A comparative modeling study on non-climatic and climatic risk assessment on Asian Tiger Mosquito (Aedes albopictus)

Farzin Shabani¹, Mahyat Shafapour Tehrany², Samaneh Solhjouy-fard¹ and Lalit Kumar³

¹ School of Environmental and Rural Science, University of New England, Armidale, NSW, Australia
² Geospatial Science, College of Science, Royal Melbourne Institute of Technology, Melbourne, Australia
³ School of Environmental and Rural Science, University of New England, Australia

ABSTRACT

Aedes albopictus, the Asian Tiger Mosquito, vector of Chikungunya, Dengue Fever and Zika viruses, has proven its hardy adaptability in expansion from its natural Asian, forest edge, tree hole habitat on the back of international trade transportation, re-establishing in temperate urban surrounds, in a range of water receptacles and semi-enclosures of organic matter. Conventional aerial spray mosquito vector controls focus on wetland and stagnant water expanses, proven to miss the protected hollows and crevices favoured by Ae. albopictus. New control or eradication strategies are thus essential, particular in light of potential expansions in the southeastern and eastern USA. Successful regional vector control strategies require risk level analysis. Should strategies prioritize regions with non-climatic or climatic suitability parameters for Ae. albopictus? Our study used current Ae. albopictus distribution data to develop two independent models: (i) regions with suitable non-climatic factors, and (ii) regions with suitable climate for Ae. albopictus in southeastern USA. Non-climatic model processing used Evidential Belief Function (EBF), together with six geographical conditioning factors (raster data layers), to establish the probability index. Validation of the analysis results was estimated with area under the curve (AUC) using Ae. albopictus presence data. Climatic modeling was based on two General Circulation Models (GCMs), Miroc3.2 and CSIRO-MK30 running the RCP 8.5 scenario in MaxEnt software. EBF non-climatic model results achieved a 0.70 prediction rate and 0.73 success rate, confirming suitability of the study site regions for Ae. albopictus establishment. The climatic model results showed the best-fit model comprised Coldest Quarter Mean Temp, Precipitation of Wettest Quarter and Driest Quarter Precipitation factors with mean AUC value of 0.86. Both GCMs showed that the whole study site is highly suitable and will remain suitable climatically, according to the prediction for 2055, for Ae. albopictus expansion.

INTRODUCTION

Invasive alien species pose a threat to biodiversity, ecosystems, agriculture, human and animal health, and consequently inflict economic damage (Pyšek & Richardson, 2010).
Invasive weeds smother and crowd out indigenous flora, thereby threatening local fauna; some release allergenic pollens harmful to many humans, while invasive waterweeds clog and choke natural waterways. The introduction of an alien flora species may concurrently introduce alien parasites, fungi, invertebrate larvae or diapausing eggs, hosted by that species in its environmental niche. Such hosted species may be potential vectors of novel pathogens into their new environment. Similarly, some invasive alien insect species may be vectors of diseases of epidemic potential (Antia et al., 2003) that can be medically, socially and economically devastating (Pimentel, 2011). Despite the advanced control mechanisms of modern public health, and stringent standards imposed at borders to control what travelers and traders carry in and out through border posts, invasive alien species still penetrate and establish an environmental presence. Whether or not the potential health and economic impacts of such invasions have been quantified, logic demands the elimination of such potentially dangerous invasive alien species as a precaution, as quickly as possible (Wittenberg & Cock, 2001). In practice, aside from invasions of pests that have an economic impact and act as vectors of disease, response is often delayed (Hulme, 2006).

*Aedes albopictus*, or the Asian tiger mosquito, a belligerent insect that bites during the day, has emerged as a threat to public health worldwide and has been identified as the vector of the Chikungunya and Dengue viruses, among others. Most recently it has been verified in Brazil that *Ae. albopictus* is a potential vector of Zika virus, of which its closest relative, *Ae. Aegypti*, has been the major vector thus far (Schaffner, Medlock & Bortel, 2013). *Ae. albopictus* is one of the world’s one hundred worst invasive species according to the Global Invasive Species Database (GISD, 2017). This devastating impact has been facilitated by a rapid spread from its native East Asian to western Pacific and Indian Ocean natural domains (Caminade et al., 2012).

While the species has had multiple introductions to Australia and New Zealand, it has not established itself there, mainly attributable to the efficiency of entomological surveillance in the airports and harbors of these countries (Ritchie et al., 2006).

*Ae. albopictus* was established in the USA in 1980, ostensibly arriving in a shipload of used tires from Japan. (Rai, 1991). Once *Ae. albopictus* establishes in a particular locality, eradication becomes virtually impossible, and costly vigilance and control becomes essential (Holder et al., 2010).

The observed suitable climate for *Ae. albopictus* growth now ranges from temperate through sub-tropical to tropical, with vegetation from savanna to evergreen and Amazon forest. It can adapt to both arid and humid conditions (Kraemer et al., 2015a; Messina et al., 2016; Vega-Rúa et al., 2014). Winter temperatures appear to be a limiting factor of further spreading of the species (Hanson & Craig, 1994; Rochlin et al., 2013a; Thomas et al., 2012), while winter precipitation may moderate the suitability of the species to colder temperatures (Hanson & Craig, 1995). The natural *Ae. albopictus* habitat was originally forest edges where they bred in tree holes, stumps of bamboo and bromeliads. Thus, the species was formerly classified as a specifically rural vector (Higa, 2011). However, *Ae. albopictus* has demonstrated an exceptional ability to adapt to new environmental conditions and establish itself. In urban and suburban environments, it may be found breeding in manmade containers such as external water tanks, animal water troughs,
bird baths, plant containers, moist organic matter and abandoned tires, in both towns and suburbs (Caputo et al., 2012). The species is now considered the major vector, and in certain areas the sole vector, of such environments (Caputo et al., 2012). Invasive alien mosquitoes often displace the indigenous mosquito territorially. However, the only known case of an invasive alien replacing another invasive alien mosquito species is the displacement of Ae. Aegypti by Ae. albopictus (Kenis et al., 2009), which has been researched and corroborated in Florida, USA. Ae. Aegypti is the major international vector of Zika, and Ae. albopictus has been recently acknowledged as a potential vector, which will certainly have an impact on an outbreak of Zika in any region of such displacement (Ding et al., 2018; Kenis et al., 2009; Nihei et al., 2014; Simard et al., 2005; Weaver & Lecuit, 2015). It should be mentioned that Ding et al. (2018) have recently mapped the spatial distribution of Aedes aegypti and Aedes albopictus for the current time through temperature suitability, NDVI, precipitation, urban accessibility, night time light, urban regions, relative humidity, and population density.

USA public health departments in both rural and urban communities, which previously had no need for developing strategies to control mosquitoes, now face the challenge of Ae. albopictus (Rochlin et al., 2013a), which poses a threat to the region without the development of novel methods of control. Existing mosquito controls generally have involved aerial spraying of easily accessible marshland and floodwater breeding grounds. However, the Ae. albopictus partiality for smaller scale, protected breeding in close range of humans in water storage and other moist semi-enclosed artifacts, evade existing control methods. The alternative means the necessity for communities falling within the paths of expansion to deal with the impact. The involvement of a complete community is vital. The crucial issue is whether new strategies can be developed at a relatively low cost. Projecting regions of expansion and general forward planning and sufficient funding through greater public awareness will be the key to effective campaigns. In terms of Ae. albopictus adaptation from rural to urban surrounds, and the need for policy makers and public health organizations to prioritize resources, crucial decisions will need to be made on whether to focus generally on regions with suitable climate, or rather on specific non-climatic parameters such as roads, lakes, rivers, altitude and slope within climatically suitable regions?

