Effects of Atmospheric Surface Layer Stability on Turbulent Fluxes of Heat and Water Vapor across the Water–Atmosphere Interface

YUSRI YUSUP
Environmental Technology, School of Industrial Technology, Universiti Sains Malaysia, Pulau Pinang, Malaysia

HEPING LIU
Laboratory for Atmospheric Research, Department of Civil and Environmental Engineering, Washington State University, Pullman, Washington

(Manuscript received 6 February 2016, in final form 5 July 2016)

ABSTRACT

Widely used numerical models to estimate turbulent exchange of latent heat flux (LE) and sensible heat flux $H$ across the water–atmosphere interface are based on the bulk transfer relations linked indirectly to atmospheric stability, even though the accurate prediction of the influence of stability on fluxes is uncertain. Here eddy covariance data collected over the water surface of Ross Barnett Reservoir, Mississippi, was analyzed to study how atmospheric stability and other variables (wind speed, vapor pressure gradient, and temperature gradient) in the atmospheric surface layer (ASL) modulated LE and $H$ variations in different stability ranges. LE and $H$ showed right-skewed, bell-shaped distributions as the ASL stability shifted from very unstable to near neutral and then stable conditions. The results demonstrate that the maximum (minimum) LE and $H$ did not necessarily occur under the most unstable (stable) conditions, but rather in the intermediate stability ranges. No individual variables were able to explain the dependence of LE and $H$ variations on stability. The coupling effects of stability, wind speed, and vapor pressure gradient (temperature gradient) on LE ($H$) primarily caused the observed variations in LE and $H$ in different stability ranges. These results have important implications for improving parameterization schemes to estimate fluxes over water surfaces in numerical models.

1. Introduction

Evidence has indicated that inland water bodies (e.g., lakes, reservoirs, wetlands, and streams) regulate surface energy balance and hydrological cycles at catchment scales (Rouse et al. 2005; Liu et al. 2012) and play a very important role in biogeochemical cycles at regional and global scales (Bastviken et al. 2011; Raymond et al. 2013). However, process-based understanding of the physical processes that drive water–atmosphere interactions is still limited, primarily because of the lack of direct eddy covariance measurements of turbulent exchange processes over inland water bodies representing a variety of morphological characteristics (e.g., size, shape, and depth) in different latitudes and climate zones (Zhang and Liu 2014). Nevertheless, some effort has been made over the past decade to examine the influence of atmospheric physical processes on radiative budget and surface energy balance, evaporation, and turbulent exchange processes, taking into account differences in size and depth of water bodies, atmospheric forcings, geographical locations, and climate conditions (Oswald and Rouse 2004; Assouline et al. 2008; Spence et al. 2013; McGloin et al. 2014b). One less understood process over inland waters is the role of atmospheric surface layer (ASL) stability in regulating turbulent fluxes of latent heat (LE) and sensible heat $H$, given the complex interaction between stability and other atmospheric variables.

ASL stability can be quantified by the dimensionless Obukhov atmospheric stability parameter $\zeta = z/L_o$, where $z$ is the height above the surface level and $L_o$ is the Obukhov length. The Obukhov length is described by $L_o = -\bar{w}/u_\theta^2/[\theta_0 + [\theta_0 - \bar{w}]]$, where $\theta_0$ is virtual potential temperature (K); $u_\theta$ is frictional velocity, which can be

Corresponding author address: Heping Liu, Dept. of Civil and Environmental Engineering, Washington State University, 405 Spokane St., Pullman, WA 99164.
E-mail: heping.liu@wsu.edu

DOI: 10.1175/JHM-D-16-0042.1

© 2016 American Meteorological Society
measured by the eddy covariance system (m s\(^{-1}\)); \(k\) is the von Kármán constant (0.4); \(g\) is acceleration due to gravity (9.8 m s\(^{-2}\)); \(w\) is vertical velocity (m s\(^{-1}\)); and \((\overline{w\theta_e})_\text{H}\) is vertical kinematic heat flux, which can be measured by the eddy covariance system (K m s\(^{-1}\)) as well. It is widely believed that turbulent exchanges of LE and \(H\) are promoted under unstable conditions \((\zeta < 0)\) and depressed under stable conditions \((\zeta > 0)\) in the ASL; this is due to the influence of the ASL stability on the turbulent transfer intensities of LE and \(H\), as usually described by the bulk transfer coefficients for moisture \(C_E\) and heat \(C_H\), respectively (Lenters et al. 2005; Verburg and Antenucci 2010; Bouin et al. 2012). Turbulent exchanges of LE and \(H\) are also strongly driven by mechanically induced mixing (as quantified by \(u_s\)), which is associated with wind speed. However, an increase in mechanically induced mixing tends to reduce both stable and unstable stratifications of the ASL, weakening the controls of stability on turbulent exchange. How this interlinked modulation of stability and mechanical mixing affects the role of other atmospheric forcings in regulating turbulent processes requires further exploration. Two other variables that significantly affect these exchanges are the temperature gradient \(\Delta T = T_e - T_s\) (K) and the humidity gradient \(\Delta q = q_s - q_a\) (g kg\(^{-1}\)) between the water surface and the measurement height, where \(T_s\) is the water surface temperature; \(q_s\) is the saturation specific humidity at \(T_s\); and \(q_a\) and \(T_a\) are the specific humidity and air temperature at the height \(z\), respectively (Stull 1988; Assouline et al. 2008; Zhang and Liu 2014). The above processes can be quantified by the bulk transfer relations (Fairall et al. 2003):

\[
LE = \rho_a L_v C_E U \Delta q \quad \text{and} \quad H = \rho_a c_p C_H U \Delta T,
\]

where \(\rho_a\) is air density (kg m\(^{-3}\)), \(L_v\) is latent heat of vaporization \((=2.54 \times 10^6\, \text{J kg}^{-1})\), \(U\) is mean wind speed (m s\(^{-1}\)) at 4 m above the water surface, and \(c_p\) is specific heat of air (JK\(^{-1}\) kg\(^{-1}\)). Note that specific humidity \(q\) is used to calculate \(C_E\) while our discussion in the subsequent sections uses vapor pressure, following previous studies (Zhang and Liu 2014). The bulk transfer relations are widely used in determining turbulent fluxes across air–sea interface in numerical weather and climate models (Fairall et al. 2003). Variables \(C_E\) and \(C_H\) are parameterized to quantify the influence of ASL stability on turbulence intensity based on the Monin–Obukhov similarity theory (Stull 1988). However, \(C_E\) and \(C_H\) are subject to large uncertainties when applied to inland waters, particularly under low wind speeds (Xiao et al. 2013). Low wind speeds usually correspond to very unstable ASL conditions, implying that applications of \(C_E\) and \(C_H\) under these conditions are uncertain. Moreover, drag coefficients under nearly neutral stratification are observed to be significantly larger than those under unstable stratification, and the stability dependence was not clearly observed for \(C_E\) and \(C_H\), inconsistent with the Monin–Obukhov similarity theory (Tsukamoto et al. 1991; Xiao et al. 2013; Li et al. 2016). These previous studies indicate that a physical explanation of the influence of stability on turbulent transfer requires further work.

