NOAA Technical Memorandum GLERL-129

IMPROVING MONTHLY GREAT LAKES ICE COVER OUTLOOKS

Raymond A. Assel[1], Sheldon Drobot[2], and Thomas E. Croley II[1]
[1]NOAA, Great Lakes Environmental Research Laboratory, Ann Arbor, MI 48105
[2]The National Academies, 500 5th St. NW, Washington, DC 20001

Great Lakes Environmental Research Laboratory
Ann Arbor, Michigan

June 2004

UNITED STATES
DEPARTMENT OF COMMERCE

Donald Evans
Secretary

NATIONAL OCEANIC AND
ATMOSPHERIC ADMINISTRATION

Conrad C. Lautenbacher, Jr.
Administrator

NOTICE

 This is GLERL Contribution No. 1315.

This publication is available as a PDF file and can be downloaded from GLERL's web site: www.glerl.noaa.gov. Hard copies can be requested from GLERL, Information Services, 2205 Commonwealth Blvd., Ann Arbor, MI 48105. pubs.glerl@noaa.gov.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Improving Monthly Great Lakes Ice Cover Outlooks

Raymond Assel, Sheldon Drobot, and Thomas E. Croley II

ABSTRACT. Prediction of ice growth in the Great Lakes is important for commercial navigation, channel maintenance, water level and flow regulation, and winter operations planning. Current 30-day forecasts, issued on the first of the month for the first of the following month, mainly use forecasts of air temperature. They enable calculation of accumulated freezing degree-days (AFDDs), which are used to identify similar historical events and associated ice cover as a forecast. More information is now available to ice forecasters, and we investigate its use in simple statistical models. The information considered here is limited to observations available at the time of a forecast, but include AFDDs, various telecommunication indices, and current ice cover. Additionally, the potential of AFDD forecasts is assessed in a statistical regression between ice cover and AFDDs during the month between the time of making the forecast and the start date of the forecast. (Actual AFDDs represent the best we could hope to forecast and so its use reveals the potential improvement that could be realized if a forecast of AFDD was developed.) Likewise, the potential of a mechanistic lake thermodynamics model is also assessed in a statistical correlation between ice cover and model outputs.

1. INTRODUCTION

Each winter, most commercial navigation on the Great Lakes and the St. Lawrence Seaway is halted due in large part to the hazard caused by ice formation. Thirty-day graphic forecasts of ice conditions, i.e. forecast ice charts (see Figure 1 for an example), and observational ice charts are used by various US and Canadian federal government agencies (the US Coast Guard, Canadian Coast Guard, US Army Corps of Engineers, International Niagara Board of Control, St. Lawrence Development Corporation, and the St. Lawrence Seaway Authority) as an aid in planning winter related operational activities on the Great Lakes and their connecting channels. These activities include closing navigation locks in early winter and opening them the following spring to ocean going vessels as well as intra-lake traffic (at Sault St. Marie between Lake Superior and Lake Huron, at the Welland Canal between Lakes Erie and Ontario, and on the St. Lawrence Seaway at the outlet of Lake Ontario), placing ice booms at the head of the Niagara River and in the St. Lawrence River, and removal in late fall and installation the next spring of navigation aids that would be destroyed by ice during the winter. The US Navy/NOAA National Ice Center (NIC) issues 30-day forecasts of ice conditions on the Great Lakes (http://www.natice.noaa.gov/pub/great_lakes/forecasts/) each winter on the first and fifteenth of every month from December through March. Snider (1974) originally developed the forecast methodology as essentially an analogue method using 30-day air temperature forecasts to calculate accumulated freezing degree-days. Databases of freezing degree-days and historical ice charts are then searched to find the closest analogue winters. This is the current basis for 30-day forecasts.

The potential benefits for skillful 30-day forecasts of Great Lakes ice cover are significant, given that over 1.4 billion metric tons of cargo (with an estimated value of $200 billion) have been transported through the Great Lakes since 1959 (Allardice and Thorp, 1995). Current NIC forecasts represent one approach (analogue) to making long-range (30-day) forecasts, but do not fully include recent findings that variations in ice cover are associated with teleconnections such as the Tropical Northern Hemisphere index and the El Niño Southern Oscillation index (Rodionov et al., 2001). These recent findings and a recent study of summer ice severity in the Beaufort Sea (Drobot and Maslanik, 2002) offer hope that more skillful forecasts are possible. In this study we develop another approach to making long-range ice forecasts for the Great Lakes. Several empirical statistical models are developed to make 30-day forecasts of Beginning of Month (BOM) lake-averaged ice cover. Separate models are developed for each Great Lake (Superior, Michigan, Huron, Erie, and Ontario) for each of three BOM dates (January 1, February 1, and March 1). The predictor variables and BOM ice cover datasets and each model type are described and discussed. The best model for each lake for each month is identified in terms of

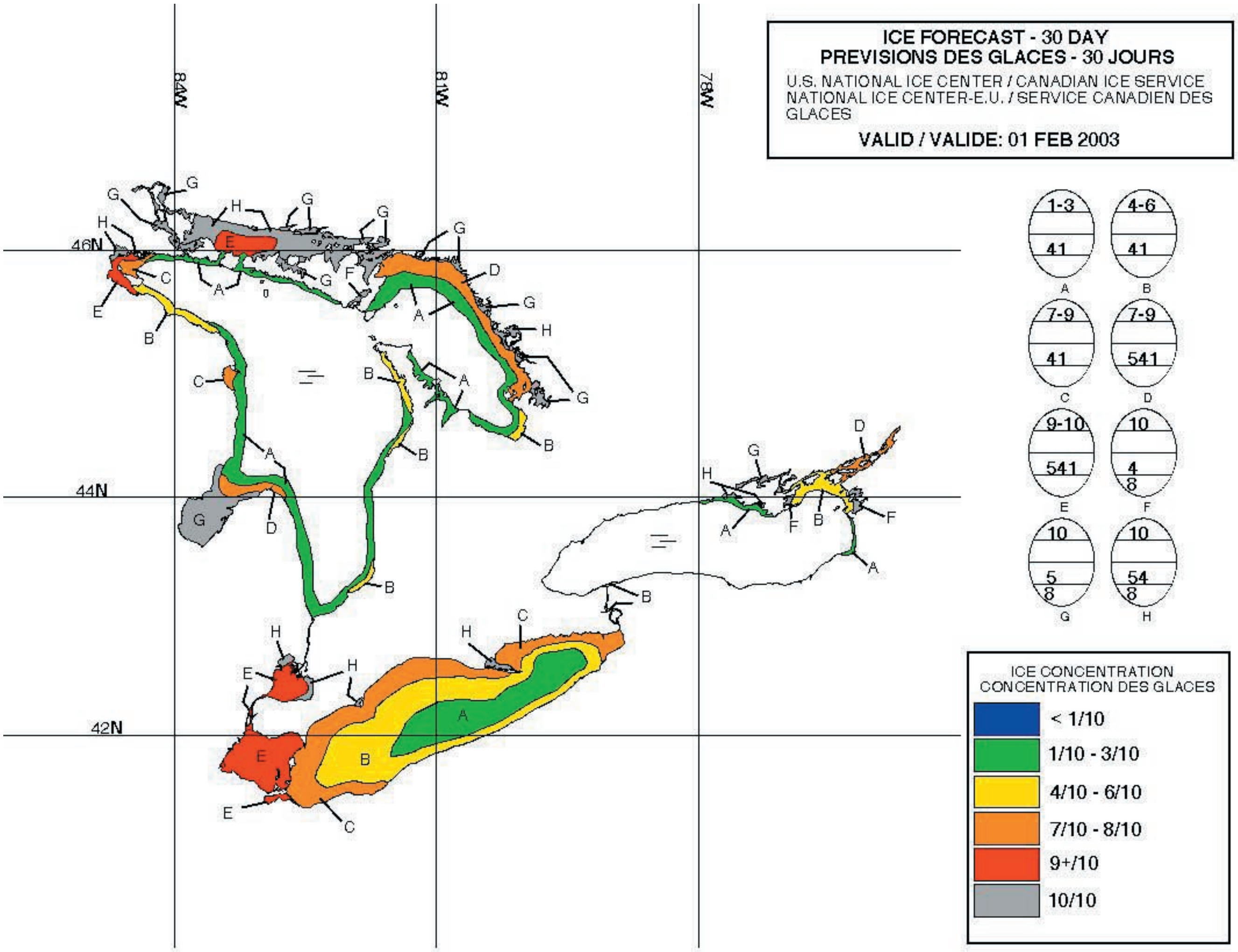

Figure 1. Example graphic forecast product for Lakes Huron, Erie, and Ontario.

mean absolute error and skill score. A discussion of why some models are better than others for certain BOM dates is given within the context of the variations of BOM lake averaged ice cover and possible causes for those variations. The potential use of a mechanistic model to make 30-day ice forecasts is also addressed briefly. Results are summarized within the context of work needed to implement an experimental 30-day forecast based on these models.

