Climate change impacts on banana yields around the world

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Nutritional diversity is a key element of food security[1–3]. However, research on the effects of climate change on food security has, thus far, focussed on the major food grains[4–8], while the response of other crops, particularly those that play an important role in the developing world, are poorly understood. Bananas are a staple food and a major export commodity for many tropical nations[9]. Here we show that for 27 countries – accounting for 86% of global dessert banana production – a changing climate since 1961 has increased yields by an average of 1.37 T.ha^{-1}. While past gains have been largely ubiquitous across the countries assessed, African producers will continue to see yield increases into the future. Moreover, global yield gains could be dampened or disappear in the future, reducing to 0.59 T.ha^{-1} and 0.19 T.ha^{-1} by 2050 under the RCP 4.5 and 8.5 climate scenarios, respectively, driven by declining yields amongst the largest producers and exporters. By quantifying climate-driven and technology-driven influences on yield, we also identify countries at risk from climate change and those capable of mitigating its effects, or capitalising on its benefits.

Bananas are widely cultivated in tropical and sub-tropical regions around the world, where they can provide a substantial proportion of affordable calories, dietary diversity and income[9-11]. Bananas are also ubiquitous in their availability in non-producing regions through international trade, which accounts for 15% of global production[12]. This international trade supplements nutritional diversity in non-producing countries, while making a large contribution to local and national economies in producing countries. For example, bananas and their derived products constitute the second largest agricultural export commodity of Ecuador and Costa Rica[13]. Globally, bananas (together with plantains) are amongst the top ten crops in terms of area of cultivation, yield and calories produced[10]. Given the importance of this crop for subsistence and trade, it is surprising how poorly represented bananas are in global assessments of climate change impacts on food and nutritional security[4-6].

Quantifying the optimal climatic conditions for banana productivity is central to assessing the crop's climate sensitivity, and thereafter, predicting the potential impacts of climate change on banana production systems. Ideally, this requires the collation of data from experiments and field trials conducted over a range of environmental conditions, including sub-optimal combinations. While few such experiments have been conducted[14-19], some of which constitute the core of most banana production models currently used (e.g. Global Agro-Ecological Zones; GAEZ), major challenges remain. Firstly, the small number of published studies, coupled with small sample sizes within them and the limited breadth of environmental conditions assessed, are inadequate to derive generalisable estimates of optimal conditions for a crop so widely cultivated across the world. Second, estimates of productivity-climate relationship parameters have not been rigorously validated against large quantities of observed production data. Consequently, the representation of bananas in existing crop models is likely to be based on abstractions derived from shared plant characteristics[1], which may not accurately predict effects of climate change on productivity.

Here we assess the climate sensitivity of global dessert banana (banana, hereafter) productivity or yield using a combination of national and sub-national production datasets from 27 countries (Table 1) spanning varying time periods (Supplementary table S1), coupled with previously published expert information on banana physiology. In all, the data used in our analyses account for approximately 86% of the world's banana production and covers 80% of global area under cultivation. The selected countries include the world's largest and regionally important producers, as well as the largest exporters of bananas, e.g. Ecuador, Colombia, Costa Rica, Ivory Coast, Philippines, etc.[20]. This large geographically stratified set of nations is exposed to diverse climatic conditions – ideally suited for climate sensitivity assessments. We statistically fitted observed yield data from the 1281 geographic units over multiple years to elevation corrected mean annual temperature and total annual precipitation using a beta function[21]. This allowed us to empirically identify the optimum climate space for banana productivity, and develop a climate-driven relative yield coefficient model for bananas. Model fitting involved partitioning the observed data into six regional subsets (Table 1), resulting in six regional models and a single global model. Models were constructed at these two scales to assess the validity of using a single global model for bananas, given that regions and countries can vary widely in cultivation practices and cultivars of bananas grown. Thereafter, we employed the regional models to quantify historical climate change effects on productivity, as well as the contribution of change in cultivation efficiency over time (technology trend), and project the future impacts of climate change.

In our global model, optimum mean annual temperature for banana productivity was estimated at 26.7°C (95% confidence interval = ± 0.04°C; Fig 1; Supplementary table S2), which is very similar to the commonly used optimum temperature of 27°C[10,22,23]. However, the optimum temperatures for regional models varied considerably, ranging from 20.1°C (95% CI = ± 0.1°C) for Brazil, to 30.4°C (95% CI = ± 0.1°C) for Africa (Fig 1; Supplementary table S2). Optimum total annual rainfall in our global model was estimated at 1673 mm (± 13 mm), which falls within the range previously reported[23] (900 mm – 1700 mm). But again, regional models varied substantially (Fig 1; Supplementary table S2), with India showing the lowest optimum rainfall of 327 $mm.y^{-1}$ (95% CI = ± 16 $mm.y^{-1}$) and China requiring the highest (2924 $mm.y^{-1}$; 95% CI = ± 27 $mm.y^{-1}$). Hence, relying on a single global model to understand the climate sensitivity of banana productivity is likely to result in considerable error at regional, national and sub-national scales.

