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Research article

Pooled lagged effect of runoff on leptospirosis cases in Colombia

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ABSTRACT

Leptospirosis is a global zoonotic disease caused by spirochete bacteria of the genus *Leptospira*. The disease exhibits a notable incidence in tropical and developing countries, and in Colombia, environmental, economic, social, and cultural conditions favor disease transmission, directly impacting both mortality and morbidity rates. Our objective was to establish the pooled lagged effect of runoff on leptospirosis cases in Colombia. For our study, we included the top 20 Colombian municipalities with the highest number of leptospirosis cases. Monthly cases of leptospirosis, confirmed by laboratory tests and spanning from 2007 to 2022, were obtained from the National Public Health Surveillance System. Additionally, we collected monthly runoff and atmospheric and oceanic data from remote sensors. Multidimensional poverty index values for each municipality were sourced from the Terridata repository. We employed causal inference and distributed lag nonlinear models to estimate the lagged effect of runoff on leptospirosis cases. Municipality-specific estimates were combined through meta-analysis to derive a single estimate for all municipalities under study. The pooled results for the 20 municipalities suggest a lagged effect for the 0 to 2, and 0–3 months of runoff on leptospirosis when the runoff is < 120 g/m^2. No effect was identified for longer lagged periods (0–1, 0 to 4, 0 to 5, and 0–6 months) or higher runoff values. Incorporation of the multidimensional poverty index into the meta-analysis of runoff contributed to the models for the lagged periods of 0–3, and 0–4 months.

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1. Introduction

Leptospirosis is a global zoonotic disease affecting humans and animals in both urban and rural settings. It is endemic in countries with humid tropical and subtropical climates, particularly impacting young adult males. Disease risk factors include a high reservoir population and various environmental, recreational, and occupational factors [1–3]. The immune phase of illness generally lasts from 4 to 30 days. The disappearance of leptospires from the blood and cerebrospinal fluid coincides with the appearance of IgM antibodies. The organisms can be detected in almost all tissues and organs, and urine for several weeks, depending on the severity of the disease [4, 5].

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It is estimated that the infection causes approximately one million cases and approximately 58,900 deaths per year, with a worldwide fatality rate of 6.85 % [6]. Due to underdiagnosis or misdiagnosis, sometimes resulting from inadequate infrastructure and clinical suspicion, the exact number of human cases remains unknown [7]. The incidence of the disease is ten times higher in tropical regions due to a combination of factors, including high temperature, humidity, rainfall, and socioeconomic factors such as poor sanitation and close contact with domestic animals [8]. Human leptospirosis is closely associated with poverty, where substandard housing conditions and inadequate local infrastructure facilitate exposure to rodent reservoirs [1,6,9].

In Latin America, the two main risk groups for leptospirosis are urban slum dwellers and farmers. The incidence of the disease in these risk groups varies from country to country due to differences in underlying poverty conditions. For example, in Colombia, the incidence of the disease in 2018 and 2019 was 1.15 and 0.18 per 100,000 inhabitants, respectively. People with higher socioeconomic vulnerability accounted for more than 54 % of cases [1,10,11]. Regarding housing characteristics, 3.1 % of observed cases had no sewage system, 40.6 % had contact with stagnant water, and 34 % of the cases had garbage in the peridomicile [10,12].

Currently, more than 180 species of leptospires have been detected, with over 200 serological varieties or serovars. Mammals are the only class of animals capable of transmitting the disease, although leptospires have been identified in reptiles and birds [13,14]. It is considered an environmental disease, and its transmission depends on interactions between humans and mammalian reservoir hosts [3], especially rodents, which can transmit the infection to domestic farm animals, dogs, and humans [6,15]. Once excreted in the urine, leptospires can survive for months to years in relatively moist environments. The optimal conditions for the survival of the bacteria in water are a temperature in the range of 28–38 °C [14].

Runoff occurs as a consequence of an excess of water reaching the ground surface in relation to the soil's infiltration capacity. The magnitude and temporal trends of runoff depend on the intensity of rainfall and the slope [16]. Runoff is also influenced by the type of vegetation and the type of soil. The current infiltration capacity of a particular soil is conditioned by the soil water content [17]. The role of runoff in the dynamics of leptospirosis is not yet clear, and few previous studies have evaluated the effect of runoff on leptospirosis incidence [18,19].

Randomized controlled trials are the gold standard for obtaining unbiased estimates of the effect of exposure on an outcome [20]. However, in most cases, conducting such experiments in epidemiology is not feasible due to ethical or practical objections [21–23]. As a result, researchers often need to address questions about effects using only observational data, which can introduce confounding bias [23]. The common practice among researchers is to adjust their regression models for all available potential confounders. However, improper adjustments can introduce more bias in the estimation of the treatment effect, especially when adjusting for a collider variable, which is a special type of variable characterized by being influenced by two or more variables [23–27].

