SUPPLEMENTARY MATERIAL

African Entomology, 2024

The Asian Citrus Psyllid (*Diaphorina citri*) in Africa: using MaxEnt to predict current and future climatic suitability, with a focus on potential invasion routes

C.J.M. van Steenderen*, E.V. Mauda, W. Kirkman, K.T. Faulkner and G.F.I Sutton

*Correspondence: clarke.vansteenderen@ru.ac.za

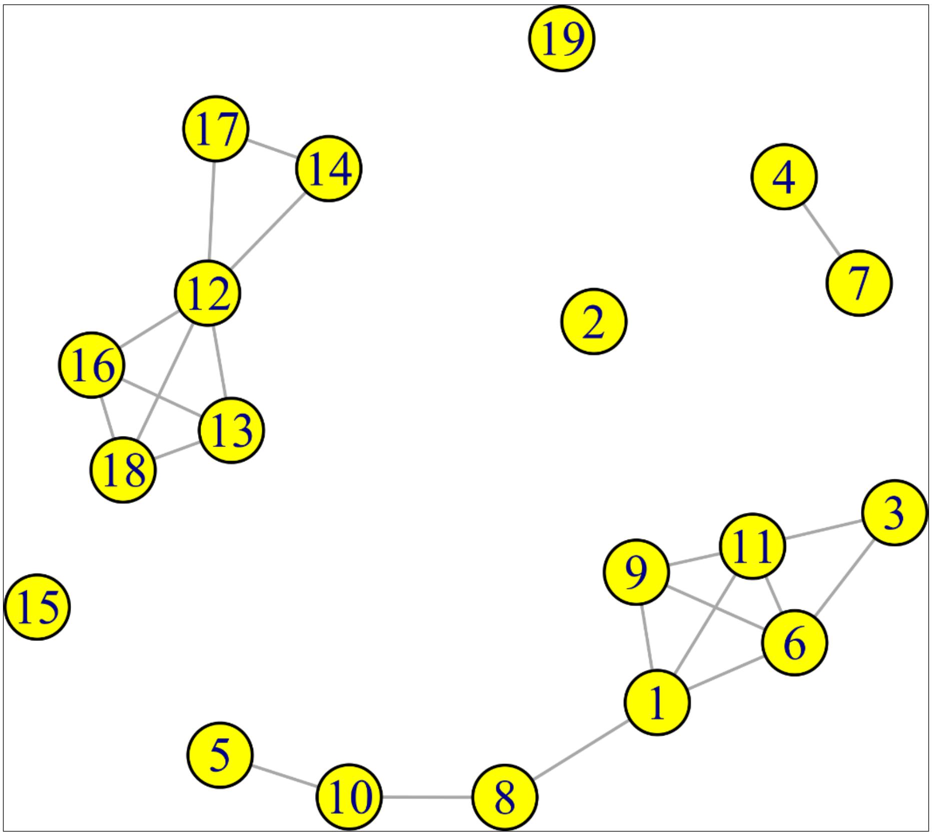

Figure S1: A correlation network (Pearson's test) exploring the relationship between all 19 climatic variables. Correlations ≤ 0.7 were retained.

