Multiple Regimes of Wind, Stratification, and Turbulence in the Stable Boundary Layer

ADAM H. MONAHAN, TIM REES, AND YANPING HE
School of Earth and Ocean Sciences, University of Victoria, Victoria, British Columbia, Canada

NORMAN MCFARLANE
School of Earth and Ocean Sciences, and Canadian Centre for Climate Modelling and Analysis, University of Victoria, Victoria, British Columbia, Canada

(Manuscript received 22 October 2014, in final form 18 March 2015)

ABSTRACT

A long time series of temporally high-resolution wind and potential temperature data from the 213-m tower at Cabauw in the Netherlands demonstrates the existence of two distinct regimes of the stably stratified nocturnal boundary layer at this location. Hidden Markov model (HMM) analysis is used to objectively characterize these regimes and classify individual observed states. The first regime is characterized by strongly stable stratification, large wind speed differences between 10 and 200 m, and relatively weak turbulence. The second is associated with near-neutral stratification, weaker wind speed differences between 10 and 200 m, and relatively strong turbulence. In this second regime, the state of the boundary layer is similar to that during the day. The occupation statistics of these regimes are shown to covary with the large-scale pressure gradient force and cloud cover such that the first regime predominates under clear skies with weak geostrophic wind speed and the second regime predominates under conditions of extensive cloud cover or large geostrophic wind speed. These regimes are not distinguished by standard measures of stability, such as the Obukhov length or the bulk Richardson number. Evidence is presented that the mechanism generating these distinct regimes is associated with a previously documented feedback resulting from the existence of an upper limit on the maximum downward heat flux that can be sustained for a given near-surface wind speed.

1. Introduction

The stably stratified boundary layer (SBL) presents ongoing challenges to observational characterization and physical modeling (e.g., Poulos et al. 2002; Fernando and Weil 2010; Holtslag et al. 2013; Mahrt 2014). Understanding the behavior of the lower atmosphere under conditions of stable stratification is important for accurate simulations of nocturnal near-surface temperatures, including the occurrence of fog and frost (e.g., Walters et al. 2007; Holtslag et al. 2013), modeling of lower-atmospheric wind variability and extremes (e.g., He et al. 2010; Monahan et al. 2011; He et al. 2012), and characterization of pollutant dispersal and air quality (e.g., Arya 1998; Salmond and McKendry 2005).

When large-scale pressure gradients are moderate or strong, or in overcast conditions, the stratification is generally relatively weak and mechanically driven turbulence remains sustained. The classical model of turbulent quantities decreasing upward from a surface layer characterized by Monin–Obukhov similarity theory generally holds in this situation (e.g., Mahrt et al. 1998; Pahlow et al. 2001; Grachev et al. 2005; Mahrt 2014). Under clear skies and relatively weak pressure gradient forces, the turbulence can collapse and the near-surface flow can become decoupled from that above (e.g., Derbyshire 1999; Banta et al. 2007; Williams et al. 2013; Mahrt 2014). The collapse of turbulence can occur abruptly as the mechanical driving of the boundary layer is reduced (Sun et al. 2012; Van de Wiel et al. 2012a,b; Liang et al. 2014; van Hooijdonk et al. 2015).

In this collapsed state, turbulence tends to be dominated by intermittent bursts (Kondo et al. 1978; Van de Wiel et al. 2002a,b, 2003; Acevedo and Fitzjarrald 2003; Nakamura and Mahrt 2005; Ohya et al. 2008; Medeiros...
and Fitzjarrald 2014; Mahrt 2014; Vercauteren and Klein 2015), which are responsible for most of the turbulent transport (Nappo 1991; Coulter and Doran 2002; Doran 2004; Basu et al. 2006; Acevedo et al. 2006; Williams et al. 2013). These bursts tend to be localized both horizontally and vertically (Acevedo and Fitzjarrald 2003; Nakamura and Mahrt 2005). No single mechanism appears to be responsible for these turbulent bursts. They have been associated with a range of processes, including passing density currents (e.g., Sun et al. 2002); propagating solitary and internal waves (e.g., Sun et al. 2004; Meillier et al. 2008); Kelvin–Helmoltz-like shear instabilities (e.g., Blumen et al. 2001); and interactions between the lower atmosphere and the underlying surface (e.g., Van de Wiel et al. 2003). It has long been recognized that such bursts of turbulence can break down the near-surface inversion (e.g., Durst 1933; Gifford 1952; Geiger 1965; Businger 1973; Nappo 1991; Acevedo and Fitzjarrald 2003; White 2009). If they are sufficiently strong, these turbulent mixing events can (but do not necessarily) drive transitions from strong to weak stable stratification.

Based on the observational results discussed above, the SBL is often classified into weakly and very stably stratified regimes (respectively denoted the wSBL and vSBL; cf. Okamoto and Webb 1970; Kondo et al. 1978; Mahrt 1998; Acevedo and Fitzjarrald 2003; Shravan Kumar et al. 2012; Liang et al. 2014; Mahrt 2014; van Hooijdonk et al. 2015; Vercauteren and Klein 2015). Other regime classifications have been suggested. For example, some studies consider a third transitional regime between the wSBL and the vSBL (e.g., Mahrt et al. 1998; Conangla et al. 2008), or separate the vSBL into very weak (bottom up) and moderate (top down) turbulence regimes (e.g., Sun et al. 2012). Grachev et al. (2005) separate the stable ABL into four regimes based on the character of turbulence and the relative importance of the Coriolis force and turbulent fluxes in the momentum budget, while Williams et al. (2013) define five regimes distinguished by stability and degree of mixing. Even more complicated classification schemes are those of Kurzeja et al. (1991) or the Pasquill stability classes (Arya 1998). Another class of SBL regime classifications uses external parameters, such as the geostrophic wind and radiative forcing, rather than internal variables, such as turbulence, stratification, and shear (e.g., Van de Wiel et al. 2002b, 2003; Bosveld and Beyrich 2004). While some studies have defined the regimes in terms of a single metric such as $z/L$, where $L$ is the Obukhov length, or the Richardson number (Kondo et al. 1978; Mahrt et al. 1998) other studies have emphasized the need for more than one measure of ABL structure to separate these regimes (e.g., Van de Wiel et al. 2002b, 2003; Grachev et al. 2005; Williams et al. 2013; van Hooijdonk et al. 2015).

