Uncertainties In The Effectiveness of Biological Control of Stem Borers Under Different Climate Change Scenarios In Eastern Africa

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Abstract

Climate change (CC) is expected to significantly affect biodiversity and ecosystem services. Adverse impacts from CC in the Global South are likely to be exacerbated by limited capacities to take adequate adaptation measures and existing developmental challenges. Insect pests today are already causing considerable yield losses in agricultural crop production in East Africa. Studies have shown that insects are strongly responding to CC by proliferation, shift in distribution or by altering their phenology, which is why an impact on agriculture can also be expected. Biological control (BC) has been proposed as an alternative measure to sustainably contain insect pests but few studies predict its efficacy under future CC. Using the species distribution modelling approach Maxent, we predict the current and future distribution of three important lepidopteran stem borer pests of maize in eastern Africa, i.e., *Busseola fusca* (Fuller, 1901), *Chilo partellus* (Swinhoe, 1885) and *Sesamia calamistis* (Hampson, 1910), and two of their parasitoids that are currently used for BC, i.e., *Cotesia flavipes* (Cameron, 1891) and *Cotesia sesamiae* (Cameron, 1906). Based on these potential distributions and data collected during household surveys with local farmers in Kenya and Tanzania, future maize yield losses are predicted for a business-as-usual scenario and a sustainable development scenario. Accordingly, we found that BC of the three stem borer pests by *C. flavipes* and *C. sesamiae* will be less effective under more severe CC resulting in a reduced ability to curb maize yield losses caused by the stem borers. These results highlight the need to adapt BC measures to future CC to maintain its potential for environmentally-friendly pest management strategies. The findings of this research are thus of particular relevance to policy makers, extension officers and farmers in the region and will aid the adaptation of smallholder agricultural practices to current and future impacts of CC.

Keywords: Kenya, Tanzania, stem borer pests, Integrated Pest Management, Species distribution modelling, Maxent

31 1. Introduction

32 Anthropogenic climate change (CC) will have substantial impacts on human-environment interactions, including the
33 provisioning of important ecosystem services (IPCC, 2014). Countries in the Global South are predicted to be more
34 exposed to the impacts of CC (Christensen et al., 2007), as they often lack the financial, institutional and human resources
35 to cope with climatic and environmental change (Abeygunawardena et al., 2009). Many African countries are particularly
36 vulnerable (WMO, 2019; Boko et al., 2007) and it is expected that the adverse effects of CC and environmental
37 degradation will significantly constrain future economic and social development of the continent (AFDB et al., 2019;
38 Baarsch et al., 2020; Boko et al., 2007) .

39 Kenya and Tanzania have achieved notable economic growth over the past decades (UN DESA, 2020; UNDP et al., 2018;
40 World Bank, 2021), which has gradually translated into improved healthcare and education (World Bank, 2021).
41 Agriculture continues to play an important role in many developing East African economies, and in particular in Kenya
42 and Tanzania where the agricultural sector contributes significantly to national GDP and constitutes a major source of
43 labor (ILO, 2021; Salami et al., 2010; World Bank, 2021). Still more than half of the working population works in the
44 agricultural sector (World Bank, 2021). In East Africa, agricultural activity is dominated by smallholder farmers (Salami
45 et al., 2010). Smallholder farmers hereby typically cultivate small plots and primarily produce for home consumption.
46 They are highly vulnerable to external shocks, such as extreme weather events, pest and disease outbreaks or market
47 fluctuations (Morton, 2007; Salami et al., 2010). Maize is an essential staple crop in sub-Saharan Africa (SSA) and the
48 most important crop in Kenya and Tanzania (IITA, 2021; FAO, 2021a). In general, agricultural productivity in Africa
49 remains significantly below the global average and is even lower than in other regions of the Global South (IFPRI, 2016;
50 Salami et al., 2010). For instance, the average maize yield in East Africa was only 1.95 tonnes per hectare (t/ha) in 2019
51 (Kenya 1.77 t/ha and Tanzania 1.65 t/ha) compared to the 5.8 t/ha globally (FAO, 2021a). Low agricultural productivity
52 is one reason why food insecurity is still a major concern in the region (FAO et al., 2020). FAO data from 2019 reveals
53 the dire situation in the region in terms of food (FAO et al., 2020). Despite some success in reducing undernourishment
54 in the early 2000s, the figures have recently started to rise again and future projections of undernourishment in East Africa
55 are worrisome such that Sustainable Development Goal (SDG) 2 by 2030 seems unlikely (FAO et al., 2020). An eminent
56 threat to agricultural production and food systems is CC (FAO et al., 2020; IPCC, 2019; Thornton et al., 2014). Increasing
57 climate variability, environmental degradation and the corresponding profound impacts on ecosystems will have direct
58 effects on agricultural production and food security in East Africa and beyond (Anyu et al., 2012; FAO et al., 2020;
59 Sundström et al., 2014). Furthermore, the forecasted continued strong demographic growth in both countries will most
60 likely exacerbate the situation (Thomas & Zuberi, 2012; UN DESA Population Division, 2019).