2. DATA

Assel (2003) created a digital Great Lakes ice cover data set to construct time series of daily ice concentration for locations in a grid over each Great Lake and used those grids to make computer animations that portray the seasonal progression of the spatial distribution patterns of ice cover for each winter season from 1973 to 2002. Here, we use this 30-winter data set of ice concentration to calculate lake averaged ice cover for each of the Great Lakes for BOM dates of: January 1, February 1, and March 1 for winters from 1973 to 2002; see Table 1.

We developed regression models to forecast the BOM ice cover with a 30-day lead. Predictor variables include monthly average accumulated freezing degree days (AFDDs) for each Great Lake as shown in Table 2; see Assel (1986) for description of methods used to calculate AFDDs. Predictor variables also include BOM ice cover and teleconnection indices, obtained from the NOAA Climate Prediction Center; see Table 3 for a list of final potential predictors. We compute the monthly lake-averaged AFDDs for National Weather Service (NWS) stations surrounding each lake from 1972 through 2002. Figure 2 displays these stations graphically. Lake Superior

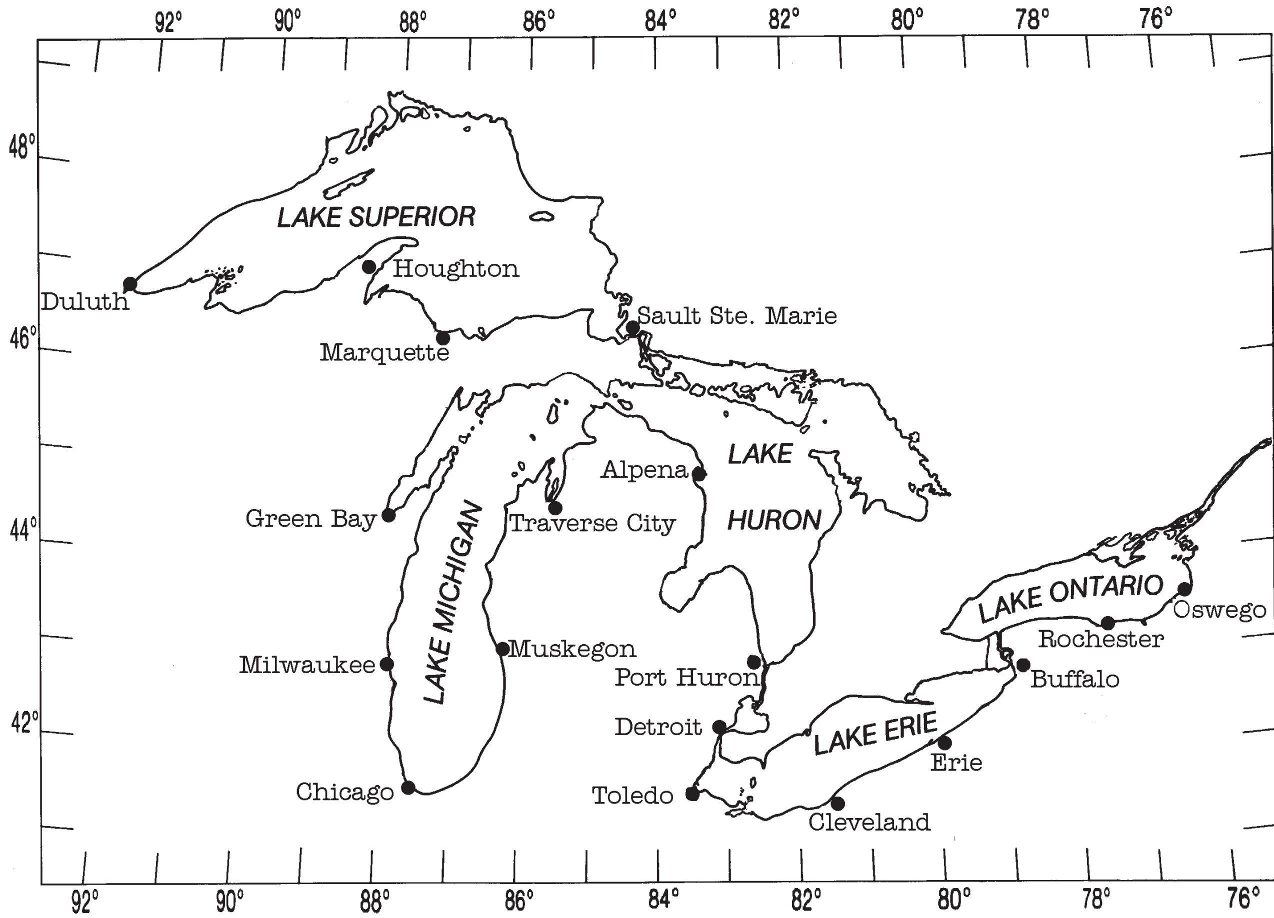

Figure 2. Freezing degree-day stations used to calculate lake averages.

used stations at Duluth, Houghton, Marquette, and Sault Ste. Marie. Lake Michigan used stations at Green Bay, Milwaukee, Chicago, Muskegon, and Traverse City. Lake Huron used Alpena and Port Huron. Lake Erie used Detroit, Cleveland, Erie, and Buffalo. Lake Ontario used Rochester and Oswego. We also obtained monthly teleconnection data for November, December, and January from 1972 through 2002. Except for the Southern Oscillation Index (SOI), the teleconnection data are derived with rotated principal component analysis on 700 hPa data, north of 20°N (Barnston and Livezey, 1987). The SOI is based on the adjusted difference in sea level pressure between Tahiti and Darwin. We did not utilize February data since the February teleconnection data are not available in time to forecast BOM March ice conditions.

3. METHODS

3.1 Forecast development

We developed four models to assess the statistical predictability of BOM ice cover with a 30-day lead. The simplest is the climatological model (C), which predicts the BOM ice cover as the long-term value;

$$I_m = C_m \tag{1}$$

where I_m is predicted BOM ice cover on a given Great Lake for month m, and C_m is the climatological ice cover on the same Great Lake for month m. For example, we would forecast the Lake Superior BOM January ice cover with the historical mean BOM January Lake Superior ice cover. The climatological model is often considered the baseline technique for assessing forecast improvements of other methods—if a new model cannot improve upon the forecast skill of the climatological model, then it is not worth implementing.

The second approach is the anomaly propagation model (AP), which predicts the BOM ice cover as the linear translation of the BOM ice cover anomaly from the preceding month:

$$I_m = C_m\left(\frac{O_{m-1}}{C_{m-1}}\right) \tag{2}$$

where O_m is observed BOM ice cover for month m. For example, if the January BOM ice cover on Lake Huron is 30% below average, then we would forecast the February BOM for Lake Huron as 30% below average. The concept of this model is that if ice growth is averaged over a month, then the anomaly will propagate over the month. This model also could be termed a "persistence of anomaly" forecast. Since there is no reported BOM lake-averaged ice cover in December, the anomaly propagation model cannot be utilized for the January forecast.

