Climatological Features of the Weakly and Very Stably Stratified Nocturnal Boundary Layers. Part I: State Variables Containing Information about Regime Occupation

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ABSTRACT

The atmospheric nocturnal stable boundary layer (SBL) can be classified into two distinct regimes: the weakly SBL (wSBL) with sustained turbulence and the very SBL (vSBL) with weak and intermittent turbulence. A hidden Markov model (HMM) analysis of the three-dimensional state-variable space of Reynolds-averaged mean dry static stability, mean wind speed, and wind speed shear is used to classify the SBL into these two regimes at nine different tower sites, in order to study long-term regime occupation and transition statistics. Both Reynolds-averaged mean data and measures of turbulence intensity (eddy variances) are separated in a physically meaningful way. In particular, fluctuations of the vertical wind component are found to be much smaller in the vSBL than in the wSBL. HMM analyses of these data using more than two SBL regimes do not result in robust results across measurement locations. To identify which meteorological state variables carry the information about regime occupation, the HMM analyses are repeated using different state-variable subsets. Reynolds-averaged measures of turbulence intensity (such as turbulence kinetic energy) at any observed altitude hold almost the same information as the original set, without adding any additional information. In contrast, both stratification and shear depend on surface information to capture regime transitions accurately. Use of information only in the bottom 10 m of the atmosphere is sufficient for HMM analyses to capture important information about regime occupation and transition statistics. It follows that the commonly measured 10-m wind speed is potentially a good indicator of regime occupation.

1. Introduction

Observations of the nocturnal stable boundary layer (SBL) show abrupt changes of physical properties, motivating a classification into physically distinct regimes. The simplest classification considers two regimes: one very stable with weak and intermittent turbulence, and another weakly stable with sustained turbulent activity (e.g., [Sun et al. 2012](#); [Vignon et al. 2017b](#)). Transitions between these regimes remain one of the least understood phenomena in the planetary atmospheric boundary layer (PBL) and challenge physical understanding as well as accurate simulation in weather and climate models ([Holtslag et al. 2013](#); [Mahrt 2014](#)). In this study the long-term statistics of these two regimes and their transitions are analyzed using long-term observational tower observations. Data from towers in different meteorological settings are used to assess the generality of these statistics.

A number of physical processes govern SBL dynamics, such as anisotropic turbulent mixing, radiative cooling, low-level-jet formation, gravity waves, katabatic flows, and fog or dew formation. Although the SBL has been extensively studied, many individual processes and their interactions are incompletely understood as non-stationarities of the flow and inhomogeneities of the surface allow a diversity of ambiguous interpretations of observations ([Mahrt 2007](#)), hindering developments of model parameterizations and resulting in errors of SBL representation in atmospheric models for weather and climate ([Dethloff et al. 2001](#); [Gerbig et al. 2008](#); [Bechtold et al. 2008](#); [Medeiros et al. 2011](#); [Kyselý and Plavcová 2012](#); [Tastula et al. 2012](#); [Stern et al. 2013](#); [Bosveld et al. 2014](#); [Stern et al. 2015](#)). Misrepresentation of the SBL includes unrealistic decoupling of the atmosphere from the surface resulting in runaway surface cooling ([Mahrt 1998b](#); [Walsh et al. 2008](#)); overestimation of the PBL height ([Bosveld et al. 2014](#)); and underestimation of the wind turning with height within the PBL ([Svensson and Holtslag 2009](#)), low-level-jet

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speed (Baas et al. 2009), or near-surface wind speed and temperature gradients (Edwards et al. 2011). Global and regional weather and climate models often use an artificially enhanced boundary layer drag under stable conditions in order to improve simulations of the large-scale flow (Holtslag et al. 2013). This approach has led to the introduction of long-tailed stability functions not justifiable by observations. In such models, turbulence is artificially sustained under very stable conditions.

Turbulence and its interactions with submesoscale motions (motions slightly larger than turbulence) are subgrid-scale phenomena for climate and weather modeling and will remain so for the foreseeable future. Submesoscale motions such as density currents, gravity waves, or microfronts have been found to initiate SBL regime transitions in several observational studies (e.g., Sun et al. 2002, 2004, 2012). Such motions can locally enhance the shear, resulting in the production of turbulence, which can propagate toward the surface. Gaining a better understanding of the mechanisms causing transitions within the SBL is important for simulations of nocturnal near-surface properties such as temperature structure, which controls the formation of fog and frost (Walters et al. 2007; Holtslag et al. 2013). This improvement accompanies a better representation of surface wind variability and wind extremes (He et al. 2010; Monahan et al. 2011; He et al. 2012). More accurate simulations of these properties are also important for simulations and assessments of pollutant dispersal, air quality (Salmond and McKendry 2005; Tomas et al. 2016), harvesting of wind energy (Storm and Basu 2010; Zhou and Chow 2012; Dörenkämper et al. 2015), and agricultural forecasts (Prabha et al. 2011; Holtslag et al. 2013).

Classification of data into separate regimes with different characteristics is a conceptual simplification that helps organize understanding of the physical processes present in the SBL. A range of different classification schemes of SBL regimes exists, based on different conceptualizations of what constitutes a regime. Based on the Reynolds-averaged mean state and turbulence intensity profiles, the most common classification scheme distinguishes between the weakly stable boundary layer (wSBL) and the very stable boundary layer (vSBL) (Mahrt 1998a; Acevedo and Fitzjarrald 2003; Mahrt 2014; van Hooijdonk et al. 2015; Monahan et al. 2015; Vercauteren and Klein 2015; Acevedo et al. 2016; Vignon et al. 2017b). The wSBL describes a regime of weakly stable stratification, often found under cloudy or overcast conditions or moderate to strong winds, with sustained turbulence due to mechanically driven shear instabilities. This regime conforms to the classical understanding of turbulence in the PBL with turbulent

quantities decreasing with height and near-surface profiles, which are well described by Monin–Obukhov similarity theory (MOST) in horizontally homogeneous conditions (e.g., Sorbjan 1986; Mahrt 1998b; Grachev et al. 2013). The vSBL, on the other hand, describes strong statically stable stratification, often under clear-sky conditions or relatively weak winds, with turbulence profiles that can be decoupled from the surface (Banta et al. 2007), turbulence intensities that can increase with height, or highly anisotropic turbulent motions (Mauritsen and Svensson 2007). The turbulence intensity is not continuous in this regime and MOST does not hold since turbulence quantities do not scale with the mean gradients (Sun et al. 2012), partially as a result of the fact that submesoscale motions lead to interactions with turbulence (e.g., Vercauteren and Klein 2015). In consequence, the turbulence intensity is nonstationary and intermittent.

Recent research has introduced the concept of an altitude-dependent wind speed threshold $U_{\min}$ separating the wSBL (for $U > U_{\min}$) from the vSBL (for $U < U_{\min}$). The existence of a threshold $U_{\min}$ was inspired by the concept of a maximum sustainable turbulent sensible heat flux that can balance the net radiative cooling of the surface (van de Wiel et al. 2007, 2012a,b; van Hooijdonk et al. 2015; Holdsworth et al. 2016). Evidence of two regimes that can be conceptually separated by $U_{\min}$ has been presented for the Royal Netherlands Meteorological Institute (KNMI) Cabauw observatory in the Netherlands (van Hooijdonk et al. 2015; van de Wiel et al. 2017) and Dome C in Antarctica (Vignon et al. 2017b). However, the existence of an unambiguous value of $U_{\min}$ is not clear as variations with different PBL conditions are evident across the different sites. Another proposed threshold was introduced to distinguish between strong turbulent and weak turbulent flow in the CASES-99 study (Sun et al. 2012). For wind speeds larger than the observed threshold, the turbulence kinetic energy (TKE) and the friction velocity u_* increase almost linearly with wind speed, while below the threshold the dependence on the wind speed is much weaker. A third wind speed threshold has been defined as the wind speed at which vertical gradients of TKE and u_* reverse sign (Acevedo et al. 2016). Above the threshold, near-surface TKE decreases with height implying a fully coupled boundary layer with turbulence that is mainly generated by shear near the surface. Below this threshold near-surface TKE initially increases with height away from the surface, characterizing a decoupled system where TKE is generated aloft and transported downward. Even though these definitions lead to different threshold values, they are based on the common physical concept of a regime

with sustained, mechanically driven shear turbulence distinguished from a regime with on average much weaker turbulence intensity.

A conceptual model by [van de Wiel et al. \(2017\)](#) provides further insight into the origins of two distinct SBL regimes defined in terms of Reynolds-averaged mean quantities. This model considers an equilibrium surface energy budget coupled to a bulk parameterization of atmospheric turbulent transport with fixed near-surface wind speed, such that all feedbacks between the atmosphere and the surface (e.g., strength of atmosphere–surface coupling) are described by a single parameter related to surface thermal conductivity. This model produces a characteristic strong increase in equilibrium inversion strength for winds weaker than a predicted value $U_{\min}$. The model also predicts the existence of multiple equilibria and fold bifurcations near the threshold wind speed for weak atmosphere–surface coupling. Behavior qualitatively similar to the predictions of this model is found in tower observations at Cabauw and Dome C. Even though the model is able to describe key aspects of the structural characteristics of the SBL regimes, it is highly idealized. In particular, it treats near-surface wind as a fixed external parameter rather than as being determined by the dynamics of the PBL itself.

Other classification schemes have suggested a third transitional regime (tSBL) separating the vSBL from the wSBL ([Mahrt 1998a, 2014](#)). In such schemes the vSBL is an extremely stable regime that is governed almost entirely by radiative fluxes such that turbulent fluxes are so weak that the soil heat flux comes nearly into balance with the energy loss at the surface ([van de Wiel et al. 2003](#)). Direct numerical simulations have also been interpreted in terms of a three-regime behavior ([Ansorge and Mellado 2014](#)). In their simulations, the wSBL shows only slightly weakened TKE profiles relative to neutral stratification, the tSBL shows significant decreases of 50% of integrated TKE, and the vSBL is characterized by an almost complete collapse of turbulence. A different set of three distinct regimes have been also hypothesized by [Sun et al. \(2012\)](#), in which the third regime is distinguished from the vSBL by the presence of intermittent top-down turbulent bursts.

A classification of the SBL into four different scaling regimes has also been proposed (e.g., [Grachev et al. 2005, 2008](#)): the wSBL, which obeys MOST; the transitional regime separating the wSBL from the vSBL in which MOST is not valid but can be redefined in a local similarity theory ([Nieuwstadt 1984](#)); the turbulent Ekman layer; and the intermittently turbulent Ekman layer. The latter two regimes, neither of which can be

described by similarity theories, are together associated with the vSBL. In such a classification scheme the non-dimensional parameter z/L (where z is the height above the surface and L is the Monin–Obukhov length) or the Richardson number (Ri ; e.g., [Kondo et al. 1978](#); [Mahrt 1998b, 1999](#)) act as natural separators of the different regimes. In particular, the vSBL corresponds to $Ri \geq Ri_{cr}$, where Ri_{cr} is the critical Richardson number. Even though such a Ri_{cr} is theoretically useful, observations, however, suggest that such number is absent as turbulent fluctuations, though decreasing with increasing stability, can persist beyond a Ri_{cr} (e.g., [Mauritsen and Svensson 2007](#)).

