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Environmental risk factors of airborne viral transmission: Humidity, Influenza and SARS-CoV-2 in the Netherlands

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ABSTRACT

Objective: The relationship between specific humidity and influenza/SARS-CoV-2 in the Netherlands is evaluated over time and at regional level.

Design: Parametric and non-parametric correlation coefficients are calculated to quantify the relationship between humidity and influenza, using five years of weekly data. Bayesian spatio-temporal models—with a Poisson and a Gaussian likelihood—are estimated to find the relationship between regional humidity and the daily cases of SARS-CoV-2 in the municipalities and provinces of the Netherlands.

Results: An inverse (negative) relationship is observed between specific humidity and the incidence of influenza between 2015 and 2019. The space-time analysis indicates that an increase of specific humidity of one gram of water vapor per kilogram of air (1 g/kg) is related to a reduction of approximately 5% in the risk of COVID-19 infections.

Conclusions: The increase in humidity during the outbreak of the SARS-CoV-2 in the Netherlands may have helped to reduce the risk of regional COVID-19 infections. Policies that lead to an increase in household specific humidity to over 6g/Kg will help reduce the spread of respiratory viruses such as influenza and SARS-CoV-2.

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1. Introduction

Previous experimental evidence indicates that that the aerosolization of secretions lubricating the vocal cords can be a major source of microscopic droplet (microdroplet) virus infections (Morawska et al., 2009). Evidence of airborne spread of the severe acute respiratory syndrome virus (SARS) is provided by Yu et al. (2004). Recent studies also suggest the possibility of airborne transmission of SARS-CoV-2 through respiratory air droplets and aerosols (Morawska and Cao, 2020).

Weather factors—such as humidity and temperature—are suspected of playing a role in the transmission of viral particles through aerosolized droplet nuclei or aerosols. Particularly, differences in humidity are suspected to provide an explanation for the observed variability of influenza and its transmission (Shaman and

Kohn, 2009). Weather conditions can have a similar effect on SARS-CoV-2 (COVID-19), as airborne inactivation of the human coronavirus 229E is affected by temperature and relative humidity (Ijaz et al., 1985), and in experimental settings both temperature and absolute humidity affect the environmental survival of surrogates of mammalian coronaviruses (Casanova et al., 2010).

Based on observational data, the relationship between SARS-CoV-2 and weather has been recently analyzed in published studies (Gupta et al., 2020, Ma et al., 2020, Carta et al., 2020, Bukhari et al., 2020, Guo et al., 2020, Qi et al., 2020) and pre-prints (Crema, 2020, Bukhari and Jameel, 2020, Liu et al., 2020, Oliveiros et al., 2020, Raines et al., 2020, Sajadi et al., 2020). All of these studies find a negative correlation between absolute humidity and the spread of SARS-CoV-2, indicating that low levels of humidity increase the risk of COVID-19 cases. In Sajadi et al. (2020), for example, weather conditions are investigated worldwide, and Sajadi et al. (2020) conclude that the community transmission of SARS-CoV-2 is consistent with average temperatures of 5° to 11°C, combined with low specific humidity between 3 to 6 g/kg. Humidity seems to be the most important factor in viral spreading, while temperature play a less important role (Crema, 2020).

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Our study provides new evidence about the relationship between specific humidity and the risk of influenza and COVID-19 cases. Five years of hourly weather data from 34 regional weather stations in the Netherlands is analyzed against five years of weekly data of influenza cases, as well as daily regional data of COVID-19 cases, hospitalizations, and deaths. The Netherlands has accurate and easily accessible data that allows for a high-resolution and precise estimation of the relationship between weather conditions and the spread of viral diseases. As time trends of viral transmission can vary substantially in time and at sub-national level, the combination of high spatial and temporal resolution captures the heterogeneity of viral spreading across time and space.

In our study, parametric and non-parametric correlations are calculated for specific humidity and influenza/SARS-CoV-2 at country-level. An inverse (negative) relationship is observed between specific humidity and the incidence of influenza between 2015 and 2019, but a positive correlation is found between specific humidity and the reported cases of COVID-19. Since the positive correlation between specific humidity and COVID-19 may be caused by the use of aggregated data at national level—besides the lack of herd immunity—a Bayesian spatio-temporal disease model for the Netherlands is estimated at municipality and province level. This model allows to quantify the relation of COVID-19 cases with the specific humidity in the Netherlands at regional sub-national levels and over time.

The results of the spatio-temporal disease model indicate that the increase of specific humidity during the outbreak of the SARS-CoV-2 helped to reduce the risk of regional COVID-19 cases in the Netherlands. Specifically, the estimations suggest that an increase of specific humidity of one gram of water vapor per kilogram of air (1 g/kg) may be related to a reduction of approximately 5% in the risk of COVID-19 infections. This result, however, is conditional to the observed data in the study and may be susceptible to unaccounted risks and confounding factors.

