PROBABILISTIC FORECASTS OF SOLAR INSOLATION

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ABSTRACT

Meteorological forecasts of incident solar radiation are valuable for solar resource owners and others. Most previously described forecast methods provide a single predicted value. However, a well-calibrated forecast probability distribution is more useful in that it could be used to make optimum decisions under any decision rule. We demonstrate methods of constructing and evaluating probabilistic forecasts of cloudiness (as observed from geostationary satellites) for a given location by combining climatology with weather prediction model output. We use metrics from information theory for forecast skill assessment. We consider two locations, New York City (representing a moist temperate climate) and Nevada (representing a sunny desert climate). We find that probabilistic forecasts conditioned on weather prediction model output improve on climatology at both locations. At Nevada the key limitation for accurate forecasts appears to be the weather model's representation of cloudiness, while at New York weather predictability is also important.

1. INTRODUCTION

An increasingly integrated power grid together with enhanced computational and load management capabilities increase the value and necessity for supply and demand forecasts. Meteorology plays a particularly critical role in solar and wind power generation [1]. Here, we concentrate on deriving one-day-ahead forecasts of cloudiness, based on combining climatology and numerical weather prediction, to aid in solar power deployment.

Most previous studies of cloudiness forecasts for solar applications have assessed deterministic (point) forecasts. Such studies used for forecast calibration and assessment measures of accuracy such as mean square error and bias that are suitable for comparing point forecasts with subsequent observations [2–10]. However, in recognition of the value for decision making of explicit, well-calibrated assessments of uncertainty, here we construct fully probabilistic forecasts. We use measures of accuracy suitable for assessing the correspondence of a forecast probability distribution (PDF) with the subsequent observation, notably the information gain (IG; measured in bits) of a forecast PDF compared to a baseline "no-skill" PDF [11, 12].

2. BACKGROUND AND NOTATION

Consider a probabilistic forecast $p(x)$ for the value of a meteorological quantity of interest x (at a specific place and time). This forecast is a probability mass function if the possible range of x (perhaps suitably discretized) has finitely many values, in which case $p(x)$ can be expressed as a vector, the elements of which are nonnegative and sum to 1, containing the probability of each possible outcome x_i. If x is a continuous variable, its forecast $p(x)$ would be a probability density function. Here, we will assume that the variables of interest have finitely many possible values and forecasts are in the form of probability mass functions, though generalization to continuous variables is possible. Let x_o be the observed outcome. A perfect probabilistic forecast $p_{\text{perfect}}(x)$ would be one where $p(x_o) = 1$ and

$p(x_i) = 0$ for all other $x_i \neq x_o$. Also, a baseline or little-skill forecast $p_{\text{baseline}}(x)$ can be defined, perhaps one that specifies equal chances for each possible outcome or one that is based on previous experience at the site (climatology). In general, how good a probabilistic forecast is can be quantified by evaluating how close $p(x_o)$ is to 1 – that is, how much confidence is put on the forecast of the right event. A measure based on information theory is relative entropy (RE), equivalent to the Kullback-Liebler divergence between the forecast and observation:

$$\text{RE} = -\log(p(x_o)), \tag{1}$$

RE is nonnegative; it is zero for a perfect forecast, and in general should be "small" for a good forecast. We define the forecast system's mean information gain or IG as the expected difference in RE between it and a baseline forecast, which in practice is estimated by averaging RE over many forecast times or places:

$$\langle \text{IG} \rangle = \langle \text{RE}_{\text{baseline}} - \text{RE} \rangle. \tag{2}$$

$\langle \text{IG} \rangle$ has information units such as bits (depending on the base of the logarithm taken in Eq. 1), and should be positive for a forecast system that is skillful (that is, better than the baseline forecast). A normalized measure of forecast skill relative to a hypothetical perfect forecast is offered by the information skill score (ISS):

$$\text{ISS} = \frac{\langle \text{IG} \rangle}{\langle \text{IG}_{\text{baseline}} \rangle}. \tag{3}$$

ISS is zero for the baseline forecast and 1 for a perfect forecast.

