


ASSIGNMENT 2 STATISTICAL CLIMATOLOGY		
Student's Code	 AIMS African Institute for Mathematical Sciences CAMEROON	Deadline
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1 Download Satellite data

In this part, it is a question of choosing a location in the world and downloading the corresponding climate data. For this, we are interested in Cameroon more precisely in the city of Garoua. Garoua is a city with a tropical climate. It would be interesting to study the distribution of precipitation in this area. To download our data we used the source CHIRPS and following the steps:

- We first go to Google map to get our coordinates (longitudes and latitudes).
- After enter it in CHIRPS platform and it look like this:

If you want to restrict the range along a grid, choose here.

	name	range
X	Longitude	13.375E to 13.625E
Y	Latitude	9.375N to 9.625N
T	Time	1 Jan 2004 to 31 Dec 2013

Restrict Ranges

Figure 1: setting ranges from CHIRPS source

After Downloaded the data, this is how it appear in R-instat:

	X	Y	.T	requested_X	requested_Y	prop	date
1	13.38	9.375	2453006	13.4	9.38	0.000e+00	2004-01-01
2	13.38	9.375	2453007	13.4	9.38	0.000e+00	2004-01-02
3	13.38	9.375	2453008	13.4	9.38	0.000e+00	2004-01-03
4	13.38	9.375	2453009	13.4	9.38	0.000e+00	2004-01-04
5	13.38	9.375	2453010	13.4	9.38	0.000e+00	2004-01-05
6	13.38	9.375	2453011	13.4	9.38	0.000e+00	2004-01-06
7	13.38	9.375	2453012	13.4	9.38	0.000e+00	2004-01-07
8	13.38	9.375	2453013	13.4	9.38	0.000e+00	2004-01-08
9	13.38	9.375	2453014	13.4	9.38	0.000e+00	2004-01-09
10	13.38	9.375	2453015	13.4	9.38	0.000e+00	2004-01-10
11	13.38	9.375	2453016	13.4	9.38	0.000e+00	2004-01-11
12	13.38	9.375	2453017	13.4	9.38	0.000e+00	2004-01-12
13	13.38	9.375	2453018	13.4	9.38	0.000e+00	2004-01-13
14	13.38	9.375	2453019	13.4	9.38	0.000e+00	2004-01-14
15	13.38	9.375	2453020	13.4	9.38	0.000e+00	2004-01-15
16	13.38	9.375	2453021	13.4	9.38	0.000e+00	2004-01-16
17	13.38	9.375	2453022	13.4	9.38	0.000e+00	2004-01-17
18	13.38	9.375	2453023	13.4	9.38	0.000e+00	2004-01-18
19	13.38	9.375	2453024	13.4	9.38	0.000e+00	2004-01-19

Figure 2: Satellite data for Garoua city from CHIRPS source

This data is about precipitation or rain in Garoua Cameroon from 2004 to 2013. We have choose this period of time because is was the one who contain much of data after trying several time to download the data.

Challenge in the process of downloading the satellite data

The way way to dowload satellite data is very different for the classic one.

- First you need to register on their website, that was the case for CM SAF.
- Too many steps: You need to get the coordinate in Google map
- One of the main challenge is that, you can not visualize your data before downloaded them. That why we were trying to download the same data many time until you have a data that can satisfied you.

Now we have our data, we can try to do some analysis we did with station data in the previous assignment.

1.1 PICSA graphs with satellite data

We can first look at the descriptive statistic by doing the summary table. To do it **Describe > One Variable > Summarise**, and we obtain the following table:

```

      X      Y      .T      requested_X      requested_Y
Min.   :13.4  Min.   :9.38  Min.   :2453006  Min.   :13.4  Min.   :9.38
1st Qu.:13.4  1st Qu.:9.38  1st Qu.:2453919  1st Qu.:13.4  1st Qu.:9.38
Median :13.4  Median :9.38  Median :2454832  Median :13.4  Median :9.38
Mean   :13.4  Mean   :9.38  Mean   :2454832  Mean   :13.4  Mean   :9.38
3rd Qu.:13.4  3rd Qu.:9.38  3rd Qu.:2455745  3rd Qu.:13.4  3rd Qu.:9.38
Max.   :13.4  Max.   :9.38  Max.   :2456658  Max.   :13.4  Max.   :9.38

      precip      date      year      month_abbr
Min.   : 0.00  Min.   :2004-01-01  Min.   :2004  Jan   : 310
1st Qu.: 0.00  1st Qu.:2006-07-02  1st Qu.:2006  Mar   : 310
Median : 0.00  Median :2008-12-31  Median :2008  May   : 310
Mean   : 2.57  Mean   :2008-12-31  Mean   :2008  Jul   : 310
3rd Qu.: 2.28  3rd Qu.:2011-07-02  3rd Qu.:2011  Aug   : 310
Max.   :57.44  Max.   :2013-12-31  Max.   :2013  Oct   : 310
                                (Other):1793

      day_in_month      doy
Min.   : 1.0  Min.   : 1
1st Qu.: 8.0  1st Qu.: 93
Median :16.0  Median :184
Mean   :15.7  Mean   :184
3rd Qu.:23.0  3rd Qu.:275
Max.   :31.0  Max.   :366

```

Figure 3: Summarise Table for Garoua data

The first thing we notice looking at this table is that there is no missing value. So our period of time was well choose. We can also notice that there is no much rain in Garoua. The maximum for precipitation was 57.44 and the minimum 0.

Now let look at the PICSA graphs to have a better vew on this data. Now lets go to **Climatic > PICSA > Rainfall Graph**. We will obtain the following graph.