The third model is termed the observational linear regression model (OLR), which predicts BOM ice cover from regression analysis, developed using observed ice cover, AFDD, and teleconnection data:

$$I_m = \beta_0 + \beta_1 X_1 + \ldots + \beta_n X_n \tag{3}$$

where β_0 is the intercept, β_1 is the regression coefficient of the first independent variable, X_1 is the value of the first independent variable, β_n is the regression coefficient of the n^{th} independent variable, and X_n is the value of the n^{th} independent variable. [Note that the subscripts in (3) denote different things; the subscript on ice cover is the month, and the subscripts on each independent variable are the variable numbers.] The regression coefficient β_n measures the increase I_m associated with an increase in I_m (slope) with constant levels of the other independent variables. In discussing regression output, we also utilize the standardized regression coefficient, β_n^*, which measures the increase in I_m (in standard deviations of I_m, σ_{I_m}) associated with an increase in X_n of one standard deviation, σ_{X_n}, with constant levels of the other independent variables. Higher values of β_n^* indicate greater impact of variable n on prediction of I_m.

$$\beta_n^* = \frac{\sigma_{x_n}}{\sigma_{I_n}}\beta_n \tag{4}$$

We developed the OLR model in a 3-step approach, and it contains at least one, but possibly more, independent variables to predict BOM ice cover. Initially, we correlated BOM ice cover data with all observed AFDD and teleconnection data available at the time of forecast. For instance, we correlated BOM February ice cover with all AFDD and teleconnection data from December and BOM January ice cover, all of which are available on 1 January when the BOM February forecast is made. In the second step, we enter all variables statistically correlated with the BOM ice cover (see Table 3) into a stepwise regression model for selection of a tentative model. The third step tests the tentative model for statistical viability. Statistically, tentative models are examined for multicollinearity using the variance inflation factor (VIF). The VIF measures size of the variance of an estimated regression coefficient relative to situations where variables $X_1,\ldots,X_n$ are not linearly related. The VIF is computationally complex and interested readers are referred to Neter et al. (1990). Nonetheless, the application of the VIF is simple. If the VIF is greater than 10.0, then substantial correlation exists between predictor variables $X_1,\ldots,X_n$ and the precision of an estimated coefficient is likely poor (Neter et al., 1990). When variables are uncorrelated, the VIF is 1.0 and an estimated coefficient's precision is good.

The final model is termed the Perfect AFDD linear regression model (PLR), which is mathematically similar to the previous model, except that X_1 is the observed value of the AFDD for the month between the forecast issue date and the forecast date. Conceptually, the aim of this model is to assess how well perfect predictions of the upcoming month's AFDDs will improve the model. Rogers (1976) demonstrated that there was a strong link between maximum ice cover and AFDDs over the Great Lakes, so it is likely that adding predicted AFDDs to the model will improve the model accuracy. Although models cannot perfectly predict AFDDs, by utilizing the perfect

AFDD forecast we provide some insight into whether predictions of AFDDs should be included in the statistical model. As with the OLR, we used the VIF to assess the precision of the regression coefficients.

3.2 Forecast Evaluation with Monte Carlo Simulations

We assessed all models for accuracy by computing their mean absolute error (*E*) and forecast skill score (*S*). Error *E* is simply the average absolute error between predicted and observed values, and it gives a physically meaningful description of error

$$E = \frac{1}{T}\sum_{m=1}^{T} abs\left(I_m - O_m\right) \tag{5}$$

where *T* is number of months in an evaluation period.

Skill *S* provides a relative assessment of how well other models compare with the climatological model (Wilks, 1995)

$$S = \frac{E_{ref} - E}{E_{ref}} 100\% \tag{6}$$

where E_{ref} is the error of the climatological model and *E* is the error of one of the other three methods described above (anomaly propagation, observational linear regression model, or perfect AFDD linear regression model). If $E=0$, then the skill score is 100%, the maximum value. If $E=E_{ref}$, then the skill score is 0%, indicating no improvement over climatology. If $E>E_{ref}$, then the skill score is negative, and the method is worse than climatology. If $0<E<E_{ref}$, then the skill score is positive, and the method is better than climatology.

We evaluated the models with a cross-validated data set. We used independent data for good estimates of model accuracy; if we evaluated models with data used in developing them, they would appear to have unrealistically low errors. The Monte Carlo cross-validation technique used here randomly selects two thirds of the data for model development, and uses the remaining one third for evaluation. We generated 1000 samples for a robust estimate of model error and skill score.

4. RESULTS

4.1 Variability in BOM Conditions

On average, Lake Ontario has the lowest mean BOM ice cover for all months, and Lake Erie has the highest; see Table 4. This distribution is similar to the expected maximum ice covers for each Great Lake (Assel et al., 2003). Lake Ontario has the lowest interannual variability in BOM ice cover, as expressed by the standard deviation, compared with the other Great Lakes. Lake Erie has the highest interannual variability for BOM January and February ice cover while Lake Superior has the highest interannual variability for BOM March.

In general, ice cover is related to air temperature, wind conditions, and heat storage capacity of the lake; Rodionov et al. (2001) notes that high winds can produce up-welling of warm water, and they also can break up the ice cover. In either case, ice cover can change dramatically over a winter season. The higher interannual variability in Lake Erie BOM ice cover is likely related to its relatively shallow mean depth (at 19 m, Lake Erie is the shallowest lake) and low volume (483 km^3). With the low volume, heat storage capacity is smallest for Lake Erie and, therefore, it is most responsive to interannual atmospheric variations. The high interannual variability in Lake Superior BOM March ice cover is likely due to its northern location and to variations in atmospheric conditions in February. During winters, when enough heat has been extracted from the lake by the end of January, extensive ice formation can occur if low air temperatures persist in February and winds are relatively calm. Lake Ontario's low interannual variability in BOM ice cover is due to the combination of its relatively mild winter air temperatures, which are only marginally lower that those for Lake Erie, and a lake volume (1634 km^3) that is three times that of Lake Erie.

4.2 Forecasting BOM Conditions

Understanding interannual variability is particularly important for model development; the climatological model will perform better for lakes with lower interannual variability. (If there were no interannual variability, then the climatological model would give perfect forecasts; as interannual variability increases, climatological model forecasts degrade). For example, the cross-validated climatological mean absolute errors are lowest for Lake Ontario and highest for Lake Erie; see Figure 3. As noted above, atmospheric conditions exert a greater influence over Lake Erie than they do over Lake Ontario, due to differences in heat storage capacity. Since the interannual variability, as measured by the standard deviation, increases from January to March in all lakes, the errors also increase for all lakes, except Lake Erie, where the interannual variability is at its maximum in February. As the reference model, the skill score for the climatological model is zero for all lakes and all months; see Figure 4.

As noted previously, BOM ice cover data begins in January, so the anomaly propagation model is only applicable for February and March. Excluding Lake Ontario, the errors of the AP models are lower than climatology in February, and in many cases the errors for the AP are much lower than climatology; see Figure 3. The AP model is also better than climatology in March for all lakes. Additionally, the forecast skill is larger for March than for February, see Figure 4, suggesting ice conditions from the previous month are more important for forecasting March ice conditions than they are for forecasting February ice conditions.

