Associations between rocky mountain spotted fever and veterinary care access, climatic factors and landscape in the State of Arizona, USA

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Abstract

Rocky Mountain Spotted Fever (RMSF) is a potentially fatal tick-borne disease historically prevalent in the eastern and south-eastern U.S. Since the early 2000s, there has been a notable rise in RMSF cases in the south-western U.S. Despite the documented role of dogs in tick-borne disease transmission, research on the influence of other factors, such as veterinary care access, climatic conditions and landscape characteristics on RMSF incidence is limited. This study investigated the combined impact of these factors on RMSF using county-level temperature, relative humidity, precipitation, land cover, dog populations and veterinary care access in Arizona from 2006 to 2021. Employing a spatial negative binomial regression model, the study revealed significant associations between veterinary care access, precipitation, relative humidity, shrubland, and RMSF incidence across three models incorporating lagged effects (0-month, 1-month, and 2-month) for climatic variables. A key finding was that counties experiencing higher veterinary care access were more likely to report lower RMSF case counts (incidence rate ratio (IRR): 0.9237). The mean precipitation consistently showed the highest positive IRR (1.8137) across all models, indicating its strong influence. In contrast, relative humidity (IRR: 0.9413) and shrubland presence (IRR: 0.9265) demonstrated significant negative associations with RMSF incidence. These findings underscore the importance of veterinary care access, climatic factors, and land cover in shaping RMSF dynamics, particularly in regions with increasing incidence rates.

Introduction

Rocky Mountain Spotted Fever (RMSF) is a potentially fatal tick-borne disease (TBD) caused by the bacterium *Rickettsia rickettsii*. It is one of the most severe rickettsial infections in humans and is considered the deadliest tick-transmitted disease in the United States (U.S.) (Biggs *et al.*, 2016; Deshpande *et al.*, 2024). The disease disproportionately affects communities across the U.S., particularly in the southern and south-western regions (Folkema *et al.*, 2012; Traeger *et al.*, 2015). RMSF has an average incubation period of 3-14 days and its tick vectors follows a three-stage life cycle, with larvae and nymphs primarily infesting small animals, such as mice, while adult ticks prefer larger mammals, including raccoons and dogs (Nelson, 2015). The primary vectors of *R. rickettsii* are *Dermacentor variabilis* (American Dog Tick) and *D. andersoni* (Rocky Mountain Wood Tick) though *Rhipicephalus sanguineus* (Brown Dog Tick) has emerged as a key vector in the Southwest (Demma et al., 2006; Traeger *et al*., 2015).

Although RMSF derives its name from the Rocky Mountains, it is more prevalent in the central and southeastern United States. Currently, the highest incidence of RMSF cases is reported in Arkansas, Oklahoma, Missouri, Tennessee, and North Carolina, which collectively account for nearly 60% of national cases (CDC, 2021). The disease has also been documented in Arizona, New Mexico, Utah, Montana, Nevada and Texas, though the incidence in these states is comparatively lower. Over the past two decades, the Centers for Disease Control and Prevention in the U.S. (CDC) has observed a significant upward trend in RMSF cases, with the incidence rate increasing from 2 cases per million in 2000 to over 8 cases per million in 2008 (CDC, 2021). Although RMSF was rarely reported in Arizona historically, this State has seen an increase in recent years associated with other tick species (CDC, 2021). In 2003, the first documented case of RMSF transmitted by the Brown Dog tick was reported in Arizona (Demma *et al.*, 2005). Since then, the Arizona Department of Health Services (ADHS) has documented more than 450 cases, predominately among Native Americans (ADHS, 2023). The average annual incidence in the Navajo Nation, the largest indigenous tribe in the U.S. occupying 70,000 square km of land in north-eastern Arizona, southeastern Utah, and north-western New Mexico, was 136 cases per 100,000 persons (2009-2012), more than 150 times greater than the national average (Drexler *et al.*, 2014). This rate far exceeds RMSF incidence among non-indigenous populations in the southwestern U.S.

Indigenous communities often have fewer resources to prevent and treat RMSF, exacerbating the impacts of this disease (Alvarez *et al.*, 2014). Since 2012 the number of cases reported in the Navajo Nation has declined—for instance, one county reported a decrease from 84 cases (2006–2012) to 36 cases (2012–2018) (ADHS, 2023) —due to intervention efforts focused on the Brown Dog tick tests and treatment. However, reported cases began increasing again in 2018 and no testing for dogs has been conducted since the COVID-19 pandemic due to the lack of resources for RMSF prevention and control and reduced access to veterinary health care (Nelson, 2015; ADHS, 2023; Navajo Nation Animal Control Program, 2023), manifested through decreased operational capacity of existing facilities and disruptions to community-based animal health programs serving rural areas (ADHS, 2023; Navajo Nation Animal Control Program, 2023). Dog overpopulation, common across Navajo communities, further compounds the problem as dogs are a common host of Brown Dog ticks that transmit RMSF. Information from the Navajo Nation Veterinary Management Program (NNVP) indicates that this kind of tick is the primary one found on dogs in the area (Navajo Nation Animal Control Program, 2023).

