Ice Dynamics in Lake Model Surface Energy Balance Uncertainty

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Abstract:

The physical processes of heat exchange between lakes and the surrounding atmosphere are important in simulating and predicting terrestrial surface energy balance. While one-dimensional lake models have been used in predicting environmental changes in ice dynamics and water temperature, little work has been done on identifying drivers of model uncertainty in heat fluxes at multiple time scales. These heat fluxes play a large role in the physical process of ice growth and decay on the lake surface, as well the influence that the lakes have on the regional climate. We evaluated a pair of one-dimensional lake models, FLake and GLM, to compare modeled latent and sensible heat fluxes against observational data collected by an eddy covariance tower during a one-year period in 2017, using Lake Mendota in Madison, Wisconsin as our study site. While our initial hypothesis identified transitional periods of ice cover as a leading source of model uncertainty, we instead found that the models failed to account for a large growth in upward latent heat fluxes that occurred from late August into late December, a pattern which was confirmed by a second eddy covariance tower on the southern shore of the lake. Our results ultimately showed that one-dimensional models are effective in predicting sensible heat fluxes but are considerably less sensitive to latent heat fluxes than the observed relationships of latent heat flux to environmental drivers. These results can be used to focus future improvement of these lake models especially if they are to be used for surface boundary conditions in regional numerical weather models.

Introduction:

Lakes influence both physical and chemical changes to climate at regional special scales and time scales varying from days to hundreds of years. At short time scales (hours to days), lakes play in important role in driving the surface energy balance as the lake surface creates a region of lower albedo, more moisture, and lower roughness relative to land, leading to greater surface heat uptake, stronger latent heat fluxes, and increases the surface wind speeds (Thiery et al. 2014). At longer time scales (seasons to years), the lake annual ice cover varies with changing surface temperature, which in turn plays a role in long-term climate feedbacks including carbon cycling. Climate effects of reduced lake ice have not been well studied, however two observations have been made. The first is that reduced lake ice allows for greater evaporation in winter and greater snowfall due to lake effect snow. The second is an increased emission of greenhouse gases. Lake ice cover is assumed to act as a barrier that prevents greenhouse gasses from escaping until the ice is thawed, however greenhouse emissions would continue throughout winter without sufficient ice cover to hinder emissions (Brown and Duguay, 2010). In addition, ice and snow cover mitigates the ability of lakes to serve as carbon sinks during the winter months (Tranvik et al. 2009).

Lakes have received considerable attention for their role in regional carbon cycles. In comparison to the surrounding land, lakes are stronger drivers of carbon cycling (Algesten et al. 2004). The total carbon storage of lakes on a global scale is estimated at approximately 60% of the carbon concentration of the oceans (Cole et al. 2007), and lakes are estimated to emit approximately 0.3 Pg of carbon per year (Raymond et al. 2013). Lakes are also strong methane emitters which can influence climate at regional scales (Krinner 2003).

The increased attention given to lakes had given greater incentives for appropriate means to study lakes. A growing number of lakes now have *in situ* data often provided by eddy covariance flux towers, which are able to measure carbon dioxide emissions from over water (Miller et al. 2010) and assign CO_2 fluxes by means of covariance between fluctuations in CO2 and turbulent vertical wind velocity over the surface (McGillis et al. 2001). Eddy flux measurements have also been used to identify variation in evaporation (Lenters et al. 2005) and the surface energy balance of lakes (Rouse et al. 2003) over annual timescales. The second means of lake analysis is by means of modeling, which has received subsequent attention for the ability to predict future ice dynamics due to climate forcings (Yao et al. 2014). These models have been tested against observational data primarily for aquatic variables and have produced acceptable predictions of water temperature for a study done in Africa (Thiery et al. 2014) as well as a global study involving 32 different lakes (Bruce et al. 2018). Less work however has been done on analyzing model uncertainty on lake-atmosphere interactions on shorter timescales where climatological changes can be neglected.

Our analysis seeks to identify a possible source of model uncertainty in the predicting the surface energy balance over a lake. In mid-latitude lakes, transitional periods of surface freezing at night and melting during the day can create month-long periods of changing ice cover, which complicates the latent heat transfer due to significant variability in ice presence. Spatial variability in sensible heat flux can also ensue, as the ice creates a buffer which hinders lake-atmosphere interactions. The limited attention given to observational ice thickness in the model input leads us to believe that these transitional periods could lead to significant model bias in both latent and sensible heat fluxes in comparison to periods of no ice cover or total ice cover. For communities such as Madison, Wisconsin, where lakes cover a significant amount of the surface, these heat fluxes could act as drivers of weather at a mesoscale. Therefore, inefficient model predictions in these latent and sensible heat fluxes could have detrimental impacts on the ability of these one-dimensional models to be utilized for forecasting purposes. Our study seeks to ascertain whether or not these transitional periods are in fact periods of greater than average model uncertainty in predicting sensible and latent heat fluxes.

Methods:

Observational data for the years of 2012-2016 were supplied by means of an eddy covariance flux tower on the Picnic Point (PP) peninsula on the western shore of Lake Mendota. The flux tower is equipped with a CSAT3 LI7500 three dimensional sonic anemometer, which uses three pairs of transducers to calculate magnitude and direction of both horizontal and vertical wind, and determines sensible and latent heat fluxes by means of eddy covariance. The tower measures temperature and relative humidity with a Rotronic temperature and humidity sensor. The data was gap filled by means of marginal distribution sampling (REddyProc package, Lasslop et al., 2010) so as to be continuous throughout the one-year period.

The Lake Mendota buoy is deployed over the deepest part of the lake (43.0995, -89.4045) and is equipped with a thermistor string which gives temperature measurements from the surface to 20m depth. Data collection occurs every minute (Reed et al. 2018).

Solar radiation was observed on the top of the nearby Atmospheric, Oceanic and Space Sciences Building using a pyranometer. However, much of these data were missing for the end of 2017, and for this time period we used solar radiation data collected from the NOAA SOLRAD station at Dane County Regional Airport for the yearly solar radiation data, as our analysis showed little variability in solar radiation between the lake and nearby airport. In addition, the eddy flux tower did not measure longwave radiation, and so we made use of the SOLRAD station to supply longwave radiation as well.

