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Multi-epoch species distribution modeling of ticks in Arkansas: Expanded ecological niche and the vector-borne disease landscape

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Abstract

This research quantifies and maps the spatiotemporal variability of ticks across Arkansas, particularly in the context of environmental change. Boolean logic-based ecological niche suitability maps and species distribution models were generated at 250 m spatial resolution across a 16-year range (2009–2024), divided into one four-year training epoch and two six-year modeled epochs (2009–2014 and 2019–2024). The niche maps were used to generate a pseudo-absence grid based on biophysical characteristics that was then paired with tick presence data sampled from across the state between 2015 and 2018 to train a Random Forest model. The Random Forest species distribution model displayed an average probability difference of +13.1% across Arkansas for the more recent epoch (2019–2024), as compared to the earlier epoch (2009–2014). K-Fold cross validation was performed to evaluate the model's performance (PR-AUC = 88.6%; ROC-AUC = 87.8%) and feature importance testing showed that evapotranspiration was a key predictor of tick presence.

1 Introduction

Hard ticks (Ixodidae) are a medically significant vector group of hematophagous arachnids that rely on animal hosts for nourishment, habitat access, and range expansion (Nuttall, 2009; Tsao et al., 2021). Unlike many species whose ranges are constrained by narrow environmental requirements, ticks exhibit ecological plasticity that allows them to exploit a variety of host species and persist across diverse landscapes (Bouchard et al., 2019; Habibullah et al., 2021). Their dispersal is largely passive, governed by host movement patterns, which makes understanding host ecology critical for mapping tick distribution (Estrada-Peña, 2008). As global changes occur, ixodid tick populations are expected to expand into regions and seasons that were previously unsuitable, which historically limited tick activity (Cunze et al., 2022). The Southeastern U.S. provides favorable habitat for ticks due to its warm, humid climate and diverse landscapes, including deciduous and coniferous forests, grasslands, pastures, and savannas that support high host density and consistent moisture levels essential for tick development (Hammett, 1992). Climate models predict that much of the Eastern U.S., including the Southeast, will experience increased temperature and precipitation under future scenarios, enhancing the suitability of these habitats for tick survival and reproduction (Crimmins, 2023). Regional-scale projections have already documented the spatiotemporal expansion of ticks into the northern and eastern parts of the U.S., offering critical insights for emergent TBD risk in states like Arkansas (Butler et al., 2024). As Arkansas is known for its presence of ticks, it can serve as a bellwether for assessing the localized impacts of environmental change on tick distribution and disease risk.

1.1 | Arkansas and tick-borne disease

An ecological niche refers to a complete set of biotic and abiotic conditions required for a species to survive, reproduce, and fulfil its functional role within an ecosystem (Takola & Schielzeth, 2022). When environmental conditions change, species experience an ecological niche shift, or a

change in their geographic and temporal distribution patterns (Gabriele-Rivet et al., 2015; Guisan et al., 2014). Fundamental ecological niche primarily relates to abiotic factors that contribute to species presence or absence, while realized ecological niche of a species considers both biotic and abiotic factors (Frake et al., 2024). Abiotic factors include landscape ecology and land cover, as well as climate, such as temperature, precipitation, and humidity (Estrada-Peña, 2008). Biotic factors that impact tick niche include host availability and density, vegetation and habitat availability, predation, and host seeking behavior (Han et al., 2023).

Arkansas is medically notable for its high annual incidence of spotted fever rickettsiosis (SFR/ *Rickettsia*), a nationally notifiable disease capable of causing severe morbidity and mortality in advanced cases (ADH, 2024b, 2025; CDC, 2021; Frank & Dowling, 2019). From 2009–2024, there were an average of 166 SFR cases across all Arkansan counties (minimum of 0 cases in St. Francis County, Arkansas, and maximum of 650 cases in Benton County, Arkansas), with an average prevalence rate of 25.5/100,000 citizens (maximum of 134/100,000 in Stone County, Arkansas) (ADH, 2025); Stone County has a notably high proportion of forested area, where ticks are known to prosper. Likewise, much of the state's terrain is heavily forested, providing suitable habitat for ticks and their host species such as deer, raccoons, and birds, which increasingly overlap with human environments (Kilpatrick et al., 2014; Malhotra, 2022; Panella et al., 2024; Tsao et al., 2021). Wildlife movement into urban areas facilitates the spillover of ticks and pathogens into built environments, particularly in cities that enable animal passage through developed spaces when nearby natural spaces become less advantageous (Bayles et al., 2013; Pokhrel, 2023). This urban-wildland interface is a critical factor in TBD emergence and warrants focused spatial monitoring within Arkansas's municipalities. Considering the natural and human environmental alterations and risks of disease, spatial models are needed to map the ecological niche of ticks at local scales.

Importantly, microclimates play an integral role in tick survival from early stages to adulthood and breeding (Kemppinen et al., 2024). Microhabitat conditions are important to monitor because they facilitate the ticks' host-seeking and questing behaviors. At local geographic scales, hospitable microhabitat conditions are referred to as microrefugia, which are vital components of understanding tick niche and necessitate mapping ecological niche at the finest spatial scales possible (Marquez et al., 2025; Van Gestel et al., 2022). By aggregating multi-year epochs, interannual weather variations normalize into climate baselines, allowing for a deeper understanding of broad-scale changes in temperature, humidity, and precipitation, and ultimately tick niche. Similarly, land change can occur intra-annually, but evaluating landscape characteristics like land-use, vegetative health indices, gross primary productivity (GPP), and evapotranspiration (ET) over multi-year timescales provides a broad view of overall change.

While existing abundance maps largely emphasize the Southeastern U.S. (CDC, 2024; Springer et al., 2014; Tsao et al., 2021), they often fail to capture the localized dynamics, where detailed spatial analysis remains limited (Frank & Dowling, 2019). By applying fine-scale geospatial modeling techniques and data, this research addresses that gap and establishes Arkansas as a prototype for ecological niche modeling across other states in the U.S. Additionally, it offers an approach to disaggregating tiers of suitability in regions where tick presence is largely ubiquitous. Similar geographic approaches have been successfully implemented in other regions, such as Eastern Europe, where climate and environmental data have been used to generate detailed tick suitability maps (Estrada-Peña, 2008), demonstrating this method's applicability.

1.2 | Objectives

Understanding environmental change at a fine scale elucidates tick species habitability across space and time in Arkansas and indicates shifting ecological standards of the region at large. The research questions guiding this study are: (1) What is the spatiotemporal distribution of tick habitat

suitability across Arkansas? and (2) Where have variations in environmental conditions altered tick habitat suitability across the state? It is hypothesized that tick suitability has expanded both spatially and temporally across Arkansas, and that continued changes will further extend the geographic range and active season of tick populations. This hypothesis is supported by prior research on ecological niche shifts and vector expansion, which has demonstrated significant impacts on human and veterinary health outcomes (Estrada-Peña, 2008; Gabriele-Rivet et al., 2015; Guisan et al., 2014).

There are five endemic species of ticks in Arkansas (*Amblyomma americanum, Amblyomma maclatum, Dermacentor variabilis, Ixodes scapularis,* and *Rhipicephalus sanguineus*) (ADH, 2024a), as well as ticks of medical significance that are not currently endemic, such as *Haemaphysalis longicornis* (Arkansas Department of Agriculture, 2018). These different genera vary in their questing behavior and host preference at different stages of their lives (Leal et al., 2020). Given the passive geographic expansion of ticks via host movement and shifting environmental conditions, the questing behavior and host preference of a given tick species will impact their realized ecological niche (Han et al., 2023). Thus, this study sought to evaluate the shifting fundamental niche of ticks, map probability distributions, and elucidate the underlying environmental factors observed changes. This study employs deterministic methods, such as raster-based ecological niche modeling (ENM) using Boolean thresholding, as well as species distribution modeling (SDM) using machine learning (i.e., Random Forest) approaches, to examine how the ecological niche of ticks in Arkansas differs over time.

2 Materials and Methods

2.1 | Study Area

This study encompasses the state of Arkansas. *Figure 1a* displays the land cover/land use (LCLU) of region, including the abundant forests, pastures, agriculture, and water bodies that make up much of the Arkansan landscape (Dewitz, 2023; Esri & USGS, 2025). To the east, Arkansas is

predominantly cultivated croplands, which includes rice and soybean farms. Urban areas can be seen in the center of Arkansas near the capital, Little Rock, and in Northwest Arkansas, home to Fayetteville, Rogers, and Bentonville. Other population centers are found throughout Arkansas and are of widely ranging sizes and varied surrounding ecological conditions. The diverse landscapes of Arkansas make for an optimal region of interest for elucidating ecological niche shift of ticks.

