# Vapour pressure deficit determines critical thresholds for global coffee production under climate change

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**Abstract**

Our understanding of the impact of climate change on global coffee production is largely based on studies focusing on temperature and precipitation. However, climate indicators that could trigger critical threshold changes in productivity, such as vapour pressure deficit (VPD) and soil moisture, remain unexamined at the global scale. Here we investigate temperature, precipitation, soil moisture and VPD effects on global Arabica coffee productivity. We show that VPD during fruit development is a key indicator of global coffee productivity, with yield declining rapidly above 0.82 kPa. The risk of exceeding this threshold rises sharply for most countries we assess, if global warming exceeds 2°C. At 2.9 °C, countries making up 90% of global supply are more likely than not to exceed the VPD threshold. The inclusion of VPD and the identification of thresholds appear critical for understanding climate change impacts on coffee and for the design of adaptation strategies.

Coffee is produced in over 70 countries and supports the livelihoods of millions of farmers[1], driving a multi-billion $ (US) value chain that supplies millions of people each day. Arabica coffee (*Coffea arabica*) is reported to be highly sensitive to climate variability[2-7]; and robusta coffee (*C. canephora*), the other main coffee species, is now deemed to be more climate sensitive than previously supposed[8]. However, climate impacts on coffee, while well explored, have largely focused on temperature and precipitation[2,4,6]. Climatic variables, including, soil moisture and those representing atmospheric drying, such as vapour pressure deficit (VPD) have not been investigated, despite being important limiting factors of global ecosystem productivity[9,10]. More importantly, there has been no investigation into whether changes in these climatic variables could trigger threshold responses in global coffee productivity.

Following the Intergovernmental Panel on Climate Change, here a threshold refers to a relatively large, abrupt and possibly irreversible change in systems caused by global warming[11]. In the context of coffee production a threshold may occur when there is an abrupt increase in the rate of coffee yield decline in response to a small increase in a climate stress. Non-linear and potential threshold responses to climatic variability have been investigated in health, economic and ecological research[12-18]. In contrast, research on global-scale climate thresholds important for agricultural systems, including coffee, is limited to studies examining potential non-linear temperature effects on annual crops[19-23].

The possibility of threshold responses in coffee yields to small changes in climate variables, while unexamined, could be expected because of the way plants respond to water stress and hydraulic dysfunction[24]. For example, it is well known that plants can cope with rising

VPD by reducing stomatal conductance and increasing transpiration [10,25]. However, once a certain VPD threshold is reached a cascade of feedbacks are triggered resulting in a rapid reduction in photosynthesis and growth, with experimental studies highlighting declines in both reproductive success and yield as a consequence[25,26]. In managed agricultural systems rising VPD may not necessarily cause mortality, as in forests[27], but may nonetheless still lead to rapid declines that make production economically unviable. Importantly, the negative effects of rising VPD on productivity even occur in well-watered systems[26]. Despite this the climatic values that could trigger such a physiological response in global scale coffee productivity have not been assessed for VPD or any other climatic variables. Understanding and quantifying climate induced threshold responses for agricultural production under climate change therefore poses a unique and important research challenge.

Here we analyze global-scale Arabica coffee production responses to key seasonal climate drivers, namely temperature, rainfall, soil moisture and vapor pressure deficit (VPD) in the fruit development seasons, and test for threshold responses that could translate into rapid coffee yield declines under climate change. We use Food and Agriculture Organization (FAO) data from 13 of the worlds' most important Arabica-producing countries (accounting for 91.2% of global production in 2019, https://fdc.nal.usda.gov/) with TerraClimate data[28] and global coffee production intensity mapping[29]. We undertake three discrete analyses. First, we identify the key climate drivers of coffee production using non-linear regression models. Second, we quantify thresholds for key climate variables using threshold analyses[30]. Third and finally, we calculate the probability of exceeding the key climate thresholds we identify under baseline (1985–2015), as well as under 2 °C and 4 °C warming futures[31] and identify the amount of global warming that causes the breach of a critical climate threshold in 13 of the worlds' most important Arabica-producing countries.

## Results

### Vapour pressure deficit as a key indicator of coffee productivity

Regression models showed that the effect of growing season vapour pressure deficit (VPD) and mean maximum temperature on Arabica yields is non-linear, with the rate of change in yield varying as VPD and temperature increase (Fig. 1ab). In contrast, growing and flowering season rainfall had much less of an effect on Arabica yields (Extended Data, Fig. 1).

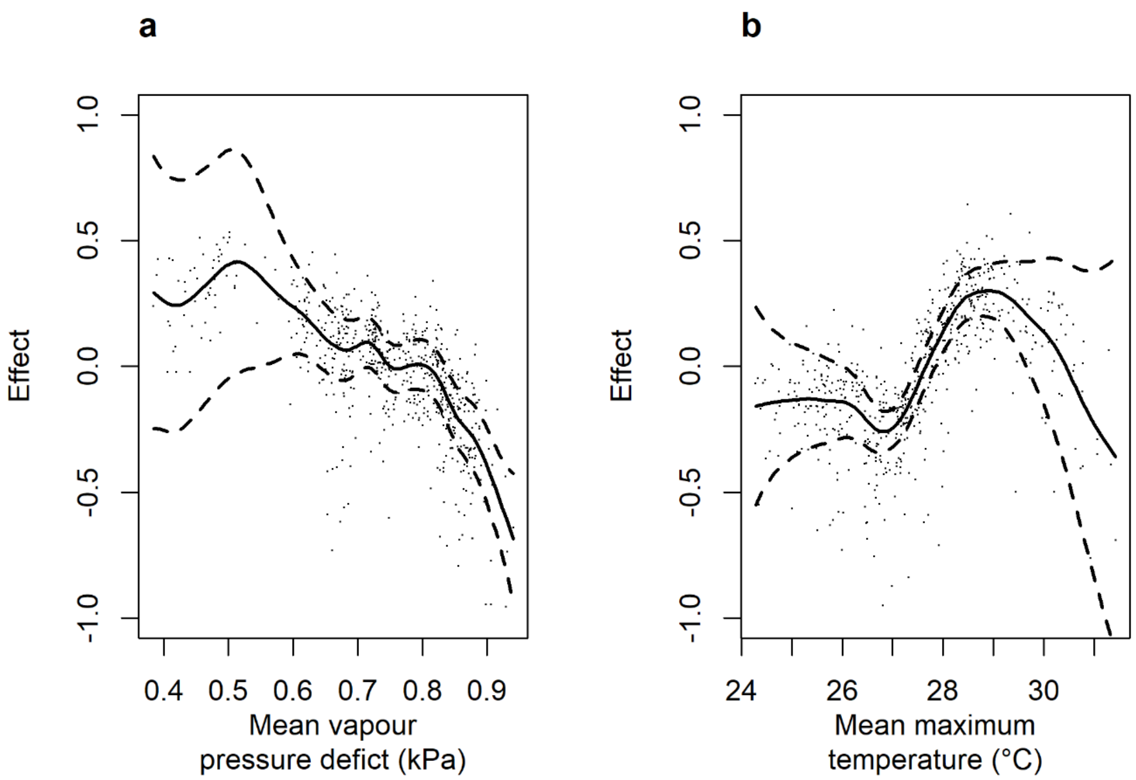


**Fig 1.** Marginal effects (when the effects of all other covariates are held constant) of the key climate drivers of Arabica yields from the best GAM model identified from model selection **a.,** vapour pressure deficit (VDP) in the growing season and **b.,** mean maximum temperatures in the growing season. The solid black line is the mean effect and dashed lines are 95% confidence intervals. Points are partial residuals. Data is from country-level coffee yield data from between 1961-2017 for 13 of the most important coffee producing countries globally (Brazil, Colombia, Costa Rica, El Salvador, Ethiopia, Guatemala, Honduras, Kenya, Mexico, Nicaragua, Peru, Tanzania and Venezuela). Selected countries were

restricted to those that produced >20,000 metric tonnes (MT) in 2019, accounting for 91.2% of Arabica coffee production in 2019 (see methods for details).

**A vapour pressure deficit threshold for coffee**

We used threshold regression analysis to test whether thresholds were present and to estimate the values of these points of abrupt decline in Arabica coffee yield in relation to the two climate variables (i.e., VPD and maximum temperature) showing a non-linear relationship with Arabica yields from regression modelling. Threshold regression analysis identified a threshold at a VPD of 0.82 kPa (0.82–0.88 kPA, 95% Confidence Interval) (Fig. 2) and for mean maximum temperature at 29.22°C (28.97–29.53°C, 95% Confidence Interval) (Extended Data, Fig. 2). The two approaches (GAM and threshold regression analysis) give congruent results for the relationship between VPD, maximum temperatures and Arabica yields.

Arabica yields decline rapidly beyond the 0.82 kPa VPD threshold (i.e. mean VPD during the flower and fruit development season), declining by up to ~400 kg/ha (i.e., c. 50% relative to the global long-term mean yield) with a small change in VPD (~0.1 kPa) (Fig 2). Similarly, Arabica yields decline rapidly as growing season (flower and fruit development) mean maximum temperatures rise above 29.22 °C though not as sharply as when the VPD threshold is exceeded and with much greater uncertainty (Fig. 1ab, Extended Data, Fig. 2).

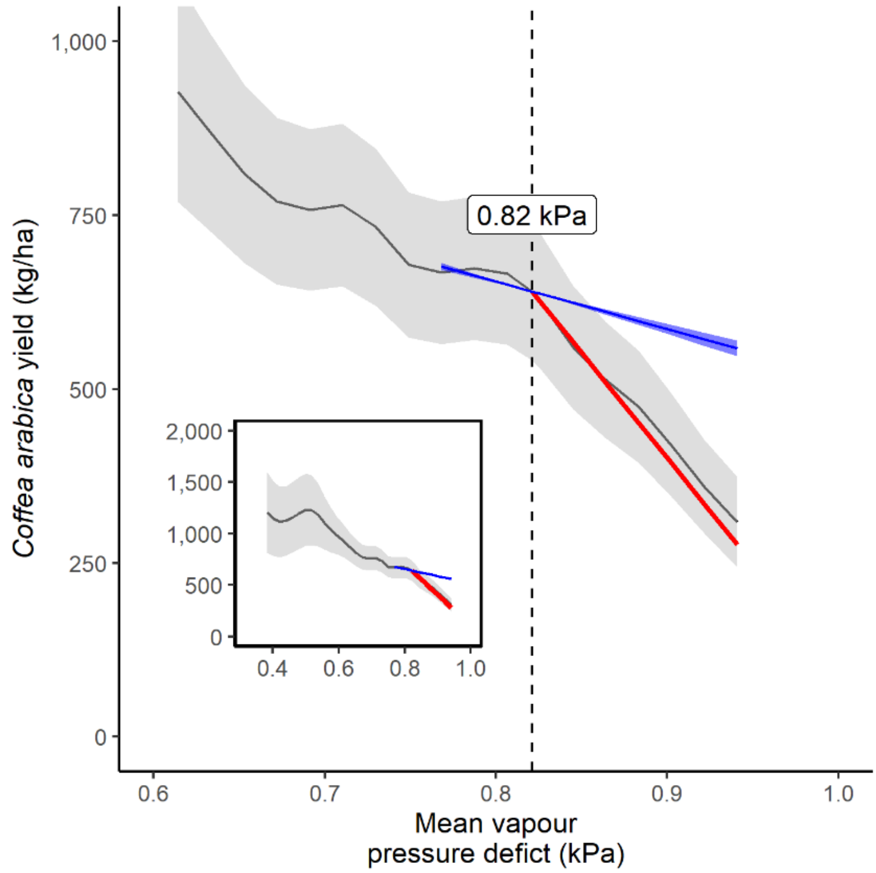


**Fig. 2: Predicted coffee yield response to vapour pressure deficit (VPD) and the estimated VPD threshold**. Arabica (*C. arabica*) yields relationship with mean vapour pressure deficit in the growing season (flower and fruit development) while other covariates are held constant at their mean. Black dashed line is the estimated VPD threshold. The blue line is the relationship between VPD and yield before the 0.82 kPa threshold and the red line after passing the VPD threshold. The inset box shows predicted coffee yields response across the entire VPD gradient. Grey coloured shaded areas are 95% confidence intervals. Extended data Fig. 2 shows the predicted coffee yield response to mean maximum temperature and associated estimated threshold. Data is from country-level coffee yield data from between 1961-2017 for thirteen of the most important coffee producing countries globally (Brazil, Colombia, Costa Rica, El Salvador, Ethiopia, Guatemala, Honduras, Kenya, Mexico, Nicaragua, Peru, Tanzania and Venezuela). Selected countries were restricted to those that produced >20,000 tonnes in 2019, accounting for 91.2% of Arabica coffee production in 2019 (see methods for details).

