Detrending with Empirical Mode Decomposition (DEMD): Theory, Evaluation, and Application

by

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Robert Walko

Thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in the Department of Civil & Environmental Engineering in the Graduate School of Duke University

2013
ABSTRACT

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Abstract

Land-surface heterogeneity (LSH) at different scales has significant influence on atmospheric boundary layer (ABL) buoyant and shear turbulence generation and transfers of water, carbon and heat. The extent of proliferation of this influence into larger-scale circulations and atmospheric structures is a topic continually investigated in experimental and numerical studies, in many cases with the hopes of improving land-atmosphere parameterizations for modeling purposes. The blending height is a potential metric for the vertical propagation of LSH effects into the ABL, and has been the subject of study for several decades. Proper assessment of the efficacy of blending height theory invites the combination of observations throughout ABLs above different LSH scales with model simulations of the observed ABL and LSH conditions. The central goal of this project is to develop an apt and thoroughly scrutinized method for procuring ABL observations that are accurately detrended and justifiably relevant for such a study, referred to here as Detrending with Empirical Mode Decomposition (DEMD).

The Duke University helicopter observation platform (HOP) provides ABL data [wind ($u$, $v$, and $w$), temperature ($T$), moisture ($q$), and carbon dioxide ($CO_2$)] at a wide range of altitudes, especially in the lower ABL, where LSH effects are most prominent, and where other aircraft-based platforms cannot fly. Also, lower airspeeds translate to higher resolution of the scalars and fluxes needed to evaluate blending height theory.
To confirm noninterference of the main rotor downwash with the HOP sensors, and also to identify optimal airspeeds, analytical, numerical, and observational studies are presented. Analytical analysis clears the main rotor downwash from the HOP nose at airspeeds above 10 m s⁻¹. Numerical models find an acceptable range from 20-40 m s⁻¹, with the upper limit imposed by the potential interference of a growing compressed air pocket preceding the HOP nose. The first observational study finds no impact of different HOP airspeeds on measurements from ~18 m s⁻¹ to ~55 m s⁻¹ over a stable marine boundary layer (MBL). Another set of observations studies HOP and tower data, using the Duke University Mobile Micrometeorological Station (MMS) over an MBL, and concludes that HOP sensible heat (SH), latent heat (LE), and carbon dioxide (F_{CO2}) fluxes align well with MMS findings. The HOP sensors provide ABL data at 40 Hz, as well as a real-time display of \( \theta \) for in-flight ABL height estimation. Sensor calibration and alignment procedures indicate usable ABL measurements.

HOP data are especially susceptible to the spurious influence of platform motion on ABL data, largely due to the low-altitude and low-airspeed capabilities of the HOP. For example, HOP altitude motion in the presence of a lapse rate can cause spurious \( T \) fluctuations. Empirical mode decomposition (EMD) can separate HOP data into a set of adaptive and unique intrinsic mode functions (IMFs), often with physical meaning. DEMD aims to correct for spurious contributions to HOP data, while merging EMD with a correlation analysis to adjust data without eliminating relevant ABL dynamics.
To evaluate DEMD efficacy, two-dimensional synthetic $T$ fields with simulated turbulence over a prescribed lapse rate are sampled with altitude fluctuations similar to HOP flights, and with a wide range of $T$ perturbation and sampling path parameter variations. DEMD recovers the prescribed lapse rate within 1% on average for the 552 test cases passing the filtering criteria. The method is further evaluated via application to vertical cross sections taken from the Ocean-Land-Atmosphere Model (OLAM) large-eddy simulation (LES) results, where DEMD shows improved accuracy of SH recovery.

DEMD is applied to three low-altitude HOP flight legs flown on 19 June 2007 during the Cloud and Land Surface Interaction Campaign (CLASIC), both as an example of practical application and to compare DEMD to the initially proposed method (Holder et al. 2011, hereafter H11). H11 dictates the elimination of correlated IMFs, along with other subtle differences from DEMD, which also eliminates any ABL motions embedded in those IMFs. As suspected, the H11 method produces marked reductions of variances and turbulence kinetic energy (TKE) and substantial deviations in SH, LE, and $F_{CO2}$ compared to DEMD. DEMD detrends without unnecessary elimination.

DEMD is vital for ensuring accurate scalars and fluxes from HOP data, and a strategy for future research is presented that integrates properly detrended observations from the CLASIC HOP dataset with OLAM simulations to explore LSH effects on ABL processes and evaluate blending height theory.
Dedication

For Emily and Daniel, wife and son, and incomparable friends
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1. Introduction

1.1 The Significance of the Blending Height

Spatial variability in land-cover has significant effects on atmospheric conditions such as heat, moisture and carbon balances, which, in turn, strongly influence larger scale circulations. The atmospheric boundary layer (ABL) behaves very differently over wet (or vegetated) land as compared to dry (or bare) land, for example. Over dry land, radiation energy generates surface temperature ($T$) increases and can lead to high sensible heat flux (SH), low humidity and a deep ABL; contrarily, radiation energy over wet/vegetated land causes evapotranspiration, which can result in higher latent heat flux (LE), lower $T$ and a shallow ABL. Thus, water availability for evapotranspiration is a significant factor in ABL processes (Avissar 1992), and different scales of land-surface heterogeneity (LSH) lead to complex interactions between the aforementioned competing tendencies.

Global climate models (GCM) are commonly used to predict future climate states, but still include uncertainties in their representation of land-atmosphere interactions, particularly with subgrid-scale parameterizations of LSH and turbulent and mesoscale circulations (Weaver and Avissar 2001). These uncertainties can obviously be compounded over extended prediction timeframes, so clarifying the influence of LSH is a necessity. Many observational and numerical studies have been previously conducted to explore ABL behavior above LSH, and some of these have considered the blending
height concept, which could be a critical scaling factor in determining LSH influences on ABL processes.