2. Data

Weekly data of influenza reports were collected for the years 2015 to 2019 from the [Nivel Primary Care Database](#) (Nivel Zorgregistraties Eerste Lijn). Daily COVID-19 data (Reported Infections, Hospitalizations and Mortality) was provided by The Dutch National Institute for Public Health and the Environment (RIVM). RIVM is the government agency focused as Centre for Infectious Disease Control (CDC), under supervision of the Dutch Government. The COVID-19 data covers the twelve provinces and the 355 municipalities in the Netherlands, from March 13th to July 9th.

Specific humidity (q) was calculated with the data from 34 weather stations, spread across The Netherlands. This data was provided by The Royal Netherlands Meteorological Institute (KNMI), the Dutch national weather service. Since KNMI only reports relative humidity (h), specific humidity q was calculated using the Rotronic formula¹, which is based on the UK National Physical Laboratory guide for the measurement of humidity (National Physical Laboratory 1996):

$$q = \xi \frac{hd_w}{(d_m - d_w)} \quad (1)$$

In (1), q is specific humidity of air vapor mixture (expressed in g/Kg), h is relative humidity (in percentage), d_w is the density of water vapor (kg/m³), d_m is density of the moist or humid air

¹ The Rotronic technical note about humidity definitions is freely available at: https://www.rotronic.com/media/productattachments/files/h/u/humidity_definitions_weba.pdf?_ga=2.192612136.342104324.1597340506-398495933.1597340506

(kg/m³) and $\xi = .622$. Specific humidity is analyzed instead of relative humidity because relative humidity is affected by the surrounding temperature. Specific humidity in contrast remains the same in indoor and outdoor conditions². The hourly weather data provided by the KNMI was aggregated at daily and weekly levels using the average values during the time periods.

Additional population data was used in the spatial-time models to calculate the incidence of SARS-CoV-2 at intra-regional level. This data was provided by the national statistical office, Statistics Netherlands (CBS) and is also used by the RIVM.

3. Methods

Parametric and non-parametric correlation coefficients were calculated between specific humidity q and the incidence of influenza and SARS-CoV-2. Spatio-temporal disease models were estimated with the daily data of specific humidity (q_{it}) and SARS-CoV-2 (y_{it}) in the Netherlands. Spatial dependence in the latent component of the disease mapping is modelled by specifying neighborhood relationships among the area-level risks (Blangiardo et al., 2020, Kim and Castro, 2020).

In the space-time analysis, the Besag-York-Mollié (BYM) spatio-temporal model (Besag et al., 1991) is used to estimate the impact of specific humidity on the risk of SARS-CoV-2 (COVID-19) cases at province and municipality level. In the BYM model, the number of SARS-CoV-2 cases follows a Poisson stochastic process for each area i and time points t , $y_{it} \sim \mathcal{P}(\lambda_{it})$, as in Blangiardo et al. (2020). The parameter λ_{it} is defined by the ecological regression:

$$\begin{cases} \lambda_{it} = E_{it} p_{it} \\ p_{it} = \exp(\alpha + v_i + u_i + (\beta_t + \tau_i)t + \beta_q q_{it-\ell}) \end{cases} \quad (2)$$

where E_{it} is the expected number of cases in each area, at each point in time, p_{it} is the ratio between the number of observed cases y_{it} and the number of expected cases, α is the average rate of cases in all the areas, v_i is the unstructured area-specific effect, which follows a Gaussian prior $v_i \sim \mathcal{N}(0, \sigma_v^2)$, and u_i is the spatially structured area-specific effect, $u_i \sim \mathcal{N}(0, \sigma_u^2)$. The area-specific effect u_i is modelled with an intrinsic conditional autoregressive prior that takes into account the number of j -areas which share boundaries with the i -areas ($j \neq i$), i.e. the neighbors of each province/municipality (Blangiardo and Cameletti, 2015).

In (2), the temporal component t is modelled with a parametric approach (Bernardinelli et al., 1995), where β_t represents the global time effect, and $\tau_i \sim \mathcal{N}(0, 1/\sigma_\tau^2)$ is the differential trend that captures the interaction between time and space. Specific humidity levels ($q_{it-\ell}$) with a lag of ten days ($\ell = 10$) were included as a risk factor in the spatio-temporal models to evaluate the impact β_q on the risk of SARS-CoV-2 cases. The lag of ten days ($\ell = 10$) reflects the time span between the environmental exposition to SARS-CoV-2, the incubation period, testing and the effective registration of the positive cases in the RIVM records. When the incidence of SARS-CoV-2 per 100,000 population is used as the dependent variable, a Gaussian likelihood is used instead of the Poisson model in equation (2)³.

4. Results

Figure 1 shows the weekly historical patterns of specific humidity q and the incidence of influenza in the Netherlands, from 2015

² For example, weather stations may report a temperature of 5°C and a relative humidity of 35% for the outside environment (equal to a specific humidity of 1.87g/kg). However, inside the households, the temperature can be 21°C with a relative humidity of 12% due to heating systems, but specific humidity will remain the same (1.87g/kg) regardless of the temperature.