**Soil moisture and the vapour pressure deficit threshold**

The relationship between VPD and soil moisture is debated and at times difficult to disentangle, particularly in moisture-limited conditions[9,22]. However, as the inclusion of soil moisture did not improve model performance (Extended Data, Table 3), our results suggest that soil moisture is a relatively less important indicator of global coffee yield variability than VPD. Furthermore, in our dataset soil moisture and VPD are only weakly correlated (Pearson r = 0.15) (Extended Data, Fig. 4) (i.e. soil moisture was not excluded in the best model because of collinearity with VPD, but because it did not add substantial additional explanatory power). These findings are consistent with recent global scale assessments, which show that while soil moisture is the dominant factor driving ecosystem production responses to dryness in most areas, this is not the case in the tropics where VPD dominates[9]. Likewise, our results, focusing on the tropics, suggest that VPD is a key indicator of coffee productivity.

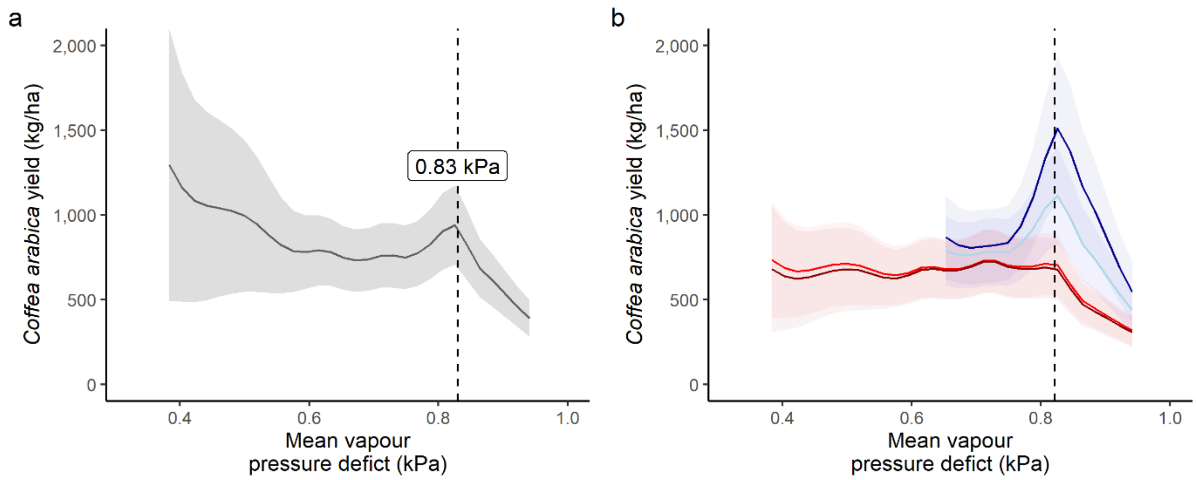


**Figure 3. a.,** Predicted Arabica yields in response to VPD for the best model including soil moisture. **b.,** Predicted Arabica yields for very high soil moisture values (dark blue line = 90th percentile of soil moisture, light blue line = 75th percentile) with predictions constrained to where data is available and very low soil moisture (red line = 25th percentile and dark red line 10th percentile). Shaded coloured areas are 95% confidence intervals for predictions**.**

Still, since soil moisture could affect the relationship we find between yield and VPD, we investigated a model including soil moisture and its interaction effect with VPD (Fig. 3). The

VPD threshold estimate identified from this interaction model was 0.83 kPa (0.82 - 0.84 kPa, 95% Confidence Interval), which overlapped that of the best model without soil moisture (Fig. 2, Fig. 3a). Moreover, the VPD threshold is still evident even at very high soil moisture values (i.e. the 75th and 90th percentiles of soil moisture in our dataset) (Fig 3b) (see also Methods and Extended Data, Fig. 5). Although, at very high soil moisture there appears to be an increase in yield as VPD increases, this only continues up until the 0.82 kPa threshold is reached, at which point yield declines. This could be because increasing VPD when soil moisture is high may favor flowering conditions and / or prevent disease, although further research is needed to investigate this.

**Global warming and the vapour pressure deficit threshold**

Figure 4 maps the probability of surpassing a vapour pressure deficit (VPD) threshold of 0.82 kPa for the current coffee-growing areas of the world's most important Arabica-producing countries under different warming scenarios (see Methods for warming scenario details). We map scenarios of 2 °C and 4 °C global temperature increases above pre-industrial (1850–1879) conditions, to provide two policy-relevant futures for assessing and communicating the sensitivity of global coffee production to climate change[31]. Depending on emissions, 2°C of global warming above pre-industrial levels is expected between 2035–2050 and 4 °C between 2060–2095[32-34].

We project that when the 2°C threshold is breached, seven of 13 Arabica-producing countries assessed have a non-zero probability of surpassing the VPD threshold under baseline (1985–2015) conditions (Fig. 4a). *Arabica*-producing countries most likely to exceed a VPD of 0.82 kPa in any given year under baseline conditions include El Salvador, Ethiopia, Guatemala, Kenya, Mexico, Peru and Tanzania (Fig. 4a). The number of Arabica-dominant producing countries with a greater than zero probability of surpassing the VPD threshold increases from seven under baseline conditions to 10 under 2 °C of global warming (Fig. 4ab). Relative to baseline conditions Honduras (0.00 to 0.90 probability of passing the threshold), Ethiopia (0.07 to 0.70), Venezuela (0 to 0.53), Peru (0.31 to 1.00) and Guatemala (0.62 to 1.00) show large climatic shifts that markedly increase the likelihood of surpassing the 0.82 kPa VPD threshold (Fig. 4ab).

The probability of exceeding the VPD threshold again increases considerably when moving from a 2 to 4°C global warming scenario (Fig. 4bc). Under a 4°C global warming scenario, all 13 of the Arabica countries assessed have > 0.75 probability of surpassing the 0.82 kPa VPD threshold (Fig. 4c). A 4°C global warming scenario sees Brazil, Costa Rica and Colombia shift from having a 0 probability of passing the 0.82 kPa VPD threshold under a 2 °C warming scenario to a high probability (> 0.75) of exceeding it (Fig 4c). It is certain (probability=1.00) , according to our analysis that under a 4°C global warming scenario the VPD threshold of 0.82 kPa will be breached in 12 of the 13 Arabica-producing countries we assess, with Costa Rica the only exception (probability=0.76).

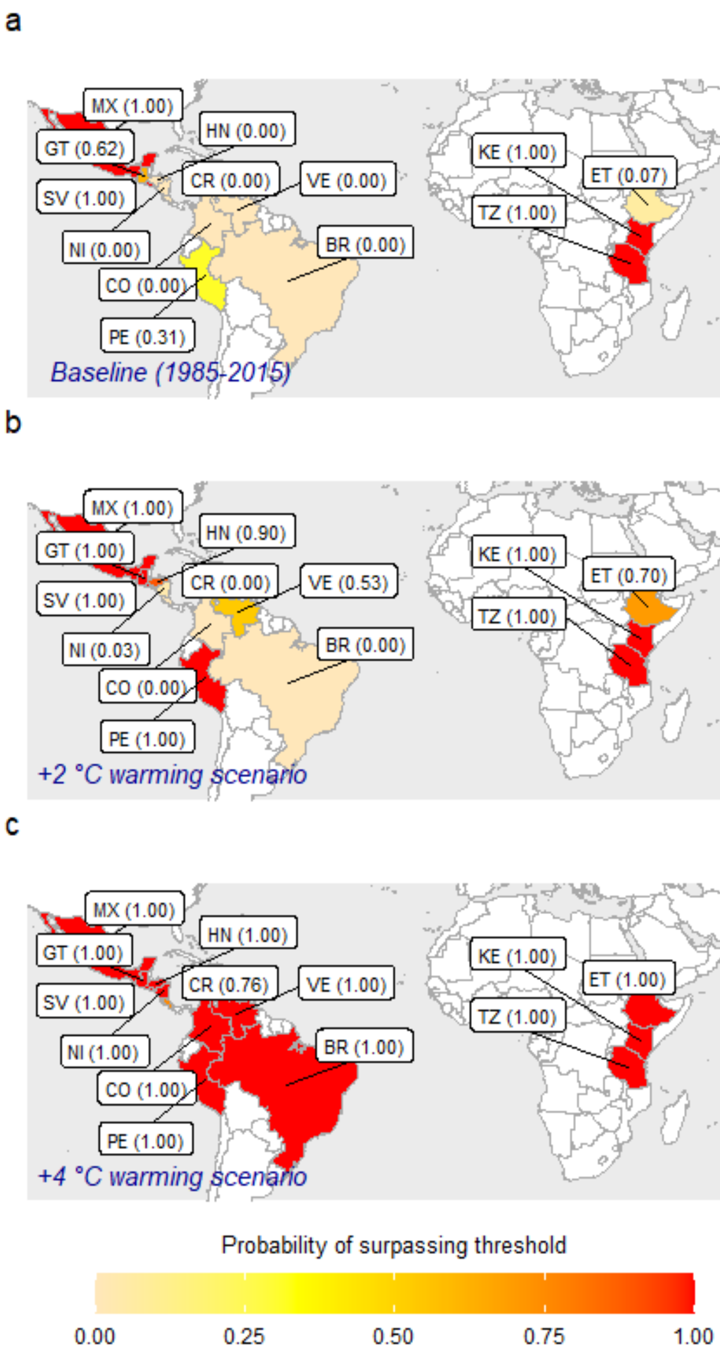


**Fig. 4: Probability of surpassing the vapour pressure deficit (VPD) threshold in Arabica (*C. Arabica*) producing countries under different climate scenarios**. **a**, under baseline (1985–2015) climatic conditions. **b**, under a 2 °C warming scenario. **c**, under a 4 °C warming scenario. Light yellow colours correspond to a low probability (i.e., < 0.25) of exceeding the 0.82 kPa VPD threshold and red colours to a high probability (i.e., > 0.75). Brazil (BR), Colombia (CO), Costa Rica (CR), El Salvador (SV), Ethiopia (ET), Guatemala (GT), Honduras (HN), Kenya (KE), Mexico (MX), Nicaragua (NI), Peru (PE),Tanzania (TZ) and Venezuela (VE).

**Over 2 °C of warming reduces Arabica supply**

To identify the amount of global warming that pushes a country past the vapour pressure deficit (VPD) threshold we interpolated between each of TerraClimate's 30-year baseline, 2 °C and 4 °C climate change scenarios for each country (Fig. 5a; see Methods for details). Based on each country's contribution to global supply (https://fdc.nal.usda.gov/), once 2°C of global warming is surpassed, possibly occurring by 2035–2050[32-34], there is a rapid increase in the percentage of global supply that exceeds the VPD threshold (Fig. 5b). At 2 °C of global warming countries making up 25% of global supply are more likely than not (probability of 0.53) to have breached the VPD threshold. At 2.5°C, 75% of global supply has a 0.25 probability of exceeding the threshold, at 2.69 °C this increased to a probability of 0.5 and at 2.85 °C to a probability of 0.75. At 3.03 °C, by 2050–2075 under a high emissions scenario[32-34], when Brazil breaches the threshold, countries currently contributing 75% to global supply are, according to our analysis, certain to exceed the VPD threshold (Fig. 5b; Extended Data, Fig. 6 & 7).