61 Insect pests are damaging crops and may cause considerable yield losses (De Groote, 2002; Gofitshu et al., 2017; Kfir et
62 al., 2002; Oerke, 2006; Youdeowei, 1989). Recent studies show that pest insects are sensitive to temperature and strongly

63 respond to CC (Ladányi & Horváth, 2010; Lehmann et al., 2020; Mwalusepo et al., 2015; Stange & Ayres, 2010) by
64 altering their distribution, abundance and phenology (Biber-Freudenberger et al., 2016; Godefroid et al., 2020; Lehmann
65 et al., 2020; Mwalusepo et al., 2015; Skendžić et al., 2021; Urvois et al., 2021). This will come with all the inherent
66 consequences for agricultural production and food security in East Africa and other regions of SSA leading to new
67 challenges for pest management (Biber-Freudenberger et al., 2016; Lehmann et al., 2020; Mwalusepo et al., 2015;
68 Skendžić et al., 2021). The use of synthetic pesticides for crop protection has stagnated at a low level in SSA (FAO,
69 2021b). Across SSA, pesticide-based measures for pest control are of limited relevance to most smallholder farmers,
70 which is mainly due to financial constraints, limited availability and lack of training (Kamau et al., 2018; Williamson et
71 al., 2008). However, in response to current developments in many African countries that lead to rising income, a growing
72 population, increasing food demand and changing dietary preferences, previously used traditional pest control methods
73 are likely to be progressively replaced by application of synthetic pesticides (Schreinemachers & Tipraqsa, 2012; Snyder
74 et al., 2018). Though, smallholders are often not equipped with the necessary training to adequately and efficiently apply
75 agrochemicals (Naidoo et al., 2010) and regulations on pesticide use are lenient (Haggblade et al., 2021; Karungi et al.,
76 2011). Environmental and health concerns are an increasingly visible consequence of this development (Karungi et al.,
77 2011; Negatu et al., 2021; Snyder et al., 2018; Tsimbiri et al., 2015).

78 Given that CC presumably impacts the distribution and spread of insect pests, it is likely that crop health and yields will
79 also be affected. Hence, effective, sensible and anticipatory management and mitigation approaches are ever more
80 important to minimize adverse impacts of CC on agricultural production. This will not only be essential when trying to
81 build a resilient food system that can secure nutrition for the local population in the long-term, but also with regard to
82 environmental degradation and the sustainable use of land resources. Integrated Pest Management (IPM), aiming at
83 promoting healthy crops while minimizing disruptions to the environment and ecosystems (Barzman et al., 2015), can be
84 an alternative or complementary approach to pesticide-based crop protection (Bale et al., 2008; Barzman et al., 2015).

85 One approach in IPM is biological control (BC), a long-used and effective method in the prevention and containment of
86 pest outbreaks, that uses biological agents to control harmful organisms (FAO, 2021c; Bale et al., 2008). Among the BC
87 agents, larval parasitoid species have been reported to efficiently control open-field crop pests and are also largely used
88 in the containment of stem borers (Bale et al., 2008; Cugala & Omwega, 2001; Dejen et al., 2013). However, species'
89 responses to CC differ (Ladányi & Horváth, 2010) and established interactions of species used in BC programs may be
90 disrupted (Mwalusepo et al., 2015; Skendžić et al., 2021; Thomson et al., 2010). Such climate-induced disruptions have
91 the potential to render proven BC relationships ineffective (Thomson et al., 2010). Even though a number of studies are
92 predicting the future distribution of pest species under CC (Lantschner et al., 2018), little is known about the impact of
93 CC on the distribution of important BC agents. We therefore investigate the distribution of three maize borer species in

Kenya and Tanzania in relation to the spread of their respective parasitoid BC agents used in the region to predict the future prevalence of these pests and the role of BC in reducing associated maize yield losses under different CC scenarios.

2. Materials and methods

2.1.1 Species and presence records

This study investigates the potential current and future habitat suitability and distribution of three important maize pests in East Africa, the lepidopteran stem borers *Busseola fusca* (Fuller), *Sesamia calamistis* (Hampson) (both Lepidoptera: Noctuidae), and *Chilo partellus* (Swinhoe) (Lepidoptera: Crambidae) (CABI, 2021a; De Groote, 2002; Kfir et al., 2002). *B. fusca* attacks different cereal crops, in particular maize and sorghum (CABI, 2021a; Kfir et al., 2002). It is native to Africa and widely established across the central, eastern and southern parts of the continent (CABI, 2021a). The invasive stem borer *C. partellus*, native to Asia (CABI, 2021a), is a major pest of maize, sorghum and pearl millet, but also infests other important crops (CABI, 2021a). It has a high adaptive capacity and tolerates a wide range of environmental conditions (CABI, 2021a; Mutamiswa et al., 2017). Hence, *C. partellus* is a competitive colonizer, that now is widely present across Africa, and has been reported to increasingly dominate and displace certain native African stem borer species (CABI, 2021a; Mutamiswa et al., 2017; Kfir et al., 2002). *S. calamistis* attacks maize, sorghum, pearl millet, rice, wheat and sugarcane (CABI, 2021a). Indigenous to Africa, it is widely distributed throughout 33 countries in SSA (CABI, 2021a). Despite its presence in East Africa, *S. calamistis* is of less importance there to maize production than *B. fusca* and *C. partellus* (Cugala & Omwega, 2001; Nsami et al., 2001; Tamiru et al., 2007).

We additionally predict the potential distribution of two important BC agents of stem borers, the gregarious larval endoparasitoids *Cotesia sesamiae* (Hampson) and *Cotesia flavipes* (Hampson) (both Hymenoptera: Braconidae) (CABI, 2021b). The two parasitoids are strategically used as BC agents of stem borer pests in South, Central and East Africa (Dejen et al., 2013; Kaiser et al., 2017; Overholt et al., 1997). Being native to Pakistan (CABI, 2021b), *C. flavipes* has been introduced in Kenya in 1993 as part of a BC program of *C. partellus* (Kfir et al., 2002; Omwega et al., 2006). Since, then, use of the parasitoid has been successful in controlling the spread of stem borers in many countries of SSA (Kaiser et al., 2017; Overholt et al., 1997). *C. flavipes* attacks a broad range of insect pests (CABI, 2021b), including *B. fusca* and *S. calamistis*. The endoparasitoid *C. sesamiae* is indigenous to Africa, widely distributed across SSA with only few proven records outside the continent (CABI, 2021b). Even though *C. sesamiae* is less frequently used in BC programs, it can effectively suppress the spread of different lepidopteran pests, including *C. partellus*, *B. fusca* and *S. calamistis* (CABI, 2021b; Kaiser et al., 2017).

