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TICK ABUNDANCE AND HABITAT DYNAMICS IN URBAN PARKS: A STUDY OF MICRO- AND MACRO- HABITAT INFLUENCES IN THE OKLAHOMA CITY METROPOLITAN AREA

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MELISSA ROSAURA MARQUEZ
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TICK ABUNDANCE AND HABITAT DYNAMICS IN URBAN PARKS: A STUDY OF MICRO- AND MACRO HABITAT INFLUENCES IN THE OKLAHOMA CITY METROPOLITAN AREA

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BY THE COMMITTEE CONSISTING OF

Dr. Anni Yang, Chair

Dr. Daniel Becker

Dr. Michael Wimberly

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Abstract

Most studies on tickborne diseases in the U.S. have been concentrated in suburban and rural areas. This has led to a lack of understanding about the risks of such diseases in urban settings, where environmental conditions vary, and human-tick interactions differ significantly. Several previous studies, including a recent study in Oklahoma City in 2017-2018, have investigated how microhabitat conditions within sampling locations can impact tick abundance. However, microhabitat conditions only capture a limited spatiotemporal range, typically confined to the immediate sampling site and period. Monitoring macro-environmental conditions via Earth observations could enhance our understanding of tick ecology on a larger scale. Here, we hypothesize that integrated monitoring of micro- and macro-habitat conditions can better capture tick abundance in urban parks. Specifically, we hypothesize that tick abundance in urban parks is influenced by microclimate factors like higher humidity levels or deeper leaf litter, and by macro-environmental conditions such as habitat type and spatial arrangement. We collected ticks from 13 parks in the Oklahoma City Metropolitan area using CO2 traps and flagging techniques. At sampling transects, we gathered micro-environmental data, including temperature, humidity, wind speed, and vegetation types, and assessed macro-environmental conditions such as land cover, incorporating landscape metrics. Our analysis identified key factors influencing tick abundance in urban parks, revealing that solar radiation negatively affects tick abundance, while soil pH, woody vegetation, and forest cover have positive effects. For adult ticks, leaf litter depth and solar radiation are negative predictors, while woody vegetation and forest percentage positively influence their abundance. Nymph tick abundance increases with lower solar radiation and relative humidity and is positively correlated with soil pH. Overall, both micro-environmental variables and landscape metrics are crucial in predicting tick abundance across different life stages. The results underscore the complex interplay between environmental factors and tick distribution, with implications for public health strategies in urban planning and park management.

Introduction

Ticks transmit more pathogen species (bacteria, parasites, and viruses) than any other group of blood-feeding arthropods worldwide, which poses significant threats to public and veterinary health (Durden, 2006). In the US, common tick species such as *Amblyomma americanum, Amblyomma maculatum, Dermacentor variabilis, and Ixodes scapularis* have contributed to the rise in tick-borne diseases over the past two decades. These diseases include spotted fever group rickettsiosis, anaplasmosis, ehrlichiosis, alpha-gal syndrome, Powassan virus, and Lyme disease (R. J. Eisen & Paddock, 2021; Paddock & Goddard, 2015; Rosenberg, 2018; Sonenshine, 2018).

The abundance and distribution of ticks are shaped by various concurrent factors, including abiotic factors, habitat types, and host populations (R. J. Eisen et al., 2016; Ostfeld et al., 1995; Randolph, 2004; Wilson et al., 1984). Microclimate conditions have been found to significantly affect ticks, as they inhabit the interface of soil and vegetation where they undergo development, seek shelter between questing events, and replenish body water lost during questing (Schulze & Jordan, 2005). Ticks require blood meals from hosts, which can range from small mammals to livestock, birds, reptiles, and humans, for their development through all life stages (larvae, nymphs, and adults), often acquiring pathogens in the process. Thus, the population, distribution, and movements of wildlife hosts are also known to affect the abundance of ticks and the prevalence of the pathogens they carry (Allan et al.,2010; Levi et al., 2012; Patrick & Hair, 1977). Furthermore, habitat physiognomy, referring to the physical attributes of habitats, such as plant diversity and composition, plays an important role in influencing microclimate, host abundance, and movement, thereby affecting tick survival and feeding success and ultimately shaping their abundance and spatial distributions (Semtner & Hair, 1973).

Most studies on tickborne diseases in the U.S. have been concentrated in suburban and rural areas (LaDeau et al., 2015). This has led to a lack of understanding about the risks of such diseases in urban settings, where environmental conditions vary, and human-tick interactions differ significantly. Urban parks are vital in the ecology of ticks and the transmission of tick-borne diseases, serving as potential hotspots for tick populations by providing suitable habitats for ticks and their wildlife hosts. Green spaces also facilitate increased human contact with nature, thereby heightening the potential for exposure to ticks and the pathogens they carry (Mackenstedt et al., 2015; Mathews-Martin et al., 2020). Kowalec et al., (2017) found *Ixodes ricinus* tick population and disease risks in urban parks in Poland are similar to those in natural forest settings with peak densities occurring in the spring-early summer in both areas, which suggest that urban parks also offer conditions conducive to tick proliferation. Therefore, understanding the ecology of ticks in urban parks is essential for developing strategies to mitigate the risk of tick-borne diseases in urban residents.

Previous research has shown that microenvironment conditions such as microclimate and vegetation significantly affect tick abundance and activities in urban parks. Buczek et al. (2014) found that microclimate conditions within urban heat islands can affect the abundance and activity of *Ixodes ricinus* nymphs and females. In Europe, whether ticks display unimodal (one peak) or bimodal (two peaks) activity), depends on microclimate conditions (Buczek et al., 2014). Noden et al. (2023) observed that tick abundance is influenced by factors such as microclimates, urbanization, fine-scale vegetation, and deer presence. However, microenvironment conditions only capture limited spatiotemporal range, often confined to the specific sampling site and period. Monitoring macro-environmental conditions through Earth observations at a larger scale and over regular intervals could provide a broader understanding of tick ecology.

Macroenvironment in urban parks, especially landscape structure including landscape composition and configuration, affects tick abundance in multifaceted ways. Ticks have evolved to be adaptable, yet many tick species have specific habitat preferences and even specific plant communities (Allan, Dutra, et al., 2010; L. Eisen et al., 2006; Estrada-PeñA, 2001). Particularly, fragmented forest areas with the higher amount of forest edge habitat are often correlated with higher tick density, most likely due to more optimal environmental conditions and higher density and activity of wildlife hosts (Simpson et al., 2019; Walsh, 2013). Urban areas exhibit pronounced habitat fragmentation, which can greatly restrict the movement of wildlife. However, human infrastructures such as buildings, roads, and canals can sometimes facilitate wildlife movement in urban environments and spatial distributions of tick populations in urban settings (Tack et al., 2011). For instance, VanAcker et al (2019) demonstrated that forested parks with better connectivity have higher densities of nymphal ticks and that the level of park connectivity strongly impacts the prevalence of *Borrelia burgdorferi* infection in nymphs.

As urbanization progresses and green spaces become more fragmented, understanding how landscape structure impacts tick abundance and distributions becomes increasingly important. In an urban-focused study, Gregory et al. (2022) found that canopy cover around yards strongly predicts the presence of *I. scapularis* and *A. americanum* ticks, fencing offers protection against these species, and log and brush piles leads to increased detection of ticks. A study in North Central Florida's recreational greenspaces showed that habitat type (natural or manicured) and the surrounding landscape significantly affected *A. americanum* and *I. scapularis* tick abundance, with more ticks found in natural than in manicured habitats (Bhosale et al., 2023). Despite studies on ticks being conducted across the United States, few studies have investigated urban tick ecology from a comprehensive combination of micro- and macro-lens. Research specifically focusing on tick abundance and its influencing factors is notably scarce in the central United States, particularly in the Great Plains region (Noden et al., 2023).

Here, we collected ticks using flagging and CO_2 trapping methods in 13 parks across the Oklahoma City Metropolitan area and investigated the drivers of tick abundance in urban parks. We hypothesize that integrated monitoring of micro- and macro-habitat conditions can better capture tick abundance in urban parks. We hypothesize that tick abundance in urban parks increases with microclimatic conditions that include higher humidity levels and deeper leaf litter. Additionally, we predict that macro-environmental factors such as the type and spatial arrangement of habitats also positively influence tick abundance. Specifically, more forest habitats that are fragmented within the park are expected to support higher tick populations due to their favorable microclimates and sheltering capabilities.

Methods

Study Area

Oklahoma is in the south-central region of the United States. The Oklahoma City Metropolitan area is comprised of seven Oklahoma counties: Canadian, Cleveland, Grady, Lincoln, Logan, McClain, and Oklahoma. According to the U.S. Census Bureau, this combined centralized region of Oklahoma covers 6,359 square miles and is home to more than 1.4 million residents (Oklahoma Employment Security Commission, 2023). The Oklahoma City Metropolitan area is characterized by cross timbers and southern tallgrass prairie ecoregion (Omernik, 2004). The climate in Oklahoma varies from humid subtropical in the eastern regions to semi-arid in the western parts. The average annual temperature in the metropolitan area is 60°F / 16°C with an average rainfall between 30 inches/76.2 centimeters to 40 inches/101.6 centimeters. Elevation in the metropolitan area varies from 1,000 feet to 1,400 feet (*Oklahoma Climatological Survey*). Summers in Oklahoma City are hot and muggy, with temperatures typically ranging from 29.4°C /85°F to33.9°C/ 93°F and high humidity levels. The season extends from early June to mid-September, characterized by clear skies and occasional thunderstorms, particularly in May, the wettest month (Weather Spark).

Although only a small percentage of ticks carry disease-causing bacteria, viruses, or protozoa, numerous cases of tickborne illnesses are reported annually across the United States. Lyme disease has become notably more prevalent in the last decade. In Oklahoma specifically, some of the most frequently reported diseases include Rocky Mountain spotted fever, ehrlichiosis, tularemia, and anaplasmosis. These observations highlight both the local and national impact of tickborne diseases (L. Eisen & Eisen, 2023; Osikowicz et al., 2024; Small & Brennan, 2021).

