DALARNA
UNIVERSITY

Degree Project

Level: Second-cycle

Evaluating the efficiency of the Swedish government policies to control the spread of Covid-19.

Author: Runaj Khatiwada and Shweta Chalise

Supervisor: Moudud Alam and Murshid Saqlain

Examiner: Siril Yella

Subject/main field of study: Microdata Analysis

Course code: MI4002

Credits: 15 ECTS

Date of examination: 2021-01-20

Abstract

Different public health interventions such as social distancing, quarantine, use of masks in a public place, airport, and public transport restriction, closing of school, college, and shops, or even city lockdown were implemented around the world to control the spread of highly transmissible virus ‘‘SARS-CoV-2’’ which is responsible for the current pandemic of Covid-19 disease. Like other countries, Sweden also introduced policies like banning public gatherings, commencing distance learning, keeping social distance in public places, suspending flights to and from different countries, closing religious places, banning visits to elderly homes, and many more. This paper examines if such action or recommendations are effective in controlling the spread of Covid-19 disease.

The efficiency of these policies at each county in Sweden was evaluated and the effect of temperature on Covid-19 was analyzed using the data from the last week of December 2019 to the last week of September 2020. The statistical inferences were drawn from the multivariate time series model (hhh4) in R. Similarly, QGIS and ggplot2 library in R were used for descriptive analysis.

Among all the studied policies, banning the crowd on restaurants and bars, and restricting the number of people for demonstration in Sweden were the most effective methods to reduce the rate of disease spread in almost all the counties. The number of ICU and death cases were low during high temperature in Sweden. The outcome of this study can be useful to implement health policy to manage similar disease outbreaks in the future.

Keywords: Covid-19, public health intervention, hhh4 model, QGIS.

Acknowledgments

We would like to offer our sincere gratitude to our supervisors Moudud Alam and Murshid Saqlain for their guidance and kind support throughout this thesis. Thank you for your motivation, patience, good mood and humor.

We are extremely thankful to Diego Giuliani, an associate professor from the University of Trento, Italy for providing us the insightful pieces of information regarding the hhh4 model in R software. We are equally grateful to Thobias Bergqvist from Swedish Meteorological and Hydrological Institute for helping us collect the necessary weather data.

We would like to express special thanks to our families and friends for their continuous encouragement and support throughout this thesis.

Contents

Glossary

Reproduction Number (R_0): The number of people who are infected by the primarily infected people during the entire period of their infection.

Data idiosyncrasies: It is an unusual behavior or an odd feature of data that might provide misleading information sometimes.

Autoregressive effects: The prediction of future value based on past value.

Asymptomatic: It is either a person or their condition in which they do not show the symptoms of some disease despite being infected.

Etiology: It is defined as the cause or the reason behind things.

Epidemic: It is the occurrence of any infectious disease in a community at a particular time.

Endemic: It is an infectious disease that is regularly found in a certain area.

Pandemic: It is a disease that is widespread over the larger part of the country or around the world.

Spatiotemporal: Belonging to space and time.

Contact tracing: It is the process of identifying and controlling the people who have been exposed to any disease to avoid further transmission.

Chapter 1. Introduction

At the end of the year 2019, a cluster of pneumonia of unknown etiology was identified at Wuhan city, in Hubei province in China. The patients had similar symptoms like dry cough, difficulty in breathing, fever, and lung inflates in X-ray (Lu et al., 2020). The causative agent was identified as Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2). Later, the World Health Organization (WHO) named the infectious disease as Coronavirus 2019 (Covid-19) (WHO, 2020c). The disease rapidly began to spread around the world. On 11 March 2020, WHO characterized the disease as a pandemic due to its severity and alarming spread (WHO, 2020b). While Covid-19 often leads to the mild symptoms common to other respiratory infections, it also causes severe disease among certain groups, including older populations and individuals with underlying health issues such as cardiovascular disease and diabetes (Salgotra et al., 2020).

Within the first three months of its emergence, almost 1 million people around the world were infected and 50,000 died due to Covid-19. The virus transmitted rapidly and over 10 million people were infected and 500,000 died by the six months throughout the world. It was estimated that about 40% of infected people can transmit the virus before they develop any symptoms of the disease (NIH,2020). As of December 20, 2020, there have been about 75.1 million confirmed cases of Covid-19 including about 1.68 million deaths (WHO, 2020a). It is spreading rapidly in an immune naive population and consequently deaths are rising steeply, and health systems are under strain. The disease has become a serious global health issue however several vaccines are now permitted for immunization and others are in their trial phases. Different nations have introduced several non-pharmaceutical measures for disease prevention and control. Public health interventions like school closures, social distancing, closure of non-essential businesses is mandated to slow down the growth of the current pandemic. Some countries like China, Italy, Spain have imposed a complete lockdown to reduce the contact rates between the people thereby reducing the transmission of Covid-19 (Flaxman et al., 2020).

The first Covid-19 case in Sweden was detected on 31^{st} January in Jonkoping (Roden, 2020). Since then, the situation started getting worse and the government had to take several steps for its containment. To control the spread of Covid-19 the Swedish government has implemented various kinds of interventions. It was advised not to travel to Hubei from 12^{th} February 2020. The policy was followed by the travel ban to elderly homes, social distancing, the prohibition of gathering more than 50 people at a time, closure of school and colleges, work from home as far as possible, and so on (MSB, 2020).

Our study focuses particularly on Sweden because it has a different approach to contain Covid-19 compared to other European countries. Some of the European countries like Germany, Italy, Spain, France, Switzerland, Belgium, Denmark, Norway, UK, and Austria ordered the lockdown within their territories while Sweden applied various other policies except lockdown to reduce the transmission of the disease (Flaxman et al., 2020). Wuhan, the place where Covid-19 originated, has a population of 11.08 million which is more than the population of Sweden (10.23 million) but the spread of the virus was under control within the three months of the disease outbreak (Pan et al., 2020). On the contrary, Sweden is still (as of the end of December 2020) struggling to control the disease spread. This intrigued us to analyze the efficiency of the Swedish government policies towards the containment of Covid-19.

1.1. Aim of the study

The aim of the study is to evaluate the efficiency of the interventions of the Swedish government to control the spread of Covid-19 in Sweden. We collected the necessary data from various sources available on internet and filtered them out as per our requirements. We aimed to draw the statistical inference from the multivariate time series (hhh4) model using R software. We fitted the spatiotemporal model with three components: Epidemic-within, Epidemic-between, and Endemic. We compared the effects of neighboring counties and temperature to the county itself. To check the efficiency, we investigated the coefficients of the policies and temperature along with their standard error. We examined the non-clinical policies such as visiting ban to the elderly house, restricting public gathering of more than 50 people, advice against non-essential travel to and from Sweden, suspend flights to Iran from Sweden, distance learning, urge the people to take precautions like wash hand, avoid crowd, work from home.

Chapter 2. Literature Review

2.1. Covid-19

Coronavirus is a large group of viruses that generally cause mild to modest upper-respiratory-tract ailment, like the common cold (NIH, 2020). While there are hundreds of coronaviruses and the greater part of them infect animals or birds such as pigs, cats, camels, and bats. Occasionally, these viruses reach to humans and cause a disease. There are seven types of coronaviruses known to affect people among which four types of them can cause mild to moderate infections and the rest of them can cause some lethal illnesses. The recent outbreak Covid-19 is caused by SARS-CoV-2 (NIH, 2020).

The health experts are exploring ways to treat and prevent human coronavirus infections. However, some vaccines are on market, their effectiveness are yet to be observed. In this onerous situation, the worldwide control of the disease is almost impossible, that is why it is necessary for country-wise mitigations. Meanwhile, effective surveillance is the prerequisite for blocking the source of infections (Venugopal et al., 2020).

2.2. Public Health Intervention

Individual behavior as well as government action is crucial to control the spread of Covid-19. It is essential to maintain social distancing, early self-isolation, and to seek medical advice remotely unless the symptoms are severe. Some of the methods government have implemented are mandated quarantine, stopping mass gathering, banning unnecessary travels, closure of educational institutes, workplace where the infection has been identified, and isolation of households, cities, or towns. Along with this, they have tried to provide proper diagnostic facilities and remotely accessed health advice, together with specialized treatment for people with compromised health.

One of the important steps is contact tracing which is carried out to reduce the spread of the disease. The paper (Anderson et al., 2020) suggested, 70% of contacts must be traced successfully to control the early spread when the reproduction number (R_0) is 2.5. The contact tracing can be effective to reduce the transmission during the early stage of the outbreak while it will become challenging for the logistic timely tracing on many contacts per case. It can create a super-spreading event and the contact tracing can be ineffective. This situation can lead to the need for broader-scale social distancing interventions (Keeling et al., 2020). Social distancing reduces the value of R_0. During the warm temperature of summer in China, social distancing reduced the disease transmission by 60% when R_0 was 2.5 (Anderson et al., 2020).

2.3. Studies on association of public health intervention and control of Covid-19

2.3.1 Wuhan, China

In a study the temporal associations between public health interventions and control of Covid-19 were evaluated in which the rate of confirmed cases and effective R_0 in different periods according to key interventions were compared in Wuhan, China (Pan et al., 2020). The laboratory-confirmed cases were described in terms of age, sex, and occupation. The epidemic curve was plotted based on the symptom onset date and important intervention date. The geographical distributions of daily rates of Covid-19 cases across Wuhan city through the 5 periods of interventions were presented using ArcGIS.

A modified Poisson regression with robust variance was used to evaluate the relationship between age, sex, time, and health care occupation with disease severity (mild and moderate vs severe and critical). The R_0 was calculated using the method developed by (Cori et al., 2013). From this study, it was concluded that multifaceted public health measures (including but not limited to intensive intracity and intercity traffic restriction, social distancing measures, home confinement and centralized quarantine, and improvement of medical resources) reduced the number of new Covid-19 cases, rates of confirmed cases, and R_0. Wuhan travel ban delayed the epidemic progression by 3 to 5 days in mainland China and it reduced the disease importation to other countries by nearly 80% (Pan et al., 2020).

2.3.2. Italy

In Italy, major three steps were followed to restrict Covid-19. Firstly, some of the municipalities in the Lombardy and Veneto regions were subjected to quarantine. Secondly, entire Lombardy and some provinces in other northern regions were isolated from the rest of the country, and lastly, nationwide lockdown was declared (Giuliani et al., 2020). Lodi, the first place to quarantine experienced a significant decrease in the number of newly diagnosed cases after the third week of the quarantine and the number was decreased by half. Whereas same result was not observed in the metropolitan city having large population and with more active social behavior without effective implementation of control measures. Some provinces of Florence and Naples could not show the containment of the Covid-19 despite going for the lockdown. This study suggested that the peculiarities of local territory should be considered for the control strategies to be effective at the national level. The data about the spatial-temporal distribution of Covid-19 infections at the province level consist of multivariate count time series whose spatial references were in the form of irregular spatial lattices. Therefore, areal Generalized Linear Models (GLMs) were used for proper regression (Giuliani et al., 2020).

2.3.3. European region

A research was carried out by Flaxman et al. (2020) to estimate the effects of non-pharmaceutical interventions on Covid-19 in 11 European countries namely Austria, Belgium, Denmark, France, Germany, Italy, Norway, Spain, Sweden, Switzerland, and the United Kingdom. The number of death cases was analyzed to measure the extent to which the transmission of Covid-19 was reduced. The trends that were observed in the death data were reproduced and empirically driven predictions within the short period were produced by representing the Covid-19 infection process with a semi-mechanic, joint, Bayesian hierarchical model. Partial pooling was used to utilize more information, to overcome data idiosyncrasies, and enable more timely estimates. R_0 was modeled as a piecewise constant function that changed only when a new intervention occurred in different countries. According to (Flaxman et al., 2020), most of the interventions were implemented with rapid success in different countries thus it was difficult to calculate the individual effect of each intervention. It was analyzed that only the effect of lockdown was identifiable that reduced the R_0 by 81% in these countries.

2.3.4. Spain

Aleta & Moreno (2020) evaluated the potential incidence of Covid-19 and the effectiveness of the containment measures in Spain. The researchers used the stochastic SEIR metapopulation model to study the spatial and temporal transmission of Covid-19. Such model class and the data-driven versions allowed to obtain realistic estimates for the spatial incidence of the disease and its temporal dynamics. The metapopulation model was composed of two dynamics: disease dynamics and mobility dynamics. The study (Aleta & Moreno, 2020) concluded that the isolation or quarantine of the infected person was the most effective strategy in Spain. This method is advantageous for an asymptomatic infectious individual as well. Some policies like traffic restriction, self-protection measures, social distancing practices, and closure of public places also delayed the spread of the disease.

Chapter 3. Methods

In this thesis, the number of death and number of ICU cases due to Covid-19 are analyzed as the measures of the disease spread. The effect of government policies on these two outcome measures is analyzed. The number of infected cases would be a more direct measure of disease spread. Since the data collection for the number of infected cases may not be always reliable due to various reasons such as people residing at a farther distance from the testing center would not get tested or error in test result (Kennedy et al., 2020). Therefore, we take the number of deaths, and ICU cases, as proxies. These measures are very highly correlated with the actual disease spread, and very accurate data are available on these counts.

To get a preliminary idea about the association between the outcome variable, and policies and confounding variables, descriptive statistics, and graphic data visualization tools were used. Statistical inferences were drawn by using multivariate time-series analysis. In the rest of this chapter the statistical methods, models are explained, and the data collection and data preparation steps are described.

3.1. Statistical Analysis

For the statistical inference, a multivariate time series model was built to see the effectiveness of all the policies introduced by the Swedish government. We utilized the surveillance package (Meyer et al., 2017) from the R software (R Core Team, 2015) for this purpose.

3.1.1. hhh4 Model

The number of ICU cases and the number of deaths in each county were studied using the hhh4 model available in the surveillance package. With the use of this package, we monitored and estimated the spatial and temporal behavior of the infections. The model hhh4 (Meyer et al., 2014) was used to fit an autoregressive Poisson or negative binomial model to a multivariate time series of counts. In our case, the role of the hhh4 model was to decompose the entire system mean into two main components: Epidemic and Endemic. Both components allow the log-linear predictors of covariate and the random intercepts.

The expected number of deaths or the ICU cases in each county of Sweden for a particular time was obtained from the additive decomposition of the mean of the components: epidemic-within, epidemic-between, and endemic.

$$\mu_{r,t} = \lambda_r Y_{r,\,t-1} + \Phi_r \sum_{r' \neq r} \omega_{r',\,r}\, Q_{r',\,t-1} + e_r\, v_{r,\,t} \quad (1)$$

The subcomponents can be modeled through the log-linear specifications as:

$$\log(\lambda_{r,t}) = \alpha_r^{(\lambda)} + \beta^{(\lambda)^T} Z_{(r,\,t)}^{(\lambda)} \qquad (2)$$

$$\log(\Phi_{r,t}) = \alpha_r^{(\Phi)} + \beta^{(\Phi)^T} Z_{(r,\,t)}^{(\Phi)} \qquad (3)$$

$$\log(v_{r,t}) = \alpha_r^{(v)} + \beta^{(v)^T} Z_{(r,\,t)}^{(v)} \qquad (4)$$

3.1.1.1. Epidemic-within sub-model

In the given equation (1), r and t represent the counties of Sweden and the time (week number) respectively. The first term on the right-hand side gives the epidemic-within component that models the death and ICU case within the same county. $Y_{r,\,t-1}$ gives the number of deaths or ICU cases in a particular county(r) at the time (t-1) that is the previous week. This is assumed to follow a negative binomial distribution.

The first component on the right-hand side of equation 1 gives the temporal behavior of the infection within the county in the previous week. It incorporates the deaths and ICU cases reported in the previous week (t = t-1) and that has a direct effect on $\mu_{r,t}$ which is affected by the factor of λ_r. The parameter $\lambda_r$is the coefficient whose value changes among the county due to the arbitrary effect that allows the different nature in the elements of death cases.

With the short period time series, the epidemic-within autoregressive parameter is assumed to remain unchanged over time considering there is not any significant external covariate. Thus, equation 2 becomes

$$\log(\lambda_{r,t}) = \alpha_r^{(\lambda)} \qquad (5)$$

which means the internal spread of the disease depends only on the spatially varying intercept $\alpha_r^{(\lambda)}$.

3.1.1.2. Epidemic-between sub-model

The second term in the right-hand side of equation 1 is the epidemic-between component. This component is used to model the average number of deaths and the ICU cases ($Q_{r',\,t-1}$) of the counties r' which are the neighboring counties of r in the previous week (t-1). The coefficient $\omega_{r', r}$ is positive only when the counties r' and r share the same border else the value of $\omega_{r'}$ is zero. Φ_r is the coefficient that is used to identify the magnitude of the effect of the inter-county spread of the disease and the changes between the counties based on their populations and some unidentified means that spread the disease.

The epidemic-between autoregressive parameter is reduced to:

$$\log(\Phi_{r,t}) = \alpha_r^{(\Phi)} + \beta^{(\Phi)} \log e_r \qquad (6)$$

This relation shows that the different counties have different tendencies to be affected by their neighboring counties which depend on their population density. It shows that densely populated county can have more deaths and ICU cases compared to lightly populated counties.

3.1.1.3. Endemic sub-model

In equation 1, the third component on the right-hand side is the endemic component, it models the data on each county where the spatial and the temporal autoregressive effects have been considered. In this component, the term er represents the population of the county r, and vr,t represents the different weeks.

Nine different policies have been introduced (Table 2) and categorical value of temperature (Table 1) in addition to existing terms er and vr,t the endemic sub-model was taken into account.

$$\log(V_{r,t}) = \alpha_r^{(v)} + \sum_{i=1}^{p} P_{i,r,t}\beta_i^{(v)} + \sum_{j=1}^{q} T_{j,r,t}\beta_{p+j}^{(v)} + \beta_{p+q+1}^{(v)} t + \beta_{p+q+2}^{(v)} t^2 \quad (7)$$

where, $\mathbf{P}_{i,r,t}$ is the dummy variable for i^{th} policy, we have altogether 9 policies for this model making p=9.

