Infectious diseases

Determinants of public interest in emerging and re-emerging arboviral diseases in Europe: A spatio-temporal analysis of cross-sectional time series data

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Keywords

Arboviral diseases • Emerging diseases • Disease interest • Google Trends • Perceived susceptibility

Summary

Introduction. *Climate change, the resulting geographical expansion of arthropod disease vectors, and increasing international mobility are contributing to the emergence of arboviral diseases in Europe. Public interest in vector-borne diseases and a subsequent gain of awareness and knowledge are essential to control outbreaks but had not yet been systematically assessed prior to this analysis.*

Methods. *Trends, patterns, and determinants of public interest in six emerging and re-emerging arboviral diseases were assessed in a spatio-temporal analysis of Google Trends data from 30 European countries between 2008 and 2020 while controlling for potential confounders.*

Results. *Only public interest in endemic arboviral diseases in Europe displays seasonal patterns and has been increasing since 2008, while no significant patterns or trends could be determined for public interest in non-endemic diseases. The main drivers for public interest in all six analysed arboviral diseases are reported case rates, and public interest drops rapidly as soon as cases decline. For Germany, the correlation of public interest and the geographical distribution of locally-acquired reported cases of endemic arboviral infections could be shown on a sub-country level.*

Conclusions. *The results of the analysis indicate that public interest in arboviral diseases in Europe is heavily impacted by perceived susceptibility on a temporal as well as on a spatial level. This result may be crucial for the design of future public health interventions to alert the public to the increasing risk of infection with arboviral diseases.*

Introduction

Arthropod-borne viruses, often abbreviated as arboviruses, are a group of RNA viruses which are mainly transmitted via hematophagous arthropod vectors between vertebrate hosts [1]. Arboviruses pathogenic to humans include dengue virus (DENV), yellow fever virus (YFV), chikungunya virus (CHIKV), Japanese encephalitis virus (JEV), West Nile virus (WNV), Crimean-Congo haemorrhagic fever virus (CCHFV), tick-borne encephalitis virus (TBEV), Rift Valley fever virus (RVFV), and Zika virus (ZIKV). While infections in humans are often asymptomatic, symptomatic infection can range from a mild febrile illness to severe disease such as encephalitis or haemorrhagic fever, which may cause long-term impairment and death [2, 3].

Arbovirus transmitting vectors, which include mosquitoes, ticks, fleas, and sandflies, are primarily found in tropical and subtropical regions [4, 5]. However, the geographical distribution of arboviral vectors and the frequency and magnitude of epidemics caused by arboviruses have been increasing globally during the past decades [6]. In sub-Saharan Africa, arboviral infections are expected to replace Malaria as most urgent public health problem [7]. DENV, endemic in only nine countries during the 1960s, has become endemic in more than 100 countries all over the world, causing an estimated 390 million infections per year with an eight-fold increase in the past two decades [6, 8, 9].

In Europe, climate change, urbanisation, and international mobility have led to the emergence of exotic arboviruses and to the geographical expansion of endemic arboviruses [10, 11]. In the past 40 years, five invasive mosquito species have established habitats on European territory [12], and locally-acquired, vector-borne cases of CHIKV, DENV, and ZIKV infection have been reported [13-15]. While infections with tick-borne CCHFV have remained at a low rate, its geographical range is expanding, with Spain reporting its first two CCHFV cases in 2016, and further cases in 2018 (two) and 2020 (three). WNV cases reached an unprecedent peak in 2018 with 1605 cases, a reported case rate eight times higher than the previous year [16, 17]. The European Centre for Disease Prevention and Control (ECDC) has called for immediate strengthening of surveillance and preparedness activities [18].

Awareness of arboviral diseases is not only considered important for clinicians in Europe [19-22]. Public awareness, interest, and knowledge of arboviral diseases are crucial to prevent and combat epidemics [23-25]. While public interest and its determinants have been analysed for select arboviral infections, disease vectors, and regions [26-29], a comprehensive study of public interest in arboviral diseases in Europe had not been attempted to date.

In recent years, Google Trends data has emerged as a powerful tool in healthcare research to assess online seeking behaviour as a representation of public interest and disease awareness [30-33]. Google Trends data represents the popularity of key words used to query the internet search engine Google, reflecting relative public interest and awareness [30, 34]. The Google Trends platform (trends.google.com) provides quantitative data on a country- and sub-country level since 2004 [35]. Relative popularity of a search term is measured by using a sample of Google searches, normalizing it to the location and time of a query, and scaling it on a range from zero to 100 to generate an interest index. A Google Trends value of 100 represents peak popularity of a query during the time period of interest at a specified location, while a value of 50 indicates 50% of the maximum search volume [35-37].

Google Trends is frequently used as a data analysis tool in healthcare research for infodemiological and infoveillance studies, e.g., to assess geographical and temporal web interest in diseases, disease awareness, online health information seeking behaviour as well as for the prediction of outbreaks and epidemics [31, 36-43]. In this study, we will use Google Trends data for a comprehensive spatio-temporal analysis of public interest in three endemic and three non-endemic arboviral diseases in 30 European countries from 2008 to 2020.

Aim and objectives

This study aims to assess public interest in emerging and re-emerging arboviral infectious diseases in the European population and identify its determinants. To achieve this, the following objectives were set: First, to assess public interest in arboviral diseases in Europe using Google Trends data since 2008. Second, to identify determinants of public interest in arboviral diseases in European countries based on the acquired data. Third, to explore the spatial correlation of public interest and case rates on a sub-country level, using the example of Germany in 2020.

Methods

Study design

Using a cross-sectional study design with observational data, data collection included the extraction of the complete available epidemiological data from 30 European countries on arboviral diseases with an average of at least five cases per year as well as the extraction of the complete available Google Trends data representing public interest in arboviral diseases in 30 European countries since 2008. Trends and patterns of public interest were described and analysed via ordinary least squares (OLS) regression [44].

Potential determinants and confounders of public interest such as reported case rates, the proportion of the foreign-born population, latitude, gross domestic product (GDP), and preventive care expenditure were examined in a Prais-Winsten regression analysis, which considers the spatio-temporal nature of the data and is a proven method for the analysis of disease interest using Google Trends data [32]. The independent variables for this analysis were chosen based on prior studies on specific arboviral diseases in select countries, which showed a correlation of public disease interest, awareness, and knowledge with incidence rates [27, 45], immigration status [46, 47], socio-economic status [28] and exposure to public health campaigns [29, 48].

Germany, Europe's most populous country, was selected for an analysis on a sub-country level, correlating Google Trends data from German federal states in 2020 with geographical coordinates via OLS regression and comparing the results to the locations of reported cases.

Acquisition and processing of epidemiological data

For the six arboviral diseases with an average of at least five reported human cases per year since 2008 (CCHFV, CHIKV, DENV, TBEV, WNV, and ZIKV infection), the reported case numbers and notification rates (per 100,000 population) for all available countries were extracted from the ECDC Surveillance Atlas of Infectious Diseases (SAID) database on January 10, 2022.

For all diseases except CCHFV infection, a categorisation into locally-acquired and travel-associated cases was provided. Rates of locally-acquired cases per 100,000 population were extracted for TBEV and WNV infection. For CHIKV, DENV, and ZIKV infection, rates of locally-acquired cases per 100,000 population were calculated using the numbers of locally-acquired reported cases per year and the World Bank total population per country data for the respective years (indicator code: SP.POP.TOTL) [49]. The extracted SAID data on ZIKV infection further included information on the number of reported infected pregnant women, with case rates being calculated accordingly.

Acquisition and processing of Google Trends data (public interest)

Google Trends query data reflecting public interest in these arboviral diseases was obtained from the Google Trends platform using the first "Disease" topic suggestion as respective keyword for each disease, e.g., chikungunya virus infection (Disease), on January 21, 2022, with the time frame being set from 2008 to present. Disease topics include various terms from queries in any language that are related to a specific disease [30].