We selected 13 urban parks for our field sites, with eleven being the same as those studied by Roselli (2019) and the addition of one new park in Norman (Figure 1). Furthermore, due to safety concerns, Dolese Park included in Roselli's (2019) study was substituted with Saxon Park in Norman, Oklahoma. It is worth noting that some sites mentioned in Roselli (2019) are located outside of park boundaries. However, as our focus is specifically on urban parks, we confined all sampling activities within park boundaries. We conducted tick collections with the permits issued by the Parks and Recreation Departments of the City of Oklahoma City, the City of Norman, and the City of Edmond.

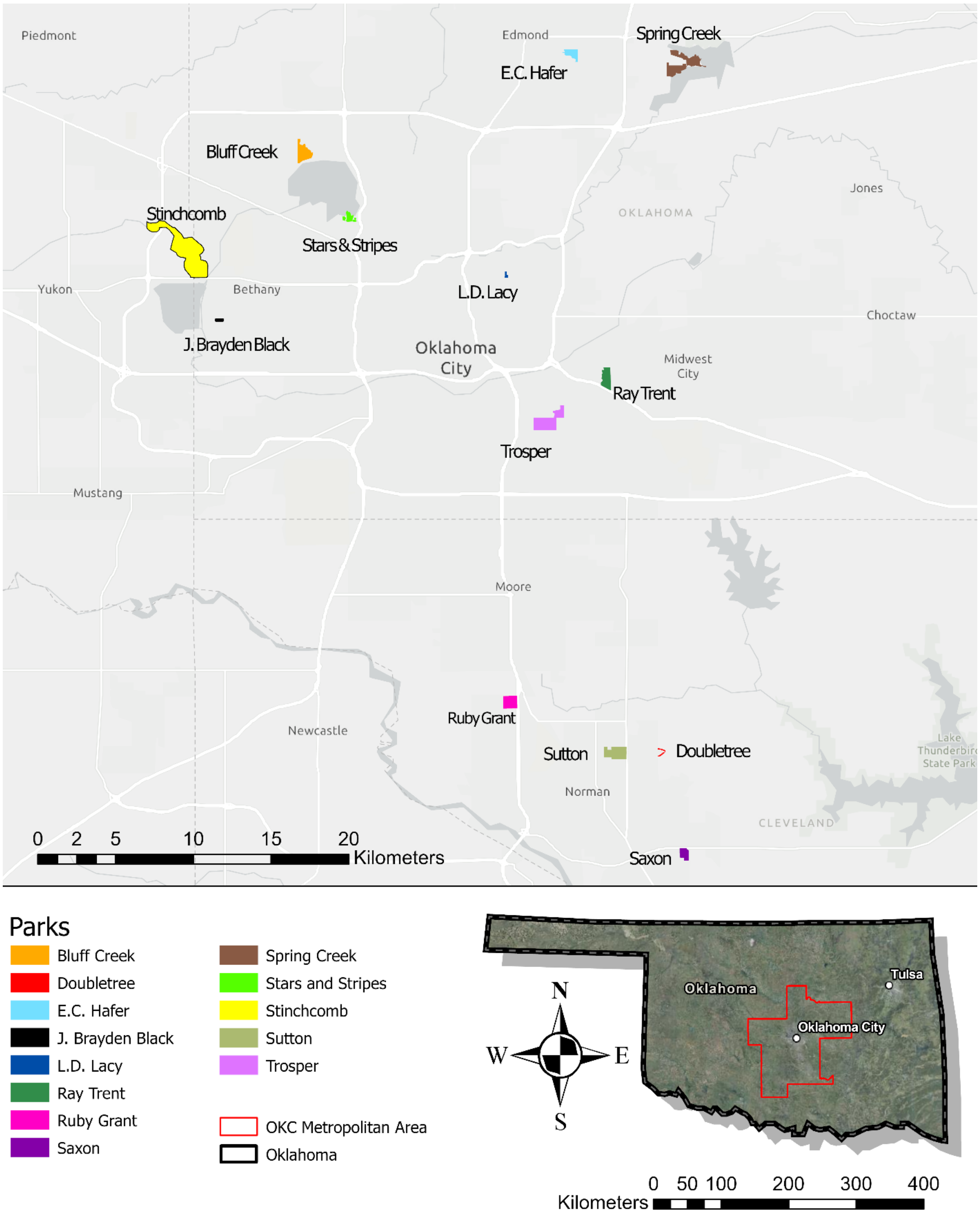

Figure 1. Tick sampling was conducted in thirteen urban parks in Oklahoma City and Norman, OK, USA, from May to July 2022. The main map displays the polygons representing each park,

which vary in size and shape (ESRI 2024, Redlands CA, USA) Park polygons were downloaded from data portals from the City of Norman, Oklahoma City, and City of Edmond. The inset map emphasizes the Oklahoma City Metropolitan area, encompassing seven different counties.

Tick Collection

In each park, we randomly generated six 50-meter transects per visit using the "Create Random Points" and "Bearing Distance to Line" geoprocessing tools in ArcGIS Pro 3.1.1 (ESRI Inc., Redland, CA). Adjustments were made to some transects to accommodate inaccessible areas within the parks. Despite these modifications, the transects were distributed in a way that ensured a random and representative sampling of the diverse vegetation types and provided comprehensive spatial coverage of the parks. This approach was aimed at providing an accurate presentation of tick distribution across vegetation types and park areas. We conducted two tick collection surveys in each park, establishing six transects per visit, from May 30 to July 31, 2023, during which we collected both adult and nymph ticks. The timing of these surveys was dependent on inclement weather conditions, and the second sampling effort was conducted 2-3 weeks after the initial survey (Table 1).All tick collections were conducted by the same four field personnel. We used two methods for tick surveillance, flagging and CO_2 traps. Ticks are highly sensitive to carbon dioxide (CO2) emissions, especially from warm-blooded animals such as humans and other mammals, as they rely on CO2 to locate hosts for feeding. CO2 traps simulate this natural mechanism by releasing CO2, thereby attracting ticks toward the trap, which can be effective for collecting larvae, nymphs, and adult ticks. We positioned one CO_2 trap at a distinct random location along each of the 50-meter transects. Traps were constructed with a plastic container of dry ice (solid CO2) placed at the center of a plywood board, which was lined with wide masking tape (Noden et al., 2017). We left the CO2 traps active for approximately one hour and documented the opening and closing times. Ticks discovered on the tape or board were gathered into a 50ml tube (CELLTREAT Scientific Products, Pepperell, MA, USA) filled with

10ml of 70% ethanol for preservation. The second method employed for tick collection involved flagging each transect using a light-color $1m^2$ cotton flannel fabric (Jo-Ann Stores, Hudson, OH, USA) attached to a wooden dowel. Flagging is one of the commonly used methods to sample questing ticks (Sonenshine & Roe, 2014). These ticks are usually found perched on vegetation, with their legs extended, awaiting a passing host to which they can attach. During the flagging, the flannel fabric was inspected for ticks every 15 meters or every 30 seconds, and any ticks found attached to the flag were placed in a 50ml tube containing 10ml of 70% ethanol for preservation. All ticks collected through both methods were identified to species, life stage, and sex using a Zeiss Stemi SV-11 stereomicroscope and established pictorial keys (Dubie et al., 2017; Keirans & Litwak, 1989).

Microclimate Data

Ticks are ectothermic, relying on the external environment to regulate their body temperature. As such, they are often found in areas that provide the right balance of humidity and temperature to support their survival (Needham & Teel, 1991). Air temperature (°C), relative humidity, wind speed (m/s), and solar radiation (W m-2) was recorded using a ClimaVUE™50 - Compact Digital Weather Sensor (Campbell Scientific, Inc. Logan, UT, USA)(Table 1.) During the sampling event of each transect, we placed the ClimaVUE™50 next to the CO_2 trap to collect microclimate conditions for ticks. The ClimaVUE™50 was securely mounted on a stable wood stand that was 1ft or 0.3048 m in height to ensure the microclimate weather conditions are measured at surface level. To consider potential seasonal variations and their influences on tick ecology during the study period, we also included 'Month' as a categorical variable in our models (Table 1).

Vegetation Sampling

At each 50m transect, four random points were generated to measure leaf litter depth, soil pH, percent ground cover, and sky-view factor (SVF). We measured the depth of the leaf litter by inserting a solid ruler into the litter until it encountered resistance from the soil (Roselli, 2019). We used a soil tester to measure soil pH (SOILPHU, Amazon Inc, Seattle, WA, USA). We assessed the percentage of ground cover by employing a 1x1 meter square sampling frame made from polyvinyl chloride (PVC) pipes and visually estimating the coverage percentage of various elements, including bare ground, leaf litter, coarse woody debris (such as fallen dead trees and branches), and graminaceous, herbaceous, and woody vegetation (Roselli, 2019). We used a Canon EOS 6D (Canon U.S.A., Inc, Melville, NY, USA) and Rokinon 8mm F3.5-HD Fisheye lens (Rokinon, Samyang Optics, Masan, South Korea) to capture the canopy or the sky hemisphere. The camera was placed in the center of the square sampling frame to take each image. The SVF quantifies the visible sky at a specific location, providing a simple way to represent the three-dimensional structure of the built environment as a two-dimensional metric. The SVF percentage for each image was determined using Photoshop software. The images were converted to grayscale, and a threshold was then applied to transform the images into binary photos. The threshold level, which varied for each image, distinguished between sky (white) and obstructions (black). The number of white pixels represents the visible sky area. The SVF was calculated as the ratio of sky pixels to total pixels, multiplied by 100, i.e., (sky pixels / total pixels) * 100.