The probability of surpassing the VPD threshold increases with global warming temperatures (relative to pre-industrial) for each country (Fig. 5c). El Salvador, Kenya, Tanzania and Mexico, collectively accounting for ~5.5% of global supply, surpass the threshold under baseline conditions (i.e. at 0.7 °C above pre-industrial conditions). At 1.41 °C, Guatemala (3.56% of global supply) will surpass the VPD threshold (Fig. 5c), collectively c. 9% of global supply. Currently global warming of the land surface is at 1.2 °C above pre-industrial levels[31,35]. As global warming temperatures increase from 2 to 3°C Peru, Honduras, Venezuela, Ethiopia, Nicaragua, Colombia and Brazil, together accounting for 81% (collectively c. 90%) of global supply, have a rapidly increasing probability of exceeding the

VPD threshold (Fig. 5bc). Costa Rica (1.25% of global supply), is the country least likely to pass the VPD threshold (Fig. 5c). Only at 4.14 °C, according to our analysis, is Costa Rica certain to breach the VPD threshold.

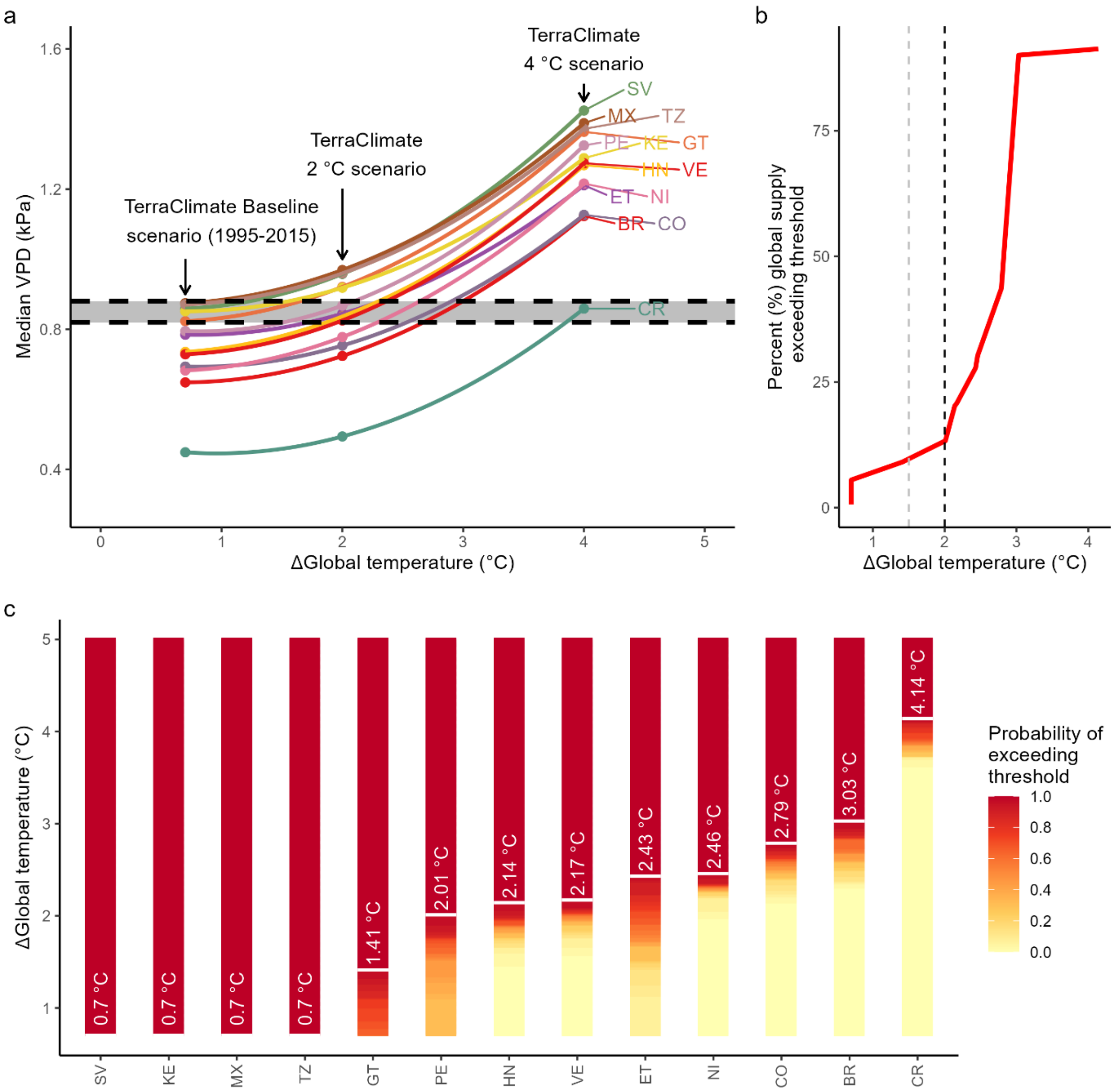


**Fig. 5**: **The relationship between global warming, the vapour pressure deficit (VPD) threshold and global Arabica coffee supply**, **a**, Relationship between change in global mean annual temperature (above pre-industrial levels) and VPD. See Fig. 4 for country codes **b**, Percentage of supply exceeding the 0.82 kPa VPD threshold as a function of global mean annual temperature. Grey dashed line is 1.5 °C and black 2 °C **c,** Global temperature corresponding with a breaching of the threshold. White horizontal line and text correspond to the global mean annual temperature at which that country has a probability of 1 of exceeding the VPD threshold.

## Discussion

Despite the importance of coffee production to the economies of coffee growing countries, there has been no analyses of the key climate variables most affecting coffee yields at a global scale, nor whether they could trigger threshold responses. Although work does exist exploring how climate affects coffee suitability[6,7] these almost exclusively focus on precipitation and temperature[2,7,8]. Recent work also highlights the importance of the combined and seasonal effect of rainfall and temperature[6,7]. Our results re-iterate these findings at a global scale and further highlight that a combination of climate parameters, and in particular the interplay between precipitation and temperatures, and their seasonality explain the climate sensitivity of Arabica coffee[3,4,7]. In our study, growing season (i.e. the fruit development period) VPD, which represents the evaporative effect of relative humidity (%RH) and temperature, seems to capture this combined impact on global scale coffee yields well, or at least better than temperature and precipitation by themselves.

Even though VPD is driven by temperature increase, it is likely that VPD limits coffee productivity not entirely through heat stress, but also through plant water stress. Water stress results not just from reductions in precipitation and soil moisture, but from increasing atmospheric demand, which increases plant water demand[36,37]. Studies on maize suggest that temperature rises that increase atmospheric demand (i.e. VPD) and thus plant water requirements, may have an even stronger influence on plant water stress than typical variations in precipitation[21,36]. As such, our finding that precipitation and soil moisture variation has a relatively minimal impact on global coffee yields should not be taken to mean that coffee is insensitive to water stress. The opposite in fact. The high sensitivity of

Arabica coffee to VPD suggests that it may be highly sensitive to water stress and that temperature increase which drives VPD higher is a key indicator of this sensitivity.

The role of water stress is also highlighted by the offsetting effect of very high soil moisture on yield loss (up to +20% at a VPD of around 0.9 kPa) (Fig. 3b). This highlights the possible role that increasing soil moisture (e.g. through supplemental irrigation) could have in mitigating some of the negative impacts of passing the VPD threshold. However, over 95% of the coffee growing areas in the countries we assess are non-irrigated[29] and whether wide-scale irrigation is a sustainable and feasible strategy for alleviating rising VPD impacts requires more research, which would also need to include ecosystem impact, economic, carbon accounting and socio-economic studies. Even though we emphasize that while plants may acclimate to increasing VPD, particularly under well-watered conditions, there are still major costs to growth at high VPD, even with zero water stress, leading to changes in plants nitrogen balance, a reduction in primary productivity and plant yields[26].

Consideration of plant water status and stress also points to a possible mechanism through which to interpret the threshold response of coffee yield to increasing VPD that we show here. Plants can cope with rising VPD at the leaf level by reducing stomatal conductance, increasing transpiration and lowering photosynthesis[10,26]. In turn, these leaf level adaptations to increasing VPD manifest in reduced plant mass, flower numbers and yield[10,26]. These physiological effects of VPD on plants occur even in well-watered conditions[26], which may explain in part why we find a threshold response to VPD, albeit with some moderation of losses[22], even when soil moisture is high. Importantly, this suggests that future increases in VPD, and potentially the threshold value we find here, will reduce coffee productivity to some extent regardless of changes in soil water status. Further research is needed to test the magnitude of the negative effect of VPD on coffee under different watering regimes both at the finer farm scale and experimentally.

Recent research has emphasized the positive effects that elevated $CO_2$ has on coffee photosynthetic functioning[38,39]. Numerous studies have shown that elevated $CO_2$ levels, alter coffee leaf physiological responses to temperature and promote higher water-use efficiency, which could mitigate climate change impacts on coffee production[38,39]. However, beyond leaf physiological responses the effects of elevated $CO_2$ on coffee yields are unclear. In a two-year study of elevated $CO_2$ levels (550 µmol/mol) on two varieties of Arabica only one variety in one year (of the 2 varieties tested over two-years) showed an increase (+14.6%) in yields at elevated $CO_2$ levels (550 µmol/mol) [40]. More recently, a longer-term 4-year study showed no increase in yields at elevated $CO_2$ levels (550 µmol/mol)[41].

Nonetheless, studies on other plant species have shown that increased water-use efficiency at high $CO_2$ can partly off-set the negative effects of high VPD[36,42]. There has been no assessment of the role of $CO_2$ fertilization on coffee productivity under VPD stress. As such, our findings highlight an important avenue for future research in quantifying the possible role of $CO_2$ in offsetting coffee yield losses from increasing VPD under climate change[26].

It should be noted that these results are based on a country-level analyses. At finer scales there is likely to be heterogeneity within countries – with some being more or less likely to breach the VPD threshold at different global temperatures. It is also important to emphasize that these calculations do not factor in the movement of Arabica production to newly emerging areas of suitability as the climate changes. This has substantial potential in countries with plentiful elevation capacity, such as Ethiopia[7], but globally this may be limited and is fraught with diverse social, environmental and economic challenges, including land use change issues, land tenure rights, and human migration.

While FAO data is well suited to our macro-scale analyses, and widely used in climate impact studies at the global scale[43-45], we acknowledge the importance of future regional and farm-level investigations testing whether the VPD relationships and threshold values we find here are also applicable at finer scales (e.g. at farm-level). As transpiration rates vary through the day as atmospheric demand fluctuates[37], experimental studies directly measuring coffee stress responses (over hourly to daily timescales) could also be especially valuable in elucidating the mechanism through which VPD may cause threshold responses in coffee productivity (e.g. predominantly through water stress, heat stress or another pathway).

Alongside finer scale studies, there is also a need to experimentally test whether management interventions can offset yield declines that occur once the VPD threshold is surpassed[26]. This is critical for informing finer-scale management adaptation options (e.g. shading, irrigation and fertilizer use). Investigating the effectiveness of management interventions will be all the more important if, as is suggested for other species, rising VPD effects are still negative even when irrigated. If this is the case for coffee as well, investigation of plant breeding traits that confer resilience to higher VPD, in both the common coffee crop species and other coffee species that are better adapted to warmer[5] and drier climates[46] will be critical. Farm-level micro-climatic management manipulations that alter VPD effects, such as shading[47] and tree spacing[27], could also be important.

