Application Guideline

Explaining the scientific background of developing
the Climate Information Toolkit for the Pacific (CLIK℗)
and the Pacific Island Countries Advanced Seasonal Outlook (PICASO)
and how to best utilize these systems.

APCC APEC CLIMATE CENTER
SPREP Secretariat of the Pacific Regional Environment Programme
PACIFIC ISLANDS FORUM SECRETARIAT
CLIKp Climate Information Toolkit for the Pacific
PICASO

The Republic of Korea-Pacific Islands Climate Prediction Services project (ROK-PI CliPS) seeked to provide nationally-tailored seasonal climate prediction information and build the prediction capacity of the Pacific Island Countries and Territories (PICT).

This project was funded by the Government of Korea through the Pacific Island Forum Secretariat (PIFS) and was implemented by the APEC Climate Center (APCC) and the Secretariat of the Pacific Regional Environment Program (SPREP).

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Message from the APCC Executive Director

In the face of climate change, the Pacific Island region will be affected by increased temperatures, sea-level rise, and exacerbated natural disasters. The variation in climate patterns may lead to an increase in tropical cyclone frequency and intensity.

Through the ROK-PI CliPS project, funded by the Republic of Korea government, the APEC Climate Center made efforts to improve the overall capacity of the Pacific Islands to generate high quality climate forecasts, which can help in preparing for extreme climate events such as droughts and tropical cyclones. Highly skilled climate predictions can provide Pacific Island governments with valuable time to manage drinking water, provide early warning for farmers, and prepare for potential tropical cyclones.

By providing hybrid dynamical and statistical downscaled climate information, APCC and SPREP are delivering tailored information specifically designed and localized to the Pacific Island region. Through the Climate Information ToolKit for the Pacific (CLIK℗) and the Pacific Island Countries Advanced Seasonal Outlook (PICASO), the Pacific Islands will be able to independently utilize the APCC Multi-Model Ensemble data to generate tailored and localized forecasts for their countries.

This application guideline serves to explain the scientific background of developing CLIK℗ and PICASO and how best to utilize these systems. We hope that this book will serve to provide a lasting guide on the project outputs.

APCC would like to thank the Republic of Korea government, SPREP, the Pacific Island Forum Secretariat, and the respective governments of Cook Islands, Federated States of Micronesia, Fiji, Kiribati, Marshall Islands, Nauru, Niue, Palau, Papua New Guinea, Samoa, Solomon Islands, Tonga, Tuvalu, and Vanuatu for their active participation and support throughout the project duration.

HJung

Dr. Hong-Sang Jung
Executive Director
APEC Climate Center

Message from the SPREP Director-General

The Pacific continues to face challenges to adapt to the impacts of climate variability due to the influence of El Niño Southern Oscillation (ENSO) and other drivers but also long term climate change.

The understanding of climate and its influence on every aspect of our lives is an essential part of good decision making, for Governments, communities and individuals. Nowhere is this truer than in the Pacific, where our islands and our vast ocean experience tropical cyclones and typhoons, earthquakes, volcanic eruptions, tsunami, drought, storm surges and flash floods.

As the global climate grows less predictable and extreme events become more common, the role of our meteorological and climate services become increasingly vital. In our region we are rising to address this through a range of joint initiatives and actions under the Pacific Meteorological Desk Partnership, based at the Secretariat of the Pacific Regional Environment Programme (SPREP).

One key project is the Republic of Korea-Pacific Islands Climate Prediction (ROK-PI CliPS) project which has helped improve the role and capacity of National Meteorological Services to provide climate information services to support decision making in all levels of society. This was achieved through the provision of tailored climate information trainings on the use of and tools i.e (a) Climate Information ToolKit for the Pacific (CLIK®) and the Pacific Island Countries Advanced Seasonal Outlook (PICASO) for Cook Islands, Federated States of Micronesia, Fiji, Kiribati, Nauru, Niue, Palau, Papua New Guinea, Republic of the Marshall Islands, Samoa, Solomon Islands, Tonga, Tuvalu and Vanuatu.

ROK-PI CliPS project is one of the most successful initiatives managed by SPREP which is jointly implemented with APCC. SPREP is pleased that the application guidelines will provide further support to the operational use of CLIK® and PICASO by aligning it to daily standard operating procedures.

I personally would like to extend our sincere appreciation towards the Government of the Republic of Korea for their funding support, the Pacific Islands Forum Secretariat, APCC and all the National Meteorological Services in the region for their ensuring the success of the ROK-PI CliPS project.

Mr. Leota Kosi Latu
Director General
Secretariat of the Pacific Regional Environment Programme

APCC Introduction

The APEC Climate Center (APCC) is a non-profit organization located in the Republic of Korea that aims to enhance the socio-economic well-being of the Asia Pacific region by utilizing up-to-date scientific knowledge, applying innovative climate prediction techniques, and promoting application of climate information through various programs for capacity building and reducing climate risks in the region. APCC provides assistance to countries in developing and implementing applications of climate information to climate-sensitive sectors like disaster management, agriculture, and water management to improve their performance. In order to enhance the impact of its services, APCC conducts various training programs to assist capacity building in regional developing countries.

APCC was established in 2005 upon its endorsement at the APEC Senior Official Meeting with the mission to enhance the socio-economic well-being of APEC member economies by utilizing up to date scientific knowledge and applying innovative climate prediction techniques. APCC is working towards achieving this mission through our work in climate prediction and climate information services, climate information application and climate change response, and capacity building activities.

Through climate prediction and climate information services, APCC produces and provides value-added, reliable, and timely climate prediction to countries in the APEC region, while serving as a key climate information center to distribute climate data, prediction, and related tools. Through climate information application and climate change response, APCC leads in developing and applying interdisciplinary application techniques, through combining climate and other related sectors to serve social needs and respond to climate change in specific countries and regions. Through capacity building, APCC assists developing economies from the APEC region and beyond in building their capacities to produce reliable climate prediction information and to maintain and utilize APCC products created through the Center's climate information application research.

SPREP Introduction

The Secretariat of the Pacific Regional Environment Programme (SPREP) is a regional intergovernmental organisation that provides assistance and technical advisory services to Pacific island countries and territories in the protection and management of their environment to ensure they achieve sustainable development for present and future generations.

The work of SPREP is guided by the SPREP Strategic Plan 2017–2026 which has four core priorities to help achieve resilient and sustainable Pacific communities, those being Climate Change Resilience, Ecosystem and Biodiversity Protection, Waste Management and Pollution Control as well as Environmental Governance, with our Ocean as an overarching theme.

SPREP's membership comprises 21 Pacific Islands: American Samoa, Commonwealth of the Northern Mariana Islands, Cook Islands, Federated States of Micronesia, Fiji, French Polynesia, Guam, Kiribati, Republic of the Marshall Islands, Nauru, New Caledonia, Niue, Palau, Papua New Guinea, Samoa, Solomon Islands, Tokelau, Tonga, Tuvalu, Vanuatu and Wallis and Futuna. The five metropolitan Members are: Australia, New Zealand, France, the United Kingdom, and the United States of America.

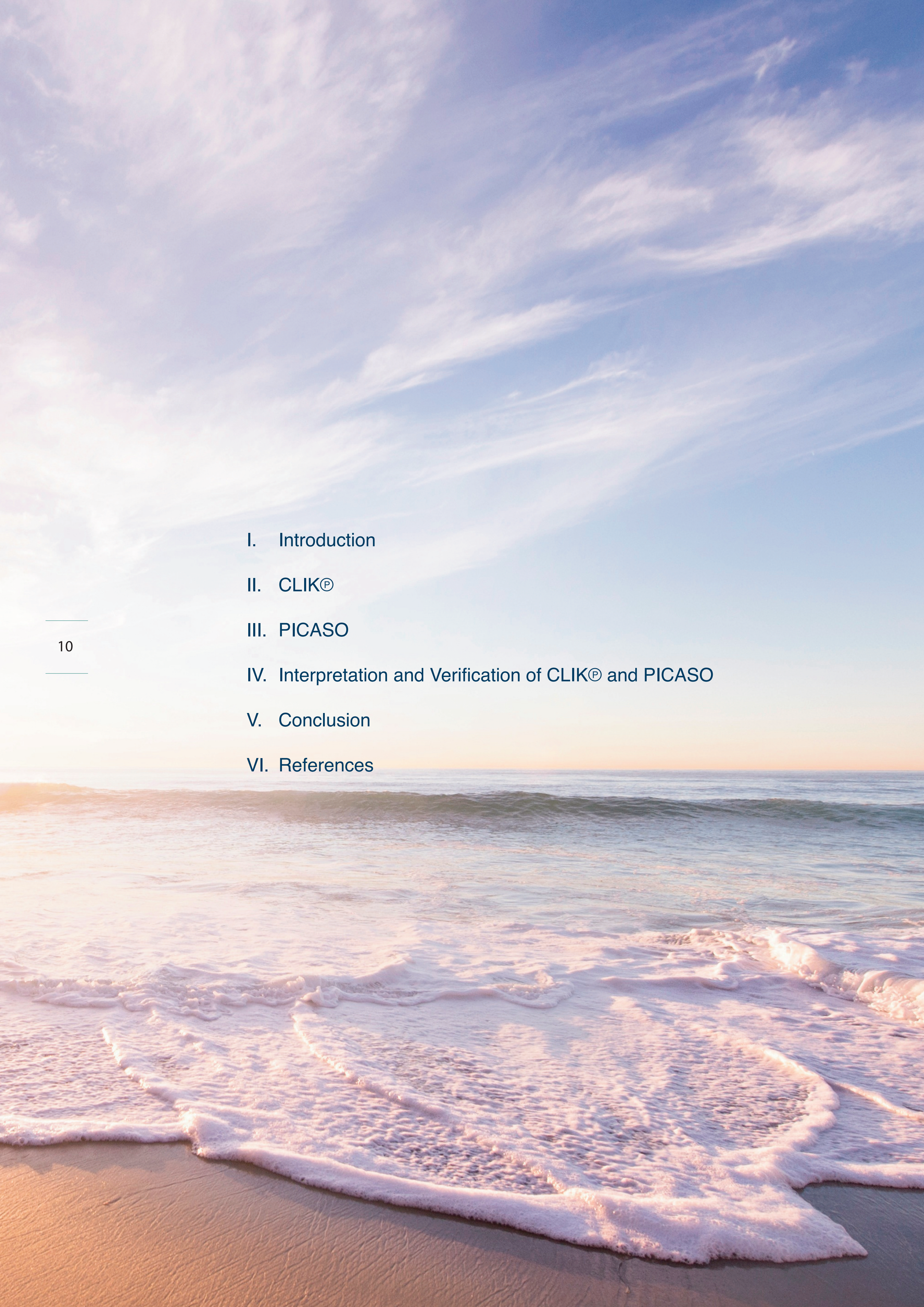
The SPREP Strategic plan 2017- 2026 is also guided by Member commitments to the strategic directions for the region set out in the Framework for Pacific Regionalism, the priorities defined by the SAMOA Pathway, commitments to the Sustainable Development Goals, the Paris Agreement, and other important regional and global commitments.

SPREP has a current staff of more than 100, with at least 20 devoted to working full time on climate related issues. SPREP is a regional centre of excellence and the lead Pacific organisation in climate change and meteorology work. It is the home of the Pacific Meteorological Desk Partnership (PMDP). The PMDP is a regional coordinated mechanism which comprises of the Apia based Secretariat consisting of (SPREP and the World Meteorological Organisation), and a Partners consortium [which interact closely together] to provide combined efforts to support national met services.

It has implemented over 100 donor-assisted regional projects in climate change, meteorology and environmental management, in general, and in Climate Change Adaptation and Disaster Risk Reduction mainstreaming, in particular. SPREP has had long experience in managing regional/multi-country projects, including Global Environment Facility (GEF)-funded and UNDP-supported projects. It has many years of accumulated experience as a GEF executing agency (EA) for several major regional environment projects, particularly on climate change and biodiversity. It has also implemented projects on climate change supported by various donor agencies.

SPREP will continue to assist member countries through the provision of technical advice and support. SPREP provides a strict and extensive fiduciary, governance, project management and other organisational performance standards consistent with requisite standards of governance for delivery of donor funded projects and programmes in the Pacific Islands.

SPREP will host the Pacific Climate Change Center. The establishment of the Pacific Climate Change Centre (PCCC) which will also assist the regional coordination for Meteorology in the region. In addition to other functions, the PCCC will provide a platform for training on climate, weather, ocean and water science and applied research, for PMC expert panels to conduct their business, to act as a catalyst for climate action and function as a shared regional resource for capacity building and training programmes for the region. It will also allow for researchers and institutions from outside the region to find a home space to share their expertise, through secondments, workshops and collaborative research.



I Introduction

1.1 Republic of Korea-Pacific Islands Climate Prediction Services Project

The Pacific Islands region is one of the world's most vulnerable regions to climate change. The Pacific Island Countries and Territories (PICT) depend on their food production systems, fisheries, which are both expected to be largely affected by climate change. There is also an expected increase in intensity and frequency of tropical cyclones that have the potential to cause widespread destruction throughout the island region. These factors make it essential for these islands to adapt and to prepare for the challenges posed by climate change. However, it is impossible to know which adaptive measures to take when there is a lack of high quality climate information to support the planning and management of climate risks.

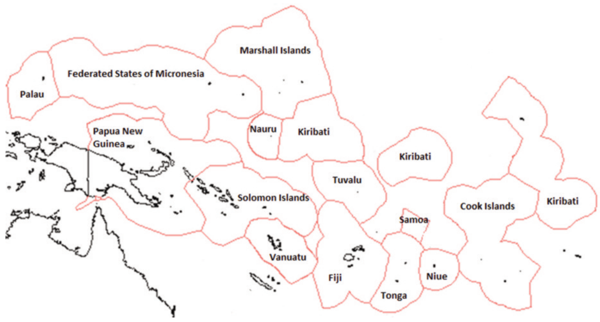


Figure 1. ROK-PI CliPS project beneficiary countries (total 14): Cook Islands, Federated States of Micronesia, Fiji, Kiribati, Marshall Islands, Nauru, Niue, Palau, Papua New Guinea, Samoa, Solomon Islands, Tonga, Tuvalu, and Vanuatu.

