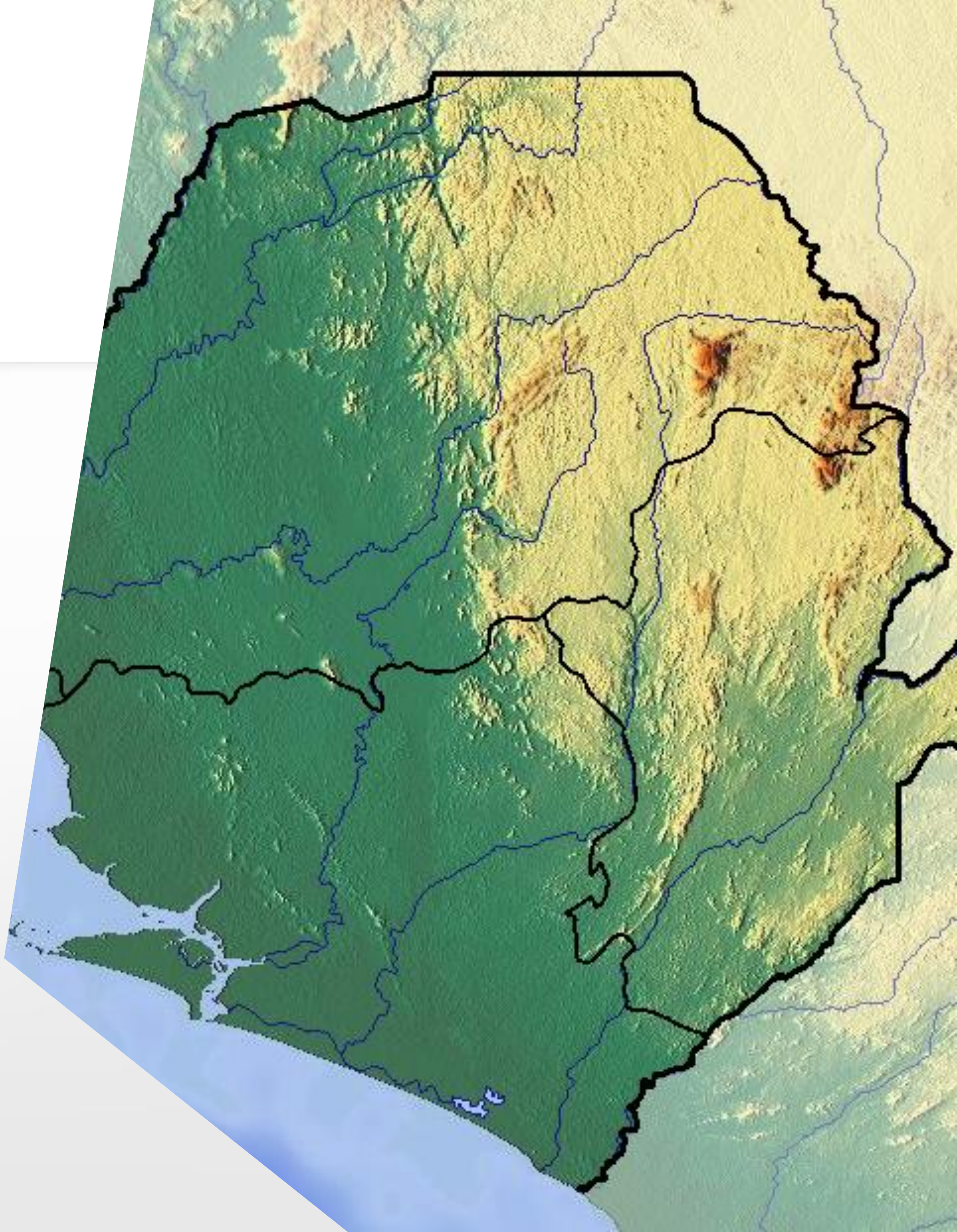
# SIERRA LEONE

## REPRODUCTIVE HEALTH INVESTIGATION



GROUP 2 PROJECT

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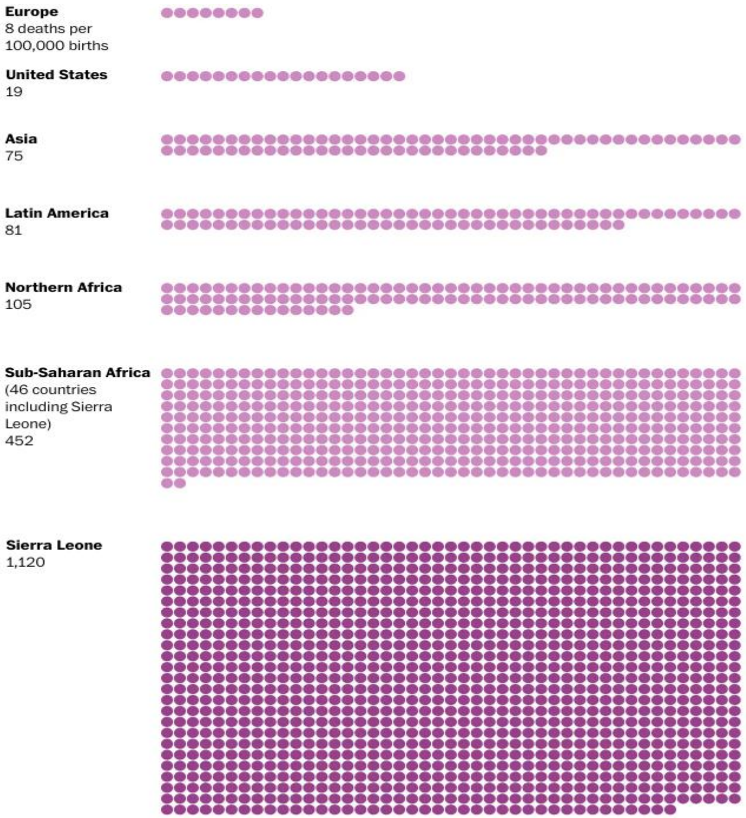
# UNDERSTANDING THE DILEMMA

**SIERRA LEONE** has **HIGHEST** Maternal Mortality Ratio in the World!

Poor Healthcare Practices

Sub-standard Healthcare Facilities

Non-Equipped Healthcare Facilities

# KEY FACTS:
## PREGNANCY ISSUES

High Maternal Mortality Rate
Lack of Access to Healthcare
Complications during Childbirth
Malnutrition + Anemia
High Rate of Teenage Pregnancies
Limited Family Planning Options

# ON THE HORIZON
## Positive Developments

**Efforts to improve access to care:**

Geographical Transportation Boundaries

Access to prenatal care

Skilled birth attendants

Emergency obstetric care

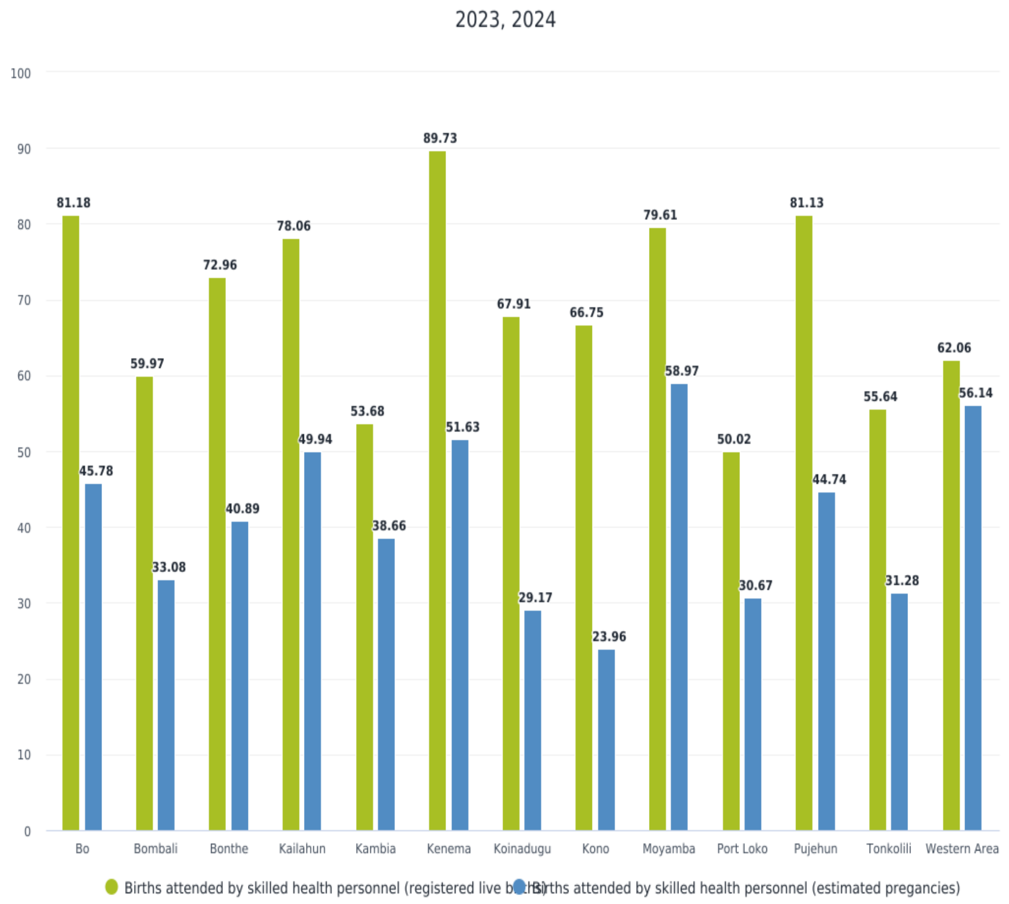
**Reduction in maternal mortality rate**

## Question 3: Create a comparative chart between all the districts for Births attended by skilled health personnel (registered live births) and Births attended by skilled health personnel (estimated pregnancies).

**Assumptions Made:** All months of 2023 and 2024 were combined to display

**DHIS2 input:**

- o **Data Visualizer App:** Line Chart Type
- o **Series:** Selected "Births attended by skilled health personnel (registered live births)" &"Births attended by skilled health personnel (estimated pregnancies)."
- o **Category:** Selected level "District" and "Sierra Leone"
- o **Filter:** Yearly Fixed Periods of 2023 and 2024




- **Which district has the highest registered live birth Percentage?** District Kenema with value of 89.73

- **Which district has the highest difference in percentage between registered live births and estimated pregnancies?** District Kenema with value of 37.5

## Q.4a: In Question 3, please describe (not just list) the various indicators that have been used.
## Q.4b: Create a table that shows the value of Q.3 indicators for all districts in 2023.