The answer to this question is synonymous with the aim of this study which sets out to determine whether Ae. albopictus distribution is more associated with non-climatic parameters or climate suitability?

The current distribution of Ae. albopictus in the southeastern region of the USA was used to develop two separate models for this species of mosquito, based on (i) regions with suitable non-climatic factors, and (ii) regions with suitable climate. The non-climatic model comprised a data-driven Evidential Belief Function with six conditioning factors: (i) altitude, (ii) slope, (iii) aspect, (iv) distance of locality from road, (v) distance of locality from river and (vi) geology, through ArcGIS. The climatic model was based on two GCMs of Miroc3.2 and CSIRO-MK30 for the current time under RCP 8.5 scenario and employed MaxEnt software. We hold the view that the methodology and results of this study will promote active surveillance of Ae. albopictus, as well as other invasive insect species. The results of this study will emphasize the need for increasing awareness to promote vigilance...
and effective control and eradication mechanisms, complementing the current online information networks of the relevant government and non-government bodies.

**METHODOLOGY**

**Study area selection**

The study site is located between 75°30′00″W and 92°00′00″W, and 25°00′00″N and 36°30′00″N in USA (Fig. 1). In selecting the study site, we looked for an area exhibiting variations of each conditioning factor, as well as *Ae. albopictus* presence. For example, in terms of altitude, the study area should display a range of altitudes. Our selected study area had an altitude range from 0 m to 2,031 m above sea level. For geology, the study area had 80 different geological fractures.

**Spatial datasets**

**Inventory factors**

In the study, 70% of the *Ae. albopictus* presence layer, an inventory factor obtained from Global Biodiversity Information Facility database (*Global Biodiversity Information Facility, 2017*) and *Kraemer et al. (2015b)*, were used for model training while the remainder 30% was reserved for model validation (Fig. 1). The training and testing points cover all the study area and the testing points were selected randomly.
**Conditioning factors**

The six geographical conditioning factors (i) altitude, (ii) slope, (iii) aspect, (iv) distance of locality from road, (v) distance of locality from river and (vi) geology, with a grid cell size 90 × 90 m were used to run the EBF model. The quantile classification scheme was used for all conditioning factors, as recommended by Tehrany, Pradhan & Jebur (2013). Altitude, slope and aspect layers were generated from DEM data obtained from EarthExplorer (2014) as shown in Figs. 2A–2C respectively. Distances from road and river layers were generated by Euclidean Distance tool and divided into ten classes using the quantile method, as shown in Figs. 2D and 2E respectively. The geology layer, obtained from the United States Department of Agriculture (USDA) (United States Department of Agriculture, 2017) contained 80 different types of lithology as shown in Fig. 3. The elevation layer was included as it depicts climate variations and the physical barriers limiting dispersion. The road, river and geological layers were included as the greatest densities of *Ae. albopictus* occur in urban environments (Rochlin et al., 2013a).

**Non-climatic modeling**

Evidential Belief Function (EBF), which is also called Dempster-Shafer theory of evidence, was developed by Dempster (Dempster, 1967), based on the Bayesian theory of subjective probability. Its advantages are the relative flexibility with which it accepts uncertainty and its ability to aggregate beliefs from many sources of evidence (Thiam, 2005). Rather than estimating the validity of probabilities, the Dempster-Shafer technique calculates the nearness of the evidence in proving the validity of a hypothesis (Pearl, 1990). Applications of EBF have been effective in many fields of research that utilize GIS data (Malpica, Alonso & Sanz, 2007).

To produce a hazard index of presence of *Ae. albopictus*, the conditioning factors were expressed individually as acquired weights and then aggregated (Eq. (1)).

Assuming a set of *Ae. albopictus* presence conditioning factors *C* = (*C*<i><sub>i</sub>, i = 1, 2, 3, …, n), consisting of mutually exclusive and exhaustive factors *C*<i><sub>i</sub>, C represents the frame of discernment, and a fundamental probability assignment is represented by the function *m*: *P*(*C*) → [0, 1].

The set *P*(*C*) includes all subsets of *C*, as well as *C* itself and the empty set. *m*: *P*(*C*) → [0, 1] is described as a mass function and satisfies *m*(*Φ*) = 0 and ∑<sub>*A*</sub>*m*(*A*) = 1, in which *Φ* represents the empty set and *A* represents any subset of *C*. The *m*(*A*) estimates to what degree the evidence supports *A*, which is denoted by *Bel* (*A*), a belief function.

There are four basic evidential belief functions attributable to a proposition, based on evidence. These four functions establish the degree of: (i) Belief (*Bel*), (ii) Disbelief (*Dis*), (iii) Uncertainty (*Unc*) and (iv) Plausibility (*Pls*). *Bel* represents the lower bound and *Pls* represents the upper bound of probability (Althuwaynee, Pradhan & Lee, 2012; Awasthi & Chauhan, 2011). *Unc* is established by the difference between *Bel* and *Pls*, and represents the ignorance. *Dis* represents the degree of probability that the proposition is false.

*Dis* = 1 − *Pls* or 1 − *Unc* − *Bel*, such that *Bel* + *Unc* + *Dis* = 1. For a case of *C*<i><sub>ij</sub> zero presence of *Ae. albopictus*, implying that *Bel* = 0, *Dis* is reset to zero, whether that is
the case or not (Carranza, Hale & Faassen, 2008). EBF can be estimated on the basis of a subjective judgment or calculated on the input of data (Srivastava, Mock & Gao, 2011). By superimposing the inventory map (L) of Ae. albopictus onto the six individual conditioning factor maps, we ascertained the number of pixels with Ae. albopictus presence and absence, for each separate conditioning factor. Assuming that $N(L)$ represents the total of presence pixels and $N(C)$ the total pixels comprising the study site, $C_{ij}$ represents the $j$th class attribute of Ae. albopictus presence conditioning factors $C_i$ ($i = 1, 2, \ldots, n$), $N(C_{ij})$ is the total of pixels for class $C_{ij}$, and $N(L \cap C_{ij})$ is the Ae. albopictus presence pixels in $C_{ij}$.
Figure 2 (…continued)
Figure 3  Geology of the study area.