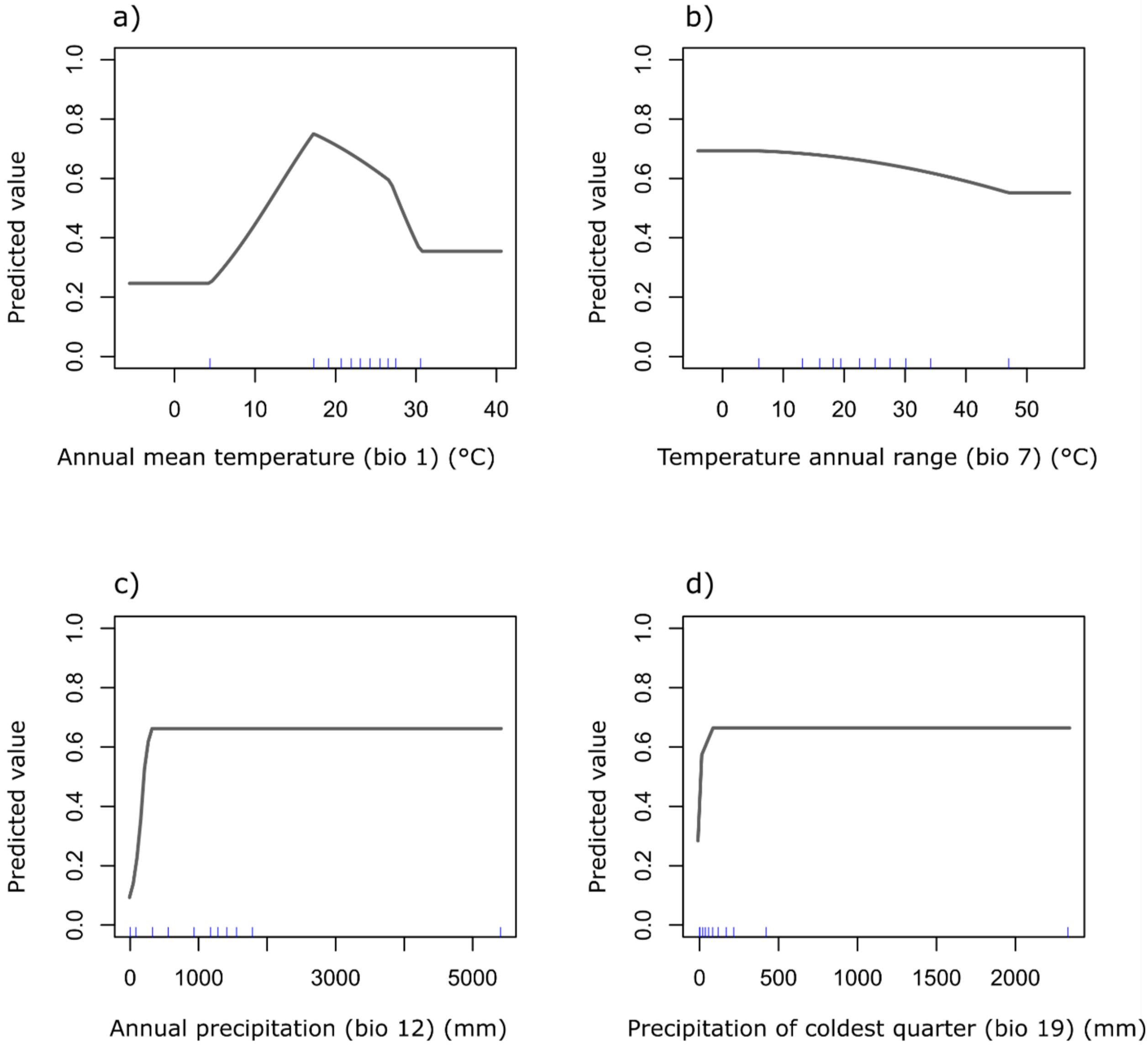

Figure S2: Response plots for retained individual predictor variables, namely a) annual mean temperature, b) annual temperature range, c) annual precipitation, and d) precipitation of the coldest quarter. Error bars not shown.