Different atmospheric variables affect turbulent fluxes in coupled, nonlinear ways. For example, LE responds nonlinearily to changes in \(U\) and \(\Delta e\), the gradient between the vapor pressure at the water surface \(e_s\) and air \(e_a\) (i.e., \(\Delta e = e_s - e_a\)), depending on the magnitude of \(\Delta e\) (Zhang and Liu 2014). On average, changes in \(U\Delta e\) account for more than 60% of the variation in turbulent exchanges of LE, as found in Zhang and Liu (2014). Influences of \(U\), \(\Delta e\), and their product \((U\Delta e)\) on LE depend upon time scales. Mean wind speed may not be as significant as \(\Delta e\) in regulating LE at seasonal time scales (Lenters et al. 2005; Nordbo et al. 2011), whereas \(\Delta e\) is a deterministic variable affecting LE at subseasonal and seasonal time scales (Lenters et al. 2005). One study performed at a Mediterranean lagoon demonstrated that \(\Delta e\) was more responsible than \(U\) for producing sudden peak evaporation at diurnal time scales (Bouin et al. 2012). In contrast, a study of three lakes in Canada demonstrated that \(U\) was the most significant factor regulating LE over hourly time scales, followed by the land–water temperature contrast and land–water vapor pressure contrast, which are related to the ASL stability and \(\Delta e\) over water, respectively (Granger and Hedstrom 2011). Variable \(H\) varies diurnally in sine wave patterns and follows the diurnal variations of \(\Delta T\), suggesting that \(H\) is largely correlated with \(\zeta\), though this correlation is weak at the seasonal time scale (Zhang and Liu 2014). However, over a Mediterranean lagoon, \(H\) was generally modulated by \(\Delta T\) on both the diurnal and seasonal time scales (Bouin et al. 2012). Nordbo et al. (2011) indicate that \(U\) increases the correlation between \(H\) and \(U\Delta T\) by some marginal amount over a small boreal lake. These previous studies suggest that a complex interaction of atmospheric variables affects LE and \(H\). It is recognized that this nonlinear behavior of atmospheric variables regulating flux exchange is likely attributed to the modulation of stability through turbulent transfer intensity (i.e., \(C_E\) and \(C_H\), which are known to be functions of \(\zeta\) and roughness length); however, detailed data analysis investigating the role of stability in regulating the impacts of atmospheric variables on turbulent exchange over water remains limited.
Over large, deep, high-latitude lakes in Canada, which have high thermal inertia, an unstable ASL usually persists in fall and winter when overwater air is colder than the water surfaces; in contrast, a stable ASL persists in late spring and summer when overwater air is warmer than water surface on a daily and seasonal basis (Blanken et al. 2003; Rouse et al. 2003; Oswald and Rouse 2004). These large lakes undergo relatively low evaporation and sensible heat exchanges under stable conditions until late fall, after which \( H \) and \( LE \) are gradually enhanced under unstable conditions (Rouse et al. 2005). Approximately 85%–90% of the annual evaporation occurs during the unstable period (Rouse et al. 2003). The \( H \) and \( LE \) over small and medium lakes in high latitudes exhibit similar variation patterns as the season progresses, but with high \( H \) and low \( LE \) (i.e., large Bowen ratio) as compared to \( H \) and \( LE \) over large lakes (Rouse et al. 2005). Over Lake Tanganyika, a large and deep lake in West Africa, the ASL is unstable throughout almost the entire year, leading to a 13% and 18% increase in the annual sensible and latent heat loss from water, respectively (Verburg and Antenucci 2010).

Over a midlatitude lake of moderate area, there exist diurnal variations in the ASL stability conditions, with a stable ASL during a short period of time in late afternoon and an unstable ASL during the rest of the day, although daily and monthly averaging results in an unstable ASL throughout a year (Liu et al. 2009, 2012). Such diurnal variations in the ASL stability conditions are also observed over small and medium lakes in different latitudes (Nordbo et al. 2011; Bouin et al. 2012; McGloin et al. 2014a). Occasionally, cold air mass bursts associated with extratropical cyclones enhance instability and mechanical mixing, generating large \( H \) and \( LE \) pulses that contribute approximately 50% of the annual \( H \) and 28% of the annual \( LE \) (Liu et al. 2012; Zhang and Liu 2014).

These previous studies demonstrate significant impacts of the unstable and stable stratifications as a whole on turbulent fluxes of \( LE \) and \( H \); however, detailed exploration of how different stability ranges cause changes in \( LE \) and \( H \) remains insufficient and thus is the first objective of this study. Since ASL stability is not the only driver of turbulent exchange of water vapor and heat across water–atmosphere interface, another objective of our study is to analyze the relative roles stability, mechanical mixing, and other variables (e.g., \( U \), \( \Delta e \), and \( \Delta T \)) play in regulating \( LE \) and \( H \). This paper is framed in the following way to address the corresponding science questions in each section. The variations of \( LE \) and its drivers under different ASL stability ranges are discussed in sections 3a and 3b while the changes of \( H \) and its drivers under different ASL stability ranges are discussed in sections 3c and 3d. Finally, the changes of the bulk transfer coefficients, \( C_L \) and \( C_H \), in different ASL stability ranges are examined in section 3d. Our study demonstrates how different ranges of atmospheric stability modulate the influence of mechanical mixing and atmospheric variables on energy exchange processes nonlinearly across the water–atmosphere interface at the half-hourly time scale. Therefore, our study has important implications for process-based understanding of the water–air interactions, parameterizing turbulent processes in lake models, and studying the dynamic processes on trace gas exchange.

2. Methodology

a. Site and instrumentation

To achieve the mentioned objectives, here we analyze eddy covariance data measured over a large inland water body from August 2007 to February 2008. We chose this period because it covered a wide range of climate conditions—from cold to warm and from dry to humid—with large fluxes and stability ranges. This ensures that our results are representative of turbulent exchange processes over midlatitude, medium-sized inland water bodies.