3. DATA AND METHODS

As an example of generating and evaluating probabilistic forecasts for solar energy application, we consider forecasting daytime cloudiness, defined as $C = 1 - \exp(-\text{COD})$, where COD is cloud optical depth. C ranges from 0 for clear skies to almost 1 under thick clouds, and $1 - C$ is the factor by which clouds are expected to decrease direct solar irradiance at the surface. We chose locations in Nevada (NV, 38°N 118°W) and near New York City (NYC, 40.8°N 74°W), representing desert (less cloudy) and temperate midlatitude (more cloudy) conditions respectively. We considered data from 2005-2007, with the first two years used for forecast calibration and the last year for forecast validation. COD data were obtained from geostationary satellite images at visible wavelengths as processed by the International Satellite Cloud Climatology Project (ISCCP). For this exploratory study we used ISCCP cloudiness data as our 'observations' since ground-based cloudiness data are not publicly available for many locations of interest, while ISCCP data are available almost globally over the period 1983-2009 at a horizontal resolution of about 30 km (though here we averaged pixels adjacent to the closest one to our study sites, so the effective resolution was closer to 90 km) and a time resolution of 3 hours and have been validated against surface observations [13, 14]. The ISCCP algorithm (or other, similar ones) could be applied in near real time to estimate cloudiness for locations of interest from geostationary satellite feeds [15]. Cloudiness is well correlated with surface solar irradiance and therefore has a strong impact on solar power output, although other factors such as haze could also play a role at particular sites, and global solar irradiance decreases less rapidly than $1 - C$ for high values of COD [2, 16].

The North American Mesoscale Model (NAM) is a numerical weather prediction model run every 6 hours on a 12 km grid by the National Environment and Climate Prediction (NCEP) center (`http://www.emc.ncep.noaa.gov/index.php?branch=NAM`). It is useful for climatological work due to its long operational history dating back to 1979. When a weather model field is combined with current observational data, the result is called an 'analysis'; it is considered the best representation of the atmosphere possible for the set of incorporated observations, and is used to initialize forecasts. In this work, cloud fraction in the NAM analysis is used to compare current conditions captured by the model to cloud observations from ISCCP, serving as a baseline for comparisons with NAM forecasts. Since satellite observations of cloud cover are not currently included in weather model analysis [17], the work described below is a comparison of two independent data sets.

The ISCCP cloudiness was discretized into 10 bins each of width 0.1. To test the developed methodology, we considered 'forecasting' cloudiness for the validation period based on either (a) climatology – the calibration period frequency distribution; (b) analysis – the calibration period frequency distribution conditional on NAM analysis (nowcast) cloud fraction category; or (c) 24-hour prediction – the calibration period frequency distribution conditional on NAM cloud fraction category as probabilistically forecast using the 24-hour NAM forecast. These three hindcasts are designated Climatology, Analysis, Prediction respectively. Since archived 24-hour NAM forecasts were not available for the 2005-2007 period, they were simulated based on the analysis-forecast confusion matrix derived for pairs of forecasts and validating analyses from July-November 2013.

4. RESULTS AND DISCUSSION

The climatological frequency distribution of cloudiness according to ISCCP is shown in Figure 1ab. Cloudy skies are much more common in NYC, but slightly cloudy

