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Effects of temperature and mobility on COVID-19 incidence

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ABSTRACT

Background/Objective: The purpose of this study was to evaluate the association between COVID-19 weekly case numbers with the trend, average temperature (AT) and mobility (MOB) at the national level and by regions, in Portugal.

Methods: We compiled a weekly dataset including COVID-19 case numbers, average temperature and mobility during the period of March 23, 2020, to August 30, 2022. Negative binomial regression was fitted to estimate the effect of covariates on the COVID-19 case numbers.

Results: We observed a significant increasing effect over time in most regions, negative temperature effect, in all regions, and a positive mobility effect, in most regions, on the number of cases using a two-week lag.

Conclusion: Increased mobility and low temperatures were associated with higher numbers of cases of COVID-19 infection.

Introduction

Coronavirus disease (COVID-19) is an infectious disease caused by the SARS-CoV-2 virus, which was first detected in Wuhan City, Hubei province of China, in December 2019 [1]. Due to the rapid spread of the virus and the high degrees of contagion, on March 11, 2020, the World Health Organization (WHO) declared the COVID-19 outbreak a global pandemic [2]. In Portugal, the first confirmed case of the disease was reported on March 2, 2020. Since then, until July 08, 2022, there have been more than 5,23 million reported positive cases and 24,273 associated deaths [3].

The vaccine is one of the biggest strategies now for preventing the infection, but the emergence of new variants has shown that it is impossible to predict precisely how the SARS-CoV-2 virus will evolve [4].

Some studies have examined the impact of mobility on COVID-19 transmission. The study of Oztig and Askin [5] showed that countries which have a higher number of airports are associated with a higher number of COVID-19 cases. A recent study showed that the mandatory use of masks in public transit resulted in a 10% decrease in the number of infected people, also super-spreading events had significant increases in the number of positive cases [6]. In another study, researchers found that, globally, the social distancing policies significantly reduce the COVID-19 spread rate over two weeks [7]. A study conducted in Portugal showed that mobility in retail and recreation, grocery and pharmacy, and public transport has a higher correlation with new COVID-19 cases than mobility in parks, workplaces or residences. However, this relationship is lower in districts with lower population density [8].

Human-to-human, environment-to-human, and pollution-to-human transmission are considered the main modes of virus transmission [9]. However, some studies have suggested that meteorological factors such as temperature may influence the transmissions of coronavirus. The lower temperature was associated with an increased risk of COVID-19 cases in several studies [10–13]. On the other hand, another study suggested that temperature is positively associated with human mobility and human mobility is positively related to the COVID-19 transmission rate [10].

The present study aimed to evaluate the association between trend, average temperature, mobility, and weekly confirmed case numbers of COVID-19, for each region and at the national level. Understanding the associations between these factors with COVID-19 infection will help design preventive interventions to halt the spread of the virus.

Keywords:
Covid 19, Temperature, Mobility, Negative binomial regression

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Materials and Methods

Study design and data sources

An observational study was conducted with all confirmed cases of COVID-19 at the national level, and, by regions, reported to the Data Science for Social Good Portugal (DSSG) from the start of the pandemic until 03 January 2022 [14].

The average air temperature (ºC), in mainland Portugal, was obtained from the Portuguese Institute for Sea and Atmosphere, I.P. (IPMA, IP) [15] and the mobility (%) nformation was obtained from a company specialized in Data Science and Advanced Research (PSE). The PSE Mobility Index is a composite index that reflects the population in circulation, the distances travelled and the travel times of the Portuguese population [16]. Because mobility data is only available weekly, the confirmed cases from COVID-19 were transformed into weekly incidence. For this study, data was considered from March 23, 2020, to August 30, 2022, because mobility data after August 09, 2022, and average temperature data before March 23, 2020, were not available on the respective websites.

