Full title (250 characters): **Transmission of West Nile virus and other temperate mosquito-borne viruses occurs at lower environmental temperatures than tropical diseases**

Short title (70 characters): **Temperature-dependent transmission of temperate mosquito-borne viruses**

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ABSTRACT (427 WORDS)

Temperature is a key driver of mosquito-borne disease because it affects the physiology and life history traits of mosquitoes and the pathogens they transmit. These trait thermal responses are typically nonlinear and vary by species. However, the impact of temperature on many important temperate mosquito-borne diseases has never been quantified, and it is unclear if thermal responses of temperate mosquito-borne diseases differ systematically from the patterns found in better-studied tropical systems. These environment–transmission relationships are critical for understanding current seasonal and geographic distributions of disease and future shifts due to climate change. We used a mechanistic, trait-based approach to characterize temperature-dependent transmission of 10 vector–pathogen pairs in an overlapping network of mosquitoes (*Culex pipiens*, *Cx. quinquefascsiatus*, *Cx. tarsalis*, *Aedes triseriatus*, and others) and viruses (West Nile virus [WNV], Eastern and Western Equine Encephalitis viruses [EEEV and WEEV], St. Louis Encephalitis virus [SLEV], Sindbis virus [SINV], and Rift Valley Fever virus [RVFV]), most of which have predominantly temperate geographic distributions worldwide. We found that several of these temperate pathogens have lower thermal limits (8.6–19.0ºC) and optima (22.7–26.0ºC) that are cooler than those of tropical pathogens (lower thermal limits: 16.2–22.8ºC; optima: 25.4–29.1ºC), as expected based on geography. However, their upper thermal limits (31.9–37.8ºC) were very similar to those of tropical pathogens (31.4–34.5ºC). Together, these patterns led to wider thermal breadths (NUMºC) for several of the temperate viruses compared to most tropical pathogens (NUMºC). Among temperate viruses, thermal limits for transmission varied more and were more uncertain than the optima. While the qualitative shapes of trait thermal responses generally matched prior studies, lifespan declined monotonically at temperatures above 14ºC for the temperate *Culex* vectors, in contrast to

unimodal responses observed within this temperature range for tropical species. We validated the mechanistic models with independent data on human disease cases. The incidence of WNV across US counties responded unimodally to temperature and peaked at 23.9ºC, closely matching model predictions (optima for WNV in North American vectors ranged from 23.9–25.2ºC). Additionally, data on the month of onset of cases of WNV, SLEV, and EEEV suggested that temperature is important for determining the seasonality of transmission. The thermal responses for parasite development rate, vector competence, biting rate, and lifespan, all of which varied among species and determined thermal limits in models, are a critical need for future empirical work. Because temperature effects on vector-borne disease transmission are pervasive and nonlinear, and climate regimes are changing rapidly, trait-based models are a key tool for predicting how temperature will affect mosquito-borne disease dynamics.

INTRODUCTION

Temperature is a key driver of transmission of mosquito-borne diseases—including globally important pathogens like malaria and dengue—because the mosquitoes and pathogens are ectotherms whose physiology and life history depend strongly on environmental temperature [1–7]. These temperature-dependent traits drive the biological processes required for transmission. For example, temperature-dependent fecundity, development, and mortality of mosquitoes determine whether vectors are present in sufficient numbers. Temperature also impacts the mosquito biting rate on hosts and probability of becoming infectious.

Mechanistic models based on these traits and guided by principles of thermal biology predict that the thermal response of transmission is unimodal: transmission peaks at intermediate temperatures and is inhibited at extreme cold and hot temperatures [2–11]. This unimodal pattern is predicted consistently across mosquito-borne diseases [2–7] and supported by independent empirical evidence for positive relationships between temperature and human cases in many settings [5,12–15], but negative relationships at extremely high temperatures in other studies [2,15–17]. Accordingly, increasing temperatures due to climate change are expected to shift disease distributions geographically and seasonally, as warming should increase transmission in cooler settings but decrease it in settings near or above the optimum for transmission [18–21]. Thus, mechanistic models have provided a powerful and general rule describing how temperature affects the transmission of mosquito-borne disease. However, thermal responses vary among mosquito and pathogen species and drive important differences in how transmission responds to temperature, including the specific temperatures of the optimum and thermal limits for each vector–pathogen pair [2–7]. We currently lack a framework to describe or predict this variation, even at the broadest scales. For instance, mosquitoes and mosquito-borne diseases

span the tropical–temperate climate gradient, yet it is unclear if there are systematic differences in the way temperature affects transmission of different species across this gradient.

Filling this gap requires comparing mechanistic, temperature-dependent transmission models for many vector–pathogen pairs, which are currently lacking for several reasons. First, the number of relevant vector–pathogen pairs is large because many mosquitoes transmit multiple pathogens and many pathogens are transmitted by multiple vectors. Second, empirical data are costly to produce and existing data are often insufficient because experiments or data reporting were not designed for this purpose. Third, compiling these data is labor-intensive and fitting thermal responses is technically challenging. Accordingly, many vector–pathogen pairs lack temperature-dependent transmission models altogether or have models that only include a subset of the relevant traits. Here, we address these challenges by systematically compiling data and building models for understudied mosquito-borne disease systems. Accurately characterizing the thermal limits and optima for these systems is critical for understanding where temperature currently promotes or suppresses transmission and where climate change will increase, decrease, or have minimal effects on transmission.

In this study, we model the effects of temperature on a suite of widespread, important, and largely temperate mosquito vectors and viruses that currently lack complete temperature-dependent models. We selected this group of mosquito-borne diseases because many of the viruses share common vector species and several vector species transmit multiple viruses (Fig 1). These temperate viruses include: West Nile virus (WNV), St. Louis Encephalitis virus (SLEV), Eastern and Western Equine Encephalitis viruses (EEEV and WEEV), and Sindbis virus (SINV) [22–24] (summarized in Table 1). We also included the primarily tropical Rift Valley fever virus (RVFV) because it shares two key vector species, *Culex pipiens* and *Cx. quinquefasciatus* [25]

(summarized in Table 1). All the viruses cause febrile illness and a variety of severe disease symptoms, including long-term arthralgia and neuroinvasive syndromes with a substantial risk of mortality in severe cases [22–25]. WNV is found across Africa, Europe, Asia, Oceania, and North America. It first invaded North America in 1999 [22] and is now the most common mosquito-borne disease in the US and Canada. SLEV, EEV, and WEEV occur primarily in the US (Table 1), with occasional cases in Canada and Central and South America [26,27]. SINV occurs in northern Europe and southern Africa [24]. RVFV originated in eastern Africa and now also occurs across Africa and the Middle East [25]. These pathogens primarily circulate and amplify in wild bird reservoir hosts (except RVFV, which primarily circulates in livestock). For all six viruses, humans are dead-end or unimportant reservoir hosts [28,29], in contrast to pathogens like malaria, dengue virus, yellow fever virus, and Ross River virus, which can sustain infection cycles between humans and mosquitoes [28,30,31]. Most transmission of RVFV to humans occurs through direct contact with infected livestock, although it also occurs to a lesser extent via the typical mosquito-borne transmission route, i.e., bites from infected vectors [29].

We primarily focus on *Culex pipiens*, *Cx. quinquefasciatus*, and *Cx. tarsalis*, well-studied species that are important vectors for many of the viruses and for which appropriate temperature-dependent data exist for nearly all traits. Although the closely-related *Cx. pipiens* and *Cx. quinquefasciatus* overlap in their home ranges in Africa, they have expanded into distinct regions globally (Fig 2) [32]. *Cx. pipiens* occurs in higher-latitude temperate areas in the Northern and Southern hemisphere, while *Cx. quinquefasciatus* occurs in lower-latitude temperate and tropical areas (Fig 2A). In contrast, *Cx. tarsalis* is limited to North America but spans the tropical-temperate gradient (Fig 2B). In this system of shared pathogens and vectors with distinct geographical distributions, we also test the hypothesis that differences in thermal performance

underlie variation in vector and pathogen geographic distributions, since temperate environments provide cooler temperatures and a broader range of temperatures than tropical environments. Thermal responses from other vector species were also included in some models: *Ae. taeniorhynchus* (SINV and RVFV), *Ae. triseriatus* (EEEV), *Ae. vexans* (RVFV), *Cx. theileri* (RVFV), and *Cs. melanura* (EEEV). Additionally, we compare our results to previously published models [2–4,6,7] for transmission of more tropical diseases by the following vectors: *Ae. aegypti*, *Ae. albopictus*, *Anopheles spp.*, and *Cx. annulirostris*.

We use a mechanistic approach to characterize the effects of temperature on vector–virus pairs in this network using the thermal responses of traits that drive transmission. Specifically, we use experimental data to measure the thermal responses of the following traits: vector survival, biting rate, fecundity, development rate, competence for acquiring and transmitting each virus, and the extrinsic incubation (development) rate of the virus within the vector. We ask: (1) Do these temperate vectors have qualitatively similar trait thermal responses to more tropical vectors? (2) Do temperate vectors transmit disease at lower temperatures, and across a broader temperature range, than tropical vectors? (3) How do the thermal responses of transmission vary across vectors that transmit the same virus and across viruses that share a vector? (4) Which traits limit transmission at low, intermediate, and high temperatures? Broadly, we hypothesize that variation in thermal responses is predictable based on vectors' and viruses' geographic ranges.

Mechanistic models allow us to incorporate nonlinear effects of temperature on multiple traits, measured in controlled laboratory experiments across a wide thermal gradient, to understand their combined effect on disease transmission. This approach is critical when making predictions for future climate regimes because thermal responses are almost always nonlinear,

and therefore current temperature–transmission relationships may not extend into temperatures beyond those currently observed in the field. We use Bayesian inference to quantify uncertainty and to rigorously incorporate prior knowledge of mosquito thermal physiology to constrain uncertainty when data are sparse [3]. The mechanistic modeling approach also provides an independently-generated, *a priori* prediction for the relationship between temperature and transmission to test with observational field data on human cases, allowing us to connect data across scales, from individual-level laboratory experiments, to population-level patterns of disease transmission, to climate-driven geographic variation across populations. Using this approach, we built mechanistic models for 10 vector–virus pairs by estimating thermal responses of the traits that drive transmission. We validated the models using observations of human cases in the US over space (county-level) and time (month-of-onset). The validation focuses on WNV because it is the most common of the diseases we investigated and has the most complete temperature-dependent trait data.