The two models were supplied with input data from the flux tower measurements, using solar radiation data from the nearby SOLRAD site. The GLM model required an input of air temperature, shortwave and longwave radiation, relative humidity, wind speed, and rain accumulated. The flux towers supplied all the input information except for solar radiation and longwave radiation, which was recorded by the nearby SOLRAD station. This information was compiled into a single spreadsheet with hourly input data taken in by the model.

The model also took in a text file with information regarding lake geography, such as inflows and outflows, water column temperature, latitude and longitude, and elevation. This parameter file is input into the model at the beginning as opposed to in the form of an hourly timeseries, and so we applied the same input parameter file as used in prior modeling experiments by Dugan et al (in prep). Our aim was to fix these variables as constant and instead focus on the atmospheric dynamics as the primary forcing for the surface energy balance.

The FLake model took a similar set of input variables to the GLM model and thus we used the same input data for the shared variables. Shortwave radiation, air temperature, and windspeed were all supplied with the same hourly input data for the FLake model as we used for the GLM model. The FLake model also asked for two unique inputs: vapor pressure, and cloudiness fraction. Air humidity in mb was obtained by means of the Clausius-Clapeyron equation $e_s(T) \approx 611.2\exp\left(\frac{17.67T}{T+243.5}\right)$ to obtain the saturation vapor pressure e_s in Pa using the flux tower recorded temperature T. We subtracted the recorded vapor pressure deficit from the flux tower to obtain the vapor pressure. The other unique input, cloudiness, was estimated as a ratio of the observed solar radiation to modeled solar radiation by means of the equations for potential solar radiation given by Campbell and Norman (1998). The ratio was adjusted to remove infinite values, negative values, and values greater than 1 to arrive at an approximate number to represent the cloudiness, with 1 meaning complete cover and 0 meaning no clouds. Future work using observed cloudiness should be conducted to ensure accuracy of our methods.

Our initial goal was to do hourly comparisons of the latent and sensible heat fluxes between the two models and the observational data. However, GLM model outputs daily averaged heat fluxes, while the FLake model output hourly heat fluxes. To resolve this issue, a MATLAB daily averaging code was written to average every 24 cells of data from the FLake and flux tower to obtain daily averaged heat fluxes, these daily averaged heat fluxes were then compared against the GLM output.

For water temperature, both models provided hourly output but had different depths. For the FLake model, we were only able to perform comparisons for the surface water temperature. With the GLM model however, we analyzed data at several depths and compared those temperatures against the buoy data to try to identify water temperature differences as a possible source of model uncertainty in predicting latent heat fluxes.

Transitional periods were identified using the AOSS building rooftop camera video archive in conjunction with the Wisconsin State Climatology (WSC) ice cover archive. Dates during which the videos showed empirical evidence of ice cover variations throughout the day were considered to be transitional periods, and these time periods were the ones used when we tested for ice transition as a source of model uncertainty. Periods of “ice-on” and “ice-off” were given by the dates of freezing and melting on the WSC ice cover website.

Results:

Seasonal cycle of climate and surface energy fluxes

Temperature and solar radiation both followed expected and covarying annual cycles, with similar days of max values. Over 2017, surface air temperatures were predominantly sub-freezing until mid-March, though in February a short spike in surface temp was observed during which the temperatures were about 15 degrees C. Max surface temperature occurred during the span of June through September and peaked in early September. Solar radiation had a similar trend but was shifted slightly earlier, such that the max solar radiation value occurred in June and decreased from late June through December. A slight increase in solar radiation was observed at the very end of December and is reflected by a relative maxima at the start of the timeseries at the start of January (Figure 1).

Wind speed and relative humidity followed less pronounced trends. Max wind speed was observed in February but didn't follow an obvious pattern throughout the year. Spring and summer wind speeds were smaller than fall and winter. The maximum observed wind speed was slightly above 7 ms-1, however most of the days had average wind speeds of less than 1 ms-1. Relative humidity followed a somewhat sinusoidal trend with peaks in April and October. There was greater variance in the data during winter and spring and had less variation in summer and early fall (Figure 1).

A steady increase in the sensible heat flux from the lake to the atmosphere was observed from late January to December. The very beginning of January had high sensible heat fluxes of over 50 Wm^{-2}. The SH slowly decreased to negative by mid-February, and fluctuated about 0 until early June, at which point the sensible heat fluxes steadily increased. The peak sensible heat fluxes were observed in November and December, during which the sensible heat fluxes were greater than 150 Wm^{-2}. A slight drop occurred in late November, when the sensible heat flux was negative, however it then rapidly jumped up 150 Wm^{-2} after lake mixing (Figure 2).

The latent heat fluxes followed a similar trend, though the observed LE was only negative for a very brief time in late February. Following that brief time of negative LE, the observed latent heat flux ascended to over 100 Wm^{-2} in the following month, before dropping down to below 50 Wm^{-2}. The latent heat fluxes grew more quickly than did the sensible heat flux. The most noteworthy feature of the observed latent heat fluxes was the large increase that occurred in late September, when the latent heat flux grew from just above 100 Wm^{-2} to about 275 Wm^{-2}. The LE value remained near this value until late November when it dropped down to below 100 Wm^{-2} (Figure 2). This period of high latent heat fluxes illustrated considerable interactions between the lake and the surrounding boundary layer and likely contributed to considerable amounts of moisture deposition in the atmosphere.

Model simulations of surface fluxes and lake thermal state

Between the two models, the FLake model had better agreement with the observational fluxes. The large latent heat fluxes in early January observed by the flux tower were also captured by the FLake model, though the model predicted latent heat fluxes twice in magnitude. Additionally, like the observational data, the FLake model captured the steady increase in sensible heat fluxes in early summer, though slightly overestimated the observational fluxes. Additionally, both the FLake model and the flux tower recorded the largest sensible heat fluxes in November and December, with the observational data being nearly three times as large in November and about twice as large in December.