Early studies associated the sudden collapse of sustained turbulence for increased stability with the existence of a critical Richardson number above which turbulence cannot be maintained (Okamoto and Webb 1970; Businger 1973; Blackadar 1979; ReVelle 1993). Subsequent studies have cast doubt on the existence of such a critical Richardson number (e.g., Fernando and Weil 2010). More recent analyses interpret this collapse in terms of the existence of a maximum sustainable downward heat flux for intermediate stability (de Bruin 1994; Malhi 1995; Mahrt et al. 1998; Pahlow et al. 2001; Basu et al. 2006; Van de Wiel et al. 2007; Conangla et al. 2008; Sun et al. 2012; Van de Wiel et al. 2012a,b; van Hooijdonk et al. 2015). Increasing stability beyond this maximum reduces heat fluxes; the resulting positive feedback further enhances the stratification and suppresses turbulence until a limiting state of (on average) weak turbulence is reached. This local maximum in turbulent heat flux has been used to distinguish the wSBL from the transitional and vSBL regimes (e.g., Mahrt et al. 1998; Conangla et al. 2008; van Hooijdonk et al. 2015).

Idealized physical models of the SBL have displayed two kinds of regime behavior: parameter regions with multiple equilibria bounded by regions with only a single equilibrium (e.g., McNider et al. 1995; Derbyshire 1999; Walters et al. 2007) or parameter regions of oscillatory (limit cycle or chaotic) variability bounded by regions with a single steady state (e.g., ReVelle 1993; Van de Wiel et al. 2002a,b). Multiple equilibria and the wSBL-to-vSBL transition phase of modeled oscillations are produced by the positive feedbacks described above, while the reverse transition results from shear-driven turbulence (e.g., through formation of low-level jets) in the vSBL. This second feedback mechanism appears to be insufficiently strong in those models displaying multiple equilibria to generate sustained oscillatory behavior, although these systems can display transient oscillations (ReVelle 1993). In other models, the collapsed state is transient: after an initial reduction of turbulence intensity, the modeled SBL adjusts to a unique steady state without oscillations (Van de Wiel et al. 2012a).

Further evidence for the existence of two distinct states of Reynolds-averaged near-surface flow and stratification in the late-summer (July–September) nocturnal boundary layer at Cabauw, Netherlands, was presented in Monahan et al. (2011). This study demonstrated that the probability density function (PDF) of the 10-min-average potential temperature difference between 40 and 2 m has a long tail toward
strongly stable stratification. When conditioned on values of this potential temperature difference above or below a subjectively determined value of 1 K, the joint distribution of 10-min-averaged wind speeds at 10 and 200 m separated into two distinct populations. In the first of these, associated with strongly stable stratification, the speeds at 200 m are much faster than those at 10 m. In the second regime, with a near-surface stratification in the weakly stable to weakly unstable range, the speeds at 10 m are closer to those at 200 m. There is no evidence for distinct regimes during the day. The distinction between the nocturnal regimes in Monahan et al. (2011) was based entirely on Reynolds-averaged quantities and made no use of turbulence information.

As was found in Monahan et al. (2011), the daytime joint distribution between \( w_{10} \) and \( w_{200} \) is narrowly spread around a straight line with a slope of about 1:1.5. The marginal distributions of the speeds at these two altitudes are weakly positively skewed, and the distribution of \( \theta_{200} - \theta_2 \) is narrow with a peak at slightly unstable stratification. At night, the joint distribution of wind speeds at these two altitudes is much broader than during the day. The main body of the distribution lies along a line with a slope of about 1:3, with a shallower protrusion (of slope approximately 1:1.5) extending away toward larger values of \( w_{10} \). The marginal distribution of \( w_{10} \) is more positively skewed than during the day, while the skewness of \( w_{200} \) is smaller. Furthermore, the distribution of \( \theta_{200} - \theta_2 \) is much broader than during the day, positively skewed, and clearly bimodal with maxima near 1 and 5 K. The bimodality evident in the marginal distribution of \( \theta_{200} - \theta_2 \) is even more evident in higher dimensions. Figure 2 displays a three-dimensional scatterplot of nighttime stratification (\( \theta_{200} - \theta_2 \)), mean wind speed [0.5(\( w_{200} + w_{10} \))], and wind speed shear (\( w_{200} - w_{10} \)) for the July–September season. The presence of two distinct populations in this scatterplot is clear.

Inspection of Fig. 2 indicates that the two regimes of the Reynolds-averaged flow and stratification are not
separated by a simple stratification threshold such as that used in Monahan et al. (2011). Furthermore, it is evident that these regimes are multidimensional structures in the state space of flow and stratification at Cabauw and are therefore likely to overlap even in the three-dimensional projection displayed in Fig. 2. To distinguish the regimes in the data and allow classification of individual observations without having to subjectively decide on a dividing surface by visual inspection, we will make use of hidden Markov model (HMM) analysis (Rabiner 1989; Murphy 2012). In an HMM analysis, the data under consideration are characterized by an unobserved Markov process, which takes a set of discrete values or hidden states. Within each hidden state, the observations are assumed to be drawn from a hidden-state-dependent probability distribution. Given a specific dataset, the HMM algorithm estimates the parameters of the distributions within each hidden state, the transition matrix of the Markov process, and the most likely state occupied by each given data point. Hidden Markov model analysis has the considerable advantage relative to clustering techniques, such as mixture models, that it estimates not simply the geometry of the distributions within each regime but classifies observations into these regimes and provides an empirical dynamics of transitions between them even when the regimes overlap.

The utility of HMMs in the diagnosis of metastable regimes of large-scale atmospheric flow was demonstrated by Majda et al. (2006) and Franzke et al. (2008, 2011). Yoo et al. (2010) used HMM analysis to study the Asian summer monsoon intraseasonal oscillation and its modulation by El Niño–Southern Oscillation. Hidden Markov model–based analysis and downscaling of precipitation has been considered in Robertson et al. (2004), Greene et al. (2008), and Fu et al. (2013). The present study is the first to apply HMMs to the problem of SBL regimes [although Vercauteren and Klein (2015) have recently applied a similar analysis to study the interaction between submesoscale motions and turbulence in the SBL]. The HMM analysis is applied to long time series of 10-min-averaged nighttime wind and potential temperature observations from the Cabauw tower, and the classification scheme is used to assess the marginal distributions of these variables conditioned by regime. We also consider the properties of observed turbulence kinetic energy and fluxes in these regimes, as well as the covariability of regime occurrence with large-scale forcing (geostrophic wind and cloud cover).

The data to be considered are discussed in section 2, followed by a brief introduction to HMMs in section 3. Consideration of Reynolds-mean and turbulence fields conditioned on HMM state are presented in sections 4 and 5, respectively. A discussion including consideration of the physical mechanisms responsible for the regimes is presented in section 6. Brief conclusions follow in section 7.

2. Data

The primary dataset considered in this analysis consists of 10-min-average wind speed, wind direction, and air temperature at the 213-m tower at Cabauw in the Netherlands (51.971°N, 4.927°E) maintained by the Cabauw Experimental Site for Atmospheric Research (CESAR; cf. van Ulden and Wieringa 1996). Validated observations for the period from 1 January 2001 through 31 December 2012 are used. Wind speed and direction are measured at altitudes of 10, 20, 40, 80, 140, and 200 m. Temperature is also measured at 2 m. Surface pressure measurements are used with the temperature observations to calculate potential temperatures,
assuming hydrostatic equilibrium and a dry atmosphere. CT75 ceilometer cloud cover observations at 30-second resolution were combined into 10-min-resolution cloud occurrence data (an integer between 0 and 20), as described in He et al. (2013). These cloud data are available from 1 July 2007 to 30 September 2011. The data and current information about CESAR are available online (http://www.cesar-database.nl/).