Recently, [Vercauteren and Klein \(2015\)](#) diagnosed four regimes in temporally high-resolution vertical velocity data using a clustering technique that allowed autoregressive dynamics within individual regimes and the modulation of regime frequency by external variables. The regimes are distinguished by different interactions of turbulence with submesoscale motions. Further consideration of the bulk Richardson number showed that two of these regimes can be associated with the wSBL and the other two with the vSBL.

While the two-regime behavior in Reynolds-averaged mean data and turbulence quantities (such as turbulence intensities or turbulent fluxes) separating the flow into wSBL and vSBL regimes is clear in many observational studies, evidence of more regimes in such quantities is lacking. Most of the classification schemes involving more than two regimes focus on details of turbulence or submeso variability.

No comprehensive theory explaining all aspects of the SBL behavior exists as yet. In particular, mechanisms controlling transitions in the SBL are not well understood, and clear precursors of transitions between regimes have yet to be found. As noted above, it is not clear that a generic wind speed threshold separating the wSBL from the vSBL is identifiable as under same wind conditions large differences in the turbulent fluxes can be observed. The attribution of different regimes to the same mean-state conditions complicates the systematic investigation of the dynamical processes.

An empirical approach to distinguishing between SBL regimes that allows for different regime occupations under the same observable conditions was introduced in [Monahan et al. \(2015\)](#). Using a statistical approach known as hidden Markov model (HMM) analysis, this study separated two distinct regimes in the state space spanned by Reynolds-averaged mean values of the mean wind speed, wind speed shear (between 200 and 10 m), and potential temperature difference (between 200 and 2 m) measured on the 213-m tower of KNMI Cabauw observatory. Their analysis

of the Reynolds-averaged mean states also showed a clear separation of turbulent fluxes in a one year sample into two distinct regimes: a wSBL with strong TKE and strong vertical turbulent transport in contrast to a vSBL with weak TKE and weak vertical turbulent transport (cf. Monahan et al. 2015, their Figs. 7 and 8). Vertical shear, dry static stratification, and mean wind are natural candidate variables to describe the physical system (e.g., van de Wiel et al. 2012a,b, 2017; van Hooijdonk et al. 2015; Monahan et al. 2015) because wind speeds at two observational levels contain information about the shear responsible for the production of TKE, and stable stratification for its transformation into gravitational potential energy. Furthermore, evidence was presented of the dependence of regime occupation on external drivers such as the pressure gradient force and cloud cover. A major limitation of the study of Monahan et al. (2015) was that they considered only data from the single location at Cabauw.

In the present study we investigate to what extent the results found by Monahan et al. (2015) can be generalized to other locations using long records from towers in a range of geographical and meteorological settings with the ultimate goal of obtaining representative climatologies of SBL regime occupation and regime transitions. We use the term “climatological” in this context to refer to the characterization of statistics from many years of observations. Therefore, we first determine what state-variable space and which configuration of the HMM analysis are appropriate to investigate long-term SBL behaviors. We also assess if a third robust and physically reasonable regime can be determined by an HMM analysis in Reynolds-averaged mean data, without considering the details of the turbulent flow. Additionally, we present a detailed analysis of which meteorological state variables contain information about the regime occupation with particular focus on regime transitions. Companion papers consider the long-term occupation and transition statistics of the regimes and influences of external drivers (Abraham and Monahan 2019a, hereafter AM19a); and the generic structures of state variables across all tower stations in persistent regimes and during regime transitions (Abraham and Monahan 2019b, hereafter AM19b). In a fourth paper we use the information about SBL regime statistics obtained in this study to propose a simple stochastic parameterization that allows the simulation of SBL regime dynamics (Abraham et al. 2019).

Throughout this whole paper series, we define regimes in the SBL on the basis of the variability of long-term Reynolds-averaged state variables. As such, the regimes we diagnose are not expected to exist in one-to-one

correspondence with regimes defined in terms of the details of turbulent and submesoscale flow.

The present study is organized as follows: After an overview of the data to be considered (section 2), a short introduction to the HMM is given (section 3). Results are presented in section 4, followed by conclusions in section 5.

2. Data

Observational datasets from nine different research towers measuring standard Reynolds-averaged meteorological state variables with a time resolution no coarser than 30 min are considered (Table 1). Observations of TKE and vertical fluxes are also available at three of these sites (Cabauw, Hamburg, and Los Alamos; Table 2). The nine experimental sites differ substantially in terms of their surface conditions, surrounding topography, and meteorological setting. Tables 1 and 2 present information regarding measurement heights, data record lengths, and time resolutions, alongside references describing the experimental sites in detail. The geographic locations are illustrated in Fig. 1. Here, we give a short introduction and point out the most pertinent differences among the sites. In particular, we distinguish between land-based, glacial-based, and sea-based stations.

The land-based stations are characterized by different local conditions. Both the Cabauw and Hamburg towers lie in flat, moist, grassland areas, although the Hamburg tower is affected by the nearby large metropolitan area of Hamburg. Even though the Cabauw site is in a relatively horizontally homogeneous environment, under very stable stratification effects of surface heterogeneities are observable (Optis et al. 2014). The Karlsruhe tower is located in the Rhine valley, a rather hilly, forested area north of the Karlsruhe urban area and due to the local flow patterns often in the lee of the city. The American sites are highly affected by the surrounding topography. The Boulder tower was located on a high plateau and was surrounded by a dry, agricultural, flat area east (and often in the lee) of the Rocky Mountains. This tower was decommissioned in 2017. The Los Alamos TA-6 tower site is located in a valley surrounded by mountain ranges.

At the Karlsruhe site some nights contain lower-level wind measurements of exactly 0 m s^{-1} . These nights are excluded from the analysis as wind speeds of exactly 0 m s^{-1} are unphysical artifacts of cup anemometers for very low wind speeds. Furthermore, such discrete values are problematic for the HMM analysis we perform because its state variables are assumed to be continuous random variables.

At the Hamburg site we exclude turbulence data for north winds (335° – 25°) because of clear evidence of mast

TABLE 1. Information about the different meteorological tower sites and their measurement heights sorted alphabetically from land-based, to glacial-based, to sea-based sites. Detailed information about the sites is presented in the cited references. The data are used for Reynolds-averaged (avg) mean values of wind speed W , wind direction α , temperature T , and pressure P .

Institute	References	Geolocation	Time period	Data	Avg (min)	Measurement heights (m)
Land-based tower sites						
Boulder Atmospheric Observatory (BAO), Boulder, Colorado	Kaimal and Gaynor (1983), Blumen (1984)	40.0500°N, 105.0038°W, 1584 m	2008–15	<i>P</i>	10	Surface
				<i>W</i>	10	10, 100, 300
				α	10	10, 100, 300
				<i>T</i>	10	10, 100, 300
Royal Netherlands Meteorological Institute (KNMI), Cabauw, Netherlands	Van Ulden and Wieringa (1996)	51.9700°N, 4.9262°E, −0.7 m	2001–15	<i>P</i>	10	Surface
				<i>W</i>	10	10, 20, 40, 80, 140, 200
				α	10	10, 20, 40, 80, 140, 200
				<i>T</i>	10	2, 10, 20, 40, 80, 140, 200
Meteorologisches Institut der Universität Hamburg (MI), Hamburg, Germany	Brümmer et al. (2012), Floors et al. (2015), Gryning et al. (2016)	53.5192°N, 10.1051°E, 0.3 m	2005–15	<i>P</i>	1	2
				<i>W</i>	1	10, 50, 110, 175, 250, 280
				α	1	10, 50, 110, 175, 250, 280
				<i>T</i>	1	2, 10, 50, 110, 175, 250, 280
Karlsruher Institut für Technologie (KIT) Karlsruhe, Germany	Kalthoff and Vogel (1992), Wenzel et al. (1997), Barthlott et al. (2003), Kohler et al. (2018)	49.0925°N, 8.4258°E, 110.4 m	2003–13	<i>P</i>	10	Surface
				<i>W</i>	10	2, 20, 30, 40, 50, 60, 80, 100, 130, 160, 200
				α	10	40, 100, 200
				<i>T</i>	10	2, 10, 30, 60, 100, 130, 160, 200
Los Alamos National Laboratory (LANL), Los Alamos, New Mexico	Bowen et al. (2000), Rishel et al. (2003)	35.8614°N, 106.3196°W, 2263 m	1995–2015	<i>P</i>	15	1.2
				<i>W</i>	15	11.5, 23, 46, 92
				α	15	11.5, 23, 46, 92
				<i>T</i>	15	1.2, 11.5, 23, 46, 92
Glacial-based tower sites						
Institut Polaire Français Paul-Émile Victor (IPEV), and Programma Nazionale Ricerche in Antartide (PNRA), Dome C, Antarctica	Genthon et al. (2010, 2013), Vignon et al. (2017a,b)	75.1000°S, 123.3000°E, 3233 m	2011–16	<i>P</i>	30	0.7
				<i>W</i>	30	1.3, 2.3, 3.5, 9, 18.2, 25.6, 32.9, 41.3
				α	30	1.3, 2.3, 3.5, 9, 18.2, 25.6, 32.9, 41.3
				<i>T</i>	30	0.9, 1.9, 2.9, 10.3, 17.7, 25, 32.4, 41.6
Sea-based tower sites						
Forschungs- und Entwicklungszentrum Fachhochschule Kiel GmbH, FINO-1, Germany	Beeken et al. (2008), Fischer et al. (2012)	54.0140°N, 6.5876°E, 0 m	2004–15	<i>P</i>	10	20, 90
				<i>W</i>	10	33, 40, 50, 60, 70, 80, 90, 100
				α	10	33, 40, 50, 60, 70, 80, 90
				<i>T</i>	10	30, 40, 50, 70, 100
Forschungs- und Entwicklungszentrum Fachhochschule Kiel GmbH, FINO-2, Germany	Dörenkämper et al. (2015)	55.0069°N, 13.1542°E, 0 m	2008–15	<i>P</i>	10	30, 90
				<i>W</i>	10	32, 42, 52, 62, 72, 82, 92, 102
				α	10	32, 42, 52, 62, 72, 82, 92
				<i>T</i>	10	30, 40, 50, 70, 99
Forschungs- und Entwicklungszentrum Fachhochschule Kiel GmbH, FINO-3, Germany	Fischer et al. (2012)	55.1950°N, 7.1583°E, 0 m	2010–15	<i>P</i>	10	23, 95
				<i>W</i>	10	30, 40, 50, 60, 70, 80, 90, 100
				α	10	29, 60, 100
				<i>T</i>	10	29, 55, 95

effects under very stable conditions. For the same reasons, we exclude turbulence data for wind directions between 280° and 340° at Cabauw.

The Dome C observatory is located on a flat ice–snow surface in the interior of the Antarctica glacial shield. This glacial-based site is therefore influenced by substantially different conditions than the other sites, including a higher albedo, a lower roughness length,

and long-lasting polar nights. The sensor measurement heights are variable due to changing snow heights. The heights quoted in Table 1 represent averages over the 5 years considered.

The sea-based stations considered are the offshore research platforms Forschungsplattform in Nord- und Ostsee (FINO), which are located in the North Sea (FINO-1 and FINO-3) and Baltic Sea (FINO-2).

TABLE 2. Information about the turbulence variables measured at the weather tower sites and their measurement heights. The data used are variances in the x direction σ_u , y direction σ_v , and z direction σ_w , as well as turbulent momentum fluxes $u'w'$ and $v'w'$, and heat flux $w'T'$.

