# Comparison of Arctic clouds between European Center for Medium-Range Weather Forecasts simulations and Atmospheric Radiation Measurement Climate Research Facility long-term observations at the North Slope of Alaska Barrow site

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[1] This study evaluated the European Center for Medium-Range Weather Forecasts (ECMWF) model-simulated clouds and boundary layer (BL) properties based upon Atmospheric Radiation Measurement Climate Research Facility observations at the North Slope of Alaska site during 1999–2007. The ECMWF model-simulated near-surface humidity had seasonal dependent biases as large as 20%, while also experiencing difficulty representing BL temperature inversion height and strength during the transition seasons. Although the ECMWF model captured the seasonal variation of surface heat fluxes, it had sensible heat flux biases over 20 W m<sup>-2</sup> in most of the cold months. Furthermore, even though the model captured the general seasonal variations of low-level cloud fraction (LCF) and liquid water path (LWP), it still overestimated the LCF by 20% or more and underestimated the LWP over 50% in the cold season. On average, the ECMWF model underestimated LWP by  $\sim 30 \text{ g m}^{-2}$  but more accurately predicted ice water path for BL clouds. For BL mixed-phase clouds, the model predicted water-ice mass partition was significantly lower than the observations, largely due to the temperature dependence of water-ice mass partition used in the model. The ECMWF model captured the general response of cloud fraction and LWP on large-scale vertical motion changes but overpredicted the magnitude of the difference, especially for LWP. The new cloud and BL schemes of the ECMWF model that were implemented after 2003 only resulted in minor improvements in BL cloud simulations in summer. These results indicate that significant improvements in cold season BL and mixed-phase cloud processes in the model are needed.

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# 1. Introduction

[2] The Arctic is an area that is very sensitive to global climate change [Baker et al., 1980; Barry et al., 1993; Curry et al., 1996; Walsh et al., 2002; Hassol, 2004] while also experiencing significant changes in its surface air temperature, sea-ice cover, atmospheric circulation, precipitation, snowfall, biogeochemical cycling, and land surface [Curry and Ebert, 1992; Curry et al., 1996; Maslanik et al., 1996; Johannessen et al., 1999; Rothrock et al., 1999; Rigor et al., 2000; Wang and Key, 2003; Chapin et al., 2005; Lemke et al., 2007]. Arctic temperatures have

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increased by almost twice the global average rate in the past 100 years [*Trenberth et al.*, 2007], thus causing the Arctic sea ice extent to decrease by 2.7% per decade since 1978 [*Lemke et al.*, 2007]. Previous studies have shown that Arctic clouds play an important role in Arctic climate changes through cloud-radiation feedback coupled with ice-albedo feedback [*Curry et al.*, 1996; *Zhang et al.*, 1996; *Stone*, 1997; *Walsh et al.*, 2002; *Study of Environmental Change*, 2005].

[3] To better understand the Arctic climate, general circulation models (GCMs) have been used to simulate the Arctic climate and to project future climate changes [*Randall et al.*, 1998]. Although most models perform reasonably well at low latitudes and midlatitudes [*Gates et al.*, 1999; *Inness and Slingo*, 2003], the Arctic climate presents great challenges for GCMs because of the unique features in the Arctic, such as large annual variations of solar radiation,

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high-reflecting snow and ice surface, an extremely stable boundary layer (BL), and a shortage of water vapor [*Randall et al.*, 1985, 1998; *Cullather and Bromwich*, 2000; *Yannuzzi et al.*, 2005]. Therefore, it is not surprising that large differences in simulations of the Arctic climate exist among GCMs, such as differences in sea surface temperature, cloud fraction and properties, precipitation, and surface radiation flux [*Gates et al.*, 1999; *Inoue et al.*, 2006; *Klein et al.*, 2009].

[4] Compared to other GCMs, the European Center for Medium-Range Weather Forecasts (ECMWF) model has better overall performance due to its superior data assimilation system and more sophisticated parameterization of physical processes [Mace et al., 1998; Bretherton et al., 2000; Duynkerke and Teixeira, 2001; Buizza et al., 2005]. Given these advantages of the ECMWF model, the ECMWF-analyzed fields are widely used as initial conditions for other model simulations [Curry et al., 2000; Rinke et al., 2006; Sandvik et al., 2007] and as verification on results of other models [Gates et al., 1999; Curry et al., 2000; Dethloff et al., 1996, 2001]. Therefore, it is particularly important to assess the performance of the ECMWF model and to improve its parameterization in the Arctic region. Recently, a number of comparisons of the ECMWF model simulations with remote sensing and in situ measurements have been conducted based on intensive field programs in the Arctic region. Beesley et al. [2000] showed that the ECMWF model accurately predicted the presence of most precipitation and cloud events but also overestimated clouds lower than 1 km and above 5 km by comparing with observations from the Surface Heat Budget of the Arctic Ocean (SHEBA) during November and December 1997. Bretherton et al. [2000] found that the ECMWF model matches the SHEBA radiosonde observations above the BL, but there are large near-surface temperature errors that are believed to be associated with the ECMWF slab ice model and the assumption of the melting temperature of sea ice. Bretherton et al. [2000] also found that the model predictions did not agree with observed values for surface sensible heat flux. Xie et al. [2006] applied the objective variational analysis to compare the ECMWF forecast with observations during the Mixed-Phase Arctic Clouds Experiment (M-PACE) conducted near around Barrow, Alaska, during October 2004. The variational analysis helps to minimize the misrepresentation problems (e.g., comparing single point observations with model grid box results), where it was determined that the model performance was influenced by large-scale dynamic processes [Xie et al., 2006]. However, because of the relatively short time range, the influence of large-scale dynamics has not been thoroughly studied. Additionally, *Xie* et al. [2006] showed that the model underestimation of the surface downward longwave (LW) radiation is associated with the underestimation of BL cloud cover and liquid water path (LWP).

