Modeling precipitation patterns in South America due to the impact of water availability on crop yields

Final Project for ENV797: Time Series Analysis

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April 25, 2025

Introduction

This final project uses time series analysis to better understand changes in precipitation patterns in Argentina, Brazil, and Colombia, as we were interested in the continent of South America and these three countries are major agricultural producers of key crops globally. For context, Brazil and Argentina are two of the largest soybean producers in the world, with April 2025 estimates placing Brazil at producing 152 million tonnes—the largest soybean producer among Agricultural Market Information System (AMIS) countries—and Argentina producing 48.21 million tonnes—the third-largest soybean producing AMIS country—in 2023/2024, respectively (AMIS, 2025). For reference, the United States produced 113.27 million tonnes of soybean in 2023/2024 (AMIS, 2025). In terms of soybean exports, Brazil leads by far and Argentina comes in fourth among AMIS countries (AMIS, 2025). Colombia is a leading producer of coffee, bananas, flowers, rice, maize, palm oil, and more (Santana, n.d.). Brazil is also a leading producer of coffee, sugarcane, and corn, among other crops (IFAD, n.d. a.). In addition to soybeans, Argentina is a leading producer of wheat, corn, and wine, among other crops (ITA, 2022).

Motivation

Since in 2023 agriculture represented 7% of GDP in Argentina, 6.2% in Brazil, and 8.7% in Colombia, this group was interested in factors that could have a major impact on crop yield, one of which is precipitation (IFAD, n.d. b.). Not only is global supply of a crop like soybean partially dependent on crop yields in Brazil and Argentina, for example, but within Argentina, Brazil, and Colombia, crop production impacts the labor force, too. In Colombia, for instance, agriculture accounts for 16% of employment (IFAD, n.d. b.). In terms of the motivation behind looking into precipitation data, specifically, over 39 million hectares of land in Argentina are cultivated for farming and ranching, while only 5% of these lands have irrigation systems (ITA, 2022). As water availability is key to food production (FAO, 2015), precipitation variability can very crucially impact agricultural planning.

Relevance

Questions around changing precipitation patterns are particularly relevant given changing frequency and intensity of precipitation due to global warming (Myhre et al., 2019). The IPCC warns that rarer extreme precipitation events will become more frequent with more global warming (Seneviratne et al., 2021). The Food and Agriculture Organization has highlighted the importance of understanding "spatial changes in precipitation, in intensity and seasonal distribution" (FAO, 2015). Precipitation variability differs significantly by region. Understanding regional differences can help develop targeted adaptation strategies for, it is hoped, a more secure food system.

Objectives

Given data availability and the scope of this project, we evaluate the performance of different models used for time series analysis in fitting precipitation data for Brazil, Argentina, and Colombia, at the country level. The objectives are to determine: Using a training set of historical values and testing against more recent values, which model best fits and forecasts precipitation data for Brazil, Argentina, and Colombia? Is the magnitude of seasonality changing over time? The latter question is a question of interest in relation to the IPCC findings that extreme precipitation events will be increasing in frequency and intensity, with complex spatial distributions (Seneviratne, 2021).

Dataset information

The dataset utilized was produced by the University of East Anglia's Climate Research Unit (University of East Anglia - Climatic Research Unit, 2025). The first iteration of this data was published in 2000, and it has been continuously updated and upgraded since. The most recent version was updated just recently on March 19th of 2025, and it includes a high resolution, monthly 0.5 degree latitude by 0.5 degree longitude grid of land based observations from 1901 to 2024. They look at 10 different variables: Mean 2m temperature, diurnal 2m temperature range, precipitation rate, vapor pressure, wet days, cloud cover, frost days, minimum 2m temperature, maximum 2m temperature, and potential evapo-transpiration. Due to the relationship between crop yields and precipitation, and the importance of the agricultural sector in Brazil, Argentina, and Colombia, this report focused on the precipitation variable. The precipitation data was separated and imported to R studio in an Excel file: this initial data included monthly precipitation, seasonal values (MAM - spring, JJA -summer, SON - autumn, DJF - winter), and annual precipitation.

Methods

Data Processing & Time Series Creation An initial search of the data was conducted to identify any missing values. Only the "DJF" column had one missing value—an NA. This NA was filled using the DJF column means for the sake of continuity, but the DJF column ended up not being utilized in the processes. Instead, monthly precipitation values were utilized, since this provided the most accurate depiction of seasonal patterns and additional trends. To format the data, the monthly precipitation columns and their dates were selected, and pivot_longer() was used to reshape the data so that there was a Date column including both month and year, which allowed for a chronological precipitation column. This reshaped dataset was exported as countrymonthly_data_long.csv. Using this cleaned data, a univariable monthly time series object beginning in January 1901 with a frequency of 12 was created.

Table 1: First 10 Rows of Monthly Precipitation Data for Colombia

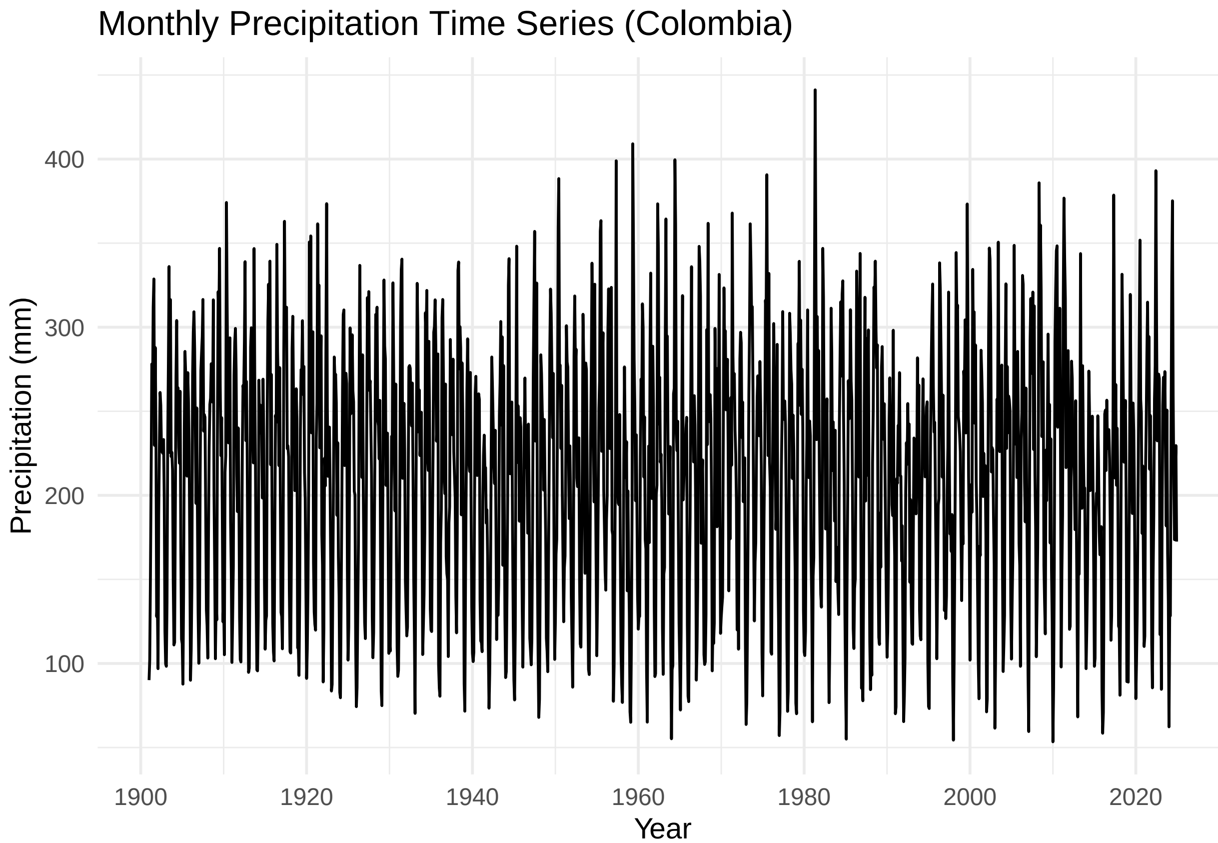
Month_Num	Date	YEAR	Month	Precipitation
1	1901-01-01	1901	JAN	90.1
2	1901-02-01	1901	FEB	102.2
3	1901-03-01	1901	MAR	150.7
4	1901-04-01	1901	APR	209.3
5	1901-05-01	1901	MAY	278.1
6	1901-06-01	1901	JUN	255.6
7	1901-07-01	1901	JUL	311.9
8	1901-08-01	1901	AUG	328.7
9	1901-09-01	1901	SEP	229.7
10	1901-10-01	1901	OCT	287.9

Table 2: First 10 Rows of Monthly Precipitation Data for Brazil

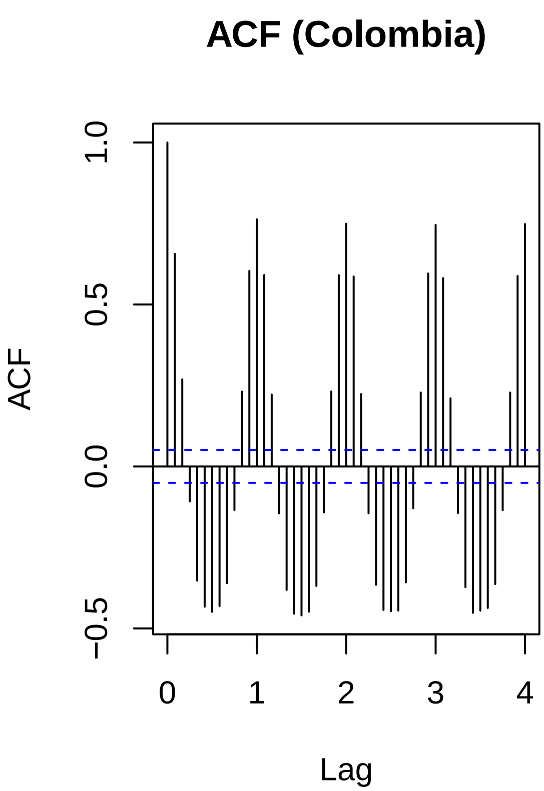
Month_Num	Date	YEAR	Month	Precipitation
1	1901-01-01	1901	JAN	235.7
2	1901-02-01	1901	FEB	223.9
3	1901-03-01	1901	MAR	241.0
4	1901-04-01	1901	APR	181.4
5	1901-05-01	1901	MAY	129.0
6	1901-06-01	1901	JUN	81.9
7	1901-07-01	1901	JUL	73.6
8	1901-08-01	1901	AUG	58.7
9	1901-09-01	1901	SEP	77.1
10	1901-10-01	1901	OCT	116.6

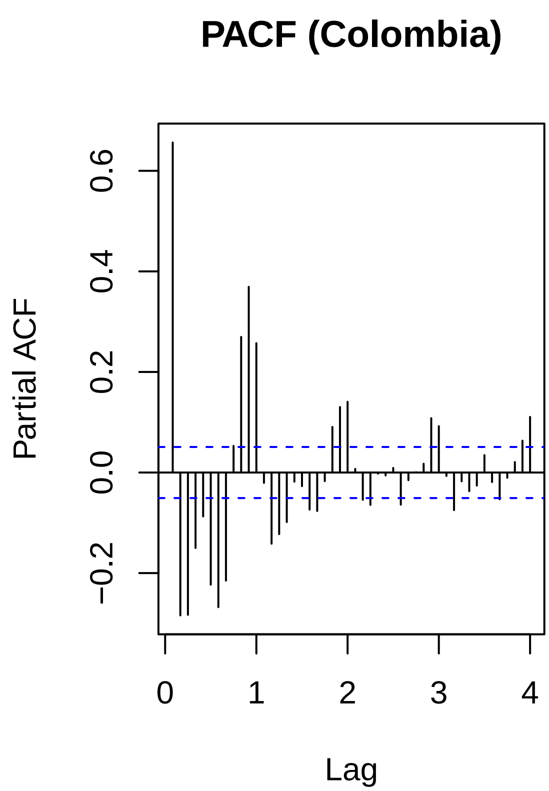
Exploratory Analysis - Plots, ACF, PACF

To visualize the data, a plot of the time series object was created for each country, and this was followed by an exploration of its patterns and autocorrelation using ACF and PACF. This information was helpful in deciding which models to use, as it provided information on the seasonality and auto regression.