Using the "compare" feature of Google Trends, the search volume can be compared between up to five different terms or regions. After identifying the country with the highest peak for each disease term, it was kept in each of the groups of five as a "benchmark" region, while the other four slots were taken by the remaining 29 countries in eight iterations to generate equally scaled data for all 30 countries.

Acquisition and processing of data for further variables

The gross domestic product (GDP) per capita in purchasing power parity (PPP) for all 30 European countries of interest from 2008 to 2020 was extracted from the World Bank database (indicator code: NY.GDP.PCAP.PP.CD) and converted to the natural log [50]. Geographical coordinates in decimal degrees for the 30 countries were taken from a public dataset provided on the Google developers platform [51]. Geographical coordinates in decimal degrees for the capitals of the 16 German federal states were extracted from https://www.gps-coordinates.net.

The indicators "health care expenditure for preventive care" as well as the more specific subcategory "health care expenditure for preventive care information, education and counseling", both as percentage of GDP, were extracted from the Eurostat dataset "health care expenditure by function" (online data code: HLTH_SHA11_HC, indicator codes: [HC6] and [HC6.1], respectively) for all available countries and years [52]. The foreign-born population per 1000 inhabitants was calculated for each country and year using the Eurostat indicator "foreign-born population" (indicator code: TPS00178) and the World Bank total population per country data (indicator code: SP.POP.TOTL) [49, 53].

Assessment of trends and patterns of online interest

For the assessment of trends and patterns of public interest in each disease, monthly Google Trends data points were averaged between all 30 countries. Data points reported as "< 1" were counted as 0.5. The Google Trends "compare "feature was used to compare the six benchmark countries for each disease term with each other. The maximum peak for each disease term and benchmark country was then used to scale the data for the other 29 countries in each disease category accordingly. After plotting the resulting values for each disease over time, trends and patterns were described. To analyse potential seasonal patterns further, Cochrane-Orcutt regression analyses with first-order serial correlation and iterated estimates were performed for each disease using the statistical software package Stata 17.0 and the 'prais' command [54, 55], with public interest in the respective disease averaged over 30 European countries as the dependent variable and the months of the year as (categorical, binary) independent variables (syntax: prais *depvar* [*indepvars*], corc). The analysis includes both original and transformed Durbin-Watson statistics. Autocorrelation plots were generated using the 'ac' command on the dependent variable (Supplementary Fig. 1). Two-tailed t tests were performed to determine the significance of coefficients of single variables, F statistics and Wald Chi-Squared tests to determine significance of Cochrane-Orcutt, OLS and Prais-Winsten regression models, respectively [56]. Significant p-values are indicated as follows: *** $p \le 0.001$; ** $p \le 0.01$; * $p \le 0.05$.

Spatio-temporal analysis of determinants of public interest

For the linear analysis of a variety of potential determinants of public interest, the monthly relative Google search volume indices reflecting public interest (not scaled between diseases) were summed up for each country, disease term, and year, to generate a value for yearly public interest, since all relevant co-variates are available as yearly values. The resulting data was used to compare public interest between countries for each disease separately.

To explore the correlation of public interest in each disease with multiple variables across all available countries and years, a linear cross-sectional time-series model with Prais-Winsten regression parameter estimation was used [57]. The Stata command 'xtpcse' computes panel corrected standard error estimates, assuming heteroskedastic and contemporaneously correlated disturbances across panels with a first-order autoregression (AR1) model autocorrelation structure [56, 58]. To compute the covariance, a pairwise selection was used to include all available observations with non-missing pairs (syntax: xtpcse *depvar* [*indepvars*], corr(ar1) pairwise). To assess the temporary nature of the influence of reported case rates on public interest, this independent variable was lagged by one year in an additional analysis using the command L1.*indepvar*. Further, the correlation of public interest and reported case rates was analysed for each country and each disease separately in bivariate OLS regression analyses using the Stata "reg" command.

Analysis of public interest on sub-country level

To analyse subregional public interest in TBEV and WNV in Germany in 2020, the Google Trends feature "interest by subregion" was used. It assigns the German federal state in which the disease term was most popular in 2020 a value of 100 and scales interest values for the remaining 15 states accordingly. States with insufficient data for the disease term are given a value of 0. The feature also includes a map of the country divided into its 16 federal states, indicating the relative popularity of a search term by colour shading. In multiple linear regression analyses using the Stata command reg, public interest values for each arboviral disease in the 16 German federal states were correlated with the geographical coordinates of the state capitals. The results were then compared to the locations of reported cases on maps marking districts with reported cases were generated on the SAID platform for the most recent available year (2020).

Results

Trends and patterns of public interest in arboviral diseases in Europe

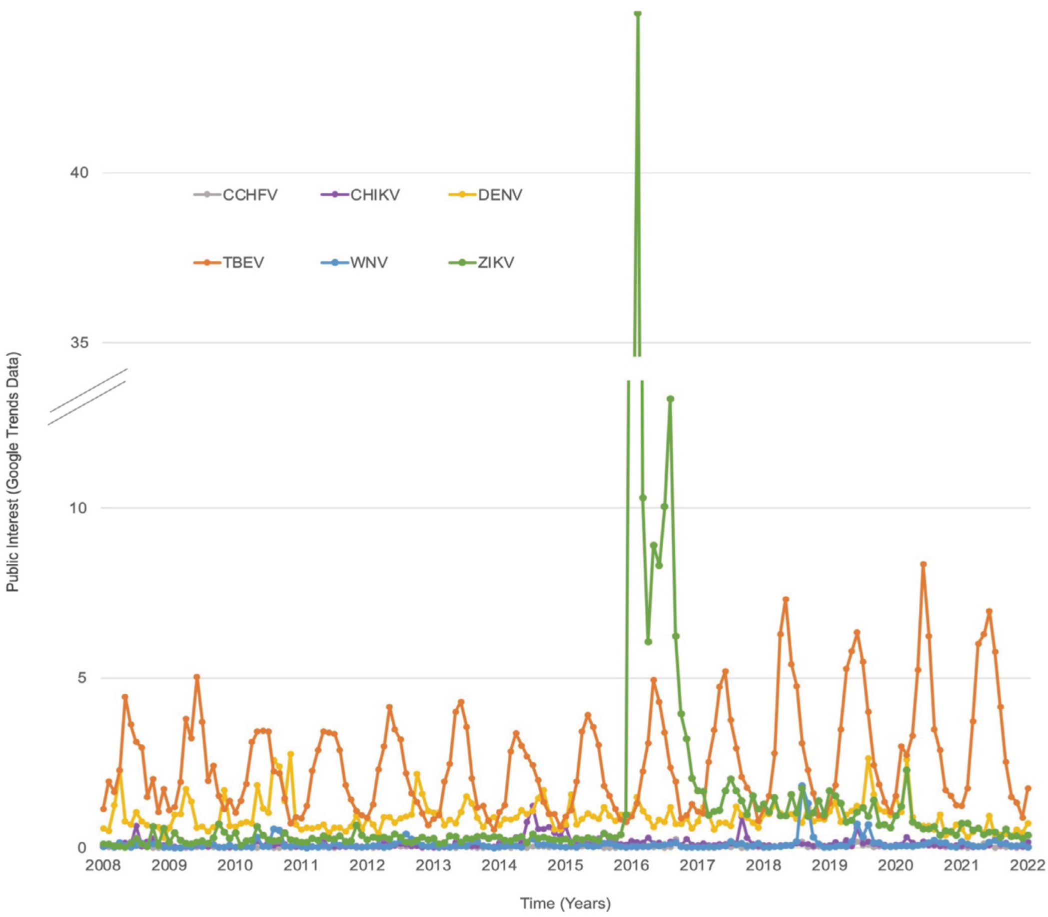
Six arboviral diseases with an average of at least five reported cases in Europe per year are recorded in the ECDC Surveillance Atlas of Infectious Diseases

(SAID). Of those, CCHFV, TBEV, and WNV infections are classified as endemic diseases in Europe, while CHIKV, DENV, and ZIKV infections are classified as non-endemic diseases [19, 59].