## Online methods

### Global coffee yield data

We took country-level coffee yield data (http://www.fao.org/faostat/en/#home) from between 1961–2017 for 13 of the most important coffee producing countries globally. Selected countries were restricted to those that produced >20,000 metric tonnes (MT) in 2019, accounting for 91.2% of Arabica coffee production in 2019 (https://fdc.nal.usda.gov/). Countries producing less coffee have less reliable reporting (e.g. some only report averaged statistics over multiple years) making them unsuitable for a global scale analysis of climate impacts. FAO data is the best available standardized dataset on agricultural productivity of crops available at a global scale. FAO uses a statistics quality assurance framework to ensure data are as accurate, reliable, comparable (e.g. over time and between geographical areas) and coherent as possible and regularly assesses and validates statistical outputs (http://www.fao.org/3/i3664e/i3664e.pdf). FAO data has been widely used in country and global scale climate impacts analyses for numerous crops[43-45]. Coffee yield data from the FAO was also screened for outliers with any centred yield observations > |3| standard deviations removed. The final dataset comprised 648 country-years of data.

The use of aggregated FAO data may be associated with some uncertainty, due to potentially unreliable reporting (e.g. under or over reporting of yields) from some countries. However, as long as any reporting biases are uncorrelated with year-to-year changes in yields and VPD, which is most likely, this does not bias our results, but simply increases their uncertainty[45]. This uncertainty is accounted for well by both the non-linear GAM and threshold regression analyses. Even so, to minimize uncertainty we restricted analysis to Arabica dominant producing countries that produced more than 20,000 MT in 2019. These countries accounted for 91.2% of all Arabica coffee production in 2019 (https://fdc.nal.usda.gov/) with countries from Africa, Central America and South America all represented (Extended Data, Table 1). Countries producing less coffee have less reliable reporting (e.g., some only report averaged statistics over multiple years) making them unsuitable for a global-scale analysis of climate impacts.

**Climate data**

Climate data was taken from the TerraClimate dataset (~ 4 km resolution)[28]. TerraClimate uses climatically aided interpolation with high-spatial resolution climatological normals from the WorldClim dataset in combination with coarser resolution time varying (i.e., monthly) data from CRU Ts4.0 https://data.ceda.ac.uk//badc/cru/data/cru_ts/ and the Japanese 55-year Reanalysis (JRA55) https://jra.kishou.go.jp/JRA-55/index_en.html. For the growing and flowering seasons (Extended Data, Table 2) each year the total rainfall, minimum and maximum temperatures, soil moisture, as well as mean vapor pressure deficit were extracted and aggregated based on coffee production mapping for each country[29].

TerraClimate soil moisture estimates are from a one-dimensional-water balance model. This model is based on a monthly time step and estimates soil moisture and runoff from water-holding capacity, precipitation and Penman–Monteith reference evapotranspiration (ET0)[20,28]. Vapour pressure deficit (VPD) is calculated as the difference between the mean saturation vapour pressure concomitant with the daily high and low temperatures and saturation vapour pressure at the daily mean dewpoint temperature (for details see https://www.climatologylab.org/terraclimate.html). As VPD measurements from the TerraClimate dataset are based on the difference between the daily minimum and maximum, they will be lower than if they are based only on daytime VPD. The TerraClimate dataset has been validated globally and has been used in large scale agricultural studies[28,31].

Climate variables were weighted, such that aggregated climate data reflected the distribution of coffee production intensity[29]. As such, climate variables are not a simple aggregation of annual climatic conditions spanning the political borders of each coffee producing country, but instead represent climatic conditions only in coffee producing areas during the time of the year that climate variability is most likely to impact coffee production[2].

For each country and climate variable then

$$C_w = \sum_{i=1}^{n} C\,P_i$$

where $C_w$ is the weighted climate variable for each country in each season per year and *P* is the proportion of production for each location (*i*) and *C* is the corresponding climate variable. Weighted climate variables were calculated for the flowering and growing season in each year as this is when production is most sensitive to climatic variability.

**Climate change scenario data**

Climate change scenario data was extracted and aggregated as outlined above. Climate scenarios corresponded to 2 °C and 4 °C above pre-industrial (1850–1879) conditions, as well as a baseline scenario (1985–2015)[31]. The TerraClimate dataset scenarios are derived from 23 CMIP5 climate models and use pattern scaling that superposes climate mean and variability on conditions from 1985–2015. These scenarios are highly flexible and allow for assessment of climate change impacts on coffee production in an interpretable way while accounting for the uncertainty that is implicitly a part of climate model projections and emission scenarios[31]. The 2 °C and 4 °C scenarios we assess here provide two policy relevant futures that can be used to assess and communicate the sensitivity of global coffee production to climate change[31]. Depending on emission scenario 2 °C of global warming is expected between 2035–2050 and 4 °C between 2060–2095[32-34].

**Identifying climate variables important for coffee production**

We used a generalized additive regression models (GAM)[48] and multi-model selection[49] to identify the key climate drivers of global coffee production. All analyses were carried out in R[50]. In the GAM

$$\log(y_{ij}) = \beta_o + f_{(x_{ij})} + z_i\varphi + \epsilon_{ij}$$

$$\epsilon_{ij} \sim Gamma(\gamma)$$

$$\varphi \sim N(0, \beth)$$

Yields (*y*) were modelled as a non-linear (*f*) function of predictor variables (*x*) for each country (*i*) and year (*j*) using a Gamma distribution with a log link. A random effect ($\varphi$) for each country (*Zi*) was included to account for the repeat measurements for each year at the country level. Random-effects control for non-independence by constraining non-independent observations to have the same intercept[51]. For example, yield observations from a particular country, may be more similar (e.g., higher on average if soils and management techniques are better) relative to yield observations from other countries. To account for temporal autocorrelation year was modelled as an autocorrelation structure of order 1[48]. There were 10 climate variables (maximum temperature, minimum temperature, total rainfall, total soil moisture and vapor pressure deficit for both the growing and flowering season) in the global model. Model selection also accounted for multi-collinearity by ensuring no models included variables with a Pearson coefficient r > |0.5|. Gross domestic product (GDP - current US$) (https://data.worldbank.org/) was included as a predictor variable to account for the influence of technological advancement on coffee yields over time[52].

As Arabica exhibits a biennial productivity cycle[53] (a productive crop one year is generally followed by a lesser crop in the following year) we tested for the influence of climate variables over two-years. This was done by systematically testing the weighted influence (in 5% increments) of the current and previous years yield on the current year's yields. So, for example, we weighted the previous year's influence at 0.95 and the currents at 0.05, then at 0.90 and 0.10 and so on through to weightings of 0.05 and 0.95 for the previous and current year's climate respectively. Multi-model selection using AIC[49], was used to identify the suite of main effect predictors, as well as the weightings of previous and current years, that most parsimoniously explained variations in yield for Arabica. In total the AIC of 14,720 models were assessed. Additionally, we incorporated a variable, Proportional previous yield (PPY), to account for the fact that because of its biennial life cycle Arabica can have light and heavy production years. This was calculated as

$$PPY = (Yield_{t-1} - Yield_{t-2})/Yield_{t-2}$$

In line with biennial production cycle of Arabica a 50/50 weighting of the previous and current years climate most parsimoniously explained yields. Additional to this, the PPY variable was also selected, suggesting that the best model and FAO data detect and account well for the biennial nature of Arabica in our assessment of climate impacts. We believe the approach we outline here accounts well for a biennial crop cycle and would be applicable to range of other biennial plants and crops underrepresented in climate impact research.

The results we present in the main text are based on a biennial life cycle model. The threshold relationship with VPD was consistent regardless of whether annual or biennial climate data was used (VPD threshold based on an annual model is 0.83 kpA, with a 95%

Confidence Interval of 0.82–0.87 kPa, Extended Data Fig. 8), while for the biennial model it is 0.82 kPa (0.82–0.88 kPA, 95% Confidence Interval).

We used nested cross-validation on the selected best model to get estimates of model error[54]. To do this we split the dataset into six temporal components. The initial model was built on the first three temporal components of the data (n=28 years, from 1961/3–1990) and tested on the fourth held-out temporal component (n=9 years, 1991–1999), then built using the first four temporal components (n=37 years, from 1961/3–1999) and tested on the fifth held-out temporal component (n=9 years, from 2000–2008) and finally built on the first five temporal components (n=46 years, from1961/3 to 2008) and tested on the final held-out temporal component of data (n=9 years, from 2009–2017).

The best models with a 50/50 weighting of the previous and current years climate all included some combination of growing season mean vapour pressure deficit, total rainfall, mean maximum temperature and flowering season rainfall. The top four models were almost identical in terms of AIC and all performed similarly well with a cross-validated $R^2$ of 0.67 - 0.70 (Extended Data Table 3). Interactions between main growing season effects were also assessed, as were interactions between each climate variable and the PPY variable. However, while these models lowered AIC they did not have a better cross-validated $R^2$ than models without interactive terms. In the main text we present threshold values and results from the model with the best model with the lowest AIC (Extended Data, Table 3), however threshold estimates and the relationship between VPD and Arabica yield was consistent regardless of model structure (Extended Data Fig. 9 and Fig. 10).

**VPD and soil moisture interactions**

We sub-set the dataset to test whether the effect of VPD altered when constrained to only high or low soil moisture conditions. However, regardless of whether the model was fit to all data - only low soil moisture or high soil moisture - the effect of VPD on Arabica yields is broadly similar (Extended Data, Fig 5). Our results are therefore consistent with a broader pattern emerging in the literature suggesting that while soil moisture is key for plant productivity in arid, semi-arid (e.g. for maize[22]) and temperate areas[9], in the tropics, where rainfall and thus soil moisture is much higher, VPD appears to be a key limiting factor on productivity.

**Threshold analyses**

As non-linear regression using a generalized additive model (GAM) is fit with a spline (a smooth function) it is not able to test for and / or identify points of abrupt change, or thresholds. Threshold regression, on the other hand, explicitly introduces a threshold parameter allowing for thresholds, or change points, to be quantified[30]. In turn, this allows for values (i.e., particular climatic conditions) to be ascribed to threshold changes and thus clear guidance and recommendations can be made about whether there are important limits that researchers, managers, farmers and policy makers should be aware, in terms of risk and planning.

Using threshold regression analysis[30] we quantified the threshold value (and its associated uncertainty) for those climate variable(s) showing a non-linear change (i.e., a threshold response) that resulted in an increase in the rate of yield decline. We focused on values greater than median as maximum temperatures and VPD are projected to increase in the coming decades under climate change[55] and because GAM analysis suggests high uncertainty at the lower end of the temperature and VPD gradient (Fig 1a, b). These thresholds are of the most importance because once surpassed they may result in rapid declines in yield that pose the greatest challenge for climate change adaptation.

For these variables we used threshold regression model estimation and inference using the package chnpt[30] in R[50]. We used a two-phase segmented threshold model where:

$$\eta = \alpha_1 + \alpha_2^T z + \beta_1 (x - e)_+ + \gamma x$$

Here *e* is the threshold parameter, *x* is the predictor with threshold effect, *z* denotes additional predictors - in this case the additional predictors are those in the best model identified from GAM multi-model selection (see above), excluding the threshold variable of interest (*x*). These additional variables were fit with a non-linear spline with the same number of knots as in the best GAM. The hinge function is *(x-e)+*, which equals *x-e* when *x>e* and 0 otherwise[30] . Uncertainty in threshold estimates were calculated using bootstrapping (n=1000), which was used to generate 95% confidence intervals[56].

As a check on reliability, we examined whether threshold estimates are being driven by anomalous country and time period conditions. To do this we sequentially held out each country and blocks of years from the threshold regression analysis. VPD threshold estimates when countries and blocks of time were held out are similar to estimates when all data is considered (Extended Data, Fig. 3). We also randomly held out 50% of all observations in the dataset and ran threshold analyses on this, repeating this process 1000 times. The VPD threshold estimate was again 0.82 kPa, although with a wider 95% Confidence Interval of between 0.75 - 0.89 kPA. The mean maximum temperature threshold values are consistent across analyses when each country is held-out from the dataset, aside from when El Salvador was excluded (Extended Data, Fig. 3). This suggests that the maximum temperature threshold values identified are driven by data from El Salvador and so may be less reliable then the VPD threshold estimates, which are insensitive to data from individual countries being removed. The mean maximum temperature threshold nonetheless does align with the reported mean maximum temperature optimal for Arabica of 28–30 °C[57].