The data were collected by an eddy covariance system located in the center of the Ross Barnett Reservoir (32°26′17.63″N, 90°1′48.00″W) in Mississippi, United States (Fig. 1). A wind rose shown in Fig. 1b describes the prevailing wind conditions at this location, which includes land–lake breeze cycle and cold and warm front events. The reservoir has a surface area of 134 km² with depths ranging from 4 to 8 m. An eddy covariance tower was installed over a stable wooden platform, which had dimensions of 3 m × 3 m and was at a height of 1 m above the water. To minimize the impacts of the surrounding land on flux footprints, the distance from the platform to shore ranged from about 2 km to more than 14 km (see section 2a for details).

The instruments mounted on the tower included a 3D sonic anemometer (CSAT3, Campbell Scientific, Inc.) and an open-path CO₂/H₂O infrared gas analyzer (IRGA, LI-7500, LI-COR, Inc.) at 4 m above the water surface, a temperature and humidity probe (HMP45C, Vaisala, Inc.) at 5.5 m, and a wind speed sensor (model 03101, RM Young, Inc.) at 4 m. Water skin temperature (i.e., \( T_s \)) was measured by an infrared temperature sensor (IRR-P, Apogee, Inc.). Surface vapor pressure (i.e., \( e_v \)) was taken as the saturation pressure at \( T_s \) (Buck 1981). A tipping-bucket rain gauge (TE525, Texas Instruments, Inc.) was used to collect 30-min accumulative precipitation. Signals from the eddy covariance system
(CSAT3 and LI-7500) were sampled at 10 Hz and signals from all other sensors were recorded as 30-min average values of 1-min samples by a datalogger (CR5000, Campbell Scientific, Inc.). All sensors/instruments were powered by six deep-cycle marine batteries that were charged with two solar panels (SP65, 65 W Solar Panel, Campbell Scientific, Inc.). More detailed information about the site and instrumentation is provided in our previous studies (Liu et al. 2012; Zhang and Liu 2013, 2014).

b. Postfield data processing

A postfield data processing program was used to process the 10-Hz raw time series data from CSAT3 and LI-7500 to obtain 30-min mean fluxes. This program participated in the postfield data processing program intercomparison activity performed in the Energy Balance Experiment (EBEX; Mauder et al. 2007) and has been updated since then (Liu et al. 2009, 2012; Zhang and Liu 2013, 2014). A detailed description of this program was well documented in our previous studies and thus is not repeated here. The LI-7500 time series data with automatic gain control (AGC) values of greater than 70 were considered to be noise and thus were removed. To minimize data spikes, the 10-Hz raw time series data with magnitudes exceeding 5 times the half-hourly mean standard deviations were replaced with linearly interpolated values (Nordbo et al. 2011). Spikes from the open-path analyzers were also removed by screening the raw data for periods of rain before performing flux calculations. A double rotation was applied to rotate the coordinate system for each 30-min period. Block averaging was used to calculate 30-min mean covariance between vertical velocity fluctuations and air temperature fluctuations and between vertical velocity fluctuations and water vapor density fluctuations, respectively. A Schotanus correction was applied to calculate sensible heat flux
from buoyancy flux (Schotanus et al. 1983). The Webb–Pearman–Leuning (WPL) correction for LE was used to correct for density effects (Webb et al. 1980). In addition, all data points with \( u_w < 0.05 \text{ m s}^{-1} \) were removed to exclude instances with underdeveloped turbulence. Data points with \( \zeta < -10 \) and \( \zeta > 10 \) were also removed because of insufficient numbers of data points for these stability ranges for statistical analysis. Because of possible influences of the tower structure on flow distortion under easterly winds (75°–105°), we removed data for these conditions. After applying these data quality criteria, considering simultaneous availability of all variables, and taking into account gaps caused by instrument malfunction, calibration error, etc., the total number of 30-min data points was reduced from 8448 to 7087 (84%) over the study period. This percentage is comparable to that in Liu et al. (2009). Since this was a process-based study, data gaps were not filled.

A footprint model developed by Kljun et al. (2004) was used to estimate source contributions to the measured flux for all available wind directions. Our calculations indicated that 90% of the flux footprint sources originated from the water surface. The footprint size varied in response to ASL stability, with a 358-m footprint corresponding to a very unstable ASL (\( \zeta < -10 \)), a 451-m footprint corresponding to a near-neutral ASL (\(-0.05 < \zeta < 0.05\)), and a 1087-m footprint corresponding to a very stable ASL (\( \zeta > 10 \)). It should be noted that under stable conditions, footprint locations can be overestimated or biased because of difficulty in modeling the contributions of sources/surfaces to the fluxes (Aubinet et al. 2012).

The influence of \( \zeta \) on LE and \( H \) and relationships between \( \zeta \) and \( U, \Delta e, \Delta T U \Delta e, \) and \( U \Delta T \) were characterized by dividing \( \zeta \) into 10 different ASL stability ranges, with \( \zeta \) ranging from \(-10 \) to \( 10 \) after performing data quality checks. The 10 ASL stability ranges are set as follows: very unstable (\(-10 \leq \zeta < -1\); \( n = 557 \), where \( n \) is the number of data points), moderately unstable (\(-1 \leq \zeta < -0.5\); \( n = 636 \)), unstable (\(-0.5 \leq \zeta < -0.1\); \( n = 2519 \)), weakly unstable (\(-0.1 \leq \zeta < 0.05\); \( n = 648 \)), near neutral (\(-0.05 \leq \zeta < 0\); \( n = 589 \)), near neutral (\( 0 \leq \zeta < 0.05\); \( n = 687 \)), weakly stable (\( 0.05 \leq \zeta < 0.1\); \( n = 333 \)), stable (\( 0.1 \leq \zeta < 0.5\); \( n = 796 \)), moderately stable (\( 0.5 \leq \zeta < 1\); \( n = 204 \)), and very stable (\( 1 \leq \zeta < 10\); \( n = 118 \)).

Since the effects of relevant parameters and driving variables on turbulent exchanges over water bodies differ based on the time scale being investigated, this study only considered the effects of \( \zeta, U, \Delta e, \Delta T U \Delta e, \) and \( U \Delta T \) on LE and \( H \) at the 30-min time scale. To study the effects of positive and negative \( \Delta e \) and \( \Delta T \) gradients on LE and \( H \), we analyzed the data in separate sets determined by \( \Delta e (\Delta e > 0 \) and \( \Delta e < 0) \) and \( \Delta T (\Delta T > 0 \) and \( \Delta T < 0) \).