Full-size DOI: 10.7717/peerj.4474/fig-3
According to (Carranza & Hale, 2003), estimation of EBFs based on data is represented by:

\[
\text{Bel}(C_{ij}) = \frac{W_{C_{ij}}(Ae. Albopictus \text{ presence})}{\sum_{j=1}^{N} W_{C_{ij}}(Ae. Albopictus \text{ absence})} \tag{1}
\]

\[
W_{C_{ij}}(Ae. Albopictus \text{ presence}) = \frac{N(L \cap C_{ij})}{N(L)} \frac{N(C_{ij}) - N(L \cap C_{ij})}{N(C) - N(L)} \tag{2}
\]

\[
\text{Dis}(C_{ij}) = \frac{W_{C_{ij}}(Ae. Albopictus \text{ absence})}{\sum_{j=1}^{N} W_{C_{ij}}(Ae. Albopictus \text{ absence})} \tag{3}
\]

where,

\[
W_{C_{ij}}(Ae. Albopictus \text{ presence}) = \frac{[N(C_{ij}) - N(L \cap C_{ij})]}{[N(C) - N(L)]} \cdot \frac{[N(C_{ij}) - N(L \cap C_{ij})]}{[N(C) - N(L)]} \tag{4}
\]

In Eq. (2) the numerator represents the proportion of *Ae. albopictus* presence pixels occurring in factor class $C_{ij}$, while the denominator represents the proportion of *Ae. albopictus* absence pixels in factor class $C_{ij}$. In Eq. (4) the numerator represents the proportion of *Ae. albopictus* absence pixels in factor class $C_{ij}$, while the denominator represents the proportion of *Ae. albopictus* absence pixels in attributes excluding factor class $C_{ij}$. The parameter $W_{C_{ij}}$ (*Ae. albopictus* presence) represents the weight of $C_{ij}$ supporting the belief that *Ae. albopictus* presence exceeds *Ae. albopictus* absence. Parameter $W_{C_{ij}}$ (*Ae. albopictus* absence) is the weight of $C_{ij}$ that supports the belief that *Ae. albopictus* absence exceeds presence.

After calculation of the EBF function for all *Ae. albopictus* presence conditioning factors, Dempster’s combination rule was introduced to produce the four integrated EBFs (Dempster, 1967). The formulae for combination of two *Ae. albopictus* presence conditioning factors $C_1$ and $C_2$ are as follows (Carranza, Woldai & Chikambwe, 2005):

\[
\text{Bel}_{C_1C_2} = \frac{\text{Bel}_{C_1} \text{Bel}_{C_2} + \text{Bel}_{C_1} \text{Unc}_{C_2} + \text{Bel}_{C_2} \text{Unc}_{C_1}}{1 - \text{Bel}_{C_1} \text{Dis}_{C_2} - \text{Dis}_{C_1} \text{Bel}_{C_2}} \tag{5}
\]

\[
\text{Dis}_{C_1C_2} = \frac{\text{Dis}_{C_1} \text{Dis}_{C_2} + \text{Dis}_{C_1} \text{Unc}_{C_2} + \text{Dis}_{C_2} \text{Unc}_{C_1}}{1 - \text{Bel}_{C_1} \text{Dis}_{C_2} - \text{Dis}_{C_1} \text{Bel}_{C_2}} \tag{6}
\]

\[
\text{Dis}_{C_1C_2} = \frac{\text{Dis}_{C_1} \text{Dis}_{C_2} + \text{Dis}_{C_1} \text{Unc}_{C_2} + \text{Dis}_{C_2} \text{Unc}_{C_1}}{1 - \text{Bel}_{C_1} \text{Dis}_{C_2} - \text{Dis}_{C_1} \text{Bel}_{C_2}} \tag{7}
\]

Integrated EBFs of the *Ae. albopictus* presence conditioning factors are applied in sequence by means of Eqs. (5)–(7). Table 1 shows the estimated EBFs for the six *Ae. albopictus* presence conditioning factors.

**Climatic data, future scenarios and climate models**

Baseline climate was represented by the WorldClim current climate dataset of BIOCLIM variables (http://www.worldclim.org). WorldClim is a high-resolution climate average for the period 1961 to 1990, with global coverage and spanning the time period over which the majority of occurrence records were collected. Possible future climates at global scale incorporated four IPCC5 greenhouse gas concentration (GHC) trajectories, which differ
Table 1  The estimated EBF for the six *Ae. albopictus* conditioning factors (i) altitude, (ii) slope, (iii) aspect, (iv) distance of locality from road, (v) distance of locality from river, and (vi) geology.

| Layer                          | Classes | Pixels in class | Belief | Disbelief | uncertainty | plausibility |
|--------------------------------|---------|----------------|--------|-----------|-------------|--------------|
| Altitude (m)                   | 0–15    | 11844138       | 23     | 8         | 69          | 92           |
|                                | 15.01–27| 11044489       | 24     | 8         | 68          | 92           |
|                                | 27.01–44| 11103435       | 16     | 9         | 75          | 91           |
|                                | 44.01–70| 11205803       | 12     | 9         | 79          | 91           |
|                                | 70.01–97| 10777866       | 8      | 10        | 82          | 90           |
|                                | 97.01–127| 10766882       | 2      | 10        | 88          | 90           |
|                                | 127.01–167| 10729677      | 5      | 10        | 85          | 90           |
|                                | 167.01–228| 10530594      | 0      | 11        | 89          | 89           |
|                                | 228.01–321| 10384667      | 4      | 10        | 86          | 90           |
|                                | 321.01–2,031| 10264963    | 1      | 10        | 89          | 90           |
| Slope (Degree)                 | 0–2.71  | 10817128       | 10     | 9         | 81          | 91           |
|                                | 2.72–5.12| 11518857       | 12     | 9         | 79          | 91           |
|                                | 5.13–7.84| 11211137       | 12     | 9         | 79          | 91           |
|                                | 7.85–10.55| 11296609      | 10     | 10        | 80          | 90           |
|                                | 10.56–13.86| 10691424      | 14     | 9         | 77          | 91           |
|                                | 13.87–17.48| 10788198      | 13     | 9         | 78          | 91           |
|                                | 17.49–21.7| 10695224       | 7      | 10        | 83          | 90           |
|                                | 21.71–26.82| 10548139      | 5      | 10        | 85          | 90           |
|                                | 26.83–33.75| 10586704      | 9      | 10        | 81          | 90           |
|                                | 33.76–76.85| 10499094      | 4      | 10        | 86          | 90           |
| Aspect (Direction)             | Flat    | 1966236        | 8      | 11        | 81          | 89           |
|                                | North   | 13716970       | 11     | 11        | 78          | 89           |
|                                | Northeast| 13146928       | 7      | 11        | 82          | 89           |
|                                | East    | 12995205       | 6      | 11        | 83          | 89           |
|                                | Southeast| 13288273      | 10     | 11        | 79          | 89           |
|                                | South   | 14219316       | 15     | 10        | 75          | 90           |
|                                | Southwest| 13358372      | 12     | 11        | 77          | 89           |
|                                | west    | 12885860       | 13     | 10        | 77          | 90           |
|                                | Northwest| 13075354      | 13     | 10        | 77          | 90           |
| Distance of locality from Road (m) | 0–252.46| 9093909        | 22     | 9         | 69          | 91           |
|                                | 252.47–757.38| 15575127   | 19     | 8         | 73          | 92           |
|                                | 757.39–1,262.3| 13129450    | 15     | 9         | 76          | 91           |
|                                | 1,262.31–1,767.22| 11372444 | 9      | 10        | 81          | 90           |
|                                | 1,767.23–2,524.59| 14065017  | 17     | 9         | 74          | 91           |
|                                | 2,524.6–3,281.97| 10968822   | 4      | 10        | 86          | 90           |
|                                | 3,281.98–4,291.81| 10815605  | 1      | 10        | 89          | 90           |
|                                | 4,291.82–5,554.11| 8877260   | 3      | 10        | 87          | 90           |
|                                | 5,554.12–7,573.78| 7524670   | 0      | 10        | 90          | 90           |
|                                | 7,573.79–64,124.67| 7230210  | 6      | 10        | 84          | 90           |

