Liquid Water Cloud Retrievals - A Bayesian Approach

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Introduction

We developed a new algorithm to retrieve properties of non-precipitating liquid water clouds from millimeter wave radar and Microwave Radiometer (MWR) data using Bayes' theorem of conditional probability. Bayes' theorem relates the inverse problem (retrieving cloud properties from remote-sensing observations) to the forward problem (modeling remote-sensing observations given a set of cloud properties). It also formally includes prior information about cloud microphysics, with this information explicitly modeled by a probability distribution function in the parameter space, not hidden in assumptions within the algorithm. The Bayesian algorithm does not make any assumptions about the shape of the cloud particle sized distribution (PSD), it is not limited to stratus-type clouds, and it provides uncertainties on each retrieved quantity.

Bayes' Theorem

Bayesian theory is a general approach to solving inverse problems such as retrieving a vertical profile of cloud properties from a set of remote-sensing observations. Following Rodgers (2000), we define the measurement vector, y, as consisting of the set of remote-sensing observations, each with an associated measurement error, and the state vector, x, as the set of unknown cloud properties we wish to retrieve, which describes the state of the atmosphere. The basis of Bayesian theory is that the inverse problem can be related to the forward problem through a set of measurements and prior knowledge about the probability of the state vector.

Bayes' theorem of conditional probability is given by

$$p_{post}\left(x|y\right)=\frac{p_{fwd}(y|x)p_{pr}(x)}{\int p_{fwd}(y|x)p_{pr}(x)} \tag{1}$$

where x and y are the state vector and measurement vector defined above. In this equation, the quantity $p_{pr}(x)$ is known as the prior probability density function (PDF) of the state x. It represents our knowledge of the possible values of x before the measurement is made. The term, $p_{fwd}\left(y|x\right)$, is the conditional, or forward, probability of the measurement given the state vector. It is represented by a forward model, which expresses our understanding of the physics that relate the desired quantities (cloud properties) to the measured properties, including the uncertainties. The denominator simply normalizes the integral. Finally, the term $p_{post}(x|y)$ is known as the posterior pdf, and is the probability of the state vector given the measurement vector. The posterior pdf is the result of applying Bayes' theorem to a set of measurements and prior information.

Inputs to Algorithm

We developed the Bayesian retrieval algorithm based on the instrumentation available at all ARM sites. The vector of observations, y, used in the liquid cloud retrieval consists of cloud locations from the active remote sensing of cloud (ARSCL) product Clothiaux et al. 2000), vertical profiles of cloud radar reflectivity from the millimeter cloud radar (MMCR), brightness temperatures at 23.8 and 31.4 GHz from the MWR, and temperature and water vapor profiles from radiosondes. The state vector, x, is based on both the observed and desired cloud properties. We wish to retrieve the radiatively important cloud properties, liquid water content (LWC) and visible extinction, which are related to the 3rd and 2nd moments of the PSD, and we observe the 6th moment of the PSD through the radar reflectivity. Therefore, the state vector consists of the profile of 2nd, 3rd, and 6th moments of the PSD, so we do not have to assume a fixed form for the size distribution.

The prior PDF, $p_{pr}(x)$, of the state vector, x, represents our prior knowledge about the microphysics of a given cloud regime, in this case boundary-layer cumulus clouds. Our prior PDF for Nauru is based on data from two field experiments focused on shallow tropical cumulus, the Small Cumulus Microphysics Study (SCMS), which took place in east central Florida in the summer of 1995 (French et al. 2000), and the Joint Hawaiian Warm Rain Project (JHWRP) which took place off the coast of Hilo in the summer of 1985 (Raga et al. 1990). We calculate the 2nd, 3rd, and 6th moments from size distributions measured by the Forward Scattering Spectrometer Probe (FSSP) 100 and Optical Array Probe (OAP) 260X (which measures large droplets) in situ probes on the National Center for Atmospheric Research (NCAR) C-130 aircraft (during SCMS) and the University of Wyoming King Air (during JHWRP). We use maximum likelihood estimation to fit a three-dimensional bimodal lognormal distribution to the observed data.

In the next section we present results of the Bayesian retrieval algorithm. Further discussion of the prior PDF, development of the forward pdf, and details of the retrieval are given in McFarlane et al. (2001), which can be found at http://nit.colorado.edu/~evans/radarcloud.html.