**Probability of exceeding global scale climate thresholds**

The relative change in the likelihood of exceeding thresholds was mapped for each country under baseline, 2 °C and 4 °C warming scenarios. The probability of exceeding the estimate threshold for was calculated as

$$P(X_i \geq x_j) = 1 - P(X_i < x_j) = 1 - F(X_i < x_j)$$

Where $x_j$ is the threshold estimate and X is the vector of the climate variable under each scenario (i), and F(.) denotes its cumulative distribution function.

**Calculating the amount of global warming that pushes a country past the VPD threshold**

To calculate the amount of global warming that pushes a country past the VPD threshold we interpolated between each of TerraClimate's 30 year baseline, 2 °C and 4 °C climate change scenarios for each country. TerraClimate uses a pattern scaling approach because the geographic patterns to climate forcing scale reasonably linear as a function of global mean temperature[31]. This means that at any location changes to local climate can be estimated through interpolation as a function of global mean temperature.

The relationship between VPD and global mean temperatures can similarly be interpolated, using a regression with a second-order polynomial. We did this at 0.01 °C increments for growing season VPD between global warming temperatures of 0.7–5 °C. Using this information, we then mapped the amount of global warming that corresponds to different probabilities of exceeding the 0.82 kPa VPD threshold. Finally, using recent data on global coffee supply (https://fdc.nal.usda.gov/) we calculated the amount of global supply that exceeds the VPD threshold at a probability of 1.


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## Contributions

J.K. conceived the initial study based on conversations with A.C, P.V, A.P.D, Y.F, V.B, and S.P., Y.F. and J.K performed the threshold analysis and J.K, R.K and T.N carried out supporting analyses. J.K. and S.P wrote the manuscript. J.K, T.N and T.M linked and analysed the climate data. All authors contributed to the critical review and writing of the manuscript.

## Data availability

The analyses is based on publicly available datasets. TerraClimate data is from http://www.climatologylab.org/terraclimate.html . Coffee yield data is from http://www.fao.org/faostat/en/#home . Coffee mapping data is from https://www.mapspam.info/

## Code availability

Code for replicating threshold analyses underpinning the results presented in the paper is available from the corresponding author on request.


Correspondence and requests for materials should be addressed to J. Kath jarrod.kath@usq.edu.au

## Extended Data

**Extended Data Table 1:** Summary statistics showing the percentage of contribution each country makes to global supply (from https://fdc.nal.usda.gov/ ) and mean and standard deviation of yield data that was used in GAM and threshold regression analysis from (http://www.fao.org/faostat/en/#home)

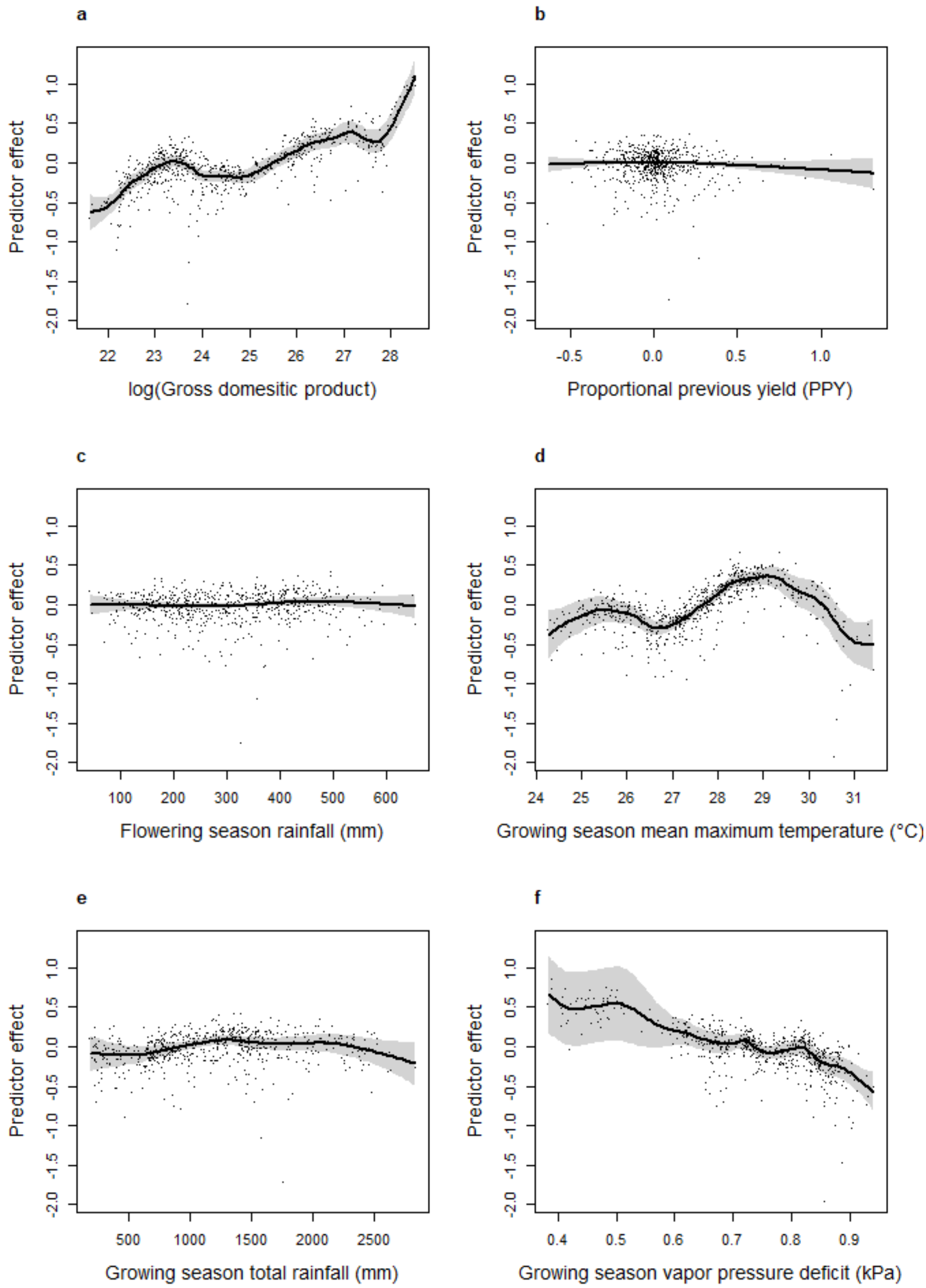
| **Country** | **Percent of global *Coffea arabica* supply** | **Mean Yield (t/ha)** | **Yield (t/ha) standard deviation** |
|---|---|---|---|
| Brazil | 46.40% | 0.759 | 0.344 |
| Colombia | 13.35% | 0.762 | 0.157 |
| Costa Rica | 1.25% | 1.17 | 0.257 |
| El Salvador | 0.63% | 0.788 | 0.253 |
| Ethiopia | 6.98% | 0.698 | 0.091 |
| Guatemala | 3.56% | 0.797 | 0.192 |
| Honduras | 6.93% | 0.682 | 0.208 |
| Kenya | 0.75% | 0.539 | 0.179 |
| Mexico | 3.47% | 0.469 | 0.106 |
| Nicaragua | 2.50% | 0.616 | 0.165 |
| Peru | 4.24% | 0.625 | 0.110 |
| Tanzania | 0.67% | 0.328 | 0.088 |
| Venezuela | 0.56% | 0.277 | 0.074 |
| **Total** | 91.29% | 0.668 | 0.289 |

**Extended Data Table 2:** The growing and flowering season months for each country and supporting references.

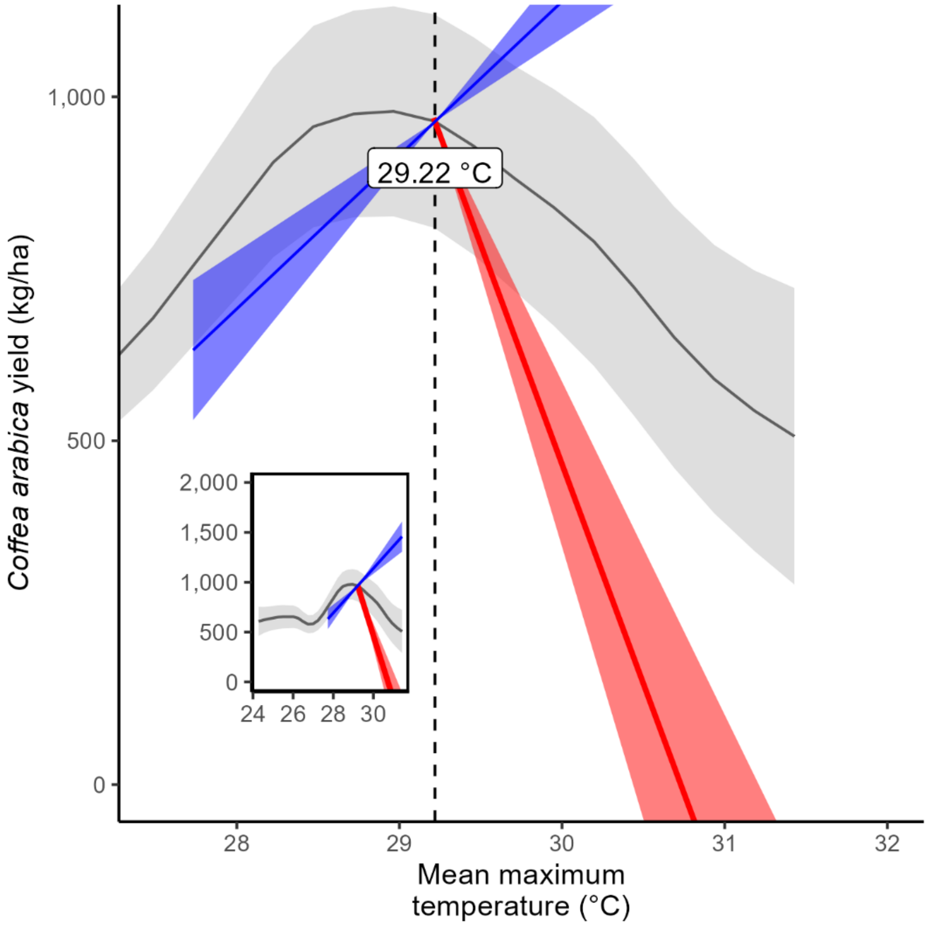
| Country | Growing | Flowering | Reference |
|---|---|---|---|
| Brazil | Dec-Jun | Sep - Nov | DaMatta FM, Ronchi CP, Maestri M, Barros RS (2007). Ecophysiology of coffee growth and production. Brazilian journal of plant physiology 19:485-510 |
| Colombia | May - Sep & Oct-Mar | Feb - Apr & May-Sep | Caravela C (2021). Harvest dashboard. https://caravela.coffee/harvest-dashboard/ (accessed on 16.03.2021).<br>Peña Quiñones, A.J., Ramírez Builes, V.H., Jaramillo Robledo, A., Rendón Sáenz, J.R. and Arcila Pulgarín, J., 2011. Effects of Daylength and Soil Humidity on the Flowering of Coffee Coffea arabica L. in Colombia. Revista Facultad Nacional de Agronomía Medellín, 64(1), pp.5745-5754. |
| Costa Rica | June - Feb | Apr - May | Cannell MGR (1985) Physiology of the coffee crop. In: Clifford MN, Wilson KC (eds) Coffee: botany, biochemistry and production of beans and beverage. Croom Helm, London, pp 108-134 |
| El Salvador | June - Feb | Apr - May | Cannell MGR (1985) Physiology of the coffee crop. In: Clifford MN, Wilson KC (eds) Coffee: botany, biochemistry and production of beans and beverage. Croom Helm, London, pp 108-135 |
| Ethiopia | Apr - Nov | Feb - Mar | Cannell MGR (1985) Physiology of the coffee crop. In: Clifford MN, Wilson KC (eds) Coffee: botany, biochemistry and production of beans and beverage. Croom Helm, London, pp 108-136 |
| Guatemala | June - Feb | Apr - May | Cannell MGR (1985) Physiology of the coffee crop. In: Clifford MN, Wilson KC (eds) Coffee: botany, biochemistry and production of beans and beverage. Croom Helm, London, pp 108-137 |
| Honduras | June - Feb | Apr - May | Cannell MGR (1985) Physiology of the coffee crop. In: Clifford MN, Wilson KC (eds) Coffee: botany, biochemistry and production of beans and beverage. Croom Helm, London, pp 108-138 |
| Kenya | May - Oct | Apr - May | Cannell MGR (1985) Physiology of the coffee crop. In: Clifford MN, Wilson KC (eds) Coffee: botany, biochemistry and production of beans and beverage. Croom Helm, London, pp 108-139 |
| Mexico | Jun- Dec | Feb - May | Wintgens JN, (2008). In Coffee: Growing, Processing, Sustainable Production: A Guidebook for Growers, Processors, Traders, and Researchers. Ed.; WILEY-VCH Verlag GmbH & Co. KGaA: Weinheim, Germany, 2008.<br>Castillo, N.E.T., Melchor-Martínez, E.M., Sierra, J.S.O., Ramirez-Mendoza, R.A., Parra-Saldívar, R. and Iqbal, H.M., 2020. Impact of climate change and early development of coffee rust–An overview of control strategies to preserve organic cultivars in Mexico. Science of the Total Environment, 738, p.140225. |
| Nicaragua | June - Feb | Apr - May | Wintgens JN, (2008). In Coffee: Growing, Processing, Sustainable Production: A Guidebook for Growers, Processors, Traders, and Researchers. Ed.; WILEY-VCH Verlag GmbH & Co. KGaA: Weinheim, Germany, 2008. |
| Peru | Dec - Mar | Sep - Nov | Wintgens JN, (2008). In Coffee: Growing, Processing, Sustainable Production: A Guidebook for Growers, Processors, Traders, and Researchers. Ed.; WILEY-VCH Verlag GmbH & Co. KGaA: Weinheim, Germany, 2008. |
| Tanzania | May - Nov | Mar - Apr | Wagner S, Jassogne L, Price E, Jones M, Preziosi R (2021). Impact of Climate Change on the Production of Coffea arabica at Mt. Kilimanjaro, Tanzania. Agriculture 11:53 |
| Venezuela | May -Sep | Feb - Apr | Rahn E, Vaast P, Läderach P, van Asten P, Jassogne L, Ghazoul J (2018). Exploring adaptation strategies of coffee production to climate change using a process-based model. Ecological Modelling 371:76-89 |