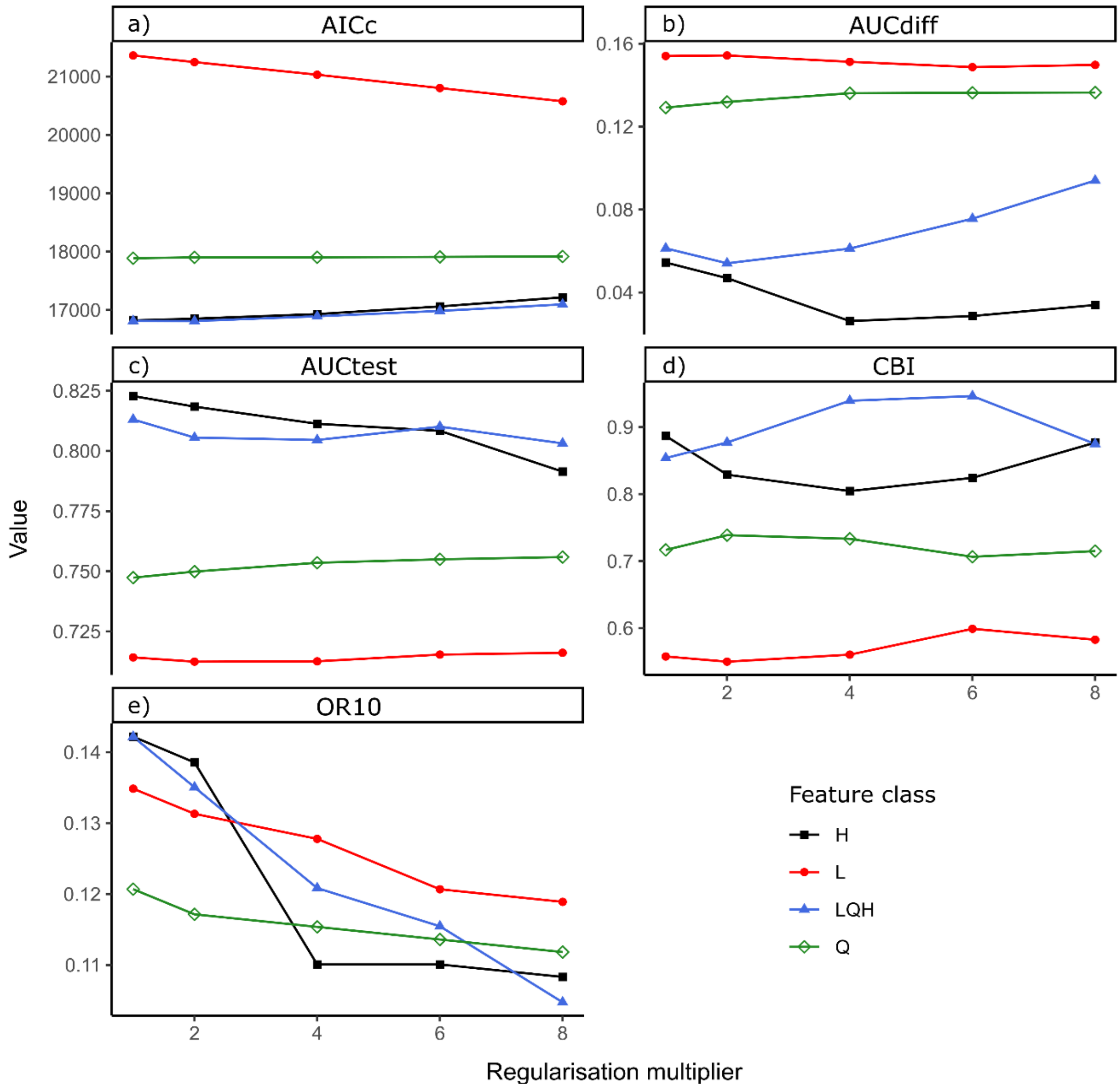

Figure S3: Model tuning experiments to determine the optimal MaxEnt configuration settings for *Diaphorina citri* climatic predictive models. Tuning was performed over a range of regularization multipliers (1 – 8) and feature classes (H, L, LQH, and Q, where H = Hinge, L = Linear, and Q = Quadratic). Model performance was assessed based on a variety of metrics, namely a) parsimony (AICc); lowest value is best, b) overfitting (AUCdiff); lowest value is best, c) discriminatory ability (AUCtest); highest value is best, d) Continuous Boyce Index (CBI); values closest to 1 are best, and e) omission rates (OR10); values closest to 0.10 are best.