The Republic of Korea-Pacific Islands Climate Prediction Services project (ROK-PI CliPS) seeks to provide nationally-tailored seasonal climate prediction information and build the prediction capacity of the PICTs. This project is funded by the Government of Korea through the Pacific Island Forum Secretariat (PIFS) and is currently being implemented by the APEC Climate Center (APCC) and the Secretariat of the Pacific Regional Environment Program (SPREP).

The main objective of the project was to strengthen the adaptive capacity of vulnerable communities to climate risks at the seasonal timescale. The project aimed to build the adaptive capacity of vulnerable communities and users of climate information and services through the strengthening of the National Meteorological and Hydrological Service (NMHS) capacity to contribute to community resiliency and national development planning.

The ROK-PI CliPS project developed region-specific downscaling methodologies and established two climate services: (1) Climate Information ToolKit for the Pacific (CLIK®), and (2) Pacific Island Countries Advanced Seasonal Outlook (PICASO). The downscaling method takes into consideration the unique geographic features of the Pacific, utilizing APCC's multi-model ensemble prediction system. Through these two systems, the ROK-PI CliPS project is introducing downscaled dynamical multi-model ensemble prediction to the Pacific Island region.

This Application Guideline, along with the Country-Based Handbooks, serve to explain the methodologies used to develop CLIK® and PICASO in order to increase the capacity of the PICT NMHS's. APCC believes that rather than simply delivering prediction systems, it is important for the climate officers in respective NMHS's to understand how the predictions are generated utilizing various defined predictors for specific weather stations. This understanding will lead to generating higher quality national monthly climate outlooks as well as decreasing the reliance of these officers on external partners for climate expertise.

1.2 Statistical and Dynamical Prediction

Statistical prediction methods estimate the future climate state by utilizing the "empirical law" to transfer current information on the predictor to the future. "Empirical law" is the relationship between current climate conditions and the future climate conditions. As statistical prediction methods utilize observed (true) data, it is generally easier to build and understand. However, due to its dependence on historical observations, there are limitations to the statistical prediction methods: (1) a long historical record is required; (2) the skill can suffer under the changing climate; (3) and the nonlinear interaction between climate factors make it harder to generate reliable forecasts.

Dynamical prediction methods are based on the governing "physical laws" describing the climate system. "Physical laws" describe the dynamics of atmosphere and oceans and are expressed by mathematical equations. Advances in the field of dynamical prediction have led to its substantial improvement and ability to overcome many limitations of statistical prediction methods such as: (1) less dependency on historical data; (2) adaptability to a changing climate; (3) consideration of nonlinear interactions between climate factors. However, dynamical prediction still has its limitations including the development and utilization of dynamical prediction require huge resources, low spatial resolution, and the presence of systematic biases.

1.3 Neutralizing Model Biases

Climate models generally produce varying results that are not always in agreement, and the Multi-Model Ensemble (MME) technique that combines predictions from different models. MME is known to show better prediction skill by decreasing the uncertainties in initial conditions and considering the diversity in model formulation. APCC has been running its APCC MME since 2005 and is based on the collection from more than dozen of the climate model predictions around the world. Figure 2 is one example of the performance of APCC MME predictions in comparison to the individual predictions. Here, you can see that the black line (APCC MME) is more closely aligned to the red line (observations) than the gray dots (individual models), indicating the higher prediction skill of APCC MME.

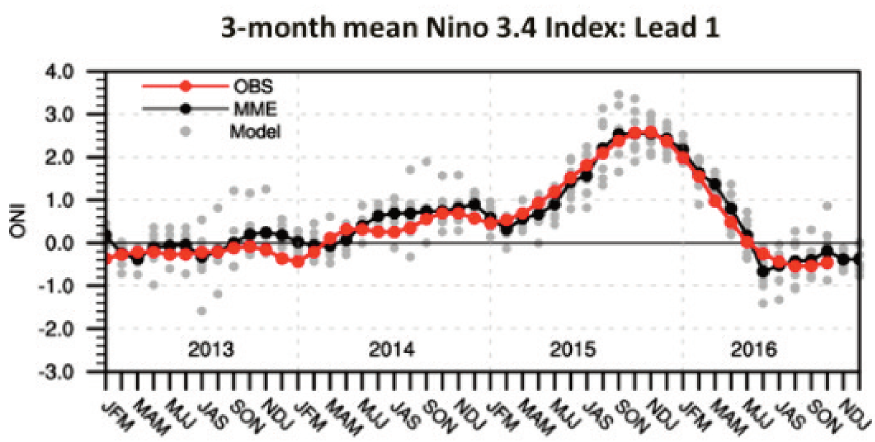


Figure 2. Observed (red) and Predicted (APCC MME: black, Individual Models: gray dots) ENSO index (3-month running mean Niño 3.4 Sea Surface Temperature Anomaly) from 2013 to 2016. The 1 month lead MME prediction of the ENSO index is closer to the observations than the individual models.

1.4 Tailoring the Dynamical Prediction

Dynamical seasonal prediction generally has low spatial resolution and therefore are not suitable for localized prediction, particularly in the Pacific Island region. Also, the dynamical climate models have systematic biases due to the limited knowledge of the climate system.

Figure 3 shows the variation between stations on the Samoan island of Upolu. Although the stations are close in distance, they can have different relationships with the large-scale prediction. However, these differences are not generally accounted for in low resolution dynamical seasonal prediction. Through the tailoring of climate prediction can address the aforementioned two issues by matching the scale and correcting the systematic errors. This can lead to more reliable predictions for each individual station.

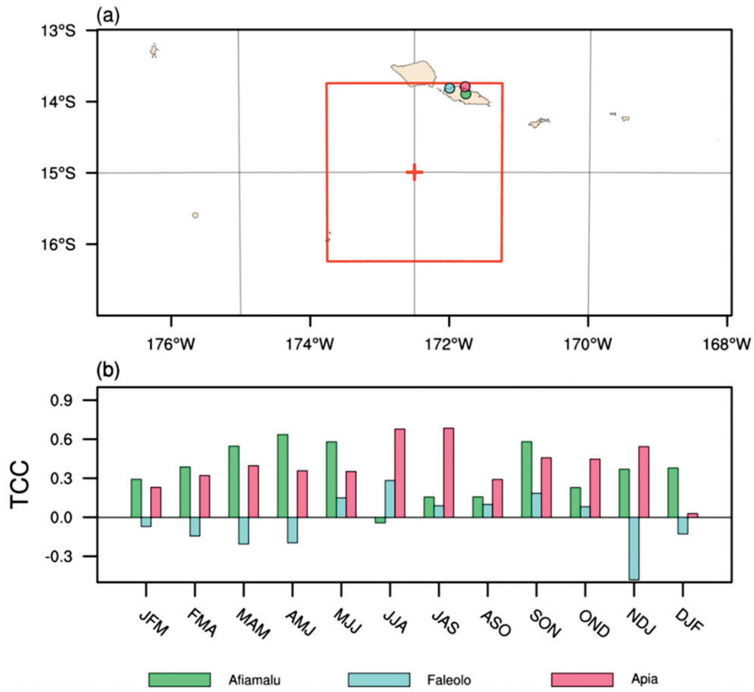


Figure 3. (a) The surrounding area (2.5° by 2.5° grid mesh) of Samoa and the locations of the three targeted stations, Afiamalu (marked as a closed circle in green), Faleolo (light blue), and Apia (pink). The representative value in the red rectangle (marked by a red cross) from model simulations is used as the common base for generating local climate predictions at the three different stations. (b) Temporal correlation coefficient (TCC) between observed and MME-simulated seasonal mean precipitation for the three stations.[1]

Therefore through the ROK-PI CliPS project, we have addressed the three main issues of providing dynamical predictions, neutralizing model biases, and tailoring the dynamical prediction. In CLIK®, we utilize the APCC MME to provide state-of-the-art dynamical multi-model ensemble prediction, and PICASO further tailors that information to account for the locality of the climate system in the Pacific region.

Sohn et. al, 2017 [1]

II CLIK℗

2.1 What is CLIK℗?

Climate Information ToolKit for the Pacific (CLIK℗) is a dynamical multi-model ensemble seasonal prediction tool and enables Pacific Islanders to easily and freely utilize the state-of-the-art General Climate Model (GCM) information from the APCC data server. CLIK℗ provides grid-based dynamical MME seasonal prediction information for the Pacific Island region; forecast values (deterministic anomaly value with a physical unit (mm/mon or degK) or tercile based probability (percent of each category); and the verification scores in each grid. The CLIK℗ products can be downloaded in both digital files and graphics, which can be directly inserted in seasonal outlooks. By merging information on future seasonal forecasts of individual climate models and their past performances, NMHS staff are able to generate their own seasonal forecast for their respective countries.

CLIK℗ is unique in that it provides the option of customizing the MME with different model combinations. It is well known that the performance of MME is higher than any single model on a global scale, and as the number of models increase, the overall skill generally increases. However, high skill is not guaranteed in specific regions or countries at all times. The best model combination for each country may not be combining all available models, but can vary in different regions and countries. MME customization enables forecasters to become familiar with the MME technique, to understand how forecasts vary with different model combination, and to eventually find the best model combination optimized to their region of interest.

CLIK℗ was designed to be highly accessible as a web-based tool (http://clikp.sprep.org/). Anyone who is interested in dynamical seasonal model data and wants to utilize them to generate their own prediction, can access CLIK℗ through the internet.

2.2 CLIK℗ Methodology

CLIK℗ provides the Pacific region with seasonal forecasts in two different ways: (1) deterministic forecast, and (2) probabilistic forecast. This section briefly introduces the techniques used to produce the two different forecasts.

● Deterministic Forecast in CLIK℗

The Deerministic MME (DMME) is based on the Simple Composite Method (SCM), which combines the selected model data by averaging individual model forecasts with equal weighting using Equation 1:

$$\mathbf{P} = \frac{1}{N}\sum_i F_i{}' \qquad \text{Eq.(1)}$$

where i indicates each model considered in MME and N is the total number of models.

As an example, let's assume there are three model forecasts: (1) model A with +100 mm/mon anomalous rainfall; (2) model B with -20 mm/mon anomalous rainfall; and (3) model C with +10 mm/mon anomalous rainfall. In this case, the DMME forecast should be +30 mm/mon according to Equation 2.

$$\frac{[(+100)+(-20)+(+10)]}{3} = \frac{(+90)}{3} = (+30) \qquad \text{Eq.(2)}$$

SCM is known to be the simplest but superior way to get deterministic forecasts. However, the variance of DMME is much smaller than the real world, even when utilizing state-of-the-art dynamical models. Therefore, it is dangerous to fully trust the DMME forecast value at each grid. For seasonal forecasts, DMME values are not often directly utilized for the seasonal outlook of small islands. Instead, the DMME output can serve as a reference to get a hint of the future large scale circulation pattern.

Table 1. Example of contingency table between forecasted and observed rainfall. The green colored cells indicate successful forecasts and the red colored cells indicate unsuccessful forecasts.

		Observed Rainfall		
		AN	NN	BN
Forecasted Rainfall	AN	7	1	3
	NN	3	10	3
	BN	6	8	6

CLIK® provides a success rate (SR) as the verification score for the DMME forecast due to its simplicity, understandability, and capability of estimating the forecast skill in a categorical sense. SR is the fraction or percentage of successful forecasts among a total number of attempts at each grid. In the case of Table 1, the SR is approximately 0.48 (successful forecasts = 22; total forecasts = 46). An SR of 0.48 is in the range of reasonable forecast skill.

● Probabilistic Forecast in CLIK®

For the probabilistic MME (PMME) forecast, CLIK® applies a parametric Gaussian fitting method for the estimation of tercile-based categorical probabilities. The tercile categorical forecast system divides rainfall conditions into three groups: below normal (BN); near normal (NN), and above normal (AN). The lower tercile (LT) and upper tercile (UT) boundaries, which divide the probability distribution into three categories, are set using the climatological Probability Density Function (PDF) (red dashed line in Figure 4). The tercile probability of a target year is estimated as a fractional area of the probabilistic distribution (e.g. black solid line in Figure 4): (1) AN = more than UT, (2) NN = between LT and UT, and (3) BN = less than LT.

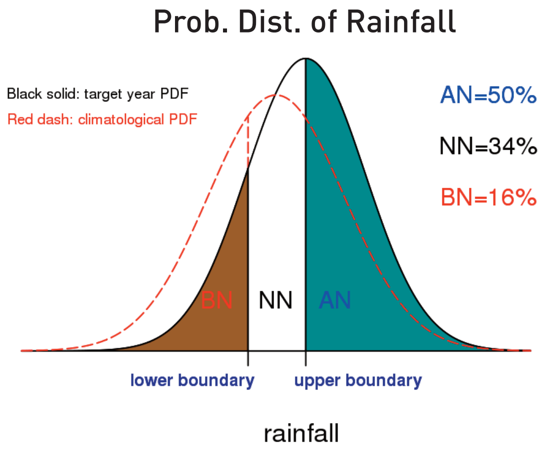


Figure 4. Diagram showing how to determine tercile probability. 50% above normal (AN), 34% near normal (NN), and 16% below normal (BN) probability is estimated.

For PMME, the tercile category probability is first estimated for individual models, and then the probability of all models are averaged for the three categories, which generates the final tercile probabilistic forecast.

CLIK® provides a Heidke Skill Score (HSS) as a verification score for the PMME forecast. Details on HSS can be found in Section 4.2.

2.3 CLIK® User Interface and Outputs

The main page of the CLIK® user interface is shown in Figure 5. Grid-scale MME prediction for Pacific region is available by selecting the target year/season, target variable, methodology (deterministic or probabilistic), and the models included in MME. What the user has to remember here is that MME forecasts can vary with different model combinations.