MODEL OVERVIEW

To understand the effect of temperature on transmission and compare the responses across vector and virus species, we used R_0—the basic reproduction number [33]. We use R_0 as a static, relative metric of temperature suitability for transmission that incorporates the nonlinear effects of temperature on multiple traits [1,34] and is comparable across systems, rather than focusing on its more traditional interpretation as a threshold for disease invasion into a susceptible population. Temperature variation creates additional nonlinear effects on transmission [35–38] that are not well-captured by R_0, [9,33,39–41] but could be incorporated in

future work by integrating the thermal performance curves fit here over the observed temperature regime.

The basic R_0 model (eq. 1) [34] includes the following traits that depend on temperature (T): adult mosquito mortality (μ, the inverse of lifespan [*lf*]), biting rate (a, proportional to the inverse of the gonotrophic [oviposition] cycle duration), pathogen development rate (*PDR*, the inverse of the extrinsic incubation period: the time required for exposed mosquitoes to become infectious), and vector competence (*bc*, the proportion of exposed mosquitoes that become infectious). Vector competence is the product of infection efficiency (c, the proportion of exposed mosquitoes that develop a disseminated infection) and transmission efficiency (*b,* the proportion of infected mosquitoes that become infectious, with virus present in saliva). Three parameters do not depend on temperature: mosquito density (M), human density (N), the rate at which infected hosts recover and become immune (r).

$$\text{Basic } R_0\text{: } R_0(T) = \left(\frac{a(T)^2 bc(T) e^{-\frac{\mu(T)}{PDR(T)}} M}{N\, r\, \mu(T)}\right)^{1/2} \qquad \text{eq. 1}$$

As in previous work [2–4,6,7,9], we extend the basic R_0 model to account for the effects of temperature on mosquito density (M) via additional temperature-sensitive life history traits (eq. 2): fecundity (as eggs per female per day, *EFD*), egg viability (proportion of eggs hatching into larvae, *EV*), proportion of larvae surviving to adulthood (*pLA*), and mosquito development rate (*MDR*, the inverse of the development period).

$$\text{Full } R_0\text{: } R_0(T) = \left(\frac{a(T)^2 bc(T) e^{-\frac{\mu(T)}{PDR(T)}} EFD(T) EV(T) pLA(T) MDR(T)}{N\, r\, \mu(T)^3}\right)^{1/2} \qquad \text{eq. 2}$$

Fecundity data were only available as eggs per female per gonotrophic cycle (*EFGC*; for Cx. *pipiens*) or eggs per raft (*ER*; for Cx. *quinquefasciatus*). Thus, we further modified the model to

obtain the appropriate units for fecundity: we added an additional biting rate term to the model (to divide by the length of the gonotrophic cycle, eqs. S1 and S2) and for *Cx. quinquefasciatus* we also added a term for the proportion of females ovipositing (*pO*; eq. S2).

To fit a temperature-dependent R_0 model for each relevant vector–virus pair, we conducted a literature survey to identify studies that measured the focal traits at three or more constant temperatures in a controlled laboratory environment. From these data, we fit thermal responses for each trait using Bayesian inference, which allowed us to quantify uncertainty and formally incorporate prior data [3] to constrain fits when data for the focal species were sparse or only measured on a limited portion of the temperature range (see *Material and Methods*). As in previous work [2–4,6,7], we fit traits with a symmetrical unimodal thermal response with a quadratic function (eq. 3) and traits with an asymmetrical unimodal thermal response with a Briére function [42] (eq. 4). For some asymmetrical responses (e.g., *PDR* for most vector–virus pairs), we did not directly observe a decrease in trait values at high temperatures due to a limited temperature range. In these cases, we chose to fit a Briére function based on previous studies with wider temperature ranges [2,4–6] and thermal biology theory [43]; the upper thermal limit for these fits did not limit transmission in the R_0 models. Lifespan data exhibited a monotonically decreasing thermal response over the range of experimental temperatures available. Based on vector life history, we fit these data using a linear function (eq. 5) that plateaued at coldest observed data point to be conservative. To overwinter, *Cx. pipiens* and *Cx. tarsalis* enter reproductive diapause and hibernate [44,45], and *Cx. pipiens* can survive temperatures at or near freezing (0ºC) for several months [44]. *Cx. quinquefasciatus* enters a non-diapause quiescent state [45,46] and is likely less tolerant of cold stress, but we wanted a consistent approach across models and other traits constrained the lower thermal limit of the *Cx. quinquefasciatus* R_0 model

to realistic temperatures.

Quadratic function: $f(T) = -q(T - T_{min})(T - T_{max})$ eq. 3

Briére function: $f(T) = q \cdot T(T - T_{min})\sqrt{(T_{max} - T)}$ eq. 4

Linear function: $f(T) = -mT + z$ eq. 5

In the quadratic and Briére functions of temperature (T), the trait values depend on a lower thermal limit (T_{min}), an upper thermal limit (T_{max}), and a scaling coefficient (q). In the linear function, the trait values depend on a slope (m) and intercept (z).

Because the magnitude of realized R_0 depends on system-specific factors like breeding habitat availability, reservoir and human host availability, vector control, species interactions, and additional climate factors, we focused on the relative relationship between R_0 and temperature. We rescaled the R_0 model to range from 0 to 1 (i.e., 'relative R_0'), preserving the temperature-dependence (including the absolute thermal limits and thermal optima) while making each model span the same scale. To compare trait responses and R_0 models, we quantify three key temperature values: the optimal temperature for transmission (T_{opt}) and the lower and upper thermal limits (T_{min} and T_{max}, respectively) where temperature is predicted to prohibit transmission ($R_0 = 0$).

RESULTS

Trait thermal responses

We fit thermal response functions from empirical data for most of the vector and virus traits that affect transmission (Table S1 and Fig 1). All mosquito traits were temperature-sensitive (3 main *Cx.* species: Fig 3, Fig 4; *Ae. taeniorhynchus*, *Ae. triseriatus*, *Ae. vexans*, *Cx. theileri*, and *Culiseta melanura*: Fig S1). For most species, the extensive data for larval traits

(mosquito development rate [MDR] and survival [*pLA*]) produced clear unimodal thermal responses with relatively low uncertainty (Fig 3A,B, Fig S1A,B). For biting rate (*a*) and fecundity traits (*pO*, *EFGC, ER*, *EV*), trait data were often more limited and fits were more uncertain, but still consistent with the expected unimodal thermal responses based on previous studies [2,4–6] and theory [43] (Fig 3C, Fig 4, Fig S1C-F). However, adult lifespan (*lf*) data clearly contrasted with expectations from previous studies of tropical mosquitoes. Lifespan decreased linearly over the entire temperature range of available data (coldest treatments: 14–16ºC, Fig 3D; 22ºC, Fig S1D) instead of peaking at intermediate temperatures (optima for tropical species: 22.2–23.4ºC) [2–4,6,7].

In general, the adult mosquito traits (biting rate, lifespan, and fecundity [*a*, *lf*, *pO*, *EFGC, ER*, *EV*]) varied more among species than the larval traits (development rate and survival [*MDR* and *pLA*]), although the high degree of uncertainty resulted in overlapping 95% credible intervals between species for most traits (Fig 3, Fig 4, Fig S1), with two exceptions. First, the thermal response for lifespan (*lf*) for *Cx. tarsalis* was significantly less steep than the response for *Cx. pipiens* (Fig 3D; 95% CIs for slope coefficients: *Cx. tarsalis* = 1.12–2.24, *Cx. pipiens* = 3.83–5.84). Second, although the symmetry of the unimodal functional form was generally consistent for each trait across species, the thermal responses for the proportion ovipositing (*pO*) and egg viability (*EV*) were symmetrical for *Cx. pipiens* and asymmetrical for *Cx. quinquefasciatus* (Fig 4 A,C). The lifespan pattern (thermal response of *Cx. tarsalis* less steep than *Cx. pipiens*) did not match any *a priori* prediction, but the differences for *pO* and EV matched predictions based on the geographic ranges of the vectors: lower-latitude *Cx. quinquefasciatus* performed better at warmer temperatures for *pO* (Fig 3A), and higher-latitude *Cx. pipiens* performed better at cooler temperatures for *EV* (Fig 3C).

The thermal responses for pathogen development rate were similar among most vector–virus pairs (Fig 5), with a few notable exceptions for the median responses: WNV in *Cx. quinquefasciatus* had a warmer lower thermal limit (Fig 5A); WNV in *Cx. univittatus* had a cooler optimum and upper thermal limit (Fig 5A); and SINV in *Ae. taeniorhynchus* had limited data that indicated a very flat thermal response (Fig 5C). By contrast, the thermal response of vector competence varied substantially across vectors and viruses (Fig 6). For example, infection efficiency (*c*) of *Cx. pipiens* peaked at warmer temperatures for WNV than for SINV (Fig 6A,G; 95% CIs: SINV = 14.1–30.5ºC, WNV = 31.9–36.1ºC), transmission efficiency (*b*) of *Cx. tarsalis* peaked at warmer temperatures for WNV and SLEV than for WEEV (Fig 6B,E,H; CIs: WEEV = 19.2–23.2ºC, SLEV = 23.5–29.7ºC, WNV = 23.9–29.3ºC), and the lower thermal limit for vector competence (*bc*) for WNV was much warmer in *Cx. pipiens* than in *Cx. univittatus* (Fig 6C; CIs: *Cx. univittatus* = 1.5–7.1ºC, *Cx. pipiens* = 15.0–17.9ºC). Infection traits for RVFV were only available in *Aedes taeniorhynchus*, a New World species that is not a natural vector for the virus.

Temperature-dependent R_0 models

Relative R_0 responded unimodally to temperature for all the vector–virus pairs, peaking at temperatures (medians: 22.7–26.0ºC, see Table 2 for CIs; Fig 7) that were cooler than or similar to previous results for tropical diseases (medians: 25.4–29.1ºC) [2–4,6,7]. Many models also had lower thermal limits (medians: 8.7–19.0ºC, see Table 2 for CIs; Fig 7) that were cooler than those for the tropical diseases (medians: 16.0–17.8ºC). By contrast, the upper thermal limits were very similar (medians: 31.9–37.8ºC, see Table 2 for CIs; Fig 7) to past models of tropical diseases (medians: 31.4–34.5ºC). Together, these patterns led to wider thermal breadths (NUMºC) for several of the temperate viruses compared to most tropical pathogens (NUMºC).

Among the temperate vector–virus pairs, the lower thermal limits were more variable than the optima, although confidence intervals overlapped in most cases because thermal limits also had higher uncertainty (Fig 7), as in previous studies [3,4,6,7]. Regardless, the *Ae. taeniorhynchus* models were clear outliers, with much warmer distributions for their upper thermal limits, and optima that trended warmer as well.