2.2 | Data

Tick ecological niche was mapped here using a simple, computationally efficient Boolean logic-based suitability approach that incorporates environmental parameters and tick physiological requirements. This study incorporates the reported requirements of several endemic species in the creation of a bioclimatic model, as there has been little work to comprehensively study the natural and laboratory hardiness of individual tick species. Thresholds used were selected from a literature review of laboratory and prior niche mapping experiments (described in the following sections). These maps display combinations of predictor variable suitability and the impact on tick niche across spatial and temporal scales (detailed in Table 1). Mapping fundamental tick niche in this manner was used to refine the sampling schema for the Random Forest SDM (RFSDM). Tick specimens were collected by citizen scientists in a non-random capturing effort described by Dowling et al. (2022). The supplied specimen data displays an urban bias, especially in Northwestern Arkansas (1,686/9,049 geotagged specimens) (Dowling et al., 2022). Further, the sampling schema resulted in an abundance of *A. americanum* (N = 5,977) and *D. variabilis* (N = 1,613) specimens, and relatively similar smaller sample pools for *I. scapularis, R. sanguineus,* and *A. maculatum* (N = 352, 271, and 278, respectively), which is displayed in *Figure 1b* (Dowling et al., 2022). These sampling biases required additional geographic stratification (described below) but also informed the decision to model endemic species together. The results also support future scientific sampling efforts of individual species for distribution modeling refinement by illuminating areas of higher suitability,

while contributing to the growing body of knowledge on changing climatic conditions and ixodid tick proliferation.

Data were analyzed and visualized in Geographic Information Systems (GIS) and statistical software including Google Earth Engine (GEE), ArcGIS, and R Studio (ESRI, 2011; Gorelick et al., 2017; R Core Team, 2023). GEE is a cloud-based geoprocessing platform that houses numerous environmental databases (Gorelick et al., 2017). GEE was utilized to compile environmental datasets across the study range and at the finest available spatial scale. GEE has been used to generate both Boolean logic ecological niche maps and probabilistic habitat suitability maps in previous studies (Crego et al., 2022; Frake et al., 2024). A sixteen-year study timeframe was selected to evaluate three epochs (i.e., one four-year training epoch and two six-year modeled epochs) to map broad-scale changes to tick suitability across Arkansas. Epoch 1 ranges from 2009–2014, the training epoch ranges from 2015–2018 (the years in which tick sampling occurred), and Epoch 2 ranges from 2019–2024. Multi-year epochs were chosen to display ecological niche shift over time and space and to normalize anomalous years into long-term climate and landscape norms. The Epoch 2 range of 2019–2024 was selected as it was the maximum available range from post-sampling to present; Epoch 1 is an equivalent pre-sampling year range.

The Normalized Difference Vegetation Index (NDVI) is often used as a proxy for vegetation abundance, density, and health, calculated as a ratio of red (R) and near infrared (NIR) reflectance (NDVI = NIR – R / NIR + R) (Tucker, 1979). Arthropods including ticks are frequently found within an NDVI range of 0.2–1.0 (Fernández-Tizón et al., 2020). Additionally, NDVI also has a known association with soil moisture, as the surface reflectance of plants (i.e., absorption of red and reflectance of NIR) indicates the health and structure of the plants, suggesting that the plants have received adequate moisture (Chen et al., 2014). NDVI is also effective for evaluating near-surface humidity, which is useful for approximating tick suitability (Al-Shehhi et al., 2011). Simultaneously,

NDVI addresses the relationship between ticks and host organisms, as areas with high NDVI are those with dense, healthy vegetation, which would be enticing to host species for foraging and habitat. Ensuring that the areas in which tick habitat suitability is highest is not just based on land-use types, but also on the vegetative productivity of the area. Forests with multiple levels of canopy cover provide ample opportunity for ticks to overwinter in the soil or in leaf litter (Diuk-Wasser et al., 2021; Ogden et al., 2004).

The National Land Cover Database (NLCD) was used to map LCLU across Arkansas, showing that forests cover approximately 57% of the state (Dewitz, 2023). Most of these forests are defined as a mix between coniferous and deciduous trees, but based on an analysis of land-use, these mixed forests are primarily deciduous. It is also important to map grasslands for tick habitats, as ticks are frequently found in overgrown grass (Arz et al., 2023). The Arkansas landscape also contains large swaths of grasslands and savannas. NLCD utilizes a 16-category code for classification of land cover types, which are produced annually at 30 m spatial resolution (Dewitz, 2023; Frake et al., 2024). Specific LCLU categories were utilized to evaluate areas of likely tick presence, including all listed forest types, grasslands, shrublands, and edges of water bodies in Table S1. Although "Developed, Open Space" (LCLU Class 21) could theoretically offer ample tick microhabitat conditions (or microrefugia), these areas were not factored as suitable in this study considering the spatial resolution of the data. We combined NDVI and LCLU suitability based on thresholds detailed in Table 2 into a land suitability layer at 30 m to evaluate landscapes that are optimally suitable for tick and host proliferation.

Atmospheric humidity is necessary for ticks to avoid desiccation (Ostfeld & Brunner, 2015). Relative Humidity (RH) above 80% is associated with improved tick health and increased host seeking and questing behaviors (Rodgers et al., 2007). This parameter is complex, as a period of low humidity can become survivable during short periods above the ticks' necessary humidity threshold.

To further address desiccation, this study utilized the Standardized Precipitation Index (SPI) with a suitable range spanning -1.29–1.99. This range ensures that times and areas of moderate-severe drought and severe flooding are displayed as unsuitable. Too much precipitation can negatively impact tick habitat suitability via washing away nests (Weiler et al., 2017). Ticks, along with other arthropods, maintain homeostasis by carefully managing their internal fluid levels to avoid desiccation via hygroreception and actively seeking preferable microclimates (Chown et al., 2011). Studies indicate that intense dry macroclimates can be avoided by seeking moist under-vegetation and decaying leaves, which will also impact the host seeking and questing behavior (Kemppinen et al., 2024).

Temperature is the primary factor that restricts the temporal component of tick suitability and tickborne illness (Diuk-Wasser et al., 2021). Ticks require temperatures above 7°C to be active (Cunze et al., 2022; van Oort et al., 2020). Below this temperature, ticks either burrow underground or attach to a larger species to use their warmth to survive colder conditions. In laboratory settings, *Dermacentor variabilis* (the American dog tick) displayed a high mortality rate at and below -13.3°C (Yunik & Chilton, 2021). Similarly, *Ixodes scapularis* (the blacklegged or deer tick) displayed a high mortality rate at -16.4°C (Eisen et al., 2016). Additionally, ticks struggle with thermoregulation when they do not have access to atmospheric or soil moisture, especially when temperatures rise above 30°C. Within the range of 18–30ºC, ticks breed and develop efficiently and the risk of TBD increases when ticks are able to feed multiple times in one year (Bansal et al., 2021; Estrada-Peña, 2008; Ogden et al., 2004). This temperature range is known as the tick's "optimal suitability" range. Temperatures above the tick's preferred temperature development zone of 18–30°C, or low humidity levels (below 80%), rapidly dehydrate ticks (Cunze et al., 2022; Ginsberg et al., 2017; Ogden et al., 2004). However, *Ixodes scapularis* (the blacklegged tick or deer tick) has been shown to withstand temperatures at and above 35°C in laboratory settings (Eisen et al.,

2016). Similarly, in laboratory settings, *Rhipicephalus sanguineus* (the brown dog tick) can withstand temperatures up to 40°C (Backus et al., 2021). Thus, temperatures below 7°C and above 40°C are considered detrimental for most tick species persistence and host seeking. The 7–40°C range will be referred to here as the "full active temperature range" of suitability, in which ticks can be present, though their host seeking would not be as aggressive as in the optimal suitability range, as shown in Table 2. Through combining all climate variables into one climate envelope, a 1 km climate layer was crafted and then combined with the landscape layer to produce the biophysical ENMs. The resulting products are referred to herein as the full ecological niche model (FENM) and optimal ecological niche model (OENM).

2.2 | Habitat suitability modeling

Our study design combines simple Boolean logic ecological niche mapping with Random Forest-based probabilistic mapping using Google Earth Engine (GEE) (Gorelick et al., 2017). Integrating individual predictor variables into combined categories allows for a simplified and interpretable approach to species ecological niche mapping. Temperature (Temp), RH, and SPI have been consolidated into a combined "climate suitability" category; one for the full ecological niche modeling (FENM) and one for the optimal temperature range (OENM). NDVI and LCLU were consolidated into a combined "land suitability" category. Boolean logic operators were used to produce combinations of environmental suitability. This allows for specification of ecological niche into five distinct categories: (1) "Unsuitable" or "Less Suitable" (unfit with respect to climate or land categories), (2) "Climate Suitable" (suitable from a climate perspective, but not from a land perspective), (3) "Land Suitable" (suitable from a LCLU perspective, but unsuitable from a climate perspective), (4) "Suitable" (combined suitability of climate and land, but outside of the optimal temperature range), and (5) "Optimal" (combined suitability of climate and land while inside the optimal temperature range). Outputs across each epoch display the variations in climate and land

suitability across the study period. The ecological niche mapping serves two core purposes. First, to display the changing climate and land suitability for ticks across time. Second, to operate as a pseudo-absence demarcation layer from which sampling was performed (i.e., for a presence/pseudo-absence SDM). True absence in an area with such abundant probability would not be possible unless purposefully sampling from areas where ticks would not be present, such as highly urbanized spaces like parking lots or water bodies. Additionally, absence sampling was not a component of the citizen science data collection effort (Dowling et al., 2022). The presence data are shown in *Figure 1b*; N = 9,049. Utilizing the OENM to estimate pseudo-absence supported the use of the probabilistic species modeling described in *Figure 2*.

