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Tailored climate projections to assess site-specific vulnerability of tea production

Neha Mittal[a,*], David P. Rowell[b], Andrew J. Dougill[a], Bernd Becker[b], John H. Marsham[a,c], John Bore[d], Anne Tallontire[a], Katharine Vincent[e], David Mkwambisi[f], Joseph Sang[g]

[a] School of Earth and Environment, University of Leeds, Leeds, United Kingdom
[b] Met Office Hadley Centre, Exeter, United Kingdom
[c] National Centre for Atmospheric Science, University of Leeds, Leeds, United Kingdom
[d] Tea Research Institute, Kericho, Kenya
[e] Kulima Integrated Development Solutions, Pietermaritzburg, South Africa
[f] Malawi University of Science and Technology, Limbe, Malawi
[g] Jomo Kenyatta University of Agriculture and Technology, Nairobi, Kenya

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A B S T R A C T

Tailored climate change information is essential to understand future climate risks and identify relevant adaptation strategies. However, distilling and effectively communicating decision-relevant information from climate science remains challenging. In this paper, we develop and apply an iterative stakeholder engagement approach and a Site Specific Synthesis of Projected Range (SPR), to co-produce future climate information for Africa's largest tea producing nations - Kenya and Malawi - for the mid-and late-21st century. SPR provides a novel analysis approach, which combines long-term station observations with projections from 29 global climate models and the first convection-permitting high-resolution climate projection for Africa (CP4A). This addresses the mismatch between spatial scales of projections, large-scale modelling uncertainties and stakeholder need for site-specific information. Iterative stakeholder engagement and communication helped to build trust, allowed use of new observation data and improved visualisations of climate information for stakeholders. SPR demonstrates site-specificity in changes in all metrics, showing risks of large changes in tea crop sensitive metrics. All nine locations analysed show substantial (up to four times) increases in heatwave days and large decreases in cold nights by 2050s compared to the current climate. While tea producers are already witnessing changing climatic conditions, potential future changes will greatly affect the resilience of tea production, thereby affecting the sustainability and quality of tea production in the region. Site specific climate information iteratively co-produced with stakeholders helps them to identify location-specific adaptation strategies and investment priorities, potentially safeguarding supply-chains and millions of livelihoods.

* Corresponding author.
E-mail address: n.mittal@leeds.ac.uk (N. Mittal).

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1. Introduction

Recognition of the need for climate information that is both useful and usable is developing rapidly alongside a growing literature on dealing with future climate uncertainties (Jones et al., 2015; Jones et al., 2017; Lemos et al., 2012; Nissan et al., 2019). Understanding users' decision-making contexts and tailoring climate information and its communication to their needs is crucial (Lemos et al., 2012). This is particularly relevant in developing countries where the area under perennial cash crops is rapidly expanding, contributing to export earnings, and providing livelihood to millions (Kastner et al., 2014). Longer economic life spans of these crops impose path dependencies on growers due to limited flexibility in their management, and this increases vulnerability to long-term climatic changes (Gunathilaka et al., 2018). Tailored climate information can support climate-resilient decision making that can safeguard future investments and support the sustainable development of rapidly transforming economies (Jones et al., 2015; Rippke et al., 2016). Improved understanding of climate processes at a local scale, and iterative engagement between users and providers can enable distillation and communication of decision-relevant climate information (Lourenço et al., 2015; Hewitt et al., 2017; Vincent et al., 2018).

Increasing focus on assessing future climate change impacts on cash crops like tea (Gunathilaka et al., 2018), coffee (Moat et al., 2017), cocoa (Bunn et al., 2019) and wine grapes (Wolkovich et al., 2018) reflect growing concerns amongst growers and supply chain stakeholders. However, such assessments are often framed as suitability studies, assessing whether current growing regions will remain suitable under future climate change, and identifying suitable locations for future expansion. Conversely, improved understanding of plausible future changes in decision-relevant metrics at a scale appropriate for supporting adaptation decision making is an important first step for adaptation (Conway et al., 2019). Here we focus on tea; a cash crop of global significance, that is socio-economically important for Africa's largest tea producing countries of Kenya and Malawi. An economic life span of over 100 years, and high climate sensitivity (Carr, 2018) makes this crop particularly important from a climate change perspective.

We iteratively engage tea sector stakeholders in both countries to identify preferences in the nature and spatial scale of metrics which would add to their understanding of the implications of a changing climate. We combine three distinct, yet complementary, sources of climate data to produce a Site-Specific Synthesis of the Projected Range (SPR) of future temperature and rainfall for the identified decision-relevant metrics. We use i) long-term observations, provided by the tea estates and national meteorological agencies, to physiographically contextualise future projections for each specific site, ii) the first Convection-Permitting high-resolution (4.5 km grid spacing) model for an Africa-wide domain (hereafter CP4A) (Kendon et al., 2019) to assess systematic biases that arise due to coarse models' use of parameterised convection and their lower resolution, and iii) 29 global climate models from phase 5 of the Coupled Model Intercomparison Project (CMIP5) to assess projection uncertainty due to model formulation. Results are then visualised according to communication preferences elicited during the stakeholder engagement process.