The blending height is a key component linking LSH to ABL processes, and can be defined as a length scale for the reduction of LSH influence with height (Mahrt 2000). Wieringa (1986) found a blending height of 60 m when investigating wind speeds over areas of heterogeneous surface roughness. Several studies explored the idea of using blending height in the formulation of effective roughness lengths (Mason 1988, Wood and Mason 1991), and Mason (1988) estimated that the blending height should be about $L/200$, where $L$ is the horizontal length scale of roughness variations. While studying ABL turbulence over heterogeneous surfaces with a large eddy simulation (LES), Albertson and Parlange (1999) noted a lower blending height for mean scalar fields than for vertical scalar flux fields, and a lower blending height for LE than for SH. Molod et al. (2003) used an “extended mosaic” modeling technique in a GCM simulation to examine blending height behavior, and found that the model blending height (MBH) varied between 50 and 500 m, generally falling at around one-third to one-half of the ABL height, and also suggested a complex dependence of MBH on local conditions.

While early work concerning the blending height was based primarily on modeling efforts, recently studies have incorporated field measurements and natural ABL conditions (e.g. Mahrt 2000). Mahrt et al. (2001) suggest that low-level aircraft measurements in a heterogeneous domain (i.e. below the blending height) should be
segmented for proper estimation of spatial variation of surface moisture fluxes. Kirby et al. (2008) have recently implemented a similar technique, using the “flux fragment” method (FFM) on aircraft-based observations above LSH, and noted that FFM efficacy should break down for measurements above the blending height.

Huang and Margulis (2009) have recently used vertical soundings and heterogeneous surface flux data from the SMACEX field campaign as initial and boundary conditions to simulate a realistic ABL with an LES. Using different LSH length scales while maintaining the mean, variance and cross-correlations of SH, LE, and momentum roughness, they found that thermal blending heights were in close agreement with literature-based predictions, while momentum blending heights were underestimated.

Finally, in one of the more promising recent observational studies, Bange et al. (2006) flew a helicopter-borne turbulence probe (Helipod) over heterogeneous and quasi-homogeneous land-surfaces at different heights as a part of two field campaigns. Comparing the different regions’ flux separations to several metrics including the blending height, they found no consistent indicator of mid-ABL mixing. However, probably due to the tethered Helipod, their lowest altitude flights were 70 to 100 m above ground level (AGL), and the next lowest altitudes flown were from 355 to 720 m AGL. Since the influence of LSH increases with lower altitude, a better clarification of the mixing structure of the ABL may be obtained by more flights at lower altitudes.
1.2 Developing a Method for Investigation

What is lacking in the literature is an investigation of blending height behavior combining field measurements at a variety of appropriate altitudes with a modeling study of the same real-world ABL and LSH conditions. This could help to determine the practical validity of theoretical blending height formulations as a metric for scaling the influence of LSH on ABL processes. A suitable tool for the modeling component is the Ocean-Land-Atmosphere Model (OLAM), which has been rigorously developed by other researchers from its beginnings as the Regional Atmospheric Modeling System (RAMS) to its current state (see Pielke et al. 1992, Cotton et al. 2003, Walko and Avissar 2008a, 2008b, Medvigy et al. 2009, and Walko and Avissar 2011).

The focus of this thesis is on the development of a thoroughly scrutinized method, referred to as Detrending with Empirical Mode Decomposition (DEMD), for obtaining relevant and properly detrended atmospheric turbulence data. Specifically, in situ ABL data are collected by the Duke University helicopter observation platform (HOP, see Avissar et al. 2009) at low airspeeds, translating to higher spatial resolution, and at an altitude range spanning the entire ABL (see Chapter 2). The HOP dataset from the Cloud and Land Surface Interaction Campaign (CLASIC) is unique and particularly suitable for further study of LSH effects on ABL processes (see Section 8.2). However, HOP motions can introduce a spurious signal to ABL data, as in the example of HOP altitude variations in the presence of a lapse rate. The motivation for DEMD application
is to isolate and eliminate these spurious contributions, while avoiding the removal of atmospheric turbulence motions (the key target to assess ABL and LSH interactions).

The remainder of the thesis is structured as follows. Chapter 2 describes the HOP, including its motivation, advantages, and general characteristics. Chapter 3 reviews studies conducted to ensure that HOP sensors are unaffected by the main rotor downwash and to assess optimal sampling speeds. Additional details on the HOP instruments and data preprocessing procedure are provided in Chapter 4. Chapter 5 introduces empirical mode decomposition (EMD) as an adaptive and efficient technique for separating HOP data into a finite set of unique components called intrinsic mode functions (IMFs), and also mentions differences between the initial detrending method and the modified version, DEMD. In Chapter 6, DEMD is evaluated using synthetic datasets and an OLAM LES simulation, and Chapter 7 shows a comparison of the initial detrending method to DEMD, where both techniques are applied to HOP data from CLASIC. Chapter 8 discusses conclusions and proposes a strategy for future research to analyze the efficacy of current blending height theory by combining this method with a particularly appropriate dataset and modeling efforts with OLAM simulations.
2. Establishment of the HOP

2.1 Motivation

As pointed out in many publications, e.g., Avissar and Pielke (1989), Avissar and Schmidt (1998), Schmid (2002), Avissar and Werth (2005), Kim et al. (2006), and also emphasized in a recent report of the National Research Council on Integrating Multiscale Observations of U.S. Waters (NRC, 2008), spatial variability of the Earth’s surface has a considerable impact on the atmosphere at all scales. Understanding the mechanisms involved in land-atmosphere interactions in this highly heterogeneous environment is hindered by the scarcity of appropriate observations. Observing the physical and chemical properties of the atmosphere near the Earth’s surface, both over land and water, remains a great challenge. This is particularly true for the turbulent fluxes of heat, trace gases and aerosols.