Monthly Precipitation Time Series (Colombia)
Precipitation (mm)
100
200
300
400
1900
1920
1940
1960
1980
2000
2020
Year

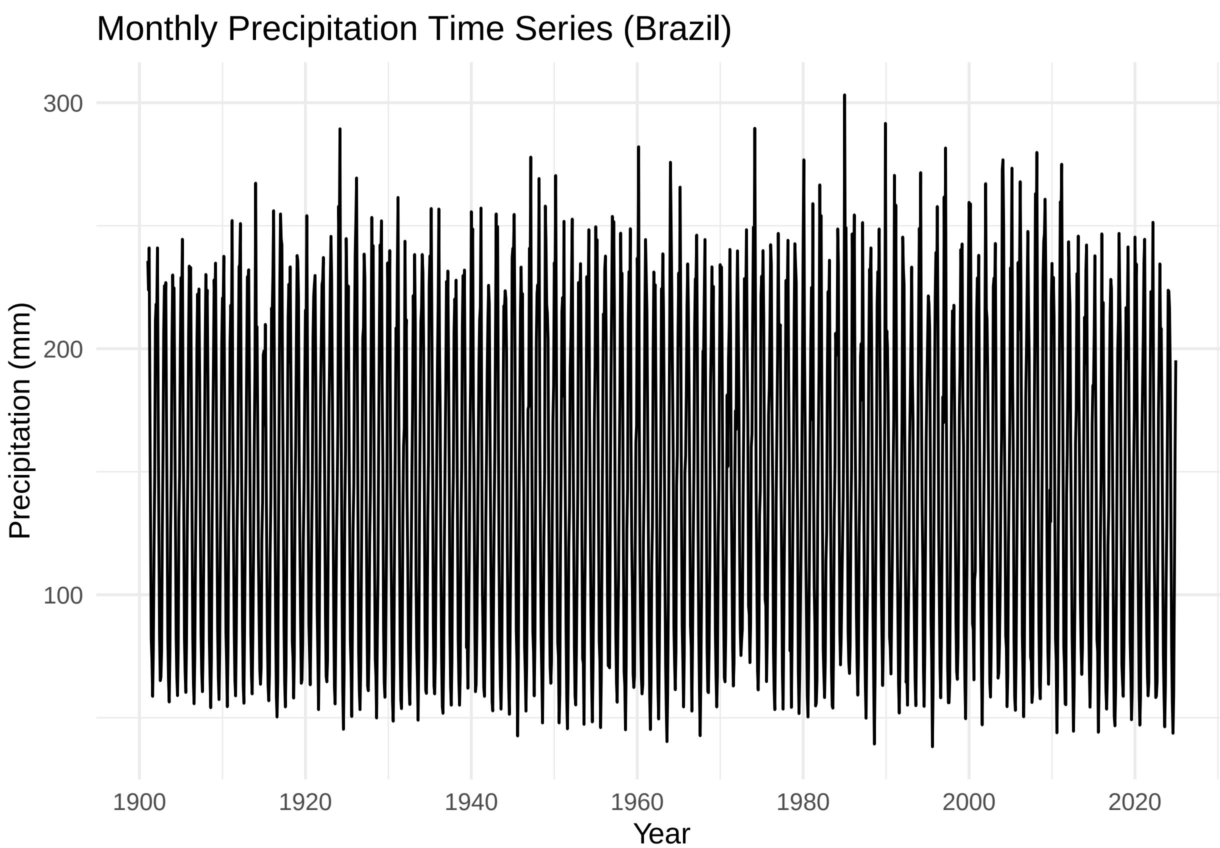
Colombia


ACF (Colombia)
ACF
−0.5
0.0
0.5
1.0
0
1
2
3
4
Lag


PACF (Colombia)
Partial ACF
−0.2
0.0
0.2
0.4
0.6
0
1
2
3
4
Lag

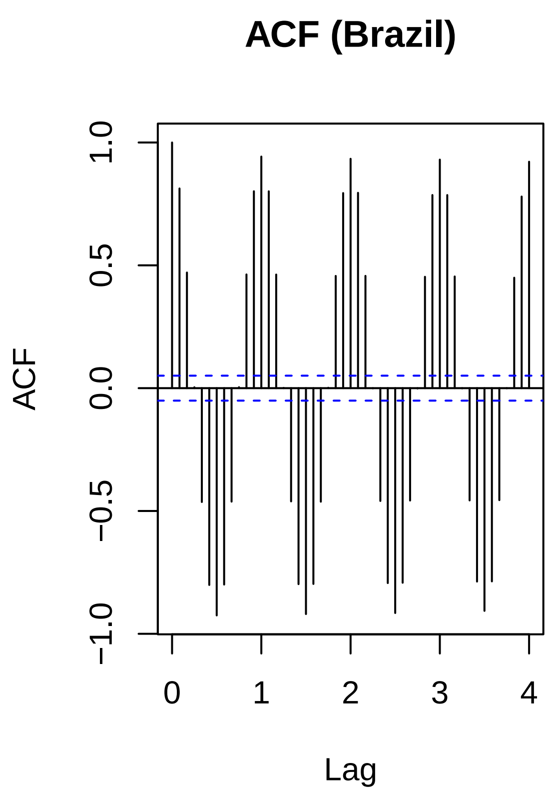
The time series graph seems to show seasonality as there are visible peaks and troughs, consistent with a seasonal climate.There's no clear upward or downward trend, suggesting the mean precipitation level has remained relatively stable over time. Moreover, although there's variation in the amplitude showing more extreme years, this doesn't appear to be systematically increasing or decreasing.

The ACF shows a wave like pattern, and the significant autocorrelation at multiple repetitive lags suggests strong seasonality, likely due to Colombia's bi-modal rainy seasons. The PACF has a significant spike at lag 1 and smaller spikes at subsequent lags, suggesting a short-term auto regressive (AR) component, where current precipitation is influenced by the previous month or two.

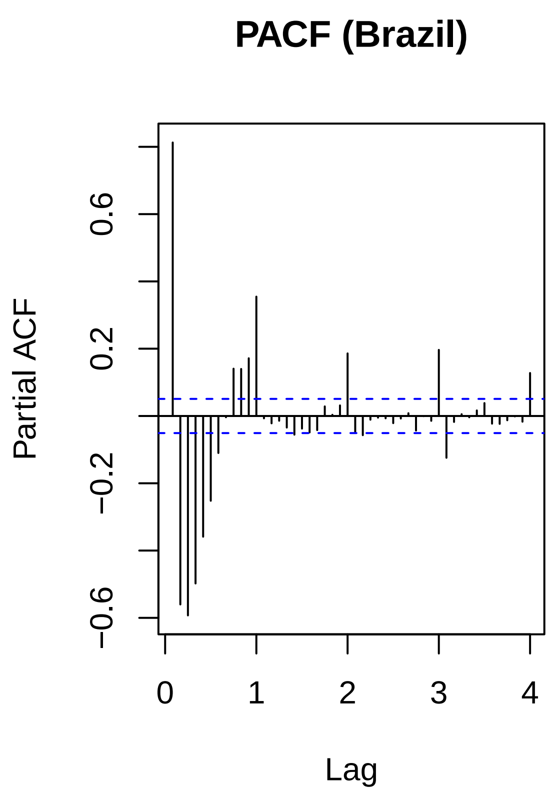


Monthly Precipitation Time Series (Brazil)
300
200
100
Precipitation (mm)
1900
1920
1940
1960
1980
2000
2020
Year