Institute	Time period	Data	Avg (min)	Measurement heights (m)
Royal Netherlands Meteorological Institute (KNMI), Cabauw, Netherlands	July 2007–June 2008	σ_u	10	5, 60, 100, 180
		σ_v	10	5, 60, 100, 180
		σ_w	10	5, 60, 100, 180
		$u'w'$	10	5, 60, 100, 180
		$v'w'$	10	5, 60, 100, 180
		$w'T'$	10	5, 60, 100, 180
Meteorologisches Institut der Universität Hamburg (MI), Hamburg, Germany	2005–15	σ_u	1	10, 50, 110, 175, 250, 280
		σ_v	1	10, 50, 110, 175, 250, 280
		σ_w	1	10, 50, 110, 175, 250, 280
		$u'w'$	1	10, 50, 110, 175, 250, 280
		$v'w'$	1	10, 50, 110, 175, 250, 280
		$w'T'$	1	10, 50, 110, 175, 250, 280
Los Alamos National Laboratory (LANL), Los Alamos, New Mexico	1995–2015	$\sqrt{\sigma_u^2 + \sigma_v^2}$	15	11.5, 23, 46, 92
		σ_w	15	11.5, 23, 46, 92

Their meteorological measurements start at about 30 m above the lowest tidal level. As a result, actual heights of the measurements above the surface are variable due to tidal and wave height variations. The heat capacity of the water surface is considerably larger than that of the surfaces at all other sites considered in this study. At the FINO towers we exclude nights with statically unstable conditions (defined as nights with two or more unstable data points in a night) as under these common conditions at sea-based sites wind speed measurements have been found to be unreliable (Westerhellweg and Neumann 2012). Furthermore, at FINO-1 nights with primary wind directions between 280° and 340° are excluded due to mast interference effects. At the other stations such an exclusion is not necessary as three wind measurements at each level exist that are 120° apart from each other.

Data records at some towers contain missing measurements. While the HMM is able to accommodate records in discontinuous blocks (such as individual nights), it requires complete records within each block. If only a single data point is missing between two measurements, we choose to fill the gap by interpolating linearly in time. Nights with missing data sequences of more than one consecutive time step are excluded from the analysis.

Preliminary analyses for land-based stations showed that the first wSBL-to-vSBL transitions often occur during the evening transition, that is, just before or during sunset. To capture these first transitions, allowing for a complete analysis of the transition statistics, we define the duration of the night on the basis of the surface energy budget. Net radiative loss at the land surface leads to surface cooling and the inversion growth. Consequently, for those sites at which the sufficient suite of radiative flux measurements are made (Cabauw,

Hamburg, and Los Alamos), we define the beginning of the night as the time the net radiative surface flux Q_N [sum of upwelling and downwelling longwave radiation (LWR) and shortwave radiation (SWR)] becomes negative. The onset of the nights defined in this way is generally earlier than the actual sunset or the time that downwelling SWR becomes zero. For these three sites we find that our nighttime definition allows us to capture the timing of the first turbulence collapse. The regime sequence during the time after sunset is unaffected by considering times before sunset in the HMM analysis. Usually Q_N changes sign between 2 and 3 h before sunset, depending on season and the large-scale circulation. To capture the development for sites that do not measure all radiative components, we define nighttime at these locations (including the sea-based sites) as starting 2 h before actual sunset given by the date and geographical location.

To include information about directional wind shears in addition to scalar shears, wind components at height h across and along the wind at the highest observation height $h_{\max}$ are defined as

$$W_h \perp W_{h_{\max}} = W_h \sin(\alpha_{h_{\max}} - \alpha_h), \quad (1)$$

$$W_h \parallel W_{h_{\max}} = W_h \cos(\alpha_{h_{\max}} - \alpha_h), \quad (2)$$

where W and α are, respectively, the wind speed and direction. Defining the components along and across the flow of the highest measured altitude results in a parsimonious measure of directional shear independent of the wind direction, providing information about the coupling of the surface flow and higher levels. Monahan et al. (2015) only considered speed differences between altitudes.

FIG. 1. Scatterplot of nighttime three-dimensional state-variable space of mean wind speed [$0.5(W_h + W_{sfc})$, with h being closest to 100 m], scalar wind shear (ΔW), and static stability ($\Delta\Theta$) between observation levels closest to the surface and h for the nine different tower sites as depicted by the maps. The bivariate joint probability distributions [calculated with the multivariate kernel density estimation of O'Brien et al. (2014, 2016)] are shown for all data (black).

Static stabilities are calculated as the potential temperature (Θ) difference between two heights. Potential temperatures are calculated from observed temperature and surface pressure assuming hydrostatic equilibrium, an acceleration due to gravity of 9.81 m s^{-2} , a specific heat capacity of $1005 \text{ J kg}^{-1} \text{ K}^{-1}$, and the specific gas constant of $287 \text{ J kg}^{-1} \text{ K}^{-1}$.

We do not use humidity information in our analysis despite its general availability at the tower sites. A preliminary analysis indicated that water vapor has minor effects on the results of the HMM analysis, so we focus on dry static stability as the measurement for stratification. However, moisture content might have an important effect in lower latitudes. A lack of observational towers in these regions prevented us from addressing this question.

3. Brief summary of the hidden Markov model

We now present a brief overview of the HMM analysis. An in-depth description can be found in [Rabiner \(1989\)](#) and an illustrative example is given in [Monahan et al. \(2015\)](#).

HMMs are statistical models to systematically detect and characterize regime behavior by identifying an unobserved, or hidden, discrete Markov chain ($\mathbf{X} = \{x_1, x_2, \dots, x_T\}$) from a time series of observable state variables ($\mathbf{Y} = \{y_1, y_2, \dots, y_T\}$) of arbitrary dimension. While the term “hidden state sequence” is often used in the HMM literature to refer to the Markov chain $\mathbf{X}$, we will use the term regime sequence to avoid confusion with input state variables. The hidden regime sequence is also called the Viterbi path (VP). The regime affiliation at any time depends both on the instantaneous state of the input vector and on the history of the regime occupation. Here, we use the HMM as a classification scheme to allocate each time step of $\mathbf{Y}$ to different SBL regimes according to the VP. We also make use of information about regime dynamics by studying the stochastic transition matrix $\mathbf{Q}$ of the VP.

The HMM analysis simultaneously estimates its parameters, $\mathbf{Q}$ and conditional distributions of $\mathbf{Y}$, making use of the following assumptions:

- 1) Markov assumption: The value x_t depends exclusively on the previous value of x_{t-1} , so

$$P(x_t = i_t | x_{t-1} = i_{t-1}, x_{t-2} = i_{t-2}, \dots, x_0 = i_0) = \mathbf{Q}_{i_t i_{t-1}} \quad \forall t \quad \text{with} \quad i \in \{0, 1, \dots, K\}, \quad (3)$$

where the evolution of the system is governed by $\mathbf{Q}$ (a $K \times K$ matrix with K a predefined number of hidden regimes) such that $\sum_{i_t} \mathbf{Q}_{i_t i_{t-1}} = 1$.

- 2) Independence assumption: Conditioned on $\mathbf{X}$, values of $\mathbf{Y}$ are independent and identically distributed variables resulting in a probability of the observational data sequence of

$$P(\mathbf{Y}, \mathbf{X} | \Lambda) = \pi_i p\left(y_0 | x_0 = i_0, \lambda_{i_0}\right) \prod_{t=1}^T \mathbf{Q}_{i_t i_{t-1}} \times p\left(y_t | x_t = i_t, \lambda_{i_t}\right) \quad \text{with} \quad i \in \{0, 1, \dots, K\}, \quad (4)$$

where $\Lambda = \{\lambda_i, \pi_i, \mathbf{Q}\}_{i \in \{0, 1, \dots, K\}}$ is the full set of parameters describing the HMM analysis, for which $\{\lambda_i\}_{i \in \{0, 1, \dots, K\}}$ is the parameter set describing the probability distributions p of y_t conditioned on the regime i of x_t , and π_i is the probability that x_0 is in regime i .

- 3) Stationarity assumption: The analysis assumes that $\mathbf{Q}$ and $\{\lambda_i\}_{i \in \{0, 1, \dots, K\}}$ are time independent.

The HMM analysis requires specification of the number K of hidden regimes and the form of the conditional distributions in each hidden regime described by the parameter set λ_i . We chose K to be 2 and 3 corresponding to two- and three-regime SBL classification schemes as discussed in [section 1](#). Since continuous variables are evaluated, λ characterizes parametric pdfs. Usually, Gaussian distributions are chosen to describe the parametric pdfs: $\lambda_i = \{\mu_i, \Sigma_i\}$, where μ_i and Σ_i are the regime-dependent mean and covariance ([Monahan et al. 2015](#)). However, many variables observed in the PBL are highly non-Gaussian. In particular, the wind speed deviates substantially from Gaussianity (e.g., [Monahan 2007](#); [He et al. 2010, 2012, 2013](#); [Monahan et al. 2011](#); [Monahan 2018](#)). To account for non-Gaussianity, the regime-dependent pdfs can be extended to a Gaussian mixture model:

$$p(y_t | x_t = i) \sim \sum_{m=1}^M c_{i,m} \mathcal{N}(\mu_{i,m}, \Sigma_{i,m}), \quad (5)$$

where $c_{i,m}$, $\mu_{i,m}$, and $\Sigma_{i,m}$ are, respectively, the mixture coefficient, the mean, and the covariance of the m th Gaussian mixture dependent on the hidden regime i . By construction, $\sum_m c_{i,m} = 1$. The use of a Gaussian mixture pdf requires the specification of the number of constituent Gaussians. Here, a mixture of five additive Gaussians is chosen as trade-off between accurate representation of the real pdfs of the variables and computational time for the HMM expectation maximization algorithm. Furthermore, for a finite dataset the quality of parameter estimates is expected to decrease as the number of parameters is increased. The results we obtain are not

substantially different if we assume the conditional distributions within each regime to be Gaussian (cf. Monahan et al. 2015).

We also consider an HMM model using only single-altitude wind observations, for which we take the conditional pdfs to be two-parameter Weibull distribution:

$$p(y_t | x_t = i) = \frac{b_i}{a_i} \left(\frac{y_t}{a_i} \right)^{b_i-1} \exp \left[- \left(\frac{y_t}{a_i} \right)^{b_i} \right], \quad (6)$$

where a_i and b_i are the scale and shape parameters. We found the Weibull estimates to be robust to the choice of estimator, so we use the simple moment-based estimator based on the conditional mean μ_i and standard deviation σ_i :

$$a_i = \frac{\mu_i}{\Gamma(1 + 1/b_i)}, \quad b_i = \left(\frac{\mu_i}{\sigma_i} \right)^{1.086}, \quad (7)$$

with Γ denoting the gamma function (Monahan 2006).

The challenge of the HMM analysis is to estimate the full set of parameters $\Lambda = \{\mu_{i,m}, \Sigma_{i,m}, c_{i,m}, \mathbf{Q}\}$ from $\mathbf{Y}$. Starting from the probability of the observed time series conditioned on the parameters $P(\mathbf{Y}|\Lambda)$ and applying Bayes's theorem to obtain $P(\Lambda|\mathbf{Y})$, the problem reduces to a maximum-likelihood estimation, which can be iteratively solved to find local maxima via the expectation maximization algorithm (Dempster et al. 1977). Having estimated Λ , the most likely regime sequence (the VP) can be calculated.

