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Original article

Evaluating spatial and temporal patterns of tick exposure in the United States using community science data submitted through a smartphone application

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ABSTRACT

Research initiatives that engage the public (i.e., community science or citizen science) increasingly provide insights into tick exposures in the United States. However, these data have important caveats, particularly with respect to reported travel history and tick identification. Here, we assessed whether a smartphone application, The Tick App, provides reliable and novel insights into tick exposures across three domains — travel history, broad spatial and temporal patterns of species-specific encounters, and tick identification. During 2019–2021, we received 11,424 tick encounter submissions from across the United States, with nearly all generated in the Midwest and Northeast regions. Encounters were predominantly with human hosts (71%); although one-fourth of ticks were found on animals. Half of the encounters (51%) consisted of self-reported peri-domestic exposures, while 37% consisted of self-reported recreational exposures. Using phone-based location services, we detected differences in travel history outside of the users' county of residence along an urbanicity gradient. Approximately 75% of users from large metropolitan and rural counties had travel out-of-county in the four days prior to tick detection, whereas an estimated 50–60% of users from smaller metropolitan areas did. Furthermore, we generated tick encounter maps for *Dermacentor variabilis* and *Ixodes scapularis* that partially accounted for travel history and overall mirrored previously published species distributions. Finally, we evaluated whether a streamlined three-question sequence (on tick size, feeding status, and color) would inform a simple algorithm to optimize image-based tick identification. Visual aides of tick coloration and size engaged and guided users towards species and life stage classification moderately well, with 56% of one-time submitters correctly selecting photos of *D. variabilis* adults and 76% of frequent-submitters correctly selecting photos of *D. variabilis* adults. Together, these results indicate the importance of bolstering the use of smartphone applications to engage community scientists and complement other active and passive tick surveillance systems.

1. Introduction

In recent decades, there has been an increase in the geographic distribution and number of tick-borne infections caused by *Ixodes* spp., *Amblyomma* spp., and *Dermacentor* spp. ticks in the United States(Alkishe and Peterson, 2022; Flenniken et al., 2022; Hahn et al., 2016; Kugeler et al., 2021; Telford and Goethert, 2004). The Northeast and Midwest regions of the country, in particular, face significant burdens of Lyme

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disease and other *Ixodes scapularis*-borne diseases; while less frequent, albeit consequential, diseases including ehrlichiosis and Rocky Mountain spotted fever are caused by agents transmitted by *Amblyomma americanum* and *Dermacentor variabilis* (Nelson et al., 2015; Raghavan et al., 2019; Rosenberg et al., 2018). Given this shifting eco-epidemiological context, public health professionals must monitor risk levels for tick-borne diseases locally, rather than rely on broad, regional assessments. Understanding tick-borne disease risk for a local jurisdiction (e.g., county) involves evaluating tick-borne infection hazard, including which tick species are established locally (and which are emerging in neighboring counties); which areas within the county are of highest risk, and which pathogens are present among tick populations. Additionally, it requires assessing where, when, and how people are exposed to infected ticks, and their capacity to respond after a tick encounter (i.e., level of vulnerability) (Diuk-Wasser et al., 2021). Acquiring data on each contributing factor carries distinct challenges. First, active tick surveillance and pathogen screening programs are resource intensive, with limited funding constraining the scope and geographic scale of field-based sampling (Centers for Disease Control and Prevention, 2022; Foster et al., 2022; Hai et al., 2014; Lyons et al., 2022; Mader et al., 2021; Nieto et al., 2018). Second, retrospective tick exposure surveys are subject to recall bias, requiring respondents to generalize about tick encounters over long stretches of time (Fernandez et al., 2019; Runyan et al., 2013). And third, surveys evaluating how people respond to tick exposures are time consuming and typically only feasible at small scales. Additionally, aggregating data to understand tick exposure patterns across broad regions carries its own limitations. Currently, in the United States, syndromic surveillance for tick bites is conducted through emergency department visitations (i.e., ICD diagnostic codes) (Centers for Disease Control and Prevention, 2021). While this provides a representative picture of the rate at which regional populations seek acute care for tick bites, critical information about the exposure (e.g., encounter location, tick species, and life stage) are missing, and necessary to inform tick-borne disease prevention.

In the midst of these challenges, tick surveillance rooted in community science (also called citizen science) offers a way to generate large volumes of data at broad (e.g., regional and national) scales in collaboration with the public. In recent years, community science initiatives have emerged as a means to gather information on tick abundance and exposure—although the programs' objectives and collection methods vary. Some programs, including one operated by Northern Arizona University, provided the public with free tick identification and pathogen testing services (Nieto et al., 2018). During 20 months, Nieto et al. received over 16,000 physical tick submissions. Alongside ticks, their team requested information on the presumed tick exposure location, and with this information generated distribution maps that expanded upon previous records of species ranges. However, travel history was not collected and tick exposure locations provided by participants is subject to inaccuracies (Nieto et al., 2018). Recently, similar programs have emerged, although focused on specific geographic areas of interest (Hart et al., 2022). Other initiatives, including eTick in Canada and TickSpotters in the United States, use online photo submission systems, wherein participants send photos of ticks, information about the encounter, and a best-guess on the species identification to teams of trained entomologists who then review these data (Koffi et al., 2017; Kopsco et al., 2021a). Over four years, TickSpotters received ~31,500 submissions from across the United States. With these data they asked a number of research questions including what factors were associated with participants' correct (or incorrect) tick species identification (Kopsco et al., 2021a). Finally, apps including TickTracker guide users through identification keys and collect exposure information, but may not include expert validation (TickTracker, 2022).

Although there are benefits to using crowd-sourced data, there are also limitations to the representativeness and quality of the data (Eisen and Eisen, 2021). Community science study populations are often biased based on socioeconomic status, recruitment effort, and interest in tick-borne diseases, creating challenges in comparing findings to the population at-large or to other data collection efforts (Fernandez et al., 2019). With respect to data quality, accuracy of species identification and the spatial precision of the encounter location are difficult to confirm (Bron et al., 2021; Eisen and Eisen, 2021). While physical tick submissions result in the highest quality assurance for species identification, establishing a pipeline for receiving ticks is time-intensive. As a first step, programs must direct sufficient resources towards participant recruitment. Often, for vector-borne diseases, target populations are incentivized by pathogen testing of submitted specimens (Hamer et al., 2018). This carries potential to overwhelm the resources of small research teams. Species identification via digital images eliminates the demand on physical resources and offers avenues of enhanced engagement with the public (Kopsco et al., 2021b). Although this method is sensitive to image quality and the experience level of the individual responsible for identifying the tick, identification can be verified by trained entomologists (Fernandez et al., 2019). Separately, with respect to exposure location, ticks may be detected on people or companion animals in locations far from where the encounter originally occurred (Centers for Disease Control and Prevention, 2022). Without detailed information on travel history or the duration of tick attachment, exposure location data are subject a high degree of uncertainty—and geographic distribution maps based self-reported data may lead to misrepresentations of risk

In 2018, our team launched The Tick App as a survey tool to gather information on human behaviors and movements associated with tick exposure while also engaging users in tick reporting (Fernandez et al., 2019). The app uniquely captures information on daily activities, which is then crossed with geolocation information on movement patterns and land cover data associated with where users may be encountering different tick species. Given the potential caveats of community science-generated data, in this paper we assessed how tick encounter submissions reported through the app informs patterns of tick exposures across a range of spatial and temporal scales (Bron et al., 2021; Eisen and Eisen, 2021). Using descriptive analyses, we evaluated the degree to which The Tick App enhances understanding of three facets of tick exposure information. We first evaluated whether a streamlined three-question sequence (on tick size, feeding status, and color) would inform a simple identification algorithm to optimize image-based identification for our program. Next, we uncovered how app-based GPS data provides an understanding of tick encounter location. Finally, we examined whether encounter-level data could be aggregated to detect broad spatial and temporal patterns of tick exposure, including seasonal variation. We focused our analyses on three medically-relevant tick species, *I. scapularis, A. americanum*, and *D. variabilis*. Lessons learned here can provide a blueprint with which to design and evaluate future tick surveillance platforms, maximizing data quality and participant engagement.

2. Materials and methods

2.1. Data sources

In this investigation, we used data from The Tick App during 2019–2021. During this study period, the app was available to participants 18 years and older living in the United States (Fernandez et al., 2019). We created a tick encounter database using two app features. The first was the "Daily Log"—a daily retrospective survey where users document their outdoor activities, any ticks encountered, and personal protection measures used to prevent tick bites. Users may also report tick encounters directly through the "Tick Report" feature. A tick encounter is defined as one or more ticks that a user reported finding on a single day. For each tick encounter submission users provided information on whom the tick(s) was found on (e.g., self, household member, or companion animal), when and where they think they picked up the tick(s) (e.g., the county and zip code; in a peri-domestic versus recreational setting), and whether the tick(s) was attached. Self-reported peri-domestic exposures included tick encounters that happened in “my yard” or “my neighbor’s property”, noting that for some users, “yards” encompassed larger swaths of private land (e.g., forested acreage and private pastures).