The Flake model's greatest period of uncertainty was from *Day 25* to *Day 115*, during which the observational sensible heat fluxes were negative while the FLake model predicted almost positive heat fluxes. As seen by the boxplot (Figure 2) the median value for the observed sensible heat flux during 2017 was approximately 10 Wm^{-2}, with the FLake model overpredicting the median and the GLM model underpredicting the model. The FLake model predicted a 75th percentile very similar to that of the observed data, but like the median it overpredicted the value of the 25th percentile. The box plot reveals that 75% of the GLM sensible heat fluxes spanned a much smaller range than either the FLake or the observational data and boasted extreme outliers above the 75th percentile. The largest value for the GLM sensible heat fluxes was small compared to the max values of both the FLake model and the observational data.

Much like the sensible heat fluxes, the GLM model was worse than the FLake model at predicting latent heat fluxes when compared to the PP tower data. For the majority of the timeseries, the observational latent heat fluxes were larger in magnitude than the FLake or GLM models. During the months of January through April, the FLake model predicted four time periods during which the latent heat fluxes were negative, however the observational data only agreed with one of those periods. The FLake model had the greatest certainty during the summer months, when it predicted a similar trend of increasing latent heat fluxes to what was observed by the data, though it also underestimated the heat flux magnitudes. The period in September when the observational latent heat fluxes spiked upwards was predicted by the FLake model, but to a much smaller degree. During the early fall latent heat spike, the observational max was near 330 Wm^{-2} while the FLake max was only about 160 Wm^{-2}.

Compared to the observational data and the FLake model, the GLM model underpredicted the latent heat fluxes by a large margin for the majority of 2017. The rate of increasing heat fluxes for 2017 was much slower for the GLM model than it was for the FLake model or the observational data. During the months of late spring through summer, the GLM model predicted latent heat fluxes ~70 fewer Wm^{-2} than the observational data, and it failed to predict the latent heat flux spike that occurred in the fall. During the time when the observational data showed latent heat fluxes of over 300 Wm^{-2}, the GLM model only predicted a latent heat flux of more than 100 Wm^{-2} and did not show a consistently large heat flux from the lake to the atmosphere. The discrepancy between the models and the observational data is further seen in the box plot of the annual latent heat fluxes. The median latent heat flux of the observational data, approximately 75 Wm^{-2}, was just about the value of the 75th percentile for the FLake plot and was larger than the upper whisker for the GLM plot. In fact, the entire interquartile range for the observational data was larger than the 75th percentile for the GLM data, showing an underestimation of the latent heat fluxes.

We compared the FLake model to the buoy water temperature data for surface water temperature during the period of buoy deployment from May 11, 2017 to November 12, 2017 (Figure 3). GLM water temperature was plotted against the buoy data and the FLake model at the surface and plotted against just the buoy data for depths of three, five, and eight meters. Both models overpredicted surface temperature, with the FLake model being high biased and never having a lower daily surface water temperature than observations. The GLM surface temp had less high bias, but generally had surface water temperatures of a few degrees higher than observations. For the water temperatures beneath the surface, the GLM model again had larger temperature vales than did the buoy, however this trend persisted until the start of August, at which point observed temperatures were larger than GLM temperatures for the duration of the timeseries at all three depths.

To test for drivers of model-observation differences, we evaluated sensitivity of fluxes to drivers, plotted as bin averages of temperature and relative humidity against latent and sensible heat fluxes for the ice-on, ice-off, and transitional periods (Figures 4-6). For the comparison between latent heat flux and temperature, the observed data showed the greatest variation with increasing temperature for the ice-off and transitional periods (Figure 6), while the FLake model was most sensitive to changing temperatures for the ice-on period (Figure 4). The GLM model was the least sensitive for all three time periods. The exact same pattern was seen for the comparison of sensible heat flux versus temperature: FLake output was most sensitive during ice-on, the observation data was most sensitive during ice-off and transition, and the GLM model was always least sensitive.

The comparison of latent and sensible heat fluxes against relative humidity showed less obvious relationships, however the trends were roughly the same as for the temperature sensitivity. The FLake model was most sensitive during the ice-on period, the observational data was most sensitive during the ice-off and transition periods, and the GLM model was consistently the least sensitive.

Discussion

Our results suggest that the models are a reliable tool for simulating sensible heat fluxes over lakes for an annual period, however lower reliability was found for latent heat flux. Primarily, the models fail to explain the large latent heat fluxes observed during the early fall months by the Picnic Point flux tower. In order to explain the underestimation of heat fluxes by the models, and possibly the cause of the spike in latent heat fluxes, we have considered two possible forcings for the increased energy transport which require future testing to verify as causes for large heat fluxes. The first is the possibility of upper atmospheric effects driving either strong upward vertical motion or a large gradient in air moisture content. The strong upward vertical motions could be explained by synoptic causes such as cyclogenesis, divergence of the adiabatic wind from acceleration in upper geostrophic flow, or frontogenesis (Martin, 2006). Analysis of upper atmospheric phenomena during the period of strongest latent heat fluxes could be used to identify possible synoptic features which may be driving stronger latent heat fluxes at the surface. One of particular interest is atmospheric stability, which has been identified as the cause for similar autumnal maxes in latent heat flux over Great Slave Lake in Canada (Rouse et al. 2003). Neither Flake or GLM can reliably incorporate these kinds of synoptic effects during their calculations, which rely exclusively on averaged surface-layer gradients (Mironov, 2008; Hipsey et al. 2014).

A second possibility involving lake biology likely would not explain in entirety the spike in latent heat fluxes but may offer insight into a possible secondary mechanism for increased energy transport. During the lake stratification periods of late May until late October, the lake experiences a bloom in blue-green algae, which changes the lake color (Fallon and Brock, 1980). From a simple thermodynamics perspective, the shortwave radiative absorptivity of an object is related to its visible color, and hence changing the lake color the amount of absorbed and reflected radiation (Petty, 2006). Previous studies have found evidence suggesting that phytoplankton populations can influence physical lake processes by means of increased surface absorptivity driving higher surface temperatures and extra loss of energy due to heat fluxes (Jones et al. 2005). A comparison of heat fluxes to phytoplankton populations in the lake could show a similar trend in Lake Mendota, which would help to explain some of the larger than modeled heat fluxes.