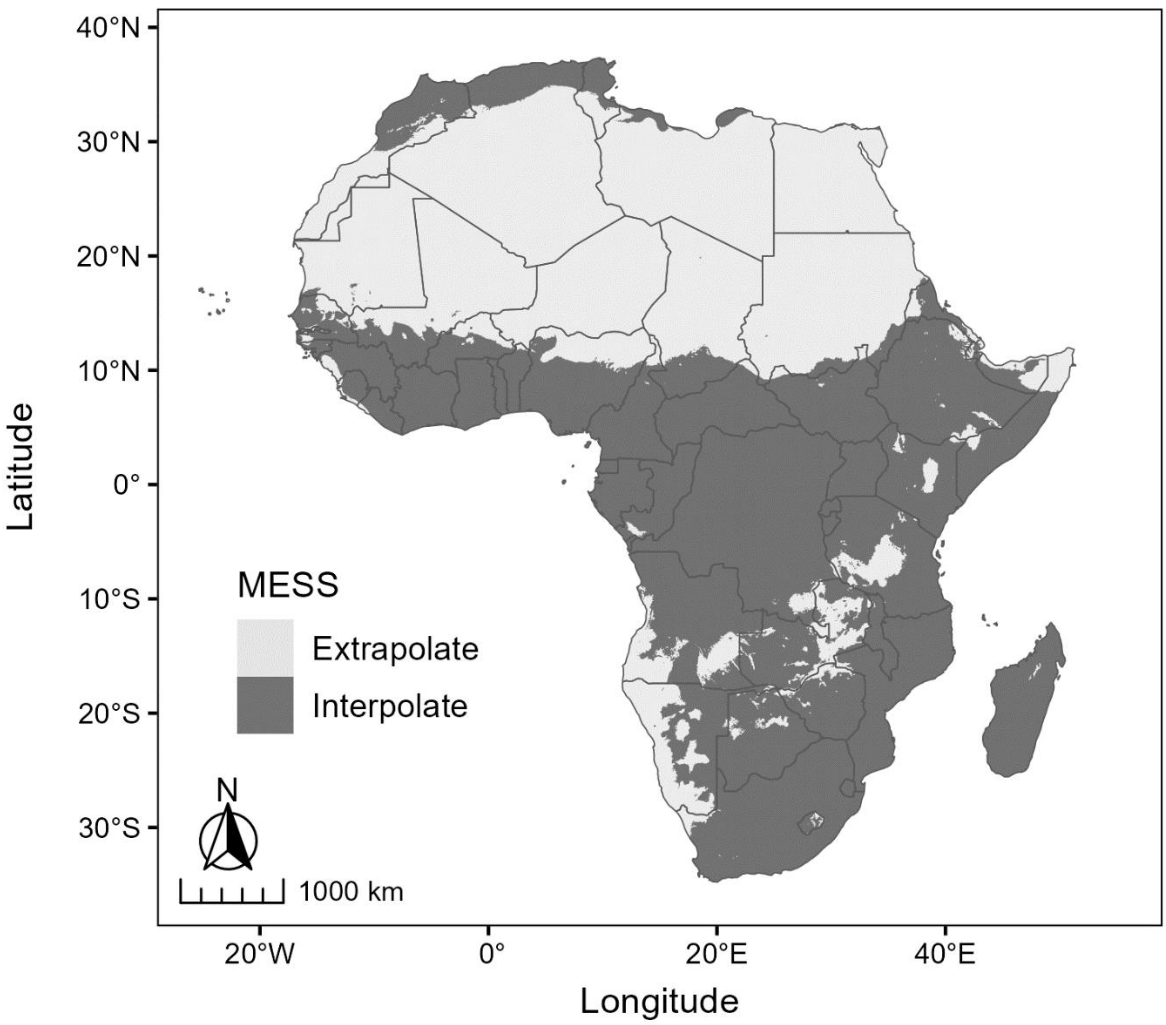

Figure S4: Multivariate Environmental Similarity Surfaces (MESS) map for *Diaphorina citri*, showing areas of interpolation (MESS+; dark grey) and extrapolation (MESS-; light grey) under current climatic conditions.