Temporal selection in sampling is vital to understanding how tick niche is changing over time, as aggregated climate aggregations across an entire year would be impacted by the extremes of both summer and winter months. This temporal boundary selection challenge is known as the Modifiable Temporal Unit Problem (MTUP), which can add a degree of uncertainty when quantifying changes to environmental norms if unrepresentative decisions are made (J. Cheng et al., 2022; T. Cheng & Adepeju, 2014; Çöltekin et al., 2011). With this in mind, pseudo-absence sampling and model training was conducted with respect to tick activity and TBD occurrence by utilizing the "peak months" of June and July (ADH, 2024a;). "Peak months" describes the months in which samples submitted to the University of Arkansas were most abundant, which is also consistent with TBD reports in data collected by the Arkansas Department of Health (ADH) TBD (Dowling et al., 2022). Point statistics were generated to evaluate the comparability of the OENM as a pseudo-absence grid to the sampled data, which showed that only 3% of all points fell within the "Unsuitable" category. Given the known generalist nature of ticks and passive nature of their distribution, this provided justification for the use of the OENM as an effective grid for pseudo-absence sampling. One limitation of the dataset used here is the non-random nature of the sampled

specimens, i.e., many submissions were reported in the areas surrounding urban centers; however, a representative variety of environmental conditions and LCLU are captured and samples in known unsuitable land cover types were excluded from training.

Random Forest is a machine learning model utilized for regression and classification via multiple decision trees. Random Forest was utilized here to evaluate the probability of tick presence per 250 m pixel based on biophysical environmental factors and observed presence and pseudo-absence data (*Figure 2*) (Liaw & Wiener, 2002). Random Forest models can be used to explore complex interactions between environmental variables and species occurrence, enabling robust probabilistic outputs with high validity if collinearity and sampling are properly factored. Testing for collinearity is essential when introducing predictor variables to a model to ensure that the model is not overfitting, underfitting, nor overemphasizing variable importance (Strobl et al., 2007). Predictor variables such as NDVI, ET, LAI, and GPP, or RH, precipitation, and drought indices address similar ecosystem and climate conditions, thus should be inspected for collinearity. However, these predictors function at different ecosystem scales and offer unique information, justifying testing their inclusion in the RFSDM despite their similarity (Farrell et al., 2019). Furthermore, since the Random Forest model is nonparametric, collinearity does not contribute to overfitting as strongly as it does in a parametric linear regression model. Testing for collinearity was performed using Pearson's r, multiple linear regression (MLR), and the variance inflation factor (VIF). MLR displays the correlative strength of a set of independent variables against a dependent variable via the R^2 metric (Maulud & Abdulazeez, 2020). A VIF value of 1 indicates no multicollinearity, VIF<5 as acceptable correlation, and VIF>5 as high multicollinearity that jeopardizes model performance (J. Cheng et al., 2022; Craney & Surles, 2007).

Evaluating the difference in probabilistic outputs across time will display the variation in the ecological niche of ticks across time from Epoch 1 to Epoch 2. Importantly, because of the training

design, the results convey specifically whether Epoch 1 or Epoch 2 was more similar to the training years, not necessarily indicating an increase or decrease in probability; however, when paired with the ENMs such a conclusion may be reasonable to infer. The OENM displayed the importance of evaluating both land and climate variables. Prior studies of tick niche have included climate and land variables, such as temperature, precipitation, GPP, ET, NDVI, RH, LCLU, SPI, and the Leaf Area Index (LAI) (Butler et al., 2024; Estrada-Peña, 2008). The RFSDM utilized in this model incorporated those variables, apart from LCLU. In the case of Arkansas, LCLU as a predictor of tick presence created a probability layer that was heavily discretized, i.e., appearing binary rather than producing a probability distribution, and did not allow for a visualization of spatial heterogeneity and was therefore excluded. Thresholds from the OENM/FENM models were solely used for producing a pseudo absence layer and were not retained for use in the distribution model to limit circularity between the ENM and RFSDM (Engler et al., 2004). This approach is similar to that of Tudge et al. (2026), where pseudo absence was sampled from LCLU areas deemed unsuitable based on expert knowledge, and Miok (2026), where pseudo absence was informed using an LLM-based approach. Histograms of each variable, across each epoch, are depicted in *Figure 4.*

Randomized pseudo-absence sampling of unsuitable OENM areas was performed with a 250 m buffer distance to prevent overlapping data, reduce overrepresentation, and create a more spatially stratified sampling, as is recommended in many SDM workflows (Crego et al., 2022; Phillips et al., 2014; Zhou & Sun, 2024) (*Figure 2*). Similarly, presence points were filtered using a 250 m buffer distance to eliminate overlapping and clustered datapoints and potential non-random sampling bias within and around urban areas (*Figures 1, 2*). The resulting training dataset included 1063 presence points and 1063 pseudo-absence points ($N = 2126$) so that presence and pseudo-absence samples had equal representation. Utilizing the sampled presence and pseudo-absence points, in conjunction with the predictor variables, the GEE Random Forest classifier

"ee.Classifier.smileRandomForest" (Gorelick et al., 2017) was employed to train the tick probability model. The model was then used to predict probability across Epoch 1 and Epoch 2 to display the relative difference of tick suitability across space and time.

Model performance was evaluated using K-Fold cross-validation with the Receiver Operator Characteristic-Area Under the Curve (ROC-AUC) and Precision-Recall Area Under the Curve (PR-AUC) metrics (Table 5) using a 70% and 30% training and testing split, respectively. The Receiver Operation Characteristic (ROC) curve is defined in machine learning by classifying the true positive (TP) and false positive (FP) of model performance, in which a total rate falls between 0 and 1 of both TP and FP (Google for Developers, 2026; Shreffler & Huecker, 2025). The Area Under the Curve (AUC) represents the probability that a model will correctly rank TP cases above FP cases, also defined from 0 to 1, as related to an established threshold from the ROC (Google for Developers, 2026). ROC-AUC and PR-AUC were calculated in RStudio (R Core Team, 2023) using the "pROC" package (Robin et al., 2011). Variable importance was measured using Mean Decrease in Impurity (MDI) and Permutation Importance (PI) (refer to Table 6). GEE utilizes MDI to measure feature importance in a rapid and computationally efficient manner, but MDI has been reported as biased toward variables with more levels or wider ranges (Strobl et al., 2007). PI measures how model accuracy decreases when a feature's values are redistributed or temporarily removed, providing a more robust evaluation of importance of each variable as they relate to the model's operation. PI was evaluated in R Studio (R Core Team, 2023) using the packages "iml" (Molnar et al., 2018), "vip" (Greenwell & Boehmke, 2020), "dplyr" (Wickham et al., 2023), and "randomForest" (Liaw & Wiener, 2002).

