DROUGHT FORECASTING

AFRICAN COUNTRIES

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Outline

- Problem Statement & Objectives
- Drought Classification & Data Selection
- Modeling
- ARCH/GARCH
- Conclusion & Future Work

PROBLEM STATEMENT & OBJECTIVES

Drought Impact and Prevalence

- **Concern:** Globally, droughts are the biggest concern from climate change
- **Prevalence:** Frequency and intensity of droughts has increased over the last century[1]
- **Impact:** Since 1900 Global droughts have affected 2 billion people and lead to more than 11 million deaths.[2]

TOP CLIMATE CHANGE CONCERNS BY REGION

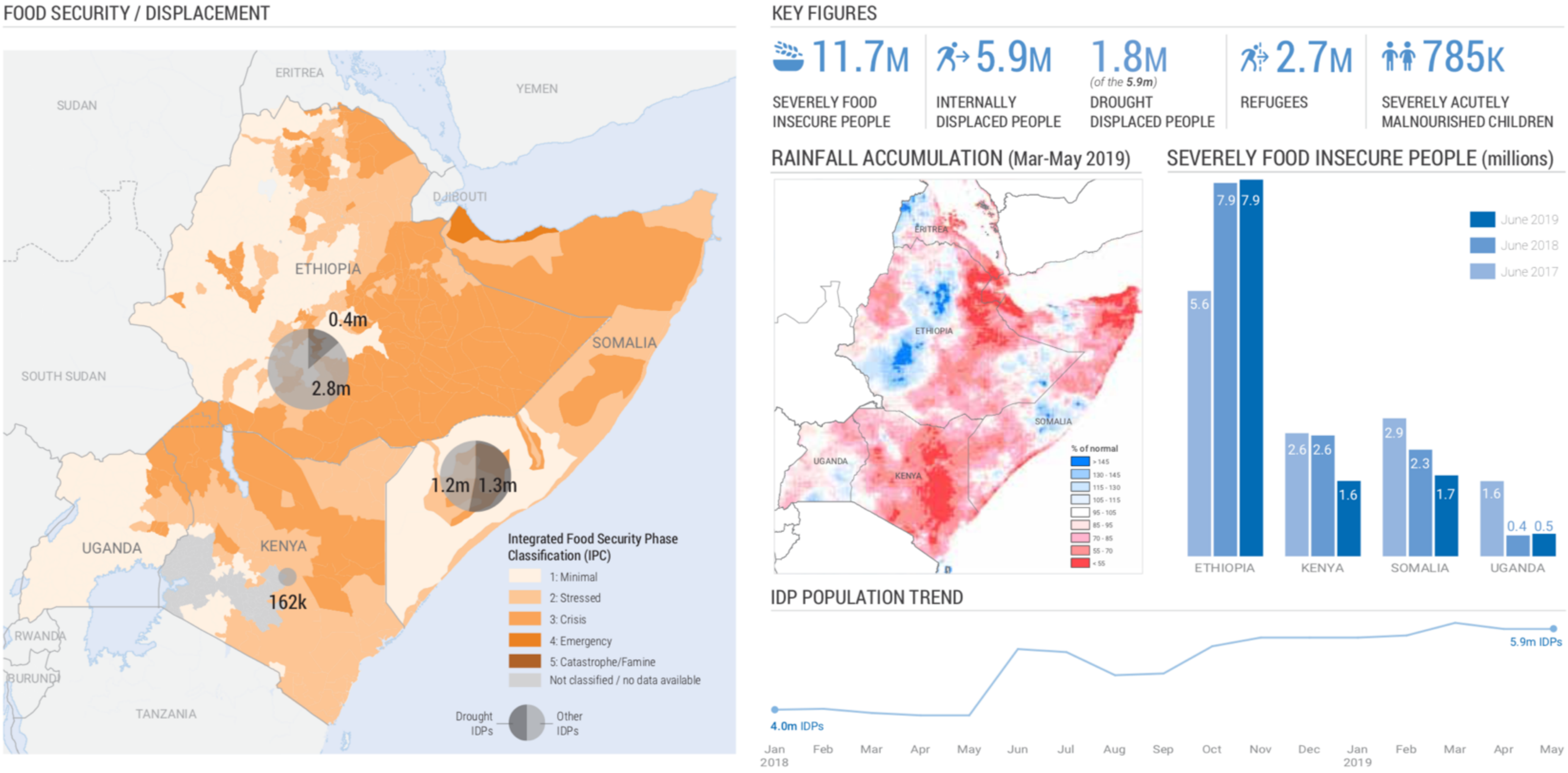
	Droughts or water shortages	Severe weather, like floods or intense storms	Long periods of unusually hot weather	Rising Sea Levels
LATIN AMERICA	59%	21%	12%	5%
AFRICA	59%	18%	16%	3%
U.S.	50%	16%	11%	17%
ASIA/ PACIFIC	41%	34%	13%	6%
MIDDLE EAST	38%	24%	19%	5%
EUROPE	35%	27%	8%	15%
GLOBAL	44%	25%	14%	6%

Note: Russia and Ukrane not included in Europe median.
Source: Spring 2015 Global Attitudes Survey. Q32
Data: Pew Research Center, November 2015,
"Global Concern about Climate Change, Broad Support for Limiting Emissions"

[1] https://climate.nasa.gov/news/2617/study-finds-drought-recoveries-taking-longer/
[2] https://www.thefiscaltimes.com/Articles/2014/09/05/High-Cost-Droughts-Around-World

Our Focus: Horn of Africa

With the goal of maximizing the impact of our predictions we have decided to focus on the region most affected by droughts.



DROUGHT CLASSIFICATOIN & DATA SELECTION

What is a drought?

There are many definitions of a drought

"Drought is caused by not only lack of precipitation and high temperatures but by overuse and overpopulation"

David Miskus – *a drought expert and meteorologist at the National Oceanic and Atmospheric Administration's (NOAA) Climate Prediction Center.*

FIVE TYPES OF DROUGHT

1. **METEOROLOGICAL** drought refers to an extended period of dry weather patterns.
2. **HYDROLOGICAL** drought refers to low water supply in our rivers, lakes, aquifers, and other reservoirs that often follows meteorological drought.
3. **AGRICULTURAL** drought occurs when a water shortage significantly damages or destroys agricultural crops.
4. **ECOLOGICAL** drought is the most recently defined type of drought and refers to ecological damage caused by the lack of soil moisture.
5. **SOCIOECONOMIC** drought refers to when a water shortage affects the supply and demand of drought commodities, such as water, food grains, and fish.

DROUGHT SELECTION FOR MODELING:
METEOROLOGICAL

Meteorological Drought Indicator: SPEI

What is SPEI?

Standardized Precipitation Evapotranspiration Index[1]:

- Measures drought severity according to its intensity and duration, and can identify the onset and end of drought episodes
- The lower the index, the more severe the drought (usual values range between -2 and 2)

Why choosing SPEI?

- It takes into account both **precipitation** and potential **evaporation** in determining drought, therefore, SPEI captures the main impact of increased temperatures on water demand[2]

Code	Classes	SPI/SPEI Interval
ew	Extreme wetness	[2, +∞[
sw	Severe wetness	[1.5, 2[
mw	Moderate wetness	[1, 1.5[
n	Normal	[−1, 1[
md	Moderate drought	[−1.5, −1[
sd	Severe drought	[−2, −1.5[
ed	Extreme drought	]−∞, −2[

[3] https://www.mdpi.com/2073-4441/10/1/65/pdf

[1] https://spei.csic.es/home.html
[2] https://climatedataguide.ucar.edu/climate-data/standardized-precipitation-evapotranspiration-index-spei

Our Data: Monthly SPEI measurements from the capitals of Somalia & Ethiopia

Datasource: https://spei.csic.es/home.html

Original TS:

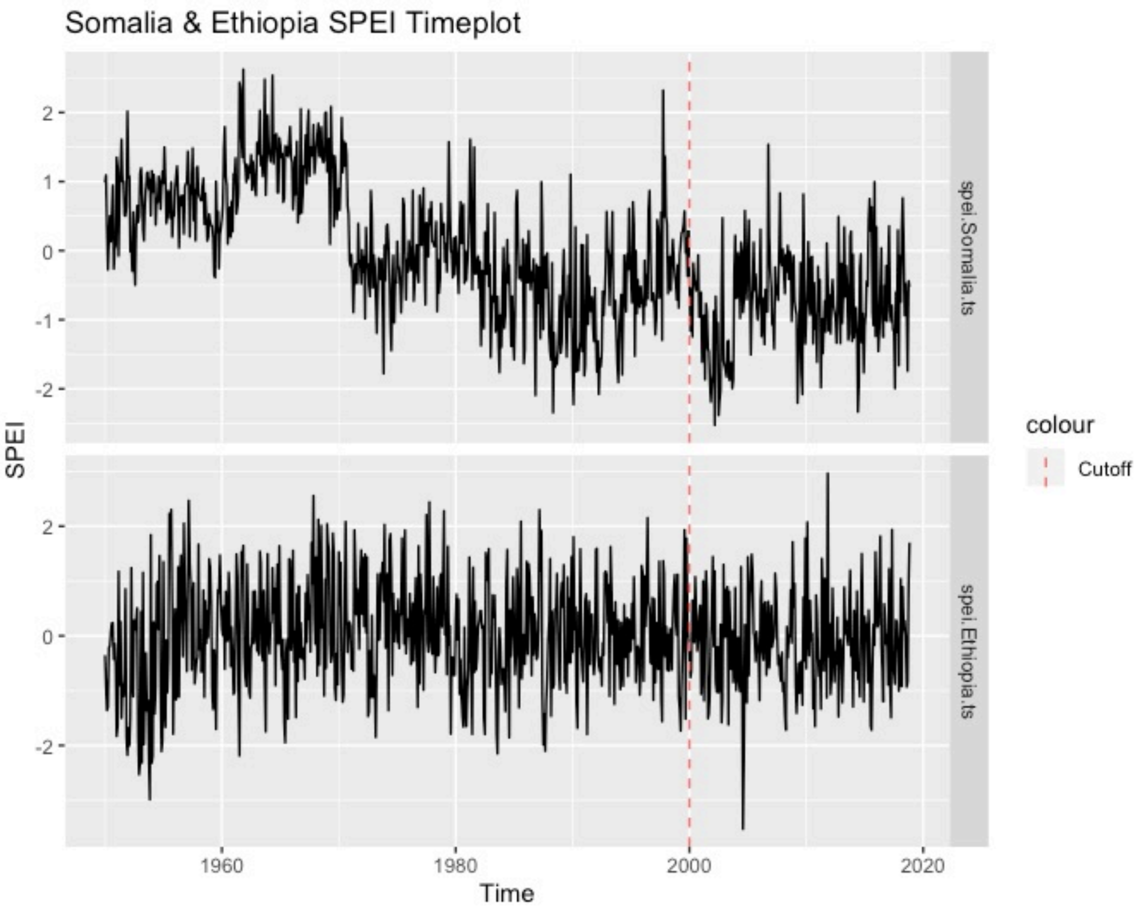
- Clear change in level across time
- In order to control for changes in data generation process (climate change), we restricted to more recent window
- Location close to the equator makes data relatively stable

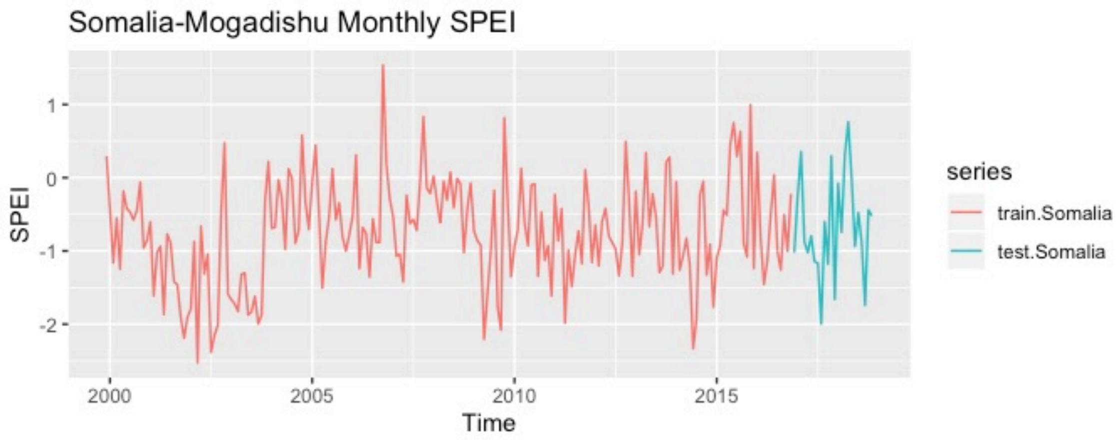
New TS window:

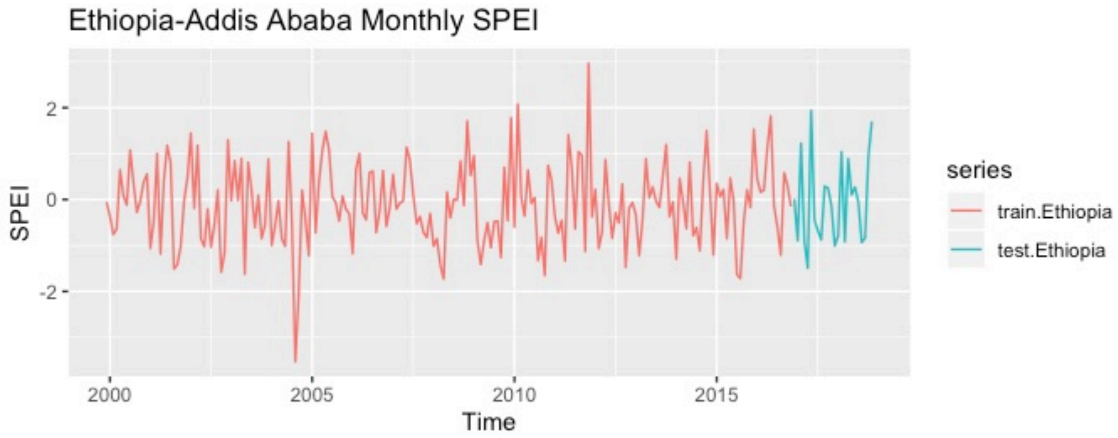
Timeframe: Dec-1999 to Nov-2018 (228 months=19years)

Train: 1999/12 - 2016/11 | **Test:**2016/12 - 2018/11

(204m = 17yrs) | (24m = 2yrs)





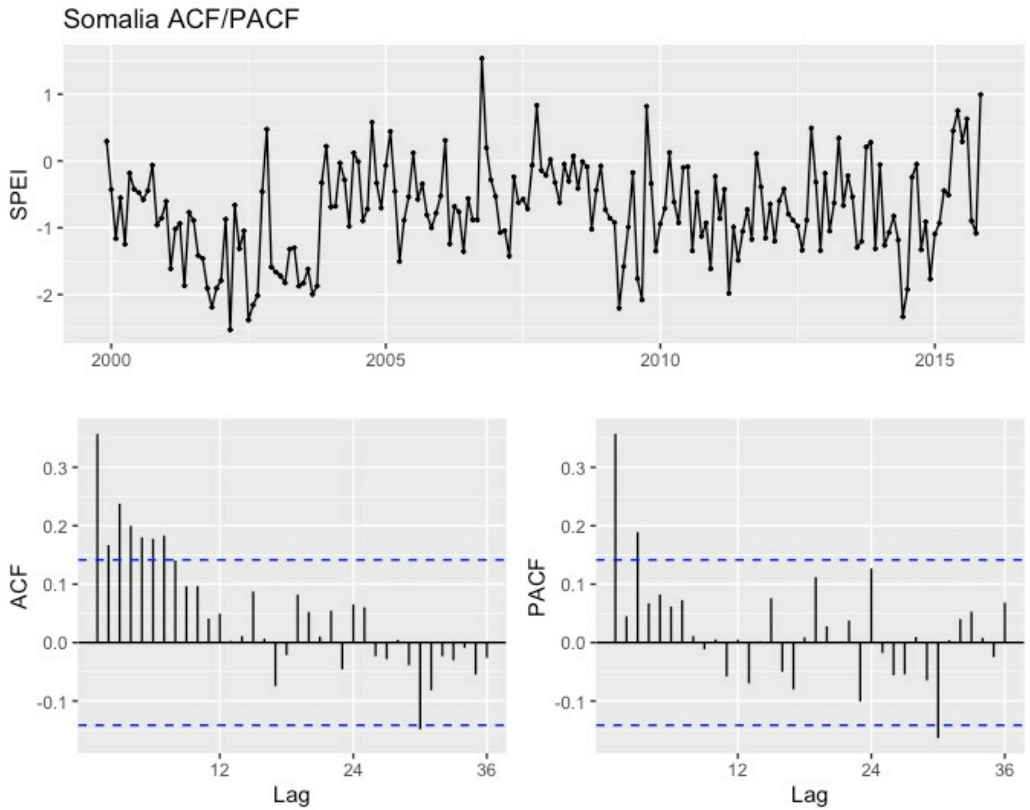


MODELING

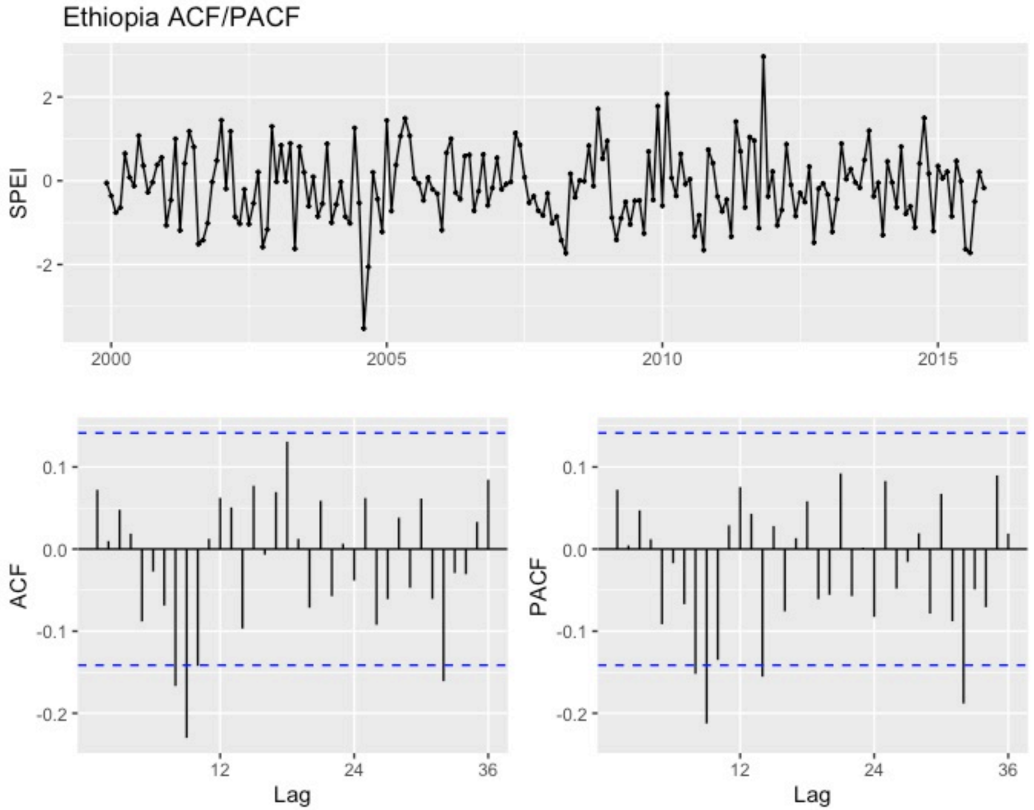
1. Benchmark Models
2. Exponential Smoothing:
   - Simple Exponential Smoothing (SES)
   - ETS
3. ARIMA, sARIMA
4. Spectral Analysis
5. VAR, Regression with ARIMA error
6. TBATS
7. Model Selection & Final Predictions

