

RESEARCH

Open Access



Climate change diminishes the potential habitat of the bont tick (*Amblyomma hebraeum*): evidence from Mashonaland Central Province, Zimbabwe

Paradzayi Tagwireyi^{1*} , Manuel Ndebele¹ and Wilmot Chikurunhe²

Abstract

Background: Understanding the response of vector habitats to climate change is essential for vector management. Increasingly, there is fear that climate change may cause vectors to be more important for animal husbandry in the future. Therefore, knowledge about the current and future spatial distribution of vectors, including ticks (Ixodida), is progressively becoming more critical to animal disease control.

Methods: Our study produced present (2018) and future (2050) bont tick (*Amblyomma hebraeum*) niche models for Mashonaland Central Province, Zimbabwe. Specifically, our approach used the Ensemble algorithm in Biomod2 package in R 3.4.4 with a suite of physical and anthropogenic covariates against the tick's presence-only location data obtained from cattle dipping facilities.

Results: Our models showed that currently (the year 2018) the bont tick potentially occurs in 17,008 km², which is 60% of Mashonaland Central Province. However, the models showed that in the future (the year 2050), the bont tick will occur in 13,323 km², which is 47% of Mashonaland Central Province. Thus, the models predicted an ~ 13% reduction in the potential habitat, about 3685 km² of the study area. Temperature, elevation and rainfall were the most important variables explaining the present and future potential habitat of the bont tick.

Conclusion: Results of our study are essential in informing programmes that seek to control the bont tick in Mashonaland Central Province, Zimbabwe and similar environments.

Keywords: Area under the curve (ROC), Climate change, Ensemble modelling, True skill statistic (TSS), Variance inflation factor (VIF)

Background

There is a notable increase in tick distribution and tick-borne diseases, particularly in the tropical and subtropical regions. Tick species of particular interest in the tropics include species in the genera *Hyalomma*,

Amblyomma and *Rhipicephalus* [1, 2]. Some of these species, e.g., the bont tick (*Amblyomma hebraeum*), are challenging to control as they have very high reproductive rates and sometimes develop resistance to standard remedies. In addition, the bont tick has a wide spatial distribution because of its ability to survive in both dry and humid environments [3, 4]. Thus, the bont tick is a significant vector for various pathogens, including the obligate intracellular proteobacterium *Ehrlichia ruminantium*, which causes heartwater disease in ruminants [5].

*Correspondence: tagwireyip@gmail.com

¹ Department of Geography, Geospatial Sciences and Earth Observation, University of Zimbabwe, 630 Churchill Road, Harare, Zimbabwe
Full list of author information is available at the end of the article



© The Author(s) 2022. **Open Access** This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>. The Creative Commons Public Domain Dedication waiver (<http://creativecommons.org/publicdomain/zero/1.0/>) applies to the data made available in this article, unless otherwise stated in a credit line to the data.

Ticks spend much of their life away from their host. As such, ticks are prone to the effects of climatic and other environmental dynamics [6]. The predicted change in climate, primarily to warmer conditions, motivates the modelling of future distribution of ticks using climate change scenarios [7]. Those niche models use various environmental variables, including elevation temperature, rainfall and humidity [8]. Recently, Land Use Land Cover Change (LULCC) has been a significant covariate in modelling tick species and tick host distribution and is often used in modelling overlaps in space and time between human activities and ticks habitats [9].

