Validation of Atmospheric Characterization and Prediction over Haleakala during the Laser Communications Relay Demonstration

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ABSTRACT

In December of 2021, NASA launched its Laser Communications Relay Demonstration (LCRD). LCRD will demonstrate bi-directional space to ground optical communications to two optical ground stations (OGS). The OGS at the Table Mountain Facility, known as OGS-1, and the OGS-2 at Haleakala summit will serve as the two ground sites. In mid-January 2022, LCRD demonstrated its first light through NASA optical telescopes. Over the next two years, LCRD will demonstrate the benefits of optical communications. Laser communications provide secure, high data rate transmission in the absence of strong atmospheric fading that includes cloud liquid water, ice, and atmospheric aberrations produced by pancake layer density gradients. Two of the major goals of LCRD are to quantify the impacts of the atmosphere on optical transmissions and to predict link handovers between OGS-1 and OGS-2. The Atmospheric Monitoring System (AMS) deployed to OGS-2 in 2017 has been collecting atmospherics in real-time and is now supporting the goal of quantifying the impacts on LCRD optical transmissions. For example, data from the AMS is providing minute by minute estimates of atmospheric fades due to clouds from a laser ceilometer as well as horizon to horizon imagery of the clouds. Additionally, AI-powered atmospheric decision aids based on the AMS are being run to support link handovers. Northrop Grumman is using a U-Net neural network and multi-layer perceptron model trained on high performance computing GPUs. The resulting decision aids are developed using many terabytes of AMS data collected over the last several years. Results prior to launch of LCRD showed a remarkable ability to predict the short term atmospheric and space environment in and around the line of sight to the spacecraft. For example, the ten-minute cloud prediction skill score beats a basic persistence forecast. This implies that the decision aids are able to predict a change in state of the atmospheric transmission, something a persistence forecast is unable to do. In addition, these predictions are showing very little bias.

This talk will provide an overview of the AMS, its real-time data collects, and its predictive capabilities. In addition, the talk will report on the development of atmospheric predictive models at OGS-2 for time scales between zero and 48 hours and subsequent validation efforts using in situ instrument and LCRD data. Comparisons to LCRD link quality performed during an on-site visit to OGS-2 highlight the benefits of using in situ data to support the validation of the atmospheric estimated link fades and predictions. The ultimate goal of this work is to show that atmospheric characterization and prediction is essential for any ground based optical system whether it be for space situational awareness (SSA) or optical communication applications. The talk will show how the independent data from LCRD may be used to validate ground-based characterization and prediction systems.

1. INTRODUCTION

NASA launched its Laser Communications Relay Demonstration (LCRD) in December 2021 to demonstrate bi-directional space to ground optical communications to two optical ground stations (OGS) at Table Mountain Facility (OGS-1) and the Haleakala summit (OGS-2). LCRD goals include demonstrating the benefits of secure, high data rate optical communications, quantifying atmospheric impacts on optical transmissions, and testing the ability to predict link handovers between OGS-1 and OGS-2.

It is well understood that atmospheric attenuation and distortion reduce the efficacy of free space optical communication (FSOC). In particular, clouds can partially or fully obscure targets, and block or require a reduction of the data rate of optical communications systems. However, with accurate characterization and prediction of atmospheric conditions, many of the negative impacts can be mitigated and even eliminated allowing for consistent and secure communication from space to ground. In support of LCRD, Northrop Grumman (NG) installed an

Atmospheric Monitoring System (AMS) at OGS-2 in 2017, which consists of a suite of instruments to provide in situ, ground-based atmospheric data [1]. This five-year archive of data along with space-based atmospheric data has been used to develop a state-of-the-art prediction system that generates high-resolution predictions of atmospheric attenuation to support decision aids for space-based laser and surveillance applications. This in situ data is also used to validate the prediction models' performances and optical communication availability at OGS-2 during LCRD in real-time.

Optical communication handover decisions require accurate short-term and long-term atmospheric information for link handover planning. Multi-time scale atmospheric predictions: out to one hour; out to two hours; and out 48 hours are generated at OGS-2 using advances in high performance computing (HPC) and machine learning/artificial intelligence (AI) techniques combined with terabytes of high-resolution ground and space-based atmospheric data. The requirements for atmospheric predictions at these time scales necessitate different sources of data, computing resources, and prediction techniques. For short-range predictions, two models have been developed based on data derived from the ground-based infrared cloud imager (ICI). The ICI produces calibrated sky radiances at each pixel within the skydome at 1-minute resolution from which an AI enhanced cloud retrieval algorithm is used to interpret each image at the pixel level as cloud or no cloud. The first model, the ICI UCFS (U-Net Cloud Forecast System), utilizes a U-Net convolutional neural network [2] to predict the probability of clouds for the entire ICI image from the current time out to 10 minutes in the future at discrete time steps. The second model, a multi-layer perceptron (MLP) model, predicts the probability that a cloud will block the line of sight (LOS) during the next minute out to 60 minutes. For mid-range predictions out to a few hours, the ground-based imager is insufficient since clouds that may impact the system in one to two hours are likely not yet in the field of view of the local ICI. Therefore, satellite imagery from NOAA (National Oceanographic and Atmospheric Administration) geostationary satellites is used. A U-Net model is trained and validated on satellite imagery and satellite-derived cloud masks to predict link availability at OGS-2 out to two hours. Accurate long-range cloud predictions cannot be derived from ground or satellite-based cloud evolution. Therefore, an enhanced version of the high-resolution Weather Research and Forecasting (WRF) model is employed. The WRF model is run in real-time and is then used as input to a MLP model to enhance WRF cloud predictions at the Haleakala summit for predictions out to 48 hours. The WRF model also simulates C_n^2 to provide a prediction of the seeing parameters at the summit of OGS-2.

All predictive models are running operationally in real-time and extensive validation efforts have been employed to compare the predictions against the in situ data at OGS-2 to assess performance accuracy. Results of these modeling efforts show that for all three time scales, the AI prediction technologies substantially outperform the baseline predictions of persistence. Comparisons to LCRD experiment data have been performed for a handful of cases from June 2022. While anecdotal in nature at this time, in situ data comparisons to the LCRD communication link shows evidence of the ability to maintain communications through clouds with transmission losses up to 6 dB (decibels).

The objective of this research is to report on the atmospheric predictive modeling development at OGS-2 for time scales between zero and 48 hours and the validation efforts using in situ instrument and LCRD data. The data and techniques used to create the components of a multi-time scale atmospheric prediction system and the validation efforts are described in this paper. Section 2 describes the instrumentation at OGS-2 and the data used to develop and validate the atmospheric models. Section 3 describes the development of two short-range predictions of clouds based on cloud classifications from a ground-based ICI and the validation scheme. The use of a U-Net to make and validate mid-range cloud predictions based upon the AI derived satellite cloud analysis is discussed in Section 4. Long-range NWP predictions enhanced using AI for the Haleakala summit is the focus of Section 5. Finally, an operational example using a qualitative assessment from LCRD at OGS-2 is shared in Section 6.

2. INSTRUMENTATION AND DATA

In 2017, Northrop Grumman (NG) installed an Atmospheric Monitoring System (AMS) at OGS-2 to collect and perform atmospheric characterization and modeling prior to LCRD and to support experiments during LCRD. The AMS consists of three main instruments, an Infrared Cloud Imager (ICI), a Vaisala ceilometer (CL51) and a Vaisala AWS 310 weather station (Fig. 1). The suite of instruments has been fully operational for over five years producing terabytes of atmospheric in situ data that NG has archived. The ICI is a ground-based, fully calibrated, passive infrared instrument that provides nearly horizon to horizon coverage of the sky. The ICI consists of a FLIR Photon 640 camera and electronics enclosure. The FLIR camera is mounted underneath a Stingray full sky lens. A rain

senor triggers a hatch cover which closes to protect the lens during inclement weather. The ICI produces calibrated sky radiances at each pixel within the skydome at one-minute resolution. NG uses an AI enhanced cloud retrieval algorithm to interpret each image at the pixel level as cloud or no cloud.