Preliminary Results from Nauru

We have performed retrievals using the Bayesian algorithm on 3 months of data (June - August 1999) from the Atmosphere Radiation and Cloud Station (ARCS) site on the island of Nauru. The ARSCL product was used to determine cloud boundaries and locations. Cloud phase was classified based on a simple temperature thresholding method, with temperatures above -10° assumed to be liquid clouds. Retrievals were attempted for all liquid clouds where maximum column reflectivities were less than 0 dBZ (to avoid precipitating clouds). Vertical profiles of LWC, vertical extinction, and effective radius

(r_e) were retrieved as well as column liquid water path (LWP) and optical depth. Figure 1 shows examples of retrieved LWC and r_e for shallow cumulus at Nauru as well as a time series of retrieved LWP and optical depth with error bars on the retrieved optical depth. Figure 2 shows the cumulative distribution functions of optical depth and LWP for the retrieved clouds.

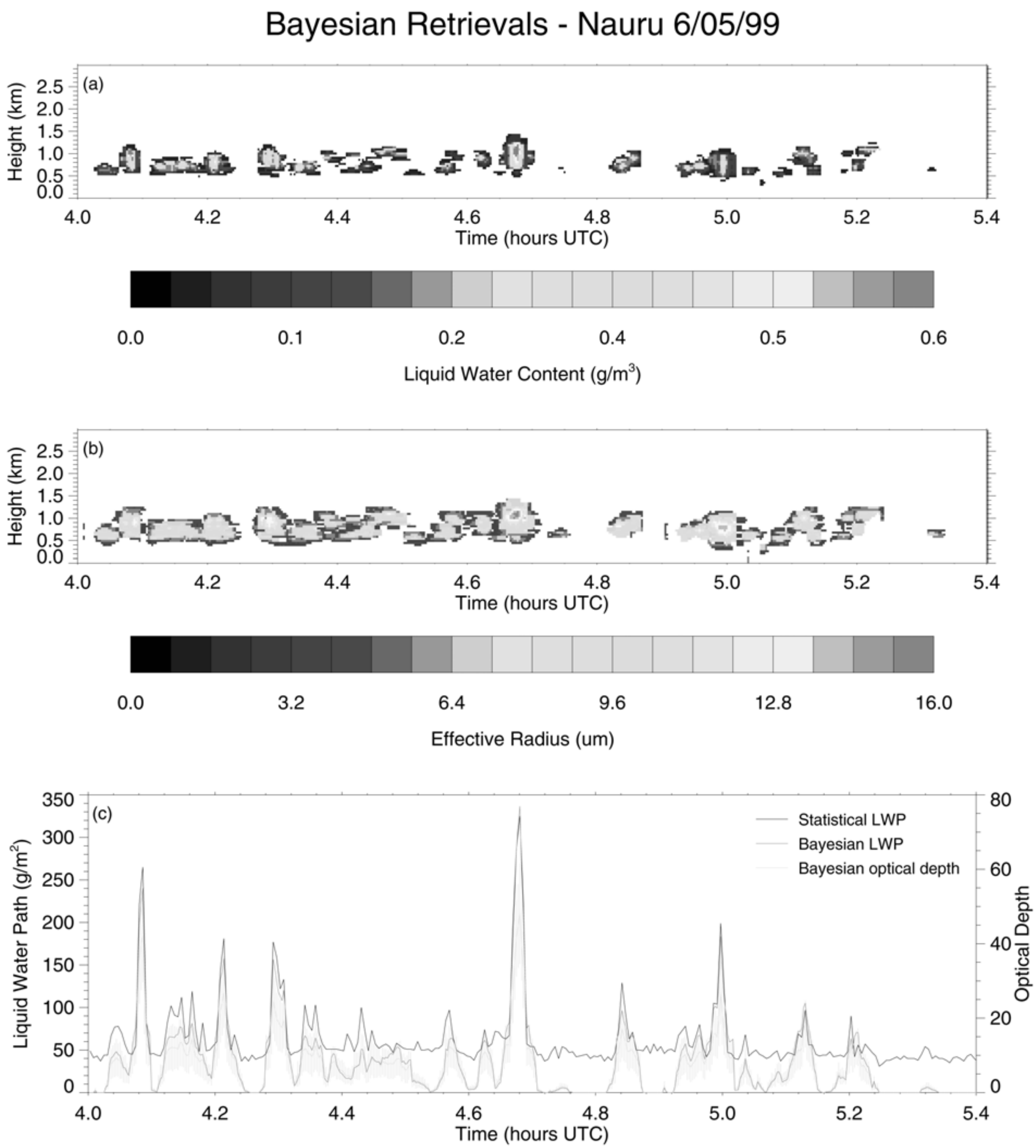


Figure 1. Examples of Bayeisan retrievals at Nauru on June 5, 1999. Time-height cross sections of (a) retrieved LWC, (b) r_e, and (c) time series of retrieved LWP and optical depth.