Hourly geostrophic vector winds from 1 January 2001 to 31 December 2012 were provided by Fred Bosveld of The Royal Netherlands Meteorological Institute (KNMI). These data are computed using a two-dimensional polynomial fit to surface pressure observations within 75 km of Cabauw, from which the gradient is calculated.

One year (1 July 2007–30 June 2008) of 10-min-resolution turbulence quantities (variances and fluxes of momentum and temperature) at altitudes of 5, 60, 100, and 180 m were also made available by Fred Bosveld. Because of mast interference, turbulence data for winds coming from 280° to 340° are unreliable and are therefore neglected. A detailed description of the turbulence data is available online (http://www.knmi.nl/~bosveld).

All data were stratified by season—January–March (JFM), April–June (AMJ), July–September (JAS), and October–December (OND)—and by time of day: daytime (0800–1600 UTC) and nighttime (2000–0500 UTC). As the HMM analysis can accommodate gaps between blocks of data in a time series but requires the data to be continuous within these, it is natural for the present analysis to divide the data by time of day rather than by a more physically motivated criterion (such as the sign of the surface heat flux).

3. Hidden Markov models

Detailed discussions of HMMs are presented in Rabiner (1989) and Murphy (2012). We present here a brief overview of HMMs for continuous random variables. In HMM analysis, it is assumed that the variability of the observed variable \( x_n \) depends on an unobserved discrete variable \( z_n \) (where \( n \) indexes time). The random variable \( z_n \) identifies the hidden state (which we will often also refer to as the regime) occupied at time \( n \); its time evolution is described by a Markov chain with stochastic matrix \( Q \):

\[
P(z_{n+1} = i | z_n = j) = Q_{ij} P(z_n = j),
\]

where \( P(z_n = j) \) is the probability that \( z_n = j \). Within any hidden state \( z_n = j \), the data \( x_n \) are assumed to be independent and identically distributed according to a hidden-state-dependent parametric PDF. We will model \( x_n \) within each hidden state as normally distributed with hidden-state-dependent mean and covariance:

\[
\text{prob}(x_n | z_n = j) \sim N(\mu_j, \Sigma_j).
\]

Given a set of observations \( x_n \) and assuming a number \( K \) of hidden states, the challenge is to estimate the parameters \( \Lambda = \{ \mu_j, \Sigma_j, Q \} \) and the sequence of \( z_n \). Rabiner (1989) presents an algorithm for the construction of the distribution of the observations conditioned on the parameters: \( p(x | \Lambda) \). Inverting this distribution using Bayes’s theorem to obtain \( p(\Lambda | x) \) allows a maximum likelihood estimate of the parameters and a most likely estimate of the hidden-state sequence to be computed via the expectation–maximization (EM) algorithm (Dempster et al. 1977).

As an illustration of the use of HMM analysis to separate distinct populations from multivariate data, we consider a discrete stochastic process with two states (\( S_1 \) and \( S_2 \)), transitions between which are governed by the stochastic matrix:

\[
Q = \begin{pmatrix}
0.9 & 0.1 \\
0.05 & 0.95
\end{pmatrix}.
\]

Within each state, the distribution of \( x \in \mathbb{R}^2 \) is taken to be Gaussian with means:

\[
\mu_1 = (0, 2.5) \quad \text{and} \quad \mu_2 = (1, 0)
\]

and covariance matrices:

\[
\Sigma_1 = \begin{pmatrix}
1 & 0.5 \\
0.5 & 1
\end{pmatrix} \quad \text{and} \quad \Sigma_2 = \begin{pmatrix}
1.5 & -0.3 \\
-0.3 & 1
\end{pmatrix}.
\]

A realization of \( 5 \times 10^4 \) points of the system equations [Eqs. (3)–(5)] was generated; marginal distributions of \( x_1 \) and \( x_2 \) and sample time series are illustrated in Fig. 3. The existence of two states underlying the dynamics is more evident in the marginal distribution and time series of \( x_2 \) than those of \( x_1 \). These two states are even clearer in a scatterplot of \( x_1 \) with \( x_2 \) (Fig. 3). Applying HMM analysis with two hidden states to this system, the estimated stochastic matrix was

\[
\hat{Q} = \begin{pmatrix}
0.899 & 0.101 \\
0.051 & 0.949
\end{pmatrix},
\]

while the estimated means and covariances were
These estimates are in excellent agreement with the true values. Marginal distributions of $x_1$ and $x_2$ conditioned on being in states $S_1$ or $S_2$ show that the states are distinguished despite strongly overlapping for each of these individual variables (Fig. 3). The separation of these two states, despite overlap, is also seen in the full $x_1$–$x_2$ space. Because the true sequence of hidden states $z_j$ is known, we can compute the HMM misclassification rate. It is found to be 1.9%. The HMM analysis has been able to separate these two populations with a high degree of accuracy, despite their considerable overlap in state space.

The time series that we will consider have gaps. Because we do not want to confuse statistical structure imposed by the regular, externally forced diurnal and annual cycle with that produced by internal dynamics, we apply HMM analysis to nocturnal data within individual seasons. Gaps in the time series arise because the end of one night is followed by the beginning of the next night without the intervening time points. At the end of a season, the next point in the time series is separated by a gap of 9 months. Rabiner (1989) describes how the HMM algorithm is extended to account for time series with such gaps.
4. Regimes in near-surface wind and stratification

The nighttime distributions of $\theta_{200} - \theta_2$, $w_{10}$, and $w_{200}$, shown for all four seasons in Fig. 4, share the dominant features characteristic of JAS discussed in section 1. The long tail of $\theta_{200} - \theta_2$ toward strongly stable stratification is evident in all seasons; a pronounced second maximum in the PDF appears only in JAS. The long tails toward large $w_{10}$ values are evident in the PDFs in all seasons, as is the absence of an extended tail toward large positive values in the PDF of $w_{200}$. For each season, the joint distribution of $w_{10}$ and $w_{200}$ is characterized by a primary population distributed around a linear axis with a relatively steep slope and a second population extending toward larger values of $w_{10}$ with a shallower slope. Two such populations are characteristic of the conceptual model of Monahan et al. (2011), distinguished, respectively, by relatively weak and strong near-surface turbulence.

