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Climate Change and the Impact on Taro in Papua New Guinea

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Abstract

In this note we present a summary of recent historical climate of Papua New Guinea (PNG), finding that rainfall has been increasing substantially compared to pre-1995 levels, but that temperature has only been rising at a moderate rate. We then examine the 5 climate models used in this study from the Intergovernmental Panel on Climate Change (IPCC) / ISIMIP / CMIP3b, discovering one – IPSL – which best reflects the climate trends noted in PNG since 1995. The climate model projections show that temperature changes in PNG are expected to be less than most other places in the world and precipitation changes in PNG are projected to be higher than most other places in the world. Despite noting that IPSL seems to best represent climate changes observed thus far, we use all 5 climate models in the DSSAT crop model for taro, investigating how each climate model will lead to changes in taro yields at each half-degree pixel (averaging almost 3,100 square kilometers in PNG). In the aggregate, we find that the IPSL model leads to the greatest projected reduction in taro yield at -6.4% for the nation, with Southern region projected to have greater than 10% yield reduction for taro. Across the 5 climate models, the median across model results suggest only a 1.6% yield reduction, while the most optimistic model projects a 4.4% gain. Because of uncertainty across climate models and different impacts across regions, as well as potentially increasing climate variability which would lead to more extreme events including droughts and floods, we recommend developing a suite of options to help farmers navigate future climate uncertainty. For example, developing and testing crop varieties that would offer better yields whether the future is wetter or drier, as well as varieties that are less sensitive to temperature extremes. Currently at least one drought-tolerant variety of taro is being developed at the PNG University of Technology in Lae, with funding from ACIAR and collaboration with the University of Queensland. These could include new varieties of taro but might also include alternative crops and farming techniques designed to protect the plants during adverse climate events.

Introduction

Papua New Guinea (PNG) is a large island nation in the western Pacific. Much of the population is dependent on their own agricultural production for food security. Taro is an important crop for the country, providing 6 percent of total calories for rural people (HIES 2009/10; Schmidt et al. 2024); studies based on FAO consumption data claim an even higher percentage (see Rosegrant et al., 2024). According to FAO, taro is the ninth leading crop in terms of cultivated land area, and the third in cultivated area among non-perennials (FAO, 2020).

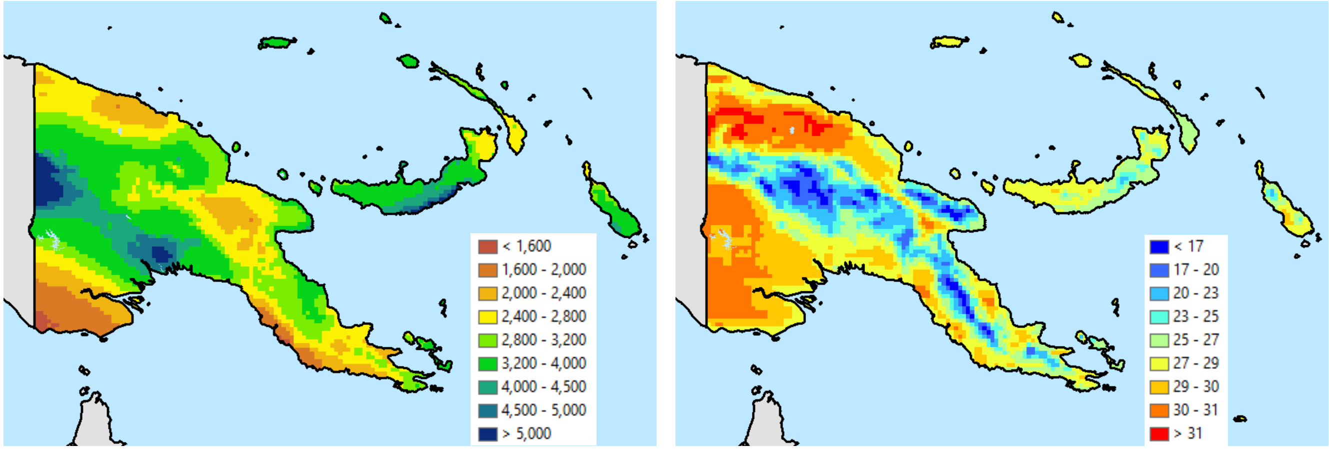
Climate change is affecting agricultural productivity globally. Only a few studies have examined the impact of climate change on agricultural productivity in PNG, and since a large proportion of households are dependent on own-farm production, understanding the impact of climate change on productivity of key staple crops, such as taro, is critical.

In this note we present data on recent climate and climate trends in the country, with a focus on regional differences to inform the nuances of climate impact and potential avenues for intervention. Then, we examine climate projections for PNG. We use the climate projections to evaluate the projected impact of climate change on taro yields using a crop model that considers planting practices (variety, sowing, input and management, etc.) and climate information to predict taro output across PNG. This is followed by a brief section describing the next step in our work plan evaluating climate change and taro and then concludes with a few final remarks.

Current Climate and Trends

Figure 1 shows the average historical annual precipitation and mean daily maximum temperature for the 1990-2020 period across the PNG landscape. Mean temperatures vary across the country based in large part on elevation (see Supplemental Figure 1). While mean precipitation is not as highly correlated to elevation, it is influenced by the interaction with the mountainous terrain of the highlands.

Figure 1: Climate averages, 1990-2020



Annual precipitation, millimeters

Mean daily maximum temperature, ^{0}C

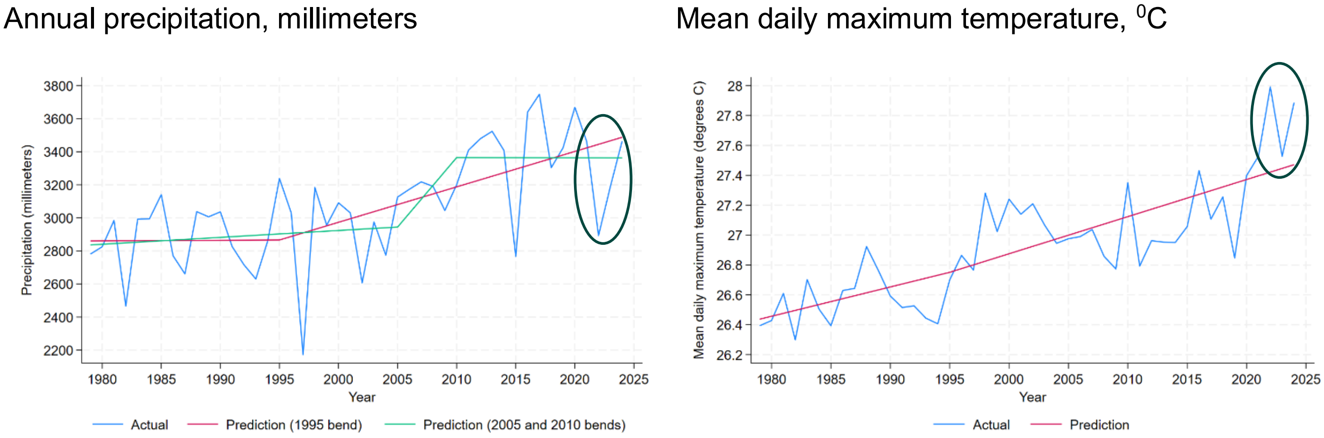
Source: MSWX (2025) and Beck et al. (2022).