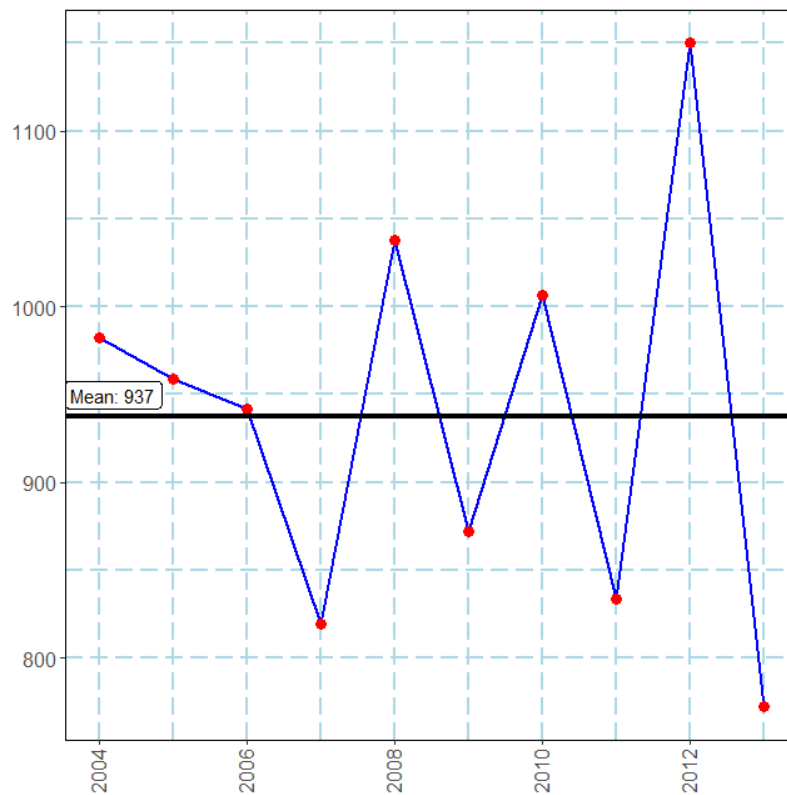


Figure 4: Sum of Precipitation for Garoua Satellite data

This graph above represent the sum of precipitation from 2004 to 2013. That's nice. We can see that even with satellite data, our graph looks like the one obtain with Station data. Looking at this graph, years 2012 and 2013 was the ones whose having much rain.

We can also look at the boxplot graph. Let's go to **Describe > Specific > Boxplot**. We obtain the following graph:

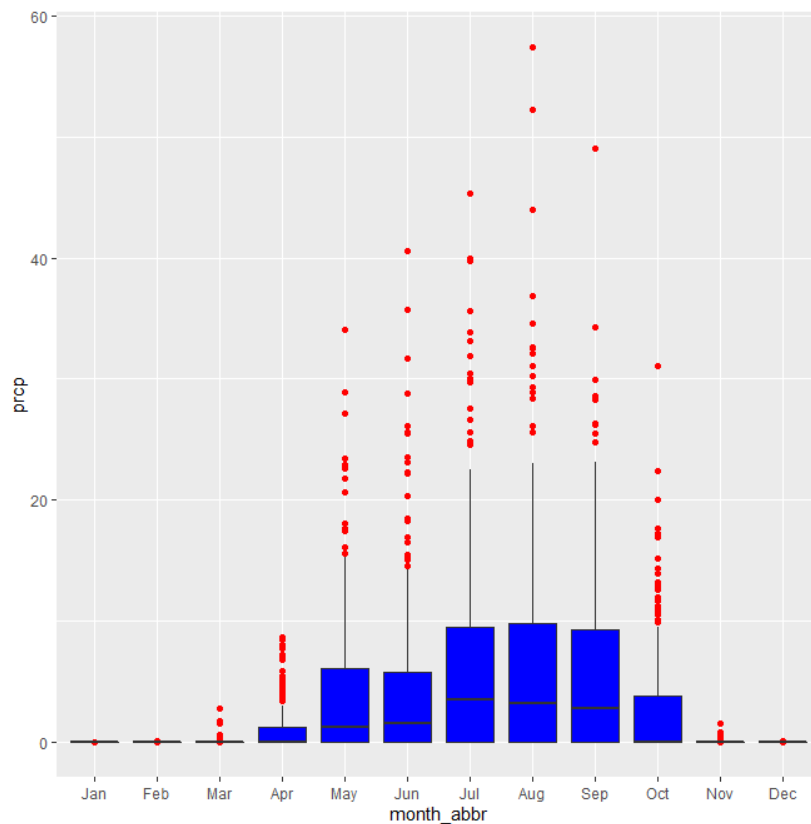


Figure 5: Boxplot of monthly rainfall totals for Garoua Satellite data

Now that we have our data and know that we can also do same analysis like with station data, lets compare have a station data for the same region and compare the two.

2 Comparison Station and Satellite Garoua Data in R-Instat

The main objective of this part is to see if it is possible to use the estimate satellite data for precipitation to complete the station data. Sp we first need to load our station data. To do this, we click on **File > Open From Library** and we choose our Garoua data.

	row.names	date	year	month	day	rain	tmin	tmax
1	18263	2004-01-01	2004	1	1	0.0	16.6	35.0
2	18264	2004-01-02	2004	1	2	0.0	18.6	36.0
3	18265	2004-01-03	2004	1	3	0.0	18.0	36.5
4	18266	2004-01-04	2004	1	4	0.0	19.0	36.2
5	18267	2004-01-05	2004	1	5	0.0	18.5	36.8
6	18268	2004-01-06	2004	1	6	0.0	20.6	38.3
7	18269	2004-01-07	2004	1	7	0.0	19.1	33.8
8	18270	2004-01-08	2004	1	8	0.0	18.5	30.2
9	18271	2004-01-09	2004	1	9	0.0	18.9	30.7
10	18272	2004-01-10	2004	1	10	0.0	19.8	29.4
11	18273	2004-01-11	2004	1	11	0.0	16.5	31.0
12	18274	2004-01-12	2004	1	12	0.0	16.8	31.8
13	18275	2004-01-13	2004	1	13	0.0	17.0	30.5
14	18276	2004-01-14	2004	1	14	0.0	17.0	29.7
15	18277	2004-01-15	2004	1	15	0.0	17.5	31.6
16	18278	2004-01-16	2004	1	16	0.0	18.5	33.0
17	18279	2004-01-17	2004	1	17	0.0	16.9	34.0
18	18280	2004-01-18	2004	1	18	0.0	17.6	34.0
19	18281	2004-01-19	2004	1	19	0.0	16.6	34.4

Figure 6: View of station Garoua data

After load the data, this is how it's look.
Now we will meerge the data station and satellite to have it as one table.