Public interest in the six arboviral infectious diseases in Europe was analysed using relative search volume indices generated from Google Trends data from January 2008 to January 2022. For each disease, the single highest interest peak in any of the 30 European countries served as a benchmark to scale the data points in any of the 29 remaining countries (see Methods). Using the Google Trends compare feature on the six benchmark countries and the respective disease, reveals how public interest values for the six different diseases relate to each other: Interest in ZIKV infection has by far the highest peak and keeps its value of 100, while data points for the other five diseases are scaled down accordingly, with peak interest in TBEV at 68%, DENV at 29%, WNV at 16%, CHIKV at 14%, and CCHFV at 6% of ZIKV peak interest. Transferring this scaling to the monthly data points averaged over all 30 countries for each disease, gives rise to Figure 1, with a ZIKV interest peak in 2016 being more than five times higher than the maximum TBEV interest peak in 2020, and values for interest in the other four diseases trailing far behind. After the abrupt initial spike in public interest in 2016 and 2017, ZIKV interest declined rapidly in subsequent years, even falling behind the interest values for TBEV and DENV infection.

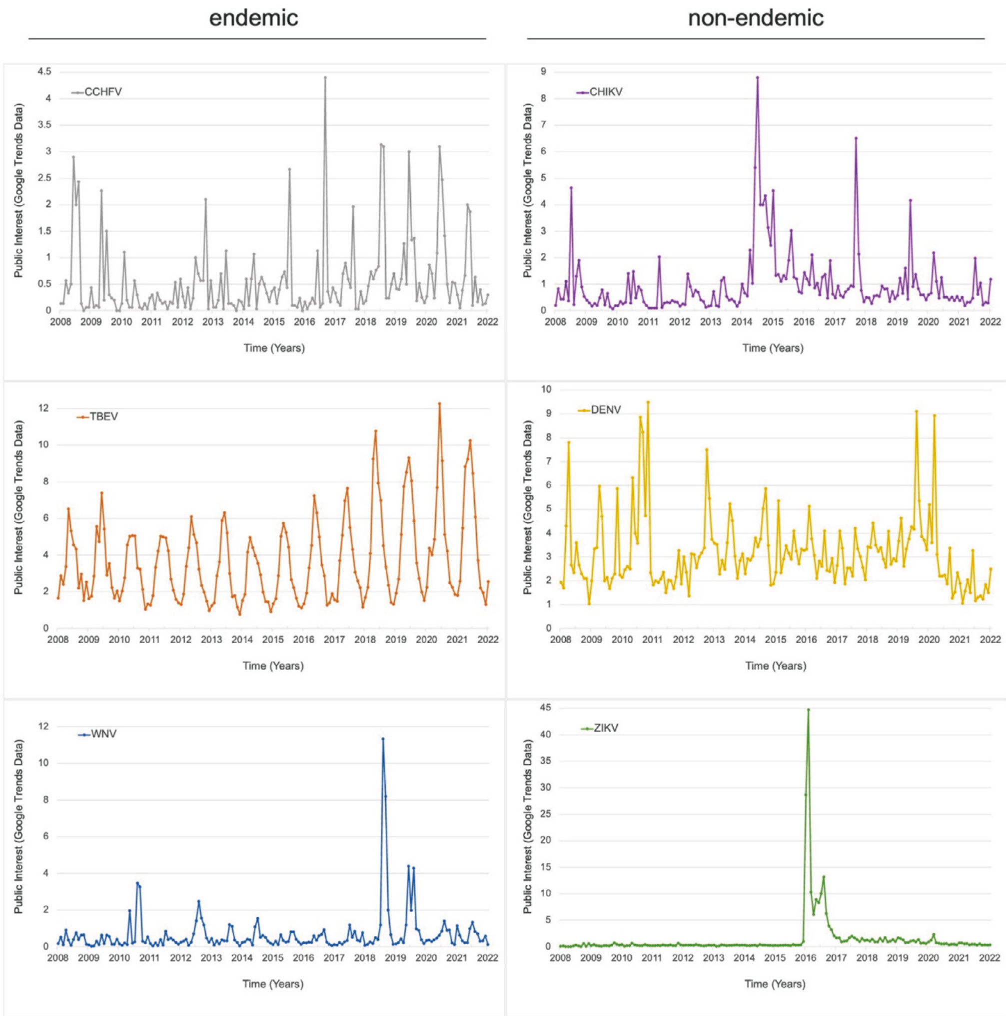
Visual inspection of the temporal distribution of public interest in arboviral diseases from January of 2008 to January of 2022 shown in Figure 1 indicates a distinct seasonal pattern for interest in TBEV infection, with a mid-year peak and a low point around the turn of the year. To investigate this phenomenon further, the average monthly public interest values for all six arboviral infectious diseases were plotted separately and unscaled between diseases (Fig. 2), revealing a more regular distribution for the three endemic diseases CCHFV, TBEV, and WNF infection, and an irregular course for the three non-endemic diseases CHIKV, DENV, and ZIKV infection.

Fig. 1. Comparison of public interest in six arboviral infectious diseases in 30 European countries.



Public interest is represented by Google Trends data from January of 2008 to January of 2022. For each disease, monthly data points were averaged over all 30 countries, then scaled according to the values of the respective benchmark countries (see Methods) to represent differences of public interest between diseases. To enhance legibility of data points with lower values of public interest compared, the y axis is broken between the values of 10 and 35.

Fig. 2. Seasonal trends of public interest in six arboviral infectious diseases in Europe.



Public interest is represented by Google Trends data from January of 2008 to January of 2022. For each of the diseases, monthly data points were averaged over all 30 countries. While the three endemic diseases CCHFV, TBEV, and WNV infection (left panel) show significant seasonal patterns, the three non-endemic diseases CHIKV, DENV, and ZIKV infection (right panel) do not (Tab. I). Public interest data is not scaled between diseases.

A Cochrane-Orcutt analysis, correlating the months of the year with public interest values for each disease, confirms this result (Tab. I): Models with public interest in the three endemic diseases are highly significant (F stats: p-value < 0.001), with maximum coefficients for the month of June for both CCHFV and TBEV, and for the month of August for WNV. Of the three models for endemic diseases, the model for TBEV shows the most distinct seasonal pattern with an adjusted R^2 of 0.65. While the coefficient for July has a slightly significant positive correlation with public interest in CHIKV infection and a negative correlation for the month of December for interest in ZIKV infection, the overall models for these two diseases are not significant, nor are the models for interest in DENV, the third non-endemic infectious disease.

As an additional independent variable, the overall order of observations was included in the respective models (Tab. I), with the first observation being January 2008 and the last (observation 168) being December 2021. Interestingly, the order of observations has a significant positive correlation for interest CCHFV and TBEV, indicating that only public interest in tick-borne endemic arboviral diseases has been increasing from 2008 to 2021. The increase of interest has the highest coefficient for TBEV (0.014), the arboviral disease with the highest and fastest increasing rate of locally-acquired cases in Europe, and lowest for CCHFV (0.003), the disease with the lowest case rate of the six. For WNV, the third endemic arboviral disease, public interest over time also has a slight positive coefficient (0.004), however it is not significant. No significant trend in public interest over time could be detected for any of the three non-endemic diseases.

While monthly public interest values seem to reveal seasonal patterns, plotting yearly values for each of the 30 European countries separately (Fig. 3) shows diverse

Tab. I. Seasonal patterns and trends of public interest in arboviral diseases in Europe from January 2008 to January 2022.