3 Results

The OENM depicts more spatial variation than the FENM, as the FENM portrays areas of less-than-optimal suitability homogenously as suitable (*Figure 3*). This is because

the optimal temperature range is constrained more narrowly than the full range (refer to Table 2), enabling more disaggregation. The OENM was used for pseudo-absence sampling and is more representative of niche variation and the general heterogeneity of tick abundance across Arkansas. Table 3 and *Figures 3 & 4* all display changes to climate and land conditions across the study timeframe. The FENM is not able to fully convey the spatial heterogeneity of tick habitat suitability due to the simplicity of the Boolean logic design, as well as the expanded temperature range depicting the majority of the state as "Suitable," except for Eastern Arkansas, an area that is largely devoted to rice and soybean agriculture (Mahbub et al., 2025). Considering the unilluminating output of the FENM, the more temperature-restrictive OENM was developed to depict fine-scale variations in suitability. This model provides a detailed view of the expansion of "Optimal" tick ecological niche in Arkansas. In Epoch 1, the Southern portion of Arkansas many optimal zones, but there are large swaths of less-than-optimal landscapes due to either land or climate-based deviations from optimal conditions. Epoch 2 displays a more spatially continuous connecting of optimal conditions across the state, expanding closer to urban areas and across previously less-than-optimal landscapes. In particular, the optimal area increased from 54,401 sq km in Epoch 1 to 100,321.81 sq km in Epoch 2. Additionally, the bar chart in *Figure 3* depicts increased suitability resulting from more advantageous climate conditions. The decrease in land suitability observed between Epochs 1 and 2 (from 68,171.31 sq km to 22,021.88 sq km) is in part a product of many of these areas becoming climate suitable, shifting pixels into the optimal category. The OENM climate and land sub-models are visualized along with the OENM results without temporal restriction across the entire study timeframe to display the ubiquitous nature of climate variations and tick suitability. When refined to the OENM, the climate sub-model expectedly is the predominant cause for temporal variations in suitability, as the land sub-model is relatively constant year-round with minor variations in NDVI in fall and winter months. Local variations in LCLU are undoubtably impactful to habitat suitability, but LCLU changes are not

impactful enough to be of note in the ENM models. The trendlines for climate and optimal suitability are all positive in nature, while the land sub-model remains constant across the timeframe indicating that the land model maintains optimal suitability across appropriate landscapes during summer months. The slope for the climate sub-model is 1613.4x + 71237 (R^2 = 0.12), and the slope for the full OENM is y= 1364.1x + 62906 (R^2 = 0.12). The spatial nature of change is less obvious in the FENM but highlighted in the OENM, further exemplifying the importance of restricting the temperature range to optimal conditions to evaluate the spatiotemporal variability of tick suitability. From the sampled and stratified presence samples, only 3% were obtained or catalogued as being from "unsuitable" landscape or climate conditions, which internally indicated successful variable threshold selection given the abundant and generalist nature of ticks in Arkansas.

The largest degree of collinearity was found between GPP and ET (Pearson's r = 0.72), and NDVI and LAI (Pearson's r = 0.64), indicating relatively strong linear relationships between these variables (Table 4). This was judged to be acceptable, as 0.7 and 0.8 are commonly accepted thresholds for identifying collinearity problems (Dormann et al., 2013; Mei et al., 2022), though further evaluation was conducted via MLR and VIF. The highest VIF among the predictor variables used in this study was with respect to ET and GPP at 2.988 and 2.974, respectively. All Pearson's r, MLR, and VIF results are listed in Table 4. K-Fold cross-validation was used to maximize the reliability of the Random Forest model results (Table 5). By partitioning the outputs into 10 folds, each fold is used for both testing and training the model. The average of each iteration indicates the model's overall performance and is depicted here by the ROC-AUC of 87.8% and the PR-AUC of 88.6%, both of which are considered very good scores. Important to note is that AUC can suffer in some models, especially those with a temporal component and those that address generalist species such as ticks (Tao et al., 2024). Temperature, NDVI, and drought were all highly valued during MDI

399 testing (2535.740, 2476.043, and 2452.139, respectively), but were then outperformed by ET, GPP,
400 and LAI in PE (0.991, 0.989, and 0.989, respectively) (Table 6). All predictor
401 variables maintained low multicollinearity but displayed strong individual performance in PE testing
402 (ranging from 0.968–0.991). Overall, the model performed well as indicated by the ROC-AUC of
403 87.8% and PR-AUC of 88.6%. Variations in the ecological niche over time are indicative of effective
404 performance of the model rather than uncertainty, as areas of high variation can be explained by local
405 environmental conditions across epochs.

406 Substantially different environmental conditions showed greater tick presence probability in
407 Epoch 2 than in Epoch 1 (13.1% greater on average) during the peak months (*Figure 5*), meaning that
408 Epoch 2 was more similar to the training period when ticks were known to be present. The increase
409 in suitability in the FENM/OENM paired with the greater presence probabilities in Epoch 2
410 suggests an advantageous shift in environmental conditions for tick proliferation, development, and
411 host-seeking behavior. All these factors point to a likely increased relative risk of TBD in Arkansas
412 across time. At fine scales, both positive and negative impacts to tick ecological niche have occurred
413 across the study timeframe. Expansion of the ecological niche of ticks is expectedly not unilateral
414 across the state; i.e., there is much heterogeneity and development that will both positively and
415 negatively impact tick niche over time and space. This shifting of tick niche is visually depicted
416 across space in *Figure 5* through an example of a greater ecologically advantageous range across the
417 Southern portion of Arkansas from Epoch 1 to 2. This mirrors the expansion shown in the OENM
418 from *Figure 3.* The histogram in Figure 5 depicts the change toward higher probability across the
419 study timeframe. Notably, there are substantially more pixels within the ~0.7–0.9 probability range in
420 Epoch 2 as compared to Epoch 1; pixels previously in the ~0.1–0.6 range shifted to greater
421 probabilities. Interestingly, there is a slight reduction in classified probability in the
422 northwestern portion of Arkansas near the Ouachita National Forest. Aggregating data to the finest

available scale (in terms of both spatial and temporal granularity, as well as temporal range) has allowed for a detailed visualization of the advancing tick niche across Arkansas. *Figure 6* displays an area of relatively low to moderate tick niche probability in Epoch 1 that was fully connected with high tick niche probability (implying greater TBD risk) in Epoch 2. Satellite imagery displays the patchwork structure of LCLU and relatedness of land-use to tick niche, and how this patchwork nature can eventually blend, creating pathways for ticks and their hosts to move through the landscape (Esri & Eartstar Geographics, 2025). The area of interest in *Figure 6* is a mixture of seasonal crops that had lower tick probability in Epoch 1 (extent average of 0.49); however, possible alterations to the land and emergent environmental conditions showed this area to be more suitable in Epoch 2, leading to an average probability of 0.62.

Figure S1 displays the distribution of sampled specimens by species using the RFSDM pipeline. AUC/ROC varied by species; *R. sanguineus* performed strongly (0.93/0.83), while *I. scapularis* suffered (0.79/0.75) (Table S2). *I. scapularis* was trained and visualized using data from October and November, as sampling peaked in Fall during the sampling epoch, which may explain some of the disparity in validation compared to other species. The distribution of sampled specimens displays similar probability variation across Arkansas to the primary RFSDM; high probability per species in wooded areas of northern and western Arkansas with a sharp decrease in presence probability in eastern Arkansas aside from important fringe habitats within otherwise unsuitable landscapes.

4 Discussion

Previous modeling of *Amblyomma americanum* has elucidated the advancing range of this medically important species across Intergovernmental Panel on Climate Change (IPCC) scenario Representative Concentration Pathway (RCP) 4.5, steadily growing from the east and midwestern regions of the United States into more northern extents (Raghavan et al., 2019). 76%

of 20,811 submitted specimens submitted during citizen science sampling were lone star ticks (Dowling et al., 2022), which had previously been more constrained to the south. Lone star ticks notably employ an aggressive host seeking strategy that introduces bias in the non-random sampling schema, which was circumvented here by aggregating all species into one overall tick category (Molaei et al., 2019). Estimating niche above species-level can elucidate important environmental tolerances across taxonomies (Smith et al., 2019). Microclimates and microhabitats are a challenge to model via remote sensing due to the coarse resolution of many datasets, which can contain diverse landscapes and environmental conditions within individual pixels (Paaijmans et al., 2013; Potter et al., 2013). The environmental conditions represented by a 250 m spatial resolution pixel are an aggregation of the biophysical and climatic variations experienced locally, e.g., inclusion of a parking lot alongside neighboring vegetation and narrow waterways along its edge, an example of microrefugia. The multi-year epochs developed for this study offer stability and enhance reliability of the increasing suitability and presence probability results but obscure the impact of inter-annual climate variations that would impact tick habitability. Future modeling efforts in Arkansas should evaluate shorter epochs and make note of extreme weather events and anomalous biophysical and climatic conditions that limit or extend tick abundance.

GPP, ET, and LAI were all highly valued in model performance and feature importance, indicating their value as predictive variables for tick ecological niche. Butler et al. (2024) reported similar results at the regional scale using generalized linear models and Maximum Entropy (MaxEnt) at a 4.8 km spatial resolution, though their model valued elevation and land cover as highly important variables (Butler et al., 2024). Their model explored the niche of species encapsulated in our study but differentiated between species to display the potential variations in distribution over multiple states. The generation of pseudo-absence data here conforms with established methods that recognize a degree of circularity as a limitation of model conditioning. The literature-driven

unsuitable climate and landscape characteristics from the OENM/FENM exerted limited constraint on the RFSDM as only a set of predictor variables were used for pseudo-absence generation (Tudge et al., 2026). Random Forest was selected over other species distribution modeling tools like MaxEnt because Random Forest is robust at handling overfitting, which was a concern considering the non-random presence sampling. Similarly, land cover was not selected as a predictor variable in the RFSDM to decrease overfitting, as specific LCLU types (e.g., open water and urban) shadowed the impact of other biophysical predictors. Early model testing displayed minimal impact from elevation's inclusion, so it was not retained in the final edition of this study's model, but it may be of greater importance at alternative scales.