HMM analyses were applied to three-dimensional vector time series,

$$
\mathbf{x} = \left( w_{200} - w_{10}, \frac{w_{200} + w_{10}}{2}, \theta_{200} - \theta_2 \right),
$$

(8)
of wind speed shear, mean wind speed, and stratification for each season individually. Based on inspection of the joint and marginal PDFs of these variables (as discussed in section 1), this analysis used two hidden states for the underlying Markov chain. We will denote these states as R$_1$ and R$_2$. Marginal and joint PDFs of $\theta_{200} - \theta_2$, $w_{10}$, and $w_{200}$ conditioned on being in state R$_1$ or R$_2$ (Fig. 4) demonstrate that the two states are associated with distinct flow and stratification structures. In this figure, as in all others displaying PDFs conditioned on regime occupation, the conditional PDFs have been scaled by the probability of regime occupation so that the sum of the conditional PDFs is the full PDF [as $P(X) = P(X | R_1)P(R_1) + P(X | R_2)P(R_2)$]. A consistent color coding is also used: blue for R$_1$ and red for R$_2$.

The first regime R$_1$ is associated with the strongest stable stratifications and relatively small $w_{10}$ and $w_{200}$. In this regime, the distributions of both $w_{10}$ and $w_{200}$ are positively skewed. In regime R$_2$, $\theta_{200} - \theta_2$ is narrowly distributed between weakly stable and near-neutral stratification. This regime is associated with the largest $w_{10}$ and $w_{200}$ values. In particular, R$_2$ populates the long positive tail in the full PDF of $w_{10}$. While the distribution of $w_{10}$ is positively skewed in this regime, the skewness of $w_{200}$ is near zero or negative. The low-slope population evident in the joint distribution of $w_{10}$ and $w_{200}$ is found to be entirely associated with R$_2$. The separation of these two populations is also evident in a three-dimensional scatterplot of the components of $\mathbf{x}$ in JAS (Fig. 2); scatterplots for other seasons are similar. Note that while the two populations R$_1$ and R$_2$ distinguished by the HMM analysis are similar to those resulting from the subjectively determined 1-K threshold on $\theta_{200} - \theta_2$ used in Monahan et al. (2011), they are not characterized by such a clear threshold in stratification.

A striking degree of consistency in the regime structure across seasons is evident in the PDFs of $w_{10}$ and $w_{200}$ (Fig. 4). This consistency is further demonstrated by consideration of the principal axes of the populations in the space spanned by $w_{10}$ and $w_{200}$, calculated as the first empirical orthogonal function (EOF) mode of $w_{10}$ and $w_{200}$ conditioned on being in either R$_1$ or R$_2$ (Fig. 5). The slopes of these axes vary little between seasons (they are slightly shallower in OND and JFM) and clearly differ between regimes.

The probabilities of occurrence of the two regimes covary with changes in the large-scale forcing. Figure 6 displays the mean hidden-state number conditioned on the geostrophic wind speed and the fractional cloud cover for the JAS season. When the large-scale pressure gradient force is weak, R$_1$ dominates, except under overcast conditions. The likelihood of R$_2$ increases with both increasing geostrophic wind speed and cloud cover. These covariations suggest a modulation of the regime occupation statistics by variations in large-scale forcing. All other factors being equal, larger values of the geostrophic wind result in a higher rate of mechanical generation of turbulence kinetic energy (TKE), enhanced mixing, and reduced stratification. Increased cloud cover reduces the radiative cooling of the surface and inhibits the formation of a strongly stratified nocturnal boundary layer. These covariations of the regime occupation statistics are consistent with their seasonal evolution (Table 1). In JFM and OND, the two regimes are equally likely, while in AMJ and JAS, the stratified regime R$_1$ is considerably more likely than R$_2$. At this midlatitude location, relatively strong geostrophic wind speed and extensive cloud cover are more common in winter than in summer.

The estimated Markov chain transition probabilities for each season are displayed in Table 2. These transition probabilities indicate a strong degree of persistence in the hidden-state time series: the probability of changing from one hidden state to another over any 10-min period is much smaller than remaining in that state. This fact indicates that transitions from one regime to another during the night are relatively rare. The observed probability of remaining in a single regime during an entire night varies with regime and season from just over 50% to 75% (Table 3). Note that if the hidden-state sequence was truly Markovian, the probability of remaining in state $j$ for an entire night would be $p_{jj}^{40}$. 
FIG. 4. PDFs of nighttime wind speed and stratification at Cabauw for all four seasons: (top) distribution of $\theta_{200} - \theta_2$ (black), (top middle) distribution of $w_{10}$ (black), (bottom middle) distribution of $w_{200}$ (black), and (bottom) joint distribution of $w_{10}$ and $w_{200}$ (black). Also shown are the conditional distributions in regime R1 (blue) and R2 (red). The red contours in the bottom row represent the conditional distribution in R2. The conditional PDFs have been scaled by the probability of regime occupation so that together their sum is the full joint distribution.
where $p_{(j-1)}$ is the probability of remaining in regime $j$ in one 10-min step, and $54$ is the number of 10-min intervals in the 9-h nocturnal period that we consider. Interestingly, the observed probabilities of remaining within a given regime for an entire night are greater than those that would be computed from the 10-min-transition probabilities in Table 2, particularly for R2. The greater persistence in regime occupation statistics than would be observed for a truly Markovian process is consistent with a memory resulting from the slow variability of the large-scale driving processes.

5. Regimes in near-surface turbulence

The HMM regimes that we have identified were determined by analysis of time series of 10-min-averaged potential temperature and wind speed. We will now investigate how these regimes relate to the observed distributions of TKE and turbulent fluxes, with a focus on JAS.

The joint PDFs of nighttime TKE at 5 and 180 m are shown in Fig. 7, along with the joint PDFs of the magnitude of the vertical eddy momentum flux $\left| \mathbf{u}'_u \mathbf{u}'_3 \right| = (\mathbf{u}'_u^2 + \mathbf{u}'_3^2)^{1/2}$ at these altitudes. At both altitudes, both the TKE and the turbulent stress take values over approximately three orders of magnitude, so these quantities were logarithmically transformed before the distributions were estimated. Inspection of the joint PDF of TKE at 5 and 180 m indicates that these two quantities are highly correlated, as the joint distribution lies along an approximately straight line. Variability around this line is greater at lower values of the TKE than at the higher values. In contrast, the joint distribution of $\left| \mathbf{u}'_u \mathbf{u}'_3 \right|$ displays a distinct kink such that, at larger values of the turbulent stress magnitude, the values at the two altitudes are correlated, while at smaller values the joint distribution is approximately horizontal and the correlation between fluxes at the two levels is small.