To examine whether our conclusions were affected by applying stricter data quality checks, we repeated our analyses using data points filtered using the Foken et al. (2004) procedure. This procedure utilizes tests of steady-state conditions, integral turbulence characteristics, and horizontal orientations to generate summarized data (“quality flags” ranging from 1 to 9, where 1 is the “best” quality flag. After removing data points with a quality flag of \( \geq 6 \), 77%, 75%, and 75% data points for LE, H, and \( u_w \) were discarded, respectively. Points with a quality flag of \( \geq 6 \) corresponded to a steady-state test range of 101%–205%, an integral turbulence characteristics range of 101%–250%, and a horizontal orientation range of \( \pm 151^\circ - 170^\circ \). Our tests indicated that the use of these stricter data quality criteria produced very little change, that is, only 8% deviation of mean values of coefficient of determination \( R^2 \) and parameters (LE, \( H, u_w, e \), etc.) of each ASL stability range, in the variations and patterns of LE, H, \( \Delta e, \Delta T, \) and \( U \) with ASL stability ranges, and did not affect our conclusions. Thus, this extensive exercise demonstrated that the quality of the data points used in our study was reliable, and the conclusions made are robust. Consequently, we kept data meeting the looser quality criteria in our analysis in order to ensure the generality and the broad applicability of our results to process-based understanding of water–atmosphere interaction and modeling applications.

3. Results and discussion

a. Variations in LE across ASL stability ranges

It is well known that LE and \( H \) are greater under unstable conditions than under stable conditions, suggesting that unstable stratifications promote turbulent exchanges of water vapor and heat while stable conditions depress these exchanges across the water–atmosphere interface (Rouse et al. 2005; Liu et al. 2009; Granger and Hedstrom 2011; Zhang and Liu 2014). However, McGloin et al. (2014a) reported that higher LE values are sometimes observed under stable conditions than under unstable conditions because of concurrent higher \( U \) and lower \( e \). Thus, it remains unclear as to how LE and \( H \) vary in response to changes in stability ranges, and how different levels of stability modulate the influence of other environmental variables on LE and \( H \). This question motivated us to have divided \( \zeta ( -10 \leq \zeta < 10) \) into 10 stability ranges (Fig. 2) and studied how changes in \( U, \Delta e, U \Delta e, \) and \( u_w \)
(\(U\), \(\Delta T\), \(U\Delta T\), and \(\hat{u}_o\)) regulated LE (\(H\)) under these different stability ranges.

Average LE under all unstable ranges (95.9 W m\(^{-2}\)) was greater than that under all stable ranges (37.1 W m\(^{-2}\); Fig. 2a, Table 1). The larger averaged LE under unstable conditions was mainly attributed to larger values of \(\Delta e\) and \(\hat{u}_o\) than those observed under stable conditions (\(\Delta e = 0.86\) vs 0.53 kPa; \(\hat{u}_o = 0.16\) vs 0.13 m s\(^{-1}\)), although \(U\) was relatively similar or even slightly lower under unstable and stable conditions (3.70 vs 3.86 m s\(^{-1}\)). Therefore, under unstable conditions, increased thermally induced turbulence, elevated moisture gradients, and slightly enhanced mechanical mixing resulted in greater evaporation (e.g., under the influence of land breezes and cold front events) than under stable conditions (e.g., under the influence of lake breezes and warm front events). Under unstable conditions, LE showed a right-skewed bell shape from the very unstable range \((-10 \leq \zeta < -1)\) to near neutral \((-0.05 \leq \zeta < 0)\). Under stable conditions, LE gradually decreased from the near neutral \((0 \leq \zeta < 0.05)\) to the very stable range \((1 < \zeta \leq 10;\text{ Fig. 2a)}\). This pattern was also seen in Li et al. (2015) but was not explained in detail. Our results revealed that the strongest unstable ASL \((-10 \leq \zeta < -1)\), usually during calm early mornings, did not correspond to the greatest LE. Instead, the greatest LE occurred in the range of \(-0.1 \leq \zeta < -0.05\).

The LE was also elevated in the stability ranges of \(-0.5 \leq \zeta < 0.1\) and \(-0.1 \leq \zeta < -0.05\), such as in the windy midafternoons. These physical processes

**Fig. 2.** Distributions of (a) LE (W m\(^{-2}\)), (b) \(\Delta e\) (kPa), (c) \(U\) (m s\(^{-1}\)), (d) \(U\Delta e\) (kPa m s\(^{-1}\)), (e) \(H\) (W m\(^{-2}\)), (f) \(\Delta T\) (\(^\circ\)C), (g) \(U\) (m s\(^{-1}\)), and (h) \(U\Delta T\) (\(^\circ\)C m s\(^{-1}\)) across the 10 different ASL stability ranges [from left to right: from unstable (red data points) to stable (blue data points); see the text for details]. Within each boxplot, the median is represented by a solid black line, and the mean is represented by a dashed black line.
Table 1. Descriptive statistics for LE, H, $\Delta e$, $\Delta T$, U, $U\Delta e$, and $U\Delta T$ ($n_{\text{unstable}} = 4949$; $n_{\text{stable}} = 2138$).

<table>
<thead>
<tr>
<th></th>
<th>LE ($Wm^{-2}$)</th>
<th>$H$ ($Wm^{-2}$)</th>
<th>$\Delta e$ (kPa)</th>
<th>$\Delta T$ ($^\circ$C)</th>
<th>$U$ (m/s)</th>
<th>$U\Delta e$ (kPa m/s)</th>
<th>$U\Delta T$ ($^\circ$C m/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st quartile</td>
<td>Unstable</td>
<td>Stable</td>
<td>Unstable</td>
<td>Stable</td>
<td>Unstable</td>
<td>Stable</td>
<td>Unstable</td>
</tr>
<tr>
<td></td>
<td>44.7</td>
<td>1.2</td>
<td>8.2</td>
<td>-10.5</td>
<td>0.53</td>
<td>0.09</td>
<td>1.1</td>
</tr>
<tr>
<td></td>
<td>Median</td>
<td></td>
<td></td>
<td></td>
<td>2.20</td>
<td>2.48</td>
<td>1.38</td>
</tr>
<tr>
<td></td>
<td>3rd quartile</td>
<td></td>
<td></td>
<td></td>
<td>3.51</td>
<td>3.77</td>
<td>2.60</td>
</tr>
<tr>
<td></td>
<td>Mean</td>
<td></td>
<td></td>
<td></td>
<td>4.93</td>
<td>4.97</td>
<td>4.39</td>
</tr>
<tr>
<td>Std dev</td>
<td>73.4</td>
<td>55.3</td>
<td>34.6</td>
<td>1.98</td>
<td>1.92</td>
<td>2.45</td>
<td>2.64</td>
</tr>
</tbody>
</table>

interpretations are also applicable to $H$ (section 3c). Thus, from Guo et al. (2015), the right-skewed, bell-shaped trend implies that the Priestley–Taylor $\alpha$ parameter would not vary linearly from unstable to stable conditions and would thus affect the accuracy of subdaily estimations of evaporation using their physical model. The LE substantially dropped when stability shifted from near-neutral conditions in the unstable regime ($-0.05 \leq \zeta < 0$; 92.0 W m$^{-2}$) to near-neutral conditions in the stable regime ($0 \leq \zeta < 0.05$; 52.4 W m$^{-2}$). Additionally, variations in LE with stability were more drastic under unstable conditions than those under stable conditions. It is argued that the Monin–Obukhov similarity theory may have large uncertainty beyond the ASL stability range of $|\zeta| < 1$ (Foken 2006). Therefore, our results extend our understanding of how stability modulates the influence of other atmospheric processes on LE under very unstable and stable conditions.