³ The data and R codes to replicate the results with R-INLA (www.r-inla.org) are freely available upon request.

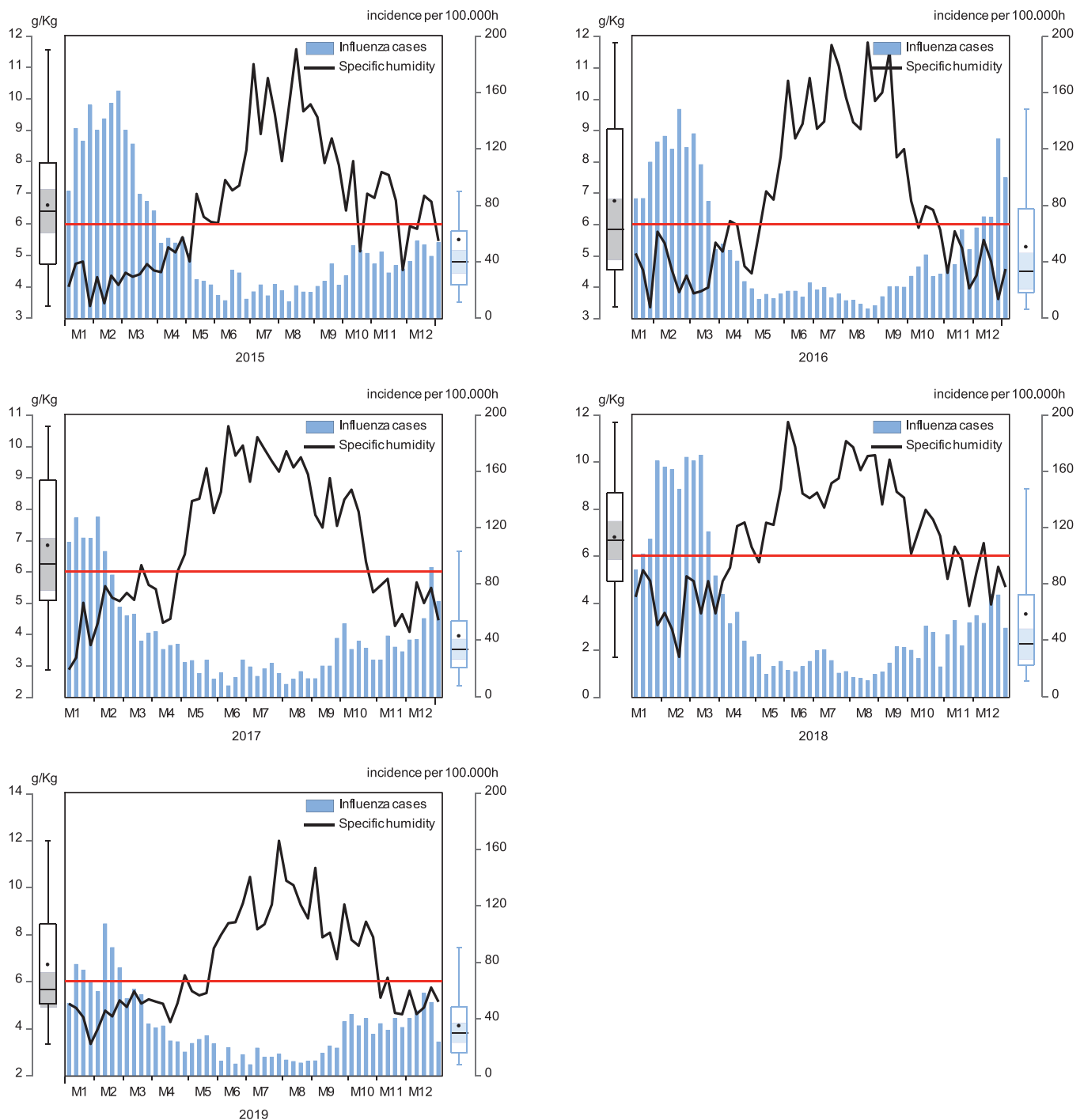


Figure 1. Specific humidity and incidence of influenza in the Netherlands Weekly historical observations per year

to 2019. Specific humidity q during the winter periods is between 3 and 6 g/kg, while in the summer specific humidity is above 8 g/kg. The highest incidence of influenza infection is observed in weeks with a specific humidity of less than 6 g/kg. Particularly, a higher incidence is observed in children of less than 4 years and individuals with 65 years or more (Figure 2a). Above 6 g/kg, a significant drop in infections is observed. The opposite is also true: the rate of influenza cases is 5.91 higher when specific humidity levels are approximately 2 g/kg compared to the average cases at 8 g/kg (Table 1).