The objective of this study was to assess the pooled lagged effect of runoff on leptospirosis occurrence in the top 20 municipalities in Colombia with the highest number of cases, while accounting for potential confounding factors for the period 2007 to 2022. Additionally, we explored whether differences in the effect of runoff on leptospirosis cases could be attributed to the multidimensional poverty index.

2. Methods

2.1. Cases data

We included in our study the top 20 municipalities with the highest number of cases of leptospirosis in Colombia (Supplementary Table 1). Daily cases of leptospirosis, confirmed by laboratory analysis, were obtained from the National Public Health Surveillance System from January 2007 to December 2022. Daily cases were grouped by month for each municipality, taking into account that the disease has an incubation period ranging between 2 and 30 days, allowing the microorganisms to be detectable for several weeks. Consequently, using daily or weekly temporal resolutions would only capture cases with a very short period of symptom development. We excluded reported cases with inconsistency in municipality or the date from the study. For each municipality, data obtained from population projections provided by the National Administrative Department of Statistics of Colombia (DANE) were used [12].

2.2. Climate data

The monthly data of runoff from January 2007 to December 2022 were downloaded from the NASA product GLDAS_NOAH025_M

Table 1
Atmospheric and oceanic indices.

Name	Detail
SST12	Sea surface temperature in El Niño region 1-2
SST3	Sea surface temperature in El Niño region 3
SST34	Sea surface temperature in El Niño region 3-4
SST4	Sea surface temperature in El Niño region 4
SOI	(Standardized anomalies Tahiti - Standardized anomalies Darwin) sea level pressure
ESOI	Standardized anomalies Indonesia sea level pressure
NATL	Sea surface temperature North Atlantic (5–20°North, 60-30°West)
SATL	Sea surface temperature South Atlantic (0–20°South, 30°West-10°East)
TROP	Sea surface temperature Global Tropics (10°South-10°North, 0–360)

version 2.1 (National Aeronautics and Space Administration-NASA, 2019). The spatial matching and monthly average runoff per municipality were obtained using the raster package in R, version 4.0.3 [28].

We obtained the monthly values of 9 atmospheric and oceanic indices (Table 1) for the period from January 2007 to December 2022 from the National Oceanic and Atmospheric Administration [29].

2.3. Multidimensional poverty index data

We included in our analysis the variable multidimensional poverty index (MPI) for each of the 20 municipalities in the study, which was obtained from the Terridata repository [30]. The MPI functions as a comprehensive metric for assessing poverty, which goes beyond income assessments. In the Colombian context, the MPI provides a complex understanding of poverty by incorporating variables such as education, health and living conditions. Using a combination of quantitative and qualitative data, the MPI constructs a multifaceted poverty profile. Drawing on data from national surveys, administrative sources and participatory approaches, the MPI assesses deprivation across multiple facets within households and communities [31]. MPI was used as a meta-predictor in the random-effect meta-regression model, following the approach outlined by Gasparrini & Armstrong [32]. This was done to assess whether the differences among the estimates of the effect of runoff on leptospirosis cases in the 20 municipalities could be explained by MPI.

2.4. Causal inference analysis

We created a directed acyclic graph (DAG) that includes runoff as the exposure variable and cases of leptospirosis as the outcome (Fig. 1). It's important to note that climate patterns on continents depend on atmospheric and oceanic conditions, as described in Table 1 [33–35]. Therefore, we considered the 9 atmospheric and oceanic indices as potential confounders of the effect of runoff on leptospirosis cases. Additionally, we included the year and month as confounders.

To understand how the atmospheric and oceanic indices behave as confounders, consider that we aim to estimate the effect of runoff on leptospirosis cases. The SST12 index is a potential confounder because it can modify the runoff. Simultaneously, this index can influence local patterns of other hydroclimate variables, such as rainfall, temperature, soil moisture, etc., which could also impact the incidence of leptospirosis [36–40]. This dual relationship of the SST12 index with both the exposure (runoff) and the outcome (leptospirosis cases) introduces confounding bias, necessitating its consideration in our analysis. The node representing the atmospheric and oceanic indices in the DAG has an asterisk (*), symbolizing the global teleconnections and interdependencies among these