Figure 2 shows the annual values for mean rainfall and mean daily maximum temperature. The graphs also include trend lines (or predicted values) based on regression results. Both graphs show results for a continuous piecewise linear regression with a knot (bend) at 1995, which appears to be a point where precipitation shifted from relatively flat to a persistent rise.[1] After 1995, based on the trend line, precipitation increases at a rate of 21.4 millimeters per year, which is over 600 millimeters increase between

1995 and 2024. For temperature, the trend line between 1995 and 2024 increases at a rate of 0.025^{0}C per year, which is just under a rise of 0.75^{0}C over that period.

The data for 2021-2024 (circled in Figure 2) makes it difficult to know how to project climate into the future, since it shows a much higher temperature than is predicted and a lower level of precipitation. It is not clear whether this represents a sharp transition to a new climate regime, or whether it is an aberration bought on by El Niño.

Figure 2: Annual climate variability and trends, national, 1979-2024



Annual precipitation, millimeters

Mean daily maximum temperature, ^{0}C

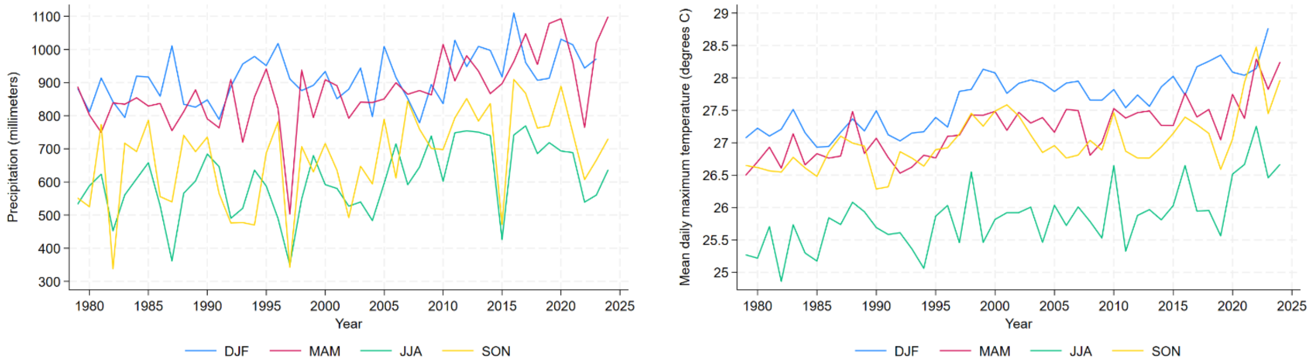
Source: MSWX (2025) and Beck et al. (2022).

Notes: The oval highlights the uncertainty of the 2021-2024 period. It is unclear whether this represents a real change in the system, such as an increase in the rate of temperature change and a decrease in precipitation, or whether this period was simply a temporary deviation, possibly brought on by El Niño. The red line shows predicted values based on a regression of the climate variable on year, with a knot (bend) allowed in 1995. For precipitation, the green line allows for 2 bends, one at 2005 and one at 2010.

When estimating the climate impact from recent historical data, uncertainty remains as to what the data are suggesting. This uncertainty is because of the existence of decadal variability, which on a graph of temperature or precipitation over time is like a sinusoidal wave that oscillates over a 20- to 60-year period. Thus, one is never completely certain which part of a change in the graph represents the longer-term climate change and which part is the decadal variability. With that being the case, and focusing on PNG precipitation, data suggest the precipitation appears relatively flat through 2005, grows through 2010, and then levels off after 2010 (as shown by the green trend line in Figure 2). Thus, it appears that the precipitation rose by 420 millimeters between the two relatively unchanging periods. For those interested in greater spatial differentiation, specific trends can be found in maps shown in Supplemental Figure 3.

Figure 3 shows seasonal precipitation and temperature for PNG. The coldest and driest period is June through August, with September through November being similarly dry but not as cool. Dry periods can do significant damage to some crops. Figure 2 and Figure 3 suggest that PNG has experienced substantially dry periods in 1982, 1987, 1997, and 2015, most of which are years associated with El Niño. The 1997 dry period spanned at least 3 quarters of the year, and the dry periods in 1982 and 2015 spanned 2 quarters. In addition to the years highlighted, there are others, that while being less severe in terms of deviations from normal rainfall, could also have been significant yield altering events, such as the 3 quarters dip in 2022, which was in the middle of a La Niña event.

Figure 3: Precipitation and temperature by season, 1979-2024


Annual precipitation, millimeters

Mean daily maximum temperature, ^{0}C

Source: MSWX (2025) and Beck et al. (2022).

Notes: “DJF” means December through February. “MAM” means March through May. “JJA” means June through August. And “SON” means September through December.

Climate Projections

The IPCC (Intergovernmental Panel on Climate Change) issues assessment reports on climate change every 6 to 8 years. The Sixth Assessment Report (AR6) initiated publication in 2021 (there is a long process and three working groups who issue related but independent reports). Much of the scientific analysis relies on the supporting climate models developed as part of a consortium that supports the IPCC known as CMIP (the Coupled Model Intercomparison Project), and the models issued for AR6 are designated as CMIP6. These climate models have data that is fairly coarse, and some of the modeling communities, including the agricultural modeling community, requires finer data. Another group, ISIMIP (the Inter-Sectoral Impact Model Intercomparison Project), downscales that data to facilitate further analysis. However, their downscaling is limited to 5 climate models, and the resulting data that is used in this analysis is what they have designated as ISIMIP3b. The 5 global climate models (also known as GCMs) that are downsized and that we use in this analysis are: GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, and UKESM1-0-LL.

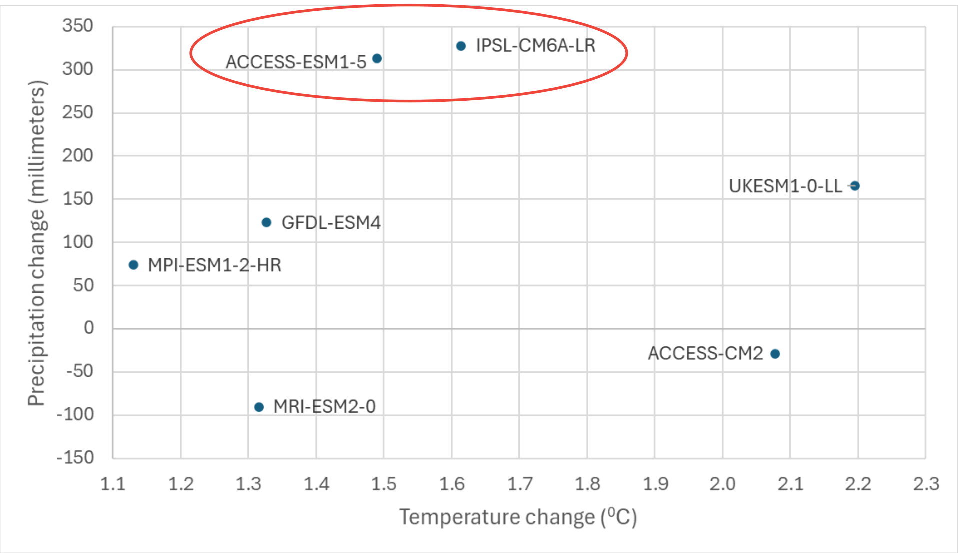
Each climate model is run by climate scientists under various emissions scenarios, which describe how atmospheric greenhouse gases evolve over time based on the respective scenario. The highest emissions scenario used is SSP585 (SSP is short for “shared socioeconomic pathway”), which is what most of the analysis in this research note is based on.[2]