**Attended by skilled health personnel**

- Maternal and Child Health (MCH) Aides
- State Enrolled Community Health Nurse (SECHN)
- Midwives
- Community Health Organizations (CHOs)

**Attended by unskilled health personnel**

- Traditional Birth Attendants
  - Trained
  - Untrained

**Live births**

- In the Community / Public Health Units (PHUs)

| Indicators for Live Birth & Estimated Pregnancies | | | | | |
|---|---|---|---|---|---|
| 2023 | | | | | |
| | Live births in the community | Live births in the PHU | Live births | Births attended by skilled health personnel (estimated pregancies) | Births attended by skilled health personnel (registered live births) |
| Bo | 1 580 | 11 533 | 13 113 | 46.25 | 81.16 |
| Bombali | 4 680 | 6 653 | 11 333 | 33.46 | 59.97 |
| Bonthe | 1 077 | 3 061 | 4 138 | 41.36 | 72.96 |
| Kailahun | 1 278 | 10 498 | 11 776 | 50.51 | 78.06 |
| Kambia | 3 871 | 6 070 | 9 941 | 39.09 | 53.68 |
| Kenema | 1 130 | 13 582 | 14 712 | 52.23 | 89.73 |
| Koinadugu | 2 026 | 3 752 | 5 778 | 29.51 | 67.91 |
| Kono | 1 740 | 4 503 | 6 243 | 24.23 | 66.75 |
| Moyamba | 1 879 | 8 149 | 10 028 | 59.65 | 79.61 |
| Port Loko | 6 930 | 7 597 | 14 527 | 31.02 | 50.02 |
| Pujehun | 1 029 | 5 554 | 6 583 | 45.25 | 81.13 |
| Tonkolili | 4 247 | 5 815 | 10 062 | 31.64 | 55.64 |
| Western Area | 14 131 | 21 924 | 36 055 | 56.78 | 62.06 |

**Births Attended by Skilled Health Personnel (Estimated Pregnancies)**

- Numerator: Live births, in both Community and PHUs, attended by skilled health personnel
- Denominator: 20% of the annual total population as an estimated expected number of pregnancies.

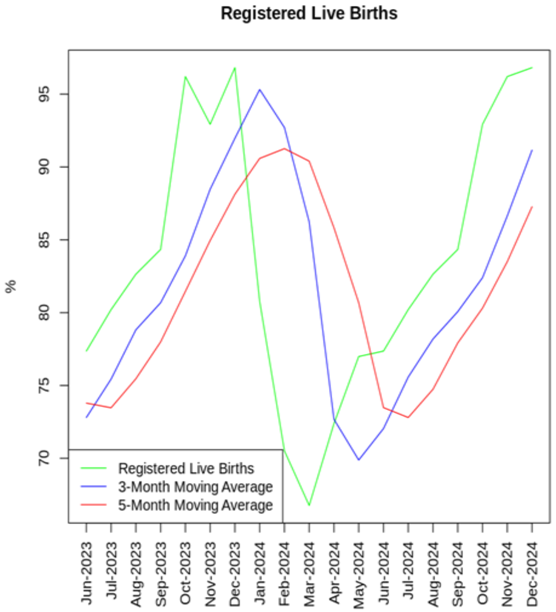
**Births Attended by Skilled Health Personnel (Registered Live Births)**

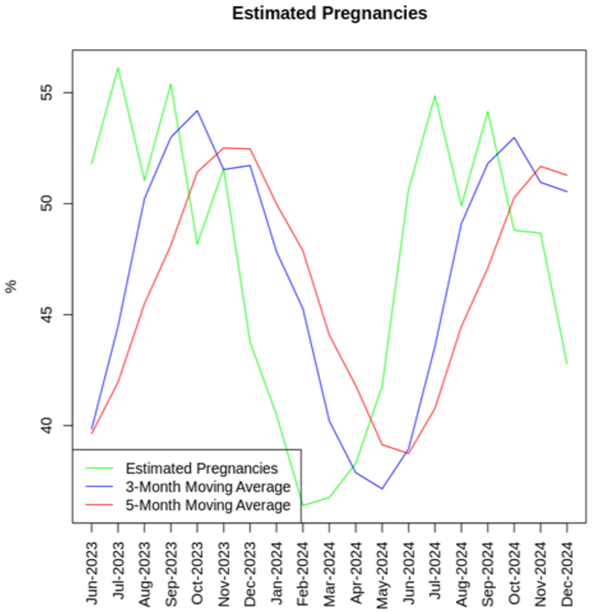
- Numerator: Live births, in both Community and Public Health Units (PHUs), attended by skilled health personnel
- Denominator: All observed live births including trained and untrained TBAs.

## Q.4b: *Using 3-month and 5-month moving averages, can you predict the values of the indicator in January 2025 for the Bo district? Which is the better of the two models when compared to the actual value of January 2024 for the Bo district?*

**Assumptions:** Weighted moving averages was not used due to the limited data range used and the availability of the most recent data values.

**Data Visualizer App:** Pivot Table
**Columns:** Data: “Births attended by skilled health personnel (registered live births)” and “Births attended by skilled health personnel (estimated pregnancies).”
**Rows:** Organisation Unit: Selected level “District” and “Sierra Leone: Bo” and Period:= Monthly Fixed Periods of 2023/2024




3-month avg. (Registered Live Births): MAE= 14.54 , RMSE= 14.54 , MSE= 18
5-month avg. (Registered Live Births): MAE= **9.81** , RMSE= **9.81** , MSE= **12.14**

For Registered Live Births, the better model is 5-month averaging with the lower MAE value of 9.81 and lower MSE of 12.14.

3-month avg. (Estimated Pregnancies): MAE= **7.36** , RMSE= **7.36** , MSE= **18.18**
5-month avg. (Estimated Pregnancies): MAE= 9.51 , RMSE= 9.51 , MSE= 23.49

For Estimated Pregnancies, the better model is the 3-month averaging with the lower MAE value of 7.36 and lower MSE of 18.18.

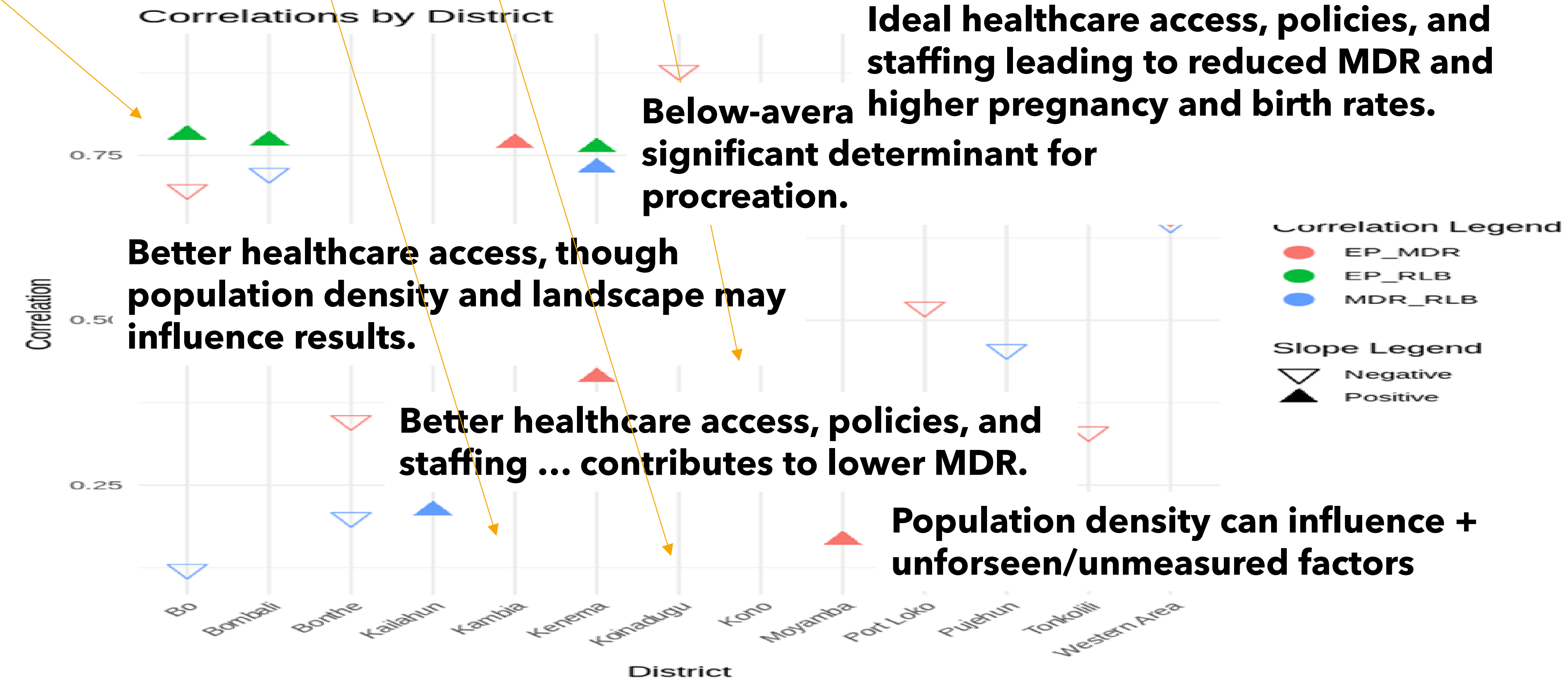
## Q.5: Adding the Maternal death rate by registered live birth to the above two indicators, please do a correlation analysis across all the districts for the months of 2024.

**Assumption:** Pearson correlation was used due to the exploration of visual linear relationships and the evaluation of the variables not being ordinal or rank-based.