Our hindcast analysis, which utilised the regional climate-yield models, suggests that climate change over the recent past (1961 to 2016) has had a net benefit on global banana yields (Fig 2a), which have increased at a rate of 0.024 $T.ha^{-1}.y^{-1}$ (95% CI = ± 0.006 $T.ha^{-1}.y^{-1}$). Over the 56 years of the hindcast assessment this translates to an average global yield increase of 1.37 $T.ha^{-1}$ (95% CI = ± 0.33 $T.ha^{-1}$). Of the 27 countries included in our analyses, 21 showed a positive effect of recent climate change on banana yields, two (Kenya and Colombia) showed no effect, and four (Brazil, Indonesia, Malaysia and Philippines) showed climate-driven yield declines (Fig 2a; Supplementary table S3). On aggregating national yield trends to regional averages, we find that Africa, China, India, as well as Latin America and the Caribbean (LAC) show positive effects of climate change on banana yields, while Brazil, and south-east Asia and Australia (SEAA) have been negatively affected (Supplementary figure S8a; Supplementary table S3). Changes in yield appear to be primarily driven by consistent increases in temperature over the recent past (Supplementary figure S9; Supplementary table S6). Countries where warming has resulted in banana growing areas experiencing more optimal temperatures have seen productivity increases, while countries where temperatures have exceeded the regional optimum, show declines. However, we note that the inclusion of irrigated production in our analyses may obscure the influence of change in precipitation on yields.

In countries such as Brazil and Malaysia, modelled climate-driven yield declines (Fig 2a) are also reflected in observed country level yield declines (Supplementary figure S10). However, large increases in observed yields in Indonesia and Philippines (Supplementary figure S10) run counter to modelled climate-driven yield declines. This could be attributed to the large positive effect of changes in cultivation efficiency or a positive technology-yield trend (an aggregate term that captures changes in cultivation practices, inputs, land management and investment in infrastructure, such as irrigation, etc.), which overwhelms the relatively smaller negative effect of climate change (Fig 3). Technology-yield trends were positive for most countries considered here, and of magnitudes much greater than climate-yield trends, thus enhancing observed country-scale yields. However, in some cases a strong negative technology-yield trend completely counteracted, and reversed yield gains due to climate change. For example, countries such as Cameroon, Ethiopia and Panama show a positive effect of climate change on yields, but a strong negative technology trend (Fig 3), resulting in an overall decline in observed yields over time (Supplementary figure S10). Hence, the capacity to capitalise on the benefits of increasingly suitable climatic conditions for banana cultivation, or mitigating against future change is strongly dependent on how countries invest in maintaining and improving their cultivation efficiency.

Regional model based forecasting revealed that by 2050, past positive effects of climate change on average global banana yields, though likely to continue, will be of lower magnitude. Yield increases could decline to 0.59 $T.ha^{-1}$ (95% CI = ± 1.38 $T.ha^{-1}$) and 0.19 $T.ha^{-1}$ (95% CI = ± 1.86 $T.ha^{-1}$) under the RCP 4.5 and more extreme RCP 8.5 climate scenarios, respectively, relative to yields modelled using long-term climate averages for 1970-2000 (Fig 2b and 2c; Supplementary tables S4 and S5). Unlike the hindcast analysis, where only four countries in our assessment showed a negative effect of past climate change on yield, negative responses could be more widespread amongst countries in the future. Ten countries are predicted to show at least a negative trend, if not strong declines in yields (RCP 4.5 scenario). Importantly, these include India (the world's largest producer and consumer of bananas), Brazil (fourth largest producer), as well as Colombia, Costa Rica, Guatemala, Panama and Philippines, all of which are major exporters. Some countries could continue to see benefits, or indeed increased benefits, of climate change in the future. These include all 10 African countries in our assessment, as well as Ecuador (the world's largest exporter) and Honduras (also a major exporter). When aggregating future yield trends regionally, Africa unsurprisingly emerges as a key winner, while the strong positive effects of past climate change in the LAC countries declines to a positive trend. Similarly, China may not see any benefits of climate change in the future, as it did in the recent past. India could experience a major reversal with predicted negative effects of future climate change compared to positive effects in the past. Lastly, both Brazil and SEAA countries will continue along a negative trajectory into the future (Supplementary figures S8b and S8c; Supplementary tables S4 and S5).

Combining forecasted climate-driven changes in yield with the technology-yield trend estimates – which we assume to represent a country's capacity to adapt to production risks in the future – we qualitatively classified the climate risk to banana production in each of the 27 countries included in this study (Fig 4; Supplementary figure S11). Countries where forecasted climate-driven yield changes were negative, and that had negative or flat technology-yield trends in the past, were classified as 'at risk'. These included Malaysia, Panama, Nicaragua, the world's fourth largest producer – Brazil , as well as Colombia – a major exporter. The two largest producers, India and China, along with many LAC countries that are important exporters, as well as Australia, Indonesia and Philippines were classified as 'adaptable'. These countries showed potential negative effects of climate change on yields, but strong positive technology-yield trends that may mitigate climate-driven yield declines. Amongst the countries classified as at an 'advantage' - where forecasted changes in yield are strongly positive – are some of the largest current exporters (Ecuador and Honduras), and all 10 African countries that were assessed. However, it is important to note here, that our classification of risk is climate centric. Hence, realising the climate-driven advantage to banana productivity in many of the African countries will also be contingent on reversing negative technology-yield trends, e.g. by improving cultivation practices, investing in infrastructure, etc., in the future. If cultivation efficiency in the African nations can be improved, it could bolster local and regional nutritional security. In addition, it could also modify the existing configuration of the banana export market, especially given the negative impacts expected in some of the major current exporters.