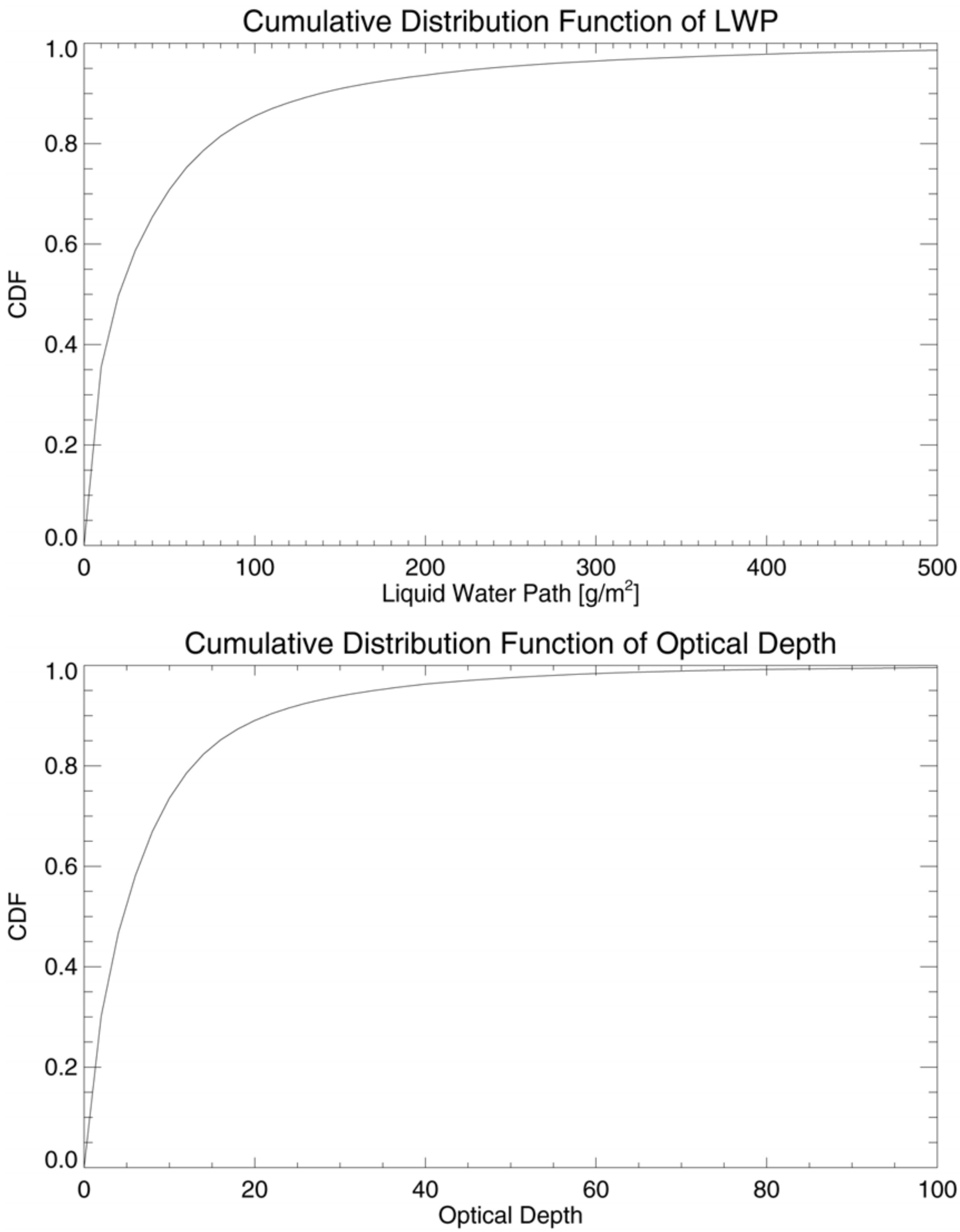


Figure 2. Cumulative distribution functions of (a) optical depth and (b) LWP for clouds retrieved during June - August 1999, at Nauru.

Validation

To assess the performance of the Bayesian retrieval algorithm, we use cloud fields generated by an explicit binned microphysics large-eddy simulation (LES) model. We simulate MWR and MMCR input "observations" from the LES fields using our forward model and adding noise (0.5 K to MWR brightness temperatures and 1 dBZ to reflectivities). Since the "true" cloud properties (the LES model values) are known, the uncertainties in the retrieval algorithm can be clearly defined, avoiding the measurement and sampling uncertainties associated with validating remote-sensing retrievals against aircraft in situ data.