Differences in relative R_0 stemmed from variation both in vector traits (e.g., in Fig 7A, with WNV in different vector species) and in virus infection traits (e.g., in Fig 7B, with different viruses in *Cx. tarsalis*). The upper thermal limit was warmer for WNV transmitted by *Cx. pipiens* (34.9ºC [CI: 32.9–37.5ºC] than by *Cx. quinquefasciatus* (31.8ºC [CI: 31.1–32.2ºC]), counter to the prediction based on vector geographic ranges. This result implies that warming from climate change may differentially impact transmission by these two vectors. Additionally, the lower thermal limit for WNV varied widely (but with slightly overlapping 95% CIs) across different vector species (Fig 7D), from 19.0ºC (14.2–21.0ºC) in *Cx. quinquefasciatus* to 16.8ºC (14.9–17.8ºC) in *Cx. pipiens* to 12.2ºC (9.7–15.3ºC) in *Cx. tarsalis* to 11.1ºC (8.1–15.4ºC) in *Cx. univittatus* (an African and Eurasian vector; Table 2). Based on these trends in the thermal limits of R_0, the seasonality of transmission and the upper latitudinal and elevational limits could vary for WNV transmitted by these different species.

Different traits determined the lower and upper thermal limits and optimum for transmission across vector–virus pairs. The lower thermal limit for transmission was most often determined by parasite development rate (*PDR*; WNV and SLEV in *Cx. tarsalis*, WNV in *Cx. quinquefasciatus*) or biting rate (*a*; WNV in *Cx. univitattus*, WEEV in *Cx. tarsalis*, EEEV in *Ae. triseriatus,* RVFV and SINV in *Ae. taeniorhynchus*, SINV in *Cx. pipiens*; Figs S11–19), which tend to have asymmetric thermal responses with high optima. However, vector competence (*bc*)

determined the lower limit for WNV in *Cx. pipiens* (Fig S10). The upper thermal limit was determined by biting rate (*a*) for the three *Cx. tarsalis* models and by adult lifespan (*lf*) for all others, although proportion ovipositing (*pO*) was also important for WNV in *Cx. quinquefasciatus* (Figs S10-S19). In all models, lifespan (*lf*) and biting rate (*a*) had the strongest impact on the optimal temperature for transmission, with biting rate increasing transmission at low temperatures and lifespan decreasing transmission at high temperatures (Figs S10-S19). This result is consistent with previous mechanistic models of tropical mosquito-borne diseases, despite the qualitative difference in the shape of the lifespan thermal response between those tropical mosquitoes and the more temperate mosquitoes investigated here [2–4,6,7].

Model validation with human case data

Incidence of human neuro-invasive West Nile disease in US counties (averaged from 2001-2016) responded unimodally to average summer temperature and peaked at 23.9ºC (Fig 8), closely matching the optima from the mechanistic models for the three North American *Culex* species (23.9–25. 2ºC; Table 2). The data provided little evidence for lower or upper thermal limits at this scale; instead, mean incidence remained flat but positive below ~20ºC and above ~28ºC, although sample size was very low above 28ºC. The month-of-onset for cases of WNV was consistent with predicted transmission, $R_0(T)$ (Fig 9). As expected *a priori* (based on the time required for mosquito populations to increase, become infectious, and bite humans, and for humans to present symptoms and seek medical care [4,6]), there was a two-month lag between initial increases in $R_0(T)$ and incidence: cases began rising in June to the peak in August. The dramatic decline in transmission between September and October corresponds also closely to the predicted decline in relative R_0. In general, the seasonal patterns of SLEV and EEEV incidence

were similar to WNV, but differed by three orders of magnitude from ~20,000 cases of WNV to ~40-50 cases of EEEV and SLEV during the peak month (Fig. 9). However, transmission of SLEV and EEEV are predicted to begin increasing one month earlier than WNV (March versus April, Fig 9), because the mechanistic models predict that the lower thermal limits for SLEV and EEEV are cooler than those for WNV in two of the three North American vectors (*Cx. pipiens* and *Cx. quinquefasciatus*, Fig 7). The month-of-onset data partially support this prediction, as cases of SLEV (but not EEEV) disease begin to increase earlier in the year than WNV, relative to the summer peak.

DISCUSSION

As climate changes, it is critical to understand how changes in temperature will affect the spread of mosquito-borne diseases. Toward this goal, we developed temperature-dependent, mechanistic transmission models for 10 vector–virus pairs. The viruses—West Nile virus (WNV), St. Louis Encephalitis virus (SLEV), Eastern and Western Equine Encephalitis viruses (EEEV and WEEV), Sindbis virus (SINV), and Rift Valley fever virus (RVFV)—occur primarily in temperate areas (except RVFV), and are transmitted by shared vector species, including *Cx. pipiens*, *Cx. quinquefasciatus*, and *Cx. tarsalis* (Fig 1). Transmission of these temperate diseases differed from that of primarily tropical diseases [2–4,6,7]: several had significantly cooler thermal optima or lower thermal limits (Fig 7, Table 2). These results were partially due to the thermal responses of lifespan, which decreased linearly with temperature over the entire temperature range (of available data, > 14ºC) for these temperate *Culex* vectors (Fig 3), whereas lifespan for more tropical *Anopheles*, *Aedes*, and *Culex* spp. responded unimodally with intermediate optimal temperatures [2–4,6,7]. The thermal limits and optima for transmission also

varied among some of the temperate mosquito and virus species (Fig 7, Table 2), largely due to differences in the thermal responses of mosquito biting rate, lifespan, vector competence, and parasite development rate. Human case data for WNV disease across the US exhibited a strong unimodal thermal response (Fig 8), and month-of-onset data for three viruses was consistent with the predicted seasonality of transmission (Fig 9). Thus, the mechanistic models captured geographical and seasonal patterns of human incidence, despite the complexity of the enzootic cycles and spillover into humans. Our key results—maximal transmission at intermediate temperatures—underscore the importance of considering unimodal thermal responses when predicting how climate change will impact mosquito-borne disease transmission.

The monotonically decreasing thermal responses for lifespan in these temperate mosquitoes (Fig 3D) contrast with unimodal responses of tropical species [2,4,6], and may reflect differing thermal physiology between species that use diapause or quiescence, two forms of dormancy, to persist over winter and those that do not (see *Model Overview*) [44–46]. *Ae. albopictus*, a species that occurs in both tropical and temperate zones, exhibits a latitudinal gradient in the United States in which more temperate populations diapause while sub-tropical populations do not [47]. Experiments could test whether the functional form of the thermal response for lifespan differs between the two groups of populations, to test this hypothesis. Despite the fundamental difference in the shape of the thermal response, lifespan plays a similarly important role in temperate and tropical systems, strongly limiting transmission at high temperatures (Figs S10–19). Nonetheless, the linear thermal responses for lifespan ultimately promoted higher transmission at relatively cool temperatures because unlike in primarily tropical species, lifespan did not decline at cool temperatures within the range measured (> 14ºC). At more extreme temperatures expected to be fatal even for diapausing mosquitoes (i.e., well below

0ºC), we expect lifespan to decline even for these temperate mosquitoes, so that the response over broader temperature ranges is unimodal.

Accordingly, predicted transmission for several of the temperate diseases peaked and extended to cooler temperatures than for the primarily tropical diseases (Fig 7, Table 2). Here, the optimal temperatures for transmission varied from 22.7–25.2ºC (excluding *Ae. taeniorhynchus* models, Fig 7). By contrast, models predict that transmission peaks at 25.4ºC for malaria [2,3], 26.4ºC for Ross River virus [6] and dengue in *Ae. albopictus* [4], 28.9ºC for Zika in *Ae. aegypti* [4], and 29.1ºC for dengue in *Ae. aegypti* [4,7] (Table 2). Additionally, SINV—the virus most geographically restricted to high latitudes (northern Europe and southern Africa) [24]—had the second coolest lower thermal limits (Fig 7, Table 2). Lower-latitude *Cx. quinquefasciatus* outperformed higher-latitude *Cx. pipiens* at warmer temperatures for proportion ovipositing (*pO*; Fig 3A), while the reverse happened at cooler temperatures for egg viability (*EV*; Fig 3C). These results imply that, to some extent, measurements of physiological traits can predict geographic patterns of transmission at broad scales. However, geographic range differences (Fig 2) did not consistently predict variation in thermal responses among the *Culex* species in this study (e.g., biting rate [*a*, Fig 3C] and adult lifespan [*lf*, Fig 3D]), indicating limits to the extent to which life history and transmission trait responses at constant temperatures predict the geographic distributions of species. For example, the ability to tolerate temperature extremes may limit species distributions more than their performance at average or constant temperatures [48]. Additionally, the upper thermal limits for the temperate vector–virus pairs in this study (31.9–34.9ºC, excluding *Ae. taeniorhynchus* models; Fig 7D, Table 2) closely matched those of tropical diseases (31.5–34.7ºC) [2–4,6,7]. This similarity may arise because maximum summer temperatures in temperate areas often match or even exceed maximum temperatures in

tropical areas. Ultimately, there may be a fundamental upper thermal constraint on transmission (in the absence of thermal adaptation) that applies similarly to all mosquitoes-borne diseases, driven by short mosquito lifespans at high temperatures. (The relatively high upper thermal limits in both *Ae. taeniorynchus* transmission models were driven by the thermal response of lifespan, which was fit to few data points; more data are needed to determine if it reflects the true thermal response in that species [Fig S1]).

Independent human case data support unimodal thermal responses for transmission and the importance of temperature in shaping seasonal and geographic patterns of these mosquito-borne diseases. Human cases of WNV [49–55] and SINV [56,57] are often positively associated with temperature. Here, we found incidence of neuro-invasive WNV disease responded unimodally to temperature across counties in the US (Fig 8), adding to prior evidence for reduced transmission of WNV [58] and other mosquito-borne diseases [2,15–17] at high temperatures. However, we could not detect lower or upper thermal limits at this scale (Fig 8). We hypothesize that temperature variation over time and across microclimates may sustain transmission in regions with low or high mean summer temperatures by providing time windows suitable for transmission [35,36,38]. The temperature-dependent models also predict the seasonality of human cases of WNV, EEEV, and SLEV (Fig 9). The 2-month lag between climate suitability and the onset of human cases, which matches previous results from other mosquito-borne diseases [4,6], arises from the time following the onset of suitable conditions required for mosquito populations to increase [59], become infectious, and bite humans, and for humans to present symptoms and seek medical care [60,61]. Transmission of the temperate viruses here may incur additional lags because human cases only result from enzootic transmission and multiple rounds of amplification within reservoir hosts may be required before

prevalence is sufficiently high to spill over into humans. Additionally, as wild birds disperse in late summer, both *Cx. pipiens* and *Cx. tarsalis* shift their feeding preferences from birds to humans, increasing transmission to people and influencing the seasonal dynamics of WNV [62]. Drought, precipitation, and reservoir immunity also strongly drive transmission of WNV [5,52,53,55] and may interact with temperature. SLEV, EEEV, and WEEV are less common in nature, and thus less well-studied, but the lower thermal limits in our study support previous findings that transmission WEEV is favored over SLEV in cooler conditions [63]. Additionally, the seasonal patterns of incidence data (Fig 9) provide some support for the model prediction that SLEV transmission is possible at cooler temperatures than WNV by North American vectors (Table 2). By contrast, mean temperature is not associated with outbreaks of RVFV, although they are highly predictable based on precipitation driven by El Niño–Southern Oscillation cycles [64,65]. Thus, disease dynamics depend on the interaction between temperature and other environmental factors, and the relative importance of temperature versus other drivers varies across systems.