(continued on next page)
| Layer | Classes | Pixels in class | Belief | Disbelief | uncertainty | plausibility |
|-------|---------|----------------|--------|-----------|-------------|--------------|
| Distance of locality from River (m) | 0–9,601.28 | 9750778 | 11 | 9 | 80 | 91 |
| | 9,601.29–22,402.98 | 11907617 | 8 | 10 | 82 | 90 |
| | 22,402.99–35,204.69 | 11317607 | 8 | 10 | 82 | 90 |
| | 35,204.7–49,606.6 | 11872683 | 4 | 10 | 86 | 90 |
| | 49,606.61–65,608.73 | 11611532 | 14 | 9 | 77 | 91 |
| | 65,608.74–83,211.08 | 10954263 | 11 | 9 | 80 | 91 |
| | 83,211.09–102,413.63 | 10793879 | 6 | 10 | 84 | 90 |
| | 102,413.64–126,416.83 | 10642544 | 7 | 10 | 83 | 90 |
| | 126,416.84–161,621.51 | 10084369 | 16 | 9 | 75 | 91 |
| | 161,621.52–408,054.31 | 9717242 | 10 | 9 | 81 | 91 |
| Geology | water | 1483703 | 0 | 1 | 99 | 99 |
| | clay or mud | 17275519 | 5 | 1 | 94 | 99 |
| | limestone | 11355836 | 9 | 1 | 90 | 99 |
| | delta | 1287865 | 10 | 1 | 89 | 99 |
| | alluvium | 3199675 | 4 | 1 | 95 | 99 |
| | sandstone | 6712321 | 6 | 1 | 93 | 99 |
| | beach sand | 4633046 | 9 | 1 | 90 | 99 |
| | sand | 25077193 | 5 | 1 | 94 | 99 |
| | dolostone (dolomite) | 2012103 | 0 | 1 | 99 | 99 |
| | mixed clastic/carbonate | 27,891 | 0 | 1 | 99 | 99 |
| | unconsolidated deposit | 1691087 | 16 | 1 | 83 | 99 |
| | calcarenite | 958,785 | 14 | 1 | 85 | 99 |
| | dune sand | 71335 | 0 | 1 | 99 | 99 |
| | silt | 1399918 | 0 | 1 | 99 | 99 |
| | indeterminate | 537 | 0 | 1 | 99 | 99 |
| | claystone | 1138234 | 0 | 1 | 99 | 99 |
| | terrace | 363141 | 0 | 1 | 99 | 99 |
| | carbonate | 1479813 | 0 | 1 | 99 | 99 |
| | shale | 3770339 | 0 | 1 | 99 | 99 |
| | mudstone | 48266 | 0 | 1 | 99 | 99 |
| | conglomerate | 1250159 | 0 | 1 | 99 | 99 |
| | black shale | 21201 | 0 | 1 | 99 | 99 |
| | greenstone | 26169 | 0 | 1 | 99 | 99 |
| | amphibolite | 563162 | 0 | 1 | 99 | 99 |
| | schist | 960674 | 0 | 1 | 99 | 99 |
| | mica schist | 1854096 | 0 | 1 | 99 | 99 |
| | quartzite | 248931 | 0 | 1 | 99 | 99 |
| | pyroxenite | 12283 | 0 | 1 | 99 | 99 |
| | phyllite | 428634 | 0 | 1 | 99 | 99 |
| | marble | 20271 | 0 | 1 | 99 | 99 |
| | felsic gneiss | 276180 | 0 | 1 | 99 | 99 |
| Layer | Classes | Pixels in class | Belief | Disbelief | uncertainty | plausibility |
|-------|---------|----------------|--------|-----------|-------------|--------------|
| tonalite | 52635 | 0 | 1 | 99 | 99 |
| dacite | 1823 | 0 | 1 | 99 | 99 |
| trondhjemite | 7813 | 0 | 1 | 99 | 99 |
| slate | 212254 | 0 | 1 | 99 | 99 |
| metasedimentary rock | 1529772 | 4 | 1 | 95 | 99 |
| orthogneiss | 87322 | 0 | 1 | 99 | 99 |
| granite | 1855440 | 3 | 1 | 96 | 99 |
| quartz monzonite | 32402 | 0 | 1 | 99 | 99 |
| granodiorite | 39584 | 0 | 1 | 99 | 99 |
| granitic gneiss | 2339458 | 2 | 1 | 97 | 99 |
| chert | 1586586 | 4 | 1 | 95 | 99 |
| quartz-feldspar schist | 23548 | 0 | 1 | 99 | 99 |
| mafic gneiss | 146884 | 0 | 1 | 99 | 99 |
| mylonite | 158219 | 0 | 1 | 99 | 99 |
| biotite gneiss | 3561030 | 1 | 1 | 98 | 99 |
| gneiss | 1525144 | 0 | 1 | 99 | 99 |
| gabbro | 148560 | 0 | 1 | 99 | 99 |
| ultramafic intrusive rock | 13,298 | 0 | 1 | 99 | 99 |
| amphibole schist | 11552 | 0 | 1 | 99 | 99 |
| hornfels | 3420 | 0 | 1 | 99 | 99 |
| charnockite | 8768 | 0 | 1 | 99 | 99 |
| augen gneiss | 19131 | 0 | 1 | 99 | 99 |
| quartz diorite | 77694 | 0 | 1 | 99 | 99 |
| arkose | 123 | 0 | 1 | 99 | 99 |
| gravel | 120,094 | 0 | 1 | 99 | 99 |
| loess | 92 | 0 | 1 | 99 | 99 |
| tectonic breccia | 479 | 0 | 1 | 99 | 99 |
| biotite schist | 17160 | 0 | 1 | 99 | 99 |
| metamorphic rock | 1063128 | 0 | 1 | 99 | 99 |
| siltstone | 66319 | 0 | 1 | 99 | 99 |
| graywacke | 153019 | 0 | 1 | 99 | 99 |
| diorite | 15751 | 0 | 1 | 99 | 99 |
| peat | 449404 | 0 | 1 | 99 | 99 |
| metasedimentary rock | 529438 | 0 | 1 | 99 | 99 |
| felsic metasedimentary rock | 928277 | 0 | 1 | 99 | 99 |
| mafic metasedimentary rock | 138759 | 0 | 1 | 99 | 99 |
| syenite | 5883 | 0 | 1 | 99 | 99 |
| paragneiss | 72466 | 0 | 1 | 99 | 99 |
| lake or marine deposit (non-glacial) | 1159949 | 0 | 1 | 99 | 99 |
| granitoid | 136910 | 0 | 1 | 99 | 99 |
| phyllonite | 15496 | 0 | 1 | 99 | 99 |
| arenite | 28543 | 0 | 1 | 99 | 99 |
in terms of GHC emission peaks. The lower the number of the trajectory, the earlier in the century it peaks.

We purposefully chose the worst (extreme) RCP8.5 (peak 2080) (Stocker et al., 2013) for incorporation into the future climate scenario in the model projections as it is not yet possible to determine which estimates of the climate change and RCPs of 2.6, 4.5, 6.0 and 8.5 are the most reliable (Randall et al., 2007). RCP8.5 is a representative concentration pathway that includes relatively high emissions of greenhouse gases. Other factors assumed in RCP8.5 are high demographic development, relatively slow economic growth, with modest progress in technology and the introduction of novel sources of energy. These factors culminate in an increased demand for energy and higher GHG emissions over the long term, without a more radical approach to the projected impact of climate change (Riahi et al., 2011).

