Variability of Net Longwave Radiation Over the Eastern North Pacific Ocean

D. A. Siegel and T. D. Dickey

Ocean Physics Group, Department of Geological Sciences, University of Southern California, Los Angeles

The net longwave radiation at the sea surface (\(\text{LW}_\downarrow\)) was measured over the eastern North Pacific Ocean for 22 days during the fall of 1982. These measurements were made from the R/P FLIP as part of the Optical Dynamics Experiment. The mean \(\text{LW}_\downarrow\) emitted from the sea surface was 52.0 W/m\(^2\) with a variance of 802.6 W\(^2\)/m\(^4\). The largest fraction of the variance was observed to be in the diurnal frequency band. \(\text{LW}_\downarrow\) and the total cloud amount exhibited significant diurnal cycles (amplitudes of 13.5 W/m\(^2\) and 7%, respectively) which were negatively correlated. \(\text{LW}_\downarrow\) measurements were compared with values obtained from seven different bulk formulas for \(\text{LW}_\downarrow\) in order to evaluate their predictive capabilities. These formulas predict less than 45% of \(\text{LW}_\downarrow\) variance, indicating that these methods are inadequate for the description of \(\text{LW}_\downarrow\) variability. Statistical predictions were made using linear hindcastors to examine the relationships between \(\text{LW}_\downarrow\) and other surface meteorological and oceanographic parameters. The signs and magnitudes of the arbitrary coefficients in the linear hindcastors are consistent with hypotheses used for a conceptual model of radiant heat transfer between two parallel gray plates through an interacting medium. The highest predictive skill levels (54.3–55.3% of the variance explained) occur for the case of a two component linear hindcastor where both the cloud layer and the water vapor concentration above the sea surface are taken into account. The success of the statistical predictions indicates that the fundamental physics relevant to \(\text{LW}_\downarrow\) variability are incorporated in the conceptual parallel plate model.

INTRODUCTION

The net longwave heat flux at the sea surface is the difference between the radiative flux of longwave electromagnetic energy (wavelengths greater than 2.5 \(\mu\)m) radiated upward from the sea surface and that radiated downward from the atmosphere. The longwave heat flux emitted from the sea surface is the graybody radiation from the surface skin of the ocean, while the flux emitted from the atmosphere is comprised primarily of graybody radiation from cloud layers. The component of the longwave radiation heat flux from space is negligible [Stephens et al., 1981]. Complicating a rather simple model of net radiative heat transfer between two parallel gray plates is the absorbing and emitting atmosphere. Major atmospheric absorbers and emitters of longwave energy include water vapor, carbon dioxide, ozone, and methane. The concentrations of these constituents vary both spatially and temporally. Another complicating factor is the spatial and temporal variability observed in cloud layers. The prediction of net longwave radiative heat flux thus requires consideration of the contributions by three components: the sea surface, clouds, and the atmosphere.

The net longwave heat flux, \(\text{LW}_\downarrow\), is one of four components in the air-sea heat flux balance,

\[
\text{Q}_\text{s} = \text{SH}_\downarrow + \text{LW}_\downarrow + Q_{\text{LS}} + Q_{\text{EX}}
\]

where \(Q_s\) is the total net heat flux; \(\text{SH}_\downarrow\) is the net solar (shortwave) radiative flux; \(Q_{\text{LS}}\) is the latent heat flux; and \(Q_{\text{EX}}\) is the sensible heat flux. Studies of the sea surface heat flux balance in mid-latitude oceans show that \(\text{LW}_\downarrow\) is generally the third largest term in the mean balance and is smaller than both the net solar (\(\text{SH}_\downarrow\)) and the latent (\(Q_{\text{LS}}\)) heat fluxes. This has been demonstrated for interannual time scales (\(T > 10\) years) by Smith and Dobson [1984] for Ocean Weather Stations (OWS) Papa (50°N, 145°W) and Bravo (56°N, 140°W), and by Dorman et al. [1974], for OWS November (30°N, 140°W). The magnitude of \(\text{LW}_\downarrow\) is important when the total net heat flux (\(Q_s\)) is to be determined. Since local changes in the upper ocean heat content are primarily determined by the flux of heat across the sea surface, adequate determination of the variability of each component in the surface heat flux budget is of great importance for the prediction and characterization of properties of the upper layers of the ocean.

There have been several previous experiments which have measured \(\text{LW}_\downarrow\) over the sea surface [Swinbank, 1963; Charnell, 1967; Paltridge, 1969; Schooley, 1969; Reed and Halpern, 1975; Reed, 1975, 1976; Simpson and Paulson, 1979, hereafter SP, 1979]. Also Lind et al. [1984] have measured downwelling longwave irradiance over the North Atlantic Ocean. Only two previous studies [Paltridge, 1969; SP, 1979] report observations made with an instrument designed to directly measure the net longwave flux during both day and night. Others report observations of \(\text{LW}_\downarrow\) as determined from indirect methods. An indirect method requires the measurement of the net allwave and shortwave radiative fluxes and the subtraction of the two in order to estimate the net longwave flux. An absolute, relative, or spectral calibration error associated with any of the individual sensors will produce error in the indirectly determined \(\text{LW}_\downarrow\).

Previous determinations of \(\text{LW}_\downarrow\) have been used to test clear sky bulk formulas (\(\text{LW}_\downarrow\) modeled for clear sky conditions is denoted as \(\text{LW}_{\text{CS}}\)). These formulas, which are presented in Table 1 (without the cloud correction terms), have been utilized for most upper ocean heat budget experiments. Previous results indicate that bulk formulas are adequate for many purposes, but some appear to perform better than others in particular situations [Reed, 1976; SP, 1979; and Fung et al., 1984, hereafter FHI, 1984]. The evaluation of the performances of these bulk formulas in predicting the variability of \(\text{LW}_\downarrow\) has received little attention previously.
In the following, observations and analysis of \( \text{LW} \uparrow \downarrow \) data taken from R/P FLIP during the Optical Dynamics Experiment (ODEX) in the fall of 1982 in the northeast Pacific Ocean are presented. A conceptual model of \( \text{LW} \uparrow \downarrow \) based upon radiant heat transfer between two parallel gray plates separated by an emitting and absorbing medium is described. Using this model, hypotheses are developed concerning the variability of \( \text{LW} \uparrow \downarrow \). Statistical prediction techniques [e.g., Davis, 1977] are employed to test these hypotheses. Also, a comparison of \( \text{LW} \uparrow \downarrow \) data with values obtained from bulk formulas is discussed. Readers familiar with radiative processes over the ocean and statistical prediction techniques may wish to advance to the instrumentation and techniques section.

**Parallel Plate Model**

\( \text{LW} \uparrow \downarrow \) is dependent upon sea surface temperature, the cloud layer conditions, and the vertical structure of atmospheric properties. A conceptual model of radiant heat transfer between two parallel gray plates separated by an absorbing and emitting medium facilitates the discussion of the response of \( \text{LW} \uparrow \downarrow \) to atmospheric and oceanographic variability. The two parallel plates are represented by the sea surface and the lowest cloud layer, while the absorbing and emitting medium is described by the vertical profiles of water vapor and temperature.