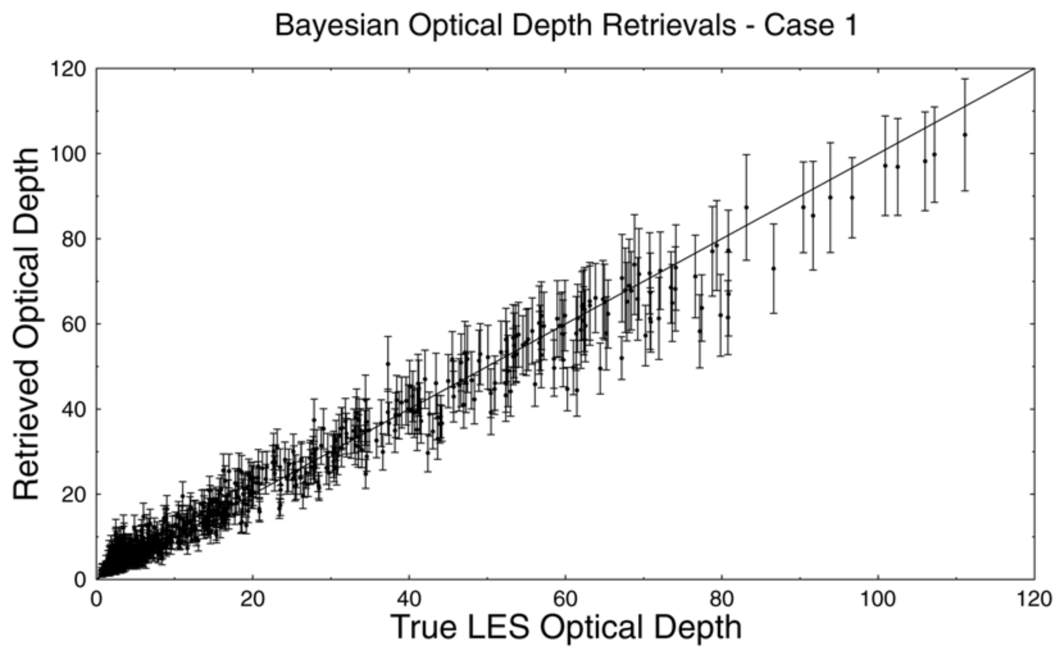
The LES model simulations are of maritime trade cumulus, initialized with measurements from the Atlantic Trade-Wind Experiment (ATEX). The model domain spans 6.4 x 6.4 km horizontally and 3 km vertically and is uniformly discretized into 32 x 32 x 75 grid cells. The output variables from the LES model consist of temperature, water vapor mixing ratio, and the explicit binned droplet size distribution at each grid point.

To examine the Bayesian retrieval algorithm, we use results from two different LES runs. The model is run for 8 hours after spin-up with output every half hour (model time). We use output from all LES scenes with more than 10 cloudy grid points. For the first LES case, this results in 11 cloudy scenes, with an average LWP of 100.5 g/m^3, average cloud fraction of 10.8 percent, and average number concentration of 97.7 cm^{-3}. The second model run (Case 2), has 15 cloudy scenes, with an average LWP of 85.2 g/m^3, average cloud fraction of 12 percent, and average number concentration of 79.8 cm^{-3}.

Figure 3 compares the retrieved and true optical depths from the LES tests using the Bayesian retrieval algorithm. Most points lie on the one-to-one line within the retrieved error bars. To further assess the Bayesian retrieval algorithm, we compared the results to retrievals performed with our implementation of the Frisch et al. (1995) algorithm. For the Frisch algorithm, an integrated LWP is needed, which we can calculate from a statistical regression on the two microwave brightness temperatures.

We performed two sets of comparisons. In the first set, the Bayesian prior PDF is derived from the LES droplet size distributions (instead of from in situ observations) and the regression coefficients for the LWP/Tb regression for the Frisch algorithm are also determined directly from the LES data. This comparison represents the performance of the two algorithms assuming that the prior statistics are well known. The results of this comparison are shown at the top of Table 1. The second set of comparisons represents a more operational set of retrievals. The Bayesian prior PDF is derived from the in situ data as described in Section 3, and the coefficients for the LWP/brightness temperatures (Tb) regression are those used operationally by ARM in their statistical LWP retrievals at Nauru. These results are shown in the middle of Table 1. We also compare the Bayesian results to two radar-only algorithms. The first assumes a lognormal distribution with fixed width of the lognormal, $\sigma_{\log} = 0.35$, and number concentration fixed to the average number concentration over the LES scenes. The second radar-only algorithm is the regression equation developed by Liao and Sassen (1994), where $Z_i = \frac{3.6}{N} \, LWC^{1.8}$, with number concentration again fixed to the average.