There are 19 General Circulation Models (GCMs) in WorldClim database and we have selected GCMs of Miroc3.2 and CSIRO-MK30, which have higher reputations and have been used for projections of many invasive species, agricultural crops and pests (Da Silva et al., 2017a; Da Silva et al., 2017b; Lamsal et al., 2017; Paterson et al., 2017; Ramirez-Cabral, Kumar & Shabani, 2017b; Ramirez-Cabral, Kumar & Shabani, 2017a; Shabani, Kumar & Ahmadi, 2016; Shabani, Kumar & Ahmadi, 2017; Shabani, Kumar & Taylor, 2012).

**Climatic modeling**

MaxEnt desktop version 3.3.3k, with modified parameters, was used to construct the climatic model (Phillips, Anderson & Schapire, 2006; Phillips & Dudík, 2008). MaxEnt requires a user-defined background of geographical data (Guillera-Arroita, Lahoz-Monfort & Elith, 2014) in order to compare the climate of a set of grid cells representing the presence of a species, with the reference set representing the climate of the sampled cells. The selected geographical data is a significant determinant of the results of the model (Elith et al., 2011) and it is important that it reflect all environmental variations covering the areas representing the presence of the species (Elith, Kearney & Phillips, 2010). The algorithm in MaxEnt estimates the maximum entropy probability distribution that approximates uniformity, based on a comparison of presence and background location interactions with a set of variables, limited by parameters imposed by the observed spatial distributions and environmental factors. Optimisation of the maximum entropy probability distribution is achieved by minimisation of the relative entropy between presence and background point
data (Phillips, Anderson & Schapire, 2006). MaxEnt, with inbuilt MESS analysis tool, has the capacity to predict future distributions, generated from two datasets of environmental variables (Elith et al., 2011). In our study, the current conditions are used to generate the model, with a set of variables utilized for projection of the future scenario (in this case 2055).

Using jackknife analysis and Pearson correlation technique to correlate coefficients, we selected the most influential variables showing low correlation ($R^2 < 0.5$) for this modeling study. Here, BIO11 (Mean Temperature of Coldest Quarter), BIO16 (Precipitation of Wettest Quarter) and BIO17 (Precipitation of Driest Quarter) were selected for the modeling. To achieve greater consistency of background data and overcome the potential for finding fewer records representing areas more recently experiencing invasions, as well as those incompletely sampled, we assigned greater prominence to the records representing less geographical proximity. However, it should be noted that without information on actual survey returns, there is no method of separating unsuitable and under-sampled areas, and that the weighting of prominence cannot overcome the fusion of these two categories of data. After using the Gaussian kernel method to establish deviations from the ArcGIS default values, the formula applied for weighting is to divide total weighted records by the weighted number of land cells of the specific area, to exclude coastal region edge effects. By adjusting the resulting grid to a range of 1–20, extreme values were excluded. This weighting method, as advocated by Elith, Kearney & Phillips (2010), reduces bias that gives prominence to the records of more densely sampled areas. Background training points were generated from the kernel density layer for the species using Hawths Tools extension (Beyer, 2004).

Model validation
The non-climatic modeling analysis was executed and validated using known Ae. albopictus presence (Fig. 1). Using training and testing Ae. albopictus presence data, validation was carried out using the area under curve (AUC) method. While training presence data was used to generate the model, the results using this data does not fully represent the model’s total efficiency. The prediction rate was measured to establish how efficiently the model and selected conditioning factors predicted Ae. albopictus presence. AUC can assess prediction accuracy qualitatively by arrangement of the calculated values of all cells of the study locations into descending order, providing an individual hierarchical ranking of the accuracy of each prediction. Thereafter, the values of cells were divided into 100 classes with accumulation intervals of 1%.

RESULTS
Non-climatic modeling
We examined, and assessed individually, six geological variable factors that directly impact the presence of Ae. albopictus in a specific locality. The altitude EBFs indicated that localities of 0 to 97 m above sea level had a high probability presence of Ae. albopictus. The belief value ($Bel$) peaked at 24 with altitudes from 15 to 27 m, while it was 5 and 0 at altitudes from 127 to 167 m and 167 to 228 m respectively (Table 1). Slope EBF indicated that classes of 2.72 to 7.84°, 10.56 to 13.86° and 33.76 to 76.85° produced $Bel$ values of 12, 14 and 4,
The three highest Aspect Bel values of 15, 13 and 12 related to the classes of South, Northwest and Southwest, respectively (Table 1). Distance from locality to road was included as a conditioning factor, as motor vehicles have been shown as a means of *Ae. albopictus* transmission. The highest Bel values for this factor were 22 and 19, representing the classes of 0 to 252 m and 252 to 757 m, respectively. For Distance of locality from river, EBF estimated the probability of *Ae. albopictus* presence, for all ten classes (Table 1). For Geology, the classes of unconsolidated deposit, calcarenite and delta scored Bel values of 16 and 14 and 41, indicating the probability of *Ae. albopictus* presence in these geological formations (Table 1).

### Probability index and suitability map

The verification results for EBF model are shown in Fig. 4. Probability index maps of *Ae. albopictus* presence produced by EBF method are shown in Figs. 5A and 5B respectively. The range is from 0 to 1, where 0 represents zero probability and 1 represents 100% probability. For producing suitability maps, as well as improving the visual interpretation of locational suitability, probability maps require some form of classification (Umar et al., 2014). There are a variety of classification techniques such as equal interval, natural break, standard deviation and quantile, the selection of which should be based on the research data characteristics and study objectives. Equal interval is suitable when the data displays a normal distribution, while standard deviation arranges the data into a fixed number of
Figure 5  Asian Tiger Mosquito probability and susceptibility maps achieved by EBF method.

DOI: 10.7717/peerj.4474/fig-5
classes. Natural break suits a dataset exhibiting a sudden or big jump. Here, in order to have a reliable judgment regarding the impact of every class of each factor on species occurrence, we attempted to reduce the influence of classification algorithm on the conditioning factors classes as much as possible. In some population analysis projects where the goal is to find a big jump in the data, natural break technique is highly recommended (Hui et al., 2010; Umar et al., 2014), while in this research, this method would not be efficient. Hence, quantile-based classification technique was found to be more appropriate to classify the factors in this study. This method groups equal number of pixels (area) into each group without any interference in the separation of the pixels. We thus selected the quantile method to produce the suitability classes. The verification results for EBF model are shown in Fig. 4. The AUC results showed 0.73 success rate and 0.70 prediction rate (Fig. 4) and these values are high enough and satisfactory for model prediction as documented in Umar et al. (2014). Our probability indexes were into five zones of suitability: very low, low, moderate, high, and very high, for EBF output (Fig. 5B).

Climatic modeling
The climatic model produced by MaxEnt, using two GCMs, Miroc3.2 (Fig. 6A) and CSIRO-MK30 (Fig. 6B), under the RCP 8.5 scenario, shows virtually the whole study site is highly suitable for *Ae. albopictus* and that this condition will persist until at least 2055. Comparing the GCM projections for 2055, CSIRO-MK30 produced a more moderate pattern of climatic suitability than Miroc3.2. Both GCM response curves show the highest probabilities of *Ae. albopictus* presence in areas with Coldest Quarter Mean Temp (bio11) from 16 to 23 °C, Wettest Quarter Precipitation (bio16) of 430 mm and Driest Quarter Precipitation (bio17) of 350 to 450 mm (Figs. 6A and 6B). The Miroc3.2 mean AUC was 0.868, while CSIRO-MK30 indicated 0.864.