[5] Most previous studies are based on relatively shortterm field experiments, and there are few studies that have focused on the evaluation of model ability in predicting seasonal changes of Arctic clouds, atmospheric variables, and BL structures, which are still remaining key science questions [*Study of Environment Change*, 2005]. Therefore, it is important to fully understand the performance of the ECMWF model in simulating Arctic cloud seasonal cycles

and to better evaluate the model deficiencies in cloud and BL parameterizations by using reliable observations over a larger time scale. To achieve this goal, 9 years of multisensor observations collected from 1999 to 2007 at the Atmospheric Radiation Measurement (ARM) Climate Research Facility (ACRF) North Slope of Alaska (NSA) Barrow site were used to evaluate the ECMWF simulations of surface variables, BL properties, and cloud properties. We also evaluated the capability of the ECMWF in predicting the influence of large-scale vertical motion on cloud properties. The detailed descriptions of data used in the study are provided in section 2. The model-predicted surface variables, BL properties, and cloud properties are compared with the observations between the period of 1999 and 2003 in section 3. The influence of large-scale vertical motion on cloud properties is also discussed at the end of this section. Section 4 evaluates the improvements of the ECMWF model with the major model upgrades after 2003. Section 5 provides a summary of the study.

# 2. Data Description

# 2.1. Observations

# 2.1.1. Atmospheric State Variables

[6] The Surface and Tower Meteorological Instrumentation implements a Vaisala HMP45D temperature and relative humidity (RH) probe to measure air temperature and RH and a Vaisala WAA251 cup anemometer to measure the horizontal wind speed. These sensors are mounted at four different heights (2, 10, 20, and 40 m) on a 40 m tower. The atmospheric pressure is measured at the base of the tower. The uncertainties of the instrumentation for RH, temperature, wind speed, and atmospheric pressure are  $\pm 2\%$ ,  $\pm 2^{\circ}$ C,  $\pm 0.17$  m/s, and  $\pm 0.15$  hPa, respectively. It is important to note that the model-simulated RH is calculated from the hybrid saturation vapor pressure for temperature between -23°C and 0°C, through the use of temperature interpolation method. Therefore, in order to match the model-simulated RH, the observed RH was then calculated from vapor pressure and saturated vapor pressure. A shaded pyrgeometer with a hemispheric field of view provides 1 min downwelling surface LW (4.0–50  $\mu$ m) radiation flux measurements with uncertainty less than  $\pm 2 \text{ W m}^{-2}$  [Philipona et al., 2001]. Sounding balloons were launched daily at around 1800 UTC, with the exception of weekends and holidays, and subsequently the inversion height was estimated from these soundings. A temperature inversion is defined as a layer in which temperature increases with altitude; however, it has been shown that this layer can include thin embedded layers (<100 m) where temperature decreases with height [Kahl, 1990; Serreze et al., 1992]. If an inversion layer has an embedded layer with more than 100 m depth, it is defined as multiple inversion layer. Inversion strength was calculated as the temperature difference between the top of the highest inversion layer and the base of the lowest inversion layer.

#### 2.1.2. Cloud Properties

[7] The cloud vertical position and layering information were retrieved from combined micropulse lidar (MPL) and millimeter cloud radar (MMCR) measurements. The cloud layer and phase detection algorithm developed by *Wang and Sassen* [2001] can differentiate among various atmospheric

targets, such as ice and water clouds, virga, precipitation, and aerosol layers. The observed cloud occurrence frequency is the ratio of the number of observed cloudy profiles and the total number of observed profiles within a 1 h time interval. In general, the cloud occurrence based on hour or longer temporal measurements is statistically similar to the cloud cover based on spatial measurements at 10 km [Dong and Mace, 2003]. The LWP was retrieved from twochannel (23.8 and 31.4 GHz) microwave radiometer (MWR) measurements, with an improved retrieval algorithm that has much lower uncertainties for low LWP clouds than current ACRF achieved results [Wang, 2007]. This algorithm has been successfully used in the Arctic region and can significantly improve MWR low LWP retrievals, especially for LWPs less than 30 g m<sup>-2</sup>. In our analyses, hourly mean LWPs were calculated as the mean of the 60 s LWP data when clouds were detected by the combined MPL and MMCR measurements. Monthly mean LWPs were calculated using the averaged hourly values. The climate modeling best estimate (CMBE) data set [Xie et al., 2010], which provides the hourly averaged cloud fraction and LWP measured by ACRF ground-based active and passive remote sensing instruments, is also used for model validation in section 4. 2.1.3. Surface Energy Fluxes

[8] The Carbon Dioxide Information Analysis Center (CDIAC) provides 30 min averaged surface latent and sensible heat fluxes, which is available at a location of 71.323°N and 156.626°W using an eddy covariance technique [*Law et al.*, 2001]. This location is approximately 1 km west of the ACRF NSA Barrow central facility. By convention, positive values of sensible and latent heat fluxes indicate fluxes leaving from the surface (upward direction). The measurements used in this study were from the level-2 data set, which had been quality checked by CDIAC using standardized techniques and had an uncertainty less than 20% [*Berger et al.*, 2001]. However, certain time periods had missing data due to instrument malfunction.

### 2.2. Model Simulations

[9] Hourly ECMWF simulations at the NSA Barrow site are archived by the ACRF External Data Center. The archived ECMWF outputs based on 12-36 h forecasts have a horizontal resolution of  $0.56^{\circ} \times 0.56^{\circ}$  and a vertical resolution of up to 91 levels in the most recent version. The lowest model level is approximately 10 m above the surface, along with a grid spacing of approximately 20 m at near surface that gradually increase with height to approximately 250 m at 2 km. The ECMWF Centre Integrated Forecasting System comprises a four-dimensional variational data assimilation system, a global atmospheric model, an ensemble prediction system, and a suite of ocean wave models [Jakob, 2001]. The scheme of cloud parameterization in the ECMWF model was originally developed by Tiedtke [1993] and referred to as T93. T93 was implemented into the ECMWF operational system in 1995 [Jakob, 1994], where the basic foundation of this scheme includes two prognostic equations for condensate (cloud liquid water and cloud ice) and cloud fraction. Both the cloud fraction and condensate are grid volume averaged variables and are determined by advection, convection, BL turbulence, nonconvective condensation processes, and evaporation. In addition, the condensate is also influenced by precipitation

processes and entrainment [*Tiedtke*, 1993]. The LWP was calculated by integrating the LWC from cloud base to cloud top. Other variables, including atmospheric pressure, 2 m temperature, 2 m RH, and surface heat flux, are diagnostic data from the ECMWF model runs and are calculated on single surface model level. The large-scale vertical motion at 850 mbar is obtained from the National Center for Environmental Prediction (NCEP) reanalysis [*Kalnay et al.*, 1996], which use a frozen state-of-the-art analysis/forecast system that performs data assimilation using past data. The reanalysis outputs are available on a  $2.5^{\circ} \times 2.5^{\circ}$  grid every 6 h at 17 pressure levels.