\( \text{LW} \uparrow \downarrow \) for this model is the net longwave flux at the bottom parallel plate. The upwelling longwave flux at the sea surface is comprised of graybody emission from the interface and of the reflected downwelling component. The downwelling flux consists of the emission of longwave energy from the cloud layer as modulated by the absorbing and emitting atmosphere.

The bottom parallel plate is the sea surface. As the sea surface warms, the amount of radiation emitted increases in proportion to its absolute temperature raised to the fourth power, thus \( \text{LW} \uparrow \downarrow \) increases. The reflection of the downwelling flux by the sea surface is not important in the present analysis because it is less than 5% of the downwelling flux [Liu and Katsaros, 1984].

The emissivity of the sea surface (\( \varepsilon \)) is 0.98 ± 0.02. The observed variability of the sea surface emissivity may be attributed to either natural variability (sea state, surface films, etc.) or instrumentation errors. This factor is not important for the present analysis, since \( \varepsilon \) varies by only a few percent [Katsaros, 1980; FHL, 1984].

The description of the cloud layer as a parallel plate is more problematic. Cloud characteristics (type, shape, thickness, cloud base altitude, temperature, effective emissivity, etc.) are all observed to vary greatly in both space and time on extremely short scales (e.g., \( O(100 \text{ m}) \) and \( O(10 \text{ min}) \)). For the present problem, the effective emissivity and the temperature of the cloud layer are needed to estimate the graybody emissions.

Further justification for the modeling of cloud layers as a single opaque gray plate is provided by the computations presented in the work by FHL [1984]. FHL studied the effects of atmospheric structure and clouds on \( \text{LW} \uparrow \downarrow \) using a numerical model based on the radiative transfer equation. They found that for a cloud thickness greater than 4 optical units, \( \text{LW} \uparrow \downarrow \) did not decrease significantly for increasing optical cloud thickness [see FHL, 1984, Figure 3]. This demonstrates that cloud layers, which are greater than 4 optical units thick, are virtually opaque and hence have effective emissivities of nearly unity. Table 8 of FHL [1984] shows that all low and medium clouds have optical thicknesses in excess of 4 (with the exception of cirrostratus clouds, which were not observed during Optical Dynamics Experiment (ODEX)). The modeling of the cloud layer as a gray plate thus has physical justification when the clouds are of low or medium type.

The case of low clouds (e.g., stratus, stratocumulus, and cumulus) is the easiest to conceptualize. Thicker low cloud layers contain higher water concentrations (vapor, liquid, or solid) than thinner ones, and hence effectively emit and absorb more infrared energy. That is, a relatively thick low cloud should have a larger effective emissivity (closer to 1.0). The cloud layer thickness can be related conceptually to the cloud layer amount. A greater amount of low clouds should correspond to a thicker cloud layer, a greater effective emissivity of the cloud layer, and hence a reduced \( \text{LW} \uparrow \downarrow \).

Midlevel (e.g., altostratus and altocumulus) and high (e.g., cirrus and cirrostratus) cloud types do not show the same strong relationship between cloud thickness and effective emissivity (see Lind and Katsaros [1982] for a review of effective emissivities for different cloud types and amounts). In general, effective emissivities for higher clouds are less than those for low clouds. Clearly, for the same cloud amount, high cloud types should exhibit a lower effective emissivity compared to low cloud types and therefore higher values of \( \text{LW} \uparrow \downarrow \) should result.

The temperature of the cloud layer is also important in determining the downwelling flux of infrared energy. Since temperature in general decreases with increasing altitude, higher cloud layers should be cooler, have lower graybody radiation fluxes, and thus result in relatively greater values of \( \text{LW} \uparrow \downarrow \).

As was mentioned previously, microphysical characteristics of clouds can vary greatly over relatively small temporal and spatial scales. These changes can result from radiative heating of cloud layers, convective motions, gravity waves, precipitation, or other causes. These changes alter the effective emis-
sivity and temperature of the cloud layer and act to complicate the parameterizations of effective cloud emissivities.

Water vapor is the only absorbing and emitting component of the atmosphere considered here. The other major absorbing gas (carbon dioxide) has been observed to vary primarily seasonally and its significance should be minimal for the temporal scale of this experiment (for example, see Keeling et al. [1985] for CO$_2$ data at OWS Papa). Other gases (ozone, methane, etc.) have been observed only in trace amounts. Furthermore, concentrations of water vapor are generally much greater and more variable than the other absorbing gases.

Water vapor concentration beneath the cloud layers affects LW$\downarrow$ by altering the upwelling and downwelling fluxes of infrared energy. The lower atmosphere is generally at radiative equilibrium [Liou, 1980]; thus an atmospheric parcel typically emits the same amount of infrared energy as it absorbs. The effect of the atmosphere is to absorb a portion of the net radiative energy between the two plates and emit the same energy isotropically. The net effect of an increase of water vapor concentration (or equivalently partial pressure) is to increase the effective gas emissivity. This increased gas emissivity then reduces the net flux between the two parallel plates and hence LW$\downarrow$.

The temperature of the air column above the ocean can also affect the LW$\downarrow$. As the air temperature increases, the amount of radiation that the air parcel emits increases. This causes the amount of radiation absorbed by the parcel to increase because of Kirchhoff's Law. The net effect again is to reduce LW$\downarrow$. Also, as the cloud layer rises through the atmospheric column, the path length between the two plates increases, and thus the effects of temperature and concentrations of water vapor on LW$\downarrow$ are greater.

In general, the radiative transfer of longwave energy is upward (positive) from the sea surface to the cloud layers. This is due to the fact that the sea surface is generally warmer and has a higher emissivity than cloud layers.

An empirical model which used similar physical concepts for the prediction of LW$\downarrow$ was constructed by Lind and Katsaros [1982]. Their model uses data from both the surface and within the atmospheric column to predict the downwelling longwave irradiance at the sea surface. Temperature and water vapor profiles can be provided by either direct observation or climatology. Cloud emissivities were assigned values based on cloud type, amount, and cloud base height. Although visual cloud observations are not easily quantified, the model quite adequately predicted the downwelling longwave heat flux when compared to observations made during the Joint Air-Sea Interaction Experiment (JASIN) in the North Atlantic Ocean (near 59°N, 13°W) during the summer of 1978. The hindcast error was 9–15 W/m$^2$ for the model and was considerably less than that obtained using standard bulk formula methods. Unfortunately, the Lind and Katsaros model cannot be applied to the present data since neither atmospheric profiles nor cloud base altitudes were measured during ODEX.