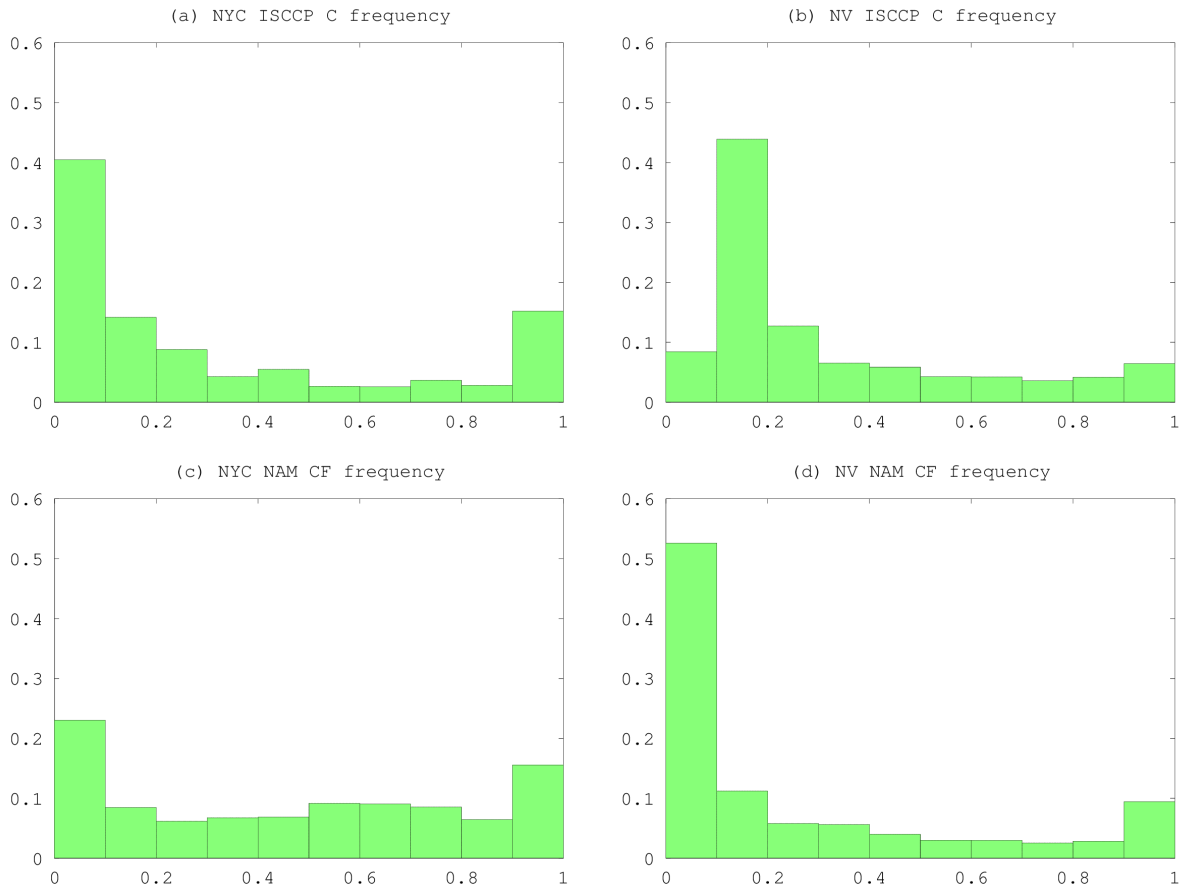

Figure 1: (a, c) Histograms of ISCCP cloudiness and NWP analysis cloud fraction, respectively, over 2005-2006 for NYC. (b, d) Same, but for NV.

conditions (*C* between 0.1 and 0.2) are more common in the NV site, perhaps due to the mountain ranges nearby. The NAM analysis cloud fraction frequencies largely reproduce the difference between the locations (Figure 1cd).

NWP analysis cloud fraction is imperfectly correlated with ISCCP cloudiness at the same location (Figure 2ab). In particular, there are many times for which the analysis shows cloud cover while ISCCP does not. The correlation in cloud fraction between the NAM analysis and the previous day's forecast tends to be better but is also imperfect, with occasional times where the analysis shows full cloud cover although clear conditions were forecast or vice versa (Figure 2cd).

Despite the inconsistent ability of the NAM analysis to capture cloudiness as seen by ISCCP, the conditional frequency distribution of ISCCP cloudiness for analysis predictions of clear versus cloudy conditions are quite different (Figure 3ab). In particular, ISCCP cloudiness is very unlikely if the analysis indicates clear conditions, although even if the analysis indicates cloudy conditions, ISCCP may not show much cloudiness (Figure 3ab). Accounting for the degradation in NAM accuracy caused by predicting 24 hours ahead slightly weakens these differences, particularly for NYC (Figure 3cd), but there remains a difference in the conditional frequency that can be exploited for improving the skill of probabilistic forecasts.

