AI & COVID

GROUP 2

Weather/Seasonality Effect on Spread of COVID-19 Infection

Research Lab Report

Submitted By

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Abstract

Since the beginning of COVID-19 pandemic there are many research and studies done on investigation for the the effect of climate variables on the increasing COIVD-19 positive cases around the world. However, the effect of meteorological parameters on COVID-19 remains controversial. This research investigates the relationship between COVID-19 cases with weather components in state Rhineland-Palatinate of Germany. Daily data on climate parameters like temperature, average humidity, wind speed are collected with the COVID-19 data of new cases, current positive cases, hospitalized, deaths for the complete RLP state from 1st Aug 2021 to 30th July 2022. The complete dataset is divided into 4 seasons autumn, winter, spring and summer. Further Kendall-tau and Spearmann Correlation correlation with significance were employed to asses, the relationship between climate variables and COVID-19 cases. In this research we also aims to provide better understanding of the exact incubation period by implementing lags from day0 to day7. We find that during the transition seasons i.e. Autumn and Spring, temperature has a negative correlation with the PCR daily positive cases. However in winter, relative humidity is more significant and has a negative relationship with Covid cases. Also for all the seasons lag3 gave the best results and was more correlated with the PCR daily positive cases.

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1 Introduction

Every year, a number of virus-infected diseases that impact human health occurs seasonally. A virus is something which enters the body of a host by using the cell's internal machinery to introduce its own genetic material, which it uses to make additional viral particles. Since ancient times, a number of seasonal virus/bacterial illnesses have caused numerous deaths in both humans and animals. To survive and minimize the effect of these disease, doctors and scientists have made efforts by developing a number of vaccines or medications. However, a larger proportion of the world's population has already been impacted by the pandemic that was initially caused by lethal virus-originating diseases.

The novel coronavirus Sars-Cov-2 outbreak that caused COVID-19 has forced the entire world to with a grave health crisis. In late December 2019, the pathogenic COVID-19 virus was discovered for the first time in Wuhan City, Hubei Province, China (Li et al. 2020). The World Health Organization (WHO) later classified COVID-19 as an international public health emergency on January 30, 2020, and recognised it as a pandemic on March 11, 2020, as this disease had not previously been found in human bodies [1]. As a result of the COVID-19 outbreak, over 598 million confirmed cases and over 6.4 million deaths have been reported globally.[2].

When pandemic outbreak to this extent happens it becomes more important for governments to manage the medical resources depending on the potential dangers. Therefore we need different models and studies to analyse the existing data of the pandemic which can help us to estimate the potential spread of COVID cases that can enable the government to form and implement evidence-based policies. This may reduce the potential damage to the economy, education, and various daily activities that have suffered during the lockdown and other government restrictions that were in place.

1.1 Literature Survey

There have been various studies done by researchers to understand how meteorological factors like temperature and relative humidity affect the spread of the SARS-CoV-2 virus. Researchers have used different methodologies to identify such relationships and reported them in various studies. One such study systematically evaluated 70 relevant peer-reviewed studies published on or before 21 September 2020 that had been implemented from community to global level on the effect of temperature on COVID cases[3]. Out of 35 of these papers, 70 studies showed a significantly negative association between temperature and COVID-19 dissemination, whereas 12 reports showed a significantly positive association. The remaining investigations discovered either no correlation at all or a weak association. The two statistical models that were used in most of the studies were correlation and regression. The study for 81 provinces of Turkey shows that temperature, air pressure and dew point are negatively correlated with COVID-19 cases [4]. Another study that investigated the effects of temperature and relative humidity on daily new cases and daily new deaths of COVID-19 which used Log-linear generalized additive model has findings which revealed that temperature and relative humidity were both negatively related to daily new cases and deaths [5].

When we compare these studies, we concluded that results of these research differ from region to region on the basis of geological-location as well as other factors like population density and governmental actions. Due to the variations in testing rates, public response, culture, etc., it is challenging to directly compare the policies of different nations. A comparative study of scenarios in China, England, Germany, and Japan [6] show that in China, there was insignificant correlations with population and meteorological factors owing to broadly strict lockdown policies. Since the beginning of pandemic, in Germany, the government responded with actions such as contact tracing and testing, followed by prohibition of gathering with strict punishment for violation. But in England, mixed signals (such as "herd immunity") were sent out in the beginning, and the government was criticised for not acting quickly in March. Hence, multivariate regression analysis revealed significant correlations between spread duration and factors in UK, but not in Germany. In Japan, citizens self-isolated during this state of emergency and had stronger correlations for the virus spread. A study that investigated the association between COVID-19 cases and two components, average temperature and relative humidity, in the 16 states of Germany was carried out with approaches namely temporal correlation, spatial auto-correlation, and clustering-integrated panel regression [7].

We have used all these research findings as a reference and discussion point for our study which will further be explained in Results and Discussion section.

2 Data Collection and Pre-Processing

2.1 Data Collection

To investigate the relation between weather parameters and COVID-19 cases, we collected weather data from Brightsky which is an open source project that uses "The DWD (Deutscher Wetterdienst)", Germany's meteorological service. BrightSky provides free weather data in a simple JSON (JavaScript Object Notation) format. We implemented a web crawler to fetch data for each district in Rhineland Palatinate region for every day from 01-08-2021 to 31-07-2022. From the weather data fetched in the crawler, Temperature, Relative Humidity(Percentage) and Wind Speed(km/h) is selected. Temperature is the measure of hotness or coldness expressed in terms of degree Celsius (℃) in our study. Relative humidity is the amount of water vapor present in the air as compared to the total amount of water vapor that air can hold at the given temperature and is measured in percentage(%). Wind speed determines how fast air is moving in the given time period measured in terms of kilometers per hour(km/h).