The Vaisala ceilometer (CL51) employs pulsed diode laser LIDAR technology, where short, powerful laser pulses are sent out in a vertical direction at zenith. The reflection of light and backscatter caused by haze, fog, mist, precipitation, and clouds is measured as the laser pulses traverse the vertical column above the site. The resulting backscatter profile is processed and stored at six second intervals to compute cloud base heights and transmission loss. Backscatter profiles are available up to approximately 16 kilometers above ground level, providing a characterization of cloud base height and thickness of up to three cloud layers. NG calculates transmission loss due clouds using the Klett [3] algorithm which is used during LCRD to assess when the optical communication link is lost due to clouds of various optical depths and thicknesses.

The AWS310 measures standard meteorological values of temperature, pressure, wind speed direction, humidity, rain, and incoming solar radiation at one-minute resolution. These in situ measurements at the Haleakala summit are the source of NG's atmospheric validation efforts to assess the performance of the atmospheric models used to support optical link handover decisions during LCRD.

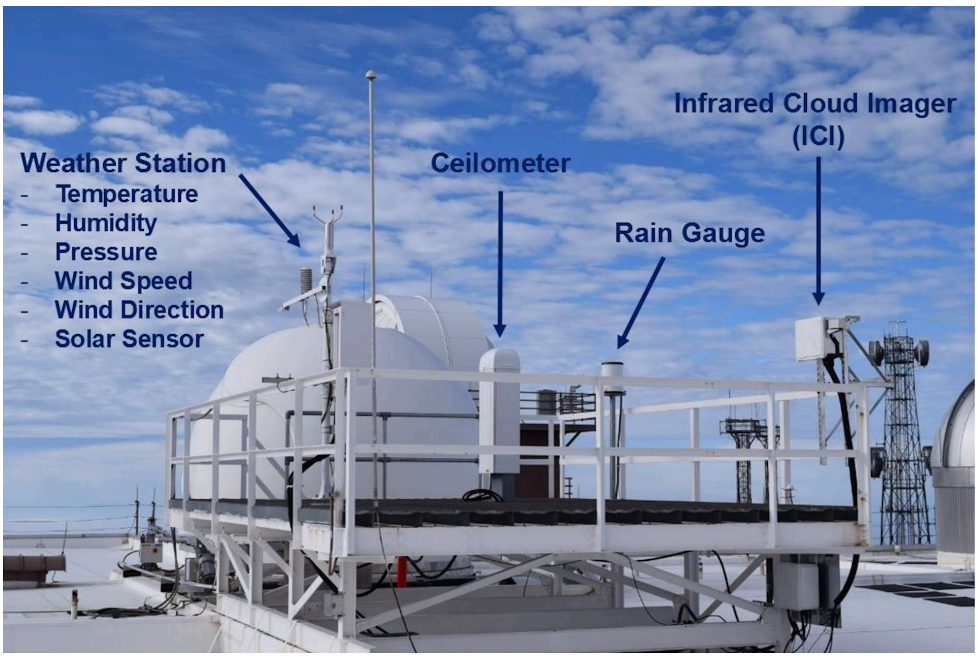

Fig. 1. Atmospheric Monitoring System (AMS) at the Optical Ground Station (OGS)-2 at Haleakala

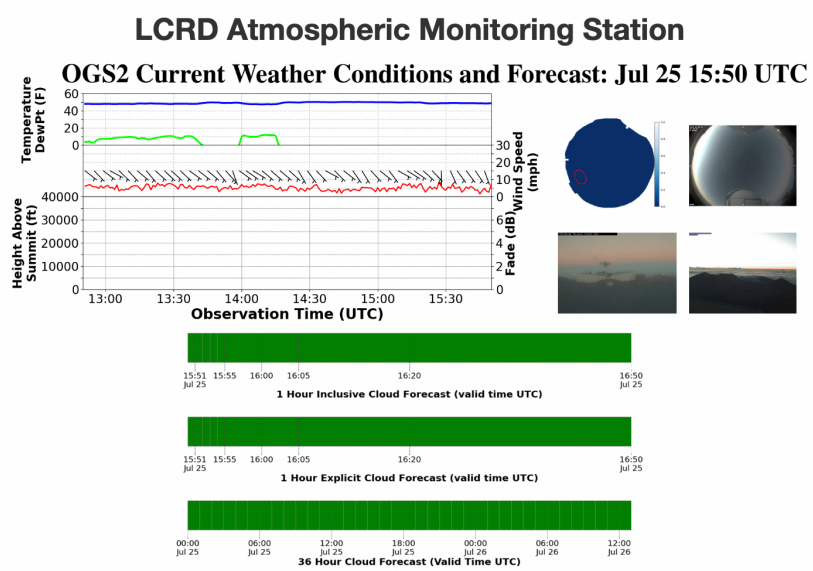

Fig 2. Realtime in situ data at OGS-2 and link availability decision aids based on model predictions of cloudiness at summit.

3. SHORT-RANGE CLOUD PREDICTION

Measurements from instrumentation on the Haleakala summit have shown the site is cloud-free over 70% of the time, and a simple persistence forecast, where the current cloud conditions are presumed to persist indefinitely, will work well in many cases. However, since a persistence forecast never predicts change, this technique fails when clouds are moving in and out of the line-of-sight (LOS) to the communications satellite. To improve upon a simple persistence cloud forecast, two separate machine learning (ML) models have been developed to predict the probability of clouds in the short term. The first model, a U-Net model, referred to as the ICI UCFS (U-Net Cloud Forecast System), predicts the probability of clouds for the entire ICI image from the current time out to 10 minutes in the future at discrete time steps. The second model, a multi-layer perceptron (MLP) model, predicts the probability that a cloud will block the LOS in the next minute out to 60 minutes.

Both models are trained using current and recent cloud data from the ICI. The ICI produces calibrated sky radiances at each pixel within the skydome, and has been collecting images at one-minute resolution for more than five years. Previous work with this data was based on a cloud retrieval algorithm that interpreted each image at the pixel level as cloud or no cloud using the clear sky background (CSB) technique [4] which evaluates many sky radiance images as a function of time of day and identifies the tenth percentile smallest values. Any deviation in sky radiance from the CSB is interpreted as a high confidence cloudy pixel. While this technique, called the ICI Cloud Mask Generator (ICI CMG), produced accurate cloud masks most of the time, it was susceptible to elevated atmospheric water vapor. During these times, which tend to occur a few days each month, the CSB technique produced an overly cloudy image, and any cloud predictions based on these images would be inaccurate.

To address this, a U-Net convolutional neural network, referred to as the ICI UCA (U-Net Cloud Analysis), was trained to assign a probability of cloud to each ICI pixel. The initial ICI UCA was trained using the ICI sky radiance as the single predictor, with the ICI CMG cloud masks used as the labeled data. However, this proved inadequate, with the ICI UCA essentially reproducing the subpar CSB-based cloud masks. To improve the ICI UCA cloud predictions, an algorithm was created to identify inaccurate ICI CMG cloud masks using the spatial characteristics of the cloud mask and the CL51 backscatter. These erroneous cloud masks were either corrected or removed from the training dataset, producing a higher quality labeled dataset with which to train the U-Net. Training with this new labeled dataset produced a more accurate ICI UCA, with the UCA able to identify clouds without over-detections during periods of elevated atmospheric water vapor as illustrated in Fig. 3. The model was further improved with the addition of precipitable water vapor (PWV) as a second predictor, trained on 3 years of ICI data (2018 – 2020), and

was made operational in August, 2021. The resulting UCA cloud probabilities are used as the inputs for the short-range cloud predictions of the ICI UCFS and the ICI MLP.