Tower-based observations are the most common available technique to record long time series of atmospheric variables over the land. However, they only provide a very limited number of points in the lower atmosphere, and even using a high-density network of towers (which is practical only at the microscale), deciphering the footprints of spatial variability in the atmospheric variables collected with them has had only very limited success (e.g., Schmid 2002). Combining towers and remote sensing techniques (from space and/or the ground) helps mitigate the obvious deficiency of point observations, yet many of the processes linking the two methods are empirical in nature
and the fundamental mechanisms needed to use such an approach more efficiently and more accurately remain to be elucidated (Kim et al. 2006).

Many different types and sizes of aircraft have been used to make spatiotemporal observations of the atmosphere. As aircraft have a limited flight time capability and are expensive to operate, they are used only in relatively short missions, typically as part of dedicated intensive field campaigns. Yet, in spite of these obvious limitations, they fulfill a key role in our observation strategy. An overview of fixed point versus airborne observations is provided in Muschinski et al. (2001). The HOP was developed to fill a gap in aircraft observation capability, as detailed in the following section, and provides unique potential for exploring LSH effects on ABL processes.

### 2.2 Advantages of HOP Measurements

In general, using large airplanes as atmospheric observation platforms allows for a full compliment of scientific investigators, as well as long flight durations, large payloads, and fast transit speeds. However, these positive characteristics are accompanied by expensive costs for fuel, maintenance, and personnel, and at the airspeeds needed for large airplanes to maintain lift (at least 60-70 m s\(^{-1}\)), turbulent fluxes are measured less accurately, as explained in detail below. While they can fly low (as they do, obviously, on landing and takeoff), it is not practical and quite risky to do it outside of an airport environment. Furthermore, the U. S. Federal Aviation Regulation (14 CFR 91.119) practically prohibits low-level flights (i.e., less than 500 ft AGL) with
airplanes over much of the continental USA, as it is difficult to find a long enough leg without operating “…closer than 500 feet to any person, vessel, vehicle, or structure.”

The full regulation reads as follows (14 CFR 91.119):

“Minimum safe altitudes: General. Except when necessary for takeoff or landing, no person may operate an aircraft below the following altitudes: (a) Anywhere. Altitude allowing, if a power unit fails, an emergency landing without undue hazard to persons or property on the surface. (b) Over congested areas. Over any congested area of a city, town, or settlement, or over any open air assembly of persons, an altitude of 1,000 feet above the highest obstacle within a horizontal radius of 2,000 feet of the aircraft. (c) Over other than congested areas. An altitude of 500 feet above the surface, except over open water or sparsely populated areas. In those cases, the aircraft may not be operated closer than 500 feet to any person, vessel, vehicle, or structure. (d) Helicopters, powered parachutes, and weight-shift-control aircraft. If the operation is conducted without hazard to persons or property on the surface - (1) a helicopter may be operated at less than the minimums prescribed in paragraph (b) or (c) of this section, provided each person operating the helicopter complies with any routes or altitudes specifically prescribed for helicopters by the FAA; and (2) a powered parachute or weight-shift-control aircraft may be operated at less than the minimums prescribed in paragraph (c) of this section.”

Small airplanes have lower costs, but they also have limitations on duration, speed and maximum payload. The slower speed (as compared to large airplanes) is an advantage for aerosol sampling and measuring turbulent fluxes, but it prohibits the use of small airplanes in areas more than ~100 km from an airport since the transit time will often require 50% or more of the allowable flight duration. This limitation is particularly relevant for offshore research missions. To alleviate the payload limit, the Network of Airborne Environmental Research Scientists (see www.naers.org) suggests simultaneously using well-coordinated aircraft, each one dedicated to a particular instrument. An important point to note is that there is no distinction in 14 CFR 91.119
between types of airplanes, and they are all subject to the same altitude restrictions, no matter how small they are.

The main advantage of the HOP is that it combines slow airspeed and near-surface flight capability (Muschinski et al. 2001; Siebert et al. 2006). The importance of slow airspeed measurements, which has been discussed in detail by Siebert et al. (2006), is maybe best illustrated with a realistic example. Assuming that a helicopter-based platform flies at an airspeed that is 1/3 that of an airplane (say, 25 m s\(^{-1}\) versus 75 m s\(^{-1}\)), it measures atmospheric variables at a spatial resolution three times higher than that obtained by the airplane if both use the exact same sensors. This is important for measuring the high-frequency turbulent perturbations that can be an important component of the turbulent fluxes in the ABL. The importance of low-altitude flight capability is illustrated in Figure 1, which shows a characteristic vertical profile of sensible heat flux (SH) in the convective boundary layer (CBL). Understandably, an airplane not allowed to fly below the altitude illustrated with the red line would be limited to sampling the CBL at heights where the absolute value of the flux is near zero. Exacerbated by the loss of accuracy and precision associated with the loss of high-frequency turbulent motions due to high airspeed (Siebert et al. 2006), this could result in measurements that generate an error in the flux calculation that is at least of the same magnitude as the flux itself.
Figure 1: Schematic profile of turbulent SH in a typical CBL ($z_i$ indicates its top), with an example of minimum airplane flight altitude (red line)

