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Title: Not so robust: Robusta coffee production is highly sensitive to temperature

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ABSTRACT

Coffea canephora (Robusta coffee) is the most heat tolerant and 'robust' coffee species and therefore considered more resistant to climate change than other types of production coffee. However, the optimum production range of Robusta has never been quantified, with current estimates of its optimal mean annual temperature range (22-30 °C) based solely on the climatic conditions of its native range in the Congo basin, Central Africa. Using 10 years of yield observations from 798 farms across South East Asia coupled with high-resolution precipitation and temperature data we used hierarchical Bayesian modelling to quantify Robusta's optimal temperature range for production. Our climate based models explained yield variation well across the study area with a cross-validated mean $R^2 = 0.51$. We demonstrate that Robusta has an optimal temperature below 20.5 °C (or a mean minimum / maximum of ≤ 16.2/24.1 °C), which is markedly lower, by 1.5 – 9 °C than current estimates. In the middle of Robusta's currently assumed optimal range (mean annual temperatures over 25.1 °C), coffee yields are 50% lower compared to the optimal mean of ≤ 20.5 °C found here. During the growing season every 1 °C increase in mean minimum/maximum temperatures above 16.2/24.1 °C corresponded to yield declines of ~14% or 350-460 kg/ha (95% credible interval). Our results suggest that Robusta coffee is far more sensitive to temperature than previously thought. Current assessments, based on Robusta having an optimal temperature range over 22 °C, are likely overestimating its suitable production range and its ability to contribute to coffee production as temperatures increase under climate change. Robusta supplies 40% of the world's coffee, but its production potential could decline considerably as temperatures increase under climate change, jeopardizing a multi-billion dollar coffee industry and the livelihoods of millions of farmers.

Keywords: Tropical agriculture; Coffee supply; Coffee yield; Night temperature; Minimum temperature; climate interactions; horticulture

1. INTRODUCTION

Two *Coffea* species alone supply most of the world's coffee – Robusta (*Coffea canephora)* and Arabica (*Coffea arabica*) (Davis et al., 2019). Robusta evolved in lowland habitats with mean temperatures between 22-30 °C (Matiello, 1998; Willson, 1999), while Arabica in high altitude areas with temperatures of 18-23 °C (Alègre, 1959). Of the two, Robusta is the most heat tolerant and 'robust' and so thought more resistant to climate change (Camargo, 2010; Pohlan & Janssens, 2010). Robusta's higher heat tolerance could make it a bulwark against the impacts of climate change on global coffee production – as temperatures rise, farmers could switch to Robusta to help maintain production (Garavito, Montagnon, Guyot, & Bertrand, 2016; Jayakumar, Rajavel, Surendran, Gopinath, & Ramamoorthy, 2017; Läderach et al., 2017). However, if this is not the case and Robusta is more sensitive to temperature than currently thought, then global coffee production could decline markedly under climate change.

Recent research has reached contrary conclusions about coffee's vulnerability to increasing temperatures. Some suggest the widespread loss, in excess of 50%, of suitable growing areas (Bunn, Läderach, Rivera, & Kirschke, 2015; Moat et al., 2017) and extinction of *Coffea* species

(Davis et al., 2019; Moat, Gole, & Davis, 2019). On the other hand, others highlight that rising CO_2 levels, which alter coffee leaf physiological responses to temperature and promote higher water-use efficiency, could mitigate climate change impacts on coffee production (DaMatta, Rahn, Läderach, Ghini, & Ramalho, 2019; Martins et al., 2016; Rodrigues et al., 2016). Reconciling these contrary conclusions is important. Without quantification of the vulnerability of coffee production to temperature increase the viability of coffee production under climate change remains unknown, risking the future of a multi-billion dollar global coffee industry and the livelihoods of millions of farmers.

Despite significant socio-economic implications, testing of how sensitive coffee production is to increasing temperatures has focused on the more heat sensitive Arabica coffee (Craparo, Van Asten, Läderach, Jassogne, & Grab, 2015). Further, studies on Robusta have been experimental (DaMatta et al., 2019; Martins et al., 2016; Rodrigues et al., 2016) performed over limited temperature gradients or use non-yield attributes (e.g. leaf physiology or occurrence records) (Bunn et al., 2015; Rodrigues et al., 2016) – all of which are indirect means of assessing coffee yield vulnerability to temperature change in the field. There are no large-scale studies that have analyzed farm-level Robusta coffee yield responses to temperature, but these are necessary to test how sensitive Robusta coffee production is to temperature increases and to accurately delineate its optimal temperature range.

Current estimates of optimal climatic growing conditions for Arabica and Robusta are founded on historical botanical explorations of the 16th century onwards and are solely based on the location of origin, which, for Robusta, is the Congo basin with a mean temperature range of 22-30 °C (Matiello, 1998; Willson, 1999). Based on this, the current and often cited optimal mean annual temperature range of Robusta is estimated to be between 22-26 or 22-30 °C (DaMatta, Avila, Cardoso, Martins, & Ramalho, 2018; DaMatta & Ramalho, 2006; Martins et al., 2016; Jayakumar, Rajavel, & Surendran, 2016; Jayakumar et al., 2017; Matiello, 1998; Rodrigues et al., 2016; Willson, 1999). There are currently no estimates for optimal minimum and maximum temperatures during Robusta's more climatically sensitive flowering and growing phases. This is despite studies showing that Robusta's relationship with minimum and maximum temperatures varies throughout the year and especially between different phenological phases (Jayakumar et al., 2016).

Outside of this optimal range, the lower and upper temperature limits of Robusta vary widely. Under experimental conditions and on young trees (1-4 years old), research indicates that Robusta is sensitive to temperatures below 17°C, with declines in vegetative growth (Partelli, Marré, Falqueto, Vieira, & Cavatti, 2013) and photosynthetic parameters (Batista-Santos et al., 2011). Although recently, several genotypes of Robusta have shown high productivity, adaptability and stability in field trials at mean temperatures of 20 °C and minimums between 10-20 °C (Martins et al., 2019). At the upper limit, the plant is able to physiologically function to 37 °C, though these assessments are restricted to leaf physiological responses, not yield, and only occur when coupled with high levels of CO_2 (i.e. 700 µl CO_2 l^{-1}) that simulate future climate warming (DaMatta et al., 2019; Rodrigues et al., 2016).