### 3. Results for the Period of 1999–2003

#### 3.1. Surface Variables and BL Structures

[10] The atmospheric BL provides the physical link between the atmosphere and surface for exchanges of heat, moisture, and momentum. Most of the BL parameterizations are developed mainly for midlatitude conditions, where a neutral or unstable BL stratification prevails [*Dethloff et al.*, 2001]. However, at the NSA Barrow site, the BL is often characterized by an extremely stable vertical stratification. This subsection provides an evaluation of the ECMWF simulations of surface variables and BL structures under such extreme conditions.

#### 3.1.1. Surface Variables

[11] Surface variables, including atmospheric pressure, 2 m temperature, 2 m and 20 m RH, surface latent heat flux, and surface sensible heat flux, were compared between the ECMWF model and the observations. The 20 m RH model variable are linear-interpolated values between the first level (about 10 m above the surface) and the second level (about 30 m above the surface) model results. Figure 1a shows that the model-simulated atmospheric pressure was close to the observations with an annual mean error of 22 hPa. For 2 m temperature (Figure 1b), the data points deviated from the 1:1 line at warmer temperature range (above  $0^{\circ}$ C). More detailed near-surface temperature differences between the ECMWF model and the observations will be discussed in section 3.1.2. The RH at 2 m (Figure 1c) showed considerable scatter and the ECMWF model systematically underestimated RH (dry bias) by annual mean of 8.1%.

[12] In order to determine the seasonal variation of the model performance in predicting near-surface humidity, the annual cycle of model error for 20 m RH and 20 m specific humidity were plotted in Figure 2 based on hourly mean data. The model error is defined as the modeled value minus the observed value, hereafter. Figure 2a shows that the model underestimated 20 m RH by 9% in the warm season (refers to months between May and October, hereafter) and overestimated it by 7% in the cold season (refers to months between November and April, hereafter). Similar trends existed at 2 and 40 m levels. These results are consistent with the results from *Beesley et al.* [2000]. The model dry RH bias in summer was also reported by Doran et al. [2002], which showed that the ECMWF model underestimated the humidity below 1 km from June to August at the Barrow site. For 20 m specific humidity (Figures 2c and 2d), the model overestimated it by a mean of 0.32 g/kg during May-July season and underestimated it by a mean of 0.2 g/kg during August-October. How these near-surface



**Figure 1.** Comparison of the model-analyzed (*x* axis) against the observed (*y* axis) based on daily mean data during 1999–2003: (a) atmospheric pressure (mbar), (b) 2 m temperature (°C), and (c) RH (%). Linear correlation coefficient (*R*) between observations and the model results are listed in Figure 1.

humidity biases impact seasonal cloud simulations will be discussed further in section 3.2.1.

[13] The annual cycles of surface latent and sensible heat fluxes from the ECMWF simulations and the CDIAC measurements in 2003 were compared in Figure 3, which shows significant seasonal variations in these fluxes with large values in the warm season and small (or negative) values in the cold season. Generally, the ECMWF model captured the seasonal trend of surface heat fluxes, but large discrepancies existed in May (the spring transition season). During this period, latent heat flux and sensible heat flux were overestimated by a mean of 34.3 W m<sup>-2</sup> and 10.7 W m<sup>-2</sup>, respectively. In the ECMWF model, the Monin-Obukhov similarity theory is used to calculate surface latent heat flux (ECMWF integrated forecasting system documentation CY31R1):

$$LHF = \rho C_{q} |U_{l}| (q_{s} - q_{l}), \qquad (1)$$

where LHF represents surface latent heat flux, is the air density,  $q_s$  is the specific humidity at the surface,  $q_1$  is the specific humidity at the first model level, U is the wind speed, and  $C_Q$  is the transfer coefficient. The overestimation of LHF in the transition season partly resulted from the biases of BL specific humidity. By calculating the gradient of specific humidity ( $q_s - q_1$ ) in the spring transition period, it was found that the model overestimated the gradient by 150%.

[14] To analyze the seasonal differences in model performance, the heat flux data set was divided into four seasons: Spring (March-May), Summer (June-August), Fall (September-November), and Winter (December-February). The scatter plots based on daily values are presented in Figure 4. For both sensible and latent heat fluxes, the slopes of the model-predicted and the observed were close to 1 in the summer and fall seasons. However, the model-predicated latent heat fluxes were statistically higher than measured values by a mean of  $\sim 19.6 \text{ W m}^{-2}$  during the summer season. The overestimation of LHF in summer partly resulted from comparing single point observations with model grid box results. The overestimation of surface latent heat flux indicates the ECMWF model provides more energy and moisture than the real situations, such biases could further feed into cloud simulations [Morrison and Pinto, 2006]. For both sensible and latent heat fluxes, the data points in winter were more scattered. The higher linear correlation coefficient in the warm season than in the cold season (Figure 4) indicates that the ECMWF model track heat flux variations better in the warm season although they are systemically overestimated. This difference may be due to the fact that the physical processes in the Arctic warm season are similar to that in the region of midlatitude, where many parameterizations used in the ECMWF model are originally developed and where the ECMWF model performs well. However, in the Arctic extreme stable BL, the ECMWF BL parameterization has difficulties in representing all related physical processes. We should note that the above statements about the discrepancies between the model results and the observations did not consider the impacts of open ocean in the ECMWF model grid box during the summer time. For example, the presence of open ocean in the ECMWF model grid box over the NSA Barrow site during summer may cause higher grid-averaged latent heat flux due to higher surface humidity over ocean than that over land [Xie et al., 2006].