When conditioned by regime, two distinct populations in these turbulence quantities become evident (Fig. 7). Regime R1 is associated with lower values of TKE at both 5 and 180 m, while in R2 the TKE levels are higher at both altitudes. The correlation of TKE between 5 and 180 m is considerably larger in R2 than in R1. Fluxes in R1 are in the range of smaller values (particularly at 180 m) and weak correlation between altitudes discussed above. In contrast, flux values in R2 are relatively

### Table 1. Regime occupation probabilities for each season:

<table>
<thead>
<tr>
<th></th>
<th>JFM</th>
<th>AMJ</th>
<th>JAS</th>
<th>OND</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p_1$</td>
<td>0.49</td>
<td>0.59</td>
<td>0.64</td>
<td>0.50</td>
</tr>
<tr>
<td>$p_2$</td>
<td>0.51</td>
<td>0.41</td>
<td>0.36</td>
<td>0.50</td>
</tr>
</tbody>
</table>

### Table 2. Instantaneous regime transition probabilities for each season.

<table>
<thead>
<tr>
<th></th>
<th>$P_{(1\rightarrow1)}$</th>
<th>$P_{(1\rightarrow2)}$</th>
<th>$P_{(2\rightarrow1)}$</th>
<th>$P_{(2\rightarrow2)}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>JFM</td>
<td>0.991</td>
<td>0.009</td>
<td>0.008</td>
<td>0.992</td>
</tr>
<tr>
<td>AMJ</td>
<td>0.990</td>
<td>0.001</td>
<td>0.014</td>
<td>0.986</td>
</tr>
<tr>
<td>JAS</td>
<td>0.986</td>
<td>0.014</td>
<td>0.008</td>
<td>0.992</td>
</tr>
<tr>
<td>OND</td>
<td>0.991</td>
<td>0.009</td>
<td>0.010</td>
<td>0.990</td>
</tr>
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high at both 5 and 180 m, as is the correlation of the fluxes at these altitudes.

One possible reason for the difference in behavior of the TKE and the stresses is the presence of nonturbulent motions (e.g., meandering motions or gravity waves) in the observed eddy velocity components, which contribute to TKE but not stress (e.g., Mahrt 1998). The joint distribution of TKE and stress at 5 m (Fig. 7) demonstrates the ratio of TKE to stress is often larger in R1 than it is in R2. This observation suggests the presence of variability in R1 that contributes to variances but not to fluxes. No such evidence of nonturbulent motions is apparent at 180 m (not shown).

Considering the marginal distributions of the along-wind component of the turbulent momentum fluxes at 5 and 180 m (Fig. 8), we see that at both altitudes the distribution is strongly skewed toward negative (downward) fluxes, with a most likely value near zero. Conditioned by regime, it is evident that the peak of the distribution is primarily associated with R1, and that the corresponding conditional distribution takes small values distributed approximately symmetrically around the mean. In contrast, the entire long tail of strong negative momentum fluxes \( u_1' u_3' \) occurs during R2 events at both altitudes. The crosswind component of the turbulent momentum flux \( u_2' u_3' \) is approximately symmetric at 5 m and slightly positively skewed at 180 m (Fig. 8). As expected, this component of the flux takes a smaller range of values than the along-wind component.

### Table 3

<table>
<thead>
<tr>
<th></th>
<th>( p(\text{stay in 1}) )</th>
<th>( p^{54}_{1\rightarrow -1} )</th>
<th>( p(\text{stay in 2}) )</th>
<th>( p^{54}_{2\rightarrow -2} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>JFM</td>
<td>0.67</td>
<td>0.60</td>
<td>0.75</td>
<td>0.63</td>
</tr>
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<td>AMJ</td>
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<td>OND</td>
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Conditioned on being in $R_1$, the turbulent flux distribution narrows and is symmetric at both altitudes. The tails of $\overline{u'_i w'_3}$ at both altitudes are associated with occupation of $R_2$.

As with the along-wind turbulent momentum flux, the turbulent temperature flux is negatively skewed with a distribution that peaks near a flux of 0 K m s$^{-1}$ (Fig. 8). At 180 m, conditioning on regime occupation results in distinct populations. The peak near zero is dominated by $R_1$, with a relatively narrow conditional distribution that is nearly symmetric. The long tail associated with strong downward temperature fluxes is associated with $R_2$. In contrast, the two populations are not separated at 5 m. Both $R_1$ and $R_2$ contribute to strong downward transport of temperature at this altitude.

We interpret the results presented in Figs. 7 and 8, as follows. The intensity of turbulence and turbulent momentum fluxes is weak in $R_1$, which is characterized by strongly stable stratification and relatively weak 10-m winds. While turbulent temperature fluxes in this regime are relatively weak at 180 m, this is not the case at 5 m. The persistence of relatively strong heat fluxes at 5 m indicates that the temperature gradients in $R_1$ are sufficiently strong to maintain these fluxes even at low TKE values or that the turbulent Prandtl number becomes quite small (e.g., Grachev et al. 2007; Sorbjan and Grachev 2010; He et al. 2012). In $R_1$, variations in TKE are only weakly coupled between 5 and 180 m, and variations of turbulent stresses at these altitudes are essentially uncoupled. This structure is consistent with a shallow turbulent layer at the surface overlaid with a quiescent layer (e.g., Banta 2008). In contrast, the TKE, turbulent fluxes (both momentum and temperature), and 10-m wind speed are relatively strong in the weakly stratified, relatively well-mixed $R_2$. In this regime, variations in turbulence intensity and fluxes are more strongly coupled in the vertical than in $R_1$ and with PDFs similar to those observed during the day (Figs. 9 and 10). Although the daytime TKE values and momentum fluxes are somewhat larger than those in $R_2$ and the turbulent temperature fluxes are generally upward (as the stratification is, in general, unstable), the similarity between the turbulence distributions in $R_2$ and those during the day is striking. In contrast, the daytime

![Figure 8](http://journals.ametsoc.org/jas/article-pdf/72/8/3178/3651102/jas-d-14-0311_1.pdf)
distributions of TKE and turbulent momentum fluxes have no features corresponding to R1.

The HMM regimes R1 and R2 separate the nocturnal near-surface TKE and turbulent momentum flux into two populations with distinct features. As was the case with the eddy-averaged populations, one of these (R2) is similar to the daytime population while the second (R1) has no daytime analog. A particularly striking aspect of this separation of the turbulence populations is that the regime classification was based on Reynolds-averaged time series of stratification and wind, and made no use of turbulence observations.

6. Discussion

a. Physical mechanism of regimes

We have presented empirical evidence for the existence of two distinct regimes of 10-min-averaged flow and stratification at Cabauw and demonstrated that these can be separated through use of a two-state HMM. While these states are distinct, the distributions of the associated 10-min-averaged and turbulence quantities overlap (Figs. 4, 7, and 8). We now investigate the related questions of the existence of a dynamically based parameter (or parameters) separating these regimes and of the underlying physical mechanism.