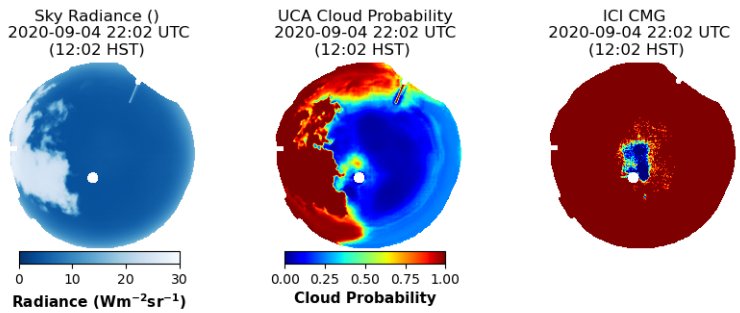

Fig. 3. ICI sky radiance (left), ICI UCA cloud probability (center), and ICI CMG (right). The ICI UCA cloud probabilities are much more accurate than the ICI CMG cloud mask, which over-detects clouds in this case.

ICI U-Net Cloud Forecast System (UCFS)

The ICI UCFS uses a series of ICI UCA cloud probability arrays (images) to predict future cloud probability arrays. For the operational model currently running for the OGS-2 ICI, the 10 most recent ICI UCA arrays spanning the most recent 10 minutes are used to make cloud predictions for each of the next 10 minutes. This is illustrated in Fig. 4, which shows the 10 input ICI images in the top row, the ICI UCFS cloud predictions for the next 10 minutes in the middle row, and the actual ICI cloud images (truth) for the forecast period in the bottom row. The UCFS cloud predictions in the middle row show the probability of cloud for each pixel in the ICI image. Note how the cloud forecast captures the right-to-left motion and general clearing evident in the preceding 10 images in the first row. If this were a perfect forecast, the middle row and the bottom row would be identical. The UCFS was trained with two years of ICI UCA data (2019 – 2020), and was evaluated on an independent 12-month period (March, 2021 – February, 2022).

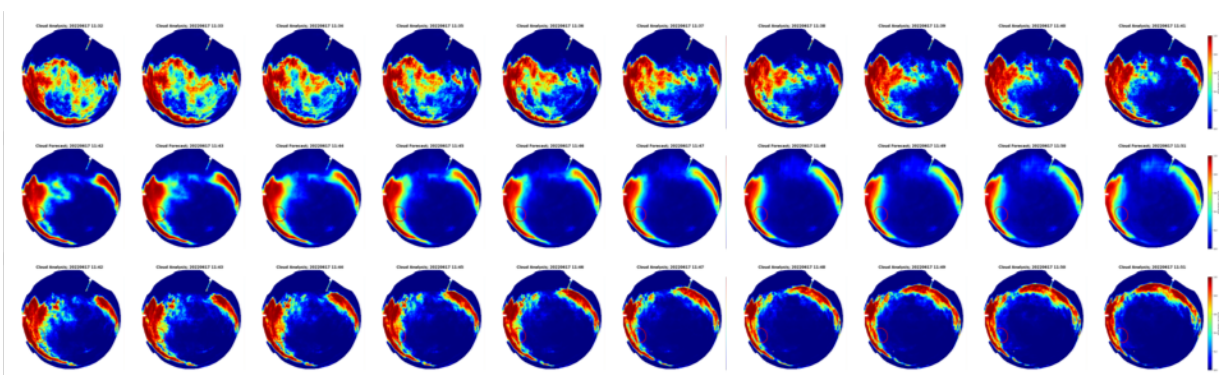

Fig. 4. ICI UCA input frames (top row), ICI UCFS predictions for the following 10 minute period at 1 minute resolution (middle row), and the actual ICI UCA for the 10 minute forecast period predicted by the ICI UCFS.

Roebber statistics [6,4] are used to assess how well the ICI UCFS is performing. These are shown for 1-10 minute predictions for the independent evaluation period of March, 2021 – February, 2022 in Fig. 5 (left). The critical success index (CSI) is 0.91 for the one-minute forecast and decreases to 0.78 for the ten-minute forecast, and all predictions have very little bias. The CSI is a useful verification measure of categorical prediction performance defined as the total number of correct event predictions (hits) divided by the total number of prediction forecasts plus the number of misses (hits + false alarms + misses). Fig. 5 also shows that the ICI UCFS significantly outperforms the persistent forecast (cyan colored symbols).

In depth analysis of conditions during which the ICI UCFS performs poorly at Haleakala shows that the most challenging predictions occur when low clouds move very quickly in and out of the ICI images. Clouds in

successive ICI images under these conditions often seem to appear and disappear at random, with no discernable motion through the field of view. To address these challenging times, the ICI UCFS predictions were separated into three categories: high confidence clear; high confidence cloudy; and uncertain. The categories are defined by ICI UCFS cloud probability thresholds, p1 and p2, where UCFS probabilities below p1 are high confidence clear and above p2 are high confidence cloudy. Probabilities between p1 and p2 are deemed uncertain. This is illustrated for the ten- minute ICI UCFS forecast in Fig. 6, where the high confidence predictions are shown in green (clear) and red (cloudy), and the uncertain range is shown in yellow. The values for p1 and p2 were optimized to maximize the forecast accuracy and CSI, while minimizing the bias. Less than 1% of one-minute predictions are uncertain, and that uncertainty percentage increases to 6.1% for the 10-minute forecast. When the Roebber statistics are computed for only the high confidence predictions, the CSI for all forecast lengths is greater than 0.9, while maintaining a bias very near 1.0 (Fig. 5, right). The Roebber plot shows how well clouds are forecast, but does not account for correct clear predictions since it is assumed those are easy to predict. When correct clear predictions are also included, the overall accuracy of the high confidence clear and cloudy predictions is greater than 98% for all forecast lengths.

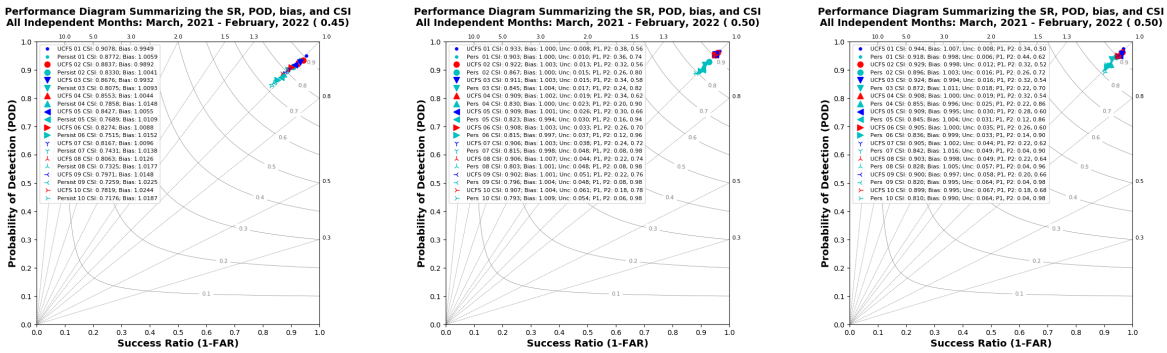

Fig. 5. Roebber statistics for all predictions (left) and for high confidence predictions (middle). The ICI UCFS predictions are shown in blue and red, and the persistence predictions are shown in cyan. The plot on the right shows the statistics for the operational model for the period of March, 2022 – June, 2022 for the high confidence predictions. The CSI shows ICI UCFS significantly outperforms the persistence forecast in all cases.

