
```

10 10 <ARIMA(3,1,2)(1,1,2)[12]>
11 11 <ARIMA(3,1,2)(1,1,2)[12]>

TSLM External Predictors

According to the Intergovernmental Panel on Climate Change (IPCC, 2021), the main factors that influence global temperature are greenhouse gas concentrations, natural weather and ocean-atmosphere patterns, and variations in solar irradiance. To see which drivers best serve our forecasting purpose, we can model these factors individually and compare their predictive performance. Of the below predictors, accurate monthly estimates are available across varying time periods. The latest are for CO₂ (1958), CH₄ and N₂O (1977). CO₂ is a more significant predictor than the others so the cutoff date for the training data used was 1958. Techniques used to simulate the monthly estimates for N₂O and CH₄ between 1958 and 1977 will be discussed below

<https://www.ipcc.ch/report/ar6/wg1/>

TSI

TSI is a measure of energy that the Earth receives from the Sun across all lengths of electromagnetic waves and plays a small but meaningful role in global temperatures. The measurement is taken at the top of Earth's atmosphere and is reported in Watts per square meter. The data from this predictor comes from <https://www.ncei.noaa.gov/products/climate-data-records/total-solar-irradiance> and is available in monthly observations dating back to 1874.

ENSO Index

ENSO is an acronym for El Niño - Southern Oscillation. The index is the measurement of the difference in sea surface temperatures (SST) from the long-term average (long-term defined as the period between 1991 and 2000) in the equatorial Pacific Ocean (Bureau of Meteorology, n.d.). Warmer than usual temperatures are referred to as El Niño and cooler than average temperatures are referred to as La Niña events. Part of the challenge of sourcing this data is that there are several different indices reported from several different locations around the world. The mostly commonly used one comes from the Niño 3.4 region. For this project the Ensemble Oceanic Niño Index (ENS ONI) is used and can be read about here <https://www.webberweather.com/ensemble-oceanic-nino-index.html>. The data extends back to 1850. The main limitation is that the modern record estimates for the ENSO index began in roughly 1950, so various statistical techniques paired with historical data and documents have been used to record estimates going back further.

In addition to the index itself, various other feature engineering steps were performed. The ENSO index is a monthly measurement so there was concern about noise unduly influencing the models. Three new variables were created with different smoothing intervals (3-month, 6-month and 12-month) to test if smoothing the variables improved model performance. In addition, it's unreasonable to assume that any differences in the ocean temperature today will

immediately effect the global temperature estimates. Indeed, El Nino and La Nina events are defined as 5 consecutive overlapping 3-month periods of temperatures above or below a 0.5 degree threshold <https://ggweather.com/enso/oni.html>. So another variable was created that took the 3-month smooth ENSO Index and added a 4-month lag.

Lastly, instead of using the numerical index, dummy variables were created to indicate the presence of an El Nino or La Nina weather event for the relevant time period.

CO2

It's well known that Greenhouse Gasses (GHG's) are the main drivers of global warming, with CO2 making up the majority of emissions. The most reliable CO2 concentration observations are reported in parts per million (ppm) and are recorded at the <https://gml.noaa.gov/ccgg/trends/>. The Manua Loa Observatory did not begin recording CO2 concentration data until 1958. However, annual atmospheric CO2 estimates derived from drilled ice cores date back to one million years. To engineer monthly estimates of CO2 concentration, a spline regression was performed on the annual estimates from 1850-1957 to smooth out the step curve. The seasonal variation was then engineered by taking the average seasonal variation of the Mauna Loa observations, scaling by a factor to account for the lower historical concentration, then adding that back to the engineered monthly observation.

As atmospheric concentration of CO2 can take time to show up in global temperatures, in addition to the current observation of CO2 being used, lagged versions were also engineered for periods of 1, 3, 5 and 10 years.

RF_CO2

Radiative forcing is not a measurement but rather a scientific principle. It is used as a way to quantify how the Earth's balance of energy (in this case measured as Watts per meter squared) changes when another variable changes. For this project, the radiative forcing of CO was measured. It was decided to only use CO as this variable is recognized as having the largest forcing effect of the various physical drivers of temperature change. The equation used to calculate the radiative forcing variable is as follows

$$RF = 5.25 \times \log(C / C_0)$$

Where C0 is defined as the reference CO concentration level prior to the industrial revolution. 278 ppm is the most widely used value.

Volcanic Activity

Volcanic eruptions can have profound effects on the climate that last anywhere from 1 to 3 years. The National Oceanic and Atmospheric Administration (NOAA) keeps a record of all known volcanic eruptions and their various attributes dating back 1000's of years. Volcanic eruptions are happening constantly. There are 613 recorded events dating back to 1850. The strength of an eruption is measured by a volcanic explosivity index (VEI). Similar to the Richter scale, this index ranges from 0 to 8 and is logarithmic. Measuring the effect size of a volcanic eruption on the overall climate is challenging and depends on several factors. For the

purposes of this project it was decided to use only volcanic events with a VEI of 4 or above. Any lower and it's unlikely the explosion would be large enough to have lasting effects. Then it was a question of how to include those events in the data. A thorough scientific exploration of the exact effect on the climate for each event was beyond the scope of this project. However 3 things are known about volcanic activity. 1) Large eruptions have an impact on the overall climate. 2) These eruptions have effects lasting 1 - 3 years. 3) These effects are not constant over that time period. So to include these events into the data, 2 pseudo-dummy variables were created. A value of 1 was used at the start of the event, and then one variable was subjected to a linear decay over a 3yr time period and another was subject to an exponential decay over the 3 year time period, to simulate the effect of ash and debris dissipating over time. In the event of overlapping eruptions, these effects were added together.

CH4 & N2O

A similar process was followed for these predictors as was used for CO2. The data was sourced from the same place, the only difference is that monthly estimates are not available until 1977

```
predictor_modeling <- read_rds("data/lagged_external_predictors.rds")  
  
length(colnames(predictor_modeling))
```

```
[1] 30
```

After feature engineering, the dataset now has 30 columns. The code used to engineer the external predictors can be found [at the end](#)

There are over 100 total combinations of external predictors, so instead of trying all of them, a handful of complementary ones are tested and reviewed to see if any other combinations are worth exploring. For example, current co2_ppm combined with la_nina and el_nino events are compared against the same but with a 10yr lag on the co2_ppm variable. If the lagged version of this model performs better, then lagged trends are worth looking further into

```
cv_data <- predictor_modeling |>  
  filter(year(Date) > 1957) |>  
  stretch_tsibble(.init = 573, .step = 60)  
  
cv_trn <- cv_data |>  
  group_by(.id) |>  
  slice(1:(n() - 60)) |>  
  ungroup()  
  
cv_valid <- cv_data |>
```

```

group_by(.id) |>
slice_tail(n = 60) |>
ungroup()

tslm_regressor_fit <- cv_trn |>
model(
  tslm_trend_season = TSLM(actual_temp ~ trend() + season()),
  tslm_log = TSLM(log(actual_temp) ~ trend() + season()),
  tslm_box_cox = TSLM(box_cox(actual_temp, lambda = 1.5) ~ trend() +
    ↪ season()),
  tslm_all = TSLM(actual_temp ~ trend() + season() + el_nino + la_nina +
    ↪ co2_ppm + ch4_ppb + n2o_ppb + TSI + volcano_forcing),
  tslm_all_box = TSLM(box_cox(actual_temp, lambda = 1.5) ~ trend() +
    ↪ season() + el_nino + la_nina + co2_ppm + ch4_ppb + n2o_ppb + TSI +
    ↪ volcano_forcing),
  tslm_ch4_co2_nino = TSLM(actual_temp ~ trend() + season() + el_nino +
    ↪ la_nina + co2_ppm + ch4_ppb),
  tslm_co2_nino = TSLM(actual_temp ~ trend() + season() + el_nino + la_nina
    ↪ + co2_ppm),
  tslm_nino = TSLM(actual_temp ~ trend() + season() + el_nino + la_nina),
  tslm_enso = TSLM(actual_temp ~ trend() + season() + ENSO),
  tslm_enso_smooth = TSLM(actual_temp ~ trend() + season() +
    ↪ enso_smooth_12),
  tslm_co2_nino_lag = TSLM(actual_temp ~ trend() + season() + el_nino +
    ↪ la_nina + co2_lag1)
)

tslm_regressor_fit |>
accuracy() |>
group_by(.model) |>
summarise(across(.cols = c(RMSE, MAE, ME), .fns = mean)) |>
arrange(RMSE) |>
kable(digits = 4)

```

.model	RMSE	MAE	ME
tslm_all_box	0.1188	0.0935	-2e-04
tslm_all	0.1190	0.0936	0e+00
tslm_ch4_co2_nino	0.1214	0.0958	0e+00
tslm_co2_nino	0.1242	0.0981	0e+00
tslm_co2_nino_lag	0.1260	0.0993	0e+00
tslm_enso_smooth	0.1299	0.1023	0e+00

.model	RMSE	MAE	ME
tslm_nino	0.1332	0.1066	0e+00
tslm_enso	0.1368	0.1107	0e+00
tslm_trend_season	0.1461	0.1176	0e+00
tslm_box_cox	0.1465	0.1178	-4e-04
tslm_log	0.1479	0.1191	8e-04

Training metrics show that all the predictors being added leads to the best model, whereas models without any predictors underperform