Analyzing ACF/PACF

SOMALIA



ETHIOPIA



ACF: Slowly Decaying
PACF: Drop off after lag = 3

Stationarity Tests	Somalia	Ethiopia
KPSS Test (H0: stationary)	0.07902	0.1
ADF Test (H1: stationary)	0.01412	0.01

ACF: Sinusoidal Pattern
PACF: Sinusoidal Pattern

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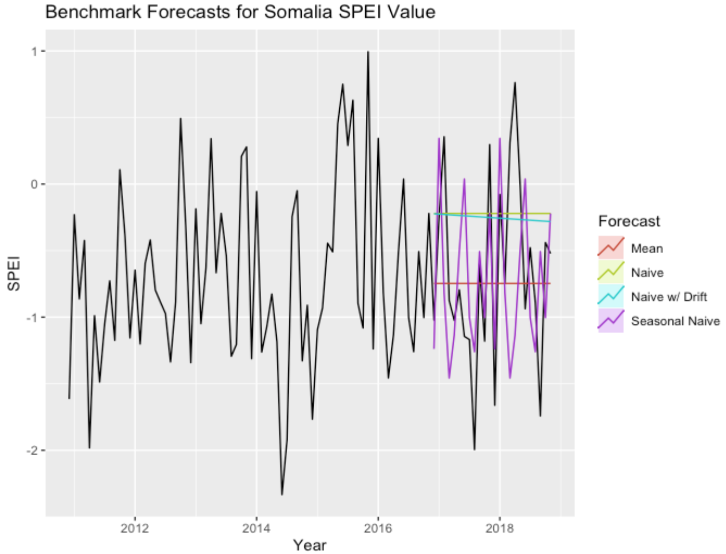
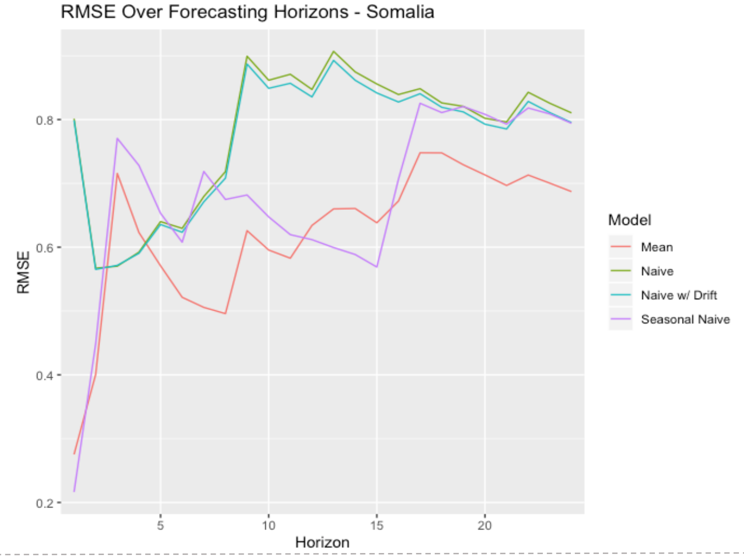
Benchmark Models

SOMALIA



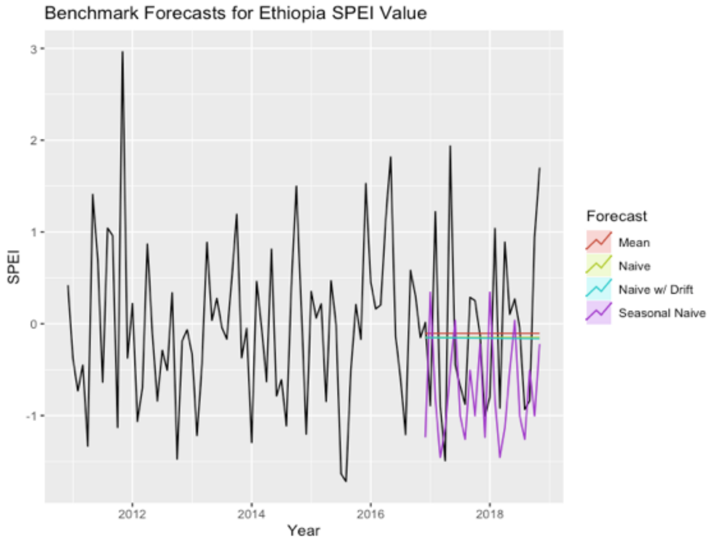


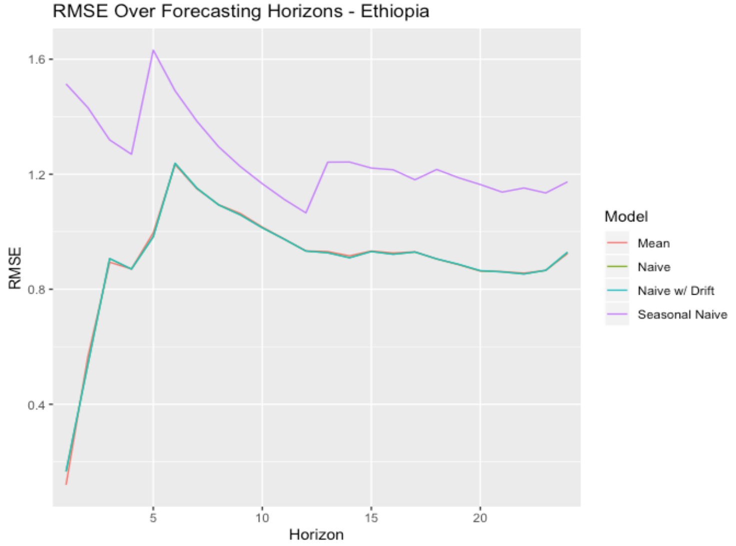
RMSE

	h=12	h=24
Naive	0.8472	0.8105
Mean	0.6341	0.6871
Seasonal Naive	0.6118	0.7941
Naive w/ Drift	0.8355	0.7953

	RMSE Overall
Naive	0.7802
Mean	0.6214
Seasonal Naive	0.68
Naive w/ Drift	0.7708

ETHIOPIA





RMSE

	h=12	h=24
Naive	0.9328	0.928
Mean	0.9335	0.9243
Seasonal Naive	1.0656	1.1736
Naive w/ Drift	0.9329	0.9293

	RMSE Overall
Naive	0.9045
Mean	0.9046
Seasonal Naive	1.2574
Naive w/ Drift	0.9046

*RMSE based on test data set

MODELING

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   - **ETS**
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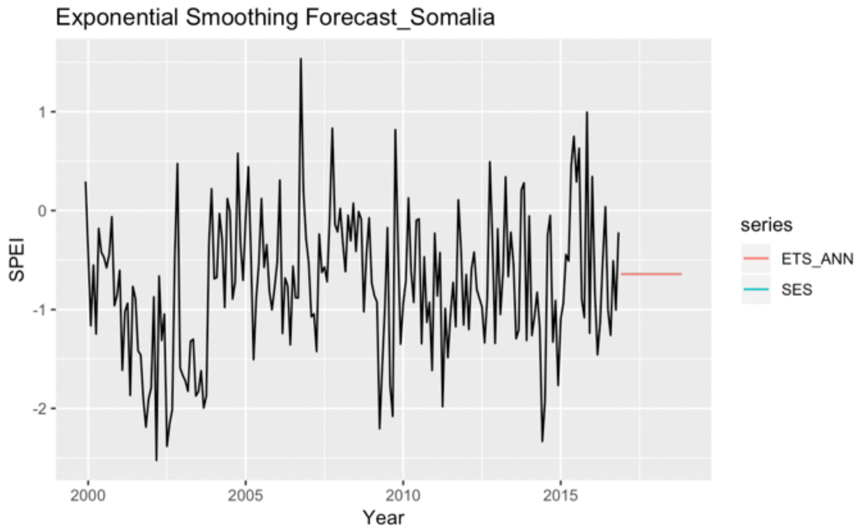
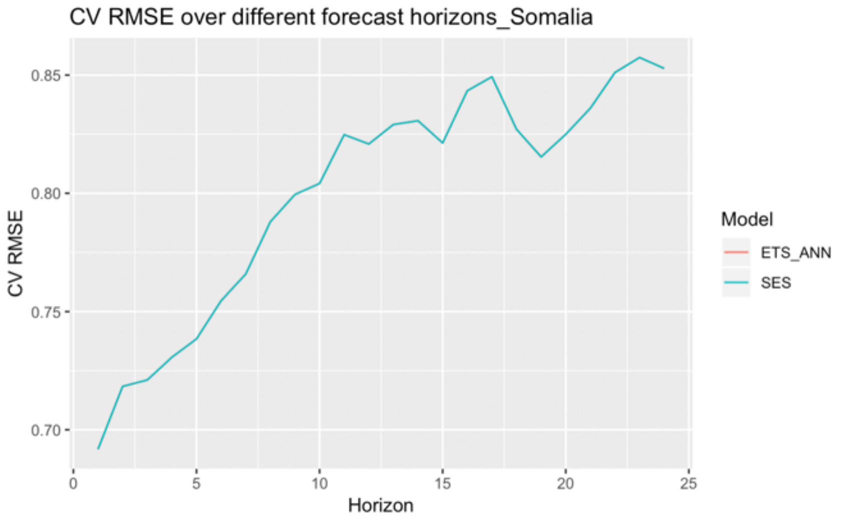
Exponential Smoothing: Simple Exponential Smoothing, ETS

SOMALIA



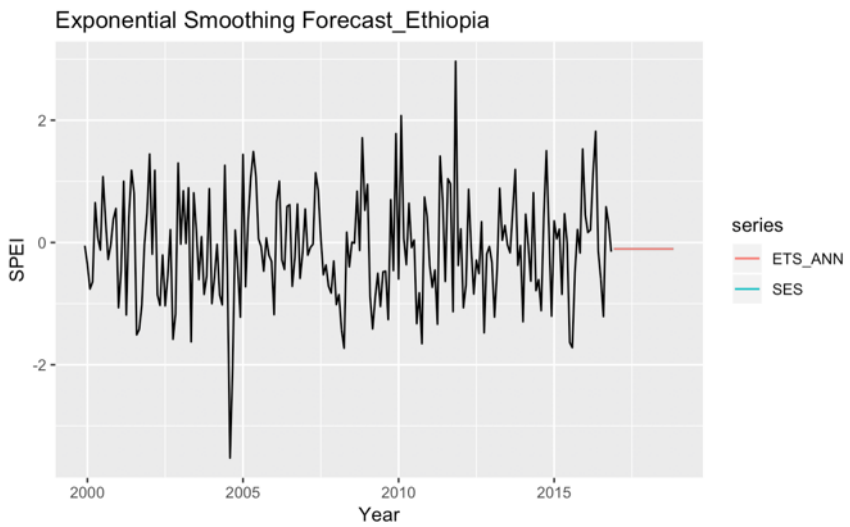


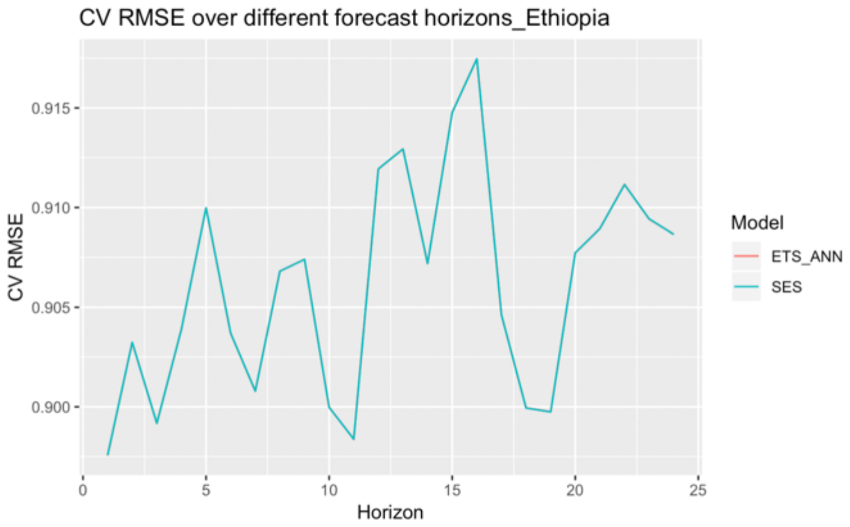
RMSE

Method <fctr>	h = 12 <fctr>	h = 24 <fctr>	AICc <fctr>
SES	0.8208	0.8528	930.0075
ETS_ANN	0.8208	0.8528	930.0075

```
Model Information:
ETS(A,N,N)

Call:
 ets(y = train_E, model = ("ANN"))

  Smoothing parameters:
    alpha = 1e-04
```

ETHIOPIA





RMSE

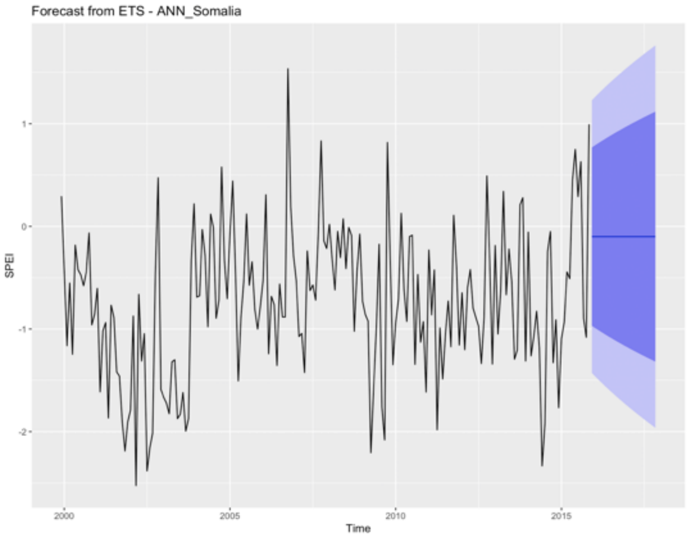
Method <fctr>	h = 12 <fctr>	h = 24 <fctr>	AICc <fctr>
SES	0.9119	0.9086	1041.0069
ETS_ANN	0.9119	0.9087	1041.0069

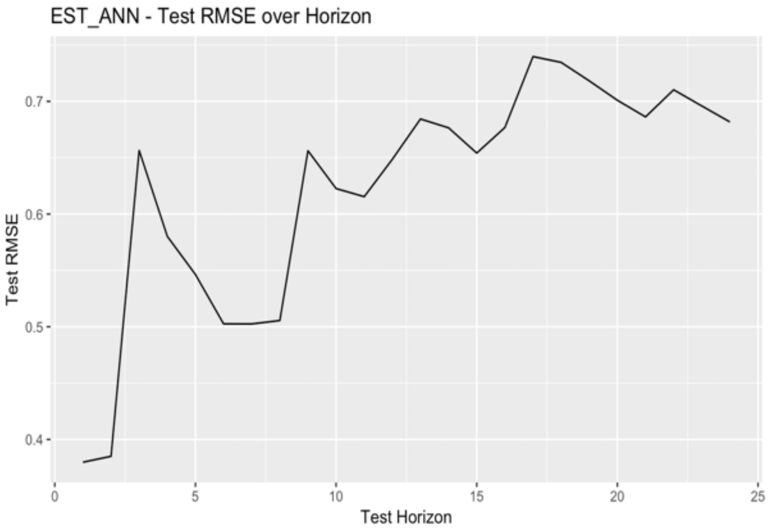
```
Model Information:
ETS(A,N,N)

Call:
 ets(y = train_S, model = ("ANN"))

  Smoothing parameters:
    alpha = 0.1883
```

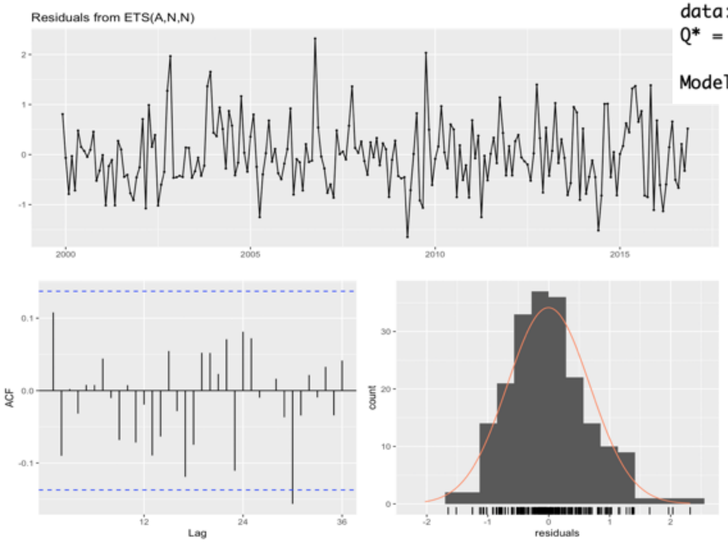
**ANN : Additive errors, no trend, non seasonality*