2.1 Merging the data

By merging the date, it would be easy for us to make different analysis to compare the two data. We are particular interesting on the rainfall, so for the satellite data we will just consider the precipitation column. To merge the data in R-instat, we click on **Prepare > Column: Reshape > Merge** and we enter the information in the dialogue box. By follow the different instruction we will obtain this:

	date	year	month	day	tmin	tmax	rain	prcp	year1
1	2004-01-01	2004	1	1	16.6	35.0	0.0	0.000e+00	2004
2	2004-01-02	2004	1	2	18.6	36.0	0.0	0.000e+00	2004
3	2004-01-03	2004	1	3	18.0	36.5	0.0	0.000e+00	2004
4	2004-01-04	2004	1	4	19.0	36.2	0.0	0.000e+00	2004
5	2004-01-05	2004	1	5	18.5	36.8	0.0	0.000e+00	2004
6	2004-01-06	2004	1	6	20.6	38.3	0.0	0.000e+00	2004
7	2004-01-07	2004	1	7	19.1	33.8	0.0	0.000e+00	2004
8	2004-01-08	2004	1	8	18.5	30.2	0.0	0.000e+00	2004
9	2004-01-09	2004	1	9	18.9	30.7	0.0	0.000e+00	2004
10	2004-01-10	2004	1	10	19.8	29.4	0.0	0.000e+00	2004
11	2004-01-11	2004	1	11	16.5	31.0	0.0	0.000e+00	2004
12	2004-01-12	2004	1	12	16.8	31.8	0.0	0.000e+00	2004
13	2004-01-13	2004	1	13	17.0	30.5	0.0	0.000e+00	2004
14	2004-01-14	2004	1	14	17.0	29.7	0.0	0.000e+00	2004
15	2004-01-15	2004	1	15	17.5	31.6	0.0	0.000e+00	2004
16	2004-01-16	2004	1	16	18.5	33.0	0.0	0.000e+00	2004
17	2004-01-17	2004	1	17	16.9	34.0	0.0	0.000e+00	2004
18	2004-01-18	2004	1	18	17.6	34.0	0.0	0.000e+00	2004
19	2004-01-19	2004	1	19	16.6	34.4	0.0	0.000e+00	2004

Figure 7: Merge Data for Garoua city

Just look at this table, we can notice that the 19 first rows are the same for **rain** and **prcp** columns. That's a good sign at first. But let's have the summarize table for a better opinion on this data.

2.2 Summaries Table

By doing the summarise table, we will have a view of all our descriptives statistic. To do this , let's go to **Describe > One Variable > Summarise** and we obtain this:

```

date          year          month          day
Min.   :2004-01-01  Min.   :2004  Min.   : 1.00  Min.   : 1
1st Qu.:2006-07-02  1st Qu.:2006  1st Qu.: 4.00  1st Qu.: 92
Median :2008-12-31  Median :2008  Median : 7.00  Median :183
Mean   :2008-12-31  Mean   :2008  Mean   : 6.52  Mean   :183
3rd Qu.:2011-07-02  3rd Qu.:2011  3rd Qu.:10.00  3rd Qu.:274
Max.   :2013-12-31  Max.   :2013  Max.   :12.00  Max.   :366

tmin          tmax          rain          prcp          year1
Min.   :11.7  Min.   :24.0  Min.   : 0.00  Min.   : 0.00  Min.   :2004
1st Qu.:20.6  1st Qu.:32.5  1st Qu.: 0.00  1st Qu.: 0.00  1st Qu.:2006
Median :23.0  Median :35.0  Median : 0.00  Median : 0.00  Median :2008
Mean   :22.7  Mean   :35.3  Mean   : 2.83  Mean   : 2.57  Mean   :2008
3rd Qu.:24.7  3rd Qu.:38.0  3rd Qu.: 0.00  3rd Qu.: 2.28  3rd Qu.:2011
Max.   :73.9  Max.   :54.0  Max.   :114.70  Max.   :57.44  Max.   :2013
NA's   :274  NA's   :2220  NA's   :3

month_abbr    day_in_month    day
Jan   : 310  Min.   : 1.0  Min.   : 1
Mar   : 310  1st Qu.: 8.0  1st Qu.: 93
May   : 310  Median :16.0  Median :184
Jul   : 310  Mean   :15.7  Mean   :184
Aug   : 310  3rd Qu.:23.0  3rd Qu.:275
Oct   : 310  Max.   :31.0  Max.   :366
(Other):1793

```

Figure 8: Merge Data for Garoua city

According to this result, we can see that summary statistic for rain is different from summary statistic for prcp. First we have 3 missing values for rain column when for prcp there is no missing values. The **mean** for **rain** is **2.83** with **114.7** as a **maximum**; for **prcp**, we have **2.57** on average with **57.44** as a **maximum**. That is a great difference.

Now that we know our data are different, let's do a correlation plot to better compare the two and confirm it.

We can also do a paired t-test to compare the means of the two columns and be sure that there is no difference. To do it we use **Model > Hypothesis Tests**. The result it's showing at the table below.

```

Paired t-test

data:  rain and prcp
t = 1.8, df = 3649, p-value = 0.08
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.02846  0.86142
sample estimates:
mean of the differences
          0.2665

```

Figure 9: T-test between rain and prcp

The results are actually showing that there is difference between the two means. the P-value is 0.08 that is greater than 0.05, So we fail to accept the null hypothesis that is for no difference.

2.3 Correlation plot

To do it in R-instat we use **Describe > Multivariate > Correlations**, enter prcp and rain; then we click on Options and choose Scatter Matrix. The result is showing below.