Among the original CMIP6 models are 2 that are produced in Australia by CSIRO[3]. Comparing the ACCESS models produced by CSIRO with the ISIMIP models in Figure 4, we find that ACCESS-ESM1-5 approximates results to the IPSL-CM6A-LR model, whereby both demonstrate significant increases in rainfall and moderate increases in temperature from 2000-2050.[4] ACCESS-CM2 is not comparable to any one of the 5 ISIMIP climate models. However, it is similar to UKESM1-0-LL in terms of temperature increase but closer to MRI-ESM2-0 in terms of rainfall reduction.

Figure 4 reveals that the climate models represent a fairly broad spectrum of how climate change may affect PNG. The UK model shows the greatest temperature rise between 2000 and 2050, almost double what the MPI model projects. Precipitation predictions vary even more: the MRI model projects almost a 100-millimeter reduction in rainfall over the same period, while the IPSL and ACCESS-ESM1-5 models both project more than a 300-millimeter increase.

Figure 4 is useful to this report in a couple of ways. First, in light of the recent historical trend of at least a 420 millimeter per year increase in precipitation through 2024 – and possibly closer to 600 millimeters, depending on the method used to estimate the rainfall trend – the wettest 2 climate models appear to be best suited to represent the future assuming that what has been recently experienced is a good indicator of what is to come. Recalling that the climate models are showing data from around 2000 to 2050, the recent historical data shows what has happened at the half-way point (i.e., 2025). While the temperature has risen at a slower rate than what these two wet climate models project, we also note a sudden jump that is seen in the 2021 to 2024 period, which may indicate that the slightly higher temperatures projected in these wetter 2 climate models may reflect realistic future temperatures. Second, while we have not yet used the CSIRO models to study climate impact on taro, as previously noted, at least at the national level, the ACCESS-ESM1-5 is similar to the IPSL model that we discuss in this note.

Figure 4: Change in precipitation and temperature in key climate models in PNG, 2000-2050



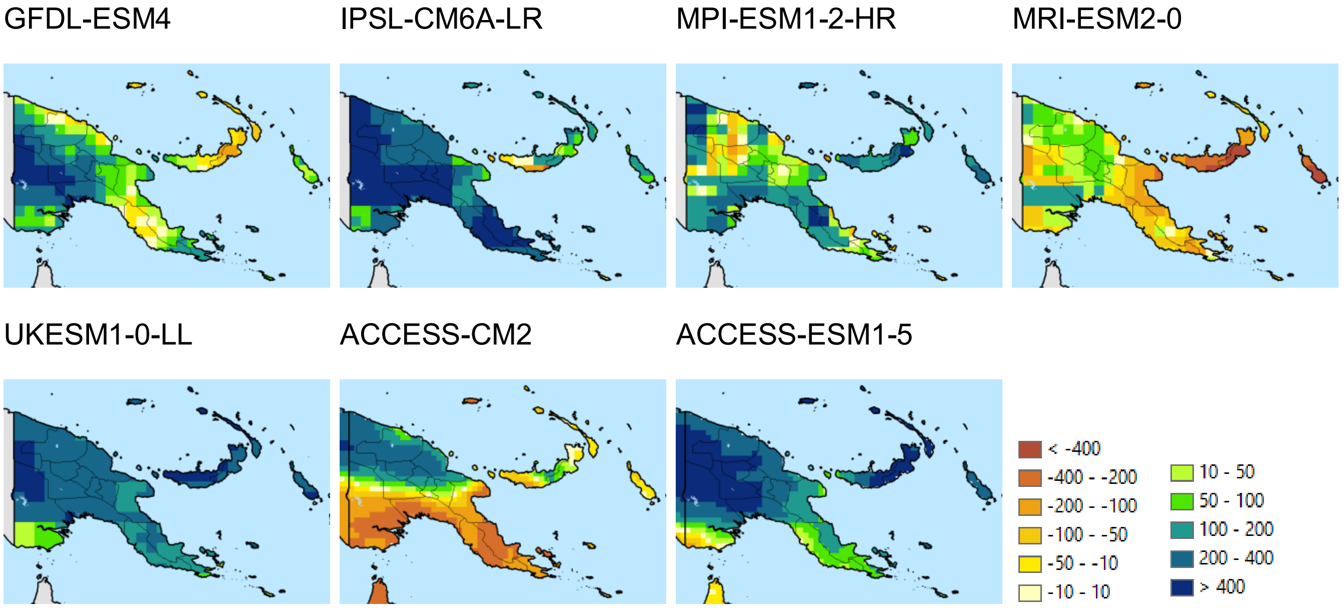
Source: NASA.

Notes: SSP585. The values in this graph differ slightly from the identically-named climate models used in maps, which are based on ISIMIP3B downscaling instead of NASA downscaling. This graph was required because in order to show the two ACCESS climate models which were not part of the ISIMIP3B downscaling. The red oval highlights the climate models that seem to be indicated by the trends observed through 2024, which show large increase in precipitation and modest increases in temperature.

Figure 5 shows the change in precipitation projected at each location in each of the climate models. To be clear, the CSIRO models are from NASA downscaling for 2000-2050 and the other 5 models in the figure are from ISIMIP downscaling (instead of NASA downscaling as was shown in Figure 4), covering the 2005-2050 period. Differences exist in aggregate values across models, as well as spatial differences within models. For example, the ACCESS-CM2 model shows the southern portion of PNG becoming substantially drier and the northern portion becoming substantially wettter, with the islands of PNG being heterogeneous. We note in Figure 5 that ACCESS-ESM1-5 is similar to IPSL-CM6A-LR in many parts of the country, though for rainfall (but as shall be seen, not temperature), the ACCESS-ESM1-5 model may be even more similar to UKESM1-0-LL.

Figure 6 shows temperature changes between 2000 to 2050. The ACCESS-CM2 projects more temperature change than any of the other models, including UKESM1-0-LL. This is slightly different than the ranking shown in Figure 4, and is due to the different nature of how the data was downscaled and processed between NASA and ISIMIP. While it cannot be seen from this figure, temperature changes in PNG are projected to be less than most other places in the world, while precipitation changes in PNG are projected to be higher than most other places in the world.