Given that the SH decreases linearly with height in the mixed layer, the entire profile could be assessed from two altitudes, yet minor absolute errors at two altitudes near the CBL top could result in large errors in derived surface fluxes. On the other hand, a sampling near the ground surface and near the top of the CBL results in a much more reliable flux profile. It is worth noting that during the Cloud and Land Surface Interaction Campaign (CLASIC) in June 2007, surface SH of less than 30 W m$^{-2}$ and ABL heights of 200-300 m were frequently observed. Thus, airplane measurements of that variable would not have been very useful given the precision and sampling frequency of even the most sophisticated, state-of-the-art sensors currently available. A similar case
could be made for any turbulent flux that varies with height in the ABL. This is even more crucial when the surface flux is dependent on the land-cover type [as is the case for heat, momentum, moisture, carbon dioxide (CO₂), and many trace gases and aerosols], in which case it is unrealistic to expect reasonable estimates of turbulent fluxes from airplane observations. The importance of low-level flights is also very important for the stable boundary layer, which is typically much shallower than the CBL and is often dominated by waves and instabilities, and by small-scale turbulence that is neither homogeneous nor stationary.

Lenschow et al. (1994) investigated the errors in fluxes calculated from in situ observational flight legs. They found that the maximum systematic and random errors relative to the surface flux could be estimated by $2.2 \frac{z_i}{(z/z_i)}^{0.5}/L_f$ and $1.75 \frac{z}{(z/z_i)}^{0.25}(z_i/L_f)^{0.5}$, respectively, where $z_i$ is the height of the CBL, $z$ is the flight altitude, and $L_f$ is the length of the flight leg. With these formulations, they estimated that flying a 4,000 m leg at an altitude of 100 m AGL in a 1,000 m deep boundary layer resulted in a maximum systematic error of 17% and a maximum random error of 49%. Flying a 10 km leg at a height of 3 m AGL, as the HOP did during CLASIC, reduces these theoretical errors (unattainable in real flight conditions) to about 1% and 7%, respectively.

The HOP could also enjoy an effectively longer duration at the designated sampling area, since it could land and refuel at locations inaccessible to fixed-wing aircraft, removing the waste of fuel and time that occurs in transit. Indeed, it is
logistically possible to bring a fuel truck to a landing site at or near the sampling area where the HOP could stop regularly for refueling. Perhaps the biggest advantage of all, which has been demonstrated with the “Helipod” (a gliding pod towed by a helicopter) described by Muschinski and Wode (1998), is the opportunity to perform marine observations far from shore using a helipad aboard a ship. Such a helipad is available, for instance, on the NOAA *David Starr Jordan* and could be adapted to fit other research vessels to make remote marine locations requiring a US Class I research ship accessible, with effectively all of the flight hours available on station for observations.

Helipads are often found on modern commercial cruisers, and cooperation with the scientific community, as demonstrated with previous research missions conducted on the *Explorer of the Seas* (www.royalcaribbean.com), is feasible. It is therefore conceivable to deploy a properly equipped HOP for marine operation in collaboration with passenger and/or cargo ships. Compared to large aircraft that can remain on station for a few hours before heading back to shore, the HOP on a ship could stay at sea for extensive periods thus providing the opportunity for long marine atmospheric campaigns. The magnitude of turbulent fluxes, aerosols and atmospheric chemistry above the oceans remain uncertain, and a HOP has the potential to revolutionize the quality and quantity of scientific information that could be gathered there.

Despite these advantages, helicopters have been used mostly for remote sensing applications (e.g., Babin 1996), and only sporadically for in-situ atmospheric sampling.
Maybe this can be attributed to the popular belief in the scientific community that atmospheric sampling from a helicopter is not feasible because of the main rotor “downwash.” But as illustrated in Leishman (2006, e.g., Figure 11.7, Page 661, among many other examples in that textbook) and discussed by Siebert et al. (2006) and in Chapter 3, even at low airspeed, the wake created by the main rotor is skewed backward and has practically no impact on the air in front of the helicopter nose. For this reason, the pitot tube of many helicopters is installed at that location (including on the Jet Ranger), so that even at airspeed as low as 6-7 m s$^{-1}$, the rotor wake has no significant impact on the helicopter instrument readings. Obviously, accurate flight instrument readings are essential for flight safety, and measuring the rotor wake instead of the undisturbed atmosphere would be unacceptable.

A few observational studies performed with helicopters are, however, quite noticeable. Among them, a series of air sampling campaigns was carried out by the Tennessee Valley Authority (TVA) with a Bell 205 specifically equipped to observe various atmospheric oxidants (e.g., Imhoff et al. 1995, Valente et al. 1998, Luria et al. 1999, among many others). Roekens et al. (1992), De Saeger et al. (1993), and Desmet et al. (1995) also conducted air quality monitoring with helicopter-based measurements. The Helipod (Muschinski and Wode 1998, Roth et al. 1999, Muschinski et al. 2001, and van den Kroonenberg and Bange 2007, among others) and the Airborne Cloud Turbulence Observation System (ACTOS) described by Siebert et al. (2006) are gliding
pods towed by helicopters, which are used to sample various atmospheric properties. While these gliding pods benefit from many of the advantages of a helicopter-based platform (e.g., time on station, operation from ships at sea, low speed), they restrict some of the maneuverability of the towing helicopter (e.g., flight very near the Earth surface, quick turns). Also, to reduce erratic movements due to turbulence, they typically fly into the wind, thus reducing the versatility of experiments that can be conducted with helicopters. For that reason, Helipod is flown at 40 m s$^{-1}$ (Muschinski et al. 2001). Siebert et al. (2006) indicate that ACTOS flies at very low speed (15 m s$^{-1}$) yet one might presume that this is mostly feasible when crosswind turbulence is quite weak. Indeed, it is challenging to maintain a small helicopter straight and level in turbulent air at low airspeeds, let alone a pod towed under such a helicopter.