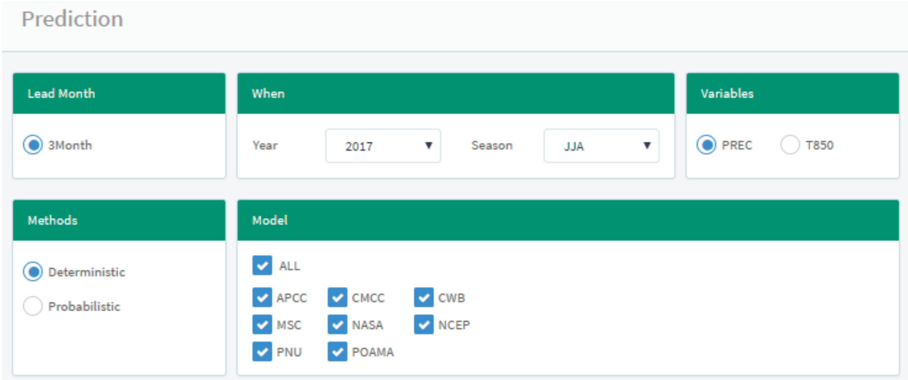


Figure 5. Screen capture of CLIK® user interface (UI) for dynamical MME seasonal prediction.

CLIK® provides the deterministic forecast output by displaying the anomalous pattern relative to the climatological pattern (how warmer/cooler or wetter/drier than normal) over the tropical Pacific region as shown in Figure 6(a). The user can move the center of map to center on his/her country of interest. CLIK® also provides the success rate (SR) by displaying color-filled contours with three degrees of skill (poor, reasonable, and high) as shown in Figure 6(b). The user can see the SR map by toggling the box on the top left. The user is able to directly download the digital data and graphic files of both the DMME prediction and verification.

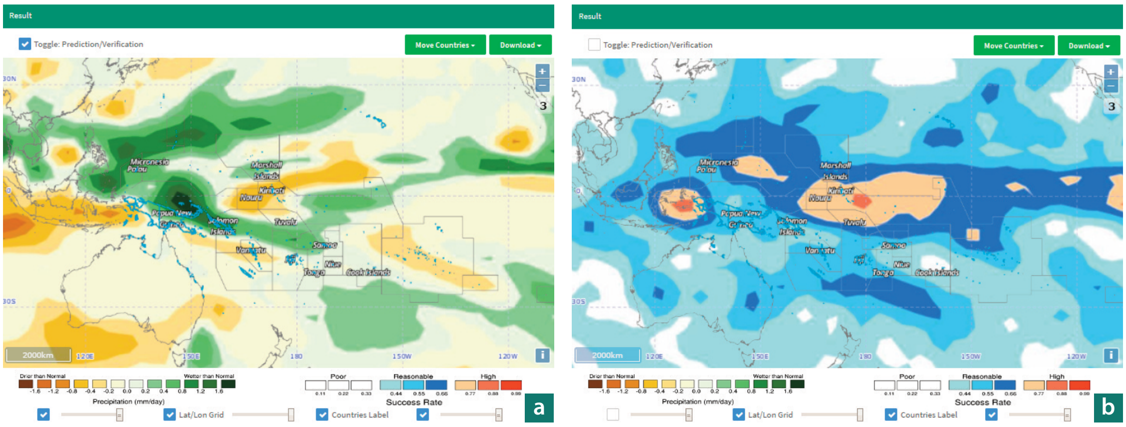


Figure 6. One example of deterministic MME (a) prediction and (b) success rate in CLIK®. This is for JJA 2017 rainfall DMME forecast with 8 models (APCC, CMCC, CWB, MSC, NASA, NCEP, PNU, and POAMA).

CLIK® provides the probabilistic forecast output by displaying the tercile category with the highest percentage probability with different color spectrums (yellow for BN, gray for NN, and green for AN) at each grid over the tropical Pacific area as shown in Figure 7(a). In the cases where some grids have similar tercile probabilities and it is difficult to select one representative category, no color (white) is displayed. CLIK® also provides a color filled grid map of HSS, where the darker red color represents higher skill, and white indicates no skill as shown in Figure 7(b). The user can see the HSS map by toggling the box on the top left. The user is able to directly download the digital data and graphic files of both the PMME prediction and verification.

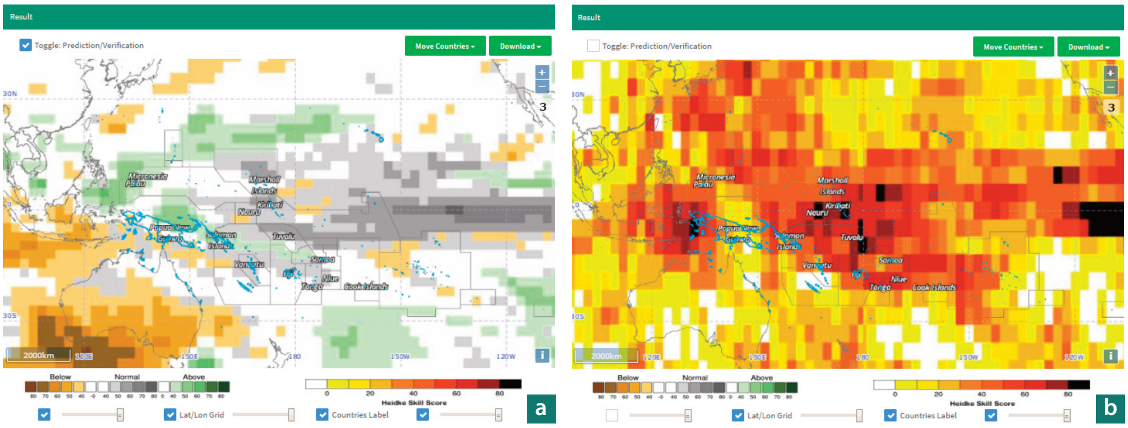
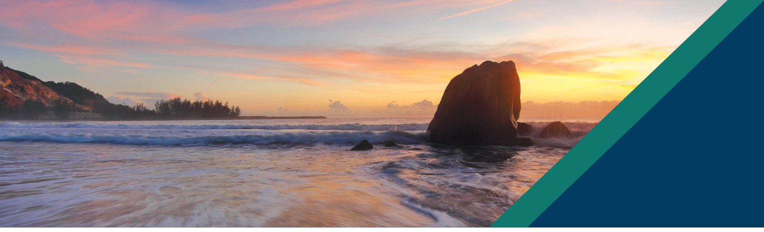


Figure 7. One example of probabilistic MME (a) prediction and (b) Heidke Skill Score (HSS) in CLIK®. This is for JJA 2017 rainfall PMME forecast with 8 models (APCC, CMCC, CWB, MSC, NASA, NCEP, PNU, and POAMA).



III PICASO

3.1 What is PICASO?

The Pacific Island Countries Advanced Seasonal Outlook (PICASO) is a PC-based seasonal prediction software tailored for the PICTs. PICASO produces tercile-based probabilistic statistically downscaled dynamical MME prediction of the seasonal mean rainfall at given weather stations by customizing the data from CLIK®. Through a series of capacity building activities, PICASO is able to be independently operated by PICT NMHSs together with SPREP, which houses and maintains the regional data and computation server for PICASO.

This hybrid dynamical-statistical prediction system offers better opportunities for reliable seasonal forecast, especially for regions where conventional statistical methods show poor prediction skill. The forecasts are based on the APCC MME prediction system and are tailored to each target station.

3.2 Methodology

● PICT Station Selection

In the first project year, precipitation data of 56 stations from 13 PICs were transferred from SPREP for the development of PICT optimized downscaling prediction system. Figure 8 displays the geographical location of those 56 station observation points. They are sparsely distributed over the expansive southwestern Pacific area. Sometimes the islands are sparely distributed even within one country. For example, Kiribati comprises of 33 coral atolls and islands spread along the equator. However, Samoa is opposite case in that its three stations are very close together since all three are located on one small island.

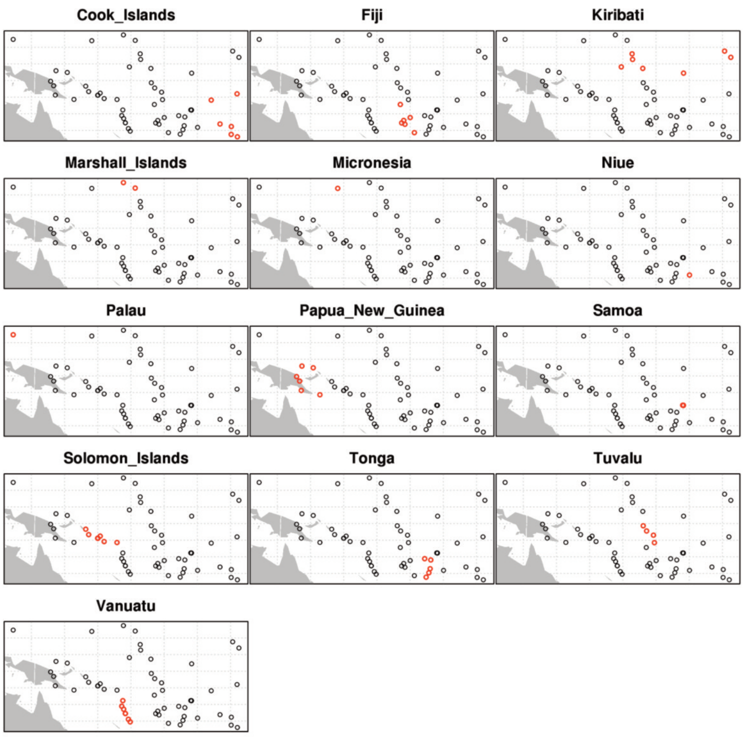


Figure 8. Geographical location of observing stations considered in this project. Red circles denote the stations of each country out of 13 Pacific Island Countries.

However, out of the 56 stations above, some have missing data. As PICASO utilizes the past relationship between local precipitation and large scale circulation pattern for the downscaled rainfall forecast, if there are many monthly precipitation data missing, it is hard to determine statistically reliable relationships.

Figure 9 displays the fraction of data missing out of total time steps (months) during the period of 1983 to 2005 (although some stations have long spells of observation data of about 100 years, PICASO uses the observation data from 1983 to 2005 to match the APCC MME data). PICASO set the station selection criterion to be less than 20% of missing data to be included, which translates to approximately 55 months of missing data according to Equation 3.

$$\mathbf{20\% \times 23\ \mathit{years} \times 12\ \frac{\mathit{months}}{\mathit{years}} = 55.2\ \mathit{months}} \qquad \text{Eq.(3)}$$

A total of seven stations (four from Cook Islands and three from Kiribati) were excluded from the development of the statistical downscaling model in accordance with the above 20% criterion. Therefore, 49 stations were selected to be the target stations for downscaled prediction in PICASO (Table 2).

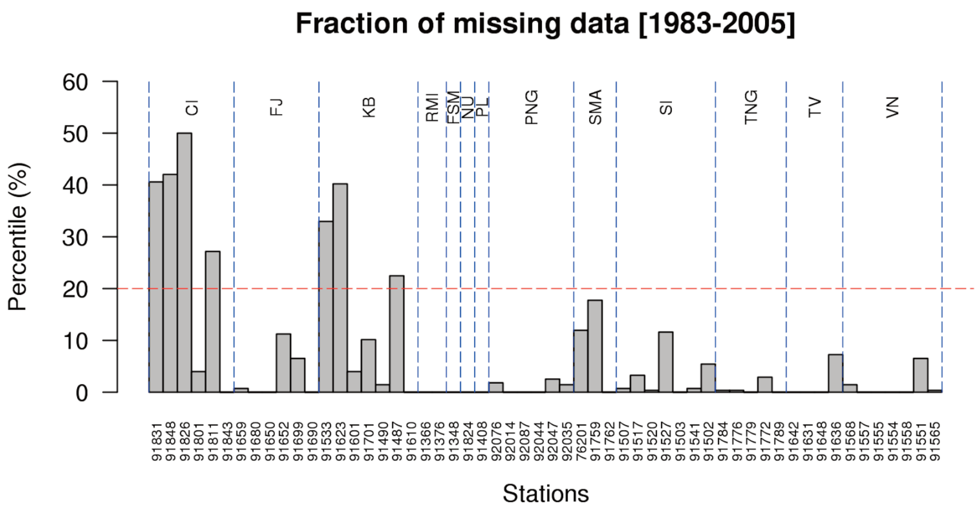


Figure 9. Fraction (%) of missing data out of total time steps during the period of 1983 to 2005. Four stations in the Cook Islands and three stations in Kiribati have more than approximately 20% missing data.

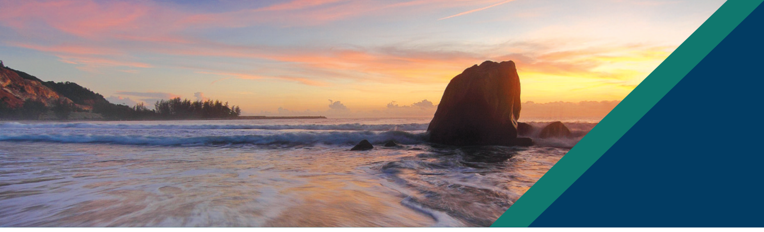


Table 2. Final 49 selected stations as seasonal prediction target points in PICASO system.

Country	Station	Country	Station
Cook Islands	Penrhyn	Solomon Islands	Auki
	Penrhyn		Honiara
Fiji	Nabouwalu		Honiara Henderson
	Nadi Airport		Kira Kira
	Rotuma		Munda
	Udu Point		Santa Cruz
	Ono I Lau		Taro Island
	Suva	Tonga	Haapai
Kiribati	Butaritari		Keppel Mata'aho Airport
	Kanton		Lupepau'u
	Kiritimati		Niuafoou
	Tarawa		Nuku'alofa
Marshall Islands	Kwajalein Bucholz Aaf	Tuvalu	Funafuti
	Majuro		Nanumea
F.S. Micronesia	Pohnpei		Niulakita
Niue	Hanan Airport		Nui
Palau	Koror	Vanuatu	Aneityum
Papua New Guinea	Kavieng		Bauerfield (Efate)
	Madang		Lamap (Malekula)
	Misima		Pekoa Airport (Santo)
	Momote		Port Vila
	Nadzab		Sola (Vanua Lava)
	Port Moresby		White Grass Airport
Samoa	Afiamalu		
	Faleolo		
	Apia		

● Identification of Potential Predictors

When the monthly rainfall data (mm/month) at the 49 selected stations were checked for seasonality, almost all of the station data presented good seasonal variability compared with the Climate Anomaly Monitoring System and Outgoing Longwave Radiation (OLR) Precipitation Index (CAMS_OPI) reanalysis data.[2] Figure 10 shows the correlation between observed station data and CAMS_OPI. Most stations are well matched for all seasons, however some station data signals are opposite from its adjacent station due to differences in geographical features.