In summary, our study quantified region specific climate-yield relationships for banana cultivation that suggests that climate change in the recent past has been beneficial to global banana productivity, but will be less so in the near future. However, we note that our analysis is based on average climatic conditions and does not account for other climate change driven threats of increased frequencies of extreme events[24], as well as the risk posed by established and emerging diseases[25–27]. In addition, our climate-yield models are based on observed production data rather than experimental assays. Hence, model fits are likely to be influenced by agro-economic factors in addition to banana plant physiology, and therefore, model interpretation requires caution (see Methods). Previous studies have largely assessed climate driven changes in the extent of land suitable for banana cultivation[10,22,23,28,29], without considering the potential for competition with other staple crops and land-use types[30]. In contrast, analyses here focused on the more practical quantity of yield changes where bananas are already being grown. In addition, we assessed the climate risk to major producer and exporter countries. We infer that future climate risks to banana production could largely be mitigated to secure local nutritional diversity and security. Nevertheless, securing supply to non-producing countries, where banana consumption is an important contributor to dietary diversity, is likely to require a reorganisation of the export market.

Competing financial interests

The authors declare no competing financial interests.

Data Availability Statement

All data used are publicly available and open access. All banana production data sources are listed in Supplementary Table S1. All climatic and topographic data sources are listed in Methods.

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Tables

Table 1. Banana producing countries (grouped by regions) used in this analysis. Country code is the abbreviation by which countries are referred to in figures associated with our analyses. Values for area harvested and production are for 2016 (ref. 21). The Exp:Prod variable represents the proportion of production that is exported. For regional names: LAC – Latin America and the Caribbean, SEAA – South East Asia + Australia.

Region	Country	Country code	Area harvested (ha)	Production (T)	Exp:Prod
Africa	Angola	AO	131455	3858066	<0.001
	Burundi	BI	195248	911193	<0.001
	Cameroon	CM	72359	1187547	0.25
	D.R. Congo	CD	83413	311087	0
	Ethiopia	ET	63213	538302	0.02
	Guinea	GN	45459	212874	<0.001
	Ivory Coast	CI	7355	330946	0.98
	Kenya	KE	63299	1288588	<0.001
	Rwanda	RW	322009	3037962	0
	Tanzania	TZ	468470	3559639	0.005
Brazil	Brazil	BR	469711	6764324	0.009
China	China	CN	430046	13324337	<0.001
India	India	IN	846000	29124000	0.004
LAC	Belize	BZ	2472	70619	>0.99
	Colombia	CO	84637	2043668	0.9
	Costa Rica	CR	42410	2409543	0.98
	Dominican Republic	DO	26834	1079781	0.36
	Ecuador	EC	180337	6529676	0.91
	Guatemala	GT	78206	3775150	0.57
	Honduras	HN	24427	707120	0.93
	Mexico	MX	78322	2384778	0.19
	Nicaragua	NI	1680	106437	0.86
	Panama	PA	6455	258891	0.96
SEAA	Australia	AU	16612	354241	<0.001
	Indonesia	ID	139964	7007125	0.001
	Malaysia	MY	28036	309508	0.08
	Philippines	PH	456641	5829142	0.24

Figures

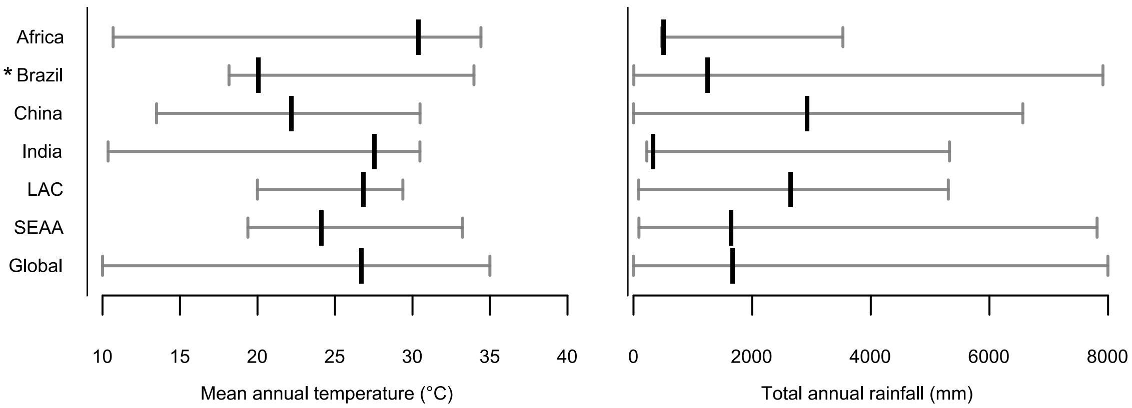

Figure 1. Climate-yield model parameter estimates for bananas cultivation. The minimum (blue vertical lines), optimum (green vertical lines) and maximum (red vertical lines) temperature and rainfall cardinal values estimated using beta functions for banana yields. Estimates are presented for each of the six regional models and a single global banana climate-yield model. For clarity, 95% confidence limits around the estimated parameters are presented in Supplementary table S2. Curves fitted to observed data are presented in Supplementary figures S1-S7. (*) See Methods for notes on interpreting results for Brazil.