Table 1. Description of environmental variables

Variable	Measurement range	Description	Accuracy
Relative humidity	0 to 100%	Average relative humidity	±3%
Solar radiation	0 to 1750 W m^{-2}	Measures the total amount of solar radiation received in a given area	±5%
Wind speed	0 to 30 m/s (0-67 mph)	Measure of the speed at which air is moving horizontally past a fixed point	0.3 m/s or 3%
Air temperature	-50 to 60 °C	Average air temperature	±0.6 °C
Woody vegetation	0 to 100%	The proportion of woody vegetation includes trees, shrubs, and other plants with woody stems seen within the PVC	
Leaf litter depth	0 to 15 cm	Depth of leaf litter depth in cm using a ruler	
Bare ground	0 to 100%	The proportion of areas without vegetation seen within the PVC	
Coarse woody debris	0 to 100%	The proportion of dead woody material, such as fallen trees, branches seen within the PVC	

Leaf litter	0 to 100%	The proportion of leaf litter seen within the PVC
Graminaecous	0 to 100%	The proportion of grasses or grass-like plants seen within the PVC
Herbaceous	0 to 100%	The proportion covered by plants that have non-woody stems, such as grasses, ferns, and wildflowers. Within the PVC
Sky View Factor	0 to 100%	Quantitative measure that represents the fraction of the sky visible from a specific point
Month	May-July	Categorical measure of the month during which data were collected, reflecting seasonal variations

Landscape Metrics

The Google Earth Engine (GEE) JavaScript API was used to process and visualize satellite imagery from the USDA National Agriculture Imagery Program (NAIP) dataset. A random forest (RF) is a machine learning algorithm that combines multiple decision trees to improve predictive accuracy and prevent overfitting. It employs techniques such as bootstrap sampling and random feature selection to create a diverse ensemble of trees, whose collective predictions offer robust and accurate results (Breiman, 2001; Cutler et al., 2007). We utilized the Random Forest algorithm to classify land cover at a 1-meter resolution, employing NAIP imagery from May to August 2021, with the red (R), green (G), blue (B), and near-infrared (N) spectral bands serving as predictors for the classification process. To create a single composite image, we calculated the mean of all images within this timeframe. Training data was generated using geometries representing five different classes: (1) forest, (2) open water, (3) urban, (4) grass, and (5) barren, with each class containing approximately 200-300 data points (Figure 2.). We applied the RF algorithm with 300 trees to our training data. To evaluate the performance of our RF model, we generated a confusion matrix and calculated various accuracy metrics, including overall accuracy, producer's accuracy, consumer's accuracy, and the kappa coefficient, by using the random forest predictions based on the same data for training and evaluation. Our model demonstrated high classification accuracy, with an overall accuracy of 99.20% and a kappa coefficient of 0.99 (Table 2.)

Table 2.Confusion matrix for land cover classification in 13 urban parks in Oklahoma City Metropolitan area

Landcover Classes	Forest	Open water	Urban	Grass	Barren	Total	User's accuracy
Forest	260	0	0	3	0	263	0.99
Open water	0	377	0	0	0	377	1
Urban	1	0	386	2	0	389	1
Grass	2	0	0	516	0	517	0.99
Barren	0	0	0	1	212	213	1
Total	263	377	386	522	212	1,759	
Producers' accuracy	0.99	1.0	0.99	1.0	1.0		

Overall accuracy: 99.4% and Kappa: 99.3%

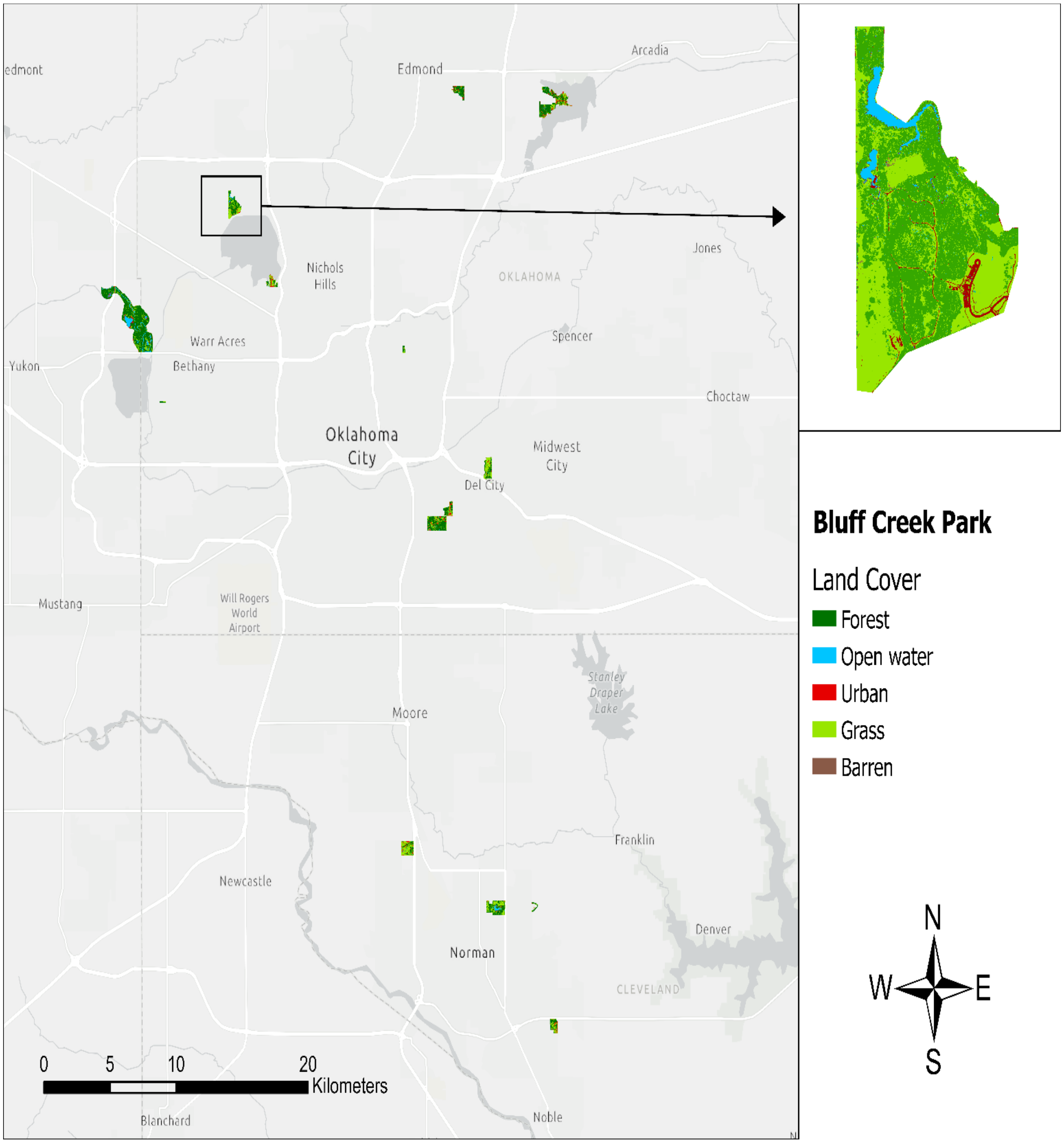

Figure 2. Landcover classification for all 13 urban parks in Oklahoma City Metropolitan Area, OK, USA. Inset map zooms in on Bluff Creek Park and its landscape is differentiated into five distinct land cover classes: forest, open water, urban, grass, and barren areas. The classification was generated using a random forest algorithm within Google Earth Engine.

In this study, we utilized a suite of landscape metrics to assess the composition and configuration of forest habitats within buffers of 25-, 50-, and 75-m radii around each transect (N=114) (Gregory et al., 2022). Due to the proximity of some transects to park boundaries, certain buffers extended beyond the park limits, incorporating surrounding land cover which could influence the metrics. The metrics were calculated using the "landscapemetrics" package in R 4.3.0 (R Core Team, 2023; Hesselbarth et al., 2019), included percent land cover, total edge (TE), number of patches (NP), Shannon's diversity index (SHDI), and Euclidean nearest neighbor distance distribution (ENN; Table 3). These metrics were chosen based on their relevance to forest habitats and their potential influence on tick populations, as supported by previous studies (Diuk-Wasser et al., 2012; Ferrell & Brinkerhoff, 2018). These measures provided insights into the extent, complexity, fragmentation, diversity, and spatial arrangement of forested areas in the landscape. All data were projected to Universal Transverse Mercator 14N World Geodetic System 1984, ensuring consistency in spatial analysis.

Table 3. Description of landcover metrics used.

Landscape Metrics	Level	Description
Percent land cover (PLAND)	Class	Percentage of forested pixels within specified buffer area
Total edge (TE)	Class	Summing the lengths of all edges that delineate forest areas.
Number of patches (NP)	Patch	Counts the total number of distinct forest patches
Shannon's diversity index (SHDI)	Landscape	Quantifies the diversity of land cover types within a landscape. It considers both the richness (number of different classes) and evenness (distribution of area among classes) of land cover types.
Euclidean nearest neighbor distance distribution (ENN)	Patch	Measures the average distance from each forest patch to its nearest neighboring forest patch. It provides an indication of the isolation and clustering of forest patches within the landscape.

Statistical Analysis

To identify the most predictive buffer size for landscape metrics in describing macrohabitat conditions for all ticks, adults, and nymphs, we conducted a univariate analysis for each landscape metric at three buffer sizes (25m, 50m, and 75m). We selected the buffer size that yielded the lowest Akaike information criterion (AIC)for the majority of landscape metrics. The model results for this optimal buffer size are presented in a later section, while results for the other buffer sizes are provided in the Supplementary section. All analyses were performed using R version 4.3.0 (R Core Team, 2023).

We conducted generalized linear mixed-effect models (GLMMs) to analyze the influence of environmental factors, encompassing both macro- and micro-habitat characteristics, on tick abundance across all 13 parks within the study area (Noden et al., 2023). Despite the differences in flagging and trapping methods aimed at capturing ticks at various questing stages (active and passive, respectively), the model results did not show a notable difference in model fit between analyses that combined data from both flagged and trapped ticks and those that included data from only flagged or only trapped ticks. Therefore, we analyzed the data and reported the results, encompassing the total number of ticks, number of adults, number of nymphs, obtained through both flagging and trapping techniques.

We examined the relationship between tick populations and a range of micro-meteorological, vegetation, and landscape factors at the transect scale (50-meter segments). We consolidated counts of adult ticks, nymphs, and the total tick population at the transect level, aggregating data from all collection periods. To standardize the micro-meteorological, vegetation, and landscape data, we applied scaling by deducting the mean and then dividing by the standard deviation, to facilitate better comparisons between predictors and to address issues of dispersion in the models. To address collinearity among these variables, we employed the 'cor()' function to evaluate correlation coefficients. For variables with coefficients exceeding 0.7, indicating high correlation, we selected between them based on the AICc (Dormann et al., 2007).