In summary, LW$\downarrow$ is generally positive (the net flux is upward from the sea surface). As the sea surface temperature increases, LW$\downarrow$ increases. If the cloud layer decreases in temperature, rises through the air column, or decreases in thickness or total amount, then LW$\downarrow$ increases. Further, as water vapor concentration or temperature of an air parcel decreases, LW$\downarrow$ increases. The validity of these physical arguments can be tested by using statistical prediction techniques outlined in the next section. Furthermore, these results can be used to quantify the relationships between the various surface measurements and lead to a better understanding of the physics which control LW$\downarrow$.

### Statistical Prediction Techniques

In order to evaluate the statistical connections between LW$\downarrow$ and other surface meteorological and oceanographic parameters, a well defined predictive formalism must be employed so that the prediction and its error can be readily evaluated objectively. Appropriate statistical analysis and prediction techniques have been reviewed by Davis [1977] who utilized these techniques for predicting sea level pressure and sea surface temperature anomalies in the North Pacific [Davis, 1976]. Following this methodology, the predicted (time dependent) longwave heat flux, $\hat{LW}\downarrow(t)$, is estimated by using a linear combination of $M$ input components, $C_i(t)$,

$$\hat{LW}\downarrow(t) = \sum_{i=1}^{M} a_i C_i(t)$$

(2)

The arbitrary coefficients, $a_i$, are optimized by minimizing the mean square difference between the sampled and predicted data or

$$a_i = \sum_{j=1}^{M} \langle C_i C_j \rangle^{-1} \langle LW\downarrow | C_i \rangle$$

(3)

where $\langle C_i C_j \rangle^{-1}$ is the inverse of the covariance matrix (where each element is the covariance between the $i$th component and the $j$th component) and $\langle LW\downarrow | C_i \rangle$ is the covariance vector. The mean square error ($e_0^2$) resulting from (3) is

$$e_0^2 = \langle LW\downarrow \| LW\downarrow \rangle - \sum_{i=1}^{M} a_i \langle LW\downarrow | C_i \rangle$$

(4)

where $\langle LW\downarrow \| LW\downarrow \rangle$ is the ensemble (true) variance of LW$\downarrow$. The square root of the mean square error ($e_0$) is referred to as the hindcast error. The Gauss-Markov theorem states that $e_0^2$ is the lowest mean square error possible from a linear predictor in the form of (2).

Linear hindcasting is an application of these techniques and illustrates how a given variable is related to the complete data set. The predictive equation (2) is referred to as the linear hindcastor. The predictive skill ($S_H$) of a hindcastor can be evaluated given the mean square error ($e_0^2$) and the sample variance of LW$\downarrow$ or ($s^2$) according to the formula

$$S_H = \left( \frac{s^2 - e_0^2}{s^2} \right)$$

(5)

The hindcast skill corresponds to the proportion of the variance explained by a linear hindcastor. For example, a hindcast skill of 0.5 indicates that the linear predictor accounts for 50% of the variance in LW$\downarrow$.

Complications can arise because of chance statistical connections between any of the parameters even though no true connection may exist. As the number of input parameters, $M$, that make up the hindcastor is increased, the hindcast skill increases because of the increased artificial predictability arising from chance connections. Davis [1976] shows that the expected value of the artificial skill ($S_A$) can be estimated from the number of input components, $M$, and the estimated number of degrees of freedom, $N^*$, according to

$$S_A = \frac{M}{N^*}$$

(6)

The number of degrees of freedom, $N^*$, can be estimated from $N^* = N/\sqrt{M}$ [Davis, 1976], where $N$ is the number of
data points in the record, $\Delta t$ is the sampling interval, and $\tau_0$ is the decorrelation time. The decorrelation time, $\tau_0$, is calculated from the integral of the autocorrelation function of $LW^+\downarrow$ from zero lag to the lag of the first zero crossing [Tennekes and Lumley, 1972].

The true predictive skill ($S_T$) is the difference between the hindcast skill and the estimated artificial skill. The true skill is the proportion of variance explained by the linear hindcastor which accounts for artificial predictability. As the number of components, $M$ in (2), is increased, a point will be reached where $S_T(M) > S_T(M + 1)$. Beyond $M$ components, no increased predictability results. This criterion can be used to limit the number of components used in the linear hindcastor.

### Instrumentation and Techniques

Observations were made from the R/P FLIP between October 20 and November 11, 1982 (Julian Days 293-315) in the northeast Pacific Ocean (near 34°N, 142°W) as part of the Optical Dynamics Experiment. A 22-day record was obtained. A full suite of radiative and meteorological instruments was deployed from a boat, ~12 m above the mean sea surface, and ~15 m from the R/P FLIP superstructure. As part of these measurements, $LW^+\downarrow$ was obtained using both direct and indirect determinations.

The R/P FLIP is ideal in most respects for this type of measurement in that the deviation of the horizontal plane rarely exceeds 2° relative to the sea surface [Bronson and Glosten, 1973]. In addition, instruments can be placed far enough away from the superstructure of the vessel that emission and reflection of infrared energy from the ship superstructure is negligible. A review of the R/P FLIP component of ODEX and the characteristics of all sensors is given in Dickey et al. [1986].

The net longwave heat flux was sampled with a net longwave radiometer (net pyrgeometer) manufactured by Middleton Instruments, Australia. This instrument consists of a net all-wave radiometer surrounded by a black polyethylene filter which removes energy with wavelengths shorter than 2.5 $\mu$m [Paltridge, 1969]. The transmission of the filter generally increases linearly with wavelength from zero transmittance at 2.5 $\mu$m to ~40% transmittance at 25 $\mu$m. Also, this filter exhibits a strong absorption peak near 14 $\mu$m [Paltridge, 1969; Hinzpeter, 1980]. By considering the spectral characteristics of the filter and the atmospheric absorption spectra (in particular the absorption bands due to water and carbon dioxide), it is evident that the response of the net longwave radiometer is also dependent on the spectral characteristics of the radiation field.

The region inside the polyethylene filter was purged of air by using dry nitrogen gas to minimize any effects that could arise from trapped gases. The filter was rotated so that differential heating of the filter by shortwave energy could not influence the net radiation sampled. The filter rotation rate was approximately 2 revolutions per second. Paltridge [1969] found no significant deviation in the net radiative flux provided that the filter rotation rate was greater than 1 revolution per second. Other possible complications can arise from leakage of visible energy through the filter, accumulation of sea spray on the filter, and radiative emission and reflection due to gray bodies associated with the sampling arrangement (e.g., platform effects). The accuracy of the net longwave radiometer has been estimated to be 7-8% of the mean [SP, 1979].

Other radiative heat flux and standard meteorological measurements were made concurrently at the same location. Radiative measurements were made with upward facing and downward facing pyranometers (Eppley Laboratories, Rhode Island, model 8-48) and a net allwave radiometer (Swissteco Australia, type S-1). The pyranometers measure radiant energy in wavelengths ranging from 0 to 2.5 $\mu$m with an accuracy of 2-3% [SP, 1979]. The net allwave radiometer has a spectral range of 0.3-60 $\mu$m with an accuracy of 2-3% [SP, 1979]. Standard meteorological measurements included wind speed and direction, air temperature, air pressure, dew point temperature, and rainfall rate. All of these data (including $LW^+\downarrow$) were sampled at a rate of once per minute and then averaged to a sampling interval of ~1 hour.