	Endemic in Europe			Non-endemic in Europe		
	Model CCHFV	Model TBEV	Model WNV	Model CHIKV	Model DENV	Model ZIKV
Independent variables	Coefficient (se)	Coefficient (se)	Coefficient (se)	Coefficient (se)	Coefficient (se)	Coefficient (se)
January	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted
February	0.058 (0.249)	**0.646* (0.260)**	-0.028 (0.303)	-0.096 (0.321)	0.419 (0.449)	1.075 (1.000)
March	0.113 (0.261)	**2.084*** (0.329)**	-0.003 (0.370)	-0.207 (0.394)	0.414 (0.538)	-1.381 (1.284)
April	0.207 (0.262)	**3.923*** (0.363)**	0.023 (0.399)	0.081 (0.426)	0.514 (0.572)	-1.870 (1.435)
May	0.496 (0.263)	**5.197*** (0.381)**	0.246 (0.412)	0.100 (0.440)	0.304 (0.586)	-1.659 (1.520)
June	**0.961*** (0.263)**	**5.421*** (0.390)**	0.477 (0.418)	0.484 (0.446)	0.078 (0.591)	-1.647 (1.563)
July	**0.844** (0.263)**	**4.265*** (0.393)**	0.615 (0.420)	0.994* (0.448)	0.111 (0.593)	-1.519 (1.577)
August	**0.674* (0.263)**	**2.461*** (0.391)**	**1.822*** (0.418)**	0.263 (0.447)	1.091 (0.592)	-1.323 (1.565)
September	0.264 (0.263)	**1.365*** (0.382)**	**1.247** (0.413)**	0.649 (0.441)	0.771 (0.586)	-1.882 (1.524)
October	0.100 (0.262)	0.582 (0.365)	0.333 (0.400)	0.178 (0.427)	0.127 (0.573)	-2.052 (1.443)
November	-0.069 (0.261)	0.025 (0.332)	0.0361 (0.373)	-0.056 (0.397)	0.713 (0.541)	-2.079 (1.299)
December	0.024 (0.249)	-0.150 (0.267)	-0.028 (0.309)	-0.269 (0.328)	-0.450 (0.457)	-2.210* (1.027)
Overall order of observations	**0.003* (0.001)**	**0.014*** (0.003)**	0.004 (0.003)	0.001 (0.003)	-0.003 (0.004)	-0.010 (0.015)
Constant	0.026 (0.216)	0.365 (0.421)	-0.048 (0.405)	0.683 (0.436)	3.134*** (0.550)	1.906 (1.833)
Rho	0.101	0.591	0.487	0.495	0.427	0.646
Adjusted r^2	0.142	0.647	0.131	0.021	0.023	-0.002
F stats (p)	**< 0.001*** **	**< 0.001*** **	**< 0.001*** **	0.223	0.206	0.473
D-statistic (original)	1.796	0.814	1.025	1.010	1.143	0.706
D-statistic (transformed)	2.000	1.932	1.838	2.24	2.081	1.701
N	167	167	167	167	167	167

Dependent variable: public interest in respective disease averaged over 30 European countries (Google Trends data). Models are estimated by an Cochrane-Orcutt AR(1) regression with iterated estimates including transformed Durbin-Watson (d) statistics. *** p ≤ 0.001; ** p ≤ 0.01; * p ≤ 0.05 (two-tailed tests). Coefficients with significant p-values are shown in light blue, with darker shades representing higher significance. Standard errors (se) are shown in parentheses below the coefficients. The month of January was omitted due to collinearity.

distributions across countries for all diseases except ZIKV infection, which has a characteristic, simultaneous course for all countries: Virtually no public interest until 2015, a rapid increase in 2015 and 2016, and a sharp decline in subsequent years.

Determinants of public interest in arboviral diseases in Europe

To examine the correlation of public interest in arboviral diseases in Europe with potential determinants and to control for possible confounders, five independent variables were included in a spatio-temporal analysis using data from 30 European countries from 2008 to 2020: reported case rates, geographical latitude of the country, percentage of foreign-born population, GDP per capita, and expenditure for preventive health care measures (Tab. II).

Reported case rates are the only variable that consistently correlates significantly with public interest in all six arboviral infectious diseases [p-values: 0.016 (CCHFV), 0.003 (DENV), < 0.001 (CHIKV, TBEV, WNV, ZIKV)]. All coefficients are positive, with the highest values for CCHFV, ZIKV, and CHIKV infection. However, this effect is only temporary: If reported case rates are lagged by just one year, the significant correlation disappears for all six diseases.
Geographical latitude has a negative correlation with public interest in all diseases but TBEV infection, meaning that interest is higher in Northern countries for TBEV, but higher in Southern countries for all others (significant results for CCHFV (p-value < 0.001), CHIKV (p-value = 0.015), and TBEV (p-value = 0.018)) (Tab. II).
The foreign-born population per 1000 inhabitants has a significant positive correlation only with public interest

Fig. 3. Diverse patterns of yearly public interest in arboviral infectious diseases in 30 European countries.

Monthly Google Trends data points from 2008 to 2020 were summed up over 12 months for each country and disease.

in ZIKV infection (p-value = 0.006). Correlation with GDP per capita (in PPP) has positive coefficients for public interest in all six diseases [significant for CCHFV (p-value = 0.043) and DENV (p-value = 0.001)], indicating a higher interest in countries with higher GDPs.

Only interest in DENV and ZIKV infection have a significant positive correlation with expenditure for preventive health care measures (p-values = 0.023 and 0.029, respectively; Tab. II). Using the more specific indicator "expenditure for preventive care information, education, and counselling programmes", however, does not result in a significant correlation with public interest in any of the diseases. Replacing the reported case rate variable with rates for only locally-acquired cases, however, leads to highly significant positive correlations for public interest in CHIKV, TBEV, and WNV (p-values < 0.001; Tab. IIIA). For the DENV model, results are not significant. For CCHFV case data, no distinction was made between locally-acquired and travel-associated cases. For the ZIKV model, the number of observations is insufficient for an analysis using locally-acquired cases. However, public interest in ZIKV is highly correlated with the case rates of ZIKV infected pregnant women (p-value = 0.004; Tab. IIIB).

Analysing public interest each of the 30 European countries separately, using reported case rates as the sole determinant in a simple linear regression is sufficient to explain variation in public interest in more than 40% of countries (p-values ≤ 0.05). For each of the six arboviral

Tab. II. Determinants of public interest in emerging arboviral diseases in Europe.

	Model	Model	Model	Model	Model	Model
	CCHFV	TBEV	WNV	CHIKV	DENV	ZIKV
Independent variables	Coefficient (se)	Coefficient (se)	Coefficient (se)	Coefficient (se)	Coefficient (se)	Coefficient (se)
Reported case rate	228.696* (94.925)	8.038*** (1.374)	21.807*** (2.995)	124.913*** (12.907)	12.056** (4.081)	141.976*** (31.696)
Latitude	-0.365*** (0.085)	2.346* (0.989)	-0.184 (0.182)	-0.710* (0.292)	-0.622 (0.360)	-0.059 (0.225)
Foreign-born population (per 1,000 inhabitants)	-0.007 (0.008)	-0.026 (0.018)	-0.008 (0.008)	0.019 (0.016)	-0.030 (0.020)	0.148** (0.054)
Gdp per capita (ln PPP)	8.817* (4.262)	7.351 (8.691)	4.453 (4.133)	13.373 (12.059)	28.127*** (8.345)	11.252 (21.206)
Preventive care expenditure (% of GDP)	12.045 (9.901)	46.821 (38.586)	18.582 (20.276)	-34.587 (28.619)	46.801* (20.578)	34.280* (15.705)
Constant	-70.009 (45.424)	-169.262* (70.394)	-34.050 (42.773)	-92.794 (116.036)	-236.919** (86.324)	-111.641 (207.521)
R^2	0.077	0.306	0.262	0.447	0.214	0.350
N observations	228	159	223	202	220	97
N countries	28	26	28	25	27	26
Wald Chi^2	43.29***	73.30***	72.91***	115.52***	133.78***	142.13***
Rho	0.311	0.691	0.477	0.397	0.361	-0.110

Models are estimated by a Prais-Winsten regression with correlated panel-corrected standard errors and a first-order auto-regressive error process. *** p ≤ 0.001; ** p ≤ 0.01; * p ≤ 0.05 (two-tailed tests). Coefficients with significant p-values are shown in light blue, with darker shades representing higher significance. Standard errors (se) are shown in parentheses below the coefficients.