Table 5 summarizes model coefficients as well as evaluation statistics for the OLR models. With the inclusion of observed AFDD and teleconnection data, the error of 14 of the 15 models is better than climatology (see

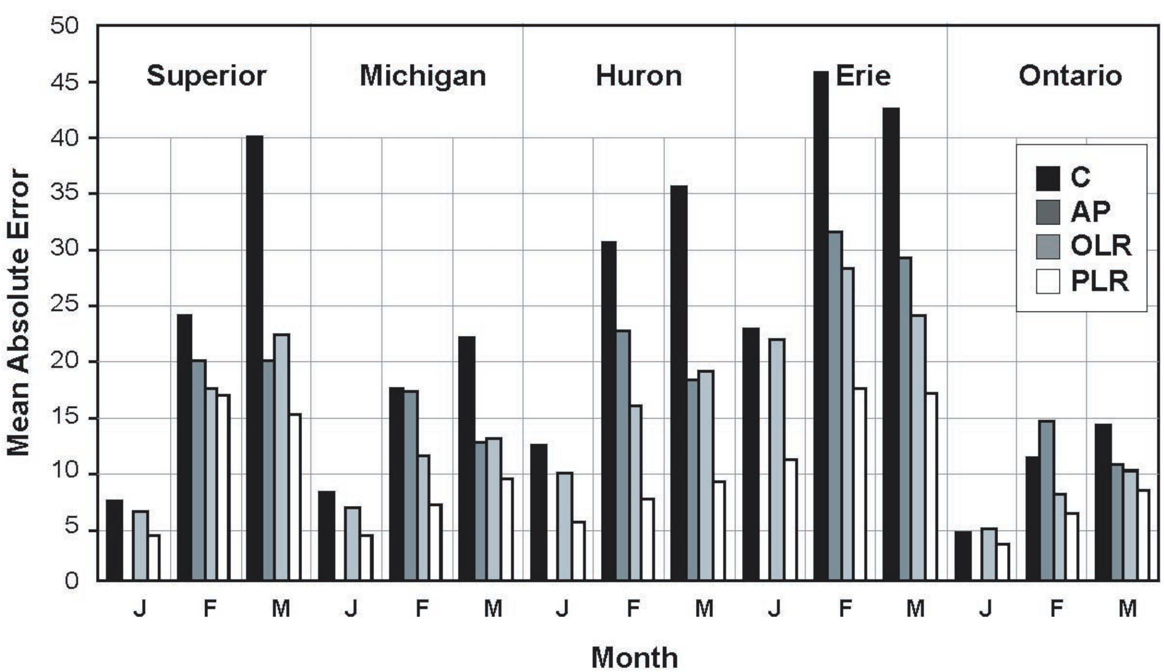

Figure 3. Mean absolute error for prediction schemes. Lower MAE values indicate better models.

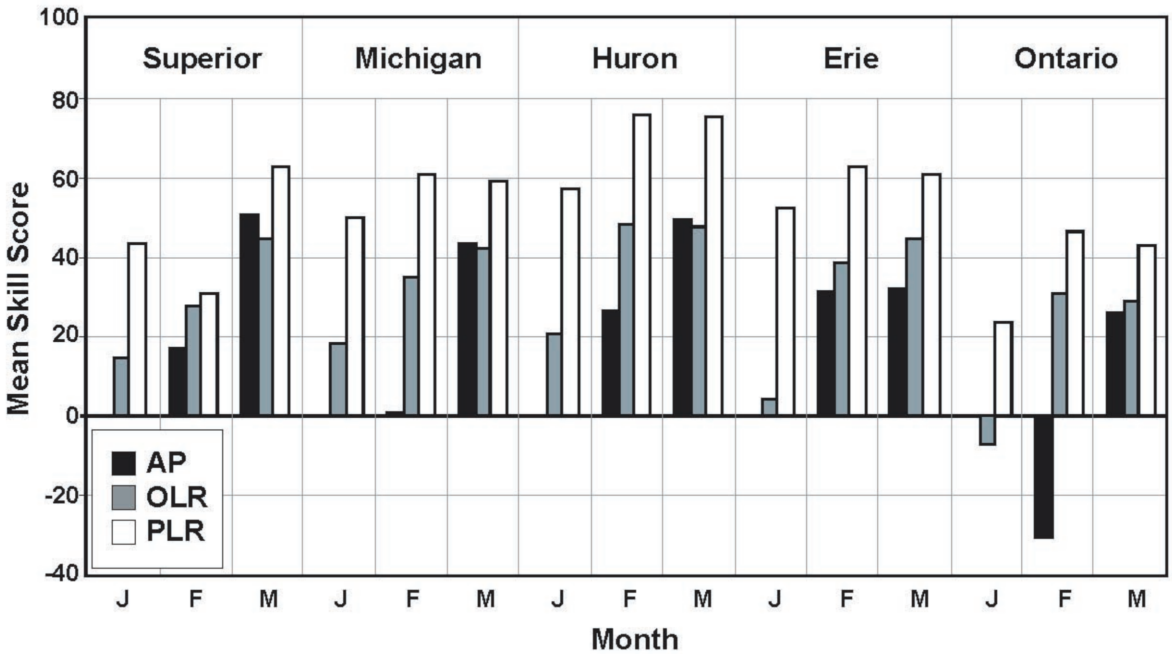

Figure 4. Skill score for prediction schemes (higher skill scores indicate better models).

Figure 3), with skill scores greater than zero (see Figure 4). Of these 14, 7 are improvements over the anomaly propagation model, and 5 have no anomaly propagation model for comparison; see Figure 4. Overall, the OLR models are superior in 11 of the 15 prediction cases; the AP model is the best for three cases and the C model remains superior for one. Table 6 summarizes the best model for each lake and month of forecast.

Physically, for BOM January predictions, the November Tropical North-America (TNH) and the November North Atlantic Oscillation (NAO) indices are the only significant predictors; see Table 5. As described by the standardized coefficients, β_n^* in Table 5, the November TNH statistically exerts more influence than does the NAO. Assel and Rodionov (1998) discussed interactions between the TNH and Great Lakes ice cover; the TNH pattern strongly affects the strength and position of upper air flow near the Great Lakes. During positive TNH phases, meridional circulation dominates, leading to cooler winter conditions and thicker ice covers (Rodionov and Assel, 2000). In comparison, positive phases of the November NAO are related to lower ice covers on 1 January. Although positive phases of the NAO are linked to cooler eastern North American temperatures, we suggest that windier conditions may increase mixing in the Great Lakes, inhibiting ice cover.

For BOM February predictions, the BOM ice cover from each lake is the most important predictor for all lakes, except Lake Ontario (see Table 5), where only the December East Atlantic-Western Russian index (EAWR) is valuable. Positive phases of the December EAWR pattern are linked to lower ice covers on 1 February. The December Southern Oscillation index (SOI) also is valuable in predictions of Lake Superior and Lake Huron. Rodionov and Assel (2000) also demonstrate that positive SOI phases (El Niño) are linked to warmer winters in the Great Lakes region, leading to reduced ice extent, and vice versa.

Finally, for BOM March, the BOM February ice cover is most important for all lakes except Lake Erie, where the AFDDs from January are more important. Over Lake Michigan, the January Polar/Eurasian index (POL) also is relevant. Rodionov and Assel (2000) suggest that the Polar/Eurasian index is the most important teleconnection in determining mean basin-wide ice conditions; during positive POL phases, the polar vortex is strengthened, leading to more zonal flow over the Eastern USA, which in turn is related to warmer winter temperatures and less ice cover.

If perfect forecasts of the upcoming month's AFDD were available, then statistical forecasts of the BOM would improve substantially; see Table 7. For instance, the mean absolute errors for the PLR model are much lower than for any other model on all lakes, with much higher skill scores; see Figures 3 and 4. As with the other models, the error is highest for Lake Erie and lowest for Lake Ontario. For BOM January forecasts, only an accurate prediction of December AFDDs is needed for all lakes, except Lake Michigan, where the November TNH also retains value. For BOM February, the January AFDDs are useful on all lakes, BOM January ice cover is relevant on all lakes except Ontario, and the December SOI remains valuable for Lake Superior. For BOM March, only two variables are needed for each lake: February AFDDs, and BOM February ice cover.

4.3 Use of Mechanistic Models

While the previous models are statistically based, mechanistic models theoretically should perform better than statistical models over short forecast times. One good candidate model already developed for estimating evaporation from the Great Lakes is GLERL's large-lake thermodynamics and heat storage model. It is a continuous-simulation model of daily lake evaporation over long time periods and is physically based to have application under environmental conditions different than those under which they were derived. GLERL developed this lumped-parameter model for each of the Great Lakes based on an energy balance at the lake's surface (Croley, 1989) and on one-dimensional (vertical) lake heat storage (Croley, 1992). Ice formation and loss is coupled also to lake thermodynamics and heat storage (Croley and Assel, 1994).