Our working hypothesis was that the period of greatest model bias would be during the transitional periods between no ice cover and complete ice cover. Analysis of the boxplots of these individual times indicates that it was the transitional period which had the greatest model uncertainty for the latent heat fluxes for both the FLake and GLM model. However, this interpretation is in part due to the fact that the transitional time period only lasted for about a month, while the ice-off period, during which we observed the huge spike in observational heat flux, lasted 10 months and thus the effect of the discrepancy between models and observational data during the latent heat spike was mitigated by the large amount of similar data between models and the flux tower outside of that time period.

Both the FLake and GLM models have shown to be reliable for predicting lake characteristics such as water temperature and thermocline depth, however these models are less reliable on predicting lake-atmospheric interactions, in part due to their relative simplicity. Both FLake and GLM are 1-dimensional models and focus primarily on surface atmospheric conditions. While this has been proven to be an acceptable means of analysis, model improvement could be made to consider more atmospheric conditions such that upper atmospheric dynamics may be factored into calculations of lake-atmosphere interactions, which are driven not only by the surface energy balance.

As we have not yet identified the direct cause of the high latent heat fluxes in mid-fall, we cannot diagnose precisely the source of the model uncertainty and what the models need to fix to improve their prediction of surface heat fluxes. However, as we have outlined, biological factors such as the algae blooms and tropospheric dynamics such as stability and vertical motion are not included in the models and therefore may play a role in the model uncertainty.

Prior work on the surface energy balance at Great Slave Lake found similar results to those of this study. The observations of that experiment suggested that the surface radiation balance does not control the turbulent heat fluxes on a daily basis, rather during the summer when the air is stable, the absorbed solar radiation is large and the sensible and latent heat fluxes are small. The opposite becomes true as the lake approaches freezing, during which the air is unstable, the absorbed solar radiation is small, and both the sensible and latent heat fluxes are maximized. A similar trend is shown for the evaporation rates, which are maximized just before freezing. The author suggests that the lake is capable of storing the absorbed radiation from summer, which creates a large gradient in energy during fall and winter and drives the strong sensible and latent het fluxes (Rouse et al. 2003).

Though we cannot acutely identify the direct sources of the model uncertainty, we can identify a few trends that we observed during the year of data collection. First, the GLM model considerably underestimates the surface heat fluxes during the entire year. Particularly during the spring and summer months, the GLM only predicts latent heat fluxes topping 50 Wm^{-2} twice, while the observational latent heat fluxes are never less than 50 Wm^{-2} and regularly exceed 100 Wm^{-2}. The trend can be seen for the sensible heat fluxes as well, during which the GLM sensible heat fluxes are primarily close to 0 Wm^{-2}, with the observational heat fluxes being closer to 20 $Wm^{-2.}$

Our analysis of the sensitivities suggested that the transitional periods did not show a significant amount of model uncertainty in comparison to the ice-on or ice-off periods. The GLM model was consistently less sensitive to changes in temperature or latent heat fluxes during all three time periods, though fluctuations in both latent and sensible heat fluxes were greater for the GLM model during the transitional period when compared to changes in relative humidity. The FLake model had a similar sensitivity trend as the observational data for the latent heat fluxes compared to the relative humidity, however the variations for the FLake fluxes were generally smaller than those of the observational data. The sensitivity of both models was greatest during the transitional periods, however they still showed less variation than the observational data for changes in both relative humidity and temperature.

The results of our sensitivity tests suggest that the transitional period was not the dominant source of model uncertainty. The models showed more variability in the heat fluxes but were still less sensitive than the observational data. The FLake model was the most sensitive for both fluxes against both relative humidity and temperature during the ice-on periods, suggesting that perhaps the model overestimates lake-atmosphere interactions during periods of total ice cover.

Conclusion

Our investigation into a possible source of model uncertainty yielded results that indicate our original hypothesis of transitional periods being dominant source of model uncertainty failed to account for significant year-round bias in surface energy balance. The sensitivity of both sensible and latent heat fluxes to changes in relative humidity and temperature was greatest for the two models during the transitional periods, however the observational data was also the most sensitive during transitional periods, and the discrepancies between model output and observational data were not significantly greater during transitional periods than ice-on or ice-off periods. The models do appear to be able to handle much of the dynamics occurring during variable ice cover when simulating the surface energy balance.

Though our original hypothesis was falsified, we did discover a significant period of model uncertainty, the period of large latent heat fluxes in early fall. The models fail to predict this spike in latent heat flux, leading to the greatest period of model uncertainty for the latent heat fluxes. These latent heat fluxes could drive considerable evaporation and precipitation. Further work should be conducted to determine the weather effects that these massive latent heat fluxes have and mechanisms that explain this large shift in flux.

Though the latent heat fluxes were poorly simulated over this time period, the models were better at calculating sensible heat fluxes. Both the FLake and GLM models predicted trends in sensible heat fluxes, though they often underestimated the magnitude of the heat fluxes. The GLM model in particular underestimated both latent and sensible heat fluxes, suggesting a need for fine-tuning the surface energy balance parameters of the model.

We have identified two possible sources of external parameters that the models do not incorporate which could explain the underestimation of heat fluxes, and possibly the spike in heat fluxes seen in fall by the Picnic Point tower. The first is upper atmospheric influences which drive stronger surface heat fluxes, by means of lower atmospheric stability or upward vertical motion. The second is biological effects due to algae blooms which occur during stratification periods and alter the absorption of radiation by the lakes. While including upper atmospheric observations into a one-dimensional model would be difficult, a surface alternative would be to estimate stability by means of the Richardson Flux Number (Holton and Hakim, 2013). As for a biological component of the models, further research should be conducted to see what effect the algae blooms have on year-long surface heat fluxes to determine how much of a difference between observational data and modeled data they provide.

Analysis of model uncertainty in the surface energy balance is still an ongoing area of research, though improvement of heat flux calculations at small time scales can in turn improve model reliability for predicting future ice cover and carbon fluxes. Prior work using the limnology tower has shown that the fall spike in latent heat flux is not an aberrant event, rather it is an annual occurrence. Improving model calculations to account for these observational trends will yield benefits not only for surface thermodynamics, but the understanding of lakes and the success of lake models overall.