Tab. III. Models using case rates for locally-acquired cases and infections in pregnant women.

A				B	
	Model	Model	Model		Model
	CHIKV	TBEV	WNV		ZIKV
Independent variables	Coefficient (se)	Coefficient (se)	Coefficient (se)	Independent variables	Coefficient (se)
Reported locally acquired case rate	248.742*** (12.670)	8.064*** (1.436)	21.595*** (3.023)	Reported case rate in pregnant women	1183.424** (411.709)
Latitude	-0.685** (0.260)	2.798** (1.024)	-0.95 (0.180)	Latitude	-0.229 (0.379)
Foreign-born population (per 1,000 inhabitants)	0.0253226 (0.030)	-0.028 (0.018)	-0.008 (0.008)	Foreign-born population (per 1,000 inhabitants)	0.233*** (0.071)
GDP per capita (ln PPP)	20.738 (13.824)	3.574 (8.929)	4.466 (4.118)	GDP per capita (ln PPP)	22.971 (26.918)
Preventive care expenditure (% of GDP)	-8.622 (20.686)	46.163 (39.202)	19.043 (20.558)	Preventive care expenditure (% of GDP)	-3.550 (19.252)
Constant	-171.760 (128.903)	-149.653* (67.699)	-33.575 (42.823)	Constant	-222.967 (251.492)
R^2	0.171	0.311	0.247	R^2	0.249
N observations	194	149	223	N observations	97
N groups	25	26	28	N groups	26
Wald Chi^2	139.66***	89.77***	72.21***	Wald Chi^2	56.94***

(A) Replacing the independent variable "reported case rate" with "reported locally-acquired case rate". **(B)** A model using reported case rates of ZIKV infection in pregnant women. Dependent variable: public interest in respective disease in 30 European countries (Google Trends data). Models are estimated by a Prais-Winsten regression with correlated panel-corrected standard errors and a first-order auto-regressive error process. *** p ≤ 0.001; ** p ≤ 0.01; * p ≤ 0.05 (two-tailed tests). Coefficients with significant p-values are shown in light blue, with darker shades representing higher significance. Standard errors (se) are shown in parentheses below the coefficients.

infections, the countries with the most significant coefficients for the correlation of public interest with case rates are shown in Figure 4. The plots show public interest based on Google Trends data closely following reported case rates. For interest in CCHFV infection, however, Spain is the only country with a significant correlation (p-value < 0.001) due to a low number of cases. Interest in ZIKV infections yields the highest

Fig. 4. Reported cases and public interest in arboviral diseases in individual European countries over time.

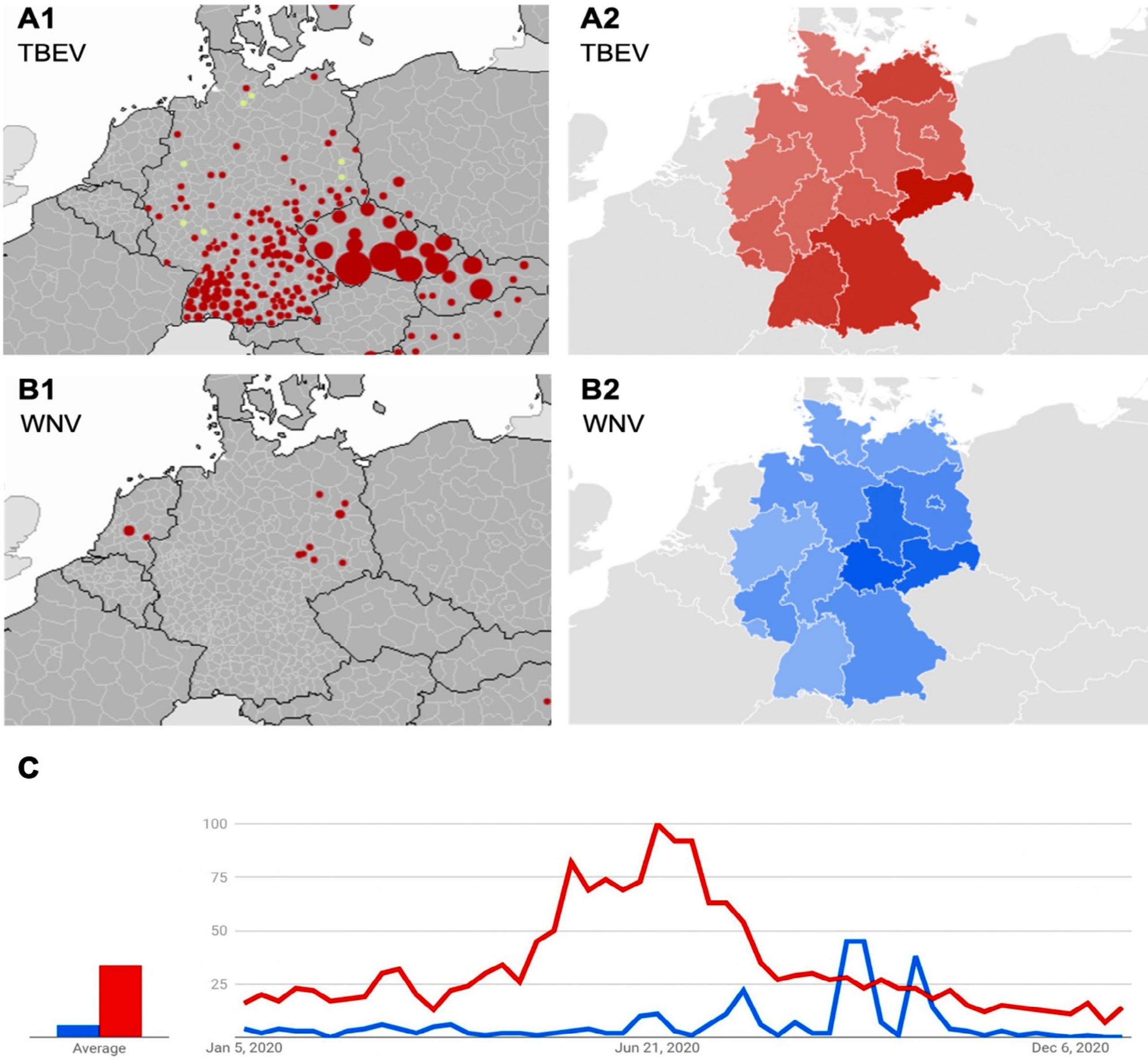
For each of the six arboviral infections, plots are shown for the countries with the most significant coefficients (p ≤ 0.05) from a bivariate analysis using reported case rates as only independent variable. For CCHFV, Spain is the only country with a significant correlation due to a low number of data points.

percentage of countries with a significant bivariate model (68 % out of all countries with sufficient data), followed by 53 % for WNV, 38 % for CHIKV, 28 % for TBEV, 27 % for DENV, and 25 % for CCHFV infection (p-values ≤ 0.05).

Public interest in arboviral diseases on sub-country level (case study: Germany)

In the ECDC Surveillance Atlas of Infectious Disease, reported case data on a sub-country level is only available for the endemic arboviral infections with TBEV and WNV

Fig. 5. Subregional analysis of TBEV and WNV in Germany in 2020.



Red dots mark regions that report one or more locally acquired confirmed cases of TBEV **(A1)** and WNV **(B1)**, with larger dot sizes representing a higher number of cases. Green dots mark regions that report zero cases. Public interest in TBEV infections is higher in federal German states located in the South-East of the country **(A2)**, while public interest in WNV infections is higher in Eastern German states **(B2, Tab. IV)**. **(C)** Comparison of weekly public interest in TBEV (red) and WNV (blue) infections over the course of 2020. Maps and plots were created using the ECDC Surveillance Atlas of Infectious Diseases database **(A1, B1)** and the Google Trends platform **(A2, B2, C)**.