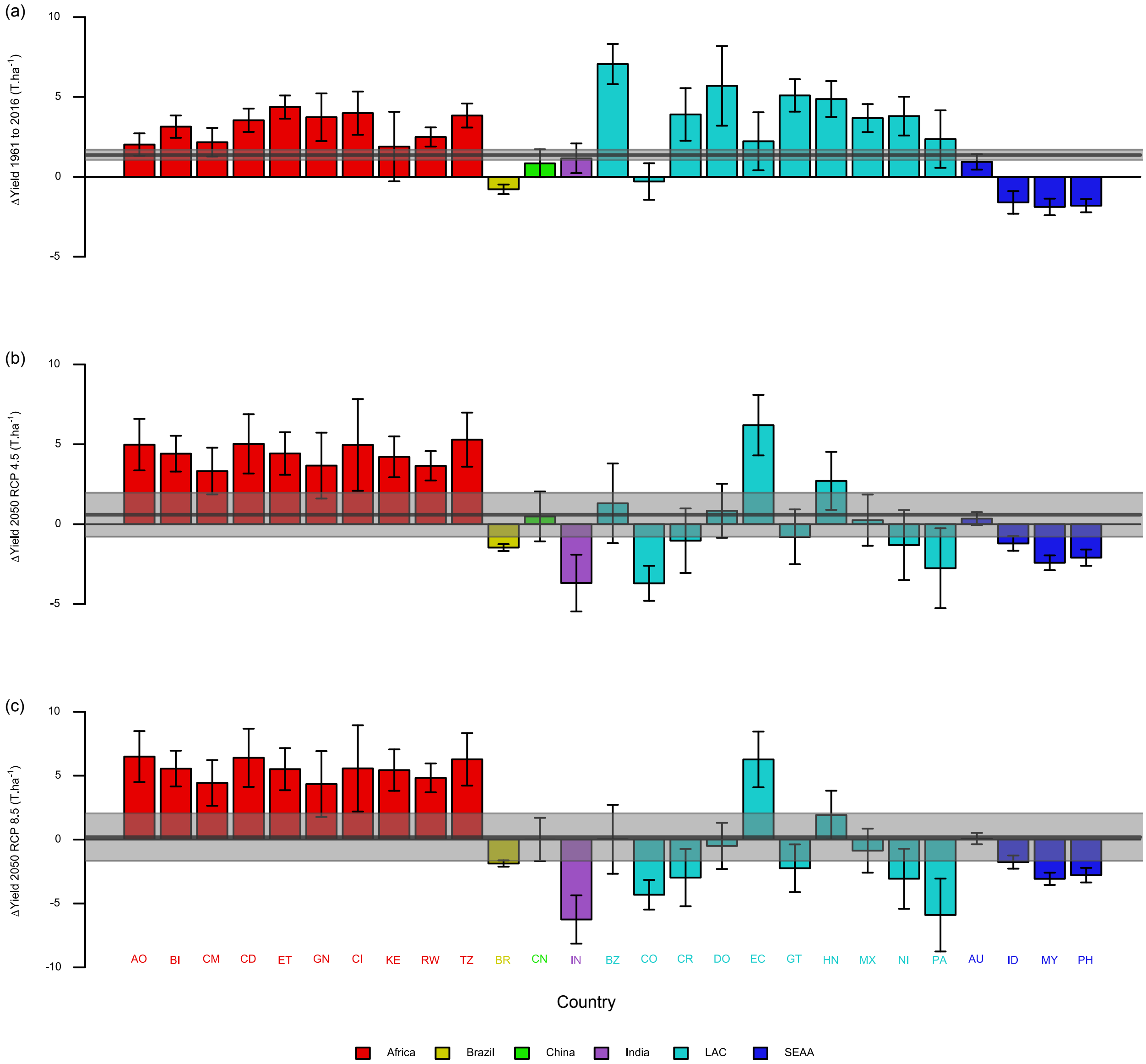

Figure 2. Effects of past and future climate change on banana yields. Modelled contribution of climate change between 1961 and 2016 on banana yields in major producing countries from a hindcast analysis **(a)**. **b,c** Predicted changes in banana yields by 2050 relative to yields modelled using long-term average climatic conditions (1970 to 2000) under RCP 4.5 **(b)** and RCP 8.5 **(c)** climate change scenarios. The black horizontal lines and grey areas in each panel represent the global area averaged change in yield due to climate change, and associated 95% confidence bounds. Error bars in all cases represent 95% confidence intervals. Each bar is associated with a two letter country name abbreviation and colour coded by region (see table 1).