Acknowledgements:

The author would like to thank the Atmospheric and Oceanic Science department as well as the Space Science and Engineering Center at UW-Madison. Further thanks given to Hilary Dugan of the UW-Madison Center for Limnology, and David Reed of the Michigan State University Center for Global Change and Earth Observations. Funding to support observations at the Picnic Point tower and Mendota buoy were provided by National Science Foundation (NSF) Atmospheric and Geospace Sciences Postdoctoral Fellowship Program (GEO-1430396) and the NSF Long-Term Ecological Research (LTER) program award to North Temperate Lakes (NTL) (DEB-1440297).

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Figures:

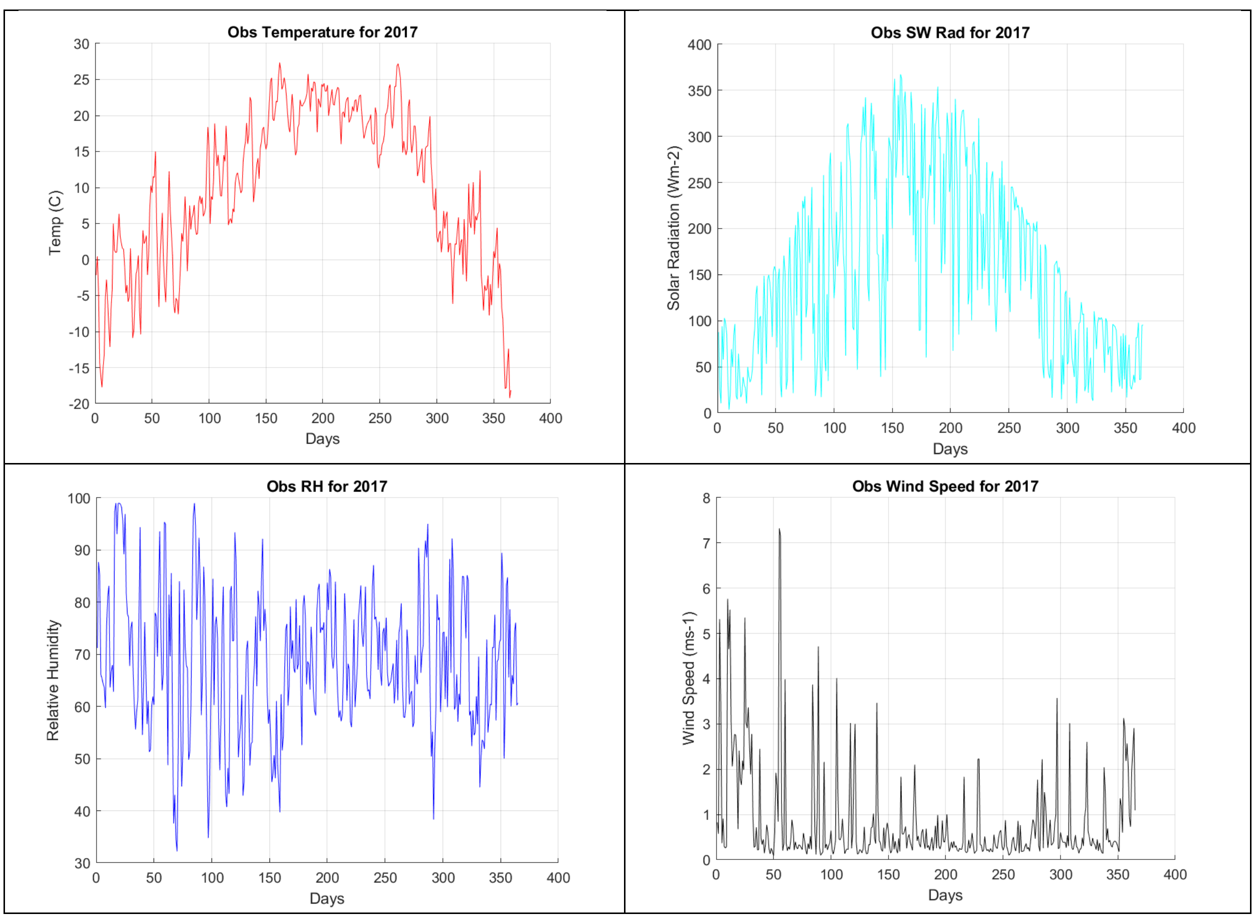
Obs Temperature for 2017
Temp (C)
Days
Obs SW Rad for 2017
Solar Radiation (Wm-2)
Days
Obs RH for 2017
Relative Humidity
Days
Obs Wind Speed for 2017
Wind Speed (ms-1)
Days

Figure 1: (clockwise from top left) Picnic Point surface air temperature for 2017; NOAA SOLRAD solar radiation for 2017; Picnic Point surface air wind speed; Picnic Point surface relative humidity for 2017