**Data Visualizer App:** Pivot Table
**Columns:** Data = "Births attended by skilled health personnel (registered live births)" and "Births attended by skilled health personnel (estimated pregnancies)."
**Rows:** Organisation Unit = Selected level "District" and "Sierra Leone: Bo" and
Period:= Monthly Fixed of 2024

| | | Births attended by skilled health personnel (registered live births) | Births attended by skilled health personnel (estimated pregnancies) | Maternal death rate by registered live births |
|---|---|---|---|---|
| Bo | January 2024 | 80.78 | 40.48 | 600.6 |
| | February 2024 | 70.51 | 36.4 | 415.37 |
| | March 2024 | 66.76 | 36.76 | 364.3 |
| | April 2024 | 72.38 | 38.3 | 489.72 |
| | May 2024 | 76.99 | 41.78 | 462.11 |
| | June 2024 | 77.36 | 50.64 | 237.53 |
| | July 2024 | 80.21 | 54.87 | |
| | August 2024 | 82.64 | 49.91 | |
| | September 2024 | 84.34 | 54.16 | 242.13 |
| | October 2024 | 92.93 | 48.8 | |
| | November 2024 | 96.21 | 48.67 | |
| | December 2024 | 96.82 | 42.78 | |
| Bombali | January 2024 | 46.71 | 30.63 | 866.55 |
| | February 2024 | 48.58 | 31.1 | 474.38 |
| | March 2024 | 48.26 | 30.8 | 356.19 |
| | April 2024 | 54.06 | 33.59 | 94.52 |
| | May 2024 | 61.83 | 39.21 | 358.42 |
| | June 2024 | 69.16 | 45.04 | 180.34 |
| | July 2024 | 68.6 | 41.08 | 94.88 |
| | August 2024 | 61.41 | 36.71 | |
| | September 2024 | 65.38 | 37.7 | 101.83 |
| | October 2024 | | | |
| | November 2024 | 70.41 | 33.12 | |
| | December 2024 | 72.17 | 34.04 | 120.48 |

## Q.5: What can you infer about the three indicators?




**Ideal healthcare access, policies, and staffing leading to reduced MDR and higher pregnancy and birth rates.**

**Below-avera significant determinant for procreation.**

**Better healthcare access, though population density and landscape may influence results.**

**Better healthcare access, policies, and staffing ... contributes to lower MDR.**

**Population density can influence + unforseen/unmeasured factors**

## Q.1 – Compare the number of stillbirths in Sierra Leone for the current year between CHC, CHP, Clinic, Hospital, and MCHP as a Table and a Pie chart.

**Table:**

**App:** Data Visualizer

**Graphic Type:** Pivot Table

**Columns:**

- Data: Sill births
- Facility Type: CHC CHP, Clinic, Hospital, MCHP

**Rows:** Period – Months this year

**Filter:** Organisation unit – Sierra Leone, grouped by Facility Types: CHC CHP, Clinic, Hospital, MCHP

**Pie Chart:**

**App:** Data Visualizer

**Graphic Type:** Pie Chart

**Series:** Facility Type - CHC CHP, Clinic, Hospital, MCHP

**Filter:**

- Data: Still births
- Period: Months This year
- Organisation Unit: Sierra Leone, grouped by Facility Types: CHC CHP, Clinic, Hospital, MCHP

## Q.1 – Compare the number of stillbirths in Sierra Leone for the current year between CHC, CHP, Clinic, Hospital, and MCHP as a Table and a Pie chart.

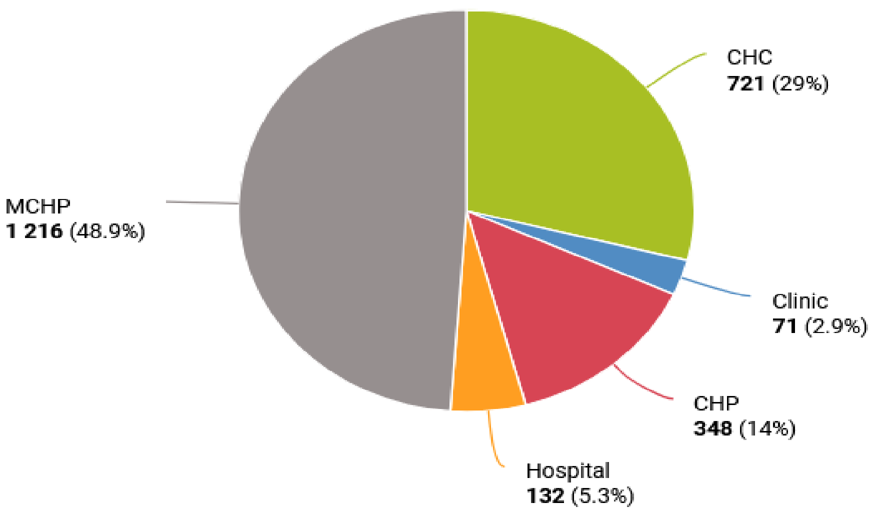
**Stillbirths in Sierra Leone for the current year between CHC, CHP, Clinic, Hospital, and MCHP**

CHC, CHP, Clinic, Hospital and MCHP groups in Sierra Leone

| | Still births | | | | | |
|---|---|---|---|---|---|---|
| | CHC | Clinic | CHP | Hospital | MCHP | Total |
| January 2024 | 74 | 8 | 43 | 7 | 91 | 223 |
| February 2024 | 68 | 2 | 24 | 13 | 132 | 239 |
| March 2024 | 130 | 1 | 32 | 8 | 127 | 298 |
| April 2024 | 50 | 8 | 44 | 10 | 127 | 239 |
| May 2024 | 71 | 28 | 29 | 6 | 114 | 248 |
| June 2024 | 77 | 4 | 28 | 9 | 117 | 235 |
| July 2024 | 34 | 2 | 31 | 15 | 86 | 168 |
| August 2024 | 50 | 4 | 41 | 13 | 133 | 241 |
| September 2024 | 68 | 1 | 28 | 2 | 87 | 186 |
| October 2024 | 33 | | 20 | 7 | 64 | 124 |
| November 2024 | 41 | 11 | 12 | 14 | 74 | 152 |
| December 2024 | 25 | 2 | 16 | 28 | 64 | 135 |
| Total | 721 | 71 | 348 | 132 | 1 216 | 2 488 |

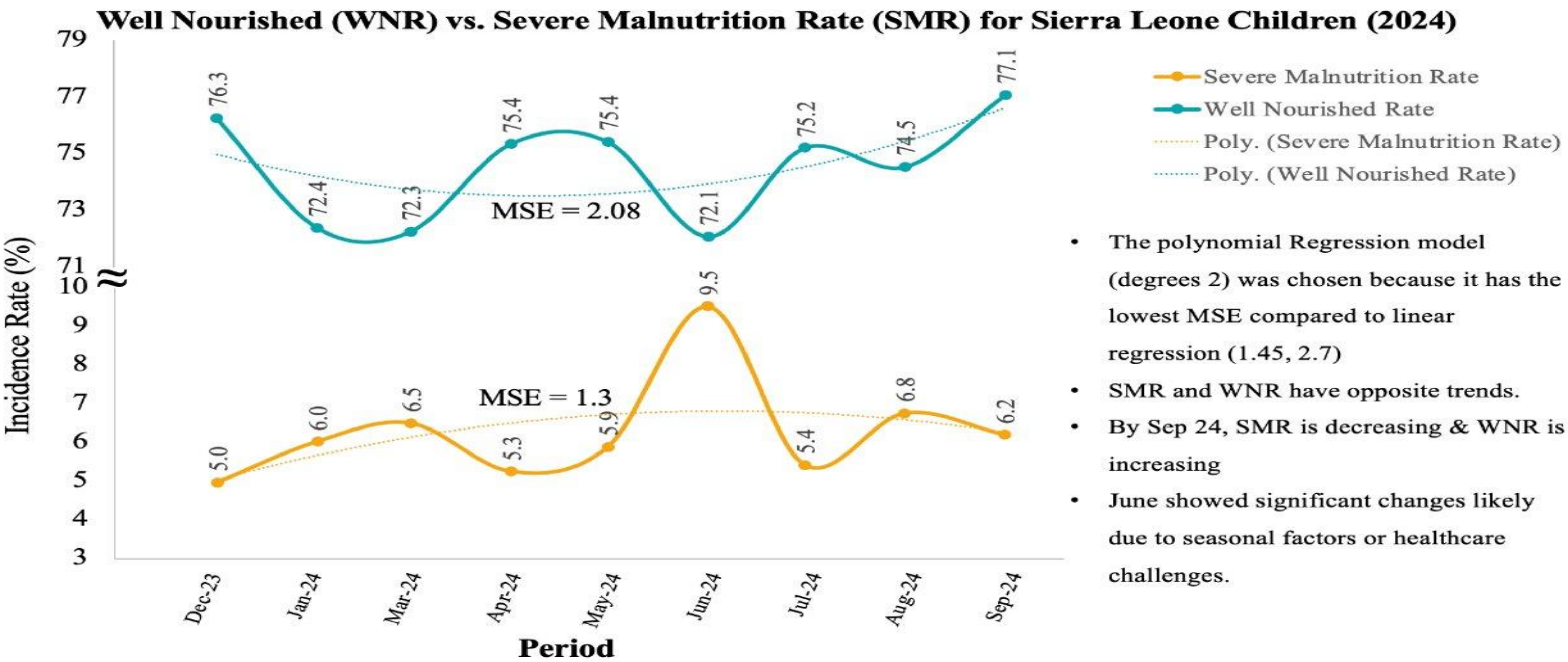
**Stillbirths in Sierra Leone for the current year between CHC, CHP, Clinic, Hospital, and MCHP**

2024 - Still births - CHC, CHP, Hospital, Clinic and MCHP groups in Sie...




The table offers insights of still births month wise., while pie chart give a visually appealing interpretation of the still birth count for the year 2024.

## Q2. What are your conclusions regarding the Severe Malnutrition rate and well-nourished rate in the population of Sierra Leone for the current year? What type of trend are you seeing?



## Q.2 – Identify the minimum number of months that will change the trend and demonstrate this change in trend.

**To find how many months are needed to change the trend**

- Check the current trend direction using the curve's shape (upward or downward).
- Add new, hypothetical data points one by one, either above or below the current trend, depending on the desired change.
- After each addition, recalculate the curve to see if the trend has reversed.