What could explain the observed variations in LE patterns across stability ranges? On average, $\Delta e$ was generally larger under unstable conditions (ranging from 0.79 to 0.90 kPa) than under stable conditions (ranging from 0.32 to 0.56 kPa). At the synoptic scale, it was found that unstable ASLs were usually associated with dry air masses (large $\Delta e$) passing over the region and that stable ASLs were associated with moist air masses (small $\Delta e$). This was because dry and cool air masses, which generally originated from the north, increased $\Delta T$ and thus produced unstable ASLs, whereas moist and warm air masses, which generally originated from the south, created a negative $\Delta T$ and thus produced stable ASLs (Liu et al. 2012). The larger averaged $\Delta e$ under unstable conditions was a primary cause of LE being greater under unstable conditions than under stable conditions. It should be noted that within each stability regime (unstable and stable), the largest $\Delta e$ did not necessarily correspond to the largest LE (Fig. 2b, 3a). This suggests that the contribution of $\Delta e$ to LE was regulated by other variables. Also, the relationship between LE and $\Delta e$ did not show any discernible pattern across the different stability ranges (Fig. 3a).

Mean wind speed was within the same order of magnitude for both stability regimes (Figs. 2c, 3b). On average, $U$ increased from 1.89 to 4.76 m s$^{-1}$ when the ASL stability shifted from very unstable ($-10 \leq \zeta < -1$) to weakly unstable and near-neutral ($-0.05 \leq \zeta < 0$) conditions, and it increased from 2.55 to 4.63 m s$^{-1}$ when the ASL stability shifted from $1 \leq \zeta < 10$ to $0 \leq \zeta < 0.05$ (Fig. 3b). Frictional velocity showed a similar variation pattern to $U$ across the 10 stability ranges (Fig. 4a). These relationships between $U$ and stability indicate that mechanical mixing increased as the ASL approached near-neutral conditions, which is a well-known ASL process over lands (Stull 1988). This process is also demonstrated by the relationship between $u_*$ and $U$ across the 10 stability ranges (Fig. 4b). When stability approached near-neutral conditions from the unstable side, an increased $u_*$ corresponded to decreased LE. In contrast, when stability approached near-neutral conditions from the stable side, an increased $u_*$ corresponded to increased LE (Fig. 3b). These different outcomes demonstrate that increased mechanical mixing does not necessarily lead to increased LE. Under unstable conditions, a given value of $U$ corresponds to a greater $u_*$ than it does under stable conditions (Fig. 4b). This suggests that vertical mechanical turbulent mixing was favored by the unstable ASLs and depressed by the stable ASLs. The degrees of wind-induced mechanical mixing under unstable and stable conditions converged as the ASL approached near-neutral conditions and $U$ reached its maximum, as shown by the merging of the two lines in Fig. 4b. Given the same $u_*$, $U$ is much larger under stable conditions than under unstable conditions (Fig. 4b). This implies that a larger $U$ is required under stable conditions than under unstable conditions to produce the same amount of mechanical mixing. Since mechanical mixing is one of the two turbulence mechanisms (along with thermally generated turbulence) to drive heat and mass transfer across the water–atmosphere interface, a certain magnitude of $U$ would cause greater LE under unstable conditions than under stable conditions (Fig. 3b).

When the stability shifted from very unstable ($-10 \leq \zeta < -1$) to weakly unstable ($-0.1 \leq \zeta < -0.05$) conditions (i.e., decreased instability), increased LE corresponded to increased $U$ and irregular changes in $\Delta e$ (an
increase followed by a decrease in $\Delta e$; Fig. 3). This suggests that mechanical turbulent mixing was the primary driver of LE and that stability and $\Delta e$ were not. When the ASL became less unstable and approached near-neutral conditions, a slight increase in $U$ from 4.68 to 4.76 m s$^{-1}$ and a decrease in $\Delta e$ from 0.84 to 0.79 kPa led to a reduction in $U\Delta e$ and thus LE (Fig. 3c). At the same time, there was almost no increase in mechanical mixing, as reflected by a consistent $u^*$ of about 0.22 m s$^{-1}$. This indicates that the further weakened
instability (i.e., the reduced thermally generated turbulent mixing) caused the reduction in LE. Under stable conditions, enhanced mechanical mixing corresponding to increased $U$ weakened the stable stratification (Fig. 3b). Increased LE was generally linked to increased $U$ as the ASL became less stratified (Fig. 3b), while changes $\Delta e$ were somewhat erratic (Fig. 3a). This indicates that under stable conditions, variations in LE were more associated with changes in stability and $U$ than with $\Delta e$. It is unclear as to what caused the substantial increase in $\Delta e$ in the $1 < \zeta \leq 10$ range that led to an increase in $U\Delta e$ and thus a slight increase in LE.