#### 3.1.2. Boundary Layer Structure

[15] The monthly mean cloud top heights of the Arctic stratiform clouds (ASCs) as well as temperature inversion base height and inversion top heights were plotted in Figure 5a, which indicates that the cloud top was primarily located inside of the inversion layer (between inversion top and



**Figure 2.** (a) The 20 m RH model error and (b) observed 20 m RH; (c) 20 m specific humidity (SH) model error and (d) observed 20 m specific humidity. Model error is defined as model – observation. The individual dot point represents hourly mean value, and the short dashed lines are weekly mean values.

inversion base). In this study, ASCs are defined as cloud base less than 2 km and cloud thickness less than 1 km. This general feature of ASCs can be explained based on the physical and thermal processes; due to the maximum radiative cooling at the base of the preexisting temperature inversion, ASCs are more likely to form near an inversion base. Furthermore, the existence of ASCs helps to maintain the temperature inversion due to effective longwave radiative cooling at the cloud top [*Curry et al.*, 1996; *Harrington et al.*, 1999; *Zhang et al.*, 1999]. Therefore, low-level cloud formation and maintenance mechanisms as well as cloud properties closely interact with the BL processes and are affected by the BL structure [*Curry and Herman*, 1985;

*Curry et al.*, 1996; *Dong and Mace*, 2003]. To better understand model cloud simulations, it is important to evaluate the ECMWF model performance in predicting the BL structures.

[16] The monthly mean inversion top heights predicted by the model and observed by radiosonde were compared in Figure 5b, which shows that the model captured seasonal variation of inversion height: lower inversion in the warm season and higher inversion in the cold season [*Kahl*, 1990; *Serreze et al.*, 1992]. However, the model-predicted inversion top was generally lower than the observed with annual mean difference of ~80 m. *Morrison and Pinto*'s [2005] modeling study also showed inversion height differences



**Figure 3.** The annual cycle of daily mean model-predicted and measured (a) surface sensible heat flux and (b) surface latent heat flux in the year of 2003 at the NSA site.



**Figure 4.** Scatter plots of the model-predicted (y axis) against measured (x axis) daily mean (a and b) sensible heat flux and (c and d) latent heat flux based on data from 2003 to 2005. The different seasons are indicated with different colors. Linear correlation coefficient (R) between the observations and the model results are listed in Figure 4.

between model simulations and observations; they contributed the differences to the model deficiencies in the BL parameterization, vertical velocity, and the initialization fields.

[17] As a complex phenomenon, the temperature inversion in the Arctic BL involves radiative cooling, warm air advection, subsidence, radiative influences from ice crystals, surface melt, and topographic influences [*Busch et al.*, 1982; *Kahl*, 1990; *Serreze et al.*, 1992]. Therefore, detailed differences between the model-simulated and observed BL inversion structures are strongly dependent on individual cases. Figure 6 shows the temperature profiles from the ECMWF model and the radiosonde data on 2 January 2001 and 30 May 2001, which represent typical temperature profiles in winter and spring seasons, respectively. As illustrated in these two examples, although the general shapes of the temperature profiles are similar, there are some noticeable differences in fine structures.

[18] The first general difference is that the observed profile had a more complicated structure, especially in winter, during which multiple inversion layers frequently occur. Because of insufficient vertical resolution or inability to capture all of the inversion generation mechanisms, the model did not represent the fine structure of the temperature profile. These deficiencies also explain why the modelpredicted inversion base was lower than the observed; for example, in Figure 6a, the ECMWF model-predicted inversion base was at ~150 m, whereas a higher inversion base was observed at ~250 m. [19] The second general difference is the inversion strength which was compared in Figure 7. The model simulations and the observations exhibited similar seasonal trends with a mean maximum strength in March and a mean minimum strength in October. However, the ECMWF model underestimated inversion strength by  $\sim 20\%$  during the warm season, whereas the model overestimated it by  $\sim 3\%$  during the cold season, which was consistent with the example cases given in Figure 6.

[20] The third general difference is near-surface temperature structure. As illustrated in the case from 30 May 2001 (Figure 6b), the model predicted that the inversion layer was surface-based (the inversion base is at the surface), whereas the observations showed a lifted inversion layer (inversion base is above the surface). The lifted inversion was associated with a mixed layer that forms above the surface, which acts to keep the inversion elevated [Kahl, 1990]. The ECMWF model generally underestimated the occurrence of the lifted inversion by ~18%. Near-surface temperature differences were also reflected in temperature biases, as illustrated in individual profiles (Figure 6) and seasonal mean temperature profiles (Figure 8). Figure 8 displays that there was near-surface cold bias in the fall and winter seasons and warm bias in the summer season. In the spring season, there was warm bias above 120 m level and cold bias below 120 m level. The warm bias coincided with the overestimation of sensible heat flux in the summer season.





**Figure 5.** The annual variations of BL properties. (a) Observed monthly mean inversion top height (dashed line), inversion base height (dotted line), and cloud top height (solid line). (b) Monthly mean inversion top height from ECMWF simulations (solid line) and radiosonde observations (dotted line).

Bretherton et al. [2000] believed that the warm bias in spring is associated with the large thermal inertia of the slab ice model, which prevented near-surface air temperatures from cooling. Although the above statement is based on the SHEBA experiment conducted over the Arctic Ocean, it could also explain the warm bias at the Barrow site that is close to the ocean. As to the cold bias in winter, Viterbo et al. [1999] attributed it to lack of the soil moisture freezing in the ECMWF model land surface scheme. In addition to the above reasons, the uncertainties in the Arctic cloud simulations and related downward longwave radiation fluxes are important factors contributing to the near-surface temperature biases. The importance of BL structures, particularly the low-level temperature inversions, to heat/moisture transfer and ASCs formation had been analyzed through observational and model studies [Andreas and Murphy, 1986; Curry, 1986; Rahl, 1990; Curry et al., 1996; Zhang and Stamnes, 1998]. In the ECMWF cloud parameterizations, both convective clouds and stratocumulus clouds use a mass-flux type parameterization [Jakob, 2001], which is dependent on convective updraft and turbulent mixing in the BL. Therefore, the poor ability of simulating BL vertical structures as described above certainly has influences on ASC simulations. The interaction between BL structures and cloud fraction will be further discussed in the following section.

**Figure 6.** Temperature profiles from the ECMWF model (solid line) and radiosonde observations (dashed line) on (a) 2 January 2001 and (b) 30 May 2001 at the NSA Barrow site.

#### 3.2. Cloud Properties

[21] The ECMWF cloud parameterizations are subdivided by the general cloud classification groups, and these include convective clouds, stratocumulus clouds, and stratiform clouds. The parameterizations of convective clouds and stratocumulus clouds are based on mass-flux parameterization [*Tiedtke*, 1989, 1993; *Gregory et al.*, 2000]. For stratiform clouds, the parameterization of cloud formation is based on nonconvective processes (i.e., condensation by lowering the saturated specific humidity), such as largescale lifting and/or diabatic cooling [*Jakob*, 2001]. The determination of the phase of the condensate is based solely



**Figure 7.** Monthly mean inversion strength from the ECMWF model (black block) and from radiosonde observations (white block).