Ticks' primary method of movement across landscapes comes from their hosts. Because of this, the probability of a tick's presence in a specified area largely depends on the movement patterns of its most recent host. This adds a layer of complexity, as truly understanding where ticks are capable of existing is different from where ticks can reliably be found. Occasionally, ticks can be found in what would typically be considered unsuitable areas, often due to host availability. Such host data are less common and regularly out of scope, as was the case in Dowling et al. (2022), and future models would benefit from including host abundance data when possible. Still, the generalist nature of ticks results in numerous potential host species in any given region of interest. In Epoch 1, the probability of tick presence is bimodal, as depicted in *Figure 5*. The greater probabilistic tick presence in Epoch 2 paired with an expanded niche in the FENM/OENM does not just indicate an expansion of tick habitability (and likely human and environmental interactions), but also more advantageous breeding conditions for ticks through previously inhospitable summer months. These conditions bolster ticks' ability to proliferate, potentially increasing future disease risk in the fall and warmer winter months.

Modeling of individual tick species was not the focus of this study due to the non-random specimen sampling effort and lack of species-specific parameterization. *Amblyomma americanum* and *Dermacentor variabilis* are both often associated with urban areas, as they are known to seek mid and large sized mammals as hosts, frequently driving human and pet interactions and further limiting species-specific sampling reliability. Generalizing to Ixodidae does conceal nuance but also illuminates the broad spatial impact of ticks across the state, and can guide future species-specific sampling efforts. These future sampling efforts may utilize known tick sampling methods, such as carbon dioxide traps and drag netting that would not have been employed by citizen scientists, as well as a more deliberate attempt to capture ticks at volumes that would produce multiple species. Additionally, pseudo absence parameterization of less-studied species may be more adequately captured using an LLM than traditional literature reviews (Miok et al., 2026).

The advantageous conditions across this season are likely to increase the relative risk of TBD transmission for humans and animals, which is vital information for health practitioners and policymakers. Arkansas is considered a rural state, so empowering local stakeholders with high resolution maps to understand their local risk aids communities throughout the state. These maps and any accompanying tools should be made available to the Arkansan public, as such fine resolution data are important for individuals, and can be used to inform policies and interventions conducted by state, city, and county governments. Administrative unit level aggregation may be necessary for policy analysis, but the maps also have relevance to the general public at the pixel scale, as the distribution of risk across space is heterogeneous and varies locally. Remote sensing of microclimate variations is currently limited, but with finer-scale climate data, understanding highly localized shifts in fundamental tick ecological niche will further facilitate public health and policy responses.

5 | Conclusion

Dynamic climatic and environmental changes across time can destabilize known ecological norms for a species in any given region. In the case of this study, such dynamic changes created more advantageous fundamental ecological niche conditions for endemic tick species in Arkansas. Notably, Epoch 2 exhibited a 13.1% greater probability of tick presence on average across Arkansas during the peak tick season of June and July as compared to Epoch 1.

The spatially continuous probability layer derived using remotely sensed data provides a robust manner of stratifying tick suitability and presence across Arkansas and serves as a bellwether for surrounding regions. Model accuracy was high (RFSDM), with an average PR-AUC of 88.6% achieved, and the workflow can be generalized across geographies. Future studies designing tick sampling schemes and TBD disease surveys will benefit from the geographic information supplied in this study's SDM and ENM. Additionally, the maps and models produced here serve as a foundation for defining and mapping fundamental and realized niche conditions for ticks across Arkansas, which will strengthen modeling efforts geared toward the finest scales. It is important to note that the parameter ranges that have been implemented for this study display the overall niche of ticks as a broad category, but do not address specific parameterizations for individual tick species. Future work could expand on the realized niche requirements per tick species, further complementing these foundational models, especially as related to invasive species such as *Haemaphysalis longicornis* (Arkansas Department of Agriculture, 2018). Lastly, the maps and data generated here, which have been made openly accessible, can be paired with socioeconomic indicators, health data, and other environmental data to serve as a basis for quantifying disease transmission risk and ultimately improving overall public health.

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5.2 | Conflicts of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

5.3 | Contributions

Primary authorship was conducted by DW. Data curation, cleaning, method testing and validation, visualization, and editing was primarily his responsibility. Funding, supervision, and aid with conceptualization were provided by BG. Tick samples were provided by AD, who also aided with conceptualization and supervision. DH and JM were included as experts to aid with editing.

5.4 | Data Availability Statement

Data used to prepare this manuscript are available on open access repositories and the results of this analysis are openly available on Harvard Dataverse (Williams et al., 2025): https://doi.org/10.7910/DVN/GJMPUN.

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FIGURE CAPTIONS AND TABLES

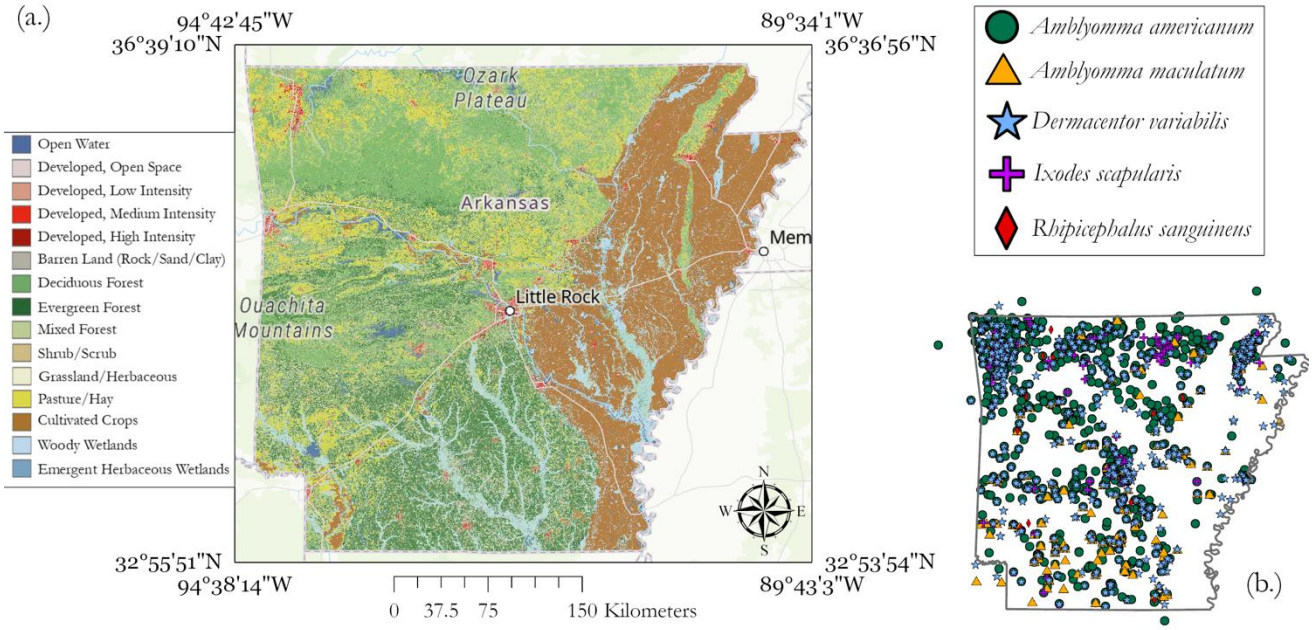


Figure 1: Land Cover and Land Use Classification of Arkansas; 2019–2024 mode from the USGS NLCD dataset (see Table 1) with basemap imagery by Esri, TomTom, Garmin, FAO, NOAA, USGS, (c) OpenStreetMap contributors, and the GIS User Community, Esri, USGS.