DISCUSSION
This study undertook a comparative assessment of the proficiency of the EBF and MaxEnt statistical methods in mapping the probability of *Ae. albopictus* expansion based on climatic and non-climatic parameters respectively. Based on AUC validation method, both EBF and MaxEnt had high prediction rates and thus both can be used to generate *Ae. albopictus* expansion probability and suitability for current and future time. Such maps would assist national, regional and local public health organizations in the identification of areas, and their degree of suitability to *Ae. albopictus* expansion or invasion, as a blueprint on which to plan and implement prevention or reduction measures, or to prepare for potential invasion. Suitability maps provide a foundation for more refined analytical tools such as hazard and risk mapping. It is important to note that the accuracy of *Ae. albopictus* expansion risk is dependent on the accuracy with which the conditioning factor values are calculated. Beyond the establishment of the class, it is essential to understand which conditioning factors impact most on *Ae. albopictus* expansion or invasion. Once the conditioning factors and associated severity of impact have been established, the information is valuable as a foundation to conservation strategies to protect areas at risk.
We also highlight that through the Miroc 3.2 model, the overall suitability remains the same by 2055, while the suitability will slightly decrease by 2055 in the CSIRO-MK30 model and the possible explanation of this difference is due to each GCM and SDM functioning slightly differently and, in line with this matter, Shabani, Kumar & Ahmadi (2017) has recently documented that comparison of the individual SDM or GCM to an ensemble approach showed that there was a better agreement between the ensemble outputs under different GCMs or SDMs. This finding is in line with Araújo & New (2007), who have recommended that using ensemble forecasting has clear advantages over single model forecasts.

Our results indicate the importance of both climate and non-climate factors on the degree of potential *Ae. albopictus* expansion. Complementary to this finding, a number of studies have shown the inability of diapausing *Ae. albopictus* eggs to survive extreme winter temperatures (Hanson & Craig, 1994). Urban habitats with high levels of organic material, such as sewerage treatment works and storm water drainage systems, can impact on the extent of *Ae. albopictus* expansion and such larval habitats should be treated with well-developed methods providing long term relief for the entire *Ae albopictus* season (Rochlin et al., 2013b). Our results also indicate that in terms of climatic suitability, and predicted future climate scenarios, this study has validity and will remain valid in the
future for *Ae. albopictus* (Fig. 6), particularly for the USA. Almost one-third of the study site was identified as being at high risk of *Ae. albopictus* expansion, based on the location of suitable non-climatic parameters alone (Fig. 5). Our results show the importance of non-climatic parameters in that these can be used to further refine high probability areas within climatically suitable regions. Thus, in terms of offering *Ae. albopictus* control services, the climatic result is not as useful on a practical basis as the non-climatic result due to the overall climate suitability of the whole study site. However, the projected future impact of non-climatic parameters on *Ae. albopictus* expansion for the future was not undertaken as the road and river layers will change.

The EBF outputs for altitude conditioning factor indicated that areas from 0 to 97m above sea level had a high probability of *Ae. albopictus* presence, which may be attributable to the greater instability of organic material, water or other non-climatic factors at higher elevations. Moisture preservation and distribution of vegetation amount are related to slope and aspect. Results showed that these factors impacted specifically on the initiation of expansion, as well as having a direct impact on suitability to expansion. The EBF outputs on distance of locality from road and river indicated that both factors had significance in *Ae. albopictus* expansion, which may be due to the greater transportability of *Ae. albopictus* eggs by vehicles, on rivers and in water catchment areas. Conversely, it is probable that geology does not impact significantly on *Ae. albopictus* expansion. Thus, altitude, slope, aspect, distance of locality from road, and distance of locality from river are the most significant non-climatic factors affecting expansions of *Ae. albopictus*.

Community education regarding *Ae. albopictus* and awareness campaigns as to home and garden sanitation and interventions from all levels of public, environmental health and vector control units, as well as private sector infestation control offering mosquito control to provide barrier treatments or other specific locality eradication methods is important. The efficiency and practicality of large-scale adulticiding should be researched, as well as determining the combination of factors which would demand the initiation of this control. Without ongoing strategies to prevent *Ae. albopictus* further expansion, the problem will have to be faced on an increased scale in the near future. Ongoing research has been examining controls involving genetic modification of the species, as well as RIDL (release of insects with dominant lethality) and the introduction of *Wolbachia* bacterium, an insect parasite (*Walker, 2016*).

**CONCLUSION**

Projected warmer winter temperatures, increasing gradually over the next few decades, will impact significantly on the potential for greater *Ae. albopictus* expansion of range in the southeastern and eastern USA. By implication, more people will live within *Ae. albopictus* range, and will potentially be subjected to more bites from the greater density of the species, thus being at greater risk of the posed arboviral threats of the species. At present, aside from small scale direct extermination of hatchings and prophylactic restriction of the specified semi-enclosed moist habitats of water and organic matter containers, by minimizing such habitats, no strategies or techniques of larger area control exists.
Thus, public health agencies, particularly in regions with little or no broad anti-mosquito strategies and techniques, may find themselves in a vacuum, in terms of vector potential of *Ae. albopictus* and a novel pathogen.

Statistical modeling is advantageous for its simplicity and user friendly qualities throughout the suitability mapping process involved. It is also capable of processing large quantities of case or region-specific GIS data relatively quickly. Sustainable urban development is dependent on effective remedies to the potential health impacts of vector hazards that can reach epidemic proportions. Our study indexed potential non-climatic factors and delineated high risk regions, demonstrating an investigative and analytical approach as a foundation for the policy makers and public health networks. We reiterate that anticipating areas of potential establishment based on non-climatic factors is the priority practical approach, where a whole region is classified as suitable for *Ae. albopictus* range extension.

### ADDITIONAL INFORMATION AND DECLARATIONS

**Funding**
The authors received no funding for this work.

**Competing Interests**
The authors declare there are no competing interests.

**Author Contributions**
- Farzin Shabani conceived and designed the experiments, performed the experiments, analyzed the data, contributed reagents/materials/analysis tools, prepared figures and/or tables.
- Mahyat Shafapour Tehrany conceived and designed the experiments, analyzed the data, contributed reagents/materials/analysis tools, prepared figures and/or tables.
- Samaneh Solhjouy-fard performed the experiments, analyzed the data, contributed reagents/materials/analysis tools, prepared figures and/or tables.
- Lalit Kumar contributed reagents/materials/analysis tools, authored or reviewed drafts of the paper.

**Data Availability**
The following information was supplied regarding data availability:

The raw data is provided in the Supplemental Files.

**Supplemental Information**
Supplemental information for this article can be found online at http://dx.doi.org/10.7717/peerj.4474#supplemental-information.
REFERENCES

Althuwaynee O, Pradhan B, Lee S. 2012. Application of an evidential belief function model in landslide susceptibility mapping. Computers & Geosciences 44:120–135 DOI 10.1016/j.cageo.2012.03.003.

Antia R, Regoes R, Koella J, Bergstrom C. 2003. The role of evolution in the emergence of infectious diseases. Nature 426:658–661 DOI 10.1038/nature02177.

Araújo MB, New M. 2007. Ensemble forecasting of species distributions. Trends in Ecology & Evolution 22:42–47 DOI 10.1016/j.tree.2006.09.010.