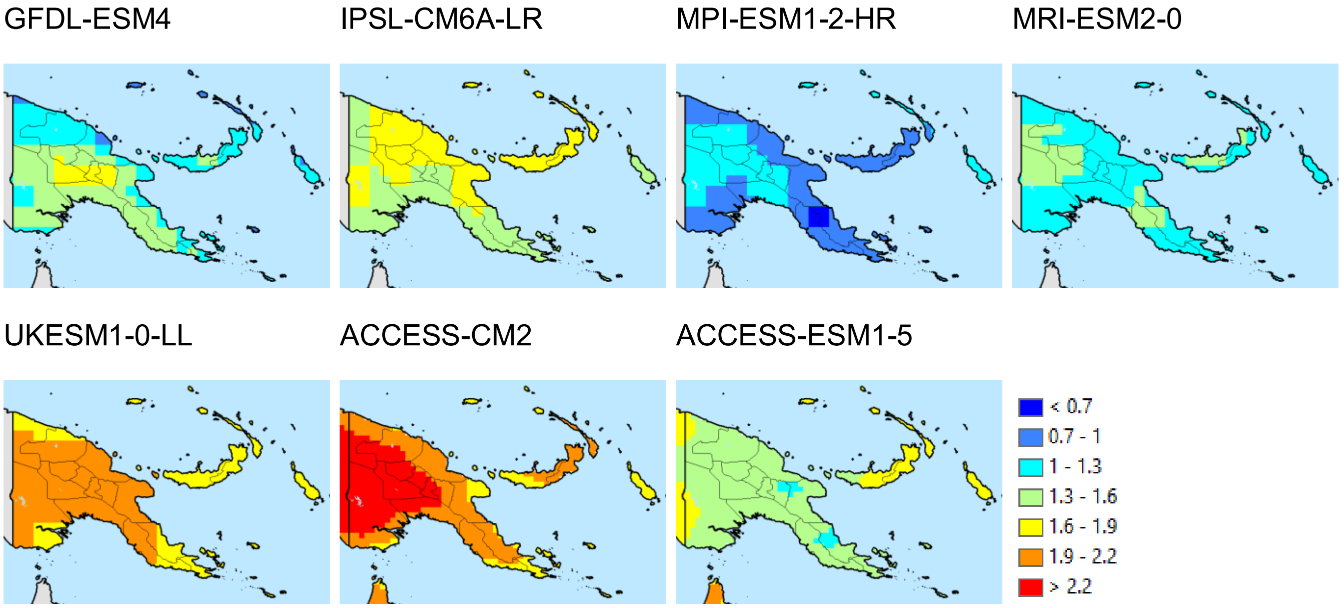
Figure 5: Change in precipitation (millimeters) in key climate models, circa 2000-2050, gridded


GFDL-ESM4 IPSL-CM6A-LR MPI-ESM1-2-HR MRI-ESM2-0

UKESM1-0-LL ACCESS-CM2 ACCESS-ESM1-5

Source: NASA (2022) and ISIMIP (2021).

Figure 6: Change in temperature (^{0}C) in key climate models, circa 2000-2050, gridded


GFDL-ESM4 IPSL-CM6A-LR MPI-ESM1-2-HR MRI-ESM2-0

UKESM1-0-LL ACCESS-CM2 ACCESS-ESM1-5

Source: NASA (2022) and ISIMIP (2021).

With the exception of MRI-ESM2-0 and possibly ACCESS-ESM1-5, the models generally agree that the northern coast and the islands will experience smaller temperature increases than the highlands, particularly the area near the Indonesian border. ACCESS-ESM1-5 does appear to be similar to IPSL-CM6A-LR.

Climate Impact on Taro from Agricultural Modeling

In our study of the impact of climate change on taro, we use a number of tools together with multiple climate datasets to create a fuller picture than we would see with just one approach to understanding climate impact. In the first step, we use the DSSAT (Decision Support System for Agrotechnology Transfer) crop model (Hoogenboom et al. 2019; Hoogenboom et al. 2024; Jones et al. 2003) to estimate yields with a gridded, daily historical weather from the MSWX dataset (Beck, et al., 2022).

DSSAT produces yields based on daily temperature, precipitation, and solar radiation, along with information on soil type, planting and harvesting dates, and various farm management practices. Because DSSAT is computationally intensive, we build a crop-yield emulator that requires only monthly precipitation and temperature data during and for 2 months preceding the growing season. This allows us to do 2 things: rapidly make predictions of yields for a thousand climates across multiple years and multiple locations; and gain a more intuitive understanding of how climate impacts yields by graphing yield response curves to monthly climate variables, which are shown in Figure 7.

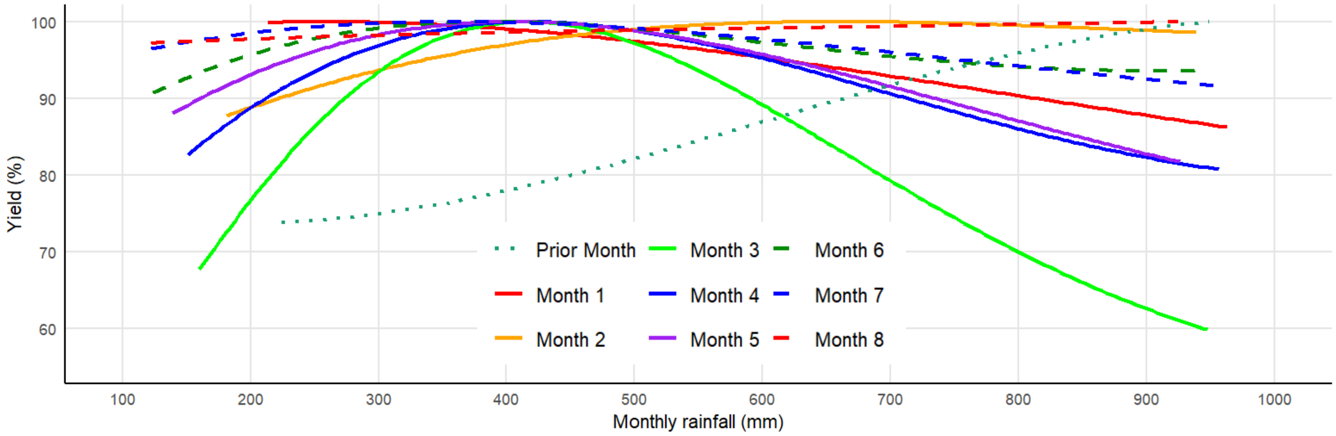
To construct the initial database of climates and associated yields from which to build the emulator, we chose 4 planting dates distributed approximately evenly throughout the year. We tried modeling with HC27 soils by Koo and Dimes (2010), resulting in large yield reductions in higher rainfalls, which experts told us were too high. To remedy this problem, we selected a soil from the WISE soil database that was less sensitive to high rainfall. We then generated yields using the historical climate data from 1980 through 2024.