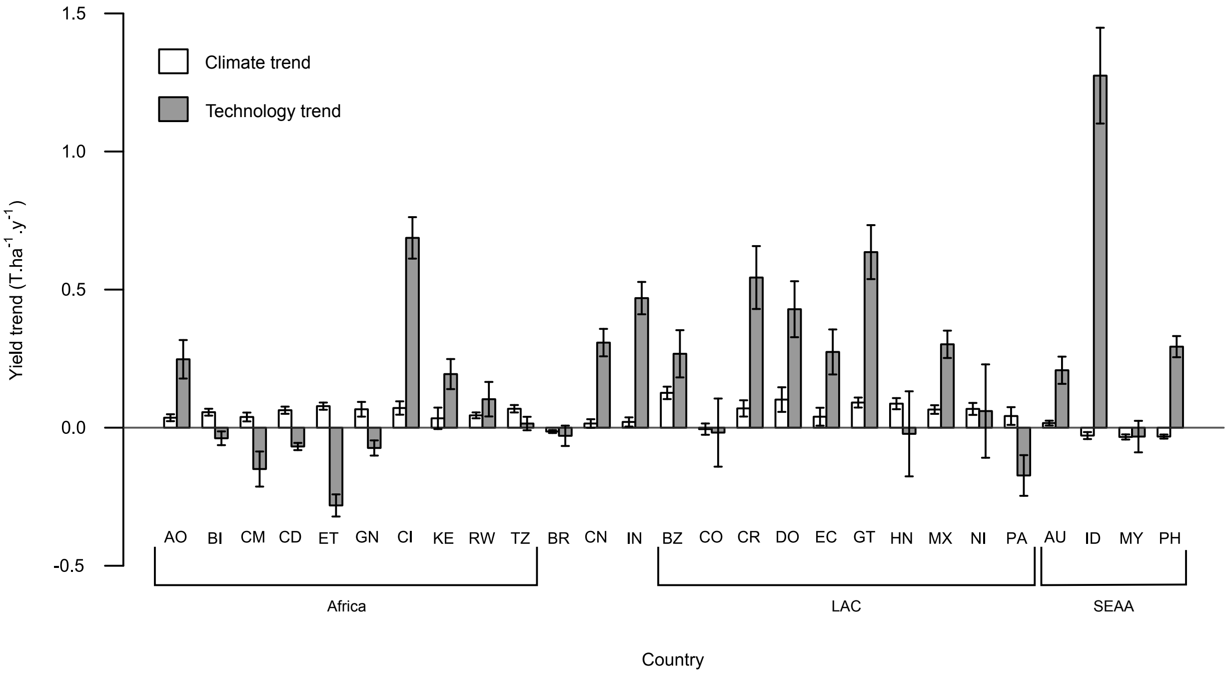

Figure 3. Effect of changes in climate and cultivation efficiency (technology) on banana yields (1961 to 2016). Error bars represent 95% confidence intervals. Countries are colour coded by region and two letter country codes (table 1) are used to label each country.

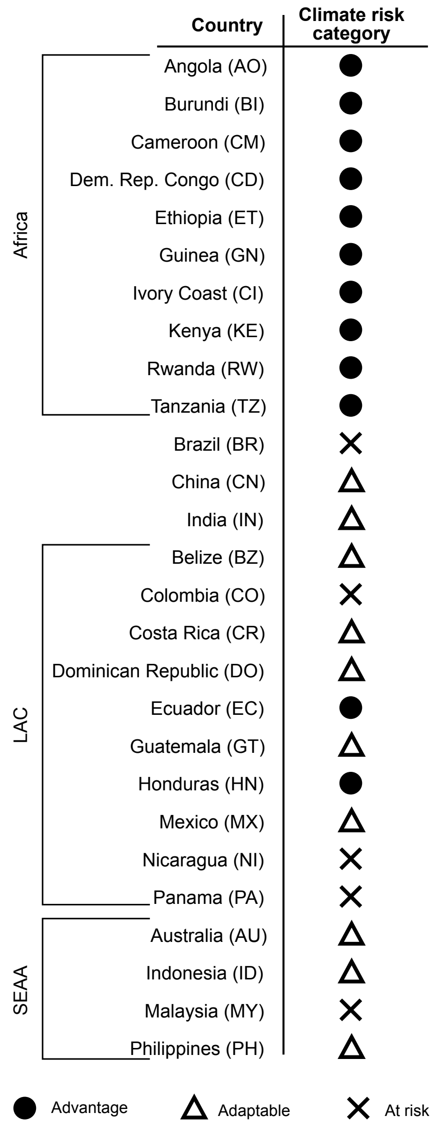

Figure 4. Future climate risk assessment for major banana producing countries (by 2050). This categorisation was carried out by combining changes in predicted yield under the RCP 8.5 climate change scenario and the effect of cultivation efficiency (technology trend) on past yields. Countries classified as ‘at risk’ are those where yields are predicted to decline due to climate change and that have shown a negative technology trend on past yields. ‘Adaptable’ countries could see future climate-driven yield declines, but mitigation could be possible given past positive technology trends. ‘At advantage’ countries are those that are predicted to experience climate-driven increases in yield by 2050.