Here we use an extensive farm-level yield dataset to quantify Robusta coffee yield sensitivity to temperature variation and its optimal temperature range in the field. Based on current literature we expected Robusta coffee yields to be highest, or optimal, at between 22-30 °C.

Ours is the first study to empirically test the validity of the 22-30 °C estimate using a spatially extensive (observations from across ~ 90,000 km^2) farm-yield observation dataset collected over a wide range of climatic conditions throughout the core Robusta producing areas of South East Asia. The dataset (7980 yield observations from 798 farms collected over 10 years) used to investigate this is from Vietnam and Indonesia, two countries which together account for 55% of the world's Robusta production. Coupled with this yield dataset we use newly developed high-resolution temperature and rainfall data (TERRA) (Abatzoglou, Dobrowski, Parks, & Hegewisch, 2018) and ERA5 (Copernicus Climate Change Service (C3S): ERA5: Fifth generation of ECMWF atmospheric reanalyses of the global climate, 2017) that allows our farm-level yield observations to be linked with accurate climate data.

2. METHODS

2.1 Study area

The study area covers high intensity Robusta production provinces of Indonesia and Vietnam in Southeast Asia (Figure 1). Temperature ranges are similar across Vietnamese and Indonesian coffee areas, with mean minimums ranging from 14-24 °C and mean maximums from 24 to 33 °C (Figure 2). Indonesian coffee growing areas, being situated closer to the equator are characterized by a monomodal climate and higher rainfall, whereas Vietnam shows a more pronounced dry and wet season and has lower rainfall (Figure 2).

Reflecting the lower rainfall in Vietnam, coffee farms here are irrigated, while farms in Indonesia are not (Amarasinghe, Hoanh, D'haeze, & Hung, 2015). Vietnamese farmers also more intensely manage their farms, applying greater amounts of fertilizer and clear more surrounding vegetation to increase sunlight and the available coffee plantation area. To account for differences in soils, management and other non-climatic factors that vary between sites we use hierarchical modelling (also known as mixed-modelling, multi-level or random effects modelling), which allows for the intercept in the model to vary amongst sites, but not the coefficient of the climatic predictors. This allowed us to quantify climatic effects while accounting for yield differences between sites, which may be higher or lower as a consequence of differences in management practices, soils, irrigation etc.(Blangiardo & Cameletti, 2015).

2.2 Coffee yield data

Coffee yield data were collected within the Sustainable Management Services (SMS) program implemented by ECOM Agroindustrial Corporation in Vietnam and Indonesia. As a part of this program, farm-level data are regularly recorded. Data were managed through the SMS database within ECOM, in addition to records keeping by individual farmers. There are approximately 7000 farmers in the program (5000 in Vietnam and 2000 in Indonesia). For this study, yield data were collected from a representative sample (~10%) of these farms, 558 farms in Vietnam and 240 in Indonesia. Yield observations were collected for each year from 2008-2017 to give a total N of 7980. Across the dataset, mean yield was 2.05 (with a standard deviation of 0.96) and ranged from 0.04 to 5 tonne/ha (Figure S1).

Each of the coffee producing provinces (Figure 1) were surveyed by district. Each district represented the range of climatic and coffee production conditions across Vietnam and Indonesia. Within each district farms were selected so as to be representative of the range of climatic and production conditions in that area (for mapping of districts surveyed see Byrareddy et al. 2019). Within each coffee producing district, of each province, 30 farms were surveyed, except for Gia Lai and Lam Dong, where extra resources allowed for 31 and 33 farms to be surveyed per district respectively. This sampling design ensured that a representative range of farms were surveyed in different climatic and environmental settings across coffee growing areas in both Vietnam and Indonesia.

Across surveyed farms mean annual temperatures ranged from ~20-27 °C. This ensured the statistical model had yield observations responding to a broad range of climatic conditions across a wide range of areas. Farms across this temperature range were surveyed in both Indonesia (20.16-27.25 °C) and Vietnam (20.44-27.37 °C). This temperature range covered the purported middle of the optimal mean annual temperature range of Robusta, from 22-28/30 °C. Although, no sites at the upper end of the estimated optimum range, over 28 °C, were available. Histograms showing the distribution of sites across mean annual temperature gradients are in Figure S2, supporting information.

All yield records were cross-checked with the SMS database to verify their accuracy. Industry based farm-level yield data has several advantages for investigating Robusta's response to temperature. First, it is collected under real world production conditions. Second, unlike in experiments, plants are not potted, which affects root growth and water deficits, or in greenhouses that can alter humidity and evaporative demand. (DaMatta & Ramalho, 2006).

2.3 Climate data

Historical station based climate data is lacking throughout many Robusta growing areas of Southeast Asia, so we used recently developed global historical climate datasets (TERRA (~4 km resolution) (Abatzoglou et al., 2018), ERA5 (~31 km resolution) (Copernicus Climate Change Service (C3S): ERA5: Fifth generation of ECMWF atmospheric reanalyses of the global climate, 2017) and TRMM (~ 25 km resolution) (Kummerow, Barnes, Kozu, Shiue, & Simpson, 1998). We tested the accuracy of these datasets with available station data to ensure strong correlation with rainfall and temperature conditions on the ground. Mean maximum and minimum temperatures were derived from a composite variable that averaged ERA5 and TERRA temperature estimates – this correlated well (Pearson $r = 0.93$, Figure S3) with station data on the ground. Total rainfall was calculated from a composite variable averaging ERA5, TERRA and TRMM – this was strongly correlated with rainfall measurements across available test stations (Pearson $r = 0.88$, Figure S4). To account for differential effects of climate on coffee during different phenological phases throughout the year, temperature and rainfall variables were calculated for the flowering (January to March in Vietnam and September to November in Indonesia) and growing season (March to September in Vietnam and November to May in Indonesia (Troung, 2017). Flowering and growing is when coffee is most sensitive to climate (Craparo et al., 2015).