Brazil

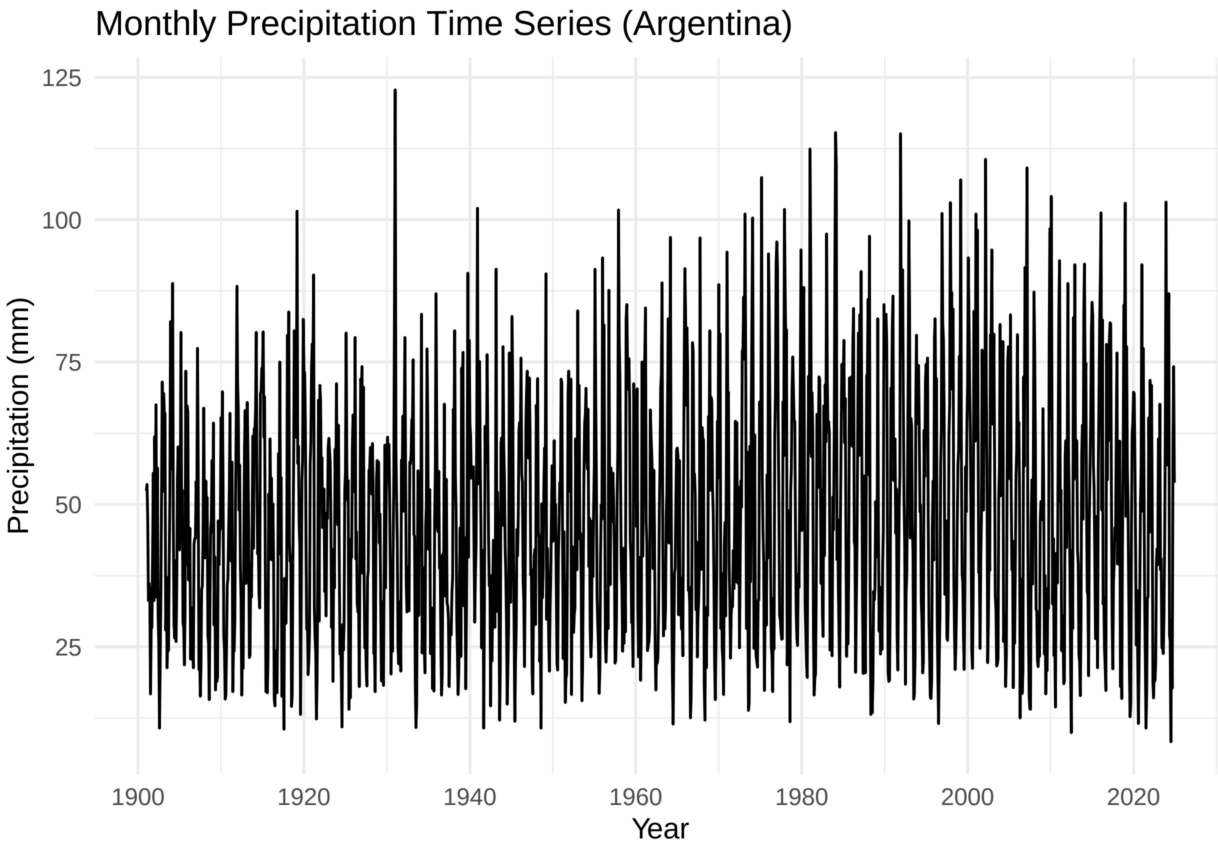


ACF (Brazil)
ACF
1.0
0.5
0.0
−0.5
−1.0
0
1
2
3
4
Lag

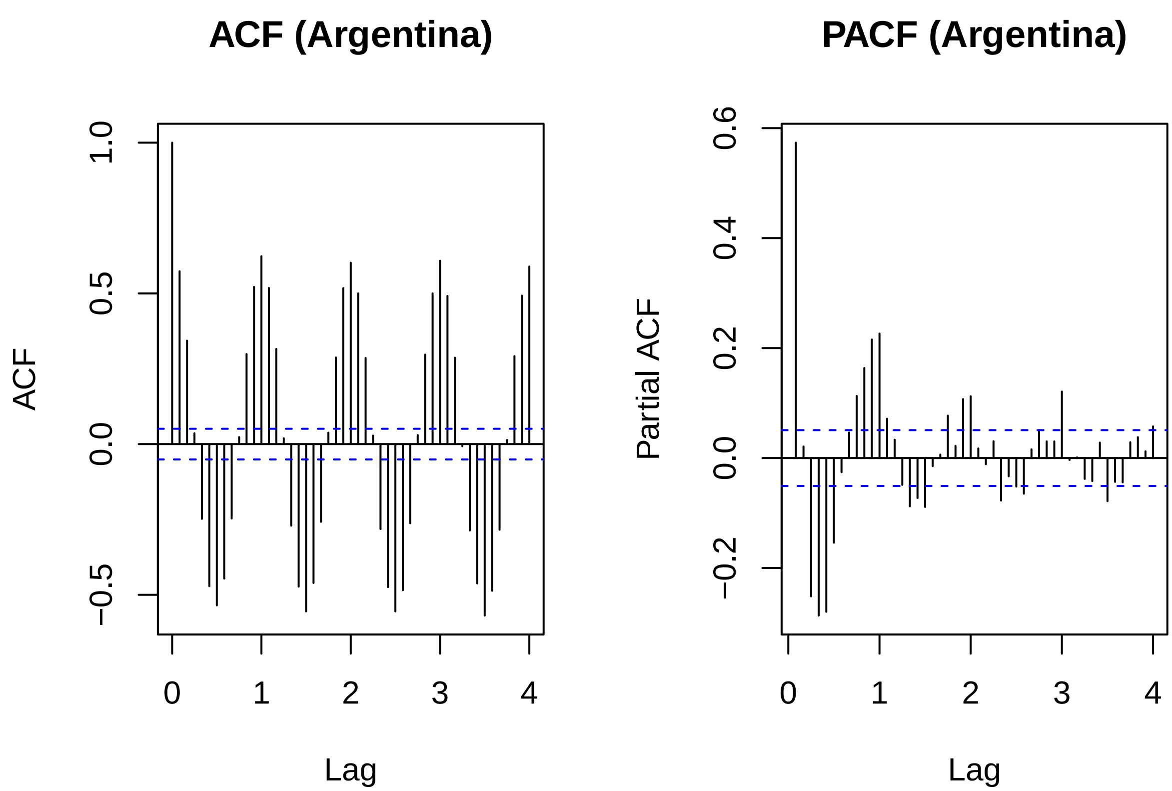


PACF (Brazil)
Partial ACF
0.6
0.2
−0.2
−0.6
0
1
2
3
4
Lag

The Brazil time series plot demonstrates a clear seasonal pattern with consistent cycles of wet and dry periods throughout the 120-year record. The precipitation values typically range from around 50mm to 250mm depending on the season. The ACF plot shows a strong wave-like pattern with significant autocorrelation at lag 12, confirming the annual seasonality in Brazil's precipitation patterns. This regular oscillation indicates well-defined wet and dry seasons that repeat annually. The PACF displays significant spikes at lag 1 and decreasing spikes at subsequent lags, suggesting a short-term autoregressive component where precipitation in one month is influenced by the previous month's conditions.


Monthly Precipitation Time Series (Argentina)
Precipitation (mm)
125
100
75
50
25
1900
1920
1940
1960
1980
2000
2020
Year

Argentina

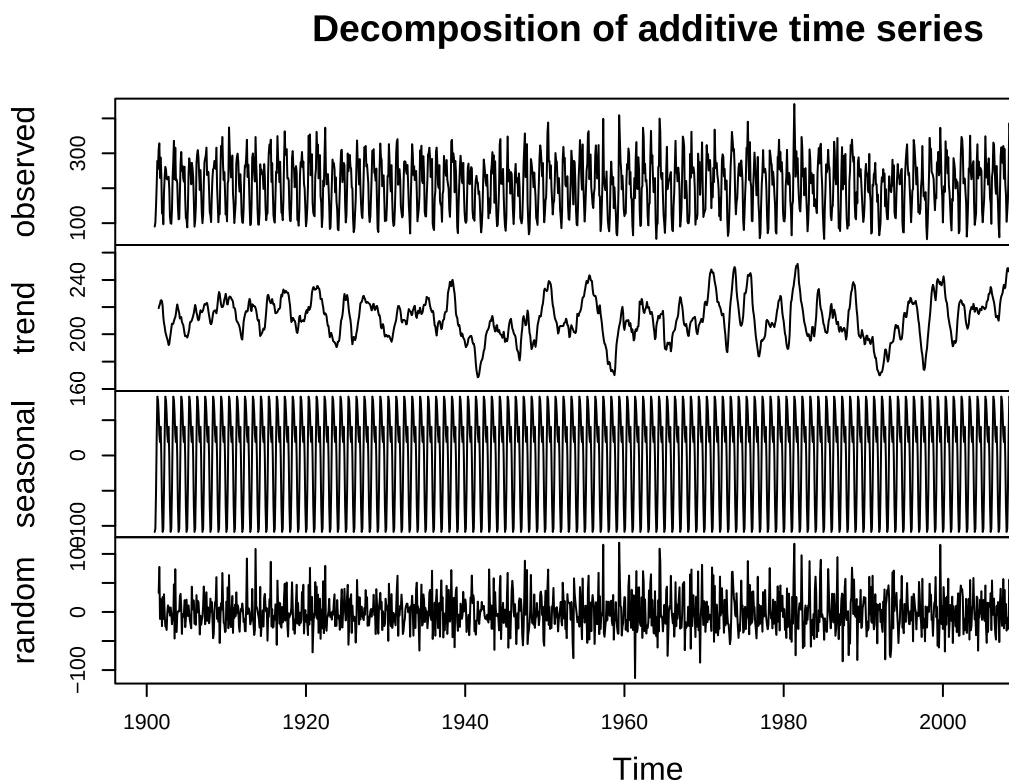

ACF (Argentina)
PACF (Argentina)
ACF
Partial ACF
1.0
0.5
0.0
−0.5
0.6
0.4
0.2
0.0
−0.2
0
1
2
3
4
Lag
Lag

For Argentina, the time series plot shows clear seasonality with equally-spaced peaks and troughs as time walks along the x-axis. There is not such a clear upward or downward trend component, so it will be interesting to decompose the series in the following section. The time series plot, itself, would not be reason to hypothesize that mean precipitation has been changing significantly over time. Moreover, although variation in the amplitude visibly might show more extreme peaks grouped between 1980-2000, conclusions cannot be drawn about whether the magnitude of seasonality has systematically increased or decreased over time.

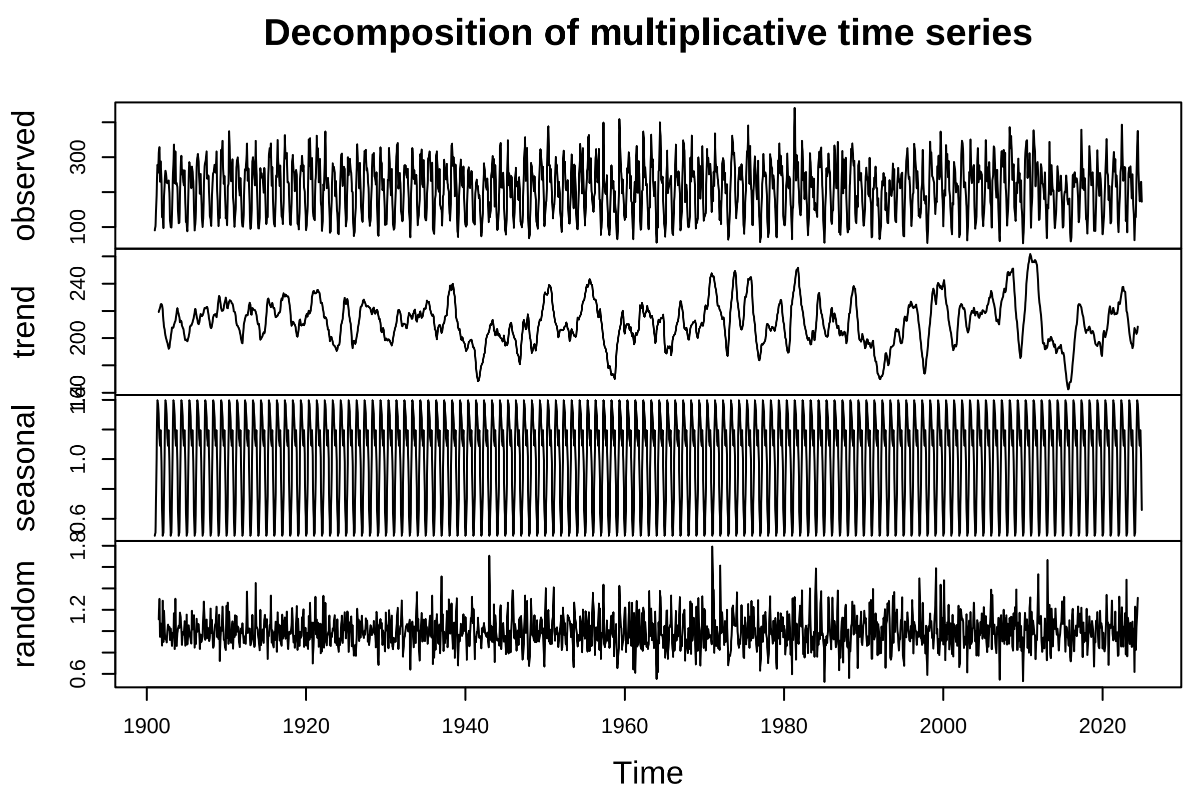
The ACF shows a wave-like pattern with peaks at each lag, but does not show slow decay. The equally-spaced wave pattern with spikes at each lag indicates the possibility of what one would certainly expect to be a seasonal component, likely due to a rainy season present across much of the country. The PACF has a significant spike at lag 1 and shows slow decay, with smaller spikes at subsequent lags. This suggests the series might have a short-term auto regressive (AR) component, where current precipitation is influenced by the previous month or two.

Exploratory Analysis - Decomposing and Detrending

The time series was also decomposed using both additive and multiplicative models in order to separate trend, seasonal, and residual components, allowing for more clear visualization prior to creating models. Following this, a linear trend model was fit to the time series object.