**Result:**
**Based on this for both rates, 1 month is needed to change the direction**

## Q.2 – Identify the minimum number of months that will change the trend and demonstrate this change in trend.

Prediction of Next Year's Severe Malnutrition Rate for each District in Sierra Leone

**Methodology**

Download the past 10 years' annual rate for each district

Check for missing values

Scale the data using a min-max scalar to avoid any potential bias

Using the ARIMA model, fit the data and predict the new year's rate

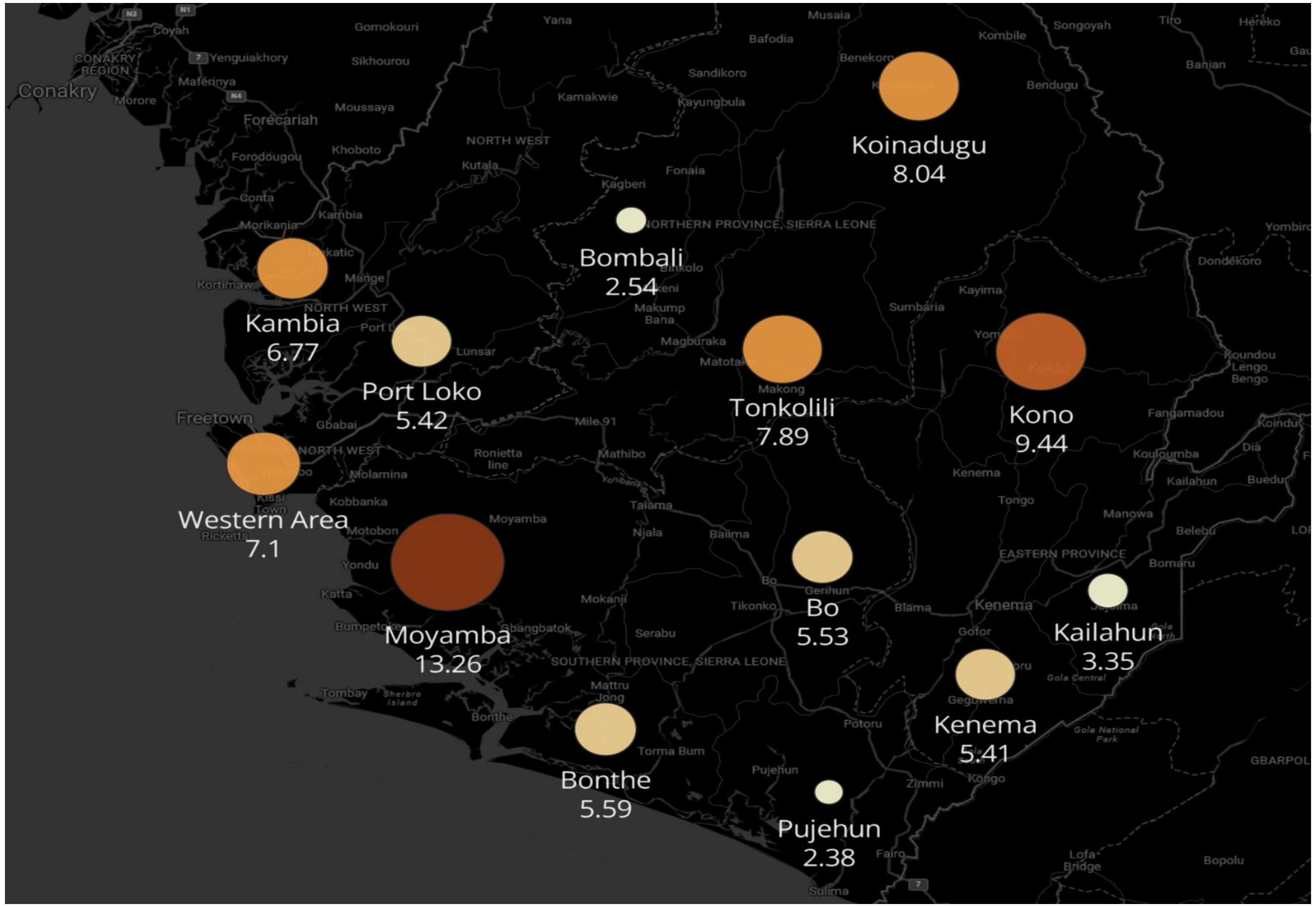
Default parameters (p=1, d=1, q=1) were used, and the model was fit for each district.

After training, predictions were made for the next year.

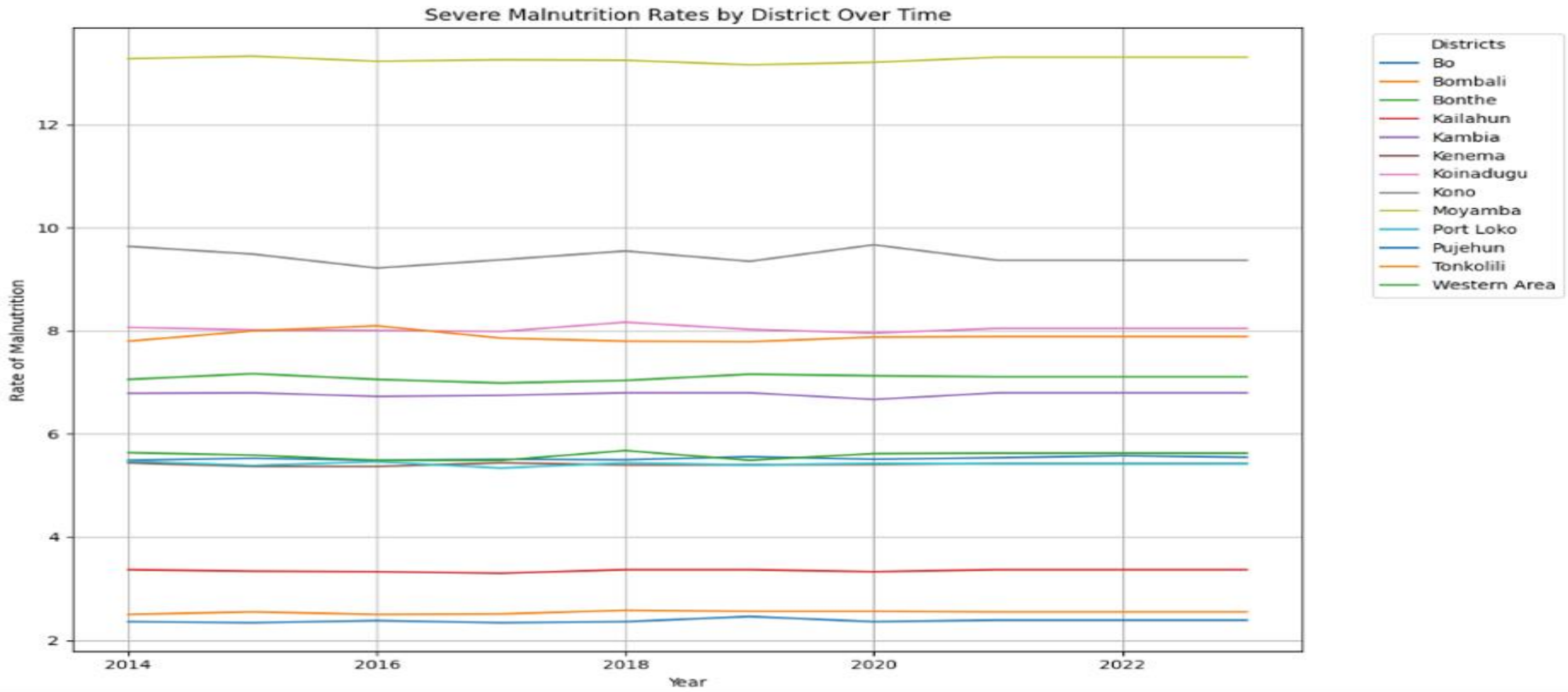
## Q.2 – Identify the minimum number of months that will change the trend and demonstrate this change in trend.

Prediction of Next Year's Severe Malnutrition Rate for each District in Sierra Leone

| 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023 | |
|---|---|
| | Weight for height <70% rate |
| Bo | 5.53 |
| Bombali | 2.54 |
| Bonthe | 5.59 |
| Kailahun | 3.35 |
| Kambia | 6.77 |
| Kenema | 5.41 |
| Koinadugu | 8.04 |
| Kono | 9.44 |
| Moyamba | 13.26 |
| Port Loko | 5.42 |
| Pujehun | 2.38 |
| Tonkolili | 7.89 |
| Western Area | 7.1 |

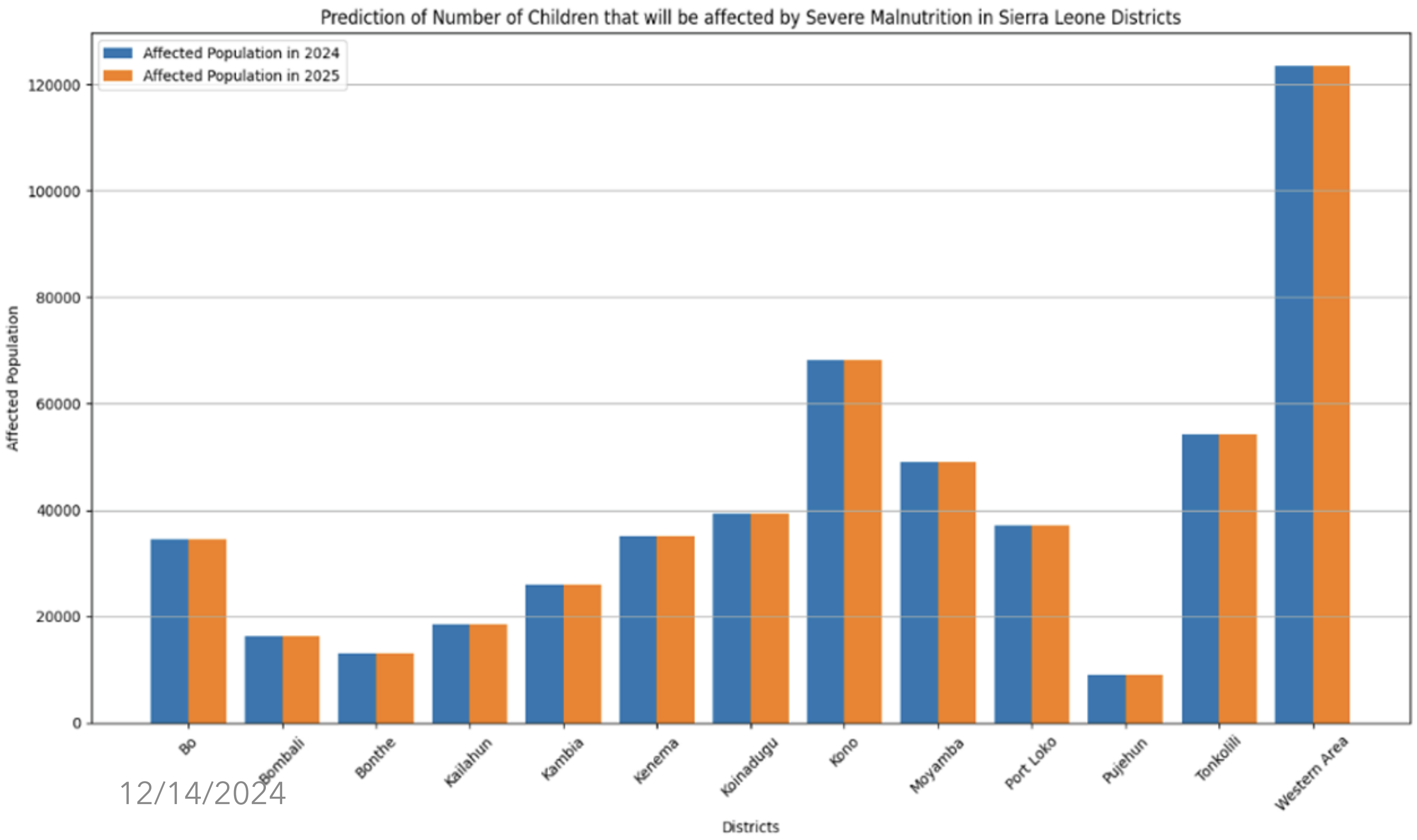


# Q.2b – Can you build a model to predict the number of severe malnourished children next year per district? Discuss some considerations when doing predictive modeling for this.