2.4 Statistical analyses

Coffee yields were modelled as nonlinear functions of climate predictor variables using hierarchical Bayesian models, which included random effects to account for any potential spatial and temporal autocorrelations resulting from the clustered nature of data observations (e.g. annual repeat measurements at a particular site). Traditional non-hierarchal linear regression models are unable to account for repeat measures or non-independence in observations. Hierarchical statistical models control for non-independence by constraining non-independent observations to have the same intercept (Harrison et al. 2018). For example, yield observations at a site, or within particular years, may be more similar (e.g. higher on average if soils and management techniques are better) relative to yield observations from other sites or during different years. To account for this, hierarchical modelling allows for the intercept (or baseline) in the model to vary amongst the same sites and years. Hierarchical statistical models efficiently account for the influence of these grouping factors (e.g. site and year) and eliminate many problems associated with spatial and temporal autocorrelation, pseudo-replication and also reduces the risk of Type I and II errors (Blangiardo & Cameletti, 2015; Dormann et al., 2013; Harrison et al., 2018). Importantly, in the context of this study because hierarchical models allow for the intercept to vary, this enabled us to quantify the effect of temperature, while accounting for differences between sites (e.g. management practices) and the non-independence resulting from repeat yield observations at each site (Blangiardo & Cameletti, 2015).

All models were fit using, an approximate Bayesian inference technique, integrated nested Laplacian approximation (INLA) using the INLA package (R Core Team, 2019; Rue, Martino, & Chopin, 2009) in R version 3.6.0 (R Core Team, 2019). In contrast to traditional Bayesian approaches, which use Markov chain Monte Carlo (MCMC) techniques, INLA provides exceptionally fast Bayesian inferences. INLA can compute very accurate approximations of the posterior marginal that are consistent with other more time consuming approaches (Rue et al., 2009). The main benefit of INLA then is its ability to provide precise estimates in seconds or minutes, rather than the hours or days needed when using Markov chain Monte Carlo algorithms, an important advantage in global change studies analyzing large climatic datasets (Rue et al. 2009, e.g. Requena-Mullor, Maguire, Shinneman, & Caughlin, 2019; Gutowsky et al., 2019).

The full model for coffee yield - the response variable y at site i at time j was as follows:

$$y_{ij} \sim N(\mu_{ij},\sigma^2)$$

$$\mu_{ij} = \alpha + \sum_p f_p(x_{ip}) + \varepsilon_{\mathrm{year}[j]} + \varepsilon_{\mathrm{site}[i]} + \varepsilon_{\mathrm{country}[i]} + \varepsilon_i$$

Error (ε) terms are random effects for year (to account for temporal autocorrelation) and site nested within each country (to account for spatial autocorrelation), with each being modelled as identically and independently distributed (IID) random variables. While εi are the residuals (i.e. the unstructured random effects). The α term is the intercept and fp (Xip) is the nonlinear effect of each parameter (modelled using 2nd order random-walk splines, which penalize deviations from a linear fit). Parameters were year, mean minimum temperature, mean maximum temperature and total rainfall. Parameters also included two-way interactions between each temperature and rainfall variable. We included year as a linear predictor to implicitly detrend the yield data with yearly effects not constrained to be equal (Auffhammer, Ramanathan, & Vincent, 2006). Year was also included as a random effect to account for the potential of yields being temporally autocorrelated, or more similar within years, possibly because of amongst other things; the biennial production cycle of coffee or from systemic loss events (e.g. disease outbreaks) in particular years. Year as a random effect thus acts as an error term that captures the variability of the effect of year on yield observations (Barr, Levy, Scheepers, & Tily, 2013). Predictors were standardized [mean(x)/1.sd(x)] (Gelman & Hill, 2007).

Mean maximum temperatures during flowering, as well as mean maximum and mean minimum temperatures during the growing season were all highly correlated (Pearson r > 0.8), so we fit each of these parameters in separate models to investigate their effects (Table S1). Within each model, correlations between predictors were |r| < 0.70 (Table S2), and below the level at which collinearity can affect regression models (Dormann et al., 2013). Model selection showed that models including mean minimum temperatures during the growing season performed the best (Table S1), so we present these results in the main text. Fixed effect climate predictors fit in each model are given in Table S1. To make our results directly comparable with current estimates, which are based on mean annual average temperatures, we also fit a model using mean annual average temperature and total annual rainfall.

We also investigated whether temperature effects varied with irrigation and fertilizer amounts. Although we caution that since we use real world farm data the irrigation and fertilizer practices are largely homogenous between years at each site (Byrareddy, Kouadio, Mushtaq, & Stone, 2019). Thus, while our dataset allows us to investigate whether temperatures limiting effect is consistent under real world production conditions, it does not necessarily allow us to investigate whether increases or decreases in these management factors would be useful in mitigating the effects of higher temperatures. Long-term experimental studies across wider irrigation and fertilizer gradients are needed to test their use for mitigating the effects of higher temperature on Robusta yields.

Cross-validation was performed by iteratively holding out all data from each site (there were 798 sites) and testing how well a model built using data from remaining sites predicted Robusta coffee yields at that hold-out site. This tests how well the model predicts yields at a site that it has not seen before. From these site level cross validations we then used the predicted and observed values to calculate a mean cross-validated R^2 for each country and province. We also carried out temporal cross-validation by iteratively holding out all data from each year (there was 10 years of data) and testing how well a model built using data from remaining years predicted Robusta coffee yields during hold-out years. Holding out entire 'blocks', or all data from each site (or year), is more appropriate than random cross-validation, which can underestimate predictive errors (Roberts et al., 2017).

3. RESULTS

3.1 During the growing season high minimum temperatures reduce Robusta coffee yields

In the growing season for every 1°C that minimum temperatures increased above 16.2 °C Robusta coffee yields declined by 350-460 kg/ha (95% credible interval), which equates to a ~ 14% reduction per degree Celsius (Figure 3a). When minimum temperatures reach 18.6 °C, average yields declines are over 25%, and by the time temperatures breach 20.7 °C declines over 50% are observed (Figure 3a; Table 1). The relationship between minimum temperatures and yield was predominantly linear, so the rate of yield decline as temperatures increased was consistent across the range of temperatures analyzed.

Mean maximum temperatures during flowering, as well as mean maximum and mean minimum temperatures during the growing season were all highly correlated (Pearson $r > 0.8$), so we fit each of these parameters in separate models to investigate their effects (Table 1; Table S1). Model selection showed that models including mean minimum temperatures during the growing season performed the best (Table S1), so we only present the results for mean minimum temperatures in the growing season in the main text. Relationships between mean maximum temperatures during the growing season and flowering were also negatively related to yield and these responses are shown in Figure S5 and S6. Mean annual temperatures were also negatively related to yields (Supplementary Figure S7A). Likewise, the effect of mean minimum temperatures was negative regardless of the level of irrigation or fertilizer, with the mean minimum temperature that yields were predicted to be highest still being ≤ 16.2 °C (Supplementary Figure S8).