```
tslm_regressor_fit |>
  glance() |>
  group_by(.model) |>
  summarize(across(.cols = c(AIC, AICc, BIC), .fns = mean)) |>
  arrange(AICc)
```

```
# A tibble: 11 x 4
  .model      AIC  AICc  BIC
  <chr>      <dbl> <dbl> <dbl>
1 tslm_log   -5722. -5721. -5659.
2 tslm_co2_nino -2606. -2605. -2530.
3 tslm_co2_nino_lag -2588. -2587. -2513.
4 tslm_enso_smooth -2555. -2555. -2489.
5 tslm_nino  -2519. -2518. -2448.
6 tslm_enso  -2490. -2489. -2423.
7 tslm_trend_season -2407. -2407. -2345.
8 tslm_all   -2365. -2363. -2274.
9 tslm_ch4_co2_nino -2349. -2348. -2271.
10 tslm_all_box -868. -866. -777.
11 tslm_box_cox -732. -731. -670.
```

Interestingly, tslm_log is the best model by far on the AICc metric, so the gains may not be all that much by adding predictors

```
tslm_regressor_fit |>
  select(tslm_all_box) |>
  tail(n = 1) |>
  report()
```

Series: actual_temp

Model: TSLM

Transformation: box_cox(actual_temp, lambda = 1.5)

Residuals:

	Min	1Q	Median	3Q	Max
	-1.3498	-0.2808	-0.0138	0.3062	1.1927

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	-1.829e+02	6.784e+01	-2.696	0.007188	**
trend()	-6.771e-03	1.535e-03	-4.409	1.21e-05	***
season()year2	6.992e-01	8.594e-02	8.136	2.00e-15	***
season()year3	2.899e+00	8.647e-02	33.525	< 2e-16	***
season()year4	6.328e+00	8.815e-02	71.788	< 2e-16	***
season()year5	9.818e+00	8.898e-02	110.341	< 2e-16	***
season()year6	1.257e+01	8.739e-02	143.882	< 2e-16	***
season()year7	1.360e+01	8.564e-02	158.751	< 2e-16	***
season()year8	1.322e+01	8.679e-02	152.368	< 2e-16	***
season()year9	1.096e+01	8.932e-02	122.746	< 2e-16	***
season()year10	7.592e+00	8.963e-02	84.702	< 2e-16	***
season()year11	3.581e+00	8.759e-02	40.887	< 2e-16	***
season()year12	1.017e+00	8.645e-02	11.766	< 2e-16	***
el_nino	1.346e-01	4.439e-02	3.032	0.002526	**
la_nina	-3.062e-01	4.695e-02	-6.523	1.37e-10	***
co2_ppm	7.708e-02	7.967e-03	9.675	< 2e-16	***
ch4_ppb	1.690e-03	5.032e-04	3.358	0.000831	***
n2o_ppb	9.750e-03	1.197e-02	0.815	0.415562	
TSI	1.334e-01	4.994e-02	2.672	0.007721	**
volcano_forcing	-9.692e-02	2.823e-02	-3.434	0.000633	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4599 on 666 degrees of freedom

Multiple R-squared: 0.9921, Adjusted R-squared: 0.9919

F-statistic: 4417 on 19 and 666 DF, p-value: < 2.22e-16

All predictors on the best performing training model show as significant except for N2O

```
tslm_fc <- tslm_regressor_fit |>
  forecast(new_data = cv_valid)
```

```

tslm_fc |>
  accuracy(cv_valid) |>
  group_by(.model) |>
  summarise(across(.cols = c(RMSE, MAE, ME), .fns = mean)) |>
  arrange(RMSE) |>
  kable(digits = 4)

```

.model	RMSE	MAE	ME
tslm_all_box	0.1471	0.1172	-0.0497
tslm_co2_nino_lag	0.1476	0.1166	-0.0234
tslm_all	0.1493	0.1196	-0.0526
tslm_co2_nino	0.1519	0.1203	-0.0409
tslm_enso_smooth	0.1519	0.1254	0.0976
tslm_ch4_co2_nino	0.1531	0.1229	-0.0627
tslm_enso	0.1578	0.1297	0.0987
tslm_nino	0.1705	0.1382	0.1017
tslm_trend_season	0.1746	0.1429	0.0990
tslm_box_cox	0.1761	0.1463	0.1004
tslm_log	0.1766	0.1398	0.0904

TSLM with a box_cox transformation and all of the predictors performed the best on the validation data. The `enso_smooth` variable also performed better than either ENSO or the nino dummy variables. These results indicate that other model combinations are worth exploring.

Adding a year lag to `co2_ppm` provided a bit of a boost on the validation data so some of the lagged variables may have more predictive power and are worth looking into

Interesting to note that adding `ch4_ppb` actually reduced model performance compared to just using `co2_ppm`

```

tslm_second_fit <- cv_trn |>
  model(
    tslm_all_lag_box = TSLM(box_cox(actual_temp, lambda = 1.5) ~ trend() +
      ↪ season() + el_nino + la_nina + co2_lag1 + n2o_lag3 + ch4_lag3),
    tslm_nino_five_lag = TSLM(actual_temp ~ trend() + season() + el_nino +
      ↪ la_nina + co2_lag5),
    tslm_enso_co2_lag = TSLM(actual_temp ~ trend() + season() + ENSO +
      ↪ co2_lag1),
    tslm_enso_smooth_lag_all = TSLM(actual_temp ~ trend() + season() +
      ↪ enso_smooth_12 + co2_lag1 + n2o_lag3 + ch4_lag3),
    tslm_all_lag = TSLM(actual_temp ~ trend() + season() + el_nino + la_nina
      ↪ + co2_lag1 + n2o_lag3 + ch4_lag3),

```

```

tslm_nino_10_lag = TSLM(box_cox(actual_temp, lambda = 1.5) ~ trend() +
  ↪ season() + el_nino + la_nina + co2_lag10),
tslm_enso_smooth_lag = TSLM(box_cox(actual_temp, lambda = 1.5) ~ trend()
  ↪ + season() + enso_smooth_6 + co2_lag10)
)

tslm_second_fc <- tslm_second_fit |>
  forecast(new_data = cv_valid)

tslm_second_fc |>
  accuracy(cv_valid) |>
  group_by(.model) |>
  summarise(across(.cols = c(RMSE, MAE, ME), .fns = mean)) |>
  arrange(RMSE) |>
  kable(digits = 4)

```

.model	RMSE	MAE	ME
tslm_enso_smooth_lag	0.1217	0.0950	-0.0063
tslm_enso_smooth_lag_all	0.1298	0.1028	-0.0476
tslm_enso_co2_lag	0.1374	0.1112	-0.0329
tslm_nino_10_lag	0.1413	0.1101	-0.0029
tslm_nino_five_lag	0.1445	0.1133	0.0057
tslm_all_lag_box	0.1464	0.1144	-0.0394
tslm_all_lag	0.1475	0.1172	-0.0420

The target variable undergoing a box_cox transformation using the smoothed enso index over 6 months and a 10 year lag in CO2 concentration performs the best out of all the models by a fair margin

```

tslm_second_fit |>
  select(tslm_enso_smooth_lag) |>
  tail(n = 1) |>
  report()

```

Series: actual_temp

Model: TSLM

Transformation: box_cox(actual_temp, lambda = 1.5)

Residuals:

Min	1Q	Median	3Q	Max
-1.448628	-0.292156	0.003149	0.296378	1.450508

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.297e+01	1.246e+00	10.410	<2e-16 ***
trend()	2.270e-04	4.573e-04	0.496	0.62
season()year2	7.171e-01	8.137e-02	8.813	<2e-16 ***
season()year3	2.934e+00	8.152e-02	35.994	<2e-16 ***
season()year4	6.402e+00	8.197e-02	78.097	<2e-16 ***
season()year5	9.928e+00	8.222e-02	120.741	<2e-16 ***
season()year6	1.263e+01	8.189e-02	154.285	<2e-16 ***
season()year7	1.362e+01	8.142e-02	167.267	<2e-16 ***
season()year8	1.316e+01	8.157e-02	161.305	<2e-16 ***
season()year9	1.087e+01	8.234e-02	132.039	<2e-16 ***
season()year10	7.474e+00	8.282e-02	90.241	<2e-16 ***
season()year11	3.528e+00	8.216e-02	42.944	<2e-16 ***
season()year12	1.024e+00	8.177e-02	12.526	<2e-16 ***
enso_smooth_6	3.182e-01	2.166e-02	14.694	<2e-16 ***
co2_lag10	4.747e-02	4.146e-03	11.450	<2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4564 on 738 degrees of freedom

Multiple R-squared: 0.9921, Adjusted R-squared: 0.992

F-statistic: 6628 on 14 and 738 DF, p-value: < 2.22e-16

And we can see from the report that all the predictors used are significant except trend. It could be that smoothing out the enso index and the 10 yr lag of co2_ppm captures most of the trend component

```
tslm_best_fit <- cv_trn |>
  model(
    tslm_enso_6 = TSLM(box_cox(actual_temp, lambda = 1.5) ~ trend() +
      ↪ season() + enso_smooth_6 + co2_lag10),
    tslm_enso_12 = TSLM(box_cox(actual_temp, lambda = 1.5) ~ trend() +
      ↪ season() + enso_smooth_12 + co2_lag10),
    tslm_no_trend = TSLM(box_cox(actual_temp, lambda = 1.5) ~ season() +
      ↪ enso_smooth_12 + co2_lag10),
    tslm_volcanic = TSLM(box_cox(actual_temp, lambda = 1.5) ~ season() +
      ↪ enso_smooth_12 + co2_lag10 + volcano_forcing)
  )
```