Previous studies have highlighted the critical role of dogs as reservoirs for *R. rickettsii*. Research by Backus *et al.* (2023) emphasizes the link between roaming dogs and intense tick infestations on the one hand and RMSF outbreaks on the other in southwestern U.S. and northern Mexico (Alvarez-Hernandez *et al.*, 2020; Backus *et al.*, 2023). Limited veterinary care access (VA) and poor tick control measures exacerbate the disease spread, particularly in underserved communities. Community-based interventions, such as those described by Drexler *et al.* (2014) and Brophy *et al.* (2024), have effectively reduced tick populations and RMSF incidence through coordinated efforts involving veterinary care, public health education, and tick control programs (Drexler *et al.*, 2014; Brophy *et al.*, 2024).

The impact of anthropogenic and climate factors on TBDs has been widely studied, with numerous studies highlighting the correlation between these diseases and climate variability (Randolph, 2004; Süss *et al.*, 2008; Georgescu *et al.*, 2012; Raghavan *et al.*, 2016; Amulyoto *et al.*, 2018). Climate change, characterized by rising temperatures and extended tick seasons, has been linked to the spread of diseases such as tick-borne encephalitis (TBE) and Lyme Borreliosis (LB), which are increasingly recognized as public health concerns in Europe and North America (Süss *et al.*, 2008; Bouchard *et al.*, 2019). Ticks rely on specific environmental conditions, including moisture, vegetation and land cover patterns to complete their life cycles, making these factors critical for predicting TBD distribution (Raghavan *et al.*, 2016; Bouchard *et al.*, 2019). For example, RMSF tick activity is influenced by humidity, with studies showing that higher average humidity and poverty levels in the central Midwestern U.S. positively correlate with RMSF incidence (Traeger *et al.*, 2015; Raghavan *et al.*, 2016). Ticks linked to RMSF have been found in woods and bushes (Gottlieb *et al.*, 2018). Additionally, climate change has been shown to affect rodent-borne RMSF cases, highlighting the connection between environmental conditions and disease transmission (Gubler *et al.*, 2001). In the Southwest, rising temperatures result in a longer tick season, increasing opportunities for RMSF transmission (Backus et al., 2024). Overall, these findings emphasize the importance of climatic factors and environmental conditions in understanding and predicting TBD dynamics, as ticks require specific habitats to survive and reproduce (Álvarez-López *et al.*, 2021; Newhouse *et al.*, 1986).

Limited research has explored how access to veterinary care, climate conditions, and landscape factors collectively influence the occurrence of RMSF in the south-western U.S. at an ecological level, particularly given that the disease emerged in this region only two decades ago. This study addresses a critical gap in the literature by investigating the interplay between environmental variables (climate, ecology and landscape) and social factors, such as VA in shaping the RMSF burden. Utilizing long-term meteorological data—including temperature, relative humidity, and precipitation—alongside landscape metrics, land cover analyses and VA, we aimed to identify correlations between these factors and RMSF incidence. This research is the first to jointly examine VA, climatic conditions, and landscape fragmentation in relation to RMSF prevalence, providing novel insights into the disease's dynamics. Given that Arizona's first RMSF cases were reported post-2000, recent socio-environmental changes may be influencing trends in disease transmission. By analyzing the complex interactions among social, environmental, and spatial factors, this study contributes to a deeper understanding of RMSF dynamics and informs targeted public health strategies to mitigate this potentially fatal disease.

Materials and Methods

Study area

This study focuses on 15 counties in Arizona (Figure 1) that have reported a high number of RMSF cases since the disease first emerged in the State. Arizona's climate is predominantly dry and semi-arid, with extreme temperatures and limited moisture. Nearly half of the State is classified as semi-arid, facing several climate-related challenges. Temperatures vary significantly with elevation, ranging from below freezing at higher elevations to over 38°C (100°F) in desert areas during summer (Hereford, 2007). Winters are generally mild, while summers are intensely hot and dry, with most precipitation occurring in winter. The limited precipitation has shaped the land cover, dominated by arid vegetation such as desert plants and grasslands, with relatively sparse forested areas.