3.2 Growing season rainfall has a positive effect on Robusta coffee yields, while flowering season rainfall a negative effect

Relative to temperature, rainfall had a comparatively small effect on yields (Figure 3b & d). Growing season rainfall had a positive relationship with yields, with rainfall above 1550 mm corresponding to the highest predicted yields (Figure 3b). Conversely, rainfall during flowering had a negative relationship with yield (Figure 3d). Relative to optimal rainfall amounts, rainfall over ~ 900 mm during flowering was associated with yield declines of over 25% (Figure 3d).

3.3 During flowering low minimum temperatures reduce Robusta coffee yields

Mean minimum temperatures during flowering were positively related to yields (Figure 3c). In flowering, when mean minimum temperatures dropped below 15.8 °C yields were 25% lower relative to optimal conditions. Optimal yields occurred with mean minimum temperatures above 21.7 °C (Figure 3c; Table 1).

3.4 Temperatures effect on Robusta coffee yields is influenced by rainfall

In both the flowering and growing season mean minimum temperatures influence on Robusta yields changed with rainfall (Figure 4). During the growing season the effect of increasing mean minimum temperatures was more negative at either extreme of the rainfall gradient (Figure 4a). As growing season rainfall declined from 2400 mm to below 1000 mm the contour for poor yields (corresponding to a 25-50% yield reduction) moves from 18.5 to 17.75 °C (see change in poor yield contour (solid blue line) in Figure 4a). The most favorable combination of conditions for Robusta yields during growing was when mean minimum temperatures were low (<17 °C) and rainfall was between ~ 1200-2700 mm (area left of suboptimal contour (solid blue line) in Figure 4a). During flowering a combination of high mean minimum temperatures and low rainfall were the most favorable conditions for Robusta yields (Figure 4b). Conversely, a combination of low mean minimum temperatures and high rainfall led to lower yields (Figure 4b).

3.5 Climate explains up to 40-60% of the variation in Robusta coffee yields

On average our model explained over half of the variation in Robusta coffee yields (cross-validated (CV) mean R^2 = 0.51 and median R^2 =0.56) (Figure 5). The model explained more variation across Vietnam (mean CV R^2 = 0.55) than in Indonesia (mean CV R^2 = 0.43) (Figure 5a). The climate variables also explained more variation when predicting to sites within each Vietnamese province, with mean cross validated R^2 values ranging from 0.52 to 0.62 (Figure 5b). Climate explained less of the variation amongst Indonesian provinces and especially in Lampung and South Sumatra where mean cross-validated R^2 values were 0.41 and 0.42 respectively (Figure 5b). Cross validation results for models built using mean maximum temperatures during the flowering and growing season are in Supplementary Table S1. Temporal cross validation results from iteratively holding out years of data are in Supplementary Figure S9.

4. DISCUSSION

Some have suggested that Robusta is highly heat tolerant and so may be resistant to climate change (DaMatta et al., 2019; Rodrigues et al., 2016). Our results challenge this claim and instead suggest previous assessments overestimate Robusta's optimal temperature range. Based solely on the location of origin, previous estimates have put the optimal annual average temperature of Robusta at between 22-30 °C (Charrier & Berthaud, 1985; Willson, 1999). However, here we show that average temperatures over 23.8 °C (or min/max of 18.6/26.5 °C) during the growing season correspond to yield declines of over 25%, while at average temperatures over 25.1°C (or min/max of 20.7/29.5 °C) yield declines are over 50%. Based on our findings an optimal growing season average temperature for Robusta would be 20.5 °C or lower (or min/max of 16.2/24.1 °C), which is 1.5°C below the lower bounds of current estimates. Further, our findings of optimal temperature for yields are substantially lower, by some 6-7 °C, from temperatures of 30/37 °C (min/max) that Robusta coffee plant leaf physiology has been shown to tolerate (Rodrigues et al., 2016).

Instead of tolerance to temperature increase, our results show Robusta is highly vulnerable to temperature, and perhaps more similar to the temperature sensitive Arabica than previously thought. In Tanzania, country level Arabica yields declined as mean minimum temperatures increased above 15 °C during the growing season, with the maximum rate of decline occurring at about 16.2 °C (Craparo et al., 2015). Similarly, our results showed that Robusta yields declined as mean minimum temperature rose above 16.2 °C. In both cases the magnitude of decline per 1 °C was comparable – Arabica in Tanzania by ~27.4%, while in this study Robusta by ~14%. The low minimum temperature optimums we observe are also in line with recent genetic studies showing that several Robusta genotypes are productive at mean temperatures of 20 °C and minimums of between 10-20 °C (Martins et al., 2019). Our findings suggest a need to reconsider Robusta coffee's vulnerability to temperature increase and its suitability as an adaptation option for maintaining coffee production under climate change.

If minimum temperature is a key driver of Robusta yield declines, as our study suggests, this advances a hypothesis that could reconcile recent research that on one hand highlights coffee's temperature sensitivity (Craparo et al., 2015; Davis et al., 2019; Moat et al., 2019) and on the other its resistance to heat stress (Martins et al., 2016; Rodrigues et al., 2016). We hypothesize that while coffee leaf physiology is resistant to heat stress from high temperatures under high CO_2 conditions cf. (Rodrigues et al., 2016), yields are not, and specifically that high night temperatures promote vegetative growth in favor of fruiting/bean production (Jung et al., 2016). This would explain why Robusta plant functioning/leaf physiology and photosynthetic rates is resistant to remarkably high temperatures (up to a min/max of 30/35-37 °C) (Da Matta, Loos, Rodrigues, & Barros, 2001; Rodrigues et al., 2016), while at the same time shows yield declines once growing season mean minimums are above 16.2 °C, as observed in this study. We also submit that if increasing minimum temperatures reduces coffee fruiting/yields (e.g. as for wheat (García, Dreccer, Miralles, & Serrago, 2015)) that this could decrease reproductive potential, and so could be a mechanism through which the loss of suitable *Coffea sp* habitat could be explained (Davis et al., 2019; Moat et al., 2017).