### 2.3 Platform Description

The Jet Ranger adopted for the HOP is a light, single engine (turbine) helicopter that was originally designed as a light observation helicopter for the US Army. Its first commercial version was certified in 1966, and while many of its components have been improved over the past 40+ years, its conceptual design dates back to the early sixties. It is simple, robust, and nimble, and based on the U. S. National Transportation Safety Board (NTSB) statistics, it is the safest, single-engine aircraft (including airplanes) flying today. It has been used extensively for military, police, news gathering, and many other
applications all over the world. As a result, it benefits from a very broad international network of technical support.

A full description of the Jet Ranger characteristics and performance is available on the manufacturer’s website (www.bellhelicopters.com), and only the most relevant characteristics for its use as the HOP are summarized in Table 1. The base operating weight (BOW) is the weight of the HOP including its permanent scientific equipment, fully fuelled, and with a 170 lb pilot. The additional payload capacity (APC), which is equal to the difference between the maximum gross weight (MGW) and the BOW, is the maximum weight of the additional scientific equipment that could be loaded on the HOP, assuming standard meteorological conditions. The Jet Ranger is certificated to a maximum altitude of 20,000 ft. However, for its application as a HOP, it is not practical to fly above 12,000 ft except in special cases. The maximum endurance provided here is based on flights conducted near the ground surface at 30 m s⁻¹ airspeed during a hot summer day in Oklahoma. It does not include the 20 min fuel reserve mandated by federal aviation regulations. While the APC for scientific instrumentation is limited, when compared to its hourly fuel consumption, it is one of the most efficient turbine helicopters. Thus, flying the Jet Ranger is comparatively cheap, which was another reason (with the safety record and technical support) to adopt it as the HOP.
Table 1: Main characteristics and performance of the HOP

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum Gross Weight (MGW)</td>
<td>3350 lbs</td>
</tr>
<tr>
<td>Base Operating Weight (BOW)</td>
<td>2950 lbs</td>
</tr>
<tr>
<td>Additional Payload Capability (APC)</td>
<td>400 lbs</td>
</tr>
<tr>
<td>Aft Cabin and Baggage Cargo Volume</td>
<td>56 ft³</td>
</tr>
<tr>
<td>Maximum Altitude for Research Mission</td>
<td>12,000 ft</td>
</tr>
<tr>
<td>Maximum Endurance for Research Mission</td>
<td>3.67 hrs</td>
</tr>
</tbody>
</table>

Seats, all unnecessary plastic covers and soundproofing material were removed from the 40 ft³ aft cabin to reduce its weight and to make room for instrument and computer racks. This resulted in an increase of the APC by nearly 120 lb. The co-pilot/passenger seat in the forward cabin was also eliminated to make room (~18 ft³) for a possible Atmospheric Chemistry Package (ACP), with inlets going straight through the HOP nose, and there is also a 16 ft³ baggage compartment located behind the aft cabin that can be exploited for additional instruments and computers.

The Jet Ranger DC generator provides 105 Amp on a continuous basis (200 Amp for 5 s and 170 Amp for 2 min). In its configuration as the HOP with its navigation and communication systems, it uses ~42 Amp in cruise flight, thus leaving up to ~63 Amp for the continuous operation of the research equipment, which consists of a data acquisition system (DAS), instruments, and sensors. The HOP pilot controls the DAS and all instruments and sensors by switches in the cockpit.

Figure 2 shows the HOP equipped with the sensors present in the research flights summarized in this thesis. This set of sensors consists of an Aventech Research,
Inc. (www.aventech.com) Advanced Airborne Measurement Solutions-20 (AIMMS-20) that measures the three components of the wind, $T$, and relative humidity, a Licor (www.licor.com) LI-7500 that measures $H_2O$ and $CO_2$, and an ultrasonic velocimeter (USV) prototype developed by the Kaijo Sonic Corporation in collaboration with Japan Aerospace Exploration Agency (JAXA) (Matayashi et al. 2005), which also measures the three components of the wind and $T$. The HOP sensors and the collection and preprocessing of its data are fully detailed in Chapter 4.

Figure 2: (Left) HOP sensors (full details in Chapter 3), (Upper Right) pilot cockpit, and (Lower Right) aft cabin viewed from the right side
As shown in the upper right of Figure 2, the HOP is equipped with the Chelton Flight Systems (www.cheltonflightsystems.com), which is a state-of-the-art navigation system that provides three-dimensional synthetic vision of the terrain with all its obstructions (including antennas, buildings, etc.), a complete flight/navigation instrumentation system, and the “Highway-In-The-Sky” (HITS), which depicts the programmable flight track in a perspective-like tunnel. This system helps perform very precise flights according to preset altitudes and coordinates of the path to be flown. It also includes traffic awareness and real-time satellite weather for enhanced safety. It is backed-up by a battery-operated portable GPS Garmin 496 (www.garmin.com) in case of electrical power loss.
3. Aerodynamic Envelope and Airspeed Operation

There is an abundance of professional literature that describes the theory, experiments, and physical and numerical models that have been developed and applied to explain the wake generated by the main rotor and its interactions with the helicopter frame while hovering and in forward flight (e.g., Leishman 2006). The next few sections summarize results from several experiments (conducted partly to dispel the aforementioned “downwash” misconception, and mostly to identify the ideal range of airspeeds for HOP measurements), including an analytical model, numerical simulations, and observations collected with the HOP.