**Extended Data Table 3.** The best models from multi-model selection (see Methods for details). The main effects predictors in the four top models as well as model structure including interactions are shown. The top four models have almost identical AIC and model performance. Note log(Gross domestic product) was selected in all best models for the below. G-RAIN=growing season rainfall, G-VPD=growing season vapour pressure deficit, G-TMAX=growing season maximum temperature and G-SOILM=growing season soil moisture.

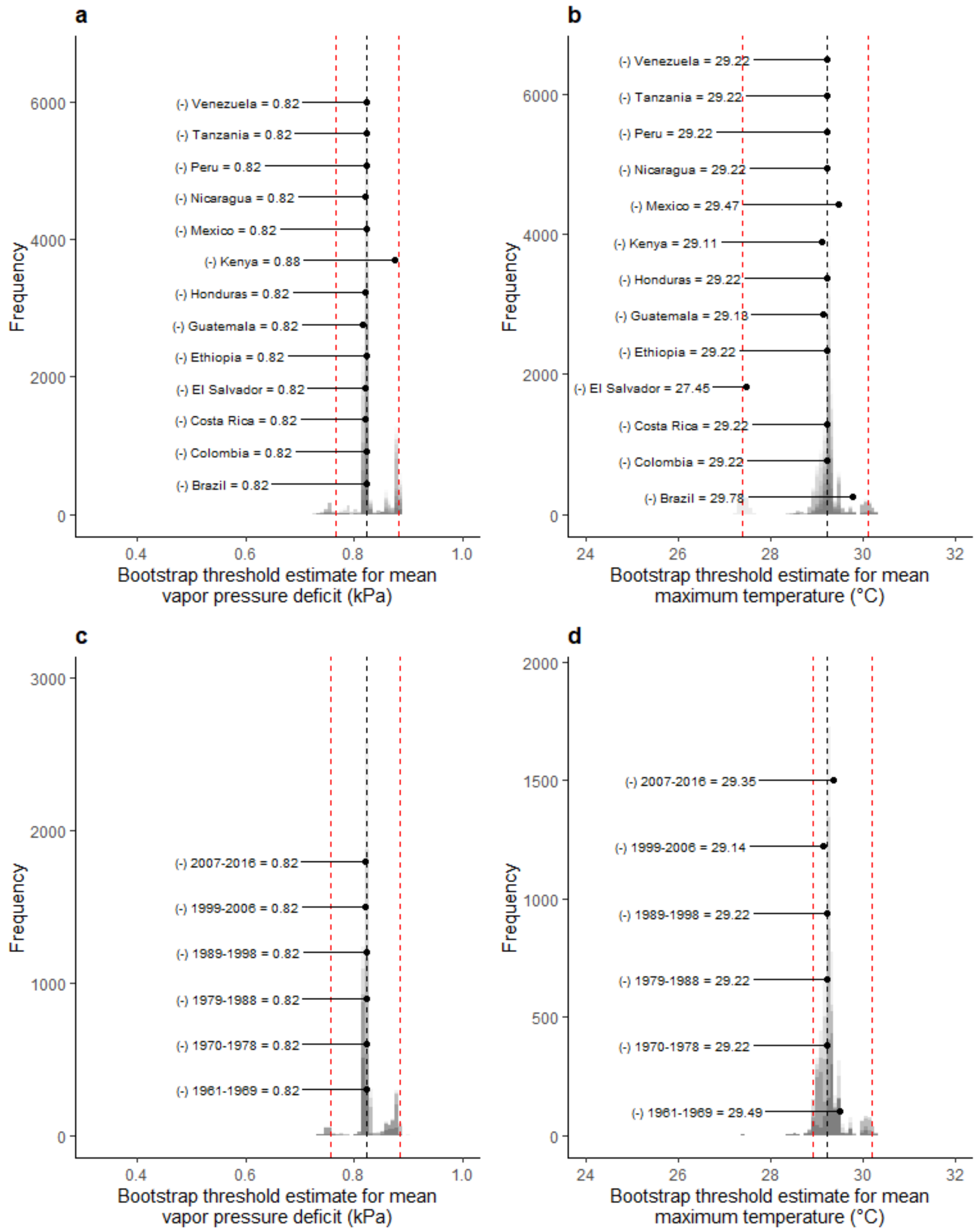
| **Model structure of top 4 four models** | **AIC** | **Cross-validated $R^2$ for hold-outs years** | | | |
|---|---|---|---|---|---|
| | | 1990-1998 | 1999-2007 | 2009-2017 | Mean $R^2$ across all hold-outs |
| G-RAIN + G-VPD + G-TMAX + PPY | -978.99 | 0.68 | 0.58 | 0.80 | 0.69 |
| F-RAIN + G-RAIN + G-VPD + G-TMAX + PPY | -978.68 | 0.67 | 0.58 | 0.80 | 0.68 |
| G-RAIN + G-VPD + G-TMAX | -978.55 | 0.69 | 0.60 | 0.80 | 0.70 |
| F-RAIN + G-RAIN + G-VPD + G-TMAX | -978.07 | 0.69 | 0.60 | 0.80 | 0.70 |
| **Best model including interactive terms** | | | | | |
| G-RAIN + G-VPD + G-TMAX + PPY +<br>G-RAIN x G-VPD +<br>G-RAIN x G-TMAX +<br>G-TMAX x G-VPD +<br>PPY x G-RAIN<br>PPY x G-TMAX<br>PPY x G-VPD | -1031.00 | 0.71 | 0.71 | 0.68 | 0.68 |
| **Best models including soil moisture** | | | | | |
| G-RAIN + G-VPD + G-SOILM + PPY | -826.17 | 0.64 | 0.48 | 0.72 | 0.60 |
| **Best models including soil moisture with interactive terms** | | | | | |
| G-RAIN + G-VPD + G-SOILM +<br>G-VPD* G-SOILM +<br>G-VPD* G-RAIN +<br>PPY x G-SOILM<br>PPY x G-VPD<br>PPY x G-RAIN | -872.12 | 0.65 | 0.49 | 0.71 | 0.60 |



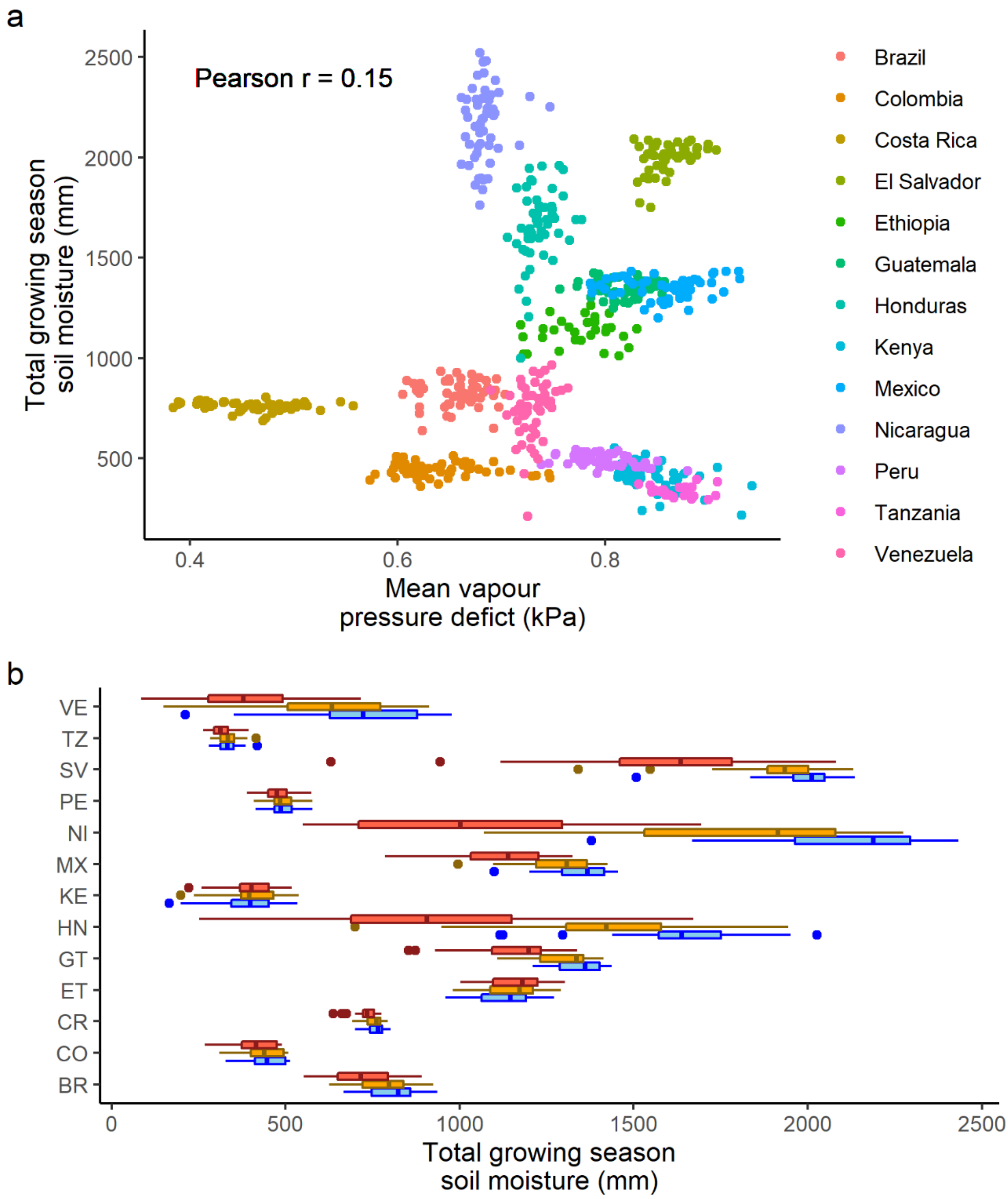

**Extended Data Fig. 1:** The influence of each predictor main effects in the best model. Grey shaded areas are the 95% confidence intervals and black dots are residuals. The y-axis is the value of the centred smooth and represents the contribution made to the fitted value of that smooth function.