**Figure 8.** Seasonal mean temperature profiles simulated by the ECMWF (solid line) and observed by radiosonde (dashed line) in (a) Winter, (b) Spring, (c) Summer, and (d) Fall based on data during 1999–2004.

on temperature and is accomplished by describing the fraction of water in the total condensate,  $\alpha_w$ , as

$$\alpha_{\rm W} = 0 \qquad T \le T_{\rm ice}$$

$$\alpha_{\rm W} = \left(\frac{T - T_{\rm ice}}{T_0 - T_{\rm ice}}\right)^2 T_{\rm ice} \le T \le T_0 , \qquad (2)$$

$$\alpha_{\rm W} = 1 \qquad T \ge T_0$$

where  $T_{ice} = 250.16$  K and  $T_0 = 273.16$  K. **3.2.1.** Cloud Fraction

[22] An example of the time-height cross section of the observed clouds in September 1999 is shown in Figure 9a, in which some unique features of Arctic clouds are presented. First, the frequency occurrence of ASCs is as high as 80% of the time in some months; second, the ASCs lasted several days; and third, the cloud base was as low as 180 m above the ground. Figure 9b shows the cloud fraction simulated by the ECMWF model during the same period. The model-predicted large-scale features, such as cloud type and cloud occurrence, matched well with the observations. However, there were significant differences in the magnitudes and in the vertical and temporal distributions of the clouds: the model-simulated cloud base was higher than the observed one, low-level clouds were underestimated by the model, and middle-level and high-level clouds lasted longer in the model simulations. These differences in the vertical distribution of the clouds may be more clearly identified from review of monthly mean cloud fraction profiles. Figure 10 shows the model-simulated and the observed cloudiness profiles during the fall and winter season. In September 1999 (Figure 10a), the model significantly underestimated cloud fraction below 1 km and overestimated cloud fraction above 1 km. Xie et al. [2006] also reported that in October (fall season), the ECMWF model underestimated BL clouds when compared with the M-PACE observations. In December 1999 (Figure 10b), the model overestimated cloud fraction below 1 km and above 4 km.

[23] To fully understand seasonal variation of the model performance in predicting cloud vertical structure, Figures 11a and 11b show the observed and simulated annual cloud cycle with a 5 year (1999-2003) averaged monthly mean cloud fraction profile. Both the model simulations and the observations show that the NSA Barrow site was dominated by low-level clouds. However, based upon the model error (i.e., model-observations) profile in Figure 11c, it is clear that there are differences in the cloud vertical structure between the model simulations and observations. The ECMWF model generally overestimated clouds above 6 km in all seasons. The differences regarding high-level clouds may partly result from observation limitations. First, the MMCR may still fail to detect tenuous cirrus clouds with very low ice water content (IWC) and small crystal size [Hogan et al., 2001; Wang and Sassen, 2002a, 2002b]; second, the MPL cannot detect high-level clouds when the low-level clouds are present, due to strong attenuation. For clouds between 2 and 4 km, the model simulated profiles were close to the observed profiles in all months except in June. For clouds lower than 2 km, model errors strongly depend on the seasons. In the cold season, the model generally overestimated clouds below 500 m. In the warm season, except in October, the model generally underestimated clouds below 500 m and overestimated clouds above this level. In October, the model significantly underestimated clouds below 2 km. These differences reflect that the ECMWF model has a difficult time in accurately representing the cloud vertical distributions, especially for the low-level clouds. The cloud vertical distributions influence the distribution of radiative fluxes; thus, misrepresentation of the cloud vertical structure will further influence the surface energy budget [Baker, 1997].

[24] Considering the critical role of low-level clouds on surface energy budget, it is important to understand how the BL variables and dynamic processes affect the seasonal variations of the ECMWF low-level cloud biases. In this paper, the model-simulated low-level cloud fraction (LCF) is calculated by using a maximum cloud overlap assumption, which is also used in other studies [*Beesley et al.*, 2000; *Xie et al.*, 2006]:

$$LCF = \max_{l=0.2km} a_l, \tag{3}$$

where  $a_l$  is the hourly cloud fraction at model level *l*. In order to calculate the observed LCF, only the cloud profiles with a cloud base less than 2 km are selected. Figure 12 shows the comparison of the monthly mean LCF that is calculated from hourly values. Because the cloud layers occurred at different heights in different times, Figure 12 cannot be simply inferred from Figure 11. The annual mean observed LCF was 52%, with maximum of 81% in October and minimum of 30% in June. The annual mean model-predicted LCF was 64%, with maximum of 78% in October and minimum of 42% in June. Although, the ECMWF model was able to capture the general seasonal trend, the model did not capture the changes of cloud amount in the transition seasons. In Spring, the observed



Figure 9. Comparison of ECMWF (a) observed and (b) model-predicted cloud fraction at the ACRF NSA Barrow site in September 1999.

LCF increased sharply from 36% in April to 54% in May. In Fall, observed LCF decreased from 81% in October to 62% in November. The transition seasons in the Arctic are accompanied by the transition of atmospheric conditions, radiation, sea ice cover, and soil thermal state [Olsson et al., 2003]. The low-level clouds are impacted by such transitions and undergo cloud property changes, especially in cloud phase [Curry et al., 1997; Harrington et al., 1999; Curry et al., 2000]. Therefore, the poor performance in capturing the trend in cloud amount in the transition seasons, in some respects, illustrates the model deficiency in simulating the mixed-phase clouds that dominate the LCF in these seasons [Pinto, 1998; Intrieri et al., 2002]. In addition to the different trends in the transition seasons, there was significant magnitude difference in the annual cycle. During the cold season, the ECMWF model overestimated the LCF by 23%. During the warm season, except in June and July, the ECMWF model underestimated the LCF by 4%. The seasonal variations in predicting the LCF could be associated with model-simulated surface variables, BL processes, and dynamic processes. In the following discussions, we will try to establish the link between simulated low clouds and these factors.