Two calibrations are involved in applying the model in a particular setting. The first determines parameters related to thermodynamics and superposition heat storage (Croley, 1992) and the effect of cloudiness on the atmospheric net long-wave radiation exchange (Croley, 1989). This calibration minimizes daily water surface temperature root mean square error (RMSE) by using methods described elsewhere (Croley and Hartmann, 1984). Meteorology data for 1948-1988 were provided by the National Climate Data Center and water surface temperature data on each of the Great Lakes, except Lake Michigan, were taken from airplane and satellite measurements. All were prepared as described by Croley (1989). Water surface temperature data for Lake Michigan from 1981 through 1985 were gleaned from areal maps prepared at the NWS Marine Predictions Branch and extended through August 1988. The second calibration determines ice formation parameters that minimize daily ice cover RMSE with these same calibration techniques. Lake-averaged ice cover for model calibration was calculated from GLERL's digital ice cover database (Assel, 1983; 2003). In most cases prior to 1973, less than 100% of a lake was observed on any given date. If less than 70% of the Lake Superior surface was observed, the ice cover for that date was not included in the model calibration. A subjective estimate of lake-averaged ice cover was made for the other Great Lakes if the data were insufficient.

Prior to calibration or model use, the (spatial) average temperature-depth profile in the lake and the ice cover must be initialized. While the ice cover is easy to determine as zero during major portions of the year, the average temperature-depth profile in the lake is generally difficult to determine. Since the effect of initial conditions diminishes with the length of a simulation, we used 2-3 years of simulation prior to the period of interest and the effects were nil from a practical point of view.

Empirical coefficients of the thermodynamics, heat storage, and ice sub-models were calibrated in an iterative process that used the two calibrations sequentially in rotation. We used independent data (lake-averaged daily surface temperature for the lake thermodynamics and heat storage sub-models and lake-averaged daily ice cover for the lake ice cover sub-model). First we minimized the RMSE of daily water surface temperature by calibrating lake thermodynamics and heat storage model parameters and holding the parameters for the ice cover sub-model constant. We then held lake thermodynamics and heat storage sub-model parameters constant and calibrated the parameters of the ice cover sub-model to minimize the RMSE of daily ice cover. Then we repeated the process until the RMSEs for both water surface temperatures and ice cover were not significantly reduced from previous iterations. In a second calibration, we used only lake-averaged daily surface temperature data to determine all parameters (both for the lake thermodynamics and heat storage sub-models and for the lake ice cover sub-model).

In order to assess whether a mechanistic model could be useful in predicting ice cover, BOM ice data observations were correlated with previous-month lake-averaged model outputs from the two versions of the model. Table 8 shows correlations for the model calibrated to observed ice cover and surface water temperatures on each Great Lake, and Table 9 shows correlations for the model calibrated to observed surface water temperatures only. Both tables indicate that there is a strong correlation between several model outputs and observed BOM ice cover, indicating that this model may have significant predictive value. The correlations between observed ice cover and model over-lake air temperature are particularly noteworthy, and strong correlations also exist between observed ice cover and model over-lake specific humidity, ice surface temperature, ice surface area, ice average thickness, and net long-wave exchange. The high correlations between observed ice cover and model over-lake air temperature are expected and echo the results from the preceding predictive models. The other strong correlations also are physically valid and, in many cases, these variables are not routinely available from another source. As such, additional research examining how the 30-day forecasts of this model correlate with ice cover might provide a completely new alternative to predicting ice cover, or more likely, several of the model outputs might be combined with the observed data to create new regression forecasts with a lower error than the current models shown here (C, AP, or OLR). Since the PLR forecasts indicate that accurate forecasts of the upcoming month's temperature, in terms of freezing degree days, would be very valuable for lowering prediction error, good forecasts of daily over-lake temperature could be utilized as a proxy for AFDDs, perhaps improving the 30-day ice forecasts substantially. Since 30-day forecasts of ice cover are not made in the Great Lakes with reference to ice thickness or some of the other variables that this model can produce, it is also likely that they may provide new information about the ice cover that is not currently available, which again may reduce the error estimate.

5. SUMMARY

This study examined improving the 30-day forecast of the Great Lakes monthly mean ice cover for the beginning of January, February, and March. The ice conditions were based on recently developed digital ice climatology. Predictive data include (1) freezing degree days obtained from NWS station data, (2) previous month observed ice cover, and (3) monthly mean teleconnection data. Additionally considered were (4) perfectly forecast freezing degree day totals for upcoming months (to determine the value of such a prediction), and (5) output from a large-lake thermodynamics and heat storage model (to determine whether a mechanistic model may prove valuable). Anomaly propagation, linear regression, and perfect linear regression models were developed from data types 1-4 and compared to climatology. The regression models were developed in a three-step approach: (a) correlate all possible data with the observed ice cover and retain only those variables with a significant correlation, (b) utilize stepwise regression to choose a good model, and (c) run 1000 Monte Carlo simulations holding 1/3 of the data for testing to obtain a more realistic error assessment. Model results were evaluated with mean absolute error and skill score. The following results emerged:

(1) With empirical data available 30 days prior to a prediction, utilizing climatology provides the lowest error for the 1 January Lake Ontario ice cover, while the anomaly propagation model supplies the lowest error for the 1 March forecast for Lakes Superior, Michigan, and Huron, and the observed linear regression model provides the lowest error for the remaining 11 predictions.

(2) For predictions of 1 January ice cover on 1 December, the mean November Tropical Northern Hemisphere teleconnection index provides the lowest prediction error, excepting Lake Ontario, where the climatological 1 January ice cover is a superior prediction. Including the November North Atlantic Oscillation index is helpful in reducing the error for Lakes Michigan, Huron, and Erie. For predictions of 1 February ice cover on 1 January, the 1 January mean lake-ice cover typically is the most important predictor, except for Lake Ontario, where the December East Atlantic-Western Russia teleconnection index is more valuable. For predictions of 1 March ice cover on 1 February, the 1 February ice cover generates the lowest error for all lakes except Erie, where the accumulated freezing degree days over Lake Erie in January provides a lower error prediction.

(3) If perfect forecasts of the upcoming month's freezing degree-days were available, the forecast equations for most months would need fewer parameters, and the error would be lower for all months. This suggests that as numerical weather models improve their accuracy of 30-day forecasts, analysts should consider utilizing these predictions more rigorously in the 30-day ice forecast.

Correlations of ice cover with a mechanistic model output show strong associations between ice cover observations and model over-lake air temperature, over-lake specific humidity, ice surface temperature, ice surface area, ice average thickness, and net long-wave exchange. Future research on a 30-day predictive mode may provide a new forecast technique, or additional data for regression forecasts, that could significantly lower the estimated error.

In this study we developed 30-day forecasting models of lake-averaged ice cover. In order to use these models in an operational forecast mode, it is necessary to relate the lake averaged ice cover to spatial patterns of ice cover on BOM dates. One way this could be done is by examining several (3, 4, or 5) winters (over the 1973-2002 period of record) where the observed BOM lake averaged ice cover is closest to the forecast lake averaged ice cover (using the models considered here) and make a subjective analysis of the ice distribution patterns based on these historical ice charts.

6. REFERENCES

Allardice, D. R., and S. Thorp. A changing Great Lakes economy: economic and environmental linkages. SOLEC Working Paper presented at State of the Lakes Ecosystem Conference. EPA 905-R-95-017, Chicago, Illinois, U.S. Environmental Protection Agency (1995).

Assel, R.A. A Computerized Ice Concentration Data Base for the Great Lakes. NOAA Data Report ERL GLERL-24. Great Lakes Environmental Research Lab., Ann Arbor, Michigan (1983).

Assel, R. A. Great Lakes Degree-day and Winter Severity Index Update: 1897-1983. NOAA Data Report ERL GLERL-29. Great Lakes Environmental Research Laboratory, Ann Arbor, Michigan (1986).

Assel, R.A. An Electronic Atlas of Great Lakes Ice Cover, Winters 1973-2002. NOAA Atlas. NOAA, Great Lakes Environmental Research Laboratory, Ann Arbor, Michigan, 2 CD-ROM set or DVD (2003).

Assel, R.A., K. Cronk, and D.C. Norton. Recent Trends in Great Lakes Ice Cover. *Climate Change* 57(1):185-204 (2003).