An emulator is produced using a statistical method – here, we use a regression – that relates yield to climate variables. In our analysis, we run a regression of the log of yield on monthly values of rainfall and mean daily maximum temperature. Because we believe the relationship is highly non-linear, each monthly climate value is converted to a fourth order polynomial. We do this for 8 months, as well as for the rainfall in the 2 months preceding planting, because we believe that soil moisture is potentially very important in explaining yields. Furthermore, because we took that perspective, we use bi-monthly rainfall as the explanatory variables (e.g., instead of month 2 rainfall we use the sum of the rainfall in months 1 and 2, and month 3 has the sum of months 2 and 3, and so on).

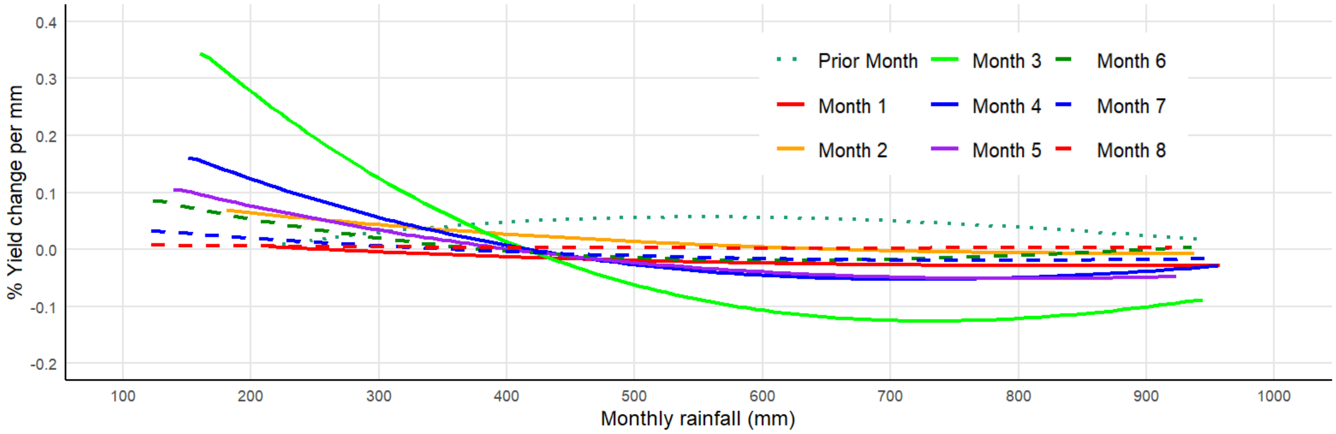
Figure 7 combines four plots to illustrate the effects of monthly rainfall and mean daily maximum temperature on taro yield across key growth stages. The endpoints of each curve represent the 5th and 95th percentiles of observed climate data, so results outside these bounds should be interpreted with caution.

Figure 7: Crop yield response to rainfall and mean daily maximum temperature and percent change in crop yield for marginal change in temperature (°C) and rainfall (mm)

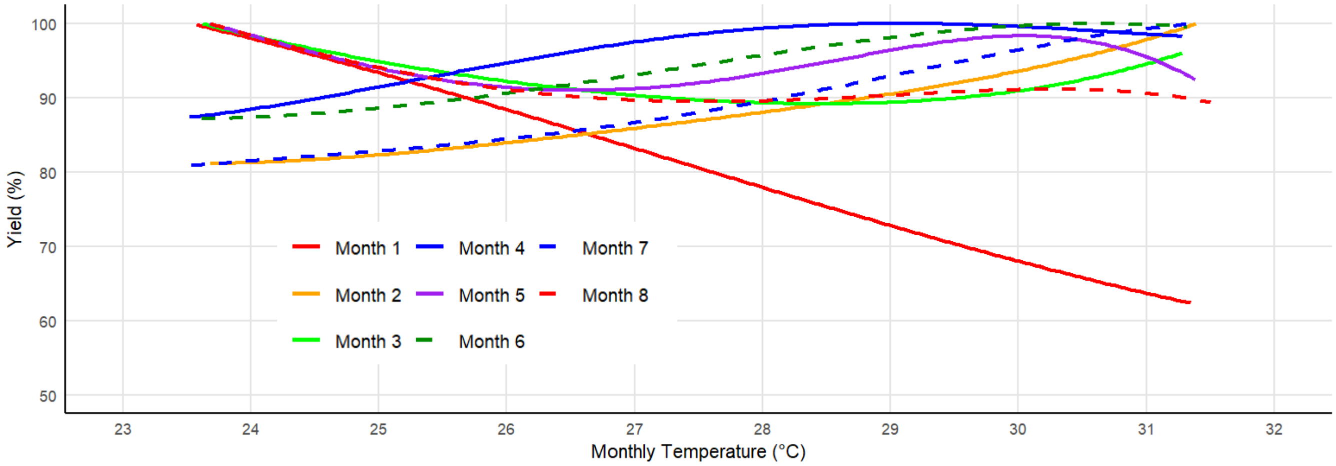
(a) Taro yield response to bi-monthly precipitation



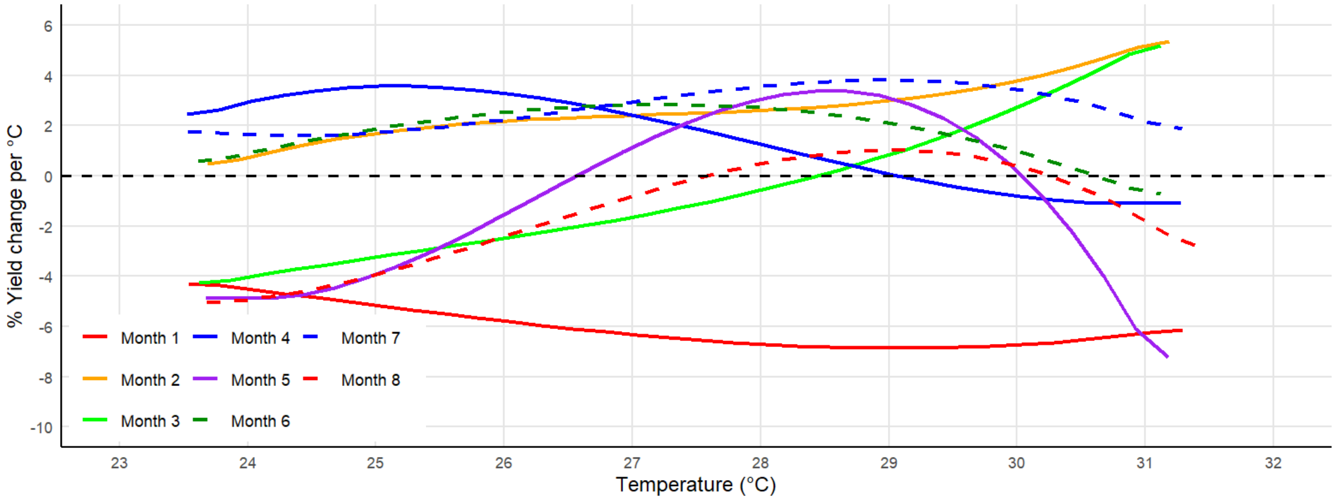
(b) Marginal effect of bi-monthly precipitation on taro yields



(c) Taro yield response to monthly mean daily maximum temperature.