While our study suggests minimum temperature is key for understanding Robusta yields, experimental work is needed to quantify the independent effects of minimum/maximum temperatures (which are often correlated in the field), as well as the proximal mechanisms temperatures may affect yields through (e.g. vapor pressure deficit or evapotranspiration). Coupled with this experimental work investigating the role of increasing CO_2 levels in mitigating increasing temperature impacts on coffee production is needed (Martins et al., 2016; Rodrigues et al., 2016). A short term, two year experimental study showed little effect of CO_2 on Arabica yields, with insignificant ($p > 0.05$) differences in yields noted under elevated CO_2 levels (550 μmol mol^{-1}) (Ghini et al., 2015). There are no equivalent studies on Robusta, nor any studies that have looked at CO_2 level and temperature interactions on coffee yields. This information is critical in order for the future impacts of climate change on coffee yields to be accurately assessed. Studies on other C_3 crops have questioned the extent to which increasing CO_2 could offset yield losses due to climate change (Long, Ainsworth, Leakey, Nösberger, & Ort, 2006). It may be that while increasing CO_2 may reduce heat stress, by for example improving higher-water use efficiency (Rodrigues et al., 2016), it may have negligible effect on countering the phenological disruptions that we hypothesize cause higher minimum temperatures to reduce Robusta yields in favor of vegetative growth.

Relative to minimum temperatures, rainfall during the growing season had a relatively small effect, but this is not surprising given high rainfall in Indonesia and irrigation practices in Vietnam (Amarasinghe et al., 2015). Contrasting the negligible effect of rainfall during the growing season, rainfall had a notable negative effect on yields in the flowering season. This is consistent with other studies, as is the finding that during flowering high mean minimums coupled with dry conditions were the most favorable for Robusta. Coffee requires moisture stress to trigger flowering (Batista-Santos et al., 2011; DaMatta & Ramalho, 2006). Excessive rain and cool conditions during the quiescent growth phase can repress flowering and this has been linked to lower yields (DaMatta & Ramalho, 2006). Our results detect this phenomenon well.

Other factors, aside from rainfall, could moderate temperatures impact on Robusta coffee yields. Of these, irrigation and fertilizer practices could be particularly important and could alter the effect of temperature on yields (DaMatta & Ramalho, 2006). Because we use real world farm data, irrigation and fertilizer practices are largely homogenous between years at each site (Byrareddy et al., 2019). As such, while we were able to investigate temperatures effect on Robusta under real world production conditions, we could not directly assess whether increases or decreases in irrigation and fertilizer beyond those currently applied would be useful in mitigating the effects of increasing temperatures. Nonetheless, we did observe that while higher levels of irrigation and fertilization corresponded to higher yields, the effect of temperature was negative regardless, with the lowest mean minimum temperature (16.2 °C) still corresponding to Robusta's highest yields. Long-term experimental field studies across a wider range of irrigation and fertilizer gradients are needed to more fully test the role of irrigation and fertilization in managing the effects of higher temperature on Robusta yields.

Tree or overstorey vegetation shading is another well-known management factor that could influence the relationship between temperature and yields. Shading provides a buffer for micrometeorological temperature in coffee systems – cooler maxima and warmer minima - of between 2 and 4°C (Vaast et al., 2006). Capturing the microclimatic variations as a result of shading and therefore the link to the mesoclimate and influence on yields at this scale is a challenge requiring further research. However, considering the vast majority of coffee in Vietnam and Indonesia is full sun/unshaded systems, microclimatic influences in this study would likely be minimal.

In addition to investigating management practices, research into how increasing temperatures affect different genotypes of Robusta is needed. South-east Asian Robusta's originate from the Congo-Uganda group (Garavito et al., 2016). However, Robusta's with different genotypes might show a greater or lesser sensitivity to temperature then what we show here. Robusta is widely distributed in its native Africa and so there may notable differences in temperature sensitivity amongst wild genotypes (Garavito et al., 2016; Martins et al., 2019). A critical avenue for future research then is the identification of high temperature resistant Robusta cultivars that may help maintain coffee production as temperatures increase under climate change.

Overall the climate predictors explained a large proportion of the variation, on average 51%, in Robusta yields amongst our study sites. Climate variability accounting for 40-60% of the variation in yield being explained by climate is consistent with studies on Arabica (Craparo et al., 2015). There are no equivalent studies that have quantified the importance of climate for Robusta yields. The sensitivity of Robusta coffee to climate is in line with research showing globally climate explains 30-60% of variation in staple annual food crops, such as rice, maize and wheat (Ray, Gerber, MacDonald, & West, 2015). Our results suggest Robusta coffee is similarly sensitive to temperature and further emphasizes the sensitivity of numerous high value plant production species to temperature increase and seasonal climatic change (Battisti & Naylor, 2009).

Robusta supplies 40% of the world coffee, underpins a multi-billion dollar coffee industry, and provides income for millions of farmers, but our results show that as temperatures increase Robusta coffee yields decline markedly. Robusta is the most heat tolerant variety of production coffee and so may have offered an adaptation option to maintain coffee production as temperatures increase under climate change. However, our findings suggest that as temperatures increase Robusta production declines of 350-460kg/ha, or ~ 14% for every 1°C increase over a mean minimum temperature of 16.2°C in the growing season. Our results suggest farmers, the coffee industry and global coffee supply are vulnerable to temperature increase from climate change.

Supporting information

Figure S1. Boxplots showing the distribution of coffee yield data for each of the study provinces.
Figure S2. Histograms showing the distribution of yield observations in relation to mean annual temperature
Figure S3. Accuracy assessment of gridded temperature datasets.
Figure S4. Accuracy assessment of gridded rainfall datasets.
Figure S5. Response of Robusta coffee yields to mean maximum growing season temperatures.
Figure S6 Response of Robusta coffee yields to mean maximum flowering temperatures.
Figure S7. Response of Robusta coffee yields to mean annual temperature and rainfall.
Figure S8. Response of Robusta coffee yields to mean minimum temperatures when interacting with irrigation and fertilizer.
Figure S9. Cross-validated model performance showing how well the model predicts yields in different years (based on year-hold out cross-validations).
Table S1. Fixed effect climate predictors and model performance.
Table S2. Correlations between fixed effect climate predictors in each of the four model structures tested

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AUTHOR CONTRIBUTIONS

J.K and A.C conceived the study and led the write up of the manuscript. V.M.B collected the data. J.K performed the analysis. V.M.B and T.N defined coffee phenology periods. All authors critically reviewed the paper and assisted with the interpretation of results and writing of the paper.