Figure 2b illustrates the inverse non-linear relationship between the levels of specific humidity and the weekly incidence

of influenza. The ordinary Pearson correlation of specific humidity with influenza cases is negative and equal to -0.6986 (t-value: -15.713 , p-value: 0.0000). The value of the non-parametric Spearman correlation is equal to -0.8083 (t-statistic: -22.0993 , p-value: 0.0000).

The inverse correlation between influenza and humidity during the wintertime season of the Netherlands is country specific. The wintertime seasonality of influenza epidemics has a period of 2 to 3 months between October and March in the Northern Hemisphere, and between May and September in the Southern Hemisphere (Lowen and Steel, 2014). Low specific humidity conditions facilitate the airborne survival and transmission of the influenza

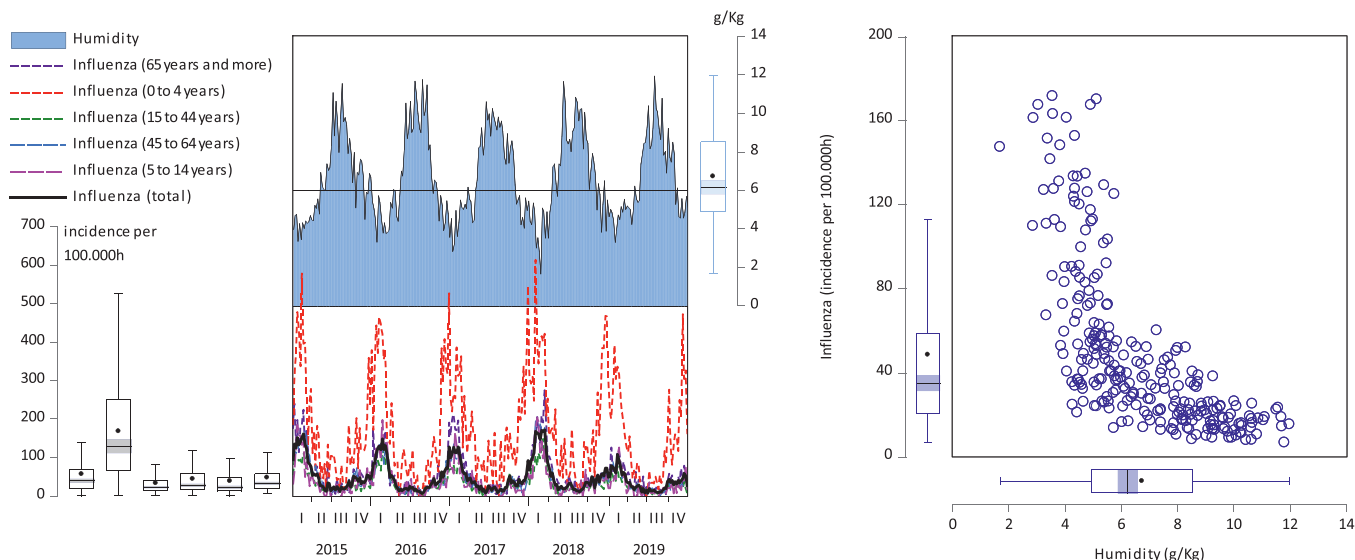


Figure 2. Specific humidity and incidence of influenza for age categories in the Netherlands.
a: Weekly historical observations (left), b: bivariate scatterplot (right)

Table 1

Average incidence of influenza cases at different intervals of specific humidity.

Specific humidity	Average incidence of influenza per 100,000 people
Below 2 g/kg	147.3
Between 2 and 3	135.4
Between 3 and 4	110.9
Between 4 and 5	79.7
Between 5 and 6	54.4
Between 6 and 7	33.2
Between 7 and 8	29.5
Between 8 and 9	24.9
Between 9 and 10	17.2
Above 10	15.8

virus in temperate regions, resulting in annual winter epidemics, but this transmission factor is less relevant for the epidemiology of influenza during rainy seasons in tropical and subtropical regions (Tamerius et al., 2013).

In the case of SARS-CoV-2, a positive correlation between humidity levels and the daily COVID-19 cases in the Netherlands was found. The Pearson correlation is equal to .7016 (t-value: 10.651, p-value: 0.0000), and the Spearman correlation is 0.8389 (t-statistic: 16.6734, p-value: 0.0000). This positive correlation can be explained by the lack of herd immunity—due to the novelty of the SARS-CoV-2—, the increasing number of tests, and the use of aggregate data at country level which does not capture the dissimilarities of specific humidity at sub-national levels in the Netherlands.

In order to consider the differential spatial and temporal patterns of specific humidity across the Netherlands during the outbreak of the COVID-19, a Bayesian spatial-time model based on a Poisson stochastics process was estimated for the number of reported cases of SARS-CoV-2, at municipality and province level. The increase in testing, which increases reported COVID-19 cases, was controlled by relativizing the number of COVID-19 cases with the population at municipality and province level, i.e. estimating an additional Gaussian space-time model for the incidence of COVID-19 cases per 100,000 people⁴.