[25] The bias in humidity simulation possibly causes the model bias in predicting LCF. In the ECMWF stratiform cloud parameterization, cloud formation and maintenance are controlled by condensation processes, i.e., the rate of change in saturated specific humidity ( $q_s$ ). New cloud formation in the grid box is also controlled by the grid mean RH, which means cloud formation is prohibited when RH is below the critical value [*Tiedtke*, 1993; *Jakob*, 2001]. Figure 2 shows the model-simulated 20 m RH had a dry bias for the period between May and October and a moist bias for the remaining months, which roughly corresponded to the periods of the model underestimating and overestimating LCF, respectively. As to the underestimation of low-level clouds in August, September, and October, this could also



**Figure 10.** Monthly mean profile (20 m vertical resolution) of cloudiness predicted by the ECMWF model and observed by lidar and MMCR at the NSA Barrow site in (a) September 1999 and (b) December 1999.



**Figure 11.** Monthly averaged vertical distribution of cloud fraction from (a) the observations and (b) the ECMWF model and (c) their differences. Both the ECMWF model and observation data are averaged from hourly data during 1999–2003.

be associated with the ECMWF deficiencies in simulating the frontal system. Ryan et al. [2000] and Xie et al. [2006] stated that the model poorly captured the frontal cloud band, thus, resulting in an underestimation of low-level clouds. By using the NCEP reanalysis data, we found that the Barrow site experienced a higher occurrence of moisture advection associated with frontal systems between August and October than in other months. Therefore, there are more chances for the model to underestimate the low-level clouds during this period. The overestimation of low-level clouds in June and July could be because part of the ECMWF model grid box over the Barrow site contains ocean. The biases of the ECMWF model in predicting BL structure could also influence the low-level cloud simulations. Although it is not clear to what extent the biases influence cloud simulations, some observational evidences suggests the close correlation between cloud properties and BL structures [Kahl, 1990; Sedlar and Tjernstrom, 2009]. This close correlation can be explained by thermal dynamic processes. For example, the lifted inversion is always associated with the surface mixing in the BL. Therefore, in this situation, moisture and energy transfer processes in the BL are strongly coupled to the lowlevel clouds.

#### 3.2.2. Cloud Liquid and Ice Water Path

[26] Given the fact that liquid water dominates the ASCs even in the mixed-phase condition and considering its

important role in cloud radiative-surface interactions, correctly predicting LWP is critical for models to correctly simulate Arctic surface heat budget [*Curry and Herman*, 1985; *Curry*, 1986; *Intrieri and Shupe*, 2004; *Shupe and Intrieri*, 2004; *Morrison and Pinto*, 2006]. In this study, the LWP from the ECMWF model were compared to the observations only when the cloud base was lower than 2 km and cloud thickness was less than 1 km. Moreover, periods



**Figure 12.** The seasonal variation of monthly mean LCF from the ECMWF model and the observations at the NSA Barrow site. Observations and model forecasts during 1999–2003 are here. The vertical bars indicate the standard deviation of monthly means among different year.

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**Figure 13.** Comparison of monthly mean (a) LWP, (b) IWP, and (c) LWP/(LWP + IWP) for the low-level clouds between the ECMWF model simulations (solid line) and the observations (dashed line) around the NSA site.

with LWP values over 300 g  $m^{-2}$  were not included because such high values were most likely due to precipitation. By looking at daily time series (not shown here), the ECMWF model predicted the occurrence of liquid or mixed-phase clouds well. However, the model-predicted LWP values for these clouds were much lower than the observed values, and the differences far exceed the retrieval uncertainties of 10 g m<sup>-2</sup>. Figure 13a shows the comparison between the modelpredicted and retrieved monthly mean LWP values based on data between 1999 and 2003. The model-predicted values were much smaller than the observed values, where the annual mean difference was 30 g m<sup>-2</sup>. Although model underestimation of LWP is generic, contributions to this bias are still complex. Xie et al. [2006] and Klein et al. [2009] suggested that the LWP error is due to the underestimation of cloud amount and difficulties in simulating the microphysics of mixed-phase clouds. Doran et al. [2002] showed that the underestimation of LWP is consistent with the dry bias in the RH, which is also presented by this study in Figure 2. However, it is not yet known to what extent, the near-surface RH bias will account for the LWP underestimation. For ice water path (IWP) (Figure 13b), the model captured the seasonal trend well, with maximum values in February and minimum values in June. Moreover, the model-simulated IWP is close to the observed value, with an annual mean underestimation of 18%. Figure 13c shows that the model significantly underestimates liquid water fraction (LWF) defined as LWP/(LWP + IWP), especially in winter. This underestimation is largely due to the model phase partition parameterization, which solely depends on temperature (equation (2)). Other than poor performance in LWF, the temperature-dependent phase partition has many

negative impacts on model performance. The liquid phase could coexist with the ice phase in the Arctic stratus clouds even if cloud temperature is below  $T_{ice}$  (250.16 K). Moreover, the temperature-dependent phase partition also produces erroneous structure in IWC profiles [Liu et al., 2007; *Xie et al.*, 2008]. As the results displayed in section 3.1.2., the cloud top temperature is normally lower than the cloud base temperature. Therefore, according to the temperaturedependent phase partition, the mixed-phase cloud top will have higher IWC than the cloud base have, which has been shown to be the opposite of some observations [*Pinto*, 1998; Intrieri et al., 2002]. The biases in cloud LWF influence the model predictions of surface LW radiative flux. Figure 14 shows that seasonal trends of surface downwelling LW (DLW) flux errors and LWF errors generally coincided with each other (i.e., larger LWF errors led to larger DLW flux errors). However, for clouds with LWP less than 50 g  $m^{-2}$ , the DLW flux is also affected by the cloud droplet effective radius, LWP, and cloud temperature. Therefore, the magnitude of model DLW flux errors was not in proportion to the magnitude of model LWF errors. For example, even though the LWF error was low in January compared to other months, the DLW flux error reached  $-20 \text{ W m}^{-2}$ .