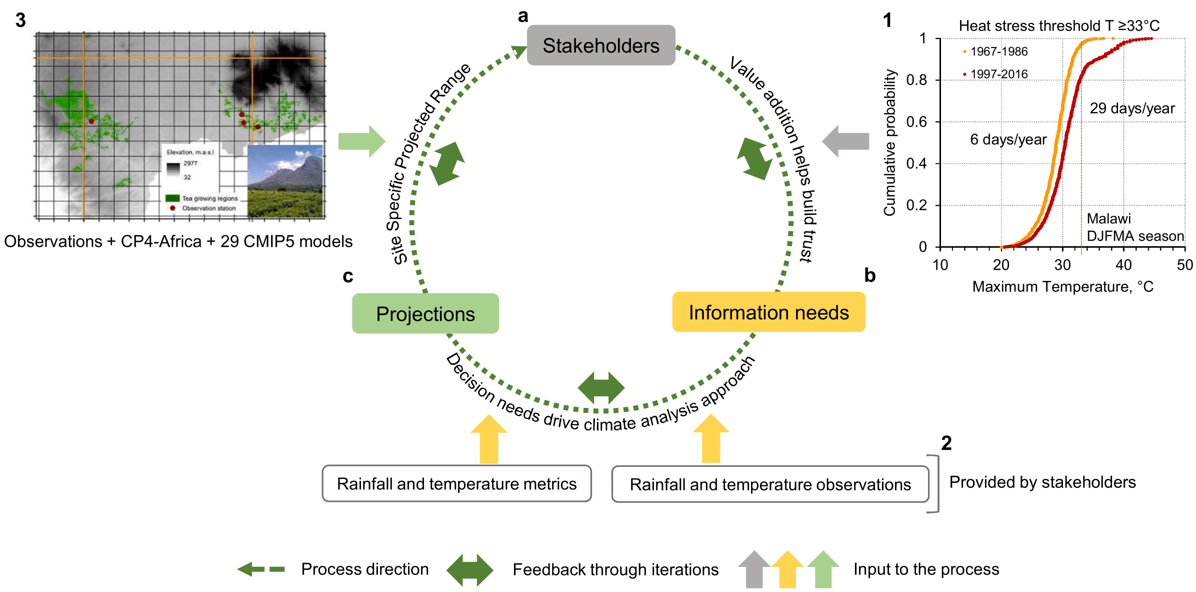

Fig. 1. Co-production process followed to tailor future climate information (here exemplified for Malawi). The green dotted line denotes the sequence of three key components in this process; a) tea-sector stakeholder engagement, b) identifying information needs of stakeholders, and c) developing projections for tea-specific decision metrics. Double-sided green arrows indicate iterative feedback between components to enhance relevance of information for stakeholders. Coloured arrows (grey, yellow and light green) are inputs to the each component of corresponding colour: 1) the visualisation of hot-day exceedance in historical climate to communicate value addition to stakeholders' understanding and build trust, 2) weather station observations provided by stakeholders and decision-relevant metrics identified by stakeholders customise future projections to stakeholders' information needs, and 3) Site Specific Synthesis of Projected Range (SPR) to communicate site-specific potential changes and associated uncertainty. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

1.1. Study area: socio-economic importance of tea for Kenya and Malawi

Kenya is the third largest tea producer and the biggest exporter of black CTC (cut tear curl) tea globally, comprising ~ 25% of world tea export. Tea contributes to ~4% of Kenya's GDP and ~22% of its export earnings. The majority (~60%) of tea is produced by ~ 700,000 smallholder farmers, a sector managed by the Kenya Tea Development Agency (KTDA). Large commercial estates contribute the remaining ~ 40%. Due to the well distributed rainfall and optimum narrow temperature range in Kenya (17–19 °C), tea is produced all year round in the counties of Kericho, Bomet, Trans-Nzoia, Kakamega, Nandi, Nyamira, Kisii and Nakuru, at an elevation of 1700–2300 meters above sea level (m.a.s.l.) in western Kenya. In recent years (2009, 2012, and 2015), incidences of drought and frost, followed by high daytime temperatures, have led to reduced yields, and in some instances mortality of tea bushes.

Malawi is the second biggest producer of tea in Africa. It contributes ~7% to Malawi's GDP and ~10% to its export earnings. The majority (~93%) of tea is produced by large commercial estates, and the remainder (~7%) is grown by ~ 18,500 smallholder farmers. ~80% of tea in Malawi is produced in the Thyolo plateau and Mount Mulanje areas in southern Malawi, at an elevation of 600–1100 m. a.s.l.. Recent incidences of reduced tea production in Malawi (2005 and 2015), due to high temperatures for consecutive days and reduced rainfall, has caused concern in the tea industry and led them to consider investments for long-term adaptation planning.

2. Methods

Fig. 1 presents a schematic of the iterative co-production process to tailor future climate information. The use of station observations provided site-specific information alongside defensible application of state-of-the-art climate science. This was enabled through the collaborative efforts of a transdisciplinary team of researchers including physical, social and natural scientists, as well as tea growers and managers with many years of experience in the industry. Tea specific climate metrics were first identified using academic literature, tea research institute reports, and observational data; and further refined by continuous engagement with in-country tea scientists and agronomists from the tea estates. Daily station observations of rainfall and temperature provided by the tea estates and the national meteorological departments are critical for bias-correcting the daily global climate model and CP4A data to produce site-specific future climate projections. These long-term station observational data were gathered through continuous engagement and trust building with the stakeholders.

Trust building was facilitated by having multiple discussions with individual and groups of tea growers, which showed how this research would add value to their decision making. For instance, we discussed changes in days when daily maximum temperature have exceeded stakeholder-defined thresholds in the observations and could exceed in the future (Supplementary Fig. 1). Stakeholders could immediately relate to the changes presented to them and see the value in further engagement to discuss their climate information needs.

2.1. Stakeholder engagement

2.1.1. Identification of stakeholders and building trust

To identify all tea sector stakeholders in western Kenya and southern Malawi, we partnered with key research and sectoral certification bodies working in the region. These include the Tea Research Institute (TRI) in Kenya, the Tea Research Institute for Central Africa (TRFCA), the Ethical Tea Partnership, and UTZ (a label for sustainable farming). Partnering with tea-specific organisations enhanced trust and helped maintain continuity in our interactions.

The stakeholders included tea producers and representatives from the large commercial tea estates (three in Malawi and five in Kenya), smallholder farmer representatives associations in Malawi and Kenya (four associations in Malawi and KTDA in Kenya), TRI and TRFCA scientists (three in Malawi and five in Kenya), and tea directorates (Tea Board of Kenya and Tea Association of Malawi). These stakeholders are representatives of their respective businesses/organisations/institutions, and are involved in decision making at various levels. The 1st round of interactions was carried out in June 2017 in Malawi and Kenya which helped us understand questions such as:

What is expected and needed in terms of climate information?; How do the day-to-day operations work in the tea industry?; What factors affect the tea production, including environmental problems (illegal cutting of fuel wood), operational issues (tea picking cycles), replanting decisions, water availability, global tea market, etc.?; How big a role does climate play?; Is it worthwhile to pursue research for providing long-term climate information?