DATA AVAILABILITY STATEMENT

Data and code used in this study is stored at HARVARD Dataverse https://doi.org/10.7910/DVN/GFGWDO

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Tables

Table 1. Optimal temperature ranges for Robusta coffee production. Robusta coffee yield condition categories (optimal, suboptimal, poor and very poor) are relative to the maximum predicted yield in relation to that climate variable, while other predictors are held at their mean.

Temperature variable (reference Figure)	Optimal (0-5% yield reduction)	Suboptimal (5-25% yield reduction)	Poor (25-50% yield reduction)	Very poor (>50% yield reduction)
Mean min. temperature in the growing season (Fig. 1a)	* ≤ 16.2 °C	16.2 – 18.6 °C	18.6 – 20.7 °C	> 20.7 °C
Mean min. temperature during flowering (Fig. 1c)	21.7 – 23.4 °C	15.8 – 21.7 °C	13.8 – 15.8 °C	NA
Mean max. temperature in the growing season (Fig. S5)	* ≤ 24.1 °C	24.1 – 26.5 °C	26.5 – 29.5 °C	> 29.5 °C
Mean max. temperature during flowering (Fig. S6)	* ≤ 25.0 °C	25.0 – 29.0 °C	29.0 – 32.9 °C	NA
Mean annual temperature (Fig. S7)	* ≤ 20.5 °C	20.5 – 22.9 °C	22.9 – 25.1 °C	> 25.1 °C

*No lower limit identified because of restrictions in temperature gradient tested.

Figure 1. Study provinces from which yield data was collected, throughout core Robusta coffee producing areas of Southeast Asia. Low = < 525 ha; Moderate = 525-1415 ha; High = 1416-3300 ha and Very high = 3301-6567 ha) (for details on Robusta coffee production intensity mapping see You, Wood, Wood-Sichra, & Wu, 2014).

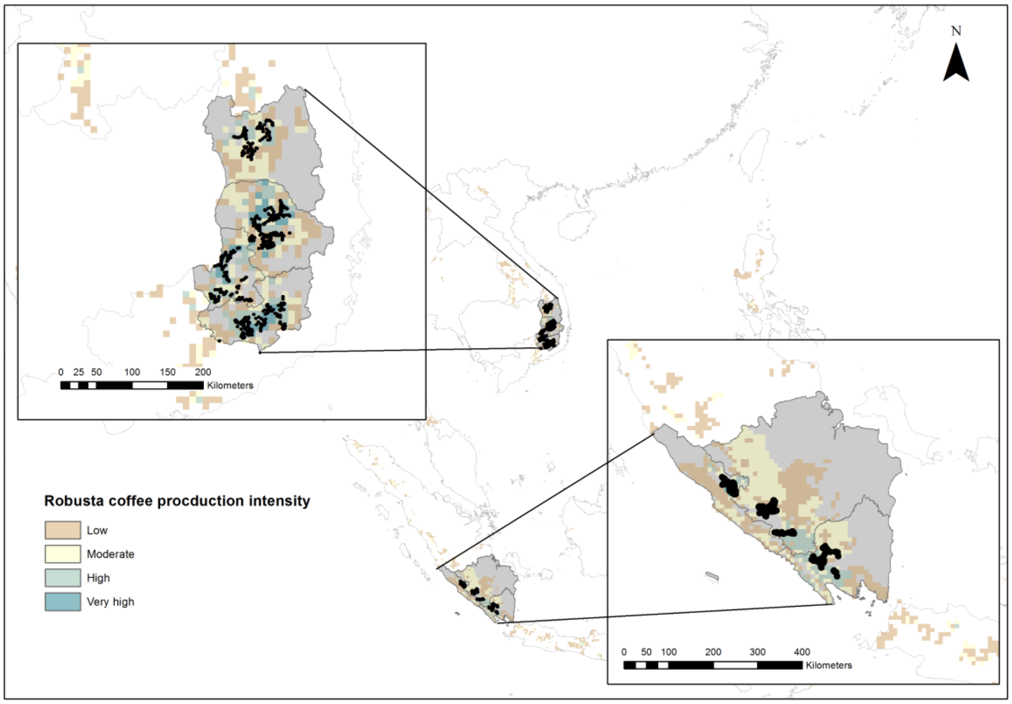
Figure 2. Boxplots showing the distribution (center horizontal line is the median, lower and upper sections are 25th and 75th percentiles respectively, whiskers show the full range of the data, except for outliers which are shown as points) of climate predictors during the (a-c) growing season and (d-f) flowering season for each of the study provinces.

Figure 3. Robusta coffee yield response to climate variables. Growing season predictors, showing (a) relationship between yield and mean minimum temperatures and (b) relationship between yield and total rainfall. Flowering season responses, showing yields relationship with (c) mean minimum temperatures and (d) total rainfall and yield. Grey shaded areas are 95% credible intervals, which show the portion of the posterior distribution that contains 95% of the values for different values of each of the climate predictors. Robusta coffee yield condition categories (optimal, suboptimal, poor and very poor) are relative to the maximum predicted yield in relation to that climate variable, while other predictors are held at their mean.

Figure 4. Robusta coffee yields response to interactions between mean minimum temperature and total rainfall. Predicted responses during (a) the growing season and (b) flowering. Robusta coffee yield condition categories (optimal, suboptimal, poor and very poor) are relative to the maximum predicted yield in relation to that climate variable, while other predictors are held at their mean. The solid coloured lines represent contours that delineate yield reductions as a percentage. For example, in (a) the area right of the red contour line (at around 20 °C) represents climatic conditions where yields are 50% lower relative to the maximum predicted yield in relation to the interaction between those climate variables, while other predictors are held at their mean.

Figure 5. Boxplots of cross validated model performance showing how well the model predicts yields at new sites (based on site-hold out cross-validations) (a) in Indonesia and Vietnam and (b) across each province in the study area. In the boxplots the center horizontal line is the median, lower and upper sections are 25th and 75th percentiles respectively, whiskers show the full range of

cross-validation results, except for outliers which are shown as points. See methods for details of cross validation procedure.