Data

RMSF outcome data

Monthly RMSF case counts for Arizona from 2006 to 2021 were obtained from the State health department (ADHS, 2023). Only laboratory-confirmed cases were included to ensure data reliability. Although longer periods of data exist, this timeframe was selected to provide the most consistent and comprehensive coverage across all variables. It is important to note that RMSF cases were recorded based on patients' county of residence, not necessarily where the infection occurred.

Covariates

These were collected across three main categories: climate, land cover and VA and covered the same study period. Land cover data, specifically the percentage of different land types in each county, were obtained using Geographical Information Systems (GIS) from the publicly available National Land Cover Dataset (2001, 2004, 2006, 2008, 2010, 2013, 2016, 2019).

Climatic variables, such as county-level averages of monthly mean Land Surface Temperature (LST), precipitation and relative humidity were extracted using Google Earth Engine (GEE) from 2006 to 2021. LST estimates were obtained from Moderate Resolution Imaging Spectroradiometer (MODIS) imagery (Friedl & Sulla-Menashe, 2022), while precipitation and Relative Humidity (RH) data were sourced from the Gridded Surface Meteorological Dataset (GRIDMET) (Abatzoglou, 2013), provided by the University of Idaho. Each dataset was first filtered to align with Arizona's county boundaries. Within GEE, monthly county-level data were generated by averaging mean values of grad cells within each county. Table 1 lists the data descriptions, data sources, and spatial resolution of each data variable.

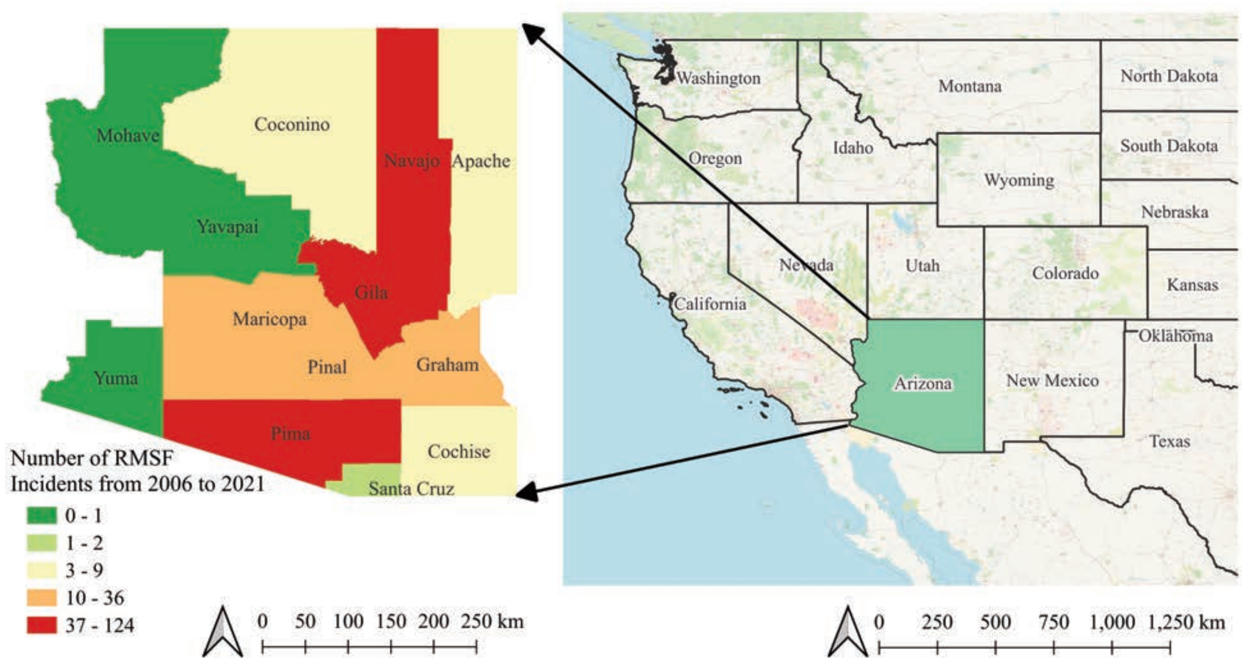

Figure 1. Study area: counties in Arizona with incidence levels of Rocky Mountain Spotted Fever (RMSF) cases during the study period.

Table 1. Description of climatic factors for predicting RMSF incidence.