2.1.2. Identification of climate metrics and stakeholder needs

We used mixed-mode surveys to engage stakeholders and gather relevant information. This included one-to-one meetings, focus group discussions, and a questionnaire. We shared a preliminary questionnaire for feedback from stakeholders and used their recommendations (including more details for greater clarity) to customise the questionnaire. This helped us improve and fine tune the questionnaire to gather information relevant to climate information needs for the future. We employed a flexible approach to elicit responses to the questionnaire to make it more convenient for the stakeholders, and to improve the quality of responses. They could respond to the questionnaire via e-mail, at the time of one-to-one meetings or they could also forward the questionnaire to other agronomists in their team. Stakeholders could therefore refer to station observations when responding to help them ground-truth their responses. The questions were aimed at identifying important months for tea yield and quality, thresholds of rainfall and temperature for optimum yield and quality in each month or season, important climate metrics and thresholds in different months/seasons, and then to tea quality parameters and adaptation strategies.

2.1.3. Tailoring uncertainty communication

To present preliminary results, we carried out iterative engagements with a focused group of identified stakeholders. In Kenya we engaged 25 stakeholders in November 2017, and 55 stakeholders in March 2018. In Malawi we engaged 20 stakeholders in June 2018 workshop, and 30 stakeholders in October 2018 workshop. The iteration helped generate stakeholder feedback regarding the ease of interpreting climate data visualisations, preferred spatial scale of information, and preferred mode of uncertainty communication in future projections. Incorporation of the feedback into the tailored climate projections helped strengthen trust, while enhancing the relevance of the visualisations to improve stakeholder usability. Table 1

2.2. Observations

Collection of station data was time consuming, requiring reassurance and trust building to ensure confidentiality of shared data. In the absence of Automated Weather Stations, tea estates usually manually digitise only monthly averages of rainfall and temperature. However, understanding the value of daily observations through initial interactions, the estates' staff digitised the daily data specifically for this research. The observational data was cleaned for errors; and outliers were checked for consistency with near-by stations. Daily climate observations including rainfall, maximum temperature and minimum temperature were collected from five tea estates in Kenya, and three tea estates and three national meteorological stations in Malawi (Supplementary Information Table 1). The observations were available for different time periods, and we use the longest available time series for better characterisation of the cumulative distribution function (CDF) curve (noting larger sampling errors for EPK and EPM due to their very short climatologies, which remain acceptable in the context of large projection anomalies). The temperature record from the observation stations of Bvumbwe (7.5 km away at 1146 m altitude) and Chileka (35 km away at 767 m altitude) were adjusted to be representative of Thyolo (at 921 m altitude). We calculated a seasonal correction factor between Bvumbwe-Chileka, and scaled it with a ratio of altitudinal differences between Bvumbwe-Thyolo and Bvumbwe-Chileka. The tea yield data in form of green leaf production were collected from the Tea Research Institute in Kenya (daily), and one tea estate in Malawi (weekly) for the 10-year period to compute a drought index (as per Duncan et al., 2016 developed for Assam, India). The index helps to quantify yield loss by assessing degree of hotness and moisture stress; two important climatic factors that cause tea crop damage.

2.3. Climate model data

Two types of climate models are analysed in this study. First, to assess projection uncertainty due to global model formulation, data from 29 global climate models are sourced from phase 5 of the Coupled Model Intercomparison Project (CMIP5) (Taylor et al., 2012). We focus on future projections for the mid- and late-21st century; 2040–2069 and 2070–2099 respectively (hereafter 2050s and 2080s). These projections are forced by the high emissions representative concentration pathway 8.5 (RCP8.5) since this has good data availability and large signal-to-noise ratios. Anomalies are computed from historical simulations that use realistic anthropogenic and natural forcings, averaging data over 1950–2005 (56 years), where we take advantage of smaller 20th century trends to permit a longer averaging period to reduce the effect of natural variability. All data are bias-corrected to the observation-based WFDEI dataset (WATCH Forcing Data methodology applied to ERA-Interim) using a state-of-the-art CDF transform, including correction of wet/dry day counts, and downscaled to a 0.5° grid (Famien et al., 2018).

To assess systematic biases that arise in CMIP5 due to the models' necessary use of parameterised convection and coarse resolution, we also analyse data from a convection-permitting version of the Met Office Unified Model run over a pan-African domain on a 4.5 km grid (CP4A). An historical simulation for 1997–2008 (Stratton et al., 2018) is forced by the observed atmospheric composition and sea surface temperatures (SSTs), and at its lateral boundaries by a similarly forced global atmosphere-only simulation. A 10-year future CP4A simulation (Kendon et al., 2019) is forced by RCP8.5 greenhouse gas concentrations, SST anomalies from the CMIP5 HadGEM2-ES projection, and lateral boundary data from a similarly forced global atmosphere-only projection, all representative of *c*. 2100. A pair

Table 1
Decision metrics and thresholds identified with stakeholders, and their role in tea physiology.

Climate metrics	Thresholds/definition	Physiological effect on tea yield and quality
Heat wave frequency (HWF)	Total number of days in sequences of 5 or more consecutive days when daily maximum temperatures > 35 °C (Malawi)/27 °C (Kenya) per year	Heat induced stress Yield response to irrigation reduces Crop failure due to inhibited growth rate (Carr et al., 1987)
Cold nights (CN)	Number of days when daily minimum temperature < 12.5 °C (Malawi)/6 °C (Kenya)	Shorter internode Increase in fiber content Reduced yield and quality (Carr, 1972)
Rainy days (RD)	Days per year when Rainfall > 1 mm	Reduced yield and quality (Carr et al., 1987)
Consecutive dry days (CDD)	Maximum number of consecutive days when daily Rainfall < 1 mm	Increased soil water deficit and evapotranspiration leads to moisture stress (Carr, 1972)
10-day dry spells (DS)	Number of periods of 10 consecutive dry days when daily Rainfall < 1 mm	Leaf shedding Drying and plant death Quality declines (Carr, 1972)
Total rainfall (TR)	Total rainfall amount	Optimum amount necessary for successful cultivation of teaExcess leads to water logging in poorly drained soils (Carr, 1972)

of comparator simulations (R25A; historical and future) were also run using an identical experimental setup, except that the grid-spacing is 25 km and convection is parameterised. This setup of CP4A and R25A is specifically to assess the impact of explicit-versus-parameterised convection and the resolution of surface heterogeneities on future climate change. Data from both CP4A and R25A are conservatively re-gridded to a regular 0.25° grid to ensure a fair comparison and noting evidence that convection-permitting models have a substantially larger gap between their grid spacing and well-resolved resolution than parameterised convection models (Berthou et al., 2019; Stein et al., 2015).