Assel R.A., and S. Rodionov. Atmospheric teleconnections for annual maximal ice cover on the Laurentian Great Lakes. *International Journal of Climatology* 18:425-442 (1998).

Barnston, A.G., and R.E. Livezey. Classification, seasonality, and persistence of low-frequency atmospheric circulation patterns. *Monthly Weather Review* 115:1083-1126 (1987).

Croley, T.E., II. Verifiable evaporation modeling on the Laurentian Great Lakes. *Water Resource Research* 25(5): 781-792 (1989).

Croley, T.E., II. Long-term heat storage in the Great Lakes. *Water Resources Research* 28(1):69-81 (1992).

Croley, T.E., II, and R.A. Assel. A one-dimensional ice thermodynamics model for the Laurentian Great Lakes. *Water Resources Research* 30(3):625-639 (1994).

Croley, T.E., II, and H.C. Hartmann. Lake Superior basin runoff modeling. NOAA Technical Memorandum ERL GLERL-50, Available from the National Technical Information Service, U.S. Department of Commerce, Sills Bldg., 5285 Port Royal Road, Springfield, VA. 22121 (1984).

Drobot, S.D., and J.A. Maslanik. A practical method for long-range forecasting of ice severity in the Beaufort Sea. *Geophysical Research Letters* 29(8):1213, doi:10.1029/2001GL014173 (2002).

Neter, J., W. Wasserman, and M.H. Kutner. *Applied Linear Statistical Models*. Third Edition, Irwin, 1181 pp. (1990).

Rodionov, S. and R.A. Assel. Atmospheric teleconnection patterns and severity of winters in the Laurentian Great Lakes basin. *Atmosphere-Ocean* XXXVIII(4):601-635 (2000).

Rodionov, S., R.A. Assel, and L.R. Herche. Tree-structured modeling of the relationship between Great Lakes ice cover and atmospheric circulation patterns. *Journal of Great Lakes Research* 27(4):486-502 (2001).

Rogers, J.C. Long-range forecasting of maximum ice extent on the Great Lakes. NOAA Technical Memorandum ERL-GLERL-007, Great Lakes Environmental Research Laboratory, Ann Arbor, Michigan (1976).

Snider, C.R. Great Lakes ice forecasting. NOAA Technical Memorandum NWS OSD 1, Ocean Services Division, Silver Springs, MD. Available from the National Technical Information Service, U.S. Department of Commerce, Sills Bldg., 5285 Port Royal Road, Springfield, VA. 22121 (1974).

Wilks, D.S. *Statistical Methods in the Atmospheric Sciences*. Academic Press, 467 pp. (1995).

Table 1. Lake averaged ice cover for beginning of month dates (%).

Year	Superior			Michigan			Huron			Erie			Ontario		
	Jan	Feb	Mar	Jan	Feb	Mar	Jan	Feb	Mar	Jan	Feb	Mar	Jan	Feb	Mar
1973	12.2	19.6	67.9	7.4	20.2	30.7	19.3	25.1	65.5	2.7	10.3	90.1	2.7	22.4	33.7
1974	12.4	21.4	73.6	5.2	15.6	30.7	11.7	24.1	61.4	10.2	8.9	57.5	5.1	7.2	14.6
1975	0.0	19.3	19.9	0.0	24.5	18.4	0.0	34.2	32.4	0.0	14.7	50.8	0.0	5.5	4.2
1976	4.0	26.1	27.3	8.7	26.0	14.2	16.8	52.3	37.5	14.8	92.7	26.5	2.8	13.9	7.0
1977	28.0	81.6	94.2	31.8	74.7	72.5	44.0	84.4	91.6	84.2	98.5	93.9	19.7	33.4	34.3
1978	8.7	17.8	91.6	8.7	33.7	61.9	21.4	64.7	95.6	44.1	98.2	100.0	5.7	26.1	47.6
1979	7.0	57.3	93.7	10.5	34.1	88.0	15.0	58.7	89.8	5.0	82.0	78.7	2.2	22.2	20.2
1980	0.0	40.3	62.9	0.0	29.1	34.0	0.0	42.1	58.3	0.0	56.9	88.1	0.0	11.0	22.5
1981	24.3	61.0	65.0	26.4	33.1	14.8	40.2	79.0	40.2	61.5	89.9	52.2	28.2	15.8	5.2
1982	4.1	42.5	73.9	2.5	44.2	38.2	6.2	67.6	80.0	0.1	96.0	94.9	0.0	33.1	27.1
1983	6.2	18.6	12.1	0.8	18.6	11.7	0.7	31.8	18.1	0.2	9.2	5.2	0.0	11.0	2.3
1984	18.1	36.8	31.4	12.5	21.8	14.9	29.5	68.1	30.6	73.0	93.6	76.4	5.3	18.5	8.0
1985	18.0	43.5	81.2	7.9	29.0	38.7	13.5	52.9	53.9	8.8	89.0	77.0	4.2	13.1	33.9
1986	12.0	41.6	85.0	18.2	30.3	64.8	25.9	66.1	73.2	90.7	95.5	87.9	10.1	20.7	43.7
1987	1.9	11.0	4.6	3.6	14.4	8.3	3.4	36.4	34.8	1.0	56.8	67.4	1.0	3.5	3.9
1988	0.0	16.3	45.4	0.0	19.7	17.7	0.0	29.1	52.4	0.0	48.6	85.6	0.0	6.4	18.9
1989	7.9	14.4	54.5	5.2	10.4	28.5	11.8	19.8	50.3	3.5	8.9	90.7	0.6	3.9	9.9
1990	28.6	33.6	55.4	31.2	17.2	23.9	36.2	30.7	59.0	57.5	30.0	45.9	17.3	10.3	29.5
1991	1.9	70.4	78.9	2.5	20.4	17.7	1.0	43.8	32.8	3.3	35.1	29.4	0.0	11.5	8.0
1992	6.1	25.0	22.8	1.6	27.2	11.0	5.0	45.2	34.8	0.2	35.8	69.1	0.5	10.3	9.3
1993	4.9	4.7	76.6	0.8	15.2	32.2	11.6	22.7	78.3	1.2	25.5	92.4	1.0	3.4	29.0
1994	9.8	85.9	95.5	10.2	50.8	59.3	23.0	89.6	96.1	26.0	95.9	92.1	5.3	46.8	30.4
1995	1.6	6.9	21.3	0.1	8.7	14.8	0.0	18.8	37.7	0.0	13.9	58.1	0.2	1.3	10.8
1996	4.4	35.5	95.6	9.4	32.2	19.9	20.5	59.1	72.6	21.5	97.6	73.3	2.4	13.7	5.7
1997	6.2	25.8	65.2	9.6	27.5	20.7	12.0	48.6	53.9	11.9	91.8	55.2	0.0	13.8	8.1
1998	1.8	8.3	2.4	1.7	10.6	5.2	7.2	20.2	13.7	1.9	2.9	0.0	0.7	4.9	1.6
1999	3.1	6.5	9.7	4.0	10.7	13.0	6.8	20.1	23.9	2.5	46.2	45.7	0.7	6.5	4.2
2000	2.3	7.8	9.0	4.4	14.7	11.8	8.0	37.9	22.1	8.8	90.7	33.8	1.4	22.3	5.8
2001	7.6	7.1	38.3	28.3	19.4	14.3	25.2	27.2	32.3	73.2	92.5	52.6	2.0	7.9	8.4
2002	1.7	5.4	4.4	2.6	6.1	9.4	3.4	9.2	12.7	5.8	1.1	0.3	0.9	1.1	2.9
Median	6.2	23.2	59.2	5.2	21.1	19.2	11.8	40.0	51.4	5.4	56.9	68.3	1.2	11.3	9.6
Mean	8.2	29.7	52.0	8.5	24.7	28.0	14.0	43.7	51.2	20.5	57.0	62.4	4.0	14.1	16.4
Std Dev	7.9	22.4	31.7	9.3	13.8	20.8	12.2	21.1	24.6	28.5	36.6	28.7	6.5	10.5	13.2

Table 2. Lake averaged AFDD for December, January, and February (°F).