Most prior studies with mechanistic models for temperature-dependent transmission of WNV do not capture the unimodal thermal response that our mechanistic models predict and that we observe in the human case data (Table 3). Two previous models predicted that transmission of WNV would increase up to the warmest temperatures they considered, 28ºC [66] and 35ºC [67]. In both cases, the daily survival rates estimated from lab experiments were far less sensitive to temperature than our measure of adult lifespan, and neither model was validated with field data. A third study with models for *Cx. pipiens*, *Cx. quiquefasciatus*, and *Cx. tarsalis*, like our study, predicted unimodal thermal responses for transmission, with very similar optima but with lower thermal limits that were ~5ºC warmer, resulting in much narrower thermal breadths (Fig

S22) [5]. This model [5] was validated with annual, state-level WNV human case data (in contrast to our county-level data averaged over time), and detected a positive effect of temperature, with no decline at high temperatures [5]. These differences in modeling and validation approaches can lead to strongly divergent predictions for the impact of climate change.

Given the unimodal relationship between temperature and transmission of these temperate mosquito-borne pathogens, we expect climate warming to lead to predictable shifts in disease transmission [18,20,21]. Warming should extend the transmission season earlier into the spring and later into the fall and increase transmission potential in higher latitudes and altitudes, although this prediction may be impacted by changes in bird migrations. However, the thermal optima for these temperate vector–virus pairs are relatively cool, so in many locations, warming could result in summer temperatures that exceed the thermal optima for transmission more frequently, reducing overall transmission or creating a bimodal transmission season [68]. Still, warming is unlikely to eliminate any of these temperate pathogens since the upper thermal limits for transmission are well above temperatures pathogens regularly experience in their current geographic ranges. More generally, our results raise concerns about the common practice of extrapolating monotonic relationships between temperature and disease incidence fit from observational data into warmer climate regimes to predict future cases [52,54].

While the data-driven models presented here represent the most comprehensive synthesis to date of trait thermal response data and their impact on transmission for these temperate mosquitoes and pathogens, additional temperature-dependent trait data would increase the accuracy and decrease the uncertainty in these models where data were sparse or missing. We recommend prioritizing parasite development rate (*PDR*) and vector competence (*bc*) data (both

estimated from the same experiments) and biting rate (*a*) data, because those thermal responses varied widely among vector–virus pairs and determined the lower thermal limits and optima for transmission in many models. Additionally, vector competence and/or parasite development rate data were missing (WNV in *Cx. quinquefasciatus*, EEEV in *Cs. melanura*, RVFV in vectors from endemic areas, transmission efficiency [*b*] for SINV) or sparse (EEEV and WNV in *Cx. univittatus*) in many cases, as were biting rate data (*Cx. univittatus*, RVFV vectors). Lifespan data—key for determining transmission optima and upper thermal limits—were the missing for *Ae. triseriatus*, *Cs. melanura*, *Cx. univittatus*, and RVFV vectors, and at temperatures below 14 ºC for all vector species, so it was unclear which functional form these thermal responses should take (linear or quadratic). While the other mosquito demographic traits did not determine thermal limits for transmission in models here, fecundity (typically as *EFD*), larval-to-adult survival (*pLA*), and egg viability (*EV*) determined thermal limits for malaria [2] and Ross River virus [6]. Thus, we recommend collecting more fecundity data (missing for *Cx. tarsalis*, *Cx. univittatus*, and *Ae. triseriatus*; sparse for *Cx. pipiens* and *Cx. quinquefasciatus*) as well. New data are particularly important for RVFV, which has a tropical distribution but for which the model depends on traits measured in *Cx. pipiens* collected from temperate regions and infection traits measured in *Ae. taeniorhynchus*, a North American species. RVFV is spread by a diverse community of vectors across the African continent, but we suggest prioritizing hypothesized primary vectors (e.g., *Ae. circumluteolus* or *Ae. mcintoshi*) or secondary vectors that already have partial trait data (e.g., *Ae. vexans* or *Cx. theileri*) [25,69]. Although temperature itself does not predict the occurrence of RVFV outbreaks, it may affect the size of epidemics once they are triggered by precipitation. Additionally, the thermal response of vector competence may vary

across vector populations and/or virus isolates even within the same species, so more data may also improve the accuracy of models without missing data.

As carbon emissions continue to increase and severe climate change becomes increasingly inevitable [70], it is critical that we understand how temperature will shape transmission of mosquito-borne diseases in a warmer future world. While data gaps are still limiting, the comparative approach is powerful for predicting similarities and differences across vectors and viruses, including systematic differences between primarily tropical and temperate diseases. Future trajectories of these diseases will depend not just on climate suitability but on land use, which governs mosquito–wildlife–human interactions, vector control activities, human and wildlife immune dynamics, thermal adaptation of vectors and viruses, and potential future emergence and spread of new vectors and viruses.

MATERIALS AND METHODS

All analyses were conducted using R 3.1.3 [71].

Vector species range maps

The distributions of *Cx. pipiens* and *Cx. quinquefasciatus* are georectified maps adapted from [32,72]. The northern boundary of *Cx. tarsalis* was taken from [73]. For the southern boundary, we drew a convex polygon using five datasets [74–78] in the Global Biodiversity Information Facility (https://www.gbif.org/).

Temperature-dependent R_0 models

We found 39 studies with appropriate temperature-dependent trait data [5,49,79–115]. When necessary, we digitized the data using Web Plot Digitizer [116], a free online tool. When lifespan data were reported by sex, only female data were used. Vector competence trait data (*b*, *c*, or *bc*) were only included if time at sampling surpassed the estimated extrinsic incubation period (*EIP*, the inverse of *PDR*) at that temperature, which resulted in the exclusion of some studies [117,118].

We fit trait thermal responses using Bayesian inference with the 'r2jags' package [119,120]. In the likelihood functions, we truncated all thermal response functions at zero when $T < T_{min}$ and $T > T_{max}$ (for eq. 3 and 4) or when $T > -z/m$ (eq. 5) to prevent trait values from becoming negative (i.e., set trait value to 0). For traits with ambiguous functional responses, we fit the quadratic and Briere and used the deviance information criterion (DIC) [121] to pick the best fit. For traits that were proportions or probabilities, we truncated the predicated values at 1. For the linear thermal responses, we also calculated the predicted trait values in a piecewise manner in order to be conservative: for temperatures at or above the coldest observed data point, we used the trait values predicted by the fitted thermal response (i.e., the typical method); for temperatures below the coldest observed data point, we substituted the trait estimate at the coldest observed data point (i.e., forcing the thermal response to plateau, rather than continue increasing beyond the range of observed data). For data-informed priors, we used gamma distributions with parameters estimated from thermal responses fit using a 'leave-one-out' approach. In other words, we fit a thermal response using all the data for a given trait except for the focal vector or vector–virus pair (e.g., for the prior for biting rate for *Cx. pipiens*, we used the

biting rate data for all species except *Cx. pipiens*). The pool of data used to fit priors also included data from other temperate *Ae.* and *Cx.* species [81,83,92,96,101,102,122–127].

When data were missing for a vector–virus pair, we substituted the most conservative (i.e., least restrictive of transmission) trait thermal response from a vector species that occurs within the geographic range of disease transmission (Table 2). When there were was more than one option for how to parameterize a model (e.g., vector competence data for WEEV in *Cx. tarsalis* were available in two forms: separately as *b* and *c,* and combined as *bc*), we calculated R_0 both ways. The results were very similar, except for the model for RVFV with lifespan data from *Cx. pipiens* lifespan in place of *Ae. taeniorhynchus* (Fig S21). See Supplement for sensitivity and uncertainty methods and results (Fig S10-19).

Model validation: spatial analysis

We obtained county-level (n = 3,109) neuro-invasive WNV disease data from 2001-2016 for the contiguous US through the CDC's county-level disease monitoring program [128]. Data were available as total human cases per year, which we adjusted to average cases per 1,000 people (using 2010 US county-level census data) to account for population differences. We averaged cases across years beginning with the first year that had reported cases in a given county to account for the initial spread of WNV and the strong impact of immunity on interannual variation [5]. Ninety-eight percent of human cases of WNV in the US occur between June and October (data described below), and cases of mosquito-borne disease often lag behind temperature by 1–2 months [6,59]. Thus, we extracted monthly mean temperature data between the months of May–September for all years between 2001-2016 and averaged the data to estimate typical summer conditions for each county. Specifically, we took the centroid

geographic coordinate for every county in the contiguous US with the 'rgeos' package [129] and extracted corresponding historic climate data (Climate Research Unit 3.1 rasters) [130] from $0.5°^2$ cells (approx. 2,500-3,000 km^2) using the 'raster' package [131]. We used the 'loess' function in base R 'stats' package [71] to fit a locally estimated scatterplot smoothing (LOESS) regression for average incidence as a function of average summer temperature to county-level data with span (smoothing parameter) = 0.6. See Fig S23 for the model fit across varying span values.

Model validation: seasonality analysis

We calculated monthly temperature-dependent relative R_0 to compare with month-of-onset data for neuro-invasive WNV, EEEV, and SLEV disease aggregated nationwide from 2001-2016 [128,132,133], using the same monthly, county-level temperature data as above. For WNV, we used the subset of counties with reported cases (68% of counties). For SLEV and EEEV we used all counties from states with reported cases (16 and 20 states, respectively). We weighted each county $R_0(T)$ by its population size to calculate a national estimate of $R_0(T)$. For WNV, the county-level estimates of $R_0(T)$ used models for three *Culex* species (*Cx. pipiens*, *Cx. quinquefasciatus*, and *Cx. tarsalis*) weighted according to the proportion of WNV+ mosquitoes reported at the state level, reported in [5]. SLEV and EEEV both only had one R_0 model. The estimated monthly temperature-dependent relative R_0 values and month-of-onset data were compared visually.

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Table 1: Properties of six viruses transmitted by an overlapping community of vectors.