Visual cloud amount and type determinations were made in conjunction with each conductivity, temperature, and depth (CTD) and optical package deployment. Estimates of full sky okta and dominant cloud type were made at least once every 3 hours during daylight. Some nighttime cloud amounts were estimated using linear interpolation because of difficulties in determining cloud parameters at night. Sea surface temperature data were provided by near-surface CTD measurements which were taken at intervals less than 3 hours.

The net longwave sensor recorded data only during the last 9 days of the experiment because of an electronic malfunction during the first 13 days. An indirect procedure was used for the first 13 days. The indirect method involves subtracting the net shortwave radiative flux from the net allwave flux as discussed previously. SP [1979] have shown that the indirect technique leads to errors because the daytime net longwave flux is the residual of two large numbers. A comparison of the direct and indirect determinations for the nine day period of direct measurements indicates that the mean was underestimated by 6.1 W/m² and the root mean square deviation was 22.4 W/m². These deviations were significant, and thus an alternative method was employed.

A linear hindcastor approach was used to evaluate $LW^+\downarrow$ during the initial 13 days of the experiment and the contribution of each radiative flux component was optimized to minimize the mean square difference between the hindcasted and directly measured determinations. The 9-day period of direct determinations was partitioned into separate day and night linear hindcastors, because the composition of the surface radiation spectrum is different during the day than during the night. The daytime net longwave heat flux ($LW^+\downarrow(t)$) was modeled as

$$LW^+\downarrow(t) = aSHI(t) + bSHJ(t) + cAll\downarrow(t) + d$$  \hspace{1cm} (7)

where $SHI(t)$ is the downwelling (incident) solar flux; $SHJ(t)$ is the upwelling (reflected) solar flux; $All\downarrow(t)$ is the net allwave heat flux; and $a$, $b$, $c$, and $d$ are the arbitrary coefficients to be determined. For the case of perfect sensors (the nonoptimized indirect method), the values of the coefficients are $a = b = c = 1$ and $d = 0$. Our approach allows adjustment in the model for mismatching of sensor bandwidths, deviations in the sensor response from ideal broadband response, and both absolute and relative calibration errors. For the nighttime hindcastor, the coefficients $a$ and $b$ in (7) were set to zero.

These daytime and nighttime models were then hindcasted against direct measurements to determine the optimized coefficients of the two models. Values for the daytime coefficients were within 10% of the values for perfect sensors. At night the coefficients were within 2% of expected values. The model
coefficients were then employed to produce a time series of the optimized indirect $L\hat{W}T\downarrow$.

The optimized indirect $L\hat{W}T\downarrow$ was compared to the 9 days of directly determined $LW\downarrow$ to develop estimates of the errors associated with the hindcasting procedure. The mean optimized indirect $L\hat{W}T\downarrow$ is greater than the mean directly determined $LW\downarrow$ by 0.7 W/m$^2$ (1.3%). The root mean square (hindcast) error was 7.2 W/m$^2$ (13.8%), and the hindcast skill, $S_m$, was 0.919. By using the estimated degrees of freedom of the 9-day directly determined $LW\downarrow$ ($N^* \approx 36$) and the maximum number of model components used ($M = 4$), the artificial skill ($S_a$) was conservatively estimated to be 0.111. The estimated true skill ($S_p$) is then 0.808, or the linear hindcastor accounted for 80.8% of the variance of $LW\downarrow$.

The frequency spectrum of the deviation between the optimal indirect hindcasted data and the direct data shows a prominent peak in the diurnal frequency band. This is consistent with the observations of SP [1979], because $LW\downarrow$ is determined as the residual of two large numbers during daylight. The diurnal band contains nearly 55% of the total deviation variance. This is an important consideration when the diurnal variability of $L\hat{W}T\downarrow$ is of interest.

The application of a hindcast model to the problem of forecasting has many difficulties, particularly when there are no data with which to determine error estimates [Dans, 1977]. For this reason, forecasting experiments were performed. First, the 9-day period of direct measurements was divided into two segments. Then optimal hindcastor coefficients were determined for each segment (as described previously) and applied to the other segment. The root mean square deviations for these forecast experiments were 8.3 and 8.7 W/m$^2$ for each half of the 9-day period. These errors do not depart greatly from the hindcast error determined by modeling the entire 9-day data set. We estimate the worst case forecasting error from the linear hindcastor to be $\sim 9$ W/m$^2$ or nearly 17% of the mean $LW\downarrow$.

**OBSERVATIONS**

A brief description of the meteorological and oceanographic context of the $LW\downarrow$ observations is given. The mean sea surface temperature was 19.79°C with a variance of 0.09°C$^2$ and decreased during the experiment from 20.46°C to 19.16°C. This is consistent with the seasonal cooling of the midlatitude North Pacific Ocean. During the experiment, several synoptic weather systems passed the R/P FLIP. These systems had temporal scales of $\sim 5$ days and wind stress amplitudes of $\sim 0.2$ N/m$^2$. These storm systems were also manifest in the records of air temperature, vapor pressure, and air pressure. The effect of biogenic surface films on $LW\downarrow$ is presumably negligible, since the mean near-surface chlorophyll-a pigment concentrations are quite low (Chl-a = 0.07 mg/m$^3$). More details concerning both the oceanographic and meteorological observations are given in the work by Dickey et al. (unpublished manuscript, 1986).

The time series of the net longwave radiative heat flux is shown in Figure 1. The sample mean ($LW\downarrow$) of the signal is 52.0 W/m$^2$ upward from the sea surface. The sample variance ($s^2$) is equal to 802.6 W$^2$/m$^4$, which gives a coefficient of variation ($s/LW\downarrow$) of 54.5%. The mean total net heat flux, $Q_n$, over the 22-day experiment is equal to a loss of 114.6 W/m$^2$ from the ocean (Dickey et al., unpublished manuscript, 1986). Errors in the estimate of $LW\downarrow$ could significantly modify the estimation of total net heat flux.

The time series of cloud amount determined from visual observations is shown in Figure 2. The apparent correlation (negative) between the observed cloud amount and $LW\downarrow$ is quite striking, but is complicated by the low frequency trends. The mean cloud amount was 0.72 (1.00 represents a totally obscured sky) and its variance was 0.06. Observed cloud types included stratus, stratocumulus, and cumulus during the experiment. Medium and high cloud types (e.g., altostratus, altocumulus, and cirrus) were observed only when the cloud amount was less than 0.5. Also apparent from these data is the large diurnal variability of the cloud amount.