To determine the statistical distribution of our data for GLMMs, we utilized the likelihood ratio test (LRT) to compare the Poisson and negative binomial distribution. Additionally, we also used LRT and AIC model comparison to determine whether zero-inflation needed to be considered in our analyses (Supplements, Table A2). We found that the negative binomial distribution significantly outperformed the Poisson distribution across all categories: all ticks ($\chi^2 = 1347.96$, $p < 0.001$), adults ($\chi^2 = 515.17$, $p < 0.001$), and nymphs ($\chi^2 = 936.94$, $p < 0.001$). However, comparisons between the negative binomial model and the zero-inflated negative binomial model showed no significant differences for all ticks ($\chi^2 = 0.0005$, $p = 0.98$), adults ($\chi^2 = 0.001$, $p = 0.97$), and nymphs ($\chi^2 = 0.0002$, $p = 0.99$). Thus, we used the standard negative binomial models for analyses.

Tick counts for all life stages (including adults and nymphs) were treated as the response variables, while vegetation, landscape, and micro-meteorological variables were considered as fixed effects. To account for the spatial non-independence of transects within the same park, parks (N=13) were treated as a random effect. We generated all additive combinations of variates and assessed the performance of the fitted models using the AICc. The AICc, or Corrected Akaike Information Criterion, extends the AIC by incorporating a penalty for the number of parameters relative to the sample size. This adjustment is crucial for small sample sizes, as it helps prevent overfitting by penalizing model complexity more stringently, ensuring more reliable model selection (Burnham & Anderson, 2002). Models were regarded as statistically indistinguishable if the AICc differences from the top model were less than 2. To test the hypothesis that combining macrohabitat conditions with microhabitat metrics can more effectively capture tick abundance in urban parks, we compared the performance of our best-selected model that includes landscape metrics to a baseline model that excludes these metrics. All our models were run using the 'glmer.nb()' from the 'Ime4' package (Bates et al., 2015). Further, we tested the residuals of the best-performing models to identify any non-linear patterns that our GLMM approach might have missed. However, no significant non-linear patterns were detected for all ticks, adults, and nymphs. We also tested for interaction effects between month and relative humidity on the abundance of different tick stages (all ticks, adults, and nymphs), given that periodical rainy season occurs in July in Oklahoma City. Interaction terms in a statistical model assess whether the effect of one variable on the outcome depends on the level of another variable.

Results

Tick Surveillance

In this study, a total of 616 ticks were collected across various parks from May to July 2023 (Table 4). The collected ticks comprised 321 adults and 291 nymphs. The abundance of ticks varied significantly among the parks, with the highest number of ticks (205) collected from Bluff Creek Park and the lowest (3) from Sutton Park. The identified species included *Amblyomma. americanum* and *A. maculatum*. *A. americanum* was the most prevalent species, accounting for 97.9% (313 out of 321) of the adult ticks and 100% (291 out of 291) of the nymphs. *A. maculatum* adults constituted 2.8% (9 out of 321) of the adult ticks. Variations in the mean number of adult and nymph ticks collected are evident across the parks and throughout the study period, reflecting both spatial and seasonal differences in tick abundance, as shown in Figure 1A.

Buffer selection for analyses

A 75m buffer size was the most predictive for the overall tick population, consistently yielding the lowest AIC values for most of the key metrics such as total edge of forest (positive effect) and number of forest patches (negative effect) (Table A1). For adult ticks, a 50m buffer size proved to be the most suitable, with several metrics like percent of forest landcover (positive effect) and SHDI (negative effect) all demonstrating the lowest AIC values at this scale (Table A1). In contrast, abundance of nymph ticks was more accurately described by metrics at a 25m buffer size, emphasizing the significance of finer-scale habitat features, since most landscape metrics such as the total edge of forest (negative effect) and SHDI (negative effect) for this life stage (Table A1). We only reported the model results of best buffer size for all ticks, adult ticks, and nymphs in the main text. However, for a comprehensive analysis, additional models were explored for each buffer size (25m, 50m, and 75m) and for distinct tick categories: all ticks, adult ticks, and nymphs. The detailed results of these additional models can be found in the supplementary materials section.

Factors impacting abundance of all ticks, adults, and nymphs

Given that ten of our competing models were within two ΔAICc of the top model, we therefore selected the most parsimonious model (Model 1.2) to describe the influence of micro- and macro-habitat factors on the overall abundance of ticks (Figure 3). This model identified solar radiation, soil pH, woody vegetation, and the percentage of forest cover as significant predictors on tick abundance. Specifically, solar radiation demonstrated a substantial negative effect (β: -0.52 ± 0.14, $P < 0.001$), while soil pH (β: 0.34 ± 0.15, $P=0.02$), woody vegetation (β: 0.39 ± 0.12, $P=0.002$), and percent of forest cover (β: 0.48 ± 0.18, $P=0.007$) showed positive correlations with tick abundance.

Similarly, for adult ticks, we selected Model 2.0 as the best model, which is more parsimonious compared to its competing model, Model 2.1,with a ΔAICc of 0.2 (Figure 3). This model included solar radiation, leaf litter depth, woody vegetation, and forest percentage (PLAND). Average woody vegetation (β: 0.32 ± 0.12, P = 0.008) and forest percentage (β: 0.53 ± 0.17, P = 0.002) exhibited positive relationships with adult tick abundance at the transect level. In other words, areas with more woody vegetation and a higher percentage of forest cover are likely to have more adult ticks. Conversely, both leaf litter depth (β: -0.43 ± 0.18, P = 0.017) and solar radiation (β: -0.38 ± 0.15, P = 0.01) demonstrated negative correlations with adult tick abundance. This indicates that areas receiving more sunlight and those with deeper leaf litter are likely to have fewer ticks.

To demonstrate the effects of different drivers on the abundance of nymph ticks at the transect level, we selected the most parsimonious model (Model 3.5) among six competing models (ΔAICc< 2). This model, with a (ΔAICc of 1.7 comparing to the top model with lowest ΔAICc value, demonstrated that lower solar radiation (β: -1.11 ± 0.24, P < 0.001) and lower relative humidity (β: -0.71 ± 0.27, P = 0.01) are associated with an increase in nymph tick observations. Additionally, soil pH was positively correlated with nymph abundance (β: 0.77 ± 0.24, P = 0.001; Figure 3), meaning higher soil pH levels result in more ticks.

Impacts of landscape metrics

Our results indicated that models incorporating both micro-environmental variables and landscape metrics more effectively captured the abundance of various tick life stages across different buffer sizes. Specifically, models integrating both micro- and macro-habitat conditions outperformed those focusing solely on micro-habitat in predicting the abundance of all ticks and adult ticks at all spatial scale (Table 6; Table A3). However, those landscape metrics did not impact the abundance of nymph ticks (Table 6; Table A3, Table A4).

Table 4.Overall abundance of ticks by life stages collected from 13 Urban Parks in the Oklahoma City Metropolitan Area, OK, USA, May-July 2023. Variation in sampling effort across parks is attributed to missing meteorological data.

Park	**Sampling efforts (total transect lengths in meters)**	**Ticks**	**Adults**	**Nymphs**	***A. americanum* Adults**	***A. maculatum* Adults**	***A. Americanum* nymphs**
Bluff Creek	300	205	102	103	102	0	103
Doubletree	600	100	58	40	58	0	46
E.C Hafer	600	23	9	14	9	0	14
J.B Black	300	4	3	1	3	0	1
L.D Lacy	600	12	10	2	10	0	2
Ray Trent	300	14	6	8	6	0	8
Ruby Grant	600	30	30	0	26	4	0
Saxon	300	84	20	64	20	0	64
Spring Creek	300	54	22	32	19	3	32
Stars and Stripes	600	20	16	4	15	1	4
Stinchcomb	300	39	21	18	21	0	18

Sutton	600	3	2	1	1	1	1
Trosper	300	28	24	4	24	0	4
Total	**5700**	**620**	**323**	**297**	**314**	**9**	**297**