For example, the Afiamalu station is around 10 km in distance to the Apia station in Samoa, but is located in high altitude area. Due to the geographical differences between the stations despite the small distance between them, the observation data signals at these stations are opposite from each other. The current GCM, with its coarse resolution, cannot represent these stations' locality. However, with tailoring of global model predictions, it is possible to reflect each station's locality and geographical features into its climate predictions.

Janowiak and Xie, 1999 [2]

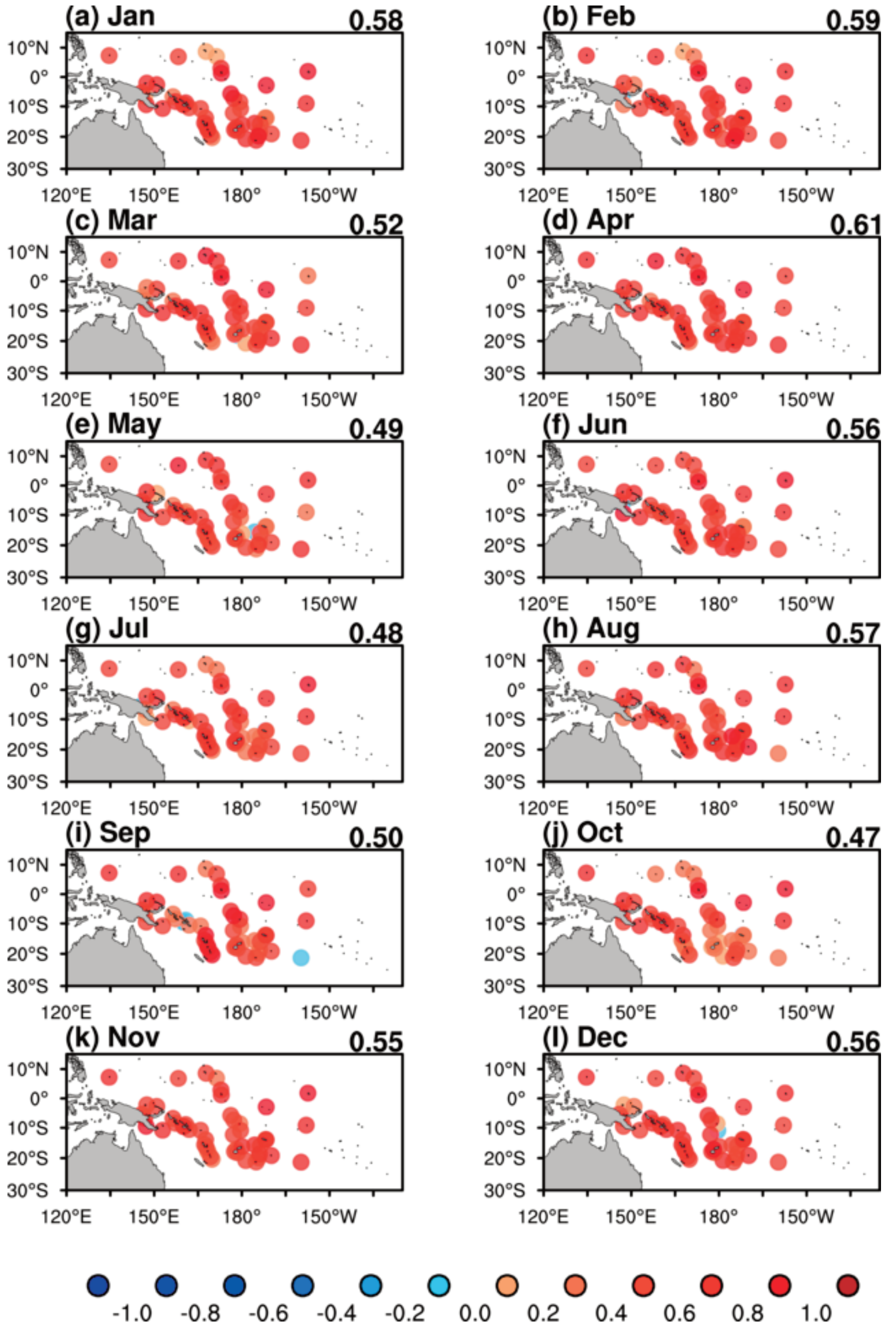


Figure 10. Correlation map between observed station data and reanalysis (CAMS_OPI) data. The number on the right upper side of each map shows the average of each station's correlation.

The tropical climate is relatively well simulated and predicted by dynamical models compared to the mid-latitude climate. However, as mentioned in the example between Afiamalu and Apia stations, stations in the PICTs are affected by small-scale processes and local topography, which cannot be resolved in GCM. Therefore, in order to address this issue, the meaningful signals for each station were manually identified.

As elaborated in the Country-Based Handbooks, predictors for each station were identified by APCC scientists in partnership with NMHS staff by considering the observed relationship between the large-scale climate variables and the target station rainfall data, as well as the dynamic model MME representation of the relationship.

● Bayesian Inference

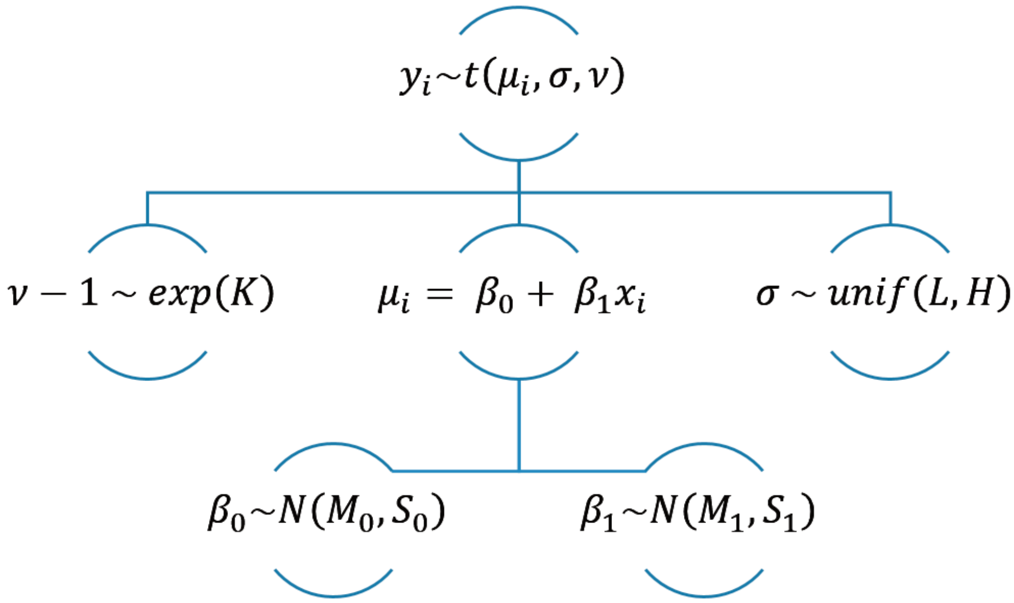
Bayes' rule can be simply stated as in Equation 4.

$$\boldsymbol{p}(\boldsymbol{\theta}|\boldsymbol{D}) = \frac{\boldsymbol{p}(\boldsymbol{D}|\boldsymbol{\theta})\,\boldsymbol{p}(\boldsymbol{\theta})}{\boldsymbol{p}(\boldsymbol{D})} \qquad \text{Eq.(4)}$$

Where $p(\theta|D)$ is the posterior credibility of θ values with the given data D, and $p(\theta)$ is the prior credibility of θ values without the data D. We update the prior credibility with the hindcast relationships (D) between the observed station measurement and the dynamic MME generated predictors, by multiplying the likelihood $(p(D|\theta))$, the probability that the data could be generated by the model with parameter value θ and scale with the evidence $p(D)$, the overall probability of the data). The evidence, $p(D)$, can be estimated by integrating the marginal likelihood as follows in Equation 5.

$$\boldsymbol{p}(\boldsymbol{D}) = \int \boldsymbol{d\theta^{*}}\, \boldsymbol{p}(\boldsymbol{D}|\boldsymbol{\theta^{*}})\boldsymbol{p}(\boldsymbol{\theta^{*}}) \qquad \text{Eq.(5)}$$

PICASO uses the Bayesian Markov-Chain Monte Carlo algorithm to numerically estimate posterior distribution of parameters, $p(\beta_0, \beta_1, \sigma, \nu|D)$ of the following diagram, and the final forecast is of the form $y_i \sim t(\mu_i, \sigma, \nu)$ where $\mu_i = \beta_0 + \beta_1 x_i$.



3.3 PICASO User Interface and Outputs

● PICASO Logo

The PICASO logo symbolizes the spirit of the Pacific Islands: a great journey to Mother Nature (cascading blue colors) on a sailing boat (triangular foreground), exploring the vast ocean full of waves (curly lines), while the sun (surrounding circle) protects their safe journey (Figure 11). There is also a semblance of a raindrop (a droplet shape), indicating that PICASO generates seasonal prediction for precipitation.

Figure 11. PICASO Logo.

● PICASO User Interface

PICASO is a beautifully designed, easy-to-use, stand-alone PC program that intuitively interacts with users. The tabs in PICASO (Figure 12), together, provide all of the information needed to generate a seasonal forecast as well as the underlying processes. The Outlook tab summarizes the essential information for generating a seasonal outlook, and the Details tab provides comprehensive information including interactive probability distributions and validation scores. The Climate Outlook for Pacific Island Countries (CO-PICs) tab shows the ENSO/Sea Surface Temperature (SST) outlook, temperature/precipitation forecast up to 6 months, and the verification skills of the APCC MME dynamical seasonal prediction. The Guide tab helps users understand the tailored rainfall forecast within a large-scale climate context. Users can easily manage their observation data in the Data tab, by directly importing, exporting, or editing the existing data. All figures and pages in PICASO can be exported as an image (PNG), so that they can be easily incorporated into the official seasonal outlook.

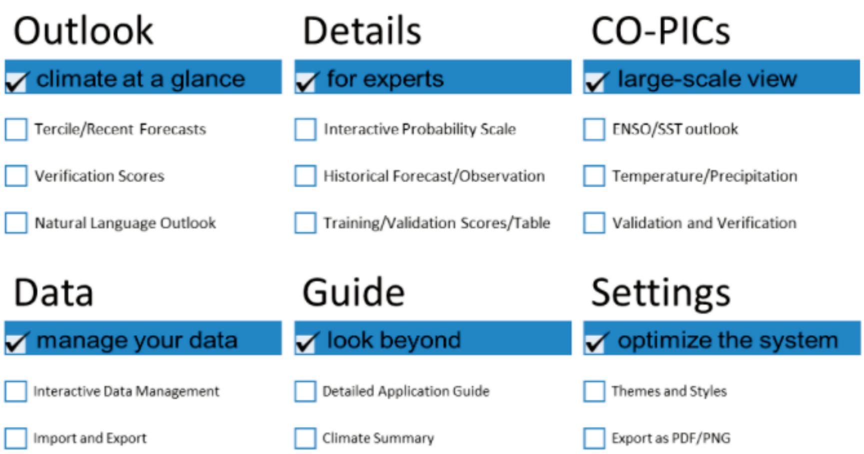


Figure 12. PICASO Menu Structure.

The Outlook tab (Figure 13) summarizes the essential information for generating a seasonal outlook in a well-organized manner. The main map is an interactive vector graphic that allows users to freely zoom in and out without losing resolution. The tercile-based probability forecasts (Figure 14(a)) are superimposed onto the map so that users can easily grasp the national precipitation tendency of their country at a glance. The bottom panel provides essential information in additional formats, i.e., the past 12-season forecasts/observations with interactive information and tercile probability bar charts (Figure 14(b)), so that users can choose from various output formats. The verification score is also provided in a simplified format to guide forecasters on the current reliability of PICASO. The "Recent Forecasts" graphic provides the past 12-season forecasts and observations with various information packed into each bar as shown in Figure 15.

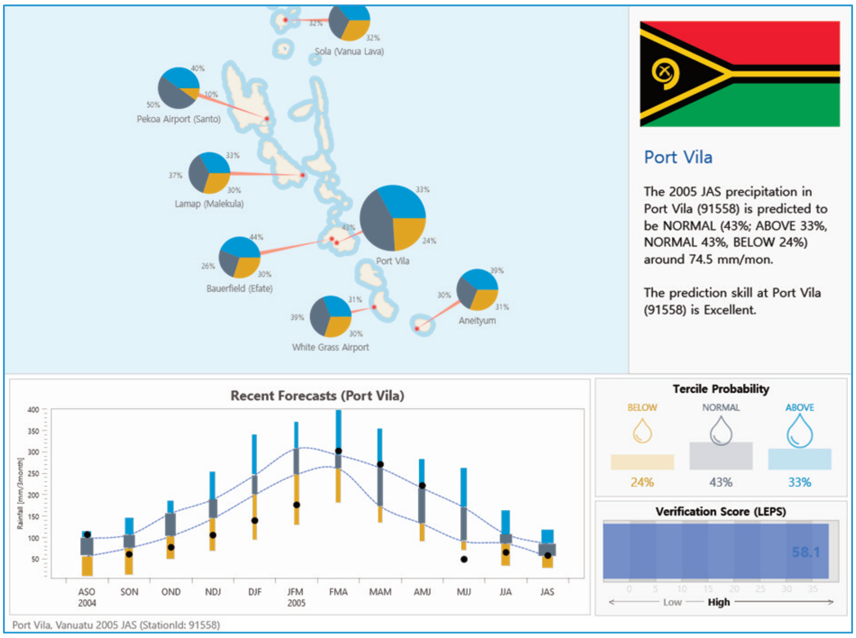


Figure 13. PICASO Outlook tab. The main vector map of geographical locations of stations is superimposed onto the tercile probability (pie charts) of the given prediction. The detailed information is given on the right panel. The past 12-month forecasts and observations and the verification scores are given at the bottom.

Forecasts can be continuous, categorical, or probabilistic. Continuous forecasts are based on temperature, rainfall amount, and geopotential height of 500 hPa. Categorical forecasts can be dichotomous or multi-category, and these can be defined by fixing a range of the continuous variables into separate categories. Probabilistic forecasts can be a continuous distribution, or can be single probability value for dichotomous events or multiple probabilities with respect to discrete probability distribution for multiple categories (based on an ensemble of multiple iterations).