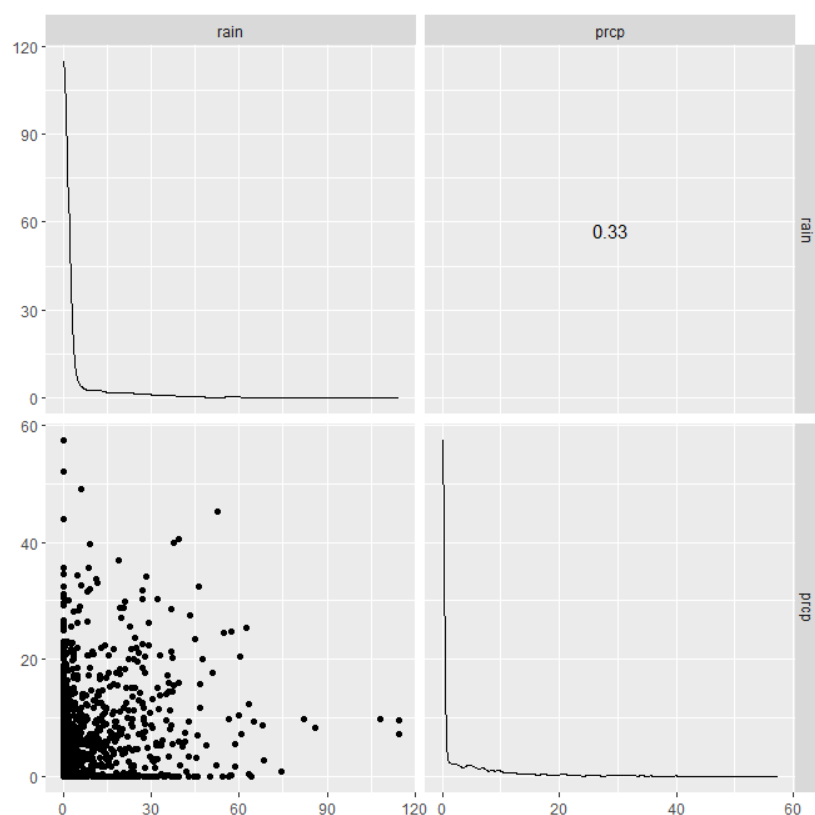


Figure 10: Correlation plot between Rain and Precipitation

Looking at this result, it seems like there is no difference regarding the shape of the satellite (prcp) and station data (rain) but the correlation is coefficient is not satisfied , 0.33 that means there is no correlation between the two. Lets look at the monthly correlation to have more precision.

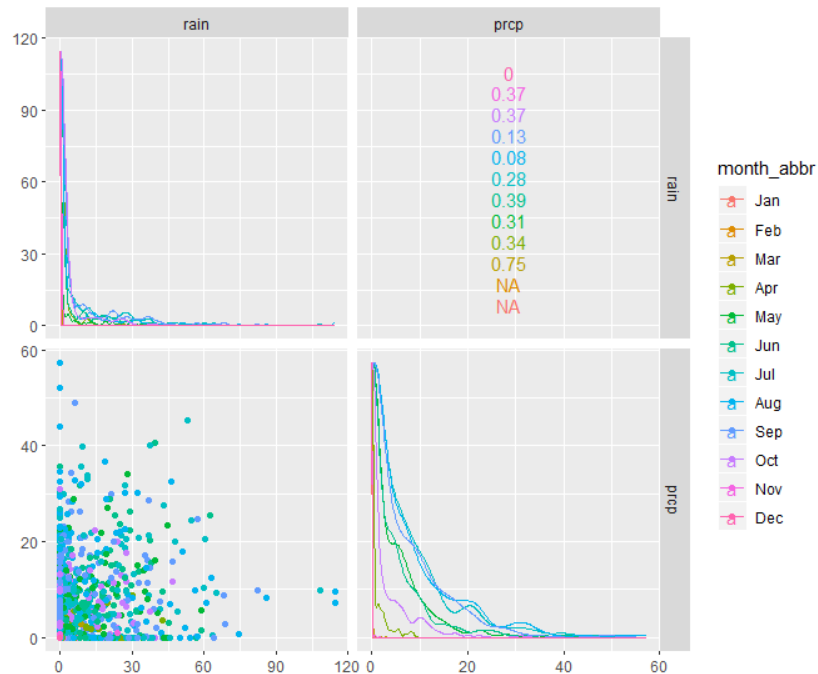


Figure 11: Correlation plot between Rain and Precipitation

Through this graph we can clearly see a difference between the shape of the satellite (prcp) and station data (rain). The shape differ from one month to another and the correlations are still small. It is just for October that we record a high correlation 0.75. This is clearly showing that shape of both variables depends on the month

Let's Fit a linear model to check whether month is significant. To do it we use **Model > Fit Model > General**. We obtain the following results:

Analysis of Variance Table

Response: rain

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
month_abbr	11	30996	2818	37	<2e-16
Residuals	3638	277032	76		

Analysis of Variance Table

Response: prcp

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
month_abbr	11	25068	2279	88.5	<2e-16
Residuals	3641	93814	26		

Figure 12: Anova table

For both of them (rain and prcp), variable month is significant. The p-value is less than 0.05. So the shape will actually depend of the month.

So let's look at the correlation plot month by month to have a better view. To do it we use **Describe > Specific > Scatterplot** we complete the dialogue box and press on Plot Options and include the months as facets, We obtain the graph below

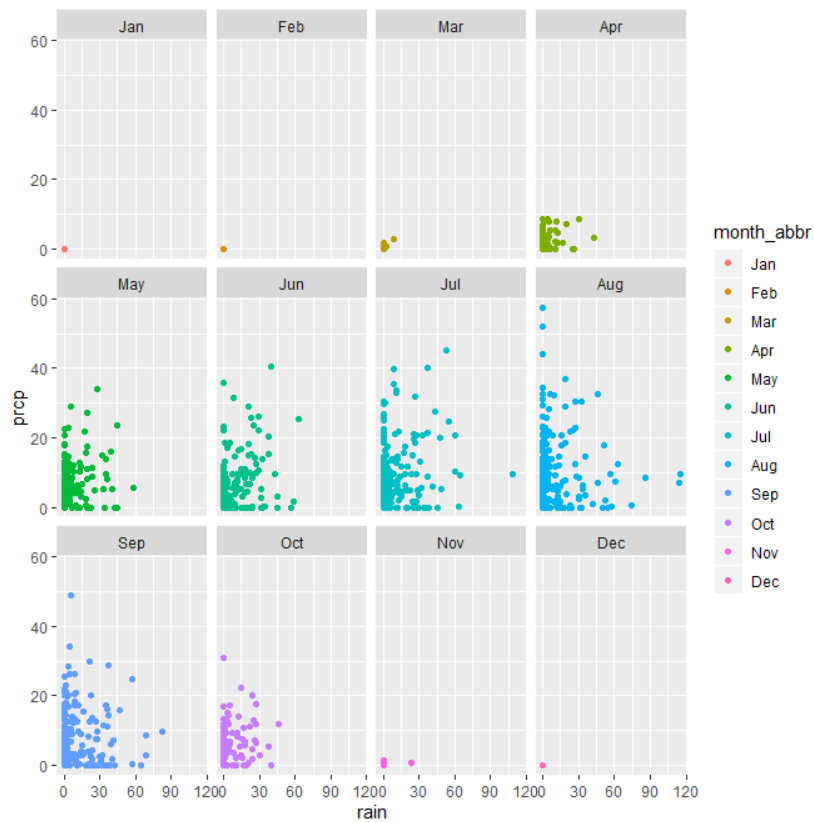


Figure 13: Monthly Correlation plot between Rain and Precipitation

As we see on the graph, January, February, March, November and December are actually dry month. May, June, July, August, September and October are the month were we usually have rain.