The variance conserving spectrum of $LW\downarrow$ is shown in Figure 3. The area under the spectrum curve (in variance conserving form) is equal to the total variance of the signal. A substantial portion of the variance of $LW\downarrow$ is associated with the diurnal frequency ($\sim 1$ cpd) and its harmonics. The second largest band of variability is associated with the lower frequency synoptic scale ($\leq 0.2$ cpd). As discussed previously, significant errors are introduced because the optimized indirect method is employed to determine the first 13 days of data. This is manifest primarily within the diurnal frequency band. The worst case forecasting error was estimated previously to be $\sim 9$ W/m$^2$. If all of this error were contained in the diurnal frequency band, a variance of $\sim 80$ W$^2$/m$^4$ would be added to this frequency band. This is far less than the value of $\sim 450$ W$^2$/m$^4$ observed for the diurnal band. Thus, the large diurnal signal shown in Figure 3 is a realistic feature of the
local meteorology. This indicates that models which attempt
to account for effects contributing to the large diurnal structures
such as those evident in the present data set.

The average daily cycle of $LW_{\uparrow\downarrow}$ and the estimated cloud
amount are shown in Figure 4. The error bars correspond to
90% confidence intervals for estimates of the mean. The other meteorological variables (with the exception of the solar radi-

tant fluxes) do not show significant diurnal cycles. As expected,
the cycles are negatively correlated; as the cloud amount in-
creases, $LW_{\uparrow\downarrow}$ decreases, and vice versa. The amplitude of the
diurnal cycle of $LW_{\uparrow\downarrow}$ is 13.5 W/m² and that of the cloud
amount is 7%. The positive peak of $LW_{\uparrow\downarrow}$ is coincident with
the solar radiation peak, whereas the positive peak of the
cloud amount is in the late evening. The diurnal ranges of the
observed $LW_{\uparrow\downarrow}$ again may be attributed in some part to the
optimal indirect method used to determine the first portion of
the time series. This effect was examined by evaluating the
daily cycle for the 9 days of direct $LW_{\uparrow\downarrow}$ measurements. Am-
plitudes of 6.8 W/m² for $LW_{\uparrow\downarrow}$ and 11% for the cloud
amount were found without any significant difference in phase
when compared to the complete data set. Thus, it is quite
likely that these diurnal signals are real and contribute a large
portion of the variability of $LW_{\uparrow\downarrow}$.

**Comparison With Bulk Formula Calculations**

The comparison of the measured $LW_{\uparrow\downarrow}$ with the $LW_{\uparrow\downarrow}$
estimated by using bulk formula techniques is of great interest
since bulk formulas are employed operationally. The predic-
tive capability of the bulk formulas can be evaluated by com-
paring $LW_{\uparrow\downarrow}$ values obtained using the bulk formulas with
directly measured values.

The form of a bulk formula model for $LW_{\uparrow\downarrow}$, $LW_{\uparrow\downarrow}$, can be
generalized if the modeled clear-sky $LW_{\uparrow\downarrow}$, $LW_{\up\downarrow}$, is
multiplied by a cloud correction factor,

$$LW_{\up\downarrow} = LW_{\up\downarrow}(1 - bCl)$$

where $Cl$ is the cloud amount (relative to a totally obscured
sky), and $b$ and $n$ are empirical constants. Usually, $n$ is as-
sumed to be either 1 or 2 and $b$ varies between 0.4 and 0.9
depending on both cloud type and latitude. Seven clear-sky
bulk formulas and the aforementioned data were used for this
analysis. The clear-sky bulk formulas, the predicted clear-sky
means, variances, and coefficients of variation are shown in
Table 1. In these formulas, $T_s$ is the dry air temperature (K) at
10 m above the sea surface, $e_a$ is the water vapor pressure (mb)
at 10 m, $T_a$ is the bulk sea surface temperature (K), $\sigma$ is the
Stefan-Boltzmann constant, $e$ is the sea surface emissivity
which is assumed to be 0.98. This assumption results in a
maximum error of 2%, since observations of $e$ are scattered
between 0.96 and unity [FHL, 1984].

Because the measured $LW_{\up\downarrow}$ shows a large amount of
variability (coefficient of variation = 54.4%), both the means
and variances of $LW_{\up\downarrow}$ determined from clear-sky bulk for-
mulas are relevant. The clear-sky formulas give similar mean
values with an average of 82.0 W/m². The clear-sky variances
show a large amount of deviation among the different bulk
formulas. In principle, the bulk formulas with lower clear-sky
variance have a lesser chance of adequately predicting the
variability of $LW_{\up\downarrow}$, because only the cloud correction terms
contribute the necessary amount of observed variance to
the prediction. The models of Swinbank [1963] and Efimova
[1961] have poorer predictive capabilities by this criterion.

The application of bulk formulas to the prediction of $LW_{\up\downarrow}$
requires that the cloud correction term be evaluated. The cloud
correction slope ($b$) in (8) was evaluated by using a least
squares regression technique. The results for each model are
shown in Table 2. The mean cloud correction slope ($b$) (using
values from all of the bulk formulas) is 0.51 for $n = 1$ and 0.61
for $n = 2$ and each has a 90% confidence interval of $\pm 0.01$.
These constants are nearly identical to those suggested by
Charnell [1967], Budyko [1974], and Bunker [1976], and are
within 10% of the constant used by Clark et al. [1974]. For
similar cloud types and latitude bands, the values determined
by Reed [1976], SP [1979], and Laeveski [1967] are larger
(greater by 25%) than the cloud correction slopes determined
here. These results can be considered to be relevant only for
this particular data set because of the relatively short observa-
tional period of the present experiment (22 days) and the sub-
jective nature of visual cloud observations.

The cloud correction coefficients ($b$) were then applied to
the bulk formulas. These results are shown in Table 2 and
 correspond to the lowest possible mean square deviation for
each bulk formula, since $b$ is optimized for each. The hindcast
skills for all bulk formulas with their respective cloud correc-
tions range from 35.1 to 44.4% of the variance explained. The
hindcast error varies between 21.2 and 22.8 W/m². These low
hindcast skills and large errors are significant and show that

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**References**


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**Figures**

1. Variance conserving autospectrum of $LW_{\up\downarrow}$. Units are W²/m². The sample variance (s²) of $LW_{\up\downarrow}$ is 802.6 W²/m².

2. Daily variation of $LW_{\up\downarrow}$ and the total amount of cloud. Units are W/m² and percent of sky obscured. The error bars represent 90% confidence intervals.
the bulk formulas perform poorly in predicting the variability of \( LW \). These results indicate that care should be exercised in the application of the bulk formulas to estimate \( LW \), particularly for temporal scales less than several days.

### Statistical Modeling

The statistical connections between \( LW \) and other parameters are discussed in this section. \( LW \) is modeled as a linear combination of meteorological and oceanographic components (e.g., equation (2)). In order to facilitate comparison with previous results, the input components are assumed to be in forms similar to those utilized in bulk formulas. An additional rationale for the choice of input components is based upon a screening process which is used to remove from consideration linear hindcastors that may have artificially high predictive skills [Davis, 1977]. The screening process as applied here uses only components in the linear hindcastors which have some a priori rationale for inclusion, just as the parameters used in the bulk formulas have an a priori rationale for their inclusion. From this analysis, the importance of each component can be evaluated in terms of its predictive capability. A list of the model components, their means and variances, estimated true predictive skills, and hindcast errors are shown in Table 3.