As the regimes were characterized from 10-min-averaged data, we first consider the possibility that they are separated by a bulk Richardson number at 10 and 200 m, respectively, $g$ is the acceleration of gravity, and $\theta_0 = 290 \text{ K}$ is a reference temperature. We focus on a bulk Richardson number rather than a gradient Richardson number, as it is more robustly estimated from observations at discrete altitudes. To emphasize the distinct contributions of stratification and shear to $R_{ib}$, the joint distribution of the numerator and denominator of Eq. (9) are presented separately in Fig. 11. As these range over several orders of magnitude, the numerator and denominator were logarithmically transformed before the distribution was computed. As with other quantities we have considered, this distribution shows evidence of two regimes: separate lobes in the PDF extend from the upper-right part of the distribution toward the upper left and toward the lower right. The presence of two lobes in the joint distribution of the numerator and denominator of $R_{ib}$ is not surprising in light of the fact that this distribution is similar to the (scaled) projection of the scatter shown in Fig. 2 into the plane spanned by the measures of stratification and shear.

When conditioned on the HMM regimes, the upper part of the distribution (including the lobe toward the upper left) corresponds to R1, while the lower lobe corresponds to R2. The overlap of these two conditional distributions is substantial. The inclined gray lines in Fig. 11 correspond to a range of values of $R_{ib}$, no single

\[ R_{ib} = \frac{g(\theta_{200} - \theta_{10})}{\theta_0 (200 \text{ m} - 10 \text{ m})} \left( \frac{\| u_{H200} - u_{H10} \|}{200 \text{ m} - 10 \text{ m}} \right)^2, \]
value of which separates the two regimes. While the entire distribution in $R_1$ falls above the $R_i = 0.1$ line, 84% of the points in $R_2$ do as well: $R_i$ does not provide a clear separation of $R_1$ and $R_2$. These results indicate that there is no critical value of $R_i$ as defined by Eq. (9).

As the single bulk Richardson number derived from 10-min-averaged data does not cleanly separate the regimes, we investigate whether these are separated by a turbulent flux-based measure. As in Mahrt et al. (1998), we consider a scatterplot of the turbulent temperature flux and $u^* = \sqrt{u''_t u''_t}$ at 5 m (Fig. 12). Curves associated with the constant Obukhov lengths of $L = 1, 10$, and 100 m are also displayed. There is a large overlap of the two populations associated with the two regimes, indicating that $R_1$ and $R_2$ are not separated by a single value of $L$. The $R_1$ population lies entirely below the $L = 100$ m line; so too does a substantial fraction of the $R_2$ population. Substantial overlap of $R_1$ and $R_2$ in $L$ is also seen in the conditional distributions of $(5\text{ m})/L$ (Fig. 12). Scatterplots of $(5\text{ m})/L$ against $u''_3 T''_5$ demonstrate the local maximum in downward heat flux for intermediate stability discussed in section 1 (Fig. 12). This feature is also seen in a plot of bin-averaged $u''_3 T''_5$ as a function of $(5\text{ m})/L$. When conditioned by regime, the $R_1$ distribution lies entirely on the high stability side of the local maximum in downward heat flux. That is, $R_1$ corresponds to the stability range of the positive feedback causing the collapse of turbulence and surface decoupling. The fact that a substantial fraction of the $R_2$ distribution also occurs in this range demonstrates that this single physical mechanism is not solely responsible for the separation of the regimes.

Considering a Couette flow with specified surface heat flux, and using a first-order, Businger–Dyer-type turbulence parameterization, Van de Wiel et al. (2007) showed that the steady-state surface momentum and heat fluxes are related by

$$\frac{u^*}{u^*_{\text{ref}}} \left( \frac{u^*}{u^*_{\text{ref}}} \right)^2 - \left( \frac{u^*}{u^*_{\text{ref}}} \right) \frac{u''_3 T''_5}{F_{\text{ref}}} = 0, \quad (10)$$

where

$$u^*_{\text{ref}} = \frac{\kappa w(z_0)}{d(z/z_0)} \quad \text{and} \quad (11)$$
Equation (10) predicts that the steady downward heat flux takes a local maximum at \( u^*/u^* N = 5^{2/3} \) (Fig. 13). For larger values of \( u^*/u^* N \), the steady states are stable. For smaller values, the steady states are unstable. The shape of this equilibrium curve results not just from the feedback between stratification and downward heat flux seen in Fig. 12 but involves changes in the entire character of near-surface flow, stratification, and turbulence. Furthermore, the collapse of turbulence is not associated with \( R_i \) increasing beyond \( R_i^c \): in this model, \( R_i = R_c(z/L)/(R_c + z/L) \), which is less than \( R_i \) at all altitudes. Van de Wiel et al. (2012a) argue that the Couette flow model is a useful approximation of the relationship between surface fluxes in the SBL. Because inertial time scales are longer than diffusive ones, internal transports of momentum dominate pressure gradient–driven accelerations in the local momentum budgets, and the wind speed at a particular near-surface altitude remains approximately constant. This altitude is referred to in Van de Wiel et al. (2012a) as the “velocity crossing point” and estimated to be about 40 m at Cabauw. Figure 13 displays joint distributions of \( u^*/u^* N \) and \( u_3^2T/F_{ref} \) estimated from the 5-m turbulence observations and the 40-m wind speeds at Cabauw using \( R_i = 0.4, z_0 = 0.015 \) m, and \( \theta_{ref} = 290 \) K. This distribution of observations is in striking agreement with the curve of Eq. (10). The value \( R_i = 0.4 \) is larger than that considered in Van de Wiel et al. (2007); changes in this value translate the distribution laterally without affecting its shape. The value of \( z_0 \) is within the range of values estimated at Cabauw (e.g., Optis et al. 2015, manuscript submitted to Wind Energy). The distributions conditioned on regime occupation separate quite cleanly, with less overlap than the conditional distributions of \( R_i \) or \( (5 \) m)/\( L \). Regime \( R_1 \) exists almost entirely in the lower, unstable branch of the \( (u_3^2T/F_{ref}, u^*/u^* N) \) curve, while \( R_2 \) occupies the stable upper branch. The clear separation of these regimes supports the interpretation of their underlying physical mechanism as being that proposed in Van de Wiel et al. (2007, 2012a,b) and van Hooijdonk et al. (2015). It is noteworthy that Van de Wiel et al. (2012b) estimate the minimum geostrophic wind needed to sustain steady near-surface turbulence under clear-sky conditions to be 5–7 m s\(^{-1}\). This range of values is consistent with geostrophic wind speeds in which \( R_1 \) dominates in low-cloud conditions (Fig. 6). Finally, we note that the lower branch corresponding to \( R_2 \) is populated despite the fact that it is unstable in the model. As discussed by Van de Wiel et al. (2007), possible reasons for the population of this branch are that the observed states are not in equilibrium and that the heat flux is not fixed but is, in fact, flow dependent. A further possibility is that the model does not represent the intermittent turbulence characteristic of the vSBL, which could potentially drive the system from the collapsed state into the vicinity of the unstable branch.

b. Relation to previously documented regimes

As discussed in the introduction, there have been many previous attempts to characterize distinct states of

\[ F_{ref} = \frac{u_3^2\theta_{ref} R_i \ln(z_t/z_0)}{\kappa g(z_t - z_0)}, \]

\( \kappa \) is the von Kármán constant, \( z_t \) is the altitude of the upper boundary at which the velocity is fixed, \( z_0 \) is the surface momentum roughness length, and \( R_i \) is a critical Richardson number (above which the turbulent fluxes vanish).
the SBL. While most of these classification approaches have been based on the state of the turbulence, the present classification was based entirely on Reynolds-averaged data.