# **3.3.** Influence of Large-scale Vertical Motion on Cloud Properties

[27] The influence of large-scale vertical motion on Arctic cloud properties had been addressed by several previous studies; however, it is shown that these studies had different conclusions. Pinto [1998] found that large-scale vertical velocity appears to be relatively unimportant for the formation and maintenance of the ASCs. Klein and Hartmann [1993] showed that the season with the highest amount of Arctic stratus clouds does not coincide with the season of the highest lower tropospheric stability (LTS). This result implies a weak correlation between ASCs amount, and large-scale vertical motion because the LTS is positively correlated to large-scale downward motion with a correlation coefficient of 0.56. However, Curry et al. [1996] indicated that large-scale vertical motion influences cloud formation through modifying the temperature inversion and cloud top radiative cooling, based upon a simulation using a one-dimensional coupled atmosphere-sea ice model. On the basis of the model simulations with a two-moment microphysics scheme, Morrison and Pinto [2005] concluded that neglecting upward motion results in weak cloud droplet activation and further reduction in the cloud liquid water content. Thus, weak upward motion is considered to be a favorable condition for initiating ASCs. Zuidema et al. [2004] also found that rising motion at 850 mbar coincided with a deeper BL and higher cloud optical depths from 1 to 10 May 1998 during the SHEBA experiment. The different conclusions explained above were based on either short-term case studies or model results. Therefore, multiyear (1999-2003) data sets are important to evaluate the impacts of large-scale vertical motion on cloud properties and also to determine how well the ECMWF model captures these properties.

[28] The NCEP reanalysis was used to provide large-scale vertical motion (omega) at 850 mbar. Cloud fractions from the ECMWF model and the observations under upward and downward motion conditions were averaged by month sepa-



**Figure 14.** Monthly mean model error for surface downwelling LW radiation (DLW) flux (solid line, left *y* axis) and liquid water fraction (LWF) (dash line, right *y* axis). Results are based on data from 1999 to 2003. LWF is defined as LWP/(LWP + IWP).

rately. Their differences (cloud fraction under upward motion minus cloud fraction under downward motion) are shown in Table 1. Both the ECMWF model and the observations showed higher cloud fraction under upward motion than under downward motion, especially for low-level and mid-dle-level clouds. The ECMWF model captured the observed trend within 3%. Monthly mean model errors of LCF under upward and downward motion were plotted in Figure 15. Although the model error under these large-scale conditions showed a similar seasonal trend, model simulations performed slightly better under large-scale upward motion than under the downward motion.

[29] A similar comparison for model-simulated and observed LWP under the upward and downward motions was presented in Figure 16. Although, observed annual mean LWP under the upward motion condition was higher than under the downward motion condition by 8.7 g m<sup>-2</sup>, significant differences mainly occurred in March, July, and August. On the other hand, the ECMWF model produced significantly higher LWP under upward motion conditions, especially from May to October.

[30] Figure 17 shows the observed cloud top height and cloud top temperature difference under the upward and downward motions. For these two comparisons, we only considered the clouds with cloud tops lower than 2 km. Clouds associated with upward motion were higher by  $\sim$ 191 m and warmer by  $\sim$ 1.3°C than clouds associated with downward motion, in terms of annual mean differences. Higher cloud top height and warmer cloud top temperature associated with large-scale upward conditions, indicated that warm air advections are mainly responsible for large-scale upward motions.

**Table 1.** Mean Cloud Fraction Difference Between Upward and

 Downward Motion (Upward - Downward)<sup>a</sup>

	Low-Level	Middle-Level	High-Level
	Cloud Fraction	Cloud Fraction	Cloud Fraction
	Difference	Difference	Difference
	(%)	(%)	(%)
Observed	10.4	11.5	5.6
ECMWF	7.5	13.6	6.3

<sup>a</sup>Data based on 4-year period from 1999 to 2003.

[31] These results clearly indicate that large-scale dynamic conditions have a significant impact on ASC properties and thereby cloud radiative forcing. Although the ECMWF model captured the general trends of large-scale dynamics on cloud fraction and LWP, the ECMWF model overestimated the impact of large-scale dynamics, especially for LWP.

# 4. Improvements of the ECMWF Model After 2003 and Their Performances

[32] The above results are based on the observations during 1999-2003 when ACRF NSA site had almost continuous high-quality data. As summarized in the Table 2, the ECMWF has made two major model improvements related to BL properties and low-level cloud properties after 2003, which are referred to as Cycle 29r1 and Cycle 31r1. The performance of each new cycle of the ECMWF on predicting the Arctic LCF, LWP, and surface heat flux are compared here in terms of monthly mean actual differences (model-observation) and relative model error (ldifference/ observation]). The observations during 1999-2007 are divided into three periods: before 2003 (Cycles before 2003, note as Cycles B2003 hereafter), between April 2005 and September 2006 (Cycle 29r1), and between September 2006 and December 2007 (Cycle 31r1). The observed cloud fraction and LWP are from the ARM CMBE that provides many quantities in one data set to support model validation over large spans of data [Xie et al., 2010].

#### 4.1. Low-Level Cloud Fraction and Liquid Water Path

[33] For LCF (Figures 18a and 18b), the cycle 29r1 had overall similar performance as the cycles B2003. The cycle 31r1 had minor improvement between March and October (with mean relative error of 32% compared with mean relative error of 36% during the same period for the cycles B2003); however, the cycle 31r1 had a worse simulation of LCF between November and February (mean relative error of 186%) when compared to the cycles B2003 (mean relative error of 67%). For LWP (Figures 18c and 18d), the new versions of the ECMWF (both cycle 29r1 and cycle 31r1) had only minor improvements or even worse performance in predicting LWP, with the exception of July. Annual mean relative errors are 59%, 56%, and 53% for the cycle 31r1, the cycle 29r1, and the cycles B2003. It is clear that the new



**Figure 15.** The seasonal variation of LCF model error under large-scale upward and downward motions. Monthly mean values are based on data from 1999 to 2003. The vertical bars indicate the standard deviation of monthly means among different years.



**Figure 16.** The comparisons of seasonal LWP variation between (a) the observed and (b) the model-predicted LWP under the large-scale upward and downward motions.

versions only have minor improvements in Arctic low cloud simulations during the summer season, and the major issues identified in section 3 (based on data before 2003) still exist.

### 4.2. Surface Heat Fluxes

[34] For sensible heat flux, the cycle 31r1 had overall better performance than the early versions (Cycles B2003), in terms of the relative error (Figures 19a and 19b). The annual mean relative errors are 205%, 165%, and 108% for the cycles B2003, cycle 29r1, and cycle 31r1, respectively. For latent heat flux, although the cycle 31r1 has better performance in May, June, and August, the improvement is



**Figure 17.** The seasonal variation of (a) observed cloud height and (b) cloud top temperature under the large-scale upward and downward motions. Only clouds with top height lower than 2 km are included in the analyses.

not as significant as the improvement of sensible heat flux. However, the actual difference (Figure 19c) shows that the Cycle 31r1 underestimated the latent heat flux between June and September, which is opposite to the prediction of the earlier cycles. Another significant difference is that the Cycle 31r1 overestimates LHF and underestimates SHF during October–December.