Tercile-based categorical probabilistic forecast is based on the probability of the below normal, near normal, and above normal categories, with respect to climatology. To construct discrete probability distribution for three categories, the lower and upper terciles can be generally estimated with equal probability distribution through the non-parametric historical ranking method[3] or the parametric approximation[4]. Unlike the deterministic categorical forecast, probabilistic forecasts are designed to quantitatively convey the level of uncertainty.

When users want to foresee the variability or deviation of precipitation in mm, for example, with respect to climatology, the deterministic forecast can be provided (i.e. anomaly map). The categorical deterministic forecast places the amplitude of deviation into one of the categories: below normal, near normal, and above normal. However, categorical probabilistic forecasts better account for the relative probabilities and uncertainties related to multi-categorical forecasts. Due to this, probabilistic forecasts are of potentially greater value to decision makers and stakeholders than deterministic forecasts.

This is why PICASO utilizes the widely accepted tercile-based categorical probabilistic forecast (Figure 14) in order to generate forecasts that not only best account for relative probabilities and uncertainties, but are also widely accepted and utilized by decision makers.

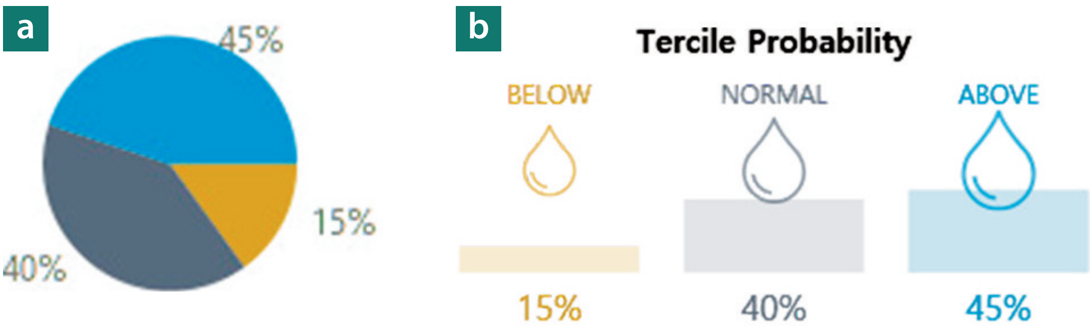


Figure 14. Tercile Probability in (a) pie graph format and (b) bar format.

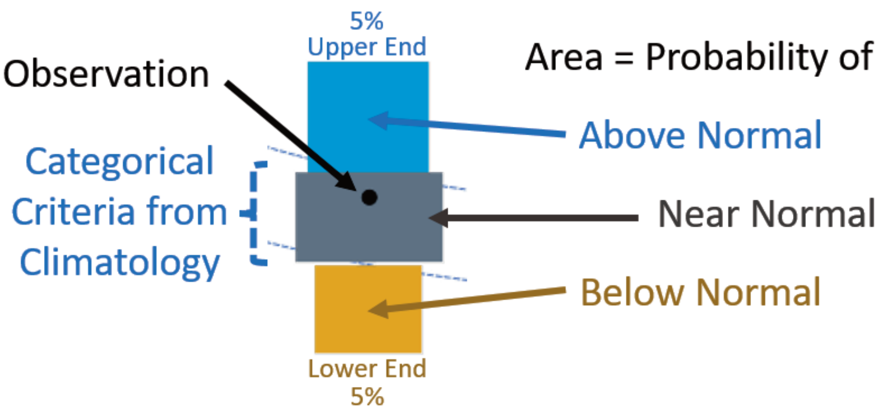


Figure 15. The many elements depicted by each bar in the recent forecast graph.

Sohn et al. 2012 [3]
Min et al. 2009 [4]

The Details tab (Figure 16) contains in-depth supplementary information that experienced forecasters may find helpful, but also provides the natural language forecast so that less experienced forecasters can easily understand the essential contents. The historical time series of observed precipitation (lines) and PICASO forecast (error bars) allow users to intuitively understand the prediction skill of PICASO for a given season and station. The verification scores, HSS and LEPS, are provided for each season and for the total period, with a detailed correctness table.

The interactive probability distribution at the top right is one of the unique features of PICASO. Users can set an arbitrary threshold value to see the probability of above/below rainfall at the given threshold value. This feature should be helpful for application sectors where a specific criterion is required.

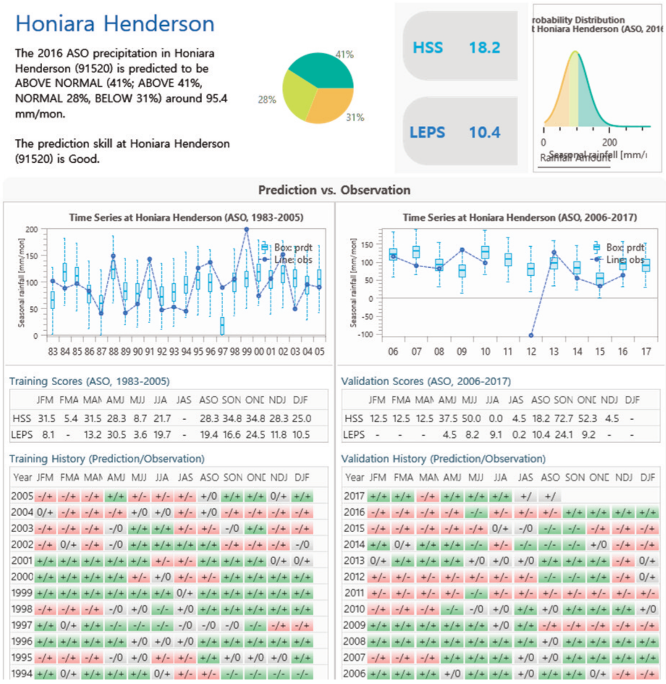


Figure 16. PICASO Details tab.

The CO-PICs tab (Figure 17) shows the global and Pacific Islands-specific climate outlook issued by APCC. The CO-PICs provides 3 and 6-month outlooks for SST and ENSO, as well as probabilistic MME seasonal temperature and precipitation prediction around the PICTs. It also provides the verification skills of the APCC's global seasonal outlook and the natural language description of the climate forecast.

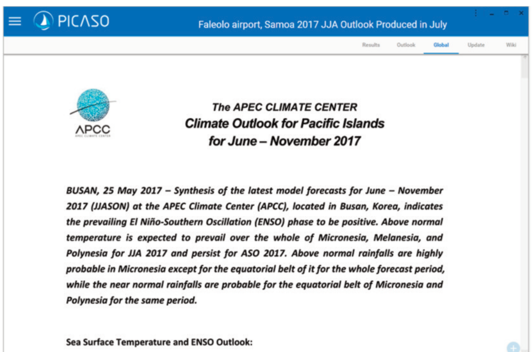


Figure 17. PICASO CO-PICs tab.

The Data tab (Figure 18) is an interface where users can store and modify the observed monthly rainfall measurements. We designed this interface to be compatible with existing data formats, by allowing the CSV format for the import and export functions. As observation data are the properties of individual countries, they are kept private inside PICASO, and can only be transferred manually using the import/export function.

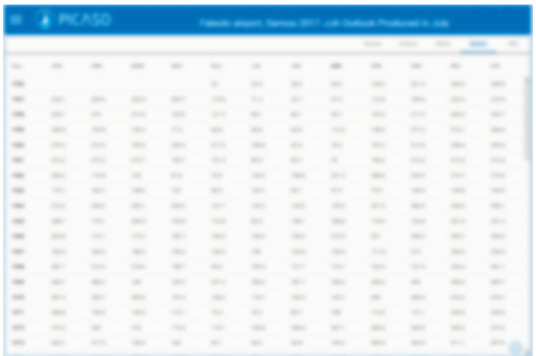


Figure 18. PICASO Data tab.

The Guide tab (Figure 19) provides detailed information of the station-based rainfall variability in relevance to the large-scale climate phenomena observed in the reanalysis and simulated by dynamical MME. It briefly explains the dominant climate factors for the given site at the given season, and links them onto the dynamical MME seasonal prediction. Users can utilize this information to interpret the large-scale climate prediction of the CO-PICs to relate tailored station-based forecast. This information has also been provided in a physical format through the Country-Based Handbooks.

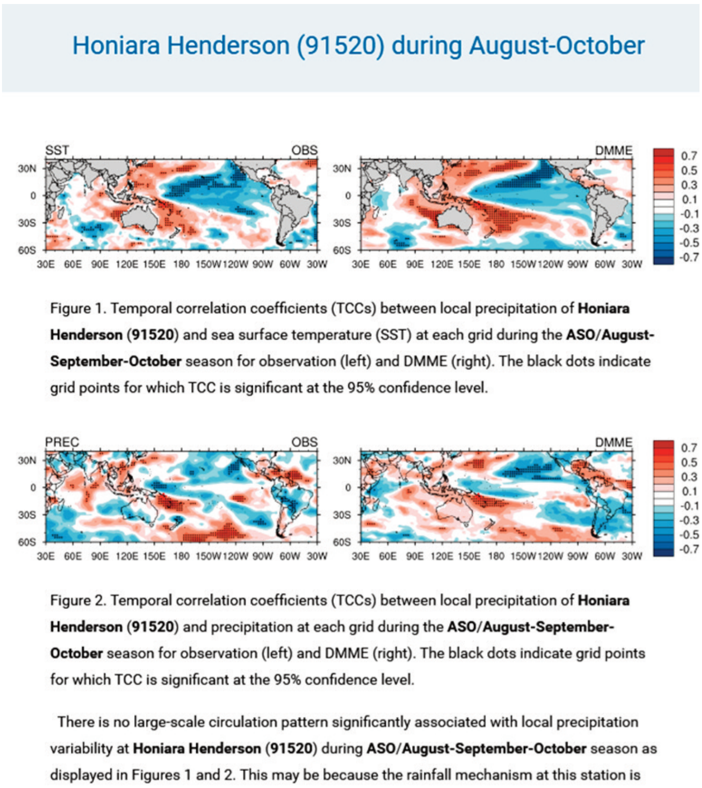
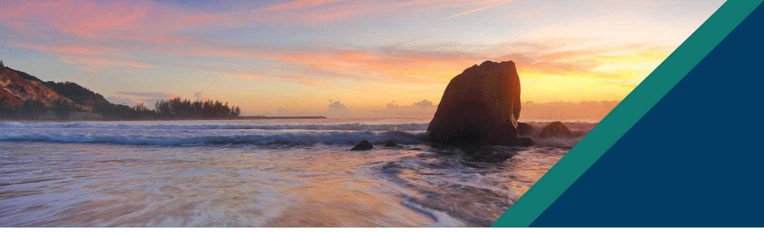


Figure 19. PICASO Guide tab.



IV Interpretation and Verification of CLIK℗ and PICASO

4.1 Application in Local Rainfall Prediction

The dynamical models used in CLIK℗ were originally invented and used for large circulation and the resolution is too coarse to resolve the station-scale climate variability. In particular, rainfall itself is the climate variable with very large locality. Therefore, CLIK℗ is more useful when predicting large-scale climate patterns (e.g. ENSO- or ITCZ-related precipitation zone, monsoon-related rainfall band, etc.) rather than station-scale climate variability. For example, the leading mode of local rainfall in PICTs is associated with El Niño-like patterns for the AMJ season (Figure 20). The stations can be grouped based on the direction and magnitude of association. The rainfall at the northwestern and southwestern Pacific stations are negatively related with the ENSO-signal, while the central Pacific stations are positively related with ENSO. As the APCC MME captures these relationships, CLIK℗ can be used to predict large-scale precipitation.

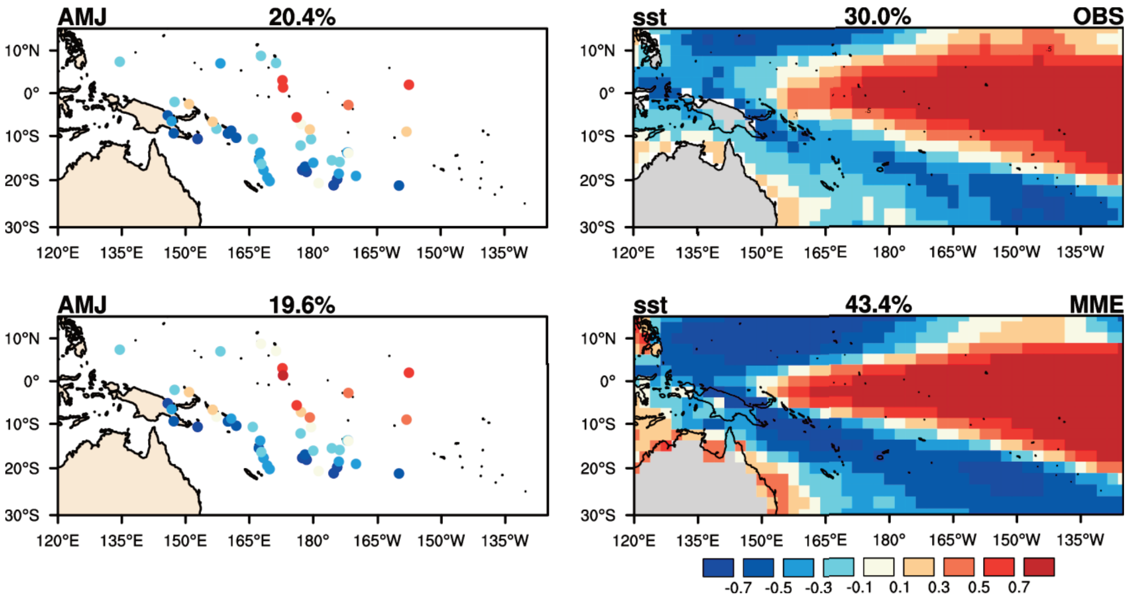


Figure 20. 1st CCA mode between local precipitations in Pacific island countries and the SST changes in the tropical Pacific from (top) observations and (bottom) MME for AMJ seasons. The one dot (left columns) indicates each station (total 64 stations). The magnitude of relation between local rainfall and SST can be shaded and found at the bottom right (as scale bar). The fractional variance of CCA is found at top center of each panel.