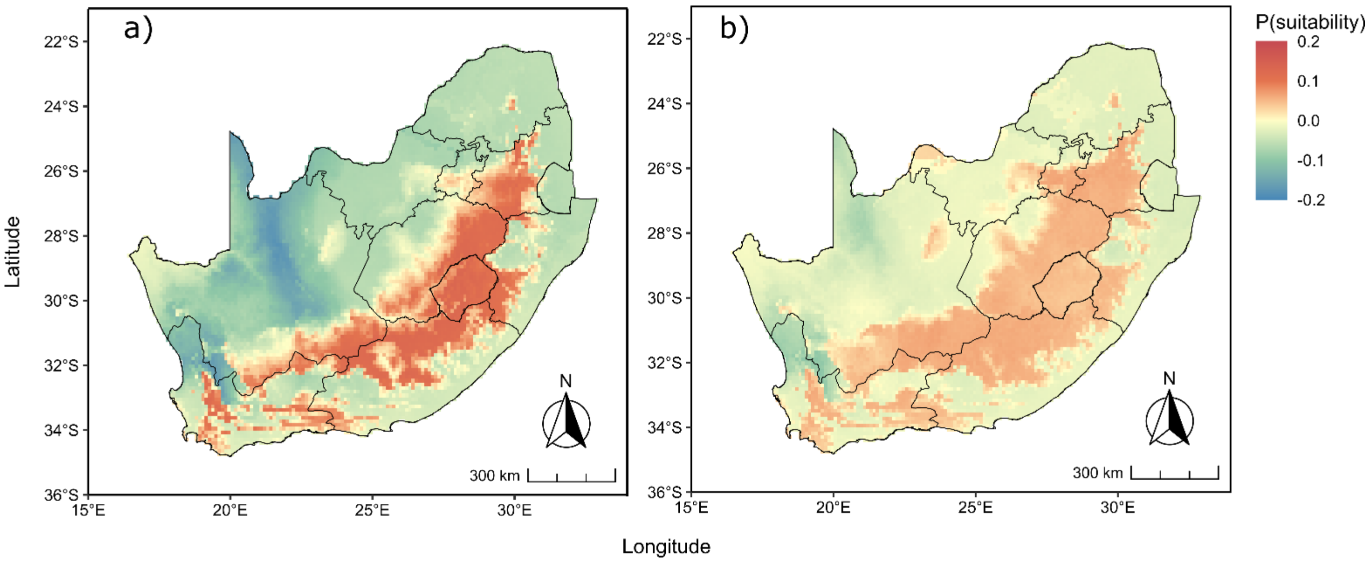

Figure S5: Predicted changes in climatic suitability between the current year and that predicted for 2070 under the scenarios a) RCP4.5 and b) RCP8.5. Note the relatively higher increase in suitability under the moderate climate change scenario in panel a).