```

tslm_best_fc <- tslm_best_fit |>
  forecast(new_data = cv_valid)

tslm_best_fc |>
  accuracy(cv_valid) |>
  group_by(.model) |>
  summarise(across(.cols = c(RMSE, MAE, ME), .fns = mean)) |>
  arrange(RMSE) |>
  kable(digits = 4)

```

.model	RMSE	MAE	ME
tslm_no_trend	0.1183	0.0927	-0.0032
tslm_volcanic	0.1191	0.0936	0.0013
tslm_enso_12	0.1211	0.0942	-0.0031
tslm_enso_6	0.1217	0.0950	-0.0063

```

tslm_best_fit |>
  select(tslm_no_trend) |>
  tail(n = 1) |>
  report()

```

Series: actual_temp

Model: TSLM

Transformation: box_cox(actual_temp, lambda = 1.5)

Residuals:

Min	1Q	Median	3Q	Max
-1.628084	-0.287697	0.001792	0.303473	1.553132

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.233e+01	2.424e-01	50.849	<2e-16 ***
season()year2	7.143e-01	8.076e-02	8.844	<2e-16 ***
season()year3	2.923e+00	8.076e-02	36.191	<2e-16 ***
season()year4	6.380e+00	8.078e-02	78.985	<2e-16 ***
season()year5	9.896e+00	8.079e-02	122.495	<2e-16 ***
season()year6	1.260e+01	8.078e-02	155.962	<2e-16 ***
season()year7	1.358e+01	8.076e-02	168.156	<2e-16 ***
season()year8	1.312e+01	8.076e-02	162.517	<2e-16 ***

```

season()year9  1.085e+01  8.077e-02 134.317    <2e-16 ***
season()year10 7.461e+00  8.111e-02  91.985    <2e-16 ***
season()year11 3.522e+00  8.109e-02  43.432    <2e-16 ***
season()year12 1.020e+00  8.108e-02  12.581    <2e-16 ***
enso_smooth_12 3.785e-01  2.500e-02  15.142    <2e-16 ***
co2_lag10      4.966e-02  6.909e-04  71.876    <2e-16 ***
---

```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4532 on 739 degrees of freedom

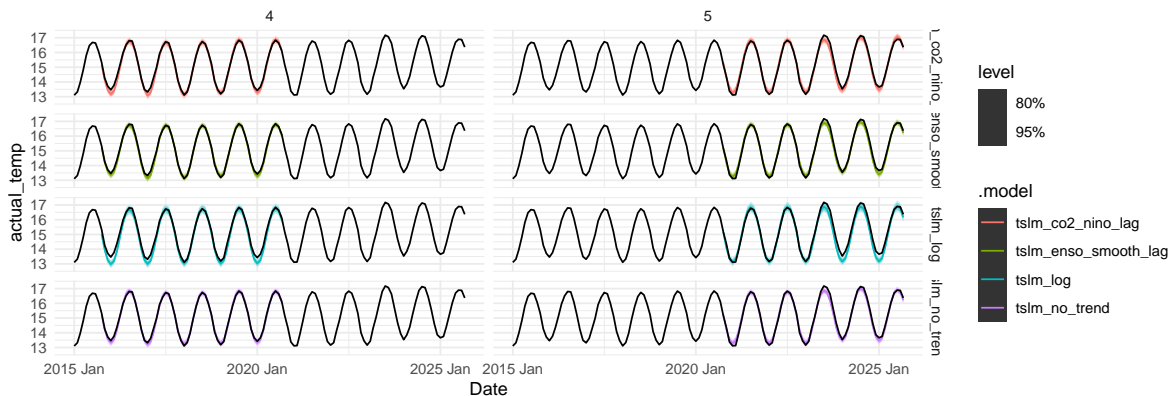
Multiple R-squared: 0.9922, Adjusted R-squared: 0.9921

F-statistic: 7239 on 13 and 739 DF, p-value: < 2.22e-16

```

tslm_fc |>
  bind_rows(tslm_second_fc) |>
  bind_rows(tslm_best_fc) |>
  filter(.id %in% c(4, 5), .model %in% c("tslm_no_trend",
    ↪ "tslm_enso_smooth_lag", "tslm_nino_50_lag", "tslm_co2_nino_lag",
    ↪ "tslm_log")) |>
  autoplot() +
  autolayer(predictor_modeling |> filter(year(Date) >= 2015), actual_temp) +
  facet_grid(.model ~ .id) +
  theme_minimal()

```



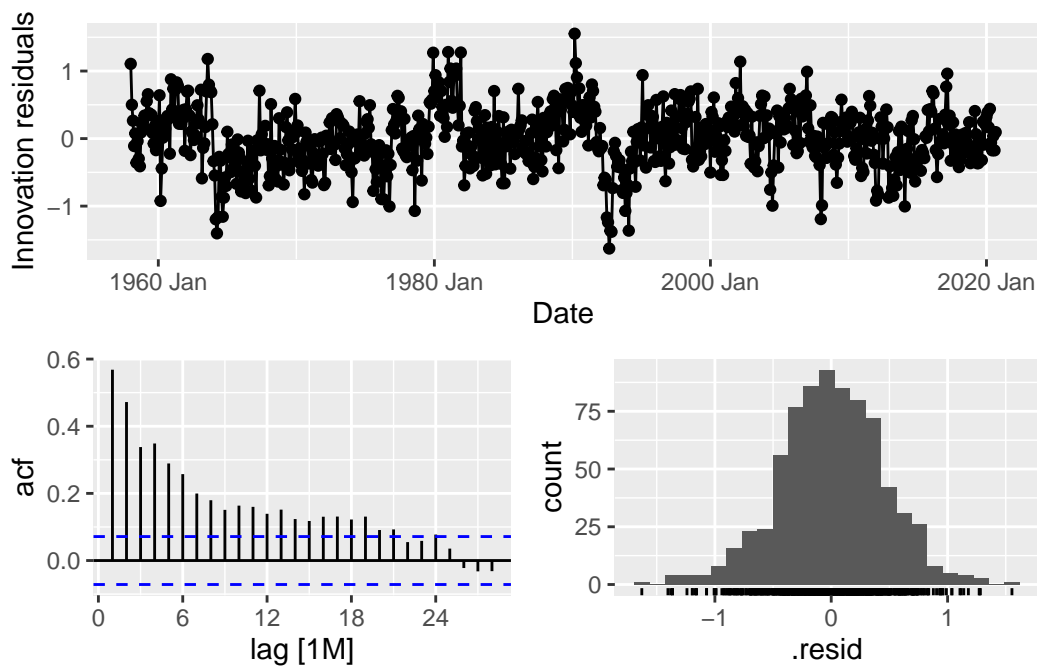
Comparing best models to the under-performing ones, we see that adding predictors, especially ones that are lagged, closes the gap in the increasing trend that other models seem to miss.

Talk more in depth about the AICc scores

```
tslm_best_fit |>
  select(tslm_no_trend) |>
  tail(n = 1) |>
  ggtime::gg_tsresiduals()
```

Registered S3 methods overwritten by 'ggtime':

method	from
+.gg_tsensemble	feasts
autolayer.tbl_ts	fabletools
autoplot.dcmp_ts	fabletools
autoplot.tbl_ts	fabletools
grid.draw.gg_tsensemble	feasts
print.gg_tsensemble	feasts



The biggest issue is that there is significant autocorrelation in the residuals, indicating there is some pattern the TSLM model doesn't catch. We'll see if the ARIMA models are able to accurately account for these factors

ARIMA External Predictors

Using a non-cv split initially to speed up fit time

```

arima_trn <- predictor_modeling |>
  filter(year(Date) > 1957) |>
  slice(1:(n() - 60))

```

```

arima_valid <- predictor_modeling |>
  filter(year(Date) > 1957) |>
  slice_tail(n = 60)

```