Applying RE to quantify the probabilistic forecast skill over the validation period, we find that the two locations have similar variability in cloudiness, as reflected in the larger RE for Climatology compared to the desert location (Table 1). The ISS for the Analysis-based 'forecast', which quantifies the degree to which the NWP analysis captures the cloudiness, is somewhat greater for the desert site, and similar in magnitude to that previous found for probabilistic seasonal forecasts of temperature and precipitation [12]. The ISS for the Prediction-based forecast, which also includes the effect of weather-prediction error, was degraded by only about 10% compared to analysis at the desert location, but

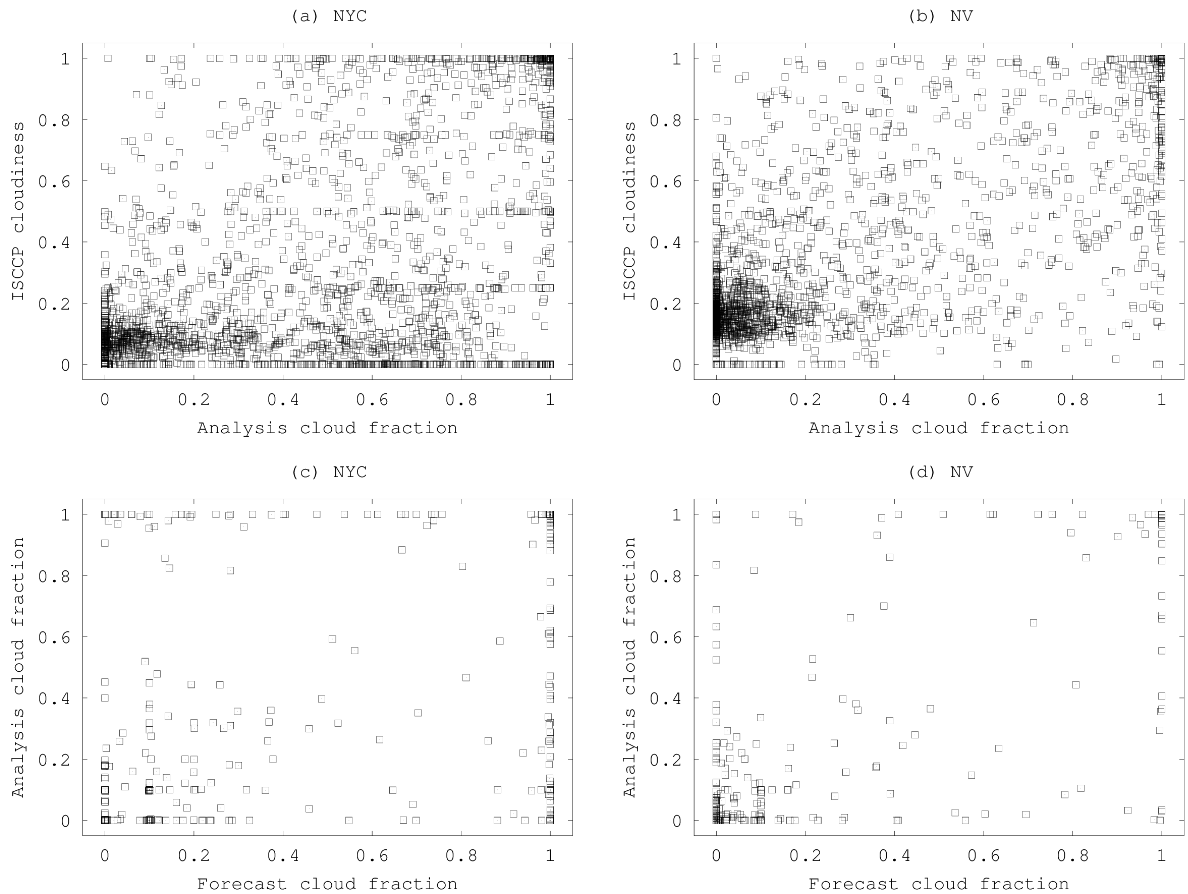

Figure 2: (a, c) Scatter plots of NAM analysis cloud fraction versus ISCCP cloudiness (for 2005-2006) and NAM 24-hour forecast versus analysis cloud fraction (for 2013), respectively, for NYC. (b, d) Same, but for NV.

reduced by over two-thirds at NYC, perhaps reflecting greater synoptic variability and lower predictability in weather there (Table 1).

Cloudiness has a strong seasonal cycle at both locations, with more clouds in winter (Figure 4ab). More interestingly, when plotted by month over the one-year validation period, the mean IG for the Analysis and Prediction forecasts appears to show pronounced variability between months (Figure 4cd), and is for example at NYC much lower in January, February, March, and August than in other months. If this variability is confirmed over more validation years, it would suggest the need for seasonally specific conditional distributions of cloudiness. Basing forecasts on an ensemble of weather model predictions may also improve skill compared to using a single model run, similar to what is found for climate prediction [18]. In the longer term, improving the representation of clouds in weather models via comparison with cloud and radiation observations [19] should also improve forecast skill for solar applications.