2.4 Markov chain with R

A Markov chain or Markov process, named after Russian mathematician, Andrey Markov (Shannon, 1948), is a mathematical system that undergoes transitions from one state to another (from a finite or countable number of possible states) in a chain like manner. It is a random process endowed with the Markov property. The Markov property states that the conditional probability distribution for a system at the next step given its current state depends only on the current state of the system, and not additionally on the state of the system at previous steps. Since the system changes randomly, it is generally impossible to predict the exact state of the system in the future.

For this part we will continue with our Garoua station data as our Rainfall dataset. The main objectives will be to:

- Fit models to the chance of rain
- Find the best models using AIC and BIC analysis
- Plot the different models obtained.

2.4.1 Fit models to the chance of rain

Preliminary

We first load our data and remove the missing value.

```
station <- read.csv("garoua.csv")
station <- na.omit(station)
```

To predict the rainfall we will pay attention on two states of Markov chain dry "d" and wet "w". To specify it in R, we create a new variable called rainday that will record d if there was not rain and w if there was rain. This is the code in R:

```
station$rainday[station$rain > 0.85] = "w"
station$rainday[station$rain <= 0.85] = "d"
```

We will also need lag variables that will record the value for the previous day.

```
station$lag1 <- lag(station$rainday, 1)
station$lag2 <- lag(station$rainday, 2)
station$lag3 <- lag(station$rainday, 3)
```

Then we combine the lags to have the previous 2 days i.e. "ww", "wd", "dw" or "dd"; And the previous 3 days.

We can now start to fit our different models.

```
station$prev1 <- station$lag1
station$prev2 <- paste0(station$lag2, station$lag1)
station$prev3 <- paste0(station$lag3, station$lag2, station$lag1)
```

Fitting zero-order MC with 3 harmonics

The first model to fit is the zero-order MC(Markov chain) with 3 harmonics.

```
form_zero <- rainday ~ (cos(doy * 1 * 2 * pi/366) + sin(doy * 1 * 2 * pi/366) +
cos(doy * 2 * 2 * pi/366) + sin(doy * 2 * 2 * pi/366)+
cos(doy * 3 * 2 * pi/366) + sin(doy * 3 * 2 * pi/366))
fit_zero <- glm(as.formula(form_zero), data = station, family = binomial, na.act
```

We now look at the Anova test

```
Analysis of Deviance Table

Model: binomial, link: logit

Response: rainday

Terms added sequentially (first to last)
```

	Df	Deviance	Resid. Df	Resid. Dev	Pr(>Chi)
NULL			2888	2880.8	
cos(doy * 1 * 2 * pi/366)	1	519.87	2887	2360.9	< 2.2e-16 ***
sin(doy * 1 * 2 * pi/366)	1	188.54	2886	2172.3	< 2.2e-16 ***
cos(doy * 2 * 2 * pi/366)	1	78.95	2885	2093.4	< 2.2e-16 ***
sin(doy * 2 * 2 * pi/366)	1	27.64	2884	2065.8	1.461e-07 ***
cos(doy * 3 * 2 * pi/366)	1	2.73	2883	2063.0	0.09850 .
sin(doy * 3 * 2 * pi/366)	1	3.71	2882	2059.3	0.05425 .

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

Figure 14: Anova table for zero-order MC with 3 harmonic

The 3 harmonic is not significant. The p value is greater than 0.05. So there is no need to do the 4 harmonic. We can still check to be sure.

The following table below is given the result for the 4 harmonic.

```

Analysis of Deviance Table

Model: binomial, link: logit

Response: rainday

Terms added sequentially (first to last)


```

	Df	Deviance	Resid. Df	Resid. Dev	Pr(>Chi)
NULL			2888	2880.8	
cos(doy * 1 * 2 * pi/366)	1	519.87	2887	2360.9	< 2.2e-16 ***
sin(doy * 1 * 2 * pi/366)	1	188.54	2886	2172.3	< 2.2e-16 ***
cos(doy * 2 * 2 * pi/366)	1	78.95	2885	2093.4	< 2.2e-16 ***
sin(doy * 2 * 2 * pi/366)	1	27.64	2884	2065.8	1.461e-07 ***
cos(doy * 3 * 2 * pi/366)	1	2.73	2883	2063.0	0.09850 .
sin(doy * 3 * 2 * pi/366)	1	3.71	2882	2059.3	0.05425 .
cos(doy * 4 * 2 * pi/366)	1	2.19	2881	2057.1	0.13862 .
sin(doy * 4 * 2 * pi/366)	1	2.88	2880	2054.3	0.08989 .

```

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

```

Figure 15: Anova table with 4 harmonic

As we were saying, even the 4 harmonic is not significant. The p-value is greater than 0.05. Let's move to the first order MC.

Fitting first-order MC

The table below is given us the Anova test for the first order MC without iteration.

```

Analysis of Deviance Table

Model: binomial, link: logit

Response: rainday

Terms added sequentially (first to last)


```

	Df	Deviance	Resid. Df	Resid. Dev	Pr(>Chi)
NULL			2887	2880.3	
cos(doy * 1 * 2 * pi/366)	1	519.49	2886	2360.8	< 2.2e-16 ***
sin(doy * 1 * 2 * pi/366)	1	188.50	2885	2172.3	< 2.2e-16 ***
cos(doy * 2 * 2 * pi/366)	1	78.92	2884	2093.4	< 2.2e-16 ***
sin(doy * 2 * 2 * pi/366)	1	27.64	2883	2065.8	1.463e-07 ***
prev1	1	3.74	2882	2062.0	0.05309 .

```

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

```

Figure 16: Anova table fit first order Markov Chain without iteration

We can also look at the fitted first order Markov Chain with iteration to see if the result of the previous day affect on the present one. The result for the Anova as showing below.

```

Analysis of Deviance Table

Model: binomial, link: logit

Response: rainday

Terms added sequentially (first to last)