```

arima_fit <- arima_trn |>
  model(
    arima_auto = ARIMA(actual_temp ~ co2_ppm + PDQ(D=1)),
    arima_box = ARIMA(box_cox(actual_temp, lambda = 1.5) ~ co2_ppm +
      ↪ PDQ(D=1)),
    arima_log = ARIMA(log(actual_temp) ~ co2_ppm + PDQ(D=1)),
    arima_all = ARIMA(actual_temp ~ co2_ppm + ch4_ppb + n2o_ppb + TSI +
      ↪ el_nino + la_nina + volcano_linear + PDQ(D=1)),
    arima_lag_one = ARIMA(actual_temp ~ co2_lag1 + PDQ(D=1)),
    arima_lag_one_nino = ARIMA(actual_temp ~ co2_lag1 + el_nino + la_nina +
      ↪ PDQ(D=1)),
    arima_enso = ARIMA(actual_temp ~ ENSO + PDQ(D=1)),
    arima_enso_smooth = ARIMA(actual_temp ~ enso_smooth_6 + PDQ(D=1)),
    arima_emissions = ARIMA(actual_temp ~ aggregate_emissions + PDQ(D=1)),
    arima_forcing = ARIMA(log(actual_temp) ~ rf_co2 + PDQ(D=1)),
    arima_enso_delay = ARIMA(actual_temp ~ enso_delay + PDQ(D=1)),
    arima_lag_3 = ARIMA(actual_temp ~ co2_lag3 + PDQ(D=1)),
    arima_physics_robust = ARIMA(log(actual_temp) ~ rf_co2 + volcano_linear +
      ↪ enso_delay + PDQ(D=1)),
    arima_volcano_basic = ARIMA(log(actual_temp) ~ ENSO + co2_ppm +
      ↪ volcano_forcing + PDQ(D = 1))
  )

arima_fit |>
  glance() |>
  arrange(AICc) |>
  select(.model, AICc, AIC, BIC) |>
  kable(align = "c")

```

.model	AICc	AIC	BIC
arima_volcano_basic	-5154.6844	-5154.8811	-5118.0171
arima_physics_robust	-5021.0184	-5021.3198	-4975.2398

.model	AICc	AIC	BIC
arima_forcing	-4925.4545	-4925.6073	-4893.3513
arima_log	-4924.9670	-4925.1637	-4888.2997
arima_enso_smooth	-1259.0458	-1259.2425	-1222.3785
arima_enso	-1254.6394	-1254.8361	-1217.9721
arima_enso_delay	-1227.5044	-1227.7011	-1190.8371
arima_lag_one_nino	-1137.8875	-1138.1888	-1092.1088
arima_auto	-1125.8302	-1126.0269	-1089.1629
arima_emissions	-1125.2980	-1125.4947	-1088.6307
arima_lag_one	-1123.8375	-1124.0343	-1087.1703
arima_lag_3	-1123.6502	-1123.8469	-1086.9829
arima_all	-962.7635	-963.2642	-903.3602
arima_box	827.9954	827.7987	864.6627

Looking through the AICc scores, the log transformations seem to result in the best models

```
arima_fc <- arima_fit |>
  forecast(new_data = arima_valid)

arima_fc |>
  accuracy(arima_valid) |>
  select(.model, RMSE, MAE, ME) |>
  arrange(RMSE) |>
  kable(digits = 4)
```

.model	RMSE	MAE	ME
arima_volcano_basic	0.1444	0.1185	0.0340
arima_physics_robust	0.1551	0.1197	0.0121
arima_all	0.1781	0.1387	-0.0221
arima_lag_one_nino	0.1934	0.1549	0.0475
arima_auto	0.1953	0.1630	0.0072
arima_box	0.1967	0.1638	0.0069
arima_emissions	0.1981	0.1662	0.0081
arima_log	0.1995	0.1654	-0.0205
arima_forcing	0.2022	0.1675	-0.0086
arima_lag_3	0.2067	0.1741	0.0328
arima_lag_one	0.2074	0.1742	0.0301
arima_enso	0.2819	0.2302	0.1923
arima_enso_smooth	0.2859	0.2347	0.2114
arima_enso_delay	0.3086	0.2519	0.2180

.model	RMSE	MAE	ME
--------	------	-----	----

The model including features for volcanic activity and non-lagged variables for CO2 and ENSO is the best overall by any metric. **include a more robust explanation of why a delay in the enso index and why co2 radiative forcing on it's own aren't strong signals**

```
# spot check models
arima_fit |>
  select(arima_volcano_basic) |>
  report()
```

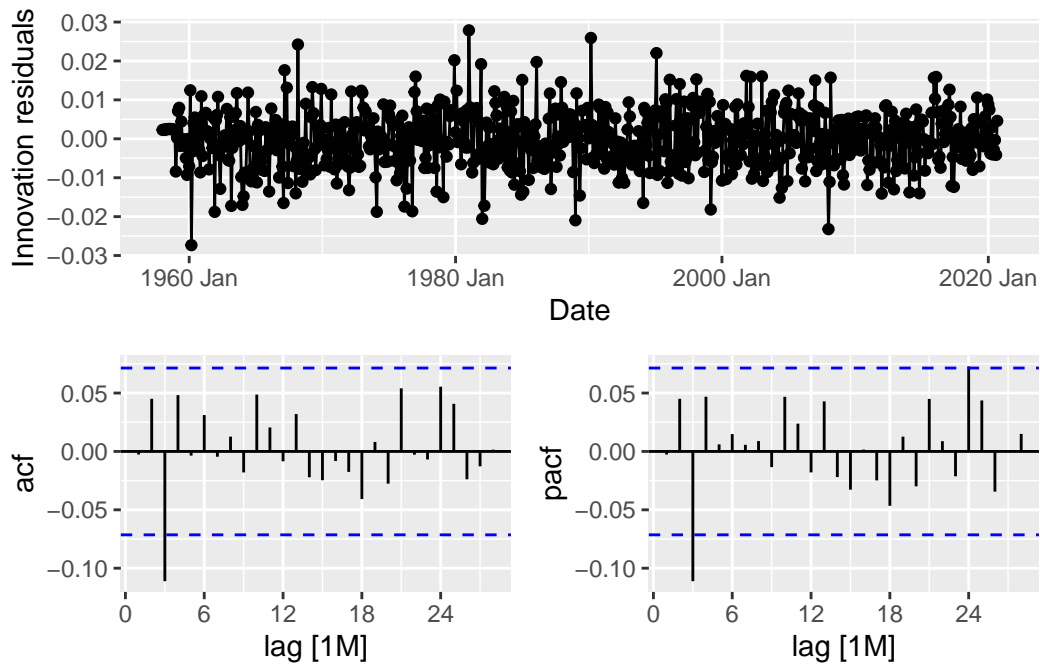
```
Series: actual_temp
Model: LM w/ ARIMA(1,0,1)(0,1,2)[12] errors
Transformation: log(actual_temp)
```

Coefficients:

	ar1	ma1	sma1	sma2	ENSO	co2_ppm	volcano_forcing
	0.8344	-0.3830	-0.9473	0.0544	0.0046	7e-04	-9e-04
s.e.	0.0326	0.0552	0.0355	0.0364	0.0007	1e-04	9e-04

```
sigma^2 estimated as 5.37e-05: log likelihood=2585.44
AIC=-5154.88 AICc=-5154.68 BIC=-5118.02
```

```
arima_fit |>
  select(arima_volcano_basic) |>
  ggtime::gg_tsresiduals(plot_type = "partial")
```



The `arima_volcano_basic` model selected AR(1), MA(1) and sMA(2) with a seasonal difference. The ACF and PACF plots still contain spikes at lag 3. Interestingly, the `arima_physics` robust model contains a spike at lag 24 but not 3. There might be something in delaying the El Nino effect by a few months that explains the autocorrelation

```
# parameter check
arima_fit |>
  tidy() |>
  group_by(term) |>
  summarize(across(.cols = c(estimate:`p.value`), .fns = mean)) |>
  arrange(p.value) |>
  kable(digits = 4)
```

term	estimate	std.error	statistic	p.value
sma1	-0.9267	0.0385	-24.1588	0.0000
sar2	-0.3306	0.0350	-9.4517	0.0000
enso_smooth_6	0.0805	0.0122	6.6143	0.0000
ENSO	0.0313	0.0052	6.3122	0.0000
ar2	0.6779	0.0864	7.8968	0.0000
sar1	-0.6278	0.0347	-18.4039	0.0013
ma2	-0.2650	0.0731	-3.6212	0.0032
enso_delay	0.0158	0.0065	3.7552	0.0120

term	estimate	std.error	statistic	p.value
la_nina	-0.0453	0.0207	-2.1940	0.0297
ma1	0.3425	0.1148	2.8495	0.0433
el_nino	0.0333	0.0177	1.8858	0.0606
aggregate_emissions	0.0006	0.0003	1.8391	0.0663
co2_ppm	0.0126	0.0064	3.2146	0.0665
rf_co2	0.0688	0.0373	1.7833	0.0902
sma2	0.0606	0.0367	1.6484	0.1025
ar3	-0.0228	0.0852	0.1827	0.1074
co2_lag1	0.0079	0.0048	1.6714	0.1114
co2_lag3	0.0069	0.0054	1.2846	0.1993
volcano_linear	-0.0054	0.0062	-1.3169	0.2395
TSI	0.0204	0.0191	1.0671	0.2863
intercept	-0.0011	0.0011	-0.9745	0.3301
volcano_forcing	-0.0009	0.0009	-0.9703	0.3322
ar1	0.1208	0.1062	2.3740	0.4273
n2o_ppb	-0.0049	0.0123	-0.3959	0.6923
ch4_ppb	0.0001	0.0009	0.0822	0.9345

Not necessarily the best way to ascertain how important variables are, but informative nonetheless. ENSO related variables and seasonal ARIMA parameters seem to be the most important to modeling this type of data

Now we'll check the best models from above as well as a few other promising predictor combinations across 5 CV splits and see how they hold up