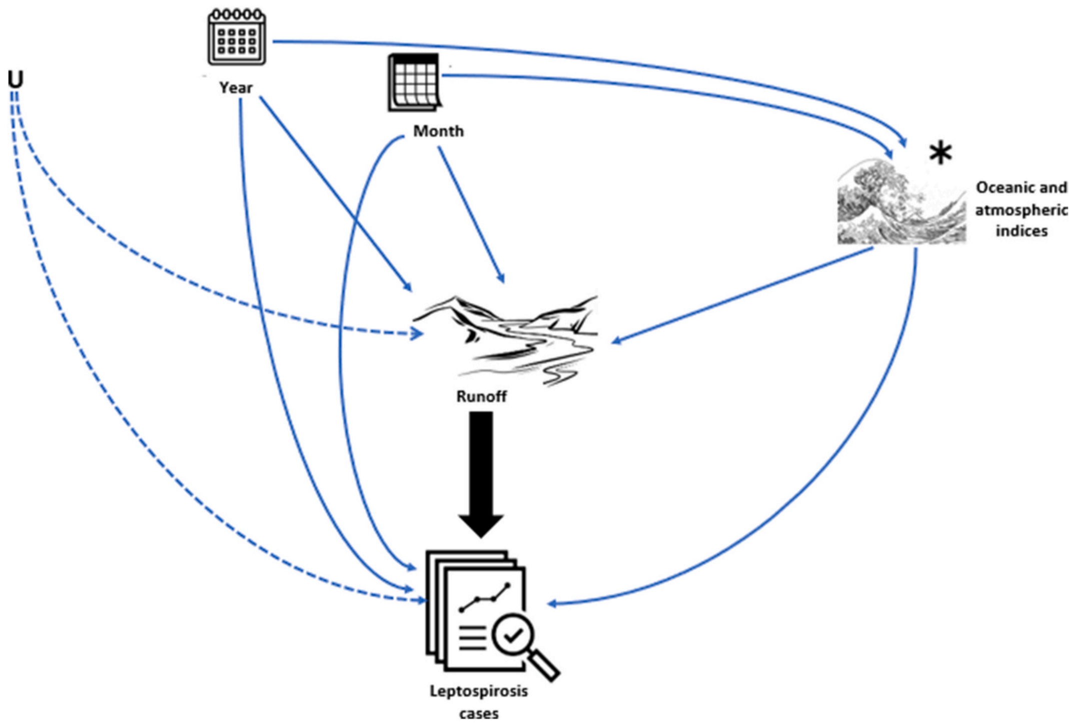

Fig. 1. The DAG illustrates the causal association of interest using a black arrow, indicating the effect of the exposure (Runoff) on the outcome (Leptospirosis cases). The "Atmospheric and oceanic indices" node encompasses the 9 indices listed in Tables 1 and it features a double arrow to represent the atmospheric and oceanic teleconnections and interdependencies among them. Additionally, dashed arrows originating from the 'U' node signify potential latent or unmeasured confounders that have the potential to introduce confusion bias into the analysis.

indices [41].

The year was included as a potential confounder because interannual variability of climate modifies the runoff pattern. Simultaneously, the years drive the long trend of leptospirosis cases (see Fig. 2). The month was also included as a potential confounder because the rainy season modifies local runoff patterns. Simultaneously, rainy months can lead to an increase in leptospirosis cases [36,39,40,42,43].

Note that we implemented the same DAG for lagged periods ranging from 0 to 1 to 0–6 months, and causal inference was applied exclusively to the fixed-effect in our statistical model (see Section 2.5 Statistical Model).

2.5. Statistical model

For each municipality, we evaluated the association between runoff and the occurrence of leptospirosis cases using a Distributed Lag Nonlinear Model (DLNM). Given the constraints of the current version of the dlnm package, which does not support implementing a gamma distribution (suitable for continuous outcome response) in the regression model. We employed a quasi-Poisson regression, a distribution function suitable for counting variables and commonly used for modeling cases data to examine this relationship.

The equation for modeling the cases of leptospirosis was as follows:

$$Log[E(Y_t)] = \alpha + \beta_1(runoff) + \beta_{2-11}(At\&Oc\ ind) + \beta_{12}(year) + \beta_{13}(month) + offset(log\ (population)\ ) \quad (1)$$

Where.

a $E(Y_t)$ *is the number of cases of leptospirosis expected in month t*
b α is the intercept term
c. β_1 is the coefficient for the effect of the runoff on leptospirosis cases, and it corresponds to the causal association of interest
d. β_{2-11} are the coefficients for effect of the 9 atmospheric and oceanic indices (*At&Oc ind*)
e. β_{12} is the coefficient for the effect of year
f. β_{13} is the coefficient for the effect of month
g. *offset*(*log*(*population*)) is the offset term of the annual population in each municipality on a logarithmic scale, which eliminates the effect of population on the association between runoff and leptospirosis cases

We evaluated the lagged response of leptospirosis cases to runoff for lagged periods ranging from 0 to 1 to 0–6 months, using the same DLNM as described in Equation (1). Predictions were computed relative to a reference value of 0.01 g/m^2 of runoff. It's important to note that the DLNM requires a basis matrix for the two dimensions of exposure (runoff) and lag [44]. For each lagged period, from 0 to 1 to 0–6 months, we tested three different models in terms of their basis matrix. The functions applied to the basis matrix for each lagged period are detailed in Table 2. The choice of functions to construct the cross-basis functions in the DLNM model was based on the technical documentation of the R packages dlnm and mvmeta [45].