Exponential Smoothing Model

SOMALIA

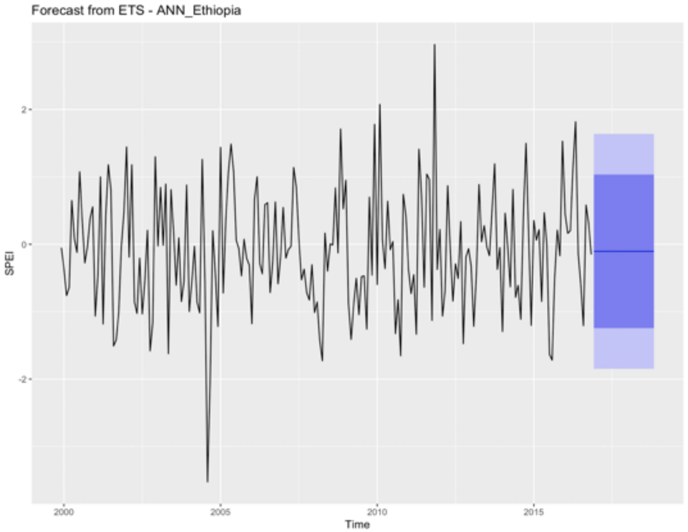


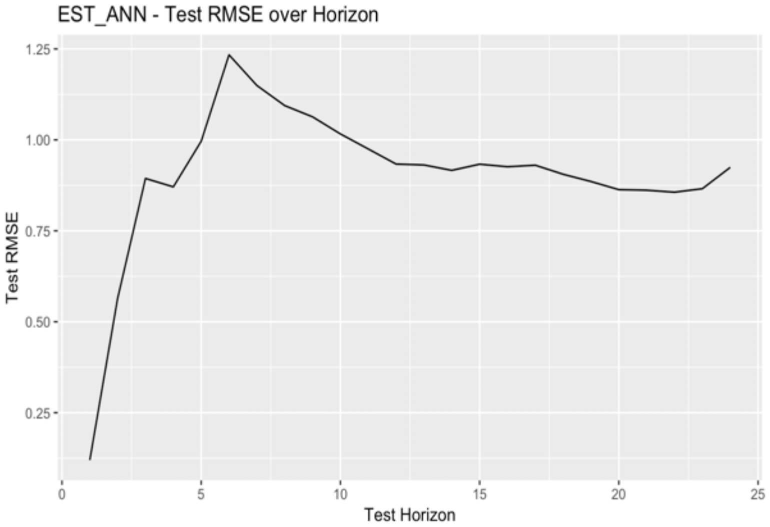


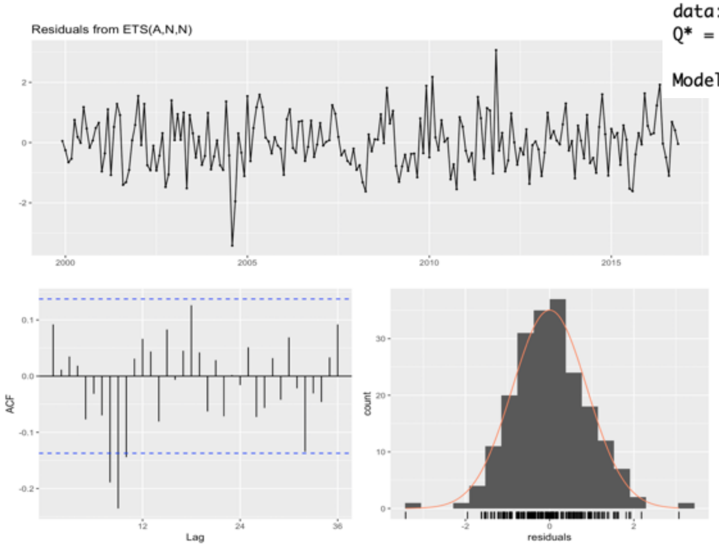



```
        Ljung-Box test

data:  Residuals from ETS(A,N,N)
Q* = 21.861, df = 22, p-value = 0.4682

Model df: 2.   Total lags used: 24
```

ETHIOPIA








```
        Ljung-Box test

data:  Residuals from ETS(A,N,N)
Q* = 40.104, df = 22, p-value = 0.01051

Model df: 2.   Total lags used: 24
```

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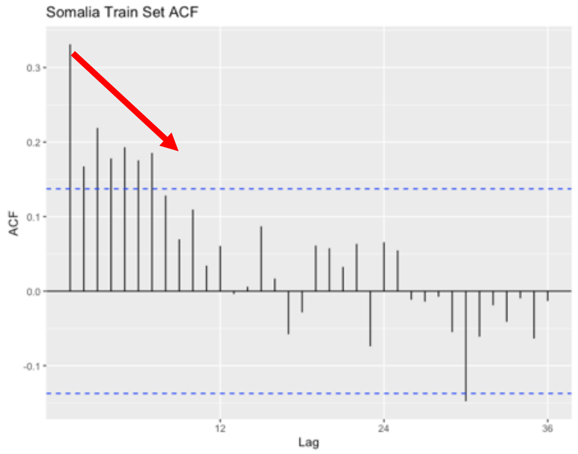
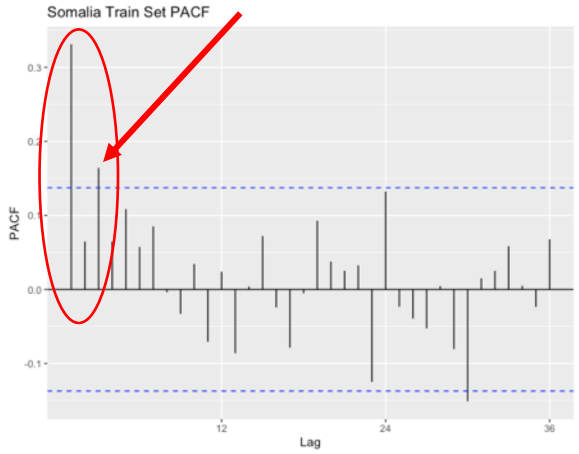
ARIMA/sARIMA Model Selection

SOMALIA





Somalia EACF Matrix

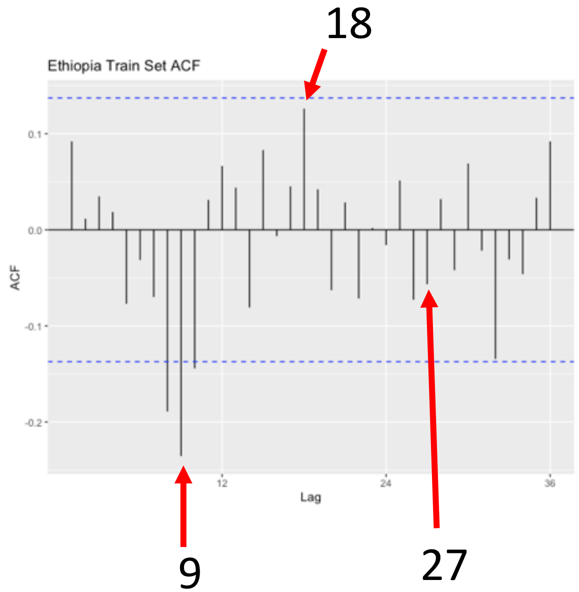
	0	1	2	3	4	5	6	7	8	9	10	11	12	13
0	x	x	x	x	x	x	x	o	o	o	o	o	o	o
1	x	x	o	o	o	o	o	o	o	o	o	o	o	o
2	x	x	o	o	o	o	o	o	o	o	o	o	o	o
3	x	x	o	o	o	o	o	o	o	o	o	o	o	o
4	x	x	o	o	o	o	o	o	o	o	o	o	o	o
5	x	x	o	o	o	o	o	o	o	o	o	o	o	o
6	x	x	x	x	o	o	o	o	o	o	o	o	o	o
7	o	x	x	x	o	x	o	o	o	o	o	o	o	o

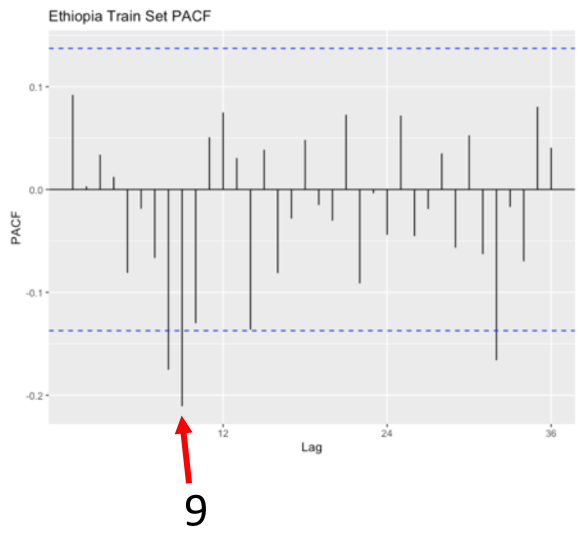
ACF:
- Slow initial decay
- No clear seasonality

PACF:
- Initial drop off at lag = 3
- No clear seasonality

Suggests -> AR(3)

ETHIOPIA





Ethiopia EACF Matrix

	0	1	2	3	4	5	6	7	8	9	10	11	12	13
0	o	o	o	o	o	o	o	x	x	x	o	o	o	o
1	o	o	o	o	o	o	o	o	o	x	o	o	o	o
2	o	x	o	o	o	o	o	o	o	o	o	o	o	o
3	x	x	o	o	o	o	o	o	o	o	o	o	o	o
4	x	x	o	x	o	o	o	o	o	o	o	o	o	o
5	x	x	x	o	o	o	o	o	o	o	o	o	o	o
6	x	o	x	o	x	x	o	o	o	o	o	o	o	o
7	x	o	o	o	o	x	o	o	o	o	o	o	o	o

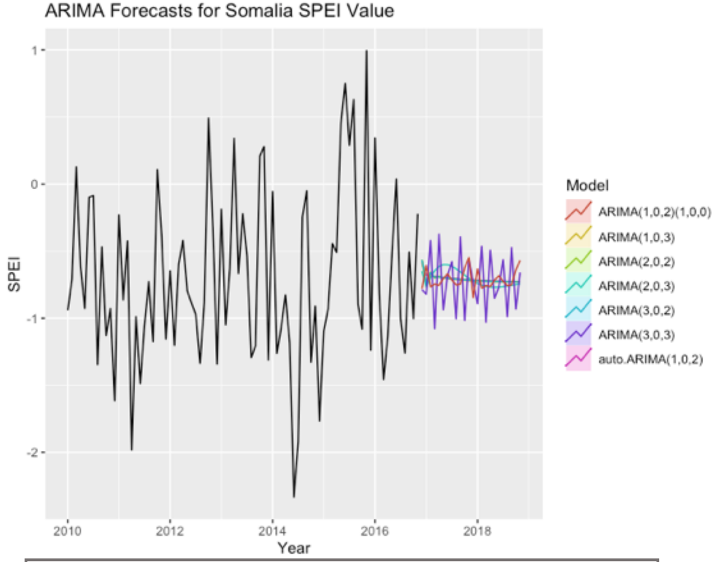
ACF:
- No clear initial drop off
- Seasonal lag of 9 decay

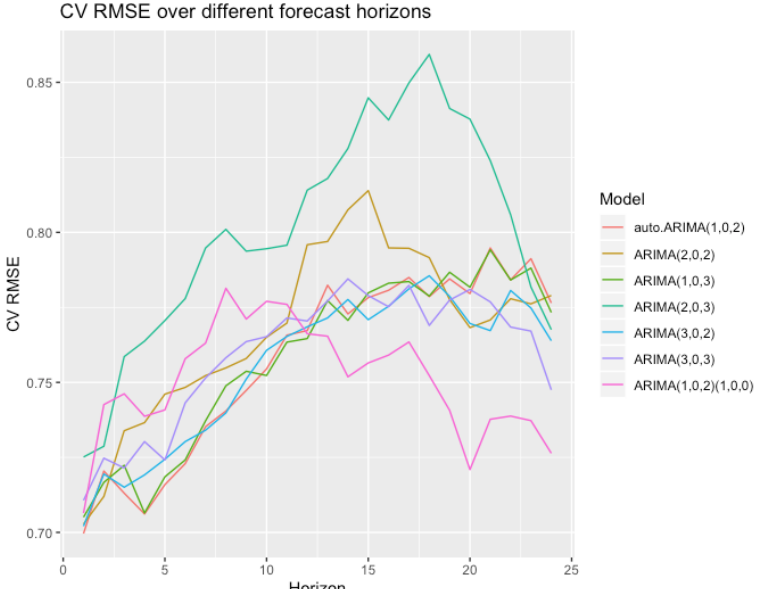
PACF:
- No clear initial drop off
- Seasonal lag of 9 drop off

Suggests -> AR(1)[9]

ARIMA/sARIMA Model Selection

SOMALIA

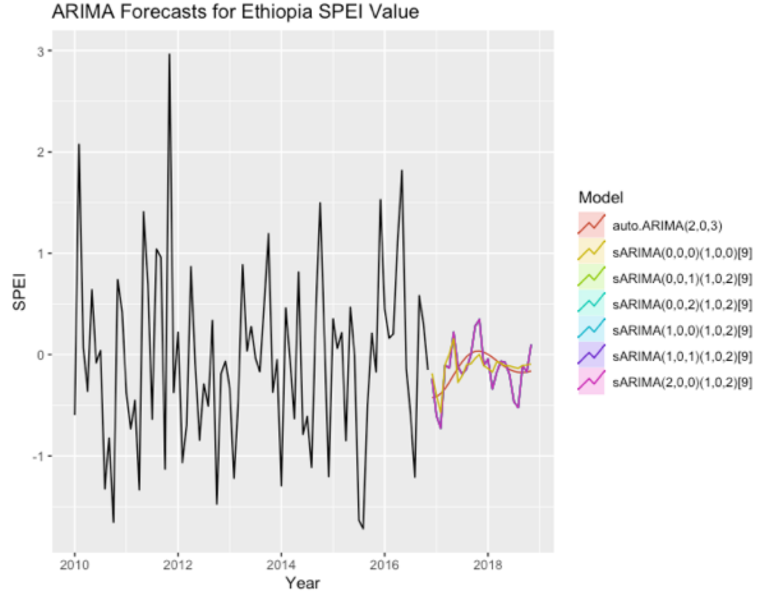


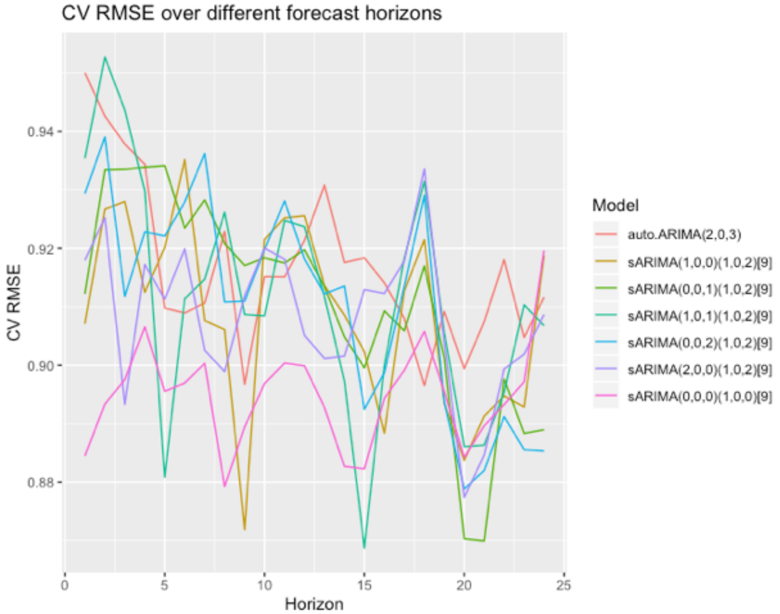


RMSE

	h = 12	h = 24	AICc
auto.ARIMA(1,0,2)	0.7673	0.7765	417.647
ARIMA(2,0,2)	0.7959	0.779	418.2527
ARIMA(1,0,3)	0.7646	0.7733	418.0269
ARIMA(2,0,3)	0.8141	0.7676	419.1866
ARIMA(3,0,2)	0.7685	0.7639	420.2698
ARIMA(3,0,3)	0.7704	0.7475	416.362
ARIMA(1,0,2)(1,0,0)[12]	0.7662	0.7264	419.4299

ETHIOPIA



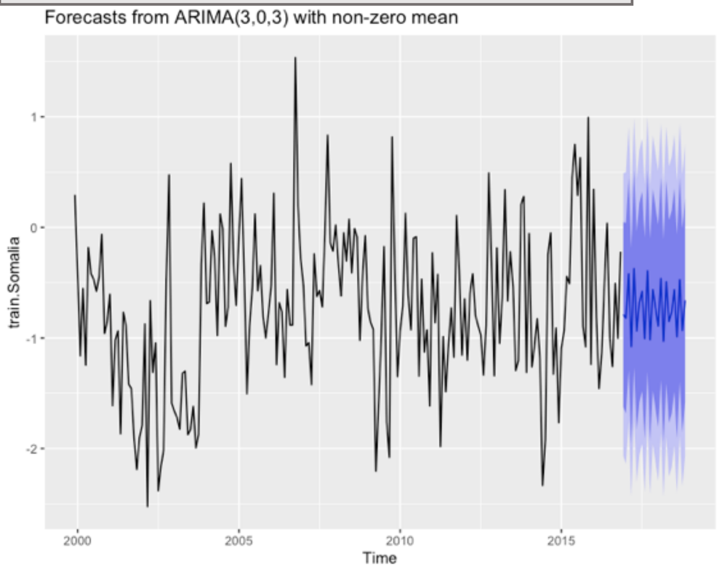


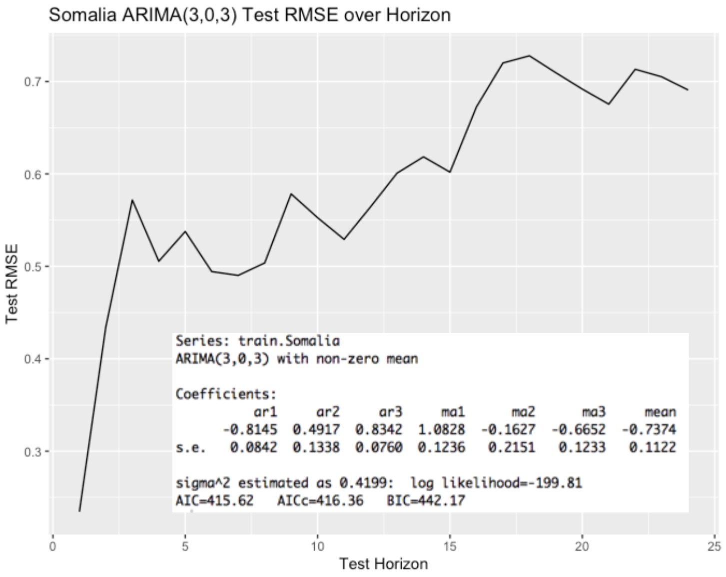
RMSE

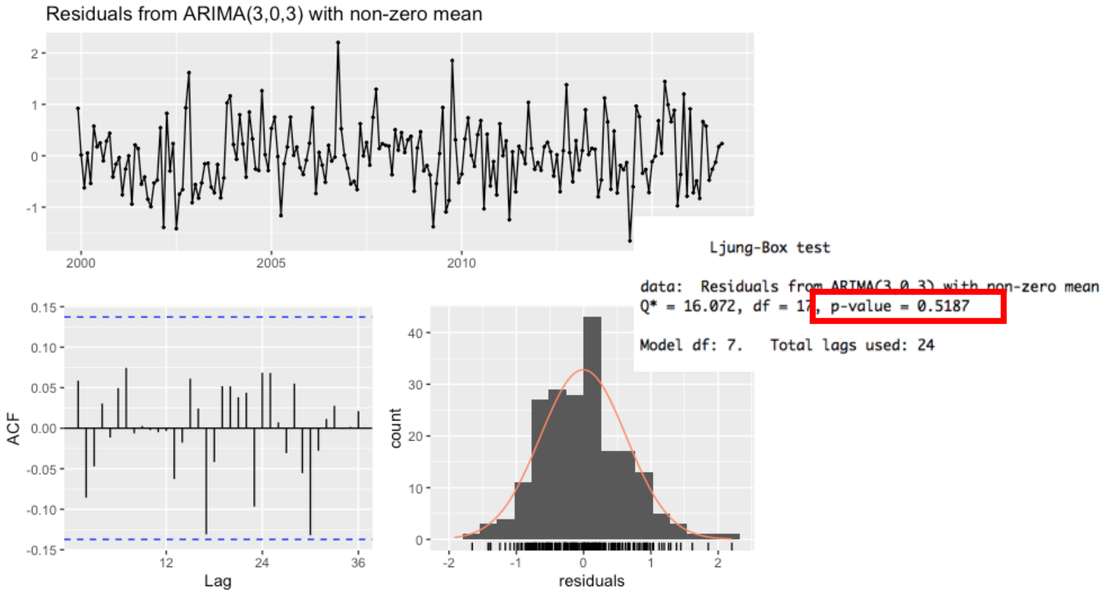
	h = 12	h = 24	AICc
auto.ARIMA(2,0,3)	0.9214	0.9116	532.0261
sARIMA(1,0,0)(1,0,2)[9]	0.9256	0.9187	524.5112
sARIMA(0,0,1)(1,0,2)[9]	0.9198	0.889	524.5152
sARIMA(1,0,1)(1,0,2)[9]	0.9237	0.9068	526.556
sARIMA(0,0,2)(1,0,2)[9]	0.9182	0.8853	526.6347
sARIMA(2,0,0)(1,0,2)[9]	0.9051	0.9087	526.6193
sARIMA(0,0,0)(1,0,0)[9]	0.8999	0.9196	523.097