Virus (*genus*)	Primary vector spp.	Geographic range	Presentation & mortality	Epidemiology & Ecology
West Nile virus (WNV, *Flavivirus*)	*Cx. pipiens*, *Cx. quinquefasciatus*, *Cx. tarsalis*	Eurasia, Africa, Australia, & North America.	Febrile illness and encephalitis. 10% mortality in neuro-invasive cases. Long-term physical & cognitive disabilities. [1,9]	The most common mosquito-borne disease in temperate North America since invading in 1999. 22,999 neuro-invasive cases and 2,163 deaths in US [3] and 5,614 reported cases in Canada [4] as of 2017, & estimated 3 million total cases in US in 2010 [1]. Typically 100-300 cases annually Europe, but over 1500 so far in 2018 [8]. Poor surveillance in Africa, but seroprevalence ~80% in some areas [2]. Birds are main reservoir and amplification hosts.
St. Louis Encephalitis virus (SLEV, *Flavivirus*)	*Cx. quinquefasciatus*, *Cx. tarsalis*	North America, primarily in US.	Encephalitis. 5-15% mortality in diagnosed cases. [3,9]	97 cases and 5 deaths recorded in US from 2008-2017. [3] Birds are main reservoir and amplification hosts. [3]
Eastern Equine Encephalitis virus (EEEV, *Alphavirus*)	*Ae. triseriatus*	North America, primarily in US.	Febrile illness and encephalitis. 33% mortality in diagnosed cases. Long-term cognitive disabilities. [3,9]	71 cases and 30 deaths recorded in US from 2008-2017. [3] Birds are main reservoir and amplification hosts. [3]
Western Equine Encephalitis virus (WEEV, *Alphavirus*)	*Cx. tarsalis*	North America, primarily in US.	Febrile illness and encephalitis. Low mortality, except in infants. [9]	The CDC does not report WEEV infection. Birds are main reservoir and amplification hosts. [3] WEEV is derived from a recombinant event between the ancestors of EEEV and SINV. [9]
Sindbis virus (SINV, *Alphavirus*), also Pogosta (Poland), Ockelbo (Sweden), & Karelian Fever (Russia)	*Cx. torrentium*, *Cx. pipiens, Cx. univittatus, Ae. taeniorhynchus*	Eurasia, Africa, & Australia; most infections occur in northern Europe & South Africa.	Febrile illness, rash, and joint pain. No mortality, but long-term disability. [5]	Poor surveillance except in Finland, where annual incidence is 2–26 per 100,000 people and seroprevalence can reach ~40% in places. [5] Birds are main reservoir and amplification hosts. Long-distance migratory birds may spread the virus between temperate zones in Northern and Southern hemispheres. [7,5]
Rift Valley Fever virus (RVFV, *Phlebovirus*)	*Ae. taeniorhynchus, Ae. mcintoshi, Cx. pipiens*	Africa & the Middle East; most infections are in Eastern Africa.	Febrile illness and encephalitis. 50% mortality in hemorrhagic cases, <1% mortality in total cases. Permanent blindness in 50% of ocular cases (<2% of cases). [10]	Livestock are main reservoir and amplification hosts, and suffer mortality and abortion. Vertical transmission via dormant eggs can also initiate epidemics. In eastern and southern Africa, low-level endemic transmission is driven by *Ae. spp.*, with large epidemics every 5-15 years driven by rainfall and blooms of *Cx. spp*. from low-lying flooded areas known as *dambos*. [6]

Table 2: Thermal optima and limits for transmission of mosquito-borne pathogens. Median temperature of the lower thermal limit (*Tmin*), optimum, and upper thermal limit (*Tmax*), with 95% credible intervals in parentheses.

R_0 Model	*Tmin* (ºC)	Optimum (ºC)	*Tmax* (ºC)
From this study:			
EEEV in *Ae. triseriatus*	11.7 (8.8 – 16.3)	22.7 (22.0 – 23.6)	31.9 (31.1 – 33.0)
WEEV in *Cx. tarsalis*	8.6 (6.3 – 13.0)	23.0 (22.0 – 24.7)	31.9 (30.3 – 35.2)
SINV in *Cx. pipiens*	9.4 (6.9 – 13.3)	23.2 (21.7 – 24.6)	33.8 (28.2 – 37.0)
WNV in *Cx. univittatus*	11.0 (8.0 – 15.3)	23.8 (22.7 – 25.0)	33.6 (31.2 – 36.9)
WNV in *Cx. tarsalis*	12.1 (9.6 – 15.2)	23.9 (22.9 – 25.9)	32.0 (30.6 – 38.6)
SLEV in *Cx. tarsalis*	12.9 (11.0 – 14.8)	24.1 (23.1 – 26.0)	32.0 (30.6 – 38.5)
WNV in *Cx. pipiens*	16.8 (14.9 – 17.8)	24.5 (23.6 – 25.5)	34.9 (32.9 – 37.6)
WNV in *Cx. quinquefasciatus*	19.0 (14.1 – 20.9)	25.2 (23.9 – 27.1)	31.8 (31.1 – 32.2)
RVFV in *Ae. taeniorhynchus*	10.6 (8.6 – 14.4)	25.9 (23.8 – 27.1)	37.8 (34.4 – 39.1)
SINV in *Ae. taeniorhynchus*	9.7 (8.3 – 13.6)	26.0 (23.9 – 27.3)	37.8 (34.4 – 39.2)
From previous studies:			
Falciparum malaria [3]	19.1 (16.0 – 23.2)	25.4 (23.9 – 27.0)	32.6 (29.4 – 34.3)
DENV in *Ae. albopictus* [4]	16.2 (13.0 – 19.8)	26.4 (25.4 – 27.6)	31.4 (29.5 – 34.0)
Ross River virus [6]	17.0 (15.8 – 18.0)	26.4 (26.0 – 26.6)	31.4 (30.4 – 33.0)
ZIKV in *Ae. aegypti* [7]	22.8 (20.5 – 23.8)	28.9 (28.2 – 29.6)	34.5 (34.1 – 36.2)
DENV in *Ae. aegypti* [4]	17.8 (14.6 – 21.2)	29.1 (28.4 – 29.8)	34.5 (34.1 – 35.8)

Table 3: Predicted optima for transmission of West Nile virus. Predict optima and thermal limits for transmission from this study and previous models.

R_0 Model	Tmin (ºC)	Optimum (ºC)	Tmax (ºC)
From this study:			
EEEV in *Ae. triseriatus*	11.8 (8.9 – 16.4)	22.7 (22.0 – 23.6)	31.9 (31.1 – 33.0)
WEEV in *Cx. tarsalis*	8.7 (6.4 – 13.1)	23.0 (22.0 – 24.7)	31.9 (30.3 – 35.2)
SINV in *Cx. pipiens*	9.4 (6.9 – 13.3)	23.2 (21.7 – 24.6)	33.8 (28.2 – 37.0)

Figure 1: Viruses transmitted by a community of vectors. The six viruses in this study (WNV = West Nile virus, SLEV = St. Louis Encephalitis virus, EEEV = Eastern Equine Encephalitis virus, WEEV = Western Equine Encephalitis virus, SINV = Sindbis virus, RVFV = Rift Valley Fever virus) and the *Culex* (*Cx.*), *Aedes* (*Ae.*), *Coquillettidia* (*Cq.*), and *Culiseta* (*Cs.*) vectors that are important for sustaining transmission to humans. Grey shading indicates an important vector-virus pair; hatching indicates available temperature-dependent data for infection traits (parasite development rate [*PDR*] and vector competence [*bc* or *b* and *c*]). The importance of each vector for transmission may vary over the geographic range of the virus. Infection data were available for SINV and RVFV in *Ae. taeniorhynchus*, although this North American mosquito does not occur in the endemic range of these pathogens. Data sources: [23–25].

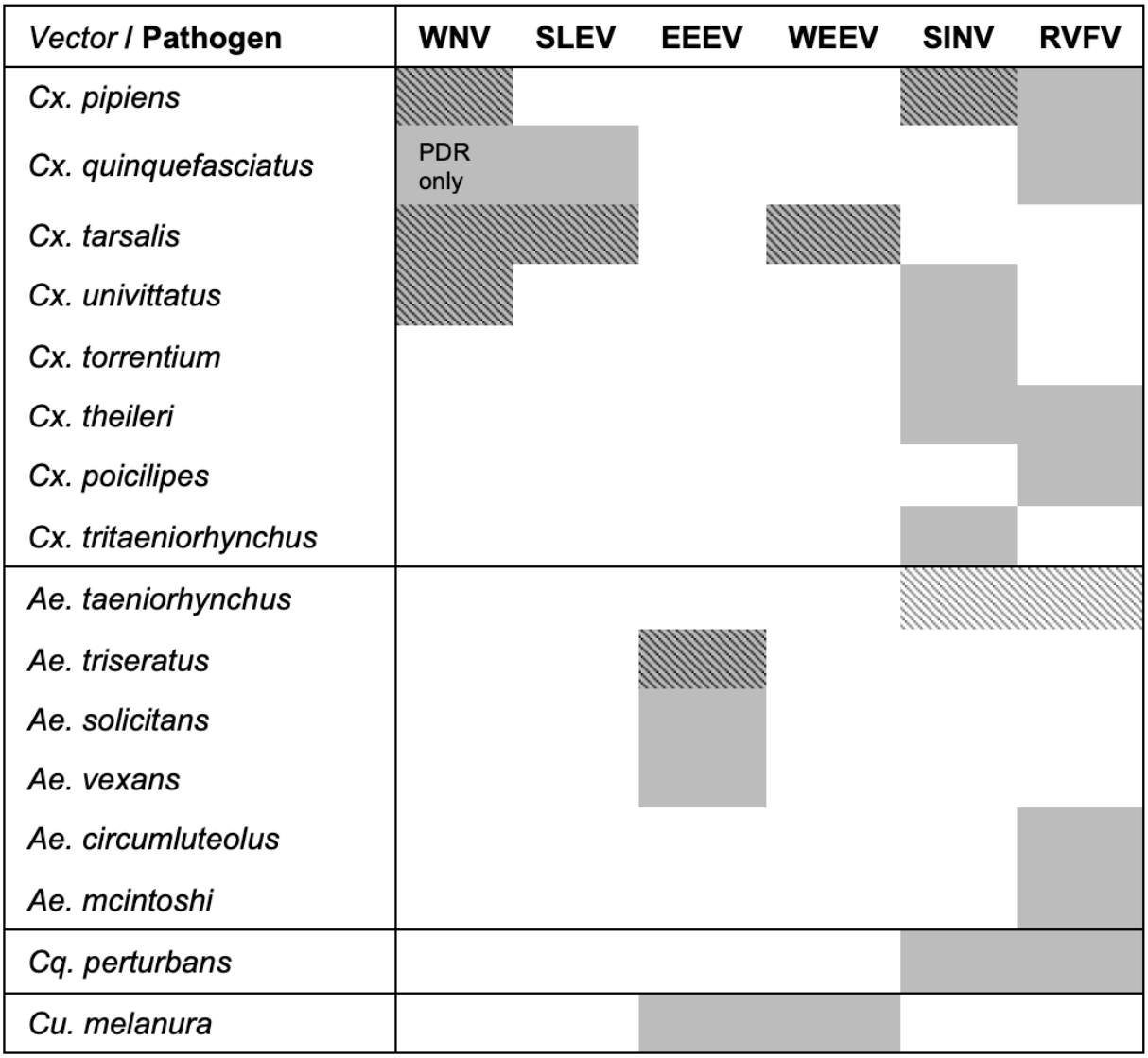


Figure 2: *Culex* spp. vectors of West Nile and other viruses have distinct but overlapping geographic distributions. The geographic distribution of the primary vectors of West Nile virus: (A) *Culex pipiens* (dark grey) and *Cx. quinquefasciatus* (red), adapted from [32,72]; (B) *Cx. tarsalis* (blue), northern boundary from [73], southern boundary based on data from the Global Biodiversity Information Facility.