b. Effects of $U$ and $\Delta e$ on LE across ASL stability ranges

Would the roles of different atmospheric variables in regulating LE vary across different stability regimes at 30-min time scales? Here we utilized statistical analysis of the relationships between LE and $\Delta e$, $U$, and $U\Delta e$ for each stability range to answer the above question (Figs. 5a–c), similar to the analyses performed by Zhang and Liu (2014) for winter and summer seasons. Our results indicate that LE had greater correlation with $U$ under unstable conditions ($R^2 = 0.54$) than under stable conditions ($R^2 = 0.06$), whereas LE had smaller correlation with $\Delta e$ under unstable conditions ($R^2 = 0.64$) than under stable conditions ($R^2 = 0.83$). The coupled effect of $U$ and $\Delta e$ improved the correlation between LE and $U\Delta e$, particularly under unstable conditions ($R^2 = 0.88$) as compared with stable conditions ($R^2 = 0.82$; Fig. 5c), a finding also observed by Zhang and Liu (2014). Figures 5a and 5b show that differences in correlations between LE and $U$ among the different stability ranges are inversely related to those between LE and $\Delta e$, reflecting that $U$ and $\Delta e$ exhibit different controls on LE under the two stability regimes. Variable $\Delta e$ was generally large under unstable conditions, providing adequate water vapor supply for evaporation. Also, unstable atmospheres promoted mechanical mixing under a certain $U$, as reflected by $u_*$ (mean $u_* = 0.16 \text{ m s}^{-1}$). Thus, under unstable conditions, turbulent exchange of water vapor was sensitive to changes in the vigorous mechanical mixing induced by high $U$ (mean $U = 3.70 \text{ m s}^{-1}$), leading to high a correlation between LE and $U$. Under stable conditions, however, $\Delta e$ became small and thus acted as a limiting variable for evaporation (Zhang and Liu 2014). When the ASL is stable, mechanical and thermal mixing are dampened, depressing vertical flux exchange and resulting in small $H$, LE, and $u_*$. Therefore, under stable conditions, changes in LE were more sensitive to changes in $\Delta e$ than changes in $U$. The sudden changes in the magnitudes of the correlations between LE and $U$ (Fig. 5a) and between LE and $\Delta e$ (Fig. 5b) when the ASL shifted from weakly unstable to weakly stable conditions suggest that stability regulated the roles of $U$ and $\Delta e$ in controlling LE variations. Based on the 30-min data points, $U\Delta e$ was the primary driver in regulating the LE variations across the
10 stability ranges (mean $R^2 = 0.86$), with the rest of the variability in LE being driven by stability-related transfer [$C_E$ in Eq. (1)]. However, the greater correlations between LE and $U\Delta e$ under unstable conditions implied that correlations between LE and stability-induced transfer (i.e., $C_E$) were lower, which suggests that $C_E$ plays a smaller role in regulating LE under unstable conditions than under stable conditions. It should be noted that the statistical analysis using the 30-min data points (Fig. 5) differs from that using the mean values of all the 30-min data points for each stability range (Fig. 2) because of the different time-scale constraints.

One striking feature observed by comparing Fig. 5 and Fig. 2 is that variations in $R^2$ between LE and $U$ across the stability ranges followed the variations in LE, while the variations in $R^2$ between LE and $\Delta e$ did not. There was a much larger correlation between LE and $U$ under unstable conditions (mean $R^2 = 0.31$) than under stable conditions (mean $R^2 = 0.01$), but a smaller correlation between LE and $\Delta e$ under unstable conditions (mean $R^2 = 0.39$) than under stable conditions (mean $R^2 = 0.71$). This reflects the changing roles of $U$ and $\Delta e$ in regulating LE under different stability regimes. The coupling of $U$ and $\Delta e$ was reflected by an increased correlation between LE and $U\Delta e$ (mean $R^2$ of 0.77 under unstable conditions and 0.70 under stable conditions). This coupling not only eliminated the changing roles of $U$ and $\Delta e$ as the stability shifted from unstable to stable regimes, but also caused the variation patterns in $R^2$ between LE
and $U\Delta e$ across stability ranges to resemble those of LE (Fig. 2a) and those of $R^2$ between LE and $U$ (Fig. 5a). Following this line of observation, we expect that when LE is normalized by $U$, the right-skewed bell distribution of LE with changes in the stability ranges under unstable conditions would be removed. Also, when LE is normalized by $\Delta e$, the variations of LE with the stability ranges should be broadened, particularly under stable conditions (Figs. 2a,b). Figures 6a and 6b present LE/$U$ and LE/$\Delta e$, respectively. After normalization, there is a steady decrease in LE/$U$ with ASL stability ranges under unstable conditions and a relatively slow decrease in LE/$\Delta e$ with the stability ranges under stable conditions (Fig. 6a). Normalization of LE by $\Delta e$ was not able to eliminate the right-skewed, bell-shaped distribution under unstable conditions, but it increased the rate of decline under stable conditions. This further demonstrates the changing roles of $U$ and $\Delta e$ on LE within different ASL stability ranges. When influences of $\Delta e$ on LE are absent, $U$ regulates LE, as demonstrated by the steeper decreasing slope from the weakly unstable to very stable ranges (from $-0.1 \leq \zeta < -0.05$ to $1 \leq \zeta < 10$; Fig. 6b) and the unique right-skewed, bell-shaped distribution in the very unstable/unstable regimes. This result also implies the nonlinear relationship between $U$ and $C_E$ (Liu et al. 1979).

c. Variations in $H$ across ASL stability ranges

In this section, we have analyzed how $H$ varied across different stability ranges in a similar fashion as in section 3a. On average, based on the 30-min data points, $H$ was 30.6 W m$^{-2}$ under unstable conditions with a $\Delta T$ of 2.8°C.
and $U$ of $3.70\, \text{m}\, \text{s}^{-1}$; under stable conditions, $H$ was $-8.88\, \text{W}\, \text{m}^{-2}$ with a $\Delta T$ of $-2.4^\circ\text{C}$ and $U$ of $3.86\, \text{m}\, \text{s}^{-1}$ (Figs. 2e–h; Table 1). Under unstable conditions, $H$ showed an increasing and then decreasing trend as stability shifted from the very unstable ($-10 \leq \xi < -1$) to the weakly unstable ranges ($-0.05 \leq \xi < 0$), transitioning from land breeze to lake breeze. The maximum $H$ occurred in the stability range of $-0.5 \leq \xi < -0.1$, which is usually in the calm early mornings under the influence of land breezes. Under stable conditions, $H$ gradually decreased and then increased as stability changed from the weakly stable ($0 \leq \xi < 0.05$) to the very stable ranges ($1 \leq \xi \leq 10$; Figs. 2e, 3d–f). The lowest $H$ occurred in the stability range of $0.1 \leq \xi < 0.5$. These results indicate that the strongest unstable ASL ($-10 \leq \xi < -1$) and strongest stable ASL ($1 \leq \xi < 10$) did not correspond to the highest and lowest $H$, respectively (Figs. 2e, 3d), which could be due to enhanced mechanically induced mixing in these ranges. Thus, assumptions of maximum $H$ under very unstable conditions and minimum $H$ under very stable conditions in some numerical models, which are based on the Monin–Obukhov similarity theory, would possibly overestimate $H$ under very unstable conditions and underestimate $H$ under very stable conditions, specifically $|\xi| > 0.5$. This is similar to the situations observed for LE.