Best ARIMA/sARIMA Models

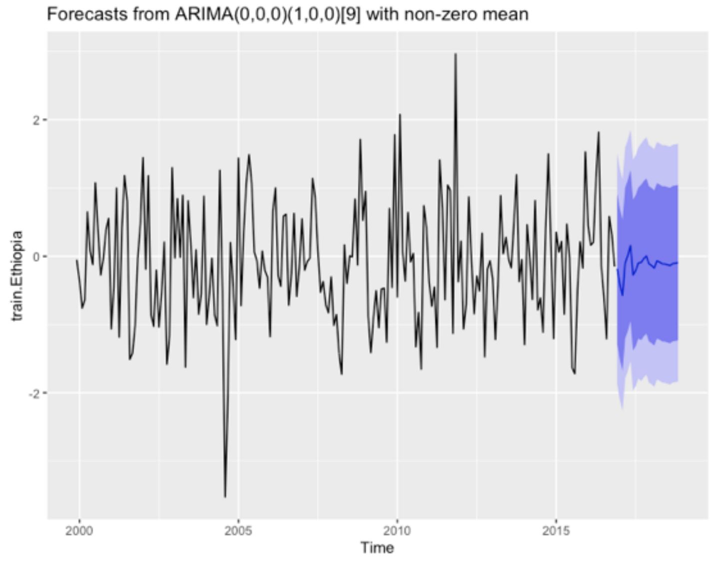
SOMALIA

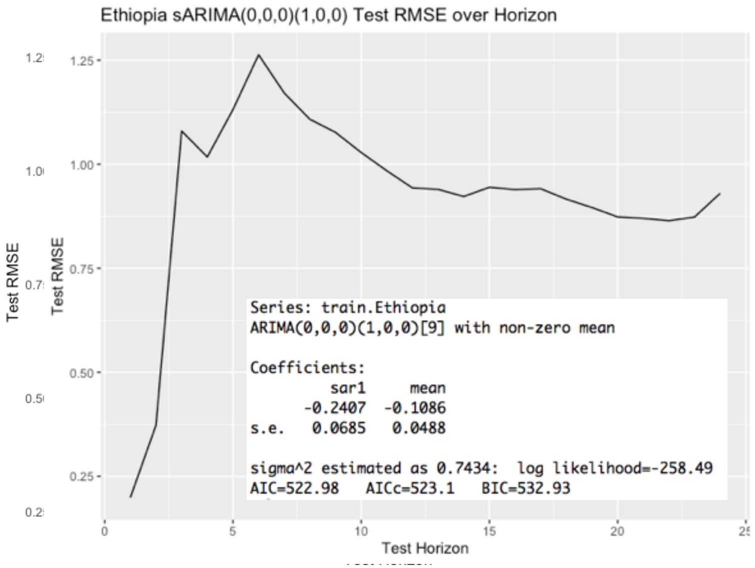


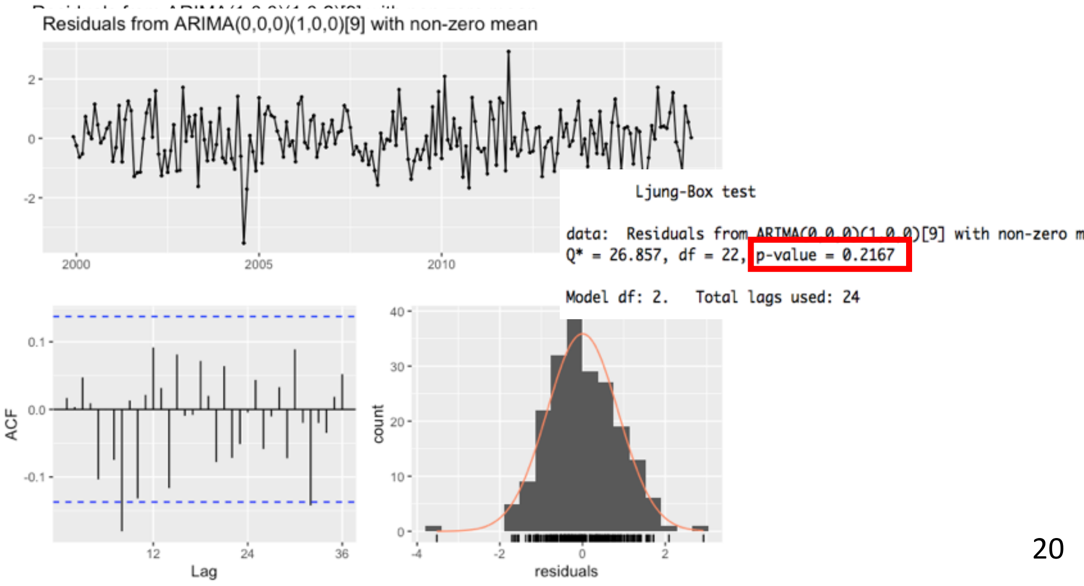




ETHIOPIA







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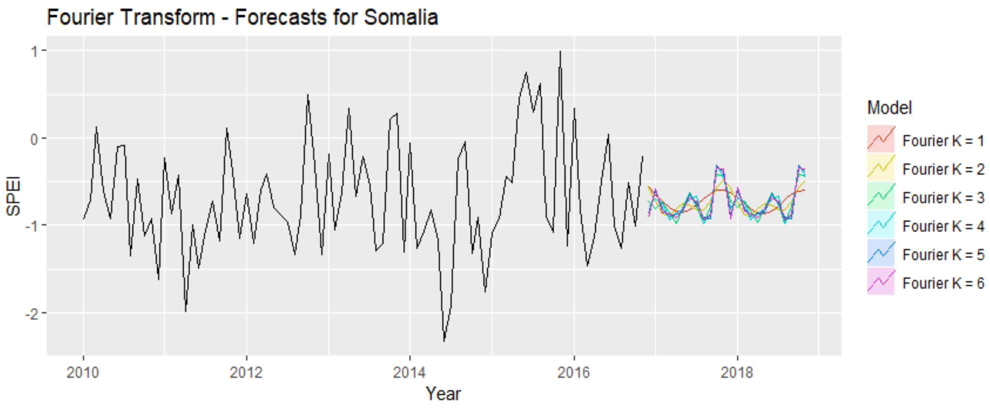
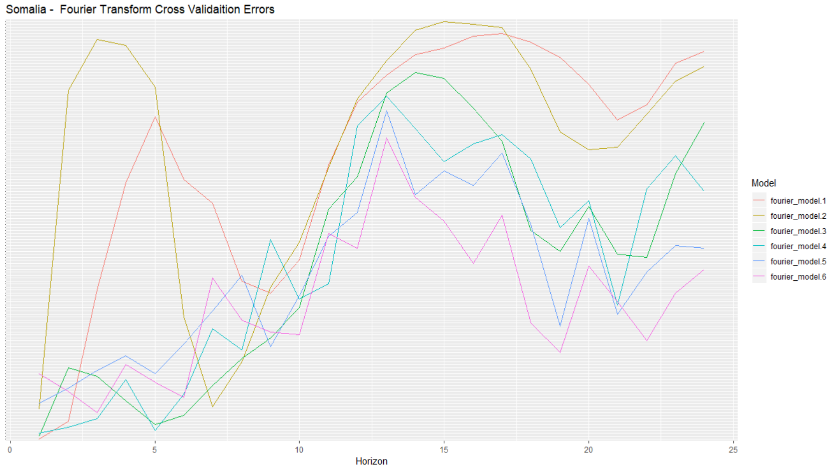
SPECTRAL ANALYSIS – Dynamic Harmonic Regression

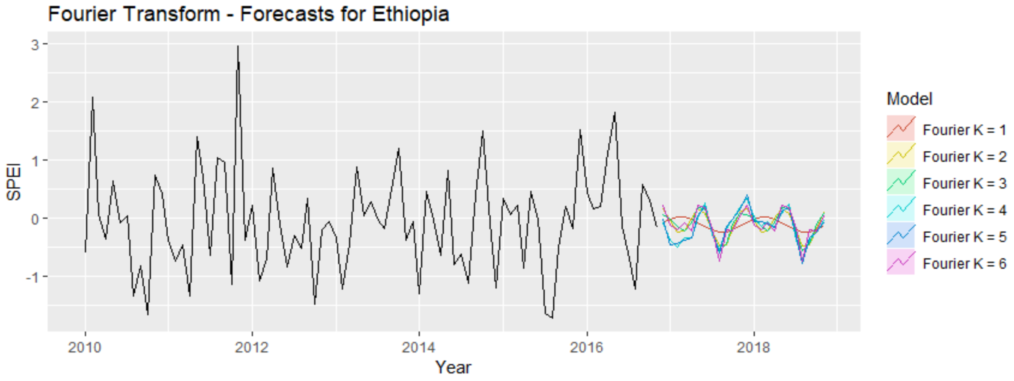
SOMALIA

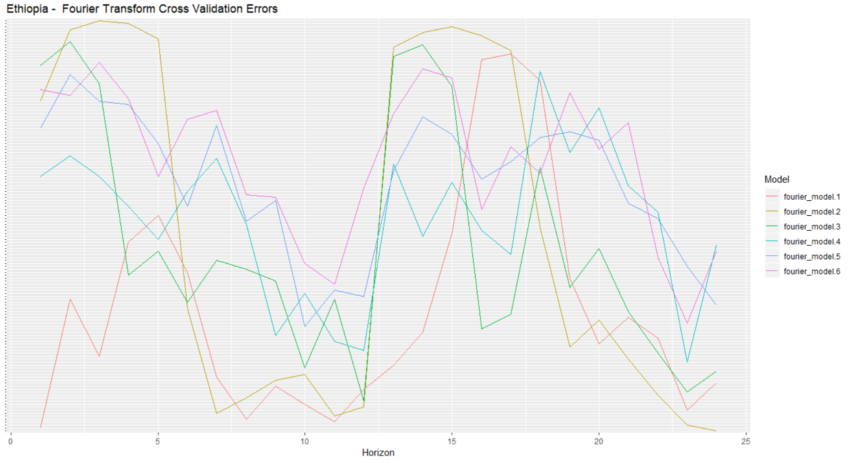




	h=12	h=24	AICc
fourier_model.1	0.6248099	0.7106073	419.2655
fourier_model.2	0.6217860	0.7077911	419.2325
fourier_model.3	0.5913117	0.6990945	416.0661
fourier_model.4	0.5973773	0.6808698	417.5349
fourier_model.5	0.6108730	0.6795433	419.4822
fourier_model.6	0.5997444	0.6721983	420.9704

ETHIOPIA

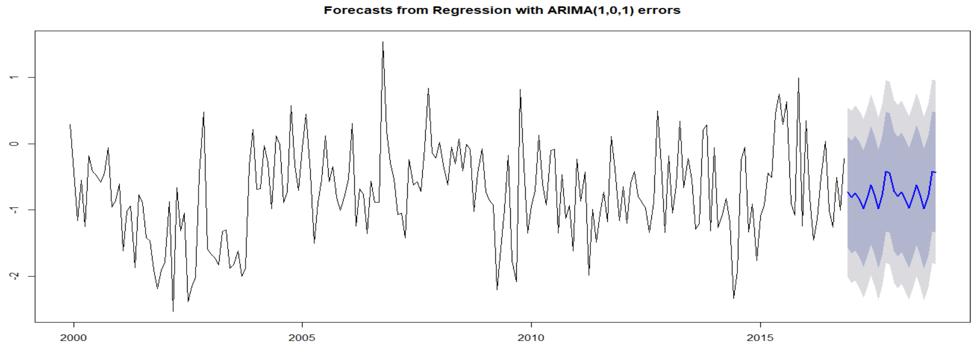


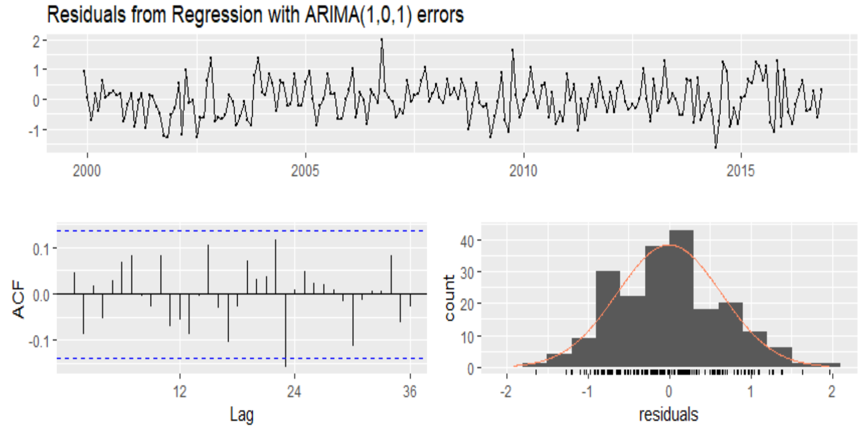


	h=12	h=24	AICc
fourier_model.1	0.9362026	0.9249248	534.9573
fourier_model.2	0.9195550	0.8944932	529.1021
fourier_model.3	0.8911184	0.8699226	532.4388
fourier_model.4	0.9008387	0.9181647	532.2842
fourier_model.5	0.8725337	0.9033669	536.2246
fourier_model.6	0.8727228	0.8935995	539.2887

SPECTRAL ANALYSIS – Best Model

SOMALIA

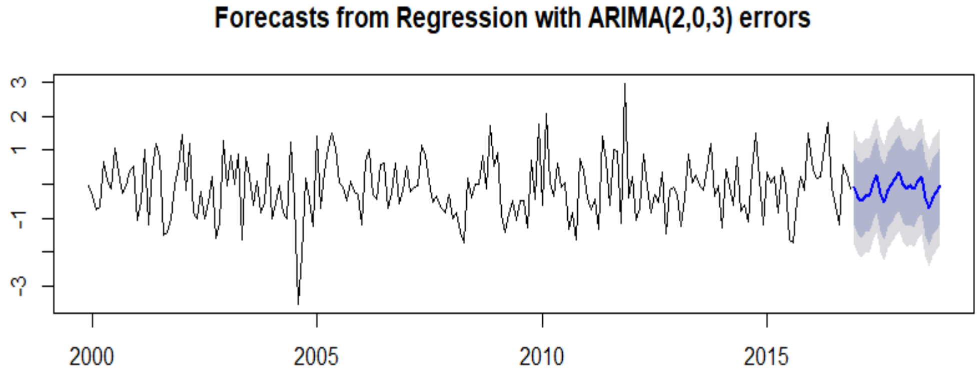


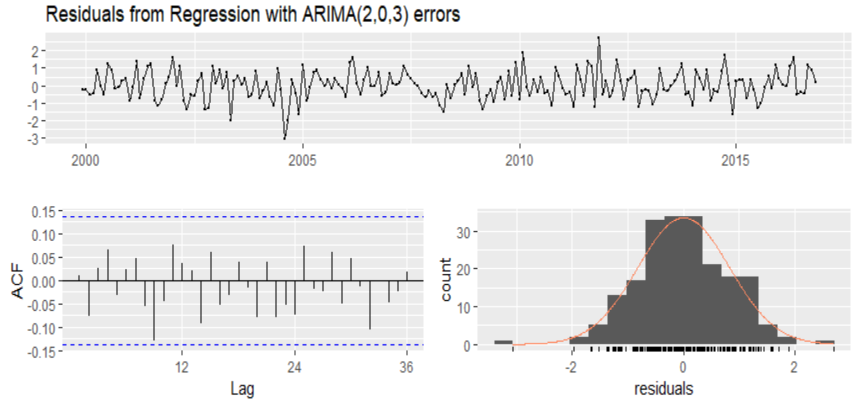


K = 3 AICC = 416.0661

```
Ljung-Box test

data:  Residuals from Regression with ARIMA(1,0,1) errors
Q* = 26.041, df = 15, p-value = 0.0376

Model df: 9.   Total lags used: 24
```

ETHIOPIA





K = 4 AICC 532.2842

```
Ljung-Box test

data:  Residuals from Regression with ARIMA(2,0,3) errors
Q* = 18.558, df = 10, p-value = 0.04625

Model df: 14.   Total lags used: 24
```

MODELING

1. Benchmark Models
2. Exponential Smoothing:
    - Simple Exponential Smoothing (SES)
    - ETS
3. ARIMA, sARIMA
4. Spectral Analysis
5. **VAR, Regression with ARIMA error**
6. TBATS
7. Model Selection & Final Predictions

Adding additional variables

Variable	Description	Reasoning
Temperature	▪ Monthly temperature in Fahrenheit (Mogadishu & Addis Ababa) ▪ Source: https://www7.ncdc.noaa.gov/CDO/cdoselect.cmd	▪ Temperature is non-deterministic ▪ Main driver of droughts; not directly captured by SPEI
Fatalities	▪ Monthly fatalities caused by civil unrest ▪ Source: https://www.acleddata.com/data/	▪ It has been shown that droughts can be a cause of civil unrest [1] ▪ We are interested in forecasting only, not necessarily in inference
ENSO Index	▪ ElNino/Southern Oscillation (ENSO) - state of the tropical pacific ▪ Source: https://www.esrl.noaa.gov/psd/enso/mei/	▪ One of the primary predictors for global climate disruption [2] ▪ Might be able to capture effects of climate change
Food prices	▪ Monthly food prices in Somali shilling (ONLY for Somalia) ▪ Source: https://data.humdata.org/group/som	▪ Food prices are soaring as a result of droughts, especially in poorer regions [3] ▪ Again, not interested in inference

training.Somalia

Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.75	-0.84 – -0.65	**<0.001**
train.Somalia.temp.diff	-0.07	-0.13 – -0.02	**0.013**
train.Somalia.fatalities.transformed	0.01	-0.02 – 0.03	0.719
train.mei.transformed.diff	-0.13	-0.43 – 0.16	0.378
train.Somalia.food.diff	0.00	-0.00 – 0.00	0.811
Observations	204		
R^2 / R^2 adjusted	0.034 / 0.015		

```
        CV           AIC          AICc           BIC         AdjR2
 0.50098566 -139.20749627 -139.08749627 -129.25313629    0.02467586
        CV           AIC          AICc           BIC         AdjR2
5.150235e-01 -1.331867e+02 -1.330667e+02 -1.232323e+02 -4.538688e-03
        CV           AIC          AICc           BIC         AdjR2
5.132213e-01 -1.336760e+02 -1.335560e+02 -1.237216e+02 -2.132195e-03
        CV           AIC          AICc           BIC         AdjR2
5.124952e-01 -1.332366e+02 -1.331166e+02 -1.232823e+02 -4.292782e-03
```