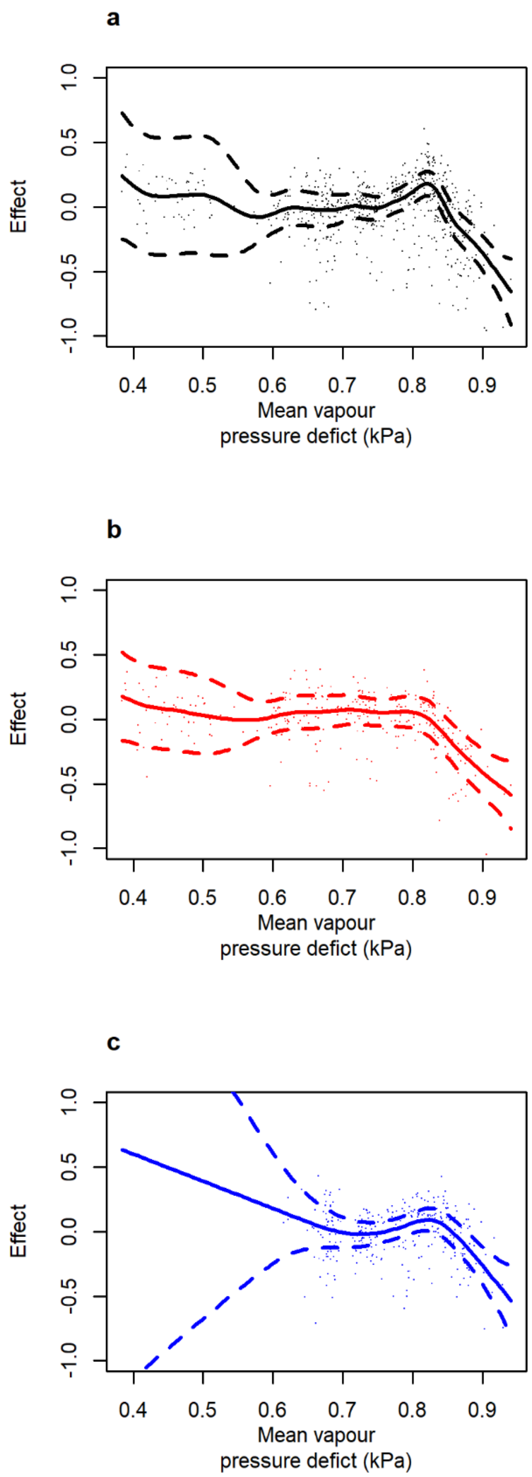

**Extended Data Fig. 2: Predicted coffee yield response to mean maximum temperature and the estimated mean maximum temperature threshold**. Arabica (*C. arabica*) yields relationship with mean maximum temperature in the growing season while other covariates are held constant at their mean. Black dashed line is the estimated mean maximum temperature threshold. The blue line is the relationship between mean maximum temperature and yield before the 29.22 °C threshold and the dashed red line after passing the mean maximum temperature threshold. The inset box shows predicted coffee yields response across the entire mean maximum temperature gradient. Grey coloured shaded areas are 95% confidence intervals.



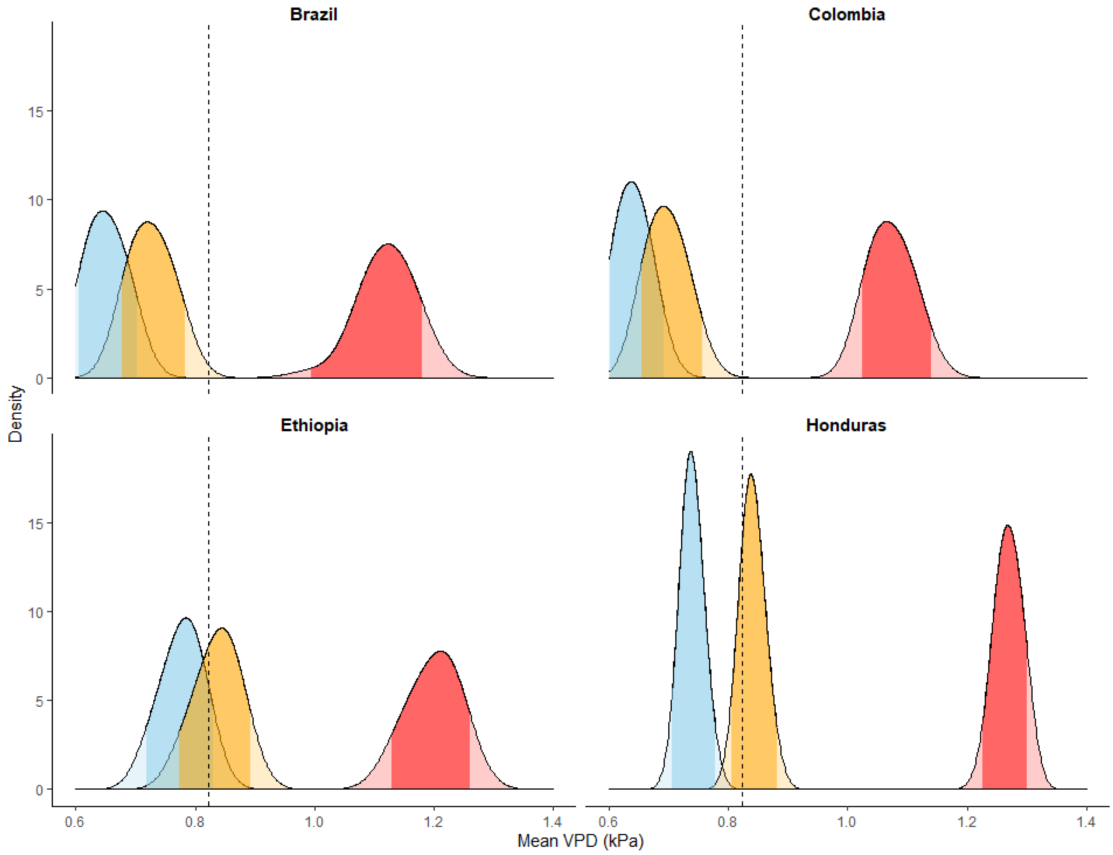

**Extended Data Fig. 3:** Testing whether threshold values vary when a particular country or block of time is excluded from analysis. The (-) designates the country (or time period) that has been excluded from analysis and the value return is the median threshold value. The black dashed line is the median threshold value of all analyses and the dashed red lines represent the 95% confidence interval of all analyses. The grey histograms and shaded in different colours for each individual hold-out analyses. **a,** is threshold the country-wise hold-out analysis for growing season vapour pressure deficit, **b,** the block of years hold-out analysis for growing season vapour pressure deficit, **c,** is threshold the country-wise hold-out analysis for growing season mean maximum temperature, **d,** the block of years hold-out analysis for growing season mean maximum temperature.



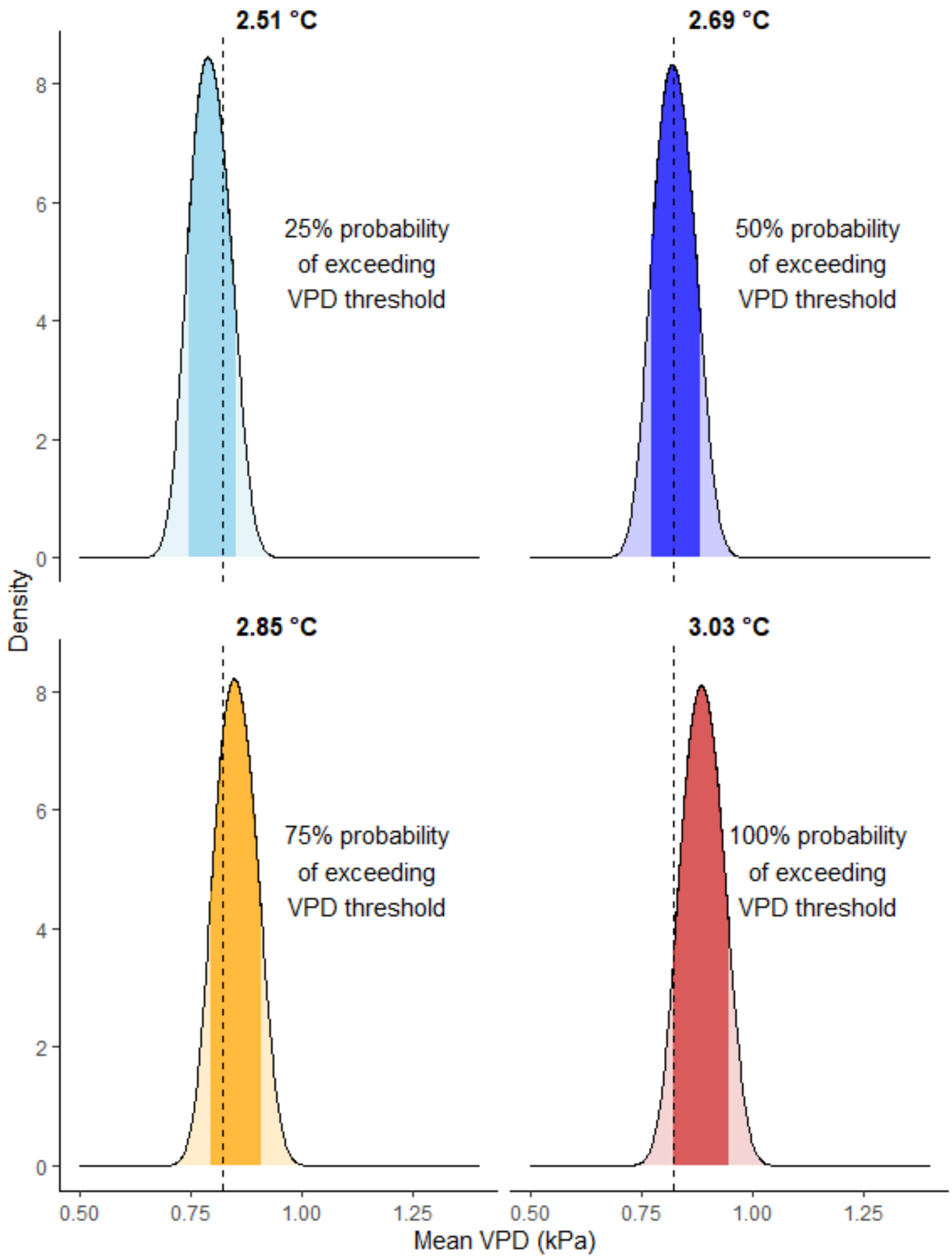

**Extended Data 4. a.,** Scatterplot showing the correlation between growing season soil moisture and vapour pressure deficit **b.,** Growing season soil moisture under baseline baseline (1985-2015) conditions. Additional boxplots show global warming scenarios of 2 °C (mustard) and 4 °C (red). The centre line of boxplots 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.