The functional form of each model component can be described in relation to its contribution to the longwave radiative flux between the atmosphere and the ocean. The component \( a_1 \) \( (a_2) \) is the amount of longwave radiation emitted from a black body at the bulk sea surface (air) temperature. Components \( b_1 \) and \( b_2 \) are referred to as temperature jump correction terms [see FHL, 1984]. These jump corrections are approximations for \( a(T' - T) \) where \( (T' - T) \) is small. These correspond physically to the net radiative flux between two parallel black plates in the absence of an interacting medium. These components can be thought to correspond in some manner to the net upwelling longwave radiation from the sea surface. The components \( c_1 \) and \( c_2 \) allow for the effects of water vapor. Previous studies have indicated that the clear-sky \( LW \) is proportional to the water vapor pressure \( (c_1) \) or its square root \( (c_2) \) (see Brutsaert [1982] for a review). The effect of clouds is represented by the components \( d_1(c_1) \) and \( d_2(c_2) \). All of these components can be found within portions of the bulk formulas shown in Table 1 or the cloud correction terms of (8).

Before the predictive skills of the various hindcastors can be evaluated, the artificial skill of each must be estimated. The number of degrees of freedom for the entire 22-day record is estimated to be 48. The artificial skill, \( S_a \), increases linearly with the number of hindcastor components \( M \), or \( S_a = M/48 \). The estimated artificial skill is used to limit the number of components in the hindcastors (equation (2)) as discussed previously. It should be noted that the sampling interval used here is \( \sim 2 \) hours to allow the inclusion of the sea surface temperature record.

The hindcast models were constructed so that only one of each “type” of component was used. That is, a four-parameter hindcastor could be \( a_1 + b_1 + c_1 + c_2 \), but not \( b_1 + b_2 + c_1 + c_2 \). This was done to facilitate the screening process. The

### Table 2. Results Using Bulk Formula Hindcasts of \( LW \)

<table>
<thead>
<tr>
<th>Bulk Formula</th>
<th>Cloud Power, n</th>
<th>Cloud Coefficient, b</th>
<th>Mean, W/m²</th>
<th>Variance, W²/m⁴</th>
<th>Detrended Variance, W²/m⁴</th>
<th>Coefficient ( a_1 )</th>
<th>Estimated True Skill, Sₚ %</th>
<th>Hindcast Error, ( S_a ), W/m²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Berliand and Berliand [1952]</td>
<td>1</td>
<td>0.55</td>
<td>52.3</td>
<td>302.2</td>
<td>-0.6</td>
<td>21.4</td>
<td>43.1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.63</td>
<td>55.3</td>
<td>515.3</td>
<td>2.4</td>
<td>21.8</td>
<td>40.8</td>
<td></td>
</tr>
<tr>
<td>Brunt [1932]</td>
<td>1</td>
<td>0.49</td>
<td>51.4</td>
<td>215.0</td>
<td>-1.4</td>
<td>21.8</td>
<td>40.5</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.57</td>
<td>53.6</td>
<td>383.5</td>
<td>0.8</td>
<td>21.5</td>
<td>42.3</td>
<td></td>
</tr>
<tr>
<td>Efimova [1961]</td>
<td>1</td>
<td>0.44</td>
<td>50.2</td>
<td>122.6</td>
<td>-2.6</td>
<td>22.8</td>
<td>35.1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.52</td>
<td>51.3</td>
<td>227.6</td>
<td>-1.6</td>
<td>21.8</td>
<td>40.7</td>
<td></td>
</tr>
<tr>
<td>Bunker [1976]</td>
<td>1</td>
<td>0.50</td>
<td>51.3</td>
<td>226.0</td>
<td>-1.5</td>
<td>21.5</td>
<td>42.2</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.57</td>
<td>53.5</td>
<td>382.5</td>
<td>0.6</td>
<td>21.2</td>
<td>44.1</td>
<td></td>
</tr>
<tr>
<td>Anderson [1952]</td>
<td>1</td>
<td>0.52</td>
<td>51.6</td>
<td>237.1</td>
<td>-1.3</td>
<td>21.5</td>
<td>42.2</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.60</td>
<td>53.9</td>
<td>408.9</td>
<td>1.1</td>
<td>21.3</td>
<td>43.3</td>
<td></td>
</tr>
<tr>
<td>Swinbank [1963]</td>
<td>1</td>
<td>0.58</td>
<td>52.0</td>
<td>222.4</td>
<td>-0.8</td>
<td>22.6</td>
<td>36.6</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.66</td>
<td>54.8</td>
<td>432.0</td>
<td>2.0</td>
<td>22.6</td>
<td>36.5</td>
<td></td>
</tr>
<tr>
<td>Clark et al. [1974]</td>
<td>1</td>
<td>0.56</td>
<td>52.6</td>
<td>330.9</td>
<td>-0.2</td>
<td>21.3</td>
<td>44.4</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.64</td>
<td>55.8</td>
<td>558.4</td>
<td>3.0</td>
<td>22.0</td>
<td>39.7</td>
<td></td>
</tr>
</tbody>
</table>

### Table 3. Statistical Model Components and Their Individual Predictions of \( LW \)

<table>
<thead>
<tr>
<th>Component</th>
<th>Mean, W/m²</th>
<th>Total Variance, W²/m⁴</th>
<th>Detrended Variance, W²/m⁴</th>
<th>Coefficient, ( a_i )</th>
<th>Estimated True Skill, Sₚ %</th>
<th>Hindcast Error, ( S_a ), W/m²</th>
</tr>
</thead>
<tbody>
<tr>
<td>( a_1 )</td>
<td>400.6</td>
<td>2.6</td>
<td>0.5</td>
<td>0.34</td>
<td>9.7</td>
<td>26.5</td>
</tr>
<tr>
<td>( a_2 )</td>
<td>395.6</td>
<td>33.9</td>
<td>33.7</td>
<td>-0.48</td>
<td>21.6</td>
<td>24.7</td>
</tr>
<tr>
<td>( b_1 )</td>
<td>5.1</td>
<td>34.8</td>
<td>34.8</td>
<td>0.50</td>
<td>23.2</td>
<td>24.4</td>
</tr>
<tr>
<td>( b_2 )</td>
<td>5.0</td>
<td>33.7</td>
<td>33.7</td>
<td>0.50</td>
<td>23.1</td>
<td>24.4</td>
</tr>
<tr>
<td>( c_1 )</td>
<td>15.56 (mbar)</td>
<td>12.74 (mbar²)</td>
<td>12.71 (mbar²)</td>
<td>-0.64</td>
<td>39.4</td>
<td>21.6</td>
</tr>
<tr>
<td>( c_2 )</td>
<td>3.93 (mbar¹/²)</td>
<td>0.21 (mbar)</td>
<td>0.21 (mbar)</td>
<td>-0.64</td>
<td>38.9</td>
<td>21.7</td>
</tr>
<tr>
<td>( d_1 )</td>
<td>0.72</td>
<td>0.06</td>
<td>0.05</td>
<td>-0.69</td>
<td>46.1</td>
<td>20.3</td>
</tr>
<tr>
<td>( d_2 )</td>
<td>0.58</td>
<td>0.10</td>
<td>0.09</td>
<td>-0.71</td>
<td>48.4</td>
<td>19.9</td>
</tr>
</tbody>
</table>

\( S_a = 2.1 \% \).
exception to this is the combination of \( a_1 (\sigma_{T_1}^+) \) and \( a_2 (\sigma_{T_2}^+) \).