It's worth mentioning that for the lagged period of 0–1 month, natural cubic splines, beta splines with larger degrees of freedom, and polynomial functions with larger degrees tend to produce overparametrized models [32]. This consideration led us to define basis matrices differently for this lagged period. The best of the three DLNM model options tested for each lagged period was selected based on the Akaike information criterion (AIC).

Global estimates (i.e., for the 20 municipalities) were obtained by pooling the results of all 20 municipalities using a random-effect meta-analysis with a strategy of restricted maximum likelihood. We estimated the relative risk (RR) of leptospirosis associated with heavy (90th percentile) and very heavy (95th percentile) runoff, relative to the reference value of 0.01 g/m^2, in the 20 municipalities.

The Cochran Q test and I^2 statistic were employed to assess residual heterogeneity in the meta-analysis. We used the Wald test to

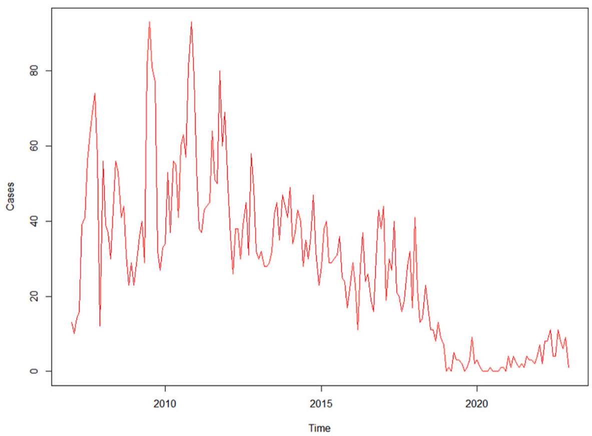

Fig. 2. Monthly cases of leptospirosis reported between 2007 and 2022 in the 20 municipalities included in the study.

Table 2
DLNM model options tested for runoff and lag parameters.

Lagged period (months)	Basis matrix parameter	DLNM option 1	DLNM option 2	DLNM option 3
0–1	runoff	function poly dg = 2	function ns df = 2	function bs df = 2
	lag	function ns df = 1	poly dg = 1	poly dg = 1
0–2, 0–3, 0–4, 0–5, 0–6	runoff	function poly dg = 2	function ns df = 3	function bs df = 3
	lag	function ns df = 2	function poly dg = 2	function poly dg = 2

poly = polynomial, dg = degree, ns = natural cubic spline, bs = beta spline, df = degrees of freedom.

evaluate the significance of the meta-predictor MPI.

As a sensitivity analysis, we conducted a random-effect meta-analysis using both maximum likelihood estimator and moments estimator strategies.

The values of the 9 atmospheric and oceanic indices were transformed into tertiles to facilitate model convergence. We assessed the conditional independences of the DAG with the R packages DAGitty version 0.3–1 [46] and ggdag version 0.2.10 [47]. Statistical analysis was performed using the R packages splines version 4.2.2, dlmn version 2.4.7 [45], and mvmeta version 1.0.3 [32].

This study was reviewed and approved by the ethics committee of the University of Santander, with the approval document number: 028/20.

3. Results

3.1. Descriptive analysis

In the 20 municipalities included in the study, 5530 cases of leptospirosis were reported between 2007 and 2022. They represent 52 % of the cases of leptospirosis that were notified in the 1122 municipalities of Colombia for the same period. Most of the cases occurred in 2010 and 2011, and the year with the fewest reported cases was 2020 (Fig. 2). Of the 20 municipalities included in the study, Cali, Barranquilla, and San José del Guaviare had the largest number of reported cases with 695, 612, and 449 cases, respectively.

3.2. Conditional independences

The only conditional independence identified in the DAG was between the variables Month and Year. This conditional independence was tested in the dataset using a linear conditional independence test, which yielded a value of 0.00 with a 95 % confidence interval (95 % CI) ranging from −0.03 to 0.03. These results provide evidence of consistency between the DAG and the dataset used for estimating the effect of runoff on leptospirosis cases.

3.3. Selection of DLNM models

According to the AIC criterion, for the lagged period of 0–1 month, the best DLNM model was model option 2, which used a natural cubic spline function with degrees of freedom 2 for runoff and a polynomial function of degree 1 for the lag. For lagged periods ranging from 0 to 2 months, 0–3 months, 0–4 months, 0–5 months, and 0–6 months, the best DLNM model was model option 2. This model employed a natural cubic spline function with degrees of freedom 3 for runoff and a polynomial function of degree 2 for the lag. The AIC values for all lagged periods and DLNM model options evaluated are provided in Supplementary Table 2.