$T_{j,r,t}$ is the dummy variable corresponding to the 3 temperature categories. t is the week number. To avoid the dummy variable trap, one of the dummies corresponding to the temperature was omitted in actual estimation. The endemic predictor vr,t is multiplied by the offset er where the value er is the total population residing in that county.

3.2. Descriptive analysis

Descriptive analysis was performed with the QGIS (Moyroud & Portet, 2018) plot and the ggplot2 library (Hadley, 2020) in R. QGIS allowed us to analyze the spatial information. In QGIS, we put all the ICU and Death cases per ten thousand population to visualize the before and after the effect of the policies between all counties in Sweden. While for ggplot2, we considered all the factors such as polices, a temperature which may impact the spread of Covid-19 and tried to observe the position of each factor in the different number of weeks. It gave us a basic understanding of government policies' effectiveness.

3.3. Data Collection

3.3.1. Number of Infected, ICU and death cases

We obtained the necessary data from the official website of the public health agency of Sweden. This website provides all public health information in Sweden. Data that were reported during the weekends were published on Tuesdays. The compilation of the report was done from Tuesday to Friday and the statistic page was updated at 14:00 on these days with daily data (Andersson, 2020). For our study, we used the weekly data that was updated at 14:00 on Thursday.

The number of infected people was reported based on the laboratory-confirmed cases reported according to the Swedish Communicable Diseases. The database was updated frequently by the treating physician or the infection control unit in each region. The number of deaths due to Covid-19 was based on the data reported to the Swedish Public Health Agency (Andersson, 2020). The number of dead people were reported who have the Covid-19 regardless of the cause of their death. The cases were recorded only when the date of death was known. The number of deaths with Covid-19 was monitored by the National Board of Health and Welfare. Covid-19 cases that ended up in ICU were maintained by the Swedish Intensive Care Registry.

The statistic provided by the Swedish Public Health Agency consist of data regarding the number of cases, number of deaths, number of ICU cases, cumulative number of new cases, cumulative number of deaths, and the cumulative number of ICU cases on each of the counties in Sweden. We filtered out the rest of the data and prepared a data frame that consists of the number of deaths, number of ICU cases, and the name of the county.

3.3.2. Demographic Data

The population of each county was obtained from the Statistic Centre Bureau of Sweden (SCB, 2020). The statistics gave the population and population changes, due to birth, death, and immigrants categorized by counties, municipalities, sex, age, marital status, country of birth, and country of citizenship. We used the total population of each county in Sweden in the year 2019. Later, the population of each county was divided by 10000 and was used as “population per 10000” in our data frame. These data were used to visualize the situation of Covid-19 death and ICU cases in all the counties of Sweden in QGIS. The population per 10000 was used to measure the similarity of the color gradient in the QGIS map which made it easier to compare with all the counties.

3.3.3. Weather data

The necessary weather data was extracted from the Swedish Meteorological and Hydrological institute (SMHI), which is an expert authority under the Ministry of the Environment. The SMHI has developed a REST API to provide all the weather-related data. It also provides information about the station and its code. This station code was used to build the correct URL to hit the request for REST API for the desired county's station. To get the list of all the stations, the corresponding county, and its code, the REST API was hit and a JSON file was fetched and was converted to the data frame. The list of all the municipalities, cities with respective county information was obtained and both the data sets were joined to get information about station city, station code and the corresponding county.

To get the temperature data for each county an URL was build. The weather data was obtained by hitting the API provided by SMHI. However, the data was available only for the last 4. The older archived data was collected by calling the corrected-archive value in the URL. We combined both data frames and eliminated the redundant data. We also converted the daily data into weekly data. Some counties had missing data as well. To compensate this, we calculated the average temperatures of its nearest weather stations and substitute the value in the missing place. The formulation to handle the missing data is defined below,

$$\mathbf{T}_n = \sum \mathbf{T}_n / n \qquad (8)$$

In equation (8), $\mathbf{T}_n$ is the temperature data on the stations of neighboring counties. Where T is the temperature, n is the count of the station. The distance to the nearest weather station depends on the county itself, but we tried to take the nearest station code for the county with missing data. The count of the neighboring station (n) is 2 or 3 depending upon the availability of the data from the station.

Further, the temperature data was converted to a categorical variable, just to avoid the non-linear effect on multivariate time series analysis (Table 1).

Table 1: Temperature Categories.

Temperature (degree Celsius)	**Value**	**Description**
< 5	0	Very low temperature
6 – 10	1	Low temperature
10 <	2	High temperature

3.3.4. Government Policies

The Public Health Agency of Sweden has made various decisions to combat the seemingly invincible situation. Numbers of policies were implemented in the country so that these policies can slow down the spread of Covid-19 disease and some of them are still in operation (as of the end of December 2020). All this information was made available publicly to the people residing in Sweden through various communication media (MSB, 2020). Different policies were announced on different dates. We categorized these policies into weekly policies. Any decisions made within one week were regarded as the same policy. Our data frame consisted of 9 different policies that were implemented in 9 different weeks. Table 2 gives the detail of the policies implemented in different dates in Sweden.

Table 2: Description of implemented policies in Sweden.

Effective Date	Week	Policies	Policy Description
2020-03-17	12	Policy 1	Suspend flights between Sweden and Iran.
2020-03-21	12	Policy 1	Suggest against unnecessary travel to northern Italy and South Korea.
2020-03-25	13	Policy 2	Advice on non-essential travel to Italy.
2020-03-26	13	Policy 2	Advice on non-essential travel to Tyrol, Austria.
2020-03-27	13	Policy 2	Police limited the number of people in gathering (500 people).
2020-03-29	13	Policy 2	Avoid non-essential travels to all other countries.
2020-03-30	14	Policy 3	Urge the public to take precautions. (avoid crowd, wash hand, do not visit hospitals or elderly homes)
2020-04-01	14	Policy 3	Remote learning.
2020-04-01	14	Policy 3	Public health agency Call for work from home in Stockholm.
2020-04-01	14	Policy 3	Temporary ban to travel Sweden from the countries outside Europe.
2020-04-01	14	Policy 3	Persons above 70 years to limit social contacts.
2020-04-02	14	Policy 3	Translation of Covid-19 information into other languages.
2020-04-03	14	Policy 3	Advice to consider only necessary trips in Sweden.
2020-04-09	15	Policy 4	Ban on crowding in restaurants, café, and bars.
2020-04-13	16	Policy 5	Prohibition on the public gathering of more than 50 people.
2020-04-15	16	Policy 5	National ban on visiting elderly homes.
2020-05-08	19	Policy 6	Mosques will remain closed during Ramadan and eid-al- fitr.
2020-05-13	20	Policy 6	Large graduation celebration ban.
2020-05-28	22	Policy 7	Travel abroad banned to July 15, 2020.
2020-05-29	22	Policy 7	Celebration on student floats banned; Extended entry ban to Sweden.
2020-06-03	23	Policy 8	Holiday camps for children allowed.
2020-06-24	26	Policy 9	More restriction on demonstration permit. Less than 50 persons were allowed for any public gathering.

3.4. Workflow

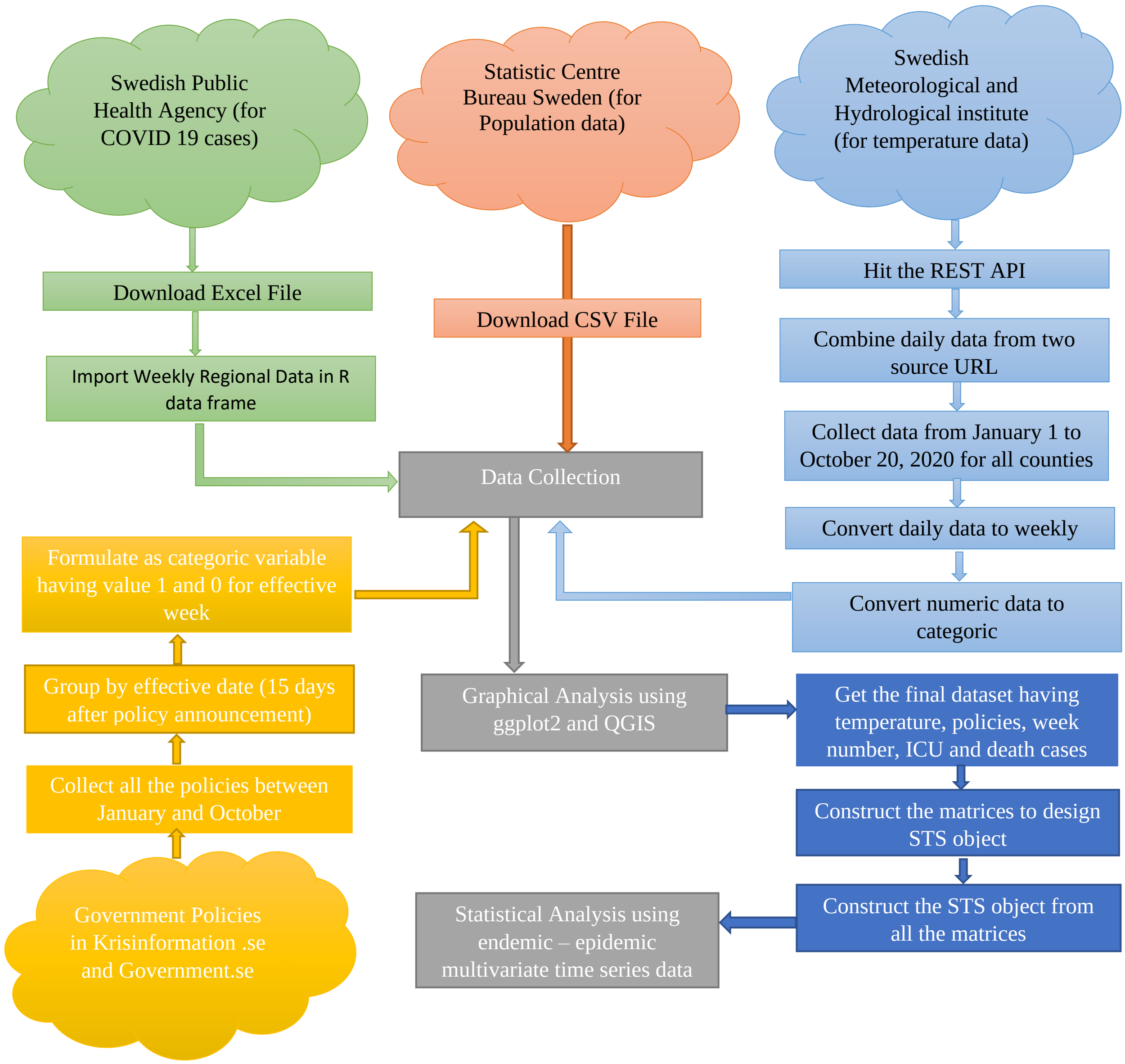

Figure 1: Workflow Diagram

3.5. Tools Used

Almost all the data manipulation and most of the data analyses were accomplished using R software. The following software and packages were used for accomplishing different task for this thesis.

ggplot2 library (Wickham, 2020): An R library for the graphical visualization of ICU and the death cases considering the factors affecting.

httr (Wickham, 2019): A package to retrieve the data provided by API in R.

Surveillance package: A package to fit the spatiotemporal model in R for of Covid-19 spread in Sweden.

dplyr (Wickham et al., 2020): A package to get the necessary set of tools to manipulate the dataset in R.

Microsoft Excel: A program to organize the data set.

QGIS (Moyroud & Portet, 2018): A software to plot the cases in different counties on the map of Sweden.

Google Maps: A web mapping service to find the weather stations.

Chapter 4. Results

Sweden has faced a big challenge in its public health sector due to the Covid-19 starting from 31st January 2020. Since that date, the country has been administering various strategies to combat the situation. We analyzed the efficiency of these interventions to contain the spread of Covid-19 in each county as well as the relation between the temperature and the spread of the disease is studied.

4.1. Results from descriptive analyses

4.1.1. Covid-19 spread over counties

Ever since the Covid-19 was identified it has affected a massive population in Sweden. The number of ICU cases and the death cases are increasing day by day. Some weeks in which the ICU and the death cases had differed notably were chosen and the spatial information of the Covid-19 cases in Sweden were analyzed (Figure 2, Figure 3, and Figure 4).

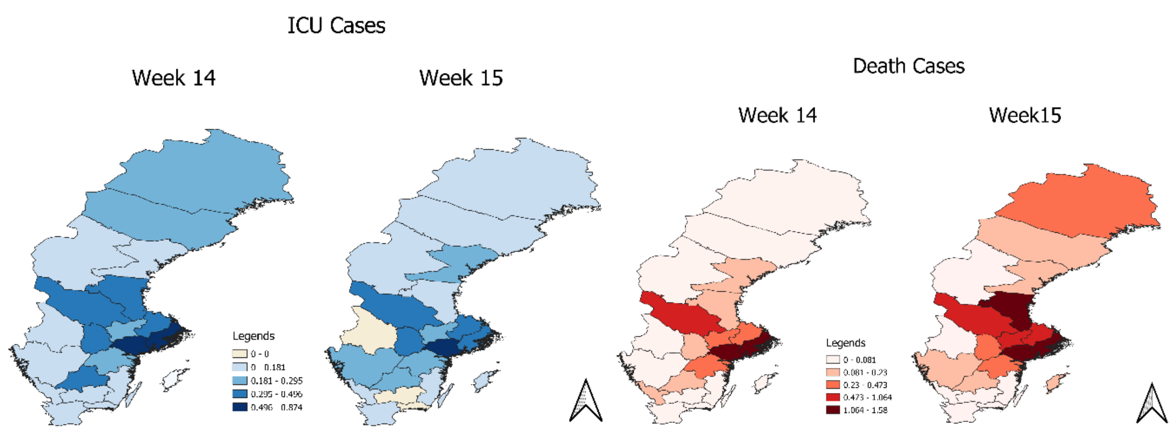

Figure 2: Number of ICU and Death cases in the first week (Week 14) and the second week (Week15) of April 2020 in Sweden

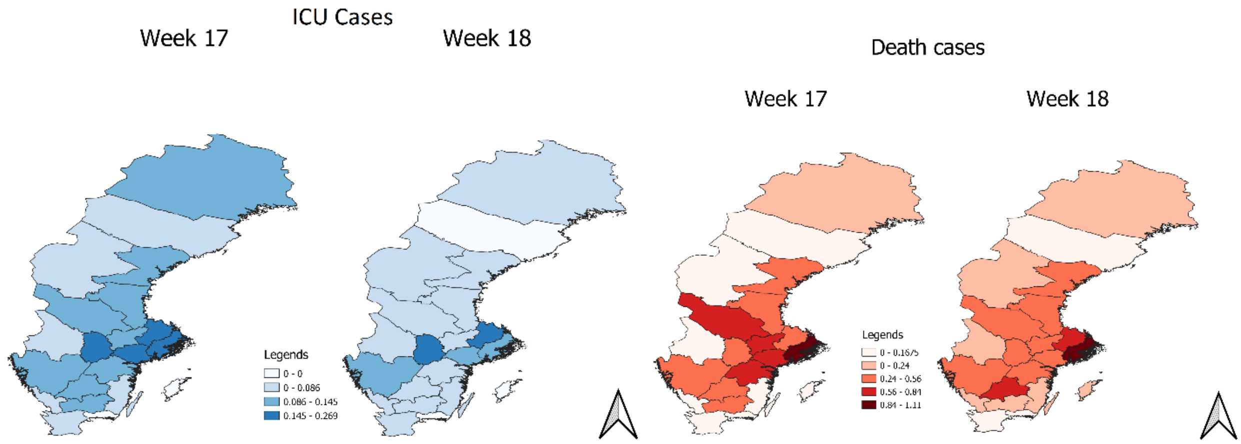

Figure 3: Number of ICU and Death cases in the third week (Week 17) and the last week (Week18) of April 2020 in Sweden

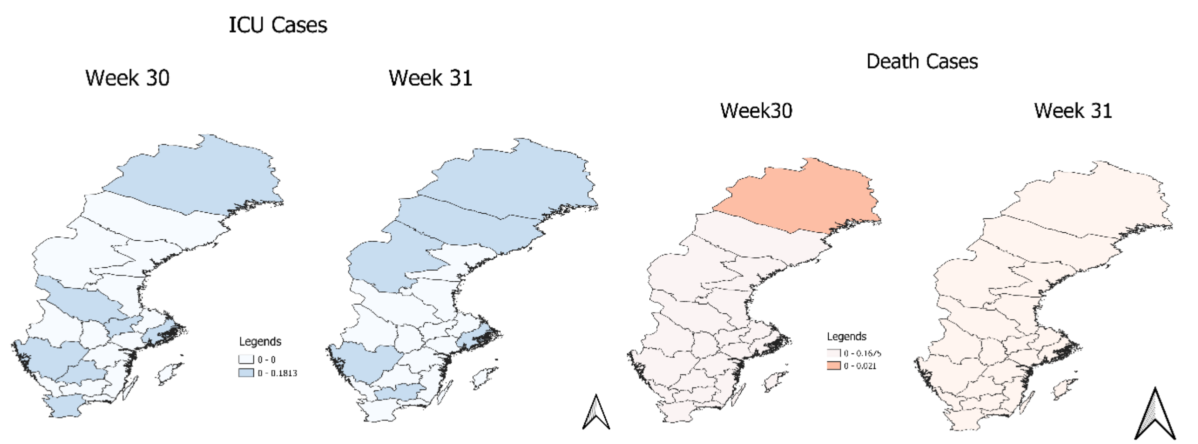

Figure 4: Number of ICU and Death cases in the third week (Week 30) and the last week (Week31) of July 2020 in Sweden

The variation in the number of ICU cases and the death cases during weeks 14 and 15 is shown in figure 1. When the ICU cases were increased in most of the counties in week 14, the Swedish government applied some policy to control it. The applied intervention minimized the ICU cases in most of the counties however it could not reduce the death cases. Thus, further restrictions were implemented. In that event, ICU cases plummeted in some of the counties during week 17 and further decreased during week 18. While the death cases were slightly minimized in some counties during week 17 but surged during week 18 as illustrated in figure 2. Hence, more strategies were required to contain Covid-19. Later, more policies were executed whose outcome is depicted in figure 3. The ICU cases in week 30 were less as compared to the previous weeks. However, after applying other interventions in week 31, it could not give the expected result and the ICU cases rose again (Figure 4). Similarly, minimized death case was noticed in only one county.