Presence records for the five species (*B. fusca*: 477, *C. partellus*: 251, *S. calamistis*: 260, *C. flavipes*: 190, *C. sesamiae*: 190) were obtained from several sources, reflecting different levels of extent and intensity of sampling efforts. Central to our research were data from a 2018 household survey conducted by researchers from the International Centre of Insect

Physiology and Ecology (*icipe*) under the cooperative project "Adaptation for Food Security and Ecosystem Resilience in Africa" (AFERIA) of *icipe*, the University of Helsinki and the University of York. The coordinates of the surveyed households that reported species presence were used for the Species Distribution Modelling (SDM) exercise in this study. These data were complemented by occurrence points downloaded from the Global Biodiversity Information Facility (GBIF) and data obtained from *icipe*'s the "Climate Change Impacts on Ecosystem Services and Food Security in Eastern Africa" (CHIESA) project that was implemented between 2011 and 2015. Additional presence points emanated from *icipe*'s "Integrated pest management strategy to counter the threat of invasive fall armyworm to food security in eastern Africa" (FAW-IPM) project.

2.1.2 Environmental variables

All environmental variables used for the SDM were downloaded in 2.5 arc minutes resolution from WorldClim version 2.1 [Coupled Model Intercomparison Project Phase 6 (CMIP6)] (Fick & Hijmans, 2017). WorldClim provides data for 19 bioclimatic variables frequently used in SDM, which are derived from temperature and rainfall data and hence constitute biologically meaningful indicators for species distribution. The bioclimatic variables consider annual averages, extreme values and seasonality (Fick & Hijmans, 2017). Global data for the bioclimatic variables is available for past, present and future climate scenarios (Fick & Hijmans, 2017). Current bioclimatic variables are based on the averages of the years 1970–2000, whereas future bioclimatic variables are derived from extrapolations and comprise the averages of the 20-year periods 2021–2040, 2041–2060, 2061–2080 and 2081–2100 (Fick & Hijmans, 2017). Future bioclimatic data is available for different General Circulation Models (GCMs) and four Shared Socioeconomic Pathways (SSPs). Since the distribution of stem borers is altitude-dependent (Cugala & Omwega, 2001; Mwalusepo et al., 2015), elevation was included as an additional environmental variable in this study. Elevation data was also retrieved from WorldClim and is based on Shuttle Radar Topography Mission (SRTM) elevation data (Fick & Hijmans, 2017). For a description of the environmental variables used for modelling check the supplementary materials.

For the projection of the SDM onto future climatic conditions, the bioclimatic variables were downloaded for three selected GCMs (CanESM5, CNRM-CM6-1 and MIROC6) that have been found to appropriately describe future climate in East Africa. The four SSPs describe different trajectories in future global development that entail different degrees of CC adaptation and mitigation. The SSPs are furthermore linked to distinct Representative Concentration Pathways (RCPs) that determine the levels of radiative forcing that are associated with the development trajectories and largely determine the intensity of CC. Accordingly, SSP1-2.6 represents an optimistic narrative of sustainable future global development, while SSP5-8.5 illustrates the worst-case emission scenario that neglects CC adaptation and will require extensive mitigation measures (Riahi et al., 2016). Given that an insight into both, the nearer future and longer-term climatic conditions, are relevant for farmers in the region, the periods 2041–2060 and 2081–2100 were considered.

158 2.2.1 Distribution modelling approach

159 The open source software Maxent for modelling species niches and distributions is one of the most popular tools used
160 among experts. We modelled the species distribution with Maxent using the ‘kuenm’ package in R (Cobos et al., 2019).
161 Maxent applies a machine-learning technique for maximum entropy modelling (Phillips et al., 2006). It uses a collection
162 of georeferenced presence-only records of a species and a set of relevant environmental variables (Phillips et al., 2006).
163 Maxent builds a model based on the distribution of maximum entropy and a set of constraints provided by the
164 environmental variables that predicts habitat suitability for each grid cell (Phillips et al., 2006). Each cell in the study area
165 is therewith assigned a probability value between 0 and 1 that categorizes habitat suitability, with 0 indicating no habitat
166 suitability and 1 marking cells that provide a perfectly suitable habitat (Phillips et al., 2006). Maxent furthermore allows
167 to project habitat suitability onto new environments in space and time (Elith et al., 2010). The projection into different
168 geographical settings might reveal habitats where a species has not been recorded yet, whereas projection in time can
169 provide information on the potential distribution of species in the past or future, which is of particular relevance in
170 predicting the potential effects of CC on species (Franklin, 2010). For projecting species distribution onto new
171 environments, the model is trained based on a sample of presence-only points and current data of selected environmental
172 variables. Based on additional environmental data that characterize habitats in different geographic areas, or represent
173 past or future environmental conditions, the model of the current distribution can be used to forecast habitat suitability
174 elsewhere or under future environmental conditions, respectively (Phillips, 2017).

175 In this study, we model the species’ potential current and future distribution. By including three GCMs from CMIP6 we
176 account for the inherent uncertainties of climate projection modelling (Beaumont et al., 2008). Future habitat suitability
177 constitutes an ensemble average across several GCMs that was obtained by calculating mean suitability rasters according
178 to SSP and time period. The suitability maps were then converted into species distribution maps by application of four
179 selected suitability threshold levels. For each CC scenario according to SSP and time period, three habitat suitability maps
180 were calculated, one for each GCM. For each habitat suitability map, four threshold levels were applied to categorize
181 species presence or absence. As a result, 12 distribution maps were available per scenario and species, which were then
182 stacked and calculated in their sum to show areas where, based on the different GCMs and thresholds, presence of the
183 species is more or less likely.