Geographic locations were categorized, according to the Nomenclature of Territorial Units for Statistics (NUTS II), into seven regions: "North", "South", "Center", "Lisbon and Tagus Valley", "Algarve", "Alentejo", "Azores" and "Madeira" [17].

Statistics Analysis

COVID-19 case numbers were described through observed weekly incidence distribution globally, and in the Portuguese region.

Negative binomial regression (NBR) and Poisson regression are models commonly used to fit epidemiological count data. However, the Poisson regression model has the assumption of identical mean and variance, but for the data used in this study this condition was not met. When there is overdispersion (variance exceeds the mean) [5,18,19] the NBR is considered more appropriate [5]. Thus, model estimation was performed using an NBR model linking weekly confirmed cases of COVID-19 to trend, temperature and mobility variables. The model is given by:

$$\log\left(\mathrm{E}\left(y_t\right)\right) = \beta_0 + \beta_1 t + \beta_2 AT + \beta_3 MOB + \varepsilon_t$$

were $E(y_t)$ is the expected number of COVID-19 reported in week t ; β_i, $i = 0,1,2,3$ are regression coefficients to be estimated; AT is the average temperature; MOB is the mobility and ε_t as an error parameter. The ε_t follows gamma distribution with mean 1 and variance α, were α is the overdispersion parameter used as a measure of dispersion.

Since the aim is to evaluate the impact of temperature and mobility on the number of cases, the association was not made directly, but with a time lag. The models were evaluated with lags of one, two and three weeks. In most cases the best fit was obtained at two weeks, considering Akaike's Information Criterion (AIC) (Table 1). This lag was used to assess the effect of the covariates under analysis on the number of cases. Multicollinearity was assessed through the calculation of the variance inflation factor (VIF). The logarithmic score and the Dawid-Sebastiani score calibration tests was used to test for miscalibration [20]. All analyses were performed with R software (version 4.0.3). Statistical hypothesis tests with a P value less than 0.05 were considered significant.

Table 1 - Akaike's Information Criterion

	Parameters				NUTS regions						
Delay	MOB	AT	t	National	North	Center	Lisbon and Tagus Valley	Alentejo	Algarve	Azores	Madeira
1-week	1	1	0	1491.9	1448.1	1171.0	1365.3	994.92	1024.8	804.65	830.98
	1	1	1	1480.3	1344.5	1150.8	1355.3	967.4	967.79	731.52	755.78
2-weeks	2	2	0	1473.9	1338.9	1158.8	1343.6	984.79	1011.4	796.55	831.57
	2	2	1	1468.2	1338.7	1144.6	1340.0	962.77	955.4	729.21	764.77
3-weeks	3	3	0	1467.2	1330.2	1155.9	1338.1	981.08	1010.1	797.32	834.21
	3	3	1	1465.4	1331.5	1147.1	1338.1	968.16	966.98	733.71	774.74

t- trend; AT- average temperature; MOB-mobility; NUTS – Nomenclature of Territorial Units for Statistics

Results

Figure 1 shows the epidemiological curve of COVID-19 weekly cases with mobility and temperature, respectively, nationwide. There were higher numbers of cases in the autumn and winter of 2021. This period also shows higher mobility index and lower mean temperature value. It is also observed that the highest synchronism of the lines is obtained for short time lags e.g., one to two weeks.