Methods

Data sources

We used a time series of annual banana production data from 27 countries (Table 1), which included all the major producer and exporter countries. Our analyses focus on dessert bananas and we exclude data on plantain production. Consequently, we did not include Uganda in this study (despite having the highest per capita banana consumption) because the East African Highland Banana which makes up the majority of Ugandan production, is (a) classified as plantain in production data available from the FAO, and (b) is cultivated at higher elevations (1400 – 2000m) than other production systems considered in this study. Data sources, spatial resolution and time period over which production data were available differed between countries (see supplementary table S1). Hereafter, we refer to the finest administrative scale at which data were available within each country as a geographic unit (GU). For example, production data were available at the whole country scale for countries such as Angola and Malaysia. Hence, in these cases, 'country' was assigned as the GU. On the other hand, for countries such as India and China, data were available at the district and province scale, respectively. Hence, individual districts or provinces were assigned as a GU. Data were 'cleaned' to remove non-sense values (e.g. where yield values were unrealistically high, or where production was reported, but area under cultivation was zero) and other values which indicated poor data quality or reliability. For instance, national scale data available from FAOSTAT (typically from 1961 to 2016) can contain a combination of officially reported values, as well as computed values (presumably when official data are not available). In such cases, we subsetted the time series of production data, such that the first data point corresponded to the first officially reported values. In the case of data from Brazil, there were many cases where data from the same GU in successive years were identical, suggesting that data were in fact not collected annually. In these cases, where three or more successive identical production and area harvested values were encountered, only the first was retained. Production and area under cultivation was used to calculate yield ($T.ha^{-1}$) – the response variable of interest – for each GU-year combination in the dataset.

Climate data from the CRU TS 4.01 product[31,32] was used to model climate sensitivity of banana yields, conduct the hindcast analysis and identify the contribution of change in cultivation efficiency (technology trend) on banana productivity over time. Mean annual temperature and total annual precipitation were extracted from the CRU dataset and assigned to the respective GU-year combinations in the production data. The temperature data was corrected for elevation. This was done to account for the lack of a good quality distribution map of banana growing areas, as well as the coarse resolution of the CRU dataset, which could result in individual pixels representing average temperatures over areas of high elevation, where bananas are less likely to grow. In other words, the relatively large area (approximately 360 km^2) covered by a single CRU pixel could encompass areas of low and high elevation, and hence, uncorrected temperature values within a pixel represent the average temperature experienced across these elevations. Since bananas are less likely to grow at higher elevations, these uncorrected temperature values do not represent the temperatures experienced in banana plantations. The elevation based temperature correction was conducted by overlaying the 90 m resolution Shuttle Radar Telemetry Mission (SRTM) digital elevation model (DEM) with the CRU temperature dataset. A lapse rate of -0.0065 $°C.m^{-1}$ was used to recalculate temperatures within each CRU pixel at the resolution of the DEM. Recalculated temperature values in DEM pixels where elevation was greater than 2000 m were eliminated (we assumed that there is a very low probability that bananas grow at elevations > 2000 m). For the remaining DEM pixels the elevation weighted average temperature was calculated. Weights were calculated using a logistic function $1/\{1 + e^{[0.005(\text{elevation} - 1000)]}\}$. The logistic function used assigns weights that tend to one for elevations < 500 m above sea level, declines in a near linear fashion from 500 m to 1500 m, with an inflection point at 1000 m (i.e. weight of 0.5 at 1000 m elevation), and tends to zero for elevations > 1500 m.

In addition to the elevation correction of temperature, climate extraction for Mexico and Australia (both with country scale production data) was restricted to administrative units where banana cultivation had previously been reported in published literature[10,22,23]. This was done to avoid climate data from extremely arid environments (where bananas are unlikely to be cultivated, and which would not be accounted for with an elevation based temperature correction) influencing the analysis. For all 10 African countries in this study (country scale production data), no usable published information of banana growing areas could be used to inform the data extraction. Therefore, modelled banana cultivation areas[33] were used to restrict climate data extraction.

For future climate, mean annual temperature and total annual precipitation for 2050 was extracted from WorldClim CMIP5 downscaled projections[34,35] (5-minute resolution bioclimatic variables) of 19 and 17 GCMs for the RCP 4.5 and RCP 8.5 climate scenarios, respectively. Change in banana yields under future climate scenarios (forecast analysis) was calculated relative to yields modelled using the long term (1970 to 2000) climate averages extracted from WorldClim 2.0[36,37]. Mean annual temperature data from WorldClim 2.0 and CMIP5 downscaled projections were also elevation corrected (as had been done with the CRU TS 4.01 temperature data).

