Crop Forecasting for 5 Staple Crops in the Federated States of Micronesia

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As the Federated States of Micronesia is experiencing rapid climate change, the ability to use science to forecast future staple crop yields is critical for the nation's sustainable food system development and food security strategies.

Climate models are one of the primary tools that scientists use to project how a region's climate will change. The Coupled Model Intercomparison Project (CMIP) is a collaborative modeling framework designed to improve climate change projections. Coupled models are computer-based models of the earth's climate, in which different types of environmental data (such as atmosphere, oceans, land, ice) are coupled together to create more holistic ecosystem-based simulations.

The previous generation Coupled Model Intercomparison Project phase 5 (CMIP5) general circulation models and the representative concentration pathway (RCP) emission scenarios informed the Pacific islands crop forecasting analysis conducted by Belle and Taylor et al. (2016).

As of the writing of this report, the latest climate models are from the CMIP6 effort and utilize narrative emissions scenarios in the form of shared socioeconomic pathways (SSPs) that offer additional socioeconomic and political drivers of how emissions may evolve over the 21st century (Eyring et al., 2016). The conventional wisdom is that these updated models do not necessarily show dramatically different projections compared to the CMIP5 suite of climate models but represent an advancement in computation methodology and are better at simulating synoptic processes (Adeyeri, 2022).

Taylor et al. (2016) cite a range of RCP emission scenarios climate projections from CMIP5, which should be reevaluated to ensure the conclusions drawn for individual crops are in accordance with the updated CMIP6 modeling framework. Following the framework of CMIP5, Taylor and others presented a suite of warming scenarios: RCP2.6, RCP4.5, RCP6.0, and RCP 8.5 which are associated with low to very high warming respectively (Table 1). In recent years, the trajectory presented by RCP8.5 is no longer considered a very likely scenario (e.g., Hausfather and Peters, 2020). Therefore, it is recommended that this range be updated to correspond with the new SSP projections and differences considered where appropriate.

All data used in this analysis come from the Intergovernmental Panel on Climate change (IPCC) Working Group 1 Interactive Atlas (Iturbide et al., 2021; Gutiérrez et al., 2021; Interactive-atlas.ipcc.ch).



Temperature

Table 1 Reproduced from Taylor et al. (2016).

Table 2.4: Projected tropical Pacific air temperature change, from 1986–2005, for three time slices and four RCPs. The 5th-95th percentiles of the range of projections are rounded to nearest 0.5°C.

RCP	2030	2050	2090
RCP2.6	0.5–1.0°C	0.5–1.0°C	0.5–1.0°C
RCP4.5	0.5–1.0°C	0.5–1.5°C	1.0–2.0°C
RCP6.0	0.5–1.0°C	0.5–1.5°C	1.5–3.0°C
RCP8.5	0.5–1.0°C	1.0–2.0°C	2.0–4.0°C

Table 2. SSP warming in °C for the Northwest Tropical Pacific relative to the mean of 1986-2005. Note SSP5-8.5 is provided but as with RCP8.5, could be considered very unlikely. Median values are presented with the 5th–95th percentile in parentheses.

SSP	**2030**	**2050**	**2090**
SSP1-2.6	0.8 (0.5–1.0)	1.0 (0.6–1.4)	1.0 (0.6–1.4)
SSP2-4.5	0.8 (0.5–1.1)	1.2 (0.9–1.6)	1.8 (1.2–2.3)
SSP3-7.0	0.7 (0.4–1.1)	1.3 (1.0–1.8)	2.6 (2.0–3.5)
SSP5-8.5	1.3 (1.0–1.7)	2.0 (1.6–2.6)	3.8 (2.9–4.8)

In comparison with Taylor et al. (2016) Table 2.4 (Table 2), the range of warming for analogous scenarios is broadly the same, with SSP1-2.6 and SSP2-4.5 showing a 0.4 and 0.3 °C higher upper range compared to the reported RCP2.6 and RCP 4.5 in Taylor et al. (2016). Similarly, the upper range of SSP5-8.5 is 0.6 – 0.8 °C warmer than the analogous RCP8.5 from the CMIP5 models. Note that Table 2 values were rounded to the nearest 0.5°C and otherwise broadly remain in line with the SSP projections for the low (SSP1-2.6) to high (SSP3-7.0) emissions scenarios. For a more likely high emissions scenario, SSP3-7.0 may be more appropriate for guidance compared to RCP8.5.

Rainfall

Taylor et al., (2016) reported total precipitation change relative to 1986–2005 as a percent change by 2090 for RCP4.5 and RCP8.5 by regional island locations (west and east FSM). This synopsis will just provide the percent changes from the CMIP6 models for the Northwestern Tropical Pacific as a whole for comparison.

Table 3. Comparison of CMIP6 and CMIP5 model simulations for analogous SSP and RCP emissions scenarios. Values are presented as a percent change in total seasonal precipitation from 1986–2005 mean

values by 2090. The median value is presented with the 5^{th} through 95^{th} percentile range presented in parentheses.