The simplest HMM analysis algorithm requires a gap-free time series. As by definition the time series considered have gaps (from the end of one night to the beginning of the next), the algorithm for estimating Λ has to be modified. We assume that variables in successive nights are independent, which is a reasonable approximation for problems in the nocturnal PBL: during the morning transition the presence of the residual layer helps the inversion break down, and the increased entrainment buoyancy flux from the residual layer in the mixed layer causes a faster PBL depth growth resetting turbulent profiles of the PBL almost every day (Blay-Carreras et al. 2014). We assume that any dependence of subsequent nights due to slowly evolving large-scale forcing is negligible. Mathematically, the new concatenated observation sequence ($\mathbf{Y} = \{\mathbf{OS}_1, \mathbf{OS}_2, \dots, \mathbf{OS}_N\}$, where N is the number of nights, and $\mathbf{OS}_n$ the observational vector in each night) then satisfies

$$P(\mathbf{Y}|\Lambda) = \prod_{n=1}^N P(\mathbf{OS}_n | \Lambda) = \prod_{n=1}^N P_n. \quad (8)$$

The estimation of the parameters in the expectation-maximization scheme for such an analysis is described in detail in Rabiner (1989).

4. Results

Motivated by Monahan et al. (2015), we first consider two-regime HMM models based on stratification, scalar wind speed shear, and depth-averaged flow at the different towers. We further address the question of whether a third regime can be robustly identified in the meteorological observations of the Reynolds-averaged mean and turbulence intensity data that we consider. We then investigate which state-variable spaces hold the majority of the hidden regime information, with a particular focus on SBL transitions. In this study, while for simplicity we often refer to the wSBL-to-vSBL transition as “turbulence collapse,” it should be kept in mind that while turbulence intensity is normally small in the vSBL this state is characterized by intermittent turbulent bursts.

a. Generic structure of the two-regime SBL

Monahan et al. (2015) have characterized the wSBL and vSBL using an HMM analysis with the three-dimensional state-variable input of wind speed shear and mean wind speed (both between 200 and 10 m), and dry static stability (between 200 and 2 m) at Cabauw. We assess the generality of these results by repeating the analysis at different tower sites. A difficulty with direct comparison is the fact that the different datasets do not share a common set of measurements or measuring altitudes. To obtain the most direct comparison of results at the nine different tower sites, data at the heights of observation levels closest to the surface (as 10-m state variables are not available for all towers) and to 100 m are used. The exception to this approach is Dome C, where the SBL is so shallow that measurements at 1 and 10 m are used.

Inspection of three-dimensional scatterplots shows two evidently distinct populations in the distribution of Reynolds-averaged mean states in the SBL at all sites (Fig. 1; cf. also Fig. 2 in Monahan et al. 2015), corresponding to one branch with very strong static stability and weak winds and to a second branch with strong winds and very weak static stability. We interpret these branches as corresponding, respectively, to the vSBL and the wSBL. The evident two-branch structure is found independent of the underlying surface type, meteorological setting, or the complexity of the surrounding area.

The bivariate pdf estimates in Fig. 1 show that Cabauw, Hamburg, Karlsruhe, Los Alamos, and

FIG. 2. As in Fig. 1, but with the scatter conditioned on HMM regimes wSBL in green and vSBL in red for the nine different tower sites.

Dome C exhibit hints of a threshold in vertical-mean wind speed separating the wSBL and vSBL populations. Such a clear regime contrast with respect to the vertical-mean wind speed corresponds well with the concept of a $U_{\min}$ below which mechanically driven turbulent mixing becomes sufficiently weak that a strong inversion can form. The other sites show a much broader domain where strong stratification can be found for moderate wind speeds. The European midlatitude land-based stations agree both in scatterplot structure and

inversion strength values. The similarity is likely due to comparable surface properties as these towers are built in cropped grasslands. As shown in the conceptual model of [van de Wiel et al. \(2017\)](#) the energetic coupling between the surface and the lower boundary layer strongly influences the inversion strength.

Even though the Boulder and Los Alamos sites experience different meteorological processes from most European land-based sites (e.g., mountain and valley breezes, katabatic winds, density currents), which can

TABLE 3. Transition probability matrices for two [$\mathbf{Q}(K = 2)$] and three [$\mathbf{Q}(K = 3)$] hidden regimes in the HMM, using mean wind speeds, scalar wind shears, and static stabilities between the surface and observational levels nearest to 100 m (10 m at Dome C) for different tower sites. Asterisks denote the regime from which the transition is coming. Transition probabilities at Hamburg, Los Alamos, and Dome C are transformed to a 10-min time resolution, as described in the text.

Tower site	Observations	$\mathbf{Q}(K = 2)$			$\mathbf{Q}(K = 3)$			
Land-based tower sites								
Boulder	$\mathbf{Y}_{\text{Boulder}} = [W_{100} - W_{10}, 0.5(W_{100} + W_{10}), \Theta_{100} - \Theta_{10}]$		wSBL	vSBL		wSBL	tSBL	vSBL
		wSBL*	0.9570	0.0430	wSBL*	0.9687	0.0278	0.0035
		vSBL*	0.0268	0.9732	tSBL*	0.0308	0.9324	0.0368
Cabauw	$\mathbf{Y}_{\text{Cabauw}} = [W_{80} - W_{10}, 0.5(W_{80} + W_{10}), \Theta_{80} - \Theta_2]$		wSBL	vSBL		wSBL	tSBL	vSBL
		wSBL*	0.9834	0.0166	wSBL*	0.9791	0.0209	0.0000
		vSBL*	0.0190	0.9810	tSBL*	0.0148	0.9620	0.0232
Hamburg	$\mathbf{Y}_{\text{Hamburg}} = [W_{110} - W_{10}, 0.5(W_{110} + W_{10}), \Theta_{110} - \Theta_2]$		wSBL	vSBL		wSBL	tSBL	vSBL
		wSBL*	0.9786	0.0214	wSBL*	0.9559	0.0435	0.0006
		vSBL*	0.0389	0.9611	tSBL*	0.0464	0.9234	0.0302
Karlsruhe	$\mathbf{Y}_{\text{Karlsruhe}} = [W_{100} - W_2, 0.5(W_{100} + W_2), \Theta_{100} - \Theta_2]$		wSBL	vSBL		wSBL	tSBL	vSBL
		wSBL*	0.9782	0.0218	wSBL*	0.9708	0.0290	0.0002
		vSBL*	0.0457	0.9543	tSBL*	0.0197	0.9483	0.0320
Los Alamos	$\mathbf{Y}_{\text{LosAlamos}} = [W_{92} - W_{11.5}, 0.5(W_{92} + W_{11.5}), \Theta_{92} - \Theta_{1.2}]$		wSBL	vSBL		wSBL	tSBL	vSBL
		wSBL*	0.9662	0.0338	wSBL*	0.9770	0.0091	0.0139
		vSBL*	0.0231	0.9769	tSBL*	0.0153	0.9534	0.0313
					vSBL*	0.0044	0.0127	0.9829
Glacial-based tower sites								
Dome C	$\mathbf{Y}_{\text{DomeC}} = [W_9 - W_{1.3}, 0.5(W_9 + W_{1.3}), \Theta_{10.3} - \Theta_{0.9}]$		wSBL	vSBL		wSBL	tSBL	vSBL
		wSBL*	0.9916	0.0084	wSBL*	0.9897	0.0094	0.0009
		vSBL*	0.0076	0.9924	tSBL*	0.0109	0.9770	0.0121
					vSBL*	0.0017	0.0120	0.9863
Sea-based tower sites								
FINO-1	$\mathbf{Y}_{\text{FINO-1}} = [W_{100} - W_{33}, 0.5(W_{100} + W_{33}), \Theta_{100} - \Theta_{30}]$		wSBL	vSBL		wSBL	tSBL	vSBL
		wSBL*	0.9833	0.0167	wSBL*	0.9777	0.0104	0.0119
		vSBL*	0.0232	0.9768	tSBL*	0.0111	0.9743	0.0146
FINO-2	$\mathbf{Y}_{\text{FINO-2}} = [W_{102} - W_{32}, 0.5(W_{102} + W_{33}), \Theta_{99} - \Theta_{30}]$		wSBL	vSBL		wSBL	tSBL	vSBL
		wSBL*	0.9908	0.0092	wSBL*	0.9674	0.0163	0.0162
		vSBL*	0.0138	0.9862	tSBL*	0.0101	0.9874	0.0025
FINO-3	$\mathbf{Y}_{\text{FINO-3}} = [W_{100} - W_{30}, 0.5(W_{100} + W_{30}), \Theta_{95} - \Theta_{29}]$		wSBL	vSBL		wSBL	tSBL	vSBL
		wSBL*	0.9918	0.0082	wSBL*	0.9734	0.0183	0.0083
		vSBL*	0.0157	0.9843	tSBL*	0.0152	0.9832	0.0016
					vSBL*	0.0163	0.0029	0.9808

substantially affect the local stability, the two-regime structure is evident. At Boulder the structures of the two regimes overlap considerably with a high density of data points in the region of low static stability and low wind speeds. This observation could be related to Boulder tower's location in the plateau east of the Rocky Mountains, where mountain processes can lead to enhanced mixing in the boundary layer causing a blurring of the two populations. The inversion strengths at both sites are similar to those at European sites.

At Dome C the coupling with the underlying ice–snow surface leads to very strong inversion strengths. The low thermal conductivity of the ice–snow surface leads to

strong radiative cooling at the surface, enhanced by the low atmospheric water vapor content resulting in efficient LWR energy loss to space. The values of the largest potential temperature differences across the first 10 m are more than twice what is measured at the mid-latitude land-based stations across the bottom 100 m.

Evidently, the inversion strengths at sea-based FINO sites are only about half as strong as over land. Over water surface cooling is ineffective due to the large surface heat capacity of the water. Instead, at these stations the vSBL is established by the advection of warm air aloft (Dörenkämper et al. 2015; AM19b). The sites show broadly similar structures, in particular

FIG. 3. Joint probability density functions of 10-m wind speeds and $\log_{10}(\text{TKE})$ values (first column) near the surface and (third column) near 100 m and probability density function of the velocity aspect ratio $\{3\text{var}(w)/[\text{var}(u) + \text{var}(v) + \text{var}(w)]$ of turbulence (VAR_{turb}) (second column) near the surface and (fourth column) near 100 m at Cabauw, Hamburg, and Los Alamos. Distributions using all data are shown in black, while distributions conditioned on wSBL and vSBL are, respectively, shown in green and red. All pdfs are calculated with the multivariate kernel density estimation by O'Brien et al. (2014, 2016).

FINO-1 and FINO-3, which are both located in the North Sea. FINO-2 is surrounded by landmasses in all compass directions and so is particularly influenced by advection of air aloft from the mainland (Dörenkämper et al. 2015), which causes slightly stronger inversions than occur at FINO-1 and FINO-3. A direct comparison of the structures at these sea-based stations to those of the land-based sites is further complicated by the fact that the observations start 30 m above the sea surface at low tide. In addition to the absence of near-surface observations, the measurement heights above the surface are variable due to tidal and surface wave variations. These variations contribute a kind of variability not seen at other stations and likely blur the two-branch structure.