We also asked users to visually assess the tick’s appearance and submit a photo of the tick. To assess appearance, users were asked to select the visual aide that most closely resembled their tick(s), characterizing size (big, medium, small), bloodfed status (flat, round [assumed to reflect $\geq$ 3 days of feeding to fully fed]), and color pattern (Fig. 1). Prompts of color patterns were: “all brown” (next to an image of an *A. americanum* male, which could also be perceived as *Haemaphysalis longicornis*, the Asian longhorned tick), “white dot” (image showing *A. americanum* female), “brown and white pattern” (image showing *D. variabilis* female, which we assumed would also be selected for *D. variabilis* males, other *Dermacentor* spp., and *A. maculatum*), or “black shield” (image showing *I. scapularis* female, which we assumed would also be selected for *I. scapularis* males and other *Ixodes* spp.). To maximize simplicity in the user-experience, we presented a limited number of images for assessing coloration. We showed photos of unfed ticks only; one set of photos had the tick filling the frame and another set had the tick next to a pencil, for scale (Fig. 1c). Additionally, we did not specify anatomical cues for the tick species.

Given that the tick may not have been available at the time of report submission, each question also included the option “I don’t know” to distinguish missing knowledge from skipped answers. Researchers trained in entomological classification gave each submitted photo a certainty score. The certainty score incorporated the researcher’s confidence in their ability to correctly identify the tick species. This was a qualitative score, considering the quality of the image, size of the tick in the image, and position of the tick. We used scores from 0–100. Scores of 1–50 indicated “I cannot tell” (in this case, we asked users to submit a new photo); 51–70 indicated “I suspect it is ‘X’ species” (in certain cases we asked users for a new photo or a photo focusing on specific anatomical areas such as the mouth parts or scutum); 71–90 indicated “I am quite certain”; and 91–100, “I am certain.” Images with certainty scores above 70 were reviewed and classified according to species, life stage, sex, bloodfed status (yes, no, unknown), and the estimated feeding duration. Bloodfed status and duration was determined using visual assessments of relative scutal versus body length, comparing photos to reference tick growth comparison charts (TickEncounter, 2021). Results were then emailed to the participant.

To evaluate tick encounter locations we used both self-reported information and GPS data. GPS data were collected for The Tick App users who enabled location services in the app (Fernandez et al., 2019). Users could opt to keep location services on continuously, allowing for GPS data to be collected at 15 min intervals, or only while The Tick App was in use. Recorded data consisted of the timestamp and coordinates (latitude and longitude) of the device, with an expected horizontal position accuracy of 7–13 m based on smartphone GPS accuracy assessments from the literature (Merry and Bettinger, 2019; Tomaštík et al., 2017). Data were not recorded when users were outside of mobile

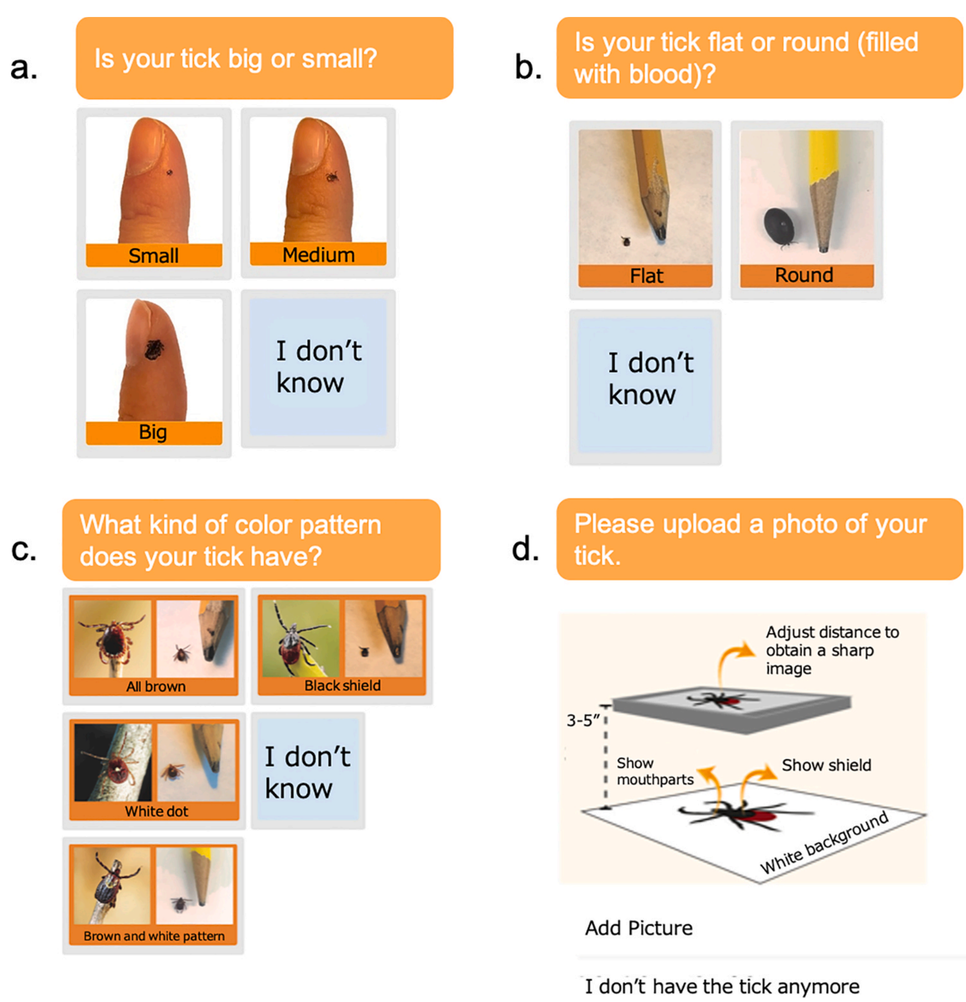

Fig. 1. The Tick App interface with the tick identification screening sequence. Upon navigating to the Tick Report feature of The Tick App, users are asked the above three-questions sequence and prompted to submit a photo for identification (with visual aides on how to obtain a high-quality image).

service range.

Here, we used two subsets of The Tick App tick encounter database during 2019–2021. For the three-question sequence for tick photo submissions and geographic and seasonal patterns across species, we used data for participants residing in the Midwest and Northeast regions (Fig. 2a, Table S1). For GPS data, we included users located throughout the contiguous United States (Fig. 2b). This work was conducted in accordance with Institutional Review Board approved protocols (2018−84, University of Wisconsin – Madison, WI, USA; and AAA3750-M00Y01, Columbia University, New York, NY, USA).(Fig. 3)

2.2. Analyses

2.2.1. Three-question sequence for photo screening

We assessed the degree to which visual aides were associated with tick species identification by trained entomologists, which would help to develop a simple identification algorithm. We used a multiple correspondence analysis (MCA) on our three-question screening variables (tick size, bloodfed status, and color pattern) and entomologist-identified tick species to examine whether user responses were associated with a particular species. Analyses were conducted using the "FactoMine" package in R.

Next, we evaluated whether user-selected tick size (the first question in the three-question sequence) served as a predictive feature for tick life stage and species. For this, we calculated the proportion of tick photos with a given entomologist-verified life stage and species assignment (e.g., adult *I. scapularis*) out of the number of photos with a given user-selected tick size (Table 3). For the second question, we assessed whether users' indication of the tick being flat or round corresponded to entomologist-determined bloodfed status. And for the third question, we assessed how users classified images of their tick based on visual aides and written prompts of the tick's color patterning (Figs. 1 and 4).

2.2.2. Location of tick encounters

For tick encounter submissions across life stages, we conducted GPS analyses among participants who: 1) provided the date that the tick was found on themselves or a household member/companion animal; 2) enabled location services; and 3) had at least three days of data and > 20 daytime and evening (04:00 AM–11:59 PM) GPS points collected in a four-day period prior to when the tick was found. We restricted analyses to a four-day period, given evidence that a majority of people who experience a tick-bite remove adult ticks within 72 h (Yeh et al., 1995). To assess travel history, we compared the zip code, county, and state of a given GPS point to the participant's jurisdiction of residence As a proxy for the duration of time spent in a given location, we analyzed the proportion of daytime and evening GPS points detected in a given location out of the total number of points collected within their four-day collection period. Additionally, we compared travel history out-of-county according to the county's urbanicity classification (Table S2): large metropolitan, medium metropolitan, small metropolitan, and rural counties.