```

	Df	Deviance	Resid. Df	Resid. Dev
NULL			2887	2880.3
cos(doy * 1 * 2 * pi/366)	1	519.49	2886	2360.8
sin(doy * 1 * 2 * pi/366)	1	188.50	2885	2172.3
cos(doy * 2 * 2 * pi/366)	1	78.92	2884	2093.4
sin(doy * 2 * 2 * pi/366)	1	27.64	2883	2065.8
prev1	1	3.74	2882	2062.0
cos(doy * 1 * 2 * pi/366):prev1	1	4.14	2881	2057.9
sin(doy * 1 * 2 * pi/366):prev1	1	5.83	2880	2052.1
cos(doy * 2 * 2 * pi/366):prev1	1	2.96	2879	2049.1
sin(doy * 2 * 2 * pi/366):prev1	1	0.42	2878	2048.7

```

Pr(>Chi)

NULL
cos(doy * 1 * 2 * pi/366) < 2.2e-16 ***
sin(doy * 1 * 2 * pi/366) < 2.2e-16 ***
cos(doy * 2 * 2 * pi/366) < 2.2e-16 ***
sin(doy * 2 * 2 * pi/366) 1.463e-07 ***
prev1 0.05309 .
cos(doy * 1 * 2 * pi/366):prev1 0.04199 *
sin(doy * 1 * 2 * pi/366):prev1 0.01572 *
cos(doy * 2 * 2 * pi/366):prev1 0.08542 .
sin(doy * 2 * 2 * pi/366):prev1 0.51446
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

Figure 17: Anova table fit first order Markov Chain with iteration

Looking at this result, we can see that the result for the previous day is significant at 0.05 level of significant. That means the fact that the day before was dry for instance can affect the day after to be also dry. Our data can confirm it.

day	rain	tmin	tmax	rainday	lag1	lag2	lag3	prev1
32	0.0	19.0	37.3	d	NA	NA	NA	NA
33	0.0	21.3	37.5	d	d	NA	NA	d
34	0.0	20.0	36.0	d	d	d	NA	d
35	0.0	24.0	33.6	d	d	d	d	d
36	0.0	21.5	32.5	d	d	d	d	d
37	0.0	23.4	30.3	d	d	d	d	d
38	0.0	21.0	30.8	d	d	d	d	d
39	0.0	19.8	28.5	d	d	d	d	d
40	0.0	20.4	27.2	d	d	d	d	d
41	0.0	21.0	28.5	d	d	d	d	d
42	0.0	20.5	31.2	d	d	d	d	d
43	0.0	20.2	32.5	d	d	d	d	d
44	0.0	21.0	33.0	d	d	d	d	d
45	0.0	20.2	34.5	d	d	d	d	d
46	0.0	22.5	34.5	d	d	d	d	d

Figure 18: A view of Garoua Rainfall data

Fitting second-order MC

The result for the Anova test is present at the table below

```

Analysis of Deviance Table

Model: binomial, link: logit

Response: rainday

Terms added sequentially (first to last)


```

	Df	Deviance	Resid. Df	Resid. Dev	Pr(>Chi)
NULL			2886	2879.9	
cos(doy * 1 * 2 * pi/366)	1	519.10	2885	2360.8	< 2.2e-16 ***
sin(doy * 1 * 2 * pi/366)	1	188.46	2884	2172.3	< 2.2e-16 ***
cos(doy * 2 * 2 * pi/366)	1	78.90	2883	2093.4	< 2.2e-16 ***
sin(doy * 2 * 2 * pi/366)	1	27.63	2882	2065.8	1.465e-07 ***
prev2	3	4.42	2879	2061.3	0.2193

```

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

```

Figure 19: Anova table fit second order Markov Chain without iteration

Without iteration , the variable **prev2** don't have effect on the rainday. let check if with iteration the value of the 2 previous day should have an impact on the actually value.

The result for the second order MC with iteration is present on the table below.


```

Analysis of Deviance Table

Model: binomial, link: logit

Response: rainday

Terms added sequentially (first to last)

              Df Deviance Resid. Df Resid. Dev
NULL                                         2886    2879.9
cos(doy * 1 * 2 * pi/366)                1    519.10    2885    2360.8
sin(doy * 1 * 2 * pi/366)                1    188.46    2884    2172.3
cos(doy * 2 * 2 * pi/366)                1     78.90    2883    2093.4
sin(doy * 2 * 2 * pi/366)                1     27.63    2882    2065.8
prev2                                     3       4.42    2879    2061.3
cos(doy * 1 * 2 * pi/366):prev2          3     14.90    2876    2046.5
sin(doy * 1 * 2 * pi/366):prev2          3     13.84    2873    2032.6
cos(doy * 2 * 2 * pi/366):prev2          3       2.90    2870    2029.7
sin(doy * 2 * 2 * pi/366):prev2          3       3.69    2867    2026.0
                                         Pr(>Chi)
NULL
cos(doy * 1 * 2 * pi/366)                < 2.2e-16 ***
sin(doy * 1 * 2 * pi/366)                < 2.2e-16 ***
cos(doy * 2 * 2 * pi/366)                < 2.2e-16 ***
sin(doy * 2 * 2 * pi/366)                1.465e-07 ***
prev2                                     0.219337
cos(doy * 1 * 2 * pi/366):prev2          0.001907 **
sin(doy * 1 * 2 * pi/366):prev2          0.003135 **
cos(doy * 2 * 2 * pi/366):prev2          0.406568
sin(doy * 2 * 2 * pi/366):prev2          0.297320
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

Figure 20: Anova table fit second order Markov Chain with iteration

We can see that the prev2 is highly significant at level 0.01. So the value of the 2 previous day will have an impact on the future day. Our last model is the third order. So let have a look on it.

Fitting third-order MC

```

Analysis of Deviance Table

Model: binomial, link: logit

Response: rainday

Terms added sequentially (first to last)

              Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
NULL                                         2885      2879.4
cos(doy * 1 * 2 * pi/366)  1   518.72      2884      2360.7 < 2.2e-16 ***
sin(doy * 1 * 2 * pi/366)  1   188.43      2883      2172.3 < 2.2e-16 ***
cos(doy * 2 * 2 * pi/366)  1    78.88      2882      2093.4 < 2.2e-16 ***
sin(doy * 2 * 2 * pi/366)  1    27.63      2881      2065.8 1.467e-07 ***
prev3                      7     9.33      2874      2056.4    0.2301
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

Figure 21: Anova table fit third order Markov Chain without iteration

Without iteration ,also the variable **prev3** don't have effect on the rain-day. let check if with iteration the value of the 3 previous day should have an impact on the actually value.

The result for the third order MC with iteration is present on the table below.