The HMM analyses at all locations considered separate the vSBL branch with a strong inversion and weak wind speeds from the wSBL branch (Fig. 2). In this figure, points in the scatter associated with the different regimes are represented by different colors. The HMM classification is particularly useful for distinguishing the SBL regimes in regions of the state space with low wind speeds and weak inversion strengths where the regimes overlap. The conditional joint pdfs of mean wind speed and inversion strength show no clear wind speed threshold separating the regimes. Similarly, a common stratification threshold

is absent. While at Cabauw, Hamburg, Los Alamos, and Dome C conditions of very weak dry static stability (smaller than 1 K) are never classified as being part of the vSBL, such a hard stratification threshold is not apparent at the other sites. The possibility exists that the populations would be clearly separated in a higher-dimensional state-variable space. However, we were unable to find such a space with the available state variables.

To compare transition matrices between sites, we bring these matrices to a common time resolution of 10 min by the transformation $\mathbf{Q}^{10/T}$ with $T = 1, 15, 30$, for Hamburg (1-min resolution), Los Alamos (15-min resolution), and Dome C (30-min resolution), respectively. The two-regime $\mathbf{Q}$ values (Table 3) are similar for the different tower sites. We analyze the sensitivity of the VPs to $\mathbf{Q}$ in Abraham et al. (2019).

The turbulence intensities are separated in a physically meaningful way by the HMM sequence of the Reynolds-averaged mean data (Fig. 3). Large values of TKE are found in the wSBL while very low TKE values are found in the vSBL. Again, no clear wind speed threshold separates these states as for intermediate wind speeds the conditional joint pdfs of TKE and wind speed at 10 m (W_{10}) overlap. Across all tower sites, consideration of measurement altitudes other than illustrated in Fig. 3 show qualitatively similar results in

FIG. 4. Probability density functions of the variance of the vertical wind component w (left) near the surface and (right) near 100 m for all data (black), wSBL (green), and vSBL (red) at Cabauw, Hamburg, and Los Alamos. All pdfs are calculated with the multivariate kernel density estimation by O'Brien et al. (2014, 2016).

joint and conditional joint pdfs of wind speeds and TKE values.

Under very stable conditions vertical turbulent motions are suppressed causing the fluctuations in the vertical to be smaller than those in the horizontal. We measure this effect by the velocity aspect ratio $3\text{var}(w)/[\text{var}(u) + \text{var}(v) + \text{var}(w)]$, where u , v , and w are, respectively, zonal, meridional, and vertical wind components. This measure should take a value of 1 for isotropic turbulence. The velocity aspect ratio measurements have smaller values near the surface than around 100 m (Fig. 3, cf. columns 2 and 4), which is reasonable due to the fact that the shears near the surface are stronger (e.g., Kline et al. 1967; Kim et al. 1971; Moin and Kim 1982; Lee et al. 1990). At Cabauw the pdfs of the velocity aspect ratio at the measuring

altitudes at 5 and 100 m show a maximum and a shoulder naturally separated by conditioning on the two HMM regimes. This separation is more evident at higher altitudes. While hints of this behavior are noticeable at the other stations, at Hamburg the conditional pdfs of the velocity aspect ratio are not separated near the surface and only very weakly separated at 110 m. At Los Alamos times of small aspect ratio are exclusively affiliated with the vSBL, although the conditional pdfs overlap substantially. One difficulty with this velocity aspect ratio measurement is that the time intervals to obtain variances differ between the stations (1, 10, and 15 min for, respectively, Hamburg, Cabauw, and Los Alamos). Longer averaging intervals most certainly include nonturbulent motions in variance calculations (e.g., Vercauteren et al. 2016; Stiperski and Calaf 2018).

FIG. 5. Scatterplots of the nighttime three-dimensional state-variable space of mean wind speed $[0.5(W_h + W_{sfc})]$, with h being closest to 100 m], scalar wind shear (ΔW) , and static stability $(\Delta\Theta)$ between observation levels closest to the surface and to h for the nine different tower sites that are (top to bottom) land-based, glacial-based, and sea-based stations. (first column) Unclassified nighttime data (black). (second column) Data as clustered into the wSBL (green) and vSBL (red) by the HMM analysis with two hidden regimes for the three-dimensional state-variable space. (third column) Data as clustered into the wSBL (green) and vSBL (red) by the HMM analysis with two

At the Hamburg site data are measured over the shortest time intervals and thus likely contain the smallest contribution of submesoscale motions at the three locations. This fact may be the reason why the pdfs of the velocity aspect ratio are not separated between the two regimes.

While this measure of turbulent velocity aspect ratio is not clearly separated between regimes, $\text{var}(w)$ values are evidently separated into the vSBL and wSBL across all stations and all measurement heights (Fig. 4). In the vSBL vertical fluctuations are very weak with probability concentrated near zero. Vertical wind fluctuations classified to be in the wSBL, on the other hand, solely populate the long tails of the distributions.

b. The three-regime SBL

While at least two distinct populations of SBL structure are evident from the two branches in scatterplots of mean wind speed, wind speed shear, and stratification, no obvious third population is apparent (Fig. 5, column 1). Furthermore, no third cluster is evident in the distributions of Reynolds-averaged turbulence intensity measures such as TKE or $\text{var}(w)$ (Figs. 3 and 4).

To further investigate if there is evidence of a robust third HMM regime in the data we consider, the analysis is repeated using $K = 3$. As our indicator of robustness, we assess if the third HMM regime is consistent across locations (as the regimes in the two-regime classification are). We choose this relatively subjective approach rather than the use of information criteria (such as those of Akaike or Bayes) to emphasize features of SBL variability that are common among measurement locations. We find that the structure of the three HMM regimes is less evidently meaningful than regime structures in the two-regime SBL. First, in contrast to the two-regime SBL, no robust structure identifying a third HMM regime appears across the tower sites considered (Fig. 5, column 4). At Cabauw and Hamburg, for instance, in the three-dimensional state-variable space analyzed here the third regime is located between a vSBL and wSBL and consists of data points from both the wSBL and vSBL as classified by a two-regime HMM analysis. For Boulder, Los Alamos, and Dome C the two-regime vSBL is cut in half with the third regime populating the weaker stratification values. At Karlsruhe, the wSBL as classified

by the two-regime SBL is divided into two regimes by a third regime. The sea-based stations show a completely different three-regime SBL structure. While the third regime at the land- and glacial-based stations populates the space of weak stratification combined with weak winds, at sea-based sites it corresponds to very weak to neutral stratification across a broad range of wind speeds. Based on the criteria we use to define regimes, no consistent three-regime structure is evident across sites. The joint pdfs of TKE and surface winds exhibit also no robust structure in a three-regime SBL. Neither can physically reasonable thresholds in the pdfs be detected (as substantial overlaps of all three regimes for intermediate values of TKE and wind speeds exist) nor is a consistent allocation of turbulence data across the towers into three regimes apparent (not shown).

If we interpret a third regime as transitional (tSBL), separating the wSBL from the vSBL (Mahrt 1998a, 2014; Anson and Mellado 2014), it is natural to expect that the system must pass through the tSBL in the transition from the wSBL into the vSBL. Rather than an abrupt change, this transition is expected to be a gradually evolving process in which the gradual strengthening of the inversion suppresses vertical fluxes, which in turn increases the inversion strength further (van Hooijdonk et al. 2017). In such a framework the probability of a regime transition from the wSBL to the vSBL [$P(\text{wSBL} \rightarrow \text{vSBL})$] would be expected to be zero and the regime persistence (transition probability to remain in the same regime) of the tSBL [$P(\text{tSBL} \rightarrow \text{tSBL})$] should be lower than those of $P(\text{wSBL} \rightarrow \text{wSBL})$ or $P(\text{vSBL} \rightarrow \text{vSBL})$. On the other hand, nonzero values of $P(\text{vSBL} \rightarrow \text{wSBL})$, interpreted as the sudden recovery of sustained turbulence (due to strong intermittent turbulence events or changes in external forcing), are consistent with this picture. The stochastic matrix at Cabauw shows such a structure (Table 3, column 4). At all other tower sites, however, $P(\text{wSBL} \rightarrow \text{vSBL})$ values are larger than zero. Even at the original time resolution of 1 min, which should be short enough to capture all transitions, $P(\text{wSBL} \rightarrow \text{vSBL})$ is larger than zero at Hamburg (corresponding to approximately two events per year). Moreover, at Karlsruhe and the sea-based sites, $P(\text{tSBL} \rightarrow \text{tSBL})$ is larger than $P(\text{vSBL} \rightarrow \text{vSBL})$. A simple exchange of these two regimes (as the HMM analysis identifies the regimes

←

hidden regimes for the one-dimensional state-variable space of the observation level closest to 10 m using the WHMM. (fourth column) Data as clustered into the wSBL (green), tSBL (blue), and vSBL (red) by the HMM analysis with three hidden regimes for the three-dimensional state-variable space.

but the interpretation is ours) does not compensate this result because under such conditions the tSBL would be populated by larger inversion strengths than the vSBL. At sea-based stations the tSBL is the most persistent regime of all.

Finally, and in marked contrast to the two-regime HMM results, composites of TKE across times of transitions (discussed in detail in AM19b) do not show systematic behavior distinguishing the tSBL from the vSBL (at Cabauw, Hamburg, and Los Alamos, those sites with turbulence records). While the two-regime SBL shows a systematic and substantial reduction in TKE at times of collapse, no such structure is evident for the three-regime SBL.

For these reasons the third regime as classified by the HMM on the basis of Reynolds-averaged mean data is neither in general naturally interpreted as a tSBL in the sense of Mahrt (1998a, 2014) or Anson and Mellado (2014) nor as a regime with turbulent burst under very stable conditions (e.g., Sun et al. 2012). The broad distribution of TKE in the vSBL regime suggests that this regime includes such intermittent turbulence events, which our HMM analysis does not partition into a third distinct regime. Such a distinction would perhaps be made if the analysis were performed on temporally higher-resolution data, which allow consideration of the detailed turbulence and submeso variability.

The structure of the three-regime SBL is also not very robust if other observational levels are used to define the three-dimensional state space for the HMM analysis. While structures of the two-regime analyses at the different tower sites do not change qualitatively using different observational levels (as discussed in the next section), substantial changes in the regime structure occur when a three-regime model is used (not shown). We conclude that for three hidden regimes no generic or meaningful structure can be found using the HMM analysis on the basis of the long-term Reynolds-averaged mean data. A similar result was found when increasing the number of hidden states beyond three. As a result, the rest of our analysis will focus on the two-regime model in developing to determine long-term statistics of the SBL regimes for the data we consider. As mentioned above our results do not exclude other classification schemes clustering the SBL on the basis of turbulence and submeso variability or of turbulence interactions with the mean flow.

c. Reference state-variable set for the HMM analysis

The HMM analysis presented above shows that the three state variables of Reynolds-averaged mean

stratification, vertical-mean wind speed, and wind speed shear produce a two-regime classification of the SBL that is robust across tower sites. We will now investigate which single variables or combinations of variables carry the majority of SBL regime occupation information. To do this, we must first establish a reference state-variable set against which HMM analyses using other input can be compared. It is expected that HMM analyses using different sets of state variables will lead to different VPs, and we do not have an external reference for the “true” sequence of regime occupation. Hence, our reference state variables from the observational data available must be defined empirically, guided by physical reasoning.