To estimate the land covers that users visited prior to tick detection, we extracted land cover classifications from the NLCD 2019 raster layer at a 30 m resolution (Dewitz, 2016). We reclassified land cover types into five categories (Table S3): developed (low-, medium-, and high-intensity development); grassy (consisting of open areas and grasslands, scrub); forested; planted/cultivated; and other (lichen, barren lands, wetlands, and open water). We examined the proportion of users' GPS points that fell within each land cover class, according to users' travel history (out-of-county travel: yes versus no; out-of-county travel on weekdays versus weekends) and exposure type (peri-domestic versus recreational). We examined travel history and exposure variables separately as a way to validate this self-reported information. Finally, for users with GPS data and a photo submission, for each of the species we analyzed the proportion of time spent in the above land cover classes. NLCD extractions were conducted using the "raster" package in R (with no spatial buffer). For descriptive bivariate analyses of categorical variables, we used nonparametric Mann-Whitney and Kruskal-Wallis tests.

2.2.3. Geographic and temporal variation across species

To examine geographic patterns of The Tick App encounter

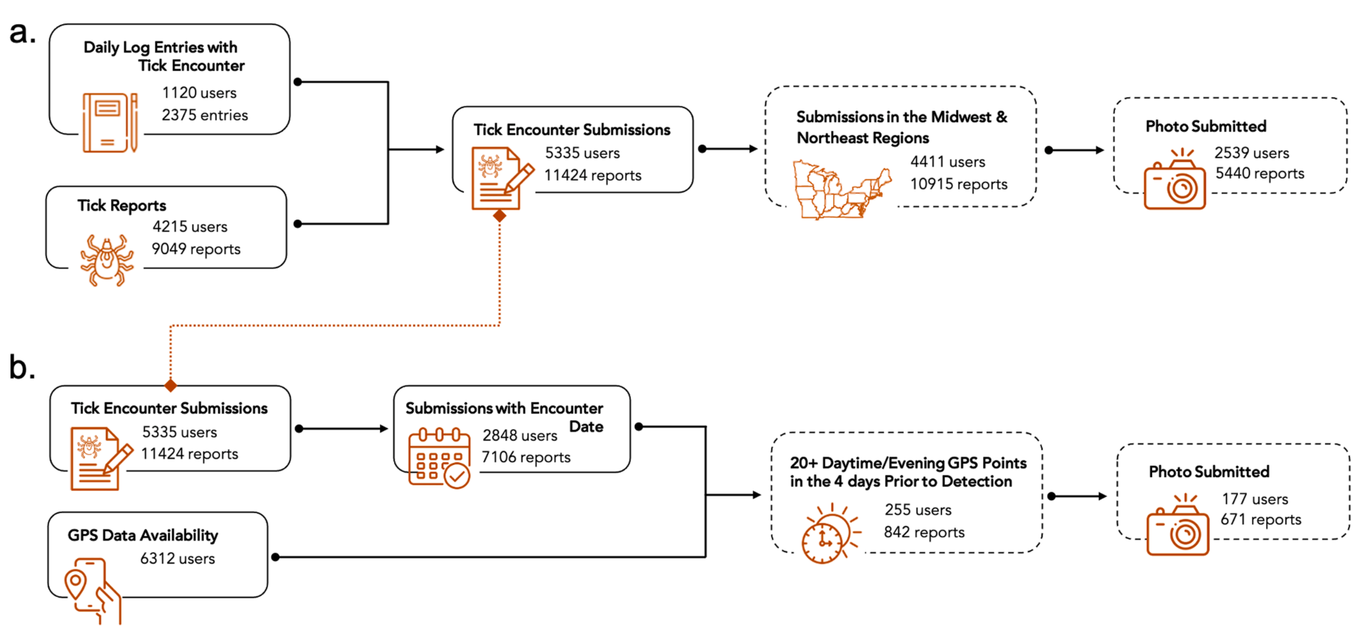

Fig. 2. Diagram of tick encounter and GPS data submissions. 2a. To analyze tick encounters, we aggregated data from Daily Log and Tick Report (i.e., without Daily Log) entries. Approximately 79% of tick encounters were made up of Tick Reports. We restricted tick encounters to the Midwest and Northeast regions, where we actively recruited participants, and which made up 96% of submissions nationwide. Of these submissions, 50% included photos of the tick, allowing for species-specific analyses. 2b. To analyze mobility data associated with tick encounters, we matched the two datasets and restricted records to users with ≥20 GPS points available in the four days preceding tick detection, with 7.4% of the original tick encounter database meeting this criterium. Out of these entries, 80% submitted a photo of the tick, allowing for GPS and species-specific analyses.

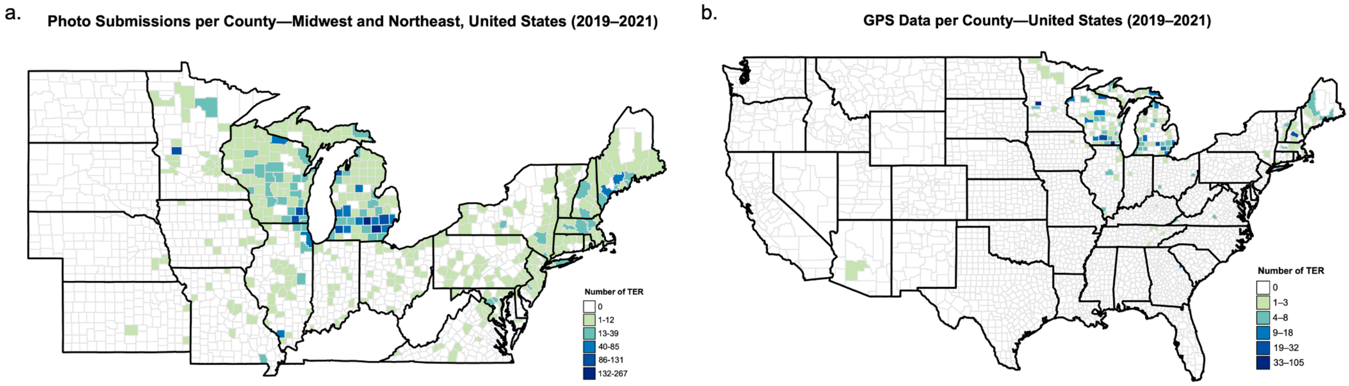

Fig. 3. Tick encounters with photo and GPS data submissions (2019–2021). 3a. Tick encounters with photo submissions were available for 352 counties in 24 states of the Midwest and Northeast regions of the Unites States. Most counties had between 1 and 12 tick encounters with photo submissions available for species-level analyses. Photo submissions were most widely available for counties in the states of Wisconsin and Michigan in the Midwest region. 3b. Tick encounters submissions with ≥20 daytime GPS points available in the four days preceding a tick encounter were available for 138 counties across 18 states in the continental United States.