(d) Marginal effect of monthly mean daily maximum temperature on taro yields



Source: Authors.

Notes: Yields are modeled across the 5th to 95th percentile range for both temperature (°C) and rainfall (mm) in each month.

The top plot, (a), shows that taro yields are highest at around 400 mm of rainfall per two-month period for most months of the growing season, with the most pronounced yield decline for high rainfall occurring in the third month of the growing season when rainfall exceeds this threshold. While very high rainfall levels can lead to lower yields, high rainfall in the month before planting is associated with greatly improved yields, highlighting the crop's reliance on adequate soil moisture at establishment. Months 2 and 8 are most tolerant of higher rainfall.

The second plot, (b), shows the marginal effect of rainfall, representing how yield changes with each additional unit of rainfall. It is the slope of the line in the top graph, (a). Steep slopes lead to large absolute values in the graph of the marginal effect. Just as taro yields decline when rainfall is too high, they also decline when it is too low. In fact, we see that the effect of drought generally has larger quantitative consequence than high rainfall. (The largest value in (b) is for month 3 at around 160 millimeters, which shows a 0.34% increase for a 1-millimeter increase in rainfall. But a 50-millimeter decrease in rainfall in month 3 if the normal rainfall is 160 millimeters would lead to a 17% reduction in yield; i.e., minus 50 times 0.34%.) Drought adversely impacts taro yields in months 3 through 6, with month 3 (sum of precipitation in months 2 and 3) being particularly sensitive to low rainfall.

For temperature, the bottom two plots reveal that taro yield responses are stage-specific. The response to temperature increases are particularly strong in month 1 (the planting month), with taro strongly preferring cooler temperatures. Months 2, 4, 6, and 7 almost always improve yields with increased temperature. The impact of temperature increases on yields for months 3, 5, and 8 depend entirely on the starting temperature.

We use the taro emulator with the 5 climate models produced by ISIMIP 3b under CMIP 6 (these are the latest downscaled climate models produced using datasets that guided the IPCC Sixth Assessment Report). They are based on the high emissions scenario, SSP585. Because we have shown that recent climate trends suggest that the IPSL model might be the best model out of the five based on observed changes in the climate between 2000 and 2024, the results for that model are in a column by itself in Table 1, while the results of all 5 climate models are summarized in the columns labeled "Median", "Minimum", and "Maximum". We provide both specific model (IPSL) results and the median (across models) results to allow for comparison, while also recognizing there remains uncertainty about the future, and the median is often the most reliable statistic in the face of a small sample and large uncertainty.

It is also helpful to look at the range from the minimum to the maximum, because one should remember that these are results that are dependent on an uncertain future climate. For the nation, the uncertainty ranges from a loss of 9.3% to a gain of 7.5% -- an almost 17-percentage point spread. This uncertainty demonstrates the risk of over-investing in solutions that only work in one possible future climate rather than investing in a suite of solutions that address various potential future problems. Figure 8 shows location-specific climate impacts on taro yields.

Table 1: Percent change in taro yield from climate change by region, 2020-2050

Unit of analysis	IPSL	Median	Minimum	Maximum
Nation	1.1%	1.5%	-9.3%	7.5%
Highlands	5.8%	2.8%	-5.2%	5.8%
Islands	2.1%	2.1%	-8.7%	2.5%
Momase	0.9%	1.4%	-9.6%	9.8%
Southern	-2.1%	-2.9%	-8.2%	-0.1%

Source: Authors.

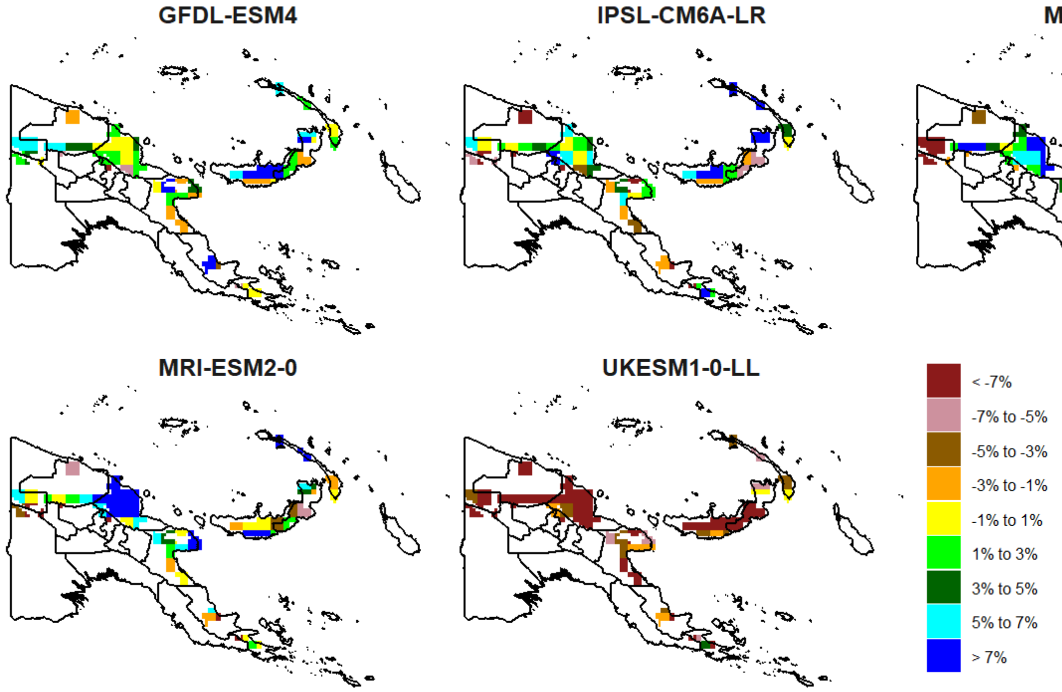
The minimum value for climate impact on yields for each region and the nation is from the UK climate model. Yield reduction in that model seems to be driven almost entirely by temperature rise, since the precipitation change is similar to the IPSL model, which resulted in projected yield increases from climate change, and the UK model stands out as the climate model with the highest temperature change. The negative values in the UK model suggests that climate change could possibly have an adverse effect on taro yields (if the UK model proves correct), though the most probable outcome (given by the median value) suggests that climate change should generally have a positive effect on taro yields, except in the Southern region, where only a relatively small share of taro is currently grown.

At the national level, climate change is projected to have a small but positive impact on yields in an average year in the IPSL model and in the median of the 5 climate models, with projections being 1.1% and 1.5% respectively. According to the IPSL model, the Highlands will benefit most from climate change, with almost a 6% gain, though not much taro is grown there, nor in Southern, where it is projected to reduce yields by 2%. Most taro is grown in Momase and the Islands, where the average gains from climate change using the IPSL climate model are around 1% and 2% respectively.