```

Analysis of Deviance Table

Model: binomial, link: logit

Response: rainday

Terms added sequentially (first to last)

              Df Deviance Resid. Df Resid. Dev
NULL                                         2885      2879.4
cos(doy * 1 * 2 * pi/366)  1   518.72      2884      2360.7
sin(doy * 1 * 2 * pi/366)  1   188.43      2883      2172.3
cos(doy * 2 * 2 * pi/366)  1    78.88      2882      2093.4
sin(doy * 2 * 2 * pi/366)  1    27.63      2881      2065.8
prev3                      7     9.33      2874      2056.4
cos(doy * 1 * 2 * pi/366):prev3  7    22.44      2867      2034.0
sin(doy * 1 * 2 * pi/366):prev3  7    23.17      2860      2010.8
cos(doy * 2 * 2 * pi/366):prev3  7    10.21      2853      2000.6
sin(doy * 2 * 2 * pi/366):prev3  7     8.89      2846      1991.7
                                Pr(>Chi)
NULL
cos(doy * 1 * 2 * pi/366)  < 2.2e-16 ***
sin(doy * 1 * 2 * pi/366)  < 2.2e-16 ***
cos(doy * 2 * 2 * pi/366)  < 2.2e-16 ***
sin(doy * 2 * 2 * pi/366)  1.467e-07 ***
prev3                      0.230087
cos(doy * 1 * 2 * pi/366):prev3  0.002130 **
sin(doy * 1 * 2 * pi/366):prev3  0.001591 **
cos(doy * 2 * 2 * pi/366):prev3  0.177234
sin(doy * 2 * 2 * pi/366):prev3  0.260734
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

Figure 22: Anova table fit third order Markov Chain with iteration

We can see that the **prev3** is highly significant at level 0.01. So the value of the 2 previous day will have an impact on the future day. Now lets see which of this models are better. To do it we need to check the AIC and BIC.

2.4.2 AIC and BIC Analysis

To do it, we type the following code:

```
AIC(fit_zero, fit_one, fit_one_int, fit_two, fit_two_int, fit_three, fit_three_i
BIC(fit_zero, fit_one, fit_one_int, fit_two, fit_two_int, fit_three, fit_three_i
```

The results are present below

	df	AIC		df	BIC
fit_zero	7	2073.330	fit_zero	7	2115.111
fit_one	6	2074.024	fit_one	6	2109.834
fit_one_int	10	2068.671	fit_one_int	10	2128.354
fit_two	8	2077.342	fit_two	8	2125.086
fit_two_int	20	2066.017	fit_two_int	20	2185.376
fit_three	12	2080.438	fit_three	12	2152.050
fit_three_int	40	2071.729	fit_three_int	40	2310.434

Figure 23: AIC and BIC analysis

Looking at the AIC **fit_two_int** is the better one. Looking at the BIC **fit_one** is the better one. Since fit one have the smaller degree of freedom, it can be consider as the better one.

2.4.3 Plots visualization

Plotting zero-order MC model

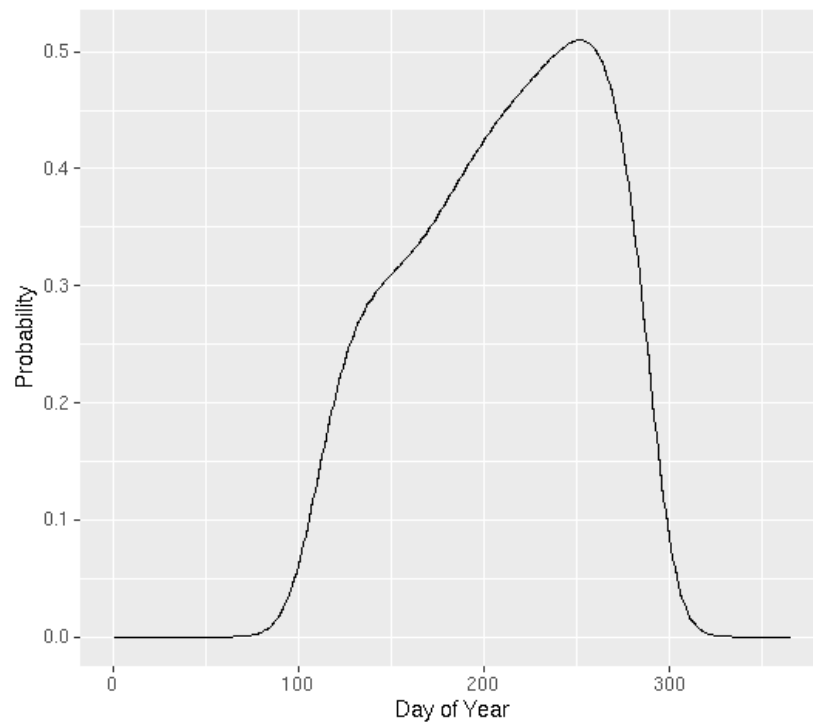


Figure 24: Plot of zero-order MC model

Plotting first-order MC model

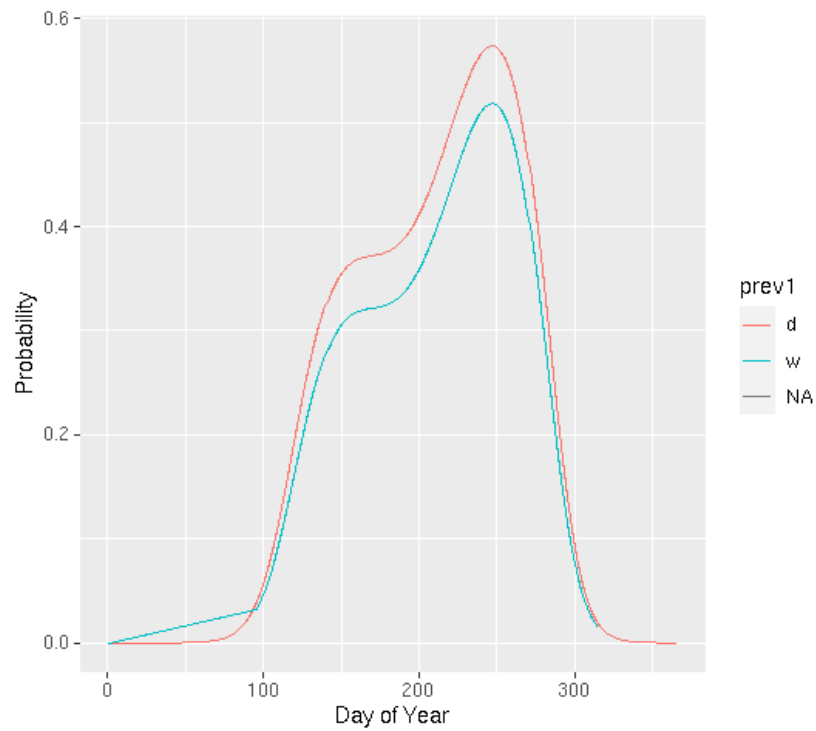


Figure 25: Plot of first-order MC model

Looking at the graph we can see that the probability of having a rain day when the previous day is dry is higher than when the previous day is wet. have rainy day.