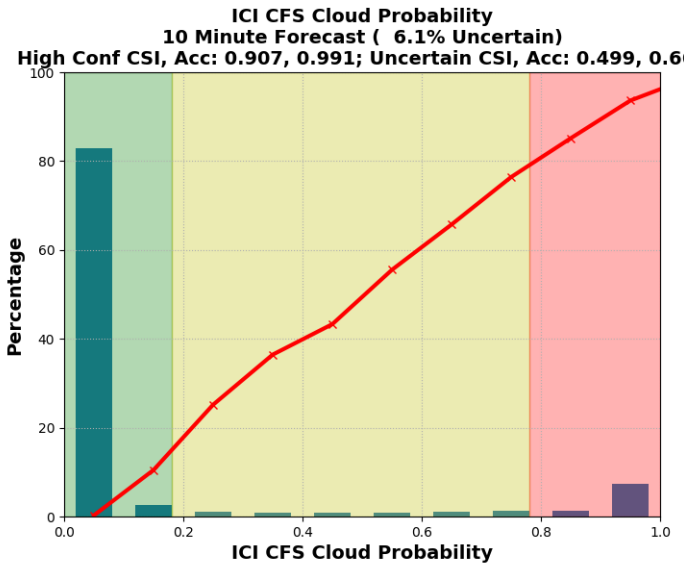

Fig. 6. Reliability plot for the ICI UCFS 10 minute forecast. The forecast is highly confident clear (cloudy) in the green (red) areas. UCFS predictions are deemed uncertain for cloud probabilities in the yellow area.

The ICI UCFS has been running operationally since May, 2022. Animations of the 10-minute UCFS predictions are created for each new ICI image (each minute). In addition, a validation graphic is generated every minute, providing a quick look at how well the ICI UCFS is performing. An example of this is shown in Fig. 7. In this figure, the background colors (green, yellow, and red) represent the ICI UCFS cloud prediction for the next 10 minutes, where each row is a separate 10-minute forecast with the most recent forecast shown in the top row, and the forecast from 30 minutes in the past is in the bottom row. In this example, the UCFS was predicting clouds or uncertain conditions early in the period (bottom half of the Fig. 7), and cloud-free conditions in the more recent predictions. The actual cloud conditions are represented by the "X" in each box. A green "X" indicates the actual LOS was clear, while a red (yellow) "X" shows the LOS was actually cloudy (uncertain). This product provides a synopsis of how well the cloud predictions have been performing over the last 30 minutes.

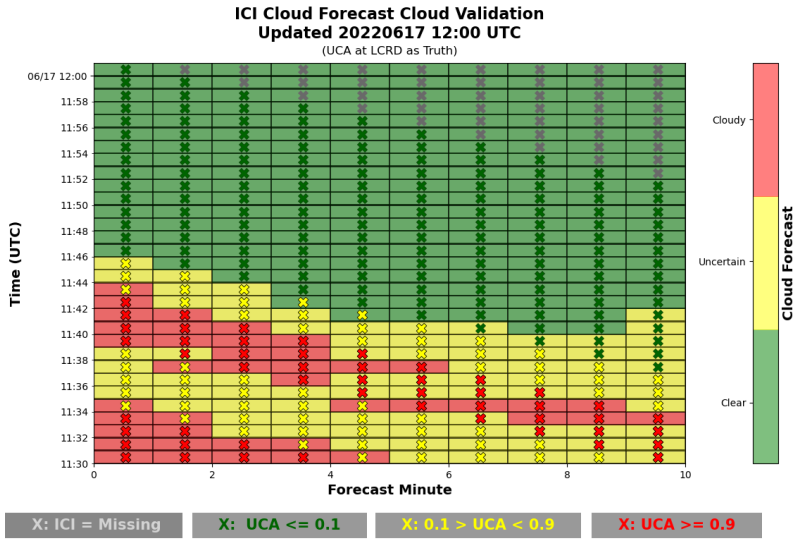

Fig. 7. ICI UCFS validation plot comparing the 10-minute forecast cloud probability (background colors) and the actual occurrence of clouds represented by the "X" symbols. Green represents high confidence clear, red represents high confidence cloudy, and yellow indicates an uncertain cloud forecast.

ICI MLP SHORT-RANGE CLOUD PREDICTION

The second short-term prediction model is a multi-layer perceptron (MLP) deep learning model, which predicts the probability that a cloud will block the LOS during the next minute out to 60 minutes. The MLP complements the UCFS in that it is optimized specifically for a single LOS, while the UCFS makes a forecast for the entire ICI FOV. A perceptron is an algorithm used to perform binary classifications of cloudy or clear. It produces a single output based on inputs by forming a linear combination using input weights. A MLP is a deep artificial neural network composed of more than one perceptron. It contains an input layer that receives the signal, an output layer that makes the prediction, and hidden layers in between that perform the computational work. The MLP is trained on input-output pairs, and models the relationship between the two by adjusting weights and biases of the model to minimize errors. The adjustments are made via back propagation relative to the mean squared error (MSE).

The ICI MLP model is trained using both current and recent cloud masks from the ICI UCA. Predictors include the cloudiness of the ICI pixel for a chosen LOS, cloud fraction for a small region around the LOS, and the cloud fraction of the entire ICI skydome. Cloud inputs include not only the current time, but recent averages going back 60 minutes. The labeled data is the ICI UCA pixel value. Predictions produced by the ICI MLP model predict whether or not the LOS will be cloudy at any time within a forecast range. For example, a 60 minute prediction is the probability that clouds in the LOS will occur anytime within the next hour.

The current ICI MLP model was trained and validated using data from March, 2018 through February, 2021. Performance results are shown for March, 2021 through June, 2022 in Fig. 8. Results show a very high CSI with

little to no bias for all forecast lengths using the same concept of high confidence cloudy, high confidence clear, and uncertain described in the preceding section.

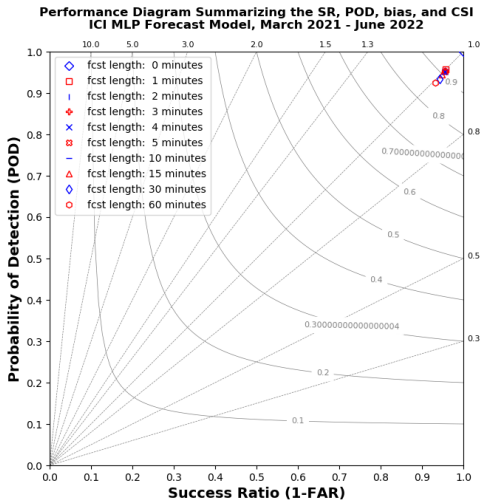

Fig. 8. Roebber diagram showing the performance the ICI MLP model for 0 – 60 minute predictions. Only confident predictions are shown. Markers in the top right corner indicate a perfect forecast. Markers along the diagonal indicate no bias. A clear bias is below and to the right of the diagonal and predictions above and to the left of the diagonal indicate cloudy bias.

The ICI MLP model has been running operationally in real-time at OGS-2 since March, 2022 when the ICI UCA became operational. Predictions are produced every minute and are shown in real-time on an operational website (Fig. 9). The ICI MLP produces a probability of cloud from 0 to 1.0. These probabilities are thresholded, by forecast length, to produce predictions that are confidently clear, confidently cloudy, and uncertain. Thresholds are chosen to maximize CSI and accuracy, while minimizing bias and uncertainty. One-minute predictions have an accuracy above 98%, a CSI of 0.92, and are uncertain only 0.80% of the time; 60-minute predictions have an accuracy close to 95%, a CSI of 0.87, and are uncertain 10.9% of the time.