- Lowest AICc for temperature (-139.09)
- Temperature is the only significant variable (1%-level)
- Low R-squared

Continuing with temperature only

training.Ethiopia

Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.10	-0.22 – 0.02	0.091
train.Ethiopia.temp.diff	-0.06	-0.11 – -0.01	**0.024**
train.Ethiopia.fatalities.transformed	0.16	-0.05 – 0.37	0.148
train.mei.transformed.diff	-0.14	-0.50 – 0.22	0.457
Observations	204		
R^2 / R^2 adjusted	0.040 / 0.026		

```
        CV          AIC         AICc          BIC        AdjR2
 0.77710279 -49.77960683 -49.65960683 -39.82524685   0.02297815
        CV           AIC          AICc           BIC         AdjR2
8.002418e-01 -4.512225e+01 -4.500225e+01 -3.516789e+01  4.159912e-04
        CV           AIC          AICc           BIC         AdjR2
5.150235e-01 -1.331867e+02 -1.330667e+02 -1.232323e+02 -4.538688e-03
```

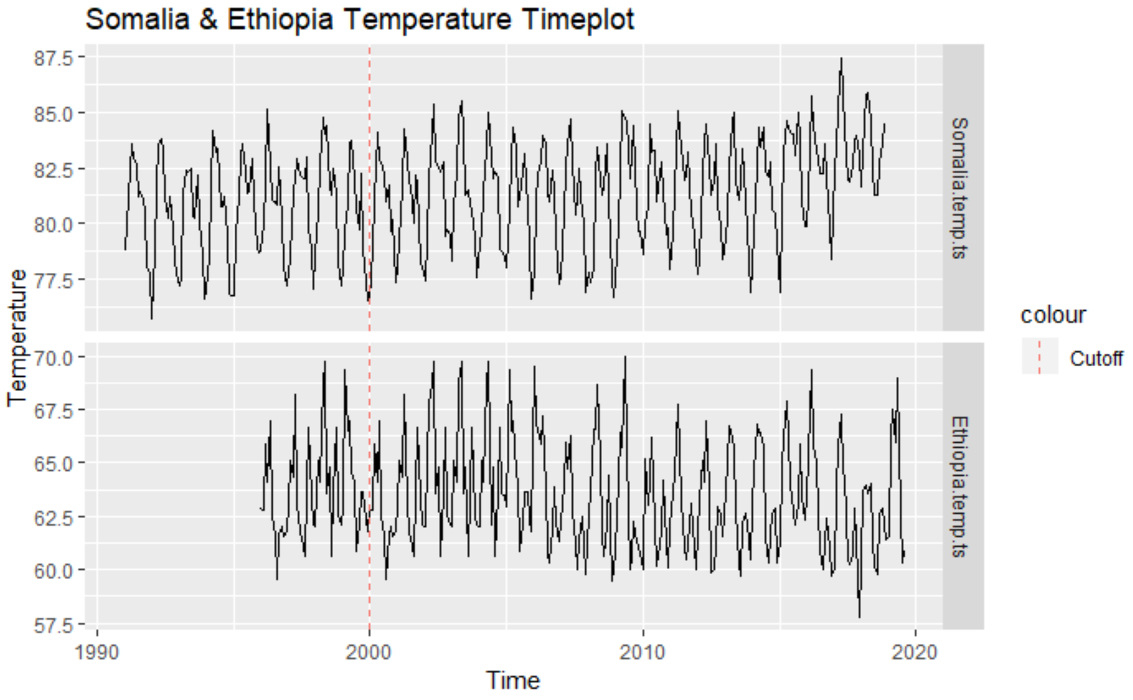
- Lowest AICc for temperature (-49.66)
- Temperature is the only significant variable (5%-level)
- Low R-squared

[1] Jones, Mattiaci, Braumoeller (2017): https://doi.org/10.1177/0022343316684662)
[2] https://www.esrl.noaa.gov/psd/enso/mei/
[3] Hill, Fuje (2018): https://editorialexpress.com/cgi-bin/conference/download.cgi?db_name=CSAE2018&paper_id=746

Temperature as explanatory variable

Original TS:

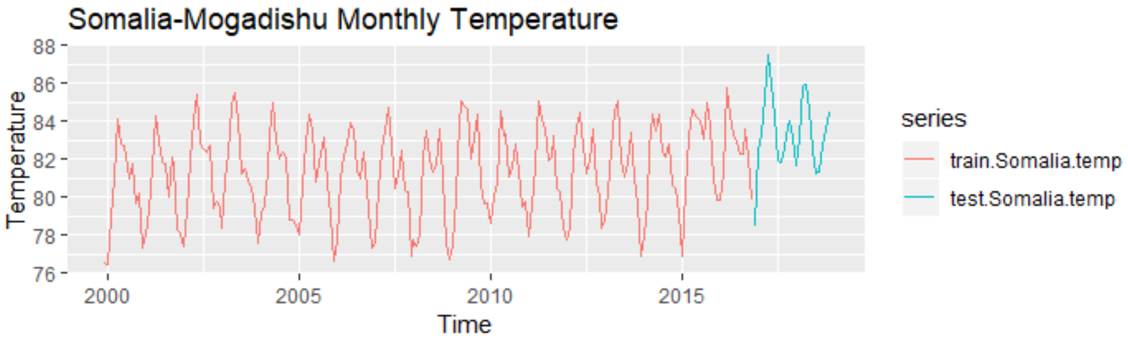
- Shows seasonality (seasons), however, location close to the equator makes data relatively stable
- No trend

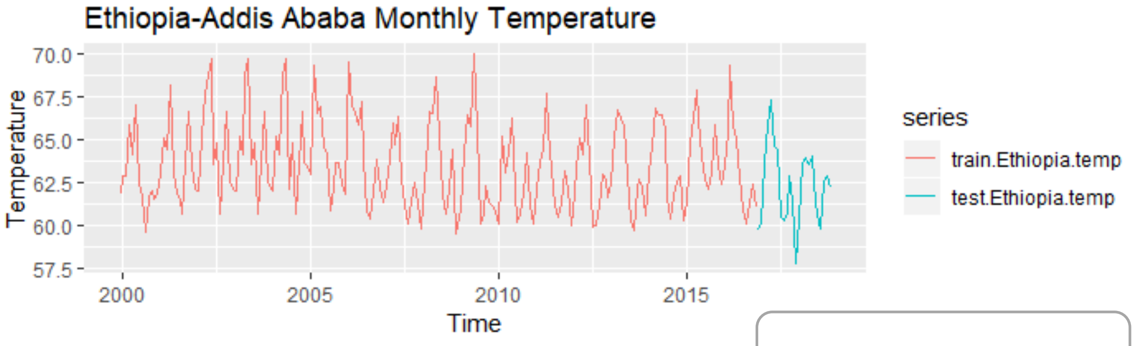


New TS window:

Timeframe: Dec-1999 to Nov-2018 (228 months)

Train: 1999/12 - 2016/11 | **Test:**2016/12 - 2018/11



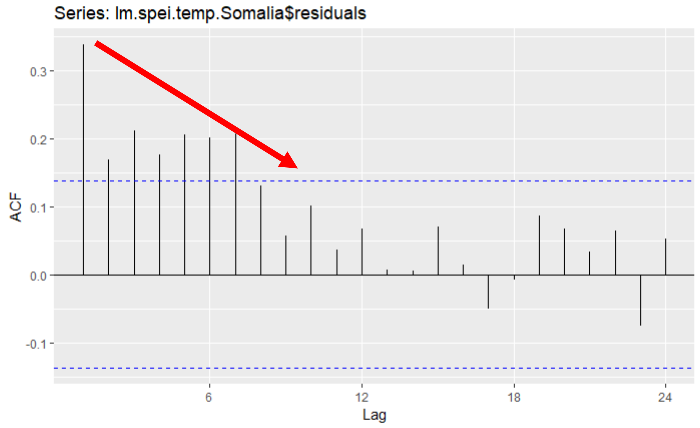


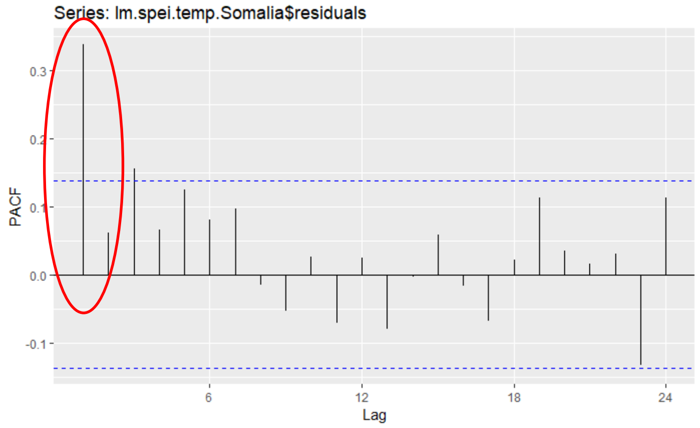
Data are stable

Stationarity Tests	Somalia	Ethiopia
KPSS Test (H0: stationary)	0.1	0.1
ADF Test (H1: stationary)	0.01	0.01

Regression with ARIMA error

SOMALIA (Regression residuals)





AR/MA	0	1	2	3	4	5	6	7	8	9	10	11	12	13
0	x	x	o	o	o	o	o	o	o	o	o	o	o	o
1	x	x	o	o	o	o	o	o	o	o	o	o	o	o

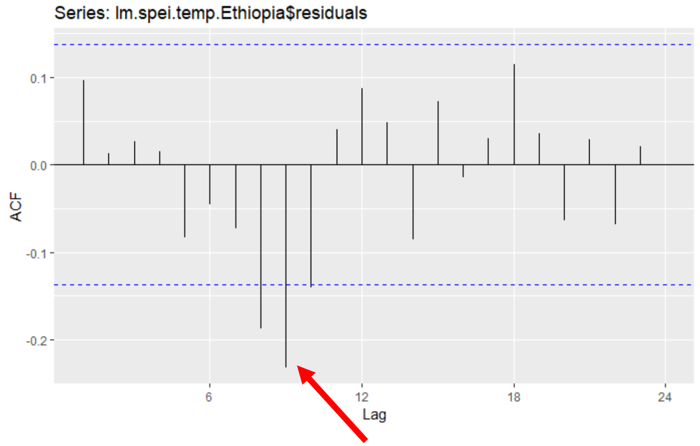
Regression residuals

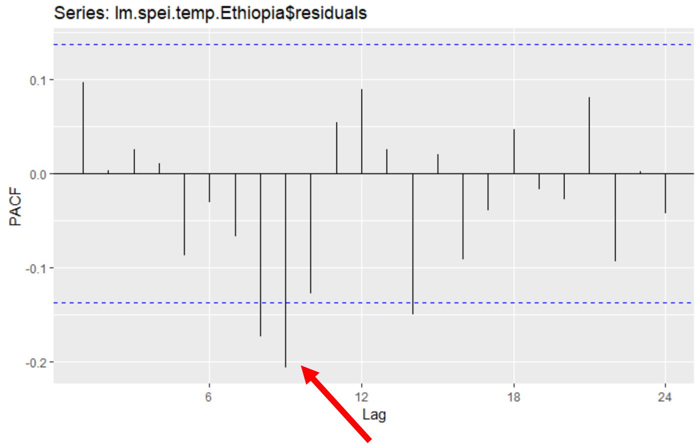
- ACF: slowly decaying
- PACF: clear drop off at lag 1

First-order differencing

Stationarity Tests	Somalia residuals
KPSS Test (H0: stationary)	0.0467
ADF Test (H1: stationary)	0.0174

ETHIOPIA (Regression residuals)





AR/MA	0	1	2	3	4	5	6	7	8	9	10	11	12	13
0	o	o	o	o	o	o	o	x	x	o	o	o	o	o
1	o	o	o	o	o	o	o	o	o	x	o	o	o	o
2	o	x	o	o	o	o	o	o	o	o	o	o	o	o
3	x	x	o	o	o	o	o	o	o	o	o	o	o	o
4	o	x	o	x	o	o	o	o	o	o	o	o	o	o

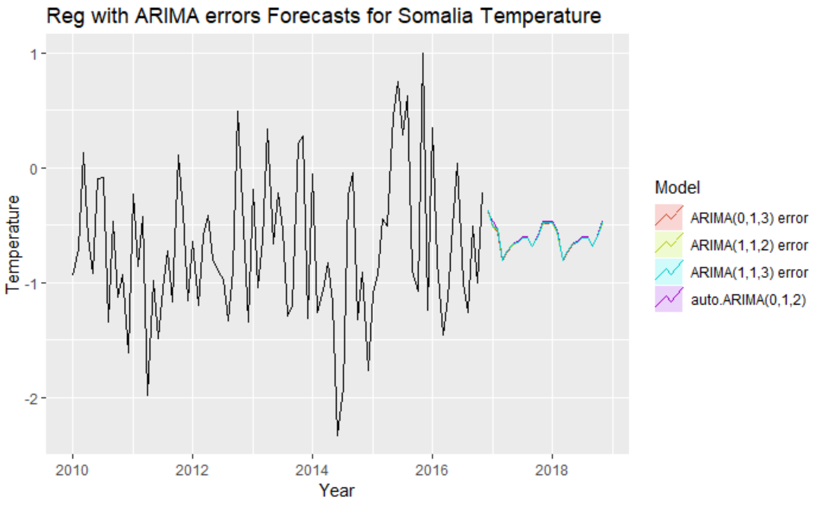
Regression residuals

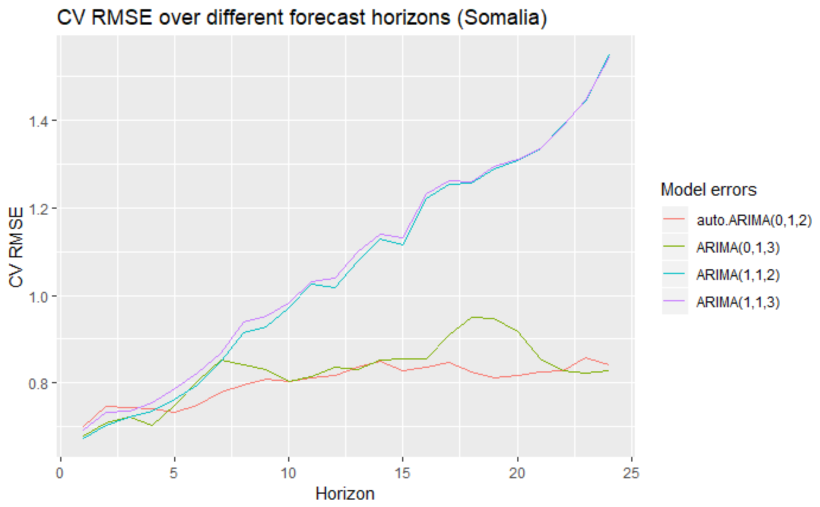
- ACF and PACF show sinusoidal pattern
- No clear drop off or decay

Stationarity Tests	Ethiopia residuals
KPSS Test (H0: stationary)	0.1
ADF Test (H1: stationary)	0.01

Regression with ARIMA error (cont.)

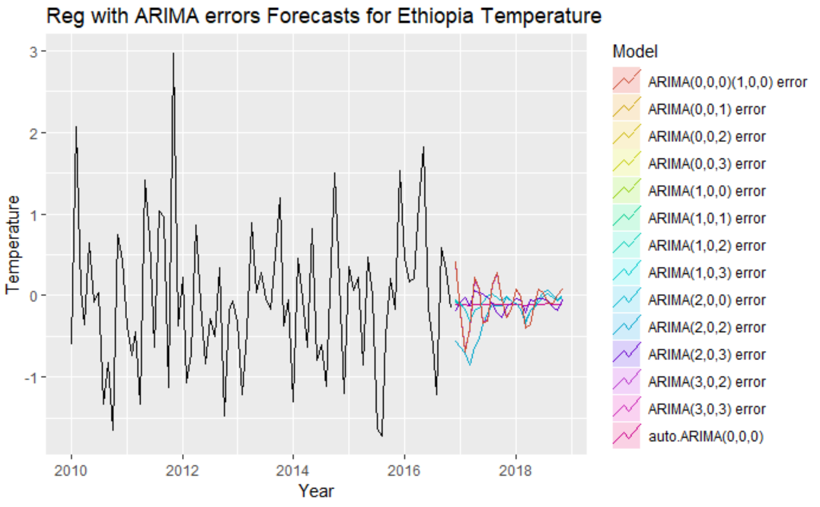
SOMALIA

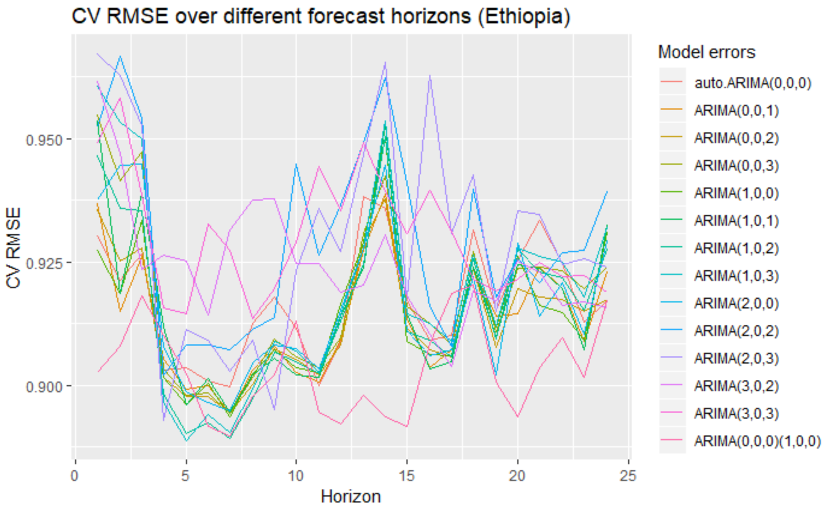




	h=12 (RMSE)	h=24 (RMSE)	AICc
auto ARIMA(0,1,2) error	0.6561	0.6561	415.4093
ARIMA(0,1,3) error	0.6555	0.6555	417.0457
ARIMA(1,1,2) error	0.655	0.655	416.7848
ARIMA(1,1,3) error	0.6549	0.6549	418.8559