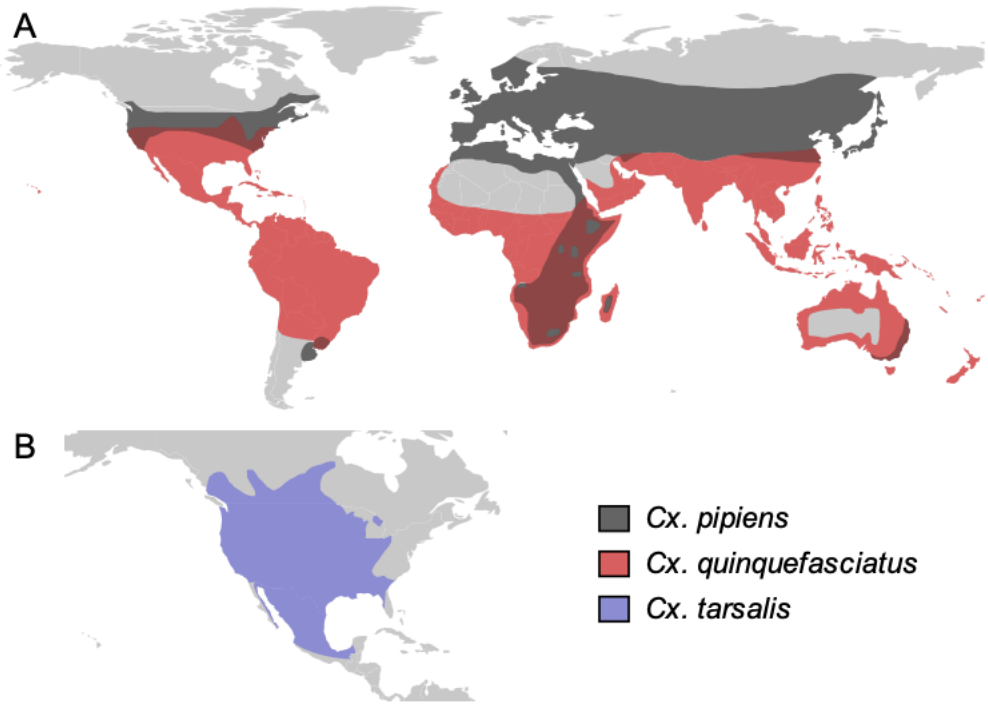
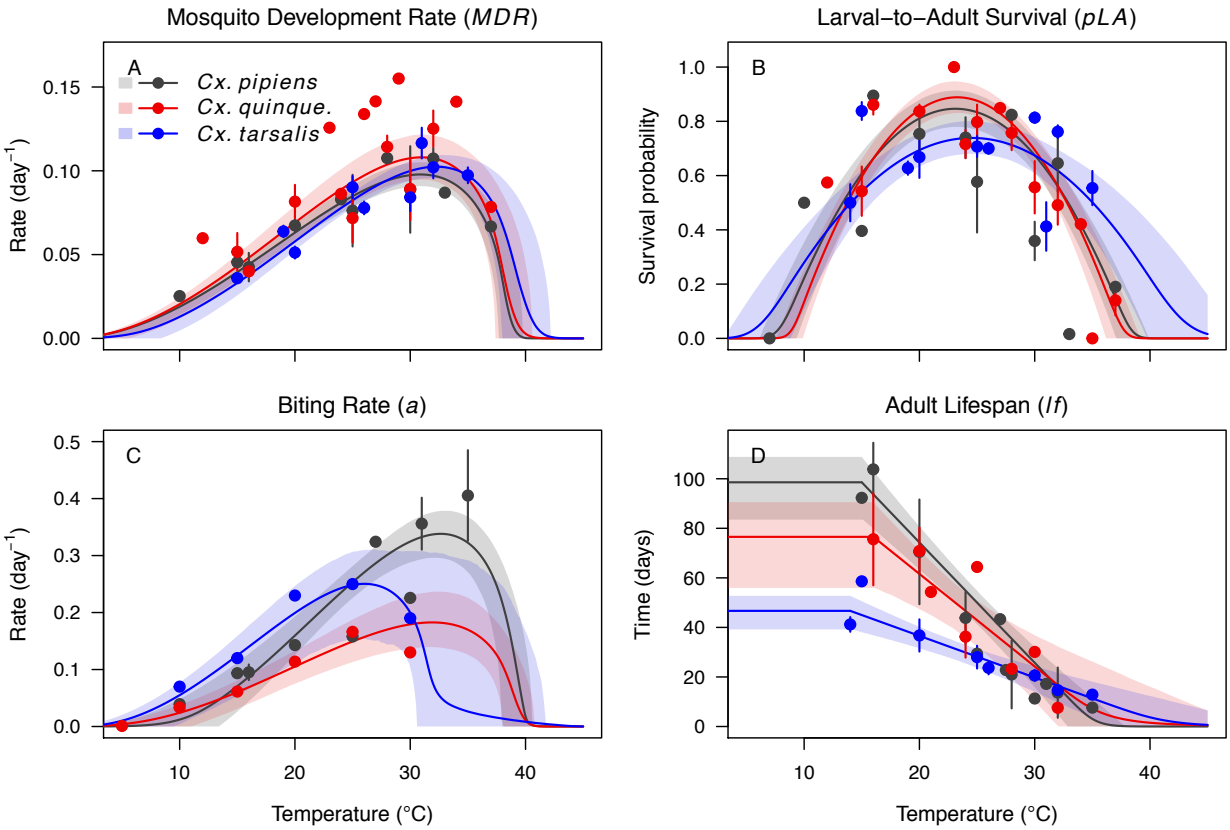


Figure 3: *Culex* spp. mosquito traits respond strongly and consistently to temperature. The thermal responses of mosquito traits for the North American vectors of West Nile virus: *Culex pipiens* (dark grey), *Cx. quinquefasciatus* (red), and *Cx. tarsalis* (blue). (A) Mosquito development rate (*MDR*), (B) larval-to-adult survival (*pLA*), (C) biting rate (*a*), and (D) adult lifespan (*lf*). Points without error bars are reported means from single studies; points with error bars are averages of means from multiple studies (+/- standard error, for visual clarity only; thermal responses were fit to reported means, see Figs S2–5). Solid lines are posterior means; shaded areas are 95% credible intervals. See Fig S1 for thermal responses for *Aedes taeniorhynchus*, *Aedes triseriatus*, *Ae. vexans*, *Culiseta melanura*.



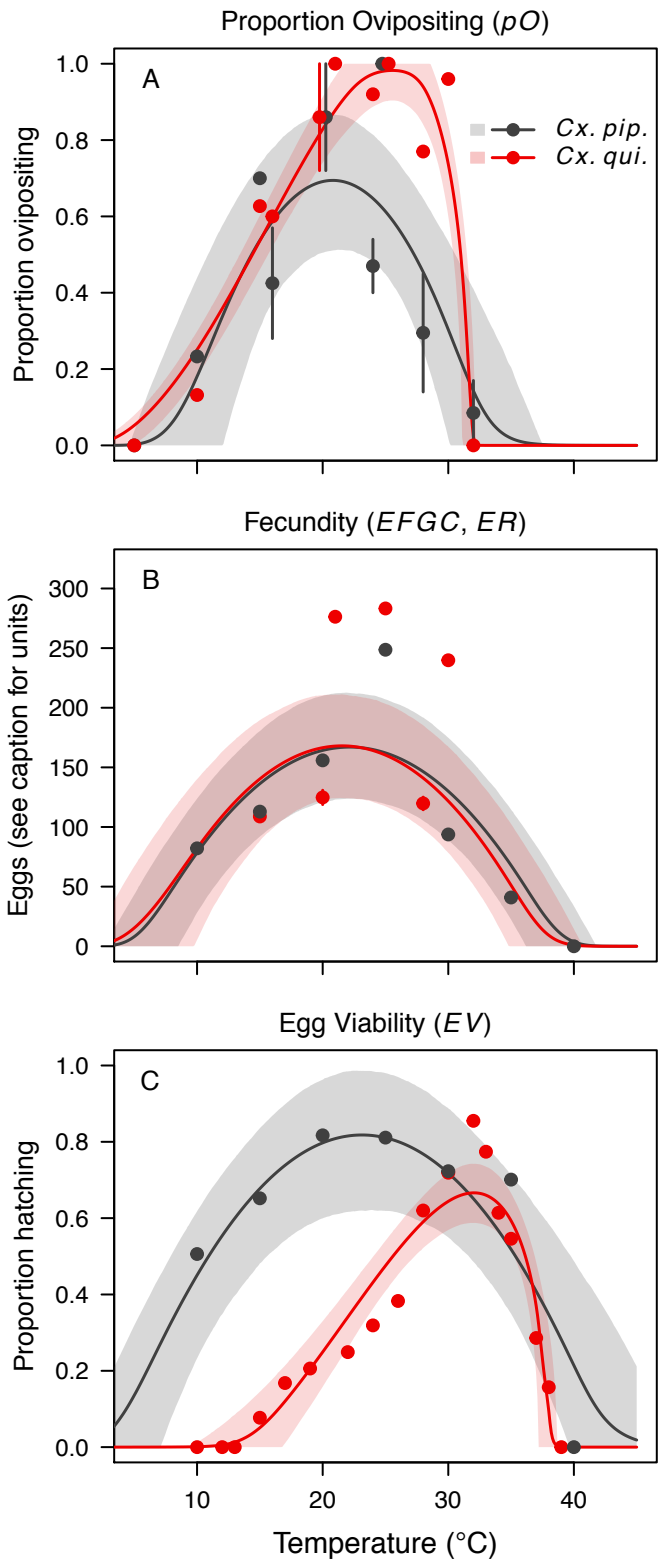


Figure 4: *Culex pipiens* and *Cx. quinquefasciatus* fecundity traits respond strongly to temperature but with different functional forms. The thermal responses of mosquito traits for the primary vectors of West Nile virus: *Culex pipiens* (dark grey) and *Cx. quinquefasciatus* (red). (A) Proportion ovipositing (*pO*), (B) fecundity (eggs per female per gonotrophic cycle, *EFGC,* or eggs per raft, *ER*), and (C) egg viability (*EV*). Points without error bars are reported means from single studies; points with error bars are averages of means from multiple studies (+/- standard error, for visual clarity only; thermal responses were fit to reported means, see Fig S6). Solid lines are posterior distribution means; shaded areas are 95% credible intervals. See Fig S1 for thermal responses for *Ae. vexans*, *Cx. theileri*, and *Culiseta melanura*.