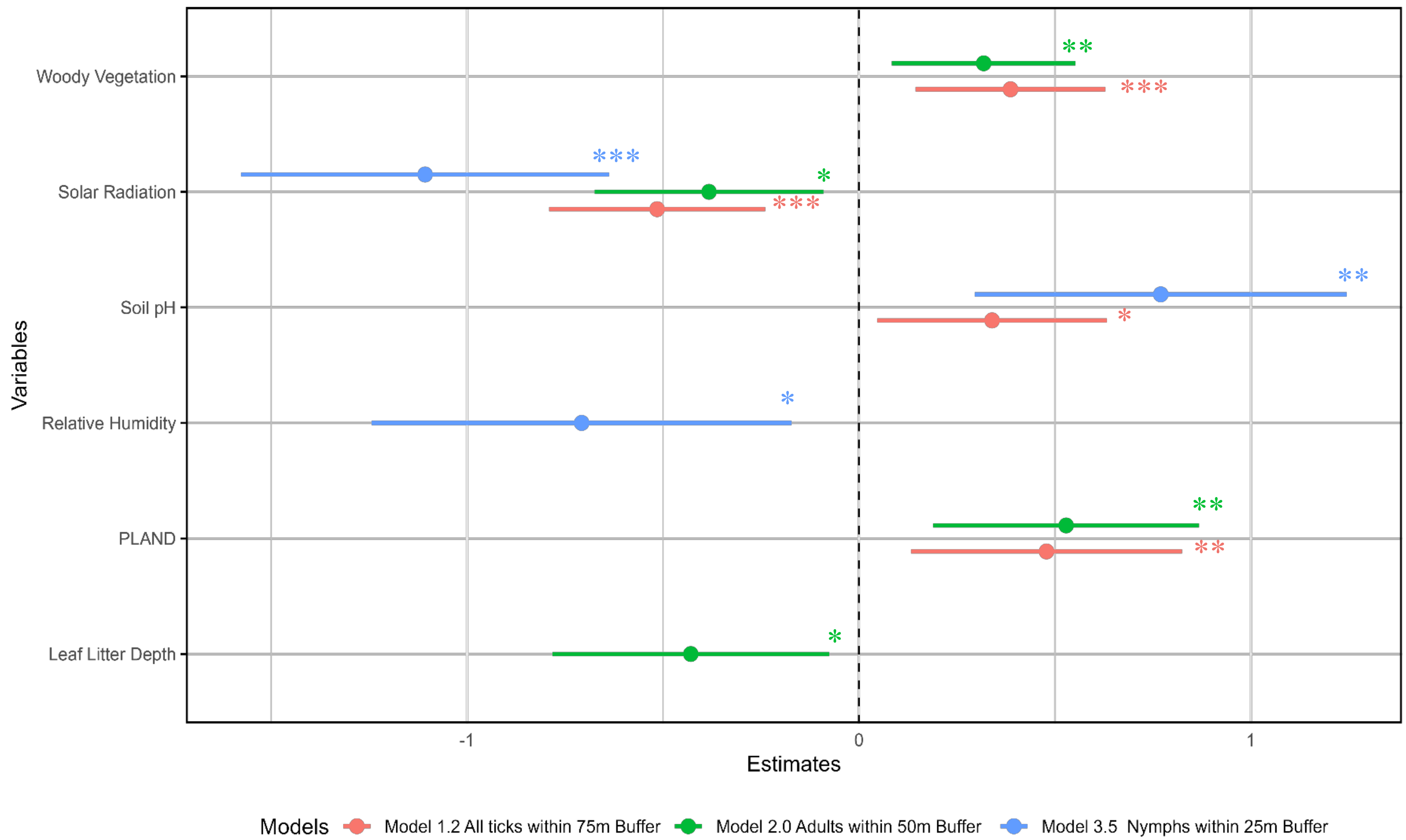

Figure 3. The effect sizes of environmental and spatial variables on tick abundance, segmented by life stage. Each point represents the estimated effect of a variable, with the lines extending from each point depicting the 95% confidence intervals. Red, green, and blue markers correspond to the best-fit models for all ticks, adult ticks, and nymph ticks, respectively, at buffer distances of 75m, 50m, and 25m. Significance levels are denoted with asterisks, where three asterisks represent a p-value less than 0.001, highlighting highly statistically significant effects.

Table 5. Top ten best-fitting models with low AICc values, analyzing the relationship between various environmental predictors and the abundance of all ticks, adult ticks, and nymphs at different buffer sizes. The columns are as follows: 1) Model No: Each unique model number; 2) Variables: Predictor variables included in each model; 3) AICc is the corrected Akaike Information Criterion value for each model, with lower values indicating a superior fit. This criterion adjusts for small sample sizes.; 4) k: The number of parameters used; 5) ΔAICc is the difference in AICc values between each model and the best model; 6) Akaike weights gauge each model's chance of being the best in a given set. The most parsimonious model, selected as the best model, is highlighted in bold. The data was collected across 13 parks in the Oklahoma City Metropolitan Area, OK, USA, from May to July 2023.

Model No	Variables	AICc	k	ΔAICc	Weight
Models assessing the factors affecting tick abundance within a 75m buffer.					
1.0	Solar radiation + relative humidity + soil pH + woody vegetation + PLAND	514.7	5	0.0	0.21
1.1	Solar radiation + relative humidity + soil pH + woody vegetation + PLAND + TE	515.7	6	1.0	0.13
1.2	**Solar radiation + soil pH + woody vegetation + PLAND**	**515.7**	**4**	**1.0**	**0.13**
1.3	Solar radiation + relative humidity + soil pH + woody vegetation + PLAND + SHDI	515.9	6	1.2	0.12
1.4	Solar radiation + soil pH + woody vegetation + graminaceous+ PLAND	516.0	6	1.3	0.11
1.5	Solar radiation + relative humidity + soil pH + woody vegetation + PLAND + TE + SHDI	516.1	7	1.4	0.10

1.6	Solar radiation + soil pH + woody vegetation + PLAND + SHDI	516.6	6	1.9	0.08
1.7	Solar radiation + soil pH + woody vegetation + coarse woody debris+ PLAND	517.3	6	2.6	0.06
1.8	Solar radiation + woody vegetation + PLAND	518.4	6	3.7	0.03
1.9	Solar radiation + soil pH + woody vegetation + SVF	519.6	6	4.9	0.02
	Models assessing the factors affecting adult abundance within a 50m buffer.				
2.0	**Solar radiation + leaf litter depth + woody vegetation + PLAND**	**427.3**	**4**	**0.0**	**0.22**
2.1	Solar radiation + leaf litter depth + woody vegetation + PLAND + ENN	427.5	5	0.2	0.20
2.2	Solar radiation + leaf litter depth + air temperature+ woody vegetation + PLAND	428.4	5	1.1	0.13
2.3	Solar radiation + leaf litter depth + graminaceous+ woody vegetation + PLAND	428.8	5	1.5	0.10
2.4	Solar radiation + leaf litter depth + woody vegetation + SVF	429.0	4	1.7	0.09
2.5	Solar radiation + leaf litter depth + coarse woody debris + woody vegetation + PLAND	429.4	5	2.1	0.08
2.6	Solar radiation + leaf litter depth + relative humidity+ woody vegetation + SVF	429.6	5	2.3	0.07
2.7	Solar radiation + woody vegetation + PLAND	430.5	3	3.2	0.04

2.8	Solar radiation + soil pH + woody vegetation + PLAND	430.9	4	3.6	0.04
2.9	Solar radiation + soil pH + woody vegetation + PLAND + ENN	431.8	5	4.5	0.02
Models assessing the factors affecting nymph abundance within a 25m buffer.					
3.0	Solar radiation + relative humidity+ soil pH + graminaceous	325.3	4	0.0	0.18
3.1	Solar radiation + relative humidity+ soil pH + coarse woody debris +PLAND	325.5	5	0.2	0.16
3.2	Solar radiation + relative humidity+ soil pH + woody vegetation+ PLAND	325.8	5	0.5	0.14
3.3	Solar radiation + relative humidity+ soil pH + PLAND	326	4	0.7	0.12
3.4	Solar radiation + relative humidity+ soil pH + woody vegetation	326.2	4	0.9	0.11
3.5	**Solar radiation + relative humidity+ soil pH**	**327**	**3**	**1.7**	**0.07**
3.6	Solar radiation + relative humidity+ soil pH + PLAND+ENN	327.3	5	2.0	0.06
3.7	Solar radiation + relative humidity+ soil pH + TE	327.5	4	2.2	0.06
3.8	Solar radiation + relative humidity+ soil pH + woody vegetation+ PLAND+ENN	327.8	6	2.5	0.05
3.9	Solar radiation + relative humidity+ soil pH + coarse woody debris	327.9	4	2.6	0.05

Table 6. Comparison of the most parsimonious models for estimating tick abundance, with and without landscape metrics, across various life stages and transect buffer sizes. The columns are as follows: 1) Model No: Each unique model number; 2) Variables: Predictor variables included in each model; 3) AICc is the corrected Akaike Information Criterion value for each model, with lower values indicating a superior fit. This criterion adjusts for small sample sizes; 4) k: the number of parameters used; 5) ΔAICc is the difference in AIC values between each model and the best model; 6) Akaike weights gauge each model's chance of being the best in a given set. Ticks and microclimate data were collected across 13 parks in the Oklahoma City Metropolitan Area, OK, USA May-July 2023.

Model No.	Variables	AICc	k	ΔAICc	Weights
Models assessing the abundance of all ticks within a 75-meter buffer.					
1.2	Solar radiation + soil pH + woody vegetation + PLAND	515.7	4	1.0	0.13
1.11	Solar radiation + soil pH + woody vegetation	520.7	3	6.0	0.01
Models assessing the abundance of all adult ticks within a 50-meter buffer.					
2.0	Solar radiation + leaf litter depth + woody vegetation + PLAND	427.3	4	0.0	0.22
2.10	Solar radiation + leaf litter depth + woody vegetation	434.3	3	7.0	0.01
Models assessing the abundance of all nymph ticks within a 25-meter buffer.					
3.3	Solar radiation + relative humidity + soil pH + PLAND	326	4	0.7	0.12
3.5	Solar radiation + relative humidity+ soil pH	327	3	1.7	0.07

Discussion

In this study, we examined tick abundance across 13 urban parks in the Oklahoma City Metropolitan area, exploring the impact of both micro- and macrohabitat factors on tick populations. Our findings reveal that tick abundance in urban parks is shaped by a complex interplay of micro- and macrohabitat influences, with distinct patterns emerging for different tick life stages. These insights offer a comprehensive understanding of the ecological dynamics that govern tick distribution and abundance in urban green spaces in the Southern Great Plains, providing valuable information for the management of tickborne diseases in urban parks.

The effects of microhabitat variables (microclimate and vegetation types) on tick abundance

Our findings indicate that tick abundance, including adults and nymphs, is significantly influenced by microhabitat factors such as solar radiation, relative humidity, and leaf litter depth. Solar radiation consistently had a negative effect on tick abundance across life stages, emphasizing the importance of shade in tick habitats to prevent desiccation (Del Fabbro et al., 2015; Schulze et al., 2001). This negative impact underscores the role of solar radiation in tick ecology, as ticks prefer less exposed habitats to maintain moisture levels. Interestingly, while solar radiation reduces overall abundance, it can positively influence tick questing behavior, which may increase with longer daylight and higher temperatures (Kiewra et al., 2014). Additionally, we included month as a variable to account for potential seasonal variations in tick activity and abundance. Despite expectations based on some of the existing literature (Jackson et al., 1996), the monthly variations did not significantly impact the models, suggesting that the specific microhabitat variables we examined may overshadow broader seasonal effects in determining tick abundance (Hroobi et al., 2021). This finding prompts a reevaluation of the relative impact of immediate environmental conditions versus broader temporal factors in the ecology of ticks.

We also discovered that soil pH positively influenced the abundance of all tick stages and nymphs. The composition of soil, such as the balance between organic and inorganic matter, and soil humidity, influenced by elements like snowpack, rainfall, wind, sunlight, and vegetation, affect tick distribution patterns (Burtis et al., 2019). Being one of the temporary edaphic species, the early developmental stages of ticks (eggs and larvae) survive within the soil. Furthermore, nymphs are commonly observed resting in the upper layer of soil. Hence, the soil environment can significantly impact tick abundance. Macko et al. (2016) reported a high density of Ixodes Ricinus in areas with slightly acidic soil reactions. In our study sites, soil pH ranged from 6 to 7, with most ticks found in areas within this range. However, there were some sites with soil pH below 4 where ticks were not observed, which explains the positive correlation.