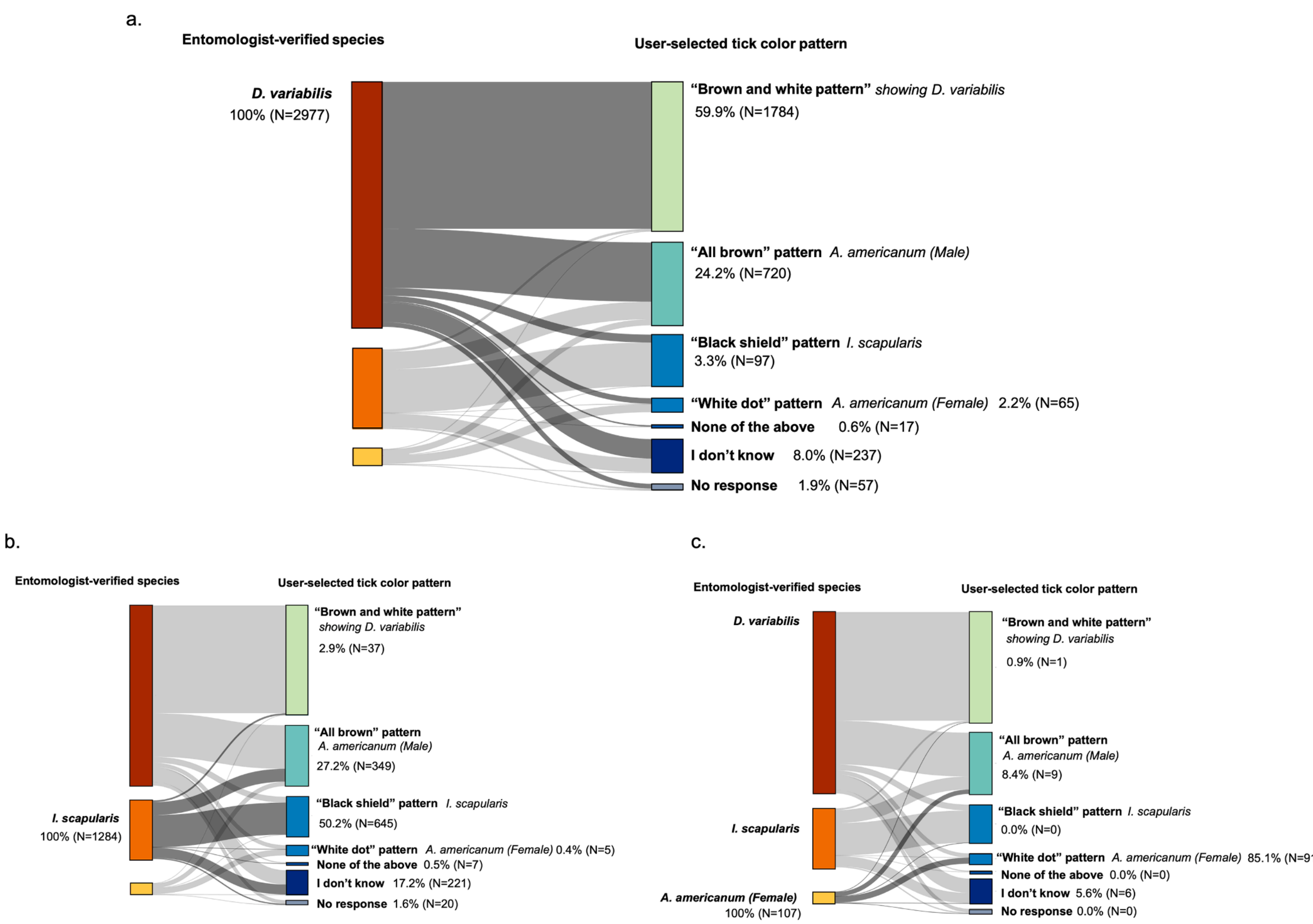

Fig. 4. Entomologist-verified classifications versus photo-based user-selected species for adult ticks. 4a. The left panel shows the entomologist-verified species identification based on submitted photos of adult ticks, and the right shows the user-selected photo based on visual guides (Fig. 1). For users with a *Dermacentor variabilis* tick, 60% selected the photo of a "brown and white pattern" tick corresponding to *D. variabilis*. 4b. For users with an *Ixodes scapularis* tick, 50% selected the photo of a tick with a "black shield" pattern, corresponding to *I. scapularis* ticks. 4c. For users with *Amblyomma americanum* females, 85% selected the photo of a tick with a "white dot" pattern corresponding to *A. americanum* females.

submissions, we compared data submitted through the app with published county-level reports of *I. scapularis* and *D. variabilis*, using participants' county of residence. With *A. americanum* making up only 7.5% of tick photo submissions, we did not generate maps for this species.

Given that most tick encounter maps do not account for travel history, we partially accounted for this with the data on hand. We mapped the counties where reports of *I. scapularis* and *D. variabilis* were generated, excluding individuals with more than 20% of their GPS points outside the users' home county in the four days prior to tick detection (in the case where both photo submissions and GPS data were available). With this data subset, we compared *I. scapularis* submissions to CDC surveillance datasets available through December 2021, as well as reports made publicly available by Centers for Disease Control and Prevention (2022), Kopsco et al. (2021b) and Nieto et al. (2018). We compared *D. variabilis* submissions to those published by the passive surveillance initiative by Nieto et al., and a review of the literature and records from the U.S. National Tick Collection and National Ecological Observatory Network conducted by Lehane et al. (2020) and Nieto et al. (2018). To demonstrate seasonal abundance patterns of The Tick App tick encounters, we used the submission date aggregated to the epidemiological week.

3. Results

Between 2019 and 2021, we received 11,424 reports of tick encounters through The Tick App. These reports were completed by 5335 unique participants in the United States, with each tick encounter report representing one or more ticks that a user found on a single day. For the first set of analyses, we restricted reports to those from the Midwest and Northeast, leaving 10,915 records completed by 4411 participants (Table 1). Across all years, the majority of participants (62%) had one encounter, with a maximum of 182 encounters (Fig. S1). Half of the encounters (51%) resulted from self-reported peri-domestic exposures, where users said that the tick was picked up in “my yard” or “my neighbor’s property”, while approximately 37% of encounters were from recreational exposure. For 12% of reports, participants were unsure of their encounter type. According to self-reports, encounters were predominantly with human hosts (71%). Overall, less than half of the human-tick encounters (39%) involved an attached tick, although this proportion varied according to the species and life stage encountered (Tables 2 and S4). Approximately one-fourth of ticks were found on dogs; with, again, less than half involving an attached tick (45%). Hosts included other companion animals (e.g., cats, rabbits, turtle), wildlife (e.g., racoon), and livestock (e.g., horses, goats). Cat encounters included a higher proportion of attached ticks compared to other hosts (61%). Approximately 3.4% of ticks were found to be loose in the environment, either in the user’s home, vehicle or outdoors; with the remaining (1.8%) collected for research or unknown purposes.

Half of the tick encounter submissions from the Midwest and Northeast included photos ($N = 5440$). We excluded 81 photos due to low image quality and retained 5359 for tick identification (Fig. 2a). A majority of the 2539 unique participants submitted a single photo (68%); however, 162 participants submitted five or more photos during the study period. Out of all submitted photos, 97% were verified as ticks and 91% were composed of three species of ticks: *D. variabilis* (56%), *I. scapularis* (29%), and *A. americanum* (7.0%). The remaining tick photos were either other (1.2%) or unknown tick species based on the photo submitted (4.3%). Across tick and host species, the majority of submissions consisted of adult ticks and very few (<1%) consisted of larvae (Table S5). For *D. variabilis*, over 99% were adults and for *I. scapularis*, 83% were adults. Among *D. variabilis* ticks associated with human hosts, 55% were adult females and 40% were adult males; while for *I. scapularis* ticks 58% were adult females and 12% were adult males. Adults made up a smaller proportion of *A. americanum* ticks associated with human hosts, with 26% adult female and 20% adult male (Table 2). For humans, while the majority of submissions were *D. variabilis* ticks, for dogs, there was roughly the same number of *D. variabilis* and *I. scapularis*; and for cats, the majority were *I. scapularis* (Table S6).

Among participants with a confirmed tick encounter, 2848 users (44%) specified the date that the tick was found and enabled GPS location services within the app (Fig. 2b). A subset of 842 tick encounter reports, completed by 255 users, had sufficient GPS data recorded for further movement pattern analysis (i.e., >20 daytime and evening GPS points in the four days prior to tick detection), with a median of 170 points per report (IQR: 63–870). A majority of reports came from users in the Midwest (82%), living in rural counties (54%) (Table S7). Finally, 671 reports, completed by 177 users, included accompanying identifiable photos of tick species, allowing for both movement and species-

Table 1
Profile of tick encounter reporters in the Midwest and Northeast regions (2019–2021)[a].

Year	2019	2020	2021	2019–2021*
Total Number of Tick Encounters Reports	$N = 1960$	$N = 3449$	$N = 5506$	$N = 10{,}915$
Unique Tick Encounter Reporters	$N = 899$	$N = 1367$	$N = 2559$	$N = 4411$
Gender: User data available	$N = 1958$	$N = 3449$	$N = 5506$	$N = 10{,}913$
Female	1160 (59.2%)	2238 (64.9%)	3353 (60.9%)	6751 (61.9%)
Male	784 (40.0%)	1169 (33.9%)	2041 (37.1%)	3994 (36.6%)
Other gender identity	4 (0.2%)	5 (0.1%)	18 (0.3%)	27 (0.2%)
Prefer not to say	10 (0.5%)	37 (1.1%)	94 (1.7%)	141 (1.3%)
Age Category: User data available	$N = 1953$	$N = 3404$	$N = 5462$	$N = 10{,}819$
18–22	37 (1.9%)	66 (1.9%)	108 (2.0%)	211 (2.0%)
23–41	770 (39.4%)	1224 (36.0%)	2271 (41.6%)	4265 (39.4%)
42–53	357 (18.3%)	772 (22.7%)	1151 (21.1%)	2280 (21.1%)
54–72	738 (37.8%)	1246 (36.6%)	1815 (33.2%)	3799 (35.1%)
73–99	51 (2.6%)	96 (2.8%)	117 (2.1%)	264 (2.4%)
Region: User data available	$N = 1960$	$N = 3449$	$N = 5506$	$N = 10{,}915$
Midwest	1349 (68.8%)	2668 (77.4%)	4417 (80.2%)	8434 (77.3%)
Northeast	611 (31.2%)	781 (22.6%)	1089 (19.8%)	2481 (22.7%)
Lyme Disease Incidence County[b]: User data available	$N = 1957$	$N = 3390$	$N = 5348$	$N = 10{,}695$
High: Increasing	238 (12.2%)	328 (9.7%)	489 (9.1%)	1055 (9.9%)
High: No Change	1249 (63.8%)	1399 (41.3%)	2057 (38.4%)	4705 (44.0%)
Low: Increasing	222 (11.3%)	787 (23.2%)	1218 (22.8%)	2227 (20.8%)
Low: No Change	227 (11.6%)	704 (20.8%)	1387 (25.9%)	2318 (21.7%)
No Cases	21 (1.1%)	172 (5.1%)	197 (3.7%)	390 (3.6%)
Returning Users: User data available	$N = 1960$	$N = 3449$	$N = 5506$	$N = 10{,}915$
One-season user	1723 (87.9%)	2564 (74.3%)	4037 (73.3%)	8324 (76.3%)
Return user	237 (12.1%)	885 (25.7%)	1469 (26.7%)	2591 (23.7%)
Number of Encounters per User [Median (Min, Max)]	1 (1, 34)	1 (1, 85)	1 (1, 136)	1 (1, 182)
Number of Submission with Images	$N = 591$	$N = 1792$	$N = 2885$	$N = 5268$

[a] Tick encounter reporters include unique users who submitted Daily Log or Tick Report (i.e., without Daily Log) entries. A tick encounter represents one or more ticks that a user reported finding on a single day.