Shear, stratification, and mean wind are natural variables to describe the turbulence energy budget and therefore the state of the boundary layer (e.g., van de Wiel et al. 2012a,b, 2017; van Hooijdonk et al. 2015; Monahan et al. 2015). However, the possibility exists that main information regarding the VP might exist in a lower-dimensional subspace of the original variables, or in other variables. Increasing the dimensionality of the input vector, on the other hand, may include even more information about the SBL structure relevant to regime affiliation, and a more accurate VP estimate. For an arbitrarily long time series, the more relevant information the HMM is provided, the more accurate the VP should be. However, consideration of more complex models for time series of fixed duration also results in an increasing influence of sampling variability on the estimation of the HMM parameters. In the following we analyze the dependence of HMM regime structure on input data using the Cabauw dataset because its long and gap-free character at all measurement heights allows for a thorough analysis of various combinations of meteorological state variables. We find qualitatively similar results at the other tower sites. The reference variable set at Cabauw is found to be $\mathbf{Y}_{\text{ref}} = [W_{200} - W_{10}, 0.5(W_{200} + W_{10}), \Theta_{200} - \Theta_2]$, the same set as was used in Monahan et al. (2015). Reference models for the other tower sites are determined following the same approach described below and are listed in Table 5.

As our first criterion for determining the reference model we consider VP robustness, defined as how well the HMM analysis of random daily subsamples of the time series reproduce the VP of the full dataset. Second, we assess the robustness of $\mathbf{Q}$ obtained from data subsamples. Third, we consider how well nights remaining in one regime throughout the entire night (“very persistent nights”) are modeled. Finally, we assess the robustness of the timing of transitions between the wSBL and vSBL considering a time window based on the maximum time lag between the lower

and upper parts of the observed PBL to experience the impacts of a transition. At Cabauw, the time window is ± 30 min.

We found that increasing the state-variable space to include variables such as wind speed and stratification at all available levels, shears of the along- and across-wind components, or surface pressures lead to essentially the same results as $\mathbf{Y}_{\text{ref}}$. Reducing the number of state variables, on the other hand, can result in substantial changes in $\mathbf{Q}$ and the VP. The reference variables set $\mathbf{Y}_{\text{ref}}$ therefore describes a minimal state-variable space for characterizing wSBL and vSBL occupation and transitions.

Finally, to justify the focus on shear and stratification as proxies for the TKE budget, we investigate the HMM structure obtained from the Reynolds-averaged turbulence data available at Cabauw, Hamburg, and Los Alamos (not shown). We find that at each location an HMM analysis with $\text{var}(w)$ at two measurement heights (as a measure of turbulence intensity, which is not contaminated by nonturbulent horizontal motions) estimates almost exactly the same VP and $\mathbf{Q}$ as the reference HMM, further justifying the choice of $\mathbf{Y}_{\text{ref}}$.

d. Regime occupation information at different altitudes

Having defined the reference models, we now investigate the Cabauw regime paths relative to those of the reference state-variable spaces using data at varying measurement heights in order to assess where regime information resides. Preliminary analyses indicated the importance of always including surface values in these calculations. Therefore, we choose the HMM inputs to be $\mathbf{Y}_{\text{obs}} = [W_{h_W} - W_{10}, 0.5(W_{h_W} + W_{10}), \Theta_{h_\Theta} - \Theta_2]$, where h_W and h_Θ are the upper altitudes of wind speed shear and stratification calculations.

Changing the values of h_Θ , h_W can result in substantially different VPs from that of the reference (Fig. 6). We find that h_Θ must be above 80 m in order to produce VP consistencies of more than 90% and to capture more than 70% of the turbulence collapse and recovery events. If only stratification information below 80 m is used, VP and transition consistencies are smaller irrespective of the wind information provided. Very persistent wSBL nights are well captured by all combinations of h_Θ and h_W information, demonstrating how prevalent the signal is in all parts of the observed PBL in these conditions with generally strong winds (AM19b). Very persistent vSBL nights, however, are not captured well using only information below 140 m. With lower altitudes of h_Θ , h_W the HMM estimates transitions toward the vSBL at later times than

the reference model. A possible explanation could be that under low wind conditions combined with warm-air advection aloft, conditions known to appear at Cabauw (Optis and Monahan 2017), the regime transition diagnosed using near-surface information does not account for the advective enhancement of stratification and the transition to the vSBL is delayed.

Taking h_W above 40 m results in evident improvements of the accuracy of the timing of the transitions relative to using lower measurement heights. This improvement might be related to the fact that the two regime transitions show opposite wind speed tendencies in the lower and upper levels as the flow changes between coupled and uncoupled flow. Van de Wiel et al. (2012a) find the velocity crossing point (at which changes in wind speed over the night are smallest) to lie between 20 and 50 m at Cabauw, consistent with the improvement in our results when h_W is above 40 m.

The importance of using h_Θ above 80 m can also be seen in the difference between $\mathbf{Q}_{\text{obs}}$ and $\mathbf{Q}_{\text{ref}}$ for $P(\text{wSBL} \rightarrow \text{wSBL})$ (Fig. 6, bottom panels). These differences decrease abruptly when h_Θ is increased above 80 m. This result is presumably due to the larger potential temperature contrast over larger differences in altitude. Even though near-surface temperature gradients in the established wSBL or vSBL differ substantially, at the times of transitions a strong difference in the near-surface temperature profile is not evident (AM19b).

In general, the differences $\mathbf{Q}_{\text{obs}} - \mathbf{Q}_{\text{ref}}$ reveal that use of wind and potential temperature information below 200 m results in a less persistent vSBL and a generally more persistent wSBL, consistent with the differences in the accuracy of the classification of nights without transitions. Absolute values of differences in $P(\text{wSBL} \rightarrow \text{vSBL})$ between $\mathbf{Q}_{\text{obs}}$ and $\mathbf{Q}_{\text{ref}}$ are mostly smaller than those of $P(\text{vSBL} \rightarrow \text{wSBL})$, so transitions leading to turbulence collapse are better captured using lower-altitude data (relative to the reference model) than are turbulence recovery transitions.

e. Regime occupation information in reference state-variable subspaces

We now investigate lower-dimensional state-variable sets in order to understand how much information is contained in the wind and potential temperature information separately. We conduct HMM analyses defining wind shear [$\mathbf{Y}_{\text{obs}} = W_{h(x)} - W_{h(y)}$; results below the diagonal in Fig. 7] and stratification [$\mathbf{Y}_{\text{obs}} = \Theta_{h(y)} - \Theta_{h(x)}$; results above the diagonal in Fig. 7] as well as analyses using one-dimensional state-variables spaces of wind speed [$\mathbf{Y}_{\text{obs}} = W_{h(x)}$; triangles with $h(x) = h(y)$ below the diagonal in Fig. 7] and potential temperature

FIG. 6. Comparison of HMM regime sequence paths of the three-dimensional state-variable space of mean wind speed, scalar wind shear between different heights (h_w), and static stability between different heights (h_θ) and the surface with the regime sequence path from the HMM analysis of $\mathbf{Y}_{\text{ref}} = [0.5(W_{200} + W_{10}), W_{200} - W_{10}, \Theta_{200} - \Theta_2]$ at Cabauw. (top left) Consistency of the Viterbi paths, (top center) accuracy of the wSBL to vSBL transitions (turbulence collapse), and (top right) accuracy of the vSBL to wSBL transitions (turbulence recovery). (middle) Consistency of nights remaining exclusively in the (left) wSBL and (right) vSBL. (bottom) Transition probability anomalies compared to the reference.

FIG. 7. Comparison of the HMM regime sequence paths of lower-dimensional state-variable spaces with HMM regime sequence paths of $\mathbf{Y}_{\text{ref}} = [0.5(W_{200} + W_{10}), W_{200} - W_{10}, \Theta_{200} - \Theta_2]$ at Cabauw. Above the diagonal line, stratification is calculated as $\Theta_{h(y)} - \Theta_{h(x)}$, and below the diagonal line, shear is calculated as $W_{h(x)} - W_{h(y)}$. Triangles above the diagonal line represent one-dimensional temperature, and triangles below the diagonal line represent one-dimensional wind speed. (top left) Consistency of the Viterbi paths, (top center) accuracy of the wSBL to vSBL transitions (turbulence collapse), and (top right) accuracy of the vSBL to wSBL transitions (turbulence recovery). (middle) Consistency of nights remaining exclusively in the (left) wSBL and (right) vSBL. (bottom) Transition probability anomalies compared to the reference.

TABLE 4. HMM analyses of different surface-based state-variable sets ($\mathbf{Y}$) at Cabauw compared to the reference $\{\mathbf{Y}_{\text{ref}} = [0.5(W_{200} + W_{10}), W_{200} - W_{10}, \Theta_{200} - \Theta_2]\}$ showing the agreement of Viterbi paths compared to the reference model for Cabauw (Cons.; %) as well as the accuracy of the wSBL to vSBL (Coll. acc.; %) and vSBL to wSBL (Recov. acc.; %), consistency of nights remaining exclusively in the wSBL (wSBL cons.; %) and vSBL (vSBL cons.; %), and the transition probability anomalies compared to $\mathbf{Q}_{\text{ref}}$. Starting regimes for the transition probabilities are denoted with an asterisk.

$\mathbf{Y}$	Viterbi path accuracy					$\mathbf{Q}$ anomaly to $\mathbf{Q}_{\text{ref}}$		
	Cons.	Coll. acc.	Recov. acc.	wSBL cons.	vSBL cons.			
W_{10}	81.33	18.67	23.03	59.76	92.24	wSBL*	0.0027	-0.0027
						vSBL*	-0.0067	0.0067
$\Theta_{10} - \Theta_2$	79.71	44.62	31.87	92.39	31.09	wSBL*	0.0029	-0.0029
						vSBL*	0.0108	-0.0108
$W_{10}, \Theta_{10} - \Theta_2$	84.80	49.41	39.09	93.33	57.09	wSBL	vSBL	
						wSBL*	0.0034	-0.0034
						vSBL*	0.0046	-0.0046
$W_{10} \parallel W_{200}, W_{10} \perp W_{200}$	85.31	29.39	32.05	64.16	95.72	wSBL	vSBL	
						wSBL*	0.0008	-0.0008
						vSBL*	-0.0055	-0.0055
$W_{10} \parallel W_{200}$	83.85	24.21	26.94	63.76	95.27	wSBL	vSBL	
						wSBL*	0.0025	-0.0025
						vSBL*	-0.0064	0.0064
$W_{10} \perp W_{200}$	42.63	3.80	9.14	4.55	26.07	wSBL	vSBL	
						wSBL*	-0.0150	0.0150
						vSBL*	0.0103	-0.0103
$W_{10} \parallel W_{200}, W_{10} \perp W_{200}, \Theta_{10} - \Theta_2$	88.41	61.77	50.45	93.49	55.91	wSBL	vSBL	
						wSBL*	0.0006	-0.0006
						vSBL*	0.0056	-0.0056
TKE ⁵	89.28	86.83	78.82	78.57	99.26	wSBL	vSBL	
						wSBL*	-0.0096	0.0096
						vSBL*	0.0064	-0.0064
W_{10}, TKE^5	87.55	68.29	67.06	67.86	99.75	wSBL	vSBL	
						wSBL*	-0.0057	0.0057
						vSBL*	-0.0002	0.0002
$\Theta_{10} - \Theta_2, \text{TKE}^5$	89.64	86.83	82.36	89.29	98.96	wSBL	vSBL	
						wSBL*	-0.0065	0.0065
						vSBL*	0.0092	-0.0092
$W_{10}, \Theta_{10} - \Theta_2, \text{TKE}^5$	90.21	86.83	79.41	80.36	99.28	wSBL	vSBL	
						wSBL*	-0.0109	0.0109
						vSBL*	0.0077	-0.0077
$\text{var}(w_5)$	91.38	89.56	88.73	93.42	99.60	wSBL	vSBL	
						wSBL*	-0.0043	0.0043
						vSBL*	0.0023	-0.0023
$W_{10}, \text{var}(w_5)$	86.88	60.00	60.00	66.07	99.91	wSBL	vSBL	
						wSBL*	-0.0026	0.0026
						vSBL*	-0.0024	0.0024
$\Theta_{10} - \Theta_2, \text{var}(w_5)$	90.86	89.27	85.29	91.07	99.18	wSBL	vSBL	
						wSBL*	-0.0046	0.0046
						vSBL*	0.0064	-0.0064
$W_{10}, \Theta_{10} - \Theta_2, \text{var}(w_5)$	91.14	87.80	79.41	83.93	99.53	wSBL	vSBL	
						wSBL*	-0.0046	0.0046
						vSBL*	0.0064	-0.0064
u^*	84.32	0.71	0.60	1.18	94.98	wSBL	vSBL	
						wSBL*	0.0026	-0.0026
						vSBL*	-0.0036	0.0036
W_{10}, u^*	82.63	0.67	0.60	0.94	95.20	wSBL	vSBL	
						wSBL*	0.0005	-0.0005
						vSBL*	-0.0047	0.0047