The time series of the components and \( LWT_1 \) were detrended before the statistical analysis was performed. This detrending procedure removes the parabolic trend that best fits the data. This enables the consideration of statistical connections between \( LWT_1 \) and other surface parameters on temporal scales between several hours and \( \sim 10 \) days. Also, each of the components was normalized to zero mean and unit variance before the arbitrary coefficients were determined.

After the detrending operation, the resulting variances of most of the components remain approximately the same (Table 3). This indicates that most of the components show little variance associated with the long-term mean trend. The exception to this is \( a_1 (\sigma_{T_1}^+) \), which shows a large reduction in variance after detrending (\( \sim 80\% \)). This large reduction in the variance of the \( a_1 \) component indicates that most of the variance for this component is associated with time scales of 10 days or longer.

The results using the one parameter linear hindcasters are also shown in Table 3. The artificial skill \( (S_T) \) is estimated to be 2.1% for this case. A zero hindcast skill translates to a hindcast error of 27.7 W/m^2 (the standard deviation of the detrended \( LWT_1 \)).

Estimated True Hindcast

<table>
<thead>
<tr>
<th>Hindcastor</th>
<th>Coefficient</th>
<th>Coefficient</th>
<th>True</th>
<th>Hindcast</th>
<th>Error,</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( a_1 )</td>
<td>( a_2 )</td>
<td>Skill, %</td>
<td></td>
<td>W/m^2</td>
</tr>
<tr>
<td>( a_1 + a_2 )</td>
<td>0.23</td>
<td>-0.42</td>
<td>24.2</td>
<td>23.9</td>
<td></td>
</tr>
<tr>
<td>( a_1 + b_1 )</td>
<td>0.18</td>
<td>0.43</td>
<td>24.1</td>
<td>23.9</td>
<td></td>
</tr>
<tr>
<td>( a_1 + c_1 )</td>
<td>0.16</td>
<td>-0.59</td>
<td>39.6</td>
<td>21.2</td>
<td></td>
</tr>
<tr>
<td>( a_1 + d_1 )</td>
<td>0.16</td>
<td>-0.59</td>
<td>39.2</td>
<td>21.3</td>
<td></td>
</tr>
<tr>
<td>( a_1 + a_2 )</td>
<td>0.20</td>
<td>-0.65</td>
<td>47.8</td>
<td>19.6</td>
<td></td>
</tr>
<tr>
<td>( a_1 + a_2 )</td>
<td>0.17</td>
<td>-0.67</td>
<td>49.1</td>
<td>19.3</td>
<td></td>
</tr>
<tr>
<td>( a_2 + b_2 )</td>
<td>1.51</td>
<td>2.00</td>
<td>23.1</td>
<td>24.1</td>
<td></td>
</tr>
<tr>
<td>( a_2 + c_1 )</td>
<td>0.30</td>
<td>-0.90</td>
<td>39.5</td>
<td>21.2</td>
<td></td>
</tr>
<tr>
<td>( a_2 + d_2 )</td>
<td>0.26</td>
<td>-0.96</td>
<td>38.5</td>
<td>21.4</td>
<td></td>
</tr>
<tr>
<td>( a_2 + d_1 )</td>
<td>-0.27</td>
<td>-0.60</td>
<td>50.5</td>
<td>19.1</td>
<td></td>
</tr>
<tr>
<td>( a_2 + d_2 )</td>
<td>-0.25</td>
<td>-0.61</td>
<td>51.5</td>
<td>18.8</td>
<td></td>
</tr>
<tr>
<td>( b_1 + c_1 )</td>
<td>-0.23</td>
<td>-0.84</td>
<td>38.6</td>
<td>21.4</td>
<td></td>
</tr>
<tr>
<td>( b_1 + c_2 )</td>
<td>-0.20</td>
<td>-0.81</td>
<td>37.8</td>
<td>21.5</td>
<td></td>
</tr>
<tr>
<td>( b_1 + d_1 )</td>
<td>0.28</td>
<td>-0.59</td>
<td>50.9</td>
<td>18.9</td>
<td></td>
</tr>
<tr>
<td>( b_1 + d_2 )</td>
<td>0.26</td>
<td>-0.61</td>
<td>52.0</td>
<td>18.7</td>
<td></td>
</tr>
<tr>
<td>( b_2 + c_1 )</td>
<td>-0.24</td>
<td>-0.85</td>
<td>38.7</td>
<td>21.4</td>
<td></td>
</tr>
<tr>
<td>( b_2 + c_2 )</td>
<td>-0.20</td>
<td>-0.81</td>
<td>37.8</td>
<td>21.5</td>
<td></td>
</tr>
<tr>
<td>( b_2 + d_1 )</td>
<td>0.28</td>
<td>-0.59</td>
<td>50.9</td>
<td>19.0</td>
<td></td>
</tr>
<tr>
<td>( b_2 + d_2 )</td>
<td>0.26</td>
<td>-0.61</td>
<td>51.9</td>
<td>18.7</td>
<td></td>
</tr>
<tr>
<td>( c_1 + d_1 )</td>
<td>-0.38</td>
<td>-0.49</td>
<td>54.3</td>
<td>18.2</td>
<td></td>
</tr>
<tr>
<td>( c_1 + d_2 )</td>
<td>-0.38</td>
<td>-0.49</td>
<td>54.6</td>
<td>18.2</td>
<td></td>
</tr>
<tr>
<td>( c_1 + d_2 )</td>
<td>-0.36</td>
<td>-0.51</td>
<td>55.1</td>
<td>18.0</td>
<td></td>
</tr>
<tr>
<td>( c_2 + a_2 )</td>
<td>-0.36</td>
<td>-0.51</td>
<td>55.3</td>
<td>18.0</td>
<td></td>
</tr>
</tbody>
</table>

\( S_T = 4.2\% \).