Climate uncertainty and variability: impact on taro yield variability and low-yield events

The taro yield change results presented thus far focus on average changes across all variability given a specific climate (described by the climate models). However, we would also like to quantify the impact of “bad weather” brought about by El Niño or other negative climate shocks, which is what we do in this section as we model the impact of climate variability on taro yields. As part of this analysis, we also account for uncertainty surrounding which climate model will most accurately describe the future.

Figure 8: Percent change in yield from climate change, 2020-2050, gridded



Source: Authors.

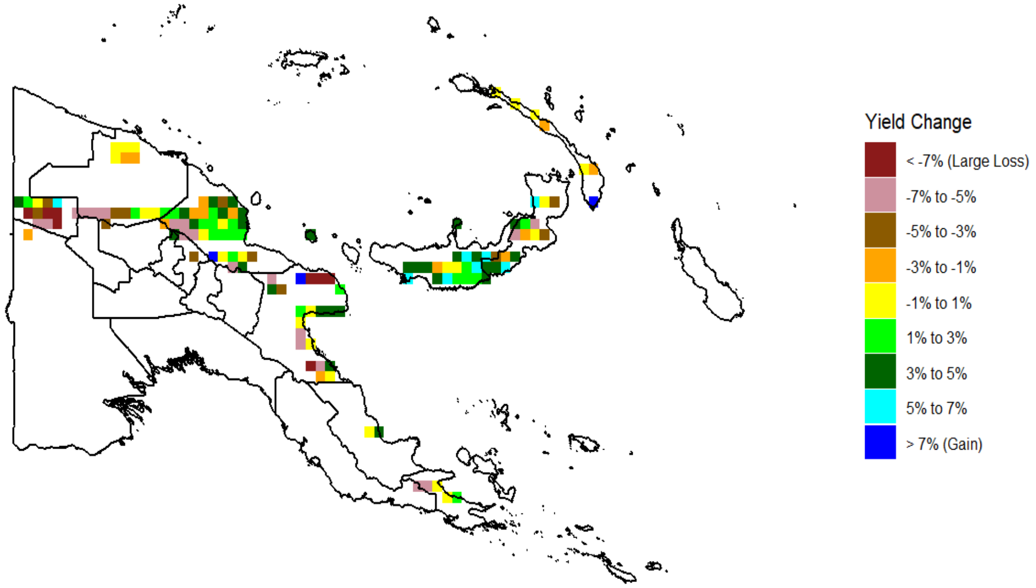
In this section, we use the MIT Integrated Global System Model (MIT-IGSM, Reilly et al., 2018), which provides an ensemble of 11,600 high-frequency distributions (HFDs) which can be thought of as smoothed climate models. In doing so, we interact them with detrended values from 43 years of monthly data from AgERA5 from 1979 to 2025, giving over 500,000 possible future climates. We take a random draw of 1,000 of these climates, and compute taro yields at each pixel for those 1,000 climates. Using a standard crop model, this would be computationally intensive, but we reduce computing time by, once again, using the taro yield emulator.

The high emissions scenario from the MIT-IGSM is based on lower greenhouse gas emission than those used to compute the 5 CMIP climate models. The MIT-IGSM high emissions seems to fit somewhere in between RCP6.0 and RCP7.0, while the CMIP models are based on RCP8.5 (the numbers reflect the level of radiative forcing in the year 2100).

Figure 9 shows changes in median yields at each location where taro is grown. Tabulations at the national and regional level are presented in Table 2. For the nation, median yield is projected to decline by 0.7% between 2020 and 2050. Among the regions, in median years, climate will improve yields by 2.7% in the Islands and lead to a 1.4% yield reduction in Momase. For many crops in many countries, the losses in bad climate years can be more significant than the losses during typical years, but for taro in PNG, percent changes in yields in the 5th percentile are very close to percent changes in median yields, though in the Highlands the losses in bad years are slightly higher than in typical years: 5.3% vs. 2.4%.

Table 2 also shows how much lower yields can be in a “bad” year (1-in-20 or 5th percentile) compared to a normal year. In 2050 at the national level, model projections suggest yields will be 90% of a normal year. For small geographic units, the reduction can be larger, with the Islands producing only 76% of a normal year in a bad year. In Table 1, we did not account for inter-annual variability in climate, but only variation across climates. At the national level, the comparison shows the minimum yield is 84% of the median, indicating that uncertainty across climate models is rather large in the CMIP climate data.

Figure 9: Percent change in median taro yield per pixel under high emission from 2020 to 2050



Source: Authors.

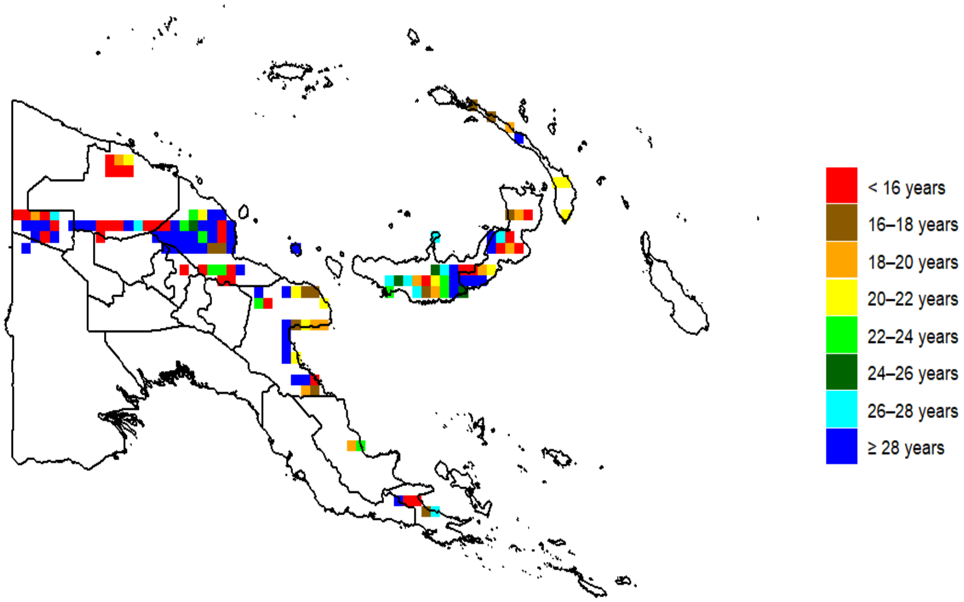
Table 2: Percent change in taro yields from climate change at various points in the distribution, 2020-2050, under the high emissions scenario

Unit of analysis	Year	Mean	5th percentile	25th percentile	Median	75th percentile	95th percentile	Percent of median in 5th percentile
National	2020	3416	3072	3234	3405	3557	3860	90.2%
National	2050	3409	3049	3232	3382	3569	3853	90.2%
Highlands	2020	3841	2949	3341	3760	4115	5367	78.4%
Highlands	2050	3770	2793	3280	3671	4096	5200	76.1%
Islands	2020	3415	2563	2977	3328	3810	4657	77.0%
Islands	2050	3477	2605	3066	3417	3845	4574	76.2%
Momase	2020	3426	3018	3283	3379	3556	3829	89.3%
Momase	2050	3393	3002	3236	3351	3540	3819	89.6%
Southern	2020	3074	2247	2841	3131	3262	3728	71.8%
Southern	2050	2971	2174	2748	3005	3163	3673	72.3%

Source: Authors.

