A FEATURE MODEL FOR ARCTIC UPPER OCEAN THERMAL STRUCTURE

Peter C. Chu
Department of Oceanography, Naval Postgraduate School, Monterey, CA 93943

1 Introduction

The radiation balance at high latitudes is dominated by presence or absence of snow and ice which affects the albedo in a great deal. Any oceanic processes that affect the snow and ice cover in polar regions will cause the change of deposition of sun's energy over the earth's surface, and hence the environmental change. Besides, the ice cover, ocean, and atmosphere exchange water mass and energy in a very complicated way. Three major feedback loops (both positive and negative), in which the upper ocean is a key component, possibly exist in a theoretical air-ice-ocean coupled system (Chu, 1990). Thus, investigation of the polar upper ocean thermal structure from observation becomes urgent. Up until now, the effort is limited to study some individual data set, e.g., AIDJEX, MIZEX, CEAREX, etc., separately. No investigation is pursued for the Arctic upper ocean thermal structure from the all available data sets. This study deals with the most complete temperature and salinity data sets in the Arctic Ocean, which is the U.S. Navy's Master Oceanographic Data sets (MOODS). To get physical insights from the data, we use a feature model (Haeger, 1994) to transfer each MOODS Arctic temperature (or salinity) profile into a set of several characteristics: sea surface temperature (SST), mixed layer depth, thermocline depth, temperature difference across the thermocline. These characteristics reveal strong temporal and spatial variabilities.

2 Master Oceanographic Data Set (MOODS)

The MOODS data set is a compilation of all reported observations over all the world's oceans. Due to the shear size (more than 5 million profiles) and enormous influx of data, quality control is a difficult task. MOODS contains different types of data: (a) temperature only profiles, (b) both temperature and salinity profiles, and temperature, salinity, (c) and sound speed profiles. We use near 30,000 temperature and salinity profiles during 1970-1988 for this study (Fig.1). To get spatial variability, we analyze the profiles in several different seas and the surround-

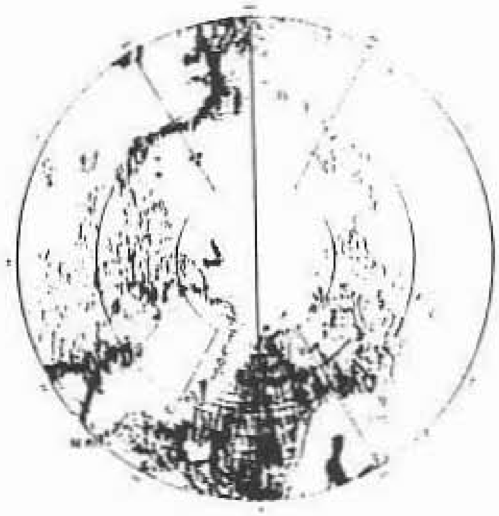

Figure 1 – MOODS temperature and salinity statior (1970-1988).

ing areas: central Norwegian Sea ($0° - 6° E, 63 - 67° N$ Beaufort Sea ($160° - 120° W, 70° - 85° N$), Gulf of Botl nia ($15° - 30° E, 60° - 67° N$), Denmark Strait ($30°$ $22° W, 62° - 68° N$), Greenland Sea ($30° W - 60° E, 60°$ $65°$), and Chuchi Sea ($180° - 160° W, 65° - 73° N$).

3 Upper Layer Structure

Arctic upper ocean experiences a strong seasonal var ation. Deep mixed layer appears in winter and sha low mixed layer shows up in summer. During winte tremendous buoyancy is lost from the ocean surface du to the heat loss and salt injection caused by the ice freez Buoyancy loss along with surface winds generate stron turbulent kinetic energy (TKE), which is transporte downward, and deepens the ocean mixed layer (OMI by entraining the deeper water into OML. On the oth hand, during summer, ocean surface gains buoyancy th damps TKE and causes the mixed layer to shallow. the downward buoyancy flux from the atmosphere t ocean is strong enough, mixed layer is very shallow wit

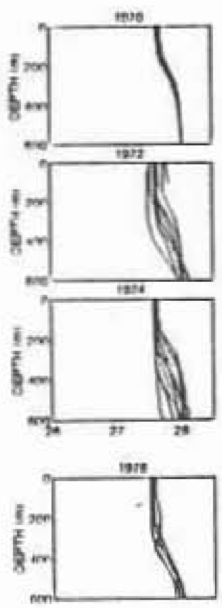

Figure 2 – January sigma-t during 1970-1977 (mixed layer type).