Climate-yield relationship estimation

Our objective was to statistically fit observed annual banana yield data to prevailing mean temperature and total annual precipitation. The resulting relationship would be used for further analyses. We expected the relationship along both climate axes to be represented by a bell-shaped or unimodal function, which was not necessarily symmetrical around its peak (i.e. around the optimum). A beta function[38] has been suggested as a suitable candidate model for such a non-linear process[39]. Here we implemented a modified version of the beta function[22] that has also been used in past banana physiology studies[14,17]. The beta function along the temperature and precipitation variables are as follows:

$$Rt = \left(\frac{Tmax-Tobs}{Tmax-Topt}\right)\left(\frac{Tobs-Tmin}{Topt-Tmin}\right)^{\frac{(Topt-Tmin)}{(Tmax-Topt)}} \quad (1)$$

$$Rp = \left(\frac{Pmax-Pobs}{Pmax-Popt}\right)\left(\frac{Pobs-Pmin}{Popt-Pmin}\right)^{\frac{(Popt-Pmin)}{(Pmax-Popt)}} \quad (2)$$

Where:

Rt = Yield coefficient for temperature

Tmax = Maximum annual average temperature, beyond which banana production stops

Tmin = Minimum annual average temperature, below which banana production stops

Topt = Optimum temperature for banana production

Tobs = Observed annual average temperature

Rp = Yield coefficient for precipitation

Pmax = Maximum total annual precipitation, beyond which banana production stops

Pmin = Minimum total annual precipitation, below which banana production stops

Popt = Optimum total annual precipitation for banana production

Pobs = Observed total annual precipitation

As both equations (1) and (2) result in a value between zero and one, a scaling coefficient (S) is also estimated while fitting the yield data to the climate variables. The scaling coefficient represents the maximum average yield under optimum conditions of temperature and precipitation. As such the function being fit is given by:

Yield = S.Rt.Rp (3)

The yield and climate data were partitioned in to six regional sub-sets (see Table 1), which were then fit to equation (3). Regional subsets were created to account for differences in cultivation practices and cultivars grown (cultivar identity was not explicitly included in our analyses as available production data does not differentiate between cultivars or varieties). Fitting models to regional, rather than country-level data subsets was also done to increase resolving power of the data, especially along the temperature axis. This attention to resolving power is important as tropical countries, in particular the small and/or island nations, can show a very limited temperature ranges in space and time, resulting in spurious non-linear model fits with unrealistic parameter estimates. Hence, relatively small countries, or those for which we only had country-scale data for were grouped into regions, while large countries (covering a larger climate space) with sub-national data formed regions by themselves (e.g. India, China and Brazil). In addition, a single 'global' model was also fitted. Here, regions were equally weighted, to account for differences in regional sample sizes.

Data were first fitted to equation (3) by brute force (10^7 iterations), such that residual sums of squares were minimised. The observed data occupied a restricted range along the temperature axis. This range logically represents the temperature space where commercial cultivation of bananas is viable, but not necessarily the physiological limits of the banana plant. Hence, estimation of Tmin and Tmax in equation (1) needed to be informed by expert opinion or previous estimates[10,22,23]. During the brute force fitting procedure, Tmin was constrained between 10°C and 20°C, while Tmax was constrained between 30°C and 35°C. Estimation of precipitation parameters in equation (2) were not similarly constrained as land management or cultivation practices could alleviate restrictions imposed by low precipitation (use of irrigation) or high precipitation (infrastructure to promote soil drainage). Hence, we assume that banana cultivation is feasible under sub-optimal/marginal precipitation conditions, subject to management intervention. As a consequence of production data including both rainfed and irrigated production systems, we treat estimated precipitation parameters with caution.

As parameters estimated for equation (3) by brute force may not represent a true optimised fit, estimated brute force parameters were used as starting values in a constrained non-linear least squares curve fitting function (implemented using the *Scipy optimize* module in Python 3.6). Measures of variation around estimated parameters using the curve fitting function may be unreliable as estimated parameters often fell outside the bounds of the data (e.g. bananas are unlikely to be cultivated at their physiological minimum or maximum temperatures). Hence, the non-linear curve fitting procedure was bootstrapped (100 iterations), where each iteration was fitted using a resampled dataset with replacement. These bootstrapped estimates were used for interpretation and further analyses.

Past contribution of climate change (hindcast) and cultivation efficiency (technology) to banana yields

Regional models from equation (3) were used to calculate modelled yield for each CRU climate dataset pixel within the GUs of interest from 1961 to 2016. These modelled annual yields were averaged at a country-scale. Where sub-national production data were available, the average yield was weighted by the area under cultivation of GUs within the country. A generalised least squares (GLS) regression was then fitted to the modelled yield data over time for each country, using the *gls* function from the *nlme* package in R. The GLS regression allowed for a 1st order autoregressive correlation structure in the residuals, to account for the correlation over time in climate data. The parameters of the GLS regression represented the climate-driven trend in yields. Modelled annual yield data were then regionally averaged (weighted by area under cultivation within GUs). Regional climate-driven yield trends were then estimated using region specific GLS regressions.