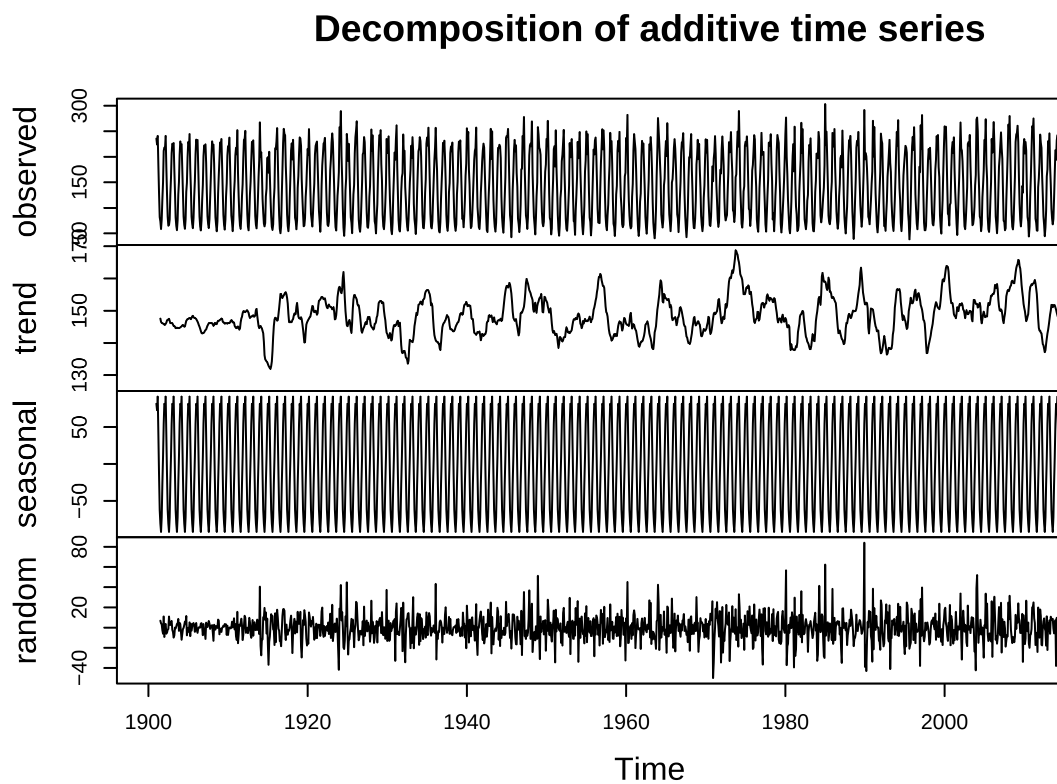
Decomposing Colombia series



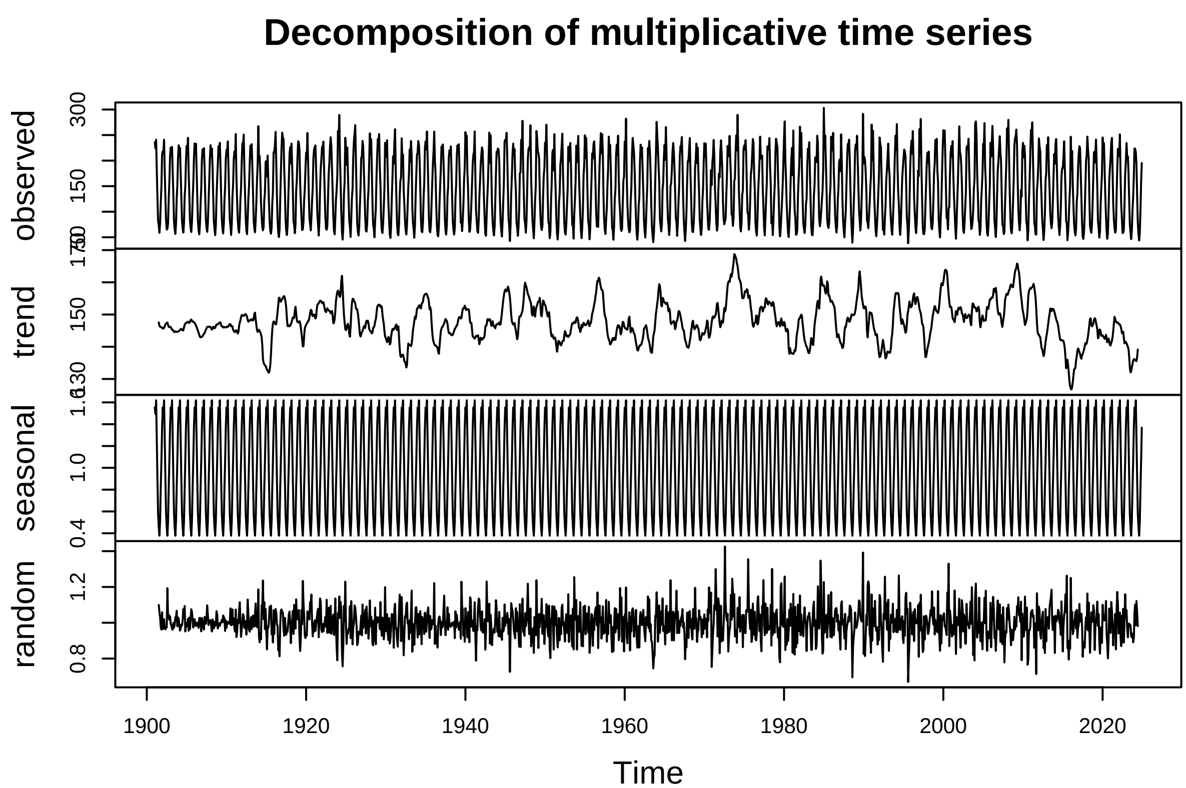
Detrending Colombia series

```
##
## Call:
## lm(formula = c_monthly_data_long$Precipitation ~ t)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -157.793  -58.482    6.642   53.388  229.718
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.123e+02  3.855e+00  55.076   <2e-16 ***
## t           -8.393e-04  4.484e-03  -0.187    0.852
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 74.31 on 1486 degrees of freedom
## Multiple R-squared:  2.357e-05,  Adjusted R-squared:  -0.0006494
## F-statistic: 0.03503 on 1 and 1486 DF,  p-value: 0.8516
```

The slope is -0.000839mm/month of rain, indicating a very small but slight negative trend in precipitation. Nonetheless, the p-value is 0.852, which is considerably higher than 0.05, meaning that it's not statistically significant. The t value of 0.187 is also very close to 0 which indicates no meaningful relationship between monthly precipitation and time.



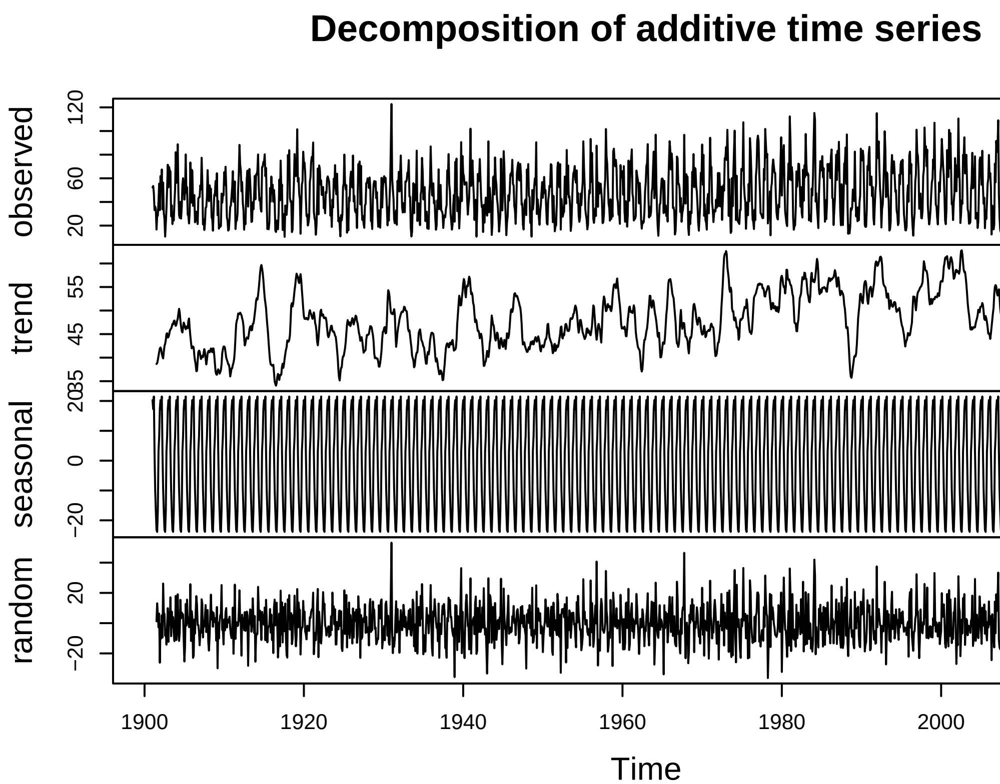
Decomposing Brazil series



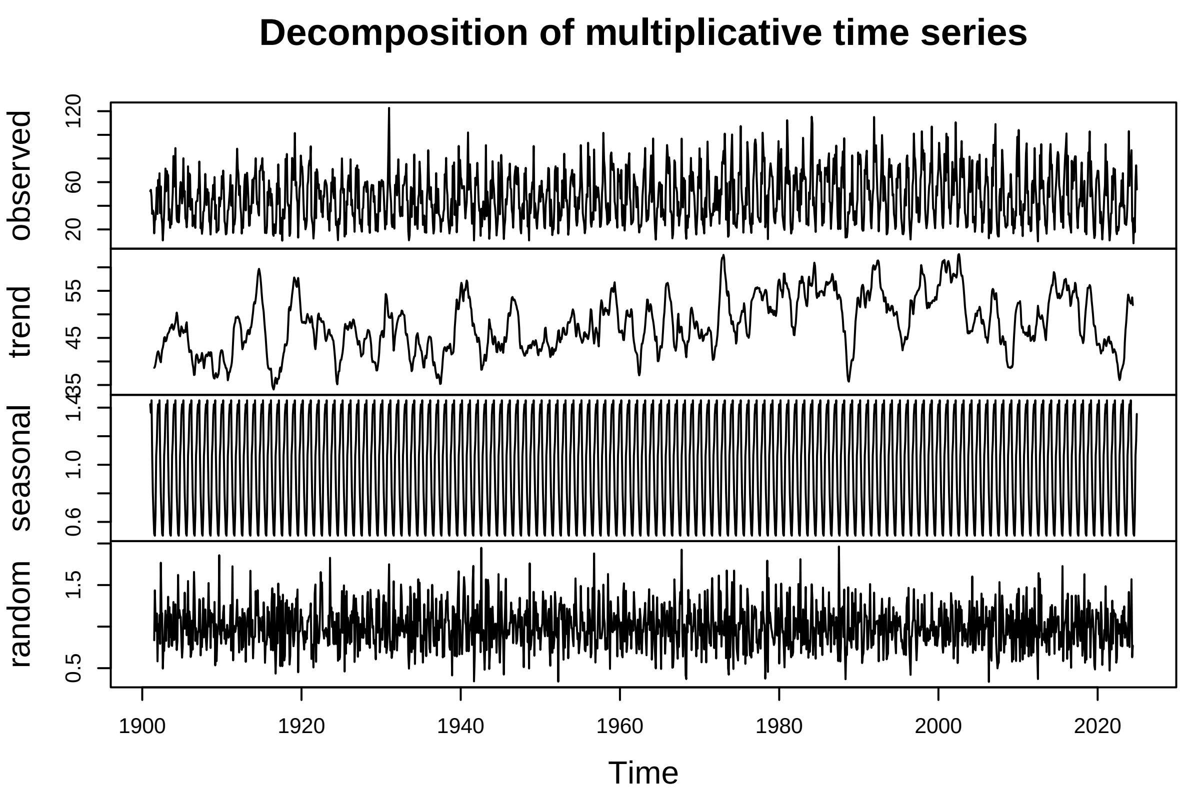
Detrending Brazil series

```
##
## Call:
## lm(formula = b_monthly_data_long$Precipitation ~ t)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -109.513  -66.421   -1.745   61.160  155.445
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) 148.091317   3.436754  43.090   <2e-16 ***
## t            -0.000333   0.003998  -0.083    0.934
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 66.25 on 1486 degrees of freedom
## Multiple R-squared:  4.667e-06,  Adjusted R-squared:  -0.0006683
## F-statistic: 0.006935 on 1 and 1486 DF,  p-value: 0.9336
```

The slope is -0.000333mm/month of rain, indicating a very small but slight negative trend in precipitation. Nonetheless, the p-value is 0.934, which is considerably higher than 0.05, meaning that it's not statistically significant. The t value of -0.083 is also very close to 0 which indicates no meaningful relationship between monthly precipitation and time. The extremely low R-squared value (4.667e-06) further confirms that time explains virtually none of the variation in Brazil's precipitation patterns over the 120-year period analyzed.



Decomposing Argentina series



Detrending Argentina series

```
##
## Call:
## lm(formula = a_monthly_data_long$Precipitation ~ t)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -43.778 -17.438  -1.704  15.149  77.065
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 43.693809   1.112531  39.274  < 2e-16 ***
## t            0.005653   0.001294   4.368 1.34e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 21.45 on 1486 degrees of freedom
## Multiple R-squared:  0.01267,    Adjusted R-squared:  0.01201
## F-statistic: 19.08 on 1 and 1486 DF,  p-value: 1.343e-05
```