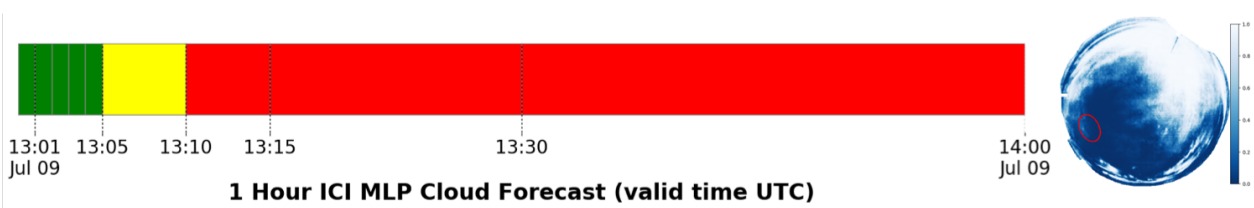

Fig. 9. A real-time ICI MLP prediction from July 2022. The 1-5 minute predictions are for a clear LOS, the 10 minute prediction is uncertain, and the 15-60 minute predictions are cloudy. The ICI image shows the clouds on the right that are predicted to block the LOS within 15 minutes.

While looking at long term statistics is valuable in measuring overall model performance, it is also important to assess how the ICI MLP model performs in real-time. To accomplish this, validation is also done in real-time and figures are posted to our webpage (Fig. 10). Predictions are made every one minute; however, so as not to be overwhelmed with information that does not always change quickly, validation is only shown for predictions at the top of each hour. The validation figure not only shows the forecast, but truth is overlaid. Truth is the mean of the ICI UCA probabilities during the forecast period. Very low probabilities indicate a clear truth; very high probabilities

indicate a cloudy truth; and probabilities in between show a truth that was cloudy, but difficult to forecast: either the clouds were thin and had hard to identify in the UCA, or it was partly cloudy during the forecast period.

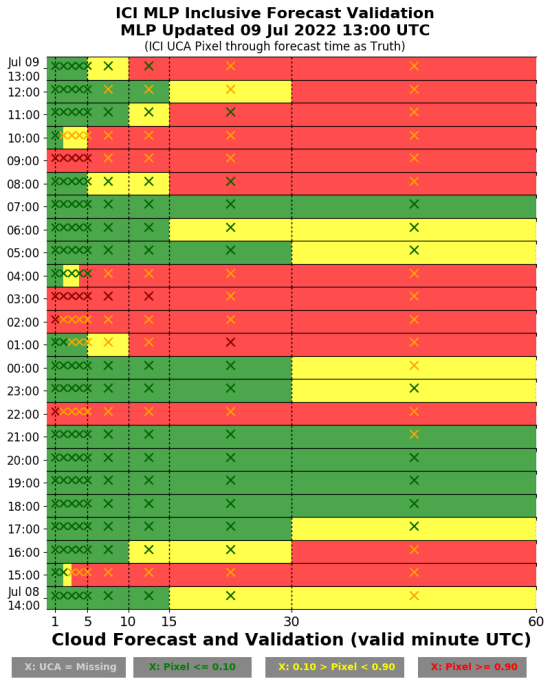

Fig. 10. MLP validation plot from July 2022. The bars show the top of hour predictions from 1-60 minutes. The "X" depicts the truth valid at that time. Green "X"s denote mean UCA probabilities of less than 0.10; red "X"s denote UCA mean probabilities greater than 0.90; and yellow "X"s denote mean probabilities from 0.10-0.90.

4. MID-RANGE CLOUD PREDICTION

Predictions of clouds for the mid-range timescale of zero to two hours at OGS-2 are based on cloud analyses derived from satellite data from the NOAA GOES-17 Advanced Baseline Imager (ABI). Using advanced machine learning approaches, NG developed the GOES-17 U-Net Cloud Analysis (G17 UCA)[4]. The G17 UCA model is a U-Net convolutional neural network trained on data from the ABI's visible channel 2 (0.64µm), shortwave infrared channel 7 (3.9µm), and longwave infrared channel 13 (10.3µm); the United States Geological Survey's (USGS's) GTOPO30 terrain height; and the solar zenith angle. The cloud analyses labeled data consists of binary cloud masks produced as part of a 25-year climatology derived from Geostationary Operational Environmental Satellite (GOES) West satellites, GOES-9, 11, 15, from 1995-2020 [5, 7]. The G17 UCA model has been running operationally over OGS-2 since April 2021 (Fig. 11) and has been shown to outperform NOAA's Binary Cloud Mask (BCM) product.

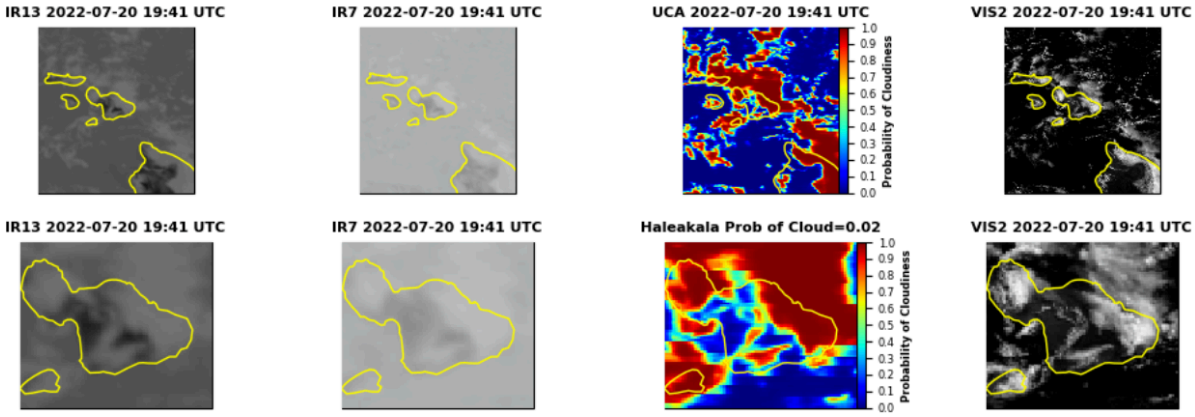

Fig. 11. G17 UCA example. Top row: OGS2 Region, Bottom row: Haleakala summit. From left to right: Infrared Channel 13, Infrared Channel 7, G17 UCA cloud probability, Visible Channel 2.

G17 U-NET CLOUD FORECASTING SYSTEM (G17 UCFS)

The G17 UCFS uses a series of G17 UCA cloud probability arrays (images) to predict future cloud probability arrays. For the operational model currently running for the OGS-2 region, the last two hours of G17 UCA images spanning from the current time to 105 minutes in the past at 15 minute intervals are used to make cloud predictions for 15 minutes in the future out to two hours. This is illustrated in Fig. 12, which shows the eight input UCA images in the top row, the UCFS cloud predictions for the next two hours in the middle row, and the actual UCA cloud images (truth) for the forecast period in the bottom row. The UCFS cloud predictions in the middle row show the probability of cloud for each pixel in the domain. Note how the cloud forecast captures the right-to-left motion while maintaining the clear sky at the summit. If this were a perfect forecast, the middle row and the bottom row would be identical. The ability to predict cloud growth or decay largely depends on whether or not the change is evident in the input frames to the model. The G17 UCFS was trained with 16 months of ICI UCA data from 2020 and 2021 and evaluated on an independent 2 month period.