(ECDC, 2022f). In 2020, TBEV cases were clustered in the South-Eastern part of Germany, while WNV cases were exclusively reported in the Eastern region, as can be seen in Figures 5A1 and 5B1, respectively.

For Germany, public interest data is available on a federal state level on the Google Trends platform. A visual inspection of the Google Trends "interest by subregion" visualisation of TBEV and WNV interest in Germany in 2020 shows increased interest in TBEV infection in the South-Eastern region of the country and increased interest in WNV infection in the Central-Eastern part (Figs. 5A2 and 5B2, respectively), congruent with the areas of reported infections.

To confirm this observation, a multiple linear regression analysis was performed, correlating public interest values for each of the six arboviral diseases on a federal state level with the geographical coordinates (latitude and longitude in decimal degrees) of each state's capital (Tab. IV).

Only the models for the two diseases endemic in Germany, TBEV and WNV, had significant results (F stats: p-values = 0.004 and 0.007, respectively), with a significant negative correlation of latitude and a positive correlation of longitude for TBEV interest (p-values = 0.003 and 0.013, respectively) and a positive correlation of longitude for WNV interest

Tab. IV. Correlation of TBEV and WNV public interest in Germany in 2020 with geographical coordinates.

	Model CCHFV	Model TBEV	Model WNV	Model CHIKV	Model DENV	Model ZIKV
Independent variables	Coefficient (se)	Coefficient (se)	Coefficient (se)	Coefficient (se)	Coefficient (se)	Coefficient (se)
Latitude	1.122 (4.571)	**-7.024**** **(1.941)**	-3.086 (2.651)	-9.962* (4.616)	-4.377 (3.026)	-6.475 (4.975)
Longitude	3.802 (3.903)	**4.756*** **(1.657)**	**8.793**** **(2.264)**	1.803 (3.942)	-3.029 (2.5849)	6.855 (4.249)
Constant	-62.990 (130.614)	371.352 (96.741)	118.005 (132.127)	526.204 (230.083)	309.716 (150.842)	297.677 (247.992)
Adjusted R^2	-0.054	0.499	0.466	0.151	0.154	0.086
F stats (p)	0.556	0.004**	0.007**	0.136	0.133	0.220
N (regions)	16	16	16	16	16	16

Dependent variable: public interest in respective disease in 16 German federal states (Google Trends data). Models are estimated by OLS regression. *** p ≤ 0.001; ** p ≤ 0.01; * p ≤ 0.05 (two-tailed tests). Standard errors (se) are shown in parentheses below the coefficients. The independent variables latitude and longitude constitute the geographical coordinates for the respective German state capitals.

(p-value = 0.002), confirming that interest in TBEV is highest in the South-East and interest in WNV is highest in the East of Germany. While the coefficient for latitude shows a slightly significant negative correlation with CHIKV interest (p-value = 0.050), the overall CHIKV model is not significant (F stats: p-value = 0.136), nor are any of the other models for interest in non-endemic diseases.

Overall, public interest in TBEV infection in 2020 was more than six-fold higher than public interest in WNV infection (Fig. 5C), with a broad peak for TBEV interest in the summer months and narrower peaks for WNV later in the year.

Discussion

Only public interest in endemic arboviral diseases increases and shows seasonal patterns

An analysis of trends and patterns of public interest in arboviral diseases across 30 European countries from 2008 to 2020 showed that significant seasonal patterns of public interest are only present in the endemic viral diseases, CCHFV, TBEV, and WNV infection, with (F statistic) p-values for each of the models below 0.001. For WNV, the two months of August and September show a significant seasonal increase of public interest, for CCHFV the three months from June to August. For TBEV, however, public interest increases most significantly during the seven months from March to September. These months closely match the seasons during which the underlying disease vectors – ticks for TBEV and CCHFV as well as *Culex* mosquitoes for WNV– are most active [60, 61].

While this analysis is the first to include a comprehensive set of arboviral diseases and countries, a seasonal pattern of public interest has previously been shown for select countries and arboviral disease-associated terms. Jensen et al. (2022) use Google Trends data of search terms synonymous with "tick(s)" in nine European countries and identify seasonal patterns that represent changes in precipitation and temperature [62], in accordance with the findings in this analysis.

Interestingly, the analysis of patterns and trends also showed that public interest in the two tick-borne endemic arboviral diseases, CCHFV and TBEV infections, was increasing significantly, while public interest in the three non-endemic arboviral diseases, *Aedes* mosquito-borne CHIKV, DENV, and ZIKV infections, showed no significant trends.

Both the existence of seasonal patterns and the increasing trends of public interest in only endemic arboviral diseases may be explained by the Health Belief Model, which maintains that health-related behaviours are more likely to occur when the perceived susceptibility to developing a health problem is high [63-65]. A population's perceived susceptibility to a disease which is already endemic would naturally be higher than to one that has not yet reached endemic status. The likelihood of catching an arboviral infection also increases temporarily during the seasons in which the respective disease vectors, i.e., ticks and mosquitoes, are most active, resulting in health-related behaviours, which in this case manifests itself in the online search for information on the disease.

Other key constructs of the Health Belief Model include perceived severity of the disease as well as perceived barriers and perceived benefits of the health action, the last of which may be a decreased risk of an arboviral infection due to preventive measures or the timely identification of symptoms of an arboviral infection, enabling the infected to seek appropriate medical treatment [66]. The concepts "cue to action" and "self-efficacy" were added to the Health Belief Model in more recent adaptions and refer to a stimulus to undertake the health action and to the self-confidence in the ability to perform the health action, respectively [65].

Among the three analysed endemic arboviral diseases, TBEV has both the highest coefficient for the increase of public interest and the fastest increasing rate of locally-acquired cases, while CCHFV, the arboviral disease with the lowest case rate, has the lowest – yet significant – positive coefficient for public interest, showing that interest in CCHFV is growing comparatively slowly.

This result indicates a correlation of public interest and case rates, which was investigated in more detail in the subsequent analysis and will be discussed in the following section.

Case rates drive public interest in arboviral diseases - but only temporarily

In a spatio-temporal Prais-Winsten regression analysis using Google Trends data from 2008 to 2020 across 30 European countries, reported case rates was the only one of five independent variables (see study design) to correlate significantly with public interest in all six analysed arboviral diseases, confirming the previous indication that case rates are an important driver of public interest ($p < 0.001$ for TBEV, WNV, CHIKV, and ZIKV; $p < 0.01$ for DENV, $p < 0.05$ for CCHFV).

The identified correlation of public interest in arboviral diseases and incidence rates in Europe is in accordance with results from studies in select countries for arboviral infections like WNV in Italy [27], DENV in Mexico [67] as well as for other viral infections such as Ebola in West Africa [68] and influenza in the United States [69].

Due to this correlation, Google Trends data was shown to be a valuable source of information for surveillance and dynamic prognostic tools to predict outbreaks and epidemics, using Google queries of disease terms such as "Zika" and "chikungunya" in Venezuela [43], of disease vectors like "ticks" in Sweden [42] or of common disease symptoms such as "bone pain" and "fever" in Singapore [70]. While surveillance via Google Trends data is considerably less expensive than conventional surveillance methods, the novel technique has also raised concerns that search queries could be more influenced by the media than by the actual disease burden, and may not be suitable for either widespread diseases with low media coverage or for rare diseases with high media coverage [71, 72].

Our analysis also revealed the temporary nature of the correlation of public interest and reported case rates. The significant correlation of yearly public interest values and reported case rates is lost for all six arboviral infections when values of reported case rates are lagged by one year. This transiency of public interest based on yearly Google Trends values confirms the previous result showing the seasonality of monthly values, indicating that public interest in arboviral diseases immediately declines when the risk of infection – or the perceived susceptibility, as stated in the Health Belief model – decreases again.