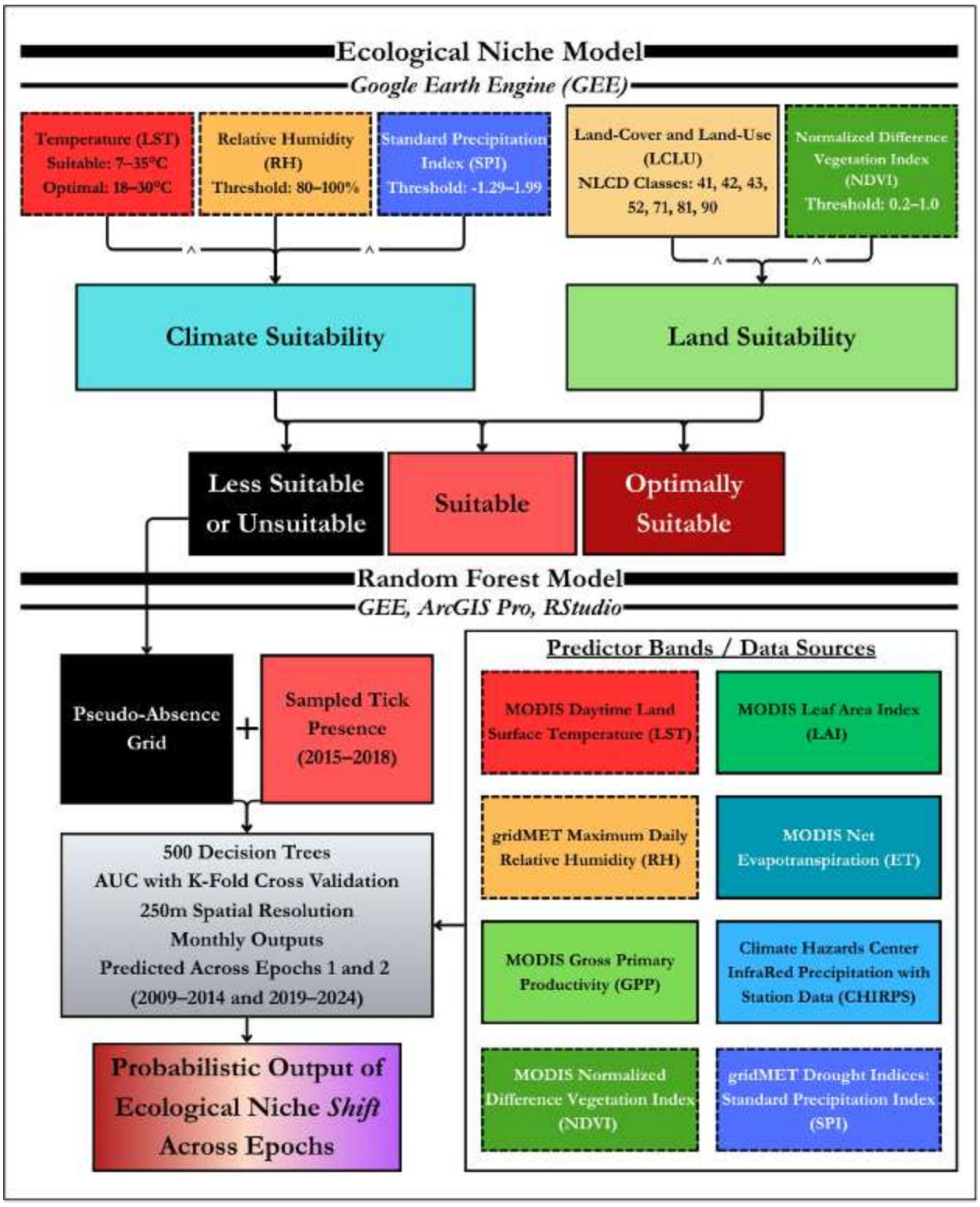


Figure 2: Visual model of process workflow, including datasets, parameters, processes, methods, and tools.

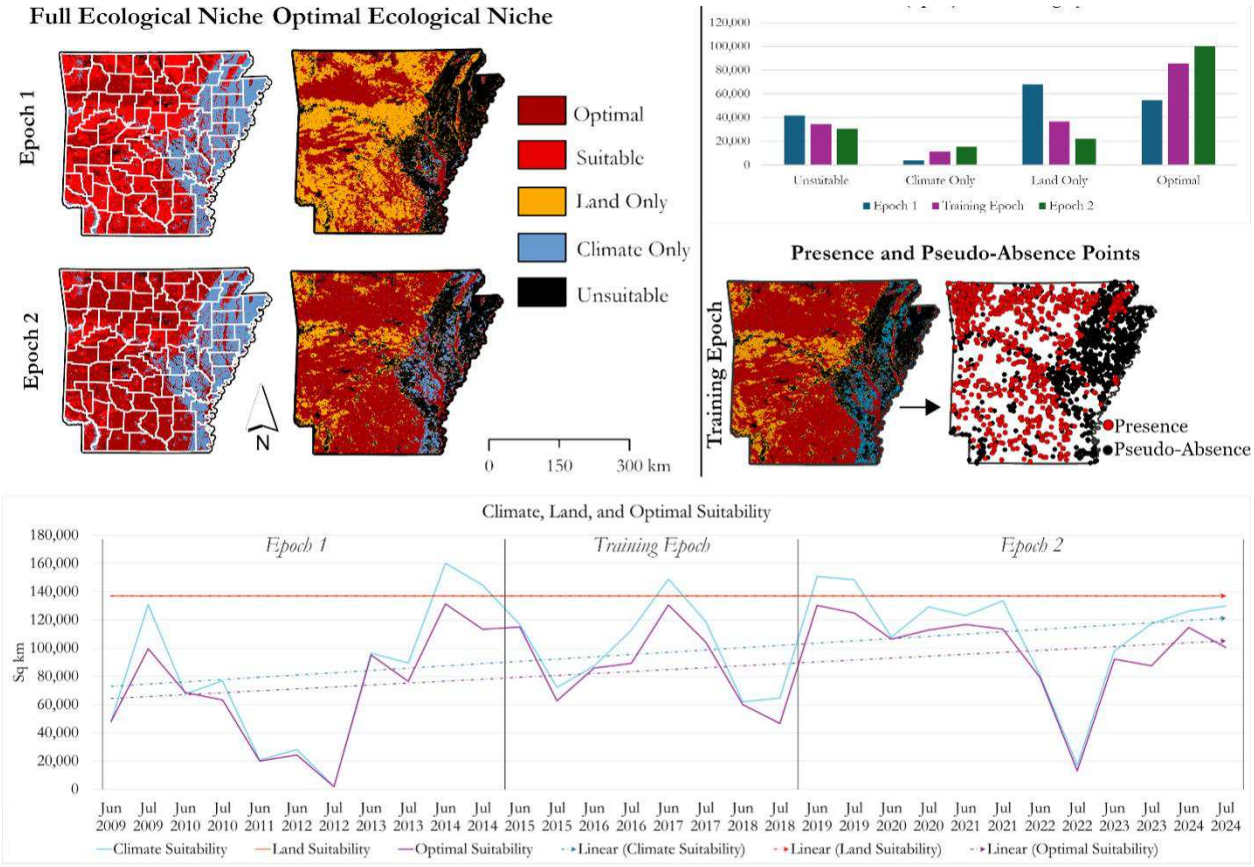


Figure 3: Depiction of the Boolean logic-based Full Ecological Niche Map (FENM) and Optimal Ecological Niche Map (OENM), and how OENM maps were utilized for pseudo-absence sampling and computationally efficient simple tick niche modeling.