184

185 2.2.2 Estimation of yield loss and BC efficacy

186 Using the distribution data of the three stem borer species, associated maize yield losses were calculated. Data on maize
187 yields in the study region were downloaded from the MapSPAM data center (IFPRI, 2020) (see supplementary materials).
188 Maize yield losses in the study area were quantified via data from the AFERIA household survey. A total sample of 225
189 household was surveyed out of which 208 households reported maize yield losses by *S. calamistis*, and 206 and 197 by

190 *B. fusca* and *C. Partellus*, respectively. The respondents were furthermore asked to quantify the yield losses by stem
 191 borers in percent. Based on these survey data, we calculated 95% confidence intervals (CIs) for maize yield losses, which
 192 were then used to project current and future losses by stem borers. We predicted areas with high probability of maize
 193 yield losses by stem borers by multiplying species distribution maps with a raster carrying values on maize yields and a
 194 raster of yield losses caused by them (Equ.1). Consequently, grid cells, where the stem borers are predicted to be present
 195 and the cultivation of maize overlap are identified as areas with potential yield losses by the pests.

$$Y_{c,p} = A_{c,p} * M_c * L_p$$

(Equation 1)

198 where $Y_{c,p}$ represents yield losses (kg/ha) for each grid cell c and each stem borer species p , $A_{c,p} = \{1,0\}$ indicates each
 199 stem borer species' presence or absence for each grid cell, M_c indicates maize yield (kg/ha) for each cell and L_p
 200 representing estimated yield losses by each stem borer (%). Furthermore, we predicted the current and future potential of
 201 using the parasitoids *C. flavipes* and *C. sesamiae* to control the pests and thereby reduce maize yield losses. As part of
 202 the AFERIA household survey respondents were asked for the potential of using the parasitoids to reduce maize yield
 203 losses caused by the respective stem borer species. Reduction potential was ranked by the respondents according to three
 204 different rank categories with rank 1: low (0–25%), rank 2: medium (25–75%) and rank 3: high (75–100%). For the
 205 calculation of the reduction potential, we used the mean value for each of the ranks, i.e., rank 1: 12.5%, rank 2: 50% and
 206 rank 3: 87.5%. We calculated the 95% CI on maize yield loss reduction to project current and future loss reduction
 207 potential by the two parasitoid species. We furthermore calculated the potential reduction of maize yield losses when
 208 using *C. flavipes* and *C. sesamiae* by multiplying the binary range maps of the natural enemy species with the maize yield
 209 loss and the reduction potential (Equ.2). Accordingly, areas where presence of each parasitoid species overlaps with areas
 210 where maize yield losses by the stem borer pests occur were identified and yield loss reduction was calculated as follows:

$$R_{c,e} = B_{c,e} * Y_{c,p} * P_e$$

(Equation 2)

213 where $R_{c,e}$ represents the potential reduction of yield losses (kg/ha) for each grid cell c by natural enemy e , $B_{c,e} = \{1,0\}$
 214 indicates parasitoid presence or absence for each grid cell, $Y_{c,p}$ indicates maize yield losses (kg/ha) and P_e represents
 215 estimated potential yield losses reduction by the parasitoids (%).

216

217 2.2.3 Sampling bias

218 The presence points used for this research have to a large extent been collected within the scope of studies conducted in
 219 Kenya and Tanzania. However, it is not known whether the concentration of presence records can be attributed to more
 220 favorable environmental conditions and hence greater habitat suitability for the species, or whether this agglomeration of

221 presence points might be due to greater sampling efforts. Geographical bias of occurrence data may, however, result in
222 low quality models (Phillips et al., 2009) and incorrect predictions of species distribution (Fourcade et al., 2014). In order
223 to account for the potentially misleading uneven geographical distribution of the presence records used in SDM, a bias
224 file was constructed. A sample of more than 700,000 presence coordinates of different insect species (Phillips et al., 2009)
225 recorded on the African continent was downloaded from GBIF. Based on these records, a kernel density estimate map
226 was constructed using the ‘MASS’ package in R and used to correct for potential sampling bias in the modelling process
227 (compare Biber-Freudenberger et al., 2016; Fourcade et al., 2014).

228

229 **2.2.4 Model calibration and best model selection**

230 Apart from the inputs required to run Maxent, a wide variety of parameter settings can be individually adjusted by the
231 user to build the best-performing model. For almost all parameters in-built default settings have been validated by the
232 developers of the software over a wide range of models. However, Morales et al. (2017) and Merow et al. (2013) indicate
233 that the adoption of Maxent’s default settings may not necessarily produce the optimal model to predict species
234 distribution. According to Radosavljevic and Anderson (2014) the individual tuning of setting parameters for each species
235 can lead to better performing models. In order to find the best-performing model for predicting habitat suitability for the
236 species under current environmental conditions, we calibrated multiple models with different settings and inputs using
237 the ‘kuenm’ package in R (Cobos et al., 2019) that allows for automated detailed model calibration and hence robust
238 selection of the best-performing model (Cobos et al., 2019). Accordingly, for each species 279 models were calibrated
239 using different sets of environmental variables (Set1: 19 bioclimatic variables and elevation, Set2: BIO1, BIO5, BIO6,
240 BIO12, BIO13, BIO14, elevation, Set3: BIO5, BIO6, BIO13, BIO14, elevation), values for the regularization multiplier
241 (0.1, 1 and 10) and multiple combinations of feature classes (linear (l), product (p), quadratic (q), hinge (h), threshold (t)).
242 For all tested models a random sample of 66.6% of presence localities was used as training data for building the models.
243 The remaining 33.3% of the presence records was set aside for testing the models. The combination of parameters yielding
244 the best-performing model for each species was selected considering statistical significance [partial Receiver Operating
245 Characteristics (pROC)], predictive ability [omission rate (OR) at 5%] and complexity [Akaike information criterion
246 (AICc)]. The model with the best selected settings in Maxent was used for modelling (see supplementary materials).