4.1.2. Time series of Covid-19 spread and temperature

The graphical representation of the ICU and the death cases considering the different policies and the temperature is obtained by using the ggplot2 library. The number of ICU cases and the death cases from week 0 to week 42 in Stockholm, Jonkoping, and Norrbotten is depicted in Figure 5.a, 5.b, and 5.c respectively. Y-axis on the left-hand side provide information about the number of death and the number of ICU cases in each county in Sweden that are separated by two different colors: red and blue for death and ICU cases respectively. The X-axis shows the number of the week starting from 0 to 42. Also, Y-axis on the right-hand side presents the different temperatures during the same period. The policies from P1 to P9 are presented at the top of the graph. The blue, red, and black lines represent the ICU cases, death cases, and the average temperature respectively.

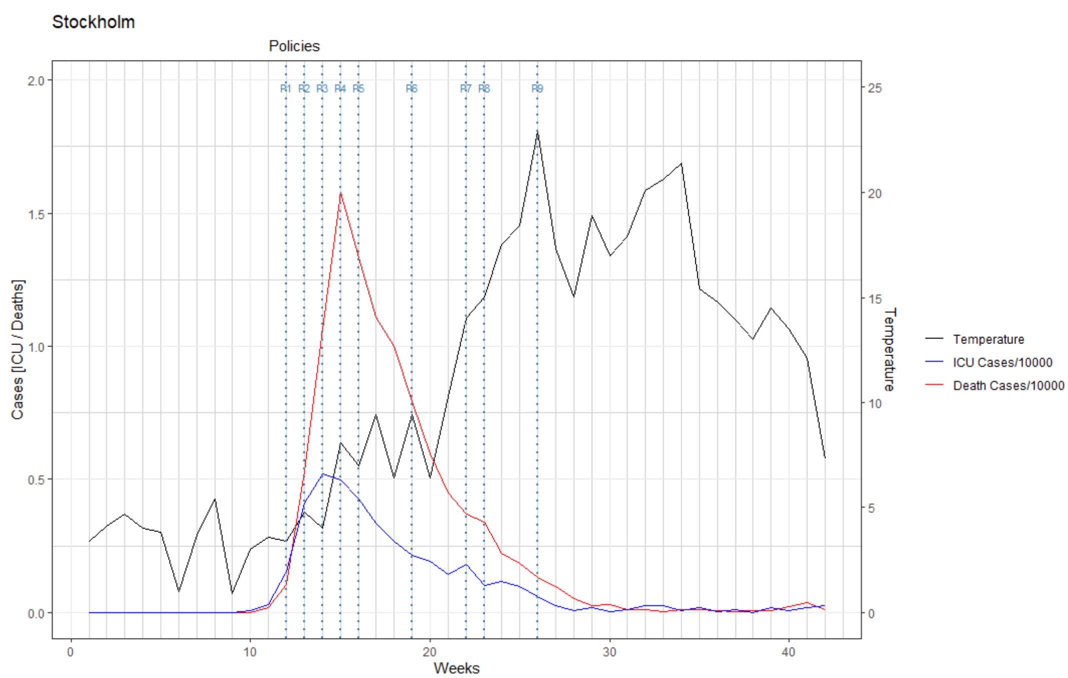

Figure 5.a: Number of death cases and ICU cases from the last week of December 2019 to the second week of October in Stockholm with its average temperature.

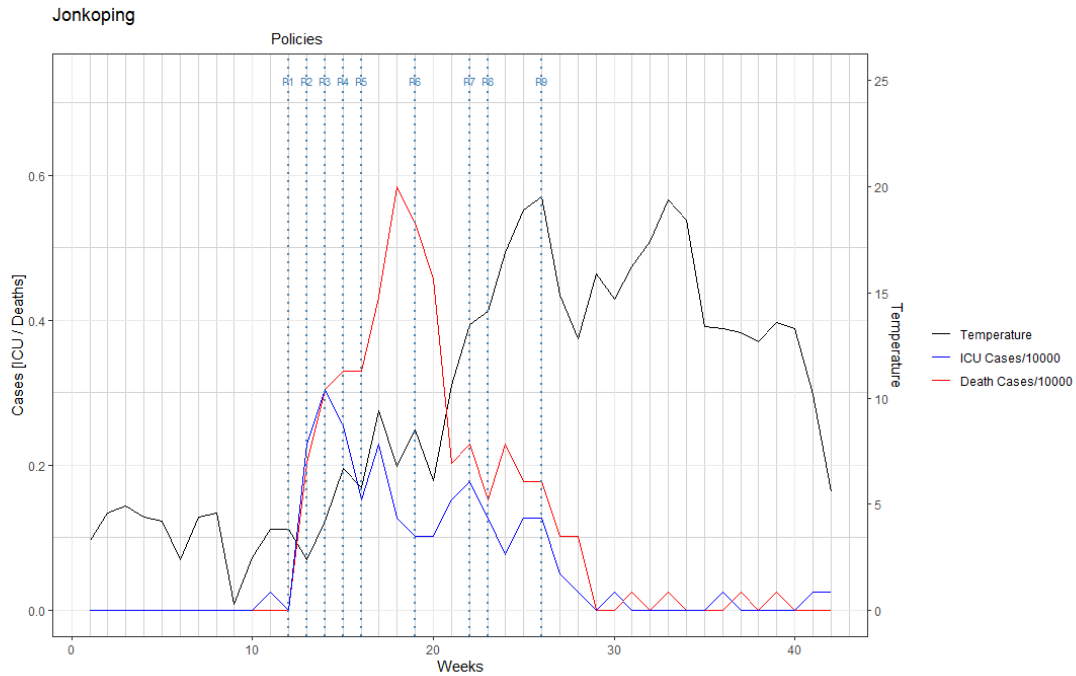

Figure 5.b: Number of death cases and ICU cases from the last week of December 2019 to the second week of October in Jonkoping with its average temperature.

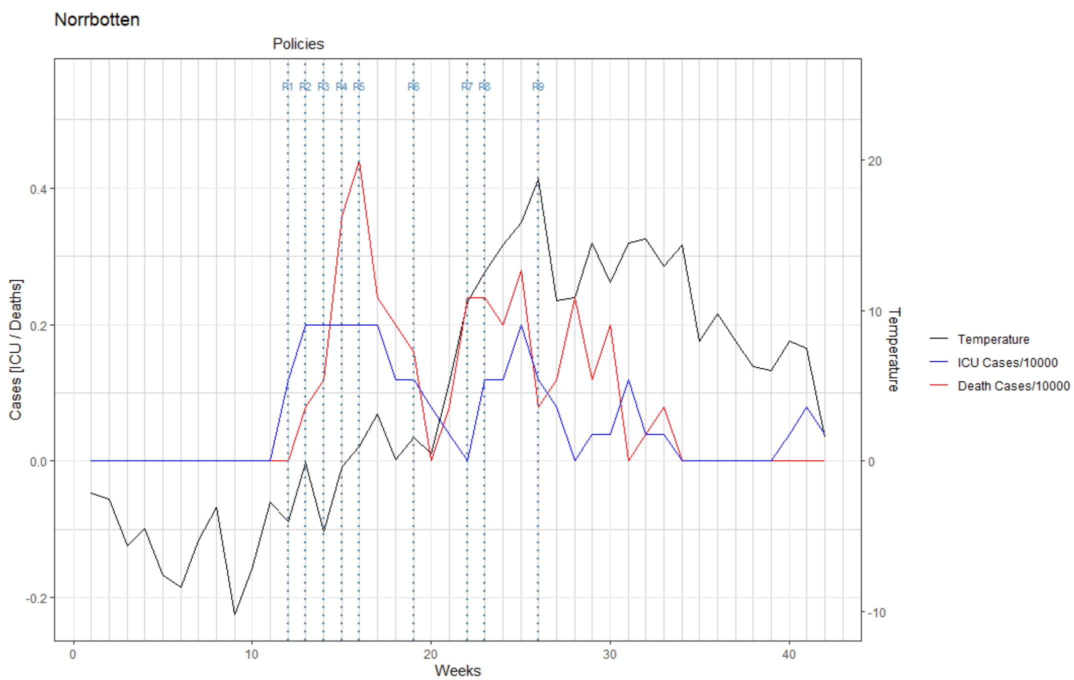

Figure 5.c: Number of death cases and ICU cases from the last week of December 2019 to the second week of October in Norbotten with its average temperature.

In Stockholm, the capital city of the country the rate of death and ICU cases started to increase from week 10. It was almost equal to 0 before week 10. Until the time there was no policy implemented. But when the case started to rise, the rate of death and ICU cases reached around 0.1 per 10000 population within the next 2 weeks. At that time, P1 was implemented. The death rate spiked to approximately 1.6 per 10000 population in week 15 when the policy P4 was implemented and gradually decreased till week 29 after the implementation of P5, P6, P7, P8, and P9. Meanwhile, the rate of ICU cases rose from 0.1 to nearly 0.55 when the policies P1, P2, and P3 were into action. The trend was almost similar for the next week but started to fall from week 16 after the implication of P5. On week 22 the rate was slightly increased to 0.22 from 0.19 with the policy P7 but with P8 it began to fall and reached the value of almost 0.01 in week 28. After week 29, the rate of both cases was fluctuating with a very small change. During the time, policy P9 was implemented. However, the temperature in Stockholm was noted to be in the range of 3ºC-10ºC within weeks 10-20. It rose drastically to about 23ºC in week 26 and slightly began to fall afterward.

Jonkoping is the county where the first case of Covid-19 was detected on 31st January, ICU cases and the death case was almost 0 till week 11. On week 11 the ICU cases rose around 0.02 and dropped back to nearly 0 from week 12 while the death case was still near 0. Until the time there was no policy introduced at all. The ICU case started to increase and reached more than 0.3 in week 14 when the policies P1, P2, P3 were already introduced and began to go down from week 15 after implementing P4 and P5. But the pattern was very different for the death case. It upsurged to approximately 0.6 until week 18 even with the policies P1, P2, P3, P4, and P5. The curve gradually decreased from week 19 and reached a value of 0.2 in week 21 because of P6. ICU case had an oscillation from week 16 to week 30 that ranged from the approximate value 0.1 to 0.01 with the implementation of P6, P7, P8, P9. The death case fluctuated between 0.2 to 0.01 from week 21 to week 30. After week 31 both cases showed some strange trend. When the death case was around 0.01 the ICU case was increased to 0.02 and vice versa. The same trend was followed from week 30 to week 40 even though P9 was already in action. The temperature of Jonkoping fluctuated from approximately 2.5ºC to 8ºC from week 10 to week 20. It increased drastically to nearly 20ºC in week 26. It fell to less than 15ºC in week 28 and again rose back to almost 20ºC in week 34.

Norrbotten is the largest county in Sweden based on the area. The ICU case was first recorded in week 12 and it slightly increased in the following week from around 0.1 to 0.2 the policies P1 and P2 were already introduced during the time. The rate was unchanged for the next four weeks despite the effect of P3, P4, and P5 and slowly fell to around 0.11 in week 18. It remained constant in week 19 and drastically decreased to almost 0 in week 22 due to the policies P6 and P7. In week 25, the ICU case suddenly increased to almost 0.2 when P8 was implemented and began to step down to nearly 0 in week 29 when P9 was introduced. Also, it increased to 0.1 in week 31 and dropped back to nearly 0 in week 34 despite the policy P9. The curve is flat till week 39 and it spiked on week 40. On the other side, the death case began to rise from week 13 and spiked to more than 0.4 in week 16. Then, the rate fell drastically to almost 0 in week 20. From week 21 it began to rise again and reached a value more than 0.2. It remained unchanged in the next week and decreased slightly to around 0.2 in week 23. However, it reached a value of more than 0.27 in week 24 and decreased to less than 0.1 in week 26. The oscillation continued from week 27 to week 34 ranging from 0.25 to almost 0. The curve is flat from week 38 to the date. There is a huge temperature variation in Jonkoping from week 12 to week 40. Initially, it was near -5ºC in week 12 and slowly it rose to 0ºC in week 13. Later in week 14, the temperature fell to -5ºC. it started to gain a positive value and increased to around 3ºC in week 17. Then, the temperature spiked to almost 20ºC in week 26. It showed the varying pattern from week 27 to week 42 ranging from 2ºC-16ºC.

In most of the other counties, the death cases and the ICU cases started to rise during the execution of policy P1. The cases escalated highly despite the enactment of policies P2, P3, and P4. The application of P5 and P6 could slightly decrease the case in almost all counties. But the result did not last for a longer period, the cases hiked back notwithstanding the policy P7 and P8. However, the cases seemed to be controlled with the policy P9. Similarly, the temperature of almost all the counties began to rise from week 11 and reached its peak at week 26. It gradually started to decrease from week 27 and had the minimum value during week 42 (Appendix B).

4.2. Modeling of Spatiotemporal Effect

We formulated our study into a spatiotemporal statistical model and made three different sub-models: epidemic-within, epidemic-between, and endemic. After mathematical formulation, we had a Surveillance Time Series (STS) object in R. This object contained Covid-19 cases (ICU or Death) multivariate matrix, neighborhood matrix, all the policies matrix, and temperature category matrix. The STS object was used to fit an hhh4 model with the random effects and neighborhood structure. The final fitted model for death and ICU cases were based on weekly data and the negative binomial distribution family was used in the model. Two results were obtained from this study.

4.2.1. Death cases

Table 3: Coefficient and Standard error for the hhh4 model for death cases.

Coefficients:			
	Estimate	**Std. Error**	
ar.1	-0.466	0.060	**Epidemic Within**
ne.1	-4.227	0.329	**Epidemic Between**
end.1	-19.429	1.569	**Endemic (Over all)**
end.t	0.464	0.220	**Endemic (Time in Week)**
end.t2	-0.006	0.003	**Endemic (Square of Time in Week)**
end.P1	2.589	0.665	**Endemic (Policy 1)**
end.P2	0.596	0.329	**Endemic (Policy 2)**
end.P3	0.386	0.304	**Endemic (Policy 3)**
end.P4	-0.152	0.346	**Endemic (Policy 4)**
end.P5	-1.061	0.496	**Endemic (Policy 5)**
end.P6	-1.069	0.443	**Endemic (Policy 6)**
end.P7	-0.866	0.883	**Endemic (Policy 7)**
end.P8	0.143	0.826	**Endemic (Policy 8)**
end.P9	-2.859	0.592	**Endemic (Policy 9)**
end.temp1	-0.341	0.237	**Endemic (Low Temperature)**
end.temp2	-0.377	0.373	**Endemic (High Temperature)**
over disp	0.170	0.025	
Log-likelihood: -1305.76 **AIC**: 2645.52 **BIC**: 2726.41 **Number of units**: 21 **Number of time points**: 41			

The coefficients of each policy, epidemic-within, and epidemic-between are tabulated in Table 3 where ar.1 represents the overall coefficient value epidemic-within sub-model. It had a negative direction in the model and the coefficient value (-0.466) was good enough to make an effect in the death count with a very low standard error of 0.06.

In Table 3, ne.1 represents the coefficient of neighborhood effect on the model. Neighborhood in this model means the Q value in the epidemic-between sub-model which is an average value of death cases in neighboring counties. This sub-model had a coefficient value of -4.227 which showed the negative direction over the model. The standard error was a bit higher (0.329) than the epidemic-within sub-model. The neighboring county effect was seen on the spread of disease as referred to the model. Similarly, end.1 represents the coefficient of the overall effect of all the variables present in the endemic sub-model. The individual coefficients of each policy is represented by the variables end.P1, end.P2, end.P3, end.P4, end.P5, end.P6, end.P7, end.P8 and end.P9 respectively. The coefficient of temperature effect is represented by end.temp1 and end.temp2. The time effect is represented by end.t and end.t2 is the squared value of week number to fit the polynomial effect in time series linear regression. In this sub-model, the overall weightage of endemic was -19.429 with a standard error of 1.569. It was observed that the policies and the temperature effect which were kept as the predictors in our model helped to reduce the death case count Sweden.

Table 3 shows the value of the individual coefficient, from which the effectiveness of each policy can be compared. Among the 9 policies, the estimate of the P9 effect had the lowest value of -2.895. That means P9 was the most effective predictor for this model. For temperature effect, 2 matrices were included those contained the categoric value for temperature as described in Table 1. Temp1 is the matrix for low temperature and Temp2 is for high temperature. The coefficient associated with both the predictors had almost similar values (-0.341 and -0.377). This indicated that there was a negative contribution of the temperature predictor in the model where the low temperature has a low standard error compared to the high temperature.