On the other hand, PICASO is recommended to be used to predict tailored local rainfall at the station-scale. Unlike purely statistical models, PICASO uses the dynamical-model-simulated large circulation pattern as a predictor, taking into consideration the nonlinearity, which is unexplainable in statistical models. In addition, it is expected that the prediction skill is generally improved in PICASO compared to CLIK℗ as PICASO undergoes post-processing and tailors the prediction results for the local climate by making full use of the reliable dynamical modelpredicted information.

4.2 Verification Scores

The PICASO system is providing two verification scores: HSS (Heidke Skill Score) and LEPS (Linear Error in Probability Space), to assist NMHS forecasters to understand the general skill/limitation of the PICASO system and to estimate the skill of PICASO's past forecasts. HSS is one of the most commonly and conventionally used verification scores for the categorical probabilistic forecast. LEPS is the most familiar verification score that has been used for approx. last 10 years in the PICT NMHS's. In both HSS and LEPS, a higher score represents a better prediction. The results of the two verifications are generally consistent but there can sometimes be differences HSS is more focused on the verification of "category" correction while LEPS is more focused on both "category" and "probability" in verifying the forecasts.

Heidke Skill Score

HSS is a metric designed to measure the fractional improvement of the forecast over the standard forecast. Here, the standard forecast represents the correct category forecast that would be expected by chance without any forecasting skill. Equation 6 shows the general HSS formula.

$$\mathbf{HSS} = \frac{SCORE_{forecast} - SCORE_{by\ chance}}{SCORE_{perfect\ forecst} - SCORE_{by\ chance}} \times \mathbf{100} \qquad \text{Eq.(6)}$$

In the actual calculation, however, the summation of points of individual attempts (forecasts) becomes the total HSS with no explicit calculation of each score term in the formula. The calculation of HSS begins with the comparison between the forecasted tercile category and observed tercile category. A point is only given for correct category forecast (green cells in Table 1). Among the correct category forecast cases, different points are given based on the probability spread. The improvement of the forecast over the standard (random) forecast is estimated by separating the unclear category forecasts from the distinct ones, and giving different points: 1 point for single category distinct forecast cases (e.g. 55% AN, 25% NN, and 20% BN), 0.33 points for equal chance (random) forecast cases (e.g. 33% AN, 33% NN, and 33% BN) and 0.5 points for ambiguous forecasts between two out of three categories (e.g. 45% AN, 45% NN, and 10% BN). A HSS score of 100 indicates a perfect forecast, and a score of -50 indicates a perfectly incorrect forecast. A score greater than 0 indicates that the forecast is better than a random forecast (climatological forecast).

Linear Error in Probability Space

LEPS is a simple and intuitive way to verify the probabilistic forecast and is estimated using the distance between the position of the forecast and the corresponding observation in their respective cumulative probability distributions. PICASO adopted the revised LEPS score[5] shown in Equation 7.

$$\boldsymbol{S}" = \left[\mathbf{3}\left(\mathbf{1} - \left|\boldsymbol{P_f} - \boldsymbol{P_v}\right| + \boldsymbol{P_f^2} - \boldsymbol{P_f} + \boldsymbol{P_v^2} - \boldsymbol{P_v}\right) - \mathbf{1}\right] \times \mathbf{100} \qquad \text{Eq.(7)}$$

In Equation 7, P_f is the cumulative distribution function of the forecast and P_v is the cumulative distribution function of the observation. The equation looks complicated, but it roughly shows that the error (the difference between the forecast and observation) in the probability space becomes smaller when the P_v line is close to the P_f line. The LEPS score ranges from -100 to 100, and a positive higher score represents better prediction.

Potts et al. 1996 [5]

4.3 Prediction Performance and Skill

PICASO results are given as tercile-based probabilistic forecasts for each station in each season. For the training period (1983 – 2005), the prediction skill was assessed using the Jack-Knife (leave-one-out) verification technique. The distribution of the forecasted values in probability space, reliability, and categorical verification was also conducted to ensure the accuracy and stability of the results. With the absence of real-time data, the results were further compared and verified using public precipitation estimates (e.g., GPCC, CMAP) during the verification period. In general, PICASO shows reasonably stable forecasts (Figure 21) for most of the seasons.

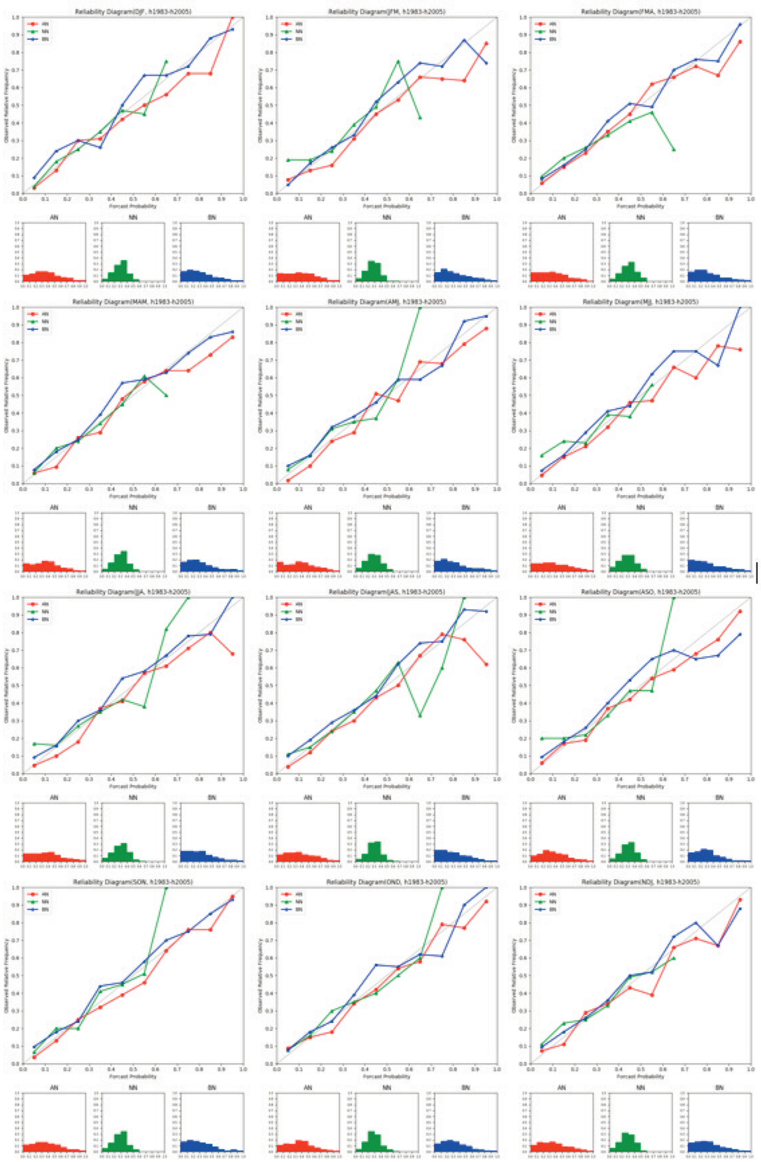
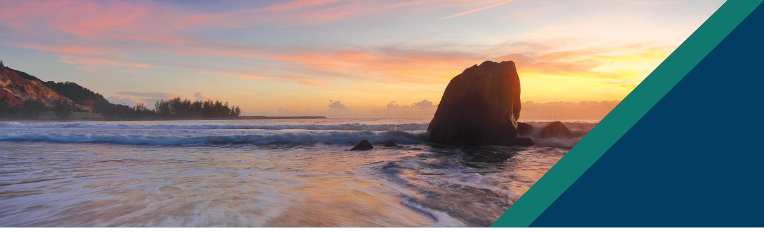


Figure 21. Reliability diagram (hindcast, collective).



V Conclusion

This Application Guideline was written in conjunction with the 13 separate Country-Based Handbooks to explain the methodologies used to develop CLIK® and PICASO, provide key information to help NMHS officers in interpreting CLIK® and PICASO outputs, and to summarize the technical aspects of the ROK-PI CliPS project.

The Climate Information ToolKit for the Pacific (CLIK®) is a dynamical multi-model ensemble seasonal prediction tool and enables Pacific Islanders to easily and freely utilize the state-ofthe-art General Climate Model (GCM) information from the APCC data server. CLIK® is unique in that it provides the option of customizing the MME with different model combinations. CLIK® was designed to be highly accessible as a web-based tool (http://clikp.sprep.org/).

The Pacific Island Countries Advanced Seasonal Outlook (PICASO) is a PC-based seasonal prediction software tailored for the PICTs. PICASO produces tercile-based probabilistic statistically downscaled dynamical MME prediction of the seasonal mean rainfall at given weather stations by customizing the data from CLIK®. This hybrid dynamical-statistical prediction system offers better opportunities for reliable seasonal forecast, especially for regions where conventional statistical methods show poor prediction skill. The forecasts are based on the APCC MME prediction system and are tailored to each target station.

APCC and SPREP are proud to have introduced downscaled dynamical MME prediction to the Pacific Island region through CLIK® and PICASO, and hope that these systems will increase the accuracy and reliability of seasonal forecasts in PICTs by become streamlined into the everyday operations of NMHS's in the Pacific.

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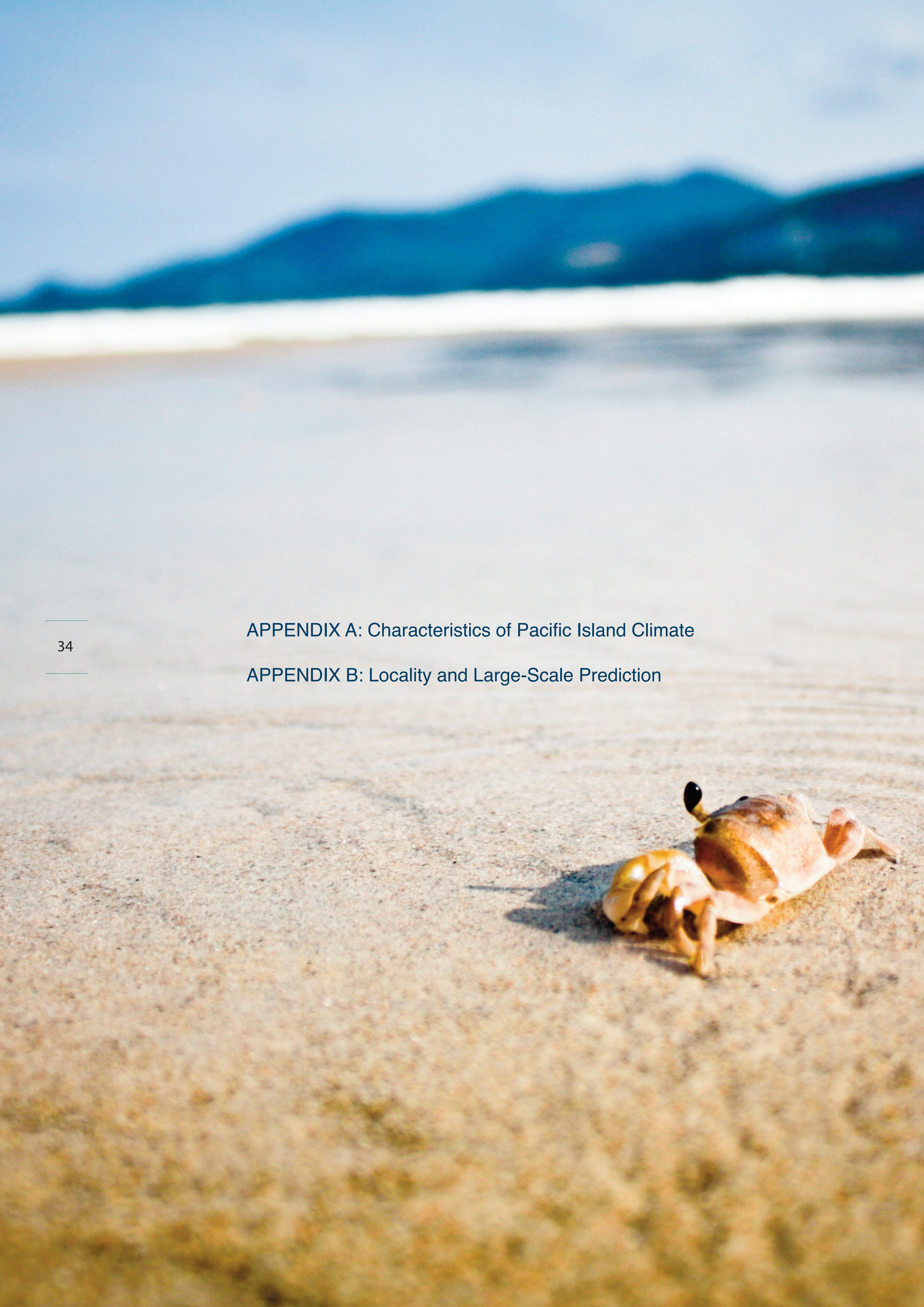


APPENDIX A: Characteristics of Pacific Island Climate

APPENDIX B: Locality and Large-Scale Prediction

A APPENDIX A: Characteristics of Pacific Island Climate

A.1 Seasonal Climatology of Temperature and Rainfall

The Pacific Islands experience diverse climatic conditions, due to latitudinal and longitudinal variations of climate in the tropical Pacific.

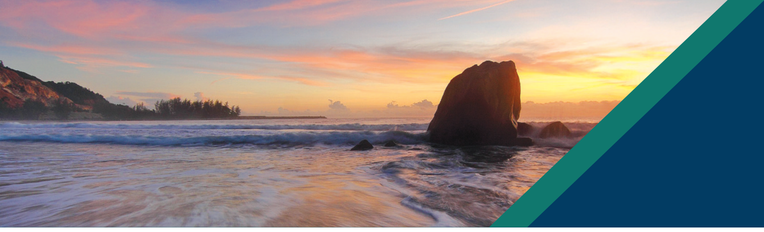
Islands in the equatorial region maintain similar temperatures throughout the year and those in the South Pacific region experience clear annual variation cycles. For example, Tonga, Niue, and Cook Islands experience this marked annual cycle by virtue of their location at the southern edge of the Pacific warm pool. Although Solomon and Vanuatu are close to the equatorial belt, SST achieves a minima of 26.5°C around August, and a maxima of about 29°C around February. The relative cool SST around August is a result of advection of cool waters by the westward flowing North Vanuatu Jet, which is part of the South Equatorial Current.