[b] We used Lyme disease case data publicly available from the Centers for Disease Control and Prevention (CDC) to estimate county-level Lyme disease incidence for The Tick App users in the Midwest and Northeast regions of the United States (2013–2017). We used the number of cases reported (confirmed and probable cases) per county and the population size obtained from the National Census in 2010 to estimate a 5-year period Lyme disease annual incidence per county and percentage change in cases within that period. This calculation is described in Fernandez et al., 2019 (Fernandez et al., 2019).

Table 2
Summary of tick encounter photo submissions for human hosts by species (2019–2021) [a].

Ixodes scapularis						*Dermacentor variabilis*						*Amblyomma americanum*					
	Life stage						Life stage						Life stage				
Sex	Adult	Nymph	Larvae	Unk.	Total	Sex	Adult	Nymph	Larvae	Unk.	Total	Sex	Adult	Nymph	Larvae	Unk.	Total
F	425	0	0	0	425 (57.6%)	F	1196	0	0	0	1196 (55.2%)	F	74	0	0	0	74 (25.9%)
M	86	0	0	0	86 (11.6%)	M	865	0	0	0	865 (39.9%)	M	58	0	0	0	58 (20.3%)
Unk./NA	2	203	6	16	227 (30.8%)	Unk./NA	101	1	0	5	107 (4.9%)	Unk./NA	5	136	8	5	154 (53.8%)
Total	513 (69.5%)	203 (27.5%)	6 (0.8%)	16 (2.2%)	738 (100.0%)	Total	2162 (99.7%)	1 (0.0%)	0 (0.0%)	5 (0.3%)	2168 (100.0%)	Total	137 (47.9	136 (47.6%)	8 (2.8%)	5 (1.7%)	286 (100.0%)
Attached	Adult	Nymph	Larvae	Unk.	Total	Attached	Adult	Nymph	Larvae	Unk.	Total	Attached	Adult	Nymph	Larvae	Unk.	
Yes	321	165	5	15	506 (68.6%)	Yes	874	1	0	2	877 (40.5%)	Yes	82	93	7	4	186 (65.0%)
No	183	25	1	1	210 (28.5%)	No	1242	0	0	3	1245 (57.4%)	No	52	39	1	1	93 (32.5%)
Unk./NA	9	13	0	0	22 (2.9%)	Unk./NA	46	0	0	0	46 (2.1%)	Unk./NA	3	4	0	0	7 (2.4%)
Total	513 (69.5%)	203 (27.5%)	6 (0.8%)	16 (2.2%)	738 (100.0%)	Total	2162 (99.7%)	1 (0.0%)	0 (0.0%)	5 (0.3%)	2168 (100.0%)	Total	137 (47.9%)	136 (47.6%)	8 (2.8%)	5 (1.7%)	286 (100.0%)
Bloodfed	Adult	Nymph	Larvae	Unk.	Total	Bloodfed	Adult	Nymph	Larvae	Unk.	Total	Bloodfed	Adult	Nymph	Larvae	Unk.	Total
Yes	233	115	3	9	360 (48.8%)	Yes	465	1	0	1	467 (21.5%)	Yes	38	83	5	0	126 (44.0%)
No	211	40	1	1	253 (34.3%)	No	1404	0	0	0	1404 (64.8%)	No	73	33	0	2	108 (37.8%)
Unk./NA	69	48	2	6	125 (16.9%)	Unk./NA	293	0	0	4	297 (13.7%)	Unk./NA	26	20	3	3	52 (18.2%)
Total	513 (69.5%)	203 (27.5%)	6 (0.8%)	16 (2.2%)	738 (100.0%)	Total	2162 (99.7%)	1 (0.0%)	0 (0.0%)	5 (0.3%)	2168 (100.0%)	Total	137 (47.9%)	136 (47.6%)	8 (2.8%)	5 (1.7%)	286 (100.0%)

[a] Data for across all host species are provided in Table S5.

level analyses.

3.1. Three-question sequence for photo screening

In the first question of our sequence, we asked users to assess the size of the tick as big, medium, or small. Among users who reported finding a big or medium tick ($N = 4228$), 97% had an adult (Table 3). However, among users who reported finding a small tick ($N = 581$), only 46% had a juvenile (i.e., larvae or nymph). At the species level, among users that reported finding a big tick ($N = 2463$), 80% had encountered an adult *D. variabilis* tick. And among users that reported finding a small tick, 39% had an *I. scapularis* adult and 32% had an *I. scapularis* juvenile tick.

In the second question, we asked users whether the tick was flat or round (to coarsely determine the bloodfed status of the tick and ability to see color patterns on the tick) and compared this to entomologist-verified bloodfed status. Using a conservative threshold ($\geq$3 days feeding duration and $\geq$71 certainty score), approximately 7.8% of ticks ($N = 408$) were bloodfed. Eighty percent of these bloodfed ticks were reported as attached, 7.5% were reported as not attached, and 12.5% did not know the attachment status or did not respond. For these bloodfed ticks, users classified 68% as round. Users labeled 62% of bloodfed *D. variabilis* adults as round, and 74% of bloodfed *I. scapularis* adults as round. In an alternative framing, 95% of submissions classified as round by users were bloodfed for $\geq$3 days, based on the engorgement index.

Finally, for the third question of our sequence assessing users' classification of tick color pattern, among users with confirmed adult *D. variabilis, I. scapularis*, and female *A. americanum* ticks, 58% selected the color pattern matching their respective species descriptions, as described in the Methods section (Fig. 4). This increased to 65% when we excluded bloodfed ticks from the analysis (Table S8). When users indicated color patterns that did not match entomologist-identified adult *D. variabilis, I. scapularis*, and female *A. americanum*, they most commonly selected the "all brown" photo showing male *A. americanum* (Fig. 4, Table S8). Notably, the proportion of entomologist-identified *D. variabilis* reports with users that selected the intended description of *D. variabilis* having a "brown and white pattern" was 56% among one-time submitters, 65% amongst users who submitted between five and nine reports, and 76% among users who submitted 10 or more reports (excluding bloodfeds from analysis).

The MCA corroborated expected associations between expert-identified tick species and user-selected color patterns, as shown in the biplot of the first two dimensions (Fig. S4). Immature stages (comprised primarily of nymphs), however, did not show clear associations with any color pattern nor other visual cues included in the three-question sequence. *Ixodes scapularis* ticks were most closely associated with "small size" as indicated by the users, while *D. variabilis* ticks were most closely associated with "big size." The user-selected shape (round versus flat) did not show a close association with tick bloodfed status. Nonetheless, the first two dimensions only explained 34% of the variance contained in the six screening variables, indicating that there is substantial variability in the user-selected features that limits the use of the size, bloodfed status, and color patterns as complete predictors of tick species.

Table 3
Tick size as a predictive feature of tick species and life stage [a].

User-selected tick size	Entomologist-verified species ID	Entomologist-verified life stage Adult (%)	Juvenile (%)
Big ($N = 2463$)	Across species	2418 (98.2)[b]	33 (1.3)
	Amblyomma americanum	82 (3.3)	25 (1.0)
	Dermacentor variabilis	1978 (80.3)	NA
	Ixodes scapularis	358 (14.5)	8 (0.3)
Medium ($N = 1765$)	Across species	1666 (94.4)	90 (5.1)
	Amblyomma americanum	90 (5.1)	53 (3.0)
	Dermacentor variabilis	903 (51.2)	NA
	Ixodes scapularis	673 (38.1)	37 (2.1)
Small ($N = 581$)	Across species	301 (51.8)	268 (46.1)
	Amblyomma americanum	17 (2.9)	84 (14.5)
	Dermacentor variabilis	55 (9.5)	1 (0.2)
	Ixodes scapularis	229 (39.4)	183 (31.5)

[a] Proportions represent the number of ticks with a life stage and species identification out of the number of ticks classified as being big, medium, or small.
[b] Example interpretation: 98.2% of ticks classified by users as big were verified by entomologists as adult ticks.