To determine if observed yield trends were driven by changes in temperature or precipitation, the relative yield coefficients for temperature (Rt; equation 1) and precipitation (Rp; equation 2) were calculated for each pixel in each year from 1961 to 2016. As with the hindcast analysis above, Rt and Rp were aggregated to the scale of countries. A GLS regression was then fitted to Rt and Rp separately, to estimate the trends in Rt (temperature RYC trend) and Rp (precipitation RYC trend). Similarly, trends for changes in mean annual temperature and total precipitation were calculated. Country-scale temperature RYC trends and precipitation RYC trends were plotted against country-scale mean annual temperature and total precipitation trends (along with associated 95% confidence intervals) and visually inspected for consistent patterns.

Modelled annual country-scale yields were subtracted from annual yield data available from FAO[20] for each of the 27 countries in the study. As modelled yields are solely climate-determined, the resulting difference in yields (tYield) represents the influence of 'technology' or cultivation efficiency on yield. We fitted a GLS regression to tYield over time and the parameter estimates of the regression represent the effect of a 'technology trend' on banana yields.

To evaluate model performance, we calculated the correlation coefficient and root mean squared error (RMSE) between (a) observed yields (country-scale) from the FAO over time and country-scale yields estimated using regional climate-yield models (hindcast yield values), and (b) observed yields (country-scale) from the FAO over time and hindcast yield values to which country-scale technology trends were added (Supplementary figure S30).

Future climate change impacts on banana yields (forecast) and climate-risk classification

The impact of future climate change on banana yields was quantified as the change in predicted yields by 2050 (future yields) relative to modelled yields given long-term average temperature and precipitation between 1970 and 2000 (current yield). Regional yield models from equation (3) were used to calculate current yield for each WorldClim 2.0 pixel within the GUs of interest. Similarly, future yields were calculated using regional models and climate data from WorldClim CMIP5 downscaled projections for 2050. Future yields were predicted using downscaled data from 19 GCMs representing the RCP 4.5 scenario and 17 GCMs for the RCP 8.5 scenario. Differences between current and future yields were averaged across GCMs for each pixel, and pixel-scale yield differences were averaged to country-scale (averages weighted by area under cultivation of GUs within countries were used when sub-national production data were available). Regional average yield differences were then calculated, weighted by area under cultivation.

Climate risk for countries was classified by combining yield differences under the RCP 8.5 scenario and estimated technology trends. This was a climate centric classification. Hence, if a country was predicted to show increases in climate-driven yields, it was classified as being at an 'advantage', regardless of its past technology trend. If a country was predicted to show a negative effect or no effect of climate on yields, and a past positive technology trend, it was classified as being 'adaptable'. Lastly, if a country was predicted to show negative effects of future climate on yields, and negative or flat past technology trend, it was classified as being 'at risk'.

Caveats and unaccounted for sources of variation

The analysis presented has utilised the best and most comprehensive data sources available at the time of writing. However, we note that further improvements in available data quality would be beneficial to carry out an even more accurate and fine grained assessment. A few shortcomings of the data used include – varying spatial resolution of the datasets, non-uniform gaps in the production time series for different regions and countries within regions, lack of variety specific production data, quantities of agricultural inputs and use of irrigation for cultivation. Fertilisation effects of increased CO_2 in the atmosphere could also have an effect on banana productivity, but has not been accounted for in our analyses. Consequently, a level of caution is required in interpreting results, especially where high variation in yield is observed across climatic gradients. For example, production data from Brazil showed a large variation across the range of mean annual temperatures and levels of total annual precipitation encompassed by the dataset. In addition, the best fit beta model for yield revealed the lowest optimum temperature (20.06°C) compared to the other regions assessed in this analysis. Such a result could be due to overlapping (and reinforcing) gradients of climatic conditions and economic indicators. Compared to the north, southern Brazil experiences cooler and more seasonal climatic conditions, and fares better in economic terms. Higher incomes in the south could facilitate greater productivity due to greater capacity for the use of agricultural inputs, and therefore, lower the estimated optimum temperature in our fitted model. Hence, model interpretation should be carried out with caution and further detailed region-/country-specific research that incorporates socio-economic variables are a logical next step.

Secondly, in the absence of robust experimental data, we have statistically modelled climate-yield relationships using a top-down approach and observed production data. However, it is important to note that the distribution of banana producing areas are not solely a consequence of the banana plant's physiology. Agro-economic considerations, such as available cultivation infrastructure, transport links and access to markets also influence where bananas are grown. The production data incorporate these factors, and hence, our model fits cannot be interpreted as a purely physiological climate-yield relationship. For example, cultivation efficiency and yields can be substantially be improved in drier areas with irrigation. However, the extent of irrigation in use was not accounted for in our analyses, and low optimum precipitation estimates (e.g. India) should be interpreted with care.

Lastly, we also acknowledge that our analyses only consider the average annual climatic condition, and do not account for seasonal variation, nor the occurrence of extreme climatic events. Future region- and country-specific research would benefit from including these parameters, especially if more detailed production data are available to cope with increased model complexity.

Code availability statement

No custom code was used in the analysis.

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