When the ASL stability shifted from $-10 \leq \xi < -1$ to $-0.5 \leq \xi < -0.1$, the concurrent increases in $U$ from $1.89$ to $3.89\, \text{m}\, \text{s}^{-1}$ and in $\Delta T$ from $3.25^\circ\text{C}$ to $3.35^\circ\text{C}$ (i.e., an increase in $U\Delta T$ from $6.92^\circ\text{C}$ to $16.08^\circ\text{C} \, \text{m}\, \text{s}^{-1}$) contributed to an increase in $H$ from $23.8$ to $38.9\, \text{W}\, \text{m}^{-2}$, although the ASL became less unstable (Figs. 3d,e). As the ASL approached weakly unstable conditions ($-0.1 \leq \xi < -0.05$ and $-0.05 \leq \xi < 0$), $H$ decreased even though $U$ increased, largely due to the combined effect of reduced thermally generated turbulent mixing and a substantially decreased $U\Delta T$ (and thus, a decreased $U\Delta T$). Given a certain $U\Delta T$ (e.g., the vertical dashed line in Fig. 3f), the differences in $H$ among stability ranges demonstrate different contributions of stability-related transfer coefficient (i.e., $C_H$) on $H$. Under stable conditions, the enhanced mechanical mixing caused by increased $U$ corresponded to the reduced $\Delta T$ as the ASL became less stratified (Figs. 3d,e). As the stability changed from very stable ($1 \leq \xi < 10$) to stable ($0.1 \leq \xi < 0.5$) conditions, the increased downward-directed $H$ (or $-H$) was linked only to increased $U$ even though $-\Delta T$ decreased. This result indicates that variations in $H$ under very stable conditions were more associated with changes in stability and mechanical mixing than changes in $\Delta T$. As the stability shifted to weakly stable conditions (i.e., $0.05 \leq \xi < 0.1$ and $0 \leq \xi < 0.05$), the decreased $\Delta T$ and the increased $U$ led to a large reduction in negative $U\Delta T$. The sensible heat flux became less negative as stability shifted from very stable to near-neutral conditions because of decreased negative $U\Delta T$ and less on enhanced mechanical mixing and reduced stably stratified atmosphere.

d. Effects of $U$ and $\Delta T$ on $H$ across ASL stability ranges

At 30-min time scales, correlations between $H$ and $U$ and between $H$ and $\Delta T$ under unstable conditions ($R^2 = 0.48$ and $0.56$, respectively) were higher than those under stable conditions ($R^2 = 0.42$ and $0.24$, respectively; Figs. 5d–f). The variations in $\Delta T$ explained variations in $H$ more (less) than $U$ did under unstable (stable) conditions. The coupled effect of $U$ and $\Delta T$ improved the correlation between $H$ and $U\Delta T$, with greater correlations under unstable conditions ($R^2 = 0.78$) than under stable conditions ($R^2 = 0.51$; Fig. 5f). This suggests that the stability-related turbulent exchange coefficient (i.e., $C_H$) explained only about 22% (100%–78%) of the variations in $H$ under unstable conditions, but up to 49% (100%–51%) of the variations in $H$ under stable conditions. When comparing the mean $R^2$ between LE and $U\Delta e$ (0.86) and between $H$ and $U\Delta T$ (0.65), the stability range played a more important role in regulating $H$ than it did in regulating LE (Figs. 5a–c vs Figs. 5d–f).

After normalization of $H$ by $U$ (Figs. 6c,d), we observed a steady decrease in $H/U$ with ASL stability ranges under unstable conditions, and a relatively slow decrease in $H/U$ with the stability ranges under stable conditions (Fig. 6c). As with LE/$\Delta e$, $H/\Delta T$ was also not able to eliminate the bell-shaped distribution under unstable conditions (Fig. 6d). This demonstrates that for unstable conditions, mechanical mixing was vital in transferring heat across the atmosphere–water interface, a finding also reported by Nordbo et al. (2011). The inability to remove the bell-shaped distribution by normalizing $H$ with $\Delta T$ suggests a nonlinear relationship between $U$ and $C_H$ (Liu et al. 1979), although the exact nature of this relationship remains unclear. This is similar to the effects of $U$ on LE that were observed after normalizing for $\Delta e$.

e. Variations in $C_E$ and $C_H$ across ASL stability ranges

The parameters $C_E$ and $C_H$, calculated by rearranging the bulk transfer relations [Eqs. (1) and (2)], were used to examine the influence of stability on turbulent transfer intensity (Fig. 7). In general, the more unstable the ASL was, the higher the potential for transferability of water vapor and heat (i.e., $C_E$ and $C_H$) across the water–atmosphere interface. Parameters $C_E$ and $C_H$ are
usually assumed to be equal for most modeling applications (Liu et al. 1979; Clayson et al. 1996; Fairall et al. 2003). However, this assumption may be problematic when describing overwater exchange processes (Tanny et al. 2008; Wang et al. 2015). Our results indicate that under stable conditions, $C_E$ was greater than $C_H$, a finding consistent with that observed in Wang et al. (2015). Under the unstable ranges, however, $C_E$ and $C_H$ were equal. Zhao et al. (2013) found that turbulent transfer of heat is generally more efficient than turbulent transfer of moisture. Note that under the weakly unstable and near-neutral ranges ($-0.05 \leq \zeta < 0$), $C_H$ became erratic simply because $\Delta T$ approached zero (Fig. 7b), but $C_E$ did not.

Variable $C_H$ varied little among the stability ranges under stable conditions (Fig. 7b), while $C_E$ decreased as the ASL became more stable. Our results imply that $C_E$ could be underestimated when $C_E$ and $C_H$ are assumed to be equal in most applications. Although the trend displayed some scatter, $C_E$ and $C_H$ decreased steadily as the ASL became less unstable, and they continued to decrease gently as the ASL became more stable. The different rates of change of $C_E$ and $C_H$ with stability under the two stability regimes suggest that $C_E$ and $C_H$ were largely dependent upon stability when the ASL was unstable, whereas they were weakly dependent upon stability when the ASL was stable.

Generally, $C_E$ and $C_H$ were largest under unstable conditions, followed by near-neutral conditions and then stable conditions. Although the mean $C_E$ under near-neutral conditions can be reasonably estimated to be 1.40, the mean $C_H$ under near-neutral conditions was less reliable because of the large change in $C_H$ (from 1.30 to 0.03) when conditions changed from unstable to stable in the near-neutral ranges. These observations were consistent with those in Verburg and Antenucci (2010).

Our $C_E$ and $C_H$ values are similar to those reported in Xiao et al. (2013), and their threshold $U$ value of 4 m s$^{-1}$ is the same as observed in this study (Fig. 8). The increased variability in $C_H$ as compared with $C_E$ when $U$ was $>4$ m s$^{-1}$ (Figs. 8b,e) was also consistent with Xiao et al. (2013).