## Q.2b – Can you build a model to predict the number of severe malnourished children next year per district? Discuss some considerations when doing predictive modeling for this.

# Severe Malnutrition Rate Predicted for 2024 & 2025




| | District | Forecast for 2024 |
|---|---|---|
| 0 | Bo | 5.990670 |
| 1 | Bombali | 2.704063 |
| 2 | Bonthe | 6.552037 |
| 3 | Kailahun | 3.534968 |
| 4 | Kambia | 7.550167 |
| 5 | Kenema | 5.749019 |
| 6 | Koinadugu | 9.648047 |
| 7 | Kono | 13.470898 |
| 8 | Moyamba | 15.424295 |
| 9 | Port Loko | 6.044507 |
| 10 | Pujehun | 2.626410 |
| 11 | Tonkolili | 10.234970 |
| 12 | Western Area | 8.267562 |

To convert the predicted malnutrition rates into the number of children, I downloaded total population data for children from the Sierra Leone Census webpage and calculated the no of malnourished children
https://sierraleone.opendataforafrica.org/kmrprpc/population-and-housing-census-sierra-leone-2004

## Q.6 – Create a table to compare ANC 2 coverage of all chiefdoms from Sierra Leone that are bordering the country of Liberia for the current year.

**App:** Maps
**Base map:** OSM Light
**Layer:** Thematic
**Data:** ANC 2 Coverage (Indicator)
**Period:** Months this year
**Organisation Unit:** Sierra Leone, Chiefdoms level

**The chiefdoms bordering the country of Liberia:**

Kissi Teng

Kissi Tongi

Luawa

Upper Bambara

Dea

Malema

Nomo

Tunkia

Makpele

Soro-Gbeima

## Q.6 – Create a table to compare ANC 2 coverage of all chiefdoms from Sierra Leone that are bordering the country of Liberia for the current year.

**Next Step:**

- **App**: Data Visualizer
- **Graphic Type**: Pivot Table
- **Data**: ANC 2 Coverage”
- **Period**: Months this year
- **Organisation Unit**: Manually selected Chiefdoms bordering the country Liberia and across the country Sierra Leone.

**Chiefdoms bordering Liberia**

Dea, Kissi Teng, Kissi Tongi, Luawa, Malema, Nomo, Tunkia, Makpele, Soro-Gbeima, Kailahun, Kenema, Pujehun, Upper Bambara

| Period / Data | ANC 2 Coverage |
|---|---|
| January 2024 | 94.63 |
| February 2024 | 95.59 |
| March 2024 | 87.86 |
| April 2024 | 101.32 |
| May 2024 | 119.58 |
| June 2024 | 121.92 |
| July 2024 | 99.91 |
| August 2024 | 96.25 |
| September 2024 | 95.06 |
| October 2024 | 77.73 |
| November 2024 | 85.18 |
| December 2024 | 75.96 |

**Chiefdoms bordering Liberia**

anuary 2024, February 2024, March 2024, April 2024, May 2024, June 2024, July 2024, August 2024, September 2024, October 2024, November 2024, December 2024

| Organisation unit / Data | ANC 2 Coverage |
|---|---|
| Dea | 79.65 |
| Kissi Teng | 54.91 |
| Kissi Tongi | 77.41 |
| Luawa | 106.71 |
| Malema | 84.43 |
| Nomo | 78.31 |
| Tunkia | 110.92 |
| Makpele | 72.81 |
| Soro-Gbeima | 75.58 |
| Kailahun | 84.5 |
| Kenema | 114.01 |
| Pujehun | 74.53 |
| Upper Bambara | 104.11 |

**Chiefdoms across the country**

Chiefdom levels in Kailahun, Bo, Bombali, Bonthe, Jawi, Kissi Kama, Mandu, Njaluahun, Peje Bongre, Peje West, Penguia, Upper Bambara, Yawei, Kambia, Dama, Dodo, Gaura, Gorama Mende, Kandu Lepiema, Koya (kenema), Langrama, Lower Bambara, ...

| Period / Data | ANC 2 Coverage |
|---|---|
| January 2024 | 81.81 |
| February 2024 | 93.72 |
| March 2024 | 87.3 |
| April 2024 | 95.61 |
| May 2024 | 111.8 |
| June 2024 | 116.97 |
| July 2024 | 100.31 |
| August 2024 | 96.58 |
| September 2024 | 99.84 |
| October 2024 | 89.73 |
| November 2024 | 79.5 |
| December 2024 | 70.97 |

## Q.6 – Is there a significant difference between these chiefdoms compared to the other chiefdoms across the country?

**CSV downloads were extracted from DHIS2**

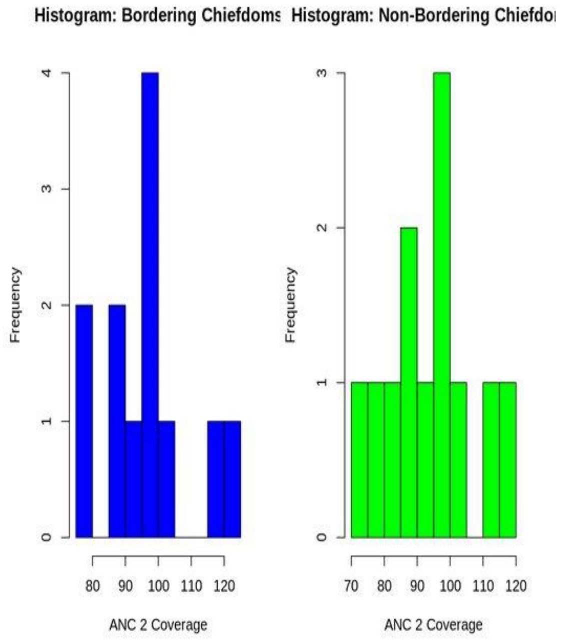
**Analysis in R (google-colab):**

- Performed Shapiro-Wilk Normality testing.
  - $H_0$ = Data is not normally distributed.

```
[ ] # Load the data
    bordering_data <- read.csv("/content/chiefdoms from Sierra Leone bordering the country of Liberia.csv")
    non_bordering_data <- read.csv("/content/Chiefdoms across the country.csv")
```

```
[ ] # Extract the ANC 2 coverage values
    bordering_coverage <- bordering_data$ANC.2.Coverage
    non_bordering_coverage <- non_bordering_data$ANC.2.Coverage

    # Ensure the values are numeric
    bordering_coverage <- as.numeric(bordering_coverage)
    non_bordering_coverage <- as.numeric(non_bordering_coverage)
```

```
[1] "Shapiro-Wilk test for bordering chiefdoms:"

	Shapiro-Wilk normality test

data:  bordering_coverage
W = 0.92106, p-value = 0.2948

[1] "Shapiro-Wilk test for non-bordering chiefdoms:"

	Shapiro-Wilk normality test

data:  non_bordering_coverage
W = 0.98165, p-value = 0.9894
```



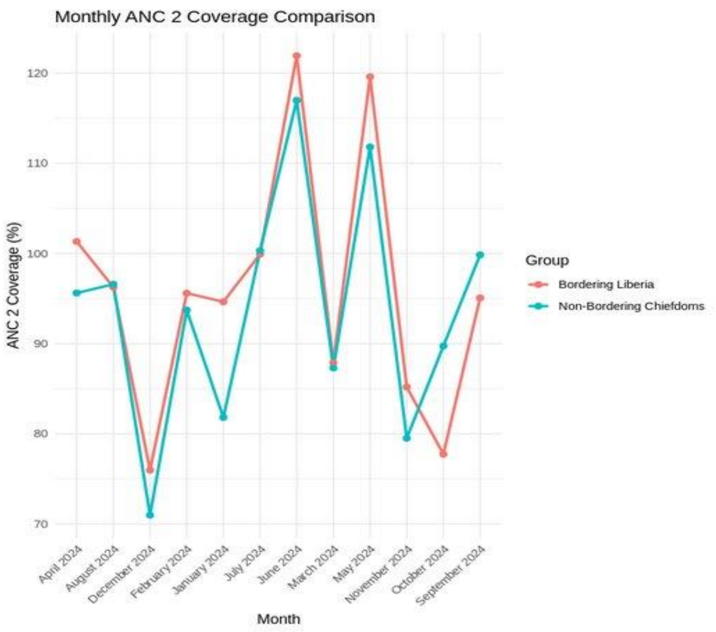

**To further understand if there is any significance difference**

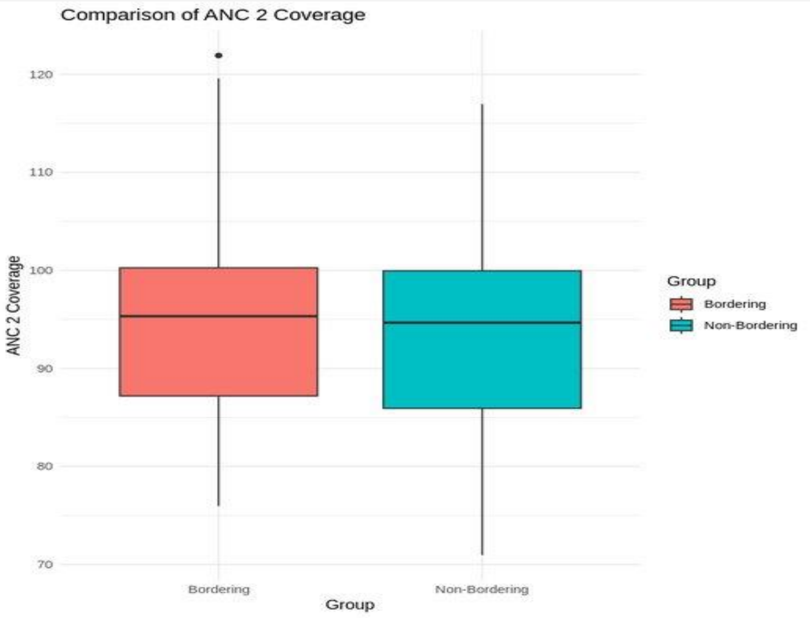
- **Performance 2-sample T-test**
  - **Independent groups**
  - **Continuous data variables**
  - **Data is almost normally distributed**

## Q.6 – Is there a significant difference between these chiefdoms compared to the other chiefdoms across the country?

```
# Conduct a t-test to compare means
t_test_result <- t.test(bordering_coverage, non_bordering_coverage,
                        alternative = "two.sided",
                        var.equal = FALSE)

# Print the t-test results
print("T-test result:")
print(t_test_result)
```

```
[1] "T-test result:"

        Welch Two Sample t-test

data:  bordering_coverage and non_bordering_coverage
t = 0.40286, df = 21.87, p-value = 0.691
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -9.284927 13.759927
sample estimates:
mean of x mean of y
 95.91583  93.67833
```




- No statistically significant difference in ANC 2 coverage between chiefdoms bordering Liberia and other chiefdoms across Sierra Leone for the current year.
- The mean ANC 2 coverage for bordering chiefdoms (95.92%) vs non-bordering chiefdoms (93.68%).
  P-value (0.691) indicates that this difference is likely due to random variation rather than a true disparity.
- 95% confidence interval [-9.28 , 13.76] includes zero, further supporting this conclusion that ANC 2 coverage appears relatively consistent across Sierra Leone, regardless of proximity to the Liberian border.