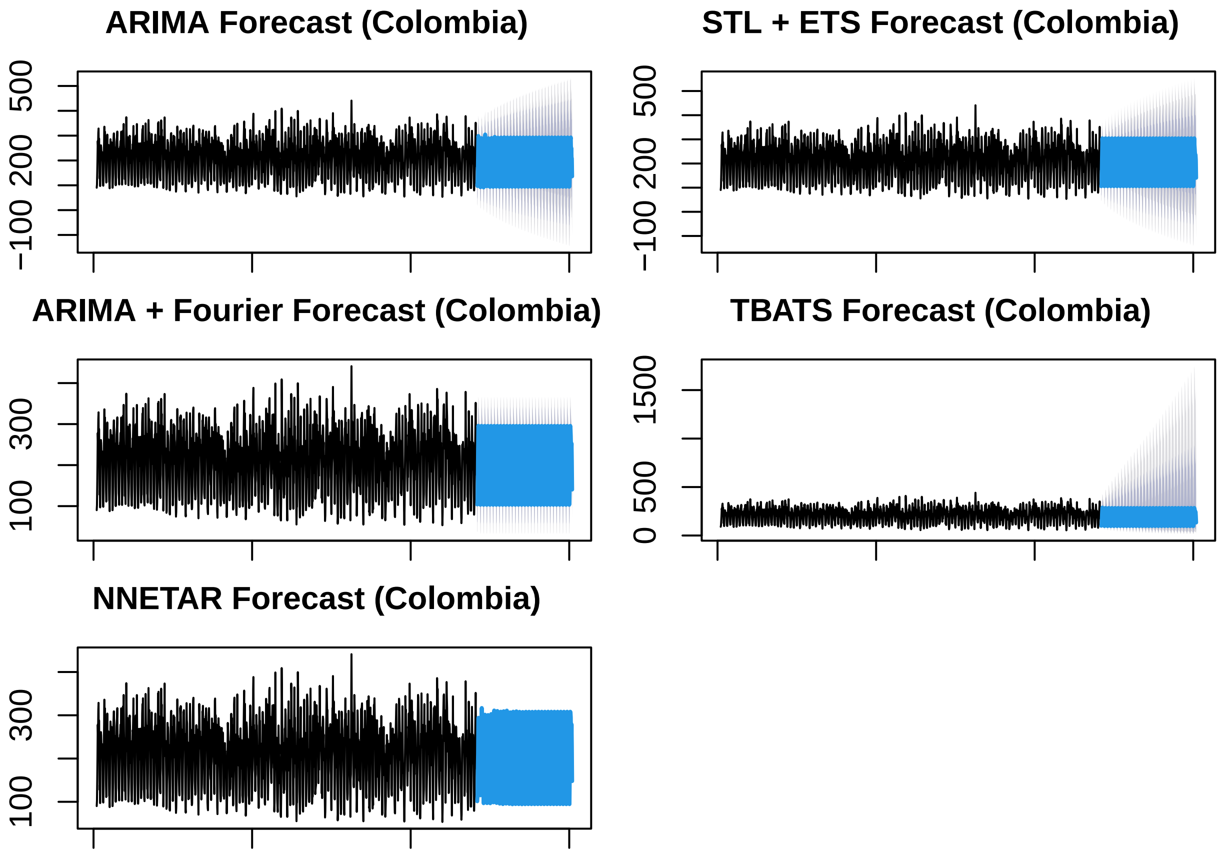
Fitting a linear trend to the Argentina time series for monthly precipitation, the slope is 0.0057 mm/month of rain with p-value well below 0.05 (1.343e-05). This would indicate a very small but slight positive trend in precipitation. The t value of 4.368 is not as close to zero as for Colombia and Brazil; there is some confidence that the null hypothesis that there is no change over time can be rejected and that mean precipitation increasing slightly over time for Argentina.

Models

The data was split into training and testing data sets. The training data set covered January 1901 to December 2020, and the testing data set included January 2021 to December 2024. Then, five models were select to apply to the training data:

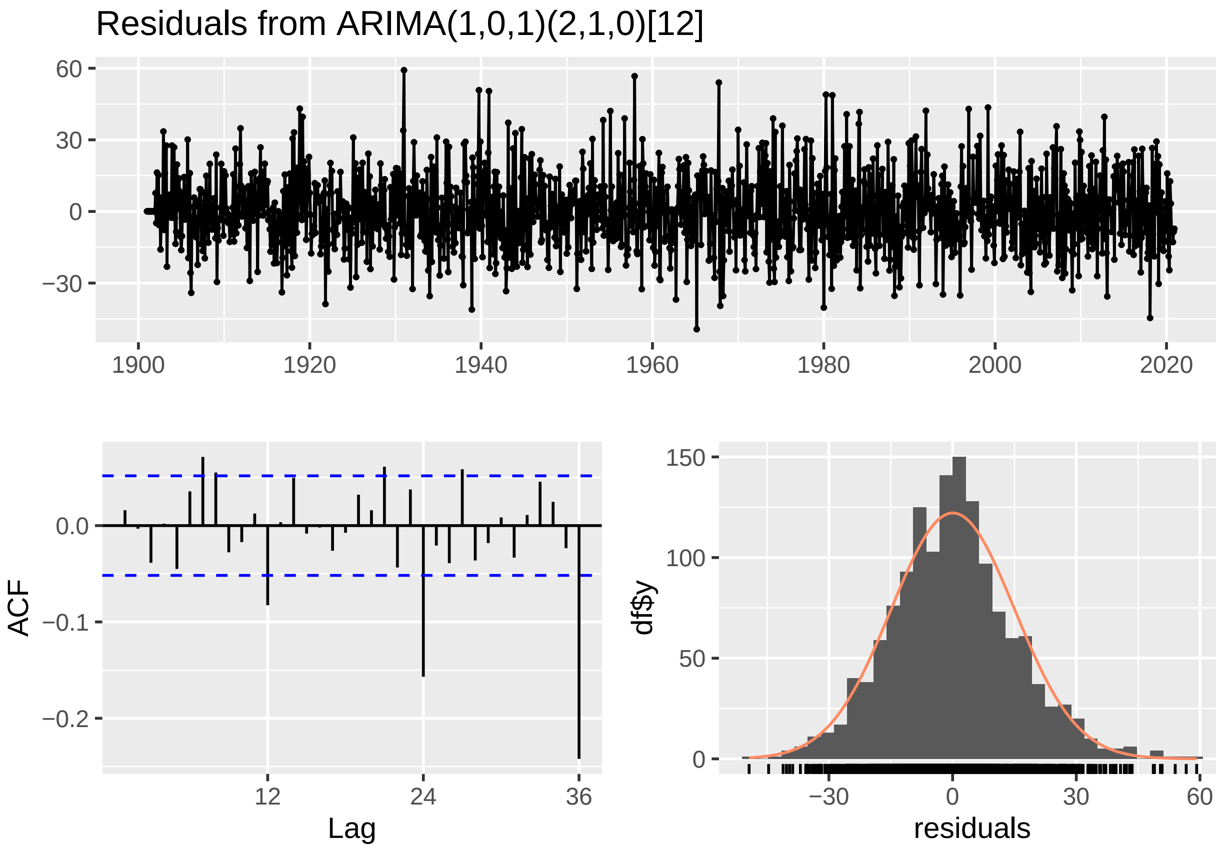
1. ARIMA
2. STL + ETS
3. ARIMA with Fourier Terms
4. TBATS
5. Neural Network Autoregression

Each model generated a forecast and their accuracies were assessed using the metrics ME, RMSE, MAE, MPE, MAPE, ACF1, and Theil's U. Finally, an overlay plot with all forecasts plotted on one graph was generated, allowing for visual comparison between models.