3.1 Analytical Study

Rotor performance in flight was first derived and explained by Glauert (1935) based on the analysis of marine propellers proposed by Rankine (1865) that was further developed by Froude (1878) and Froude (1889), which is often referred to as the “Rankine-Froude Momentum Theory.” It is thoroughly described in most introductory textbooks on helicopter aerodynamics (e.g., Leishman 2006), and a simplification of this flow model is adopted here.

Figure 3 shows the magnitude of the airflow velocity through the rotor, and the resultant airflow velocity and the angle of the rotor wake obtained with this model at various airspeeds, from hover to the maximum cruising speed of ~60 m s⁻¹. The upper section of the figure shows the induced velocity (vi), resultant velocity (U), and resultant
wake angle ($\beta$) defined from normal to the plane of rotation at the rotor blade tip as aligned with the longitudinal axis of the HOP and above its nose [$\beta = \arctg[v_{\infty} \cos \alpha/(v_i + v_{\infty} \sin \alpha)]$]; $v_{\infty}$ is the free-stream velocity and $\alpha$ is the angle between the rotor plane of rotation and the free-stream direction] for the Jet Ranger at various airspeeds. The lower section of Figure 3 shows the location of the wake leading edge as a function of distance from the blade root ($x$) and plan of rotation ($z$) normalized by the rotor radius ($R$) at airspeeds of 5 m s$^{-1}$, 10 m s$^{-1}$, 15 m s$^{-1}$, 20 m s$^{-1}$, and 30 m s$^{-1}$. Note that all calculations take into account that the rotor diameter of the Jet Ranger is 10.16 m, and that with one pilot on board, fully fueled, and with its current sensors and data acquisition system, the HOP mass is about 1,400 kg. The mast tilt angle on the Jet Ranger leads to an assumption of $\alpha = 6^\circ$. It is interesting to note that the induced-air velocity decreases rapidly with airspeed and, as a result, the wake angle switches from vertical at hover to about 68$^\circ$ at an airspeed of 15 m s$^{-1}$. The angle between the tip of the blade (when aligned with the front of the helicopter) and the nose of the helicopter is about 57$^\circ$, which is cleared of the rotor wake at an airspeed of about 10 m s$^{-1}$. This very simple analysis is clearly supported by the observations of Leishman and Bagai (1991).
3.2 Numerical Study

Flight of the Jet Ranger at different airs speeds was simulated with FLUENT (www.fluent.com), a state-of-the-art commercial computational fluid dynamics (CFD) software. Figure 4 illustrates some of the simulation results, and a detailed description of their setup and analysis is provided in Avissar and Abehserra (2008). The figure shows streamlines near the front of the Jet Ranger flying at airs speeds of (a) 10 m s\(^{-1}\), (b) 20 m s\(^{-1}\),
(c) 30 m s\(^{-1}\), (d) 40 m s\(^{-1}\), (e) 50 m s\(^{-1}\), and (f) 60 m s\(^{-1}\). Dark blue and red colors indicate airflow velocities that are significantly lower (-10 m s\(^{-1}\)) and higher (+10 m s\(^{-1}\)) than the undisturbed air, respectively. Initially, the streamlines are horizontal and the background airspeed is constant in space and time. Therefore, any impact from the helicopter on the airflow is seen on these graphs as a departure of the streamlines from horizontal and/or a change of color. It is interesting to note that, concerning the main rotor wake position at different airspeeds, there is no conceptual difference between these results and those obtained with the quite simple analytical study discussed in the previous section. This emphasizes the robustness of the assumptions and simplifications made in our analytical study.

Figure 4: FLUENT simulation results for airspeeds of (a) 10 m s\(^{-1}\), (b) 20 m s\(^{-1}\), (c) 30 m s\(^{-1}\), (d) 40 m s\(^{-1}\), (e) 50 m s\(^{-1}\), and (f) 60 m s\(^{-1}\) [note lower (blue) and higher (red) velocities]
The FLUENT simulations show that as the helicopter flies faster, a “pocket” of compressed air develops and grows in front of it, creating another zone of air disturbance that is independent of the main rotor. This additional disturbance is similar to that observed in front of airplanes, and is affected by the shape of the aircraft as well as its airspeed. This is well simulated with the CFD but ignored in the analytical study. Figure 5 shows the airspeed disturbance generated by the rotor alone (R) and the airframe alone (AF) of the Jet Ranger relative to the disturbance generated near the tip of an airplane nose (similar in size to a Twin Otter) flying at an airspeed of 60 m s⁻¹ (red column). This disturbance is defined, similar to turbulence kinetic energy (TKE), as half the sum of the velocity perturbation variances in the three directions relative to the aircraft movement (i.e., longitudinal, lateral, and vertical). All results are derived from FLUENT simulations and are averaged values for a 2 m wide and 1 m high plane centered at the tip of the nose of the aircraft. The various colors are for different distances from the tip of the nose (0, 0.5, 1, … and 3 m). Airplanes like the Twin Otter, whose propellers are located on its wings far away from its nose, are frequently used for research missions [see, e.g., the Center for Inter-Disciplinary Remotely Piloted Aircraft Studies (CIRPAS), online at www.cirpas.org].
Figure 5: Airspeed disturbance of the rotor alone (R) and airframe alone (AF) of the Jet Ranger compared to an airplane similar in size to a Twin Otter

All results in Figure 5 are normalized by the disturbance near the nose of the airplane and one can see that at a speed of 60 m s⁻¹, the helicopter airframe disturbance is only about 70% that of the Twin Otter. Of course, the size of the cabin and the shape of the nose are important factors in this relation and this only indicates that given the small size of the helicopter, it is less disturbing than a larger research airplane. Interestingly, however, the sum of the airframe and rotor disturbances is still much smaller than that of the airplane airframe. Also, at airspeeds of 20-40 m s⁻¹, the total disturbance in front of the helicopter nose is much smaller than that obtained in front of the airplane flying at 60 m s⁻¹, at least within the first meter from the tip of the nose, where it is easier to install most sensors and inlets. At these airspeeds, neither the main-rotor wake nor the airframe of the HOP significantly disturbs the atmosphere at this location.
3.3 Observational Studies