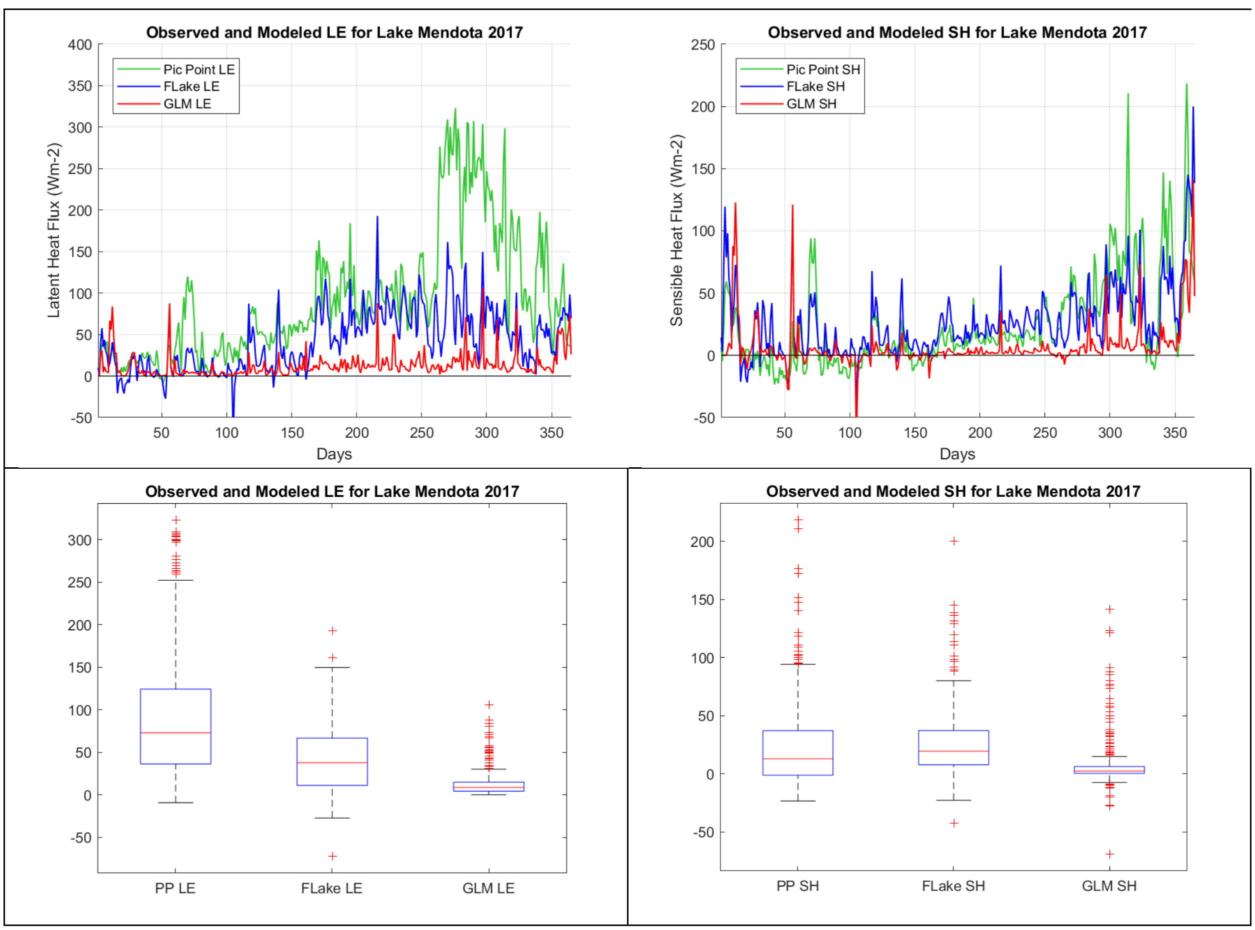

Figure 2: (clockwise from top left) Picnic Point and model latent heat fluxes for 2017; Picnic Point and model sensible heat fluxes for 2017; Boxplot of 2017 Picnic Point and modeled sensible heat fluxes; Boxplot of 2017 Picnic Point and modeled latent heat fluxes

Figure 3: (By row, left to right) Boxplot of 2017 ice-on Picnic Point and modeled latent heat fluxes; Boxplot of 2017 ice-on Picnic Point and modeled sensible heat fluxes; Boxplot of 2017 ice-off Picnic Point and modeled latent heat fluxes; Boxplot of 2017 ice-off Picnic Point and modeled sensible heat fluxes; Boxplot of 2017 transition Picnic Point and modeled sensible heat fluxes; Boxplot of 2017 transition Picnic Point and modeled sensible heat fluxes

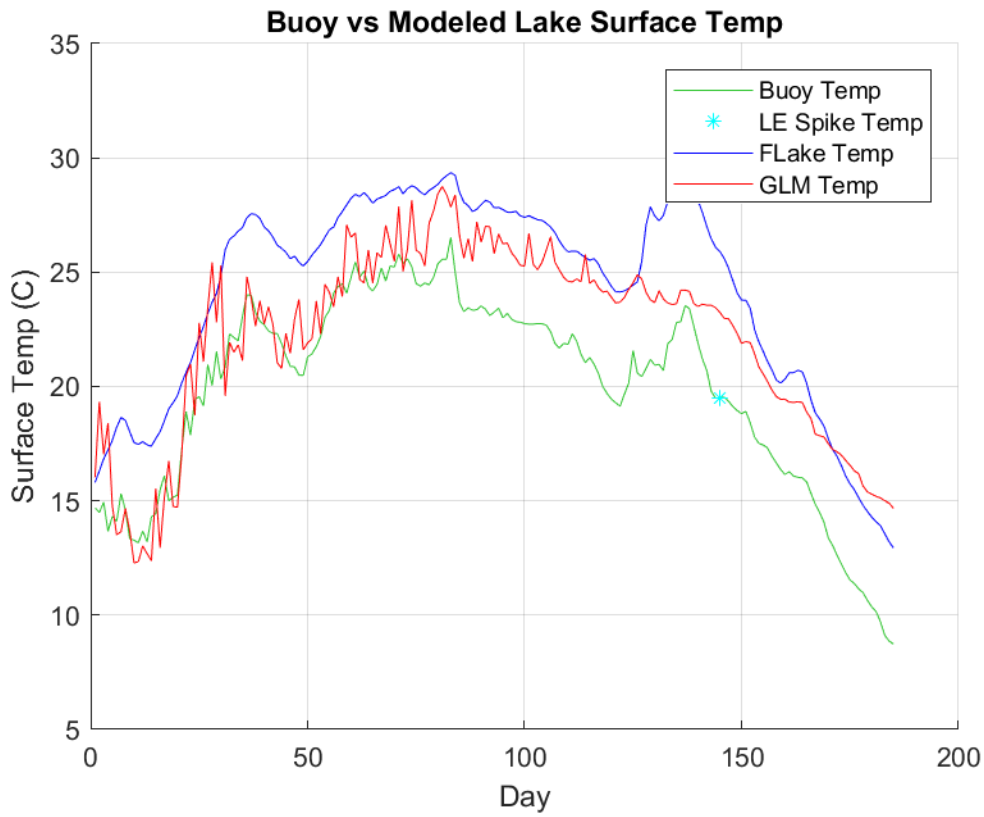

Figure 3: Buoy and modeled surface temperatures from May 12, 2017 to Nov 11, 2017. The cyan star corresponds to the day during which the spike in latent heat flux was observed by the Picnic Point tower