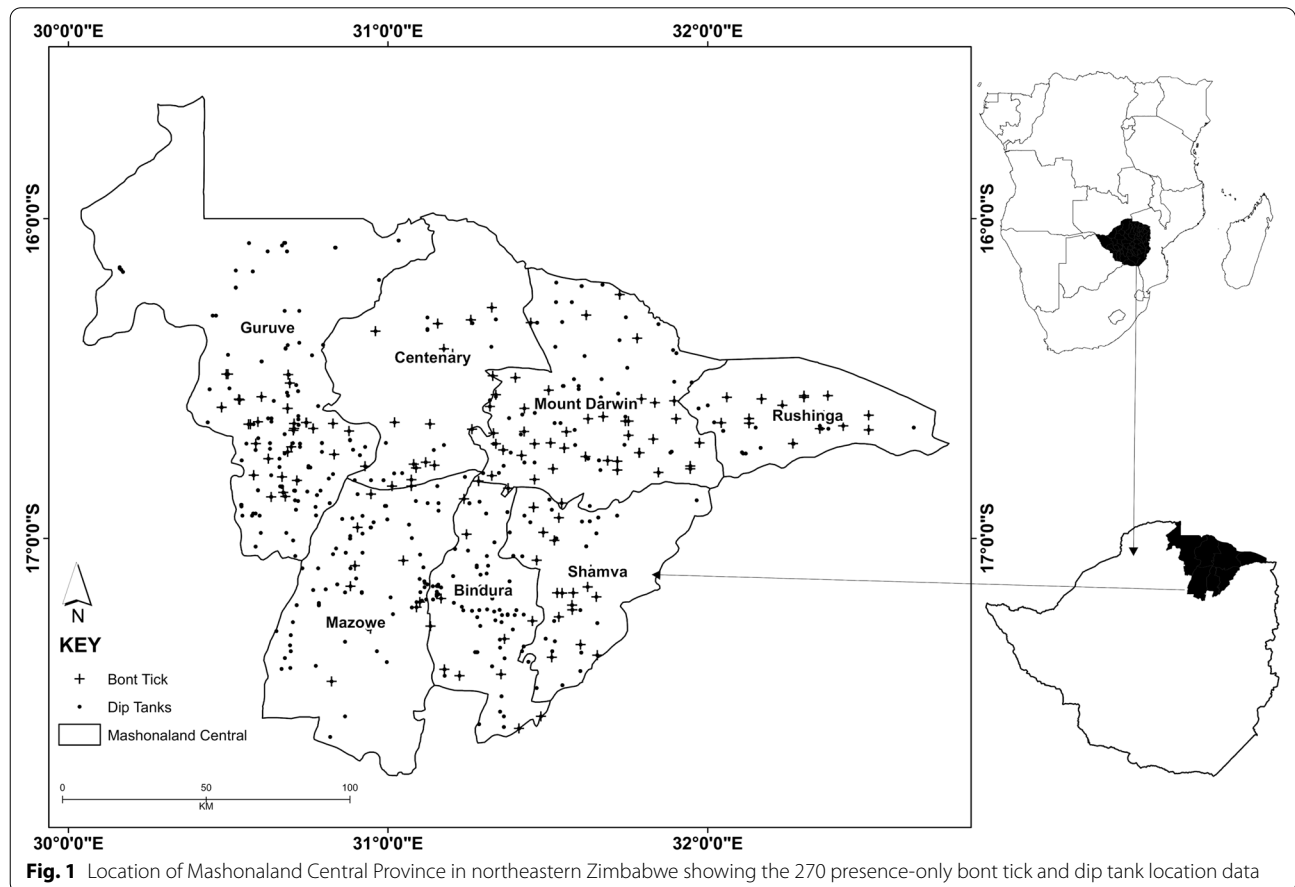
The present and future distribution of ticks must be known to support vector management programmes [10]. However, while bont ticks are notorious for animal husbandry, their present and future spatial distribution and the drivers of that distribution are primarily unknown. This study used bont tick presence-only data and a suite of climate change scenarios data and environmental covariates to model the present and future distribution of one of the most notorious ticks in Mashonaland Central province, Zimbabwe. The objectives of this study were twofold: (1) identify the change in the potential habitat

of bont tick between current time (2018) and future 2050 and (2) identify the drivers of the spatial distribution of bont tick. Results of this study are essential in informing programmes that seek to control the bont tick in Mashonaland Central Province, Zimbabwe, and similar environments.

Methods

Study site

The study area was Mashonaland Central Province, Zimbabwe, located between 30.04° E–32.75° E and 17.97° S–15.40° S, comprising 28,347 km² of land (Fig. 1). According to the Zimbabwe National Census 2012 statistics, the province’s population was 1,152,520 inhabitants. A wide range of land tenure types coexists in the province, including communal areas, newly resettled small scale farming (A1), newly resettled large scale farming (A2), small-scale commercial farming, extensive-scale commercial farming and old resettlement areas [11]. The province comprises regions of varying agricultural potential, including Agro-ecological Region 2, which receives as much as 1000 mm of annual rainfall, to Agro-ecological Region 5, which receives < 450 mm of annual



rainfall [12]. The area experiences a wet season (October to April) and a dry season (May to October).

Administratively, Mashonaland Province consists of eight districts: Bindura, Centenary, Mt Darwin, Guruve, Mbire, Rushinga, Shamva and Mazowe. Agriculture is the basis of the economy as the province is predominantly rural [13]. As such, the majority of the inhabitants of the province are small-holder farmers whose livelihoods depend on crops (e.g. maize, wheat, tobacco) and livestock (e.g. cattle, sheep, goats and poultry). However, cattle farming experiences economic losses due to tick-borne diseases, typical to resource-poor cattle owners in Africa [14].

Like other provinces in Zimbabwe, Mashonaland Central Province's tick control is based on dipping cattle in plunge dips (concrete plunge tanks) containing acaricides diluted in large volumes of water. Farmers have to dip their cattle weekly during the wet season and fortnightly during the dry season. It has been the responsibility of the government to supply acaricides. However, the communal farmer pays a reasonable fee to the Department of Veterinary Services so that their herds of cattle benefit from the tick control exercise [14]. Dipping in acaricides has been a compulsory exercise since its legislation in 1914, and it has been one of the successful methods of tick control in livestock [15].

Tick species geographical data

Veterinary extension officers collected ticks at all the cattle dipping facilities for which location coordinates were known. The procedure of getting the ticks involves manually restraining every tick-infested animal at the dipping facility to allow the physical examination. The veterinary officers used the morphological identification method to identify the tick species following [16] plus guides including [17] and completed tick inspection forms using morphology. The veterinary officers are experts in tick species identification. Since cattle dipping is done weekly during the wet season and fortnightly during the dry season, veterinary officers inspected cattle for ticks and recorded tick presence data every month from 2010. The tick species collected for the 2018 year of study were *Rhipicephalus decoloratus* (African blue tick), *Rhipicephalus sanguineus* (s.l.) (brown dog tick), *Rhipicephalus evertsi* (red-legged tick) and *Amblyomma hebraeum* (bont tick).