3.2. Location of tick encounters

With the GPS data we initially assessed travel away from the users' residence (in the four days prior to finding the tick). A small percentage of reports (11%) included travel outside the participants' state of residence; whereas 61% of reports included travel outside the county and 84% outside the zip code of residence (Fig. S5a). When assessing available self-reported travel history, 347 reports included the county where the user thought they picked up the tick, and 345 included the zip code (Table S9). Of the reports with this information available, we did not detect GPS points in the county or zip code where the user stated they picked up the tick (in the four days prior to tick detection) for 43 (12%) and 50 (19%) reports, respectively. However, when we extended our search window to the 30 days prior to tick detection, an additional 19 reports included GPS points within these locations.

Out-of-county visitation in the four days prior to tick detection varied according to the urbanicity level of the users' county of residence. Approximately three-quarters of users from large metropolitan and rural areas traveled out-of-county; whereas a smaller percentage, 50–63%, of users from small and medium metropolitan areas did (Fig. S5b). For travelers from large metropolitan and rural counties, more out-of-county visitation took place on weekends compared to weekdays; whereas travelers from medium and small metropolitan counties had higher out-of-county visitation during the week (Fig. S5c).

With respect to land cover, overall, users spent more time in developed or planted/cultivated classes compared to forest, grasses, and other land covers. However, partitioned by travel history and urbanicity, out-of-county travelers from medium and small metropolitan areas spent less time in developed areas, and more time in forested and planted/cultivated areas compared to non-travelers (Mann-Whitney test; $p < 0.01$). Travelers from these urban counties spent more time in non-developed areas on weekends compared to on weekdays. Travelers from rural areas spent slightly more time in developed, grassy, and other land cover types, but less time in planted/cultivated areas compared to non-travelers (Fig. 5a); with more time in planted/cultivated areas on weekdays compared to on weekends (Mann-Whitney test; $p < 0.01$) (Fig. 5b).

To validate self-reported exposure location, we examined both the urbanicity of the users' county of residence and their land cover visitation patterns. More than half of users with self-reported peri-domestic exposures were from rural counties (56%) while those with recreational exposures were from rural (44%) and medium metropolitan areas (21%). Across counties, users with peri-domestic exposures spent a greater proportion of their time in planted/cultivated and developed land covers compared to other land cover types (Mann-Whitney test; $p < 0.01$). Whereas users with recreational exposures spent a greater proportion of their time in developed land cover compared to planted/cultivated, grassy, forested, or other land cover classes (Mann-Whitney test; $p < 0.01$) (Fig. 5c).

Among submissions with both GPS data and photos available, 363 included encounters with *D. variabilis*, 42 with *I. scapularis*, and 10 with *A. americanum*. Among *D. variabilis* reports, 81% visited grassy areas, 61% visited forest, and 52% visited planted/cultivated areas. However, when distinguishing the amount of time spent in different land cover types, we found significant differences (Kruskal-Wallis chi-squared; $p <$

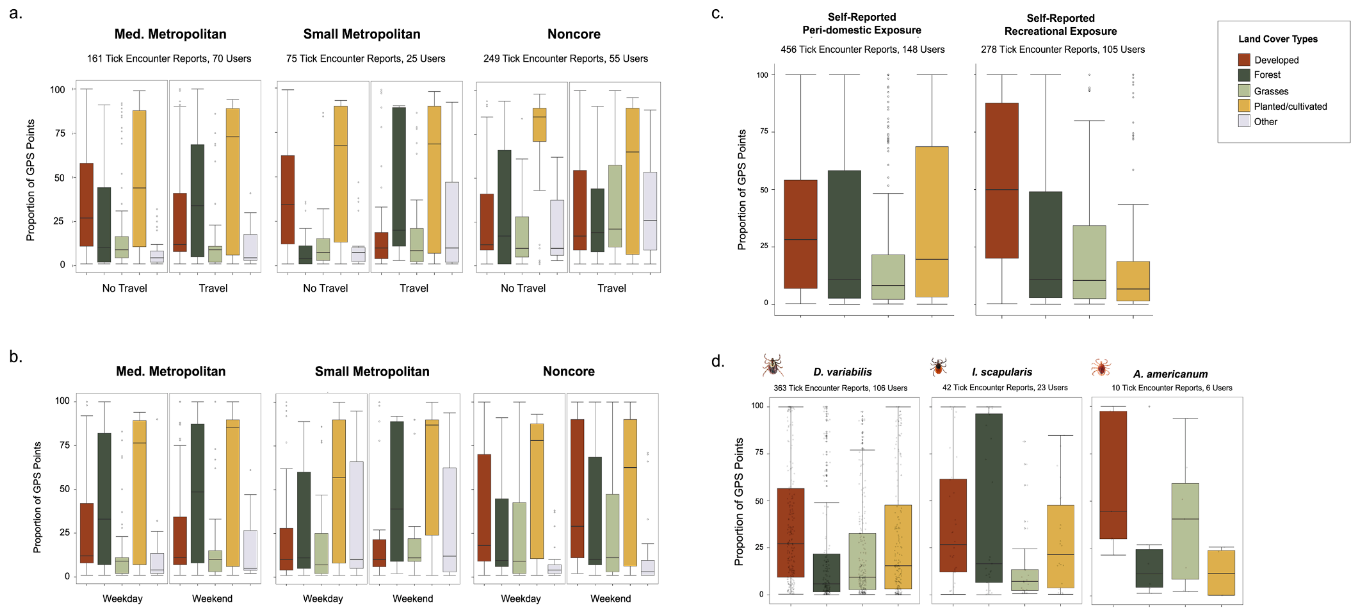

Fig. 5. Land cover exposure by county of residence, exposure type, and species. 5a. Boxplot comparing five-category land cover classifications between travelers versus non-travelers for medium and small metropolitan counties and rural counties. 5b. Among travelers, boxplot comparing five-category land cover classifications for weekdays versus weekends for medium and small metropolitan counties and rural counties. 5c. Boxplot comparing five-category land cover classifications for peri-domestic versus recreational exposures ("Other" land cover class is excluded from plot due to low percentages. The median proportion of GPS points in other land cover was 3.2% for peri-domestic exposures and 2.9% for recreational exposures). 5d. Boxplot comparing five-category land cover classifications for the three tick species ("Other" land cover class is excluded from plot due to low percentages —the median proportion of GPS points in other land cover was 0.0% for *Dermacentor variabilis*; 0.0% for *Ixodes scapularis*; and 3.1% for *Amblyomma americanum*).