On the other extreme, a clear annual cycle is absent over Palau, where SST is warm throughout the year, ranging between 27.8°C and 29.2°C. A strong semi-annual cycle with peaks in May/June and October/November is apparent over Palau. Although Kiribati is the island closest to the equator (1.8°N), SST is mild throughout the year, ranging between 26.5°C and 27.8°C. This rather salubrious state of climate is due to its location at the western edge of the Pacific cold tongue. The influence of the cold tongue on Kiribati's pleasant climate is in sharp contrast to Tuvalu, which lies more than 700 km south of the equator, compared to Kiribati which is only about 200 km away from the equator. Tuvalu, despite its greater distance from the equator, experiences temperatures of around 29.8°C throughout the year, as it is embedded in the middle of the west Pacific warm pool.

To some extent, rainfall over the islands and their annual cycle is a reflection of the annual cycle in SST. Thus, the largest rainfall occurs over warmer SSTs of Palau, while the lowest rainfall is over Kiribati. However the seasonal variations of SST and rainfall appear to have different patterns. While over Palau, a distinct annual cycle cannot be discerned in SST, a clear annual peak in rainfall is seen during June. Similarly for Tuvalu, the largest rainfall occurs in December and January, corresponding to the strengthening of the South Pacific Convergence Zone (SPCZ). Kiribati experiences a peak in rainfall during March/April coinciding with the annual relaxation of trade winds and the weakening of the cold tongue during this period that draws the Intertropical Convergence Zone (ITCZ) closer to the equator.

Interannual variation of SST is moderate over most of the PICTs, with most locations experiencing a standard deviation of around 0.8°C or below. This may be related to their location within the west Pacific warm pool. On the other hand, Kiribati stands out for its strong interannual SST variations, owing to its location at the eastern edge of the warm pool which experiences strong SST anomalies during ENSO events. The timing of the increase of SST standard deviation towards the northern winter season also is consistent with the influence of ENSO. Rainfall anomalies also show a similar spike during the northern winter, likely reflecting ENSO's influence over Kiribati. However, the strongest amplitude of rainfall standard deviation is found over Cook Islands and Tuvalu from December to February, coinciding with the peak phase of ENSO. With the exception of Palau and Solomon Islands, the remainder of the islands have maximum amplitude of rainfall standard deviation during the northern winter season. Palau experiences two maxima in rainfall variability - one in February and the other in northern summer, while over Solomon Islands, a clear increase of rainfall standard deviation is observed during June/July.

It is clear that ENSO is the dominant interannual factor in the rainfall variations of the PICTs. Strong negative correlations are observed from September to October over Palau, Cook Islands, Niue, Solomon Islands, Tonga, and Vanuatu. These reflect a reduction of rainfall during El Niño events, as the convections move eastward and equatorwards during the peak El Niño phase. On the other hand, Kiribati and Tuvalu experience



an increase of rainfall towards El Niño's peak phase. Surprisingly the strong variations during northern summer over Palau and Solomon have close to zero correlation with ENSO, suggesting that the rainfall variations during this season may be affected by other factors.

A.2 El Niño Southern Oscillation

El Niño is characterized by unusually warm ocean temperatures in the equatorial central and eastern Pacific, as opposed to La Niña, which is characterized by unusually cold ocean temperatures in the equatorial central and eastern Pacific. El Niño is an oscillation of the ocean-atmosphere system in the tropical Pacific. The time scale of El Niño is about 4 years, but its periodicity varies largely for 2-8 years. Though El Niño is a tropical phenomenon, it causes tremendous global changes in weather and climate systems.

During El Niño, the trade winds relax in the central and western Pacific, leading to a flattening of the thermocline due to deepening of the thermocline in the eastern Pacific, and shallowing of the thermocline in the west. The deepened thermocline in the eastern Pacific reduces the efficiency of upwelling to cool the surface, leading to sea surface warming. In addition, it cuts off the supply of nutrient rich thermocline water to the euphotic zone, leading to a drastic decline in primary productivity. Warm sea surface over the central and eastern Pacific provides a favorable condition for active convection, so the active convective region is moved to the central Pacific during the El Niño phase, with eastward expansion of the western Pacific warm pool. Since the tropical deep convection is an important heat source in inducing atmospheric circulation, tropical circulation dramatically changes as the convection migrates to the central Pacific during the El Niño phase. Therefore, the weather and climate systems in PICTs are largely affected by the evolution of El Niño and La Niña.

As the active convection is shifted to the central Pacific during El Niño phase, the western Pacific convection, which is climatologically the strongest, tends to be suppressed because the equatorial convective anomalies induce a pair of low-level cyclonic circulation in the western part of the heating of the off-equator in the both hemispheres as a result of the so-called Gill-types response. The cyclonic circulations accompany equatorward wind anomalies in the western Pacific, which advects the dry moist state energy to the western Pacific. This plays a role in suppressing the convection in the western Pacific. Therefore, the Maritime continent exhibits dry conditions during El Niño phase. In addition, the enhanced equatorial convection strengthens the sinking motion over the subtropics, so that the precipitation over the subtropical Pacific tends to decrease during El Niño phase.

As a result, El Niño directly affects climate variability in countries throughout the tropical Pacific region, and accounts for much of the interannual variability in station records in PICTs. Seasonal rainfall patterns in countries to the north of the equator are driven to a large extent by the ITCZ. The position and intensity of the ITCZ is largely controlled by El Niño and La Niña conditions. Likewise, climate systems of the southwest Pacific countries are heavily influenced by the mean position and seasonal cycle of the position, intensity, and extent of the SPCZ. The SPCZ shifts substantially in response to the changes in SST gradients and position of surface wind convergence, which are closely related to El Niño conditions. Therefore, the changes in its position affect the mean and extreme rainfall in southwest Pacific countries. Seasonal rainfall variability in the western extremity of the Pacific is strongly influenced by the west Pacific monsoon, whose strength, timing, and extent are also affected by the phase of ENSO, particularly by El Niño-related variations in the trade winds.

It is reported that droughts caused by the El Niño effect in the Pacific are serious and increasingly regular. Each El Niño event has resulted in water shortages and droughts in American Samoa, Fiji, Kiribati, Marshall Islands, Federated States of Micronesia, Papua New Guinea, Solomon Islands, Samoa, Tonga, and Vanuatu. In addition, such drought conditions increase risk for large wild fire damage to many PICTs, and is generally increased during El Niño years.

During the El Niño phase, the tropical troposphere tends to be warmer because large energy is released to the atmosphere and ocean via sensible and latent heat fluxes. The precipitation responses are quite zonally asymmetric, while the temperature response to El Niño forcing is zonally uniformly warm. In addition, there are sinking motions in most land areas, compensating for the upward motion during El Niño, which will lead to adiabatic warming in the lower troposphere. Also, the sinking motion implies the presence of less clouds, which is related to more shortwave radiation. Throughout these processes, most tropical land areas including PICTs tend to be warmer than normal state.

As discussed above, the PICTs' climate is closely related to El Niño. However, it is fairly limited to predict their climate variability based on the typical El Niño relationship. It should be noted that there is strong seasonality of El Niño-related tropical responses. For example, El Niño responses in the PICTs are largely determined by the position of ITCZ and SPCZ, which show strong seasonal matches. In addition, since every El Niño has a different face (i.e. pattern, magnitude, and evolution), their impacts can be quite different among inter-El Niño events. Therefore, dynamical understanding of how the tropical forcing modulates tropical circulation and convection is crucial when applying El Niño information to regional predictions.

A.3 Madden-Julian Oscillation

The Madden-Julian Oscillation (MJO) is the dominant mode of intraseasonal variability in the tropics, characterized by oscillating convection anomalies at planetary spatial scales of zonal wavenumbers 1-3.[6] The convection anomalies are coupled with atmospheric circulation fields, all together propagating from the Indian Ocean to the central Pacific Ocean at time scales of 30-90 days. It is Madden and Julian, who first discovered the phenomenon[7]. They performed the power spectral analysis on daily surface pressure and zonal winds, which were obtained from the radiosonde data on Canton Island (3°S, 172°W). The analysis was then expanded to include data from 20 tropical stations across all the ocean basins, which revealed coherent fluctuations especially over the eastern Hemisphere.[8] After these pioneering papers, the MJO has been a topic of numerous studies, including observational campaigns, theoretical approaches, and modelling comparisons. Still, it is an important topic for both research communities and operational centers due to its possible role in improving forecast skill and understanding on the subseasonal to seasonal timescale.

Zhang, 2005 [6]
Madden and Julian, 1971 [7]
Madden and Julian, 1972 [8]

Many characteristics of the MJO can be overviewed by examining the MJO index of Wheeler and Hendon[9], called the Real-time Multivariate MJO index (RMM). The RMM is one of widely accepted MJO indices for both research and operational use. Also, it is common practice that we define the location of the MJO following the eight MJO phases following Wheeler and Hendon. The RMM consists of two indices, RMM1 and RMM2, which are principal components of two leading empirical orthogonal functions (EOFs). The EOF analysis method is a statistical technique to objectively retrieve structures that explain most of the variance of chosen data. For RMMs, the two EOFs are obtained from the covariance matrix of daily outgoing longwave radiation anomalies and 200- and 850-hPa zonal wind anomalies, all averaged over the equatorial band (15°S - 15°N). Before combined, each variable is normalized by its global variance. The anomaly is obtained as a deviation from the seasonal cycle. In addition, the interannual time scale fluctuation, such as ENSO, is removed by subtracting the 120-day running average. As a result, RMMs extract the dominant coupled mode in the tropics at intraseasonal time scales. The two EOFs explain the eastward propagation of the MJO.

The first leading mode (EOF1) shows negative OLR anomaly centered near 120°E, which corresponds to the enhanced convection over the Maritime Continent and the western Pacific (solid curve in Figure 22). This enhanced convection anomaly is coupled with convergence and divergence of zonal circulation at lower and upper troposphere, respectively (dashed and dotted curves in Figure 22).

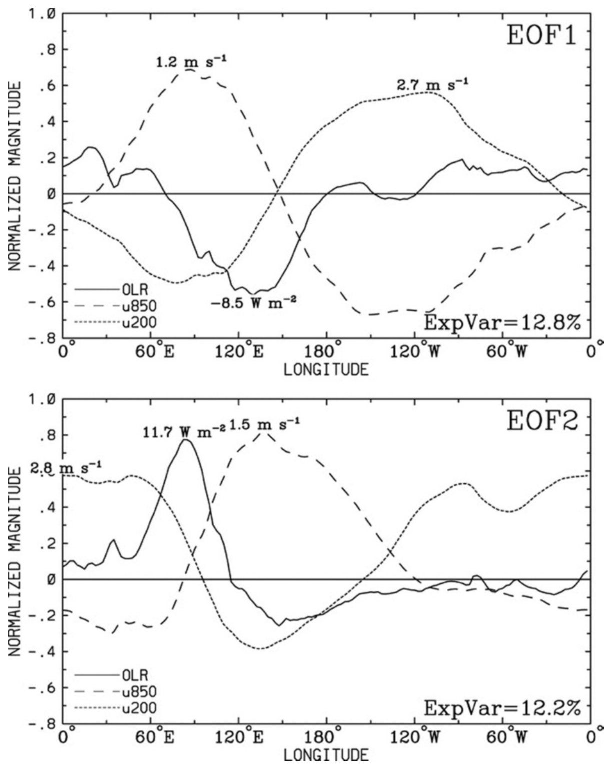


Figure 22. EOF1 and EOF2 of OLR and 200- and 850-hPa zonal wind (u200 and u850, respectively). The numbers on the curves indicate the field anomaly that occurs for a 1 standard deviation perturbation of the RMMs. EOF1 and EOF2 respectively explain 12.8% and 12.2% of the total variance. [From Wheeler and Hendon (2004)]

Wheeler and Hendon, 2004 [9]

Similarly, the second EOF (EOF2) shows a dipole pattern of convection and circulations, which apparently explains the eastward shift of EOF1 pattern. As can be seen in Figure 23, the RMM1 leads RMM2 by about 10 days, indicating the speed of eastward propagation. Using this lead-lag relation between RMMs, the lifecycle of the MJO is divided into eight phases, with phase 1 (phase 5) corresponding to the reduced (enhanced) convection over the Maritime Continent and the western Pacific Ocean.

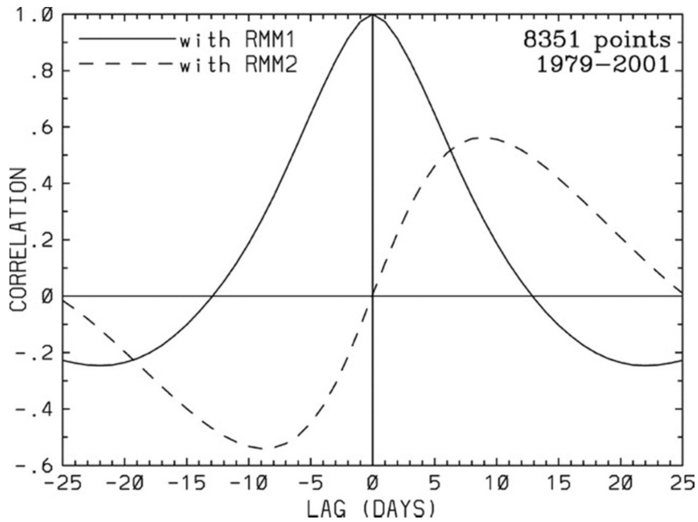


Figure 23. Lag correlations between RMM1 and RMM2 for all seasons. [Wheeler and Hendon (2004)]

The temporal and spatial scales of the MJO is well captured by the RMMs. For example, RMM1 and RMM2 exhibit considerable power between 30-80 days, while the power of the third leading principal component does not show much enhanced variance at the time scale. Also, wavenumber-frequency power spectrum of the reconstructed outgoing longwave radiation from the two EOFs explains much of the eastward propagating power at intraseasonal and planetary scales.

Given the understanding on the MJO, we now pose two practical questions: (1) what would be the major meteorological impacts of the MJO on the Pacific Island countries; and (2) can we use the MJO for the subseasonal prediction over the Pacific Island countries.