⁴ The Netherlands increased COVID-19 testing from 55,000 weekly tests in March to 110,000 tests per week in July 2020. The testing was only focused on care work-

ers in March, but now the entire population is subject to testing. Due to the possible bias caused by testing, space-time models were also estimated using data of the number of hospitalizations, and similar results were obtained as those for reported cases. The results for hospitalization are available upon request.

⁵ Similar results were obtained using different priors and after controlling for non-pharmaceutical interventions. These results are included as supplementary material of this study.

Table 2 shows the results of estimating the fixed-effects $\{\alpha, \beta_t, \beta_q\}$ of the spatio-temporal model. The low standard deviation of the posterior means in all the models indicates a good level of accuracy in the integrated nested Laplace approximation of the approximate Bayesian inference. The value of the exponentiated estimate of β_t implies a 1% daily rate of infection of SARS-CoV-2 in the Netherlands from March to July of 2020. The negative sign of the mean estimate of β_q —as well as the sign of the low and upper limit of the 95% credible interval—suggests that regions with higher specific humidity levels have, on average, lower number of COVID-19 cases in the Netherlands. Specifically, the estimated values of $\hat{\beta}_q = -0.045$ at province level and $\hat{\beta}_q = -0.047$ at municipality level in the Poisson space-time model indicate that an increase of one gram of water vapor per kilogram of air (1 g/kg) is related to a reduction of around 5% in the risk of COVID-19 cases⁵.

Similar results are obtained using a Gaussian space-time model for the incidence of SARS-CoV-2 cases per 100,000 population in the Netherlands. On average, regions with higher levels of specific humidity showed a lower incidence of COVID-19 cases per 100,000 people, on a magnitude of $\hat{\beta}_q = -6.67$ at province level and $\hat{\beta}_q = -8.64$ at municipality level.

Figure 3 shows the area-specific relative risks of COVID-19 in the Netherlands—at province and municipality level—calculated with the random-effects $\vartheta = \exp(v_i + u_i)$ estimated with the spatio-temporal models. The regions located in the North of the country, where specific humidity tends to be higher, show a lower risk of COVID-19 cases. In contrast the regions with less specific humidity, in the South East of the country, display higher levels of relative risk of SARS-CoV-2 cases.

Interestingly, municipalities with the highest concentration of conservative orthodox Calvinist Protestants in the country, i.e. those in the ‘Bible belt’, have a higher risk of SARS-CoV-2, compared to other regions in the Netherlands. The identification of this type of regions with a high risk of COVID-19 cases can help to allo-

Table 2
Estimation results: Besag-York-Mollie spatio-temporal disease model of daily (t) COVID-19 cases and specific humidity (q) in the Netherlands

	Parameter	Area's break	Mean estimate	Standard deviation	Credible interval	
					2.50%	97.50%
Number of cases of SARS-CoV-2 (COVID-19)	α	Province	7.096385	0.093949	6.909104	7.283473
		Municipality	3.728711	0.043771	3.642679	3.814641
	β_t	Province	0.012539	0.000038	0.012464	0.012613
		Municipality	0.012254	0.000036	0.012182	0.012325
	β_q	Province	-0.044876	0.000358	-0.045578	-0.044174
		Municipality	-0.04696	0.000359	-0.047666	-0.046256
	σ_v^2	Province	1.92E+03	1.93E+03	1.33E+02	7.08E+03
		Municipality	6.72E-01	7.64E+00	8.08E-01	5.71E-01
	σ_u^2	Province	3.40E-01	1.35E-01	1.44E-01	6.66E-01
		Municipality	2.15E-01	4.65E-01	5.14E-01	9.79E-02
	σ_τ^2	Province	1.06E+05	4.20E+04	4.48E+04	2.07E+05
		Municipality	6.09E-06	7.72E-05	7.14E-06	5.24E-06
Incidence of cases of SARS-CoV-2 (COVID-19) per 100,000h	α	Province	108.813271	2.905202	103.1092	114.512511
		Municipality	137.685074	0.866277	135.984264	139.384447
	β_t	Province	2.210863	0.04992	2.112849	2.308794
		Municipality	2.535121	0.0149	2.505866	2.564351
	β_q	Province	-6.67267	0.689306	-8.026052	-5.320431
		Municipality	-8.637712	0.213028	-9.055959	-8.219813
	σ_v^2	Province	1.28E-04	3.24E-04	3.31E-04	6.71E-05
		Municipality	5.51E-03	1.40E-01	5.98E-03	5.12E-03
	σ_u^2	Province	3.59E-03	8.84E-03	7.54E-03	1.76E-03
		Municipality	5.84E-03	3.77E-01	6.02E-03	5.66E-03
	σ_τ^2	Province	1.22E+06	3.15E+06	2.46E+06	6.16E+05
		Municipality	4.13E+00	1.01E+02	4.47E+00	3.80E+00