Our results indicated that areas with denser woody vegetation had higher tick populations, supporting the well-established notion that ticks prefer shaded microhabitats to avoid dehydration. (Gleim et al., 2014; Ostfeld & Keesing, 2000). Additionally, *A.americanum,* the major species observed in our study, is considered a generalist that can inhabit various environments but tends to avoid overly grassy areas (Springer et al., 2015). Though other studies suggest that *A.americanum* is minimally influence by vegetation variables (Fryxell et al., 2015; Noden et al., 2023), Gilliam et al. (2018) indicate that different life stages of *A. americanum* may respond differently to vegetation types, with larval ticks showing a weak negative correlation to bare ground, and fewer adults found in areas with abundant leaf litter and coarse woody debris. On the other hand, *A. maculatum*, or the Gulf Coast tick, is typically associated with grass prairies and coastal uplands (Hertz & Kaufman, 2014), yet there are small number of them found in our study, which indicate that the pattern might be primarily dominated by *A.americanum*.

Interestingly, we found a negative correlation between relative humidity and tick abundance in the models for nymph ticks. This contradicts previous studies suggesting higher tick activity with increased humidity (Cupp, 1991; Schulze et al., 2001). Additionally, deeper leaf litter was associated with a decrease in tick abundance in model of adult ticks, which also contrasts with the understanding that leaf litter provides a protective microhabitat aiding in tick survival (Schulze et al., 2001; Vail & Smith, 1998). The discrepancies between our findings and previous research could be due to several factors. For example, the randomization and variation in the placement of our transects could have introduced variability in the microclimatic conditions experienced by the ticks. Moreover, the presence of inaccessible forested areas within some parks may have led to an underrepresentation of ticks in these ideal microhabitats within our samples. Specifically, Brayden Black Park, the smallest park with a mix of grassy and densely forested areas, had less than half of the transects along the forest edges, with the remainder in open, grassy areas that were more exposed to sunlight. Roselli (2019) also reported limited accessibility in this park, placing only eight transects to represent major vegetation cover types. Such variability in microhabitat conditions, coupled with sampling accessibility limitations, may have influenced the observed relationship between humidity, leaf litter depth, and tick abundance. In addition, since nymph abundance was not influenced by seasonality or its interaction with relative humidity, it suggests that seasonal variation is not the primary factor explaining the discrepancies in humidity.

The effects of macrohabitat variables (landscape metrics) on tick abundance

Our findings suggested that the landscape composition of the park, especially the percentage of forest cover, significantly affects tick abundance with a positive relationship. This finding aligns with previous research (Ferrell & Brinkerhoff, 2018), which suggests that forest areas may provide suitable habitats for ticks. Forested areas are known to provide suitable habitats for both ticks and their hosts, including deer, which are primary hosts for adult ticks of many species, including the black-legged tick (*I. scapularis*) responsible for the transmission of Lyme disease (Diuk-Wasser et al., 2021), as well as small mammals such as rodents, rabbit, and birds, which often serve as blood meal for larvae and nymph ticks.

A fragmented landscape typically features a large number of edge areas, which increase interactions between adjacent ecosystems and cause more biotic and abiotic changes across boundaries (Murcia, 1995). Such environments often have different microclimatic conditions compared to forest interiors or open areas, with transitional zones potentially having higher humidity levels and temperature fluctuations, attracting a diverse array of hosts conducive to tick survival and activity. However, in our urban-focused study, the landscape configuration of the park did not seem to significantly impact tick abundance, although various studies highlight the complex relationship between habitat fragmentation, edge effects, and tick abundance in more varied spatial contexts. For instance, Stein et al. (2008) study demonstrates a preference for forest edges among adult and nymph stages of *A. americanum* in rural settings. Similarly, Simpson et al. (2019) observed that in more forested and fragmented areas, there is higher prevalence of tick-borne pathogens and more dynamic tick populations. Interestingly, they also noted lower tick turnover in less fragmented areas, suggesting that landscape configuration influences tick stability (Simpson et al., 2019). Furthermore, the increase in edge habitats due to urbanization has been shown to enhance interactions among *I. scapularis* ticks, their hosts, and humans, thereby intensifying tick population dynamics (Diuk-Wasser et al., 2021). While rural studies show clear impacts of landscape features on tick populations, the influence in urban settings might be modified or less pronounced.

Additionally, landscape metrics did not significantly affect nymph tick abundance in our study area, despite some positive relationships suggested in previous work. The discrepancies between our findings and previous studies could be due to our focus on urban parks, which are predominantly community or neighborhood parks, with Stinchcomb being an exception. These parks are often relatively small and have similar design and planning strategies, typically featuring playgrounds, trails, and open grass areas, which might lead to limited variations in the spatial arrangement of forested areas within these parks.

Limitations

Our study has several limitations that warrant consideration. Firstly, in our vegetation sampling approach, we aggregated plant species into broad categories such as graminaceous and herbaceous. However, the different life stages of *A. americanum*, the species we primarily collected, may exhibit varying responses to specific vegetation types. (Gilliam et al., 2018). A more detailed analysis of vegetation, including the examination of invasive plant species, could potentially provide a clearer understanding of the relationship between vegetation variables and tick abundance (Allan, Goessling, et al., 2010; Noden et al., 2021; Williams et al., 2017). Invasive species, in particular, may alter habitats in ways that increase the presence of host animals, thereby indirectly influencing tick abundance. Secondly, our field collections during June and July of 2023 overlapped with a period of high precipitation in Oklahoma City, marked by frequent and substantial rainfall events, particularly in July. These weather conditions considerably affected our field design and may have constrained our sample size. The extended moisture in vegetation within dense forest areas, persisting for several days post-heavy rainfall, impeded our efficiency in collecting ticks. Future research should build on these results through longitudinal studies that account for seasonal and yearly fluctuations in tick dynamics, offering a more detailed insight into tick ecology in urban settings. Thirdly, our study's conclusions are somewhat constrained by the absence of data on the abundance and composition of potential urban hosts, such as birds and coyotes. While the inclusion of macrohabitat variables, i.e., landscape metrics, may serve as a proxy for host abundance due to their impact on host species, a more thorough understanding of these hosts' roles in tick ecology is essential. Future studies should incorporate assessments of host abundance and composition in urban parks to enhance our understanding of the factors that influence tick populations and improve the management of tick-borne diseases in urban settings (Ferreira et al., 2023; Hamer et al., 2012; Levi et al., 2012).

Conclusion

Our study on tick abundance in urban parks within the Oklahoma City Metropolitan area underscores the complex interplay between microhabitat and macrohabitat factors. Our key findings indicate that microhabitat elements such as solar radiation, relative humidity, and leaf litter depth significantly impact tick populations. Notably, parks with lower solar radiation, more woody vegetation, and slightly acidic soil pH hosted more ticks. Furthermore, macrohabitat factors like forest cover percentage also play essential roles in influencing tick dynamics, with parks having more forest cover showing higher tick abundance. We also found a negative relationship between relative humidity and nymph tick abundance. This study provides valuable insights for park managers and residents to develop effective tick management strategies and raise awareness about ticks and tick-borne diseases. It also informs the public about preventive measures to reduce tick exposure in urban parks. Additionally, the research helps identify areas with high tick abundance in urban parks, allowing pet owners to exercise caution and monitor their pets closely in those areas to avoid tick-infested zones.

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Appendix

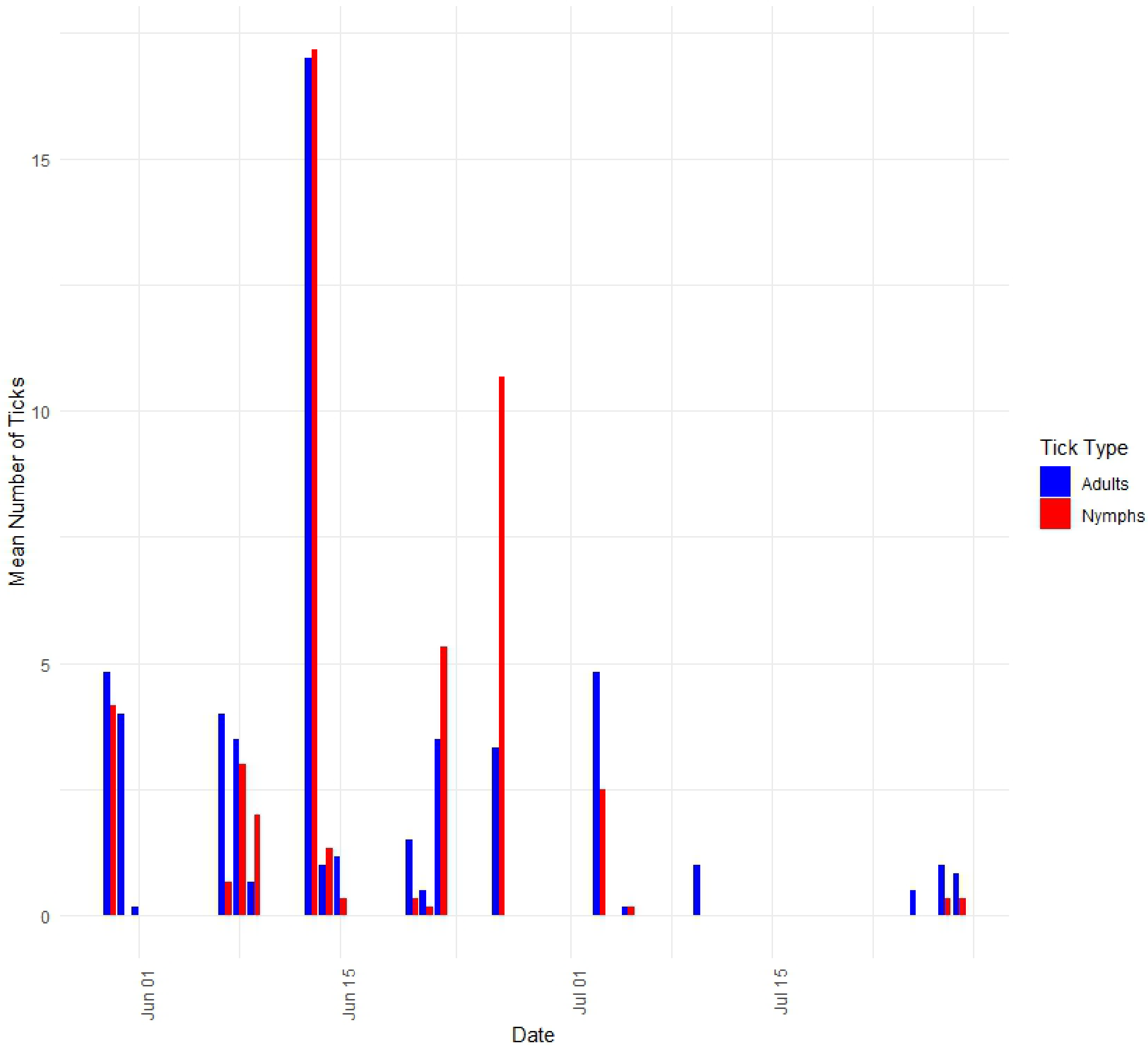

Figure A1. Mean number of adult and nymph ticks collected from transects (n = 114) across different dates per park (May 30- July 28, 2023). Dates with no recorded data, indicative of non-visit days, are represented by gaps in the chart.