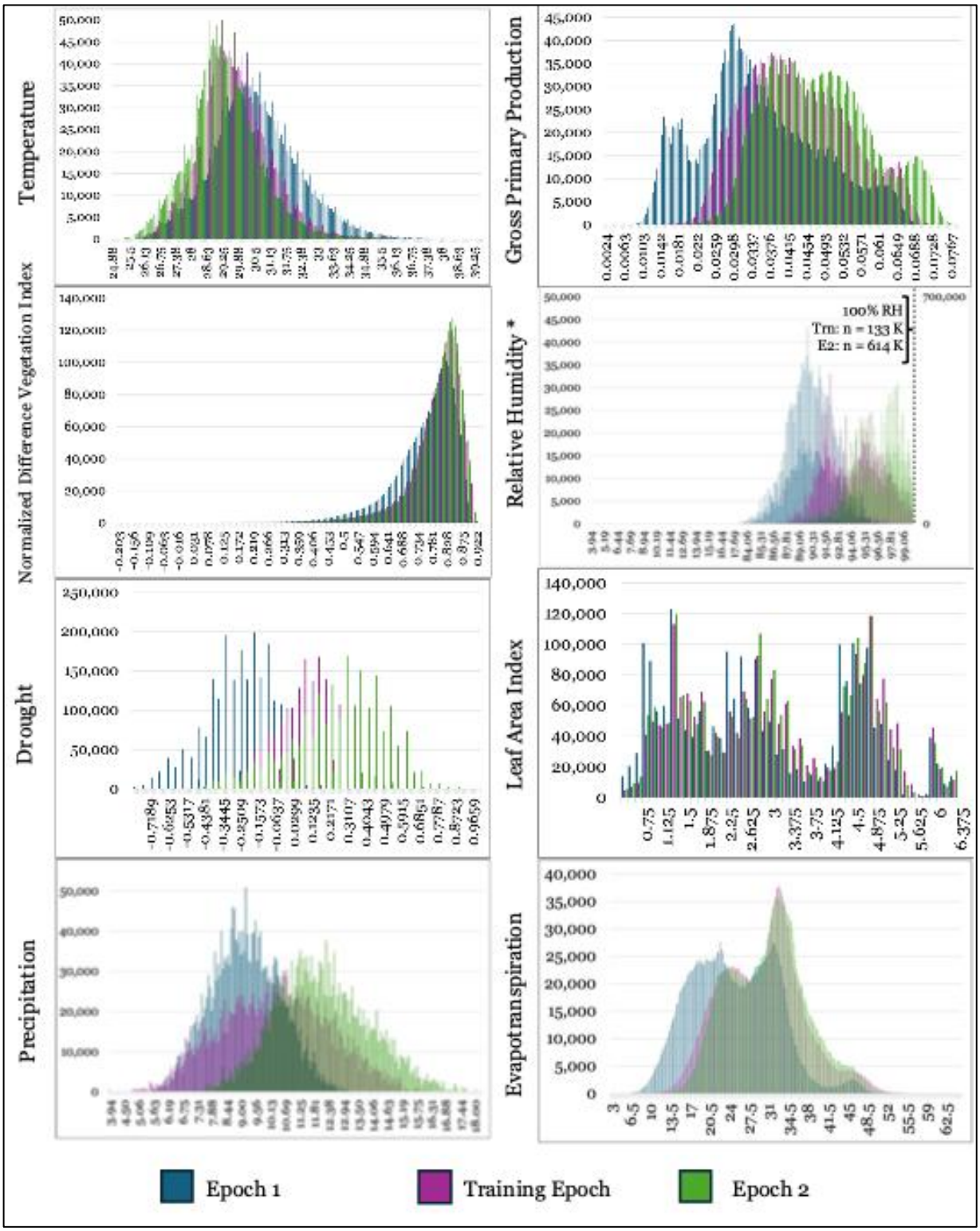


Figure 4: Chosen predictor variables across epochs. E1 stands for Epoch 1, Trn stands for the training epoch, and E2 stands for Epoch 2.

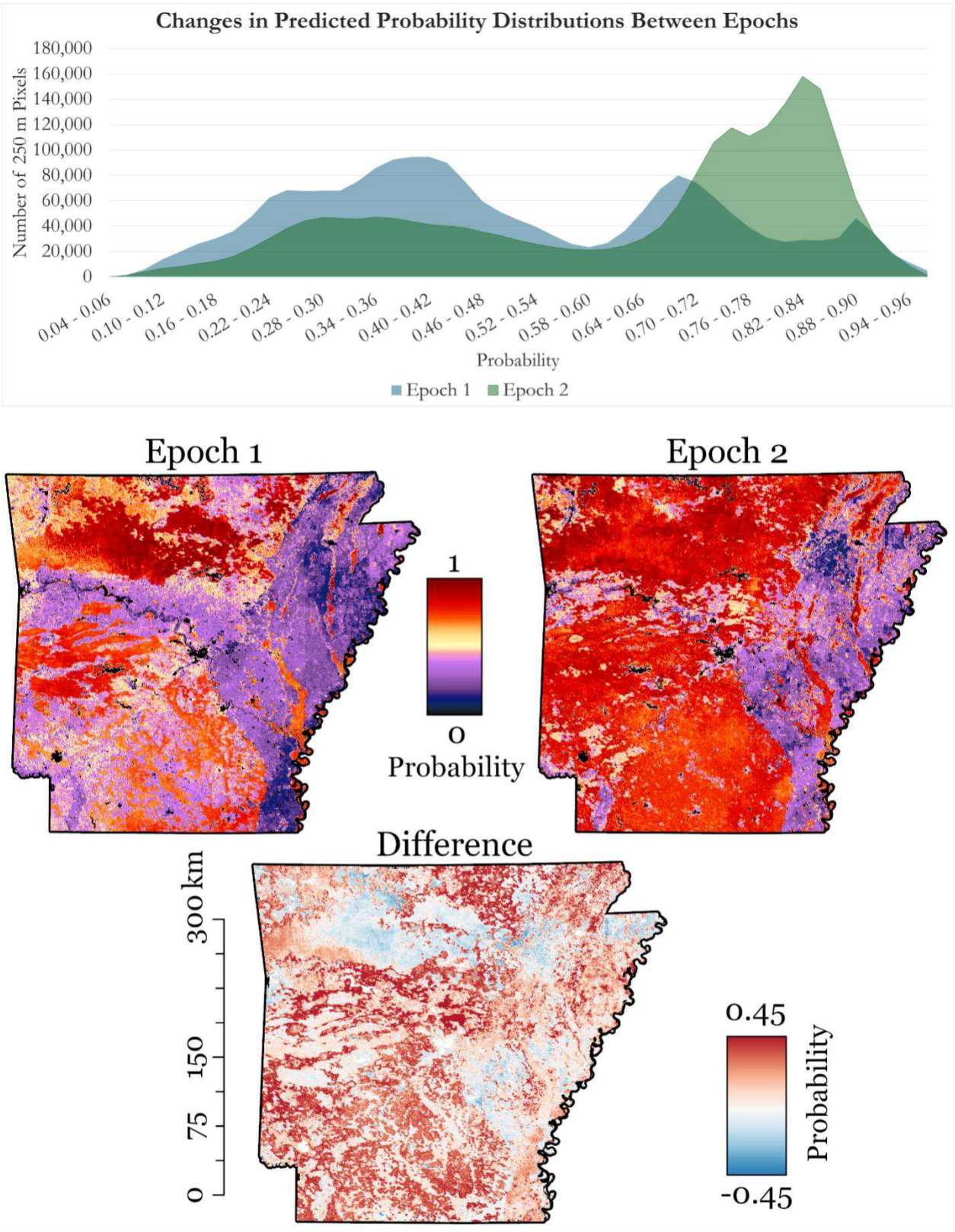


Figure 5: Depiction of tick probability distribution in June and July across epochs.

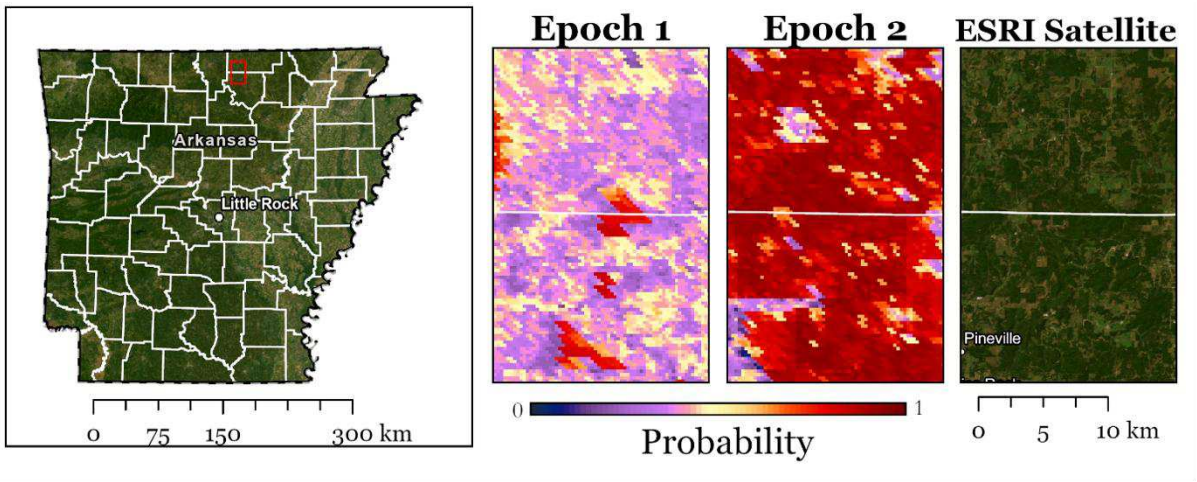


Figure 6: Fine-scale depiction of tick ecological niche shift across epochs and across two counties, ranging from lower risk to higher risk across epochs with comparative satellite basemap imagery from Earthstar Geographics, Sources: Esri, TomTom, Garmin, FAO, NOAA, USGS, (C) OpenStreetMap contributors, and the GIS User Community.