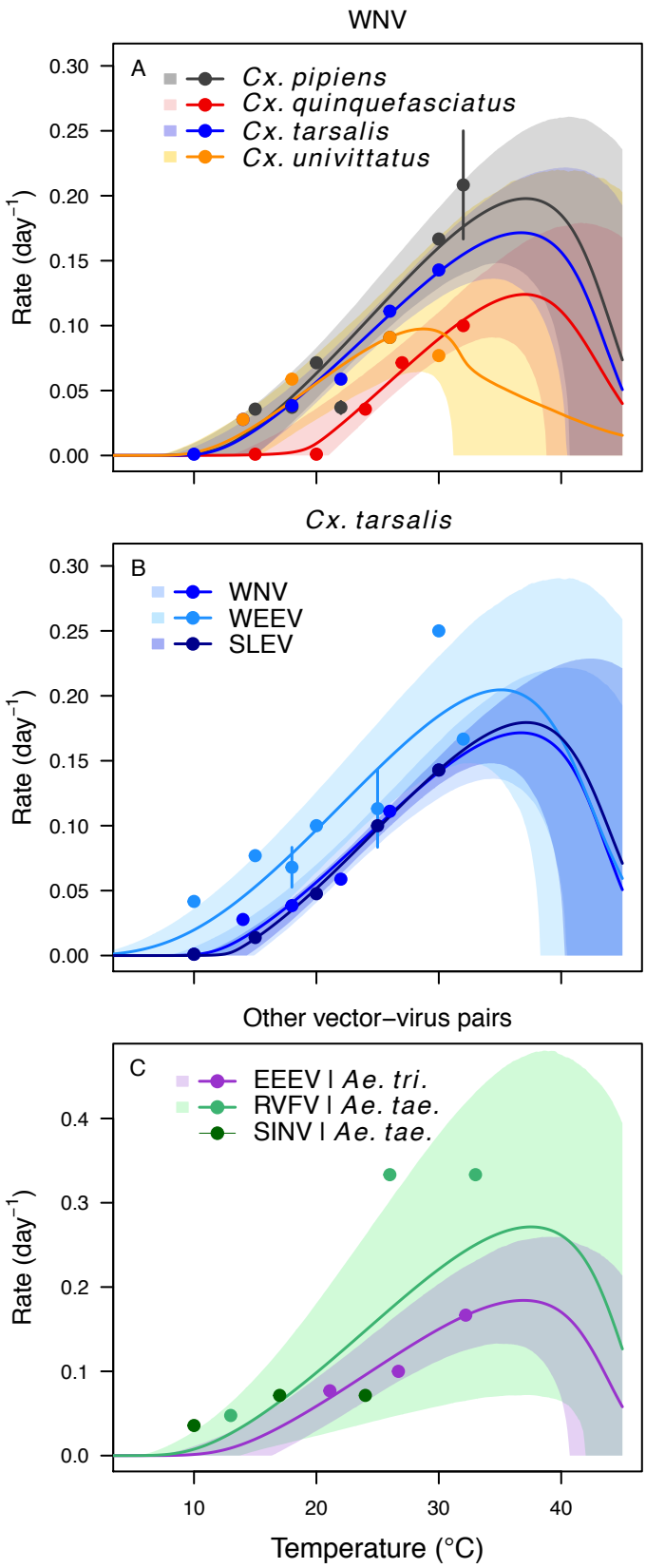


Figure 5: Pathogen development rates have high thermal optima. Thermal responses of pathogen development rate (*PDR*). (A) West Nile virus in *Culex pipiens* (dark grey), *Cx. quinquefasciatus* (red), *Cx. tarsalis* (blue), and *Cx. univitattus* (orange). (B) Three viruses in *Cx. tarsalis*: West Nile virus (same as in A, blue), Western Equine Encephalitis virus (light blue), and St. Louis Encephalitis virus (dark blue). (C) Eastern Equine Encephalitis virus in *Aedes triseriatus* (violet), Rift Valley Fever virus in *Ae. taeniorhynchus* (light green), Sindbis virus in *Ae. taeniorhynchus* (dark green). We did not fit a thermal response for Sindbis virus in *Ae. taeniorhynchus* because the limited data responded weakly to temperature and did not match our priors. We used informative priors based on thermal biology theory and data from other systems to fit the decrease at high temperatures (see *Model Overview*); other traits determined the upper limits of the R_0 models. Points without error bars are reported means from single studies; points with error bars are averages of means from multiple studies (+/- standard error, for visual clarity only; thermal responses were fit to reported means, see Fig S7). Solid lines are posterior distribution means; shaded areas are 95% credible intervals.

Figure 6: Vector competence responds strongly to temperature and varies across vector and virus species. Thermal responses of infection efficiency (*c*, # infected / # exposed; first column), transmission efficiency (*b*, # transmitting / # infected; second column) or vector competence (*bc*, # infected / # exposed; third column) for vector–virus pairs. First row (A,B,C): West Nile virus in *Culex pipiens* (dark grey), *Cx. tarsalis* (blue), and *Cx. univitattus* (yellow/orange). Second row: (D,E,F) Western Equine Encephalitis virus in *Cx. tarsalis* (light blue). Third row (G,H,I): Sindbis virus in *Aedes taeniorhynchus* (dark green), Sindbis virus in *Cx. pipiens* (light gray), St. Louis Encephalitis virus in *Cx. tarsalis* (dark blue), Eastern Equine Encephalitis virus in *Ae. triseriatus* (violet), and Rift Valley Fever virus in *Ae. taeniorhynchus* (light green). Points are means of replicates from single or multiple studies (+/- standard error, for visual clarity only; thermal responses were fit to replicate-level data, see Fig S8, Fig S9). Solid lines are posterior distribution means; shaded areas are 95% credible intervals.

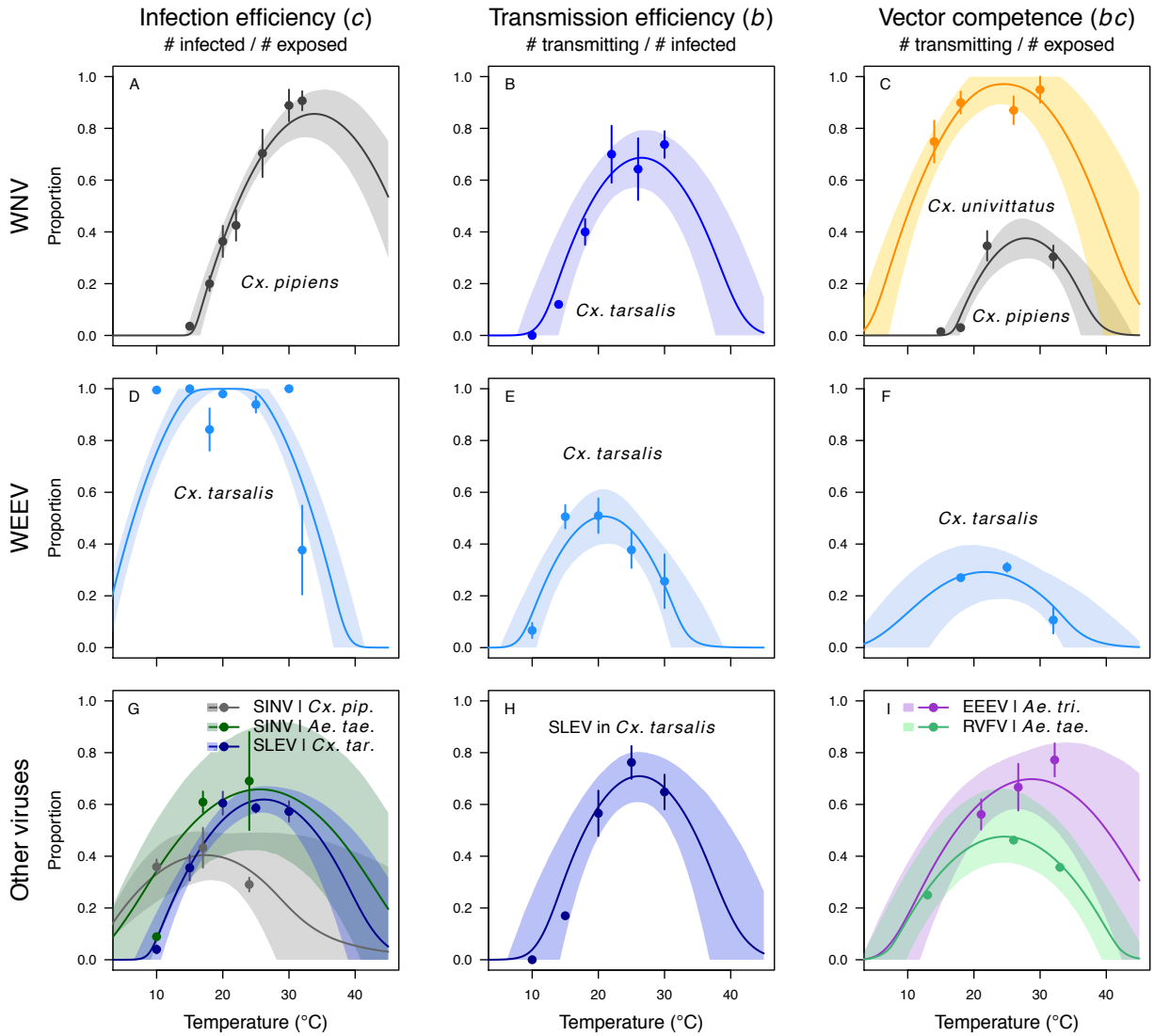


Figure 7: Unimodal thermal responses of transmission (relative R_0) for ten vector-virus pairs. Posterior mean relative R_0 for (A) West Nile virus (WNV) in *Culex pipiens* (dark grey), *Cx. tarsalis* (blue), *Cx. quinquefasciatus* (red), and *Cx. univitattus* (orange); (B) three viruses in *Cx. tarsalis*: WNV (same as in A, blue), Western Equine Encephalitis virus (WEEV, light blue), and St. Louis Encephalitis virus (SLEV, dark blue); (C) Sindbis virus (SINV) in *Aedes taeniorhynchus* (dark green) and *Cx. pipiens* (light grey), Rift Valley Fever virus (RVFV) in *Ae. taeniorhynchus* (light green), and Eastern Equine Encephalitis virus (EEEV) in *Ae. triseriatus* (violet). (D) Posterior median and uncertainty estimates for the lower thermal limit, optimum, and upper thermal limit. Points show medians, thick lines show middle 50% density, thin lines show 95% credible intervals.