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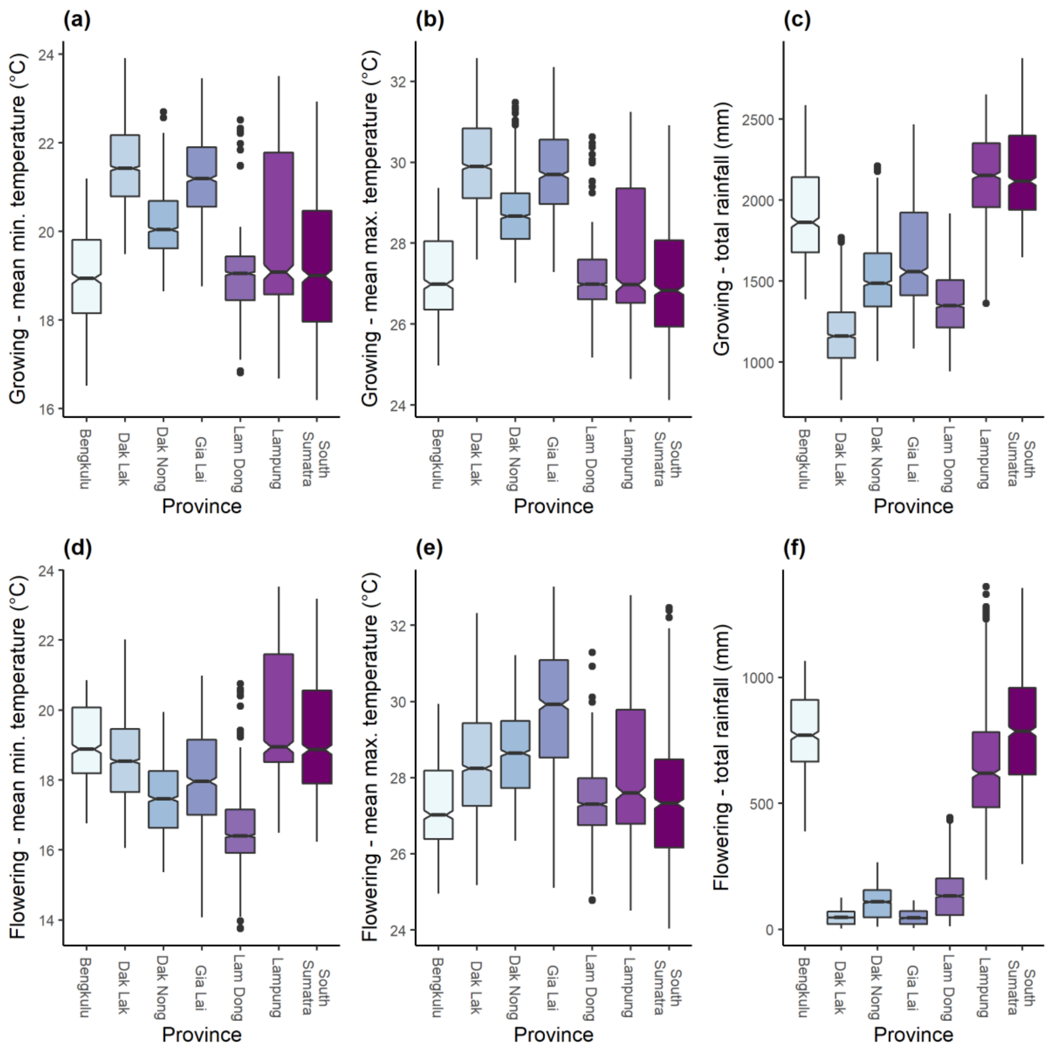

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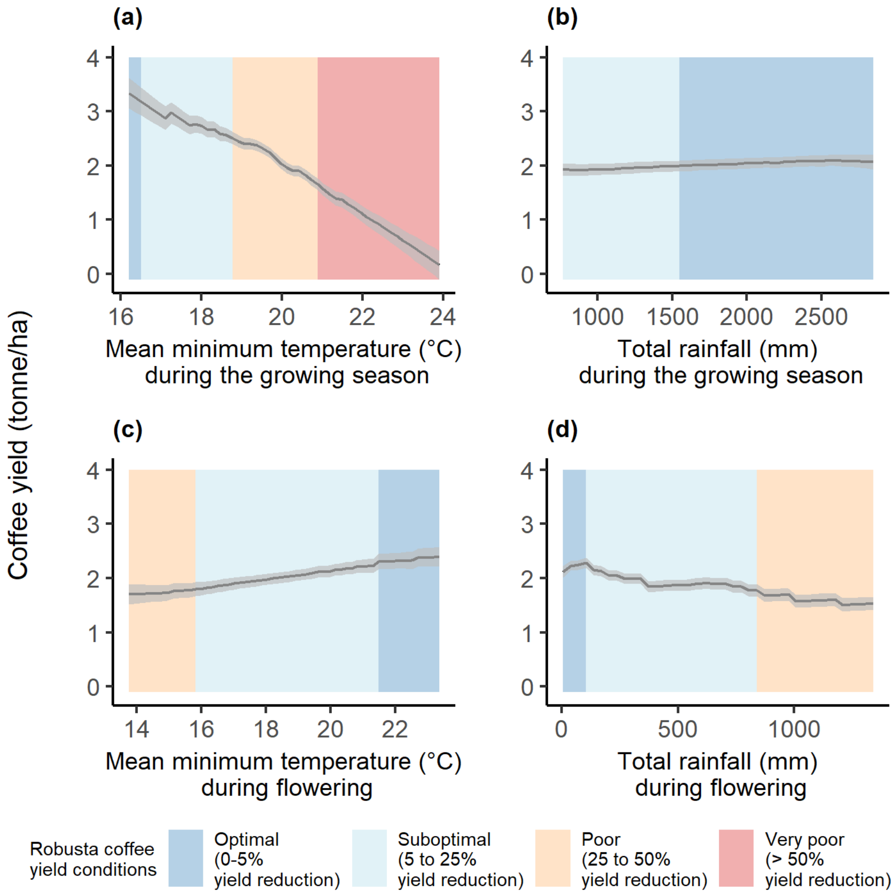