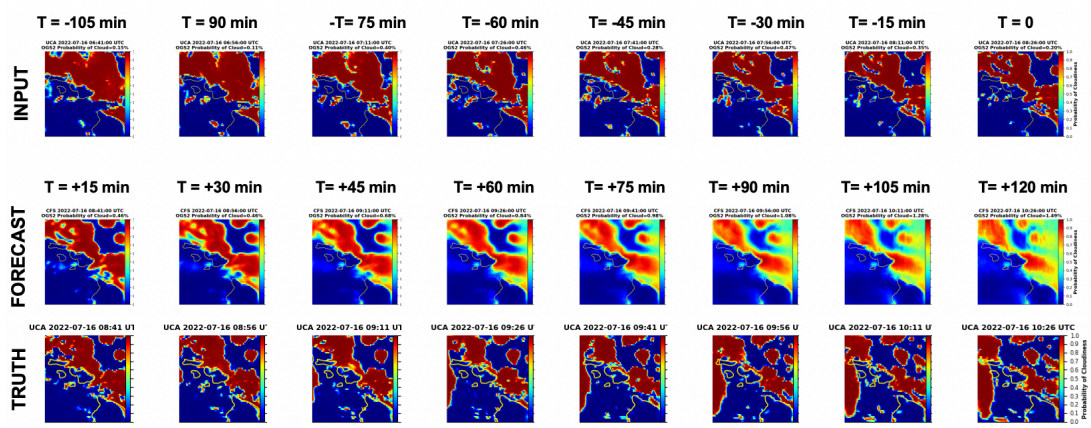

Fig. 12. G17 UCA input data to U-Net model (top row), G17 UCFS model predictions for the following 2 hour period at 15min resolution (middle row), and corresponding G17 UCA valid at the 2 hour forecast period.

The G17 UCFS metric for success is whether or not the UCFS forecast performs better than a persistence forecast, specifically at the Haleakala summit. The Roebber performance statistics for January, 2022 (Fig. 13 left) show that the UCFS beats persistence at all forecast lengths from 15 minutes to two hours with little bias, and that improvement over persistence increases with forecast length. While still beating persistence, overall forecast skill in

June, 2022 (Fig. 13 right) is lower than January due to the variable nature of clouds in the summer at Haleakala when the trade wind pattern can break down allowing clouds to breach the summit.

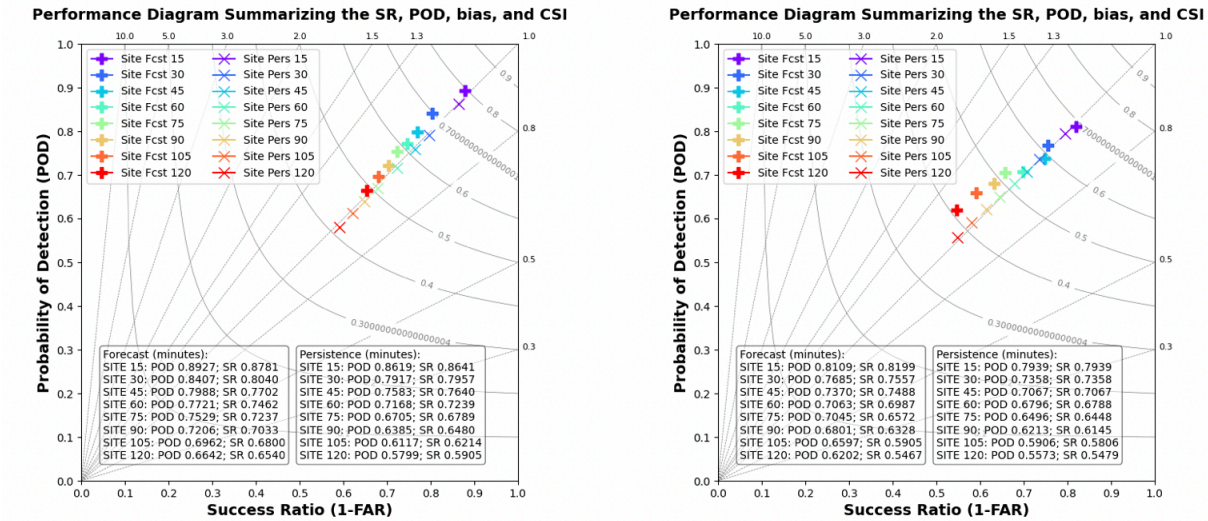

Fig. 13. Roebber statistics for forecast lengths 15 to 120 minutes for January 2022 (left) and June 2022 (right). The ICI UCFS predictions are represented by "+", and the persistence predictions are represented by "X".

The G17 UCA and the UCFS are both running operationally as of April, 2021. The NOAA GOES-17 data is ingested every five minutes, processed, and then inferenced using the U-Net UCA model to produce a real-time cloud analysis. This cloud analysis, along with the previous seven cloud analyses at 15 minute resolution, are used as input to the UCFS model, which then produces a real-time prediction out to two hours. Animations of the cloud analyses and predictions are created for each new G17 image (every five minutes). In addition, a validation graphic is generated for every G17 image processed, providing a quick look at how well the G17 UCFS is performing. An example of this is shown in Fig. 14. In this figure, the background colors (green, yellow, and red) represent the G17 UCFS cloud prediction for the next two hours at the Haleakala summit, where each row is a separate two hour forecast with the most recent forecast shown in the top row, and the forecast from four hours in the past is in the bottom row. In this example, the G17 UCFS was predicting clear conditions early in the period (bottom half of the figure), and cloudy or uncertain conditions in the more recent predictions. The actual cloud conditions are represented by the "X" in each box which is based on the in situ measurements by the ICI at OGS-2. A green "X" indicates the actual LOS was clear, while a red (yellow) "X" shows the LOS was actually cloudy (uncertain). This product provides a synopsis of how well the cloud predictions have been performing over the last four hours.

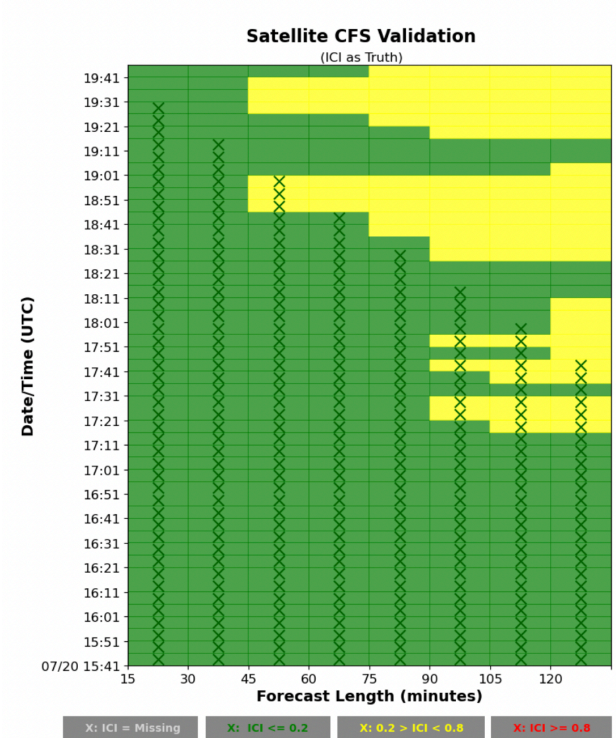

Fig. 14. UCFS validation plot from July 2022 comparing the 15 to 120-minute forecast cloud probability (background colors) and the actual occurrence of clouds represented by the "X" symbols. Green represents high confidence clear, red represents high confidence cloudy, and yellow indicates an uncertain cloud forecast.

5. LONG-RANGE CLOUD PREDICTION

The best approach to long term forecasting is to use Numerical Weather Prediction (NWP). NWP models use sophisticated dynamical models to predict meteorological variables within a regional or global grid, and are used by weather agencies to make daily weather predictions. However, these global and regional weather predictions are generally too coarse in spatial resolution to provide enough accuracy at the highly local scale that is required for space-based laser and surveillance applications. This work shows the benefit of applying an AI technique to the predictions of a high-resolution, regional NWP model.