247

248 **3. Results**

249 **3.1 Habitat suitability under current and future climatic conditions**

250 The mean Area under the ROC Curve (AUC) values of training data for all five species over 15 replicate models runs are
251 above 0.98 (supplementary materials) and hence confirm excellent performance of our models.

252 The probability of habitat suitability was modelled for each species for current climatic conditions and different CC
253 scenarios. Current habitat suitability in the study area and predicted future suitability for the period 2081–2100 are shown
254 in Fig. 1. The optimistic scenario SSP1-2.6 that describes sustainable global development with low challenges in
255 mitigation and adaption is contrasted with the worst-case scenario SSP5-8.5 to demonstrate the changes in suitable
256 habitats according to two opposing scenario pathways (results for SSP2-4.5 and SSP3-7.0, as well as for all scenarios in
257 2041–2060 available in supplementary materials). Under current climatic conditions, high suitability for *B. fusca* is
258 predicted in the border areas of Kenya and Tanzania but is forecasted to decline under both projected pathway scenarios.
259 While under SSP1-2.6 habitat suitability is predicted to decrease only in areas with currently very high suitability, in
260 scenario SSP5-8.5 habitat suitability declines at a significantly higher rate and across the whole study region. Regions
261 that are now highly suitable are predicted to become largely unsuitable for the stem borer under this scenario. It is therefore
262 to be expected, that under more severe CC the associated changes in habitat suitability will have considerable adverse
263 effects on *B. fusca*. A similar observation can be made from the projections of habitat suitability for *S. calamistis*. At
264 present, the border regions of both countries show relatively high habitat suitability, which is predicted to decline in the
265 future under both SSPs. However, in case of SSP5-8.5 the decline in habitat suitability is dramatic for the period 2081–
266 2100, indicating that habitat, which is currently highly suitable, will become largely unsuitable. Furthermore, overall
267 habitat suitability in the study area will decrease remarkably and areas providing suitable habitats for *S. calamistis* will
268 be restricted to only a few scattered localities. Current and predicted future habitat suitability for *B. fusca* and *S. calamistis*
269 is noticeably lower than for the invasive *C. partellus*, reflecting the greater tolerance for a wide range of environmental
270 conditions and high adaptability of the latter species that also facilitates its successful invasion into new environments.
271 Current probability of habitat suitability for *C. partellus* is high to very high across large areas of the study region. Yet
272 also this invasive stem borer is predicted to be impacted by changing future climate under the shown SSPs. While for
273 SSP1-2.6 areas with very high habitat suitability are forecasted to slightly decrease, these are predicted to be considerably
274 reduced under scenario SSP5-8.5. Hence, also for *C. partellus* habitat suitability is likely to be more adversely impacted
275 under more severe CC. Habitat suitability for the natural enemies *C. flavipes* and *C. sesamiae* is also predicted to decline
276 in the future under both SSPs. This decline is, however, less pronounced under SSP1-2.6. Areas of currently very high
277 suitability for *C. flavipes* will shrink. For SSP5-8.5 in 2081–2100 areas that are highly suitable at present will become
278 unsuitable, while regions of medium suitability will establish in northwestern Kenya. Currently there is only limited
279 habitat suitability for the native *C. sesamiae* concentrating in the border region of Kenya and Tanzania. However,
280 suitability is predicted to further decline for the considered time period and both SSPs. Under the pessimistic scenario
281 SSP5-8.5 only a few scattered regions of medium suitability will remain. Accordingly, under severe CC large parts of the
282 study region are predicted to become unsuitable for *C. sesamiae*. Furthermore, habitat suitability for the native species *B.*

283 *fusca*, *S. calamistis* and *C. sesamiae* will be more adversely impacted by severe CC than for the non-native ones, i.e., *C.*
284 *partellus* and *C. flavipes*.

285

286 **Fig. 1** Probability of habitat suitability under current climatic conditions and in 2081–2100 for SSP1-2.6 and SSP5-8.5
287 calculated as multi-model average from GCMs CanESM5, CNRM-CM6-1 and MIROC6. Probability of habitat suitability
288 ranges between 0 (low probability of suitable habitat) and 1 (perfectly suitable habitat). Grid cells with great suitability
289 carry high probability values and are displayed in dark red, whereas cells with low suitability show low probability values
290 and are colored in lighter red and white

291

292 In this study different suitability threshold levels were selected (Balance training omission, predicted area and threshold
293 values Cloglog threshold (thereafter bto), Maximum training sensitivity plus specificity Cloglog threshold (mtss), Equal
294 training sensitivity and specificity Cloglog threshold (etss), 10th percentile training presence Cloglog threshold (tp)) to
295 convert habitat suitability maps into binary species range maps (for specific values see supplementary materials).
296 Selection of several threshold values has advantages over application of a single threshold, as it considers the inherent
297 uncertainties.