District-wise COVID-19 data is collected for the state of Rhineland Palatinate, Germany for the period from 01-08-2021 to 31-07-2022 for analysis. COVID-19 data was collected from the official Rhineland Palatinate (RLP) website. This data was extracted from the daily official reports of the State Investigation Office based on SARS-CoV-2 data from the IfSG reporting system for Rhineland-Palatinate.

2.2 Data Pre-Processing

Out of the various fields that are available in the COVID-19 data, we selected PCR (Polymerase Chain Reaction) positive count, PCR positive hospitalised count and Deceased count. In the Figure 2.1 Daily PCR positive cases of Rhineland-Palatinate are shown.

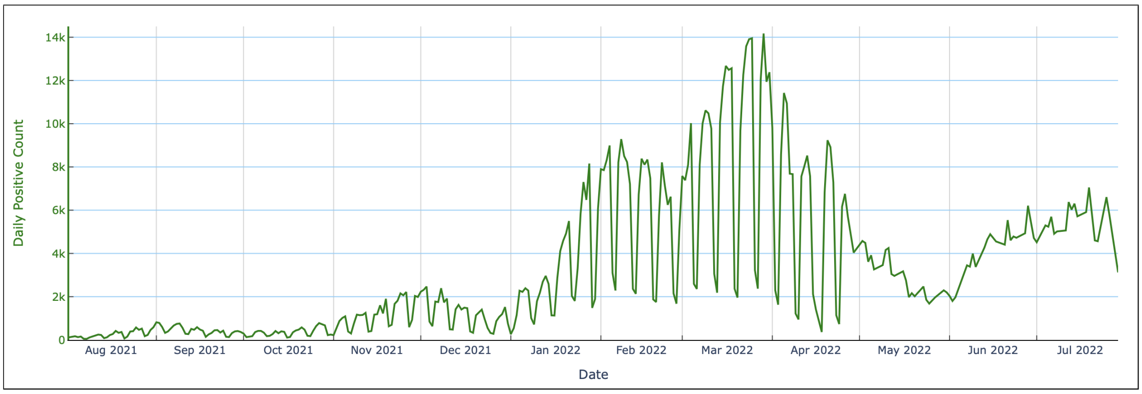

Figure 2.1: Daily PCR Positive Count of Rhineland-Palatinate

For the weather parameters, an index containing latitude, longitude and distance between each district in RLP was calculated. This distance matrix was used to identify the closest district for fetching missing values in the weather data. Using this distance based interpolation method missing weather parameters are handled. All the three weather parameters are averaged and grouped by district name and date.

We have divided the COVID-19 data-set into seasons for further analysis as below:

- Autumn : September, October and November (31-08-2021 to 30-11-2021)
- Winter : December, January and February (01-12-2021 to 28-02-2022)
- Spring : March, April and May (01-03-2022 to 31-05-2022)
- Summer : June and July (02-06-2022 to 29-07-2022)

The average temperature of our complete data-set is 10.13 °C and average wind speed is 12.77 km/h. Also the average relative humidity is 75.61 %. In the figure 2.2, relation between temperature and relative humidity for the complete data-set is shown.

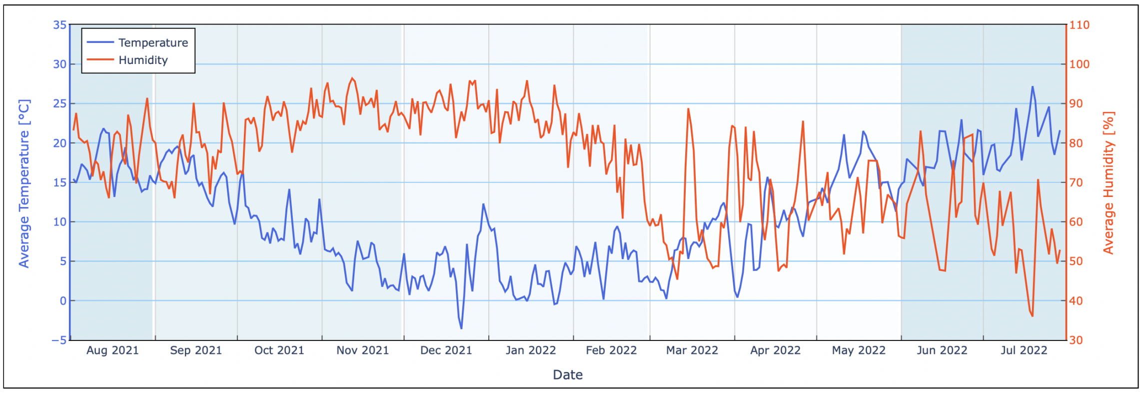

Figure 2.2: Temperature and Relative Humidity for all Seasons

3 Methodology

We conducted visual histogram test to check if daily PCR positive count versus it's frequency of occurrence follows a normal distribution. The Figure 3.1, shows that daily PCR positive count data does not form a "bell-shaped" curve and is not normally distributed. We also conducted Kolmogorov-Smirnov test, defined as non-parametric goodness-of-fit test used to identify if two distributions differ, to verify if our null hypothesis that the data-set follows a normal distribution. We obtained test statistics as 1.0 and pvalue as 0.0. Assuming an alpha value of 0.05, the obtained p-value is less than 0.05. Hence, we reject our null hypothesis. This indicates that the daily PCR positive count distribution in the COVID-19 data-set does not follow a normal distribution. We used Kendall-tau and Spearmann Correlation techniques for our analysis since the COVID-19 data is not normally distributed and hence, these are the most suitable techniques. For calculating correlation values, in COVID-19 data, PCR positive count, PCR positive hospitalised count and Deceased count as well as in weather data, Temperature, Relative Humidity and Wind speed was used. We used Statistical functions for masked arrays from SciPy for calculating kendalltau and spearman The significance value was calculated for each of these obtained correlation values. Based on the highest absolute correlation value and True significance, we identified the following fields for COVID-19 data and weather parameters in each season for our further analysis:

- Autumn : PCR positive count & Temperature
- Winter : PCR positive count & Relative humidity
- Spring : PCR positive count & Temperature
- Summer : PCR positive count & Temperature

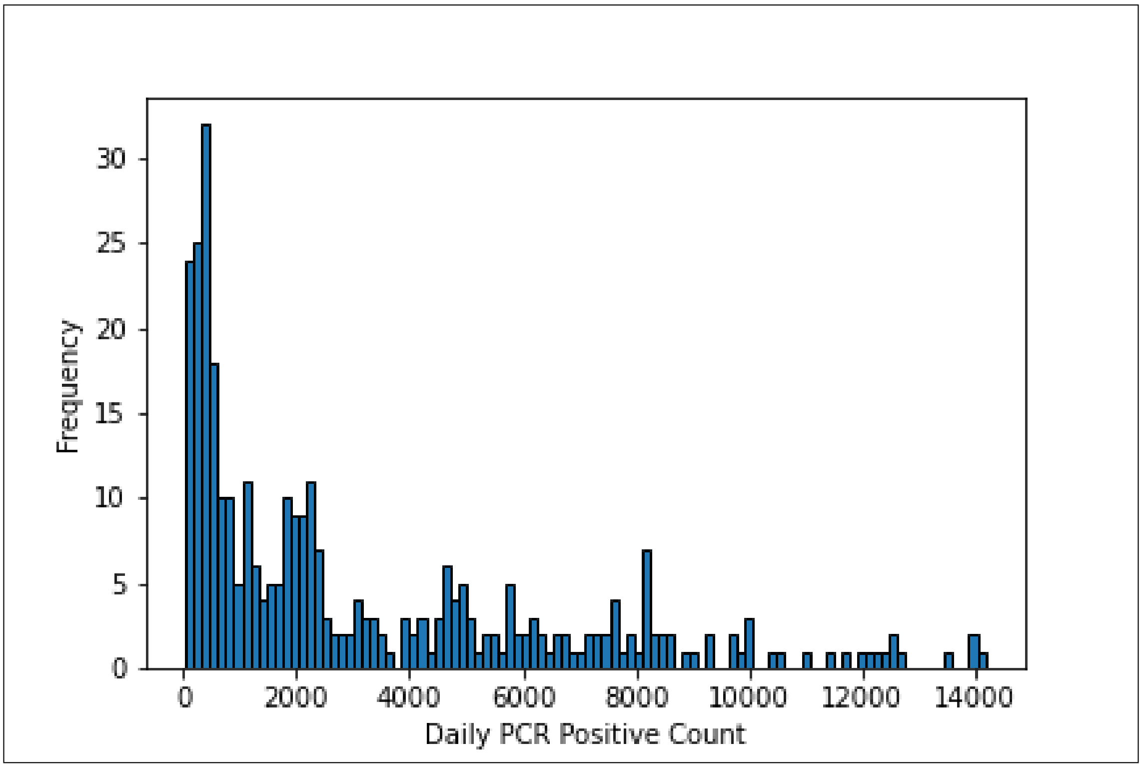

Figure 3.1: Daily Positive Count versus Frequency histogram

In order to conduct further analysis in each season, we identified a seven day period where the dominant weather parameter has the highest effect on COVID-19 cases. This is done considering the weather parameters and its correlation sign.

3.1 Autumn

In Autumn, temperature has a negative correlation with daily PCR positive count as seen in the figure 3.2. Temperature is negatively correlated with PCR positive count with a value of -0.2884 in Kendall-Tau correlation and -0.4444 in Spearmann correlation. Thus, we aggregated daily average temperature and found a seven day period where the aggregated average temperature is the lowest as shown in figure 3.3, since temperature is negatively correlated with PCR positive count. The seven day period is from 22-11-2021 to 28-11-2021. The average temperature during this period is found to be 2.21990 ℃. For the whole autumn data-set, temperature varied from 0.2144℃ to 21.5℃ and average temperature is 10.11℃. Daily PCR positive count varied from : 109 to 2212. The lag days calculation in the autumn season as shown in table 3.1, did not provide an exact lag day in which the cases peaked. One of our observations to explain this scenario is that the positive cases steadily increased during the whole of autumn season.