3.4. Random-effect meta-analysis

The pooled RR of the effect of runoff on leptospirosis for the 20 municipalities and for lagged periods ranging from 0 to 1 to 0–6 months is displayed in Fig. 3. For the lagged periods of 0–2, and 0–3 months, the analysis indicated an effect of runoff on the RR of leptospirosis that differed from 1, as evidenced by the estimation of the 95 % CI. This effect was observed in the range of 0.01–120 g/m^2, and 50–100 g/m^2 of runoff, respectively (Fig. 3B and 3C).

Across all the analyzed lagged periods, the highest runoff values were either slightly positively associated (lagged periods 0 to 1 (Fig. 3A), 0 to 4 (Fig. 3D), 0 to 5 (Fig. 3E) and 0 to 6 (Fig. 3F)) or negatively associated (lagged periods 0 to 2 (Fig. 3B), 0 to 3 (Fig. 3C)) with the RR of leptospirosis. However, these associations did not significantly differ from 1 always, as indicated by the estimation of the 95 % CI (Fig. 3). In the 20 municipalities included in the study, the highest RR of leptospirosis at the 90th percentile (276 g/m^2) and 95th percentile (291 g/m^2) of runoff occurred during the lagged period of 0–6 months. However, both values of RR were not significantly different from 1, according to the estimation of the 95 % CI (Fig. 3F).

The p-value of the Cochran Q test for the association between runoff and leptospirosis evidenced that there was heterogeneity across the 20 municipalities included in the study in all lagged periods (Table 3). The global heterogeneity for all lagged periods across the 20 municipalities according to the I^2 statistic showed values between 48.40 and 63.70 % (Table 3).