298 The potential distribution of the stem borer and parasitoid species under current climatic conditions, as well as for the CC
299 scenarios SSP1-2.6 and SSP5-8.5 in 2081–2100 varies significantly (Fig. 2). Among the stem borers the invasive *C.*
300 *partellus* is predicted to be currently most widely distributed, whereas distribution of the native stem borers concentrates
301 around the border area of the study region. The modelled current distribution of the parasitoids is less widespread than
302 for the stem borers. Under future CC the distribution of all five species is predicted to slightly shift or decrease for SSP1-
303 2.6. Areas that currently show high likelihood of species presence are less likely to inhabit them in the future. For SSP5-
304 8.5 a significant reduction in the distribution of all five species is forecasted. Under the worst-case scenario, *C. sesamiae*
305 becomes extremely rare in the study region, while the distribution of *C. flavipes* will shift towards northwestern Kenya.
306 The predicted presence of the stem borer species is reduced across the entire study area

307

308 **Fig. 2** Sum of 4 binary range maps (current distribution) and 12 binary range maps (future distribution) obtained by
309 application of 4 threshold levels, with each binary layer showing either species presence (1) or absence (0). Predicted
310 species distribution under current climatic conditions and for pathways SSP1-2.6 and SSP5-8.5 for period 2081–2100.
311 Grid cells where predicted species presence is likely are colored in red and orange, whereas grid cells where presence is
312 less likely are colored in blue

313

3.2 Pest impact on maize yields

We calculated 95% CIs of maize yield losses for each stem borer based on the household survey data. With an average loss of 28.72%, [95% CI 26.65, 30.79], yield losses by *C. partellus* are highest, followed by *B. fusca* with an average loss of 27.86%, [95 % CI 25.77, 29.96], and *S. calamistis* with 27.25%, [95% CI 24.9, 29.59]. Predicted mean current and future yield losses by the three stem borers shown as mean value and for suitability threshold level bto (Fig. 3) (for minimum and maximum losses, as well as losses for SSP2-4.5 and SSP3-7.0, time period 2041–2060 and thresholds mtss, etss and tp see supplementary materials). Compared to current levels, maize losses are predicted to slightly decrease for *B. fusca* in SSP1-2.6, while remaining relatively stable for *C. partellus* and *S. calamistis*. Yield losses by all three species are predicted to decrease significantly until 2081–2100 under pathway SSP5-8.5. This decrease can be attributed to the notable decline in habitat suitability (Fig. 1), which is projected to result in reduced future species presence in the study area (Fig. 2). Hence, maize yield losses associated with the stem borer species are expected to decline under more severe CC, while remaining at a higher level for SSP1-2.6. Nevertheless, the degree of yield losses largely depends of the suitability threshold applied (see supplementary materials), with bto showing a remarkably larger area of predicted yield losses.

Fig. 3 Predicted mean maize yield losses (in kg/ha) by the stem borers *B. fusca*, *C. partellus* and *S. calamistis* under current climatic conditions and in 2081–2100 for SSP1-2.6 and SSP5-8.5 for suitability threshold bto. Grid cells with high predicted yield losses are colored in darker orange to brown, whereas cells where maize yield losses by the species are low are colored in lighter orange and white

3.3 Future role of BC in reducing maize yield losses by stem borers

Based on the household survey data, *C. flavipes* is with 53.68% [95% CI 50.2, 57.16], slightly more effective than *C. sesamiae* with 51.39% [95% CI 47.84, 54.93] in reducing yield losses by stem borers. The potential of using the natural enemies *C. flavipes* and *C. sesamiae* to reduce maize yield losses caused by the stem borer species varies depending on the two scenarios SSP1-2.6 and SSP5-8.5 in 2081–2100 (Figs. 4 and 5) (for minimum and maximum reduction potential, as well as possible reduction of yield losses by BC for SSP2-4.5 and SSP3-7.0, time period 2041–2060 and thresholds mtss, etss and tp see supplementary materials). In general, *C. flavipes* has a greater potential to reduce *B. fusca* maize yield losses than *C. sesamiae*. Yet, its potential to reduce losses by *B. fusca* is predicted to decline for both developmental pathways, especially in SSP5-8.5. Furthermore, *C. flavipes* is predicted to be more effective in reducing maize yield losses caused by the invasive *C. partellus* than *C. sesamiae*. For both BC agents the potential to reduce maize yield losses by *C. partellus* is predicted to decline. Whereas SSP1-2.6 entails a less significant decrease, the worst-case scenario SSP5-8.5 is predicted to result in a remarkably lower reduction potential. The same is true for containing maize yield losses caused

346 by *S. calamistis*; here also *C. flavipes* shows a higher reduction potential. However, areas in which stem borer-caused
347 maize yield losses can be reduced by BC with the two parasitoids are predicted to decline under the studied CC scenarios.
348 While the reduction potential by *C. flavipes* is predicted to be significantly reduced under SSP5-8.5, the BC potential of
349 *C. sesamiae* will have almost entirely vanished under that scenario. Analysing the predictions for the future effectiveness
350 of using the two natural enemy species to reduce maize yield losses by the three stem borers in the study region, we
351 therefore conclude that the more severe CC will be, the bigger is the decrease in the BC reduction potential of the two
352 *Cotesia* species.