ETHIOPIA

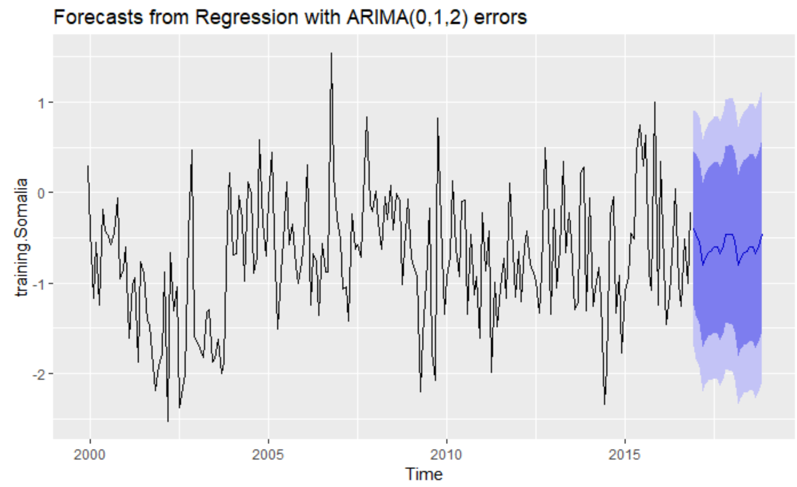


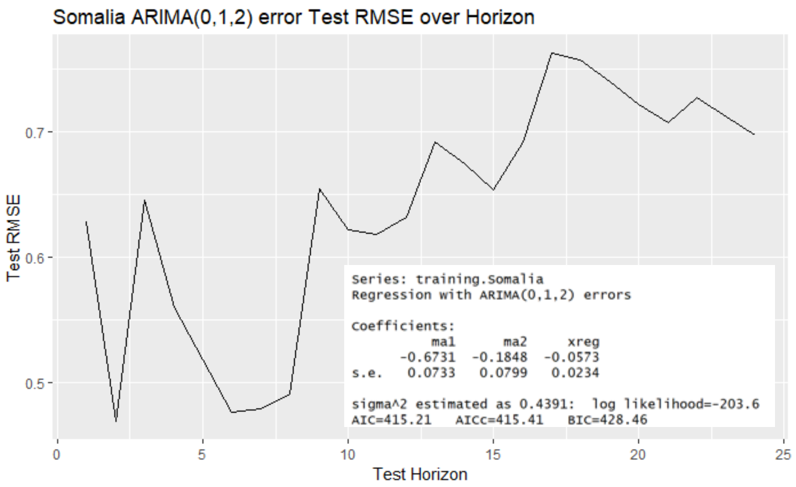


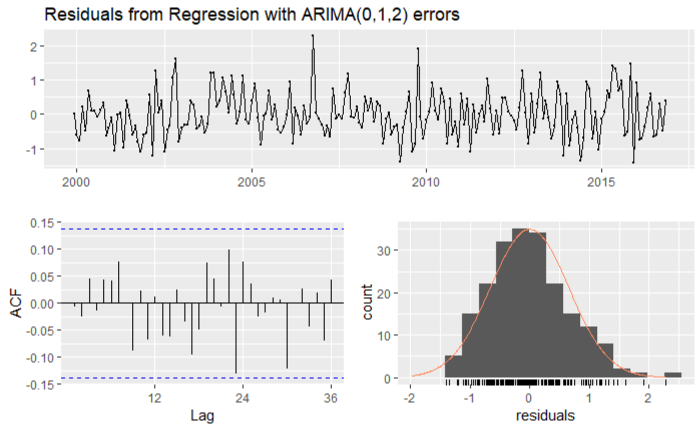
	h=12 (RMSE)	h=24 (RMSE)	AICc
auto ARIMA(0,0,0) error	0.8842	0.8842	532.7804
ARIMA(0,0,1) error	0.8766	0.8766	533.3825
ARIMA(0,0,2) error	0.8765	0.8765	535.4715
ARIMA(0,0,3) error	0.8763	0.8763	537.488
ARIMA(1,0,0) error	0.8765	0.8765	533.3613
ARIMA(1,0,1) error	0.8765	0.8765	535.4599
ARIMA(1,0,2) error	0.8765	0.8765	537.5658
ARIMA(1,0,3) error	0.8762	0.8762	539.6009
ARIMA(2,0,0) error	0.8765	0.8765	535.4616
ARIMA(2,0,2) error	0.8378	0.8378	524.8566
ARIMA(2,0,3) error	0.8635	0.8635	536.2324
ARIMA(3,0,2) error	0.8485	0.8485	532.9033
ARIMA(3,0,3) error	0.8472	0.8472	534.5732
ARIMA(0,0,0)(1,0,0)	0.8549	0.8549	523.6917

Regression with ARIMA error (cont.)

SOMALIA

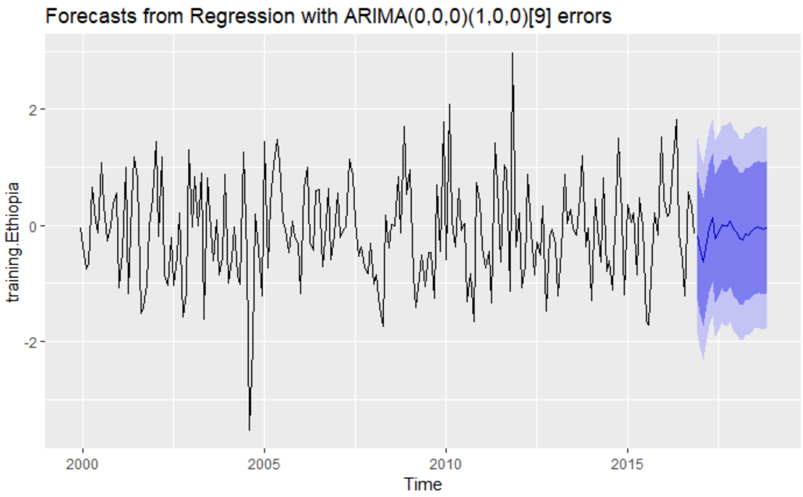


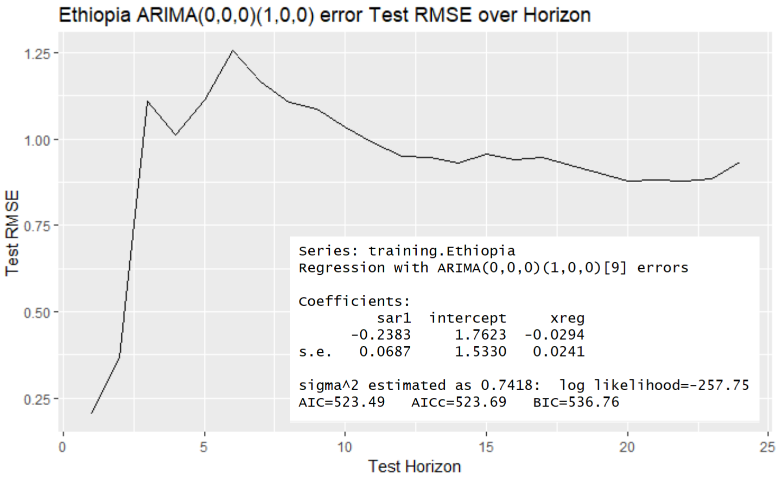





```
Ljung-Box test

data:  Residuals from Regression with ARIMA(0,1,2) errors
Q* = 19.474, df = 21, p-value = 0.5547

Model df: 3.   Total lags used: 24
```

ETHIOPIA





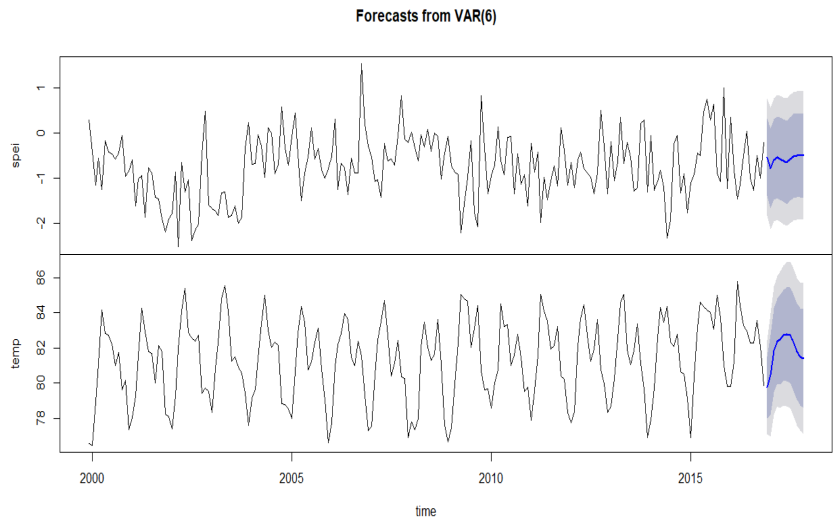

```
Ljung-Box test

data:  Residuals from Regression with ARIMA(0,0,0)(1,0,0)[9] errors
Q* = 27.33, df = 21, p-value = 0.1602

Model df: 3.   Total lags used: 24
```

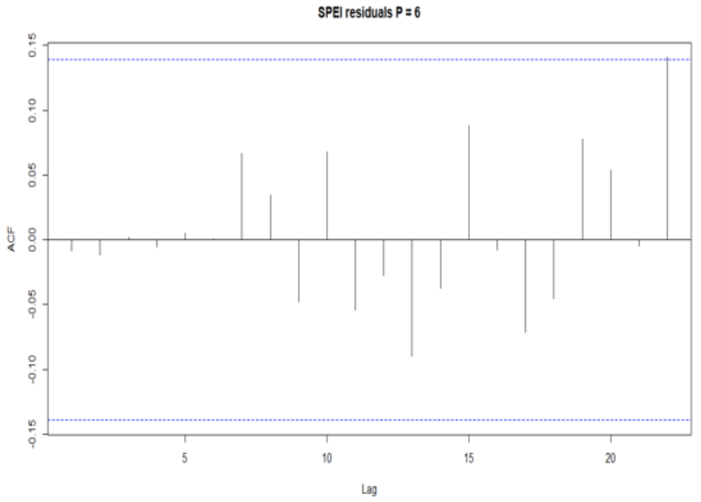
VAR

SOMALIA

```
AIC(n)  HQ(n)  SC(n) FPE(n)
    10      3      2     10
```

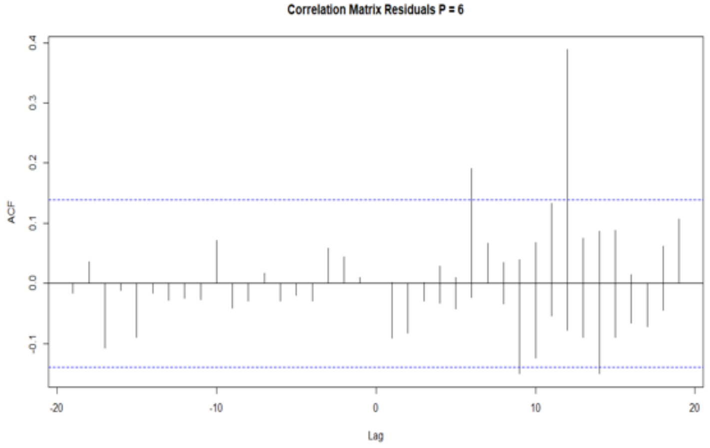
forecast_horiz	12	24
var_model.1	0.6938	0.7044
var_model.2	0.7019	0.6961
var_model.3	0.6845	0.6925
var_model.4	0.6751	0.7017
var_model.5	0.6880	0.6928
var_model.6	0.6717	0.6959
var_model.7	0.6763	0.6986
var_model.8	0.6790	0.7118
var_model.9	0.7030	0.7081






```
Residual standard error: 0.6637 on 184 degrees of freedom
Multiple R-Squared: 0.199,      Adjusted R-squared: 0.1424
F-statistic: 3.516 on 13 and 184 DF,  p-value: 6.516e-05
```

```
Covariance matrix of residuals:
        spei    temp
spei  0.4405  -0.195
temp -0.1950   1.871

Correlation matrix of residuals:
        spei    temp
spei  1.0000 -0.2147
temp -0.2147  1.0000
```



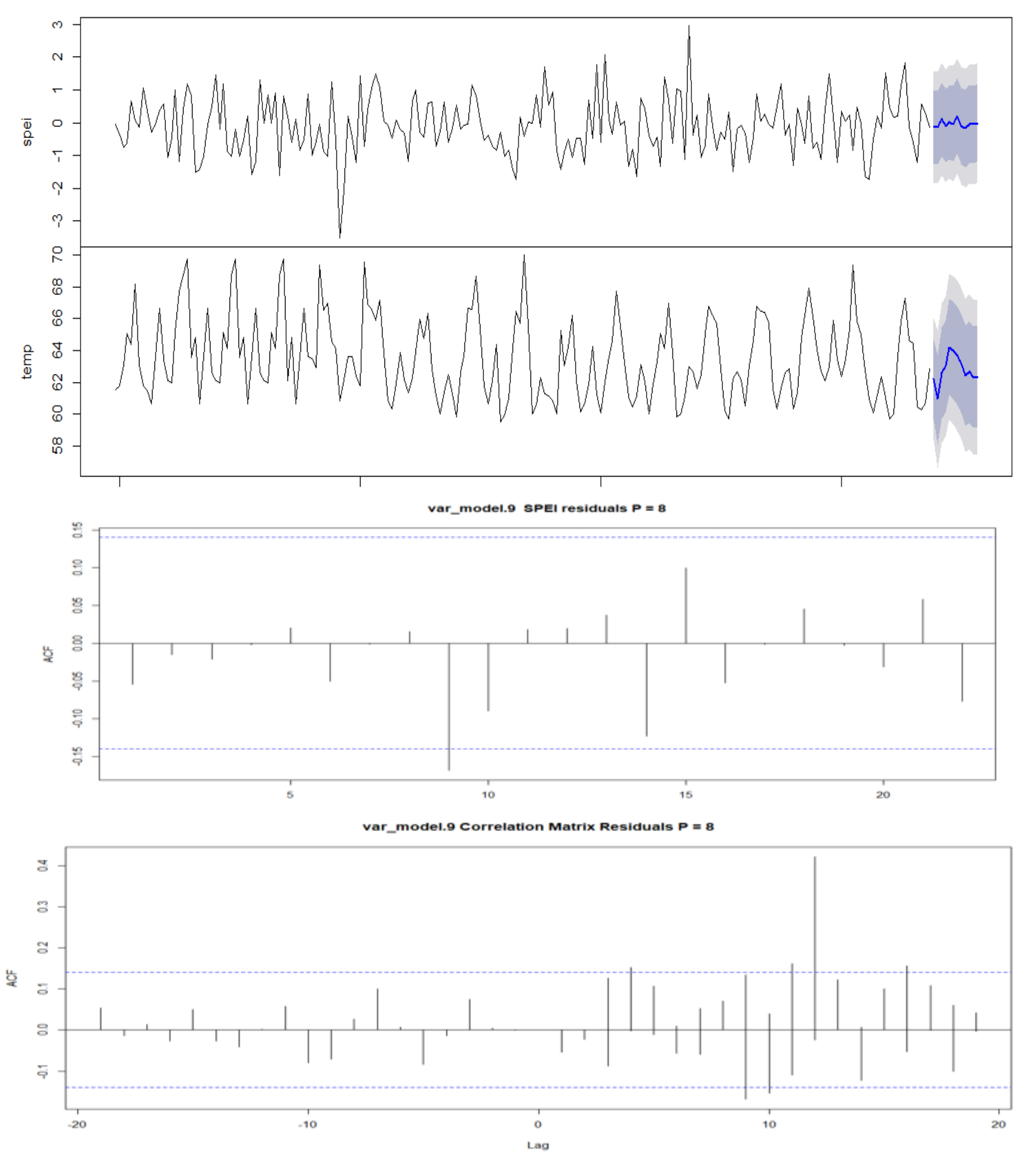
VAR

ETHIOPIA

```
AIC(n)  HQ(n)  SC(n) FPE(n)
     9      2      1      9
```

forecast_horizons	12	24
var_model.1	0.9379	0.9224
var_model.2	0.9390	0.9228
var_model.3	0.9463	0.9264
var_model.4	0.9459	0.9265
var_model.5	0.9645	0.9357
var_model.6	0.9644	0.9374
var_model.7	0.9417	0.9253
var_model.8	0.9172	0.9093
var_model.9	0.9354	0.9109

Forecasts from VAR(8)




```
Residual standard error: 0.867 on 178 degrees of freedom
Multiple R-Squared: 0.1469,     Adjusted R-squared: 0.06542
F-statistic: 1.803 on 17 and 178 DF,  p-value: 0.03063
```

```
Covariance matrix of residuals:
         spei     temp
spei  0.75171 -0.09516
temp -0.09516  3.81798

Correlation matrix of residuals:
         spei     temp
spei  1.00000 -0.05617
temp -0.05617  1.00000
```

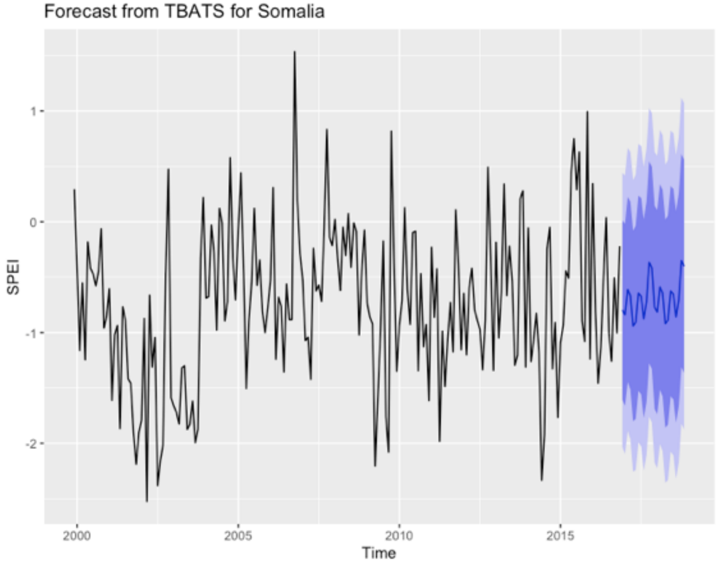
MODELING

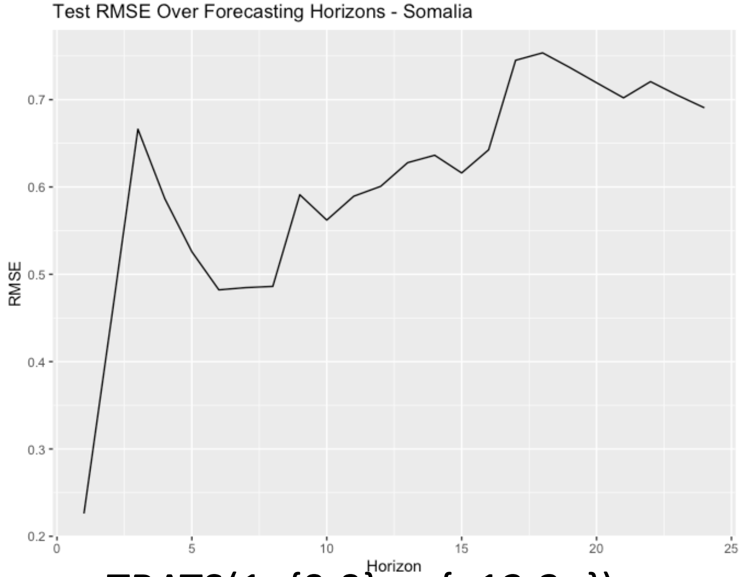
1. Benchmark Models
2. Exponential Smoothing:
    - Simple Exponential Smoothing (SES)
    - ETS
3. ARIMA, sARIMA
4. Spectral Analysis
5. VAR, Regression with ARIMA error
6. **TBATS**
7. Model Selection & Final Predictions