2.4. Local downscaling, bias-correction and uncertainty of model projection data

A number of issues must be addressed to utilise climate model data in the most appropriate manner for the development of climate services aimed at local decision makers: first, climate threshold exceedance rates may exhibit high spatial heterogeneity (e.g. in mountainous regions), creating a scale mismatch between climate model projection data and stakeholder needs; second, there are numerous plausible approaches to formulating climate models, particularly in their detail, leading to a wide range of climate projections and necessitating a risk-based approach; and third, the CMIP5 ensemble also exhibits biases that are systematic across all models, with examples being an underestimation of the high tail of the distribution of rainfall (Stratton et al., 2018) or the effects of interactions between diurnal cycle errors and large-scale seasonal means (Birch et al., 2014). Here we combine observed and model data to calculate a plausible range of distributions of daily temperature and rainfall that are bias-corrected and downscaled for specific tea plantations for the mid- and late-21st century. A quantile mapping (or CDF transform) approach (Stainforth et al., 2013) was used to optimally combine the data.

For the late-21st century, this being close to the period of CP4A data availability, the observed and model data are amalgamated in probability space to provide the site-specific Synthesis of the Projected Range (SPR) of the distributions of daily temperature or rainfall data:

$$SPR_Q^{2080s} = Obs_Q + \overline{\Delta CMIP5_Q^{2080s}} + 0.83(\Delta CP4A_Q - \Delta R25A_Q) \pm 2SD_Q^{2080s} \quad (1)$$

computed for all cumulative quantiles Q at a resolution of 0.1%, where Obs is the observed data, Δs are climate projection anomalies (using the difference between CDFs computed over 2070–2099 and 1950–2005 for each CMIP5 model then averaged over all models, or computed over all the years for the CP4A and R25A projection-minus-historic CDFs), SD is the inter-model standard deviation of the 29 ΔCMIP5 CDFs, with the 0.83 constant relates to 2100 and the 2080s, as described below. Eq. (1) thus computes a plausible range for each quantile, i.e. a maximum and minimum value. This range of distributions is computed for each tea plantation (using model data at the grid box encompassing the observation site) and for each of the two seasons. Fig. 3

To explain Eq. (1), we separate it into the following three stages, illustrated by Supplementary Fig. 3:

(1) The ensemble mean of CMIP5 projected anomalous CDFs is added to the observed CDF at the tea site (Supplementary Fig. 3 a, d), noting that this can also be interpreted as removing, from the mean of CMIP5 projection CDFs, the scale-dependent difference between observations on a 0.5° grid (the CMIP5 historical mean, bias-corrected to WFDEI) and point data at the tea plantation. This scale-dependence will be highest in regions of large topographic variability. In the example shown, the bias-corrected model data (thin green line) is too warm relative to the tea site (thick blue line) on all days, and too dry on the 20% of wettest days and too wet on other days. Eq. (1) removes these scale-dependent biases.

(2) The bias in CMIP5 projections due to the use of convection parameterisation and relatively low resolution is estimated by comparing the CP4A projected anomalous CDF with that of R25A. To correct for the slightly different time periods of the CMIP5 and CP4A projections, ΔCP4A and ΔR25A data are scaled by the ratio of HadGEM2-ES global annual mean temperature anomalies for these periods, i.e. ($\Delta T_{Glo}^{2080s}/\Delta T_{Glo}^{\sim 2100} = 0.83$). At Thyolo in DJFMA (Supplementary Fig. 3b), R25A (thin red line) slightly overestimates the projected warming on 80% of days, whereas at Sotik in ONDJFM (Supplementary Fig. 3 e), R25A underestimates the increase in rainfall intensity in all but the driest 40% of days (cf. CP4A, the thick green line) due to its use of convection parameterisation and lower-than-ideal resolution (Stein et al., 2015). The third term on the right-hand side of Eq. (1) corrects for these biases.

(3) Uncertainty due to plausible approaches to formulating climate models is included as ± twice the standard deviation of the CDFs across the CMIP5 ensemble. Additionally, for metrics that cannot fall below zero, any negative values are clipped to zero, and occasional slight deviations of the SPR rainfall CDFs from monotonic behaviour at low values is corrected by re-sorting quantiles into value order. The resulting plausible projection ranges are substantial (Supplementary Fig. 3c,f; green shading), but with a clear consensus of considerable warming being common across sites and seasons, and in the example of Sotik a consensus of enhanced rainfall for both light and intense events.

To provide ranges for the local distributions of temperature and rainfall for the mid-21st century, we modified the late-21st century calculation above to compute:

$$SPR_Q^{2050s} = Obs_Q + \overline{\Delta CMIP5_Q^{2050s}} + 0.45(\Delta CP4A_Q - \Delta R25A_Q) \pm 2SD_Q^{2050s} \quad (2)$$

where the notation follows that of Eq. (1), except that the CMIP5 projection CDFs are computed over 2040–2069 and the ΔCP4A and ΔR25A scaling is ($\Delta T_{Glo}^{2050s}/\Delta T_{Glo}^{\sim 2100} = 0.45$).

Four critical assumptions underlying Eqs.1 and 2 should be highlighted: (a) the climate change anomalies described by each term are homogeneous at sub-grid scales, (b) the impact of explicit convection and ultra-high resolution is similar across models, (c) remaining systematic modelling biases are of second order, and (d) the long-term evolution of local temperature and rainfall anomalies scales approximately linearly with global mean warming. Unfortunately, the extent of the validity of – and sensitivity to – these assumptions cannot be tested here, since maximal use is already made of climate information. Rather, they point to key topics for further research, and amplify a message of application potential, which must be updated as new evaluations, knowledge and understanding emerge.

2.5. Computation of threshold exceedance durations

To compute metrics of the number of consecutive days above or below a given temperature or rainfall threshold, time series of the projected future climates are required. Each model time series must be downscaled and bias-corrected, undertaken here by transforming the CDFs of each CMIP5 model's projected time series. The projected daily sequencing was retained for each model, so that uncertainties in their projected change in the length of hot or dry spells can contribute to the SPR, which are then used to compute a plausible range for the relevant metrics.