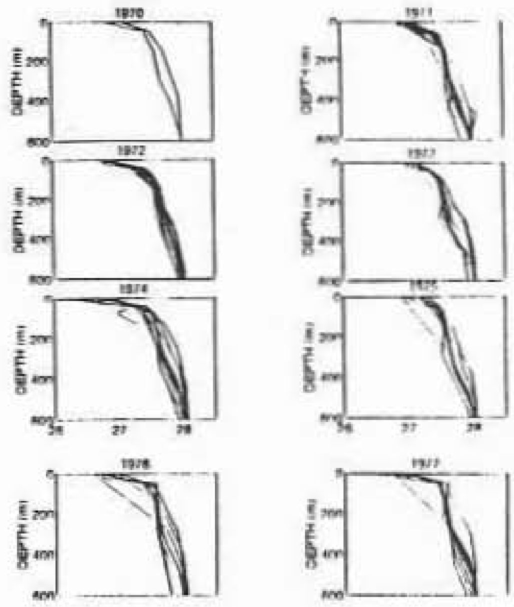

Figure 3 – July sigma-t profiles during 1970-77 (stratified type).

a strong pycnocline below the mixed layer. To investigate the seasonal and interannual variations of the thermal structure, we plot 1970-84 January (Fig.2) and July (Fig.3) σ_t profiles in the central Norwegian Sea.

Comparing Fig.3 with Fig.2, we found that (a) the seasonal variation is very strong, (b) the winter mixed layer depth is near 300 m, and the summer mixed layer depth is approximate 10 m, (c) interannual variability is quite weak.

4 Upper Ocean Feature Model

Most profiles exhibit mixed layer, thermocline (or halocline, pycnocline), and deep layer. To grasp the major features of the profiles, a feature model has been developed in the Naval Oceanographic Office (Haeger, 1994) for diagnosing upper ocean thermal structure from temperature and salinity observational profiles. The model was originally called the Gradient Model. Several parameters, which represent major characteristics of each temperature profile, are SST, OML depth, thermocline depths, and thermocline temperature difference. Similar sets of parameters exist for salinity and density profiles, e.g., sea surface salinity (SSS), pycnocline density difference, etc.. The feature model transforms each profile into a set of these parameters. The feature model contains three components: (a) first guess feature model, (b) high-resolution profiles interpolated from observations, (c) fitting of high-resolution profiles to the feature model.

4.1 Gradient space

If we consider profiles in the gradient space, i.e., $G_T = \partial T(z)/\partial z, G_S = \partial S(z)/\partial z$, each profile can be represented by the surface value (SST or SSS) plus the gradients, e.g.,

$$[SST, G_T(0,z_1), G_T(z_1,z_2), ..., G_T(z_{n-1}, z_n)]$$

for the temperature profiles. Here, $n+1$, is the number of data points, and $z_i (i = 1, 2, ...n)$ are the depths of the data points. For example, 100 temperature/depth points would produce 99 gradient values. If the surface value is included, we have the same amount of data in the gradient space as in the original data set. It is difficult to easily glean physical meaning from large number of gradient/flection point combinations.

4.2 Thermal Feature Model

Observation shows that the ocean reveals layered structure (Fig.4). Based on the continuity of T and $\partial T/\partial z$

at interfaces of any two layers, a feature model can be constructed as:

$$\widehat{T}^{(m)}(z) = G_T^{(m)} z + SST, \quad z \in [-d_1, 0]$$

$$\widehat{T}^{(en)}(z) = \frac{(z+d_1)}{(d_2-d_1)} \left[(G_T^{(m)} - \overline{G}_T^{(en)}) z + d_2 G_T^{(m)} - d_1 \overline{G}_T^{(en)} \right] + \widehat{T}^{(m)}(-d_1), \quad z \in [-d_2, -d_1]$$

$$\widehat{T}^{(th)}(z) = G_T^{(th)}(z + d_2) + \widehat{T}^{(en)}(-d_2), \quad z \in [-d_3, -d_2]$$

$$\widehat{T}^{(tr)}(z) = \frac{(z+d_3)}{(d_4-d_3)} \left[(G_T^{(th)} - \overline{G}_T^{(tr)}) z + d_4 G_T^{(th)} - d_3 \overline{G}_T^{(tr)} \right] + \widehat{T}^{(th)}(-d_3), \quad z \in [-d_4, -d_3]$$

$$\widehat{T}_1^{(d)}(z) = G_T^{(d1)}(z + d_4) + \widehat{T}^{(tr)}(-d_4), \quad z \in [-d_5, -d_4]$$

$$\widehat{T}_2^{(d)}(z) = \frac{(z+d_5)}{(H-d_5)} \left[(G_T^{(d1)} - \overline{G}_T^{(d2)}) z + H G_T^{(d1)} - d_5 \overline{G}_T^{(d2)} \right] + \widehat{T}_1^{(d)}(-d_5), \quad z \in [-H, -d_5] \tag{1}$$