Figure 10 focuses on the change in the 5th percentile: the 1-in-20-year low-yield event. In places with climate worsening in the bad weather yields, low-yield events occur more frequently. The locations colored red indicate locations where the low yield would occur more frequently than every 16 years. It appears that while several locations will have low yield occurring more frequently, more locations appear to be projected to have less frequent low-yield events, with the navy royal blue color indicating it would occur less often than every 28 years.

Figure 10: Frequency in 2050 of a 1-in-20-year low-yield event from 2020



Source: Authors.

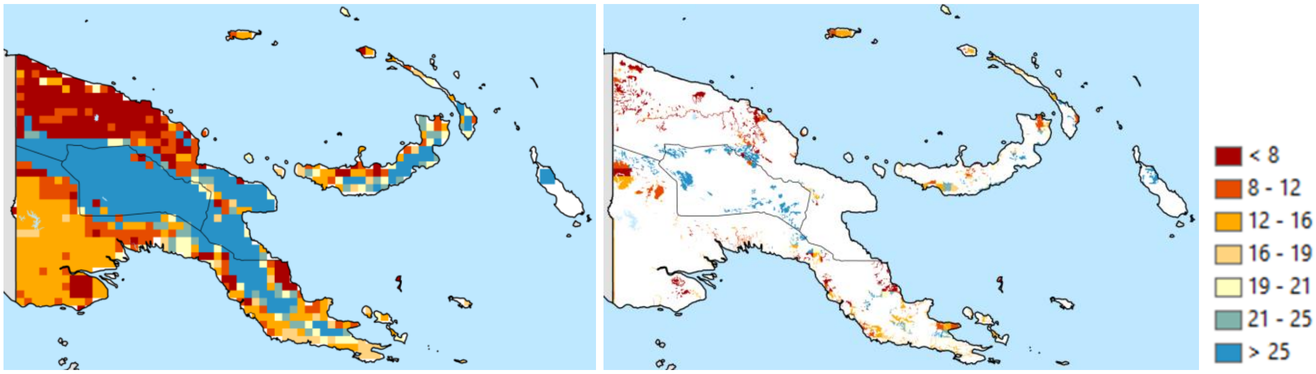
We did a similar analysis for corn (maize) to evaluate the impacts of climate change on corn production in PNG. Corn has been proposed as a potential crop to expand in lowland areas for greater livestock feed, thus it merited a brief evaluation of potential yield changes that may occur due to climate change. Figure 11 shows the frequency of low-yield events for rainfed corn under climate change, using a corn emulator to impute inter-annual variability of corn production. The analysis is based on the same random sample of 1,000 climates that we used for the taro analysis.

Results suggests that in the highlands regions (where little corn is grown), there will be fewer low-yield events in the future, primarily because corn prefers higher temperatures than what the highlands typically experience. However, in Momase and Southern Region, where a majority of corn is currently grown, corn production is projected to experience greater frequency of low-yield events. For example, the dark red areas in the map in Figure 11 suggest that a current 1-in-20-year low yield event will occur more frequently than every 8 years, increasing the probability of significantly low corn yields by more than double.

Final word

Taro is an important staple crop for Papua New Guinea, contributing to stable calorie consumption for both rural and urban households (6.0% and 1.3% of total consumption, respectively), according to the 2009/10 HIES (PNG National Statistical Office, 2010). The impact of climate change on agricultural productivity in Papua New Guinea has not been well-modeled in the past, and understanding the impact on an important crop like taro is important to national food security. Our analysis revealed that projected change in average taro yields is likely to be small, with the CMIP6 datasets suggesting that the gain at the national level will be around 2% over 45 years and the MIT-IGSM suggesting that it will decline by around 1% over 30 years. The largest losses for taro were found using the UK GCM, tempering the optimism of having low climate impacts in the median model.

Figure 11: Frequency in the 2040s of 1-in-20 low-yield year from 2020 for rainfed corn



Source: Authors.

Notes: Image on the left shows all of PNG while the image on the right emphasize areas in which corn is likely grown based on Bourke et al. (1998).

These results suggest that while climate change cannot be ignored, it is more important to invest in increasing productivity. Since the UK model, which led to relatively large reductions in yields, is one with the largest temperature increases, it would also be helpful to reduce risk by developing a taro cultivar that is tolerant of higher temperatures. Corn also was sensitive to higher temperatures and therefore if the government plans to advocate for expanding corn cultivation, developing varieties that are heat tolerant would be essential. Additional investments might include developing improved varieties of taro that perform better under wetter conditions but could also include increasing availability of fertilizers. As mentioned previously, because of the uncertainty across climate models, it makes good sense to invest in a suite of options for farmers that would allow them to adapt to a variety of climate changes and not simply the most likely changes. To help develop resilience in low-rainfall years, since taro is highly sensitive to drought, developing drought-resistant varieties could also be very helpful, and as mentioned previously, is being worked on at the PNG University of Technology in Lae, with funding from ACIAR and collaboration with the University of Queensland.

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ENDNOTES

[1] The rainfall trend and variation noted with the MSWX data are virtually identical to those found in an alternate gridded climate dataset, AgERA5 (Boogaard et al. 2020). The main difference is that annual rainfall in PNG in AgERA5 is shifted up by around 700 millimeters per year. The means for the Climate Research Unit Time Series (CRU-TS) dataset (Harris et al. 2020) and the Princeton Global Forcings (PGF) dataset (Sheffield, Goteti, and Wood 2006) seem to align fairly well with the MSWX dataset, but both of those show a structural break around 1998 in which high variability switches inexplicably to very low variability, and so the annual values seem unreliable in those two datasets. The annual variability of those two before 1998, however, appears similar to that of the MSWX, leading us to believe that the MSWX is possibly the best climate data out of the four datasets, with variability agreeing with all datasets prior to 1998 and agreeing with AgERA5 after 1998 in which we believe CRU and PGF to be unreliable; and the mean of MSWX agreeing with that of CRU and PGF, especially prior to the structural break in 1998.

[2] The next highest emissions scenario is SSP370, which is very similar to SSP585 through 2050, which is as far into the future that this report projects. ISIMIP3b also has a lower emissions scenario, SSP126.

[3] We did not use them because they were downscaled in a different manner than the 5 from ISIMIP3b which we had already committed to using since these are the 5 models currently used by most teams working on agriculture and climate change.

[4] To be clear, however, the values presented in Figure 4 were all downscaled by NASA (we needed to use NASA data to consider the CSIRO models) and therefore may differ somewhat from the ISIMIP models due to differences in algorithms used by each organization, not to mention different methods the authors of this study used to process them.

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