```

arima_second_fit <- cv_trn |>
  model(
    arima_enso_log_co2 = ARIMA(log(actual_temp) ~ ENSO + co2_ppm + PDQ(D =
      ↪ 1)),
    arima_auto_10 = ARIMA(log(actual_temp) ~ ENSO + co2_lag10 + PDQ(D = 1)),
    arima_physics_robust = ARIMA(log(actual_temp) ~ rf_co2 + volcano_linear +
      ↪ enso_delay + PDQ(D = 1)),
    arima_forcing = ARIMA(log(actual_temp) ~ rf_co2 + enso_smooth_6 + PDQ(D =
      ↪ 1)),
    arima_auto_10_enso_6 = ARIMA(log(actual_temp) ~ enso_smooth_6 + co2_lag10
      ↪ + PDQ(D = 1)),
    arima_robust_enso_6 = ARIMA(log(actual_temp) ~ rf_co2 + volcano_linear +
      ↪ enso_smooth_6 + PDQ(D = 1)),
    arima_co2_10_volcano = ARIMA(log(actual_temp) ~ co2_lag10 +
      ↪ volcano_linear + PDQ(D = 1)),
    arima_co2_3_nino = ARIMA(actual_temp ~ co2_lag3 + el_nino + la_nina +
      ↪ PDQ(D = 1)),
  )

```

```

    arima_co2_3_nino_tsi = ARIMA(actual_temp ~ co2_lag3 + el_nino + la_nina +
      ↪ TSI + PDQ(D = 1)),
    arima_physics_robust_decay = ARIMA(log(actual_temp) ~ rf_co2 +
      ↪ volcano_forcing + enso_delay + PDQ(D = 1)),
    arima_physics_robust_decay_enso_3 = ARIMA(log(actual_temp) ~ rf_co2 +
      ↪ volcano_forcing + enso_smooth_3 + PDQ(D = 1)),
    arima_lag_3_enso = ARIMA(log(actual_temp) ~ co2_lag3 + ENSO + PDQ(D=1)),
    arima_physics_enso_3 = ARIMA(log(actual_temp) ~ rf_co2 + enso_smooth_3 +
      ↪ PDQ(D=1))
  )

arima_second_fc <- arima_second_fit |>
  forecast(new_data = cv_valid)

arima_second_fc |>
  accuracy(cv_valid) |>
  select(.model, RMSE, ME, MAE) |>
  group_by(.model) |>
  summarize(across(.cols = c(RMSE, MAE, ME), .fns = mean)) |>
  arrange(RMSE) |>
  kable(digits = 4)

```

.model	RMSE	MAE	ME
arima_auto_10_enso_6	0.1225	0.0947	-0.0047
arima_physics_robust_decay_enso_3	0.1233	0.0946	0.0005
arima_forcing	0.1266	0.1005	-0.0005
arima_robust_enso_6	0.1273	0.1018	-0.0004
arima_physics_enso_3	0.1304	0.1012	-0.0011
arima_lag_3_enso	0.1322	0.1044	0.0084
arima_auto_10	0.1356	0.1083	-0.0048
arima_enso_log_co2	0.1358	0.1076	-0.0304
arima_physics_robust	0.1376	0.1065	0.0158
arima_physics_robust_decay	0.1379	0.1064	0.0142
arima_co2_10_volcano	0.1597	0.1268	-0.0218
arima_co2_3_nino_tsi	0.1598	0.1275	0.0563
arima_co2_3_nino	0.1608	0.1290	0.0624

Across multiple folds, the forcing models and models that smooth out the enso index and/or utilize a lagged CO2 concentration variable perform the best. All the results are fairly close

and would probably trade places over different subsets of the data so choosing the best one will require consideration of other factors

```

arima_second_fit |>
  glance() |>
  select(.model, AICc, AIC, BIC) |>
  group_by(.model) |>
  summarize(across(.cols = c(AICc, AIC, BIC), .fns = mean)) |>
  arrange(AICc) |>
  kable(align = "c")

```

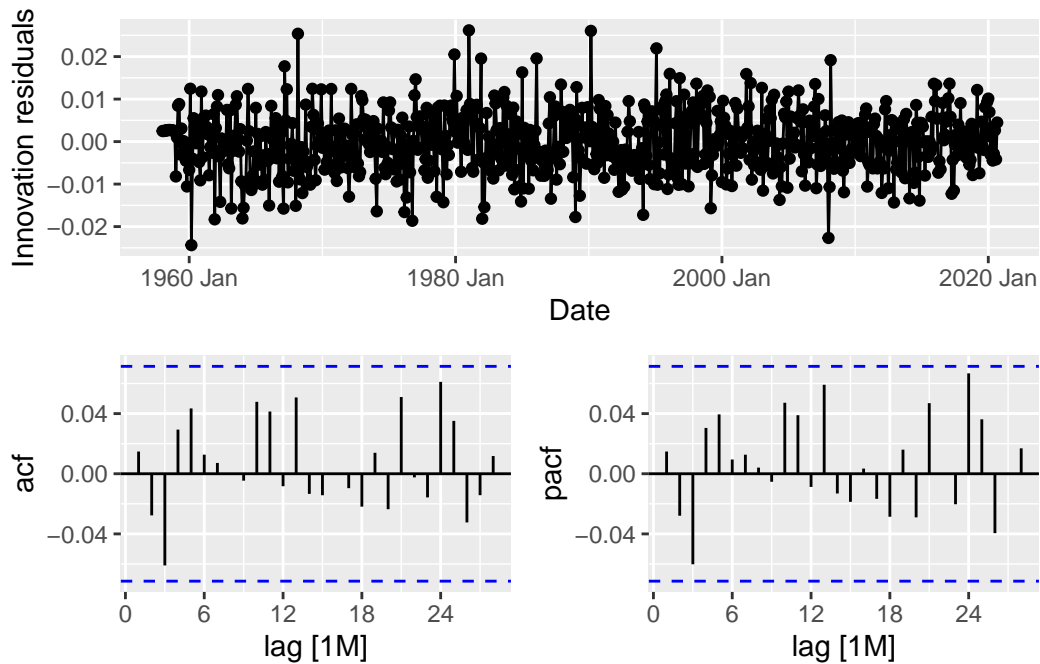
.model	AICc	AIC	BIC
arima_physics_robust_decayenso_3	-4299.9720	-4300.3234	-4256.9483
arima_auto_10	-4272.7611	-4272.9678	-4240.2055
arima_physicsenso_3	-4271.2614	-4271.5471	-4232.5938
arimaenso_log_co2	-4260.9085	-4261.1570	-4225.8582
arima_lag_3enso	-4257.9412	-4258.1951	-4221.9284
arima_auto_10enso_6	-4211.9089	-4212.1762	-4175.0569
arima_physics_robust	-4196.0189	-4196.3555	-4153.8237
arima_physics_robust_decay	-4195.2754	-4195.6120	-4153.0802
arima_robustenso_6	-4191.8260	-4192.1806	-4148.8485
arima_forcing	-4177.1452	-4177.4457	-4137.6491
arima_co2_10_volcano	-4140.9632	-4141.2000	-4105.7470
arima_co2_3_nino_tsi	-929.6644	-930.1066	-881.4664
arima_co2_3_nino	-917.6065	-917.9743	-873.7559

The top model by AICc was second best metric wise. It's also clear from the bottom models that a log transformation of the response variable drastically improves the models

```

arima_second_fit |>
  select(arima_physics_robust_decayenso_3) |>
  tail(n = 1) |>
  ggtime::gg_tsresiduals(plot_type = "partial")

```



```

arima_second_fit |>
  select(arima_physics_robust_decay_enso_3) |>
  tail(n = 1) |>
  augment() |>
  features(.innov, ljung_box, lag = 24) |>
  kable(digits = 3, align = "c")

```

.id	.model	lb_stat	lb_pvalue
5	arima_physics_robust_decay_enso_3	17.372	0.832

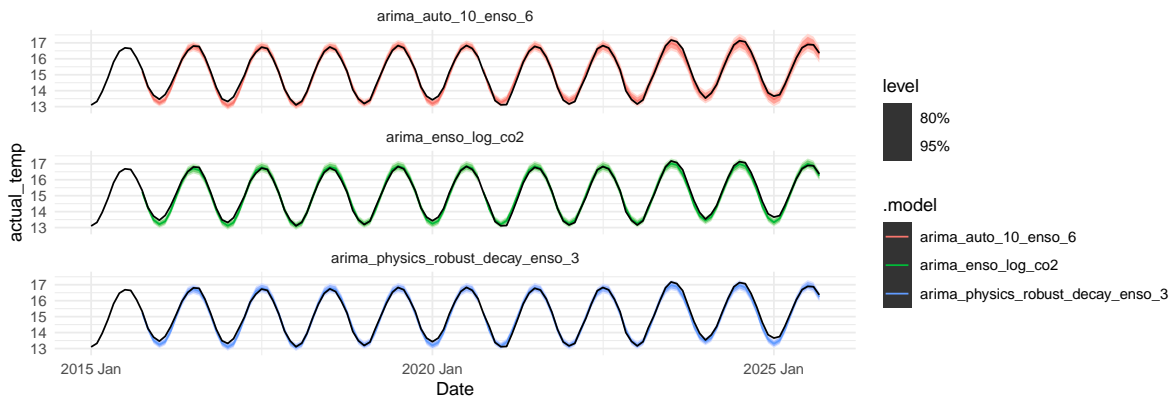
No autocorrelation spikes in the residuals and the Ljung-Box test confirms that the residuals resemble white noise for the `arima_physics_robust_decay_enso_3` model. Most other models have a spike at lag 3 or lag 24. The only other top model without any autocorrelation is `arima_physics_enso_3` so a 3 month smoothing of the ENSO index seems to take care of it