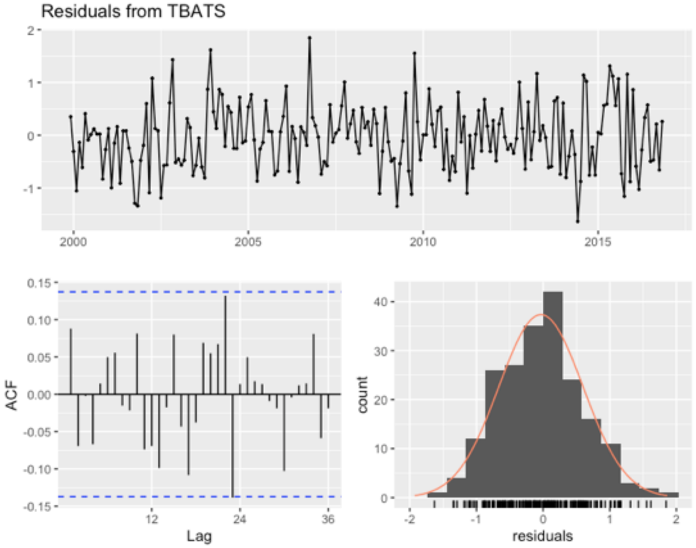
TBATS

SOMALIA

TBATS(1, {0,0}, 0.952, {<12,3>})



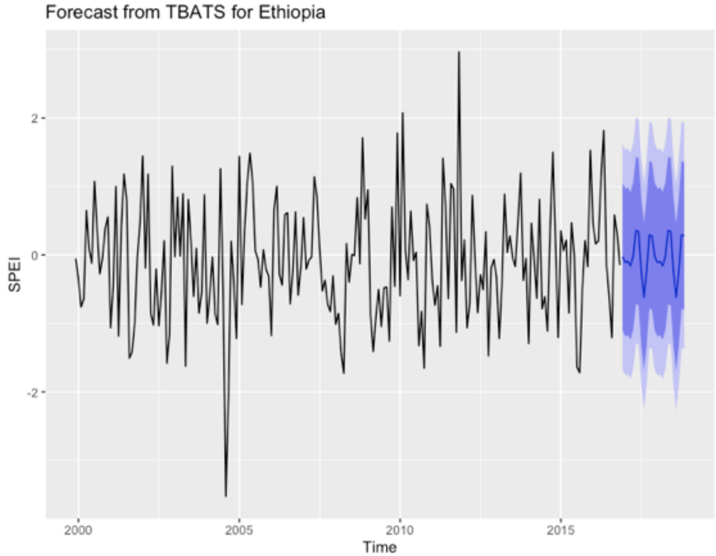


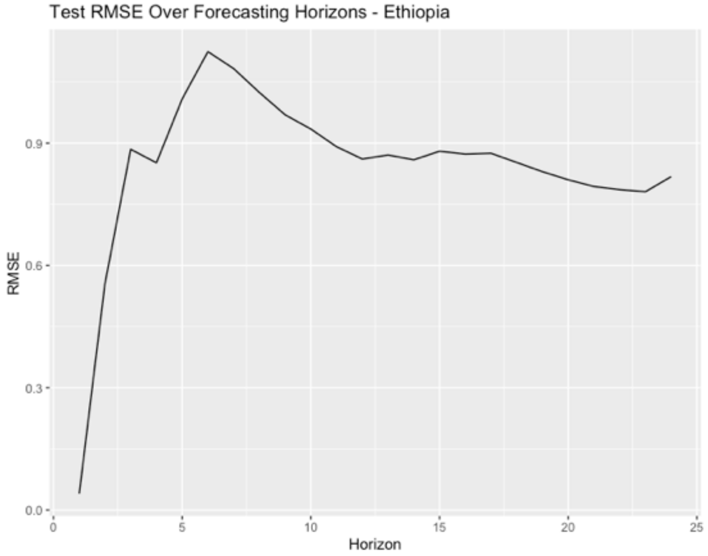


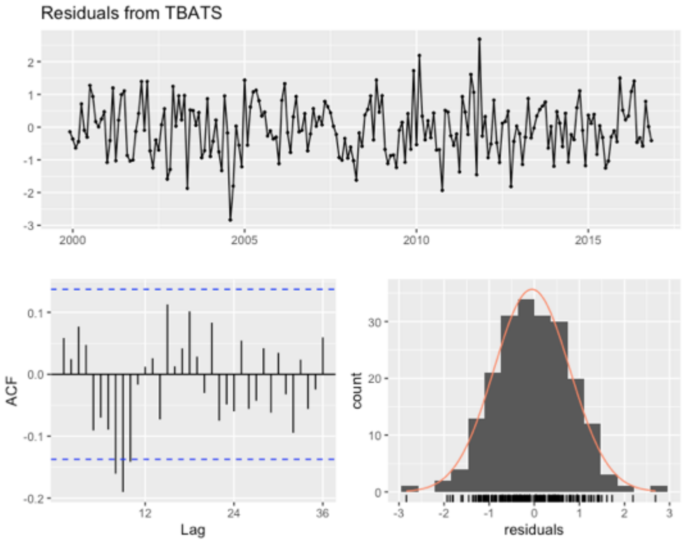
Lambda = 1
Arma Error = {0,0}
Damping = 0.952
Seas. P = 12
Fourier Terms = 3

ETHIOPIA

TBATS(1, {0,0}, -, {<12,3>})







Lambda = 1
Arma Error = {0,0}
Damping = none
Seas. P = 12
Fourier Terms = 3

MODELING

1. Benchmark Models
2. Exponential Smoothing:
    - Simple Exponential Smoothing (SES)
    - ETS
3. ARIMA, sARIMA
4. Spectral Analysis
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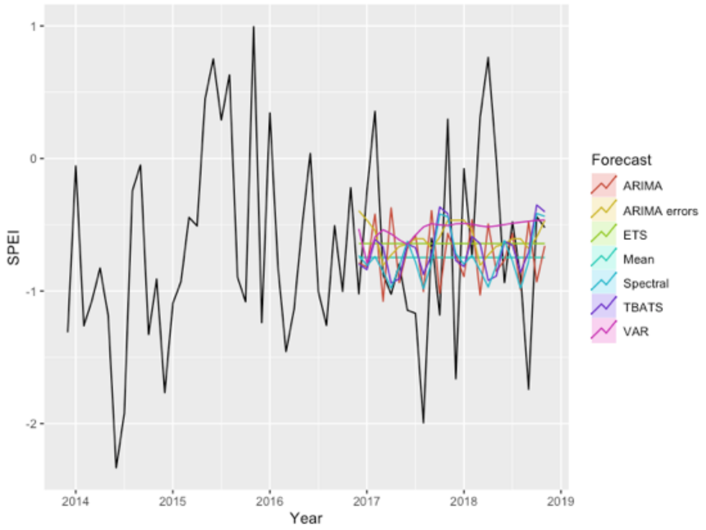
6. TBATS
7. **Model Selection & Final Predictions**

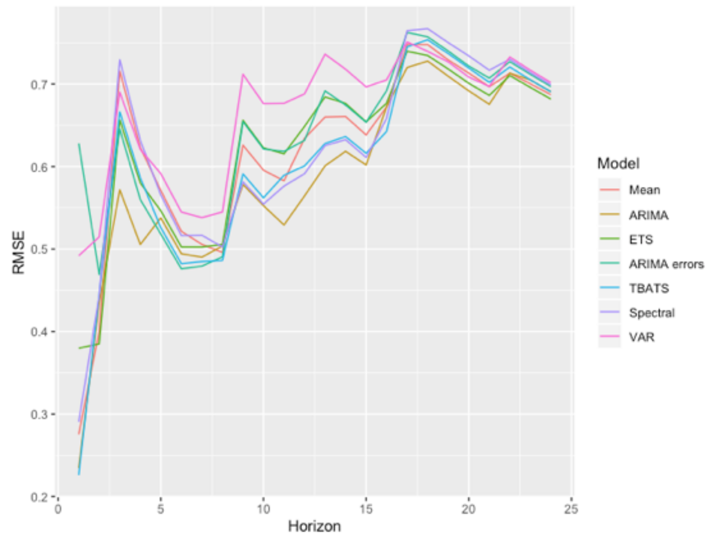
Model Selection

SOMALIA

Best Model Forecasts for Somalia SPEI Value



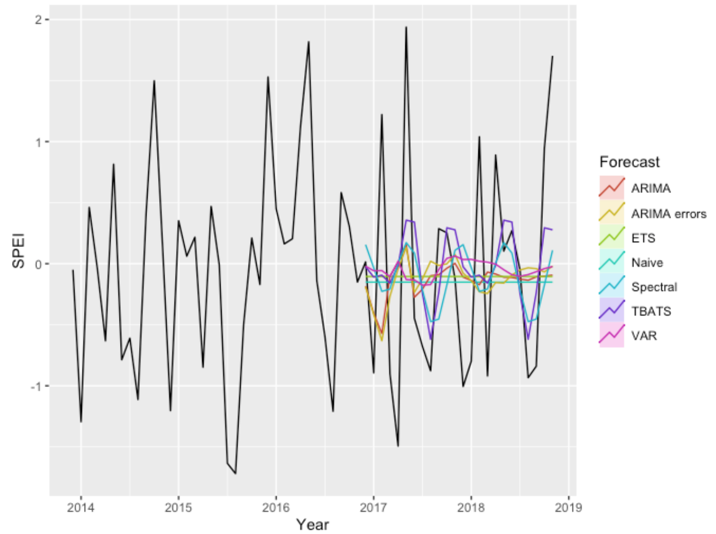
RMSE Over Forecasting Horizons - Somalia



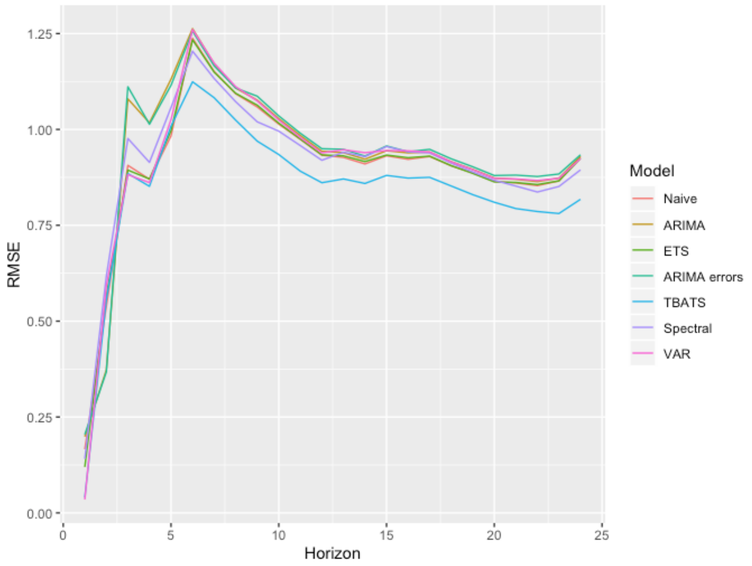
	h=12	h=24	Mean
Mean	0.6341	0.6871	0.6214
ARIMA	0.5644	0.6907	0.5885
ETS	0.6486	0.6817	0.6234
ARIMA errors	0.6318	0.6969	0.6387
TBATS	0.6007	0.6906	0.6059
Spectral	0.5913	0.6991	0.6209
VAR	0.688	0.7017	0.6633

ETHIOPIA

Best Model Forecasts for Ethiopia SPEI Value



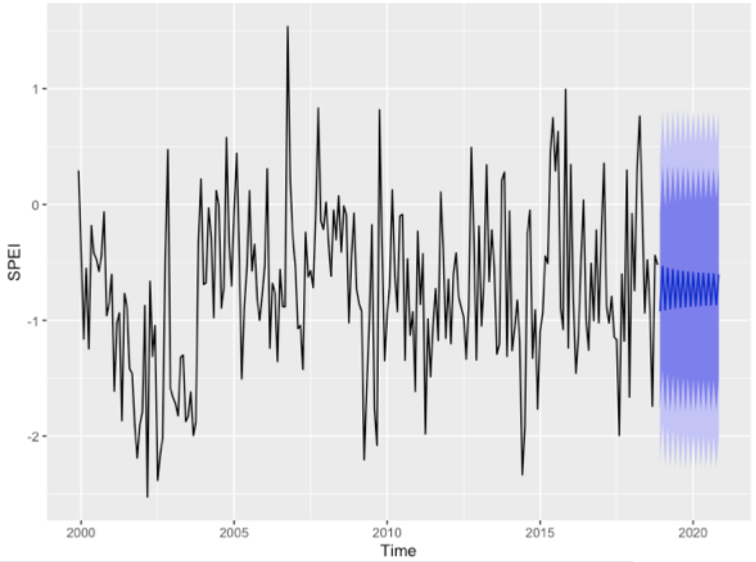
RMSE Over Forecasting Horizons - Ethiopia

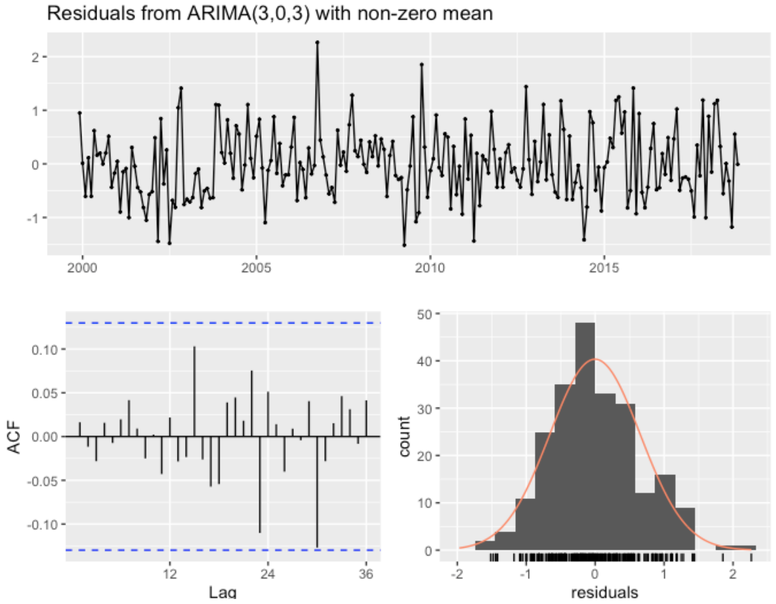


	h=12	h=24	Mean
Naive	0.9328	0.928	0.9045
ARIMA	0.9429	0.9299	0.9283
ETS	0.9335	0.9244	0.9046
ARIMA errors	0.9497	0.9339	0.9338
TBATS	0.861	0.8178	0.844
Spectral	0.9196	0.8945	0.909
VAR	0.9388	0.9239	0.9121

2019-2020 Predictions

SOMALIA





Code	Classes	SPI/SPEI Interval
ew	Extreme wetness	[2, +∞[
sw	Severe wetness	[1.5, 2[
mw	Moderate wetness	[1, 1.5[
n	Normal	[−1, 1[
md	Moderate drought	[−1.5, −1[
sd	Severe drought	[−2, −1.5[
ed	Extreme drought	]−∞, −2[

```
        Ljung-Box test

data:  Residuals from ARIMA(3,0,3) with non-zero mean
Q* = 12.452, df = 17, p-value = 0.7721

Model df: 7.   Total lags used: 24
```

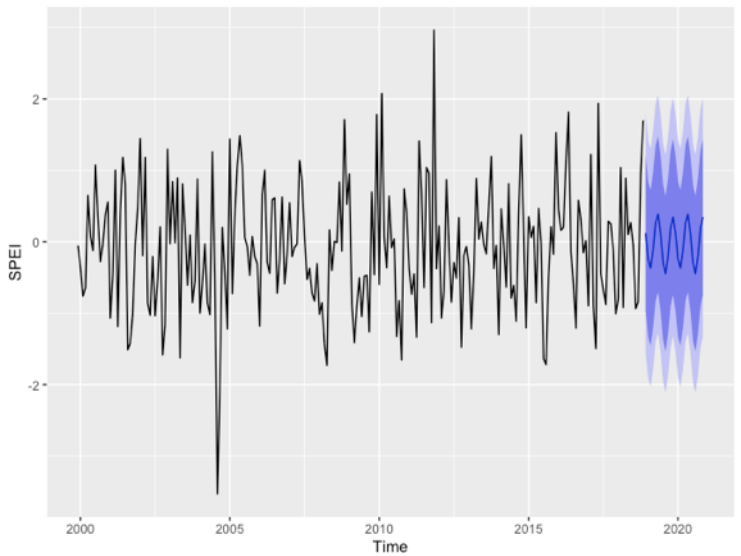
	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Aug 2019	-0.8872	-1.7978	0.0235	-2.2799	0.5056
Aug 2020	-0.868	-1.7846	0.0485	-2.2698	0.5337

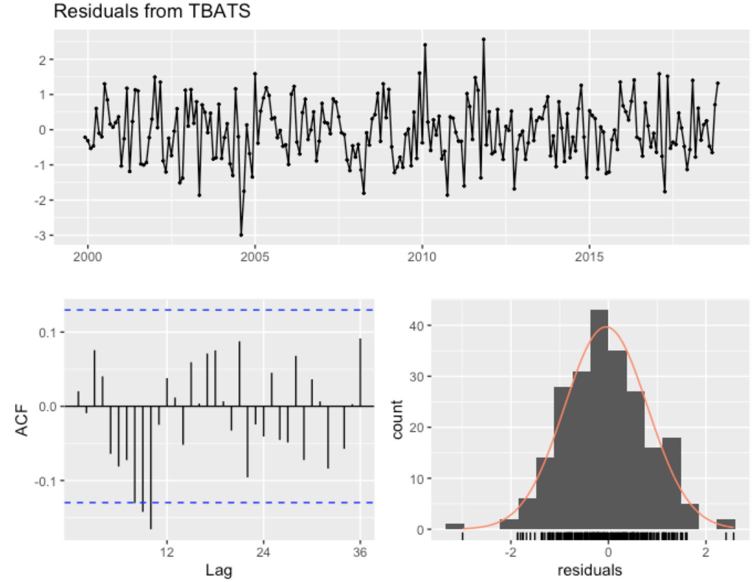
Africa

Severe Drought Puts 2 Million Somalis at Starvation Risk

By Mohamed Sheikh Nor
May 28, 2019 01:02 PM

ETHIOPIA





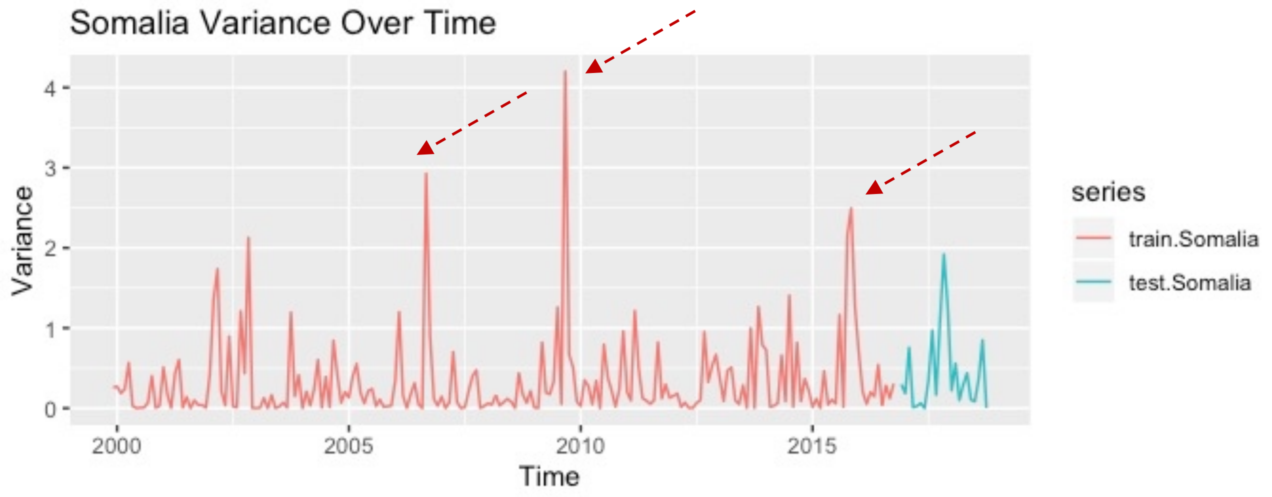

```
        Ljung-Box test

data:  Residuals from TBATS
Q* = 31.024, df = 16, p-value = 0.01336

Model df: 8.   Total lags used: 24
```