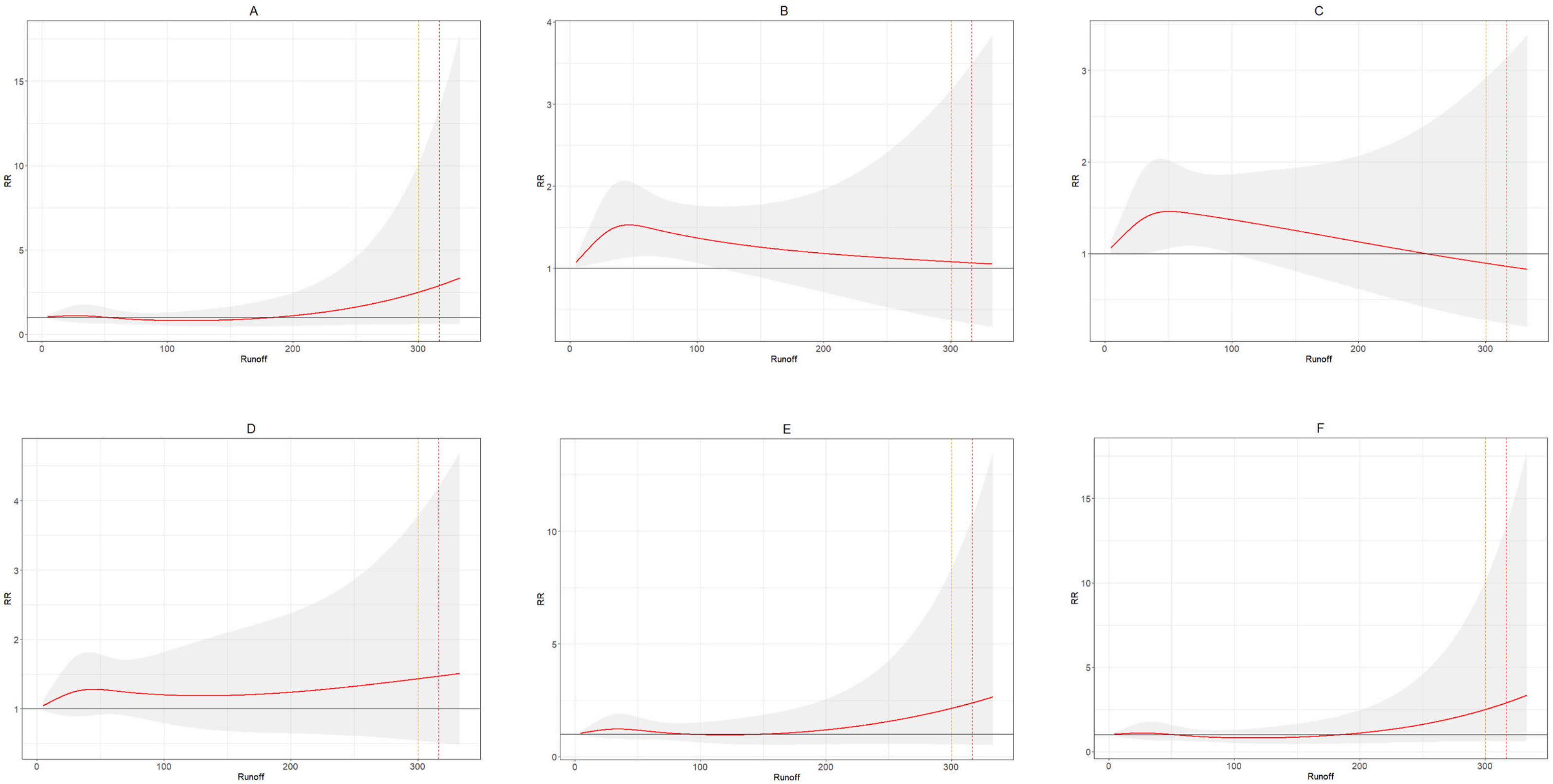

Fig. 3. Pooled effect of runoff on the RR of leptospirosis in the 20 municipalities included in the study, for the lagged period of 0–1 (A), 0 to 2 (B), 0 to 3 (C), 0 to 4 (D), 0 to 5 (E), and 0 to 6 (F) months. The red line corresponds to the mean effect, and the gray band corresponds to the 95 % CI. Vertical dotted lines correspond to the 90th percentile (orange), and 95th percentile (red) of runoff. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 3
Cochran Q test and I^2 statistic, for all lagged periods analyzed.

Lagged period (months)	Q test (p-value)	I^2 statistic
0–1	73.60 (<0.001)	48.40
0–2	114.71 (<0.001)	50.30
0–3	121.33 (<0.001)	53.00
0–4	113.64 (<0.001)	57.30
0–5	157.12 (<0.001)	63.70
0–6	151.77 (<0.001)	62.40

3.5. Meta-regression with MPI

Incorporating the meta-predictor MPI led to a reduction in the values of the Q test for all the lagged periods. Regarding the I^2 statistic, the inclusion of the meta-predictor resulted in reduced values for the lagged periods 0 to 2, 0 to 3, 0 to 4, 0 to 5, and 0–6 months (Table 4). However, it's important to note that despite the incorporation of the meta-predictor MPI, residual heterogeneity in the meta-analyses for runoff remained significant (p-value from Q test <0.05) across all the lagged periods.

Based on the p-value of the Wald test, it appears that the meta-predictor MPI does not significantly account for the variation among the 20 municipalities in the effect of runoff on leptospirosis cases, except to the lagged period of 0–3, and 0–4 months (p-value $= 0.04$ in both lagged periods). Nevertheless, there is a noticeable trend towards a higher RR of leptospirosis in the scenario of the 25th percentile of MPI (MPI $= 13.5$), particularly in conjunction with the highest values of runoff, across all the lagged periods analyzed (see Fig. 4).

3.6. Sensitivity analysis

We conducted a sensitivity analysis to assess the robustness of the effect estimate of runoff on leptospirosis cases. In this analysis, we used different methods for the multivariate meta-regression model, specifically the maximum likelihood estimator and moments estimator. The results of the sensitivity test indicated that the pattern of the effect of runoff on leptospirosis cases remained consistent even when changing the strategy of estimation. The unique difference in the sensitivity analysis occurred for the lagged period of 0–1 month (see Supplementary Figs. 1, 2, 3, and 4, as well as Supplementary Tables 3, 4, 5, and 6).

4. Discussion

This study aimed to establish the relationship between previous monthly runoff and the occurrence of leptospirosis cases in the top 20 municipalities with the highest number of cases of leptospirosis in Colombia between 2007 and 2022. We employed a random-effect meta-analysis and evaluated this relationship using the MPI through a meta-regression. Our findings suggest that there is a pooled effect of runoff on leptospirosis when the runoff is < 120 g/m^2, but only for lagged periods of 0–2 and 0–3 months. For larger lagged periods or higher values of runoff, no significant effect was identified.

Our results partially align with the observations made by Cucchi et al. [18] who evaluated the association between hydroclimate drivers and seasonal leptospirosis incidence in China. Cucchi's findings suggest that precipitation's impact on leptospirosis may be mediated through soil moisture and runoff. However, they observed only a modest association between previous weeks' runoff and leptospirosis cases. To the best of our knowledge, our study is the first to reveal the lagged effects of runoff on the occurrence of leptospirosis cases, using a causal inference approach.