The largest $C_E$ and $C_H$ (i.e., the strongest turbulent transfer capability) occurred when the ASL was strongly unstable (Figs. 7a,b). However, the largest $C_E$ and $C_H$ did not lead to the greatest LE and $H$ (Figs. 2a,d). As analyzed in sections 3a and 3c, and shown in Fig. 4b, the decreased LE and $H$ under very unstable conditions ($-10 \leq \zeta < -1$) were largely attributed to the reduced wind-induced mechanical mixing given the same levels of $\Delta e$ and $\Delta T$ (Figs. 2a–c and Figs. 2d–f). In the intermediate instability levels, large LE and $H$ were likely due to a coupled effect of adequate levels of turbulent transfer capacity ($C_E$ and $C_H$), mechanical mixing ($U$ or $u_z$), and $\Delta e$ and $\Delta T$. Under stable conditions, the low $C_E$, $C_H$, $U$, and $\Delta e$ jointly contributed to small LE and $H$. Similar to LE and $U\Delta e$ ($H$ and $U\Delta T$) in near-neutral conditions ($-0.05 \leq \zeta < 0.05$), sharp drops in $C_E$ ($C_H$) occurred as the stability shifted from weakly unstable to weakly stable conditions, which could also be due to the nonlinear relationship between $U$ and $C_E$ ($C_H$).
The relationships between $C_E$ and $U$ and between $C_H$ and $U$ have been documented (Tanny et al. 2008; Verburg and Antenucci 2010; Xiao et al. 2013). However, the effects of different stabilities on these relationships were not extensively examined in these studies. We have analyzed $C_E$ and $C_H$ under three selected ASL stability ranges of $-0.5 < \zeta < -0.1$ (unstable), $-0.05 < \zeta < 0.05$ (near neutral), and $0.1 < \zeta < 0.5$ (stable) in Fig. 8. Variables $C_E$ and $C_H$ showed very similar variation patterns under other unstable, near-neutral, and stable ranges. When $U$ was $<4$ m s$^{-1}$, $C_E$ and $C_H$ for the three stability conditions increased dramatically with decreasing $U$, which can be inaccurately modeled using the flux-gradient approach for very unstable and stable conditions (Tanny et al. 2008). When $U > 4$ m s$^{-1}$, $C_E$ and $C_H$ slightly increased with $U$ (Ikebuchi et al. 1988; Sene et al. 1991; Tanny et al. 2008; McGloin et al. 2014a) but deviated from predictions using...
the Liu et al. (1979) model. The major differences in \( C_E \) and \( C_H \) between different stability ranges are the average magnitudes of \( C_E \) and \( C_H \) when \( U > 4 \text{ m s}^{-1} \).

4. Conclusions

We have analyzed a large amount of eddy covariance data to demonstrate and describe in detail the mechanism of how stability strongly modulated the influences of \( U, \Delta e, \) and \( \Delta T \) on turbulent exchanges of LE and H across the water–atmosphere interface. For this dataset, the ASL experienced a wide range of stability conditions \((-10 \leq \zeta \leq 10)\). The LE and H over water were generally greater under unstable conditions than under stable conditions. The largest \( C_E \) and \( C_H \) occurred under the most unstable conditions, and \( C_E \) and \( C_H \) decreased when stability shifted from unstable to stable conditions. The maximum LE and H did not occur in the most unstable conditions with the largest bulk transfer coefficients (\( C_E \) and \( C_H \)), but rather in the intermediate unstable range of \(-0.1 \leq \zeta < -0.05 \) for LE and \(-0.5 \leq \zeta < -0.1 \) for H, mainly due to the effects of mechanically induced mixing, which behaved differently under different stability regimes. Under unstable conditions, \( U \) strongly regulated LE because \( \Delta e \) was sufficient, where the thermally stratified atmosphere further promoted mechanical mixing and thus LE. The coupled effect of the intermediate levels of \( C_E, U, \) and \( \Delta e (C_H, U, \) and \( \Delta T) \) caused the largest LE (H) under the intermediate unstable conditions. Under stable conditions, only \( \Delta e \) regulated LE because of the low supply of \( \Delta e \), even under increased \( U \) conditions. For H, the effects of atmospheric stability (unstable and stable conditions) were more apparent because of the somewhat direct relationship between \( \Delta T \) and \( \zeta \). However, under near-neutral conditions, the roles of \( U \) and \( \Delta T \) in regulating H depended upon whether the ASL was stable or unstable. Mean wind speed was more influential than \( \Delta T \) in regulating \( H \) in the unstable ranges, whereas \( \Delta T \) was more influential than \( U \) in the stable ranges. Under stable conditions, low \( C_E, U, \) and \( \Delta e (C_H, U, \) and \( \Delta T) \) were mainly responsible for the predominantly low LE (H). Although the trends in \( C_E \) and \( C_H \) with stability and \( U \) were similar, we found that \( C_E \) was consistently larger than \( C_H \) under stable conditions. The influence of \( C_E \) on LE is reduced under unstable conditions because of the greater influence of \( U \).

Monin–Obukhov similarity theory is used in a variety of parameterization schemes (e.g., the bulk transfer relations) to quantify the influence of stability on turbulent exchange of energy and water vapor, though its validity has been widely criticized when applied over land and water surfaces (Foken 2006; Xiao et al. 2013; Li et al. 2015). Our study indicates that the bulk transfer relations in Eqs. (1) and (2) may not be able to fully reproduce the observed coupling effect of stability, mechanical mixing, and other environmental variables across a wide range of stabilities so as to accurately simulate fluxes of heat and water vapor across the water–air interface, especially under very unstable and very stable conditions, \(|\zeta| > 0.1 \) for LE and \(|\zeta| > 0.5 \) for H. Process-based studies like ours thus provide useful information to parameterize turbulent exchange processes over water in numerical models. It should be emphasized that water–atmosphere interaction and its governing physical processes may be dependent upon lake morphology (e.g., size, shape, and depth) and atmospheric forcings that are largely associated with synoptic weather patterns. Thus, caution should be taken when extending the results in this study to other inland water bodies. Further studies are needed over lakes with various morphologies in other latitudes to provide a full-scale, process-based understanding of water–atmosphere interaction for modeling purposes.

Acknowledgments. We acknowledge support by the National Science Foundation Division of Atmospheric and Geospace Sciences (AGS) under Grant 1112938. Y.Y. acknowledges Universiti Sains Malaysia (USM) for granting his sabbatical leave to conduct this research at Washington State University (WSU) and awarding the Research University (RU) Grant 1001/PTEKIND/811316 to prepare this manuscript. We are grateful for Dan Gaillet, Billy Lester, Jason Temple, and many other people in Pearl River Valley Water Supply District in Ridgeland, Mississippi, as well as Yu Zhang, Haimei Jiang, Li Sheng, Rongping Li, Yu Wang, and Guo Zhang, who contributed to field work. We thank Justine Emilia Missik, Eric Russell, Yulong Ma, and Zhongming Gao for their useful comments during the preparation of this work, and Qianyu Zhang for her initial analyses of the data used in this work.

REFERENCES