The LES simulations show that the Bayesian algorithm is significantly more accurate than existing methods for r_e and optical depth and is comparable to current methods for LWC.



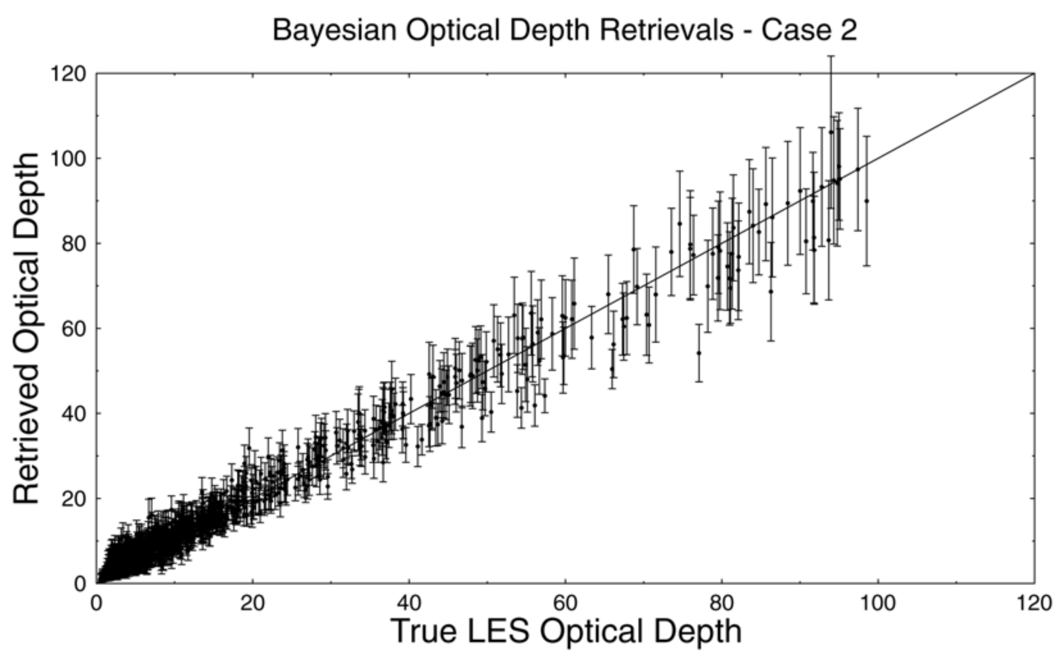


Figure 3. Scatterplot of the optical depths (and error bars) retrieved from (a) LES case 1 and (b) LES case 2 using the Bayesian algorithm and the prior PDF based on the SCMS/JHWRP in situ data.

Table 1. Median fractional errors for all retrieval algorithms over all LES scenes. Fractional errors for LWC and r_e, are defined where LWC >0.02 g/m^3; for LWP and optical depth, r, errors are defined where LWP >5 g/m^2.

		Case 1				Case 2			
	Method	r_e	**LWC**	**LWP**	**r**	r_e	**LWC**	**LWP**	**r**
LES	Bayes	0.13	0.31	0.15	0.21	0.11	0.30	0.17	0.26
Prior	Frisch	0.32	0.29	0.09	0.32	0.25	0.28	0.12	0.30
Methods	LWC-Z	--	2.66	3.5	--	--	2.04	2.77	--
	Fixed N	0.15	1.17	1.76	1.63	0.13	0.84	1.25	1.23
General	Bayes	0.14	0.32	0.17	0.20	0.12	0.29	0.18	0.21
Prior	Frisch	0.44	0.33	0.22	0.43	0.45	0.35	0.27	0.44
Methods	LWC-Z	--	2.31	3.08	--	--	1.90	2.60	--
	Fixed N	0.16	0.99	1.54	1.36	0.13	0.77	1.17	1.12

Conclusions

We have developed a new algorithm for retrieving optical depth and vertical profiles of LWC and r_e from liquid water clouds. The retrieval also includes error bars, which represent one standard deviation. Tests using cloud fields from an LES model as simulated input have shown that the Bayesian algorithm is more accurate than current algorithms for r_e and optical depth of trade cumulus clouds. We have performed retrievals on three months of data at Nauru at this point and plan to run the algorithm on all available data at Nauru and Manus.

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