Awasthi A, Chauhan S. 2011. Using AHP and Dempster–Shafer theory for evaluating sustainable transport solutions. Environmental Modelling & Software 26:787–796 DOI 10.1016/j.envsoft.2010.11.010.

Beyer H. 2004. Hawth’s analysis tools for ArcGIS. Available at http://www.spatialecology.com/htools/download.php.

Caminade C, Medlock J, Ducheyne E, McIntyre K, Leach S, Baylis M, Morse A. 2012. Suitability of European climate for the Asian tiger mosquito Aedes albopictus: recent trends and future scenarios. Journal of the Royal Society Interface 9(75):2708–2717 DOI 10.1098/rsif.2012.0138.

Caputo B, Ienco A, Cianci D, Pombi M, Petrarca V, Baseggio A, Devine G, Della Torre A. 2012. The “auto-dissemination” approach: a novel concept to fight Aedes albopictus in urban areas. PLOS Neglected Tropical Diseases 6:e1793 DOI 10.1371/journal.pntd.0001793.

Carranza E, Hale M. 2003. Evidential belief functions for data-driven geologically constrained mapping of gold potential, Baguio district, Philippines. Ore Geology Reviews 22:117–132 DOI 10.1016/S0169-1368(02)00111-7.

Carranza E, Hale M, Faassen C. 2008. Selection of coherent deposit-type locations and their application in data-driven mineral prospectivity mapping. Ore Geology Reviews 33:536–558 DOI 10.1016/j.oregeorev.2007.07.001.

Carranza E, Woldai T, Chikambwe E. 2005. Application of data-driven evidential belief functions to prospectivity mapping for aquamarine-bearing pegmatites, Lundazi district, Zambia. Natural Resources Research 14:47–63 DOI 10.1007/s11053-005-4678-9.

Da Silva R, Kumar L, Shabani F, Da Silva E, Da Silva G, Picanço M. 2017a. Spatio-temporal dynamic climate model for Neoleucinodes elegantalis using CLIMEX. International Journal of Biometeorology 61:785–795 DOI 10.1007/s00484-016-1256-2.

Da Silva R, Kumar L, Shabani F, Picanço M. 2017b. An analysis of sensitivity of CLIMEX parameters in mapping species potential distribution and the broad-scale changes observed with minor variations in parameters values: an investigation using open-field Solanum lycopersicum and Neoleucinodes elegantalis as an example. Theoretical and Applied Climatology Epub ahead of print Feb 22 2017 DOI 10.1007/s00704-017-2072-2.

Dempster A. 1967. Upper and lower probabilities induced by a multivalued mapping. The Annals of Mathematical Statistics 38:325–339.
Ding F, Fu J, Jiang D, Hao M, Lin G. 2018. Mapping the spatial distribution of *Aedes aegypti* and *Aedes albopictus*. *Acta Tropica* 178:155–162 DOI 10.1016/j.actatropica.2017.11.020.

EarthExplorer. 2014. EarthExplorer. Available at http://earthexplorer.usgs.gov (accessed on June 2016).

Elith J, Kearney M, Phillips S. 2010. The art of modelling range-shifting species. *Methods in Ecology and Evolution* 1:330–342 DOI 10.1111/j.2041-210X.2010.00036.x.

Elith J, Phillips S, Hastie T, Dudík M, Chee Y, Yates C. 2011. A statistical explanation of MaxEnt for ecologists. *Diversity and Distributions* 17:43–57 DOI 10.1111/j.1472-4642.2010.00725.x.

Global Biodiversity Information Facility. 2017. Global Biodiversity Information Facility (GBIF). Available at http://www.gbif.org (accessed on July 2017).

Global Invasive Species Database (GISD). 2017. Global Invasive Species Database (GISD). Available at http://www.iucngisd.org/gisd/.

Guillera-Arroita G, Lahoz-Monfort J, Elith J. 2014. Maxent is not a presence–absence method: a comment on Thibaud, et al. *Methods in Ecology and Evolution* 5:1192–1197 DOI 10.1111/2041-210X.12252.

Hanson S, Craig G. 1994. Cold acclimation, diapause, and geographic origin affect cold hardiness in eggs of *Aedes albopictus* (Diptera: Culicidae). *Journal of Medical Entomology* 31:192–201 DOI 10.1093/jmedent/31.2.192.

Hanson S, Craig G. 1995. *Aedes albopictus* (Diptera: Culicidae) eggs: field survivorship during northern Indiana winters. *Journal of Medical Entomology* 32:599–604 DOI 10.1093/jmedent/32.5.599.

Higa Y. 2011. Dengue vectors and their spatial distribution. *Tropical Medicine and Health* 39:S17–S27 DOI 10.2149/tmh.2011-S04.

Holder P, George S, Disbury M, Singe M, Kean JM, McFadden A. 2010. A biosecurity response to *Aedes albopictus* (Diptera: Culicidae) in Auckland, New Zealand. *Journal of Medical Entomology* 47:600–609 DOI 10.1093/jmedent/47.4.600.

Hui L, Xiaoling C, Lim K, Xiaobin C, Sagong M. 2010. Assessment of soil erosion and sediment yield in Liao watershed, Jiangxi Province, China, Using USLE, GIS, and RS. *Journal of Earth Science* 21:941–953 DOI 10.1007/s12583-010-0147-4.

Hulme P. 2006. Beyond control: wider implications for the management of biological invasions. *Journal of Applied Ecology* 43:835–847 DOI 10.1111/j.1365-2664.2006.01227.x.

Kenis M, Auger-Rozenberg M, Roques A, Timms L, Péré C, Cock M, Settele J, Augustin S, Lopez-Vaamonde C. 2009. Ecological effects of invasive alien insects. *Biological Invasions* 11:21–45 DOI 10.1007/s10530-008-9318-y.

Kraemer M, Sinka M, Duda K, Mylne A, Shearer F, Barker C, Moore C, Carvalho R, Coelho G, Van Bortel W. 2015a. The global distribution of the arbovirus vectors *Aedes aegypti* and *Ae. albopictus*. *Elife* 4:e08347 DOI 10.7554/eLife.08347.

Kraemer M, Sinka M, Duda K, Mylne A, Shearer F, Brady O. 2015b. The global compendium of Aedes aegypti and *Ae. albopictus* occurrence.
Lamsal P, Kumar L, Shabani F, Atreya K. 2017. The greening of the Himalayas and Tibetan Plateau under climate change. Global and Planetary Change 159:77–92 DOI 10.1016/j.gloplacha.2017.09.010.

Malpica J, Alonso M, Sanz M. 2007. Dempster–Shafer Theory in geographic information systems: a survey. Expert Systems with Applications 32:47–55 DOI 10.1016/j.eswa.2005.11.011.

Messina J, Kraemer M, Brady O, Pigott D, Shearer F, Weiss D, Golding N, Ruktanonchai C, Gething P, Cohn E. 2016. Mapping global environmental suitability for Zika virus. Elife 5:e15272 DOI 10.7554/eLife.15272.

Nihei N, Komagata O, Mochizuki K, Kobayashi M. 2014. Geospatial analysis of invasion of the Asian tiger mosquito Aedes albopictus: competition with Aedes japonicus japonicus in its northern limit area in Japan. Geospatial Health 8:417–427 DOI 10.4081/gh.2014.30.