3.3.1 Airspeed Range Test

The mount used to attach the sensors in front of the HOP was partly designed based on the results of the numerical simulations mentioned above (Section 3.2), and another consideration in its design was vibration reduction. To calibrate these sensors, evaluate their performance in flight, and provide additional insights on the operating range of the HOP, two low-level flights (i.e., 15-30 m ASL) were performed at various airspeeds along the Outer Banks of North Carolina on 4 September 2007. The marine boundary layer (MBL) is typically more homogeneous than the continental one, minimizing the change of turbulence during the flights (~ 42 min each). On a day with generally easterly winds (i.e., from the sea) the HOP flew 200 m offshore to minimize land effects, and the two test flights each included eight 5 min legs, with each leg at a different airspeed, from ~18 m s$^{-1}$ to ~55 m s$^{-1}$.

Figure 6 presents the power spectra from the AIMMS-20 and the LI-7500 of the three wind components ($u$, $v$, and $w$), $T$, $H_2O$ ($q$), and $CO_2$ obtained from the HOP sensors during this airspeed range test flight. The black lines indicate the raw data and the various colored lines indicate the remaining spectra after successive IMFs have been eliminated on either side of the spectra. (For details on EMD and IMFs, see Section 5.2). The red dotted lines indicate -5/3 slopes, and units for the power spectra are those of the variable variance per frequency (e.g. K$^2$ Hz$^{-1}$ for $T$). A few characteristics relevant to the
HOP and its current set of sensors are worth mentioning. For instance, one can notice that due to sensor limitations, the highest frequency of valuable data that can be used for atmospheric studies is in the 5-10 Hz range. The two-blade main rotor of the Jet Ranger has a constant 396 RPM (+/- 1-2%) that generates the disturbance peak seen in all spectra at ~13 Hz. As the flights were performed at altitudes of 15-30 m above the ocean surface in late afternoon, most of the turbulence observed was likely produced by mechanical shear.

![Figure 6: Power spectra of u, v, w, T, q, and C for the airspeed range test flight](image)

The spectra show an inertial subrange with a slope of -5/3 up to about 5-10 Hz. But unlike for the other variables, the CO₂ spectrum is noisy starting at about 1 Hz. Given that the same sensor measures simultaneously CO₂ and H₂O (with the same signal processed differently) and that the H₂O spectrum does not depict such a noisy response,
we attribute this phenomenon to the lack of CO$_2$ sources/sinks and a well-mixed CO$_2$ at this location and time that does not generate much turbulent perturbations. Also, the inertial subrange of $w$ starts at higher frequencies than that of the other two wind components and the scalars, giving the appearance of a “flatter” spectrum. This feature is a well-known phenomenon of the surface layer that is discussed extensively by Kaimal et al. (1972). However, it seems somewhat exacerbated here due to the short range of frequencies between the beginning of the inertial subrange (which according to Kaimal et al. tends to move to higher frequencies for neutral and stable surface layers as compared to unstable ones) and the rotor disturbance peak.

A sensor collecting data at much higher frequencies than the AIMMS-20 would probably show a continuation of the $-5/3$ slope at higher frequencies (beyond the rotor disturbance peak). However, as mentioned above, flying near the ground surface is particularly destructive for the sensors (due to dust and collision with insects) and the choice here of a robust sensor comes at the detriment of very high sensitivity. Furthermore, given the negligible impact that higher frequencies have on the calculation of the turbulence fluxes, the compromise seems justified, stipulating that a robust and faster sensor would improve the quality of future high-frequency studies.

Figure 7 shows the raw AIMMS-20 $T$ data collected in the airspeed range test and the $T$ variances for the different flight legs. In the lower part of the figure, the continuous blue line is the raw data, and shaded areas (light grey) indicate the time during which
the HOP is accelerating between flight legs or turning and rapidly decelerating at the end of the first flight. The colored horizontal bars indicate the flight leg lengths, and the numbers above them indicate the mean airspeed (m s$^{-1}$) of the HOP for each leg.

Figure 7: (Lower) Raw $T$ data from the HOP airspeed range test flight, and (upper) associated raw and filtered $T$ variances for each leg

The upper part of Figure 7 gives $T$ variances by leg for the raw data (blue triangles), data filtered at frequencies < 0.01 Hz (red squares) and data filtered at frequencies < 0.1 Hz (green diamonds). This filtering was accomplished by subtracting from the signal the cumulative lowest-frequency IMFs that drop off from the raw data at these cutoff points, as seen in Figure 6. Details on EMD, IMFs, and how DEMD is used to detrend the raw data are given in Chapter 5. In Figure 7, the arbitrary cutoff frequencies and elimination of IMFs illustrate the impact of removing IMFs on the variance, and highlights the unresolved challenge of separating mesoscale dynamics from turbulence (Avissar and Chen 1993, Vickers and Mahrt 2006). The high variances
seen in the raw data in leg 4 (dark green), leg 6 (light blue), and leg 9 (red) are well correlated with the obvious change of background conditions (i.e., mesoscale trend). These low-frequency changes are removed from the data series with lowest IMFs. Note that in this generally homogeneous MBL, the inertial subrange typically starts at between -0.05 Hz and -0.1 Hz. Not surprisingly, cutting the production range has a significant impact on the $T$ variance, in some legs reducing it by as much as half. Also, one can notice an increase of the filtered variances (green diamonds and red squares) in legs 5, 6, 13, 14, and 15. Quite interestingly, these occur at the same geographical location, just north of Duck, North Carolina, where land increases friction as compared to the open water of the Albemarle Sound, as shown in Figure 8. Overall, there seems to be no clear impact of airspeed on the measurements in these two flights.
3.3.2 Comparison to Tower Measurements