Table A1. Spatial scales of buffer zones utilized in modeling the abundance of life stages—ticks in general, adult ticks, and nymph ticks—across three buffer sizes: 25m, 50m, and 75m, gathered from 13 parks in Oklahoma City Metropolitan Area, OK, USA, May-July 20

Landscape metric	Coefficient estimate	P value	Buffer size, m	AIC	ΔAIC
	Ticks:				

		0.7416	<0.001	25	525.4	-
		0.7484	<0.001	50	528.1	2.7
		0.7220	<0.001	75	531.8	6.4
Percent of forest landcover (PLAND)	**Adults**:					
		0.6597	<0.001	25	437.3	1.6
		0.7437	<0.001	50	435.7	-
		0.7733	<0.001	75	437.4	1.7
	Nymphs:					
		0.70317	0.00318	25	340.6	-
		0.68286	0.0119	50	342.5	1.9
		0.515827	0.0745	75	345.5	4.9
	Ticks:					
		0.02367	0.895449	25	544.3	0.3
		0.08224	0.679043	50	544.2	0.2
		0.1112	0.591213	75	544	-
	Adults:					
Total edge of forest (TE)		0.2455	0.1570	25	449.3	-
		0.1973	0.301	50	450.2	0.9
		0.1461	0.4666	75	450.8	1.5
	Nymphs:					
		-0.17747	0.514	25	348.2	-
		-0.004076	0.989	50	348.6	0.4
		0.11318	0.691	75	348.4	0.2
	Ticks:					
		-0.2750	0.04478	25	540.5	2.0
		-0.1129	0.447474	50	543.8	5.3
		-0.4716	0.01210	75	538.5	-
	Adults:					
Number of forest patches (NP)		-0.0899	0.5051	25	450.9	2.7
		-0.1367	0.4141	50	450.6	2.4
		-0.3291	0.0726	75	448.2	-
	Nymphs:					
		-0.44505	0.0143	25	343.7	-
		0.03718	0.864	50	348.5	4.8
		-0.504876	0.0765	75	345.7	2
	Ticks:					
		-0.1030	0.492043	25	543.8	3.5
		-0.3356	0.03724	50	540.3	-
		-0.1523	0.432605	75	543.7	3.4
ENN of forest (ENN)	**Adults**:					
		-0.02646	0.874	25	451.3	0.5
		-0.1879	0.2371	50	449.9	-
		-0.1257	0.4940	75	450.8	0.9
	Nymphs:					

	-0.15876	0.433	25	348.0	4.0
	-0.54042	0.022	50	344.0	-
	-0.33003	0.207	75	347.1	3.1
	Ticks:				
	-0.3847	0.024501	25	539.2	-
	-0.2892	0.089347	50	541.4	2.2
	-0.1357	0.47103	75	543.8	4.6
	Adults:				
SHDI (SHDI)	-0.2938	0.0999	25	448.6	0.2
	-0.3043	0.0875	50	448.4	-
	-0.1952	0.2974	75	450.2	1.8
	Nymphs:				
	-0.35727	0.129	25	346.3	-
	-0.22854	0.318	50	347.6	1.3
	-0.08132	0.753	75	348.5	2.2

Table A2 Results of likelihood ratio test for model comparisons and distribution determination.

Model	Loglikelihood	χ^2	P value
All ticks			
Poisson	-956.05		
NB	-282.07	1347.96	<0.001
Zero-inflated NB	-282.07	0.0005	0.98
Adults			
Poisson	-488.46		
NB	-230.88	515.17	<0.001
Zero-inflated NB	-230.88	0.001	0.97
Nymphs			
Poisson	-651.19		
NB	-182.72	936.94	<0.001
Zero-inflated NB	-182.72	0.0002	0.99

Notes: NB indicates Negative Binomial.

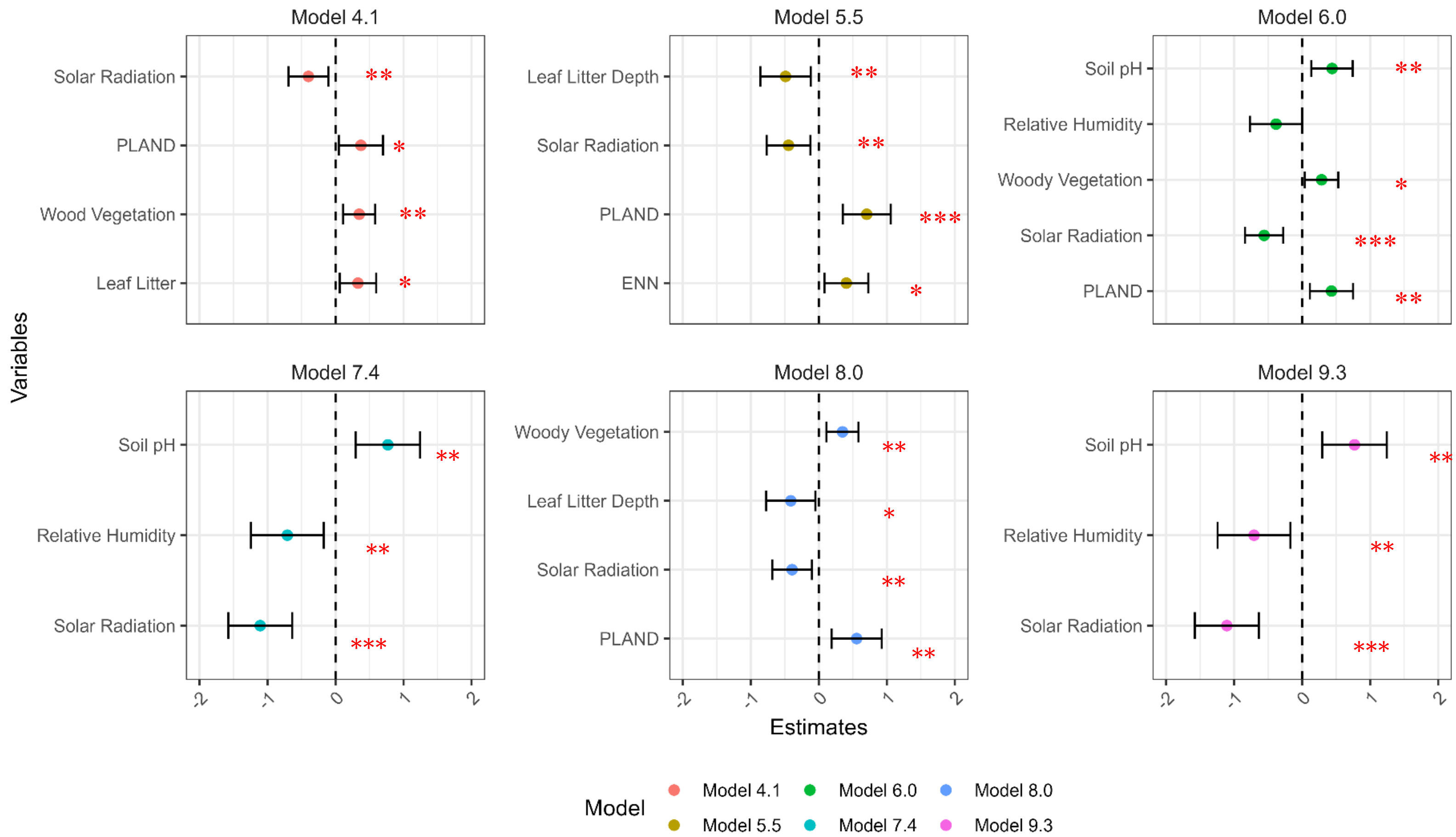

Figure A2 Coefficient estimates from top selected models demonstrate the effects of microclimate variables and landscape metrics on tick abundance within different buffer zones. Each plot corresponds to a distinct model and buffer size: Model 4.1 for all ticks within a 25m, Model 5.5 for adult ticks within a 25m, Model 6.0 for all ticks within a 50m, Model 7.4 for nymphs within a 50m, Model 8.0 for adult ticks within a 75m, and Model 9.3 for nymphs within a 75m. Predictors such as relative humidity, wind speed, solar radiation, vegetation characteristics, and landscape metrics are plotted, with error bars denoting 95% confidence intervals and asterisks signaling statistical significance. The data were collected from 13 parks in the Oklahoma City Metropolitan Area, Oklahoma, USA, from May to July 2023.

Table A3.Top ten model selection results for examining the relationships between microclimate variables, landscape metrics, and the abundance of field-collected ticks across different buffer zones (25m, 50m, 75m), including all life stages, adults, and nymphs. The columns are as follows: 1) Model No: Each unique model number; 2) Variables: Predictor variables included in each model; 3) AICc is the corrected Akaike Information Criterion value for each model, with lower values indicating a superior fit. This criterion adjusts for small sample sizes.; 4) k: the number of parameters used; 5) ΔAICc is the difference in AICc values between each model and the best model; 6) Akaike weights gauge each model's chance of being the best in a given set.