where $(\widehat{T}^{(m)}, \widehat{T}^{(en)}, \widehat{T}^{(th)}, \widehat{T}^{(tr)}, \widehat{T}_1^{(d)}, \widehat{T}_2^{(d)})$ are modeled temperatures in the mixed layer, the entrainment zone, the thermocline, the transition zone, the first and the second deep layers. H is the water depth, d_1 the mixed layer depth, d_2 the depth of the thermocline top, d_3 the depth of the thermocline bottom, d_4 the depth of the top of the first deep layer, and d_5 is the bottom of the first deep layer (Fig.4). Here, we assume constant vertical temperature gradients in the ocean mixed layer ($G_T^{(m)} \approx 0$), in the thermocline ($G_T^{(th)}$), and in the first deep layer ($G_T^{(d1)}$) and linearly varying with z in the entrainment zone, the transition zone, and the second deep layer with average values ($\overline{G}_T^{(en)}, \overline{G}_T^{(tr)}, \overline{G}_T^{(d2)}$). By forcing this feature model (1) to each observed profile, we should have a first guess of the five depths $(d_1, d_2, d_3, d_4, d_5)$ and a high resolution of temperature/depth points in the vertical in order to obtain the six temperature gradients $(G_T^{(m)}, G_T^{(th)}, G_T^{(d1)}, \overline{G}_T^{(en)}, \overline{G}_T^{(tr)}, \overline{G}_T^{(d2)})$. Such a treatment provides the most important features from the observational data.

4.3 High-resolution profiles (HP) interpolated from observations

Each MOODS profile is linearly interpolated to high resolution ($\Delta z = 0.5m$), denoted $T_j = T(z_j)$ for temperature as an example, where $z_j = z_{j-1} - 0.5m (z_0 = 0)$.

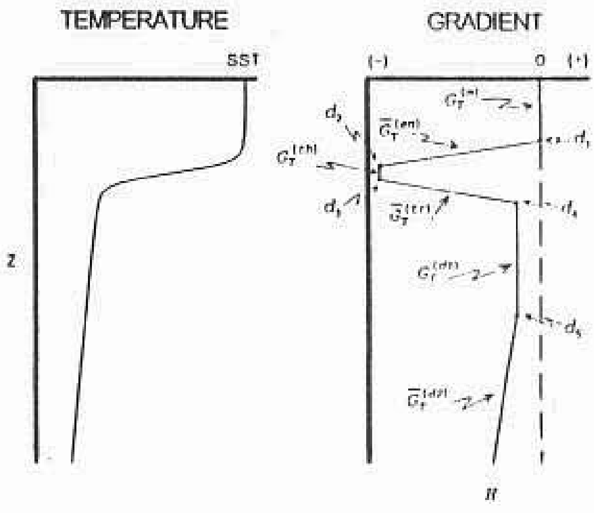

Figure 4 – Feature model

The NAVOCEANO's DBDB5 data set is used to obtain water depth H. If the five depths $(d_1, d_2, d_3, d_4, d_5)$ are known, we can divide the data set $HP = (z_j, T_j)$ into six parts (mixed layer, entrainment zone, thermocline, transition zone, first deep layer, and second deep layer). For each layer we fit (T_j, z_j) to the feature model (1), and obtain a set of temperature gradients $(G_T^{(m)}, G_T^{(th)}, G_T^{(d1)}, \overline{G}_T^{(en)}, \overline{G}_T^{(tr)}, \overline{G}_T^{(d2)})$.

4.4 Modeled profile (MP) obtained by the iteration method

A modeled profile (MP) with $0.5m$ resolution can be established by using the feature model (1) if the five depths $(d_1, d_2, d_3, d_4, d_5)$ are given. In reality, these depths are not known prior to processing the data and vary from one profile to the other. We use the iteration method to obtain the optimal MP.

First, we start with a set of first guess values of the depths and the three constant gradients,

$$D^{(0)} = (d_1^{(0)}, d_2^{(0)}, d_3^{(0)}, d_4^{(0)}, d_5^{(0)}), \quad G_T^{(0)} = (G_T^{(m_0)}, G_T^{(th_0)}, G_T^{(d1_0)}). \tag{2}$$

In this study, we choose

$$D^{(0)} = (20m, 24m, 32m, 38m, H)$$
$$G_T^{(0)} = (0, -0.5°C/m, -0.005°C/m)$$

For each profile HP, we fit the feature mode (1) to the data (z_j, T_j) since we know the depths and the constant gradients, and obtain a 0-th order modeled profile, called

$MP^{(0)} = (z_j, \widehat{T}_j^{(0)})$. The root mean square (RMS) error for mismatch of HP and $MP^{(0)}$ is computed by

$$RMS^{(k)} = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(\widehat{T}_j^{(k)} - T_j)^2} \tag{3}$$

where $k = 0$. We expect $RMS^{(0)}$ to be large.