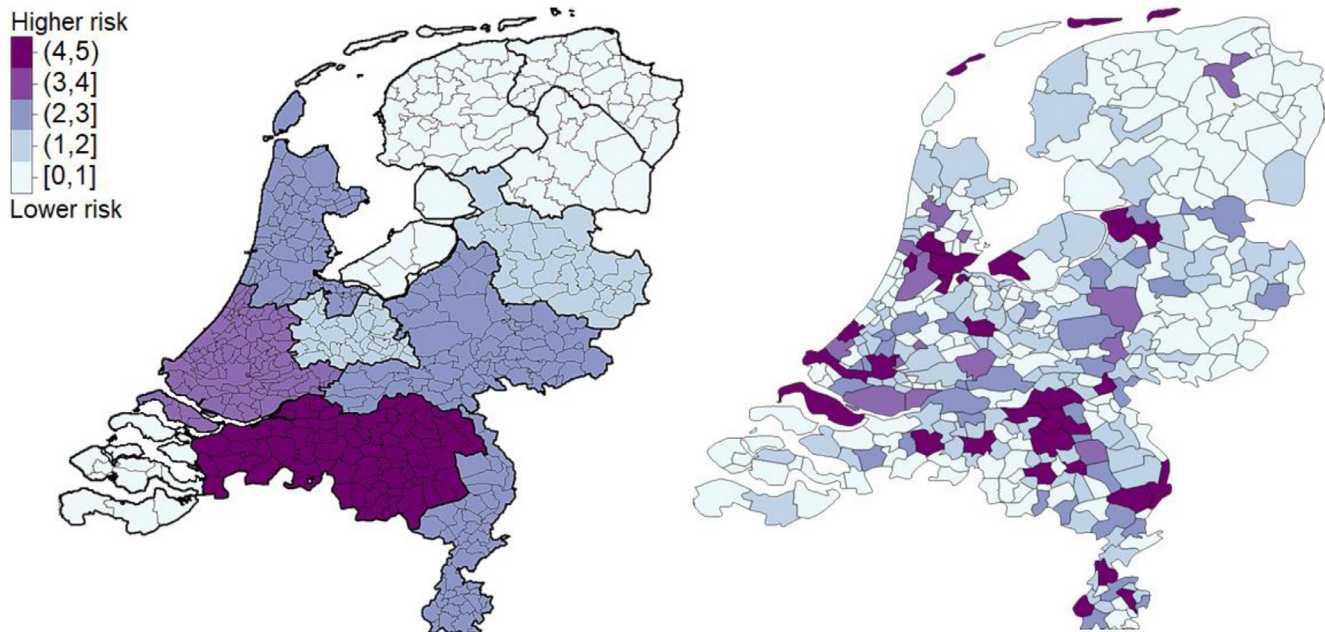


Figure 3. Area-specific relative risk* of SARS-CoV-2 in the Netherlands.

(*) Relative risk: residual risk after regional specific humidity (q) levels are considered in the modelling. Area's break: province level (left) and municipality level (right).

cate resources during the SARS-CoV-2 pandemic (Cordes and Castro, 2020).

5. Discussion

Higher levels of specific humidity (q) were found to be related to a lower number of reported cases of respiratory viruses in the Netherlands. An inverse non-linear relationship between specific humidity and influenza is observed historically between 2015 and 2019. A similar inverse (negative) relationship between specific humidity and SARS-Cov-2 cases is found using spatio-temporal mod-

els that consider the differential patterns of specific humidity (q) and SARS-Cov-2 cases at municipality and province levels in the Netherlands.

The results are in line with previous studies (Gupta et al., 2020, Ma et al., 2020, Carta et al., 2020, Bukhari et al., 2020, Guo et al., 2020, Qi et al., 2020, Crema, 2020, Bukhari and Jameel, 2020, Liu et al., 2020, Oliveiros et al., 2020, Raines et al., 2020, Sajadi et al., 2020)⁶, as our risk analysis shows that higher

⁶ Compared to these previous studies, we use more detailed data, with a high temporal and spatial resolution, in order to reduce the possibility of the ecological

levels of humidity may result in a slower spread of COVID-19 (Bukhari et al., 2020, Qi et al., 2020). The findings are consistent with the hypothesis that suggests that SARS-CoV-2 spreads through airborne aerosolization (Fineberg, 2020), since lower levels of specific humidity q lead to a higher concentration of aerosols when a dry air increases the evaporation of respiratory droplets, i.e. when droplets smaller in diameter than a few micrometers—referred to as “droplet nuclei”—evaporate to about half their initial size (Brienen et al., 2010). In the case of influenza, for example, the probabilities of exposure and infection risk of aerosol and droplet transmission are within the same order of magnitude, but intranasal inoculation leads to about 20 times lower infectivity that when the virus is delivered in an inhalable aerosol (Teunis et al., 2010).