Predictor variables

We used bioclimatic data obtained from the WorldClim Version 2 Server for both present (2018) and future (2050) predictions [18]. Specifically, we used the CCSM4 climate change scenario rcp45 with a spatial resolution of 2.5 min (Table 1).

Table 1 All Predictor variables before multicollinearity test

Code	Variable
BIO1	Annual mean temperature
B102	Mean diurnal range
BIO3	Isothermality
BIO4	Temperature seasonality
BIO5	Maximum temperature of warmest month
BIO6	Min temperature of coldest month
BIO7	Temperature annual range
BIO8	Mean temperature of wettest quarter
BIO9	Mean temperature of driest quarter
BIO10	Mean temperature of warmest quarter
BIO11	Mean temperature of coldest quarter
BIO12	Annual precipitation
BIO13	Precipitation of wettest month
BIO14	Precipitation of driest month
BIO15	Precipitation seasonality
BIO16	Precipitation of wettest quarter
BIO17	Precipitation of driest quarter
BIO18	Precipitation of warmest quarter
BIO19	Precipitation of coldest quarter
DEM	Digital elevation model
LandC	Land cover

We obtained the topographic and landcover variables from the ESA Climate Change Initiative [19] (Table 1). To model LULCC, we used the Land Change Modeler of Terrset Geospatial Monitoring and Modelling System because of its capability to incorporate Markov-Chain [20]. To model future land use and cover change up to 2050, we used a first-order Markov-Chain, a stochastic model for quantitative land change detection [21]. In addition, the Earth Explorer Aster Global DEM provided the elevation covariate [22] (Table 1).

All predictor variables were obtained in raster formats and adjusted to 1-km resolution and converted to ASCII format using ArcGIS 10.5 (Environmental Systems Research Institute, Redlands, CA, USA).

Variable selection

To deal with multicollinearity, we used the Variance Inflation Factor (VIF), where the covariate with a VIF > 10 was excluded in the modelling following Tagwireyi et al. [23]. The VIF was calculated in R using USDM package [24]. After excluding the collinear variables, we remained with ten for both the present and future modelling (Tables 2 and 3).

Table 2 Variables used for present (2018) distribution of the Bont tick

Code	Variable	Variance inflation factor
B102	Mean diurnal range	5.47
BIO3	Isothermality	6.00
BIO5	Maximum temperature of warmest month	7.40
BIO13	Precipitation of wettest month	3.79
BIO14	Precipitation of driest month	2.10
BIO15	Precipitation seasonality	8.65
BIO18	Precipitation of warmest quarter	1.46
BIO19	Precipitation of coldest quarter	5.30
DEM	Digital elevation model	1.07
LandC	Land cover	1.05

Only variables with variance inflation factor (VIF) < 10 were used in the modelling

Table 3 Variables used for future (2050) distribution of the bont tick

Code	Variable	Variance inflation factor
B102	Mean diurnal range	5.18
BIO3	Isothermality	5.62
BIO5	Maximum temperature of warmest month	7.21
BIO13	Precipitation of wettest month	3.81
BIO14	Precipitation of driest month	2.01
BIO15	Precipitation seasonality	8.27
BIO18	Precipitation of warmest quarter	1.45
BIO19	Precipitation of coldest quarter	5.13
DEM	Digital elevation model	1.03
LandC	Land cover	1.05

Only variables with variance inflation factor (VIF) < 10 were used in the modelling

Modelling procedure

The Ensemble algorithm in Biomod2 package was used for the modelling in R 3.4.4 [25]. The approach selected eight modelling techniques in fitting and averaging present and future species habitat predictions. These are generalized linear models (GLM), classification tree analysis (CTA) artificial neural networks (ANN), surface range envelope (SRE), generalized boosting model (GBM), Breiman and Cutler's random forest for classification and regression (RF), mixture discriminant analysis (MDA) and multiple adaptive regression splines (MARS).

The choice of eight modelling techniques was based on each model's efficiency, especially in the evaluation of model

Table 4 Variable importance for the present (2018) distribution model

Code	Variable	Variable contribution
B102	Mean diurnal range	0.10
BIO3	Isothermality	0.02
BIO5	Maximum temperature of warmest month	0.35
BIO13	Precipitation of wettest month	0.27
BIO14	Precipitation of driest month	0.00
BIO15	Precipitation seasonality	0.15
BIO18	Precipitation of warmest quarter	0.22
BIO19	Precipitation of coldest quarter	0.05
DEM	Digital elevation model	0.36
LandC	Land cover	0.08

response curves [26]. The default settings in all chosen modelling techniques were used because default settings usually come enhanced for species distribution models (SDMs) [27]. All models used a maximum of 100 iterations [26]. Both present and future prediction models were created using 80% of occurrences and pseudo-absence data; the remaining 20% was used for model evaluation. Binary maps were then used to classify maps as suitable or unsuitable following Muhoyi et al. [28].