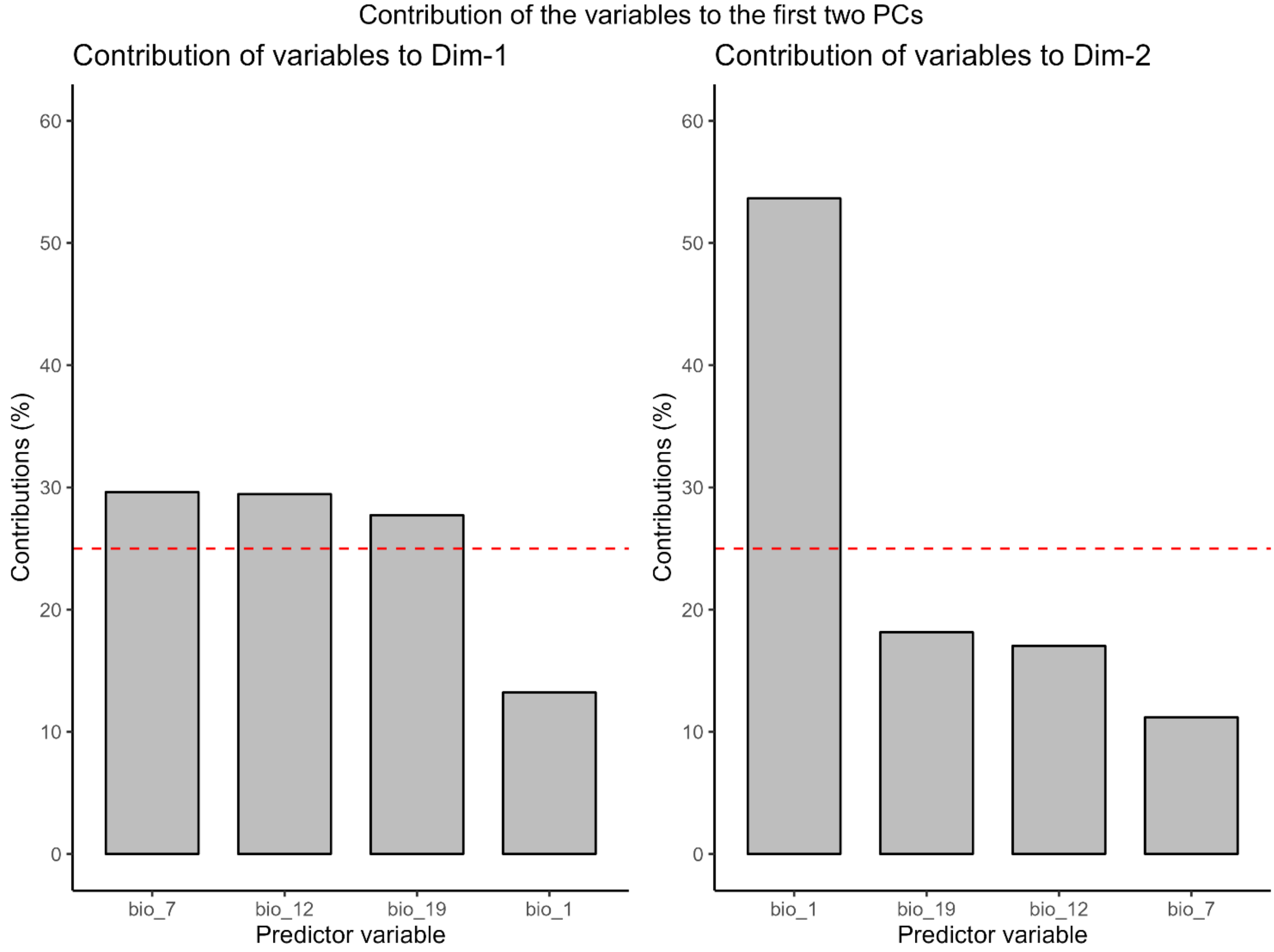

Figure S6: The percentage contribution of each predictor variable, used in the final MaxEnt models, to the principal component analysis (PCA). Principal components 1 and 2 are shown. The dotted line denotes the 25% mark.