CMIP6			
SSP2-4.5 November-April	**SSP2-4.5 May-October**	**SSP5-8.5 November-April**	**SSP5-8.5 May-October**
2.1 (-10.0–13.1)	4.7 (-1.9–10.8)	3.5 (-10.6–21.2)	7.1 (-2.7–19.9)
CMIP5			
RCP4.5 November-April	**RCP4.5 May-October**	**RCP8.5 November-April**	**RCP8.5 May-October**
5.8 (-8.8-22.3)	4.8 (-2.8-11.0)	11.8 (-2.8-23.6)	12.1 (-2.8-18.9)

Table 3 presents a comparison between the summary percent change in total rainfall of the Northwestern Tropical Pacific for the CMIP5 RCP simulations and the CMIP6 SSP simulations that are very broadly analogous (i.e., producing the same radiative forcing by 2100). Note the CMIP5 modeled percent changes are generally 3-5% higher for the November to April season than presented in Taylor et al. (2016) specifically for the Federated States of Micronesia, as the results in Table 3 represent an average of a wider area. So, when considering specific impacts to Micronesia, it may be beneficial to consider a smaller change in that season. Regardless, while the SSP2-4.5 and RCP4.5 have a very similar percent change, all of the other seasons for RCP4.5 and RCP8.5 project a consistently higher change in total rainfall compared to the analogous SSPs. When considering changes to total seasonal precipitation for use in crop management practices, it may be that the impact of total rainfall may be a bit smaller than anticipated by Taylor et al. (2016). However, the 5^{th}–95^{th} percentiles are still close between the two modeling efforts.

Models of Climate Change Impacts on Staple Crops

A summary of projected effects of climate change on the production of selected staple crops in the Federated States of Micronesia are presented in Table 4 (modified from Bell and Taylor, 2015). This summary provides estimates on the impacts of climate change on the production of five major staple crops in the FSM over the short, medium and longer-term time periods (2030, 2050 and 2090).

Staple Food Crop	Short term (2030)	Medium term (2050)	Long Term (2090)
Bananas	Low	Low to moderate	Moderate to high*
Breadfruit	Low*	Low to moderate	Low to moderate
Coconut	Low	Low to moderate	Moderate*
Taro	Low to moderate	Moderate to high	High
Swamp Taro	Moderate to high	High	High
Giant Taro	Insignificant to low	Low	Low
Yam, Wild	Insignificant to low	Low-Moderate*	Moderate*
Yam, Domesticated	Moderate to high	High	High

Bell and Taylor (2015) first presented the above table in a more expanded version and in their estimates had considered a wider range of major agricultural products across all Pacific Island countries and territories. In this synopsis, after careful analysis of that work as that of Taylor et al. (2016) and the 2023 FSM family farming household baseline survey (Rutgers University, 2014), we present a modified version of their projected models of climate change impacts to five of the staple crops grown in the Federated States of Micronesia (See Table 4). Based upon evaluation for these individual crops relative to the updated CMIP6 modeling framework and noting that total rainfall may be less than that projected by Taylor et al (2016) upon which the Bell and Tayler (2015) table was built, we estimate slightly different staple crop impacts over the short, medium, and long term. As temperature rise along with increasing sea level rise continue, the rainfall extremes, coastal floodings, saltwater instruction, and short-term adverse storms and droughts coupled to the increased pressure of diseases and insects with a predicted increased production of these crops and with the continued pressure of invasive weed species (including vines), we estimate that some of the staple crops in the FSM are will be impacted slightly more than that estimated by Bell and Taylor (2015). The changes that deviate from their projection are highlighted in Table 4 and noted with an asterisk. In general, our minor projected crop changes moved some projected impacts to be one category more 'severe' (that is based upon the range of categories defined as insignificant, low, moderate, to high impact on the crops production due to climate change).

The climate change impacts on crops by Taylor et al. (2016) were comprehensive and inclusive of a larger geographical range of Pacific Islands, while our estimates reflect FSM only, and in part were also shaped by the > 600 family farmers across the FSM that reported crop losses for these illustrative five staple crops by climate change. Family farming households reported crop losses associated with a range of climate change indicators for each of the staple crops such as flooding, excessive rains, landslides, coastal erosion, riverbank erosion, extreme heat, cyclones/hurricanes, saltwater inundation, drought, pests and disease, invasive species, (Rutgers University, 2024, pages 171-175). Current climate models do not have sufficient data points that are site and crop specific within the FSM to enable higher resolution projection capacity relative to the impact of short-term flooding, strong winds and associated damage to crops and the environment, timing, and frequency of rainfall over the years relative to the impact on each crop. Taylor et al. (2016) included an extensive review of climate change impacts and plant growth and yields, listing specific pests and diseases concluding that such biotic stresses would have differential impact on specific crops and that the inclusion of improved germplasm would be beneficial. They also reported that in some areas some of these staple crops are projected to be subjected to salt intrusion with sea level rise that would lead to inundation or more frequent flooding, affecting some crop production, such as swamp taro, which could be lost and as such was listed as under 'high impact risk' due to climate change. Subsistent family farming households reported significant losses of each of these staple crops to climate change and given their responses to specific staple crops, we provide estimates that indicate a slightly greater negative impact on some of the staple crops from climate change even under the newer CMIP6 models that don't take into the earlier worse-case scenarios relative to temperature increases.

Conclusion

In comparing annual average temperature and seasonal precipitation changes, while the CMIP6 models provide an improvement in modeling, the results are broadly very similar, apart from the median total seasonal precipitation change. The 5^{th}–95^{th} percentiles are still similar between the modeling efforts. Given how close these projections are and that their use in Taylor et al. (2016) was used as general guidance for potential crop impacts based on the direction of climate variables (warming temperatures, more rainfall), **it is likely that the impacts guidance model presented by Taylor et al. (2016) remains consistent with modern model projections**. One note is that this assessment does not include changes in rainfall extremes, storms, or ENSO which were considered in the Taylor et al. (2016) guidance.

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