Data variable	Description	Spatial resolution	Source
Precipitation, RH	County averages of monthly precipitation and relative humidity for the corresponding years.	4-km	GRIDMET (Abatzoglou, 2013)
LST	Monthly LST estimates derived from MODIS (Moderate Resolution Imaging Spectroradiometer) imagery.	500 m	MODIS imagery (Friedl & Sulla-Menashe, 2022)

RH, Relative Humidity; LST, Land surface temperature.

County population data for the study period were acquired from the U.S. Census Bureau's County Population Totals Dataset (Census Bureau, 2022). To contextualize RMSF cases in relation to potential hosts, dog ownership data were derived from the 2017–2018 AVMA Pet Demographic Survey (AVMA, 2024). The survey provided state-level estimates of dog ownership rates and total dog populations, which were projected at the county level for this study. VA was assessed by normalizing the number of veterinary clinic staff by the estimated pet population in each county, incorporating factors such as financial constraints, transportation, language, and the availability of veterinary services (Applebaum *et al.*, 2023; AVMA, 2024).

To examine the relationship between RMSF and land cover types, prior studies have identified forest and shrubland as key covariates (Atkinson *et al.*, 2012; Raghavan *et al.*, 2016; Gottlieb *et al.*, 2018). Based on this, we focused on these two major land cover types in our study. Forested land was aggregated from multiple land cover classifications across different time periods (Table 2).

The proportion of landscape was computed to forest or shrubland class according to the following equation:

$$PLAND_i = P_i = \frac{1}{A}\sum_{j}^{n_i} a_{i,j} \quad (class\ i) \qquad \text{Eq. 1}$$

where $PLAND_i$ denotes the proportion abundance of the total area occupied by the corresponding land use type i; a_{ij} the area of each patch j; and A the total landscape area of the county (m^2).

Landscape metrics were quantified and analyzed using PyLandStats (version 2.4), an open-source Python library designed for computing landscape metrics (Bosch, 2019).

Methodological approach

Since RMSF is a discrete count variable, Poisson regression is typically used to model its relationship with covariates. Poisson regression, a type of generalized linear model, assumes that count data follows a Poisson distribution, where the variance equals the mean. However, disease counts often exhibit overdispersion, meaning the variance exceeds the mean (Imai *et al.*, 2015).

To fit the over dispersed count data, this study employs a negative binomial regression model to estimate the association between VA, landscape, and climate variables and county-level RMSF case counts, while also evaluating the variance explained by these covariates (Hilbe, 2011). The model is formulated as follows:

$$Y_i|E_i \sim PoissonE_i \qquad \text{Eq. 2}$$

$$E_i = \mu_i \qquad \text{Eq. 3}$$

$$\ln(\mu_i) = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_m X_{im} \qquad \text{Eq. 4}$$

$$E_i \sim Gamma(\lambda_i, \kappa_i) \qquad \text{Eq. 5}$$

$$E(Y_i) = \mu_i \ and \ Var(Y_i) = \mu_i + \frac{\mu_i^2}{k^i} \qquad \text{Eq. 6}$$

where Y_i is the monthly RMSF cases reported in county i, Y_i follows a Poisson probability distribution with an expected count E_i. which is equal to the mean number of cases m_i for county i; b are coefficients corresponding to the explanatory variables. Each X_{ij} represents a covariate/predictor of RMSF incidence, such as temperature, relative humidity, precipitation, forest, shrubland, or VA. A population offset (typically the log of the county population) was included to account for population size differences and model incidence rather than raw counts. E_i follows a Gamma distribution with parameters l_i, k_i. Additionally, X_{im} denotes the explanatory covariates. A population offset was also included.

To account for spatial autocorrelation in RMSF cases, we employed a negative binomial regression model with a spatial lag term to address both overdispersion and spatial dependence in the count data as defined by the formula:

$$\log(\mu_i) = \beta_0 + X_i\beta + \rho W Y_i + \epsilon_i \qquad \text{Eq. 7}$$

where, WY_i is the spatial lag term and ρ the spatial autoregressive parameter that measures the influence of neighboring counties' RMSF cases on the cases of a county. By including this term, the model does not only take into account the direct consequences of explanatory variables but also the impact of adjacent counties.

The spatial negative binomial regression uses a log link function, meaning the coefficients represent the expected log change in the RMSF case count for a one-unit increase in the corresponding predictor. When exponentiated, these coefficients yield Incidence Rate Ratios (IRRs), which indicate the multiplicative change in predicted counts for a one-unit increase in the predictor and hold all other variables constant. Additionally, the total population was included as an offset in the model to account for regional-level heterogeneity, ensuring that population size differences across regions were appropriately controlled for in the analysis. To detect multicollinearity, the Variance Inflation Factor (VIF) was used, with values greater than 5 typically indicating significant multicollinearity (O'Brien, 2007). In this study, multicollinearity tests (Table 3) revealed that all variables had VIF values below 4, indicating a low degree of multicollinearity confirming the suitability of the predic-

Table 2. Definitions of each land cover aggregated variable.