5. CONCLUSIONS

We have presented a methodology for constructing probabilistic forecasts of cloudiness based on climatology and on numerical weather prediction model outputs. Our Prediction forecast could be generated almost 24 hours in advance from current model output and appears to be informative particularly in desert locations. Depending on the availability of calibration data, forecasts employing this methodology could be tailored to site-specific conditions and variables that affect solar power decision making. Such probabilistic forecasts are well suited for risk assessment and optimization of complex renewable energy supply and demand systems.

6. ACKNOWLEDGMENTS

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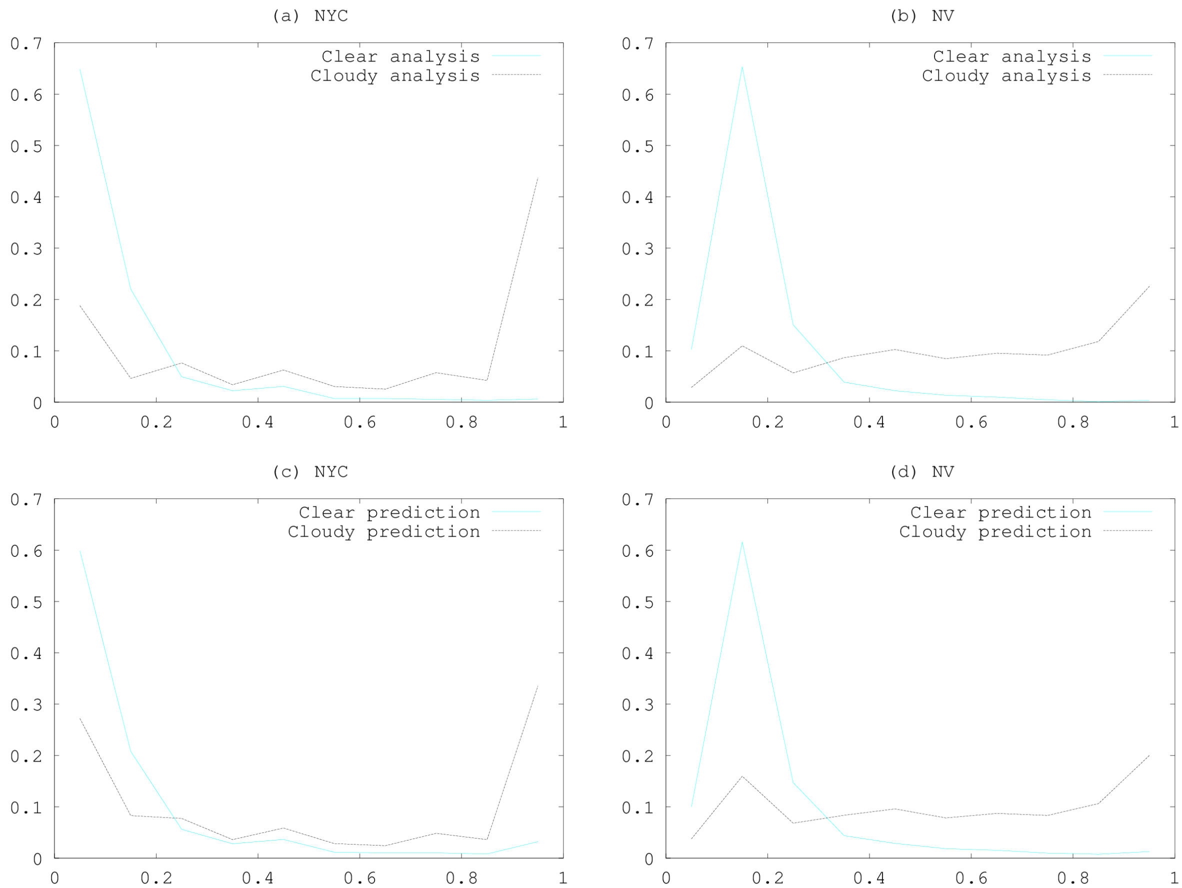

Figure 3: (a, c) Frequency distributions of ISCCP cloudiness for clear versus cloudy conditions as indicated by the NAM analysis and forecast, respectively, for NYC. (b, d) Same, but for NV.