In regards to the first question, using the RMMs, Wheeler and Hendon (2004) illustrated typical lifecycle of the MJO. For about 40-50 days, the MJO propagates from phase 1 to phase 8. To elaborate, the organized enhanced convection anomaly develops over the Indian Ocean (phase 1), propagates across the Maritime Continent (phase 5), and dissipates near the central Pacific (phase 8). The convection anomaly associated with the MJO is certainly not small; the amplitude of the OLR anomaly significant even at 99% confidence level, suggesting climatological convection is heavily altered by the intraseasonal MJO. Therefore, it is obvious that the MJO will modulate the precipitation over the Pacific Island countries, who are directly at or adjacent to the path of the MJO activity. Indeed, this can be seen from the precipitation rate composites of the MJO. [10]

Zhang, 2014 [10]

It is also known that the MJO modulates the SST. [11] This connection between ocean surface and the MJO can be easily postulated if we consider the surface wind anomalies of the MJO interacting with the ocean surface through the surface drag and latent heat flux. The PICTs, again, right at or near the location where the MJO wind is influential, contributing to the intraseasonal oscillation of the SST.

In regards to the second question, it is reported that many climate models do not yet simulate realistic MJOs.[12] It is also shown that it is difficult to improve MJO simulations without degrading the basic wind state.[13] Nonetheless, when carefully initialized, models still produce meaningful MJO forecasts up to about 25 days.[14] Thus, the MJO can be a source of predictability. In fact, Johnson et al. builds a statistical forecast model that produce weekly predictions up to 6 weeks using the relationship between the MJO phase and the distribution of the surface air temperature anomaly over North America.[15]

Therefore, it is foreseeable that the MJO will be a good source of skillful subseasonal prediction for the Pacific Island countries. It is highly likely that the field that are found to be linked with the MJO will be well predicted based on the phase and the amplitude of the MJO. For example, weekly precipitation and SST, which are found to have statistical and dynamical relationship with the MJO, will be good candidates to build such a statistical prediction model.

To conclude, the MJO is arguably the most important intraseasonal climate mode in the tropics. Planetary scale organized convection and circulation anomalies from the Indian Ocean all the way to the central Pacific Ocean with time scales of 30-90 days. The MJO makes significant imprints at surface, such as precipitation and SST. Further, its quasi-cyclic behavior with characteristic time scale raises chances that the MJO becomes a good source of predictability for subseasonal predictions. Therefore, it is important for the Pacific Island countries to monitor and to predict the MJO. The practice currently performed, for instance, by the Australian Bureau of Meteorology can be a good benchmark for the PICTs.

A.4 Tropical Cyclone

Life Cycle and Structure

Tropical Cyclone (TC) is a low pressure system that forms over warm tropical waters and has a sustained maximum mean wind (MWS) speed of 34 knots (63 km/h) or greater. The strong winds can extend hundreds of kilometers from the storm center. If the sustained MWS reach 64 knots (118 km/h, gusts in excess 165 km/h), the system is called a severe TC, hurricane, or typhoon according to regions. The center of a TC with the lowest sea level pressure is called the eye, which is characterized by light winds and often by clear skies. The diameters of eye are typically 40 km but can range from under 10 km to over 100 km. The eye is surrounded by a dense ring of cloud about 16 km high, known as the eye wall, which marks the belt of strongest winds and heaviest rainfall. TCs derive their energy from warm ocean water of at least 27 deg Celsius (80 degrees Fahrenheit) outside of a 5 degree latitude band either side of the equator. TCs can persist for many days and usually dissipate over land or colder oceans.[16]

Matthews, 2004 [11]
Hung et al. 2013 [12]
Kim et al. 2011 [13]
Vitart and Molteni, 2010 [14]
Johnson et al. 2014 [15]
http://www.bom.gov.au/cyclone/about/ [16]

Danger and Impacts

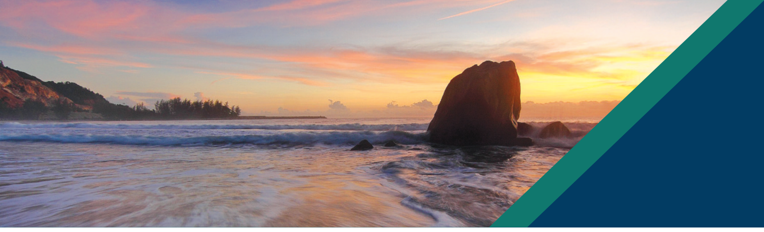
TCs are dangerous because they produce destructive winds, heavy rainfall, flooding, and storm surges. TCs have wind gusts in excess of 90 km/h around their centers and, in the most severe cases, gusts can exceed 280 km/h. These very destructive winds can cause extensive damage to infrastructure or directly impact people. During the passage of the storm center or eye, there is a temporary break in the wind, but it turns back into destructive winds in another direction. Heavy rainfall associated with the passage of a TC can produce extensive and fatal flooding. This can cause further damage and death by landslides. The heavy rain can persist as the TC moves inland and decays, hence flooding due to a decayed cyclone can occur a long way from the coast. The destructive winds accompanying TCs also produce high ocean waves, which are dangerous both for vessels out at sea and those moored in harbors. These waves can also cause serious erosion of foreshores. When TCs make landfall, storm surges can cause catastrophic damage in Pacific Island countries due to the inundation of low-lying coastal areas and the contamination of water resources by sea water.[17] In addition to direct infrastructure damage and loss of human and animal life, TCs induce the damage to vegetation and agriculture that leads to the shortage of food and increase waterborne diseases.

Although TCs can take an enormous toll on lives and personal property, they provide beneficial rains to PICTs that would otherwise be too dry. By stirring the ocean, TCs also cycle nutrients from the seafloor to the surface, boosting ocean productivity and setting the stage for blooming of marine life. Fragile barrier islands need TCs for their survival. Although TCs erode beaches on the ocean side of barrier islands, they build up the inner areas of the same islands by depositing new sediments via winds and waves. This dynamical process keeps barrier islands alive. No TCs will mean these small islands will disappear every year, especially now when the sea levels are rising rapidly. Attack of TCs, sometime, promotes the implementation of disaster plan for outer island, new technology, and agriculture crop species that can survive during salty lands.[18]

Prediction and Seasonal Forecast

Major factors for TC prediction are track, intensity, rainfall, gale wind regime, and storm surge. While skill is increasing in regard to track forecasting, intensity forecasting skill remains nearly unchanged over the past several years, which is attributed to the complexity of TC systems and an incomplete understanding of factors that affect their development. An accurate track forecast is essential to creating accurate intensity forecasts, particularly in an area with large islands such as Pacific Island countries, as proximity to land is an inhibiting factor to developing TCs. Major predictors for TC intensity prediction are the maximum potential intensity (MPI), the potential future intensity changes (POT), and the vertical wind shear (VWS). MPI represents the upper limit of TC intensity based on SST and atmospheric profiles. POT is defined as the difference between MPI and maximum wind at the initial time.[19] The VWS is defined by the magnitude of the vector difference between the two different layers, 200–850 hPa and 500–850 hPa.

http://oceanservice.noaa.gov/facts/stormsurge-stormtide.html [17]
http://www.metoffice.gov.uk/weather/tropicalcyclone/facts [18]
DeMaria and Kaplan, 1994 [19]



TC rainfall forecasting involves using scientific models and other tools to predict the precipitation expected in TCs. Knowledge of TC rainfall climatology is helpful in the determination of a TC rainfall forecast. More rainfall falls in advance of the center of the cyclone than in its wake. The heaviest rainfall falls within its central dense overcast and eyewall. Slow moving TCs can lead to the highest rainfall amounts due to prolonged heavy rains over a specific location. However, vertical wind shear leads to decreased rainfall amounts, as rainfall is favored downshear and slightly left of the center and the upshear side is left devoid of rainfall. The presence of hills or mountains near the coast acts to magnify amounts on their windward side due to forced ascent causing heavy rainfall in the mountains.

Storm surge is the abnormal rise in seawater level during a storm, measured as the height of the water above the normal predicted astronomical tide. The surge is caused primarily by a storm's winds pushing water onshore. The amplitude of the storm surge at any given location depends on the orientation of the coast line with the storm track; the intensity, size, and speed of the storm; and the local bathymetry. If the surge occurs at the same time as a high tide, the area inundated can be quite extensive, particularly along low-lying coastlines.

ENSO is known as a key climate variability that influences TC event across the Equatorial Pacific including PICTs. Most PICTs are located in the South Western Pacific (SWP) near the Pacific Warm Pool, together with the persistent easterly trade winds, and warmer SST, wetter conditions (with more convection) than on the eastern end such as Tahiti. Many studies reported that during such normal conditions, favorable environment for TC formation is present for the SWP than the eastern. During El Niño, TC occurrence shift towards the eastern end, while during La Niña years the normal climate condition is enhanced, which increases TC activities over the PICTs and west of the dateline at large.[20] Research found that the large-scale environmental factors such as SST, VWS, relative humidity, vorticity, and even MPI, are much favorable for TC genesis and development during La Niña years in the SWP.[21] This clearly demonstrates that ENSO plays a major role in the variability of TC activity over the Pacific Islands countries. It is also found that the MJO is another key modulating mechanism for TC occurrence in the central Pacific including Fiji, Samoa, and Tonga.[22]

Chand and Walsh, 2009; Diamond et al. 2013 [20]
Emanuel, 2002 [21]
Chand and Walsh, 2010 [22]

B APPENDIX B: Locality and Large-Scale Prediction

CLIK℗ uses the dynamical model with GCM, which has a coarse horizontal resolution. The spatial scales of CLIK℗ are 2.5° latitude × 2.5° longitude grid meshes (i.e., approximately about 250km). The spatial resolution is too coarse to represent the local climate variability at the station scale level. As shown in Figure 24, there are a few stations in one grid box of CLIK℗. For example, the fluctuation and variability of local rainfall at one station-level in Fiji can be quite different from each other owing to the geographical locations and mean background climate, i.e. two stations are located in in-land area or coastal line while another station are located in open ocean. However, the predicted rainfall amount (or probability) of CLIK℗ is commonly uniform to the three stations since one grid can have only one value (i.e., all calculation such as energy, momentum, and so on is done based on one grid box within the dynamical model).

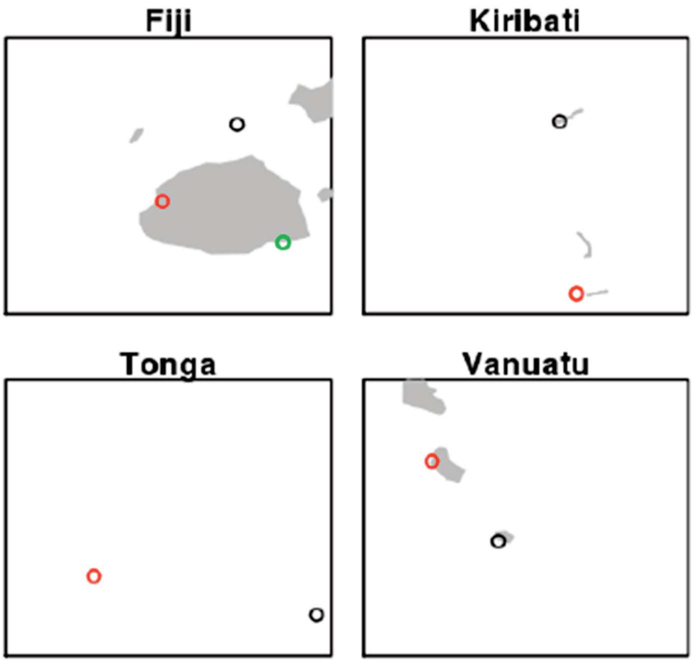


Figure 24. Geographical station locations (marked by circles) of the 4 Pacific Island countries and surrounding grid box for (upper left panel) Fiji, (upper right) Kiribati, (lower left) Tonga, and (lower right) Vanuatu. The size of grid box indicates 2.5° latitude x 2.5° longitude

As PICASO generates the locally tailored prediction value at station scale, matching forecasts and observations in spatial scale does not need any consideration during the verification process. However, matching forecasts of CLIK℗ into a station-level may be the most difficult part, many factors need to be taken into account. It is the reason why CLIK℗ is recommended for the prediction of large-scale.

For instance, for a gridded forecast such as CLIK®, there are many options for the matching process, i.e. point-to-grid and grid-to-point. The observed point is usually matched into the closest grid point using the point-to-grid method. The grid-to-point methodology is utilized to determine the predicted value for the specific station by either linear interpolation or identifying the largest value. The various matching forecast approaches can lead to differences in the associated results (as shown in Figure 25) and can finally impact the local prediction and verification results. Therefore, this should be taken into account when interpreting CLIK® results. On the other hand, there is no need for any assumption or method to get the localized value in PICASO.

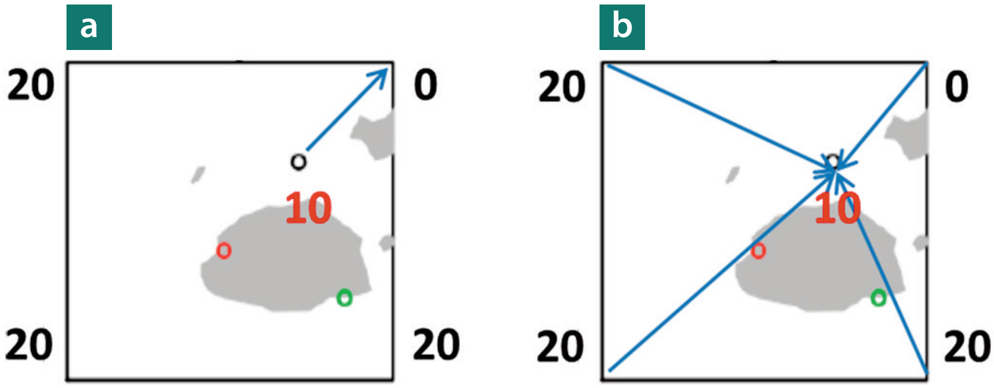


Figure 25. Two approaches of matching forecasts and observations for (a) point-to-grid and (b) grid-to-point. The forecasted values at a station with 10 of the observed value (in red) can be represented as 0 and 15 for two aforementioned approaches, respectively. In the latter way, equal weight to each grid point is crudely assumed. The values at the outside of rectangle for four grid points (in black) are the forecasted ones.

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