**Q.7 - Among the chiefdoms from Question 6, for the chiefdom which has ANC2 coverage less than 60, describe the following facts: ANC visits per clinical professional, Expected pregnancies, Population of women of childbearing age (WRA), Total Population, Total population < 1 year, Total population < 5 years.**

**Chiefdoms with ANC2 Coverage Below 60%**

**Step 1: Identifying Chiefdoms**

- **Data Selection:**

Indicator Group: ANC
Indicator: ANC2 Coverage
Period: Months this year (Relative)
Organizational Units: Chiefdom level, filtered for ANC2 < 60%.

- **Pivot Table Configuration:**

Data as columns
Period as rows
Organization Units as filters

- Output: CSV file generated for further analysis.

**Step 2: Visualizing Data**

- **Map Visualization:**

Created thematic map displaying chiefdoms with ANC2 coverage < 60%.

**Profile Description of each Chiefdom Contains:**

ANC Visits per Clinical Professional
Expected Pregnancies

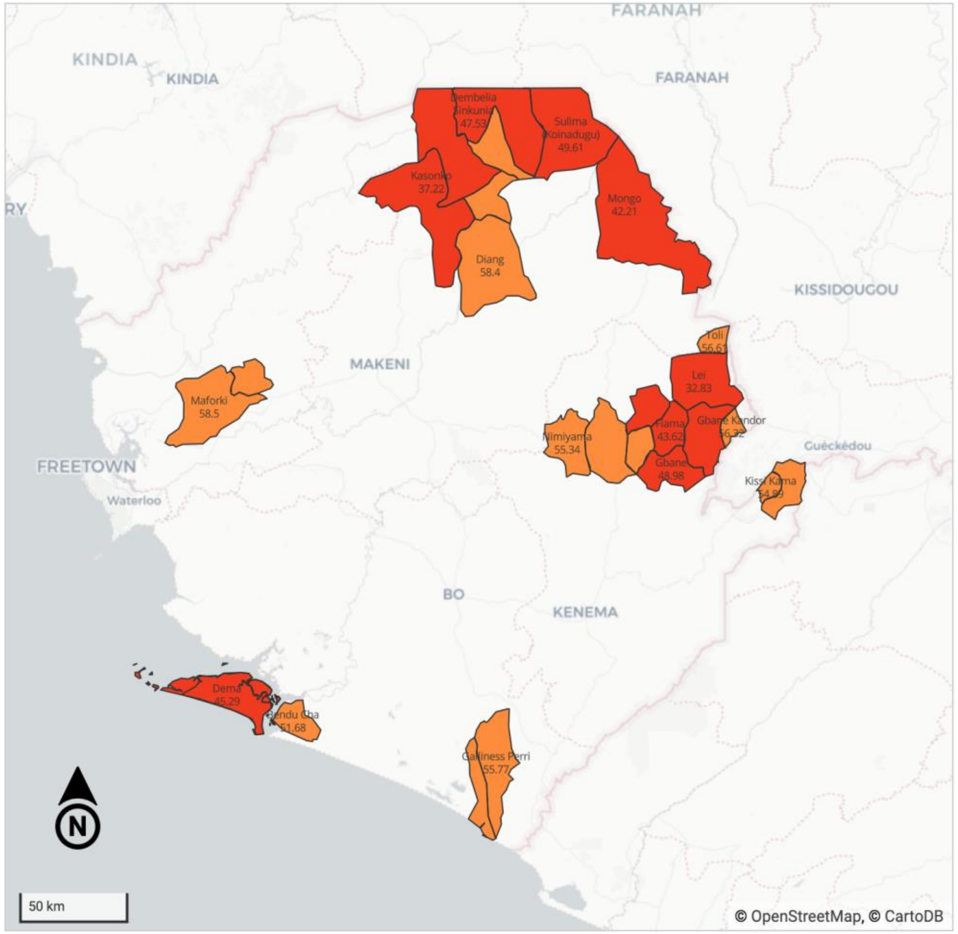
Population of Women of Childbearing Age (WRA)

Total Population

Total Population Under 1 Year

Total Population Under 5 Years

## Q.7

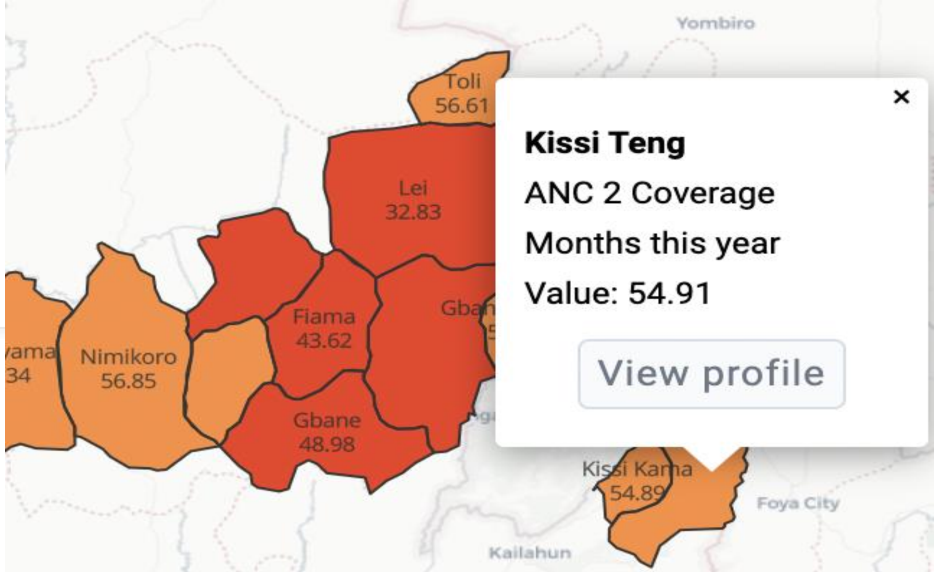



### ANC2 Coverage <60

Chiefdoms having ANC2 coverage less than 60

**ANC 2 Coverage**
Months this year

- Low 0 - 30 (0)
- Medium 30 - 50 (13)
- Medium Pl. 50 - 70 (33)
- High 70 - 80 (23)
- High Plus 80 - 90 (19)
- Great 90 - 120 (40)
- Invalid 120 - 990 (24)
- No data


| | |
|---|---|
| Expected pregnancies | 1086 |
| ANC visits per clinical professional | 350 |
| Total population < 5 years | 4020 |
| Population of women of child bearing age (WRA) | 5043 |
| Total population < 1 year | 986 |
| Total Population | 24663 |

**Facts about Chiefdom Kissi Teng**

**Q.7 - Among the chiefdoms from Question 6, for the chiefdom which has ANC2 coverage less than 60, describe the following facts: ANC visits per clinical professional, Expected pregnancies, Population of women of childbearing age (WRA), Total Population, Total population < 1 year, Total population < 5 years.**

# Key Chiefdoms which has ANC2 coverage less than 60

| Chiefdom | ANC 2 Coverage | ANC visits per clinical professional | Expected pregnancies | Population of women of childbearing age (WRA) | Total Population | Total population < 1 year | Total population < 5 years |
|---|---|---|---|---|---|---|---|
| Lei | 32.83 | | 896 | 4155 | 20317 | 812 | 3311 |
| Kasonko | 37.22 | 543.67 | 1219 | 5663 | 27692 | 1107 | 4514 |
| Gbense | 39.01 | 4789 | 3689 | 17142 | 83821 | 3353 | 13662 |
| Mongo | 42.21 | 268.13 | 1812 | 8325 | 41192 | 1650 | 6714 |
| Fiama | 43.62 | 626.77 | 814 | 3780 | 18488 | 740 | 3014 |
| Dema | 45.29 | | 240 | 1114 | 5444 | 217 | 888 |
| Bendu Cha | 51.68 | | 137 | 638 | 3115 | 125 | 508 |
| Kissi Teng | 54.91 | 350 | 1086 | 5043 | 24663 | 9886 | 4020 |
| Galliness Perri | 55.77 | 210.33 | 1588 | 7380 | 36093 | 1446 | 5884 |
| Diang | 58.4 | 225.46 | 1443 | 6706 | 32794 | 1314 | 5344 |
| Maforki | 58.5 | | 4279 | 19888 | 97260 | 3892 | 15855 |

## Question 8a – Find the chiefdom with the lowest ANC 2 coverage in all of Sierra Leone. List the facility in this chiefdom that performs poorly on this indicator and suggest reasons for the same.

**App:** Data Visualizer
**Graphic Type:** Pivot Table
**Data:** ANC 2 Coverage
**Period:** Months this Year
**Organisation Unit:** Level – Chiefdom

Sorted the pivot table by ascending ANC 2 Coverage

- Lowest ANC 2: Chiefdom Lei

**Adjusted Organisation Unit:** Level - Facilities within Chiefdom Lei.

Sorted the pivot table by ascending ANC 2 Coverage

**Adjusted Organisation Unit:** Specific Facilities within Chiefdom Lei.

**Reasons for poor performance:**

**Staffing and Reporting Issues**: Lei's poor ANC 2 coverage is linked to a severe shortage of healthcare workers or poor reporting, particularly at CHP and MCHP facilities. **Infrastructure Deficiencies**: Inadequate electricity, water, and internet infrastructure hinder effective healthcare service delivery. **Resource Strains and Retention Challenges**: High consumption-to-population ratios, long wait times, transportation challenges, lack of awareness, and socioeconomic barriers impact care quality and patient retention. **Gaps in Resource Allocation**: Despite sufficient vaccine stocks, MCHP underperforms, highlighting the need for improved staffing, resource management, community education, and follow-up visit incentives.