TABLE 4. (Continued)

$\mathbf{Y}$	Viterbi path accuracy					$\mathbf{Q}$ anomaly to $\mathbf{Q}_{\text{ref}}$		
	Cons.	Coll. acc.	Recov. acc.	wSBL cons.	vSBL cons.			
$\Theta_{10} - \Theta_2, u_*$	83.45	0.89	0.78	1.41	93.94	wSBL*	0.0029	−0.0029
						vSBL*	0.0076	−0.0076
$W_{10}, \Theta_{10} - \Theta_2, u_*$	84.24	0.78	0.78	1.33	94.17	wSBL	wSBL	vSBL
						wSBL*	0.0023	−0.0023
						vSBL*	0.0071	−0.0071

$[\mathbf{Y}_{\text{obs}} = \Theta_{h(x)}; \text{triangles with } h(x) = h(y) \text{ above the diagonal in Fig. 7}].$

The best agreement with the reference VP using only one of stratification or flow information is obtained using stratification for altitude ranges spanning the 40 m level or shear information below 40 m (Fig. 7, top row). Agreement in VP of these subdimensional state-variable spaces ranges between 80% and 95%. The stratification information is sufficient to capture 60%–70% of the turbulence collapse or recovery events. Flow measures best capture the timing of transitions when the lower level considered is 10 m. Evidently, the performance using shear information alone is not as good as using stratification information alone.

Stratification information is sufficient to identify nights that are exclusively in the wSBL, whereas near-surface flow information models the vSBL nights without transitions with almost a 100% accuracy, demonstrating that nights remaining exclusively in the vSBL show prevalent low wind conditions, which do not lead to substantial shear production of TKE (cf. section 4d and AM19b). These results again show that clear thresholds between regimes in one state variable are absent: nights staying exclusively in the wSBL can display a broad range of wind speed values and a small range of stratifications. On the contrary, wind speeds are low and steady in nights staying exclusively in the vSBL while stratification can vary over a broad range of values (cf. AM19b). The overall better performance of the HMM analysis based solely on stratification instead of the wind speed information could be related to the fact that the inversion strength is expected to change very rapidly over a narrow band of wind speeds (van de Wiel et al. 2017).

Using single-level wind speeds in the HMM analysis with Gaussian mixture parametric pdfs, best agreement with the reference is found for wind speeds at 10 m. Interestingly, including flow information at additional levels other than 10 m does not substantially improve the accuracy of the transitions (not shown). We interpret this result as being a consequence of the fact that the largest changes in wind speed during regime transitions occur near the surface.

Unsurprisingly, HMM analyses of potential temperatures at single altitudes carry essentially no regime information and the agreement of the VP is just slightly above the value of 50% expected for a completely random VP. Correspondingly, the accuracy of the transitions is about 0% and probabilities of transitions are much smaller than the reference model.

The diagonal elements of $\mathbf{Q}_{\text{obs}}$ (characterizing the persistence of the wSBL and vSBL) are overestimated using flow information alone (Fig. 7, bottom row). Consistent with the discussion above, $P(\text{wSBL} \rightarrow \text{wSBL})$ values are underestimated when only stratification information spanning the 40-m level are used and overestimated for stratification quantified entirely using altitudes below 40 m. The probability $P(\text{vSBL} \rightarrow \text{vSBL})$ is always underestimated when only stratification information is used.

f. Regime occupation information in near-surface state variables

The relatively high skill of regime identification by near-surface (bottom 10 m) data is a result of particular practical utility because surface observations are much more widely available than are tower data. Therefore, we investigate HMM analyses of surface data available at Cabauw (Table 4). As described above, reasonably good estimates of the VP are given by the one-dimensional observation state variables of the surface wind (W_{10}) and stratification ($\Theta_{10} - \Theta_2$). The results presented in Table 4 show that the combination of W_{10} with $\Theta_{10} - \Theta_2$ is found to be the best Reynolds-averaged mean surface state-variable set for the HMM analysis: the VP has almost 85% agreement with the reference state variables and captures almost 50% of turbulence collapses, 40% of the recoveries, and 94% (57%) of nights remaining in the wSBL (vSBL). This set of surface state variables alone provides much, but not all, of the information needed to obtain the reference HMM results.

The accuracy of the VP using a low-dimensional input space is also high (85% agreement) using the pair of the along- and across-wind components of

$W_{10} [\mathbf{Y}_{\text{obs}} = (W_{10} \parallel W_{200}, W_{10} \perp W_{200})]$. The along-wind component on its own performs similarly to W_{10} whereas the across-wind component on its own performs poorly. A VP agreement of almost 90% and transition accuracies of around 50% are achieved when the along- and across-wind components are combined with the near-surface stratification [$\mathbf{Y}_{\text{obs}} = (W_{10} \parallel W_{200}, W_{10} \perp W_{200}, \Theta_{10} - \Theta_2)$]. However, this result is of more theoretical than practical interest and cannot be used for a regime analysis based exclusively on surface data, as these wind components are defined in terms of the direction of flow aloft.

Using only TKE_5 , an agreement of almost 90% in the VP is found and 80% (75%) of all turbulence collapses (recoveries) are captured as well as 80% (100%) accuracy of nights remaining exclusively in the wSBL (vSBL). This result underlines again that nights remaining exclusively in the vSBL are dominated by low wind speed conditions with very low turbulence intensity. As mentioned in the discussion of the reference model, including TKE_5 at another level additional to TKE_5 is able to reproduce the reference VP with almost 100% accuracy, so the good performance of TKE_5 is unsurprising. Including W_{10} in the analysis [such that $\mathbf{Y}_{\text{obs}} = (W_{10}, \text{TKE}_5)$] does not improve the agreement to the reference substantially. A small improvement in the accuracy is achieved when near-surface stratification is included [$\mathbf{Y}_{\text{obs}} = (\Theta_{10} - \Theta_2, \text{TKE}_5)$]; no further single state variable [such as $\mathbf{Y}_{\text{obs}} = (W_{10}, \Theta_{10} - \Theta_2, \text{TKE}_5)$] further improves the results. However, the practical implications of these results are limited by the fact that TKE_5 is a state variable much less commonly observed than W_{10} or air temperature.

The single near-surface state variable that best captures the reference trajectory is $\text{var}(w_5)$, for which all comparison criteria are close to or well above 90%. Adding any other near-surface information does not improve the accuracy of the VP estimation. While TKE_5 and $\text{var}(w_5)$ are quite similar, $\text{var}(w_5)$ outperforms TKE_5 as vertical fluctuations are not contaminated by nonturbulent horizontal fluctuations.

Surprisingly, analyzing the friction velocity u_* (with or without additional information of the near-surface stratification or W_{10}) results in poor characterization of SBL transitions and nights that stay exclusively in the wSBL but not of nights remaining exclusively in the vSBL. The reasons for this poor performance are unclear.

g. Information in the surface wind alone

Wind speed at 10 m is a standard observation at operational meteorological stations. As demonstrated in the previous subsection, W_{10} carries much of the regime

information in the SBL. Therefore, it is worth examining HMM analyses of W_{10} alone in more detail. If similar accuracy of HMM analyses using W_{10} alone is found at the other tower sites considered, we can envision a systematic global analyses of the SBL behavior across a variety of climate regions, surface types, etc. This discussion will focus on the land- and glacial-based stations, as W_{10} is not available at the sea-based towers considered.

Considering all land- and glacial-based tower sites, HMM analyses using W_{10} alone generally have 75%–85% agreement with reference VPs (Table 5). Relative to the reference models at each site, HMM analyses based on W_{10} alone show less overlap between states (Fig. 5 columns 2 and 3). Classification of times of low static stability and moderate winds as vSBL rather than wSBL (as in the reference models) causes the majority of the differences in the VPs and transition times.

HMM analyses using a single wind speed variable can easily be formulated using the two-parameter Weibull distribution often used to model wind speeds (e.g., Monahan 2007; Monahan et al. 2011; He et al. 2010, 2012, 2013). Using a Weibull parametric pdf in the HMM analysis (which we denote WHMM) instead of Gaussian mixture parametric pdfs (which we denote GHMM) reduces the number of parameters to be estimated resulting in faster computations and potentially less sensitivity to sample size.

For all tower heights at Cabauw, the VP is not substantially changed using a GHMM or WHMM to analyze wind speeds (Fig. 8). However, the accuracy of the transitions increases substantially in the WHMM compared to the GHMM across all levels (Fig. 8, top-center panel) showing that the improvement is a robust result not particular to surface winds. The better agreement of the transitions is associated with the fact that the persistence probabilities are reduced while transitions become more likely (Fig. 8, bottom panels). Consistent with the previous results, W_{10} contains more information about the regime transitions than wind speeds aloft. However, this improvement in transition accuracy in the WHMM is accompanied by decreases in the accuracy of nights being classified as very persistent. In contrast, the GHMM analyses identify nights remaining in the vSBL particularly well (Fig. 8, top-right panel).

HMM analyses using surface wind speed information without stratification information misclassify some wSBL times as vSBL over land- and glacial-based tower sites (Fig. 9, first column). This misclassification rate is lower for the WHMM than for the GHMM. The pdfs of W_{10} are more clearly divided into two almost completely separated populations (relative to the reference model).