353

354 **Fig. 4** Predicted mean reduction of maize yield losses (in kg/ha) by *B. fusca*, *C. partellus* and *S. calamistis* through use
355 of *C. flavipes* under current climatic conditions and in 2081–2100 for SSP1-2.6 and SSP5-8.5 for suitability threshold
356 bto. Grid cells where parasitoid application significantly reduces the amount of maize yield losses caused by the stem
357 borer are colored in darker green, whereas cells with lower predicted reduction of maize yield losses are colored in lighter
358 green and white

359

360 **Fig. 5** Predicted mean reduction of maize yield losses (in kg/ha) by *B. fusca*, *C. partellus* and *S. calamistis* through use
361 of *C. sesamiae* under current climatic conditions and in 2081–2100 for SSP1-2.6 and SSP5-8.5 for suitability threshold
362 bto. Grid cells where parasitoid application significantly reduces the amount of maize yield losses caused by the stem
363 borer are colored in darker green, whereas cells with lower predicted reduction of maize yield losses are colored in lighter
364 green and white

365

366 4. Discussion and conclusions

367 The three studied maize stem borers and their two associated larval parasitoids are very likely to respond to CC, regardless
368 of the respective change scenario. The uncertainties inherent when making predictions on future climate and
369 environmental conditions were considered by investigating species distribution using different CC models,
370 socioeconomic pathways and time periods. Under all investigated CC scenarios habitat suitability is going to change and
371 the species are predicted to adjust their distribution. We also found that all species' future distribution strongly depends
372 on the magnitude of CC. More severe CC is predicted to cause a notable decrease in the presence of the stem borers,
373 which will result in a decline in predicted maize yield losses associated with the pests. This decline in yield losses is,
374 however, predicted to be accompanied by a decreasing potential to reduce losses caused by stem borers through the use
375 of *C. flavipes* and *C. sesamiae*. The distribution of the two natural enemies is forecasted to significantly decline under
376 severe CC, which may render established mechanisms of BC ineffective or not viable. This finding is of direct relevance

377 to farmers in the study area that control stem borers with the parasitoids, as they will likely need to adjust their pest
378 management strategies in the future.

379 For the calculation of maize yield losses, we assumed that the maize yield in the study area remains constant over time.
380 Yet, the possible introduction of improved crop varieties with higher resilience to climate variability and attack by stem
381 borers, the emergence of higher-yielding varieties or changes in productivity could affect future yields (Bänziger et al.,
382 2006; IFPRI, 2016). We also did not consider the impact of CC on maize plants and yields themselves and assume that
383 the geographic distribution of maize cultivation and yields remains constant over time, despite changing environmental
384 conditions. Though, maize plants will be affected by CC and consequently the suitability of certain regions in Africa for
385 maize production might change (Tito et al., 2018). This may eliminate maize cultivation in some areas while enabling it
386 in others (Jones & Thornton, 2003; Luhunga, 2017). The potential shift in habitat suitability for maize may create new
387 overlaps with the distribution of pests and parasitoids, which in turn impacts yields, yield losses and opportunities for BC.

388 When investigating the impact of CC on pests and agricultural crops, it is also important to determine how climate
389 variability affects the crop species. Moreover, stem borers not only damage maize but a whole range of cereal crops
390 (CABI, 2021a). Considering the potential impact of stem borers on food security, it would therefore be of great interesting
391 to investigate their relevance for other important staple crops, in particular sorghum and millet whose cultivation in the
392 region is currently pushed forward as of greater drought resilience (Burke et al., 2009; CSIRO, 2021; IFAD, 2017).

393 Other studies have also assessed the potential future distribution of pests and other species under future CC. Our findings
394 are in line with Thomson et al. (2010) outlining that CC influences interactions between herbivores and natural enemies,
395 e.g. by resulting in a mismatch in their distribution, which can reduce the effectiveness of using natural enemies for pest
396 control. Mwalusepo et al. (2015) investigated the impact of temperature change on the future distribution of maize stem
397 borers and their BC agents at a local scale along Mount Kilimanjaro and the Taita Hills of Tanzania and estimated the
398 impact on maize yields. They confirm that temperature is a key factor in determining the distribution of stem borer pests
399 and their natural enemies, corroborating results from our study. Yet, Mwalusepo et al. (2015) predict a worsening of pest
400 impact on maize production along the two mountain gradients, whereas we forecast, especially for the more distant future
401 (2081–2100), stem borer-associated maize yield losses to decline under the impact of more severe CC. Furthermore,
402 Mwalusepo et al. (2015) predict a geographical disruption in the distribution of stem borers and their natural enemies,
403 with decreased but also increased levels of BC at higher and lower altitudes, respectively. In contrast, we conclude that
404 the studied BC relationships will become less effective and even unviable under future CC. The discrepancies in the
405 findings of our study and the research by Mwalusepo et al. (2015) stem from the different modelling approaches applied
406 and inputs used. Mwalusepo et al. (2015) predict species distribution based on temperature-driven phenology models,
407 whereas our research employs a correlative method for SDM that uses maximum entropy density estimations. One
408 advantage of the latter method is that it allows to incorporate the range in potential modelling outputs by assigning habitat

409 suitability as a probability value, thereby also considering uncertainty. Furthermore, Mwalusepo et al. (2015) analyze
410 potential future species distribution according to different levels of altitude in the study area. Our study, however, included
411 elevation as homologous to the bioclimatic variables into model calibration and does not distinguish modelling outputs
412 based on elevation but draws conclusions on country level. Dynamically downscaled Regional Climate Models (RCMs),
413 as used by Mwalusepo et al. (2015), provide data at a finer resolution and capture mesoclimatic dynamics more accurately
414 which potentially results in better simulations of regional climate than coarse resolution GCMs (Beaumont et al., 2008;
415 Giorgi, 2019). In our study, we explicitly used data for the bioclimatic variables in 2.5 arc minutes resolution which is
416 based on the latest version of GCMs from CMIP6. This approach is reasonable when examining the effects of climatic
417 changes, i.e., changes in temperature and precipitation, on species distribution.