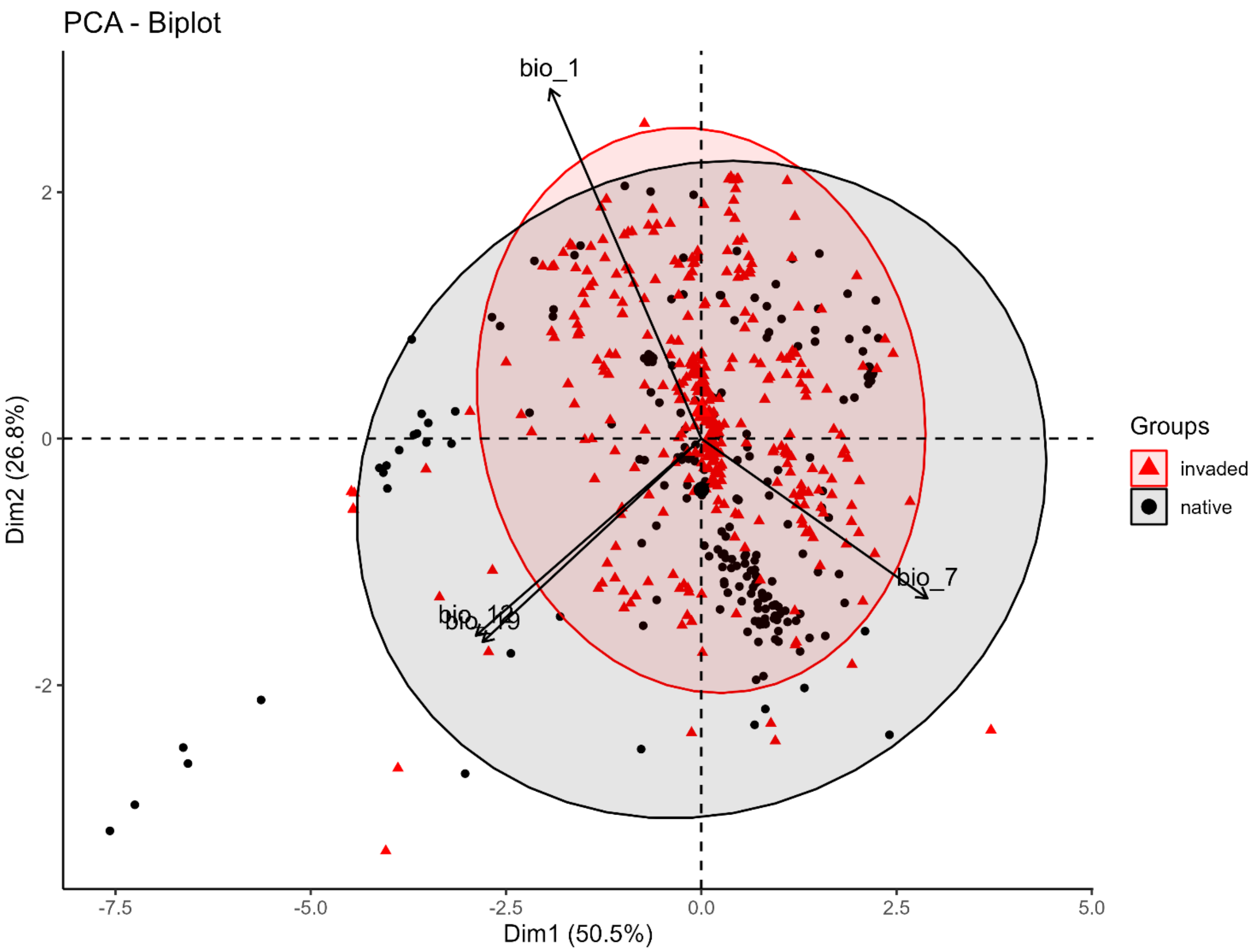

Figure S7: The results of the Principal component analysis (PCA), showing the first two components. Points are coloured according to invasive (red triangles) and native (black circles) distribution records. The loadings of each predictor variable are shown as black arrows on the plot.