For each model, time period (mid- or late-21st century), variable (temperature or rainfall), location and season, the 30-year time series of daily projection data was first transformed to a time series of daily quantiles, Q(t), computed using each time series' own CDF. A downscaled bias-corrected 2070–2099 time series was then computed by transforming the quantile time series to a temperature or rainfall time series using a similar formulation to Eq. (1):

$$ts_{t,m}^{2080s} = Obs_{Q(t)} + \Delta CMIP5_{Q(t),m}^{2080s} + 0.83\left(\Delta CP4A_{Q(t)} - \Delta R25A_{Q(t)}\right) \quad (3)$$

where m is each CMIP5 model, and each term is the value on that data's CDF at quantile Q(t). Similarly, Eq. (2) is reworked to compute $ts_{t,m}^{2050s}$. The uncertainty term (±2SD) is omitted since the transform here applied to individual models. Eq. (3) therefore preserves the temporal behaviour of the 29 CMIP5 projections, so that they can then be used to compute threshold exceedance duration metrics for each model for a location, season, and time period. Finally, projection uncertainty is computed as ± twice the standard deviation across models, for each metric.

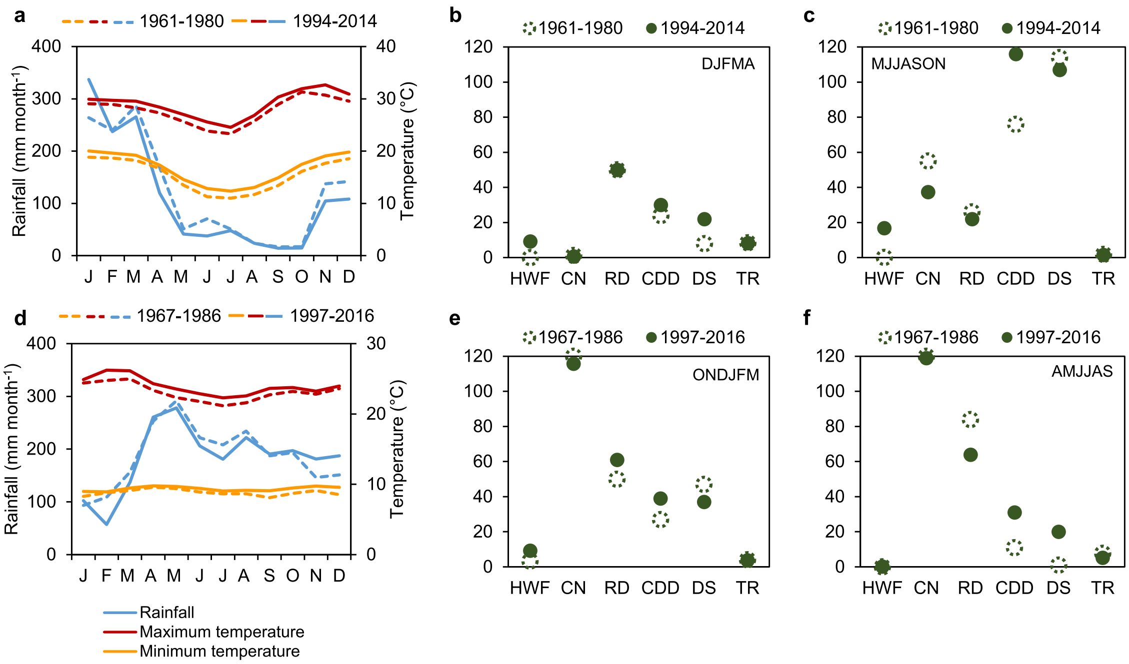

Fig. 2. a) and d) shows observed monthly climatology for Mimosa in Malawi and Tea Research Institute in Kenya respectively. b) shows seasonal decision metrics - Heat wave frequency, HWF (yr^{-1}); Cold nights, CN (yr^{-1}); Rainy days, RD (yr^{-1}); Consecutive dry days, CDD ($20\ yr^{-1}$); 10-day dry spells, DS ($20\ yr^{-1}$); and Total rainfall, TR (day^{-1}), for Mimosa station in Malawi for two time periods 1961–1980 and 1994–2014 for December to April (DJFMA); similarly, c) shows for May to November (MJJASON); e) shows for Tea Research Institute in Kenya for two time periods 1967–1986 and 1997–2016 for October to March (ONDJFM); similarly, f) shows for April to September (AMJJAS).

3. Results

3.1. Stakeholder-elicited climate metrics

In orographically and climatologically complex tea growing regions, local climate and crop suitability is a function of various factors such as altitude, orographic rainfall and land surface conditions. While tea yield is affected by different environmental and crop management factors at different time scales, relatively small climatic differences can non-linearly impact tea yield (Supplementary Fig. 2). While decision-relevant metrics are closely linked to generic agro-climatic indices, due to spatial heterogeneity and location-specificity, it is important to identify locally relevant metrics. Stakeholders in Malawi suggested that the critical threshold temperature that impedes growth when exceeded for 5 consecutive days (heat stress threshold) is 35 °C, whereas in Kenya they suggested it to be 27 °C (Table 1). This demonstrates that there are regional differences in temperature sensitivity for crops like tea, which are not always