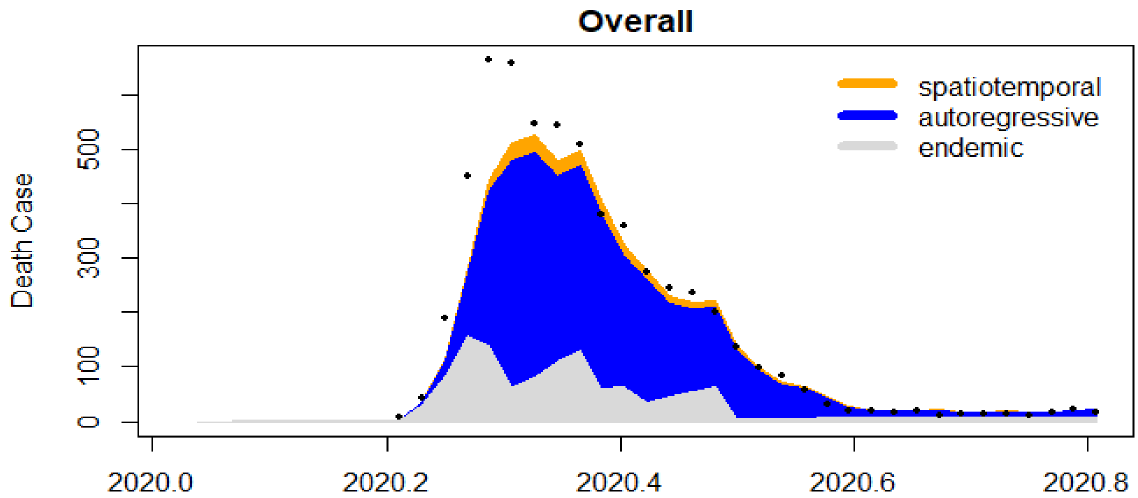

Figure 6: Spatiotemporal Plot for death cases in Sweden

The overall death cases including the relative importance of the three model components (spatiotemporal, autoregressive, and endemic) is shown is Figure 6. The blue portion represents the autoregressive part that is the epidemic-within the effect. The orange portion represents the effect of neighborhood counties effect or spatiotemporal also known as epidemic-between sub-model in the main equation. The gray portion represents the endemic sub-model which includes all the policies and temperature values. The actual number of death cases is given by the small dots on the plot. From the fitted mean plot, the largest area of it was covered by the autoregressive component which is within the county itself. A very little contribution of cases was seen from the neighboring counties and the endemic portion which is the collection of all the policies. Temperature had a remarkable contribution. In addition to this, the spatiotemporal effect was examined for the counties having a higher number of death cases. The counties with the bigger cities like Malmö, Gothenburg, and Stockholm were selected. In addition, Dalarna county was chosen to analyze the effects. The overall fitted plot is set into an object to observe the values in each week of the Covid-19 death cases time series. We have selected the values for weeks 12 to 20 which corresponds to week 13 to week 21.

Table 4: The component values of the model (from week 12 to 20).

Week	Mean	Epidemic	Endemic	Epi. Own	Epi. Neighbors	ar.exppred	ne.exppred	end.exppred
12	112.850	29.673	83.177	27.600	2.072	13.173	0.306	0.00017
13	283.641	127.195	156.447	119.183	8.012	13.173	0.306	0.00032
14	445.168	304.413	140.755	282.902	21.512	13.173	0.306	0.00030
15	511.647	447.524	64.123	416.512	31.012	13.173	0.306	0.00014
16	526.130	445.307	80.823	412.748	32.559	13.173	0.306	0.00017
17	479.196	370.047	109.149	342.493	27.554	13.173	0.306	0.00024
18	498.498	369.215	129.283	341.238	27.977	13.173	0.306	0.00027
19	406.449	347.596	58.853	319.911	27.685	13.173	0.306	0.00013
20	323.909	259.643	64.266	238.992	20.651	13.173	0.306	0.00013

The matrix fitted mean value for each week is depicted in Table 4. The corresponding mean of the epidemic and endemic is given in the second column of the table. The four columns refer to the mean epidemic (the sum of own and neighbors), endemic, autoregressive, and neighborhood components. The last three columns apply to the point estimates of the coefficient of epidemic-within, epidemic-between, and endemic respectively. These values allowed us to calculate the (time-averaged) proportions of the mean explained by the different components to be measured. After the calculation of time-averaged proportion, the result thus obtained is shown in Table 5.

Table 5: Time-averaged proportions for each component for death cases.

Time-averaged proportions	Endemic	Epidemic Own	Epidemic Neighbours
Overall	0.237	0.704	0.058
Stockholm	0.155	0.841	0.004
Västra Götaland	0.268	0.717	0.015
Skåne	0.461	0.530	0.009
Dalarna	0.224	0.696	0.080

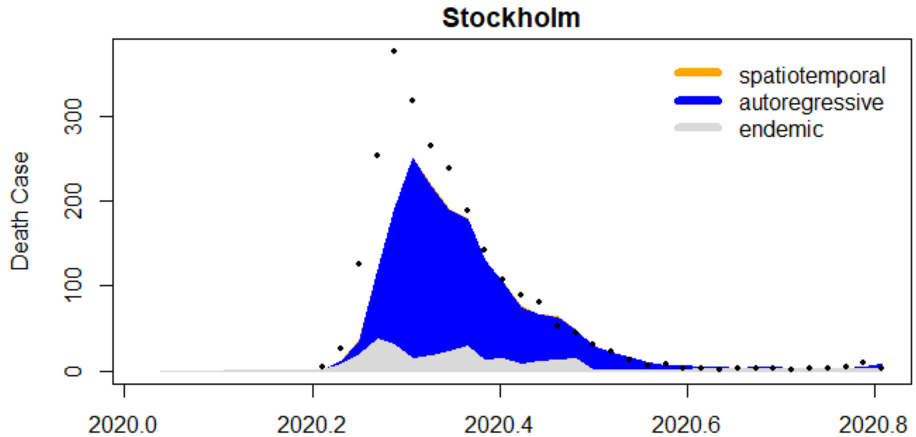

Figure 7: Spatiotemporal Plot for death cases Stockholm

The fitted mean plot for Stockholm county is represented by Figure 7. The largest area (84.1%) of overall fit was covered by the autoregressive component, that is within the county itself. Very negligible area (around 0.4%) of a spatiotemporal region was seen. The endemic portion, temperature and time effect had a notable contribution of about 15.5% but very less in comparison to autoregressive part.

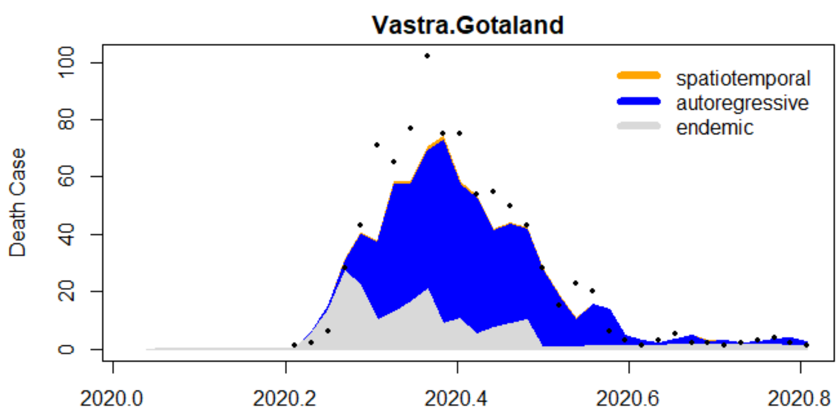

Figure 8: Spatiotemporal Plot for death cases Västra Götaland

Figure 8 shows the fitted mean plot for Västra Götaland county, the largest area of it was covered by the autoregressive component which was about 71.7% of the overall fitted. Similar to Stockholm, a small area of around 1.5% was covered with spatiotemporal effect and the endemic portion covered 26.8% of the overall fitted.

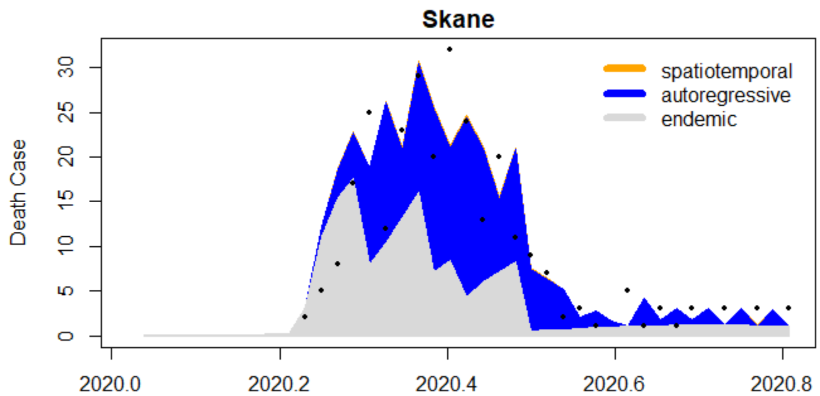

Figure 9: Spatiotemporal Plot for death cases Skåne

Figure 9 illustrates the fitted mean plot for Skåne county, it was quite different from Stockholm and Västra Götaland, the autoregressive and endemic part had an almost similar contribution of about 53% and 46.1% respectively in the fitted plot. But the contribution of the spatiotemporal submodel was very low of about 0.9% compared to those counties.

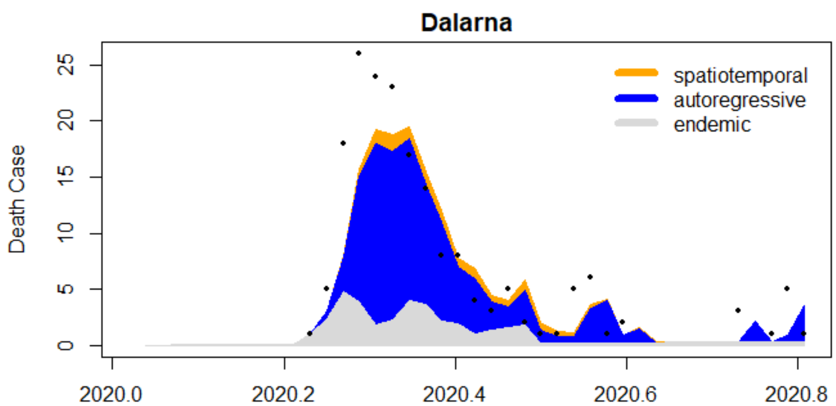

Figure 10: Spatiotemporal Plot for death cases Dalarna

The spatiotemporal plot of Dalarna is shown in Figure 10. The result was different from the other counties seen before. There was some neighborhood county effect in Dalarna. The autoregressive part had a 69.6% of contribution in the fitted model. The endemic sub-model contained 22.4% and 8% of the contribution was seen for the epidemic-between sub-model.

4.2.2. ICU Cases

Table 6: Coefficient and Standard error for the hhh4 model for ICU cases.

Coefficients:			
	Estimate	**Std. Error**	
ar.1	-0.642	0.081	**Epidemic Within**
ne.1	-3.959	0.269	**Epidemic Between**
end.1	-19.210	1.363	**Endemic (Over all)**
end.t	0.567	0.195	**Endemic (Time in Week)**
end.t2	-0.008	0.003	**Endemic (Square of Time in Week)**
end.P1	2.231	0.530	**Endemic (Policy 1)**
end.P2	0.448	0.263	**Endemic (Policy 2)**
end.P3	-0.919	0.351	**Endemic (Policy 3)**
end.P4	-0.389	0.443	**Endemic (Policy 4)**
end.P5	-1.404	0.564	**Endemic (Policy 5)**
end.P6	-0.707	0.395	**Endemic (Policy 6)**
end.P7	-0.122	0.534	**Endemic (Policy 7)**
end.P8	-0.545	0.485	**Endemic (Policy 8)**
end.P9	-2.165	0.455	**Endemic (Policy 9)**
end.temp1	-0.235	0.263	**Endemic (Low Temperature)**
end.temp2	-0.484	0.390	**Endemic (High Temperature)**
overdisp	0.123	0.026	
Log-likelihood: -1035.37 **AIC:** 2104.75 **BIC:** 2185.64 **Number of units:** 21 **Number of time points:** 41			

The value of the coefficients of each policy, epidemic within, and epidemic between for ICU cases is illustrated in Table 6. Similar to the hhh4 model for death cases, the autoregressive part (ar.1) had a significant contribution in the model in a negative direction having a value of -0.642 with a low standard error of 0.081. The epidemic-between sub-model had the coefficient value of -3.959 it also had a similar effect in the model as the death cases. In the endemic part, the time factor had a similar impact as the death cases. The coefficient value of P9 was the lowest among all the policies with the value -2.165 as seen in Table 6.

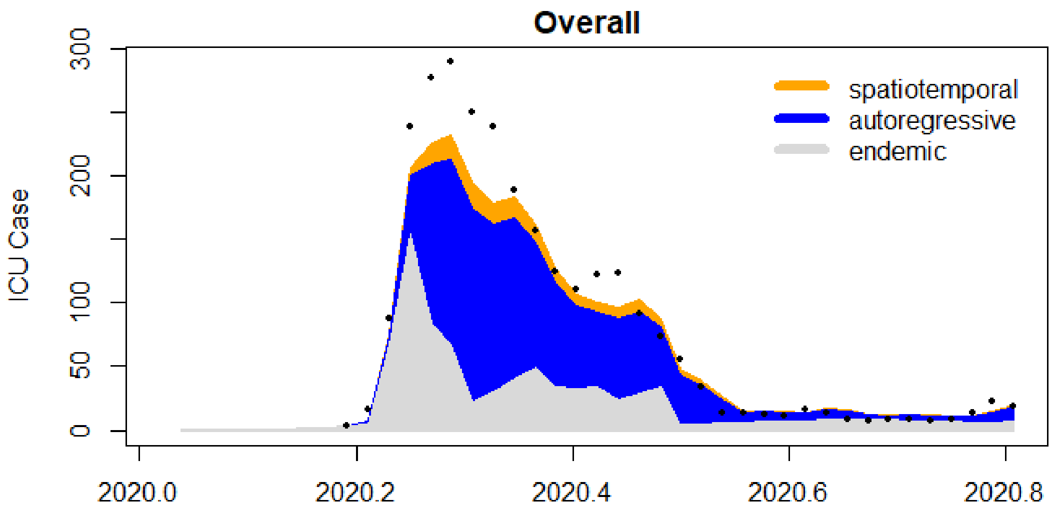

Figure 11: Spatiotemporal Plot for Overall ICU cases in Sweden for all counties

Figure 11 shows the plot of overall ICU cases including the relative importance of the three model components that are (spatiotemporal, autoregressive, and endemic). In the fitted mean plot overall for ICU cases, the largest area of Sweden was covered by the autoregressive component. A very little contribution of cases is seen from the neighboring counties and the endemic portion also had a huge contribution to increasing the ICU cases. Similar to death cases, the overall fitted plot for the ICU cases was set into an object to observe the values in each week of the Covid-19 ICU cases time series.

Table 7: The component values of the ICU model (from week 12 to 20).

Week	Mean	Epidemic	Endemic	Epi. Own	Epi. Neighbours	ar.exppred	ne.exppred	end.exppred
12	206.115	52.012	154.104	46.323	5.689	11.054	0.401	0.00031
13	225.315	141.547	83.769	125.282	16.265	11.054	0.401	0.00017
14	231.240	164.271	66.969	145.811	18.460	11.054	0.401	0.00014
15	194.415	171.867	22.548	152.128	19.739	11.054	0.401	0.00005
16	178.498	148.722	29.776	131.598	17.124	11.054	0.401	0.00006
17	183.368	142.539	40.829	125.282	17.258	11.054	0.401	0.00009
18	161.545	112.631	48.914	98.962	13.669	11.054	0.401	0.00010
19	126.755	93.323	33.431	82.117	11.206	11.054	0.401	0.00007
20	106.908	73.959	32.949	65.273	8.686	11.054	0.401	0.00007

Table 7 shows the matrix fitted mean value of ICU cases for each week. These values allowed to calculate the (time-averaged) proportions of the mean explained by the different components to be measured. After we calculate the time-averaged proportion for ICU cases, the result is shown in Table 8.

Table 8: Time-averaged proportions for each component for ICU cases

Time-averaged proportions	**Endemic**	**Epidemic Own**	**Epidemic Neighbors**
Overall	0.345	0.578	0.077
Stockholm	0.273	0.718	0.008
Västra Götaland	0.352	0.630	0.018
Skåne	0.604	0.387	0.009
Dalarna	0.355	0.525	0.120

Figure 12 shows the spatiotemporal plot for ICU cases in Stockholm. The largest area of Stockholm was covered by the autoregressive component with 71.8% of contribution in the fitted plot. The effect of neighboring counties could be ignored since there was no remarkable area of the spatiotemporal region with just 0.8% of the contribution. The endemic portion had a little contribution of about 27.4%.