Year	Superior			Michigan			Huron			Erie			Ontario		
	Dec	Jan	Feb	Dec	Jan	Feb	Dec	Jan	Feb	Dec	Jan	Feb	Dec	Jan	Feb
1973	567	473	473	292	208	220	174	194	322	25	91	197	18	118	283
1974	481	649	595	252	310	313	232	261	387	111	97	208	123	177	272
1975	279	558	434	87	219	235	85	210	210	29	68	78	20	93	119
1976	475	706	335	169	417	47	188	490	131	116	344	-48	172	404	0
1977	727	877	466	478	689	272	443	637	286	290	607	188	265	503	198
1978	474	671	571	278	505	497	224	446	444	134	382	463	137	318	425
1979	532	814	733	269	618	538	179	485	542	49	375	450	78	315	504
1980	263	586	568	53	335	357	52	302	357	-3	192	290	29	227	355
1981	549	603	391	272	399	168	341	457	159	213	390	40	284	500	-8
1982	396	868	569	199	635	341	163	568	358	101	423	249	105	482	228
1983	288	482	287	57	220	91	50	223	117	17	100	7	14	169	91
1984	732	722	206	509	462	12	373	490	24	313	390	-71	230	358	-41
1985	430	660	558	97	491	339	72	423	313	1	362	214	1	345	174
1986	680	563	500	445	324	281	348	344	300	267	192	170	218	227	223
1987	297	415	238	100	220	52	80	241	192	17	168	99	5	219	243
1988	243	650	627	65	404	346	57	331	394	30	199	212	56	228	216
1989	460	415	654	197	74	382	211	127	356	89	-29	211	129	75	260
1990	740	310	405	480	35	128	545	89	212	410	-87	-3	476	-32	79
1991	425	668	339	186	372	93	143	379	130	59	171	1	40	227	48
1992	377	450	342	101	158	56	151	242	173	46	114	31	102	197	121
1993	357	495	499	123	236	277	80	225	365	3	66	224	54	147	363
1994	357	944	675	164	586	369	175	636	437	149	434	219	163	548	312
1995	170	432	543	14	226	236	5	191	349	4	85	197	24	43	253
1996	502	715	565	263	375	268	292	373	326	214	235	162	212	286	207
1997	400	647	428	157	369	163	130	369	189	22	263	4	9	261	50
1998	212	423	75	63	154	-75	54	145	-16	28	29	-50	33	74	-10
1999	329	611	270	157	364	27	148	384	112	91	216	-39	88	276	42
2000	291	562	291	164	295	55	135	279	115	93	207	-12	91	256	56
2001	653	359	529	445	216	239	420	231	208	329	150	38	271	154	97
2002	184	329	266	95	37	22	80	100	125	78	-51	5	51	-27	1
Median	413	595	470	167	329	236	157	316	249	83	192	130	89	227	186
Mean	429	588	448	208	332	212	187	329	254	111	206	124	116	239	172
Std Dev	165	164	158	142	172	152	134	151	134	113	164	141	110	151	140

Table 3. Potential Predictors for each lake by month.

January BOM[a]	February BOM[b]	March BOM[c]
November Tropical-Northern Hemisphere (TNH Nov)	BOM January lake-averaged ice cover (BOM Jan)	BOM February lake-averaged ice cover (BOM Feb)
November North Atlantic Oscillation (NAO Nov)	December lake-averaged freezing degree days (AFDD Dec)	January lake-averaged freezing degree days (AFDD Jan)
	December Southern Oscillation Index (SOI Dec)	January Polar/Eurasian Index (POL Jan)
	December East Atlantic-Western Russia Index (EAWR Dec)	January East Pacific Index (EP Jan)
	Any variables retained in regression analysis from preceding month	Any variables retained in regression analysis from preceding month

[a]Forecast for January BOM is made BOM December.
[b]Forecast for February BOM is made BOM January.
[c]Forecast for March BOM is made BOM February.

Table 4. 1973—2002 Lake-Averaged Ice Cover Characteristics.

Lake	January BOM	February BOM	March BOM
Mean Ice Conditions (%)			
Superior	8.2	29.7	52.0
Michigan	8.5	24.7	28.0
Huron	14.0	43.7	51.2
Erie	20.5	57.0	62.4
Ontario	4.0	14.1	16.4
Standard Deviation of Ice Conditions (%)			
Superior	8.0	22.8	32.2
Michigan	9.4	14.0	21.2
Huron	12.4	21.5	25.0
Erie	29.0	37.2	29.2
Ontario	6.6	10.7	13.4
Minimum Ice Conditions (%)			
Superior	0.0	4.7	2.4
Michigan	0.0	6.1	5.2
Huron	0.0	9.2	12.7
Erie	0.0	1.1	0.0
Ontario	0.0	1.1	1.6
Maximum Ice Conditions (%)			
Superior	28.6	85.9	95.6
Michigan	31.8	74.7	88.0
Huron	44.0	89.6	96.1
Erie	90.7	98.5	100.0
Ontario	28.2	46.8	47.6

Table 5. Observational Regression Model Results.

	BOM January				BOM February				BOM March			
i	Variable	β_i	β_i^*	VIF	Variable	β_i	β_i^*	VIF	Variable	β_i	β_i^*	VIF
Lake Superior												
0	Constant	8.07			Constant	18.38			Constant	23.88		
1	TNH Nov	3.23	0.40	1.00	BOM Jan	1.39	0.45	1.01	BOM Feb	0.95	0.67	1.00
Lake Michigan												
0	Constant	8.77			Constant	18.89			Constant	6.48		
1	TNH Nov	5.61	0.59	1.00	BOM Jan	0.68	0.46	1.00	BOM Feb	0.88	0.58	1.13
2	NAO Nov	-2.78	-0.31	1.00					POL Jan	-6.19	-0.28	1.13
Lake Huron												
0	Constant	14.39			Constant	29.42			Constant	22.04		
1	TNH Nov	5.99	0.48	1.00	BOM Jan	1.02	0.55	1.02	BOM Feb	0.67	0.57	1.00
2	NAO Nov	-4.11	-0.34	1.00								
Lake Erie												
0	Constant	21.84			Constant	42.89			Constant	46.41		
1	NAO Nov	-12.17	-0.43	1.00	BOM Jan	0.69	0.54	1.00	AFDD Jan	0.08	0.43	1.00
2	TNH Nov	12.00	0.41	1.00								
Lake Ontario												
0	Constant	3.93			Constant	13.12			Constant	6.57		
1	TNH Nov	2.73	0.41	1.00	EAWR Dec	-5.94	-0.56	1.00	BOM Feb	0.70	0.55	1.00

Table 6. Summary of best models.

Month	Best prediction model
Superior	
January	OLR
February	OLR
March	AP
Michigan	
January	OLR
February	OLR
March	AP
Huron	
January	OLR
February	OLR
March	AP
Erie	
January	OLR
February	OLR
March	OLR
Ontario	
January	C
February	OLR
March	OLR

Table 7. Perfect AFDD Regression Model Results.

	BOM January				BOM February				BOM March			
i	Variable	β_i	β_i^*	VIF	Variable	β_i	β_i^*	VIF	Variable	β_i	β_i^*	VIF
Lake Superior												
0	Constant	-8.09			Constant	-33.05			Constant	-21.07		
1	AFDD Dec	0.04	0.78	1.00	AFDD Jan	0.09	0.60	1.08	AFDD Feb	0.12	0.57	1.11
2					BOM Jan	1.13	0.38	1.03	BOM Feb	0.70	0.49	1.11
Lake Michigan												
0	Constant	-1.43			Constant	0.87			Constant	-4.89		
1	AFDD Dec	0.48	0.72	1.22	AFDD Jan	0.06	0.73	1.03	AFDD Feb	0.08	0.58	1.23
2	TNH Nov	2.63	0.27	1.22	BOM Jan	0.48	0.32	1.03	BOM Feb	0.65	0.43	1.23
Lake Huron												
0	Constant	-1.31			Constant	1.13			Constant	-4.78		
1	AFDD Dec	0.08	0.88	1.00	AFDD Jan	0.11	0.76	1.19	AFDD Feb	0.14	0.74	1.05
2					BOM Jan	0.50	0.29	1.19	BOM Feb	0.48	0.41	1.05
Lake Erie												
0	Constant	-4.64			Constant	15.93			Constant	32.02		
1	AFDD Dec	0.23	0.89	1.00	AFDD Jan	0.17	0.73	1.16	AFDD Feb	0.14	0.68	1.03
2					BOM Jan	0.34	0.27	1.16	BOM Feb	0.23	0.29	1.03
Lake Ontario												
0	Constant	-1.09			Constant	1.37			Constant	0.70		
1	AFDD Dec	0.04	0.73	1.00	AFDD Jan	0.05	0.75	1.00	AFDD Feb	0.05	0.50	1.08
2									BOM Feb	0.53	0.42	1.08

Table 8. Correlations between BOM ice cover and previous-month average model variables, model calibrated to observed surface temperatures and ice concentrations.