In practice, the findings suggest that policies that lead to an increase in household specific humidity to over 6g/Kg will help reduce the spread of respiratory viruses such as influenza and SARSCoV-2. For example, the deployment of hygrometers aimed at measuring specific humidity can guide the public behavior in the face of a warning of an increased risk of infection⁷. The results also imply that the use of air conditioning (which decreases the specific humidity in a cooled area), must be complemented with humidification during the fall and winter periods, particularly when specific humidity q decreases below 6 g/kg.

Future studies can analyze influenza and humidity using the spatio-temporal framework of this study. Also, it is relevant to understand the interaction of sunlight with humidity, as sunlight radiation may act as and additional environmental factor in the reduction and prevention of the risk of SARS-CoV-2 (Rosario et al., 2020). Solar radiation plays an important role in vitamin D production, which seems to play a role in reducing COVID-19 infections (Grant et al., 2020, Whittemore, 2020).

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:[10.1016/j.sste.2021.100432](https://doi.org/10.1016/j.sste.2021.100432).

fallacy that may arise in the analysis of large spatial units that neglect the strong localized patterns of SARS-CoV-2 (Konstantinou et al., 2020).

⁷ For example, RIVM has specifically indicated that having a good indoor humidity balance can help reduce the risk of COVID-19 spreading (<https://www.rivm.nl/coronavirus-covid-19/ventilatie>). Smart social distancing regulations may take into account local humidity levels, per municipality, and allow social gatherings in outside spaces (as e.g. terraces) on humid days. At the same, social gatherings on cloudy and cold days with low humidity or in dry environments (such as restaurants), may be discouraged, unless these environments have approved humidification solutions implemented. If increased humidification is not possible, air purification with HEPA filters and ionization can be alternative solutions to deactivate viral aerosols.