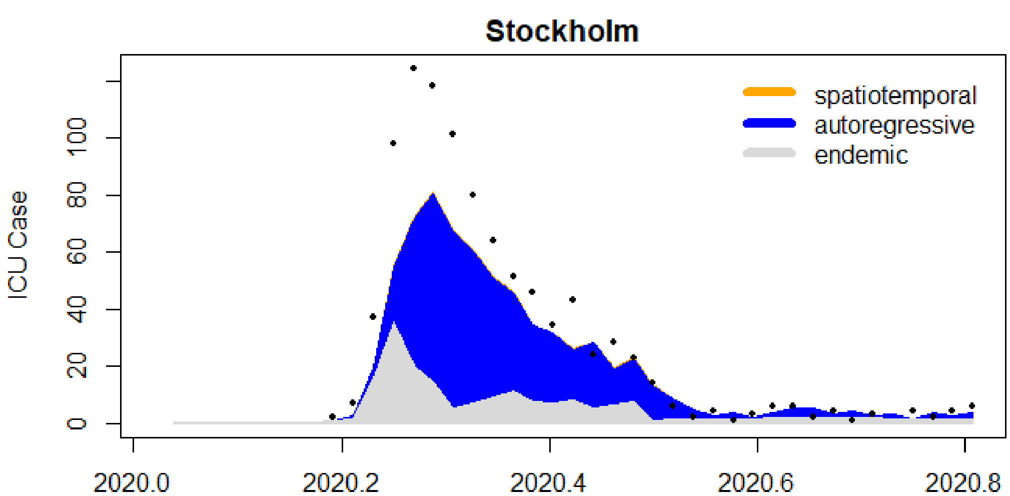

Figure 12: Spatiotemporal Plot for ICU cases Stockholm

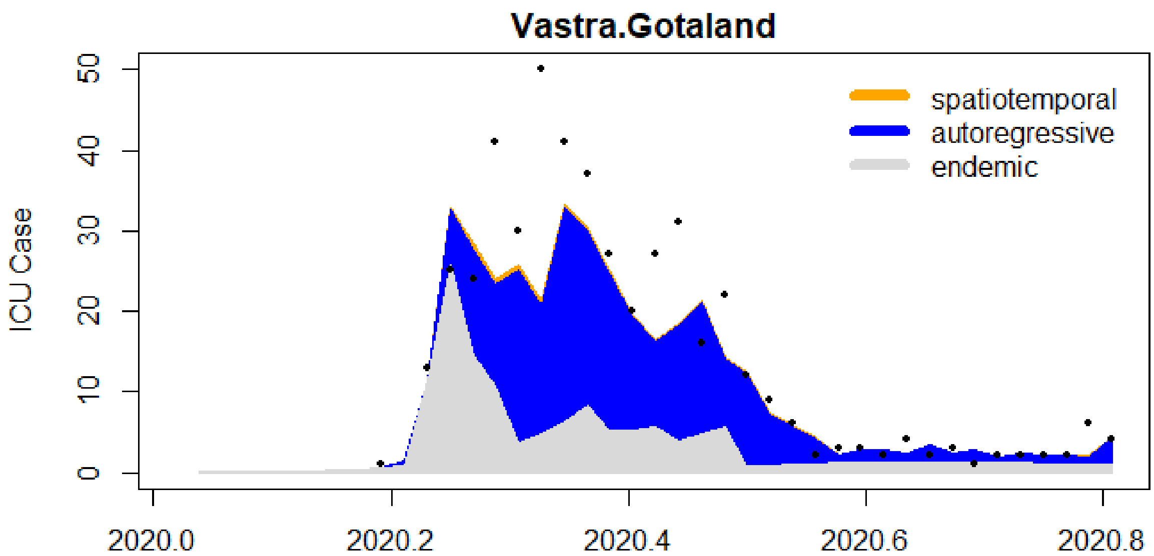

Figure 13: Spatiotemporal Plot for ICU cases Västra Götaland

Figure 13 shows the largest area of Vastra Gotaland was covered by the autoregressive component with 63% of the contribution. A small area of a spatiotemporal region was seen which had a 1.8% of contribution and the endemic portion also had a good contribution of 35.2% in the model.

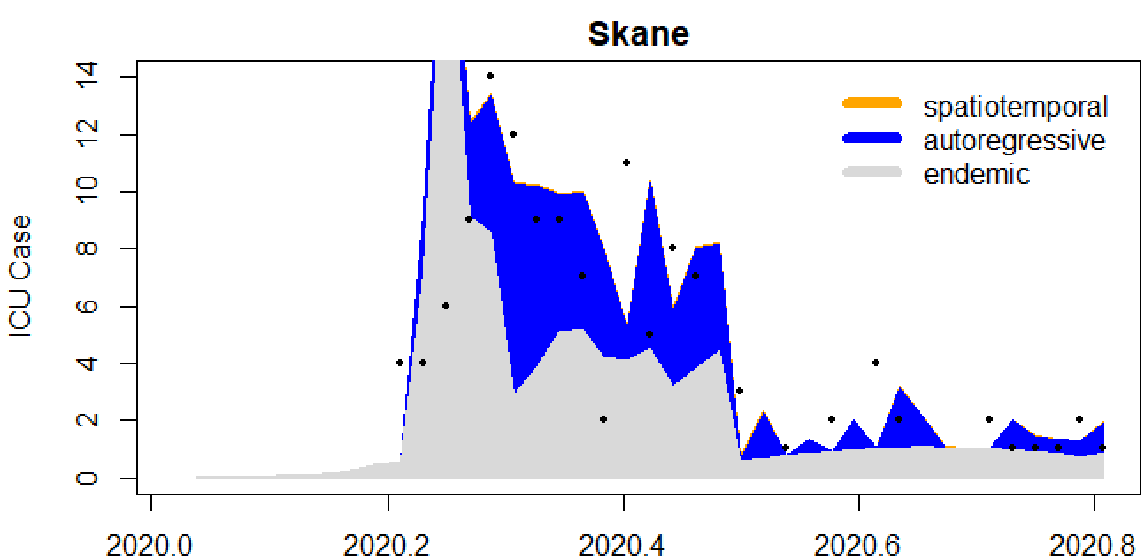

Figure 14: Spatiotemporal Plot for ICU cases Skåne

Figure 14 gives the spatiotemporal plot for ICU cases in Skåne. It shows the largest area of Skane was covered by the endemic which differed than the death case model also it was different from other counties. It had 60.4% contribution in the fitted plot. A very small area of 0.9% of a spatiotemporal region was seen and the autoregressive component also had a notable contribution of 38.7% but very less in comparison to the endemic part.

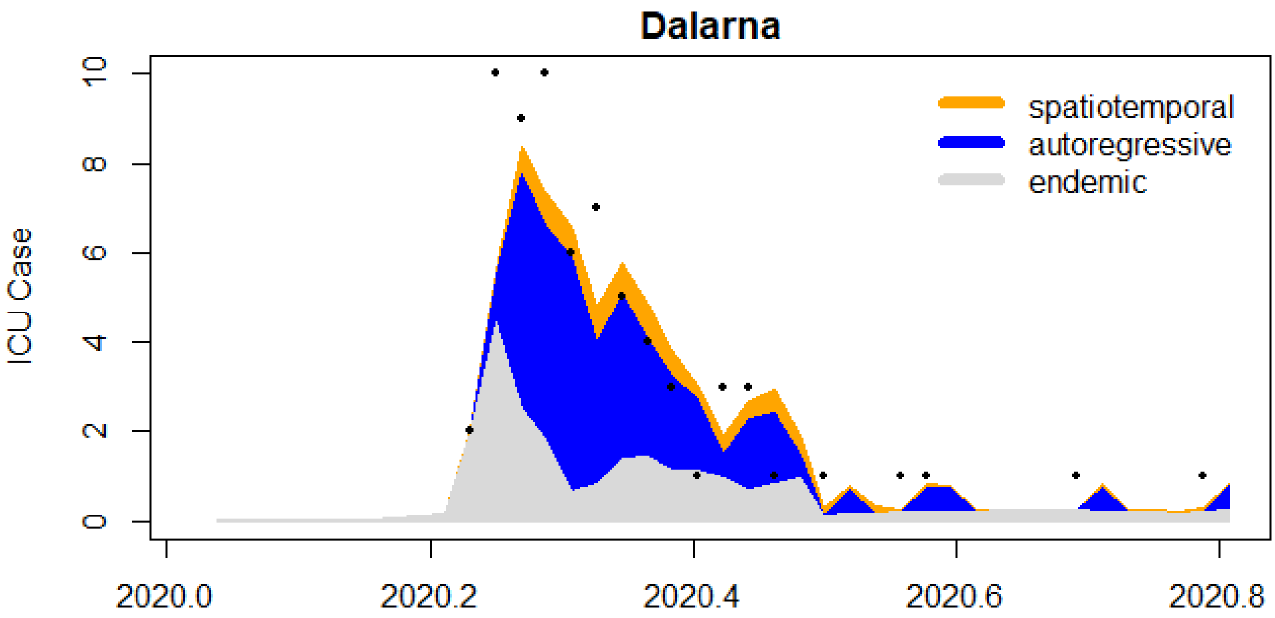

Figure 15: Spatiotemporal plot for ICU cases in Dalarna

Figure 15 shows the spatiotemporal plot for ICU cases in Dalarna. It showed largest area of Dalarna was covered by the autoregressive component with 52.5% of the contribution. A remarkable area of a spatiotemporal region was seen which had 12% of contribution and the endemic portion also had a good contribution of 35.5% in the model.

Chapter 5 - Discussion

We analyzed the trend in ICU cases and death cases in Sweden amidst the ongoing pandemic to get an idea about the effectiveness of the policies to reduce the transmission of Covid-19. The cases (ICU and death) were represented using the spatiotemporal (hhh4) model and the trend was observed on death and ICU data. Almost all the policies were implemented consecutively within a short interval of time therefore it was difficult to extract the effectiveness of each intervention in Sweden. However, the result showed that the strategies (P1), to suspend the flights between Sweden and Iran and limit the travel to Northern Italy and South Korea were not strong enough to control the spread rate in any county. The coefficient value for these policies is positive and high as seen in Table 3 and Table 6. This may be due to the reason that it was during the early days of infections in Sweden and the government had not got the proper vision to control its spread and delayed the policy implementation. Similarly, P2 had no considerable effect to minimize the ICU and death cases in all counties except Varmland and Vasterbotten. This showed that restricting unnecessary travel to all other countries and banning the gathering of more than 500 people was not sufficient to mitigate Covid-19. While in the case of Varmland and Vasterbotten, it gave a slightly better result. The reason might be the lesser population density of these counties as compared to most of the other counties. Due to lesser population density, few people could gather, and the rate of spread was slowed down. The coefficient of predictor P4 is negative which means banning the crowd in restaurants, cafes and bars were one of the effective measures to control the spread of Covid-19 in all counties in Sweden. Likewise, P5, P6, P7 were also able to reduce the ICU and death cases in most of the counties in Sweden giving the negative predictor coefficient values. It was banned for the gathering of more than 50 people, visiting the elderly homes, large graduation celebration, traveling abroad, entering Sweden. The mosques remained closed during Ramadan and Eid-al-Fitr which also aided in a reduction in ICU and death cases as similar to Germany (Kwok et al., 2020).

Meanwhile, when the children were allowed to go to a holiday camp, the death cases were increased. This might be because the children are three times more asymptomatic than the older people and they spread the disease before they show any symptoms (Jüni, Maltsev, & Bobos, 2020). Finally, there was a positive effect when it was declared to restrict the number of people for any demonstration or any public gatherings all over Sweden. This policy (P9) minimized the

ICU and death cases in almost all the counties by ensuring the physical distancing. Similar result was obtained in the study (Koh et al. , 2020). physical distancing can control the spread of Covid-19.

5.1. Spatiotemporal Effect

5.1.1. Death Cases

In Figure 6, the most dominant portion was from the autoregressive part. Most of the cases were the result of the in-county spread, regardless of this, there was a small portion of the spatiotemporal part. It means there was minor inter-county effect for the disease spread. The counties with higher death rates had a negligible inter-county effect on them (Figures 7,8 and 9). Also, the noticeable effect of the endemic part was seen in the model (Figure 6). That indicates the policies implemented by the government have a good response to controlling the disease spread. In Dalarna county (from Figure 10), a significant effect of the neighboring counties was seen.

5.1.2. ICU Cases

The spatiotemporal plot of ICU cases in Sweden (Figure 11) showed the same property as the death cases. As seen in Figure 12,13 and 14, a small inter-county effect was seen on the counties having higher ICU cases. However, the implemented policies were more effective to reduce the ICU cases in the Skane and Vastra Gotland. There was a noticeable effect of the endemic part for the overall case in the model. That indicates the policies implemented by the government have a good response to controlling the disease spread. Similarly, in Dalarna the spatiotemporal effect had the similar contribution of neighboring counties in ICU cases as well. Thus, in our model the effect of policies was more on ICU cases rather than death cases.

5.2. Temperature Effect

Despite having a large standard error during the high temperature, it can be observed that the spread of the disease depends on the temperature as well. The higher temperature helped in reduction of ICU and death cases in Sweden. Our result was similar to (Demongeot et al., 2020) which indicated that high temperature diminished the spread of Covid-19 during the early stages of epidemy.

Chapter 6 - Conclusion

The overall effect of all the policies made by Swedish government in different time intervals were evaluated and some of them were found to be fruitful for controlling the disease spread. The policies had a huge impact to reduce the Covid-19 infection. However, there are some possibilities to improve the timing of policy declaration to get more control over disease spread. The most effective policy seems to be the combined effect of all the policies made in a different time interval. After banning the public gathering in Café, restaurants, and bars the trend of Death cases decreased more significantly. However, ICU cases decreased after the implementation of policies such as closure of school and colleges, work from home, individual precaution, travel restrictions, avoiding social contacts for elder people.

Through the study of spatiotemporal effect, it was concluded that both the ICU and death cases, were influenced by the effect of neighboring counties. The lower spatiotemporal effect was observed in the counties having higher population density while higher spatiotemporal effect was found in counties with less population.

The atmospheric temperature was also found to be significant factor in disease spread. The results from the model for death and ICU cases illustrated that more cases were observed during the lower temperature than during the higher temperature. From these findings it is concluded that Covid-19 is still an unclear infectious disease and its spread is largely influenced by each country's policy.

Chapter 7 - Limitation and Future Work

This study focuses only the association between disease spread (measured with death and ICU cases) and non-clinical policies. Therefore, the effects estimates reported in this thesis may not be taken as causal effects. Further analysis is needed to identify any causal effects of the policies, using suitable methods for drawing a causal inference (Pearl, 2003).

The study can be continued in future by collecting more data for sufficient time so that the trend of disease spread can be observed in different seasons. A model for more accurate prediction of the cases can be prepared with the collection of more data. This can help decision-makers to make the strategy to fight against the disease spread in the future.

The continuation of future work may be narrowed if the developed vaccinations are effective to reduce the disease infection. But as of now (20 December 2020), there is no proper treatment protocol, so we can continue the work in the future with more datasets to evaluate the most effective policy and predict future cases more accurately.

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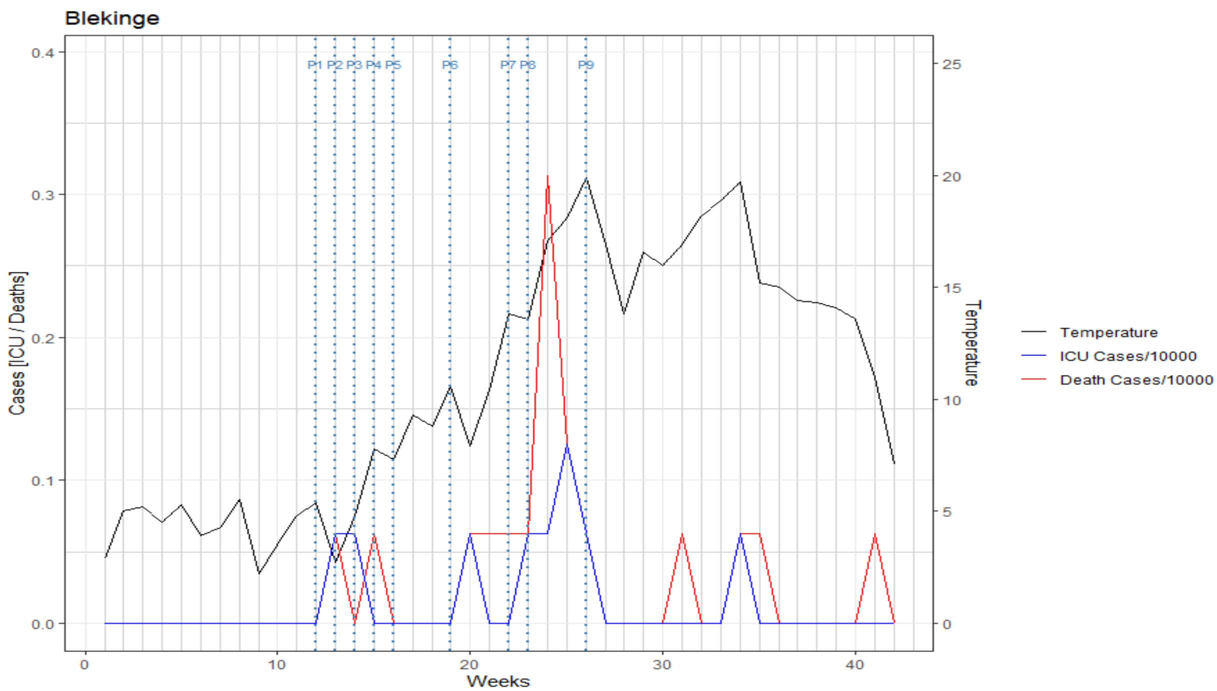
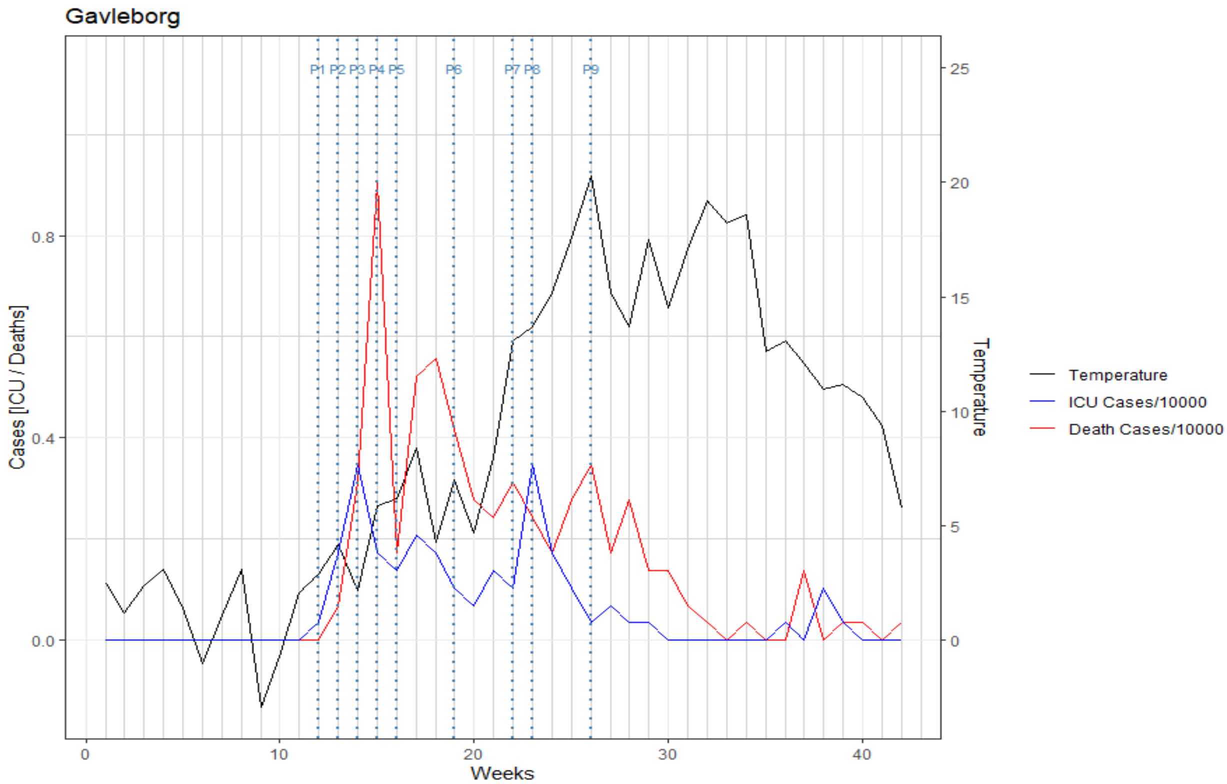
Appendices