Original land cover type	Aggregated land cover variable	Description
Deciduous forest	Forest	Areas with more than 20% vegetative cover dominated by trees taller than 5 m. More than 75% of the tree species shed leaves with seasonal changes.
Evergreen forest	Forest	Areas with more than 20% vegetative cover dominated by trees taller than 5 m tall. More than 75% of the tree species retain their leaves all year, creating a constant canopy of green foliage.
Shrub/scrub	Shrub/scrub	Areas dominated by shrubs and young or stunted trees lowewr than 5 m, which comprise more than 20% of vegetation.

tors for the regression analysis. We carried out all analyses in R statistical software version 3.6.3 and Python 3, graphical presentation in ArcGIS 10.8.

Results

Table S1 presents a statistical summary of meteorological distribution by county. The data show a wide variation as they relate to the different climatic zones within the region. Arizona's diverse topography, characterized by arid conditions and varying elevations, results in notable climatic differences across its counties. Yuma had the highest mean LST at 28.20°C, while Apache reported the highest RH and Gila the highest precipitation. Apache also had the greatest forest cover (29.3±30.59%), whereas Santa Cruz had the largest shrubland area (25.6±2.96%). VA varied widely, with Yavapai County scoring the highest (78.5) and Apache the lowest (0.954). Navajo County reported the highest average daily number of RMSF cases (11.75±12.65), followed by Gila (7.5±5.48) and Pima (7.25±11.16).

Time-series climatic data (Figure 2) showed steady and stationary distributions. LST varied significantly, with Yuma reaching 28.9°C and Apache averaging 15.40°C. Precipitation was highest in Gila (1.26 mm) and lowest in Yuma (0.29 mm), while transitional zones like Cochise and Santa Cruz exhibited showed considerable variability. RH was highest in Apache (45.47%) and lowest in hotter, drier counties such as Maricopa (33.28%) and Mohave (31.27%).

From 2006 to 2021, 467 RMSF cases were reported in Arizona (Figure 1). Gila County recorded the most cases (n=124), followed by Navajo (n=118) and Pima (n=116), while Mohave, Yavapai, and Yuma each reported only one case. Figure 3 shows the annual trends in RMSF case counts and incidence rates by county. Gila, Pima, and Navajo counties reported relatively high case numbers throughout the study period (Figure 3a). Navajo County peaked around 2009–2011, followed by a steep decline—partly due to intervention efforts—and a sharp increase around 2019–2020, likely influenced by the pandemic. Pima County showed a spike between 2011 and 2013. Gila County experienced a sharp increase after 2010, with peaks in 2013 and 2016, and remained elevated through 2020 compared to earlier years. Other counties reported lower and more sporadic case counts, with occasional minor spikes. For incidence, rates (Figure 3b), Gila and Navajo counties showed consistently high RMSF incidence throughout the study period. Gila County experienced multiple peaks around 2011, 2014, and again in 2017–2018, reaching nearly 9 cases per 100,000. Navajo County peaked sharply around 2010, then declined significantly, followed by a steep increase near 2020, indicating two distinct waves of elevated incidence. Pima County had lower incidence overall but showed a notable increase from 2019 to 2020.

To account for the temporal lag effect of climatic factors, the analysis incorporated not only data from the current month (Lag=0) but also from the previous one and two months (Lag=1 and Lag=2, respectively) for precipitation, RH and LST. The spatial negative binomial regression analysis identified several climatic factors, VA and land cover variables as significantly associated with RMSF incidence (Table 4). Across all three models incorporating different lag structures, precipitation had the strongest positive association with RMSF incidence across all lags, while VA showed the most significant negative effect ($p<0.001$) after adjusting for all covariates. Additionally, RH and shrubland were both negatively associated with RMSF incidence ($p<0.001$) after controlling other variables.

The highest and most positive IRR was observed for precipitation at lag 2 (IRR: 1.8137, CI: 1.5314-2.1482), indicating that, holding other factors constant, a one-unit increase in precipitation is associated with an 81% increase in RMSF incidence two months later. Higher RH is consistently associated with lower RMSF incidence, with a 4-6% reduction in incidence for each unit increase in RH. No significant effect was observed for LST at Lag 0 and Lag 1. However, significant negative effect at Lag 2 (IRR=0.9719, $p<0.001$) indicating a slight decrease (~2.8%) in RMSF incidence associated with a one-unit increase in LST, but only with a two-month lag. Forest and shrublands exhibited contrasting IRR

Table 3. Multicollinearity test.