Plotting first-order MC model with iteration

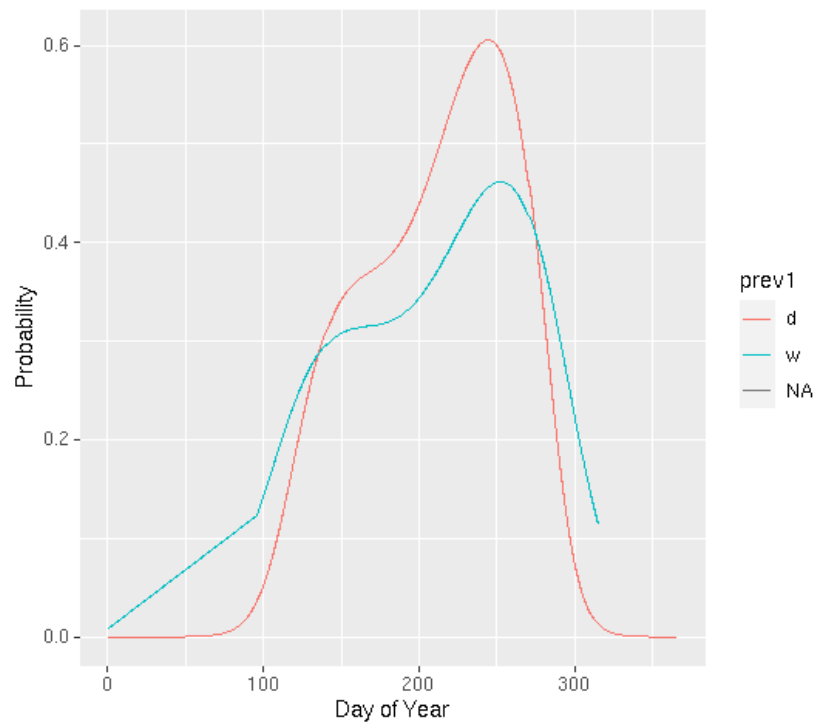


Figure 26: Plot of first-order MC model with iteration

Plotting second-order MC model without iteration

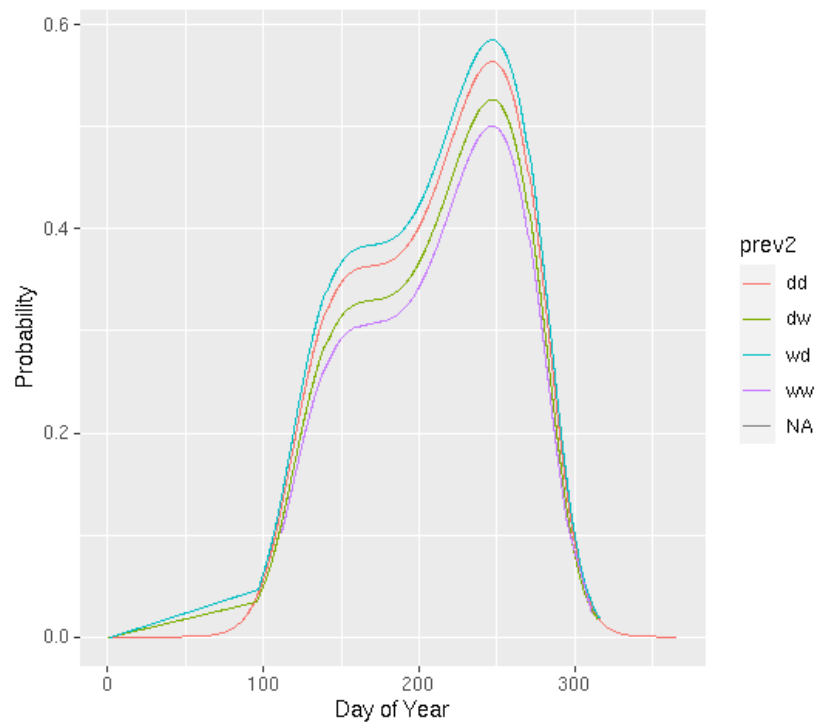


Figure 27: Plot of second-order MC model without iteration

The probability of have rain day is more higher when the two previous day was wet and dry.

Plotting third-order MC model without iteration

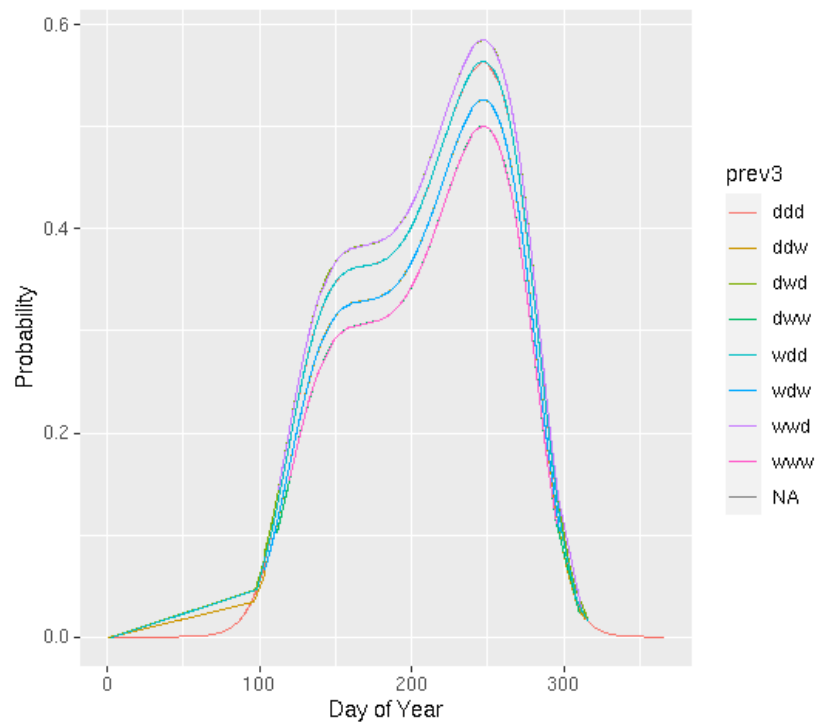


Figure 28: Plot of third-order MC model without iteration

The probability of have rain day is more higher when the three previous day was wet, wet and dry.