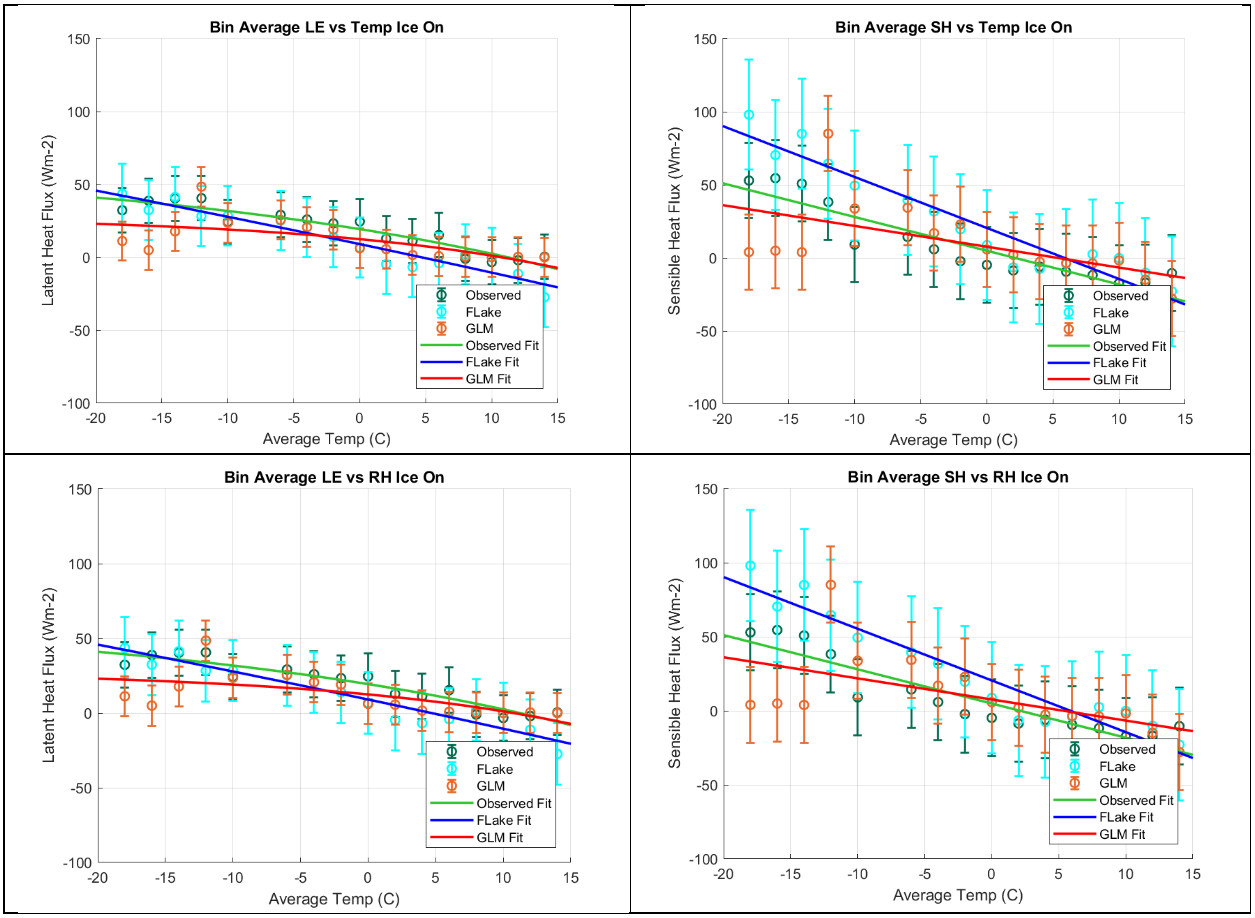

Figure 4: (clockwise from top left) Picnic Point and model bin averaged latent heat fluxes vs surface air temperature for 2017 ice-on; Picnic Point and model bin averaged sensible heat fluxes vs surface air temperature for 2017 ice-on; Picnic Point and model bin averaged sensible heat fluxes vs relative humidity for 2017 ice-on; Picnic Point and model bin averaged latent heat fluxes vs relative humidity for 2017 ice-on