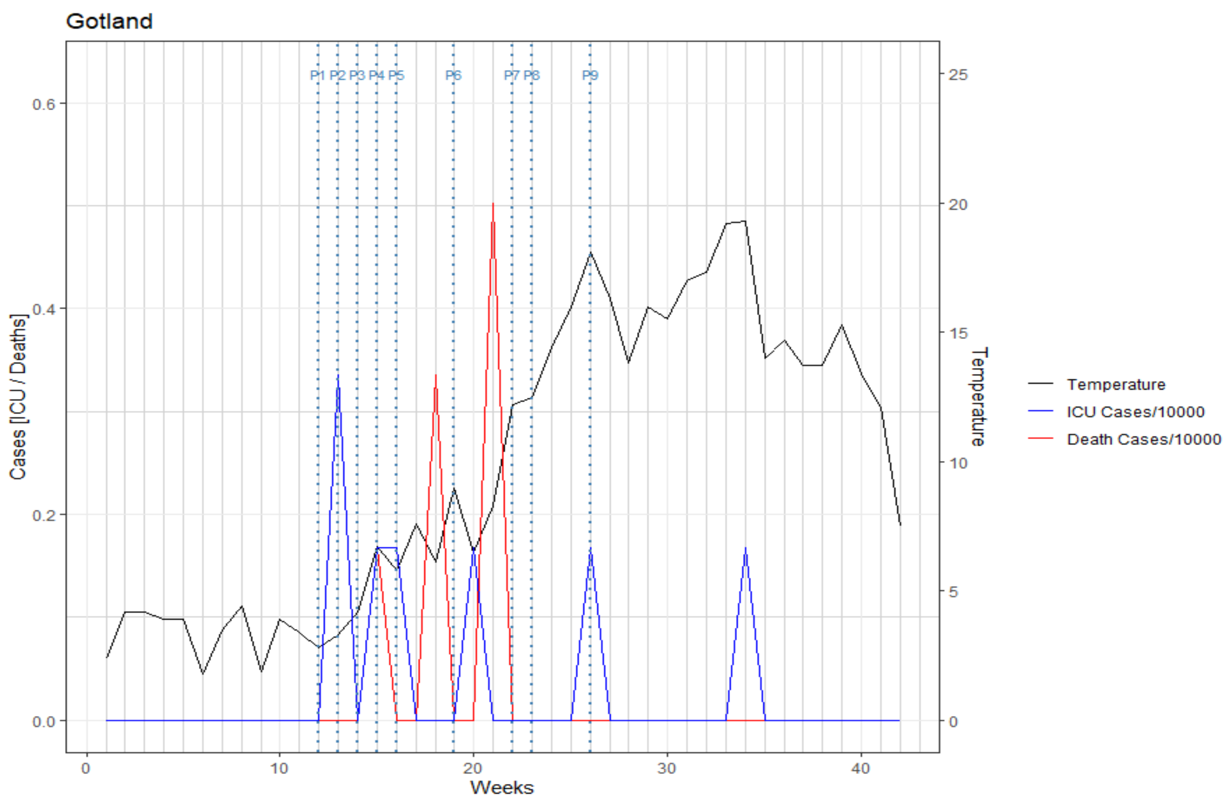
A. Sources: https://github.com/runajkhatiwada/Covid19_Thesis

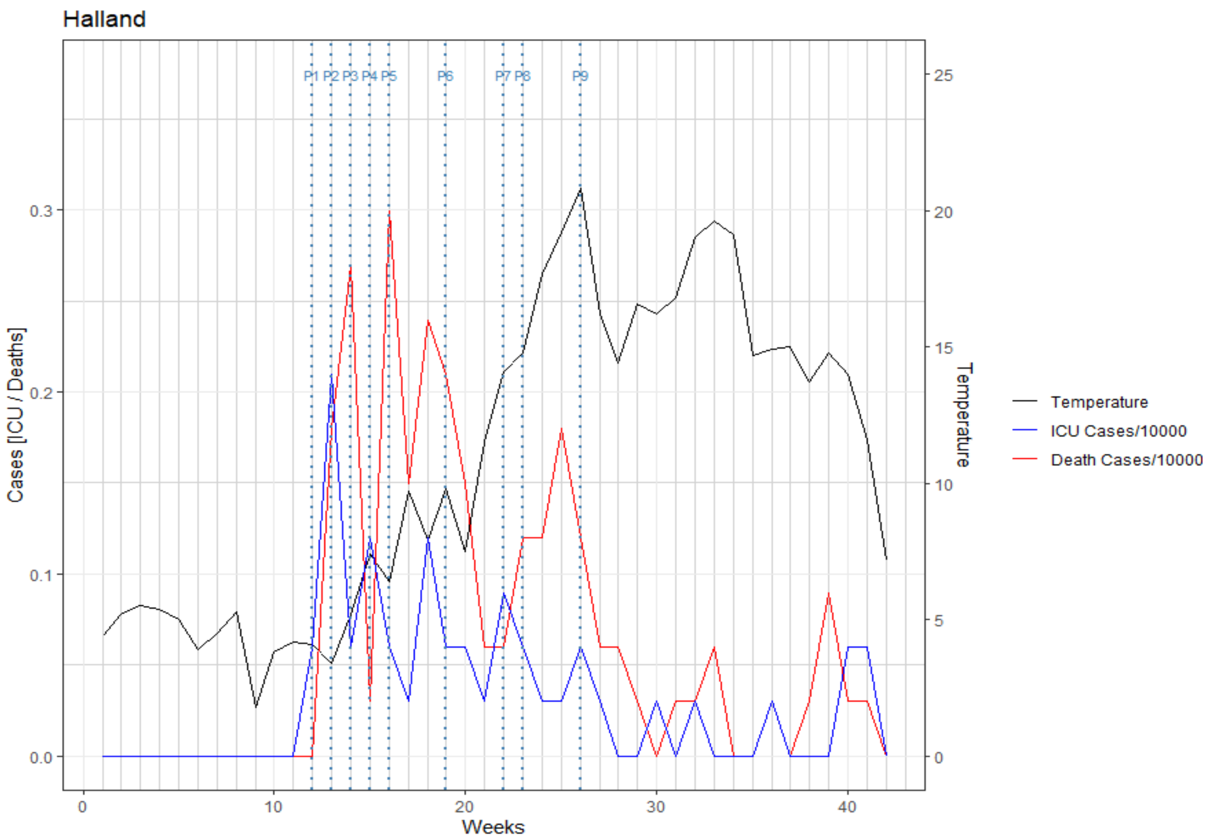
B. Number of death cases and ICU cases from the last week of December 2019 to the second week of October in each county with their respective temperature.

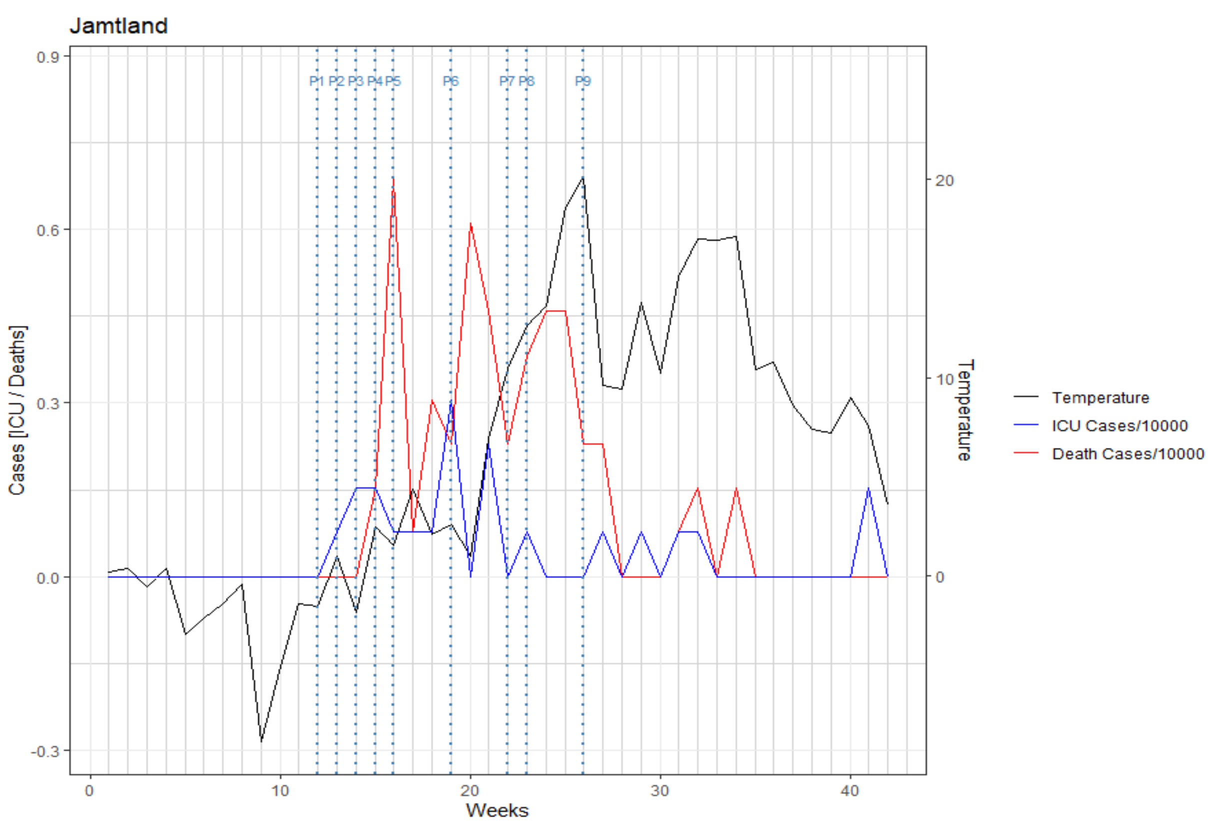


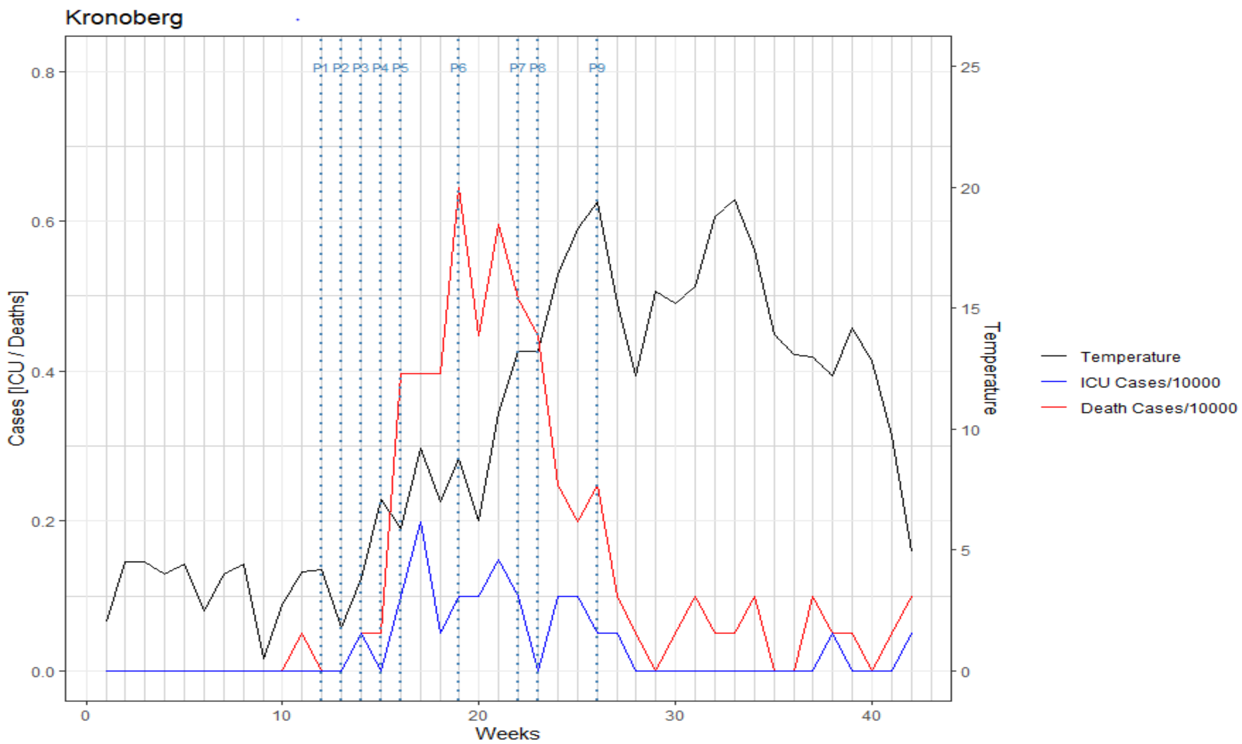

Dalarna
P1 P2 P3 P4 P5
P6
P7 P8
P9
Cases [ICU / Deaths]
0.0
0.4
0.8
0
10
20
30
40
Weeks
Temperature
0
5
10
15
20
25
Temperature
ICU Cases/10000
Death Cases/10000


Gavleborg
P1 P2 P3 P4 P5 P6 P7 P8 P9
Cases [ICU / Deaths]
0.0
0.4
0.8
Temperature
0
5
10
15
20
25
0
10
20
30
40
Weeks
Temperature
ICU Cases/10000
Death Cases/10000

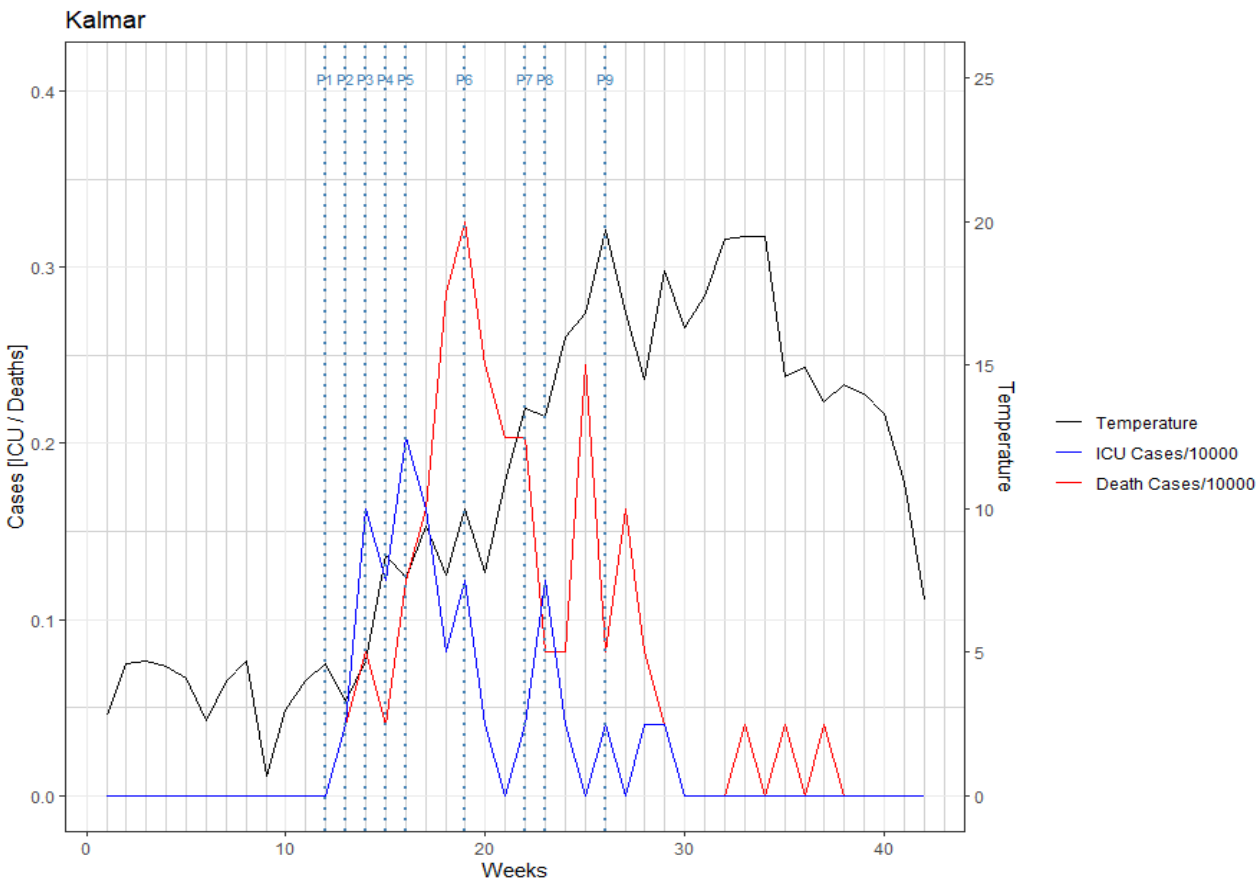

Gotland
P1 P2 P3 P4 P5 P6 P7 P8 P9
Cases [ICU / Deaths]
0.0
0.2
0.4
0.6
Temperature
0
5
10
15
20
25
0
10
20
30
40
Weeks
Temperature
ICU Cases/10000
Death Cases/10000