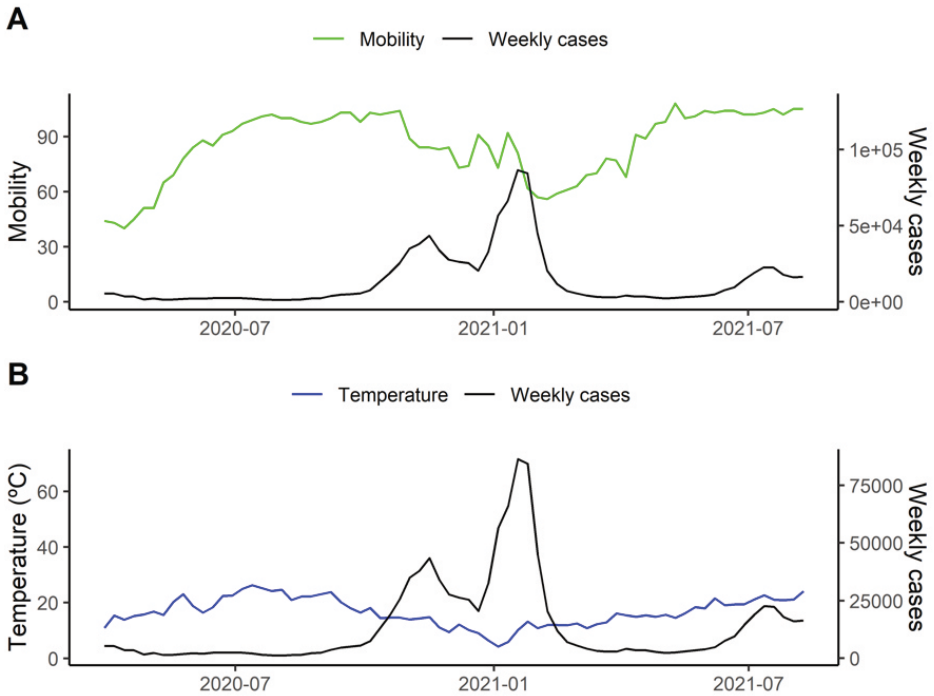

Figure 1 – Epidemiological curve of COVID-19 weekly cases with weekly average temperature (A), Epidemiological curve of COVID-19 weekly cases with weekly mobility index (B) from March 03, 2020, to August 09, 2021, in Portugal.

In Table 2 it is possible to identify, a consistency of results at the national level and in the different regions, regarding the effects of the variables t, AT and MOB on the number of cases such as:

1. increasing effect over time (significant in most regions).
2. negative temperature effect (significant in all scenarios), the lower the temperature, the greater the number of cases.
3. positive mobility effect (significant nationwide and, in all regions except Madeira), the higher the mobility the higher the number of cases.

Table 2 – Estimates of regression coefficients of the Negative binomial regression at a national level and by regions with two weeks lag.

		NUTS regions						
Parameter	**National**	**North**	**Center**	**Lisbon and Tagus Valley**	**Alentejo**	**Algarve**	**Azores**	**Madeira**
t	0,013**	0,010	0.024***	0.011**	0.028***	0.042***	0.052	0.062***
AT	– 0,186***	– 0,224***	– 0.250***	– 0.151***	– 0.210***	– 0.161***	– 0.166***	– 0.181***
MOB	0,035***	0,042***	0.035***	0.031***	0.044***	0.043***	0.022***	0.002

t- trend; AT-average temperature; MOB-mobility; ** significant at 0.01 level; *** significant at 0.001 level; NUTS – Nomenclature of Territorial Units for Statistics

For lags 1 and 3 (see additional tables 3 and 4) the effects of variables t, AT and MOB present consistency with the result of lag 2, that is, increasing effect over time, negative temperature effect and positive mobility effect. After studying the quality of the adjustment through the AIC and in order to make an analysis that would allow a comparison of the results, it was chosen to study the model with lag 2 (lowest AIC in 5 of the 7 regions).

The seasonal components were evaluated, and the existence of seasonality was verified. However, the seasonal components were not included in the model, as multicollinearity with temperature was verified, justified by the seasonal behavior of temperature.