Leptospira spp. has been detected in runoff water samples from both urban and rural areas [19]. Colonies of the pathogenic bacteria are likely mobilized along watersheds in sediments transported by runoff. Our results suggest that there is a threshold (<120 g/m^2) of runoff for lagged periods of 0–2, and 0–3 months to produce an effect on leptospirosis incidence. Higher runoff appears to flush sediments along watersheds, potentially reducing the probability of human-pathogen contact. However, more studies are needed to comprehensively understand the pattern of pathogen load mobilization along watersheds and the role of ecological variables such as runoff, soil moisture, rainfall, temperature, and vegetation, on the dynamic of cases of leptospirosis.

Some authors have suggested a possible mechanism for the relationship between hydroclimate variables and leptospirosis, involving the movement of rodent hosts from their dens as soil humidity increases, bringing them into closer proximity with human

Table 4
Cochran Q test and I^2 statistic, for all lagged periods analyzed with MPI as meta-predictor.

Lagged period (months)	Q test (p-value)	I^2 statistic
0–1	70.52 (0.001)	49.00
0–2	103.07 (<0.001)	47.60
0–3	110.31 (<0.001)	51.00
0–4	117.61 (<0.001)	54.10
0–5	142.15 (<0.001)	62.00
0–6	140.56 (<0.001)	61.60

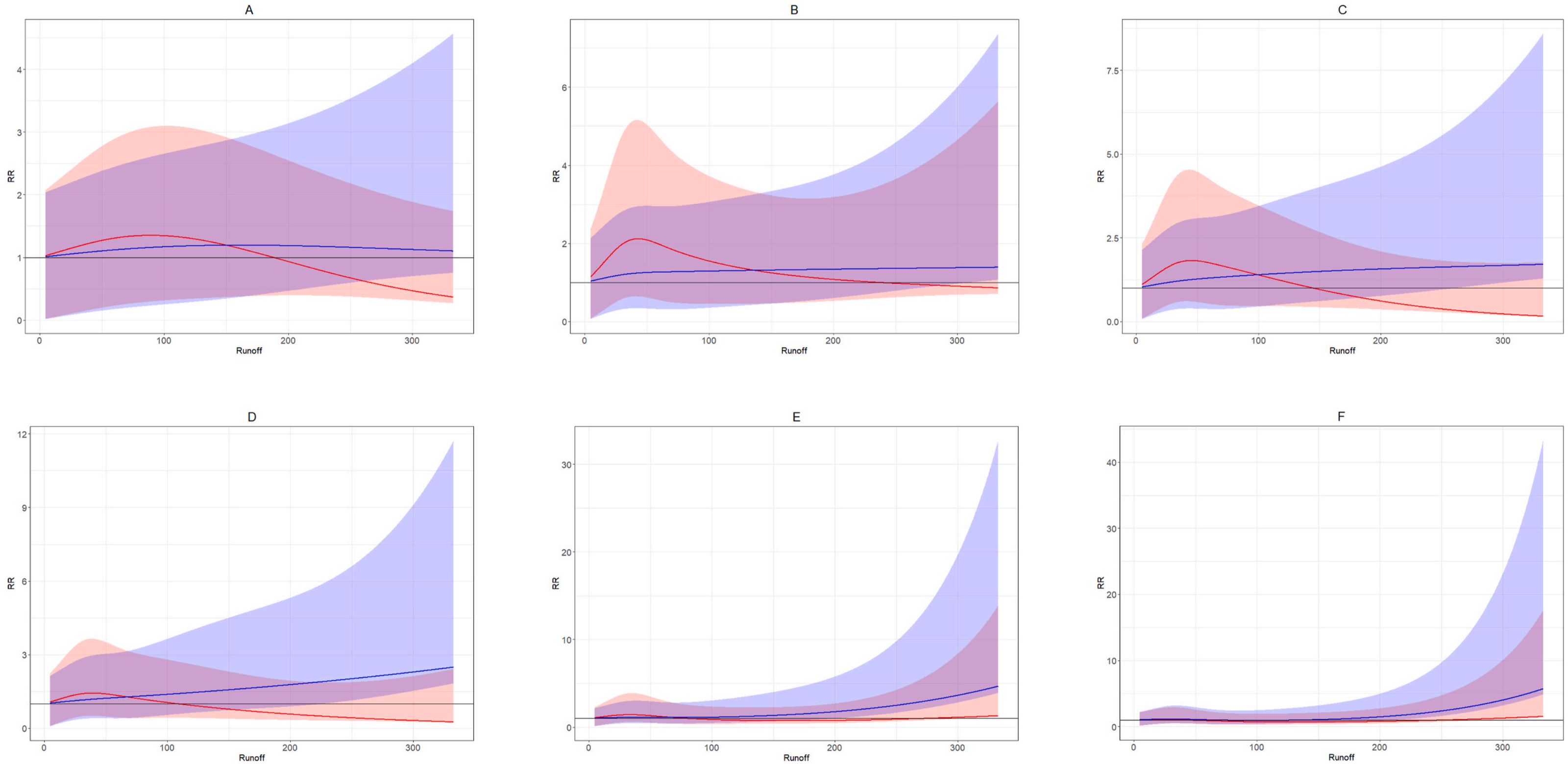

Fig. 4. Effect of runoff on the RR of leptospirosis at 25th (blue line) and 75th (red line) percentiles of MPI. The bands blue and red represent the 95 % CI of each percentile of MPI. Note that the overlapping of the blue and red bands is consistent with the p-value of the Wald test >0.05. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

populations [38,43,48,49]. However, the limited ecological evidence available indicates that rodent populations respond with longer lagged periods (>12 months) [50].