Covariate	VIF Score
Forest	2.742839
Shrub	1.356285
RH	2.768305
Precipitation	1.955987
LST	1.692275
Dog Population	2.140424
VA	3.635179

RH, Relative Humidity; LST, Land surface temperature; VA, Veterinary care access; VIF, variance inflation factor.

Table 4. Spatial negative binomial regression results.

Variable	Lag=0 IRR (CI range)	Lag=1 IRR (CI range)	Lag=2 IRR (CI range)
Forest	1.0091(0.9864-1.0323)	1.0120 (0.9899-1.0346)	1.0040 (0.9821-1.0265)
Shrub	0.9265 (0.8988-0.9549)	0.9294 (0.8998-0.9601)	0.9276 (0.8995-0.9566)
RH	0.9558 (0.9345-0.9776)	0.9592 (0.9384-0.9805)	0.9413 (0.9221-0.9609)
Precipitation	1.6187 (1.3465-1.9461)	1.5184 (1.2535-1.8392)	1.8137 (1.5314-2.1482)
LST	0.9863 (0.9682-1.0048)	0.9862 (0.9678-1.0050)	0.9719 (0.9544-0.9897)
Dog Population	1.0000 (1.0000-1.0000	1.0000 (1.0000-1.0000)	1.0000 (1.0000-1.0000)
VA	0.9252 (0.9144-0.9362)	0.9262 (0.9155-0.9371)	0.9237 (0.9130-0.9345)
Cases_lag	1.1464 (0.1788-7.3498)	1.2042 (0.1959-7.4032)	1.3071 (0.2176-7.8527)

IRR, incidence rate ratio; Significance level, 0.05 in bold; RH, Relative Humidity; LST, Land surface temperature; VA, Veterinary care access; VIF, variance inflation factor.