	Superior			Michigan			Huron		
	Jan	Feb	Mar	Jan	Feb	Mar	Jan	Feb	Mar
Over-lake air temperature	-0.83	-0.63	-0.78	-0.82	-0.79	-0.78	-0.88	-0.90	-0.86
Over-lake specific humidity	-0.78	-0.59	-0.69	-0.81	-0.78	-0.73	-0.80	-0.87	-0.81
Over-lake wind speed	0.36	0.00	0.03	0.42	0.56	0.32	0.36	0.42	0.20
Over-lake cloud cover	-0.16	-0.37	-0.46	-0.01	0.05	-0.32	0.00	-0.14	-0.40
Surface water temperature	-0.56	-0.51	-0.40	-0.63	-0.42	-0.23	-0.48	-0.61	-0.38
Lake evaporation	0.64	-0.09	-0.14	0.44	0.60	0.40	0.58	0.15	0.22
Incident short-wave radiation	0.14	0.39	0.43	-0.01	-0.09	0.31	-0.02	0.18	0.37
Reflected short-wave radiation	-0.58	-0.69	-0.83	-0.39	-0.61	-0.74	0.24	-0.83	-0.75
Net long-wave exchange	-0.74	-0.55	-0.68	-0.73	-0.77	-0.73	-0.79	-0.68	-0.79
Latent heat transfer	-0.64	0.08	0.13	-0.44	-0.61	-0.42	-0.59	-0.16	-0.24
Sensible heat transfer	-0.78	-0.19	-0.05	-0.69	-0.68	-0.55	-0.84	-0.47	-0.40
Ice surface temperature	-0.84	-0.57	-0.72	-0.84	-0.78	-0.77	-0.90	-0.83	-0.82
Ice surface area	0.69	0.68	0.75	0.86	0.68	0.72	0.48	0.86	0.66
Ice average thickness	0.72	0.63	0.73	0.88	0.63	0.66	0.49	0.84	0.62
Lake heat storage	-0.45	-0.45	-0.22	-0.62	-0.58	-0.57	-0.37	-0.61	-0.42

	Erie			Ontario		
	Jan	Feb	Mar	Jan	Feb	Mar
Over-lake air temperature	-0.79	-0.85	-0.74	-0.74	-0.80	-0.62
Over-lake specific humidity	-0.70	-0.81	-0.75	-0.71	-0.72	-0.58
Over-lake wind speed	0.52	0.49	0.20	0.27	0.57	0.50
Over-lake cloud cover	0.17	0.11	0.04	-0.16	0.09	0.23
Surface water temperature	-0.49	-0.42	-0.50	-0.57	-0.55	-0.30
Lake evaporation	0.04	-0.06	-0.14	0.39	0.60	0.52
Incident short-wave radiation	-0.16	-0.12	-0.03	0.16	-0.09	-0.22
Reflected short-wave radiation	-0.74	-0.70	-0.58	-0.25	-0.66	-0.51
Net long-wave exchange	-0.53	-0.79	-0.56	-0.59	-0.66	-0.58
Latent heat transfer	-0.06	0.02	0.12	-0.39	-0.61	-0.54
Sensible heat transfer	-0.66	-0.44	-0.11	-0.63	-0.74	-0.53
Ice surface temperature	-0.89	-0.83	-0.68	-0.76	-0.78	-0.58
Ice surface area	0.81	0.77	0.61	0.60	0.74	0.54
Ice average thickness	0.78	0.73	0.65	0.68	0.73	0.50
Lake heat storage	-0.28		-0.48	-0.44	-0.61	-0.55

Table 9. Correlations between BOM ice cover and previous-month average model variables, model calibrated to observed surface temperatures only.

	Superior			Michigan			Huron		
	Jan	Feb	Mar	Jan	Feb	Mar	Jan	Feb	Mar
Over-lake air temperature	-0.83	-0.66	-0.83	-0.83	-0.86	-0.82	-0.88	-0.90	-0.89
Over-lake specific humidity	-0.77	-0.62	-0.73	-0.80	-0.81	-0.74	-0.78	-0.87	-0.84
Over-lake wind speed	0.34	-0.20	-0.31	0.42	0.13	-0.20	0.36	0.44	-0.14
Over-lake cloud cover	-0.16	-0.37	-0.46	-0.01	0.05	-0.32	0.00	-0.14	-0.40
Surface water temperature	-0.47	-0.65	-0.59	-0.66	-0.71	-0.53	-0.54	-0.80	-0.71
Lake evaporation	0.65	-0.44	-0.59	0.62	-0.26	-0.43	0.65	0.28	-0.24
Incident short-wave radiation	0.14	0.39	0.43	-0.01	-0.09	0.31	-0.02	0.18	0.37
Reflected short-wave radiation	-0.20	-0.64	-0.80	0.16	-0.75	-0.69	0.24	-0.42	-0.64
Net long-wave exchange	-0.72	-0.49	-0.65	-0.77	-0.64	-0.69	-0.80	-0.71	-0.71
Latent heat transfer	-0.66	0.44	0.59	-0.63	0.24	0.43	-0.65	-0.28	0.23
Sensible heat transfer	-0.80	0.19	0.51	-0.75	-0.13	0.33	-0.86	-0.60	0.07
Ice surface temperature	-0.84	-0.58	-0.72	-0.84	-0.78	-0.76	-0.90	-0.83	-0.82
Ice surface area		0.66	0.72		0.73	0.63		0.42	0.60
Ice average thickness		0.61	0.68		0.75	0.56		0.40	0.54
Lake heat storage	-0.41	-0.59	-0.17	-0.59	-0.67	-0.39	-0.50	-0.78	-0.60

	Erie			Ontario		
	Jan	Feb	Mar	Jan	Feb	Mar
Over-lake air temperature	-0.81	-0.87	-0.73	-0.73	-0.81	-0.65
Over-lake specific humidity	-0.72	-0.84	-0.73	-0.69	-0.73	-0.62
Over-lake wind speed	0.47	0.29	0.32	0.27	0.47	0.41
Over-lake cloud cover	0.17	0.11	0.04	-0.16	0.09	0.23
Surface water temperature	-0.62	-0.61	-0.50	-0.52	-0.72	-0.53
Lake evaporation	0.23	-0.51	-0.18	0.57	0.33	0.15
Incident short-wave radiation	-0.16	-0.12	-0.03	0.16	-0.09	-0.22
Reflected short-wave radiation	-0.73	-0.64	-0.57	-0.14	-0.47	-0.47
Net long-wave exchange	-0.63	-0.80	-0.66	-0.66	-0.53	-0.39
Latent heat transfer	-0.25	0.50	0.12	-0.57	-0.33	-0.17
Sensible heat transfer	-0.71	0.23	-0.11	-0.70	-0.68	-0.33
Ice surface temperature	-0.89	-0.83	-0.68	-0.76	-0.78	-0.58
Ice surface area	0.82	0.71	0.64		0.56	0.49
Ice average thickness	0.71	0.70	0.52		0.62	0.50
Lake heat storage	-0.57	-0.55	-0.29	-0.49	-0.69	-0.54