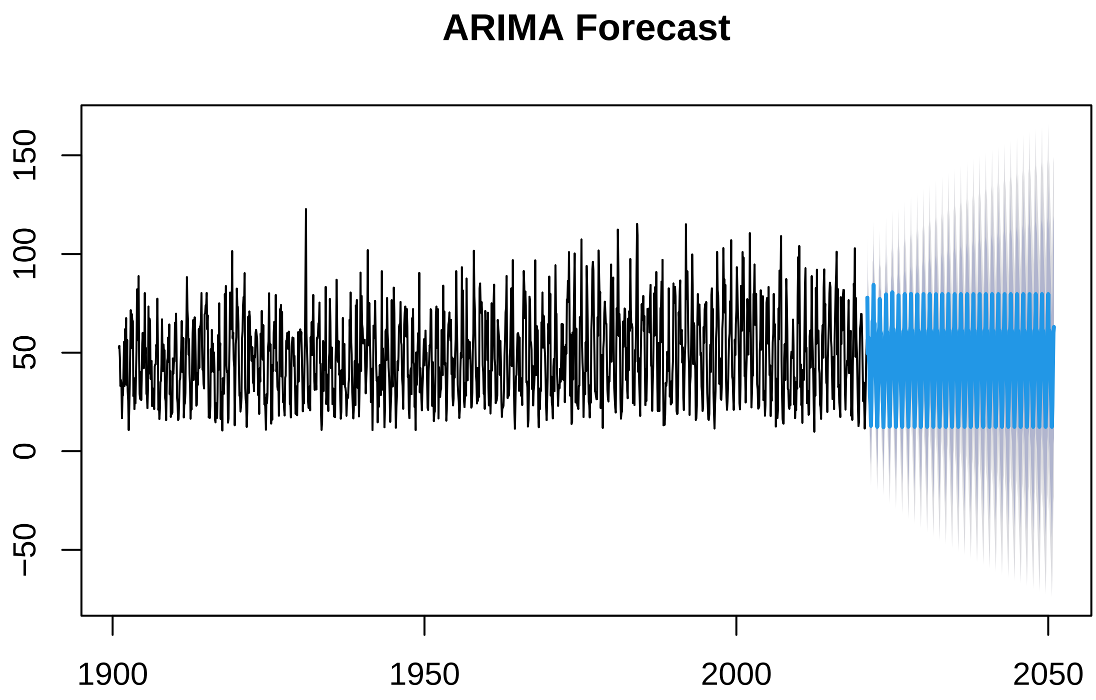
Colombia

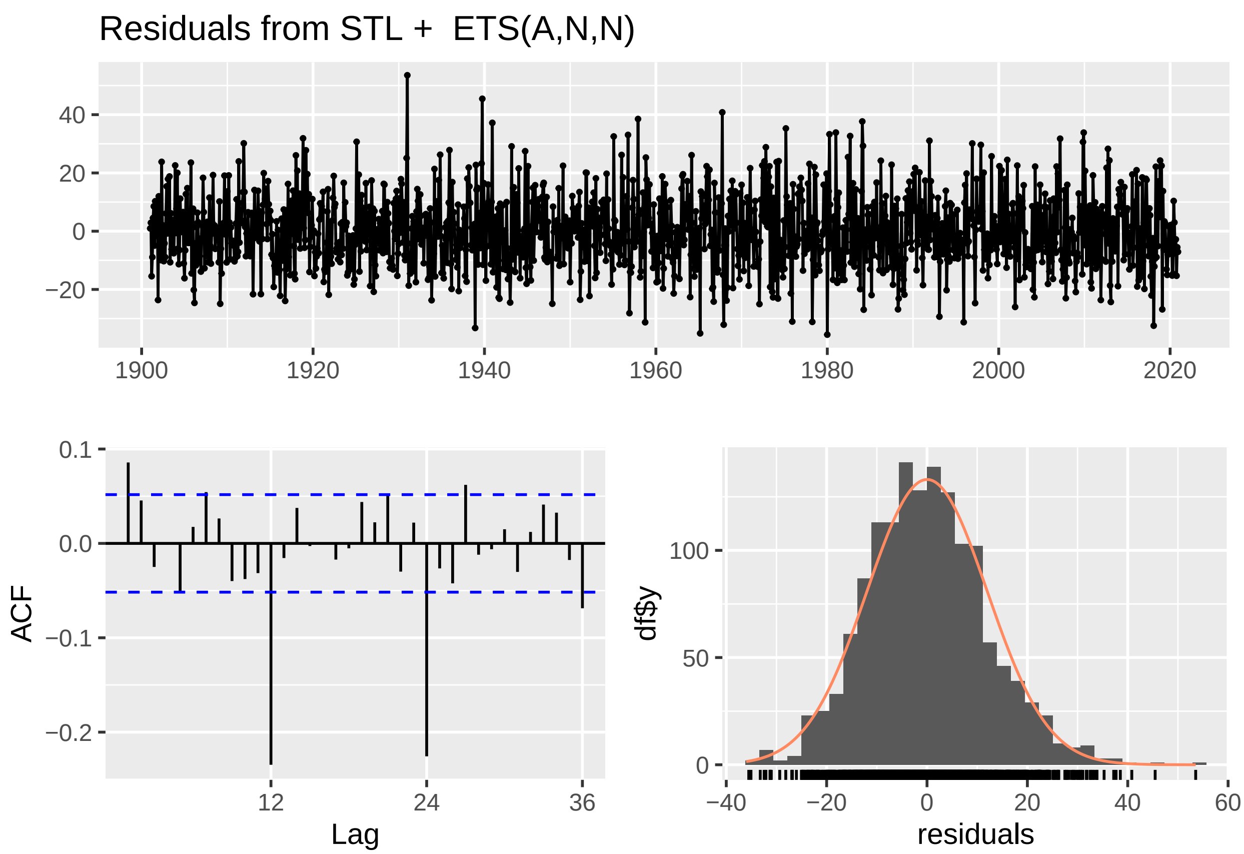
Brazil



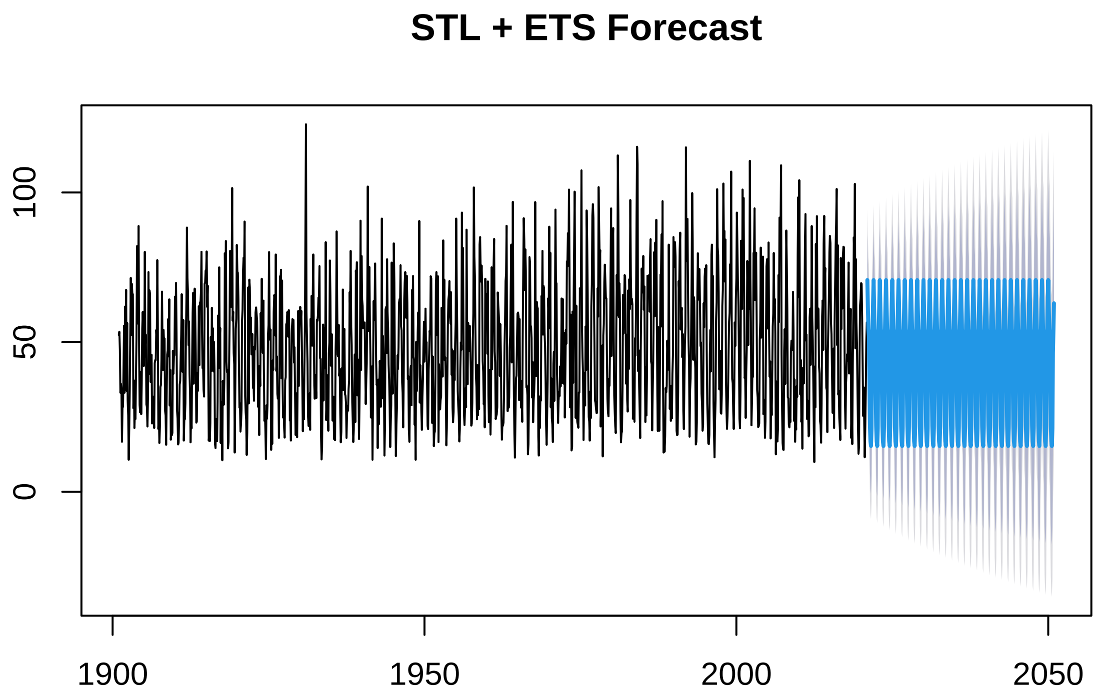
Argentina

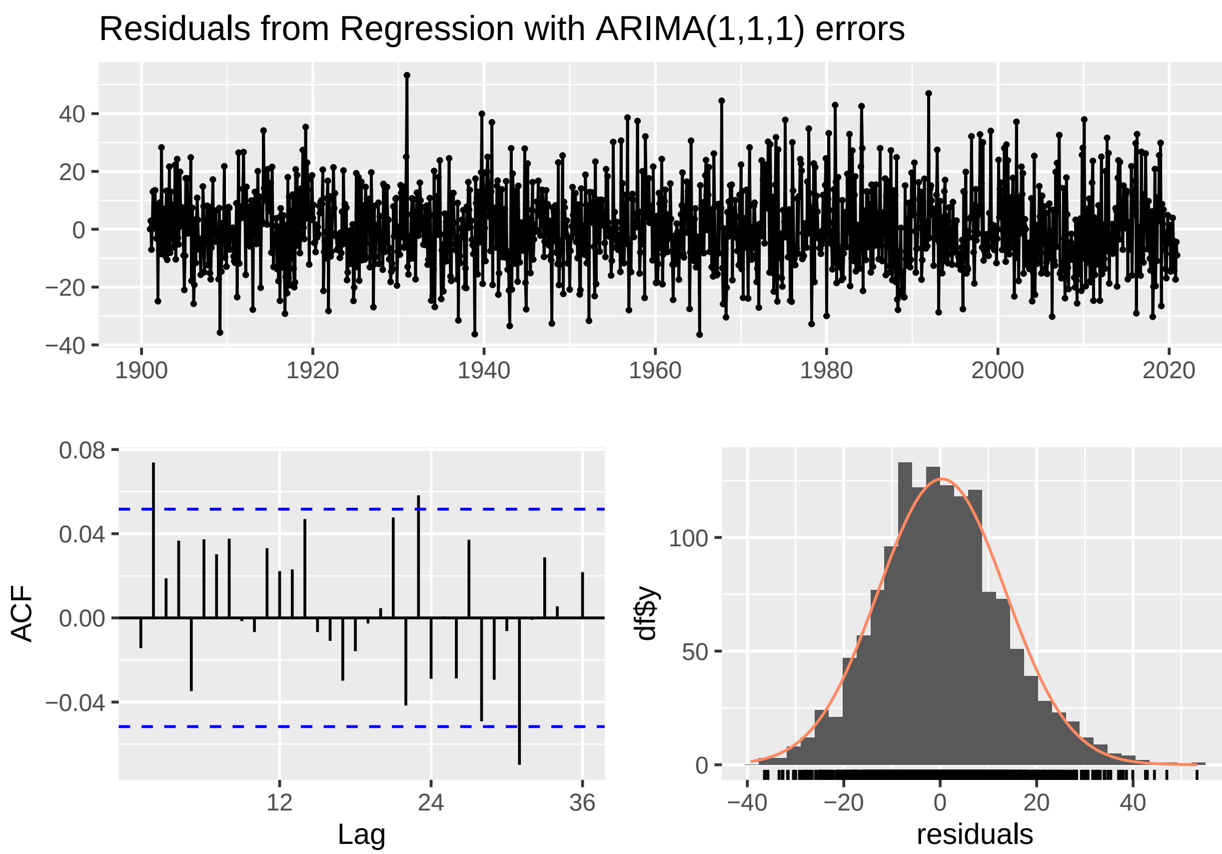
```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(1,0,1)(2,1,0)[12]
## Q* = 83.798, df = 20, p-value = 8.816e-10
##
## Model df: 4.   Total lags used: 24
```


ARIMA Forecast
150
100
50
0
−50
1900
1950
2000
2050



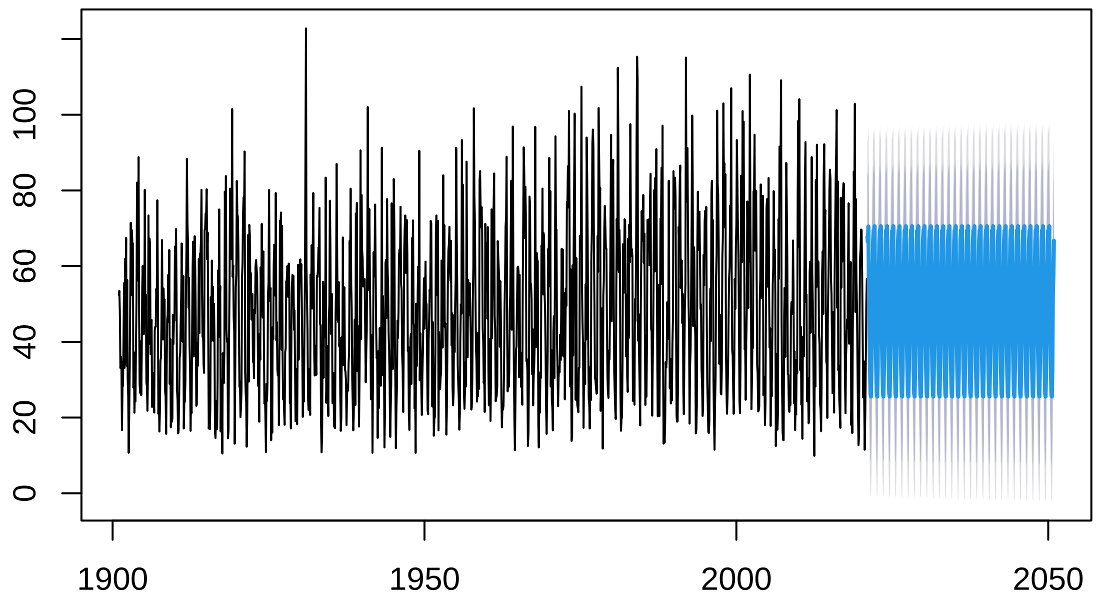

```
##
##  Ljung-Box test
##
## data:  Residuals from STL +  ETS(A,N,N)
## Q* = 196.65, df = 24, p-value < 2.2e-16
##
## Model df: 0.   Total lags used: 24
```

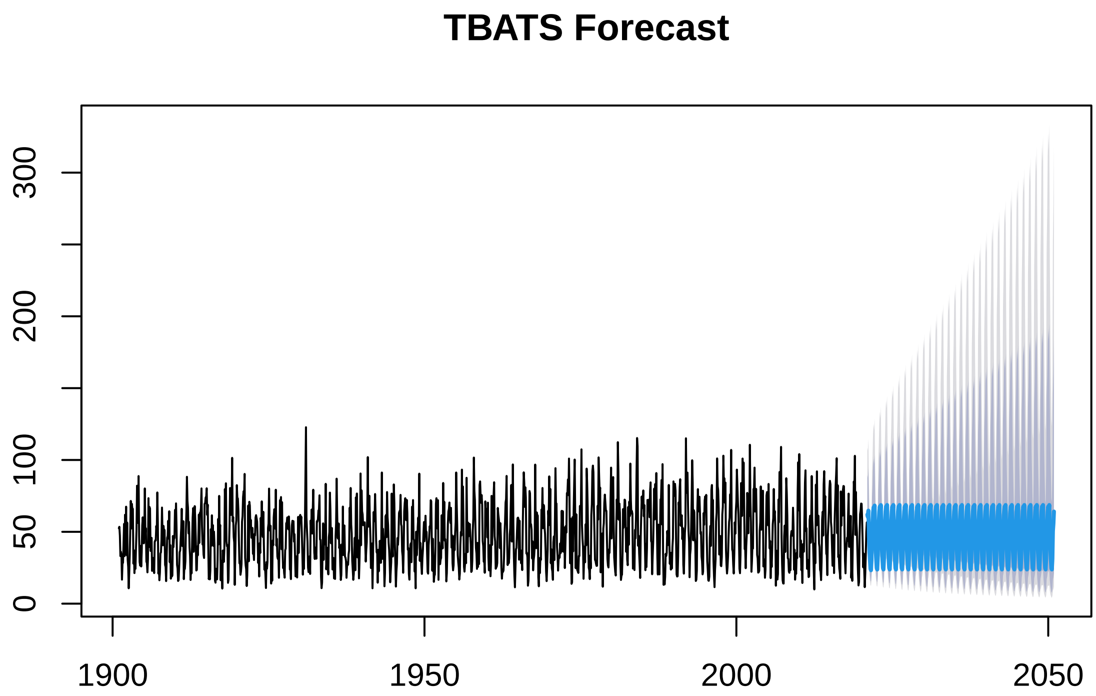

STL + ETS Forecast
100
50
0
1900
1950
2000
2050



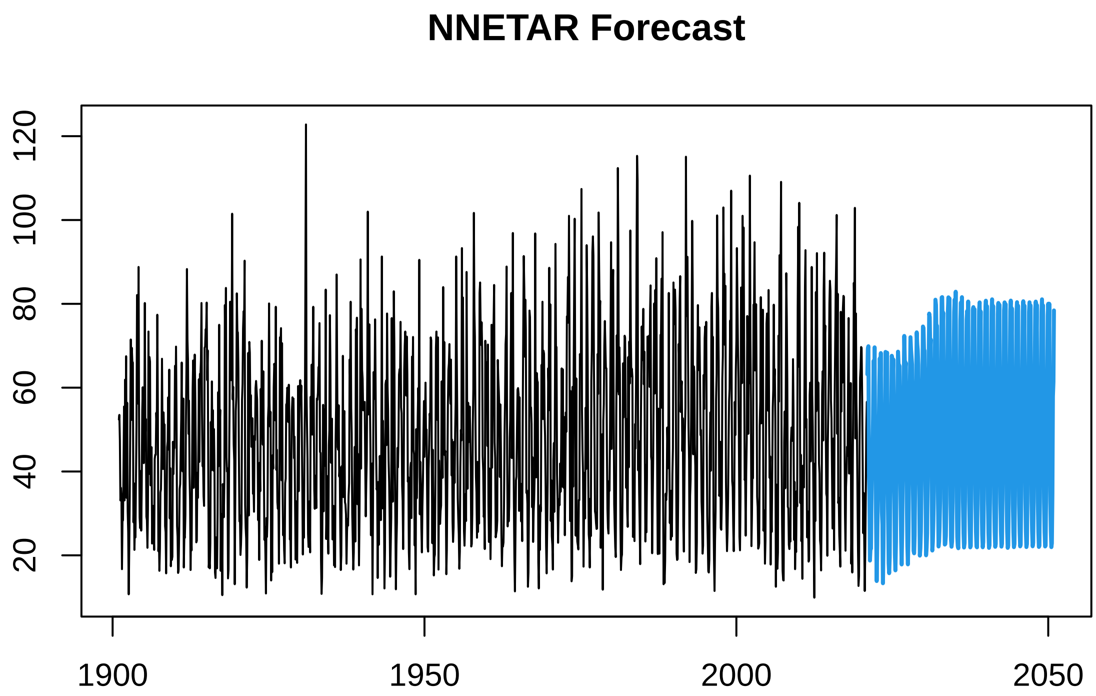

```
##
##  Ljung-Box test
##
## data:  Residuals from Regression with ARIMA(1,1,1) errors
## Q* = 38.157, df = 22, p-value = 0.01759
##
## Model df: 2.   Total lags used: 24
```