The impermanence of public interest in arboviral infections becomes immediately obvious when looking at the example of interest in Zika. For decades ZIKV had been endemic in Africa and Asia, before the Asian lineage started spreading to naïve areas, causing massive outbreaks in Micronesia in 2007, French Polynesia and other Pacific islands from 2013 on [73]. The ECDC only started recording cases after the large outbreak in South America in 2015/16, when the WHO declared ZIKV infections a "Public Health Emergency of International Concern" and clusters of foetal malformations and neurological disorder emerged [74]. After a sharp increase from 2015 to 2016, ZIKV cases have declined rapidly – and so has public interest in all European countries. At the time of writing, ECDC data for ZIKV infection is only available until 2019, which is the year the first three European cases of vector-borne ZIKV transmission were reported in France [75, 76]. Future analyses will need to determine whether vector-borne acquisition via local *Aedes albopictus* mosquitoes becomes a major transmission mode for ZIKV infections in Europe, and what effect this development may have on public interest in the disease.

The finding that public interest in diseases – represented by online health information-seeking behaviour – may be short-lived, matches results from Google Trends analyses in other contexts: The analysis of Google Trends data from six countries on the Arabian Peninsula before and after four different public health interventions, i.e., "Global Public Health Days", which were supposed to raise awareness for specific health topics such as diabetes and hypertension, showed that the search volume declined by up to 80 % within a week of peak interest [77].

Public health interventions like these awareness campaigns have also been considered in our analysis, by including the annual preventive care expenditure per country as an independent variable. However, the results show that preventive care expenditure (as percentage of the GDP) had a significant positive correlation only with public interest in DENV and ZIKV infection ($p = 0.023$ and 0.029, respectively), two closely related viruses that are primarily transmitted by *Aedes aegypti* mosquitoes [78] and have the lowest yearly average number of locally-acquired cases in Europe (5.4 and 5.8, respectively). It may be speculated that prior to public health campaigns, public awareness and knowledge is lowest for the infections with the lowest number of local transmissions, and interventions may therefore have the greatest effect.

Analysing only locally-acquired cases also shows a high positive correlation with public interest in the respective arboviral diseases, with significant results for CHIKV, WNV, and TBEV ($p < 0.001$ for all) and larger coefficients compared to the analysis using the total case rates. For ZIKV, public interest is correlated positively with the case rates of infected pregnant women ($p = 0.004$), with a coefficient more than eight times higher than for total case rates. This effect may be explained by the phenomenon that risk is perceived as being higher when future generations are potentially impacted [79-81]. Lozano et al. (2021) propose that an overestimation of the perceived risk of ZIKV transmission compared to other arboviruses is mainly caused by the fact that ZIKV is known to cause malformations in foetuses of pregnant infected women [81].

A difference in perceived risk or susceptibility may also be the reason why – even when controlling for the countries' case rates – public interest in arboviral infections with viruses that are widespread in tropical and subtropical regions such as CCHFV and CHIKV is significantly higher in European countries at a lower geographical latitude ($p < 0.001$ and $p = 0.015$, respectively), while public interest in TBEV, which is more prevalent in regions with cooler climates, is positively correlated with countries at a higher latitude ($p = 0.018$).

Spatial correlation of public interest in arboviral diseases can be shown on sub-country level

The identified correlation of public interest and geographical location could also be shown on a sub-country level in a case study using Google Trends data from the 16 German federal states in 2020. In an OLS regression, geographical coordinates of the state capitals were correlated with public interest in TBEV and WNV infection, the two arboviral diseases that are endemic in Germany. The results of this analysis showed that public interest in TBEV correlates significantly with South-Eastern coordinates, while public interest in WNV correlates significantly with Eastern coordinates. These geographical distributions closely match the locations of locally-acquired infections of the respective diseases in Germany in 2020, according to maps extracted from the ECDC Surveillance Atlas of Infectious diseases.

For WNV in Europe, the main geographical distribution are countries is in the South-East. However, an Eastern-German cluster has formed in recent years, with a distinct group of WNV strains termed the "Eastern German WNV clade" [82]. Even though TBEV infection is generally more widespread in Northern-European regions, in Germany, the main TBEV risk areas are located in the woodland habitats of the Southern States of Bavaria and Baden-Württemberg as well as the Eastern States of Thuringia and Saxony [83]. Interestingly, a significant correlation of geographical coordinates of public interest and geographical coordinates does not exist for any of the other four arboviral diseases, all of which are non-endemic in Germany.

The findings of this analysis indicate that perceived susceptibility, an important element in the Health Belief Model [63] as discussed above, also influences public interest in arboviral diseases on a sub-country level. The use of subregional Google Trends data has already proven to be useful in other contexts: In the United States, influenza-related Google queries have been used to improve flu surveillance on a state level [84]. For TBEV, a precise knowledge of the location of infections is particularly crucial, since TBEV infested ticks are known to cluster in specific focus areas [85-87].

The results of our spatio-temporal analysis point to perceived susceptibility as the main driver of public interest in arboviral diseases in Europe on all levels. This finding is in accordance with a qualitative study of vector control strategies following the ZIKV epidemic of 2015/16 in Brazil, which revealed susceptibility to infection to be a key influence on the engagement in health protection measures [88]. In Indonesia, a cross-sectional study on behaviour to prevent DENV infection found that participants with a higher perceived susceptibility showed better prevention behaviour [89]. However, an evaluation of public health messages on *Aedes aegypti* mosquito-transmitted arboviruses in Brazil discovered that less than a third of messages were aiming to convey perceived susceptibility, while "cue to action" was the most frequently featured concept of the Health Belief Model [90].

Limitations of analysis

This study is subject to several limitations. In our analysis, only arboviral diseases in the ECDC SAID with an average of at least five reported human cases per year since 2008 were considered. This excludes other arboviruses that are considered potential threats to humans in Europe [59, 91, 92], but had either an insufficient reported case count such as infections with RVFV, YFV, and the SAID category "other viral haemorrhagic fevers", or are not at all covered in the SAID, such as JEV, Usutu virus, Toscana virus, and louping ill virus infections.

A valid Google Trends analysis depends on the correct selection of key words. This may be complicated by the comparison of trends across countries with different languages as well as by queries with alternative spellings and nomenclatures [30]. Since suggested "disease topics" such as "Zika fever (Disease)" instead of individual search terms were selected for the analysis in this dissertation, queries cover a group of terms related to the disease topic that share "the same concept in any language" [35]. While this approach solves the problems regarding language, nomenclature, and spelling, the exact key words included in each disease topic are not public and can therefore not be evaluated. However, the "related queries" section on the platform includes queries searched for by users who also searched for the topic in question and may give an indication of the contents aggregated within disease topics (*the most popular related queries for the six disease topics for 30 European countries are available as Supplemental Data*). While related queries for tick-borne encephalitis (TBE) include apparent misspellings of the video platform YouTube ("you tbe"), the very distinct seasonal pattern of the TBE disease topic makes it seem unlikely that this related query, which has no apparent seasonal trends, has been included. In some countries, related queries refer to more specific encephalitis subtypes caused by TBEV, such as the abbreviation FSME for early summer meningoencephalitis in Germany, Austria, and Luxemburg. However, some queries also refer to unrelated tick-borne infections such as borreliosis. In other cases, a lack of searches may not reflect a lack of interest but a lack of inclusion of proper search terms in the disease topic. While a distortion of results cannot be ruled out, it has likely been at least partially mitigated by the simultaneous analysis of queries across 30 countries and the separate analyses for each disease, levelling out potential biases arising from the tool's inclusion of key words for disease topics.

A further limitation of Google Trends analyses may arise through the fact that only a sample of the billions of Google searches per data is used to generate Google Trends data [35]. For regions of interest that are small, sampling noise may be extensive [93] and results should be evaluated with caution. To keep sampling noise as low as possible for the analysis on sub-country level, the most populous European country, Germany, was selected for the case study.