The observed trend (although statistically non-significant) toward a higher incidence of leptospirosis in scenarios with lower MPI percentiles and high runoff values, across all the lagged periods analyzed, is intriguing. One hypothesis for this trend is that municipalities with lower MPI tend to have larger aqueduct coverage, albeit not necessarily with a water treatment supply. Higher runoff may transport the bacteria along supply basins to tanks built for aqueduct systems in municipalities with this infrastructure, increasing the RR of leptospirosis in municipalities with lower MPI.

However, other studies have identified associations between low socioeconomic status and inadequate sanitation, which can increase the risk of leptospirosis [51,52]. In impoverished conditions, illiteracy rates are higher, waste management is inadequate, and there is less capacity to cope with floods, prevent water stagnation, and ensure adequate rodent control, all contributing to the risk of disease [53]. Studies in Colombia have suggested multiple socioeconomic determinants at the municipal level that are positively associated with the occurrence of human leptospirosis [54,55].

We acknowledge that the source of the data is a significant limitation of our analysis, particularly because laboratory confirmation may not encompass all bacterial strains [56]. The genus *Leptospira* consists of hundreds of species, which can be further categorized into four subclades. Pathogenic spirochetes of the genus *Leptospira* mainly belong to the P1 group [57,58], with serologically more than 300 recognized leptospiral serotypes. Leptospirosis is a naturally occurring disease, and each serovar tends to be maintained in specific host species [3,56]. Therefore, future studies could aim to determine which strains are favored by increased runoff, identify prevalent *Leptospira* strains in different regions, and investigate how various social, administrative, and environmental factors facilitate leptospires contact and transmission.

From a causal inference perspective, our results assume that we have included all the confounding factors of treatment assignment in the causal model to obtain an unbiased estimation of the causal effect. However, as it is impractical to measure all natural phenomena, we acknowledge the presence of latent confounding bias in our estimation [23,59,60]. Similarly, the lagged regression model used (DLNM) assumes linearity and additivity functions for the relationships between the treatment, the outcome, and the confounders. This implies potential inference bias [61,62], especially if the model response form is misspecified. An alternative approach to mitigate inference bias is to estimate the causal association between runoff and leptospirosis cases using machine learning methods. However, to our knowledge, there is no machine learning algorithm available that can provide nonparametric estimates of the distributed lagged causal effect.

Finally, the sensitivity analysis revealed an unclear effect of runoff on the occurrence of leptospirosis cases for the lagged period of 0–1 month, attributed to contradictory outcomes when employing different estimators of random-effects meta-analysis. A potential explanation could be linked to the disease's incubation range (2–30 days), suggesting that some cases exhibit rapid or average symptom onset, while others may occur at the extreme end of this incubation period. This heterogeneity in symptom development could potentially influence the conducted sensitivity analyses.

5. Conclusion

In this study, we observed a lagged effect of runoff on leptospirosis cases in the top 20 Colombian municipalities with the highest number of cases between 2007 and 2022. This effect was significant for lagged periods of 0–2 and 0–3 months when the runoff was <120 g/m^2. Importantly, we found that the difference among the 20 municipalities' estimates of the runoff's effect on leptospirosis cases is unlikely to be explained by the MPI.

Our findings underscore the importance of incorporating causal reasoning into the analysis of hydroclimate variables' impact on leptospirosis occurrence. This is crucial for mitigating confounding bias and obtaining accurate estimates of the effect of such variables on leptospirosis cases.

These results have practical implications for public health policy and intervention planning in Colombia. They can inform the development of disease control strategies tailored to local social, economic, and environmental factors, particularly during periods of heavy runoff. This approach can help reduce potential risk factors for human leptospirosis associated with climate variability phenomena like El Niño and La Niña.

Data availability statement

The results can be reproduced with the dataset and scripts available in R at: https://github.com/juandavidgutier/meteorology_leptospirosis.

CRediT authorship contribution statement

Juan David Gutiérrez: Writing – review & editing, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Johanna Tapias-Rivera:** Writing – review & editing, Writing – original draft, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e32882.

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