For this work, a modified version of the Weather Research and Forecasting (WRF) model version 3.6 [8] is used to produce high resolution predictions of meteorological parameters, including clouds, over the summit of Haleakala [9]. The WRF model configuration consists of an outer domain run at 9-km resolution that contains much of the central Tropical Pacific Ocean, a regional 3-km grid centered on the Hawaiian Islands, an inner 1-km grid that contains the island of Maui and neighboring islands, and a 1/3-km resolution grid centered on the summit of Haleakala. All domains have 81 vertical levels with a resolution of approximately 50-100 m below 2 km above ground level (AGL), 150-250 m for 2–13 km AGL, and 500 m up to the model top (50 millibars). The high horizontal and vertical resolutions described here allow for more accurate forecasting of the fine-scale atmospheric circulations around Haleakala whose local meteorology is heavily influenced by the complex topography.

After the WRF predictions have been made, a MLP model is used to optimize the WRF cloud forecast at the Haleakala summit by training only on data at and surrounding the summit pixel from the WRF domain. Predictors include all surface and selected three dimensional parameters extracted from WRF forecast files. Predictors include clouds and variables including temperature, dew point, winds, and relative humidity both at the surface and different vertical levels above the summit. The MLP is trained and validated using WRF predictors from September, 2017, through September, 2021. Only forecasts for 12-48 hours are used for LCRD purposes because the WRF model needs to wait for initial conditions, and because it takes several hours to run. The WRF MLP has been running in real-time since October, 2021 and results are shown from October through June, 2022. The WRF MLP produces a

probability of cloud from 0 to 1.0. These probabilities are thresholded to produce predictions that are confidently clear, confidently cloudy, and uncertain. Thresholds are chosen to maximize CSI and accuracy, while minimizing bias and uncertainty. The clear threshold is placed at 0.25 and the cloudy threshold at 0.60. With these thresholds, predictions have a CSI of 0.61, an accuracy of 84.25%, a bias of 1.20, and are uncertain ~23% of the time.

The WRF MLP outperforms the original WRF forecast at the Haleakala summit for all forecast times. The original WRF has been shown to under-predict clouds (have a clear bias). The WRF MLP has a cloudy bias. This is due, in part to WRF predicting some of the high thin clouds that the ICI UCA tends not to resolve. The overall CSI and accuracy is higher for the WRF MLP than the original WRF. Fig. 10 shows the Roebber statistics for both the original WRF predictions and the WRF MLP. Truth is the mean ICI UCA skydome cloud amount at +/- 15 minutes from the valid forecast time. The individual WRF forecast times tend to have similar statistics, and are not very dependent on forecast length; there is also not a large sample size when looking at individual forecast lengths. Fig. 15 shows 12, 24, 36 and 48 hours, but the most representative results are those from all predictions.

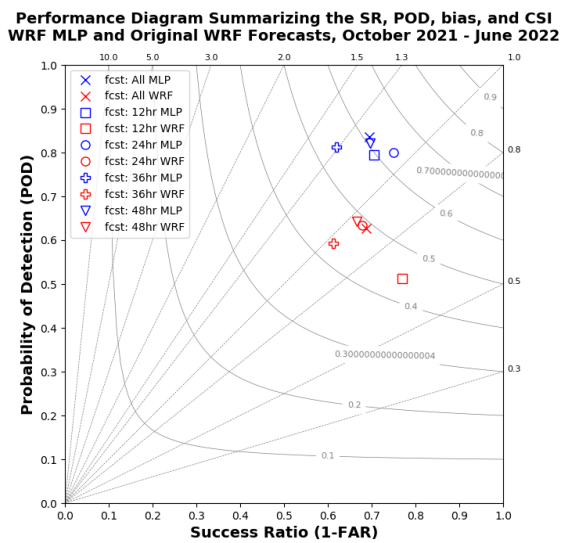

Fig. 15. Roebber plot showing the performance the WRF MLP model (blue) and the original WRF model (red) for all predictions (X), and for 12, 24, 36, and 48 hour predictions. Only confident predictions are shown. Markers in the top right corner indicate a perfect forecast. Markers along the diagonal indicate no bias. A clear bias is below and to the right of the diagonal and predictions above and to the left of the diagonal indicate cloudy bias.

Long term forecasting is important to real-time lasercom operations. It is essential to know in advance if the site is likely to be down for a long period of time, if there will be a long stretch of clear sky, or if a partly cloudy period is expected. Two weeks of WRF predictions along with forecast validation are displayed on an operational website to track these stretches of time and assess how well the model forecasted these times. Fig. 16 shows a sample validation plot. Many WRF predictions, especially during times of changing weather patterns are considered uncertain

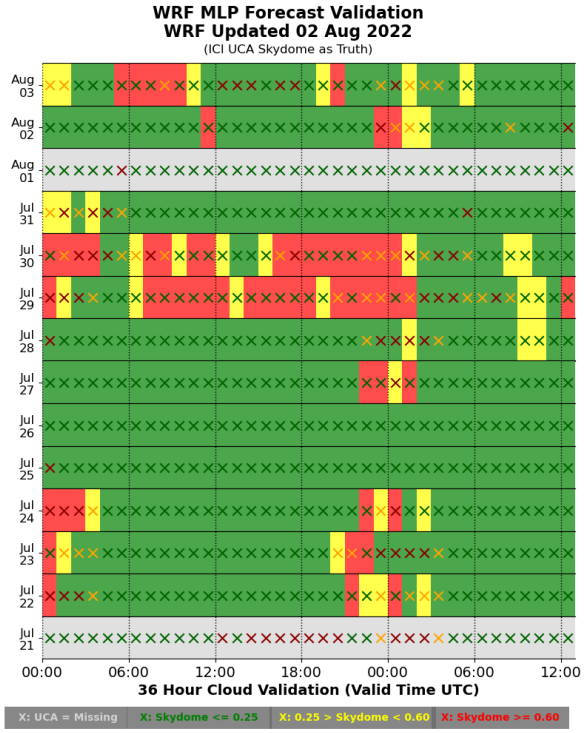

Fig. 16. A real-time WRF MLP validation product from June 30, 2022. The bars show each daily forecast from 12-48 hours. The "X" depicts the truth valid at that time. Green "X"s denote mean UCA cloud amount of less than 0.25; red "X"s denote mean UCA cloud amount greater than 0.60; and yellow "X"s denote probabilities from 0.25-0.60.

6. LINK CHARACTERIZATION

While the use of local measurements to verify model cloud predictions is beneficial, the ability to compare to link telemetry is the ultimate metric of accuracy. NG had the opportunity to observe link operations at OGS-2 under various atmospheric conditions, ranging from high thin cirrus moving at 65 knots to mid-level cumulus clouds and then slow moving, dense low clouds that produced precipitation. Two link parameters were observed and qualitatively compared to the predictions: received power and bit error rate (BER). In many cases the downlink was maintained through clouds with transmission loss less than 6 dB as estimated by the CL51 backscatter profile relative to zenith. Quality of signal as measured by the BER during cloudy periods fluctuated greatly, but values less than $10e^{-4}$ were maintained until the link was lost due to clouds. It should be noted that error free communications were often observed during times when the estimated cloud attenuation was on the order of 1-2 dB.