The true skill levels for the two component hindcasters range from 23.1 to 55.3% of the variance explained. The highest observed true skills occur for hindcasters including a combination of the vapor pressure components (\( c_1 \) or \( c_2 \)) and the cloud amount components (\( d_1 \) or \( d_2 \)). The true skills for these hindcasters range from 54.3 to 55.3%. These hindcasters correspond to the top parallel plate and the emitting and absorbing atmosphere of the conceptual model discussed previously.

Several other two component hindcasters show good predictive skills (\( S_T > 48\% \)). These hindcasters all include the effect of a cloud amount component (\( d_1 \) or \( d_2 \)) and any of the other components (\( a_1, a_2, b_1, \) or \( b_2 \)). These results, along with the previous results, indicate the importance of variations of the cloud layers to the prediction of \( LWT_1 \) variability.

For the two component hindcasters, the worst predictive capabilities (\( S_T \sim 24\% \)) occur for hindcasters where the components are comprised of the air temperature and the sea surface temperature alone (i.e., \( a_1 + a_2, a_1 + b_1, \) or \( a_2 + b_2 \)). Better predictions appear to be made when more than one of the three elements of the conceptual model are included.
served between the water vapor components and LW↑↓. The best estimated true skill (~55% variance explained) occurs for the two component hindcasts, which correspond to the cloud layers and the interacting atmosphere. Variability of the bottom parallel plate (the sea surface) does not appear to be as important for the time scales analyzed (several hours to ~10 days).

**Discussion**

The observed diurnal cycles of total cloud amount (and hence LW↑↓) can significantly alter the total net heat flux at the sea surface, but more importantly, their presence suggests that approaches used to determine LW↑↓ must account for these cycles. Presumably the diurnal cycle of LW↑↓ is driven by changes in the cloud layers and/or the vertical profiles of temperature and humidity in response to the incident solar cycle. In estimating the variability of LW↑↓, the physical processes driving these diurnal cycles must be considered.

Significant diurnal cycles of cloud parameters over the ocean have been observed by other investigators from both surface platforms [e.g., Dorman et al., 1974; Lind et al., 1984] and satellite platforms [e.g., Gruber, 1976; Short and Wallace, 1980; Minnis and Harrison, 1984]. In general, these observed cycles have statistically significant amplitudes and show that the maximum total cloud amount occurs during the nighttime to early morning period. Agreement of the amplitudes and phases of the observed diurnal cycles of cloud parameters among different experiments should not necessarily be expected. Differing localities and seasons, short observational periods, localized energetic phenomena, and possible biases due to visual cloud observations (particularly at night) all can contribute to the differences among the various observations. Regardless of the variations or their causes, diurnal cycles of cloud parameters appear to be ubiquitous features of the planetary boundary layer above the open sea. These previously observed diurnal cycles are generally consistent with the present results.

Observations of daily cycles of both downwelling longwave irradiance and cloud parameters were made during the JASIN experiment [Lind et al., 1984]. Their results do not show the strongly correlated diurnal cycles observed during ODEX. They attribute the absence of correlation between the diurnal cycles to nonlinear effects of cloudiness on downwelling longwave irradiance as well as to the effects related to the vertical profiles of water vapor and temperature.

The diurnal cycles of cloud parameters in the marine boundary layer complicate the effective modeling of LW↑↓ variability. As was demonstrated previously, bulk formula techniques perform rather poorly in predicting the variance of LW↑↓ observed during ODEX. Because a substantial portion of LW↑↓ variance is observed in the diurnal frequency band and its harmonics, bulk formula techniques in effect perform poorly in predicting the diurnal cycle of LW↑↓. This is true even though the daily cycle of the total cloud amount shows a significant diurnal amplitude (~7%). This diurnal amplitude in the observed cloud amount results in a corresponding mean diurnal amplitude of LW↑↓ of ~3 W/m² and indicates that variations in the total cloud amount in itself cannot adequately account for the diurnal changes of LW↑↓.

The success of the linear hindcasting techniques and their relationships to the conceptual parallel plate model indicate that effective models for the prediction of LW↑↓ variability can be constructed if the concepts of the parallel plate model are utilized. Several recent models for LW↑↓ have utilized this physical framework [Lind and Katsaros, 1982; Darnell et al., 1983; FHL, 1984]. These models parameterize the downwelling longwave irradiance as the gray body longwave radiation from the cloud layers minus the absorption and reemission by water vapor and other absorbing gases in the marine boundary layer. For example, the FHL [1984] model solves the full radiative transfer equation to determine LW↑↓. LW↑↓ is then the emission from the sea surface plus the sea surface emissivity multiplied by the downwelling longwave irradiance.

FHL [1984] present a model for LW↑↓ over the ocean based on a radiative transfer formulation. They illustrate the variability of LW↑↓ by varying the temperature and water vapor profiles aloft as well as cloud parameters. Their results were compared to results obtained using various bulk formulas for LW↑↓. It was found that bulk formulas perform poorly under most conditions, as was observed in the present study. Their results also indicate that cloud layers are opaque to infrared energy if their optical thickness is greater than 4 units. For almost all common low and medium cloud types this condition is satisfied. This conclusion supports the parallel plate model as a framework for estimating LW↑↓ under cloudy skies.

The model presented by Darnell et al. [1983] is driven by data derived from the TIROS Operational Vertical Sounder (TOVS) satellite sensor. These data provided atmospheric profiles of temperature and water vapor as well as fractional cloud cover and cloud top height. Cloud base height and temperature were estimated using a constant cloud thickness (50 mbar). The squared correlation coefficient relating the modeled and directly measured downwelling longwave irradiance was 0.76 and the hindcast error was 20 W/m². Darnell et al. attribute these relatively large errors to the estimation of the profile data and cloud parameters from TOVS, particularly to the inference of cloud base properties from cloud top properties.

The model of Lind and Katsaros [1982] utilizes shipboard visual observations of cloud type, amount, and base height along with vertical profiles of temperature and water vapor derived from bidaily hemispheric analyses. In addition, effective cloud emissivities are utilized to parameterize the effects of differing cloud types. Hindcast errors determined by comparing the results of their model to direct observations from two different ships during the JASIN experiment were 9.0 and 14.6 W/m². These errors are quite small and support the validity of their model formulation.

The successes of these recent modeling efforts all illustrate the utility of the conceptual parallel plate model for estimating LW↑↓ variability. The accuracy of these models appears to be hindered primarily by the data (quality and type available) used to drive the models rather than the assumptions and parameterizations used in the model formulations. Clearly, objective techniques for the estimation of cloud parameters (particularly cloud base parameters) must be developed before the reliability of these models can be tested rigorously. Presently, atmospheric profiles of temperature and water vapor can be derived from satellite-based sensors such as TOVS, but the inference of cloud base parameters from space remains subject to question [e.g., Darnell et al., 1983]. Hopefully, these problems can be solved and LW↑↓ may be determined by using improved observational data and methods for estimating LW↑↓ which utilize the conceptual parallel plate model.
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T. D. Dickey and D. A. Siegel, Ocean Physics Group, Department of Geological Sciences, University of Southern California, Los Angeles, CA 90089.

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