Our regimes $R_1$ and $R_2$ strongly resemble the classification into weakly stable, transitional, and very stable boundary layers (Mahrt 1998; Mahrt et al. 1998; Conangla et al. 2008; Mahrt 2014). Specifically, $R_1$...
corresponds to the transition and very stable boundary layers, while $R_2$ resembles the weakly stable boundary layer. In contrast with the classification used in Mahrt et al. (1998) and Conangla et al. (2008), $R_1$ and $R_2$ are not separated by a clear threshold in $z/L$ or $u_0^3/T_0$ (Fig. 12). There is also an apparent correspondence between regimes 1 and 3 of Sun et al. (2012) and $R_1$ of the present study, as well as their regime 2 with our $R_2$. Consistent with the results of the present study, Sun et al. (2012) and van Hooijdonk et al. (2015) do not find a clear threshold in either stratification or Richardson number between regime 2 and the regime 1 and 3 pair. Visual inspection of the Cabauw data under consideration was used to justify a classification scheme with two rather than three regimes. The transitional and very stable boundary layers [respectively, regimes 1 and 3 of Sun et al. (2012)] characterized by local shear-driven turbulence and intermittent bursting turbulent events are not distinguished in $R_1$. It is possible that a more refined characterization with more than two regimes would follow from the use of alternative regime classification methods (as discussed in section 6c).

In contrast with most previous regime classifications in the stable ABL, $R_1$ and $R_2$ are determined not only by the local characteristics of near-surface turbulence but by the bulk structure of the entire bottom 200 m of the atmosphere. The regimes discussed in Williams et al. (2013) are also characterized in terms of bulk boundary layer structure. Their near-neutral deep and shallow SBL classes clearly are included in our $R_2$, while their shallow and top-down vSBL are contained in $R_1$. Their transitional SBL, consisting of 2/3 of their observations, does not correspond to either $R_1$ or $R_2$ but rather is split between them. Furthermore, consistent with the results of Van de Wiel et al. (2002b, 2003), Grachev et al. (2005), and Williams et al. (2013), we do not find a single parameter (associated with either the turbulence or Reynolds-averaged data) that clearly separates the populations $R_1$ and $R_2$. Figure 13 suggests that at least two such parameters are needed.

The classification schemes of Van de Wiel et al. (2002b, 2003) and Bosveld and Beyrich (2004) are based on external parameters corresponding to the mechanical and radiative driving of the SBL. The regime diagram presented in Van de Wiel et al. (2003) qualitatively resembles the dependence of mean regime number on geostrophic wind speed and cloud cover shown in Fig. 6 if their radiative and turbulent regimes are related to our $R_1$ and continuous turbulent regime with $R_1$. In contrast with the results of Van de Wiel et al. (2002b, 2003), we do not find a sharp transition between $R_1$ and $R_2$ when occupation statistics are conditioned on these external parameters. For a broad range of radiative and mechanical forcing values, both regimes can be occupied, consistent with the suggestion that the SBL can display multiple equilibria (e.g., McNider et al. 1995; Derbyshire 1999; Walters et al. 2007).

The results of the present study are closely related to those of van Hooijdonk et al. (2015), who provide evidence of two boundary layer regimes at Cabauw using an entirely different line of reasoning to ours. Defining a normalized shear measure denoted the shear capacity (which makes use of both flow and boundary condition information), they show that this measure clearly distinguishes between the two regimes. Consistent with our results, van Hooijdonk et al. (2015) show that these regimes are not distinguished by $z/L$ or $Ri_b$ but clearly fall on either side of the maximum in sustainable downward
heat flux described in Van de Wiel et al. (2007). As with our regimes R1 and R2, the regimes in van Hooijdonk et al. (2015) are associated with changes in the entire boundary layer structure and are not characterized by local measures of stability. Although their analysis differed from ours by focusing on a cloud-free subset of nights, the results of van Hooijdonk et al. (2015) are highly complementary to those of the present study and provide compelling evidence of two modes of variability in the nocturnal boundary layer at Cabauw.

c. Directions of future research

The basic tool used by this study to diagnose the regimes of near-surface flow and stratification and their occupation statistics was hidden Markov model analysis. This approach assumed that regime transitions are governed by an autonomous Markov chain with a specified number of hidden states and that, within any hidden state, the observations are independent and identically distributed (as multivariate Gaussian).

A general difficulty with clustering analyses is that the number of clusters must be specified initially, based on some other source of information. When a clustering algorithm is tasked to find $N$ clusters, $N$ clusters will be found irrespective of the degree to which the distribution of observations is made up of discrete populations gathered around distinct centers. Franzke et al. (2008) suggest that the eigenspectrum of the Markov chain stochastic matrix can be used to estimate the number of hidden states. If the underlying dynamics are associated with $M$ hidden states with characteristic occupation time scales much longer than the time scales of variability within any hidden state, the stochastic matrix for $N > M$ should have a spectral gap after the $M$th eigenmode (arranged in decreasing order). However, for the data under consideration, such a spectral gap is not found when the HMM analysis is repeated using more than two hidden states. The time scales of variability within a given regime are not expected to be short, as within either hidden state the flow and stratification will be influenced by nontrivial internal dynamics and slow variations in large-scale driving (particularly cloud cover and the pressure gradient force). Alternatively, criteria based on measures such as the Bayesian information criterion can be used to determine regime number (e.g., Robertson et al. 2004). In the present analysis, visual inspection of the data under consideration justifies consideration of two hidden states for a first analysis.

The presence of nontrivial dynamics within the hidden states can be accommodated by considering a more general statistical model. In particular, autoregressive HMMs fit the data within a hidden state not just to a specified probability distribution, but to a first-order autoregressive process [AR(1)] model (e.g., Chiang et al. 2008). Furthermore, it is evident from Fig. 6 that the stochastic matrix is not autonomous but is conditionally dependent on the externally varying, large-scale cloud cover and pressure gradient force. Hidden Markov model analysis can be extended to nonhomogeneous HMMs, which allow modifications of transition probabilities by external variables (e.g., Robertson et al. 2004; Yoo et al. 2010; Fu et al. 2013).