Model evaluation

The partial receiving operating characteristic (partial ROC) [29] was for validating our Ensemble models by making use of area under curve (AUC) analysis and true skill statistics (TSS), which considers omission and commission errors [30]. The TSS ranges from 0.0 to 1.0. A TSS value in range 0–0.5 was considered a poor model fit, 0.6 to 0.8 an acceptable fit and valid; any values > 0.8 were considered good to excellent [31]. The AUC criteria considered a model with values from 0.0 to 0.6 as inferior, 0.6–0.9 as useful and > 0.9 as excellent following Ndaimani et al. [32]. A TSS threshold of 0.6 was used to select models for the Ensemble model, following Gallien et al. [33].

Statistical analysis

The suitable area was calculated for both present and future predictions from binary maps using the raster zonal geometry calculation function in ArcGIS 10.5. To assess whether there is a reduction or increase in the suitable habitat, a two-sample test for equal proportions using a chi-square test was executed.

Results

The Ensemble model achieved excellent success in predicting the current habitat of the bont tick (TSS=0.900, ROC=0.979). In addition, the approach was also excellent at predicting the future potential distribution of bont tick (TSS=0.898, ROC=0.976).

The variable importance analysis showed that elevation and maximum temperature of the warmest month, precipitation of the warmest month and precipitation of the wettest month are variables with high importance in explaining the occurrences of bont ticks (Tables 4 and 5). For example, the species habitat suitability is high in areas with moderate elevation ranging from 800 to 1000 m above sea level and high in areas with moderate temperatures ranging from 26 to 29 °C. Conversely, land cover, precipitation of coldest quarter and isothermality have the lowest contribution in determining bont tick habitat for present and future predictions.

Binary maps using the TSS=0.6 thresholds showed the suitable habitat to be 17,008 km² for the present

model and 13,323 km² for the future model (Fig. 2a, b), representing a decrease of bont tick potential habitat of ~ 13% (3685 km²) for Mashonaland Central Province, Zimbabwe.

The proportion of suitable habitat for the present model was 0.60, while that for the future model was 0.47. The chi-square test showed a significant difference between the present and future habitat sizes ($\chi^2=3.40$, $df=1$, $P=2E-16$).

Discussion

We observed that three covariates, i.e., rainfall, elevation and temperature, are essential in explaining the predicted spatial distribution of the bont tick for both the present (2018) and future (2050). These three covariates directly affect the living conditions of tick species and tick hosts [34]. The potential occurrences of bont ticks were high in moderate climatic conditions and moderate elevation. However, a combination of very high temperatures and high elevation and a combination of very low elevation and very low temperature did not favour the occurrence of the bont tick.

Based on the prediction results, there would be a significant ~ 13% reduction in bont tick potential habitat by 2050. The mechanisms explaining the decline include an increase in temperature, which leads to saturation deficit, a thermodynamic factor that has an inverse relationship with temperature [35]. Ticks spend part of their life cycle stage of their time below the ground surface. Therefore, below ground conditions are critical for their survival [36]. Bont ticks prefer moderate ground conditions, neither too cold nor too hot. As such, the ~ 13% reduction of bont tick habitat by 2050 reflects a strong association between climate change and tick phenology [37].

Table 5 Variable importance for the future (2050) distribution model

Code	Variable	Variable contribution
B102	Mean diurnal range	0.08
BIO3	Isothermality	0.02
BIO5	Maximum temperature of warmest month	0.20
BIO13	Precipitation of wettest month	0.23
BIO14	Precipitation of driest month	0.00
BIO15	Precipitation seasonality	0.07
BIO18	Precipitation of warmest quarter	0.26
BIO19	Precipitation of coldest quarter	0.03
DEM	Digital elevation model	0.19
LandC	Land cover	0.06