All statements made are the views of the authors and not the opinions of the funding agency or the U.S. government.

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Table 1: SKILL SCORES FOR CLOUDINESS FORECASTS

	NYC			NV		
	RE	IG	ISS	RE	IG	ISS
Climatology	2.628	0	0	2.614	0	0
Analysis	2.457	0.171	0.065	2.368	0.246	0.094
Prediction	2.574	0.054	0.021	2.393	0.220	0.084

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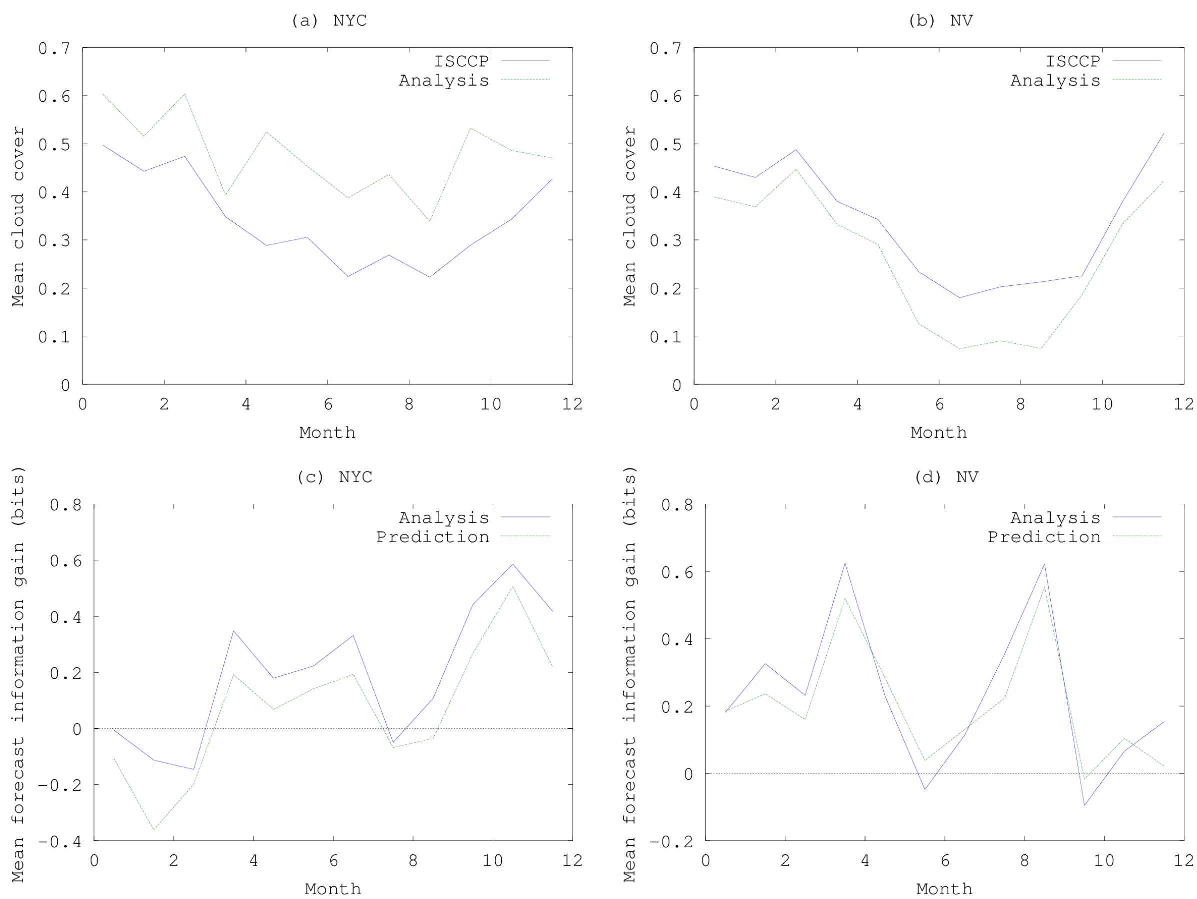

Figure 4: (a, c) Seasonal cycle of cloudiness (2005-2006) and of forecast mean information gain (2007), respectively, for NYC. (b, d) Same, but for NV.