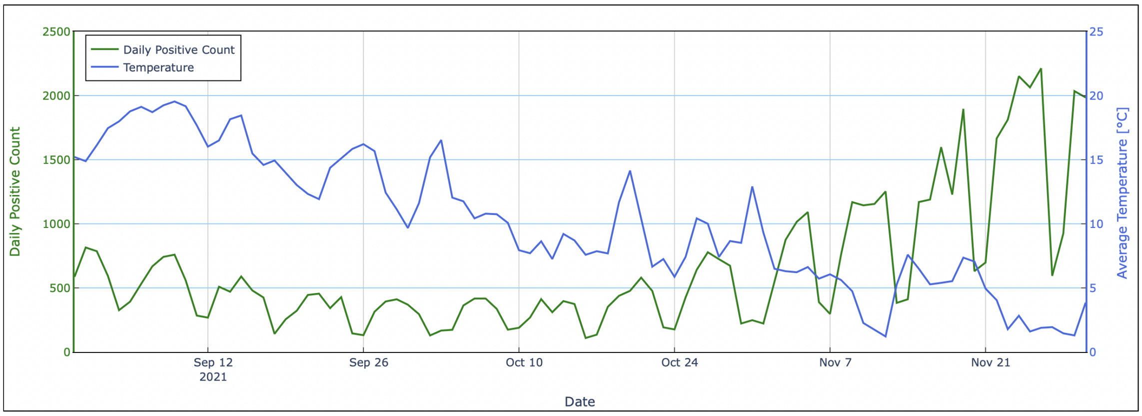

Figure 3.2: Temperature VS Daily PCR Positive Count For Autumn

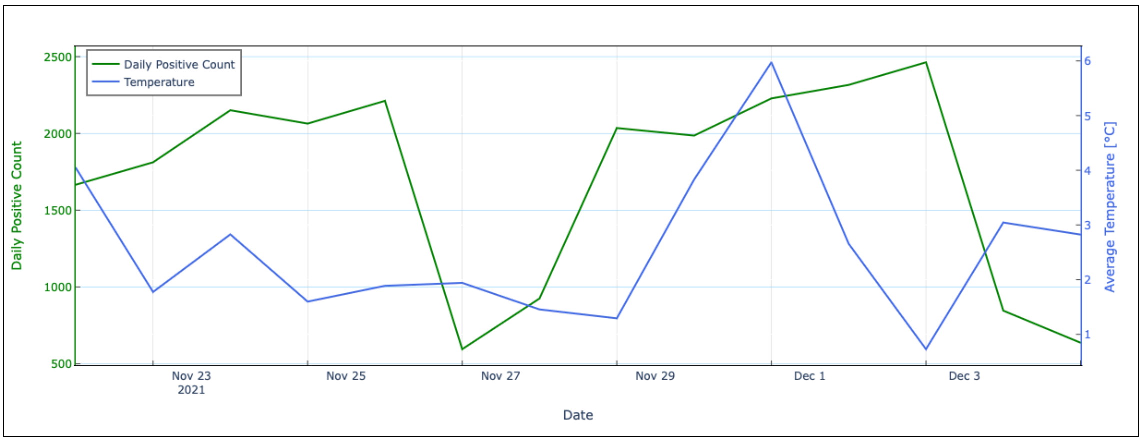

Figure 3.3: Daily PCR Positive Count vs Temperature from 22-11-2021 to 05-12-2021

Correlation Method	Season	Covid Parameter	Weather Parameter	Correlation
Spearmann	Autumn	PCR Positive Count	Temperature	-0.4444
Spearmann	Autumn	PCR Positive Count lag -1	Temperature	-0.4584
Spearmann	Autumn	PCR Positive Count lag -2	Temperature	-0.4634
Spearmann	Autumn	PCR Positive Count lag -3	Temperature	-0.4994
Spearmann	Autumn	PCR Positive Count lag -4	Temperature	-0.5322
Spearmann	Autumn	PCR Positive Count lag -5	Temperature	-0.5567
Spearmann	Autumn	PCR Positive Count lag -6	Temperature	-0.5890
Spearmann	Autumn	PCR Positive Count lag -7	Temperature	-0.6007

Table 3.1: LAG values for Autumn season with Temperature

3.2 Winter

For the Winter season, relative humidity is the dominant weather factor and it is negatively correlated with the Daily PCR Positive count as shown in Figure 3.4. Relative Humidity varies from 95% to 60.39% in this season. Daily PCR count during the same period is from 268 to 9279. Average Relative Humidity for winter is 84.41%.

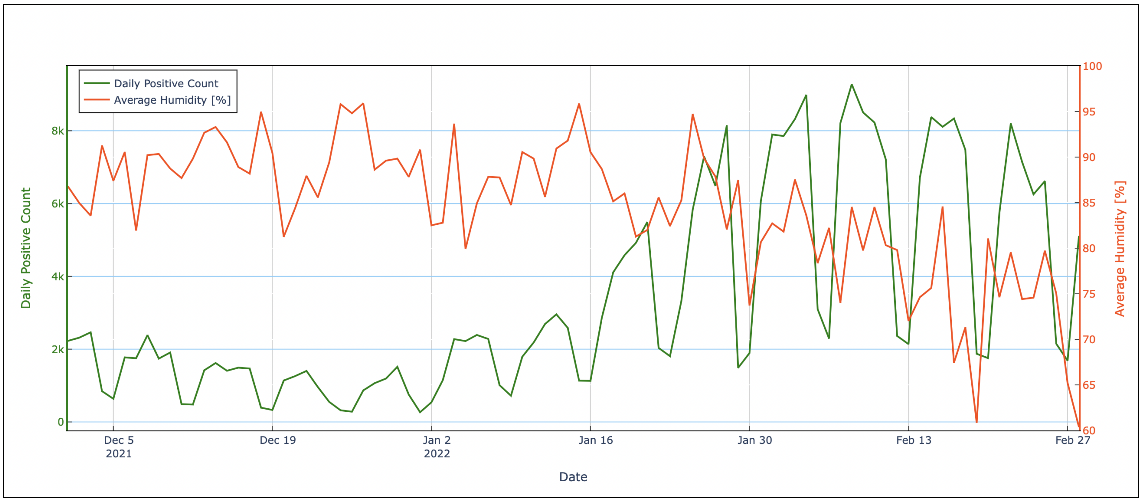

Figure 3.4: Humidity Vs Daily PCR Positive Count For Winter

The 7 day period of least relative humidity week during the winter season is from 13-02-2022 to 19-02-2022, with an average relative humidity of 72.56% . Considering the peaks from Figure 3.5, on 19th Feb, a relative humidity of 60.84% as the least value for the week was observed. The PCR Positive count on 19th Feb (lag 0) and 22nd Feb (lag 3) is 7478 and 8202 respectively. These values observed and the graph clearly shows that the low relative humidity value has an effect on increase in COVID cases after 3 days (lag 3).