```

arima_second_fc |>
  filter(.id %in% c(4, 5), .model %in% c("arima_physics_robust_decay_enso_3",
    ↪ "arima_enso_log_co2", "arima_auto_10_enso_6")) |>
  autoplot() +
  autolayer(predictor_modeling |> filter(year(Date) >= 2015), actual_temp) +

```

```
facet_wrap(~ .model, ncol = 1) +
theme_minimal()
```



Retrain the top models on the same subset of data and compare

```
final_fit <- cv_trn |>
  model(
    ets_auto = ETS(actual_temp),
    ets_additive = ETS(actual_temp ~ error("A") + trend("A") + season("A")),
    ets_box_auto = ETS(box_cox(actual_temp, lambda = 1.5)),
    tslm_no_trend = TSLM(box_cox(actual_temp, lambda = 1.5) ~ season() +
      ↪ enso_smooth_12 + co2_lag10),
    tslm_volcanic = TSLM(box_cox(actual_temp, lambda = 1.5) ~ season() +
      ↪ enso_smooth_12 + co2_lag10 + volcano_forcing),
    tslm_ens0_smooth_lag = TSLM(box_cox(actual_temp, lambda = 1.5) ~ trend()
      ↪ + season() + enso_smooth_6 + co2_lag10),
    arima_auto_10 = ARIMA(log(actual_temp) ~ ENSO + co2_lag10 + PDQ(D = 1)),
    arima_physics_robust_decay_ens0_3 = ARIMA(log(actual_temp) ~ rf_co2 +
      ↪ volcano_forcing + enso_smooth_3 + PDQ(D = 1)),
    arima_physics_ens0_3 = ARIMA(log(actual_temp) ~ rf_co2 + enso_smooth_3 +
      ↪ PDQ(D = 1)),
    arima_ens0_log_co2 = ARIMA(log(actual_temp) ~ ENSO + co2_ppm + PDQ(D =
      ↪ 1)),
  )

final_fc <- final_fit |>
  forecast(new_data = cv_valid)

final_fc |>
```

```

accuracy(cv_valid) |>
select(.model, ME:MAPE) |>
group_by(.model) |>
summarize(across(.cols = c(RMSE, MAE, ME), .fns = mean)) |>
arrange(RMSE) |>
kable(digits = 4)

```

.model	RMSE	MAE	ME
tslm_no_trend	0.1183	0.0927	-0.0032
tslm_volcanic	0.1191	0.0936	0.0013
tslm_enso_smooth_lag	0.1217	0.0950	-0.0063
arima_physics_robust_decay_enso_3	0.1233	0.0946	0.0005
arima_physics_enso_3	0.1304	0.1012	-0.0011
arima_auto_10	0.1356	0.1083	-0.0048
arima_enso_log_co2	0.1358	0.1076	-0.0304
ets_additive	0.1569	0.1272	0.0397
ets_box_auto	0.1621	0.1331	0.0342
ets_auto	0.1656	0.1348	0.0604

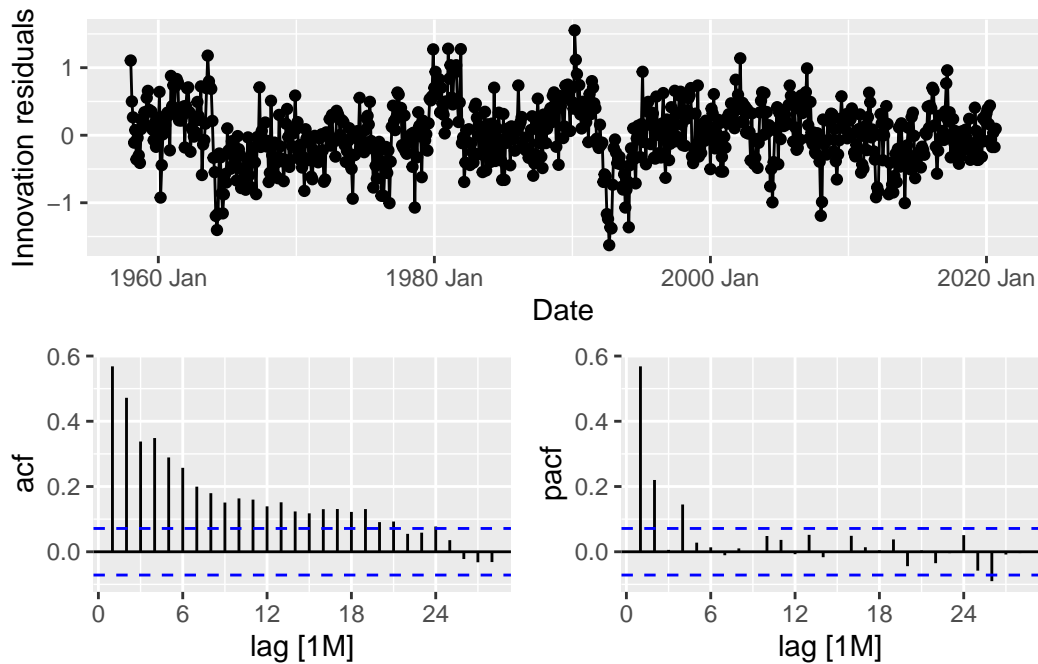
```

final_fit |>
select(tslm_no_trend) |>
tail(n = 1) |>
ggtime::gg_tsresiduals(plot_type = "partial")

```

Registered S3 methods overwritten by 'ggtime':

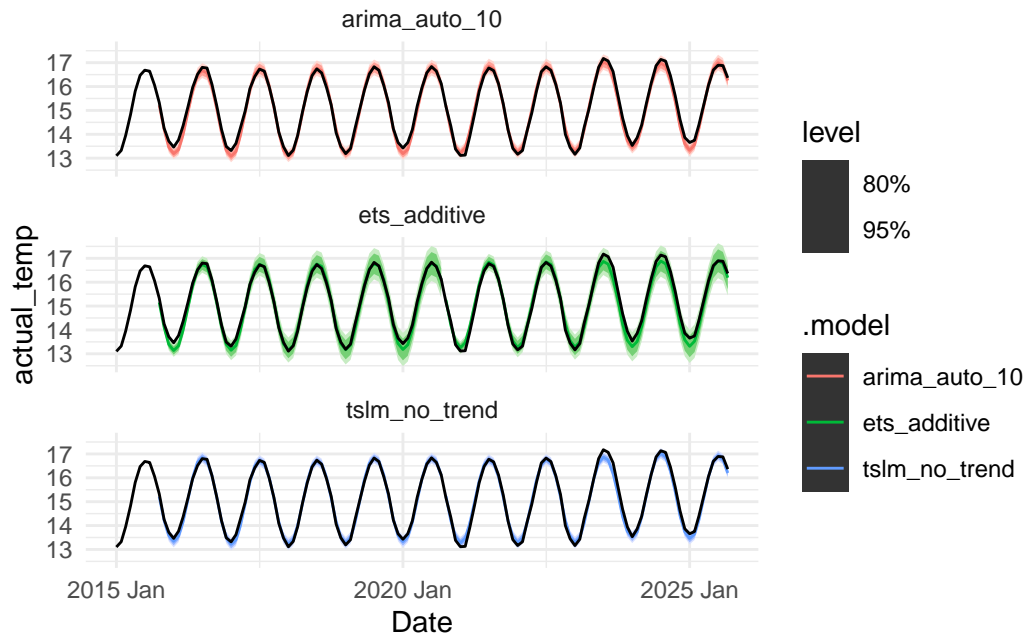
method	from
+.gg_tsensemble	feasts
autolayer.tbl_ts	fabletools
autoplot.dcmp_ts	fabletools
autoplot.tbl_ts	fabletools
grid.draw.gg_tsensemble	feasts
print.gg_tsensemble	feasts



```
final_fit |>
  select(arima_auto_10) |>
  augment() |>
  features(.innov, ljung_box, lag = 24)
```

```
# A tibble: 5 x 4
  .id .model      lb_stat lb_pvalue
<int> <chr>      <dbl>   <dbl>
1     1 arima_auto_10 19.0    0.749
2     2 arima_auto_10 45.6    0.00501
3     3 arima_auto_10 22.8    0.530
4     4 arima_auto_10 16.8    0.856
5     5 arima_auto_10 24.7    0.424
```

```
final_fc |>
  filter(.id %in% c(4, 5), .model %in% c("tslm_no_trend", "arima_auto_10",
    ↪ "ets_additive")) |>
  autoplot() +
  autolayer(predictor_modeling |> filter(year(Date) >= 2015), actual_temp) +
  facet_wrap(~ .model, ncol = 1) +
  theme_minimal()
```



```
current_baseline <- 3400921

model_data <- predictor_modeling |>
  mutate(
    lag_emissions = lag(aggregate_emissions, 12),
    enso_lag = lag(enso_smooth_12, 4)
  )

temp_model <- model_data |>
  filter(year(Date) > 1957) |>
  model(
    temp_arima = ARIMA(log(actual_temp) ~ 0 + co2_lag10 + enso_smooth_6 +
      ↪ pdq(3, 0, 2) + PDQ(0, 1, 1))
  )

# for the enso index, the average across the whole data set is 0.0470

low_enso <- predictor_modeling |>
  select(ENSO) |>
  slice_tail(n = 600)
# 0.0158

high_enso <- predictor_modeling |>
```

```

select(ENSO) |>
slice_head(n = 600)

# 0.0997

normal_enso <- predictor_modeling |>
  select(ENSO) |>
  slice(650:1249)