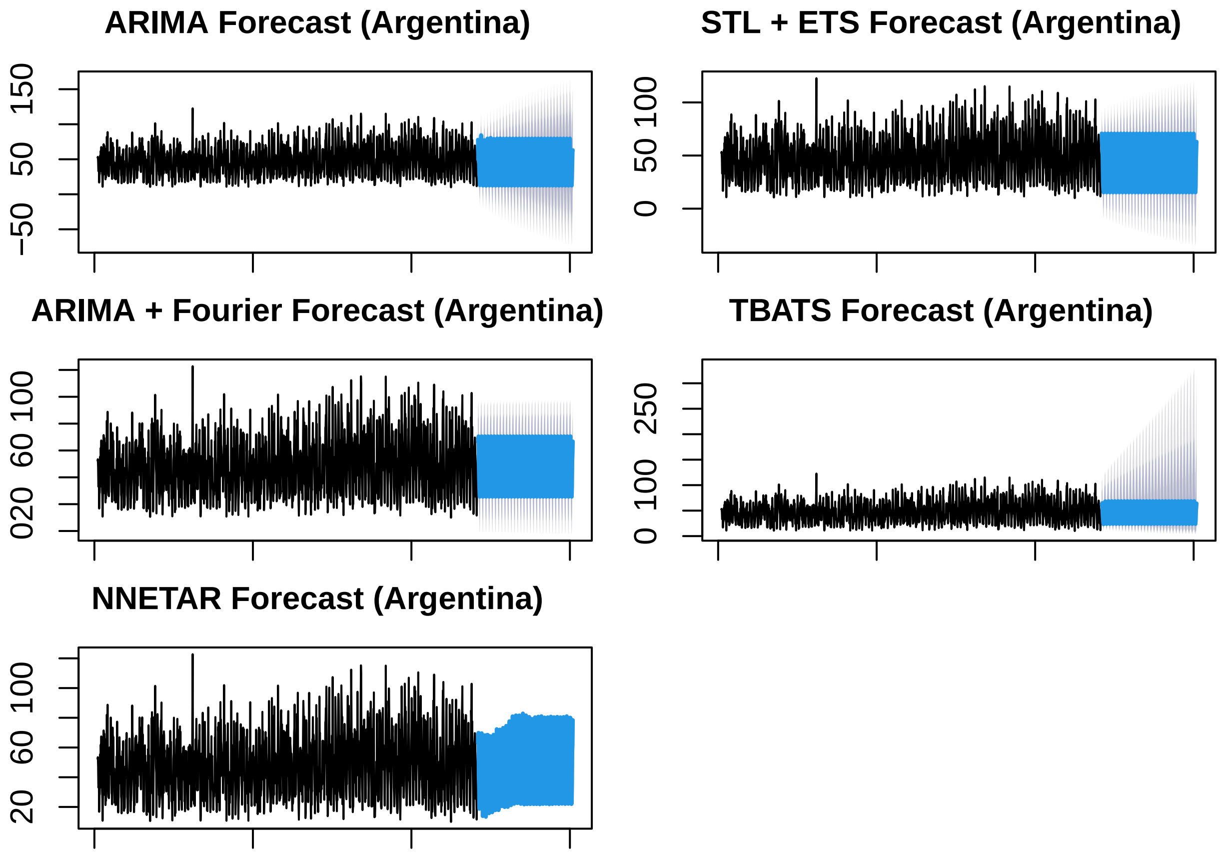
ARIMA + Fourier Forecast





TBATS Forecast
300
200
100
50
0
1900
1950
2000
2050


NNETAR Forecast
20
40
60
80
100
120
1900
1950
2000
2050



Accuracy Metrics

Table 3: Forecast Accuracy for Precipitation in Colombia

	ME	RMSE	MAE	MPE	MAPE	ACF1	Theil's U
ARIMA	12.46980	42.04259	34.32337	3.32439	16.79040	-0.02992	0.62144
STL+ETS	5.73029	37.46420	29.10067	-1.20640	15.02950	0.01863	0.47917
ARIMA+Fourier	12.46980	42.04259	34.32337	3.32439	16.79040	-0.02992	0.62144
TBATS	12.60992	37.30779	28.73991	3.04859	14.42548	0.07198	0.53294
NN	2.00964	35.73226	30.15539	-2.19741	15.93957	0.09600	0.50977

Colombia

Table 4: Forecast Accuracy for Precipitation in Brazil

	ME	RMSE	MAE	MPE	MAPE	ACF1	Theil's U
ARIMA	-2.69258	13.10436	10.44112	-2.72320	7.97570	0.37049	0.29303
STL+ETS	-1.41855	13.31046	10.87874	-2.68948	8.37876	0.34619	0.31253
ARIMA+Fourier	-6.31469	14.37847	11.94728	-6.85623	10.13015	0.25928	0.40515
TBATS	0.93528	13.62923	10.79665	-1.76025	8.37751	0.28236	0.34143
NN	-7.18652	14.43737	11.70832	-6.93827	9.75387	0.26219	0.38165

Brazil

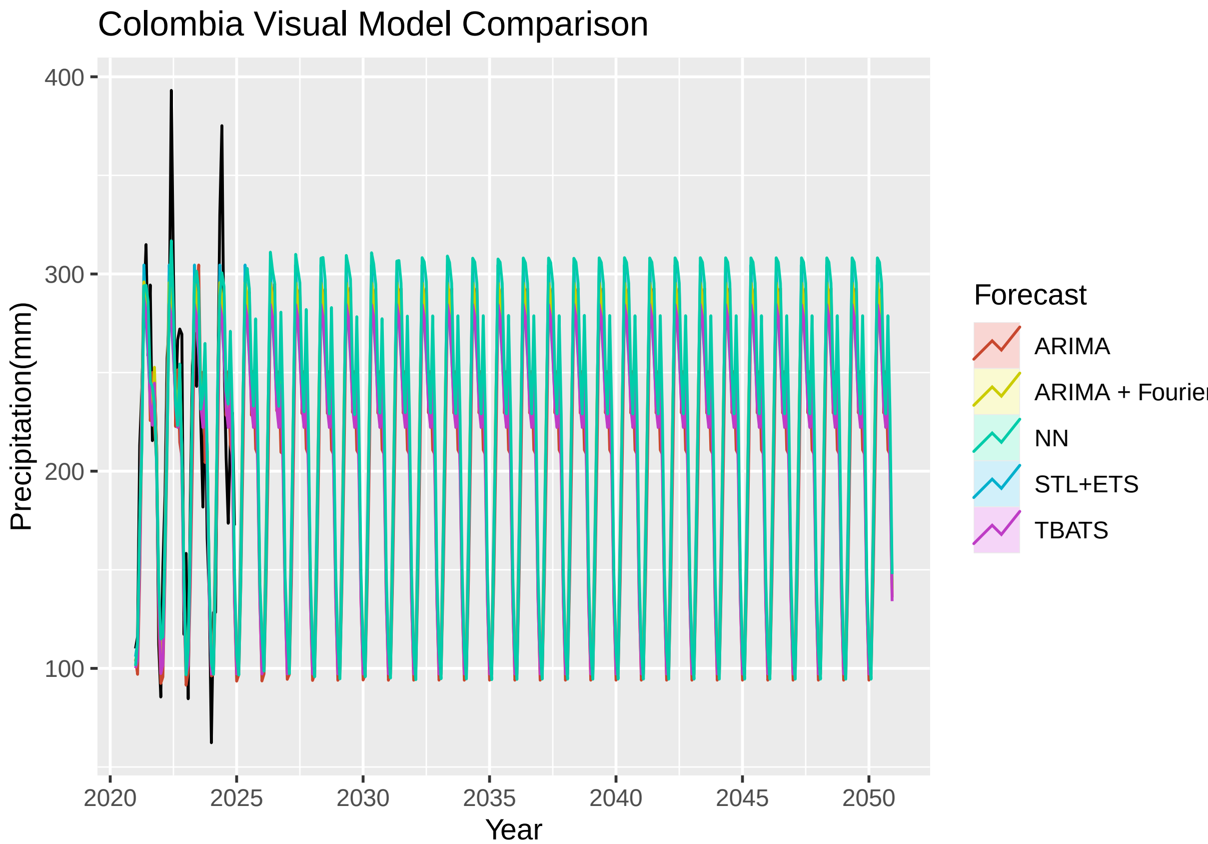
```
## Warning: There was 1 warning in `mutate()`.
## i In argument: `across(where(is.numeric), round, 3)`.
## Caused by warning:
## ! The `...` argument of `across()` is deprecated as of dplyr 1.1.0.
## Supply arguments directly to `.fns` through an anonymous function instead.
##
##   # Previously
##   across(a:b, mean, na.rm = TRUE)
##
##   # Now
##   across(a:b, \(x) mean(x, na.rm = TRUE))
```

```
##             Model     ME   RMSE    MAE   MAPE  MASE
## 1           TBATS -1.606 14.031 10.881 31.895 0.747
## 2       STL + ETS  2.517 14.157 11.293 27.557 0.776
## 3 ARIMA + Fourier -3.993 14.303 11.335 35.397 0.779
## 4          NNETAR  1.145 14.390 11.158 30.022 0.766
## 5           ARIMA  0.354 14.998 11.952 33.280 0.821
```

Table 5: Forecast Accuracy for Precipitation in Argentina

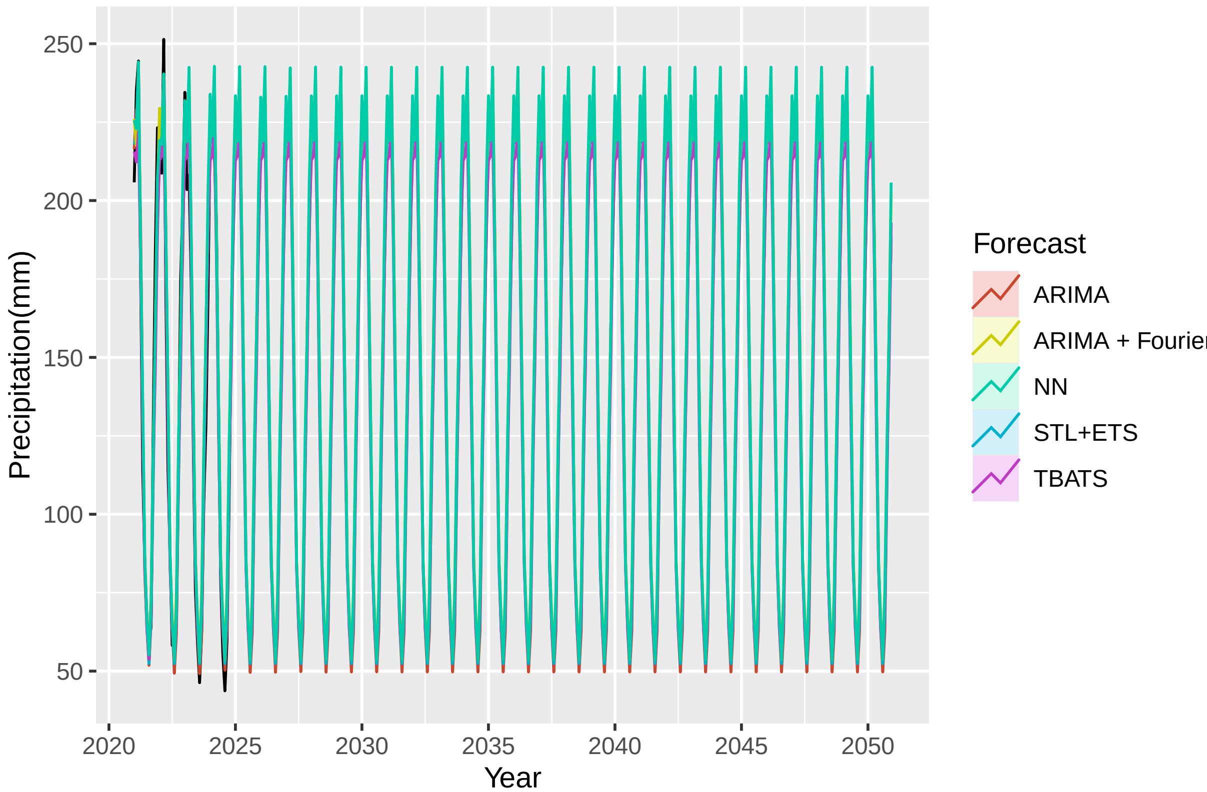
	ME	RMSE	MAE	MPE	MAPE	ACF1	Theil's U
ARIMA	0.35385	14.99799	11.95228	-11.01341	33.27962	0.06109	0.69163
STL+ETS	2.51651	14.15674	11.29266	-2.22731	27.55698	-0.04858	0.59752
ARIMA+Fourier	0.35385	14.99799	11.95228	-11.01341	33.27962	0.06109	0.69163
TBATS	-1.60611	14.03136	10.88123	-19.40098	31.89495	-0.01115	0.51750
NN	1.14510	14.38983	11.15788	-8.61794	30.02192	-0.07665	0.56686