Model No	Variables	AICc	k	ΔAICc	Weights
Models assessing the abundance of all ticks within a 25 m buffer.					
4.0	Solar radiation+ relative humidity + leaf litter+ woody vegetation + PLAND	513.5	5	0.0	0.208
4.1	**Solar radiation + leaf litter+ woody vegetation + PLAND**	**513.9**	**4**	**0.4**	**0.171**
4.2	Solar radiation + leaf litter + soil pH woody vegetation + PLAND	514.0	5	0.5	0.162
4.3	Solar radiation + leaf litter + woody vegetation + relative humidity	515.3	4	1.8	0.085
4.4	Solar radiation+ air temperature + leaf litter+ woody vegetation + PLAND	515.5	5	2.0	0.077
4.5	Solar radiation + herbaceous + leaf litter+ woody vegetation + PLAND+ENN	515.5	5	2.0	0.077
4.6	Solar radiation + leaf litter+ graminaceous + woody vegetation + PLAND	516.0	5	2.5	0.060
4.7	Solar radiation + leaf litter+ woody vegetation + PLAND + TE	516.0	5	2.5	0.060

4.8	Solar radiation + leaf litter+ woody vegetation + PLAND+ENN	516.1	5	2.6	0.060
4.9	Solar radiation + leaf litter+ woody vegetation	516.6	3	3.1	0.044
	Models assessing the abundance of adults within a 25 m buffer				
5.0	Solar radiation+ relative humidity + leaf litter depth + PLAND + ENN	427.7	5	0.0	0.275
5.1	Solar radiation + leaf litter depth+ PLAND+ENN+TE	428.9	5	1.2	0.151
5.2	Solar radiation+ SVF + relative humidity + leaf litter depth+ ENN	429.5	5	1.8	0.112
5.3	Solar radiation+ SVF + relative humidity + leaf litter depth+ woody vegetation	429.6	5	1.5	0.106
5.4	Solar radiation+ air temperature + leaf litter depth + PLAND + ENN	429.8	5	2.1	0.096
5.5	**Solar radiation + leaf litter depth+ PLAND+ENN**	**429.9**	**4**	**2.2**	**0.092**
5.6	Solar radiation+ SVF + relative humidity + leaf litter depth+ woody vegetation + ENN	430.7	6	3.0	0.061
5.7	Solar radiation + leaf litter depth+ graminaceous + PLAND+ENN	431.5	5	3.8	0.041
5.8	Solar radiation+ SVF + relative humidity + leaf litter depth+ graminaceous + woody vegetation + ENN	431.8	7	4.1	0.035
5.9	Solar radiation + leaf litter depth+ coarse.woody.debris+ PLAND+ENN	432.2	5	4.5	0.029
	Models assessing the abundance of all ticks within a 50 m buffer				

6.0	**Solar radiation + relative humidity +soil pH+ woody vegetation + PLAND**	**513.2**	**5**	**0.0**	**0.194**
6.1	Solar radiation + relative humidity +soil pH+ woody vegetation + PLAND + TE	513.7	6	0.5	0.151
6.2	Solar radiation + air temperature +soil pH+ woody vegetation + PLAND	514.1	5	0.9	0.124
6.3	Solar radiation + relative humidity +soil pH+ woody vegetation + Graminaceous + PLAND	514.2	6	1.0	0.118
6.4	Solar radiation + relative humidity +soil pH+ woody vegetation + NP + PLAND	514.6	6	1.4	0.096
6.5	Solar radiation + relative humidity +soil pH+ woody vegetation + PLAND + TE+ENN	514.8	7	1.6	0.087
6.6	Solar radiation + relative humidity +soil pH+ woody vegetation + coarse.woody.debris+ PLAND	515.0	6	1.8	0.079
6.7	Solar radiation + relative humidity +soil pH+ woody vegetation + PLAND + ENN	515.5	6	2.3	0.061
6.8	Solar radiation + relative humidity +soil pH+ woody vegetation + svf	515.9	5	2.7	0.050
6.9	Solar radiation + relative humidity +soil pH+ woody vegetation + PLAND + TE + SHDI +ENN	516.4	6	3.2	0.039
	Models assessing the abundance of nymphs within 50 m buffer				
7.0	Solar radiation+ soil pH + relative humidity + woody vegetation	326.2	4	0.0	0.152
7.1	Solar radiation+ soil pH + relative humidity + woody vegetation + NP	326.5	5	0.3	0.131

7.2	Solar radiation+ soil pH + relative humidity + woody vegetation + PLAND + NP	326.6	6	0.4	0.124
7.3	Solar radiation+ soil pH + relative humidity+ NP	326.6	4	0.4	0.124
7.4	**Solar radiation+ soil pH + relative humidity**	**327**	**3**	**0.8**	**0.102**
7.5	Solar radiation+ soil pH + relative humidity +woody vegetation + PLAND	327.2	5	1.0	0.092
7.6	Solar radiation+ soil pH + relative humidity + graminaceous + PLAND	327.4	5	1.2	0.083
7.7	Solar radiation+ soil pH + relative humidity + ENN	327.4	5	1.2	0.083
7.8	Solar radiation+ soil pH + relative humidity + PLAND	327.8	4	1.6	0.068
7.9	Solar radiation+ soil pH +air temperature	328.8	3	2.6	0.041
	Models assessing the abundance of adults within a 75 m buffer				
8.0	**Solar radiation+ woody vegetation+ leaf litter depth+ PLAND**	**427.8**	**4**	**0.0**	**0.237**
8.1	Solar radiation+ woody vegetation+ leaf litter depth+ Graminaceous+ PLAND	428.8	5	1.0	0.144
8.2	Solar radiation+ leaf litter depth+ PLAND	429.5	3	1.7	0.101
8.3	Solar radiation+ relative humidity + woody vegetation+ leaf litter depth+ PLAND	429.5	4	1.7	0.101
8.4	Solar radiation+ SVF + woody vegetation+ leaf litter depth+ PLAND +ENN	429.6	6	1.8	0.096
8.5	Solar radiation+ woody vegetation+ leaf litter depth+ coarse woody debris + PLAND	429.8	5	2.0	0.087

8.6	Solar radiation+ woody vegetation+ leaf litter depth+ PLAND +NP	429.9	5	2.1	0.083
8.7	Solar radiation+ woody vegetation+ PLAND	430.4	3	2.6	0.065
8.8	Solar radiation+ woody vegetation+ soil pH + PLAND	430.6	4	2.8	0.058
8.9	Woody vegetation + leaf litter depth+ PLAND	432.2	3	4.4	0.026
	Models assessing the abundance of nymphs within a 75 m buffer				
9.0	Solar radiation+ relative humidity+ soil pH + graminaceous	325.3	4	0.0	0.271
9.1	Solar radiation+ relative humidity+ soil pH + woody vegetation	326.2	4	0.9	0.173
9.2	Solar radiation+ relative humidity+ soil pH + woody vegetation + wind speed	326.8	5	1.5	0.128
9.3	**Solar radiation+ relative humidity+ soil pH**	**327**	**3**	**1.7**	**0.116**
9.4	Solar radiation+ relative humidity+ soil pH + coarse woody debris	327.9	4	2.6	0.074
9.5	Solar radiation+ relative humidity+ soil pH + NP	328.1	4	2.8	0.067
9.6	Solar radiation+ relative humidity+ soil pH + woody vegetation + wind speed + TE	328.8	6	3.5	0.047
9.7	Solar radiation+ relative humidity+ soil pH + TE	328.9	5	3.6	0.045
9.8	Solar radiation+ relative humidity+ soil pH + PLAND	329	4	3.7	0.043
9.9	Solar radiation+ relative humidity+ soil pH + ENN	329.3	4	4.0	0.037

Table A4. Comparison of the most parsimonious models for estimating tick abundance, with and without landscape metrics, across various life stages and transect buffer sizes. The columns are as follows: 1) Model No: Each unique model number; 2) Variables: Predictor variables included in each model; 3) AICc is the corrected Akaike Information Criterion value for each model, with lower values indicating a superior fit. This criterion adjusts for small sample sizes.; 4) k representing the number of parameters used; 5) ΔAICc is the difference in AICc values between each model and the best model; 6) Akaike weights gauge each model's chance of being the best in a given set. Ticks and microclimate data were collected across 13 parks in the Oklahoma City Metropolitan Area, OK, USA May-July 2023.

Model No	**Variables**	**AICc**	**k**	**ΔAICc**	**Weights**
Models	assessing the abundance of all ticks within a 25m buffer				
4.1	Solar radiation + leaf litter+ woody vegetation + PLAND	513.9	4	0.4	0.171
4.9	Solar radiation + leaf litter+ woody vegetation	516.6	3	3.1	0.044
Models	assessing the abundance of adults within a 25 m Buffer				
5.5	Solar radiation + leaf litter depth+ PLAND+ENN	429.9	4	2.2	0.092
5.10	Solar radiation + leaf litter depth	441.8	3	14.1	0.000
Models	assessing the abundance of adults within a 50 m Buffer				
6.0	Solar radiation + relative humidity +soil pH+ woody vegetation + PLAND	513.2	5	0.0	0.194
6.10	Solar radiation + relative humidity +soil pH+ woody vegetation	517.9	4	4.7	0.018
Models	assessing the abundance of nymphs within a 50 m buffer				
7.0	Solar radiation+ soil pH + relative humidity + NP	326.6	4	0.4	0.124
7.3	Solar radiation+ soil pH + relative humidity	327	3	0.8	0.102
Models	assessing the abundance of adults within a 75 m buffer				

8.0	Solar radiation+ woody vegetation+ leaf litter depth+ PLAND	427.8	4	0.0	0.237
8.10	Solar radiation+ woody vegetation+ leaf litter depth	435.4	6	7.6	0.005
Models assessing the abundance of nymphs within a 75 m buffer					
9.3	Solar radiation+ relative humidity+ soil pH	327	3	1.7	0.116
9.5	Solar radiation+ relative humidity+ soil pH + NP	328.1	4	2.8	0.067