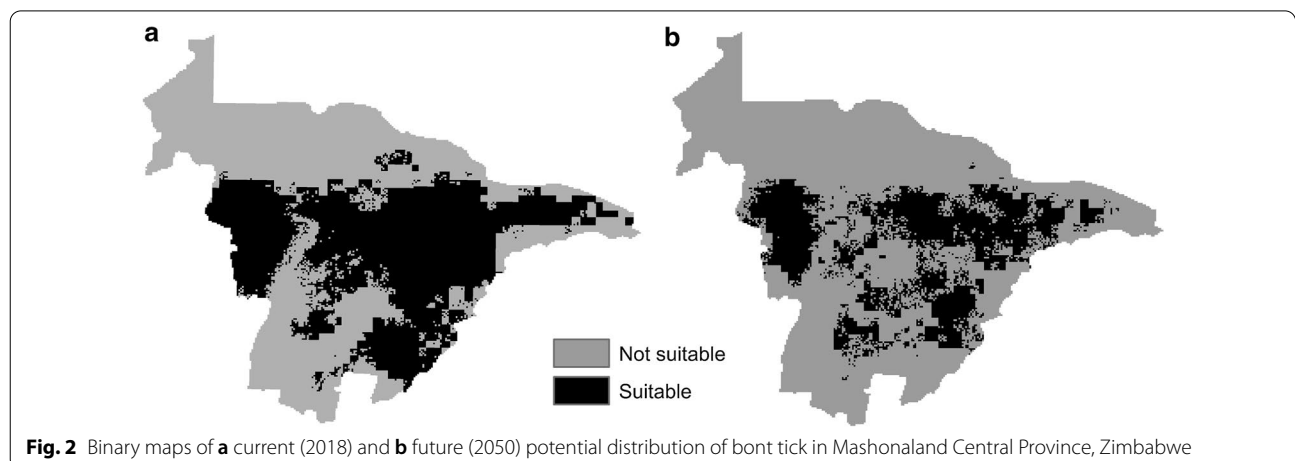
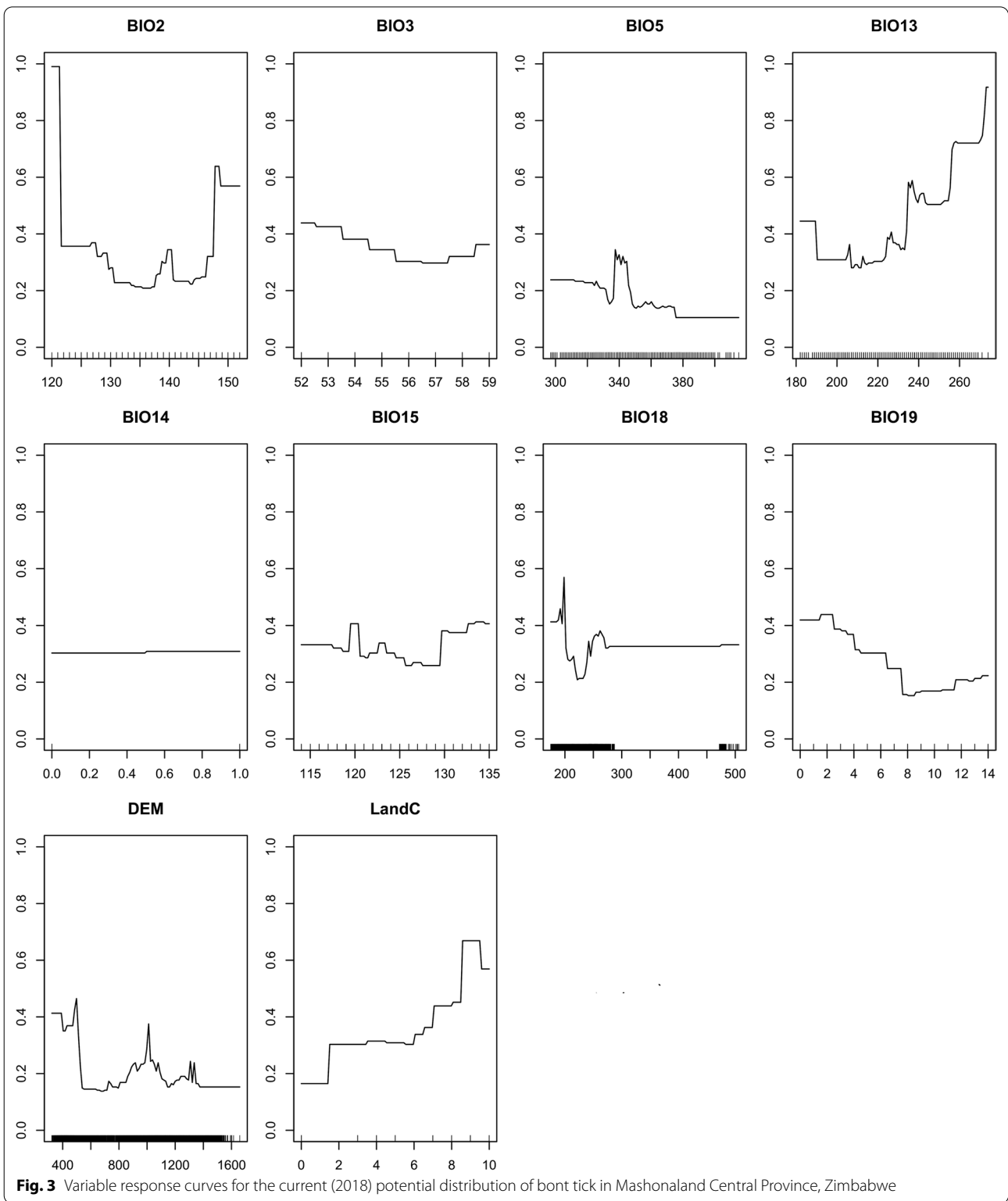
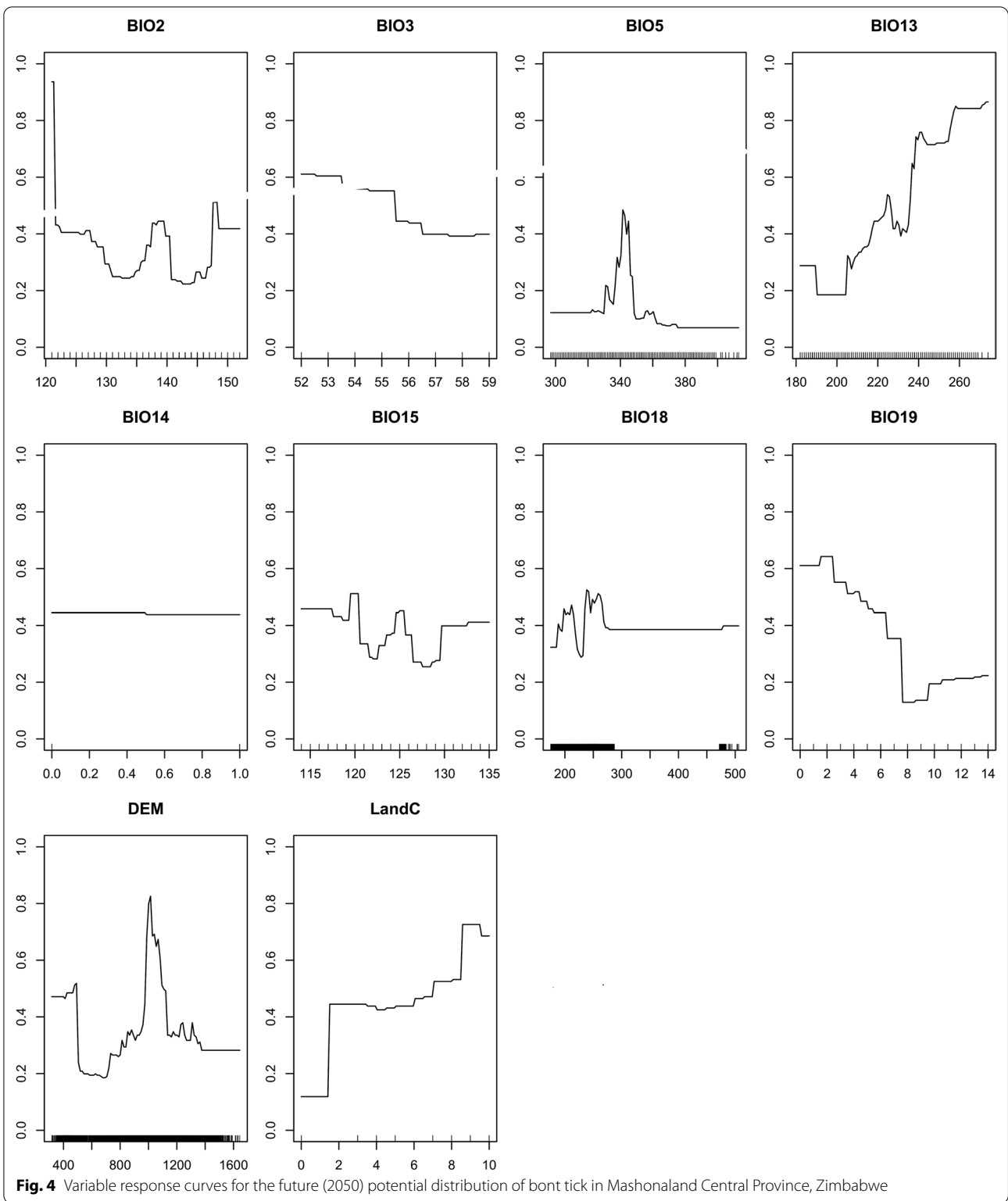