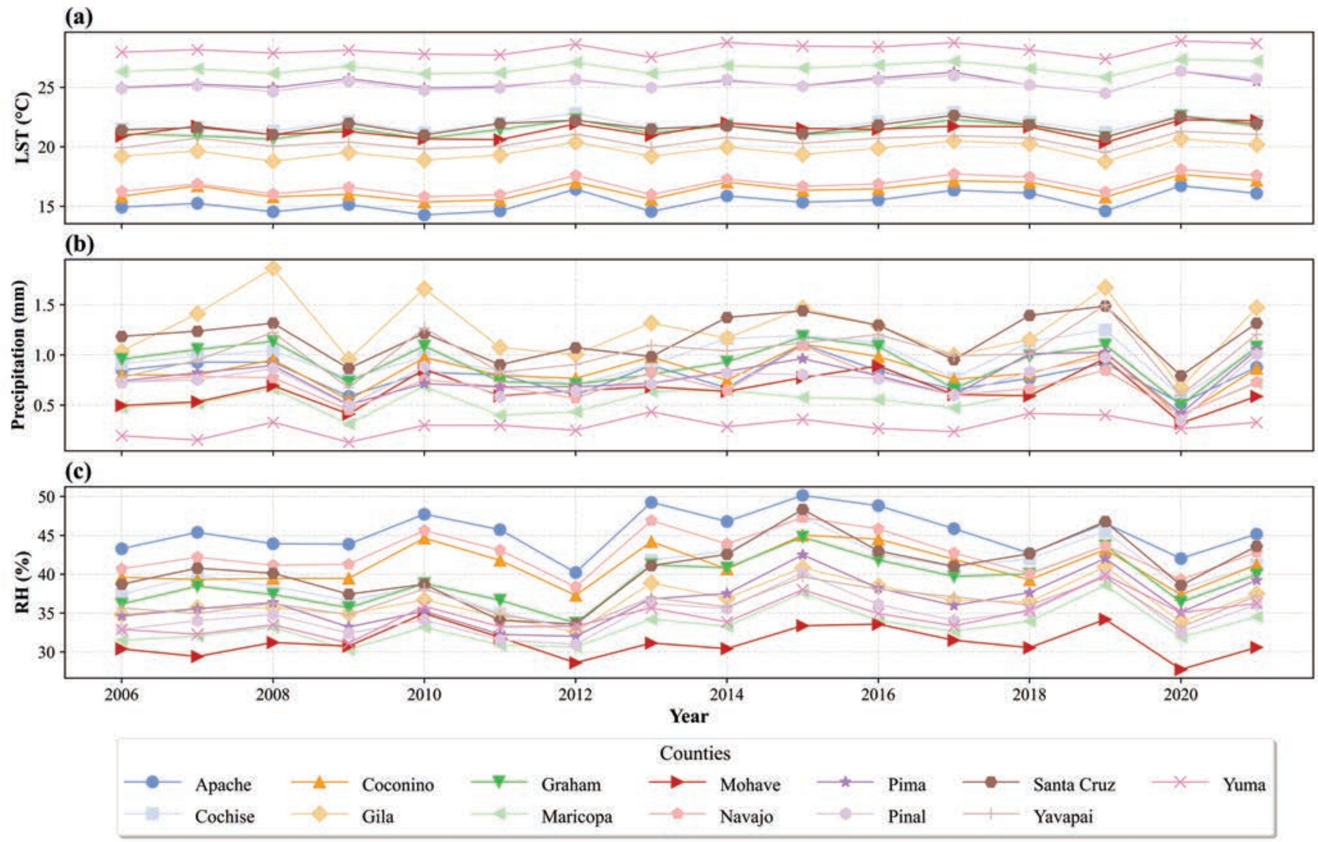

Figure 2. Annual time series trend of environmental variables in Arizona counties: (**a**) LST; (**b**) precipitation; (**c**) relative humidity.

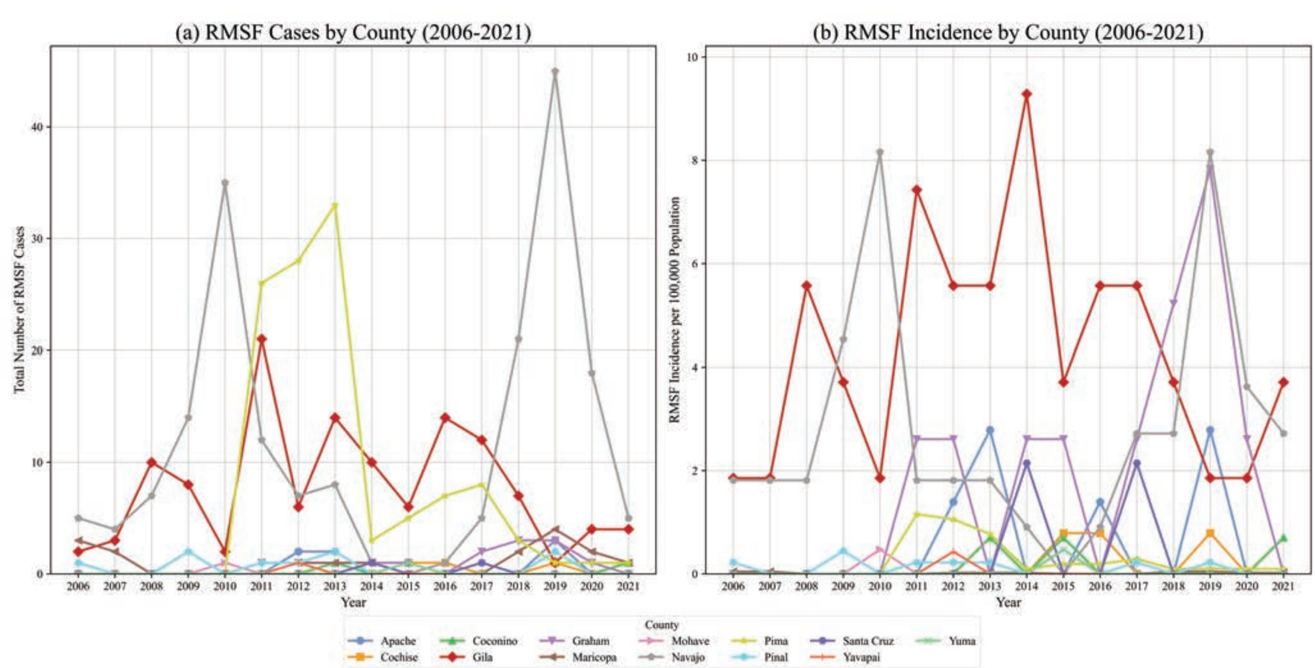

Figure 3. Time series trend of Rocky Mountain Spotted Fever (RMSF) cases and incidence rate by year.

patterns across all models, with shrubland cover emerging as a significant negative predictor (p<0.001). VA had the strongest negative association at lag 2 (IRR: 0.9237, CI: 0.9130-0.9345), meaning that for each one-unit VA increase, the expected number of RMSF cases decreased by about 7.6%. However, the dog population showed no significant association with RMSF incidence in the study area.