Halland
P1 P2 P3 P4 P5 P6 P7 P8 P9
Cases [ICU / Deaths]
Temperature
Weeks
Temperature
ICU Cases/10000
Death Cases/10000

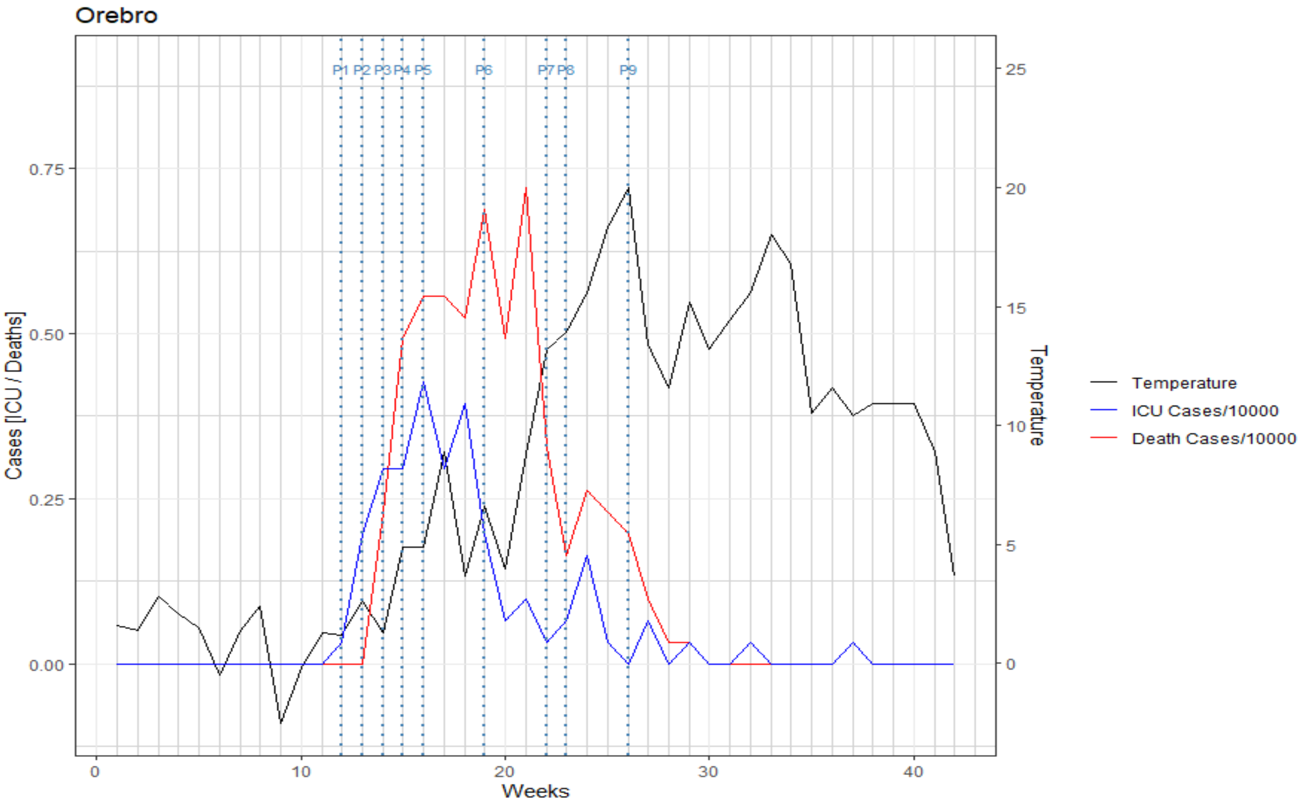

Jamtland
P1 P2 P3 P4 P5 P6 P7 P8 P9
Cases [ICU / Deaths]
Temperature
Weeks
Temperature
ICU Cases/10000
Death Cases/10000

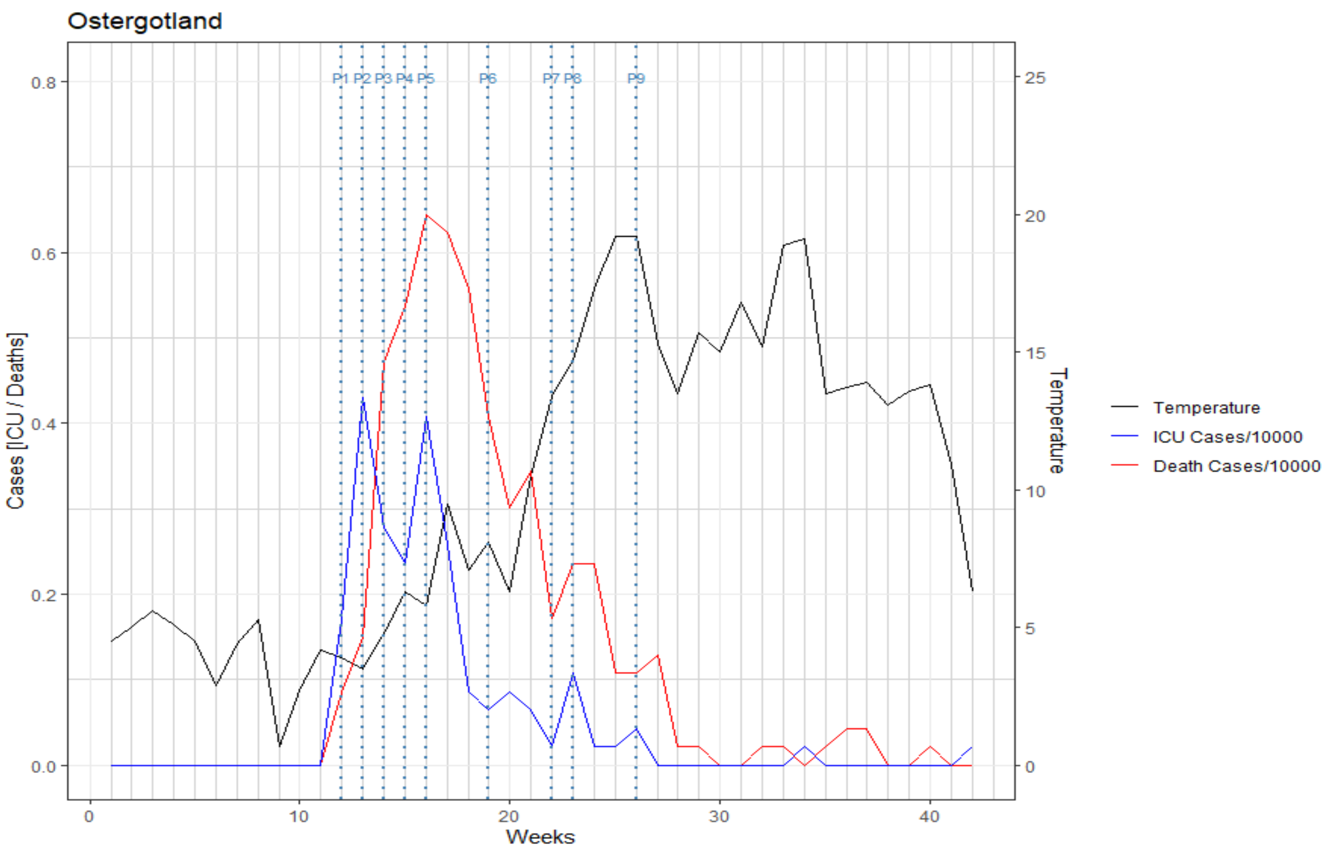


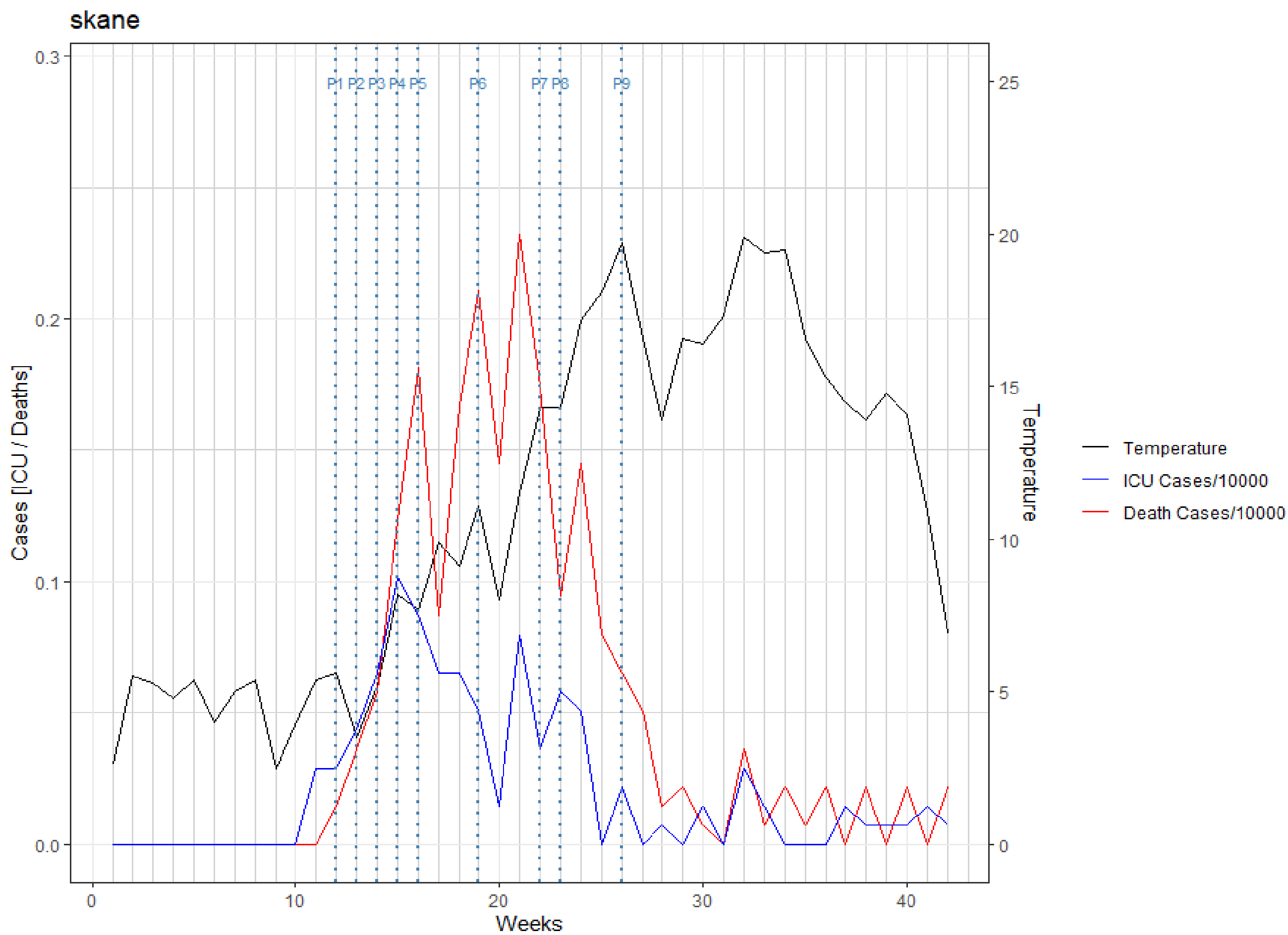
Kronoberg
P1 P2 P3 P4 P5 P6 P7 P8 P9
Cases [ICU / Deaths]
Temperature
Weeks
Temperature
ICU Cases/10000
Death Cases/10000

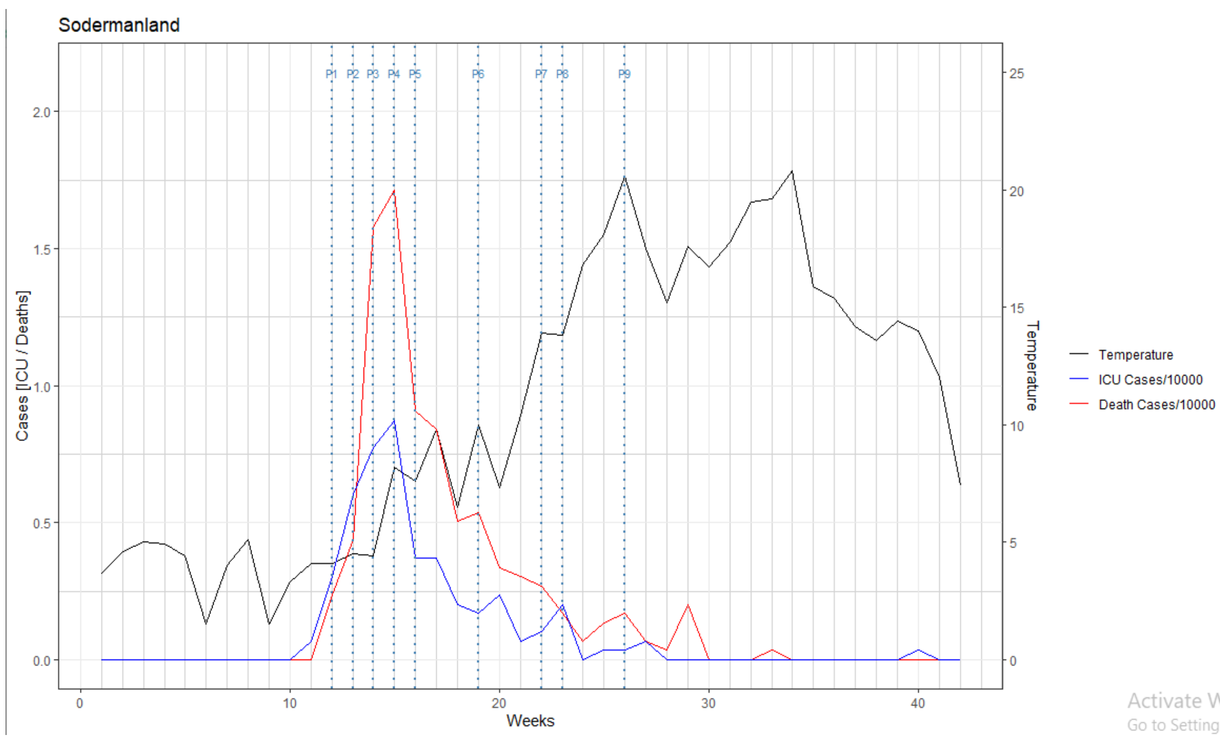


Kalmar
P1 P2 P3 P4 P5 P6 P7 P8 P9
Cases [ICU / Deaths]
Temperature
Weeks
Temperature
ICU Cases/10000
Death Cases/10000