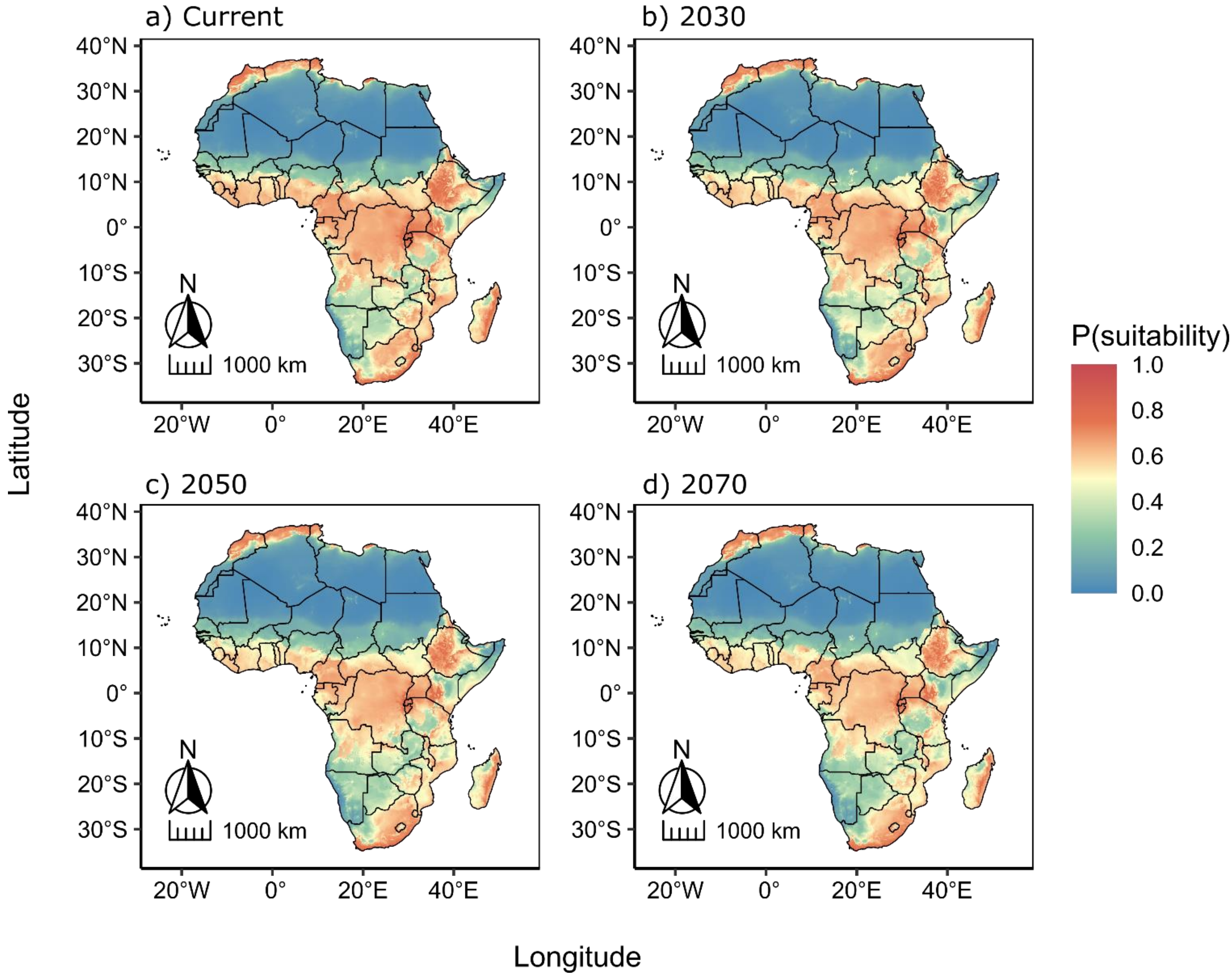

Figure S8: a) Current and b – d) future climate predictions for Africa, showing the similarity in output across the time points.

Supplementary Tables

Table S1: Excel file with all GPS occurrence data.

Table S2: Excel file with MaxEnt results, including the percentage contributions of each climatic predictor variable to the model.

Table S3: A summary of MaxEnt metrics for the optimal and default models explored.

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Parameter	Definition	Optimal value	FC = LQH; RM = 6	Default
Akaike Information Criterion corrected for small sample sizes (AIC_c)	Overall parsimony: this metric assesses model complexity and goodness of fit	Lowest AIC_c value (Kass et al., 2021)	16984.4	16812.6
Area under the curve using test data (AUC_{test})	Discriminatory ability: a measure of how well the model is able to distinguish between presence and pseudo-absence points in withheld portions of the data ('test' subset)	High. AUC < 0.8 = poor, AUC between 0.8 and 0.9 = fair, AUC between 0.9 and 0.995 = good, and AUC > 0.995 = excellent (Fielding and Bell, 1997)	0.81 ± 0.07	0.81 ± 0.05
Area under the curve difference (AUC_{diff})	Overfitting: the difference between the AUC values calculated on the training and test data	Low. Higher values indicate that the model is overfitting on the training data (Warren and Seifert, 2011)	0.076 ± 0.06	0.06 ± 0.03
Continuous Boyce Index (CBI_{test})	Discriminatory ability: the continuous Boyce Index uses presence-only data, and is a measure of how well model predictions differ from random expectations	As close to +1 as possible. Values range between -1 and 1, where -1 indicates an incorrect model, 0 indicates that the model is not different to what is expected from random chance, and +1 indicates that the model can accurately predict true presences (Hirzel et al., 2006; Manzoor et al., 2018)	0.95 ± 0.04	0.85 ± 0.02
10% omission rate (OR_{10})	Discriminatory ability and overfitting: omission rates indicate the proportion of testing localities that are incorrectly predicted by the model once converted into a binary prediction.	As close to 0.10 as possible, or lower. Larger values indicate higher degrees of overfitting (Boria et al., 2014)	0.12 ± 0.14	0.14 ± 0.09