Discussion

This study examined joint effects of climatic conditions, landcover and VA on RMSF incidence in Arizona at the ecological level. The findings revealed that VA consistently exhibited a significant negative association with RMSF incidence, indicating that counties with lower access to veterinary services were more likely to experience higher RMSF case counts. This quantitative result aligns with previous qualitative reports, such as the NNVP and Nelson (2015), which identified insufficient VA as a critical factor exacerbating RMSF burden, particularly during the COVID-19 pandemic (Nelson, 2015; Navajo Nation Animal Control Program, 2023). These studies emphasized the issue as a significant social challenge, especially in socioeconomically disadvantaged communities. The situation may worsen in the coming years due to the compounding effects of dog overpopulation and limited VA, particularly in Native American communities. This study underscores the urgent need for targeted interventions to improve VA and mitigate RMSF risks in vulnerable populations.

Climatic factors demonstrated a complex, but consistent relationship with RMSF incidence across different time lags, minimizing the impact of distinct monthly lag models. The only exception was LST which showed a significant negative association with RMSF cases only at lag 2. This may reflect a longer-term effect, consistent with previous findings that higher temperatures reduce tick physiological activity (Gage *et al.*, 2008; Raghavan *et al.*, 2016). This also suggests that extreme temperatures may hinder tick reproduction, leading to lower RMSF transmission. In our data, counties, with mean temperatures below 20°C recorded the highest RMSF case counts supporting this observation. Precipitation, on the other hand, exhibited a positive association with RMSF incidence, likely because increased moisture enhances tick and host activity, as documented in prior studies (Bokhorst *et al.*, 2008; Chen & Sexton, 2008; Raghavan *et al.*, 2016). This favorable environment supports the survival of tick life stages, particularly during dry seasons, contributing to higher RMSF transmission.

Although several studies have found that ticks are positively correlated with land cover types such as shrubland and forests, which provide suitable habitats for their reproduction and survival (Eisen, 2008), our study revealed a more complex relationship between land cover and RMSF cases, likely due to the inclusion of a broader geographic range. While forest cover was not a significant factor in our analysis, shrubland exhibited a negative association with RMSF incidence. Shrublands, characterized by low, dense vegetation and often harsher environmental conditions such as higher temperatures and lower humidity, may create less favorable conditions for tick survival and reproduction. This could explain the observed negative impact of shrubland on RMSF cases in our model. However, since study on land cover and RMSF remain limited, further research is needed to better understand the role of landscape.

Limitations and future directions

While the geographic range of RMSF is well documented, our ability to predict transmission and implement effective interventions is hindered by limited research on the hosts (e.g., dog) activities, their interactions with human behaviors, and their role in RMSF transmission within high-risk communities. To improve predictions of RMSF surges and deepen our understanding of the environment-tick-host-human interplay, it is critical to incorporate tick and host data that account for individual-level host movement. Evidence suggests that increased host mobility and insufficient VA (Volk *et al.*, 2011; Neal & Greenberg, 2022) may enhance opportunities for ticks to interact with hosts, potentially elevating tick attack rates and RMSF infection. Future research should address these gaps to advance the understanding of RMSF transmission dynamics, particularly in the southwestern U.S., an emerging RMSF hotspot associated with a distinct tick species compared to other regions. A key area for improvement is the inclusion of free-roaming dogs in studies, as they serve as significant tick hosts and may facilitate the spread of ticks across larger areas. Investigating the role of free-roaming dogs in RMSF transmission pathways, along with their interactions with ticks and humans, could provide critical insights into disease spread at a finer spatial scale.

Conclusions

This ecological study highlights the significant role of VA in RMSF incidence, a finding identified for the first time, while also corroborating the influence of climatic factors previously documented in the literature. By integrating land cover variables, the study sheds light on the complex ecological processes underlying RMSF burden, which are deeply intertwined with social challenges, such as limited VA, and climatic factors in the context of climate change. The unique climate and demographic characteristics of the study area underscore the importance of advancing tick-borne disease research, providing a foundation for RMSF prevention and management strategies in Arizona and beyond. This comprehensive analysis of RMSF risk factors provides critical insights for public health interventions and highlights the need for targeted strategies to mitigate tick-borne diseases in the context of a changing environment.

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Online supplementary materials

Table 1. Descriptive statistics of the climatic and environmental variables in the study areas.