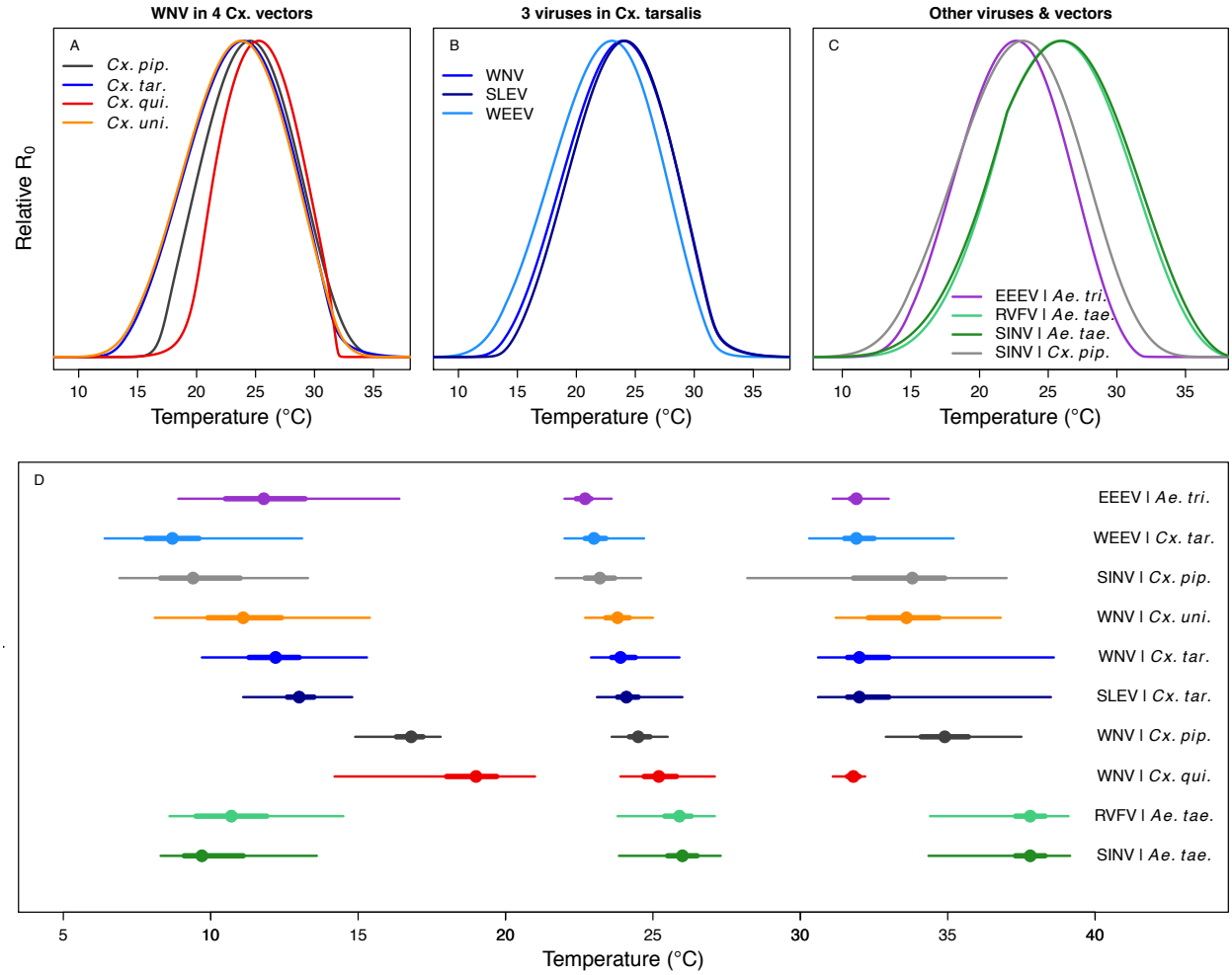


Figure 8: Incidence of human neuro-invasive West Nile disease across US counties responds unimodally to temperature, peaking at 23.9°C. Points are mean incidence (+/- SE) and mean temperature from May-September averaged from 2001-2016 for bins of 42 counties. Red contour is a locally estimated scatterplot smoothing (LOESS) regression (span = 0.6) fit to the raw county-level data (n = 3,109, binned for visual clarity). See Fig S23 for fits across a range of smoothing parameters.

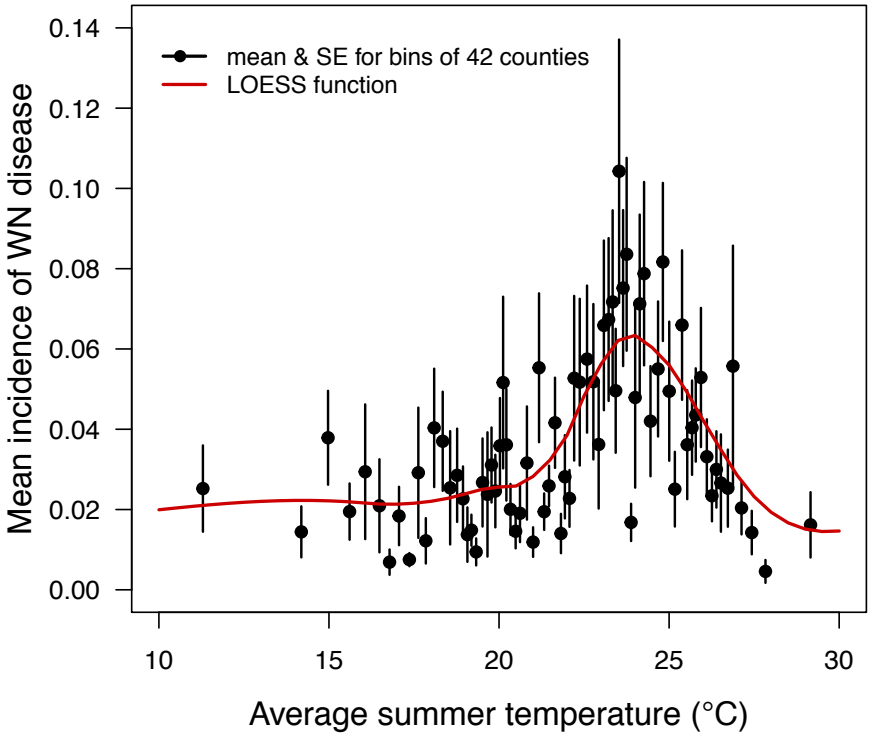
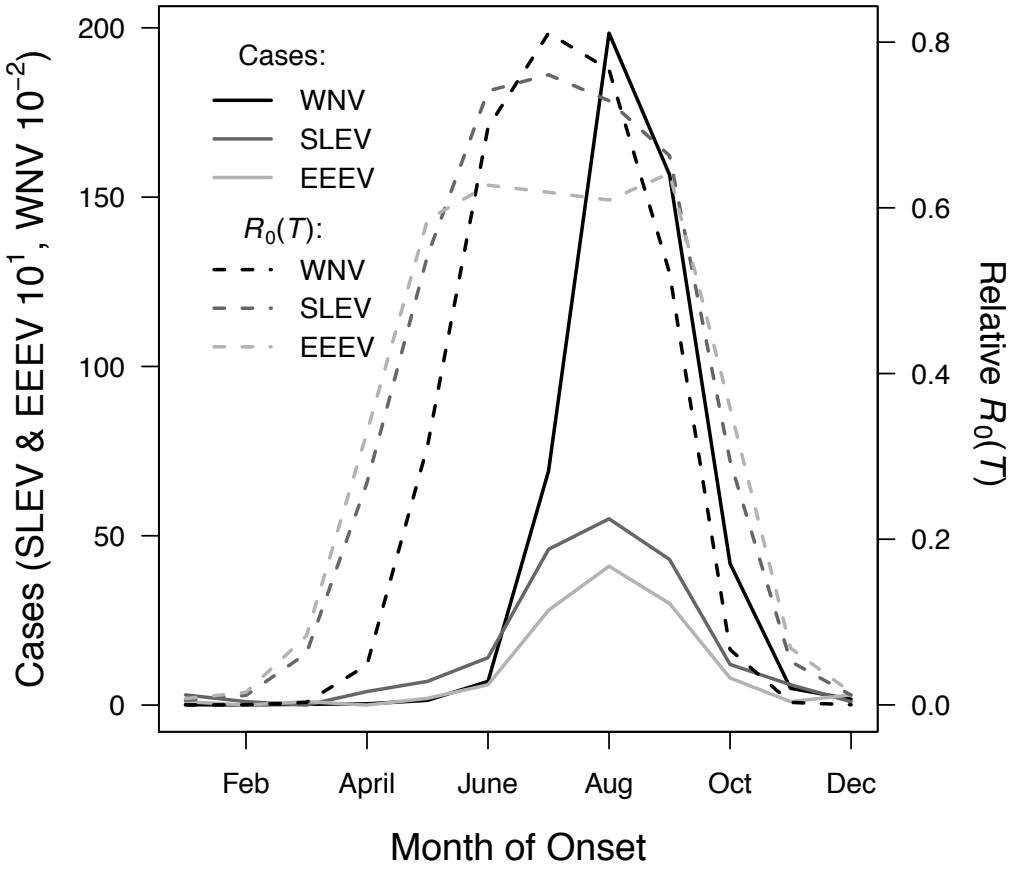



Figure 9: Temperature shapes the seasonal pattern of human cases of mosquito-borne viral diseases. Incidence (solid lines) lags behind predicted temperature-dependent R_0 (dashed lines) for human cases of neuro-invasive disease caused by West Nile virus (WNV, black), St. Louis encephalitis virus (SLEV, dark gray), and Eastern Equine Encephalitis virus (EEEV, light gray) by 2 months. This lag matches patterns in other mosquito-borne diseases, and is caused by the time required for mosquito populations to increase, become infectious, and bite humans, and for humans to present symptoms and seek medical care.