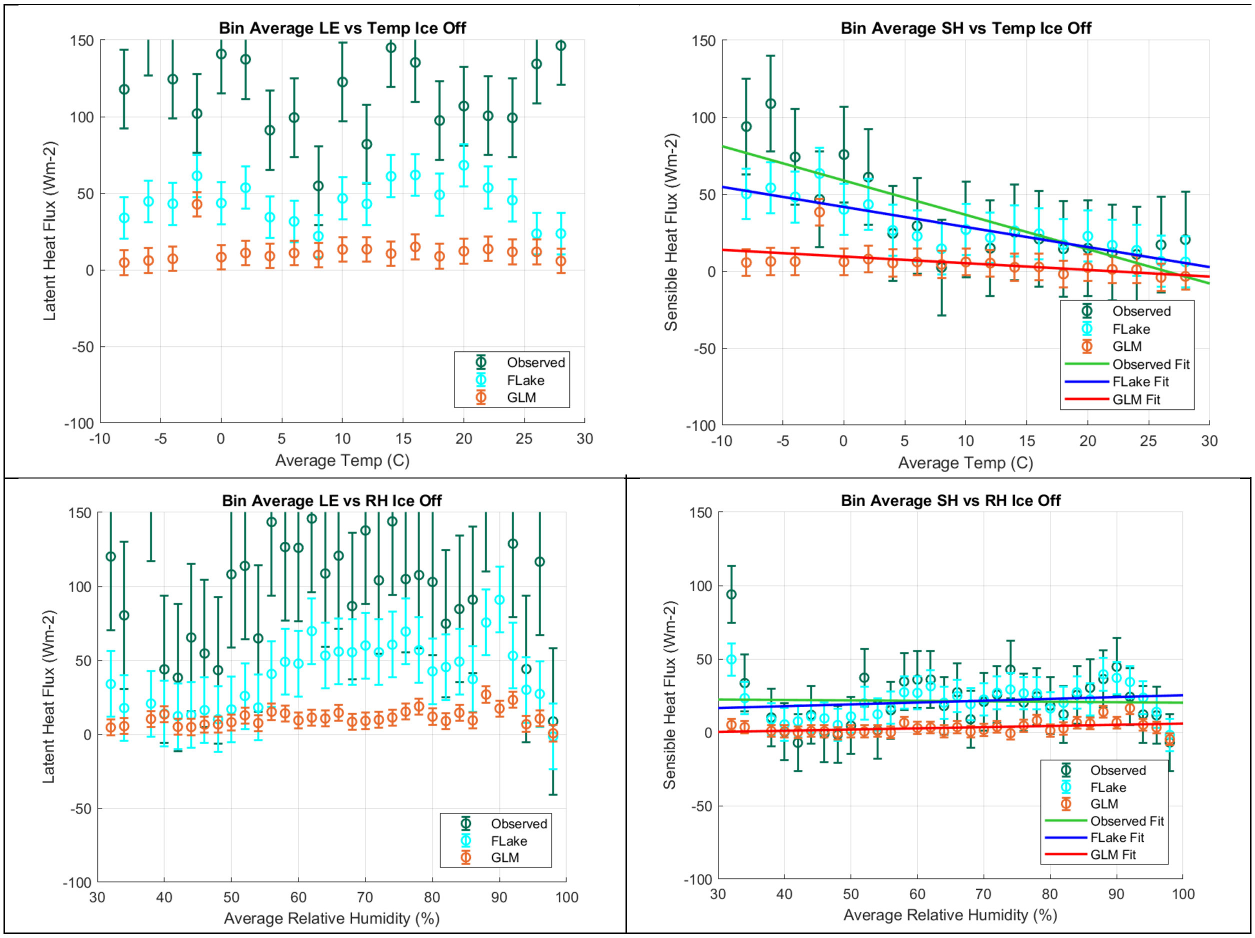

Figure 5: (clockwise from top left) Picnic Point and model bin averaged latent heat fluxes vs surface air temperature for 2017 ice-off; Picnic Point and model bin averaged sensible heat fluxes vs surface air temperature for 2017 ice-off; Picnic Point and model bin averaged sensible heat fluxes vs relative humidity for 2017 ice-off; Picnic Point and model bin averaged latent heat fluxes vs relative humidity for 2017 ice-off. Note no significant regression was found for the latent heat vs temperature plot

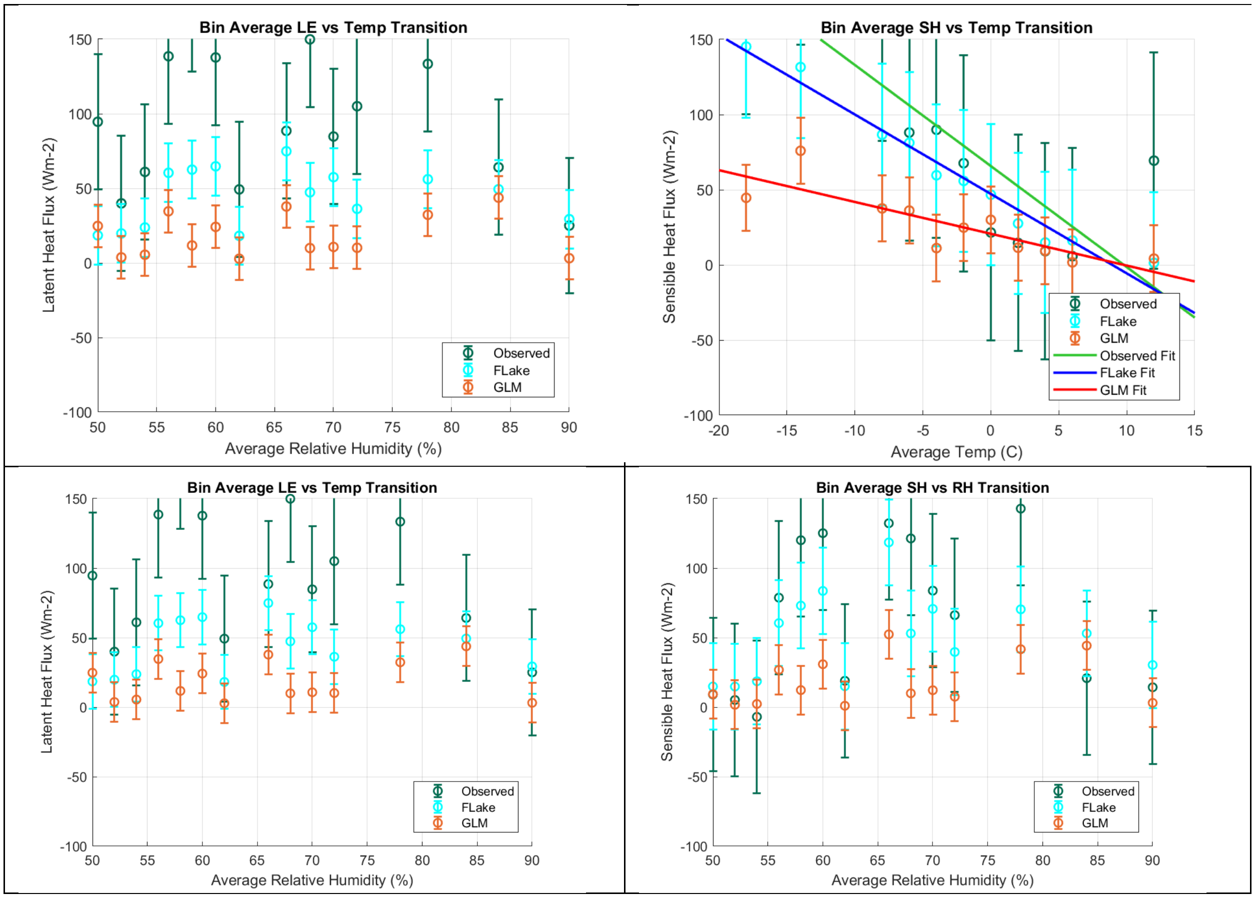

Figure 6: (clockwise from top left) Picnic Point and model bin averaged latent heat fluxes vs surface air temperature for 2017 transition; Picnic Point and model bin averaged sensible heat fluxes vs surface air temperature for 2017 transition; Picnic Point and model bin averaged sensible heat fluxes vs relative humidity for 2017 transition; Picnic Point and model bin averaged latent heat fluxes vs relative humidity for 2017 transition. Note no significant regression was found for the latent heat vs temperature plot, latent heat vs relative humidity plot, or sensitive humidity vs relative humidity plot.