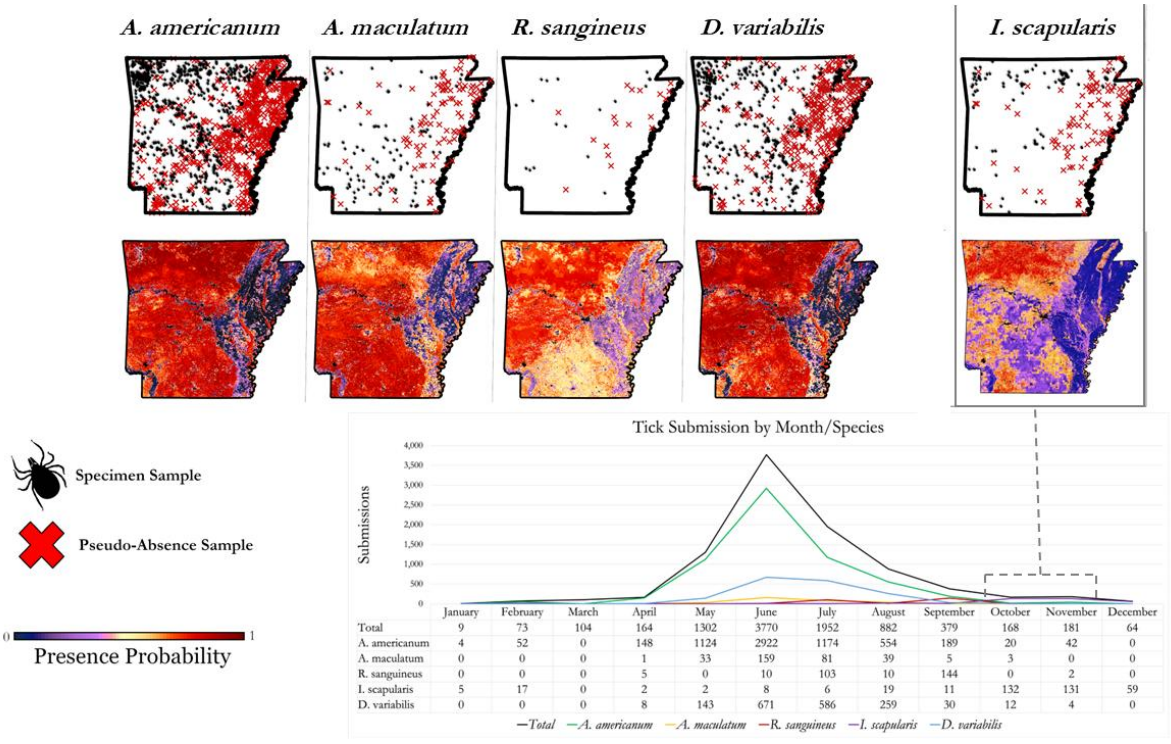


Figure S1: Species distribution modeling of individual tick species samples. I. scapularis' sampling and visualization are based upon October and November, as these months exhibited peak submission instead of June and July like the other specimens.

876

877 **Table 1:** Data sources, predictors, spatial and temporal resolutions, temporal ranges, and citations.

Data	**Predictor Variable**	**Spatial Resolution**	**Temporal Resolution**	**Temporal Range**	**Citation**
*MODIS Vegetation Indices (NDVI); MOD13Q1.061	NDVI	250 m	16-day	02/18/2000–present	Didan (2021)
*MODIS Land Surface Temperature (LST); MOD11A2.061	Temperature (LST Day)	1 km	8-day	02/18/2000–present	Wan, Hook, & Hulley (2021)
***USGS NLCD Land Use Categories	LCLU	30 m	Annual	01/01/2001–01/01/2019 AND 01/01/2021–01/01/2022	Dewitz and U.S. Geological Survey (2021) ; Dewitz (2023)
*gridMET: University of Idaho Gridded Surface Meteorological dataset	Maximum relative humidity	4.6 km	Daily	01/01/1979–present	Abatzoglou (2013)
*gridMET DROUGHT: CONUS Drought Indices	Drought index (spi14d)	4.6 km	14-day	01/01/1980–present	Leal et al. (2020)

**CHIRPS Pentad: Climate Hazards Center InfraRed Precipitation with Station data	Precipitation	5.5 km	5–day	01/01/1981–present	Funk et al. (2015)
**MODIS/Terra Gross Primary Productivity (GPP) Gap-Filled 8-Day L4 Global 500m SIN Grid V061	GPP	500 m	8-day	01/01/2000–present	Running & Zhao (2025)
**MODIS/Terra Net Evapotranspiration (ET) Gap-Filled 8-Day L4 Global 500m SIN Grid V061	ET	500 m	8-day	01/01/2000–present	Running et al. (2021)
**MODIS/Terra Leaf Area Index (LAI)/FPAR 8-Day L4 Global 500m SIN Grid V061	LAI	500 m	8-day	02/18/2000–present	Myneni et al. (2021)
TIGER: US Census States and Counties 2018	-	-	-	2018	United States Census Bureau (2018)
Tick specimens (*Amblyomma americanum*, *Amblyomma maclatum*, *Derma*	-	Arkansas	-	2015–2018	Dowling et al. (2022)

centor variabilis, *Ixodes scapularis*, and *Rhipicephalus sanguineus*)					

* - Full Ecological Niche Model (FENM)/Optimal Ecological Niche Model (OENM) and Random Forest Species Distribution Model (RFSDM) predictor variable

** - FENM predictor variable only

*** - Land Cover and Land Use (LCLU) is only used directly in the OENM

878

879 **Table 2:** Full Ecological Niche Model (FENM) and Optimal Ecological Niche Model (OENM)
880 parameters, thresholds, and supporting citations.

Parameter	**Threshold/Classes**	**Citation**
Optimal Temperature	18–30°C	Bansal et al. (2021); Ogden et al. (2004)
***Full Temperature**	7–40°C	Cunze et al. (2022); Eisen et al. (2016); van Oort et al. (2020)
NDVI	0.2–1.0	Fernández-Tizón et al. (2020)
NLCD LCLU	41, 42, 43, 52, 71, 81, 90	Dowling et al. (2022)
Max RH	80–100%	Rodgers et al., (2007); Van Oort et al. (2020)
SPI	-1.29–1.99	Rodgers et al. (2007); Weiler et al. (2017)

*Full temperature range was utilized for the FENM model to depict the distinction between suitable and optimally suitable climate conditions.

881

Table 3: Predictor average ($\bar{x}$), standard deviation (σ), and change across epochs (Δ). Average environmental conditions aggregated to the state level, per epoch reflect the overall conditions across the spatiotemporal extent.

		Epoch 1 (E1)		**Training (Trn)**		**Epoch 2 (E2)**		**E2– E1 Difference ($\Delta\bar{x}$)**
Variable	**Unit**	**$\bar{x}$**	**σ**	**$\bar{x}$**	**σ**	**$\bar{x}$**	**σ**	Δ
Drought	**SPI**	-0.25	0.17	0.12	0.21	-0.08	0.21	0.17
ET	**kg/m²**	25.29	7.82	30.21	6.72	31.06	6.95	5.77
GPP	**kg C/m²**	0.04	0.01	0.02	0.02	0.05	0.01	0.01
LAI	**Area Fraction**	3.19	1.55	3.45	1.06	3.42	1.49	0.23
NDVI	**Index**	0.77	0.10	0.76	0.10	0.80	0.08	0.03
Rain	**mm/pentad**	8.93	0.92	10.82	1.92	10.65	1.78	1.72
RH	**%**	90.08	2.13	93.57	2.9	98.18	2.45	8.10
Temp	**°C**	30.59	1.65	30.46	1.49	29.31	1.38	**-1.28**

Table 4: Pearson's Correlation Coefficient (PCC; Pearson's *r*) and Multiple Linear Regression (VIF and R^2).

	PCC (Pearson's r)								*MLR*	
	Drought	*ET*	*GPP*	*LAI*	*NDVI*	*Rain*	*RH*	*Temp*	*VIF*	*R^2*
Drought	1								1.048	0.046
ET	0.048	1							2.988	**0.665**
GPP	0.088	**0.722**	1						2.974	**0.664**

LAI	0.095	0.502	0.301	1					2.545	**0.607**
NDVI	0.063	0.487	0.374	**0.639**	1				1.944	0.486
Rain	0.087	0.168	0.403	0.037	0.082	1			1.250	0.200
RH	-0.112	0.150	-0.152	0.285	0.112	-0.093	1		1.293	0.227
Temp	-0.157	-0.292	-0.280	-0.631	-0.546	-0.095	-0.066	1	1.875	0.467

888

889 **Table 5:** K-Fold cross validation results: ROC-AUC and PR-AUC.

Fold	***ROC-AUC***	***PR-AUC***
1	0.8798	0.8841
2	0.9085	0.9006
3	0.9060	0.9106
4	0.9081	0.9251
5	0.8593	0.8646
6	0.8793	0.8797
7	0.9079	0.9301
8	0.8564	0.8648
9	0.8302	0.8547
10	0.8473	0.8409
Average	0.8783	0.8855

890

891 **Table 6:** Feature importance testing: MDI, PI, and PE.

Variable	*MDI*	*PI-Median*	*PI-Mean*	*PI-95%*	*PE*
*Drought**	2476.043	1.036	1.044	1.046	0.982
*ET***	2257.843	1.049	1.053	1.054	0.991
*GPP***	2387.370	1.049	1.050	1.053	0.989
*LAI***	1983.103	1.048	1.050	1.052	0.989
*NDVI**	2452.139	1.036	1.0373	1.043	0.977
Rain	2398.692	1.023	1.029	1.031	0.968
RH	2309.459	1.031	1.033	1.035	0.973
*Temp**	2535.740	1.029	1.038	1.039	0.977
• * - Highly valued in Mean Decrease Impurity (MDI) • ** - Highly valued in Permutation Importance (PI) and Permutation Error (PE)					

892

Supplementary Files

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