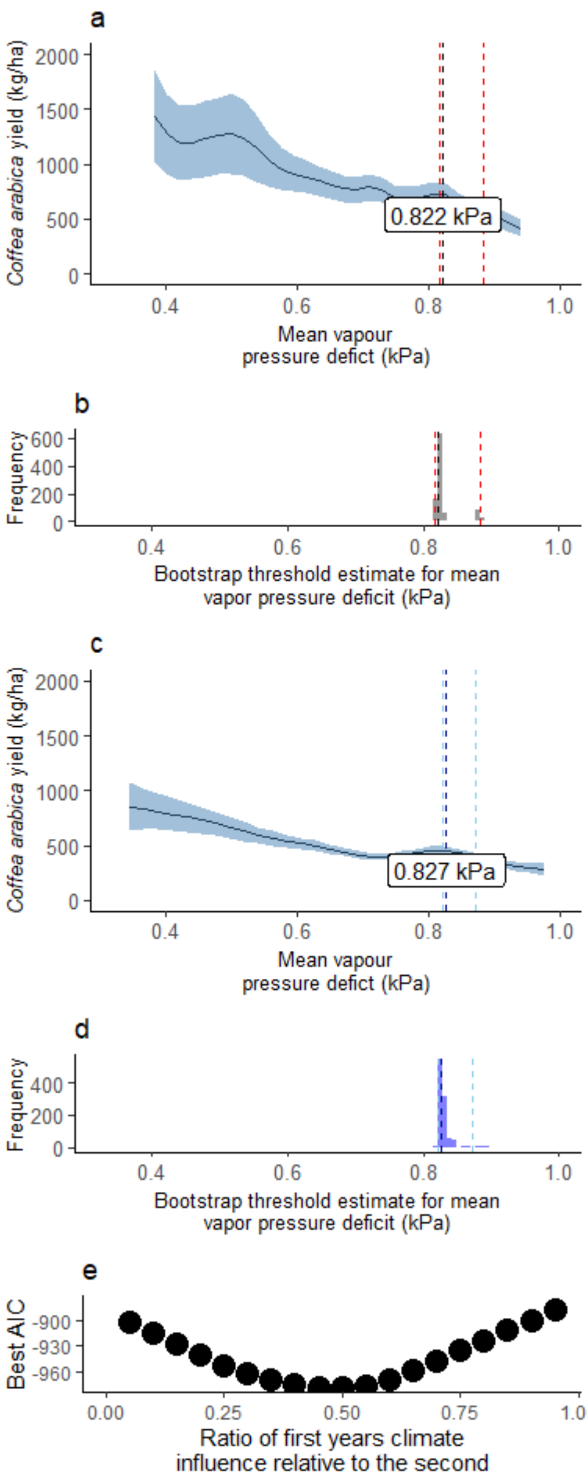

**Extended Data Fig. 5:** Marginal effects of VPD on Arabica yields under different soil moisture scenarios **a**. all data (n=648), **b**. low soil moisture (i.e. below the median total growing season soil moisture of 851 mm, n=323) and **c**., high soil moisture (i.e. above the median total growing season soil moisture of 851 mm, n=325). Points are residuals. Note the lack of data at low VPD in c., for the high soil moisture scenario.



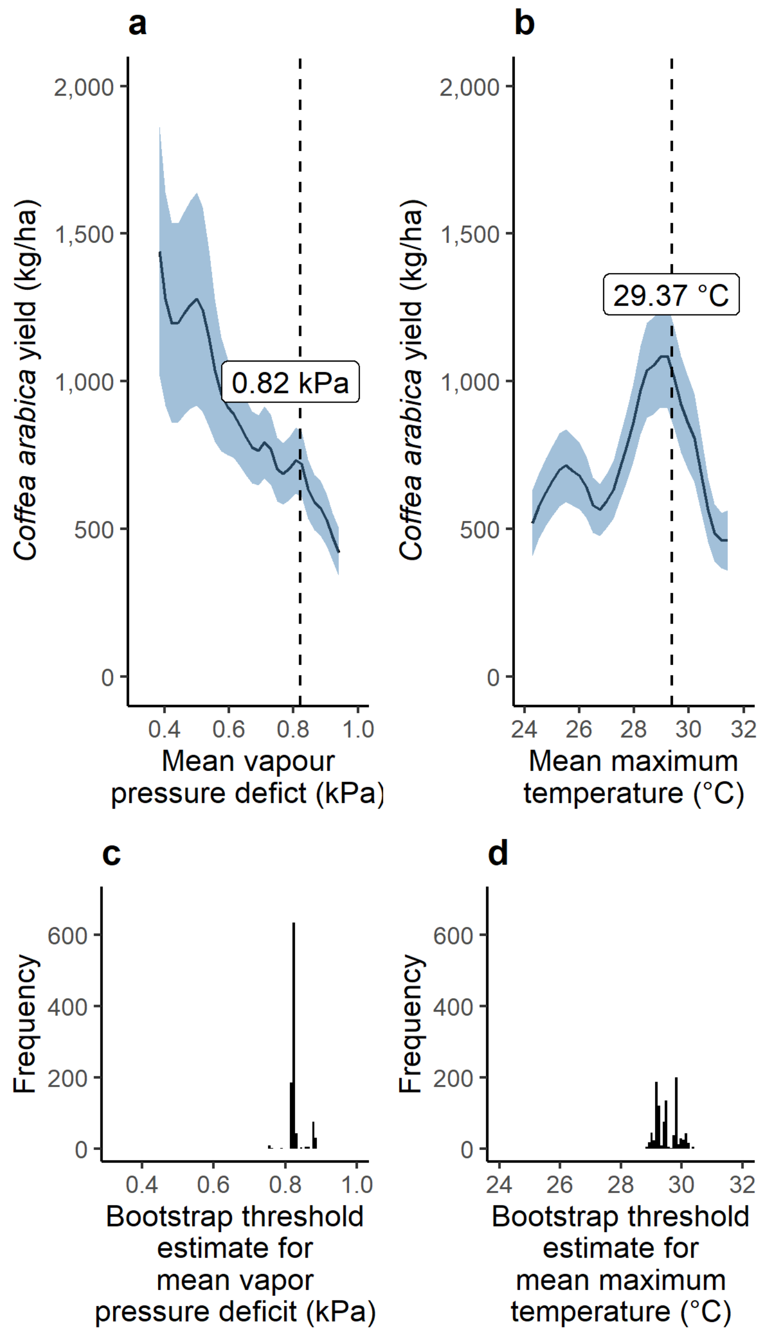

**Extended Data Fig. 6:** The density distribution of growing season VPD for the top four Arabica (*C. arabica*) producing countries (based on 2019 production levels https://fdc.nal.usda.gov/). Blue shaded density plots are baseline conditions (1985-2015), yellow density plots represent a 2 °C warming scenario and red density plots a 4 °C warming scenario. Dark shaded areas on density plots represent the range of the data from TerraClimate climate change scenarios and extended light areas are extrapolations. Dashed vertical lines represent the 0.82 kPa VPD threshold. Calculations of the probability of exceeding VPD thresholds were made on the range of actual climate change scenario data (i.e., the darker shaded areas of the density plots).



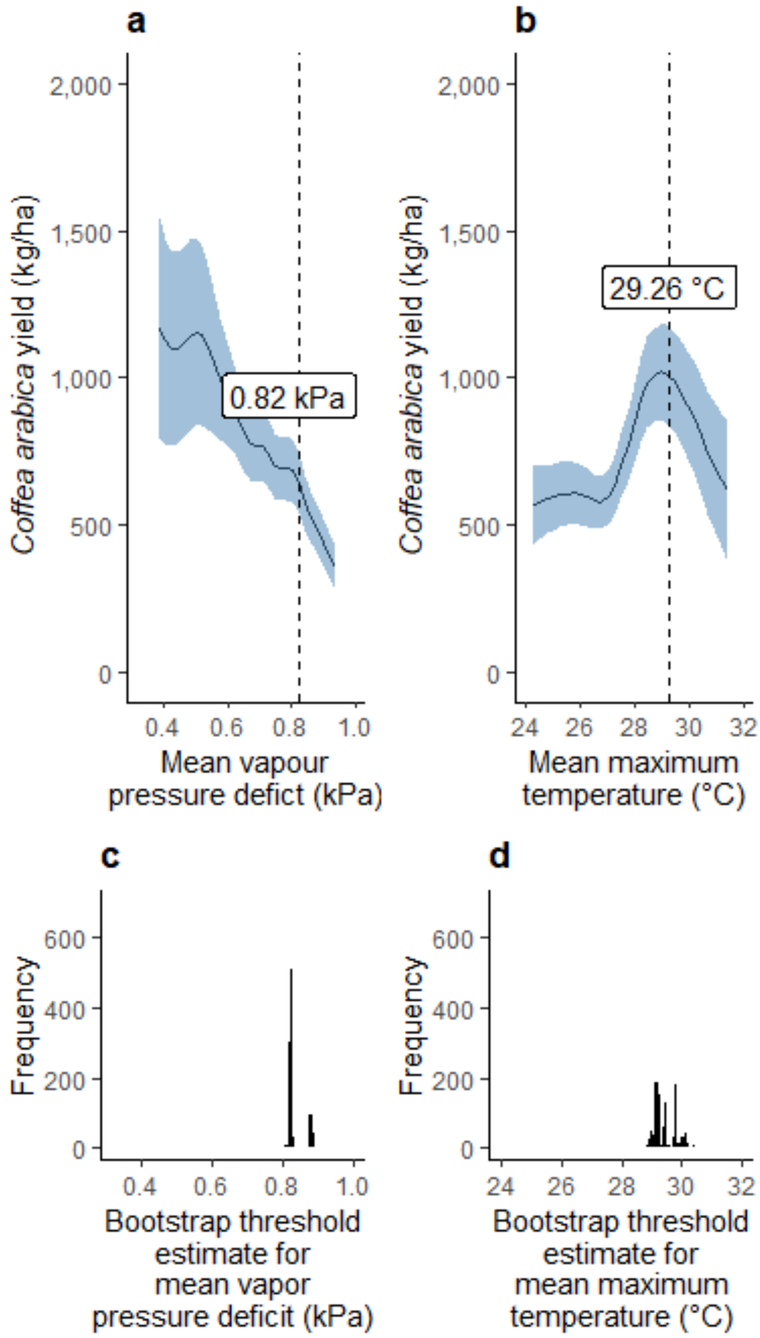

**Extended Data Fig. 7:** Density plots showing the distribution of median vapour pressure deficit (VPD) for Brazil at mean annual global temperatures corresponding with a probability of 0.25, 0.5, 0.75 and 1 of exceeding the 0.82 kPa VPD threshold. Dark shaded areas on density plots represent the range of the data from TerraClimate climate change scenarios and extended light areas are extrapolations. Calculations of the probability of exceeding VPD thresholds were made on the range of actual climate change scenario data (i.e., the darker shaded areas of the density plots).




**Extended Data Fig. 8:** The relationship between growing season vapour pressure deficit and yield in **a-b,** model and threshold estimate that accounts for the biennial life cycle of Arabica (*C. arabica*) with the past two-years of climate taken into account and a controlling variable for on and off production years (see Methods for details), **b-d,** an annual model (only accounting for the most recent seasons climate) and threshold estimate. **e,** AIC values (lower values indicate better model parsimony). A 50/50 weighting of the current and previous years seasons is the best performing model (i.e., has the lowest AIC).




**Extended Data Fig. 9. Coffee yield response to vapour pressure deficit and maximum temperatures and estimated thresholds for a model without interactions. a**, Arabica (*C. arabica*) yields relationship with mean vapour pressure deficit (VPD) in the growing season while other predictors are held constant at their mean. **b**, Arabica yields relationship with mean maximum temperature in the growing season while other predictors are held constant at their mean. Blue shaded areas are the 95% confidence interval. Black dashed line is the estimated threshold. **c**, Bootstrapped threshold estimates for the mean VPD threshold. **d**, Bootstrapped threshold estimates for mean maximum temperature.




**Extended Data Fig. 10. Arabica (*C. arabica*) yield response to vapour pressure deficit and maximum temperatures and estimated thresholds for a model with climate variable interactions only. a**, Arabica yields relationship with mean vapour pressure deficit (VPD) in the growing season while other predictors are held constant at their mean. **b**, Arabica yields relationship with mean maximum temperature in the growing season while other predictors are held constant at their mean. Blue shaded areas are the 95% confidence interval. Black dashed line is the estimated threshold. **c**, Bootstrapped threshold estimates for the mean VPD threshold. **d**, Bootstrapped threshold estimates for mean maximum temperature.

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