# 0.0469
#
# Then would need smoothed versions of these

co2_model <- model_data |>
  model(
    co2_arima = ARIMA(co2_ppm ~ lag_emissions + enso_lag + pdq(1, 1, 1) +
      ↪ PDQ(0, 1, 1)),
  )

# Model uses a 1 year lag on emissions and enso index is a 12 month smooth
↪ and 4 month lag

```

“noticed a spike at 12 and 24 for arima_auto_10 and auto was choosing ARIMA(3, 0, 2)(1, 1, 0) with enso_smooth_6 or ARIMA(2, 0, 2)(1, 1, 0) with enso_smooth_3. So added a sma term and that got rid of the spikes and the sar term showed as not significant so removed that. AICc was slightly higher using enso_smooth_6”

“Arima_auto_10_6 has lower AICc than all and residuals are white noise”

```

scenario_forecasting <- function(growth_rate, years, enso_level) {

  most_recent_observation <- predictor_modeling |> tail(1)
  baseline_aggregate <- most_recent_observation$aggregate_emissions

  annual_rate <- (1 + growth_rate/100)

  year_vector <- 1:years

  forecast <- current_baseline * (annual_rate ** year_vector)

  month_sequence <- rep(forecast, each = 12)
}

```

```

new_scenarios <- scenarios(
  enso_low = new_data(predictor_modeling, years * 12) |>
    mutate(
      ENSO = low_enso$ENSO,
    ),
  enso_norm = new_data(predictor_modeling, years * 12) |>
    mutate(
      ENSO = normal_enso$ENSO,
    ),
  enso_high = new_data(predictor_modeling, years * 12) |>
    mutate(
      ENSO = high_enso$ENSO,
    ),
  emissions = new_data(predictor_modeling, years * 12) |>
    mutate(
      total_co2 = month_sequence,
      aggregate_emissions = baseline_aggregate + cumsum(total_co2 / 1e6)
    )
)

co2_modeling_data <- new_scenarios[[enso_level]] |>
  left_join(new_scenarios$emissions, by = "Date") |>
  bind_rows(predictor_modeling) |>
  mutate(
    lag_emissions = lag(aggregate_emissions, 12),
    enso_smooth_3 = slider::slide_dbl(ENSO, mean, .before = 2),
    enso_smooth_6 = slider::slide_dbl(ENSO, mean, .before = 5),
    enso_smooth_12 = slider::slide_dbl(ENSO, mean, .before = 11),
    enso_lag = lag(enso_smooth_12, 4)
  )|>
  filter(Date >= yearmonth("2025 Oct"))

co2_ppm_fc <- co2_model |>
  forecast(new_data = co2_modeling_data)

co2_modeling_data$co2_ppm <- co2_ppm_fc$.mean

temp_modeling_data <- predictor_modeling |>
  bind_rows(co2_modeling_data) |>
  mutate(
    co2_lag10 = lag(co2_ppm, 120),
  ) |>
  filter(Date >= yearmonth("2025 Oct"))

```

```

temperature_forecast <- temp_model |>
  forecast(new_data = temp_modeling_data)

return(temperature_forecast)
}

```

External Predictor Feature Engineering Steps

```

ice_core <- read_csv("data/raw_data/annual_co2_icecore.csv")

loa_df <- read_csv("data/raw_data/mauna_loa_co2.csv")

ice_core |>
  filter(year(`C02 Date`) > 1849, year(`C02 Date`) <= 1955) |>
  add_row(
    `C02 Date` = as.Date("1956-01-01"),
    `C02 ppm` = 313
  ) |>
  add_row(
    `C02 Date` = as.Date("1957-01-01"),
    `C02 ppm` = 313
  )

co2_ts <- ice_core |>
  mutate(
    Year = year(`C02 Date`),
    Month = list(1:12)
  ) |>
  unnest(Month) |>
  mutate(
    Date = as.Date(glue::glue("{Year}-{Month}-01")),
    Date = yearmonth(Date)
  ) |>
  select(c(Date, `C02 PPM`)) |>
  filter(year(Date) > 1849, year(Date) < 1958) |>
  as_tsibble() |>
  fill_gaps(.start = yearmonth("1850-01"), .end = yearmonth("1958-02")) |>
  fill(`C02 PPM`, .direction = "down")

```

```

loa_ts <- loa_df |>
  mutate(
    Date = as.Date(glue::glue("{year}-{month}-01")),
    Date = yearmonth(Date)
  ) |>
  rename(`CO2 PPM` = average) |>
  select(Date, `CO2 PPM`) |>
  as_tibble()

co2_ppm <- bind_rows(co2_ts, loa_ts)

```

The annual data for ice core co2 was cut between 1850 and February 1958, then fill gaps was used to create NA rows for monthly data in between years, then the NA values were filled in with the most recent known observation. This data was then joined with the known observations from Mauna Loa

```

# Annual CO2

annual_co2 <- read_csv("data/raw_data/annual_co2_emissions.csv")

co2_land_use <- read_csv("data/raw_data/annual_co2_land_use_emissions.csv")

# Monthly CO2

monthly_co2 <-
  ↪ read_rds("data/raw_data/global_monthly_emissions_1970_2024.rds")

monthly_co2_bio <-
  ↪ read_rds("data/raw_data/global_monthly_emissions_landuse_1970_2024.rds")

month_co2 <- monthly_co2 |>
  select(c(Year:Dec)) |>
  group_by(Year) |>
  summarize(across(.cols = c(Jan:Dec), .fns = sum)) |>
  pivot_longer(cols = c(Jan:Dec), names_to = 'Month', values_to =
    ↪ "CO2_Emissions") |>
  mutate(
    date_string = paste(Year, Month, "01", sep = "-"),
    Date = yearmonth(date_string)
  ) |>

```

```

select(c(Date, CO2_Emissions))

month_co2_bio <- monthly_co2_bio |>
  select(c(Year:Dec)) |>
  group_by(Year) |>
  summarize(across(.cols = c(Jan:Dec), .fns = sum)) |>
  pivot_longer(cols = c(Jan:Dec), names_to = 'Month', values_to =
    ↪ "CO2_Bio_Emissions") |>
  mutate(
    date_string = paste(Year, Month, "01", sep = "-"),
    Date = yearmonth(date_string)
  ) |>
  select(c(Date, CO2_Bio_Emissions))

combined_monthly <- month_co2 |>
  left_join(month_co2_bio)

final_monthly <- combined_monthly |>
  mutate(Total_CO2 = CO2_Bio_Emissions + CO2_Emissions) |>
  select(c(Date, Total_CO2))

annual_convert <- annual_co2 |>
  filter(Year < 1970) |>
  uncount(12, .id = "Month") |>
  mutate(
    Date = make_yearmonth(year = Year, month = Month),
    monthly_co2 = (World * 3664) / 12
  ) |>
  select(Date, monthly_co2) |>
  as_tsibble(index = Date)

annual_bio_convert <- co2_land_use |>
  filter(Year <= 1969) |>
  uncount(12, .id = "Month") |>
  mutate(
    Date = make_yearmonth(year = Year, month = Month),
    monthly_bio_co2 = (Average * 3664) / 12
  ) |>
  select(Date, monthly_bio_co2) |>
  as_tsibble(index = Date)

```

```
combined_monthly_convert <- annual_convert |>
  left_join(annual_bio_convert)

earlier_co2_data <- combined_monthly_convert |>
  mutate(Total_CO2 = (monthly_bio_co2 + monthly_co2)) |>
  select(c(Date, Total_CO2))
```

Monthly CO2 emission estimates from 1970 - 2024 were combined with annual emissions dating back to 1850. The annual estimates were in million tons of carbon, while the monthly estimates were in gigagrams of CO2, which is equal to 1000 metric tons. First, to convert the annual estimates to gigagrams, the values need to be multiplied by 3.664 to convert carbon to CO2 weight, then multiplied by 1000 to convert to gigagrams

```
global_temps <- read_csv("data/converted_global_temp.csv")

tsi <- read_rds("data/raw_data/monthly_tsi.rds")

ch4 <- read_rds("data/raw_data/annual_ch4.rds")

full_ch4 <- ch4 |>
  filter(year(`CH4 Date`) >= 1849) |>
  mutate(Date = yearmonth(`CH4 Date`)) |>
  rename(ch4 = `CH4 Value`) |>
  select(Date, ch4) |>
  as_tsibble() |>
  fill_gaps(.start = yearmonth("1850-01"), .end = yearmonth('2025-09')) |>
  fill(ch4, .direction = "down")

full_tsi <- tsi |>
  mutate(Date = yearmonth(time)) |>
  select(Date, TSI) |>
  as_tsibble() |>
  fill_gaps(.start = yearmonth("1850-01"), .end = yearmonth('2025-09')) |>
  fill(TSI, .direction = "updown")

co2_ts <- co2_ppm |>
  mutate(Date = yearmonth(Date)) |>
  rename(co2_ppm = `CO2 PPM`) |>
  select(Date, co2_ppm) |>
  as_tsibble()
```

```

full_reg <- global_temps |>
  select(Date, actual_temp) |>
  mutate(Date = yearmonth(Date)) |>
  as_tsibble() |>
  left_join(earlier_co2_data, by = 'Date') |>
  left_join(full_ch4, by = "Date") |>
  left_join(full_tsi, by = "Date") |>
  left_join(co2_ts, by = "Date")

```

The annual data for ch4 was cutoff from 1850. Fill gaps can create NA rows for monthly data in between years, then the NA's can be fill in with the most recent known observation.

The TSI data extends from 1874 to 2023 so a similar process can be used to extend it from 1850 to Sept 2025.