| January 2024, February 2024, March 2024, April 2024, May 2024, June 2024, July 2024, August 2024, September 2024, October 2024, November 2024, December 2024 | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Foakor MCHP | Gbongongor CHP | Komba Yendeh CHP | Kongoifeh MCHP | Kundundu MCHP | Ngelehun CHC | Njandama MCHP | Saiama MCHP | Badjia | Lei |
| ANC 2 Coverage | 44.67 | 49.36 | 35.87 | 25.74 | 15.77 | 239.47 | 279.23 | 46.03 | 251.11 | 32.83 |
| BCG Stock PHU | 30 | 265 | 60 | 23 | 83 | 353 | 107 | 132 | 460 | 593 |
| Measles Stock End Balance | 106 | 73 | 41 | 83 | 23 | 327 | 80 | 134 | 407 | 460 |
| OPV Stock PHU | 89 | 254 | 40 | 56 | 89 | 262 | 112 | 175 | 374 | 703 |
| Staffing - Reporting rate | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Staffing - Reporting rate on time | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Staffing - Actual reports | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Staffing - Actual reports on time | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Staffing - Expected reports | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Consumption vs population | 767.82 | 727.78 | 784.54 | 771.43 | 764.41 | 767.13 | 694.92 | 750.6 | 746.04 | 765.89 |
| ER Census reports produced Result vs Target | | 71.24 | 71.81 | 119.01 | 102.48 | 95.32 | | 156.96 | 95.32 | 97.58 |
| ER Children trained on key survival skills Result vs Target | | 119.09 | 95.74 | 107.4 | 115 | 106.65 | | 143.33 | 106.65 | 110.11 |
| ER Teacher accommodation constructed Urban Result vs Target | | 157.78 | 87.9 | 74.77 | 94.51 | 71.24 | | 121.09 | 71.24 | 95.15 |
| ER Teacher training programs designed Result vs Target | | 168.5 | 74.05 | 114.33 | 130.59 | 96.99 | | 133.11 | 96.99 | 110.27 |
| ER Teachers trained Result vs Target | | 94.24 | 117.84 | 75.12 | 109.48 | 88.51 | | 74.78 | 88.51 | 97.43 |
| ER Technical support visits Result vs Target | | 90.47 | 105.17 | 111.07 | 85.68 | 87.56 | | 71.88 | 87.56 | 94.05 |
| ER Technical support visits Rural Result vs Target | | 70.18 | 111.8 | 89.93 | 100.6 | 104.55 | | 66.44 | 104.55 | 90.97 |
| ER Visits in schools Rural Result vs Target | | 157.14 | 100 | 141.72 | 69.52 | 148.1 | | 70.78 | 148.1 | 98.04 |
| Still births | 1 | | 3 | | | 25 | 3 | 1 | 28 | 5 |
| Maternal death | | 2 | | 1 | | 1 | 2 | | 3 | 3 |
| Maternal death rate by registered live births | | 13 333.33 | | 2 127.66 | | 649.35 | 4 255.32 | | 1 492.54 | 1 724.14 |
| Moderate malnutrition rate | | | | | | 12.98 | | | 12.98 | |
| Severe malnutrition rate | | | | | | 2.03 | | | 2.03 | |

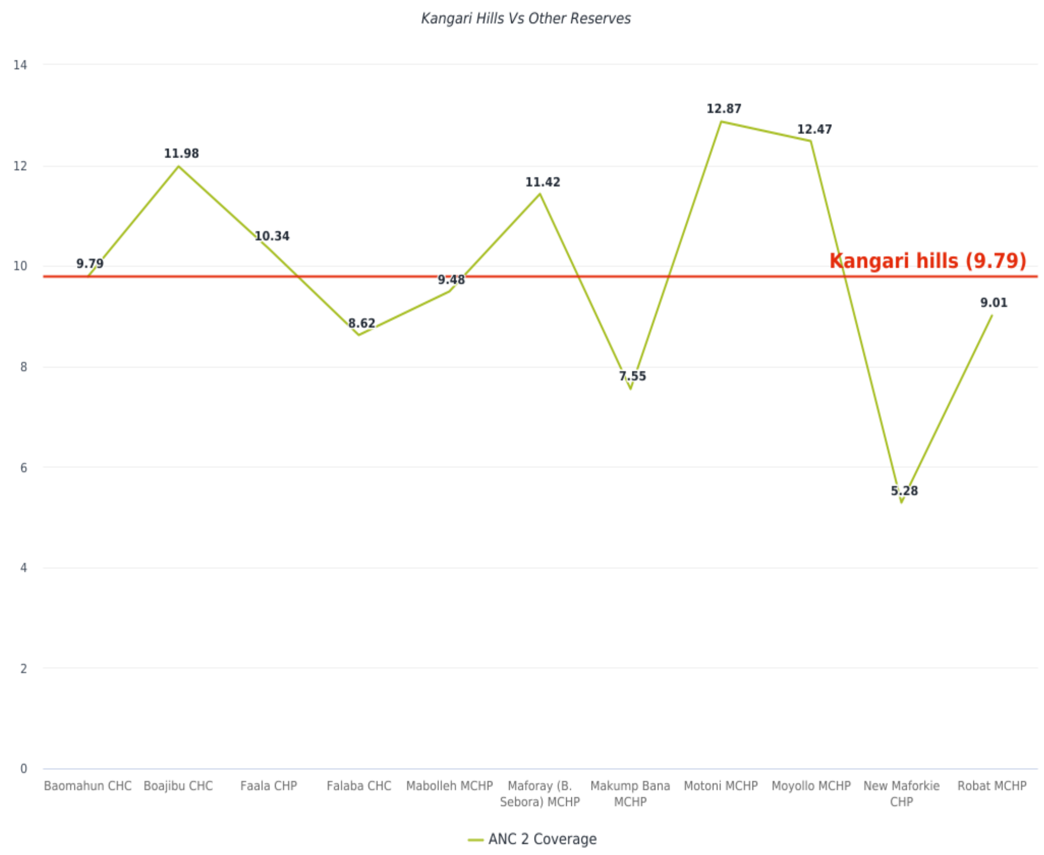
## Question 8b – List the ANC2 coverage for a facility inside the KangariHills Forest Reserve and compare it to other facilities that are inside/or bordering other forest reserves in all of Sierra Leone.

**App:** Maps (OSM Detailed)
**Period:** Last 10 years
**Layer:** Facilities (Level – Facilities) across Sierra Leone
**Adjusted Layer:** Identified Facilities around Forest Reserves and manually selected them
**Added Layer:** Thematic (Data: ANC 2) only included those facilities above
Converted Map data to Data Visualizer then **Graphic Type:** Line chart

**Kangari Hills Forest Reserve:** Baomahun CHC ANC2 coverage of 9.79% **Comparison to Other Forest Reserves:**

- Facilities like Mabolleh MCHP and Robat MCHP had similar coverage levels.
- Motoni MCHP and Moyollo MCHP exhibited significantly higher coverage.
- The Baomahun CHC's coverage falls within the mid-range of values observed for other facilities.

**Conclusion:** The ANC2 coverage of the Baomahun CHC suggests that the data collected for this facility is comparable in quality to many other facilities across Sierra Leone.



# Q.9 - monthly choropleth maps of ANC1 coverage for all chiefdoms in Sierra Leone from Jan 2023 to June 2024.

Using the Data Visualizer app, monthly choropleth maps of ANC1 coverage for all chiefdoms in Sierra Leone were created for January 2023 to June 2024.

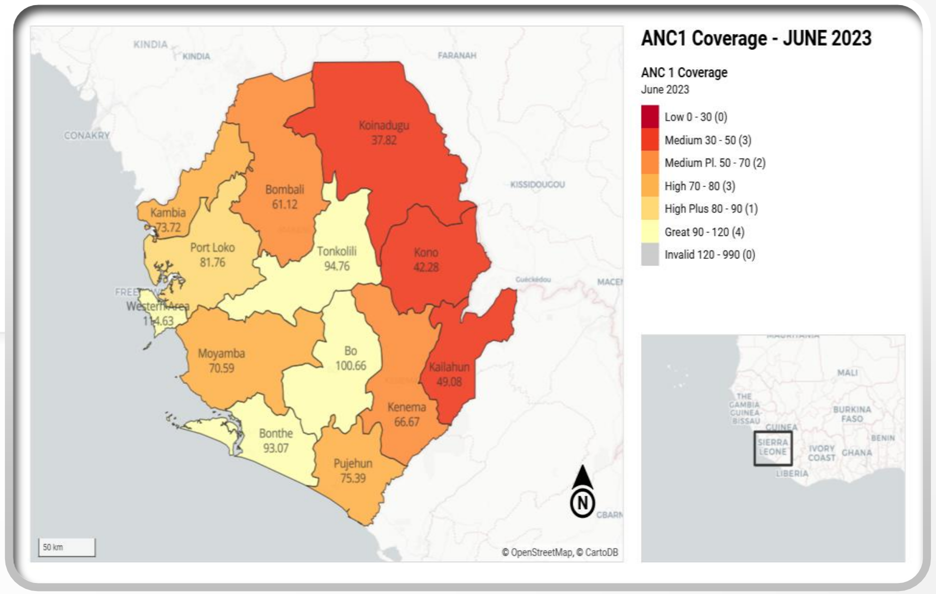
- The Indicator used was ANC1 Coverage, categorized into legend bins.
- Analysis of Choropleth Maps:

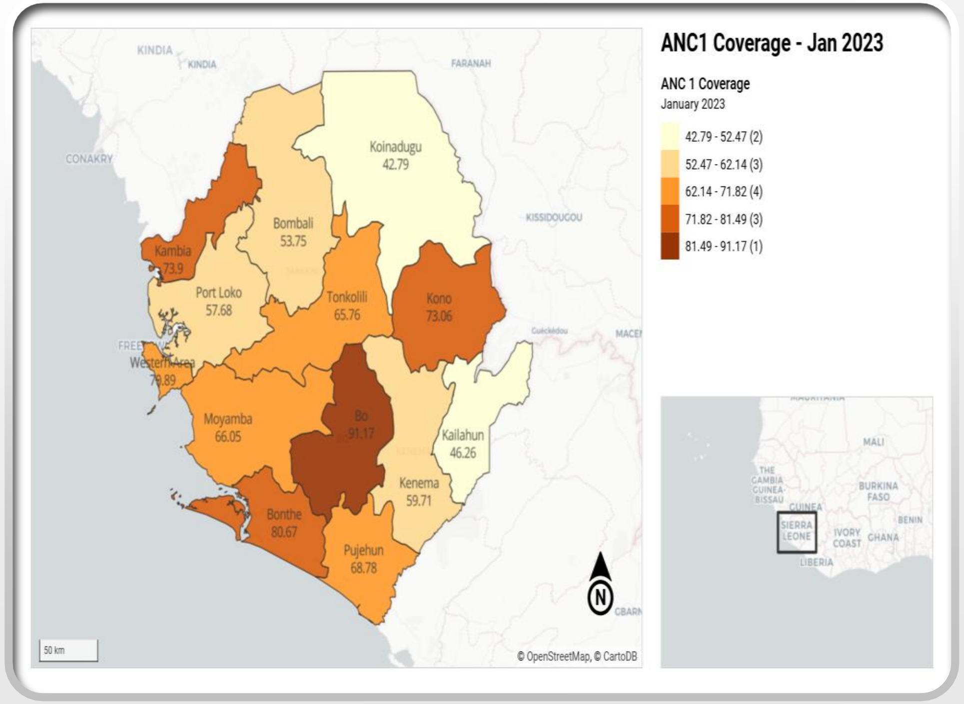
**Trends:**

- Urban areas like Freetown consistently showed high ANC1 coverage (≥90%), categorized as "Great" or "Exceptional."
- Rural areas, including Sittia, displayed lower coverage, often in the "Medium" or "High Plus" categories.