Paterson R, Kumar L, Shabani F, Lima N. 2017. World climate suitability projections to 2050 and 2100 for growing oil palm. The Journal of Agricultural Science 155:689–702 DOI 10.1017/S0021859616000605.

Pearl J. 1990. Reasoning under uncertainty. Annual Review of Computer Science 4:37–72 DOI 10.1002/0470018860.s00028.

Phillips S, Anderson R, Schapire R. 2006. Maximum entropy modeling of species geographic distributions. Ecological Modelling 190:231–259 DOI 10.1016/j.ecolmodel.2005.03.026.

Phillips S, Dudík M. 2008. Modeling of species distributions with Maxent: new extensions and a comprehensive evaluation. Ecography 31:161–175 DOI 10.1111/j.0906-7590.2008.5203.x.

Pimentel D. 2011. Biological invasions: economic and environmental costs of alien plant, animal, and microbe species. Boca Raton: CRC Press, 463.

Pyšek P, Richardson D. 2010. Invasive species, environmental change and management, and health. Annual Review of Environment and Resources 35:25–55 DOI 10.1146/annurev-environ-030909-095548.

Rai K. 1991. Aedes albopictus in the Americas. Annual Review of Entomology 36:459–484 DOI 10.1146/annurev.en.36.010191.002331.

Ramírez-Cabral NZ, Kumar L, Shabani F. 2017a. Global risk levels for corn rusts (Puccinia sorghi and Puccinia polysora) under climate change projections. Journal of Phytopathology 7: Article 5910.

Ramírez-Cabral N, Kumar L, Shabani F. 2017b. Global alterations in areas of suitability for maize production from climate change and using a mechanistic species distribution model (CLIMEX). Scientific Reports 7(1):5910 DOI 10.1038/s41598-017-05804-0.

Randall D, Wood R, Bony S, Colman R, Fichefet T, Fyfe J, Kattsov V, Pitman A, Shukla J, Srinivasan J. 2007. Climate models and their evaluation. In: Climate change 2007: the physical science basis contribution of working group I to the fourth assessment report of the IPCC (FAR). Cambridge University Press, 589–662.
Riahi K, Rao S, Krey V, Cho C, Chirkov V, Fischer G, Kindermann G, Nakicenovic N, Rafaj P. 2011. RCP 8.5—a scenario of comparatively high greenhouse gas emissions. *Climatic Change* 109:33 DOI 10.1007/s10584-011-0149-y.

Ritchie S, Moore P, Carruthers M, Williams C, Montgomery B, Foley P, Ahboo S, Van Den Hurk A, Lindsay M, Cooper B. 2006. Discovery of a widespread infestation of *Aedes albopictus* in the Torres Strait, Australia. *Journal of the American Mosquito Control Association* 22:358–365 DOI 10.2987/8756-971X.

Rochlin I, Gaugler R, Williges E, Farajollahi A. 2013a. The rise of the invasives and decline of the natives: insights revealed from adult populations of container-inhabiting *Aedes* mosquitoes (Diptera: Culicidae) in temperate North America. *Biological Invasions* 15:991–1003 DOI 10.1007/s10530-012-0345-3.

Rochlin I, Ninivaggi D, Hutchinson M, Farajollahi A. 2013b. Climate change and range expansion of the Asian tiger mosquito (*Aedes albopictus*) in Northeastern USA: implications for public health practitioners. *PLOS ONE* 8:e60874 DOI 10.1371/journal.pone.0060874.

Schaffner F, Medlock J, Bortel WV. 2013. Public health significance of invasive mosquitoes in Europe. *Clinical Microbiology and Infection* 19:685–692 DOI 10.1111/1469-0691.12189.

Shabani F, Kumar L, Ahmadi M. 2016. A comparison of absolute performance of different correlative and mechanistic species distribution models in an independent area. *Ecology and Evolution* 6:5973–5986 DOI 10.1002/ece3.2332.

Shabani F, Kumar L, Ahmadi M. 2017. Climate modelling shows increased risk to eucalyptus sideroxylon on the Eastern Coast of Australia compared to eucalyptus albens. *Plants* 6(4):E58 DOI 10.3390/plants6040058.

Shabani F, Kumar L, Taylor S. 2012. Climate change impacts on the future distribution of date palms: a modeling exercise using CLIMEX. *PLOS ONE* 7:e48021 DOI 10.1371/journal.pone.0048021.

Simard F, Nchoutpouen E, Toto J, Fontenille D. 2005. Geographic distribution and breeding site preference of *Aedes albopictus* and *Aedes aegypti* (Diptera: Culicidae) in Cameroon, Central Africa. *Journal of Medical Entomology* 42:726–731 DOI 10.1093/jmedent/42.5.726.

Srivastava R, Mock T, Gao L. 2011. The dempster-shafer theory: an introduction and fraud risk assessment illustration. *Australian Accounting Review* 21:282–291 DOI 10.1111/j.1835-2561.2011.00135.x.

Stocke T, Qin D, Plattner G, Tignor M, Allen S, Boschung J, Nauels A, Xia Y, Bex V, Midgley P. 2013. IPCC, 2013: summary for policymakers in Climate Change 2013: the physical science basis, contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, New York.

Tehrany MS, Pradhan B, Jebur MN. 2013. Spatial prediction of flood susceptible areas using rule based decision tree (DT) and a novel ensemble bivariate and multivariate statistical models in GIS. *Journal of Hydrology* 504:69–79 DOI 10.1016/j.jhydrol.2013.09.034.
Thiam A. 2005. An evidential reasoning approach to land degradation evaluation: Dempster-Shafer theory of evidence. Transactions in GIS 9:507–520 DOI 10.1111/j.1467-9671.2005.00232.x.

Thomas S, Obermayr U, Fischer D, Kreyling J, Beierkuhnlein C. 2012. Low-temperature threshold for egg survival of a post-diapause and non-diapause European aedine strain, Aedes albopictus (Diptera: Culicidae). Parasites & Vectors 5:100 DOI 10.1186/1756-3305-5-100.

Umar Z, Pradhan B, Ahmad A, Jebru M, Tehrany M. 2014. Earthquake induced landslide susceptibility mapping using an integrated ensemble frequency ratio and logistic regression models in West Sumatera Province, Indonesia. Catena 118:124–135 DOI 10.1016/j.catena.2014.02.005.

United States Department of Agriculture. 2017. United States Department of Agriculture home page. Available at https://www.usda.gov/ (accessed on January 2017).

Vega-Rúa A, Zouache K, Girod R, Failloux A, Lourenço-de-Oliveira R. 2014. High level of vector competence of Aedes aegypti and Aedes albopictus from ten American countries as a crucial factor in the spread of Chikungunya virus. Journal of Virology 88:6294–6306 DOI 10.1128/JVI.00370-14.

Walker M. 2016. Controlling the Asian tiger mosquito, a potential zika vector, is possible but difficult. Entomology Today. Available at https://entomologytoday.org/2016/06/29/controlling-the-asian-tiger-mosquito-a-potential-zika-vector-is-possible-but-difficult/.

Weaver S, Lecuit M. 2015. Chikungunya virus and the global spread of a mosquito-borne disease. New England Journal of Medicine 372:1231–1239 DOI 10.1056/NEJMra1406035.

Wittenberg R, Cock M. 2001. Invasive alien species: a toolkit of best prevention and management practices. Wallingford, Oxon: CABI International.