Using in situ data, NG is able to provide both quantitative and visual context of the types of clouds causing attenuation to the optical signal. The zenith pointing CL51 provides critical information on the density of clouds through the backscatter profile from which transmission loss is estimated. While the CL51 is not pointed directly at LCRD, the zenith pointing CL51 provides a good estimate of transmission loss, which can be scaled to the 30° elevation angle of LCRD. Analysis of the ICI imagery has shown a high degree of correlation of clouds between zenith and 30°. However, when cloudiness across the skydome is not homogeneous, there are cases when the zenith pixel may be clear while the LOS to LCRD is cloudy and vice versa. Fortunately, the ICI sky radiance imagery produced every minute provides a visual context of clouds moving across the skydome, and shows when either or both LCRD and zenith pixels are impacted by clouds. The temporal correlation of clouds between the LCRD LOS and zenith is also high, so what is observed in the LOS is generally captured by the CL51 seconds before or after.

Fig. 17 highlights an example from OGS-2 on June 27, 2022, when the optical signal was lost due to a mid-level alto-cumulus cloud at 19:32 UTC (9:32AM HST). The optical link remained down for six minutes until 19:38 UTC. When the LOS was lost at 19:32 UTC, the CL51 fade estimate was only 0.45 dB or ~1 dB when corrected for

elevation angle, and when the link was reestablished at 19:38 UTC, the CL51 transmission loss was 3.25 dB or 6.5 dB when corrected for zenith angle. In this case, there was a 6-minute time lag until the cloud deck that caused the signal loss moved through zenith (Fig. 17 lower right), which explains why the transmission loss was offset. However, the corresponding ICI sky radiance images at 19:32 UTC (Fig. 17 upper right) and at 19:38 UTC (Fig 17 lower right) confirm that clouds covered the LOS and not the zenith pixel when the link was lost and that the LOS had only thin clouds when the link was reestablished. The CL51 measured losses greater than 2.5 dB (>= 5 dB corrected for elevation angle) for over 4 minutes. The short-term ICI UCFS model (Fig. 18), which predicts clouds out to ten minutes, correctly began predicting that clouds would impact the LOS at 19:32 UTC, eight minutes prior to the actual outage. The model also began predicting that the LOS would become cloud free at 19:41, 10 minutes earlier at 19:31 UTC.

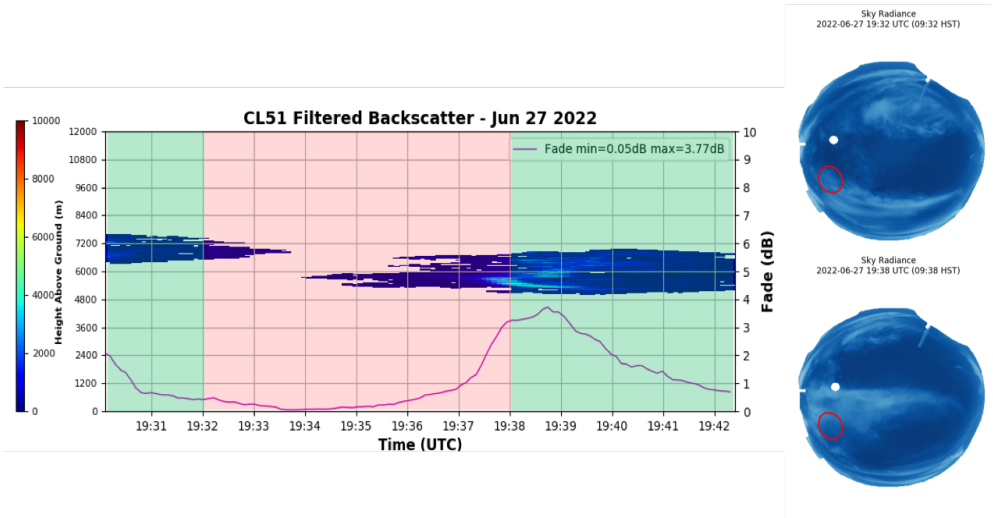

Fig. 17. OGS-2 CL51 backscatter and transmission loss used to compare to the downlink. Red shaded area highlights outage from 19:32-19:38UTC. Green shaded area highlights when link was reestablished at 19:38 UTC and remained active through 20:00 UTC. ICI (upper right) sky radiance (upper right) shows clouds impacting line of sight when the link was lost. ICI (lower right) sky radiance shows thin clouds at LCRD when the link was reestablished.

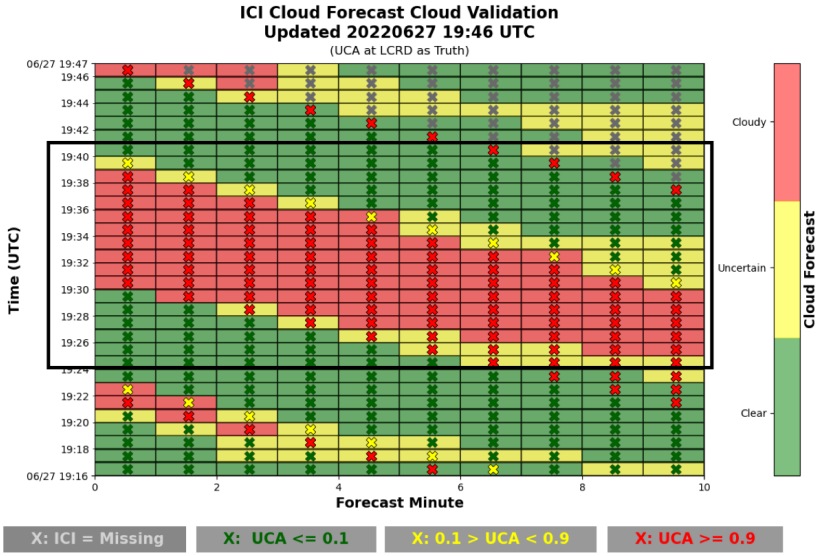

Fig. 18. ICI UCFS validation plot. ICI UCFS model correctly began predicting clouds to impact LCRD starting at 19:24 UTC, eight minutes prior to when clouds actually obscured the LOS at 19:32 UTC. ICI UCFS model also correctly predicted that LOS would be cloud free at 19:41 UTC, ten minutes earlier at 19:31 UTC.

7. DISCUSSION AND SUMMARY

The accurate characterization and prediction of atmospherics, and clouds in particular, is vital to space-based laser and surveillance applications. The ability to predict clouds at different time scales from zero to 48 hours directly impacts mission decisions, from minute-to-minute link handover decisions, to longer-range schedule and maintenance planning. The continued development of NG's model prediction system demonstrates that AI-powered cloud predictions consistently and significantly outperform both persistence and NWP cloud predictions. Validation efforts based on in situ and LCRD data highlight the models' accuracies and abilities to support optical missions. These efforts also provide vital feedback to further improve model capabilities.

The AMS at OGS-2 is the source of a growing archive of in situ data that along with space-based atmospheric data has been used to develop a state-of-the-art prediction system that generates high-resolution predictions of atmospheric attenuation to support decision aids for space-based laser and surveillance applications. NG's cloud prediction modeling system supports three distinct time scales. For short-range predictions, two models are used to provide predictions out to 10 minutes and 60 minutes, the deep learning model ICI UCFS and the MLP model, respectively. For mid-range predictions out to two hours, the satellite-based G17 U-Net cloud analysis and forecast system is used. Finally, long-range cloud predictions are based on the AI enhanced WRF model cloud predictions at the Haleakala summit for predictions out to 48 hours.

Validation efforts using in situ data at OGS-2 provide real-time verification of accuracy and essential information on how models may be improved in the future. Recent efforts to compare predictions to the LCRD downlink are directly impacting ongoing modeling improvements. This effort also enhances the understanding of the limits of optical communication due to atmospherics which is critical for link budget planning and mission operations. As LCRD telemetry becomes more widely available, a larger scale quantitative analysis of the prediction system will be performed.

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