Second, we use the iteration method to obtain optimal MP for each HP profile. Each depth can only be adjusted one vertical grid (Δz or $-\Delta z$) for one iteration. From the kth order (k starting from 0, the first guess) set of depths, $D^{(k)}$, we have $242(= 3^5 - 1)$ different combinations of the depth adjustment,

$$D_m^{(k+1)} = D^{(k)} + \delta D_m^{(k)}, \tag{4}$$

where

$$\delta D_1^{(k)} = (d_1^{(k)} + \Delta z, d_2^{(k)}, d_3^{(k)} d_4^{(k)} d_5^{(k)}),$$
$$\delta D_2^{(k)} = (d_1^{(k)} - \Delta z, d_2^{(k)}, d_3^{(k)}, d_4^{(k)}, d_5^{(k)}),$$
$$\cdots\cdots$$
$$\delta D_{242}^{(k)} = (d_1^{(k)}, d_2^{(k)}, d_3^{(k)}, d_4^{(k)}, d_5^{(k)} - \Delta z).$$

Use (1) to obtain 242 modeled profiles, among which we pick up a profile with minimum RMS error as the $(k+1)$ th order set of depths, $D^{(k+1)}$. We repeat this procedure until the minimum RMS error is achieved. When the number of iterations exceeds a prescribed number (400), the process is halted and the RMS error is compared to a criterion ($0.5°C$). If $RMS < 0.5°C$, we obtain an optimal set of depths and gradients. If $RMS > 0.5°C$, we reject the feature model (1), i.e., the HP profile can not be fitted by the feature model.

5 Mixed Layer Features

The feature model (1) transforms any profile (if not rejected) into a set of five depths $(d_1, d_2, d_3, d_4, d_5)$ and six gradients $(G_T^{(m)}, G_T^{(th)}, G_T^{(d1)}, \overline{G_T}^{(en)}, \overline{G_T}^{(tr)}, \overline{G_T}^{(d2)})$. These parameters represent most important physical features and are insensitive to the first guess values. The first guess values determine the number of iterations. A good selection of first guess values reduce the number of iterations. Fig.5 shows both seasonal and interannual variations of the mixed layer depth (d_1) in the central Norwegian Sea ($64-67°N, 0-6°E$). The ocean mixed layer is usually deep during winter ($150-300m$) and shallow during summer ($< 50m$). The horizontal distribution of d_1 in the Arctic Ocean (for the same time period) shows large spatial variation.

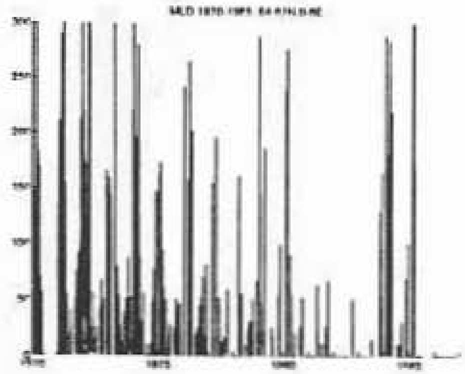

Figure 5 – Temporal variation of central Norwegian Sea mixed layer depth.

6 Conclusion

The feature model depicted in this paper is based on both the thermal structure and the statistics and demonstrates a good capability to obtain physical insights from observed temperature and salinity profiles. The model uses iteration method to obtain optimal set of the parameters: depths and gradients. The model clearly shows large thermal variabilities and two-type structure. This feature model can also be used to process output from any dynamical model and to obtain meaningful products, i.e., OML depth, thermocline depth, thermocline strength, and deep layer stratification.

7 ACKNOWLEDGMENT

Author is grateful to Steve Haeger and Michael Carron at the Naval Oceanographic Office for providing software and valuable suggestions, and to Laura Ehret and LT Charles Fralick at the Naval Postgraduate School for programming assistance. This work was funded by the Naval Oceanographic Office and the Naval Postgraduate School.

References

Chu, P.C., 1990: Air-ice-ocean feedback mechanisms and ice oscillation on millennial time scales. **Annals of Glaciology, 14,** 28-31.

Haeger, S.D., 1994: A gradient model for Baring Sea temperature structure. **U.S. Naval Oceanographic Office Technical Report,** in press.