Table 3 – Estimates of regression coefficients of the Negative binomial regression at a national level and by regions with one week lag

		NUTS regions						
Parameter	**National**	**North**	**Center**	**Lisbon and Tagus Valley**	**Alentejo**	**Algarve**	**Azores**	**Madeira**
t	0,019**	0,016*	0.030***	0.018***	0.034***	0.047***	0.057***	0.068***
AT	– 0,174***	– 0,219***	– 0.234***	– 0.135***	– 0.196***	– 0.139***	– 0.149***	– 0.167***
MOB	0,022***	0,028***	0.018*	0.019**	0.029***	0.026***	0.008	0.010

t- trend; AT-average temperature; MOB-mobility; ** significant at 0.01 level; *** significant at 0.001 level; NUTS – Nomenclature of Territorial Units for Statistics

Table 4 – Estimates of regression coefficients of the Negative binomial regression at a national level and by regions with three- week lag

		NUTS regions						
Parameter	**National**	**North**	**Center**	**Lisbon and Tagus Valley**	**Alentejo**	**Algarve**	**Azores**	**Madeira**
t	0,009*	0,005	0.020***	0.006**	0.022***	0.039***	0.050***	0.060***
AT	– 0,194***	– 0,237***	– 0.259***	– 0.159***	– 0.217***	– 0.147***	– 0.180***	– 0.186***
MOB	0,044***	0,056***	0.048***	0.036***	0.052***	0.047***	0.030***	0.010

t- trend; AT-average temperature; MOB-mobility; ** significant at 0.01 level; *** significant at 0.001 level; NUTS – Nomenclature of Territorial Units for Statistics

Figure 2 illustrates the fit of the model to the data nationwide. Overall there is agreement between the observed and predicted values. A greater discrepancy is observed in the summer of 2021, but the model proved to be calibrated. There is no evidence for miscalibration in all regions evaluated (p>0.05).

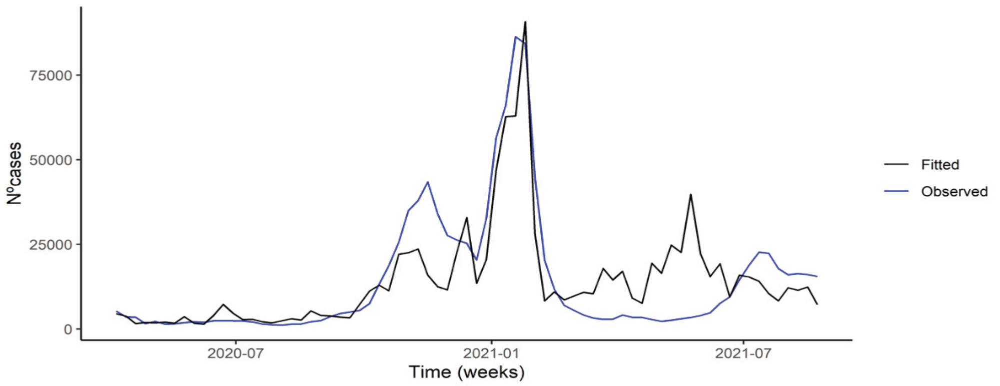

Figure 2 – Observed and fitted number of cases from March 23, 2020, to August 09, 2021, in Portugal.al.

Discussion

Our study suggested that temperature and mobility influenced the case numbers of COVID-19. Negative association between COVID-19 case numbers and temperature were found in all the regions and a positive association with mobility in most regions. This is consistent with results from previous studies [10,13]. Other studies have also investigated the effects of temperature on respiratory diseases and found a positive association between temperature and the number of cases [21,22]. The conflicting results might be explained by different climates (e.g., humidity) and characteristics of the populations under study.

During the study period, the peak of the pandemic wave was reached in January 2021, a period when Portugal was considered the worst country in the world in terms of infection and mortality rates [23]. The lifting of some restrictions during the Christmas season, implying more mobility for people, may be associated with this scenario.

This paper also has some limitations. First, the average temperature used in the analyses by region is for mainland Portugal. Second, other factors, such as humidity, population density, atmospheric pollution could impact the incidence of COVID-19, were not included in the model.

In conclusion, high mobility and low temperature were associated with higher numbers of cases of COVID-19 infection.

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