TABLE 5. Information about the reference state-variable sets and the reference transition probability $\mathbf{Q}_{\text{ref}}$ of HMM analyses at land- and glacial-based tower sites as shown in Table 1. Starting regimes for the transition probabilities are denoted with an asterisk. HMM analyses of the surface winds with Gaussian mixture parametric pdfs (G) or Weibull parametric pdfs (W) are compared to the reference stating the agreement of Viterbi paths as compared to the reference (Cons.; %) as well as the accuracy of the wSBL to vSBL (Coll. acc.; %) and vSBL to wSBL (Recov. acc.; %), consistency of nights remaining exclusively in the wSBL (wSBL cons.; %) and vSBL (vSBL cons.; %), and the transition probability anomalies compared to $\mathbf{Q}_{\text{ref}}$. Transition probabilities at Hamburg, Los Alamos, and Dome C are transformed to a 10-min time resolution.

Reference				HMM analysis of W_{10}								
				Viterbi path accuracy					$\mathbf{Q}$ anomaly to $\mathbf{Q}_{\text{ref}}$			
				Cons.	Coll. acc.	Recov. acc.	wSBL cons.	vSBL cons.				
Tower site, observations	$\mathbf{Q}_{\text{ref}}(K = 2)$											
Land-based tower sites												
Boulder, $\mathbf{Y}_{\text{ref}} = [W_{100} - W_{10}, 0.5(W_{100} + W_{10}), \Theta_{100} - \Theta_{10}]$	wSBL	vSBL	G	75.67	31.78	30.60	93.90	91.80	wSBL	vSBL		
									wSBL [*]	-0.0080	0.0080	
	wSBL [*]	0.9570	0.0430						vSBL [*]	-0.0042	0.0042	
			W	72.64	48.26	47.85	93.43	82.88	wSBL	vSBL		
	vSBL [*]	0.0268	0.9732						wSBL [*]	-0.0269	0.0269	
									vSBL [*]	0.0228	-0.0228	
Cabauw, $\mathbf{Y}_{\text{ref}} = [W_{200} - W_{10}, 0.5(W_{200} + W_{10}), \Theta_{200} - \Theta_2]$	wSBL	vSBL	G	81.33	18.67	23.03	59.76	92.25	wSBL	vSBL		
									wSBL [*]	0.0027	-0.0027	
	wSBL [*]	0.9850	0.0150						vSBL [*]	-0.0067	0.0067	
			W	80.67	32.02	30.85	65.41	72.08	wSBL	vSBL		
	vSBL [*]	0.0175	0.9825						wSBL [*]	-0.0041	0.0041	
									vSBL [*]	0.0034	-0.0034	
Hamburg, $\mathbf{Y}_{\text{ref}} = [W_{250} - W_{10}, 0.5(W_{250} + W_{10}), \Theta_{250} - \Theta_2]$	wSBL	vSBL	G	77.61	32.19	38.83	80.51	93.86	wSBL	vSBL		
									wSBL [*]	-0.0300	0.0300	
	wSBL [*]	0.9776	0.0224						vSBL [*]	0.0212	-0.0212	
			W	77.78	49.55	52.66	80.65	91.98	wSBL	vSBL		
	vSBL [*]	0.0312	0.9688						wSBL [*]	-0.0050	0.0050	
									vSBL [*]	0.0688	-0.0688	
Karlsruhe, $\mathbf{Y}_{\text{ref}} = [W_{200} - W_2, 0.5(W_{200} + W_2), \Theta_{200} - \Theta_2]$	wSBL	vSBL	G	74.09	50.88	45.77	85.71	94.95	wSBL	vSBL		
									wSBL [*]	-0.0185	0.0185	
	wSBL [*]	0.9809	0.0191						vSBL [*]	-0.0030	0.0030	
			W	72.42	53.03	47.89	84.65	95.26	wSBL	vSBL		
	vSBL [*]	0.0339	0.9661						wSBL [*]	-0.0249	0.0249	
									vSBL [*]	-0.0019	0.0019	
Los Alamos, $\mathbf{Y}_{\text{ref}} = [W_{92} - W_{11.5}, 0.5(W_{92} + W_{11.5}), \Theta_{92} - \Theta_{1.2}]$	wSBL	vSBL	G	75.27	27.14	38.26	50.29	87.53	wSBL	vSBL		
									wSBL [*]	-0.0096	0.0096	
	wSBL [*]	0.9662	0.0338						vSBL [*]	-0.0095	0.0095	
			W	70.36	41.35	46.07	52.49	49.70	wSBL	vSBL		
	vSBL [*]	0.0231	0.9769						wSBL [*]	-0.0196	0.0196	
									vSBL [*]	0.0144	-0.0144	
Glacial-based tower sites												
Dome C, $\mathbf{Y}_{\text{ref}} = [W_9 - W_{1.3}, 0.5(W_9 + W_{1.3}), \Theta_{10.3} - \Theta_{0.9}]$	wSBL	vSBL	G	83.70	13.64	21.43	—	—	wSBL	vSBL		
									wSBL [*]	-0.0005	0.0005	
	wSBL [*]	0.9916	0.0084						vSBL [*]	-0.0031	0.0031	
			W	86.39	33.33	21.43	—	—	wSBL	vSBL		
	vSBL [*]	0.0076	0.9924						wSBL [*]	-0.0015	0.0015	
									vSBL [*]	0.0000	0.0000	

Winds aloft are classified similarly by the GHMM or WHMM and agree at some stations remarkably well with their reference HMMs.

5. Conclusions

Long-term records of Reynolds-averaged mean data at nine tower sites at locations around the world with

different surface types (water, grassland, and ice-snow) and surrounding terrain of different complexity (flat surfaces, mountain ridges, and metropolitan regions) show a clear common structure of two distinct regimes in the nocturnal stable boundary layer (SBL). At all tower sites, the three-dimensional distribution of mean wind speed, wind shear, and stratification exhibits one population with weak static stability and moderate to

FIG. 8. HMM regime sequence paths of one-dimensional wind speeds with Gaussian mixture parametric pdfs (solid lines) or Weibull parametric pdfs (dashed lines) compared to the HMM regime sequence paths of $\mathbf{Y}_{\text{ref}} = [0.5(W_{200} + W_{10}), W_{200} - W_{10}, \Theta_{200} - \Theta_2]$ at Cabauw. (top left) Consistency of Viterbi paths (black), (top center) accuracy of wSBL-to-vSBL transitions (red) and accuracy of vSBL-to-wSBL transitions (green), and (top right) the accuracy of nights remaining completely in the wSBL (green) and vSBL (red). (bottom) Transition probability anomalies compared to the reference.

strong winds, referred to as the weakly stable boundary layer (wSBL), and a second population with strong static stability and moderate to weak winds, referred to as the very stable boundary layer (vSBL).

Hidden Markov model (HMM) analyses at the different tower sites are able to separate these data into two physically reasonable regimes that are robust across the different locations. The classification finds no clear wind speed or stratification threshold separating regimes: under similar conditions of weak wind speed and weak stratification the HMM can assign different regimes based on the history of the regime occupation sequence. HMM analyses of this three-dimensional state-variable set classify both the Reynolds-averaged means as well as averaged measures of turbulence intensity into distinct states. In the wSBL, large turbulence kinetic energy (TKE) and vertical velocity variance values are found whereas the vSBL shows generally weak turbulence intensity. Observations of vertical fluctuations as classified by the HMM to be in the vSBL are almost completely suppressed while the wSBL is associated with much larger variability.

HMM analyses of these data using three hidden regimes do not produce robust results either in the

regime sequence or in the transition probabilities, where we have defined robustness in terms of similarity of regime structures across the tower sites. A third regime blurs overlapping regions in Reynolds-averaged mean and eddy state-variables joint probability distributions, resulting in less clear physical interpretations of the Reynolds-averaged mean data classification.

HMM analyses of the two-regime SBL using higher-dimensional input spaces of Reynolds-averaged mean variables or averaged measures of turbulence intensity (such as TKE or the variance of the vertical velocity component) yield the same results as the three-dimensional analysis. This provides further justification that the shear and stratification information in these data that describe TKE production and consumption are sufficient to study the long-term statistics of the vSBL and wSBL.

Considering the representation of SBL regime occupation in lower-dimensional datasets, we find that the best results are obtained using stratification and wind shear measured relative to the lowest observational altitude. Stratification and shear individually estimate the regime state sequence reasonably well but have lower accuracy in capturing the timing of transitions.

FIG. 9. Probability density functions of the three-dimensional reference state variables of (left) dry static stability, (center) near-surface wind, and (right) wind aloft (as used in the HMM analyses) for the land- and glacial-based tower sites. Pdfs of the reference HMM analysis (solid) are compared to HMM analyses of the surface winds with Gaussian mixture parametric pdfs (dashed) or Weibull parametric pdfs (dotted) for all data (black), wSBL (green), and vSBL (red). All pdfs [calculated with the multivariate kernel density estimation by O'Brien et al. (2014, 2016)] of wSBL and vSBL classified data are scaled by the probability of regime occupation so that their sum is equal to pdfs of the full dataset.

Stratification information accurately captures nights that are exclusively in the wSBL while near-surface shear information capture those remaining exclusively in the vSBL.

Of particular practical importance is the potential use of surface observational data for the classification of regimes. For land-based stations, quite accurate representations of regime occupation in the SBL are given by near-surface turbulence intensity or a combination of near-surface stratification and near-surface wind speed. The near-surface wind itself (which is a measure of the shear between the measurement height of typically 10 m and the surface) is also a reasonably good state variable for regime classification. We analyzed the near-surface wind speed with Gaussian mixture (GHMM) and Weibull parametric (WHMM) distributions in the HMM analysis and find that, relative to the reference, the WHMM estimates the occurrence of regime transitions slightly better than the GHMM.

As surface winds are extensively measured around the world, an interesting direction of future research will be a surface wind-based SBL regime analysis, potentially allowing a more detailed characterization of influences of different surface types and climatological regions as the tower sites are mostly located in the Northern Hemisphere midlatitudes. Furthermore, the transition probabilities obtained and the information they contain can be used in order to inform stochastic parameterizations of the SBL in models for weather and climate (He et al. 2012). Such an analysis is presented in Abraham et al. (2019).

In a companion paper (AM19a) the statistics of regime occupation and transitions as well as the influence of external drivers on these are investigated. The regime occupation sequence allows an investigation of the behavior of Reynolds-averaged mean and turbulence state-variables changes across transitions and within nights without transitions between SBL regimes. These analyses are presented in a second companion paper (AM19b).

Different conceptualizations of SBL regimes have been presented in the literature (e.g., Grachev et al. 2005, 2008; van de Wiel et al. 2012a,b, 2017; Sun et al. 2012; Mahrt 2014; Acevedo et al. 2016; cf. section 1). In this study, we have defined regimes using a specific statistical model (HMM analysis) in terms of the variability of Reynolds-averaged data rather than the detailed structure of turbulent and submesoscale variability. The fact that our analysis found only two regimes to be robust across measurement locations does not imply that alternative regime definitions using (for example) temporally higher-resolution data could result in more than two robust regimes. An important direction of future

study is a systematic intercomparison of different regime classification schemes using different methodologies and data types.

One further limitation of this study is that all tower sites considered are located in the mid- to high latitudes. We found no evidence that moist processes (other than the radiative effect of clouds; cf. AM19a) have a strong effect on the formation of the SBL or transitions between SBL regimes at these locations. However, moist processes might be important in tropical regions. A lack of access to data from observational towers in these regions prevented us from analyzing such effects. Data from the 325 m Amazonian Tall Tower Observatory (ATTO; Andreae et al. 2015) would permit such an analysis; this is an interesting question for future research.

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