```

new_df <- read_rds("data/raw_data/enso_index.rds")

row_index <- which(new_df$Year == 2024)

if (length(row_index) == 1) {
  new_df[row_index, "MAR"] <- 1.13
  new_df[row_index, "APR"] <- 0.77
  new_df[row_index, "MAY"] <- 0.23
  new_df[row_index, "JUN"] <- 0.17
  new_df[row_index, "JUL"] <- 0.04
  new_df[row_index, "AUG"] <- -0.12
  new_df[row_index, "SEP"] <- -0.26
  new_df[row_index, "OCT"] <- -0.27
  new_df[row_index, "NOV"] <- -0.25
  new_df[row_index, "DEC"] <- -0.60
}

new_df_long <- new_df |>
  pivot_longer(
    cols = c(JAN:DEC),
    names_to = "Month",
    values_to = "ENSO"
  ) |>
  mutate(
    Date_String = glue::glue("{Year}-{Month}-01"),
    Date = yearmonth(as.Date(Date_String, format = "%Y-%b-%d"))
  )

```

```

) |>
select(Date, ENSO) |>
as_tsibble()

new_df_long <- new_df_long |>
select(-enso_smooth) |>
mutate(
  enso_smooth_12 = slider::slide_dbl(ENSO, mean, .before = 11, complete =
    ↪ TRUE),
  enso_smooth_6 = slider::slide_dbl(ENSO, mean, .before = 5, complete =
    ↪ TRUE),
  enso_smooth_3 = slider::slide_dbl(ENSO, mean, .before = 2, complete =
    ↪ TRUE),
  enso_delay = lag(enso_smooth_3, 4),
  rf_co2 = 5.35 * log(co2_ppm / 278)
)

```

The enso index data from the Ensemble ONI websites most recent observation is February of 2024. NOAA has the most up to date values so a vector of up to date values was used to fill in the rest of the year. Then 3, 6 and 12 month smoothed versions of the index were created to reduce the effect of noise. Then a delayed version of the index was created by using a 4-month lag on the 3 month smoothed index.

The radiative forcing metric of CO2 was evaluated by taking the log transformation of the CO2 concentration divided by the pre-industrial baseline then multiplied by 5.35. This is a simplified version of the more complex IPCC formula.

```

library(zoo)

# CO2 data

mauna_loa <- read_csv("data/raw_data/mauna_loa_co2.csv")
icecore <- read_csv("data/raw_data/annual_co2_icecore.csv")

# Annual estimates
n2o <- read_csv("data/raw_data/n2o_annual.csv")
ch4 <- read_csv("data/raw_data/ch4_annual.csv")

# Monthly estimates
mauna_n2o <- read_csv("data/raw_data/n2o_monthly.csv")
mauna_ch4 <- read_csv("data/raw_data/ch4_monthly.csv")

```

```

# Convert to tsibble
loa_ts <- mauna_loa |>
  mutate(
    Date = make_yearmonth(year = year, month = month)
  ) |>
  rename(co2_ppm = average) |>
  select(Date, co2_ppm) |>
  as_tsibble()

# Average seasonal component for known observations
seasonal_trend <- mauna_loa |>
  mutate(
    Date = make_yearmonth(year = year, month = month)
  ) |>
  select(Date, average) |>
  as_tsibble() |>
  model(STL()) |>
  components() |>
  as_tibble() |>
  group_by(month(Date)) |>
  summarise(co2_season = mean(season_year)) |>
  rename(month = `month(Date)`)

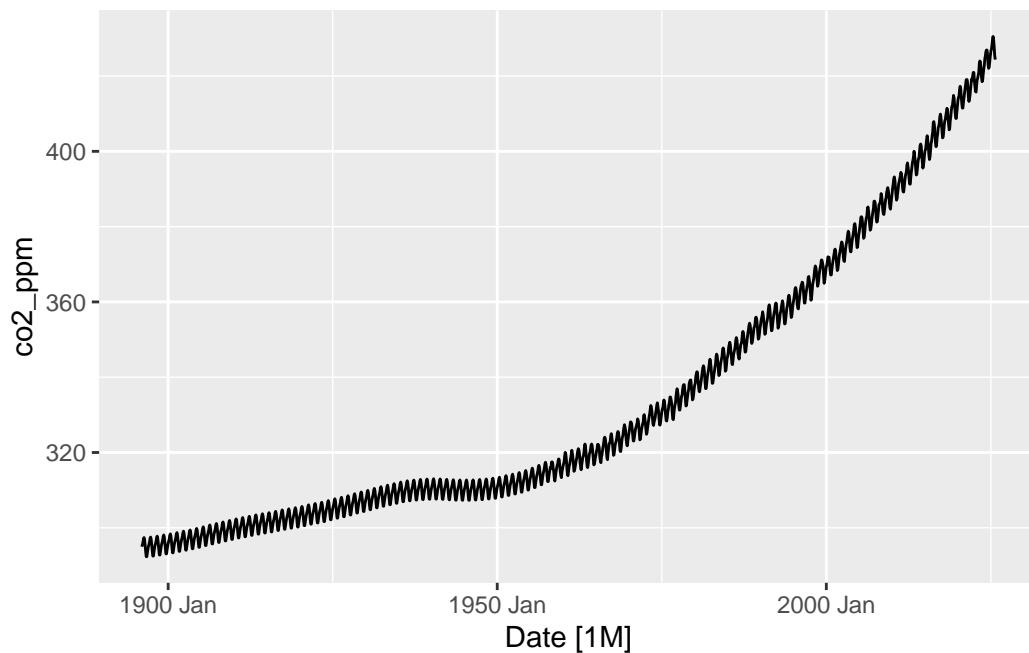
# Regress and interpolate annual estimates up until most recent known monthly
  ↪ observation
full_ts <- icecore |>
  mutate(
    Date = yearmonth(`CO2 Date`)
  ) |>
  rename(co2 = `CO2 PPM`) |>
  select(Date, co2) |>
  complete(Date = seq(min(Date), max(Date), by = 1)) |>
  filter(between(year(Date), 1850, 1957)) |>
  complete(Date = seq(min(Date), yearmonth("1958-02"), by = 1)) |>
  as_tsibble() |>
  mutate(
    co2_ppm = na.spline(co2)
  ) |>
  mutate(month = month(Date)) |>
  left_join(seasonal_trend, by = "month") |>
  mutate(
    scale_factor = co2_ppm / mean(mauna_loa$average),
    final_co2 = co2_ppm + (co2_season * scale_factor)
  )

```

```
) |>
select(Date, final_co2) |>
rename(co2_ppm = final_co2) |>
bind_rows(loa_ts)
```

The `zoo` library can be used to perform a spline regression on the annual estimates we replicated across monthly values to even out the step curve. Then the average seasonal component can be estimated from the true monthly observations, multiplied by a scale factor, then added back to the corresponding interpolated observation. The results can be see below

```
predictor_modeling |>
  autoplot(co2_ppm)
```



The trend remains the same but the seasonal pattern now looks similar to the post-1957 observations

```
new_df <- new_df |>
  select(-enso_smooth) |>
  mutate(
    enso_smooth_12 = slider::slide_dbl(ENSO, mean, .before = 11, complete =
      ↪ TRUE),
```

```

    enso_smooth_6 = slider::slide_dbl(ENSO, mean, .before = 5, complete =
      ↪ TRUE),
    enso_smooth_3 = slider::slide_dbl(ENSO, mean, .before = 2, complete =
      ↪ TRUE),
    enso_delay = lag(enso_smooth_3, 4),
    rf_co2 = 5.35 * log(co2_ppm / 278)
  )

df <-
  ↪ read_tsv("C:/Users/tkbar/Downloads/volcano-events-2025-12-03_09-46-47_-0800.tsv")

volcano <- df |>
  select(Year, Mo, Name, VEI) |>
  drop_na() |>
  filter(VEI > 0) |>
  mutate(
    Date = make_yearmonth(year = Year, month = Mo),

  ) |>
  select(Date, VEI)

df |>
  filter(Year == 2022)

volcano_clean <- volcano %>%
  filter(VEI >= 4)

calculate_decay <- function(current_date, eruption_table, decay_months = 36,
  ↪ tau = 12) {

  curr_d <- as.Date(current_date)
  erup_d <- as.Date(eruption_table$Date)

  window_start <- curr_d - months(decay_months)

  active_indices <- which(erup_d <= curr_d & erup_d > window_start)

  if (length(active_indices) == 0) {
    return(0)
  }
}

```

```

time_span <- lubridate::interval(erup_d[active_indices], curr_d)
months_elapsed <- time_span %/% months(1)

strengths <- exp(-months_elapsed / tau)

return(sum(strengths))
}

climate_tsibble_updated <- lagged %>%
  mutate(
    volcano_forcing = map_dbl(Date, calculate_decay, eruption_table =
      ↪ volcano_clean)
  )

```

The volcanic events with a lower VEI than 4 are filtered out as their impact on the climate is most likely too minimal to significantly impact the global climate. A dummy variable is created for the presence of the event, then an exponential decay formula extending over the course of 3 years was applied. Overlapping events were summed