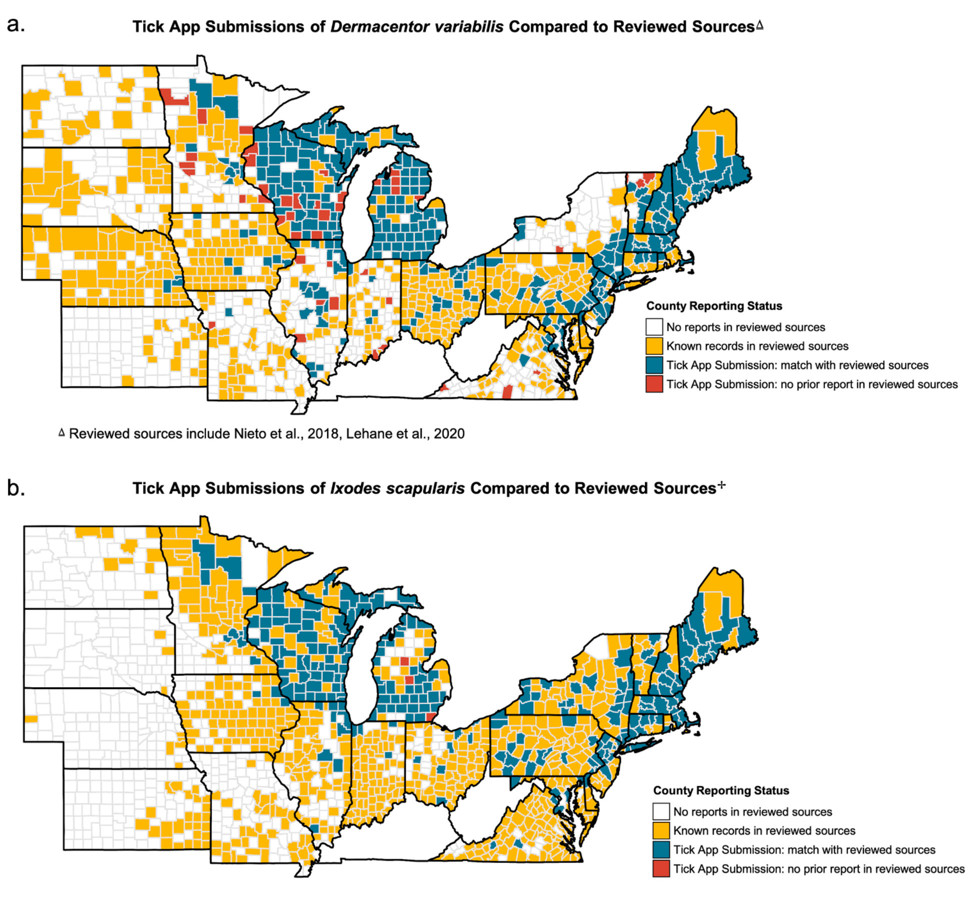

Fig. 6. Comparison of *Dermacentor variabilis* and *Ixodes scapularis* reports with known records. 6a. County map comparing The Tick App *Dermacentor variabilis* reports with known records from Nieto et al. and Lehane et al. With The Tick App records, we excluded individuals who had more than 20% of their GPS points outside of their county of residence. We identified 44 counties that did not have records of *D. variabilis* in these reviewed sources (shown in red), and 278 counties that matched known records of where the species has been reported (shown in teal). 6b. County map comparing The Tick App *Ixodes scapularis* reports with known records from CDC (2021) surveillance data, (Kopsco et al., 2021b and Nieto et al., 2018). We identified three counties with new reports of *I. scapularis* (shown in red), and 241 counties that matched known records of where the species has been reported (shown in teal).

0.01), with users spending significantly more time in planted/cultivated land covers compared to forested or grassy land cover types (Dunn's test; $p < 0.01$) (Fig. 5d). For encounters with *I. scapularis*, 88% visited forest; 52% visited planted/cultivated areas and 60% visited grassy areas. Finally, among *A. americanum* encounters, nine included time spent in grassy areas; only two reports included >1% of GPS points in forested areas. Due to low sample size, we did not examine statistical differences in the time spent in each land cover for *I. scapularis* or *A. americanum*.

3.3. Geographic and temporal variation across species

County-level tick encounter submissions reflected known distributions for *D. variabilis* and *I. scapularis.* To partially account for travel history, we excluded data from 60 individuals who had more than 20% of GPS points outside of their county of residence. With this restricted data, during 2019–2021, we received *D. variabilis* reports from 322 out of the 1404 counties (23%) in the Northeast and Midwest regions of the United States; 44 counties did not have records of *D. variabilis* published in Lehane et al. (2020) and Nieto et al. (2018) (Fig. 6a). A subset of these counties ($N = 4$) had tick encounter submissions from multiple users, with more than one life stage identified, and no out-of-county travel documented, providing multiple lines of preliminary evidence that the tick species may be present locally. We received *I. scapularis* reports from 259 out of the 1404 counties (18%) in the region (Fig. 6b). Three counties in Michigan did not have previous records of *I. scapularis*, compared to 2021 CDC tick surveillance reports as well as data published by Centers for Disease Control and Prevention (2022), Kopsco et al. (2021b) and Nieto et al. (2018) (Fig. S6).

We also assessed whether temporal patterns of photo submissions corresponded to the species' known phenologies (Fig. S3). For *I. scapularis*, we received 963 photo submissions across all months. However, we noted seasonal differences in when adult versus nymphal ticks were reported. For adults, there were two distinct peaks in submissions. The first peak occurred between late March–May, reflecting questing activity for overwintering populations; the second took place between late September–November, corresponding to increases in autumnal populations. Notably, the earliest report was January 5–14th (2021) and the latest December 10–20th (2019), providing consistent winter detections. For nymphs, we received photo submissions between April–November, with a peak in June. Across all years, the earliest submissions were April 5–12th in the Midwest (2021) and the latest November 9–16th (2020) for the Midwest and Northeast regions. For *A. americanum*, we received 345 adult and nymphal photos between April–September of our study period. For *D. variabilis*, we received 2971 adult photo submissions between April–late August. Across species, while the Midwest region had a larger volume of photos than the Northeast, we did not observe marked differences in the temporal patterns of submissions between regions.

4. Discussion

The Tick App is designed to better understand tick exposures in the United States and provide users with new tools for understanding ticks and tick-bite prevention. The app joins the ranks of other community science research programs in producing a robust dataset of both human and companion animal encounters with medically-relevant ticks across expansive geographic regions (Kopsco et al., 2021c; Saleh et al., 2019). With reports primarily generated from the Midwest and Northeast, United States, and skewed towards the Midwest, *D. variabilis* ticks made up the largest proportion of submissions. This differed from the Tick-Spotters program, for example, which had data skewed towards the Northeast region and received similar proportions of *D. variabilis* and *I. scapularis* ticks (Kopsco et al., 2021b). Therefore, we emphasize the importance of socio-ecological context when assessing tick hazard and exposure from passive tick report programs (Bron et al., 2020). Our study offers new insights by examining tick encounter location and travel history by local context. We parsed out the proportion of time spent in natural versus developed areas, and within-county versus out-of-county based on users' self-reported information. These distinctions enhance our understanding of tick-encounter locations, and indicate important areas for integration with field-based research.

Understanding where tick encounters have occurred, accounting for travel history, is key to determining whether local risk is emerging or established. Given the volume of cases in endemic regions, state health departments often have limited capacity to conduct case investigations and collect travel history data. Those that do, gather this data in a variety of ways—including open-ended questions about travel in the 30 days prior to symptom onset, or specific questions about the destination county and reason for travel (Michigan Department of Health and Human Services, 2022; West Virginia Department of Health and Human Resources, 2022). Additionally, at the time of analysis, travel history was not publicly available for concurrently operating community science-based surveillance programs (Kopsco et al., 2021b; Nieto et al., 2018). With location services through The Tick App, we have started to address gaps in knowledge regarding travel history in tick encounter risk. Among our submissions, we noted that while a majority of reports included travel outside the users' county and zip code of residence, only 11% included travel out-of-state and less than 2% included travel inter-regionally, indicating that most travel-associated encounters do not involve long-distance travel. We also detected a greater percentage of GPS points in the counties and zip codes where users reported picking up the tick when using a 30-day window prior to tick detection (as opposed to four days). This discrepancy may reveal oversights as to users' dates of travel, a lack of familiarity with the length of time that ticks remain attached, or potential survival of ticks in clothing or equipment followed by subsequent tick-host encounters.

Travel history is essential when aiming to incorporate community science-derived data into tick distribution maps (Eisen and Eisen, 2021). Often, such distribution maps are based on users' residential information, under the assumption that encounters occur within-county. We observed a high degree of out-of-county travel in the days preceding tick detection, and therefore urge caution when interpreting these maps as providing precise information on tick encounter risk. However, by aggregating information from multiple encounter reports and data sources, we strengthen preliminary indications that tick species are emerging for a given jurisdiction or surrounding area (Porter et al., 2021). These data also provide preliminary locations for field-based, active surveillance to ultimately confirm tick presence within the area.

When examining time spent in different land covers, the substantial proportion of time spent in both developed and planted/cultivated land cover classes likely reflects blurred social and spatial boundaries between urban and rural areas in the Midwest, United States (Lichter and Brown, 2011). Nevertheless, with GPS data we gleaned information on activity patterns associated with travel history among heterogeneous subpopulations. For instance, nearly three-quarters of tick encounter submissions for residents living in large metropolitan and rural counties had travel history out-of-county in the four days preceding the tick encounter; whereas just over half of medium and small metropolitan residents did. Additionally, travelers from medium and small metropolitan areas spent less time in developed land cover, and more time in forested, planted/cultivated, and other landscapes compared to non-travelers; with more time spent in natural areas on weekends. Travelers from rural counties, on the other hand, spent slightly more time in developed, grassy, and other landscapes, but significantly less time in planted/cultivated land cover types compared to non-travelers. Transportation studies in the United States have indicated that rural residents are more mobile than urban residents, on average covering 38% more mileage per day, with a higher proportion of households having a vehicle available (Pucher and Renne, 2005; Santos et al., 2011). Socioeconomic transitions have affected the travel patterns of rural workers, such that they often commute to surrounding urban or other rural counties for commercial activities and work, potentially explaining our observation of more travel to developed areas and less travel to planted/cultivated areas on weekends (Lichter and Brown, 2011). Given that natural areas are riskier for tick encounters, travel out-of-county may pose a greater issue for data reliability (with respect to encounter location) among urban county residents compared to rural ones. An important caveat to the generalizability of these results is that two-thirds of the study period took place after the start of the COVID-19 pandemic, during which travel restrictions shifted outdoor activity patterns in the United States. In a previous investigation, we found that self-reported peri-domestic activity was higher for Tick App users in medium and small metropolitan areas compared to those in large metropolitan areas, potentially explaining the lower proportion of users from these smaller urban areas that traveled outside of their home jurisdiction (Fernandez et al., 2021).