Figure 3.5: PCR Count vs Relative Humidity from 13-02-2022 to 19-02-2022

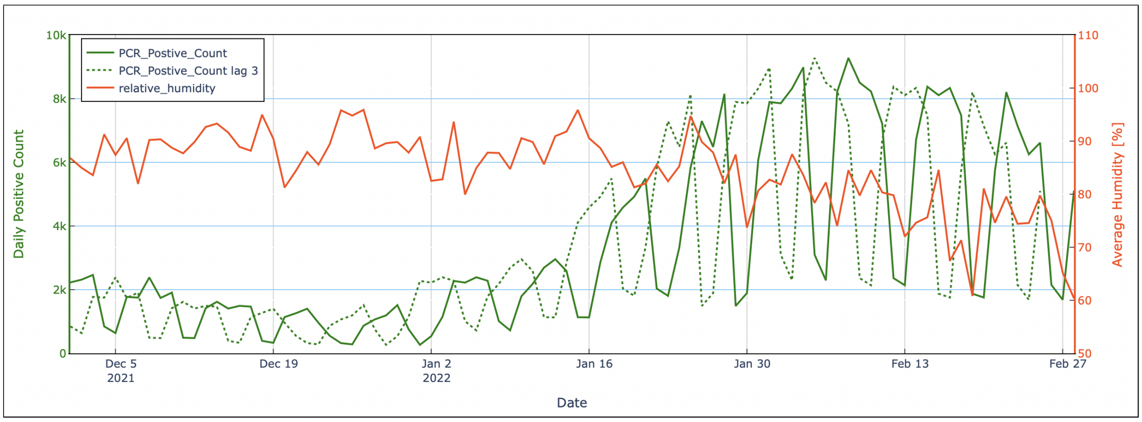

Figure 3.6: Adjusted PCR Count vs Relative Humidity for lag 3 For Winter

Correlation Method	Season	Covid Parameter	Weather Parameter	Correlation
Spearmann	Winter	PCR Positive Count	Relative Humidity	-0.5433
Spearmann	Winter	PCR Positive Count lag -1	Relative Humidity	-0.5209
Spearmann	Winter	PCR Positive Count lag -2	Relative Humidity	-0.5303
Spearmann	Winter	PCR Positive Count lag -3	Relative Humidity	-0.5500
Spearmann	Winter	PCR Positive Count lag -4	Relative Humidity	-0.5378
Spearmann	Winter	PCR Positive Count lag -5	Relative Humidity	-0.4298
Spearmann	Winter	PCR Positive Count lag -6	Relative Humidity	-0.4651
Spearmann	Winter	PCR Positive Count lag -7	Relative Humidity	-0.5433

Table 3.2: LAG values for Winter season with Relative Humidity

3.3 Spring

For the whole of Spring season data-set as shown in figure 3.7, temperature is negatively correlated with daily PCR positive count (Kendall-Tau: -0.1951, Spearmann: -0.2981). Correlation calculated for relative humidity and wind speed with COVID-19 parameters has False significance. Thus, we excluded these parameters for our further analysis.

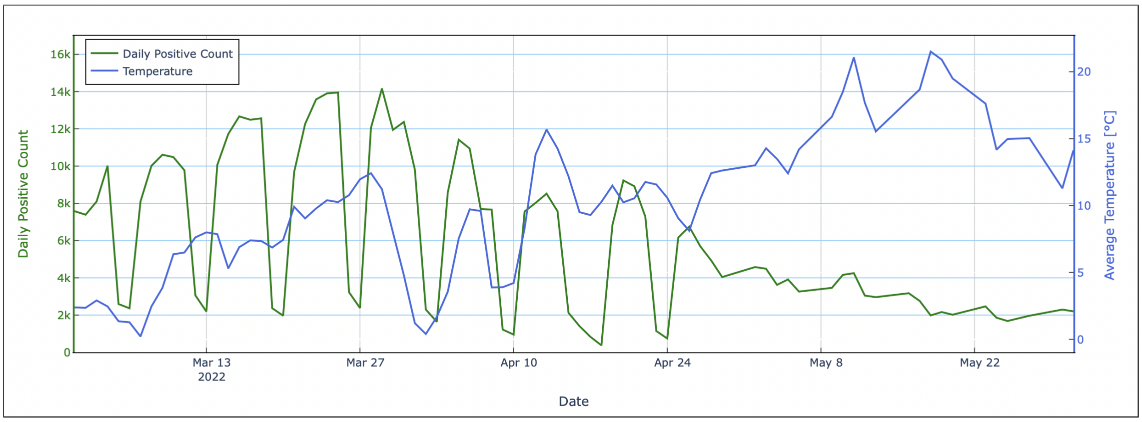

Figure 3.7: Temperature Vs Daily PCR Positive Count For Spring

Minimum temperature for spring is 1.21 ℃ and maximum is 19.54°C. Average Temperature was recorded at 9.94°C. Active positive cases varied from 373 to 14163.

The lag days calculation for Spring season shown in table 3.3 yielded Lag 3 to have the highest negative correlation with Daily PCR Positive count and Temperature(-0.391 °C).