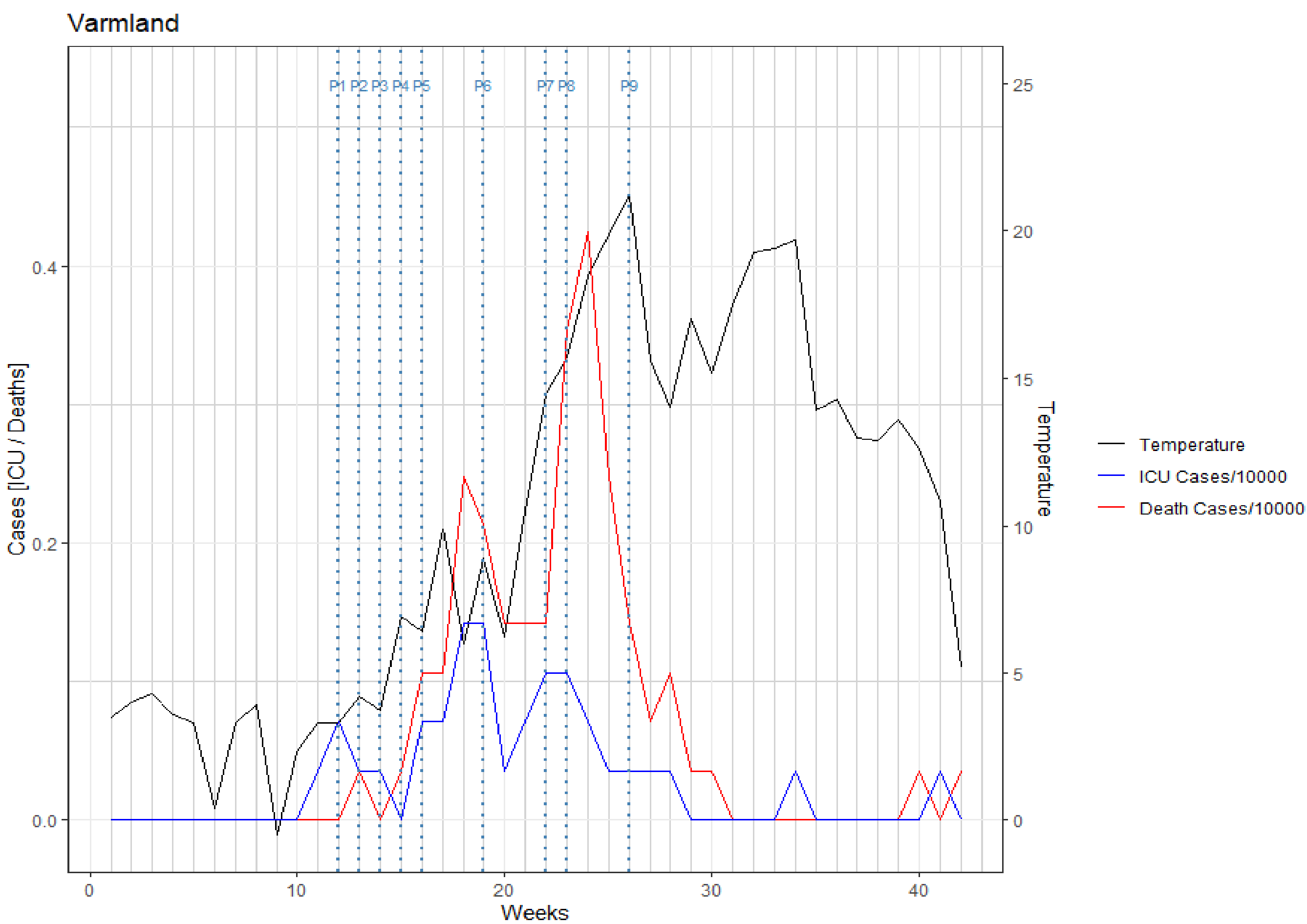

Orebro
P1 P2 P3 P4 P5
P6
P7 P8
P9
Cases [ICU / Deaths]
Temperature
Weeks
Temperature
ICU Cases/10000
Death Cases/10000

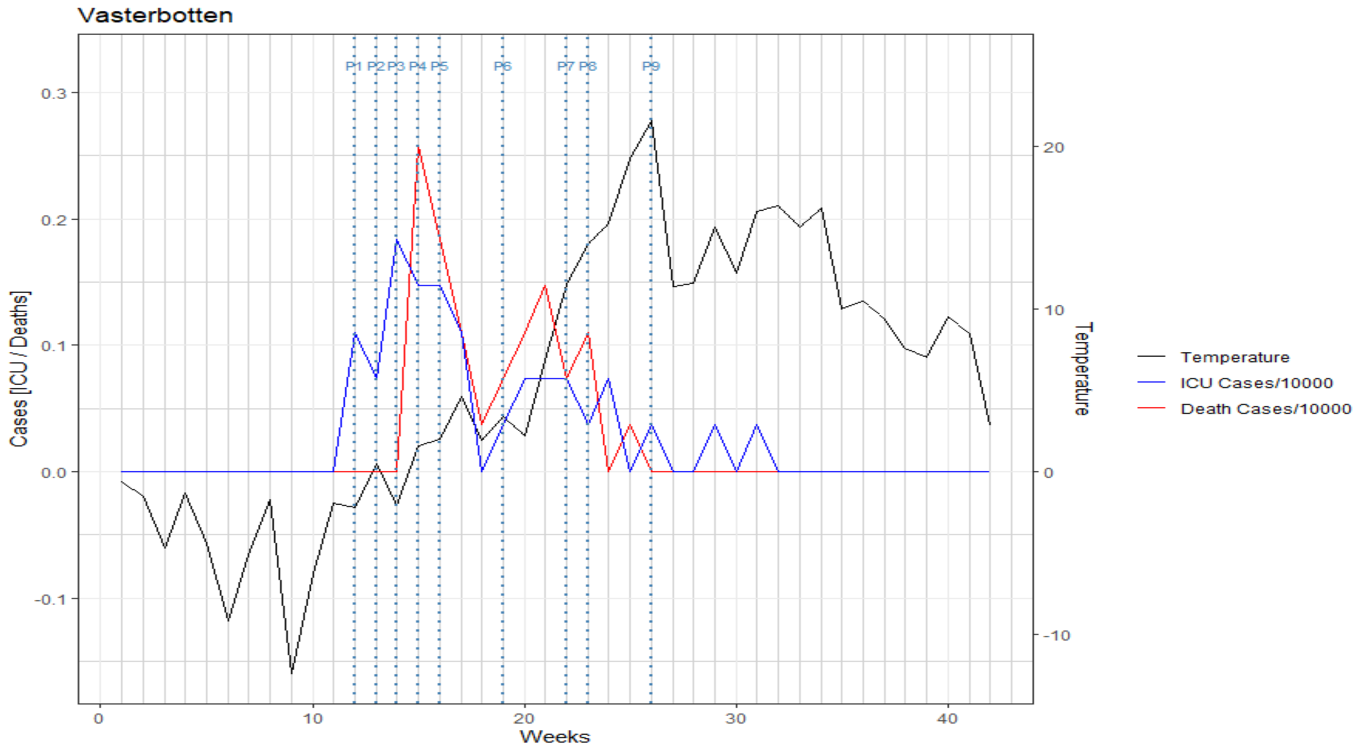

Ostergotland
P1 P2 P3 P4 P5
P6
P7 P8
P9
Cases [ICU / Deaths]
Temperature
Weeks
Temperature
ICU Cases/10000
Death Cases/10000

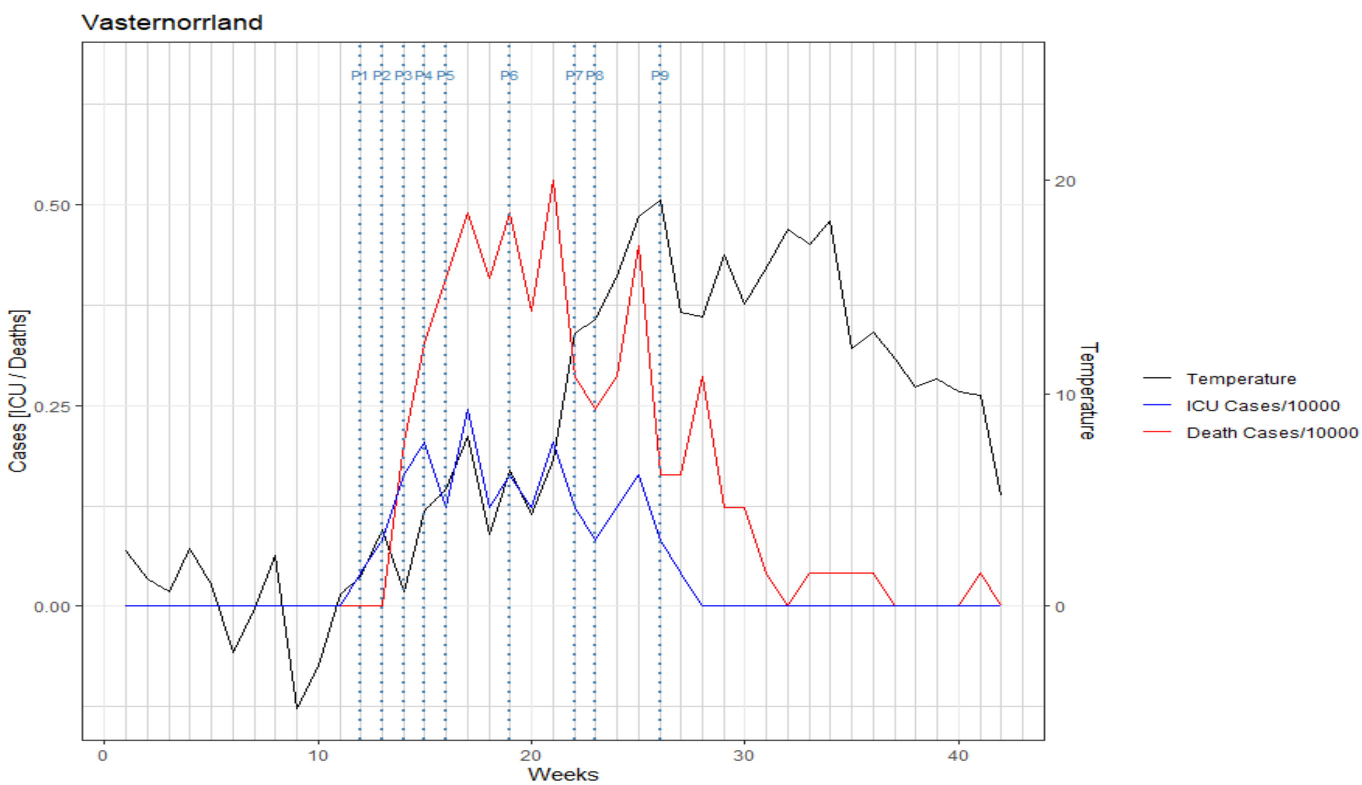

skane
P1 P2 P3 P4 P5
P6
P7 P8
P9
Cases [ICU / Deaths]
Temperature
Weeks
Temperature
ICU Cases/10000
Death Cases/10000

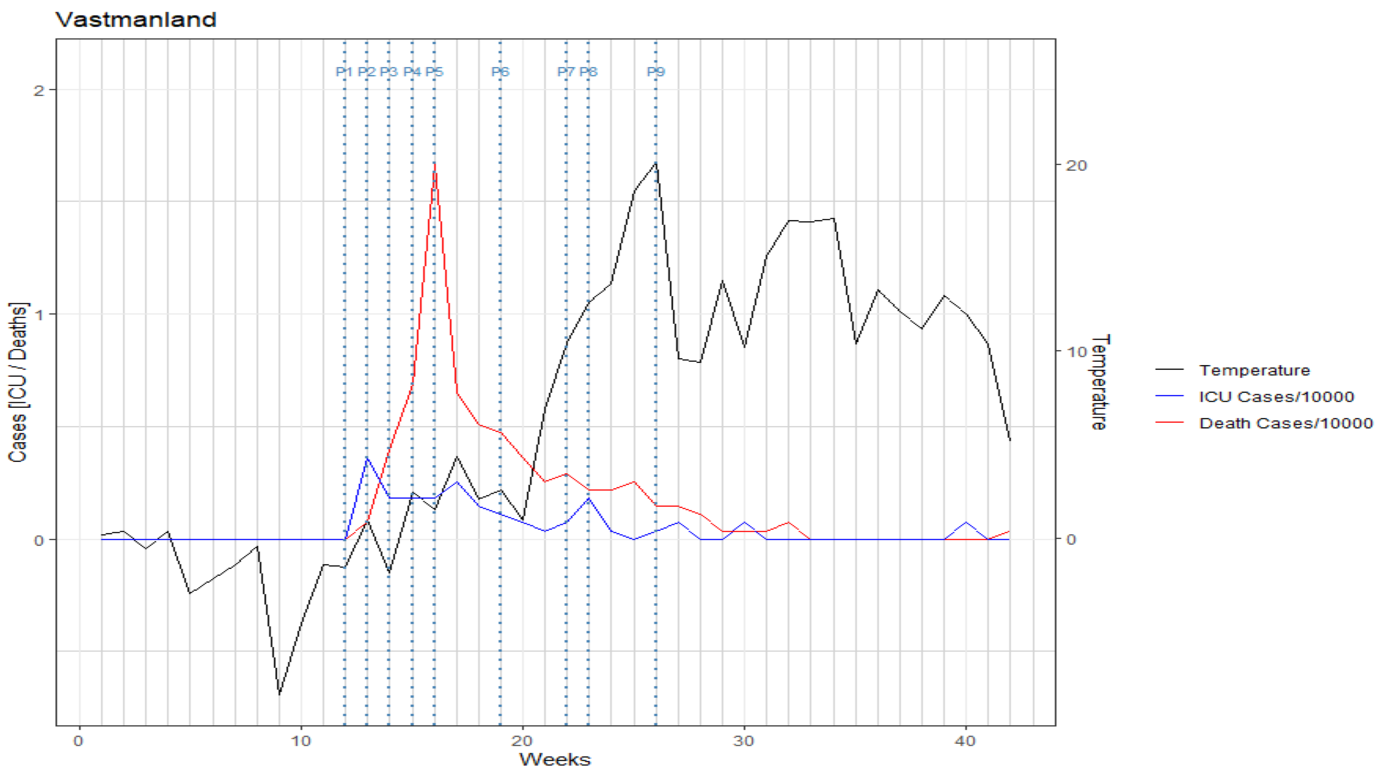

Sodermanland
P1 P2 P3 P4 P5
P6
P7 P8
P9
Cases [ICU / Deaths]
Temperature
Weeks
Temperature
ICU Cases/10000
Death Cases/10000

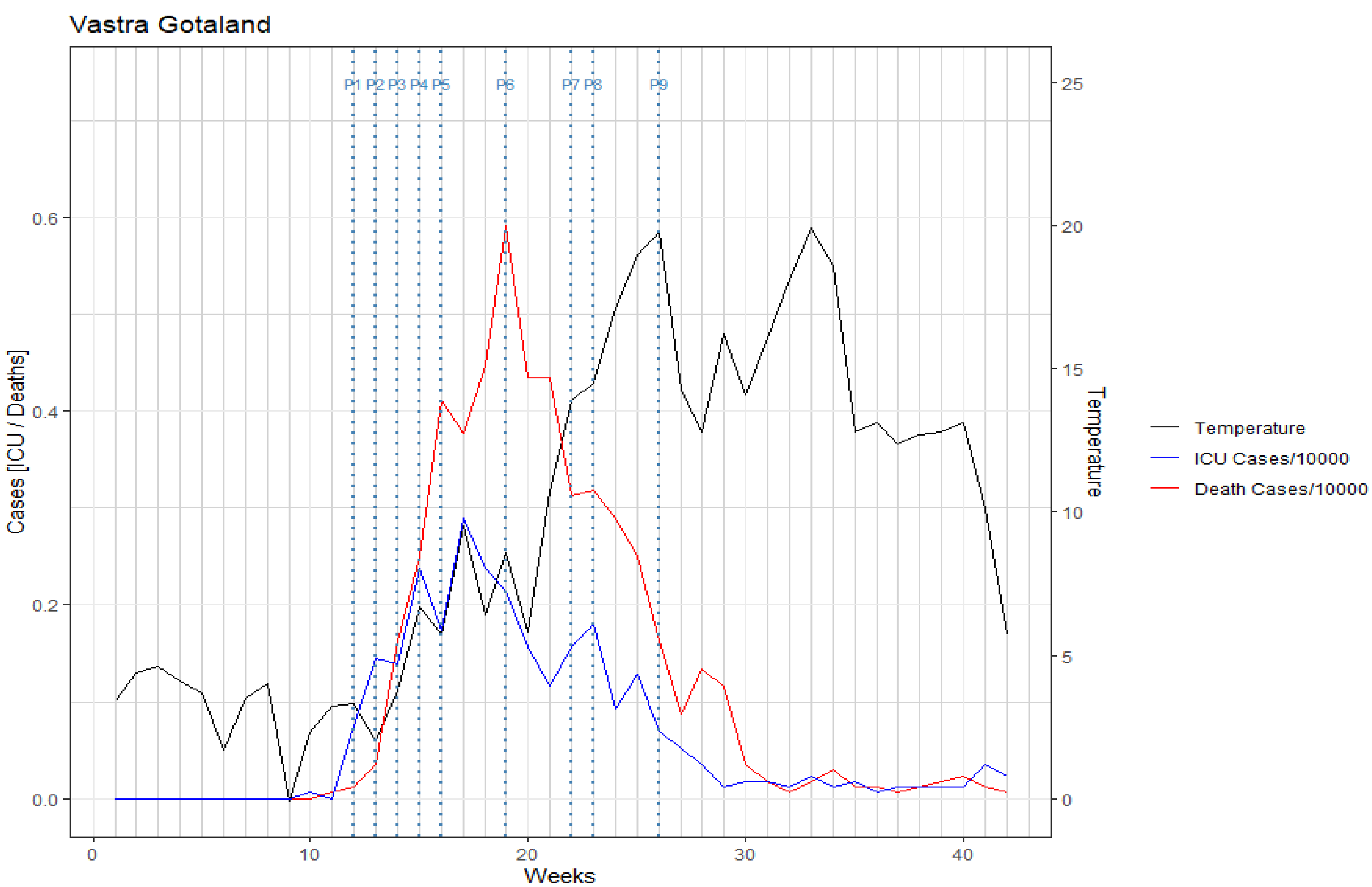

Uppsala
P1 P2 P3 P4 P5
P6
P7 P8
P9
Cases [ICU / Deaths]
Temperature
Weeks
Temperature
ICU Cases/10000
Death Cases/10000


Varmland
P1 P2 P3 P4 P5
P6
P7 P8
P9
Cases [ICU / Deaths]
Temperature
Weeks
Temperature
ICU Cases/10000
Death Cases/10000


Vasterbotten
P1 P2 P3 P4 P5 P6 P7 P8 P9
Cases [ICU / Deaths]
Temperature
Weeks
Temperature
ICU Cases/10000
Death Cases/10000


Vasternorrland
P1 P2 P3 P4 P5 P6 P7 P8 P9
Cases [ICU / Deaths]
Temperature
Weeks
Temperature
ICU Cases/10000
Death Cases/10000


Vastmanland
P1 P2 P3 P4 P5
P6
P7 P8
P9
Cases [ICU / Deaths]
Temperature
Weeks
Temperature
ICU Cases/10000
Death Cases/10000


Vastra Gotaland
P1 P2 P3 P4 P5
P6
P7 P8
P9
Cases [ICU / Deaths]
Temperature
Weeks
Temperature
ICU Cases/10000
Death Cases/10000