Visual Model Comparison



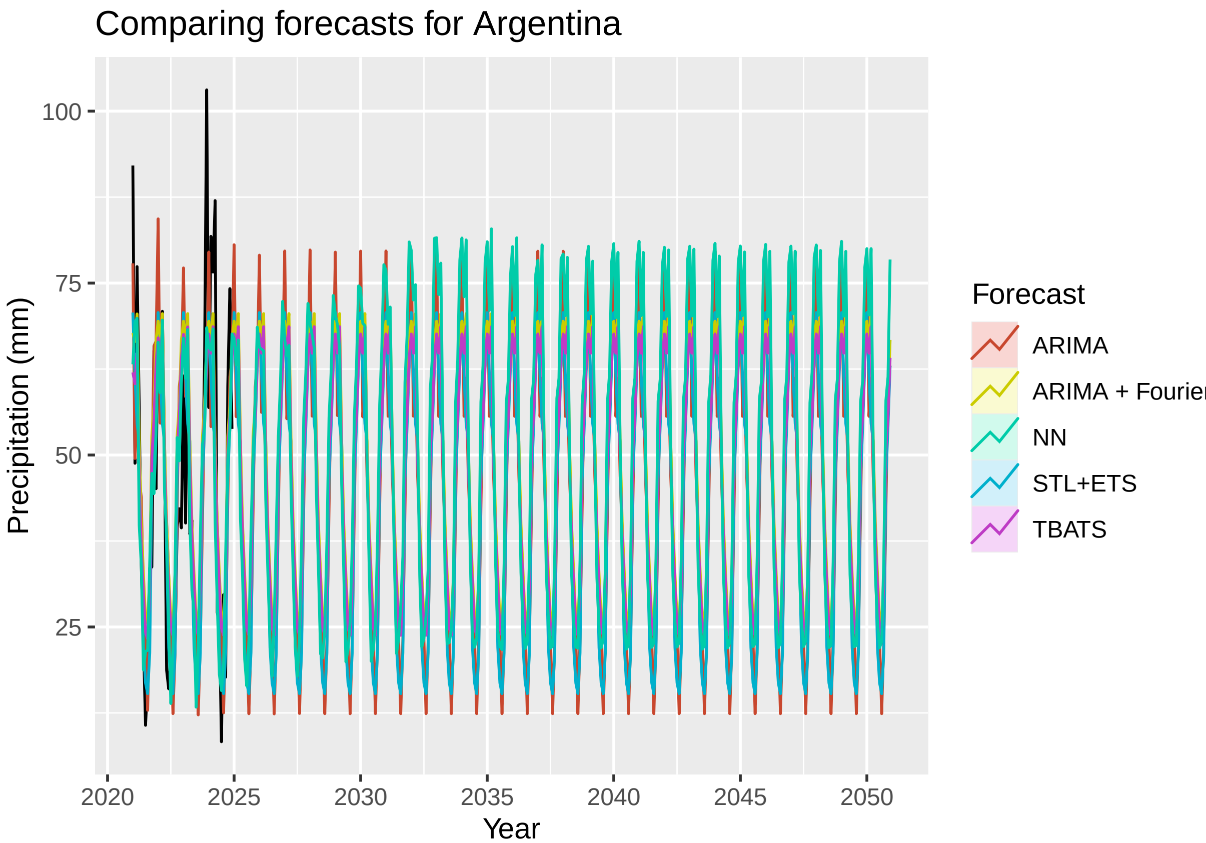
Colombia

ARIMA: The ARIMA model captures seasonality relatively well, but the forecast band is wide, indicating increasing uncertainty over time. It has the lowest RMSE meaning the smallest magnitude of error and the best Theil U score, indicating that the model performs well compared to a naive model.
STL + ETS: The STL + ETS model shows a smooth forecast curve with seasonality retained. Although the variance increases, it remains relatively controlled. The model has the best MAPE, meaning that the average magnitude of the errors is the lowest, and the best residual autocorrelation, indicating that more of the errors are random and not correlated with previous error.
ARIMA + Fourier: This model is similar to regular ARIMA, but it captures cyclical seasonal components more clearly, which may not be so necessary here since the accuracy scores are the same as the ARIMA model.
TBATS: TBATS shows an aggressive increase in forecast uncertainty, which may indicate model over fitting or extrapolation issues. The forecast seems relatively unstable after 2030, and none of the accuracy scores outperform the other models, indicating that it isn't the best fit.
NNETAR: This model captures the general seasonal shape, but the forecast appears more rigid and less sensitive to variation. It is the worst performer across the models, with a high RMSE indicating a high magnitude of error, a high MAPE, and the worst Theil's U. Therefore, NNETAR isn't a good fit.



Brazil

The visual comparison of forecasting models for Brazil shows that all five models (ARIMA, STL+ETS, ARIMA+Fourier, TBATS, and Neural Network) capture the strong seasonal precipitation pattern. The ARIMA model demonstrates the best performance based on accuracy metrics, with the lowest RMSE (13.10) and best Theil's U score (0.29303). The forecast visualization shows consistent seasonal cycles continuing into the future, with precipitation ranging from approximately 50mm in dry months to 250mm in wet months. The forecast confidence bands widen gradually over time, representing increasing uncertainty in long-term predictions. All models maintain the same seasonal pattern without projecting any significant changes in seasonality or extreme events.



Argentina

ARIMA: The ARIMA model captures seasonality relatively well, but the forecast band is wide and widens over time, indicating increasing uncertainty. It has the second-highest RMSE, meaning the second-highest magnitude of error (as sensitive to outliers) and the highest MAE, or average magnitude of errors with less sensitivity to outliers. As a percentage, the average magnitude of errors of the ARIMA (MAPE) for Argentina is also second-highest.
STL + ETS: The STL + ETS model shows a smooth forecast curve with seasonality retained. This model does not do a good job of capturing and forecasting any non-seasonal cyclical patterns or random components. Uncertainty of the forecast increases over time, similarly to the ARIMA model. This is the model with the lowest, or best, MAPE, meaning it has the smallest average magnitude of the errors. It also has the second-lowest RMSE and MAE.
ARIMA + Fourier: This model had the largest-magnitude bias in its forecast (ME). Although similar to regular ARIMA, it performed better on RMSE and MAE scores.
TBATS: As in the forecasts for Colombia, TBATS shows an aggressive increase in forecast uncertainty over time. In the case of Argentina, however, the TBATS has the lowest RMSE and MAE scores and second-lowest MAPE.
NNETAR: The NNETAR was the model with the lowest-magnitude bias in the forecast. Nevertheless, the Neural Network model had the highest RMSE, second-highest MAE, and its MAPE score was the middle performer among models.
MASE values, not shown here, were < 1 for all models, indicating that these models are not performing better than the naive model.
To test if any of the above models would perform better without outliers, tsclean() was run on the time series object, but identified no outliers. Moving forward with all original maximum and minimum values was preferred anyway, given that this project sought to learn about exactly that: the *extreme* precipitation values over time.

Summary

Time series analysis was applied to precipitation patterns in Argentina, Brazil, and Colombia using monthly data from 1901 to 2024. Five forecasting models were evaluated: ARIMA, STL+ETS, ARIMA with Fourier Terms, TBATS, and Neural Network Autoregression to determine optimal prediction methodologies for each country. Training data from January 1901 to December 2020 was utilized, with model validation performed against testing data from January 2021 to December 2024. Model performance was assessed using multiple accuracy metrics (ME, RMSE, MAE, MPE, MAPE, ACF1, and Theil's U). The analysis aimed to identify changes in precipitation seasonality patterns, particularly relevant given IPCC projections of increasing extreme precipitation events due to climate change. These findings are significant considering recent research showing that Central South America received only 44% of average total precipitation during the last four months of 2022, highlighting the increasing variability in regional rainfall patterns (Rivera et al., 2023).

Conclusion

The analysis found no pattern in precipitation periods over time - there was no significant increase or decrease, and extremities also didn't systematically increase or decrease. This is contradictory to what the wider data displays; IPCC projections show that precipitation patterns are meant to be increasingly variable due to climate change, indicating that agricultural producers in these regions will face adaptation challenges related to changing water availability patterns. This could be because the data we used is country wide, and our three selected countries have large land areas, and therefore, experience different patterns across the regions. Therefore, perhaps if we used data in more localized, smaller regions, we would have found patterns changing over time; there may not be an overall change across entire countries because variability could average out to appear consistent, but in small areas, more frequent droughts or higher rainfall likely exist.

Regardless, the topic remains important and precipitation pattern monitoring and forecasting for agricultural planning in regions with limited irrigation infrastructure is crucial. Recent research has confirmed that in South America, rainfall patterns are projected to shift significantly, with decreases expected in the eastern northern Andes, southern Andes in Chile, and Amazonia, while increases are projected for southeastern South America and the northern Andes (Almazroui et al., 2021). These changes have significant implications for agricultural productivity. As noted by the Economic Commission for Latin America and the Caribbean, climate change effects on temperature and precipitation patterns could reduce rural incomes by as much as 20% in some South American countries (ECLAC, n.d.). Furthermore, NASA research suggests that climate change may affect the production of key crops like maize as early as 2030, with projected yield declines of up to 24% in regions including Brazil (NASA, 2023).

Limitations and insights on how to improve the model

Predicting changes in frequency and intensity of extreme precipitation events is deeply complex and, as stated in the IPCC Sixth Assessment report, "increases in the intensity of extreme precipitation at regional scales will vary, depending on the amount of regional warming, changes in atmospheric circulation and storm dynamics (high confidence)" (Seneviratne et al., 2019). Regarding limitations, it should be noted that, while we use precipitation data at the country level, precipitation patterns can vary drastically within each country, which contain multiple and varying ecosystems. Forecasting precipitation levels at the country scale does not account for precipitation patterns across different regions within a country. To make these models more helpful, time series models could be used could to analyze and forecast precipitation within key crop-producing provinces; in Argentina, for instance, this could be the provinces of Santa Fe, Córdoba, and Buenos Aires, where climate, water tables, and precipitation vastly differ from the southern tip of Argentina's Misiones, Tierra del Fuego, and Jujuy provinces.

Contribution statement of this report

Introduction, motivation, relevance, objectives, and limitations within the conclusion – Gaby
Dataset and methods – Chloe
Summary – Weilin
Conclusion – Weilin & Chloe
Code & analysis for Brazil – Weilin
Code & analysis for Argentina – Gaby
Code & analysis for Colombia – Chloe

Github repository link

https://github.com/chloeyoung26/CzarniakWangYoung_ENV797_TSA_FinalProject-.git

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