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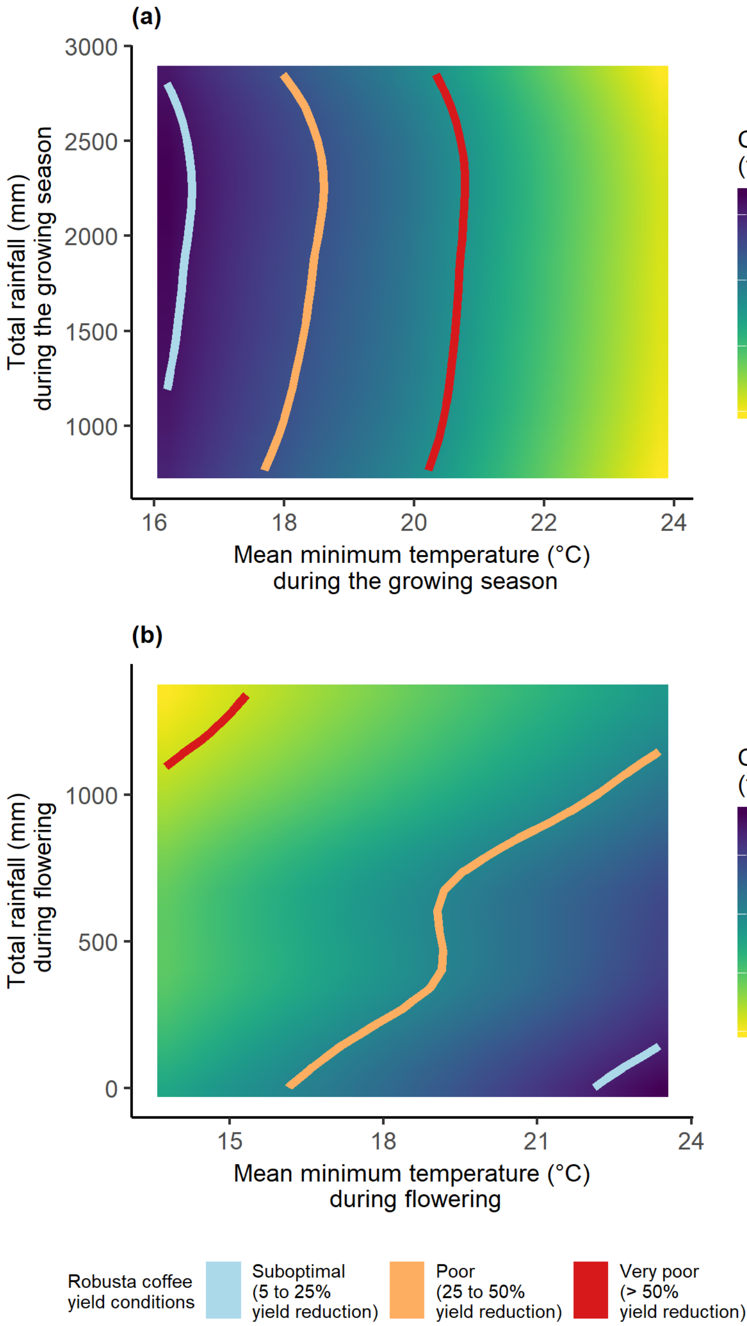

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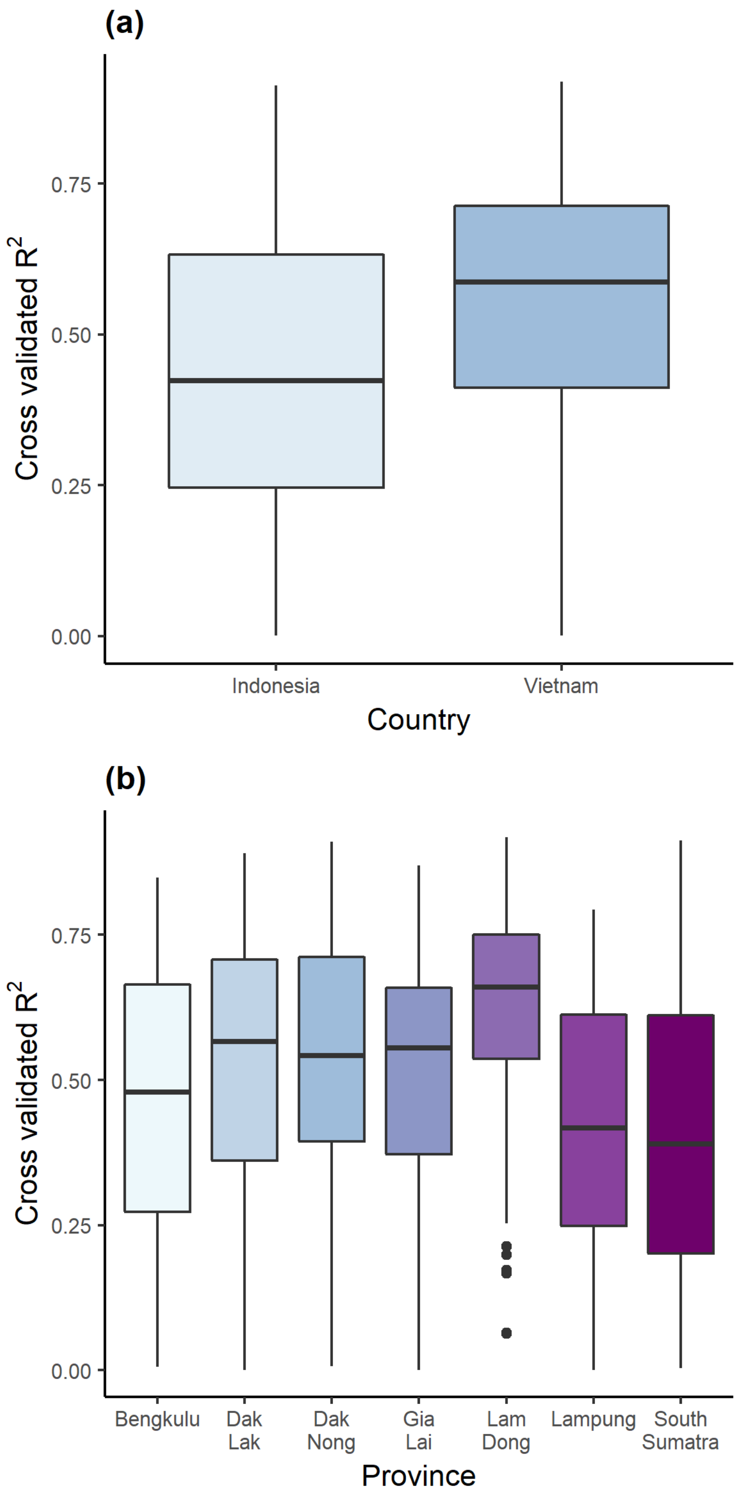

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