Similar to the approach in the Autumn season, here, we considered a 7 day period of lowest temperature for our further analysis. The seven day period identified is from 01-03-2022 to 07-03-2022, where the average temperature value is 1.855 °C . Taking into consideration the peaks seen figure 3.9, 7th March has the lowest temperature in the week. 0.2144 °C is the observed lowest temperature value. Daily PCR Positive count for the same day is 8097 whereas Daily PCR Positive count for 9th March (lag 2) and 10th March (lag 3) is

Correlation Method	Season	Covid Parameter	Weather Parameter	Correlation
Spearmann	Spring	PCR Positive Count	Temperature	-0.2981
Spearmann	Spring	PCR Positive Count lag -1	Temperature	-0.281
Spearmann	Spring	PCR Positive Count lag -2	Temperature	-0.3502
Spearmann	Spring	PCR Positive Count lag -3	Temperature	-0.391
Spearmann	Spring	PCR Positive Count lag -4	Temperature	-0.3537
Spearmann	Spring	PCR Positive Count lag -5	Temperature	-0.31
Spearmann	Spring	PCR Positive Count lag -6	Temperature	-0.2092
Spearmann	Spring	PCR Positive Count lag -7	Temperature	-0.0776

Table 3.3: LAG values for Spring season with Temperature

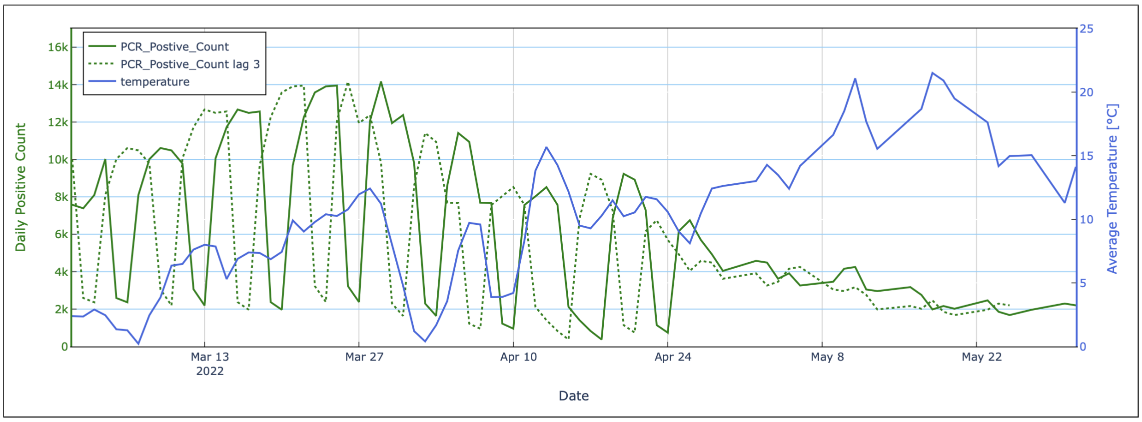

Figure 3.8: Adjusted PCR Count vs Temperature for lag 3 For Spring

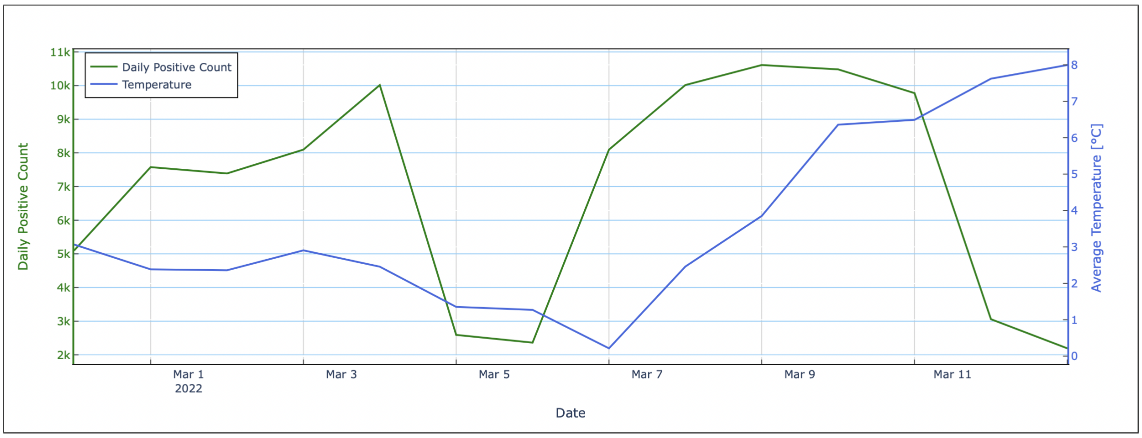

Figure 3.9: Daily PCR Count vs Temperature from 01-03-2022 to 07-03-2022

observed to be 10611 & 10482 respectively. From these observations and the graph, it is evident that due to low temperature, the cases increased with a lag of 3 days.

3.4 Summer

For the Summer season, temperature is the dominant weather factor and it is positive correlated with the Daily PCR Positive count as shown in figure 3.10 with Kendall-Tau correlation being 0.3744 and Spearmann correlation being 0.5334. Temperature varies from 14.54°C to 27.19°C in this season. Daily PCR count during the same period is from 1800 to 7041. Average Temperature for summer is 19.55 °C.