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Aug 2019	-0.4446	-1.5327	0.6435	-2.1087	1.2195
Aug 2020	-0.4446	-1.5337	0.6445	-2.1103	1.2211

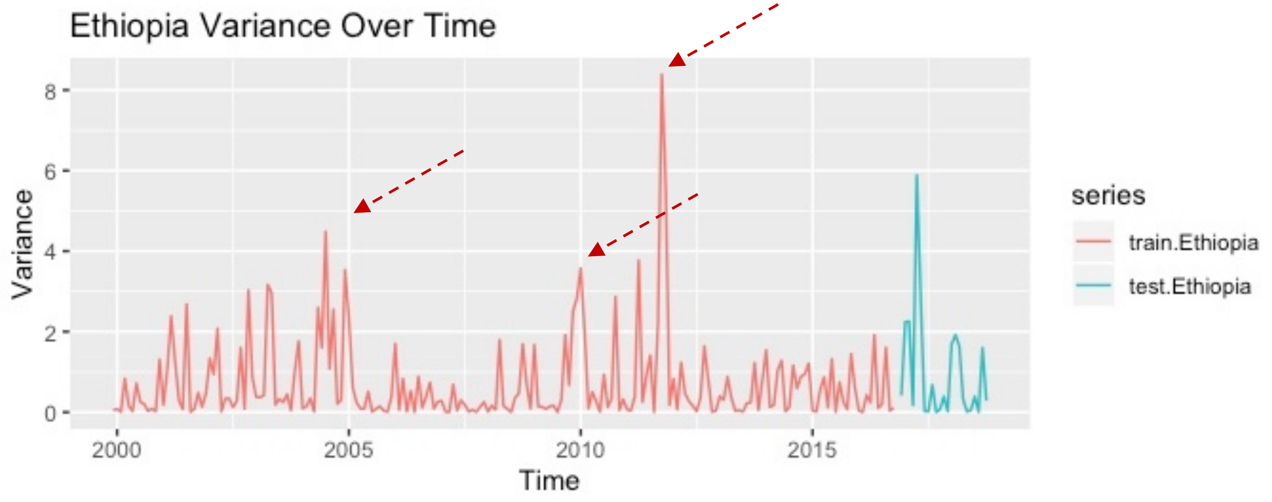
ARCH/GARCH

Variance Over Time

SOMALIA



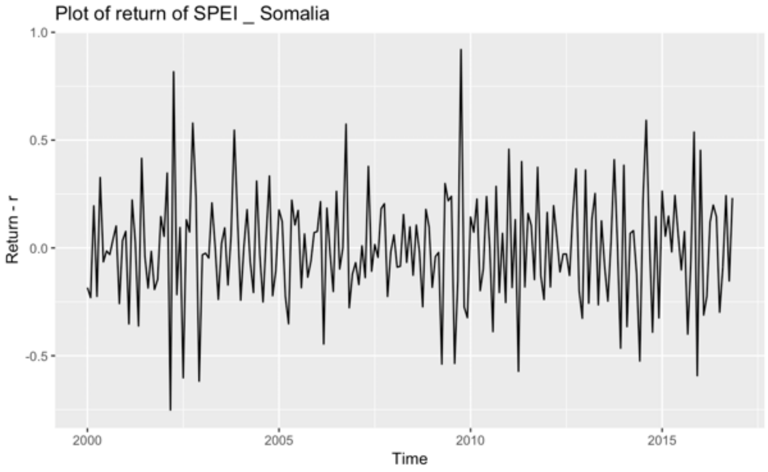
ETHIOPIA



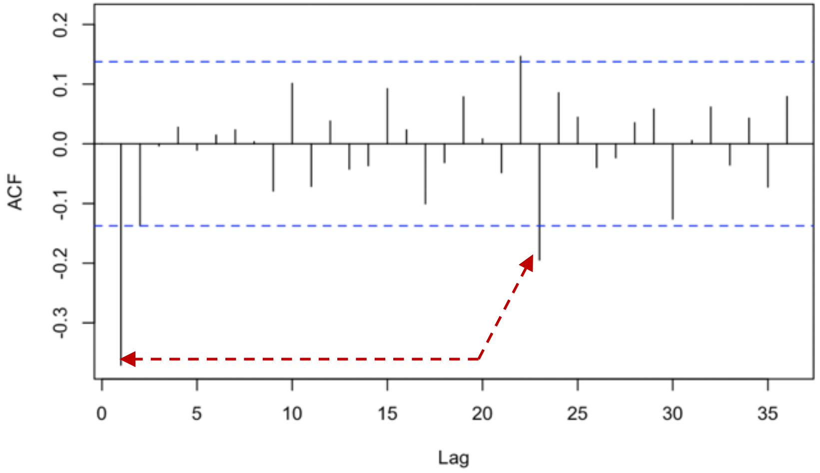
High variance of SPEI in both Somalia and Ethiopia over the period suggests that ARCH/ GARCH model would be a good choice in forecasting drought.

ARCH/GARCH – Somalia

SOMALIA



ACF PLOT




```
        Box-Ljung test

data:  return_S
X-squared = 28.352, df = 1, p-value = 1.012e-07
```

ARIMA

```
Call:
arima(x = return_S, order = c(1, 0, 0), method = "CSS")

Coefficients:
          ar1  intercept
      -0.3724    -0.0003
s.e.   0.0652     0.0124

sigma^2 estimated as 0.05874:  part log likelihood = -0.33
```

GARCH(1,1)

```
Call:
garch(x = return_S, order = c(1, 1))

Model:
GARCH(1,1)

Residuals:
     Min       1Q   Median       3Q      Max
-2.93084 -0.67511  0.01416  0.65600  3.23208

Coefficient(s):
    Estimate  Std. Error  t value Pr(>|t|)
a0   0.01910     0.01207    1.583  0.11344
a1   0.14702     0.08088    1.818  0.06911 .
b1   0.57499     0.21834    2.633  0.00845 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

The Ljung-Box test indicates that the return is not white noise, which is serially correlated and predictable. ARCH(1) model essentially regress r onto its 1st lag.

```
Diagnostic Tests:
        Jarque Bera Test

data:  Residuals
X-squared = 1.3773, df = 2, p-value = 0.5023
```

Accept the null hypothesis that the conditional distribution of the return is normal distribution

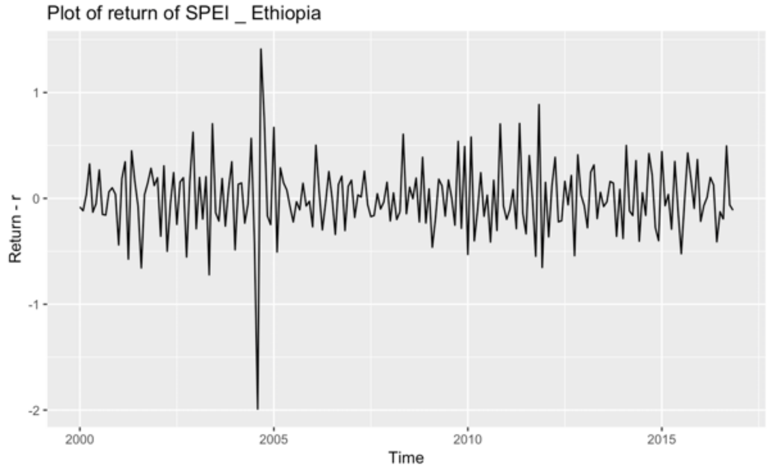
Overall, the return of SPEI in SOMALIA follows an GARCH(1,1) process.

```
        Box-Ljung test

data:  Squared.Residuals
X-squared = 1.9471e-05, df = 1, p-value = 0.9965
```

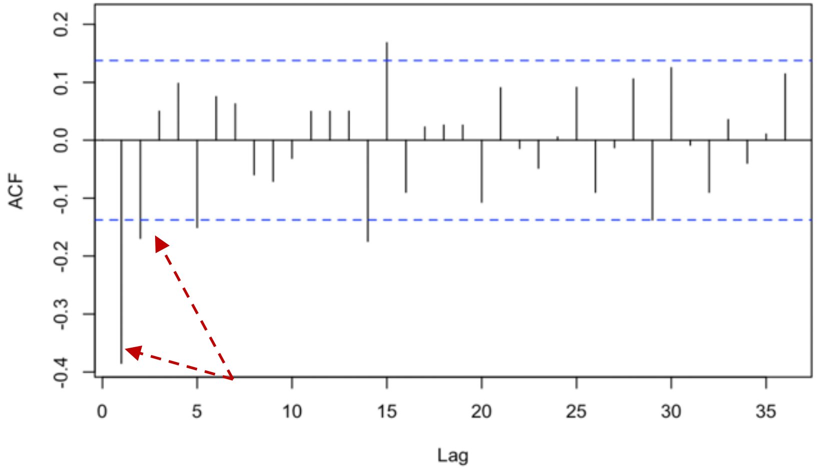
ARCH(1) model is adequate with white noise error

ARCH/GARCH – Ethiopia

ETHIOPIA



ACF PLOT




```
        Box-Ljung test

data:  return_E
X-squared = 30.536, df = 1, p-value = 3.277e-08
```

ARIMA

```
Call:
arima(x = return_E, order = c(1, 0, 0))

Coefficients:
          ar1  intercept
      -0.3834     0.0001
s.e.   0.0646     0.0162

sigma^2 estimated as 0.102:  log likelihood = -56.38,  aic = 116.77
```

GARCH(1,1)

```
Call:
garch(x = return_E, order = c(1, 1))

Model:
GARCH(1,1)

Residuals:
    Min      1Q  Median      3Q     Max 
-4.9157 -0.6252 -0.0659  0.6145  2.3306 

Coefficient(s):
    Estimate  Std. Error  t value Pr(>|t|)    
a0   0.04010     0.01807    2.219 0.026459 *  
a1   0.37516     0.10385    3.612 0.000303 ***
b1   0.32148     0.19838    1.621 0.105119    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

The Ljung-Box test indicates that the return is not white noise, which is serially correlated and predictable. ARCH(1) model essentially regress r onto its 1st lag.

```
Diagnostic Tests:
        Jarque Bera Test

data:  Residuals
X-squared = 43.956, df = 2, p-value = 2.851e-10
```

Rejects the null hypothesis that the conditional distribution of the return is normal distribution

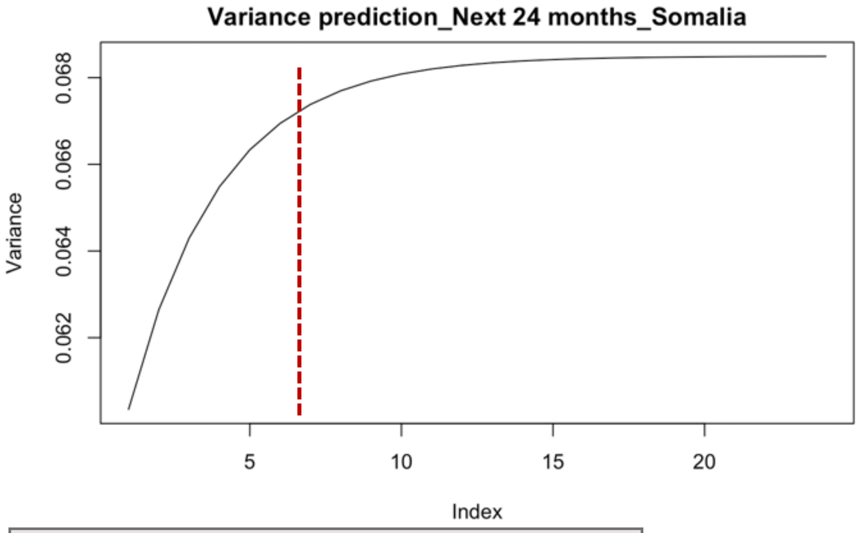
```
        Box-Ljung test

data:  Squared.Residuals
X-squared = 0.059288, df = 1, p-value = 0.8076
```

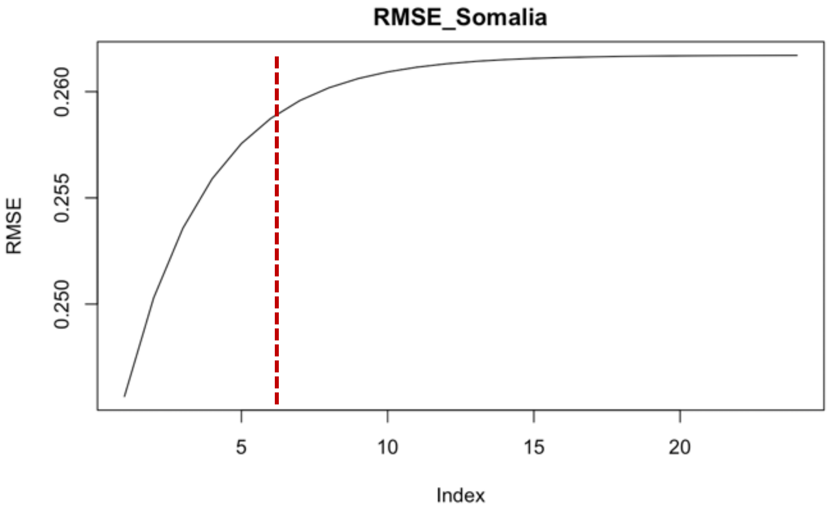
ARCH(1) model is adequate with white noise error

Overall, the return of SPEI in ETHIOPIA follows an ARCH(1) process.

ARCH/GARCH – Forecasting

SOMALIA

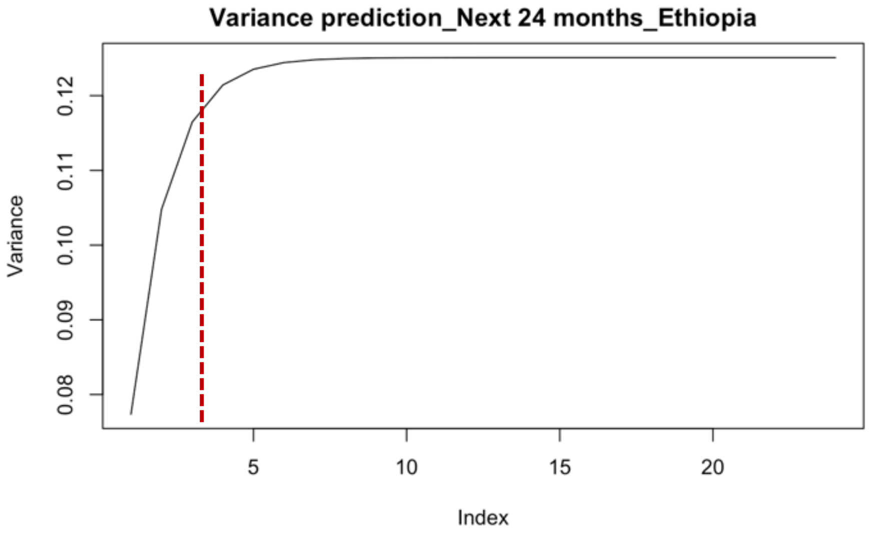


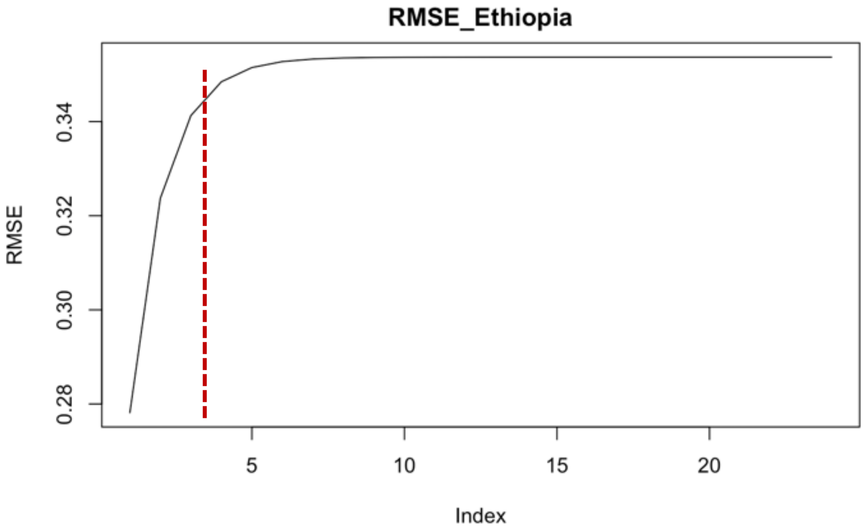


Dataset_Somalia <fctr>	Variance <fctr>
Training	0.0683
Test	0.092

In the long term, the variances converge to the mean of the variance of the unconditional variance.

ETHIOPIA





Dataset_Ethiopia <fctr>	Variance <fctr>
Training	0.1203
Test	0.1287

CONCLUSION & FUTURE WORK

Conclusion & Future Work

Best models:

- Somalia: ARIMA(3,0,3)
- Ethiopia: TBATS

Why is forecasting SPEI difficult?

- SPEI patterns are close to white noise
- Weather patterns are some of the most complex & difficult to model
- SPEI index is composed multiple attributes, each of which is prone to external influences

What future work is needed?

- Get more/better cross-sectional data to improve explanatory power
- Model SPEI for more regions in the world to see what models apply to different environments


THANK YOU!

APPENDIX

References

- Temperature Data:
  - https://www7.ncdc.noaa.gov/CDO/cdoselect.cmd
- SPEI Data
  - https://spei.csic.es
- Conflict/Fatalities Data
  - https://www.acleddata.com/data/
- Food Price Data
  - https://data.humdata.org/group/som
  - https://data.humdata.org/group/eth
- Visuals
  - https://reliefweb.int/sites/reliefweb.int/files/resources/HoA_Humanitarian_Snapshot_21June2019f.pdf
  - https://reliefweb.int/sites/reliefweb.int/files/resources/HOA_drought_updates_snapshot_Mar2017_latest.pdf
  - https://reliefweb.int/sites/reliefweb.int/files/resources/HOA_drought_updates_snapshot_Nov032017.pdf