# 5. Summary

[35] Because of the unique features in the Arctic, such as a large annual variation of solar radiation, high-reflecting snow and ice surface, an extremely stable BL, and low water vapor amounts, some model physical parameterizations that were developed mainly based on observations at low latitude and midlatitudes may not be applicable to the Arctic, resulting in poor model performance. In order to assess the ECMWF model performance in the Arctic region, observational data from 1999 to 2007 at the NSA Barrow site were used to compare with the model simulations. Particularly, we tried to link the surface variables, BL properties, and cloud properties together and used these relationships to determine how they influenced each other. We also evaluated the capability of the ECMWF to capture the influence of large-scale vertical motion on cloud properties. The following results were obtained from this study:

[36] 1. Although the ECMWF model-simulated surface pressure and 2 m temperature were close to the observations, there were large discrepancies in 2 and 20 m RH. The ECMWF model-simulated 2 m RH is systematically drier than the observations, with an annual mean dry bias of 8.1%. The 20 m RH model error showed distinctive seasonal variation with a dry bias in the warm season and moist biases roughly corresponded to the periods when the model underestimated and overestimated LCF, respectively. For latent heat flux, the ECMWF model-predicted values were statistically higher than measured values by ~19.6 W m<sup>-2</sup> during the summer season, which was partly due to the model biases in simulating near-surface specific humidity.

**Table 2.** Changes of the ECMWF Model Related to Boundary

 Layer Properties and Low-Level Cloud Fraction After 2003

Time	Version	Changes
5 April 2005	Cycle 29r1	New moist BL scheme [ <i>Kohler</i> , 2005] that generate more stratocumulus clouds in subtropical highs and better at generating low-level clouds in some anticyclonic conditions, use of MODIS winds, wavelet <i>J</i> <sub>b</sub> , assimilation of rain-affected radiances
12 September 2006	Cycle 31r1	Revisions to the cloud scheme including treatment of ice supersaturation that increases the upper tropospheric humidity and decreases high-level cloud cover and cloud ice amount [ <i>Tompkins et al.</i> , 2007]



**Figure 18.** The ECMWF model performance in predicting (a and b) LCF and (c and d) LWP in terms of monthly mean actual difference (model - observation) and relative error (l(model-observation)/ observation)) for ECMWF cycles before 2003 (B2003), Cycle 29r1, and Cycle 31r1.

The overestimation of surface latent heat flux indicated that the ECMWF model supplies more energy and moisture into the BL than the real situations. inversion generation mechanisms, the ECMWF model did not accurately represent the fine structure of the vertical temperature profile in the BL, especially in the winter season when multiple inversion layers often occur. The ECMWF model also underestimated inversion strength by  $\sim 20\%$ 

[37] 2. Because of insufficient vertical resolution or because of the simple fact of not being able to capture all



**Figure 19.** The ECMWF model performance in predicting (a and b) sensible heat flux and (c and d) latent heat flux in terms of monthly mean actual difference (model - observation) and relative error (l(model-observation)/observationl) for ECMWF cycles before 2003 (B2003), Cycle 29r1, and Cycle 31r1.

during the warm season and overestimated it by  $\sim 3\%$ during the cold season. Near-surface temperature biases displayed strong seasonal dependence; warm biases occurred in the summer, whereas cold biases occurred in the fall and winter. The warm bias coincided with the overestimation of sensible heat flux in summer. The uncertainties of Arctic cloud simulations and related downward longwave radiations are important factors in the near-surface temperature biases.

[38] 3. For LCF, the ECMWF model captured the general seasonal trend; however, the model did not capture the changes of cloud amount in the transition season or the magnitude of the cloud annual cycle. During the cold season, the ECMWF model overestimated the LCF by 23%. During the warm season, the ECMWF model underestimated the LCF by 4%, except in June and July. The model biases in predicting low-level clouds were possibly a result of the model deficiencies in simulating frontal systems and the model biases in humidity, surface latent heat flux, and BL structures. Furthermore, the ECMWF model overestimated high-level clouds by 5.4% and underestimated clouds between 2 and 4 km by 4.5%.

[39] 4. The ECMWF model-simulated LWPs were lower than the observed values by ~57%, with an annual mean difference of  $30 \text{ g m}^{-2}$ . In contrast, the model-simulated IWPs in BL clouds were in better agreement with the observations (~18.5% underestimation). Liquid water fraction was significantly underestimated, especially in winter. This was largely due to the model parameterization of phase partition, which is solely temperature dependent. The biases in cloud liquid path and water fraction influenced the model's ability to predict surface LW radiation.

[40] 5. Large-scale vertical motion can influence the cloud properties; both the ECMWF model and the observations showed higher cloud fraction under upward motion than under downward motion, especially for low-level and middle-level clouds. Similarly, LWP was higher under upward motion than under downward motion. Although the ECMWF model captured the general trends of large-scale dynamics on cloud fraction and LWP, the ECMWF model overestimated the impact of large-scale dynamics, especially for LWP.

[41] 6. The ECMWF has made two major model improvements related to BL properties and low-level cloud properties after 2003, which are referred to as Cycle 29r1 and Cycle 31r1. The results show that the new versions only have produced minor improvements in Arctic low cloud and LWP simulations during the summer season, and major issues identified in section 3 based on data before 2003 still exist. Although the Cycle 31r1 had overall better performance in simulating sensible heat flux than the early versions (Cycles B2003), it had provided only minor improvements in latent heat flux.

[42] Although the ECMWF model showed reasonably good skill in simulating Arctic clouds, the model weaknesses discussed above certainly indicate that more efforts are needed to improve model physics parameterization in this region. It is reasonable to expect that sophisticated treatments of BL processes, especially in the cold season, while coupling with larger-scale dynamics could improve the ASC simulation. Phase partition in ECMWF clearly needs to be improved for better simulations of Arctic mixedphase clouds. Long-term ACRF observations over the

Arctic region offer unique data sets to improve these aspects in models.

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