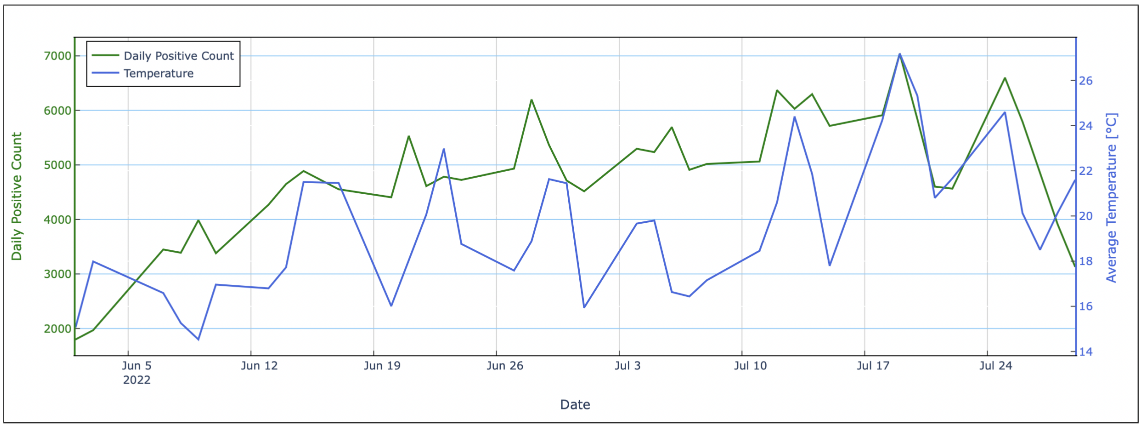

Figure 3.10: Temperature VS Daily PCR Count For Summer

For Summer, the 7-day period is from 07.06.2022 to 17.06.2022 as shown in figure 3.11 and average Temperature is found to be 17.6 °C (Positive Correlation). After the 7 day period for each season, we considered a 7 day incubation period (until Lag 7) for each season.

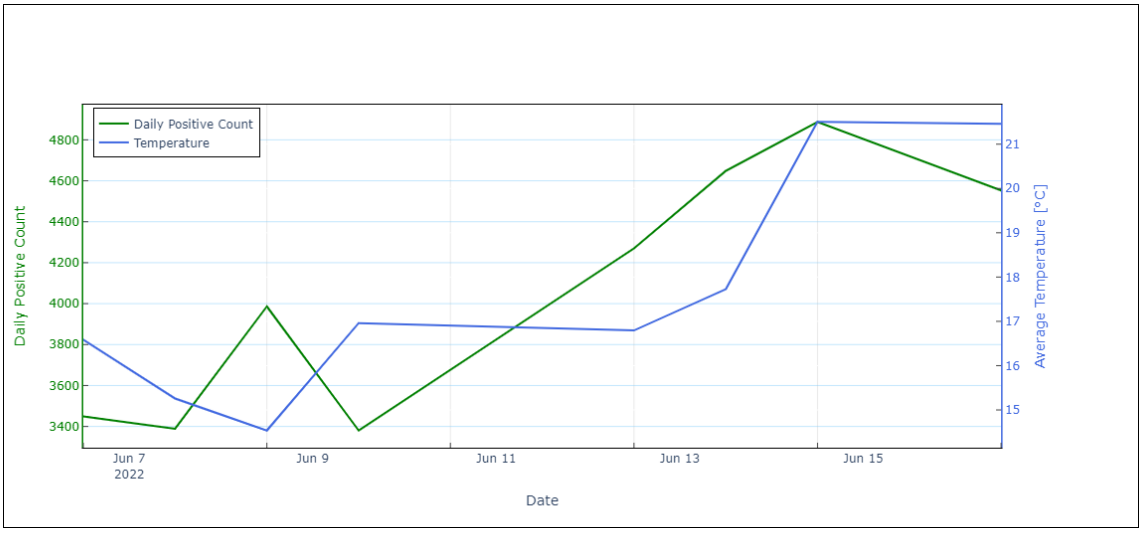

Figure 3.11: Daily PCR Count vs Temperature from 07.06.2022 to 17.06.2022

Correlation Method	Season	Covid Parameter	Weather Parameter	Correlation
Spearmann	Summer	PCR Positive Count	Temperature	0.6667
Spearmann	Summer	PCR Positive Count lag -1	Temperature	0.7857
Spearmann	Summer	PCR Positive Count lag -2	Temperature	0.8095
Spearmann	Summer	PCR Positive Count lag -3	Temperature	0.8095
Spearmann	Summer	PCR Positive Count lag -4	Temperature	0.6905
Spearmann	Summer	PCR Positive Count lag -5	Temperature	0.9286
Spearmann	Summer	PCR Positive Count lag -6	Temperature	0.881
Spearmann	Summer	PCR Positive Count lag -7	Temperature	0.8571

Table 3.4: LAG values for Summer season with Temperature

4 Result and Discussion

4.1 Autumn

During the seasons of Autumn (Average Temperature: 10.11 °C, Minimum Temperature: 0.2144 °C, Maximum Temperature: 21.5 °C) and Spring (Average Temperature: 9.94 °C, Minimum Temperature: 1.21 °C, Maximum Temperature: 19.54 °C), the temperature range was between $-$ 6.28 °C to + 14.51 °C which is found to be favourable in the growth of COVID virus [8] Temperatures above 55 °C have proven to rapidly inactivate poliovirus ($\leq$ 30 minutes) in growth media and sewage [9]. Whereas, on the contrary, at lower temperatures, virus tends to survive longer in a variety of environmental media [10].

We have also considered the Government guidelines that were in place. During the starting of Autumn season (23-08-2021 to 11-09-2021), 3G rule was applied to indoor activities. Also, Universities and schools were permitted to have face-to-face teaching with 3G rule. This was slightly changed from (12.09.2021 to 21.11.2021) wherein 2G+ regulations were applied and compulsory isolation for infected staff and students were regulated. But, by the end of Autumn (22.11.2021 to 30.11.2021), mandatory mask regulations for all the employees, 2G rule for indoor activities and 3G rule for universities were in place. This confirms that at least 2G rule was in place for the whole of Autumn season, yet from our observation by the end of Autumn (22.11.2021 to 05.12.2021) as shown in figure 3.3, it is evident that there is an increase in COVID cases with a significant negative correlation with temperature change.