The simple HMM analysis considered in this study does a reasonable job of separating the two regimes, as is evident in Figs. 2, 4, and 7. While it is not expected that generalizing the HMM analysis will change the regime classification obtained using two regimes, the dynamics of the estimated Markov chain may be more physically meaningful. Extending the present analysis by considering autoregressive and nonhomogeneous HMMs is an interesting direction of future study. The fact that the hidden-state process does not appear to be Markovian (Table 3) can also, in principle, be accommodated by extending the data into a higher-dimensional embedding space spanned by time-lagged copies of the data (e.g., Broomhead and King 1986; Horenko et al. 2008).

Another valuable direction of future research would be to apply the finite-element variational approaches recently introduced by Horenko (Franzke et al. 2009; Horenko 2010a,b; O’Kane et al. 2013; Risbey et al. 2015), particularly the finite-element, bounded-variation, vector autoregressive factor method (FEM-BV-VARX) that allows both autoregressive dynamics within individual regimes and modulation of regime variability by external variables. In a recent analysis, Vercauteren and Klein (2015) used FEM-BV-VARX to characterize the interaction of turbulence with submesoscale, non-turbulent motions. This work, which was carried out as the first step in the development of parameterizations of intermittent, submeso-induced turbulence, would naturally inform the improvement of the highly simplified parameterizations used in Monahan et al. (2011) and He et al. (2012).

The HMM analysis presented in this study modeled the data distribution within any hidden state as multivariate Gaussian. In fact, the conditional distributions are not Gaussian, as is evident in the marginal distributions shown in Fig. 4. The conditional wind speed PDFs, in particular, display distinct skewness (generally positive at 10 m and either positive or negative at 200 m). The use of Gaussian distributions in the analysis is therefore an approximation, justified a posteriori by the clear regime separation that is found. Another direction of future research would be to repeat the HMM analysis using a parametric distribution allowing for the evident non-Gaussian structure in the marginal distributions. It
is not evident what form such a distribution would take, as no physically justified parametric distribution exists for wind speed [e.g., Monahan (2014); although the Weibull distribution is often used as an empirical fit], and the multivariate distribution would need to model both wind speeds at different altitudes and the potential temperature difference (all of which are correlated). Another natural question raised by the present study is the extent to which the regime structure characterized at Cabauw generalizes to other locations. The character of turbulence and flow in the stable ABL is strongly influenced by local conditions (e.g., Acevedo and Fitzjarrald 2003), so it may be expected that this regime structure is specific to the location under consideration. In particular, although the vicinity of the Cabauw tower is relatively flat, the structure of turbulence is still affected by the presence of internal boundary layers (e.g., Optis et al. 2014, 2015, manuscript submitted to Wind Energy). While this local sensitivity is almost certainly true in regards to the details of the regimes, there is evidence that their existence and general character occur more broadly than at this one location. Most of the studies documenting multiple regimes of stable ABL structure discussed earlier were conducted using data collected at locations other than Cabauw. Beyond this, the extended tail in the PDF of \( w_{10} \) under stable stratification, which we have interpreted in terms of the existence of these two regimes, is observed at many locations across the planet (He et al. 2010; Monahan et al. 2011). Extending the present analysis to other locations is another important direction of future study, although relatively few datasets exist with a long record of temporally high-resolution observations at multiple altitudes in the bottom few hundred meters of the atmosphere.

While the analysis presented in this study provides evidence regarding the feedback resulting in the separate regimes, it does not provide direct insight regarding transitions between these regimes. The transition from \( R_2 \) to \( R_1 \) resulting from the collapse of turbulence is expected to occur when the radiative loss of energy by the surface cannot be balanced by downward turbulent heat transport. The reverse transition is presumably driven by variations in geostrophic wind or cloud cover or by the intermittent turbulent events characteristic of the vSBL (e.g., Banta 2008; White 2009). These events can be driven by local processes, such as the increase in near-surface shear (e.g., Blumen et al. 2001; Van de Wiel et al. 2002a, 2012a) or the propagation of remote disturbances (e.g., Sun et al. 2002, 2004). Studies of intermittent turbulence in the vSBL indicate that there are often multiple such events during the night (e.g., Coulter and Doran 2002; Nakamura and Mahrt 2005). The fact that such events appear to be more common than transitions from \( R_1 \) to \( R_2 \) during a given night indicates that not all bursts of turbulence are sufficiently strong to break down the inversion (e.g., Acevedo and Fitzjarrald 2003). A more detailed consideration of the mechanisms responsible for regime transitions is a third interesting direction of future study.

7. Conclusions

This study used a two-state hidden Markov model to diagnose the structure of nocturnal boundary layer regimes from long observations of wind and temperature at the 213-m tower at Cabauw, Netherlands, and to classify individual 10-min observations into these two regimes. The regimes were found to correspond to a low–wind speed, strong-stratification, low-turbulence state (regime \( R_1 \)) and a high–wind speed, weak-stratification, high-turbulence state (regime \( R_2 \)). Furthermore, the regime structures separate two populations in the joint distribution of wind speed at 10 and 200 m. The probability distributions of both 10-min-averaged and turbulence variables in \( R_2 \) are similar to those observed during the day. Regime occupation statistics were found to co-vary with external forcing such that \( R_1 \) is more common under conditions of clear skies and low geostrophic wind speed, while \( R_2 \) is more representative of cloudy conditions and strong geostrophic winds. While no single turbulence or Reynolds-averaged quantity was found to separate these two states, it was found that they correspond well to the stable and unstable branches of the idealized Couette flow model of Van de Wiel et al. (2007, 2012a).

Further work is required to characterize in more detail the mechanisms responsible for transitions between these regimes [it is anticipated that no single mechanism is at work (cf. Mahrt 2014)] and to extend this analysis to other locations. This study provides further insight into the physical mechanisms controlling the probability distribution of near-surface wind speeds over land (He et al. 2010; Monahan et al. 2011; He et al. 2012, 2013), as well as variations of near-surface temperature and air quality (e.g., Salmond and McKendry 2005; Holtslag et al. 2013). Furthermore, it has provided clear evidence of regimes that can be interpreted as more than “prototypes” (cf. Mahrt 1998, 2014) and which are clearly present in the geometric structure of the distribution of near-surface flow and stratification and the temporal variability of these quantities.

Acknowledgments. The authors gratefully acknowledge the provision of 10-min-averaged tower data for this study by the Cabauw Experimental Site for Atmospheric
Research (CESAR) and the turbulence and geostrophic wind data by Fred Bosveld. We also thank Bas van de Wiel, Nikki Vercauteren, and one anonymous reviewer for their thoughtful comments, which improved this manuscript. AHM was supported by the Natural Sciences and Engineering Research Council of Canada (NSERC) Discovery Grant Program. TR and YH were supported by the NSERC CREATE Training Program in Interdisciplinary Climate Science.

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