418 We focused our study at three stem borer pests and two important natural enemy species. The emergence of new pests or
419 BC agents as a result of CC was not part of this study. For instance the 2016 introduction into Africa and subsequent wide
420 spread of the neotropical fall armyworm (FAW), *Spodoptera frugiperda* (J.E. Smith) (Lepidoptera: Noctuidae) (Goergen
421 et al., 2016) initially lead to spectacular increases in maize losses and near suppression of all other lepidopteran stem
422 borer species in the FAW affected countries (Hailu et al., 2021; Sokame et al., 2021). This new pest will probably also
423 modify the expected changes in the distribution and abundance of the here modelled stem borers and their parasitoids.
424 Such developments pose new challenges for pest management that will, among others, require the adaption of BC
425 strategies. It is hence of great interest to investigate the distribution of a broader range of pests and their natural enemies
426 to obtain a more holistic picture on relevant insect pests, their impact on staple crop production and the potential of BC
427 to be able to offer more concrete advice to farmers (Biber-Freudenberger et al., 2016). We found that the invasive stem
428 borer *C. partellus* and the exotic parasitoid *C. flavipes* are and will be more widely distributed under CC, indicating that
429 they are less prone to CC. Hence, research on invasive pests and possibilities for their containment, e.g., via BC, needs to
430 be intensified. For that, modelling could be indefinitely repeated using presence data for all organisms of interest. Given
431 the low agricultural productivity in the region and the prevailing deficiencies in the food system (IFPRI, 2016), we
432 demonstrate that maize stem borers are and to a certain extend will continue to be a threat to food security in the future.
433 Therefore, effective control measures need to be applied to mitigate their proliferation and reduce associated yield losses.
434 Empowering relevant actors to anticipate changes in insect distribution triggered by CC will be essential in building a
435 more resilient food system that is less prone to external shocks (Bottrell & Schoenly, 2018).

436 We believe our results to be of high relevance for farmers, extension officers and policy makers in Kenya and Tanzania,
437 as they provide estimations not only of future pest distributions, but also of associated yield losses and the potential of
438 BC to contain these pests. Hence, this study can serve as a blueprint to identify future pests as well as their potential
439 natural enemies in East Africa and beyond, which will help farmers to adjust their farming and pest management strategies
440 to changing environmental conditions. As anticipatory and effective pest management is fundamental in reducing yield

441 losses, policy makers and extension officers could support farmers in adapting their practices to increase the resilience of
442 local agricultural systems. To our knowledge this is one of very few studies that combines the prediction of future pest
443 species distribution with the potential of BC under different CC scenarios while also considering the impact on maize,
444 which is the most relevant crop in the study area. Pesticide-based pest control measures are increasing in importance;
445 however, sustainable methods of pest control need to be promoted to avoid adverse impacts on health and the
446 environment. The examined BC relationships have been proven effective at present, but we forecasted that their potential
447 under future CC will substantially decline. Assuring the continued efficacy of BC to avoid dis-adoption, increasing
448 skepticism among farmers and turn towards synthetic pesticides, is key in building a sustainable and environmentally-
449 friendly food system. We therefore suggest an increasing consideration of pest species as well as the potential of different
450 BC strategies under varying environmental and climatic conditions.

451

452 **Supplementary materials**

- 453 1) Presence records
- 454 2) Overview presence records and sources
- 455 3) Distribution of species' presence points used for modelling
- 456 4) Description of environmental variables
- 457 5) Overview of best-performing calibrated models
- 458 6) Summary of mean of training AUC of best-performing model
- 459 7) Contribution of environmental variables to the models
- 460 8) Habitat suitability maps for all scenarios
- 461 9) Overview of suitability thresholds applied and their specific values
- 462 10) Distribution maps for all scenarios
- 463 11) Maize yields in the study area
- 464 12) Maize yield losses caused by stem borers, all scenarios
- 465 13) Potential of BC to reduce maize yield losses by stem borers, all scenarios

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Figures

Figure 1

Probability of habitat suitability under current climatic conditions and in 2081–2100 for SSP1-2.6 and SSP5-8.5 calculated as multi-model average from GCMs CanESM5, CNRM-CM6-1 and MIROC6. Probability of habitat suitability ranges between 0 (low probability of suitable habitat) and 1 (perfectly

suitable habitat). Grid cells with great suitability carry high probability values and are displayed in dark red, whereas cells with low suitability show low probability values and are colored in lighter red and white

Figure 2

Sum of 4 binary range maps (current distribution) and 12 binary range maps (future distribution) obtained by application of 4 threshold levels, with each binary layer showing either species presence (1) or absence (0). Predicted species distribution under current climatic conditions and for pathways SSP1-

2.6 and SSP5-8.5 for period 2081–2100. Grid cells where predicted species presence is likely are colored in red and orange, whereas grid cells where presence is less likely are colored in blue

Figure 3

Predicted mean maize yield losses (in kg/ha) by the stem borers *B. fusca*, *C. partellus* and *S. calamistis* under current climatic conditions and in 2081–2100 for SSP1-2.6 and SSP5-8.5 for suitability threshold bto. Grid cells with high predicted yield losses are colored in darker orange to brown, whereas cells where maize yield losses by the species are low are colored in lighter orange and white

Figure 4

Predicted mean reduction of maize yield losses (in kg/ha) by *B. fusca*, *C. partellus* and *S. calamistis* through use of *C. flavipes* under current climatic conditions and in 2081–2100 for SSP1-2.6 and SSP5-8.5 for suitability threshold bto. Grid cells where parasitoid application significantly reduces the amount of maize yield losses caused by the stem borer are colored in darker green, whereas cells with lower predicted reduction of maize yield losses are colored in lighter green and white

Figure 5

Predicted mean reduction of maize yield losses (in kg/ha) by *B. fusca*, *C. partellus* and *S. calamistis* through use of *C. sesamiae* under current climatic conditions and in 2081–2100 for SSP1-2.6 and SSP5-8.5 for suitability threshold bto. Grid cells where parasitoid application significantly reduces the amount of maize yield losses caused by the stem borer are colored in darker green, whereas cells with lower predicted reduction of maize yield losses are colored in lighter green and white

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