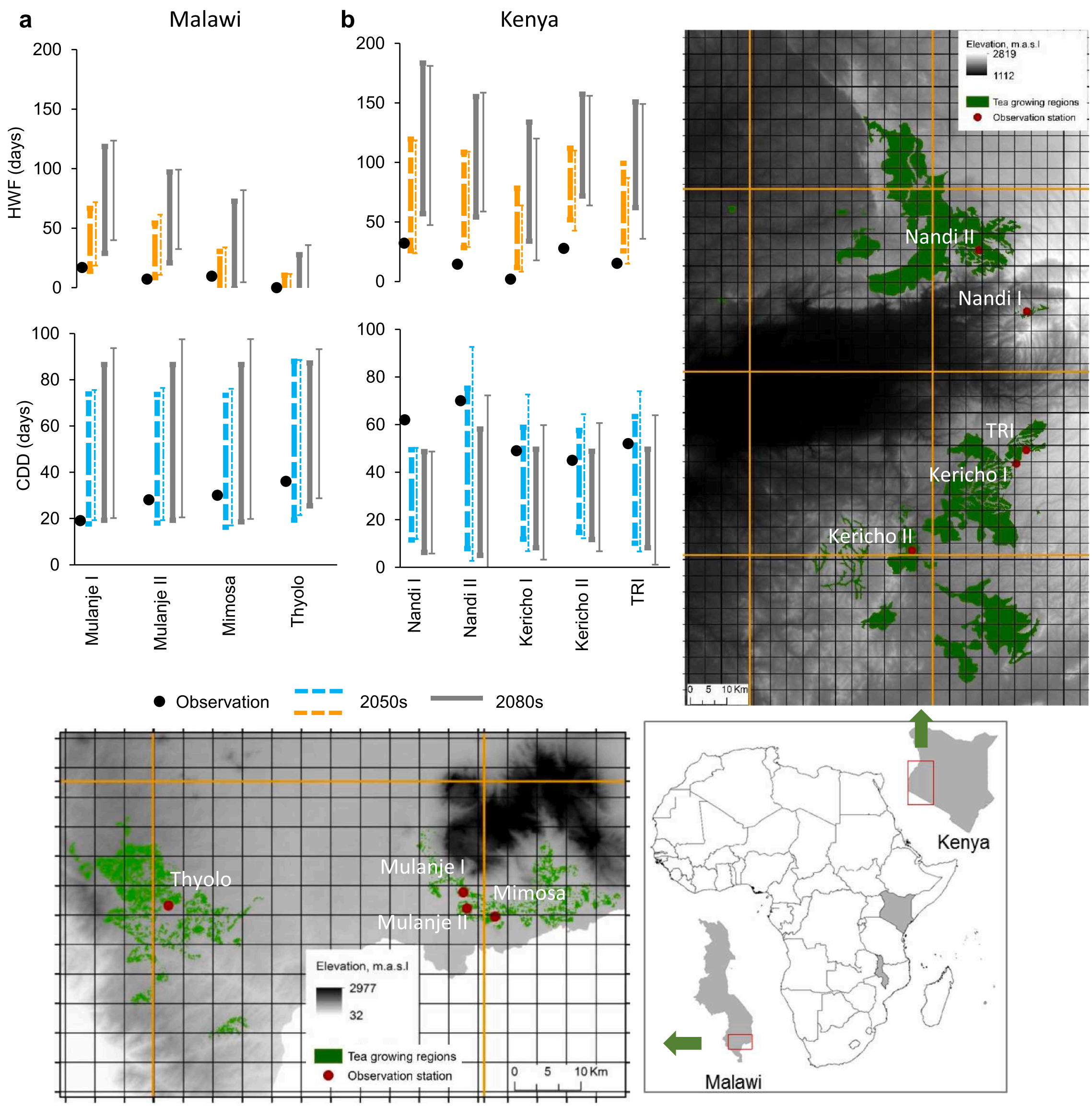

Fig. 3. Tea growing sites represented as red dots in southern Malawi and western Kenya are shown in a grid map of 50 km (yellow lines) and 4.5 km (black lines). 50 km grids represents bias corrected CMIP5 data and 4.5 km grid represent CP4A data. black dot represents observations, orange and blue dotted lines represent projected range for Heat wave frequency, HWF (yr^{-1}), and Consecutive dry days, CDD (30 yr^{-1}) respectively for December-April (DJFMA) at four sites in Malawi (a), and for October-March (ONDJFM) season at five sites in Kenya (b) for the mid-century (2050 s) and end-century (2080 s) (grey lines). The projected range is shown as ± 2 ensemble standard deviations. Thinner lines show project ranged computed without CP4A data. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

captured by future crop suitability mapping. Stakeholders in both regions suggested that a relatively well-distributed monthly rainfall is critical for maintaining yield and suggested similar key rainfall indices (Table 1) linked to evaporation rates and antecedent soil moisture levels from previous months' rainfall. Such regional specificities have influenced the historical evolution of crop management strategies and choice of crop varieties in Kenya and Malawi. Stakeholders' decisions and perceptions of long-term changes have also evolved over time due to perceived and observed intensity of extreme events such as the 2005 drought in Malawi (Nyirenda, 2006). These experiences, along with physiological traits of existing tea varieties, informed the stakeholders' choice of metrics (Table 1).

3.2. Historical changes

The sign and magnitude of changes in historical seasonal climatology and decision metrics are a function of geographical location. Comparison of two time periods in the past 50 years based on station data from Malawi and Kenya tea research institutes shows an increase in both maximum and minimum temperature across all months, with a corresponding increase in heatwave frequency and decrease in cold night frequency (Fig. 2). While a change in rainfall seasonality is observed, changes in rainfall metrics indicate mixed signals.

3.3. Potential future changes

The SPR for temperature-based metrics indicates an increase in heatwave days and a decrease in cold nights for all sites and seasons in both Kenya and Malawi for both time horizons 2050s and 2080s (Fig. 3, Fig. 4, and Fig. 5). However, uncertainties in the magnitude of changes in heatwave frequency are substantial. These range from the possibility of small increases at some stations to the likelihood at others of increases of more than 100 heatwave days per year during the 2050s (approximately four times that of current climate). The SPR approach provides seasonal and site-specificity to this information. For instance, in Malawi, Mulanje is at a lower altitude (600–653 m.a.s.l.), and projections show larger increases in hot day incidences and 10-day dry spells, compared to Thyolo (921 m.a.s.l.) (Fig. 4). Similarly, there are differences between Kericho II compared to other sites in Kenya (Fig. 5). Projections show that damaging cold nights will become less frequent by the 2050s, and will be extremely rare by the 2080s. This potential benefit to tea growth will be more than offset by the heat stress damage associated with prolonged high temperatures that can also be expected to negatively affect tea quality (Ahmed et al., 2019).