With respect to exposure type, users with self-reported peri-domestic exposures spent more time in planted/cultivated land covers. Agricultural landscapes, therefore, may be an under-recognized setting for tick exposures. Furthermore, exposures seem to occur while users are conducting activities around the property, whether related to landscape maintenance or farming. Based on users' self-reported outdoor activities, both in rural and metropolitan counties, primary peri-domestic activities included gardening, mowing the lawn, and removing brush from their yard (for approximately 60, 30, and 9% of surveys submitted); nonetheless, in rural counties, users also reported conducting agricultural activities in approximately 9% of surveys (versus ~3% in metropolitan counties) (unpublished results from The Tick App). Users with recreational exposures spent a higher proportion of their time in developed land covers, and visited planted/cultivated, forested, grassy, and other land covers (including open water) to a lesser extent. This indicates that users with recreational exposures spend much of their time in low-risk, developed land covers, but may travel to natural areas to conduct the commonly reported outdoor activities, including hiking, bird watching, fishing, and spending time at the beach (Bron et al., 2020). To better understand self-report data, qualitative and mixed methods studies are warranted to disentangle perceived land covers and activities of risk, compared to the actual time spent conducting activities in these landscapes.

By merging GPS and photo submission data, we explored land cover types that may contribute to different tick species exposures—although with a limited sample size. We found that users who encountered *D. variabilis* spent significantly more time in planted/cultivated areas compared to forested areas. This corresponds to documented habitat associations of *D. variabilis*, where adult ticks are detected primarily in open areas—for example at highest densities clustered in agricultural areas and more rarely in wooded habitat with dense vegetation (Mathisson et al., 2021; Stein et al., 2008; Trout Fryxell et al., 2015). We did not have sufficient submissions with *I. scapularis* or *A. americanum* for statistical comparisons. Even still, *I. scapularis* encounters were associated with individuals who spent more time in forested land cover compared to planted/cultivated or grassy areas, and reflects what is known about *I. scapularis* as a primarily forest-dwelling species. And the 10 submissions with *A. americanum* corresponded to individuals who spent a greater proportion of time in grassy areas compared to planted/cultivated or forested areas. While there is not yet a consensus on habitat associations for *A. americanum*, multiple investigations (conducted in different geographic locations in the United States) have indicated their negative association with high-density vegetation, and adult female preference for open canopy sunlight (Ferrell and Brinkerhoff, 2018; Koch and Burg, 2006; Mathisson et al., 2021; Trout Fryxell et al., 2015). These results indicate that we may be able to detect user visitation patterns that correspond with known tick habitat associations. This also suggests that human mobility data should be integrated with field studies of tick densities to further our understanding both tick hazard and exposure.

We also explored whether user-selected photos can inform a simple algorithm for species identification. We found that a majority of users correctly identified their specimens as ticks, with only 3% of photo submissions comprising of non-tick arthropods, comparable to the TickSpotters program which reported 5% of photos being non-ticks (Kopsco et al., 2021a). Prompts of tick coloration and size guided users towards species and life stage classification moderately well, with 65% of users with *D. variabilis* adults "correctly" selecting the image of a "brown and white pattern" tick and 62% classifying *I. scapularis* adults as having a "black shield" (excluding bloodfed ticks attached three or more days). Additionally, users classified bloodfed ticks as round with moderate success; bloodfed *I. scapularis* adults were classified as round to a greater extent than *D. variabilis* adults. Future efforts may involve modifying and validating this three-question sequence to increase the reliability of user-selected photo classifications. Furthermore, this simple algorithm may be integrated with emerging machine learning techniques to expedite tick identification processes and minimize human error (Justen et al., 2021; Kopsco et al., 2021a).

Interestingly, we found that users with 10 or more submissions of adult ticks were more successful in differentiating adult species compared to the overall user population. This is indicative of a generally well-informed user sub-group, or highlights a potential role of The Tick App in knowledge-building around tick species recognition (Fernandez et al., 2019). Future studies are planned to evaluate The Tick App as an educational tool. Eisen and Eisen (2021) comment that user-based tick identification without expert validation should be incorporated judiciously, and with approximately 60% of all adult species identified correctly, we concur and strongly caution against the use of this information for medical decision-making. However, with tick burdens on the rise in the United States, public knowledge-building and empowerment around tick exposures are important (and measurable) outcomes. Therefore, we find it important to continue engaging with users in species identification. Increasingly, ecologists are harnessing community science data via mobile applications such as eBird and iNaturalist for educational and research purposes. eBird investigations incorporate observer expertise scores, where the assessment of observer metrics and inclusion of these data in species distribution models has been shown to improve model performance (Johnston et al., 2018). As initiatives for tick species identification gain traction, we see the potential for integrating statistical corrections and expert indices as a means of data quality assurance.

Furthermore, we find community science to be of critical importance, both to address current data gaps and to confront the current socio-scientific context in the United States. Specifically, there is a landscape of unfamiliarity, misconception, and contentiousness surrounding ticks and tick-borne disease information (situated within sentiments towards public health and scientific institutions more broadly) (Beck et al., 2022; Hook et al., 2015; Mattoon et al., 2021). For example, Kopsco et al., found that some survey respondents are more likely to trust non-traditional sources of tick-borne disease prevention information (e.g., online forums) compared to established public health sources (e.g., the Centers for Disease Control and Prevention) (Kopsco et al., 2022). Yet, in a knowledge, attitudes and behavior survey in the Midwest, participants were more likely to use personal prevention strategies if they had seen tick-borne disease prevention messages compared to participants who had not seen such messages (Beck et al., 2022). Approximately 40% of the aforementioned study respondents found online or printed materials useful, and 22% indicated that they would find a smartphone app very helpful. In contrast to printed materials, a smartphone app has the potential to build community and engage hard-to-reach information seekers in a bidirectional manner (Cardona, 2013). In particular, lack of tick-borne disease awareness and language barriers have been identified as contributing factors in the under- and delayed diagnosis of Lyme disease among Spanish-speaking populations in the United States (Beck et al., 2022; Hu et al., 2019; Maxwell et al., 2022). A future direction of The Tick App will be to make the platform available in additional languages, starting with Spanish.

Our study has several limitations, as with any passive surveillance and observational study. Our conclusions are limited to a population that uses smartphone technology and frequently engages in outdoor activities, and therefore, cannot be generalized to the general population. Given that The Tick App is marketed as an app to better understand human exposure to ticks, we expect that people at greater risk of tick encounters and previous tick exposure use it more frequently, introducing self-selection bias. Moreover, our population does not include people under 18 years of age, limiting conclusions for younger age groups. Additionally, in part due to detection biases, our database was highly skewed towards *D. variabilis* submissions, precluding robust analysis for *I. scapularis* and *A. americanum* or cross-species comparisons. However, the data suggest that The Tick App user base is continuing to expand, indicating potential to address such research questions in the future. Finally, GPS data were available for only a small percentage of overall tick encounter submissions, and even when data were available, we were limited by the number of points that were recorded. While the inclination is an aspiration towards larger datasets, we caution the need to balance the granularity of the information collected with the confidentiality and privacy of users. For example, with location services, we were legally obligated to ask users whether they chose to have their location data taken continuously, or only while using the application. Based on our observations that more tick encounter reports are generated via Tick Reports as opposed to Daily Logs, users may be opening the app with the specific intent of submitting a tick report rather than logging their activities over time. While location data provide novel insights into mobility patterns and land cover exposure, such restrictions importantly safeguard user protection.

This paper provides descriptive analyses demonstrating how The Tick App contributes to current passive tick encounter surveillance across tick identification, travel history and habitat exposure, as well as spatial and temporal patterns of species-specific tick encounters. We emphasize the importance of complementing this information with field-based entomological and social surveys to assess local risk of tick-borne diseases incorporating environmental hazard, exposure, and vulnerability.

CRediT authorship contribution statement

Pallavi A. Kache: Data curation, Methodology, Investigation, Formal analysis, Visualization, Writing – original draft, Writing – review & editing. **Gebbiena M. Bron:** Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – review & editing, Project administration, Supervision. **Sandra Zapata-Ramirez:** Data curation, Data curation, Writing – review & editing. **Jean I. Tsao:** Conceptualization, Methodology, Writing – review & editing, Funding acquisition. **Lyric C. Bartholomay:** Conceptualization, Methodology, Writing – review & editing, Funding acquisition. **Susan M. Paskewitz:** Conceptualization, Methodology, Writing – review & editing, Funding acquisition. **Maria A. Diuk-Wasser:** Conceptualization, Methodology, Writing – review & editing, Funding acquisition, Supervision. **Maria del Pilar Fernandez:** Conceptualization, Methodology, Investigation, Data curation, Writing – review & editing, Project administration, Supervision.

Declaration of Competing Interest

None declared.

Data availability

Data will be made available on request.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ttbdis.2023.102163.

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