In some cases, public interest in arboviral diseases may have been substantially influenced by variables not included in this analysis. Hantavirus haemorrhagic fever and hantavirus pulmonary syndrome are emerging diseases in Europe that are not caused by an arbovirus but by a rodent-borne virus (robovirus), orthohantavirus or hantavirus [93, 94]. In late March 2020, shortly after the onset of the COVID-19 pandemic, Google searches for keywords related to orthohantavirus spiked more than 10 times higher than the previous maximum peak in the Google Trends data, which dates back to 2004 [95]. This sudden increase of interest does not seem to have been caused by rising incidence rates. On the contrary, the number of reported hantavirus infections in 2020 had dropped to its lowest point since the start of ECDC reporting in 2008 [96]. However, a "viral" post claiming that hantavirus had emerged as a new fatal virus in China and could potentially cause a COVID-19 like pandemic, had started spreading rapidly across social media after one fatal case of hantavirus infection had been reported in the Chinese Shandong province on March 24, 2020 [97-99]. This example shows that random and seemingly minor occurrences like a single fatality may have a major and hardly predictable impact on public interest in diseases. Triggers for these phenomena may not always be identifiable in retrospect.

Less surprisingly, a major world event such as the COVID-19 pandemic may have influenced public interest in other viral diseases as well, either by drawing attention to or deflecting attention from other potential viral threats. However, the data collected for this analysis does not seem to show outliers for public disease interest in 2020 compared to other years.

The COVID-19 pandemic also may have had an impact on reported case rates of arboviral diseases through travel restrictions, rising outdoor activities, and underdiagnoses due to overburdened healthcare systems. Underdiagnoses, however, do not only occur during a global pandemic. Especially emerging diseases are frequently underdiagnosed due to a lack of knowledge among clinicians as well as due to insufficient standardised diagnostic testing methods when unexplained and non-specific febrile illnesses occur [19, 22].

Conclusion

This work marks the first comprehensive spatio-temporal analysis of Google Trends data from 30 European countries to assess trends, patterns, and determinants of public interest in emerging and re-emerging arboviral diseases.

The results of this analysis indicate that public interest in arboviral diseases in Europe is heavily impacted by perceived susceptibility on a temporal as well as on a spatial level. Only public interest in the three endemic arboviral diseases, CCHFV, TBEV, and WNV, displayed significant seasonal patterns, with a significant increase of public interest since 2008 for the tick-borne infections with CCHFV and TBEV. While controlling for potential confounders, a Prais-Winsten regression showed that public interest in all six analysed arboviral diseases, including non-endemic CHIKV, DENV, and ZIKV infections, is driven by reported case rates. This effect is temporary, and public interest drops rapidly when cases decline. A correlation of public interest in arboviral infections and the geographical distribution of locally-acquired reported cases could be shown both on a country level in Europe as well as on a sub-country level in a case study using Google Trends data from German federal states.

In future studies, the presented results could be validated and supplemented by further quantitative analyses that include other novel data streams such as Twitter data and Wikipedia edits as well as traditional data collection methods such as surveys. The latter would enable both the acquisition of demographic metadata and an evaluation of the impact of specific public health interventions and awareness campaigns on public interest arboviral diseases. Future public health interventions should focus on perceived susceptibility being the main driver of public interest and attempt to alert the public to the increasing risk of infection with currently non-endemic arboviral diseases.

Ethical approval

Ethical approval for this study was obtained from the Ethics Committee at the Health Department of the University of Essex Online prior to data acquisition

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Conflict of interest statement

The author declares no conflict of interest.

Authors' contributions

The author developed the research concept and design, collected and analysed the data, interpreted the results and wrote the manuscript.

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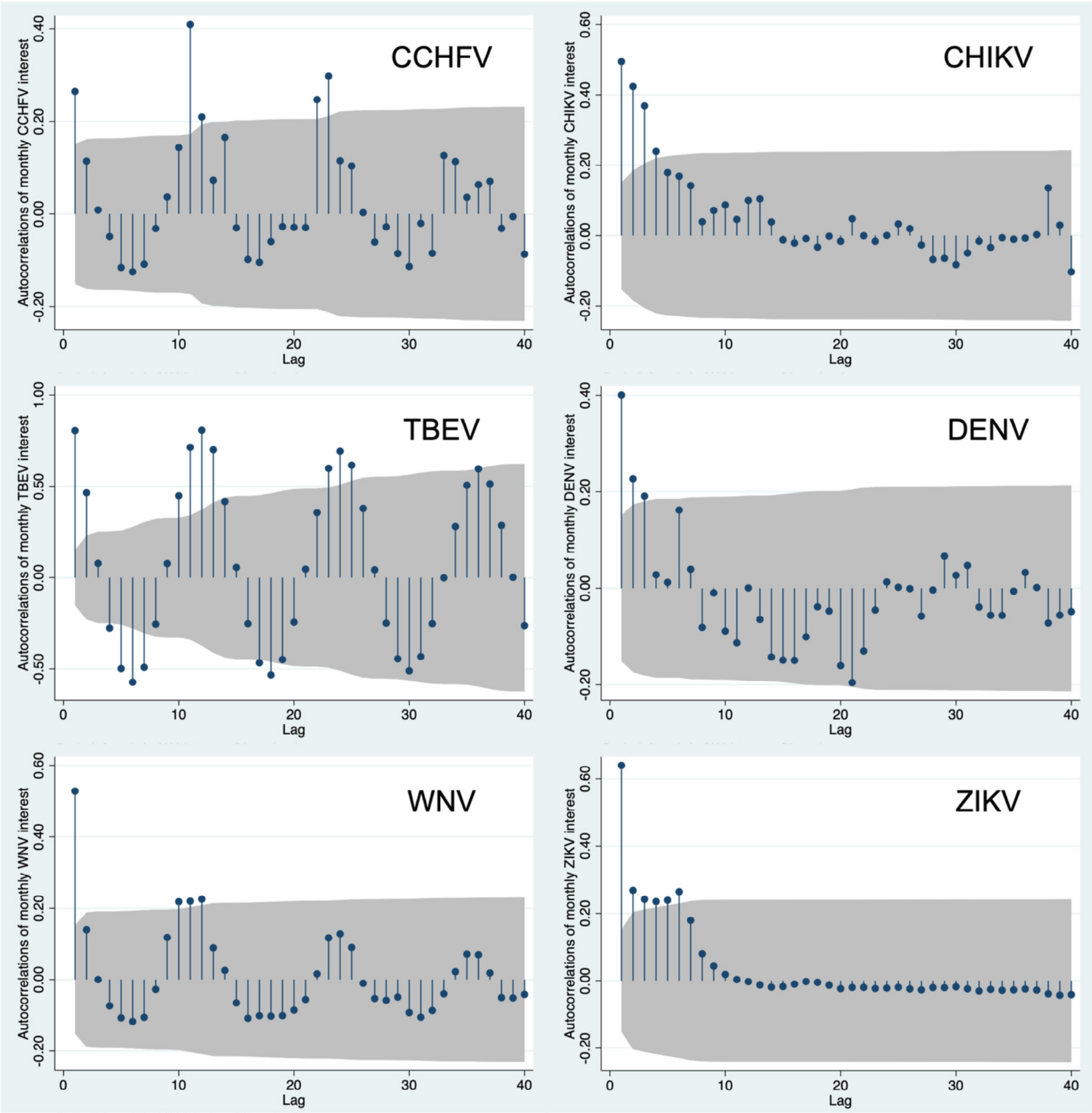
Supplementary Fig. 1. Autocorrelation plots of monthly disease interest averaged over 30 European countries from January 2008 to January 2022.



The autocorrelation visible in the plots is corrected by using an Cochrane-Orcutt AR(1) regression with iterated estimate for the analysis of trends and patterns of public interest.