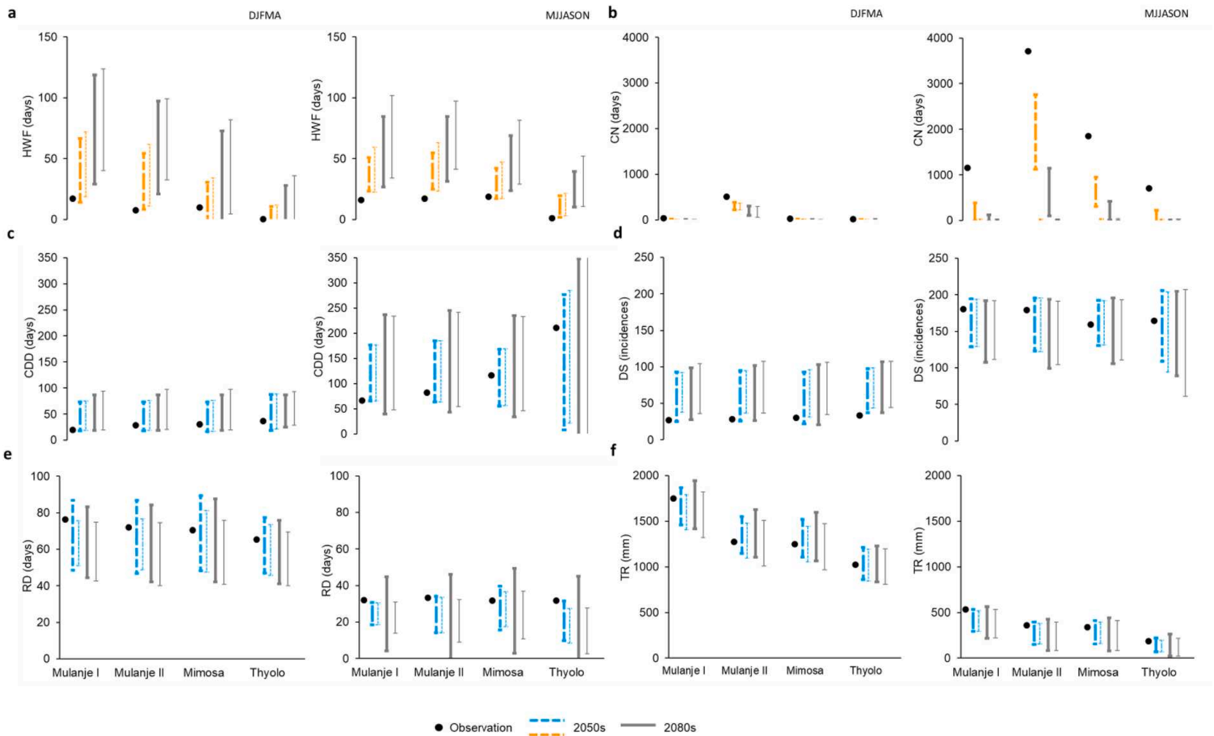

Fig. 4. For Malawi, black dot represents observations, orange dotted lines represent projected range for temperature metrics (Heat wave frequency, HWF (yr^{-1}); Cold nights, CN (30 yr^{-1})); and blue dotted lines represent projected range for rainfall metrics (Rainy days, RD (yr^{-1}); Consecutive dry days, CDD (30 yr^{-1}); 10-day dry spells, DS (30 yr^{-1}); and Total rainfall, TR (day^{-1})); for December-April (DJFMA) and May-November (MJJASON) season at four sites for the mid-century (2050 s) and end-century (2080 s) (grey lines). The projected range is shown as ± 2 ensemble standard deviations. Thinner lines show project ranged computed without CP4A data. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

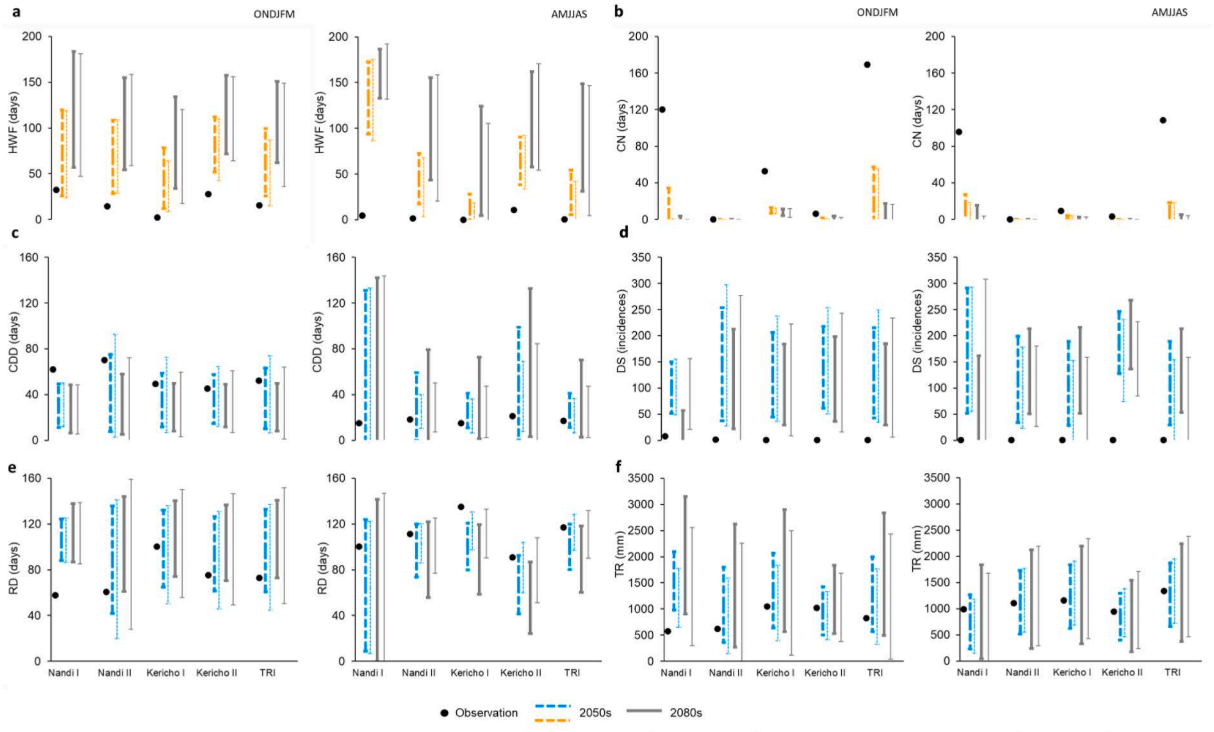

Fig. 5. Same as Fig. 4 but for Kenya for October-March (ONDJFM) and April-September (AMJJAS) seasons for five stations.