**Temporal Insights:**

- Seasonal patterns were observed, with slight dips in coverage during certain months, possibly due to rainy season challenges.
- Gradual improvement in coverage was noted over the 17 months for both urban and rural regions.



## Using this data as the training set for the appropriate algorithm, forecast the legend category (i.e., legend bin) for ANC1 coverage for Sittia and F July 2024.

- Low 0 - 30 (0)
- Medium 30 - 50 (1)
- Medium Pl. 50 - 70 (2)
- High 70 - 80 (3)
- High Plus 80 - 90 (1)
- Great 90 - 120 (5)
- Invalid 120 - 990 (1)

```r
install.packages("dplyr")  # Install dplyr if not already installed
library(dplyr)

# Define file paths
average_data_path <- "/content/sample_data/averagedata.csv"  # Path to input file
output_file_path <- "/content/sample_data/data_with_legend.csv"  # Path to save the output

# Load the dataset
average_data <- read.csv(average_data_path)

# Define the logic for the 'Legend' column based on 'Total'
average_data <- average_data %>%
  mutate(
    Legend = case_when(
      Total >= 0 & Total < 30 ~ "Low",
      Total >= 30 & Total < 50 ~ "Medium",
      Total >= 50 & Total < 70 ~ "Medium Pl.",
      Total >= 70 & Total < 80 ~ "High",
      Total >= 80 & Total < 90 ~ "High Plus",
      Total >= 90 & Total < 120 ~ "Great",
      Total >= 120 & Total <= 990 ~ "Invalid",
      TRUE ~ NA_character_  # Catch any unexpected values
    )
  )

# Preview the modified data
head(average_data)

# Save the modified data to a new CSV file
write.csv(average_data, output_file_path, row.names = FALSE)
```

```
Installing package into '/usr/local/lib/R/s
(as 'lib' is unspecified)
```

A data.frame: 6 × 5

| | periodname | organisationunitname | dataname | Total | Legend |
|---|---|---|---|---|---|
| | <chr> | <chr> | <chr> | <dbl> | <chr> |
| 1 | Apr-23 | Freetown | ANC 1 Coverage | 72.17 | High |
| 2 | Apr-24 | Freetown | ANC 1 Coverage | 110.42 | Great |
| 3 | Apr-24 | Sittia | ANC 1 Coverage | 87.53 | High Plus |
| 4 | Aug-23 | Sittia | ANC 1 Coverage | 164.49 | Invalid |
| 5 | Aug-23 | Freetown | ANC 1 Coverage | 94.68 | Great |
| 6 | Dec-23 | Freetown | ANC 1 Coverage | 97.31 | Great |

# Validate your model prediction against actual data.

```r
# Convert periodname to datetime format
data$periodname <- dmy(paste("01", data$peri

# Filter data for Freetown and Sittia up to June 2024
filtered_data <- data %>%
  filter(periodname <= "2024-06-30" & organisationunitname %in% c("Freetown",

# Initialize forecast results
forecast_results <- list()

# Forecasting using ARIMA
for (region in c("Freetown", "Sittia")) {
  region_data <- filtered_data %>% filter(organisationunitname == region) %>%
  time_series <- ts(region_data$Total, frequency = 12)
  model <- auto.arima(time_series)
  forecast_value <- forecast(model, h = 1)$mean[1]
  forecast_legend <- assign_legend(forecast_value)
  forecast_results[[region]] <- list(Forecasted_Value = forecast_value, Foreca
}

print(forecast_results)

# Load actual data for July 2024
actual_july_data <- read_csv("/content/sample_data/julyactual.csv")

# Validation
validation_results <- list()

for (i in 1:nrow(actual_july_data)) {
```

```
$Freetown
$Freetown$Forecasted_Value
[1] 109.012

$Freetown$Forecasted_Legend
[1] "Great"


$Sittia
$Sittia$Forecasted_Value
[1] 164.34

$Sittia$Forecasted_Legend
[1] "Invalid"


Rows: 2 Columns: 5
── Column specification ──────────────────────────
Delimiter: ","
chr (4): periodname, organisationunitname, dataname, Legend
dbl (1): Total

ℹ Use `spec()` to retrieve the full column specification for this data.
ℹ Specify the column types or set `show_col_types = FALSE` to quiet this message.
    Region Actual_Value Forecasted_Value Actual_Legend Forecasted_Legend
1 Freetown        95.72          109.012         Great             Great
2   Sittia       110.12          164.340         Great           Invalid
  Percentage_Error Legend_Match
1         13.88634         TRUE
2         49.23721        FALSE
```

| REGION | ACTUAL VALUE | FORECASTED VALUE | ACTAL LEGEND | FORECASTED LEGEND | PERCENTAGE ERROR | LEGEND MATCH |
|---|---|---|---|---|---|---|
| FREETOWN | 95.72 | 101.9 | GREAT | GREAT | 6.51 | TRUE |
| SITTIA | 110.12 | 164.3 | GREAT | INVALID | 49.23 | FALSE |

# Q.10 - Create 3 interpretations: Sentiment Analysis

## Overview

Analyzed feedback on 3 interpretations: Line Plot (I1), Table (I2), and Map (I3)

Sentiment scores calculated for each comment (C1, C2, C3)

## Bar Plot Visualization:

X-axis: Comment IDs (C1_I1 to C3_I3)

Y-axis: Sentiment Scores

Color-coded by Report Type (Line Plot, Table, Map)

## Key Findings:

Line Plot (I1): Highest avg. sentiment (3.75)

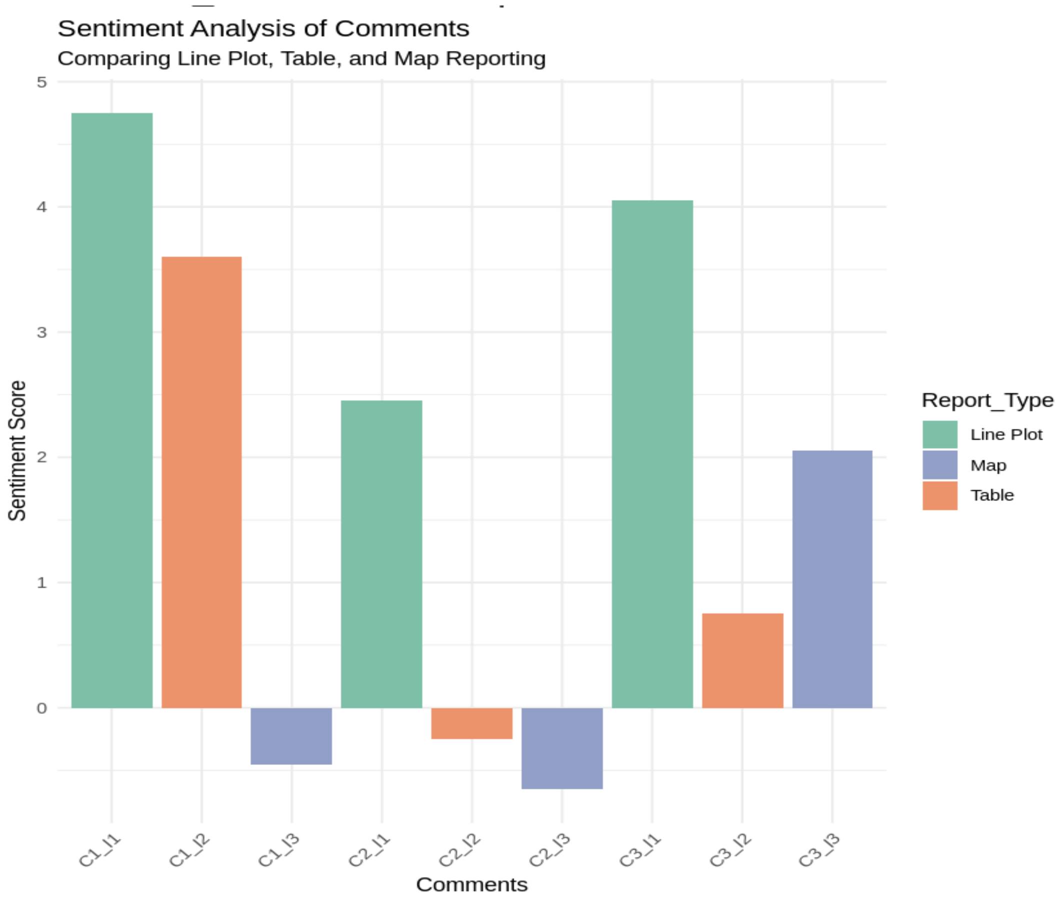
C1_I1: 4.75, C2_I1: 2.45, C3_I1: 4.05

Table (I2): Mixed reactions (avg. 1.37)

C1_I2: 3.60, C2_I2: -0.25, C3_I2: 0.75

Map (I3): Lowest avg. sentiment (0.32)

C1_I3: -0.45, C2_I3: -0.65, C3_I3: 2.05



# Q.10 - Create 3 interpretations: Sentiment Analysis

**Insights:**

Line plots most effective for visualizing trends over time

Tables provide detailed data but evoke mixed reactions

Maps highlight geographic disparities but need improvement

**Recommendations:**

Prioritize line plots for trend analysis

Enhance tables with additional context (e.g., regional breakdowns)

Improve map designs with better readability and contextual information

Consider combining visualization methods for comprehensive analysis

Conduct further user testing to refine all visualization types

# CONCLUSIONS

**Insights from the Analysis**

- Identified disparities in healthcare services, with rural areas like Sittia lagging behind urban centers like Freetown in ANC coverage and child health outcomes.
- Observed trends in severe malnutrition and well-nourished rates, emphasizing the impact of seasonal and resource-related factors.
- Prediction models, such as ARIMA, provided insights into malnutrition trends, highlighting the value of data-driven approaches.

**Recommendations**

- Expand healthcare access and staffing in rural areas to reduce disparities.
- Prioritize seasonal interventions to mitigate malnutrition peaks.
- Utilize predictive analytics to guide future resource allocation and policy decisions.

**Learning as a Student**

- Gained hands-on experience with DHIS2 and predictive modeling techniques.