References

- Besag, J., York, J., Mollié, A., 1991. Bayesian image restoration, with two applications in spatial statistics. *Ann. Inst. Stat. Math.* 43 (1), 1–20.
- Bernardinelli, L., Clayton, D., Pascutto, C., Montomoli, C., Ghislandi, M., Songini, M., 1995. Bayesian analysis of space-time variation in disease risk. *Stat. Med.* 14 (21–22), 2433–2443.
- Blangiardo, M., Bouliari, A., Diggle, P., Piel, F.B., Shaddick, G., Elliott, P., 2020a. Advances in spatiotemporal models for non-communicable disease surveillance. *Int. J. Epidemiol.* 49 (Supplement_1) i26–i37.
- Blangiardo, M., Cameletti, M., Pirani, M., Corsetti, G., Battaglini, M., Baio, G. (2020). Estimating weekly excess mortality at sub-national level in Italy during the COVID-19 pandemic.
- Blangiardo, M., Cameletti, M., 2015. *Spatial and Spatio-Temporal Bayesian models With R-INLA*. John Wiley & Sons.
- Brienen, N.C., Timen, A., Wallinga, J., Van Steenbergen, J.E., Teunis, P.F., 2010. The effect of mask use on the spread of influenza during a pandemic. *Risk Anal.* 30 (8), 1210–1218.
- Bukhari, Q., Massaro, J.M., D’Agostino, R.B., Khan, S., 2020. Effects of weather on coronavirus pandemic. *Int. J. Environ. Res. Public Health* 17 (15), 5399.
- Bukhari, Q., & Jameel, Y. (2020). Will coronavirus pandemic diminish by summer? Available at SSRN 3556998.
- Carta, M.G., Scano, A., Lindert, J., Bonanno, S., Rinaldi, L., Fais, S., Orrù, G., 2020. Association between the spread of COVID-19 and weather-climatic parameters. *Eur. Rev. Med. Pharmacol. Sci.* 24 (15).
- Casanova, L.M., Jeon, S., Rutala, W.A., Weber, D.J., Sobsey, M.D., 2010. Effects of air temperature and relative humidity on coronavirus survival on surfaces. *Appl. Environ. Microbiol.* 76 (9), 2712–2717.
- Cordes, J., Castro, M.C., 2020. Spatial analysis of COVID-19 clusters and contextual factors in New York City. *Spat. Spatiotemporal Epidemiol.*, 100355.
- Crema, E., 2020. The SARS-COV-2 outbreak around the Amazon rainforest: the relevance of the airborne transmission. medRxiv.
- Fineberg, H.V. National Research Council, 2020. Rapid Expert Consultation On the Possibility of Bioaerosol Spread of SARS-CoV-2 For the COVID-19 Pandemic (April 1, 2020). The National Academies Press NRC. The National Academies Press, National Research Council, Washington, DC.
- Grant, W.B., Lahore, H., McDonnell, S.L., Baggerly, C.A., French, C.B., Aliano, J.L., Bhattoa, H.P., 2020. Evidence that vitamin D supplementation could reduce risk of influenza and COVID-19 infections and deaths. *Nutrients* 12 (4), 988.
- Gupta, S., Raghuvanshi, G.S., Chanda, A., 2020. Effect of weather on COVID-19 spread in the US: a prediction model for India in 2020. *Sci. Total Environ.*, 138860.
- Guo, X., Zhang, H., Zeng, Y., 2020. Transmissibility of COVID-19 in 11 major cities in China and its association with temperature and humidity in Beijing, Shanghai, Guangzhou, and Chengdu. *Infect. Dis. Poverty* 9, 87.
- Ijaz, M.K., Brunner, A.H., Sattar, S.A., Nair, R.C., Johnson-Lussenburg, C.M., 1985. Survival characteristics of airborne human coronavirus 229E. *J. Gen. Virol.* 66 (12), 2743–2748.
- Kim, S., Castro, M.C., 2020. Spatiotemporal pattern of COVID-19 and government response in South Korea (as of May 31, 2020). *Int. J. Infect. Dis.*
- Konstantinou et al., 2020. Long-term Exposure to Air-Pollution and COVID-19 Mortality in England: a Hierarchical Spatial Analysis. medRxiv.
- Liu, Y., Ning, Z., Chen, Y., Guo, M., Liu, Y., Galí, N.K., Liu, X., 2020. Aerodynamic Characteristics and RNA Concentration of SARS-CoV-2 Aerosol in Wuhan hospitals During COVID-19 Outbreak. medRxiv.
- Lowen, A.C., Steel, J., 2014. Roles of humidity and temperature in shaping influenza seasonality. *J. Virol.* 88 (14), 7692–7695.
- Ma, Y., Zhao, Y., Liu, J., He, X., Wang, B., Fu, S., Luo, B., 2020. Effects of Temperature Variation and Humidity on the Death of COVID-19 in Wuhan. *Science of The Total Environment, China*.
- Morawska, L.J.G.R., Johnson, G.R., Ristovski, Z.D., Hargreaves, M., Mengersen, K., Corbett, S., Katoshevski, D., 2009. Size distribution and sites of origin of droplets expelled from the human respiratory tract during expiratory activities. *J. Aerosol. Sci.* 40 (3), 256–269.
- Morawska, L., Cao, J., 2020. Airborne transmission of SARS-CoV-2: the world should face the reality. *Environ Int.* 105730.
- National Physical Laboratory, 1996. A Guide to the Measurement of Humidity. The Institute of Measurement and Control. United Kingdom https://rotronic.com/media/productattachments/files/n/p/npl_guide_to_humidity.pdf.
- Oliveiros, B., Caramelo, L., Ferreira, N.C., Caramelo, F., 2020. Role of Temperature and Humidity in the Modulation of the Doubling Time of COVID-19 Cases. medRxiv.
- Qi, H., Xiao, S., Shi, R., Ward, M.P., Chen, Y., Tu, W., Zhang, Z., 2020. COVID-19 transmission in Mainland China is associated with temperature and humidity: a time-series analysis. *Sci. Total Environ.*, 138778.
- Raines, K.S., Doniach, S., Bhanot, G., 2020. The Transmission of SARS-CoV-2 is Likely Comodulated By Temperature and By Relative Humidity. medRxiv.
- Rosario, D.K., Mutz, Y.S., Bernardes, P.C., Conte-Junior, C.A., 2020. Relationship between COVID-19 and weather: case study in a tropical country. *Int. J. Hyg. Environ. Health*, 113587.

- Shaman, J., Kohn, M., 2009. Absolute humidity modulates influenza survival, transmission, and seasonality. *Proc. Natl. Acad. Sci.* 106 (9), 3243–3248.
- Sajadi, M.M., Habibzadeh, P., Vintzileos, A., Shokouhi, S., Miralles-Wilhelm, F., Amoroso, A., 2020. Temperature and Latitude Analysis to Predict Potential Spread and Seasonality for COVID-19 Available at SSRN 3550308.
- Tamerius, J.D., Shaman, J., Alonso, W.J., Bloom-Feshbach, K., Uejio, C.K., Comrie, A., Viboud, C., 2013. Environmental predictors of seasonal influenza epidemics across temperate and tropical climates. *PLoS Pathog.* 9 (3), e1003194.
- Teunis, P.F., Brienen, N., Kretzschmar, M.E., 2010. High infectivity and pathogenicity of influenza A virus via aerosol and droplet transmission. *Epidemics* 2 (4), 215–222.
- Yu, I.T., Li, Y., Wong, T.W., Tam, W., Chan, A.T., Lee, J.H., Ho, T., 2004. Evidence of airborne transmission of the severe acute respiratory syndrome virus. *N. Engl. J. Med.* 350 (17), 1731–1739.
- Whittemore, P.B., 2020. COVID-19 fatalities, latitude, sunlight, and vitamin D. *Am. J. Infect. Control.*