Fig. 2 Binary maps of **a** current (2018) and **b** future (2050) potential distribution of bont tick in Mashonaland Central Province, Zimbabwe





Current studies and literature suggest land cover-land use as one of the essential factors in predicting the potential distribution of tick species [1, 2]. However, in our models, land cover and land use were not essential in explaining the potential distribution of bont tick for present and future predictions. Therefore, we speculate that land use and land cover change in our study area is insignificant to influence the spatial distribution of the bont tick.

The response of probability of the presence of the bont tick against the covariates for the present and the future models had very few differences. The models showed an increase in temperature (BIO5) leading to a decrease in the probability of bont tick present, with high sensitivity at around 26 °C to 29 °C (Figs. 3 and 4). Analysis of the elevation response curve showed high sensitivity response at moderate elevation (Fig. 3), with increases in altitude leading to a low probability of bont tick presence. Since elevation and temperature are related directly, the exact mechanisms of the saturation deficit suggested by Herrmann and Gern [37] could apply.

The weakness of our study is onefold. Using only cattle controlling points for the tick presence data technically excludes ticks not attached to cattle in the study. Future researchers could improve the modelling process by using other data collection methods with more comprehensive sample coverage than our study. However, our results are useful because of two major strengths of our approach. The first strength is our use of authenticated bioclimatic variables that have global spatial coverage. Thus, the variables are available to other scientists to validate our findings [38]. Second, our models maintain high validity and reliability by using the Ensemble model, which extracted the best of eight models [39]. As such, the results of our study are essential in informing programmes that seek to control the bont tick in Mashonaland Central Province, Zimbabwe, and similar environments.

Conclusion

We successfully evaluated the association between environmental variables and bont tick occurrences in Mashonaland Central Province, Zimbabwe. We observed that the most critical environmental covariates which drive bont tick distribution are temperature, rainfall and elevation. We also successfully predicted both present (2018) and future (2050) bont tick potential habitat and observed that there would be a huge reduction of the potential habitat of the ticks by 2050. The study, however, could not include other tick host species in the modelling process; neither was it able to include tick samples outside tick control points. Therefore, we recommend considering tick data in all species that offer a host to bont tick as well as considering the abundance of those species

in future work. This study provides baseline information for long-term tick eradication programmes.