Projected plausible ranges for rainfall metrics also exhibit seasonal and site specificity, but with large uncertainties (Fig. 3, Fig. 4, and Fig. 5). In Malawi, the direction of wet season (DJFMA) rainfall change is uncertain, although a majority of models project an increase in the frequency and duration of 10-day dry spells, resulting in moisture stress and growth cessation. Given that 80% of the tea in Malawi is produced during the wet season, this is very likely to affect tea yields. In Kenya, model projections for the Short Rains season (ONDJFM), indicate a likelihood of increased rainfall totals, but with more frequent 10-day dry spells. For the Long Rains (AMJJAS), projected changes in total seasonal rainfall are more mixed, with most models suggesting a decrease in rainfall frequency and an increase in consecutive dry days (Fig. 5). Risks from soil water deficit when combined with increased hot day incidences could lead to crop failure (Rigden et al., 2020). Currently, Kenya has a more consistent yield across months because of the relatively weaker seasonality of rainfall, so a stronger future seasonality of rainfall will enhance the seasonality of yield, which would affect crop management cycles, with implications for production and employment. Future stronger rainfall seasonality in Kenya will necessitate irrigation infrastructure investment to maintain tea yield, as has already been observed in Malawi.

Information on the plausible range of change is essential for stakeholders to understand key metrics to help evaluate the applicability of different adaptation strategies (Blaser et al., 2018; Howe et al., 2019). In the iteratively developed visualisations of results, we present a range rather than the mean or median values. This reflects our focus on site-specificity and potential changes across the tea-growing region, but also the preference of stakeholders for including uncertainty information. They preferred this to being presented with a single definitive future which can be misleading and could falsely influence their decisions (Supplementary Fig. 4).

4. Discussion and conclusion

The explicit representation of convection in pan-Africa simulations represents a step-change in African climate modelling, since the representation of convection is a fundamental limitation for the global climate models: for extremes and their climate change (Jones et al., 2017), for regional climate (Marsham et al., 2013) and for global change (Sherwood et al., 2014). The orography of tea growing regions is also much better resolved in CP4A, which has been shown to improve orographic rainfall in East Africa (Finney et al., 2019). The addition of fine-scale information from a convection-permitting model has a statistically significant impact on the SPR (Supplementary Fig. 5), although for the tea-relevant metrics identified here, this impact is less than the spread amongst coarse climate models. This highlights the critical importance of reducing large-scale regional uncertainty from global projections for this context. Anticipated reductions in the spread amongst models, by eliminating those least capable of representing relevant future mechanisms (Rowell, 2019), will further enhance the relative value of fine-scale convection-permitting modelling.

The transdisciplinary research process used in this study integrates three crucial components of tailoring climate information: 1) stakeholder engagement, 2) identifying stakeholder needs, and 3) global and regional climate projections (Fig. 1). Iterative and long-term engagement of stakeholders, and transparency in the research process fostered greater trust and bi-directional flow of information between researchers and stakeholders, which enhanced credibility, salience/relevance and legitimacy of the climate information. The iterative process provided opportunities for – and challenge between – both users and developers of climate information through critical dialogue aimed at an improved understanding and provision of decision-relevant climate information. We show how tailoring projections to crop and location-specific thresholds generates information that stakeholders find valuable for their long-term decision making. Station observations, hitherto not in the public domain, were shared by tea estates, enhancing our ability to physiographically contextualise the projections for different stations. Bringing such privately-owned information into the public domain can help to develop more locally contextual projections (Dinku et al., 2014). Since there are finer spatial climatological differences between tea-producing regions, these location-specific projections help stakeholders identify crop management strategies that are locally effective. With this tailored information, stakeholders can then better prioritise long-term adaptation strategies and adaptation pathways from the wide range of sectoral adaptation strategies. By better capturing the climate change signal for different sites, and by combining station observations and model data in a probability space, SPR is a step towards building a more locally-relevant medium and long-term risk profile that can guide future breeding programmes for climate-smart tea cultivars (Carr, 1972; Wambulwa et al., 2017).

Across most stakeholder-elicited metrics, projections indicate greater certainty in the sign compared to the magnitude of potential future change. Site-specific differences in SPR suggests some value in the downscaling approach, but uncertainties introduced by the climate model projections are not always reduced. This highlights the recognised need to employ approaches that help take adaptation decisions under uncertainty, given that there are irreducible uncertainties in the future evolution of drivers of future climate (Bhave et al., 2016). Better understanding and communication of uncertainties and changing risks could help in developing risk-based adaptation responses. For example, our projections indicate a substantial increase in heatwave frequency across all sites. This is crucial for a crop with a long economic life cycle because the process of crop breeding, delivery and adoption can take decades and will require significant resources and investment in research (Pironon et al., 2019). While understanding potential future temperature and rainfall changes and associated uncertainty is critical, tea yield and quality also depend on other factors such as humidity, solar radiation, soil and nutrients factors as well as crop management decisions (Ahmed et al., 2019). Such complex interaction between different factors makes the assessment of future tea yield and quality changes particularly challenging. Future work could focus on evaluating the ability of site-specific adaptation strategies to address future climate risks under key uncertainties, including: risk reduction value, resource availability, governance and policy changes, consumer demand, and global supply chain factors.

Providing information for decision-making under climate change requires stronger collaboration across disciplines and decision-makers, increased use of state-of-the-art climate science approaches, and iteratively incorporating user feedback (Conway et al., 2019). We present an example emphasising the role of iterative stakeholder engagement, and a novel SPR approach for tailoring and communicating climate information and of the uncertainty in plausible future climates, for a climate-sensitive crop in sub-Saharan Africa. Such an approach is an important first step towards providing usable future climate information for high-value cash crops and to enable better-informed adaptation decision-making across the tea sector and supply chains.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Author contributions

All authors contributed ideas and edited the manuscript. N.M. and A.J.D. designed and conducted the study, B.B., D.P.R, and J.H.M.

conceptualised the analysis, N.M. and B.B. conducted the analysis, N.M., A.J.D. and D.P.R wrote the manuscript. D.M. and J.S. helped with data collection. A.T. and K.V. provided useful edits.

Appendix A. Supplementary data

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