4.2 Winter

Our study shows that temperature does have significant effects on increase or decrease in COVID-19 cases in Autumn, Spring and Summer seasons. During winter, an average temperature of 3.92 °C is observed. Though studies have shown that the temperature range − 6.28 °C to + 14.51 °C is found to be favourable for the growth of viruses like COVID-19 [8], relative humidity has a higher significant correlation to daily PCR positive count than temperature.

Various previous studies have shown that during cold winters, since the outdoor air is drawn indoors and heated to a suitable temperature for human survival, it highly lowers the indoor RH and hence affects the health of the residents in such closed spaces. Due to the COVID-19 pandemic, most of the people were confined to closed spaces due to various government restrictions like lock downs and quarantine rules. By heating the temperatures of indoors, the indoor RH becomes less than 40% which makes humans more vulnerable to infectious viral respiratory diseases like COVID-19. The lower indoor RH also makes it suitable for viruses like SARS-CoV-2 virus become more infectious and spread at a higher rate.[11]

Even though the average RH observed during winter in our study is 84.41%, the indoor RH that is maintained in most of the closed spaces is around 40%. The low indoor RH results in dry or moisture-free air which facilitates longer distance transmission of infectious aerosols which in turn will be inhaled by other humans and hence result in further spreading of viruses like SARS-CoV-2. Due to the dryness in the air, viruses also survive on surfaces for a longer period of time thus resulting in increasing the possibility of infection to more humans.[11].

From another study, it is suggested that, at a high relative humidity, such as $> 70\%$, viruses survive under moist conditions in the air droplets due to salts. These salts crystallize and keep the virus active for longer period. Dry but cool indoor environments such as what is found in winters results in viruses to survive for longer time in the air [12].

Another possible reason for the significant effect of RH during winters is due to low ventilated spaces. As per Government guidelines, 2G (Admission for only vaccinated, recovered individuals) rule was applied between 01-12-2021 to 13-01-2022. During the same period 3G (Admission for only vaccinated, tested, or recovered individuals) rule was applied for universities to remain open in presence mode. This restricted the individuals to stay within their houses or within closed spaces. Also, the low temperatures in the environment generally made people remain indoors during winters. Hence, in such environments, the lower ventilation facilities [13] [14] [15] [16] [17] increase the likelihood of infected persons sharing air with susceptible persons and resulting in higher risk of infection. The obstructed airflow passage in indoors can largely increase airborne pathogen concentration and lead to a higher risk of airborne transmission and infection [18].

Even though there was a mask mandate and at least 2G+ rule was followed during the whole of winter season, the survival time of the virus on surfaces was higher due to low indoor RH [19] which in turn lead to the increase in COVID-19 cases.

4.3 Spring

During the start of Spring season, Robert-Koch Institute (RKI) along with Federal Government of Germany predicted that, effect of Omicron variant of COVID-19 virus has reached it's peak and there will be a decline in COVID-19 cases by the end of Spring. Hence, most of the government regulations like contact restriction, 2G rule in retail stores, in-depth protective measures, home-office obligation, and hot spot regulation is removed. Yet, mask requirement and social spacing e.g.: in public transport is still in place to serve as a basic protection. From our visualization of results, it is evident that during the first half of Spring season (01.03.2022 to 13.03.2022), there is significant negative correlation of temperature with COVID-19 cases and there is an evident rise in COVID-19 infections. But, during the end of Spring (after April 24^{th}), it is observed that there is a decline in COVID-19 cases as shown in figure 3.7. Even though the regulations and restrictions were relaxed, there is no evidence of increase in COVID-19 cases during this time.

4.4 Summer

During the Summer season, our study shows that Temperature (Average Temperature: 19.55 °C) has a positive correlation to COVID-19 cases. Previous studies have also indicated that in Jakarta with average temperature (26.1 - 28.6 °C) [20] and Bangladesh with average temperature (23.6 - 31.1 °C) [21] have a significant positive correlation to COVID-19 cases. Even though the average temperature recorded was not in the mentioned range, we have also observed a significant positive correlation of temperature to the COVID-19 cases. From April 1st, all the other regulations except mask mandate and social distancing in public transport was removed.

Temperature is negatively correlated with PCR postive count in winter but is positively correlated with PCR postive count in summer. We believe this is because of the inconsistent reporting during summer. As a drop in cases was observed by the end of spring season, the RLP government passed a regulation to stop weekend and holiday reporting. Due to this, data obtained after the weekend or a holiday contained PCR positive cases from those missing days as well, hence resulting in inconsistent and incorrect case counts.

5 Limitations

Through our findings we provide preliminary evidence that the COVID-19 pandemic may be partially affected by temperature and relative humidity. However there can be other factors as well which various other studies show that can be a crucial factor to identify the increase or decrease in the cases.

- Vaccination data, rate of vaccination and recovered data is not considered for this analysis.
- Less reporting of cases during weekends– this can be because many testing centers are not open over the weekends or partly open(for lesser time duration).
- During the Infection peak, it was mandatory to get tests (3G and 2G+ rules) to enter various office spaces or other event locations. This increased the test rate during weekdays.
- During summer, we have very less data points(lesser summer months data) and weekend data on RLP website is missing. The reason for this is, as cases drastically declined, Government mandated to close most of the testing centers and stopped weekend reporting.
- Other factors which may influence spread of infection like age, air pollution, population density, Vitamin D Levels, Moving Population [22], is not taken into consideration.
- Other weather parameters(UV Index, Rainfall etc) are not included in this research [4].
- Variance is very less with respect to weather conditions in the Rhineland palatinate.

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