Acknowledgements

We are grateful to the Veterinary extension officers who collected ticks at all the cattle dipping facilities in Mashonaland Central Province, Zimbabwe, and identified the ticks to species level. We are also thankful to the Department of Veterinary Services for sharing their data with the authors and allowing the data and the study to be published.

Author contributions

PT and MN conceived and designed research, ran the models and wrote the manuscript. WC reviewed the manuscript. All authors read and approved the final manuscript.

Funding

This study did not receive any funding.

Availability of data and materials

The *Amblyomma hebraeum* presence only raw data used in the study is published at https://figshare.com/articles/dataset/Climate_change_diminishes_the_potential_habitat_of_the_bont_tick_Amblyomma_hebraeum_evidence_from_Mashonaland_Central_Province_Zimbabwe_Raw_data/19816729.

Declarations

Ethics approval and consent to participate

This study did not require ethical approval.

Consent for publication

All authors read and approved the manuscript and approved it for publication.

Competing interests

The three authors have no conflict of interest regarding this manuscript.

Author details

¹Department of Geography, Geospatial Sciences and Earth Observation, University of Zimbabwe, 630 Churchill Road, Harare, Zimbabwe. ²Department of Veterinary Services, 1327 Atherstone Road, Bindura, Zimbabwe.

Received: 13 September 2021 Accepted: 30 May 2022

Published online: 28 June 2022

References

1. Watt G, Parola P. Scrub typhus and tropical rickettsioses. *Curr Opin Infect Dis.* 2003;16:429–36.
2. Dantas-Torres F. Biology and ecology of the brown dog tick, *Rhipicephalus sanguineus*. *Parasites Vectors.* 2010;3:26.
3. Dabasa G, Zewdei W, Shanko T, Jilo K, Gurmesa G, Lolo G. Composition, prevalence and abundance of Ixodid cattle ticks at Ethio-Kenyan Border, Dillo district of Borana Zone, southern Ethiopia. *J Vet Med Anim Health.* 2017;9:204–12.
4. Sands AF, Apanaskevich DA, Matthee S, Horak IG, Matthee CA. The effect of host vicariance and parasite life history on the dispersal of the multi-host ectoparasite, *Hyalomma truncatum*. *J Biogeogr.* 2017;44:1124–36.
5. Ribeiro JM, Anderson JM, Manoukis NC, Meng Z, Francischetti IM. A further insight into the sialome of the tropical bont tick, *Amblyomma variegatum*. *BMC Genom.* 2011;12:1–11.
6. Randolph S. The impact of tick ecology on pathogen transmission dynamics. In: Bowman AS, Nuttall PA, editors. *Ticks: biology, disease and control*. Cambridge: Cambridge University Press; 2008. p. 40–72.
7. Kearney M, Phillips BL, Tracy CR, Christian KA, Betts G, Porter WP. Modelling species distributions without using species distributions: the cane toad in Australia under current and future climates. *Ecography.* 2008;31:423–34.
8. Otranto D, Wall R. New strategies for the control of arthropod vectors of disease in dogs and cats. *MUVE.* 2008;22:291–302.

9. Lambin EF, Tran A, Vanwambeke SO, Linard C, Soti V. Pathogenic landscapes: interactions between land, people, disease vectors, and their animal hosts. *Int J Health Geogr.* 2010;9:54.
10. Ehrmann S, Liira J, Gärtner S, Hansen K, Brunet J, Cousins SA, et al. Environmental drivers of *Ixodes ricinus* abundance in forest fragments of rural European landscapes. *BMC Ecol.* 2017;17:1–14.
11. Foti R, Nyakudya I, Moyo M, Chikuvire J, Mlambo N. Determinants of farmer demand for fee-for-service extension in Zimbabwe: the case of Mashonaland Central province. *J Agric Educ Ext.* 2007;14:95–104.
12. Vincent V, Thomas R. An agroecological survey of southern Rhodesia part 1: agro-ecological survey: government printers, Salisbury. 1960.
13. Njaya T, Mazuru N. Emerging new farming practices and their impact on the management of woodlots in A1 resettlement areas of Mashonaland Central Province in Zimbabwe. *ADPR.* 2014;2:1–19.
14. Sungirai M, Baron S, Moyo DZ, De Clercq P, Maritz-Olivier C, Madder M. Genotyping acaricide resistance profiles of *Rhipicephalus microplus* tick populations from communal land areas of Zimbabwe. *Ticks Tick Borne Dis.* 2018;9:2–9.
15. Norval R. Tick infestations and tick-borne diseases in Zimbabwe Rhodesia. *J S Afr Vet Assoc.* 1979;50:289–92.
16. Dantas-Torres F, Latrofa MS, Annoscia G, Giannelli A, Paris A, Otranto D. Morphological and genetic diversity of *Rhipicephalus sanguineus* sensu lato from the New and Old Worlds. *Parasites Vectors.* 2013;6:1–17.
17. Walke AR. Ticks of domestic animals in Africa: a guide to identification of species. Edinburgh: Bioscience Reports; 2003.
18. Mpakairi KS, Ndaimani H, Tagwireyi P, Zvidzai M, Madiri TH. Futuristic climate change scenario predicts a shrinking habitat for the African elephant *Loxodonta africana*: evidence from Hwange National Park, Zimbabwe. *Eur J Wildl Res.* 2020;66:1.
19. Blasi C, Capotorti G, Orti MMA, Anzellotti I, Attorre F, Azzella MM, et al. Ecosystem mapping for the implementation of the European biodiversity strategy at the national level: the case of Italy. *Environ Sci Policy.* 2017;78:173–84.
20. Kumar KS, Bhaskar PU, Padmakumari K. Application of land change modeler for prediction of future land use land cover: a case study of Vijayawada City. *IJATES.* 2015;3:773–83.
21. Muller MR, Middleton J. A Markov model of land-use change dynamics in the Niagara Region, Ontario, Canada. *J Landsc Ecol.* 1994;9:151–7.
22. Faundeen JL, Kanengieter RL, Buswell MD. US geological survey spatial data access. *J Geospat Eng.* 2002;42:145–145.
23. Robinson TP, Wint GW, Conchedda G, Van Boeckel TP, Ercolei V, Palamara E, et al. Mapping the global distribution of livestock. *PLoS ONE.* 2014;9:e96084.
24. Gilbert M, Nicolas G, Cinardi G, Van Boeckel TP, Vanwambeke SO, Wint GW, et al. Global distribution data for cattle, buffaloes, horses, sheep, goats, pigs, chickens and ducks in 2010. *Sci Data.* 2018;5:1–11.
25. Tagwireyi P, Wenga T, Ndaimani H, Mpakairi KS. Environmental correlates of cheetah *Acinonyx jubatus* space-use in a savanna landscape. *Afr J Wildl Res.* 2020;50:157–66.
26. R Development Core Team. R: a language environment for statistical computing. Vienna: R Foundation for Statistical Computing; 2010. <http://www.r-project.org>.
27. Thuiller W, Lafourcade B, Engler R, Araújo MB. BIOMOD—a platform for ensemble forecasting of species distributions. *Ecography.* 2009;32:369–73.
28. Ren Z, Peng H, Liu Z-W. The rapid climate change-caused dichotomy on subtropical evergreen broad-leaved forest in Yunnan: reduction in habitat diversity and increase in species diversity. *Plant Divers.* 2016;38:142–8.
29. Gomes VH, Ijff SD, Raes N, Amaral IL, Salomão RP, de Souza Coelho L, et al. Species distribution modelling: contrasting presence-only models with plot abundance data. *Sci Rep.* 2018;8:1–12.
30. Hardlife M, Henry N, Paradzayi T, Mpakairi KS, Eliah G. Predicting the invasion of a southern African savannah by the black wattle *Acacia mearnsii*. *J For Res.* 2019;31:1–9.
31. Peterson AT, Papeş M, Soberón J. Rethinking receiver operating characteristic analysis applications in ecological niche modeling. *Ecol Modell.* 2008;213:63–72.
32. Allouche O, Tsoar A, Kadmon R. Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic TSS. *J Appl Ecol.* 2006;43:1223–32.
33. Morin X, Thuiller W. Comparing niche- and process-based models to reduce prediction uncertainty in species range shifts under climate change. *J Ecol.* 2009;90:1301–13.
34. Ndaimani H, Tagwireyi P, Sebele L, Madzikanda H. An ecological paradox: the African wild dog *Lycaon pictus* is not attracted to water points when water is scarce in Hwange National Park, Zimbabwe. *PLoS ONE.* 2016;11:e0146263.
35. Gallien L, Douzet R, Pratte S, Zimmermann NE, Thuiller W. Invasive species distribution models—how violating the equilibrium assumption can create new insights. *Glob Ecol Biogeogr.* 2012;21:1126–36.
36. Gazi U, Yapar D, Karasartova D, Gureser AS, Akdogan O, Unal O, et al. The role of Treg population in pathogenesis of Crimean Congo hemorrhagic fever. *Virus Res.* 2018;250:1–6.
37. Herrmann C, Gern L. Survival of *Ixodes ricinus* (Acari: Ixodidae) under challenging conditions of temperature and humidity is influenced by *Borrelia burgdorferi* sensu lato infection. *J Med Entomol.* 2014;47:1196–204.
38. Ostfeld RS, Brunner JL. Climate change and Ixodes tick-borne diseases of humans. *Philos Trans R Soc Lond B Biol Sci.* 2015;370:20140051.
39. Eisen RJ, Eisen L, Ogden NH, Beard CB. Linkages of weather and climate with *Ixodes scapularis* and *Ixodes pacificus* (Acari: Ixodidae), enzootic transmission of *Borrelia burgdorferi*, and Lyme disease in North America. *J Med Entomol.* 2016;53:250–61.

Publisher's Note

Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Ready to submit your research? Choose BMC and benefit from:

- fast, convenient online submission
- thorough peer review by experienced researchers in your field
- rapid publication on acceptance
- support for research data, including large and complex data types
- gold Open Access which fosters wider collaboration and increased citations
- maximum visibility for your research: over 100M website views per year

At BMC, research is always in progress.

Learn more biomedcentral.com/submissions