To provide a comparison between measurements from the HOP and from a tower with similar sensors, a series of short flights was performed at around 2 p.m. (EST) on 26 March 2007 at the U. S. Army Corps of Engineers Coastal Station at Duck, North Carolina. Figure 9 shows and the location of the Duke University Mobile
Micrometeorological Station (MMS) on the 560 m pier (red arrow) and the 3 km HOP flight legs (red dashed line). The wind direction was from the ocean, and the HOP flew into the wind at the same altitude (15 m ASL) as the MMS sensors, which include a sonic anemometer and a Licor LI-7500.

Figure 9: Setup for HOP comparison to tower measurements, with the location of the MMS (red arrow), the HOP flight legs (red dashed line), and the wind direction (red triangle in yellow orientation star)

Figure 10 shows fluxes of SH, LE, and F_{CO2}, with dots for the approximately 3 min HOP flight leg means and a solid line for the MMS 20 min averages. Grey shadings indicate one standard deviation (1/2 on each side of the mean) for the MMS fluxes. In general, and as expected near the ocean surface, mean fluxes were small during this period. However, the tail of a front, which was generating strong winds, was still passing through the area when we started the flights, resulting in high standard deviations during the first flight legs. The standard deviations show a rapid decrease
after the front passed. Figure 10 shows that the 3 km HOP flight leg fluxes fall within one standard deviation of the 20-min averaged MMS values for all legs with SH, and for 5 of the 6 total legs for LE and F$_{CO2}$.

Figure 10: Fluxes of SH, LE, and F$_{CO2}$ from the comparison of HOP data (dots) and MMS data (solid lines)
4. Data Collection and Preprocessing

4.1 The HOP Sensors

As mentioned briefly in Section 2.3, the HOP instrument suite included three sensors for the research flights discussed in this thesis. The upper left of Figure 2 shows the sensors on the front of the HOP, connected by a mount designed to damp vibrations, and the DAS in the aft cabin can be seen in the lower right of the figure. For convenience, a closer view of the HOP sensors from the upper left of Figure 2 is given here as Figure 11. The three sensors include: 1) an Aventech Research, Inc. (www.aventech.com) Advanced Airborne Measurement Solutions-20 (AIMMS-20) pressure transducer, a Licor (www.licor.com) LI-7500 gas analyzer, and a Kaijo Sonic Corporation & Japan Aerospace Exploration Agency (JAXA) prototype ultrasonic velocimeter (USV) (Matayashi et al. 2005). Both the AIMMS-20 and USV have a data output rate of 40 Hz, and the LI-7500 has an output rate of 160 Hz, which is reduced to 40 Hz for consistency with the other sensors when calculating fluxes.
Figure 11: Closer view of HOP sensors (from Figure 2, upper left)

The AIMMS-20 is a differential pressure-based sensor that measures the three components of the wind relative to the aircraft for various meteorological applications (e.g., Mickle 2005, Beswick et al. 2008). Other probes, including the well-known NOAA-ATDD “Best Aircraft Turbulence” (BAT) probe, are based on the same concept and theory, which are well described in the literature (e.g., Brown et al. 1983, Crawford and Dobosy 1992, Wood et al. 1997). Sensors of this type use relatively inexpensive components and are robust, a must for airborne applications (Crawford and Dobosy 1992, Beswick et al. 2008).
The AIMMS-20 consists of four modules: 1) an air-data probe located on the nose of the HOP, which senses $T$, humidity, barometric pressure, the three-dimensional aircraft-relative airflow vector and the three-axis acceleration and magnetic field measurement; 2) an inertial measurement unit that provides three-axis acceleration and three-axis angular rates; 3) a dual processor global positioning system (GPS) that includes dual antenna inputs for differential carrier-phase measurement (one antenna is on the nose and the other is on the tail of the HOP); and 4) a central processing module that, among other functions, converts the inertial and GPS phase, position, and velocity data into precise attitude data (roll, pitch, and true heading). This processed information is shared with all other sensors on the HOP, and the AIMMS-20 is also used to coordinate the clock between the different sensors and to trigger data storage. The AIMMS-20 conducts anti-alias filtering internally by using a 50 Hz corner frequency analog filter, then oversamples digitally at 200 Hz before a digital second-order low pass filter is applied at 20 Hz. Finally, data is output and collected at a rate of 40 Hz.

The LI-7500 Open Path CO$_2$/H$_2$O gas analyzer consists of two components: 1) the analyzer sensor head that is mounted on the nose of the HOP, and 2) the control box, which houses the electronics and is located in the aft cabin. The sensor head has a 12.5 cm open path, with single-pass optics and a large, 1 cm diameter optical beam. Reference filters centered at 3.95 $\mu$m and 2.40 $\mu$m provide for attenuation corrections at non-absorbing wavelengths. Absorption at wavelengths centered at 4.26 $\mu$m and
2.59 µm provide for measurement of \( CO_2 \) and \( H_2O \), respectively. These features minimize sensitivity to drift and dust, which can accumulate during normal operation.

The LI-7500 is operated without the use of Licor software, which typically gives output rate options of 5, 10 or 20 Hz, and instead, the raw data is collected through the analog output of the Licor control box at an output rate of 160 Hz, which is reduced to 40 Hz for temporal coordination with the AIMMS-20 data. This reduction, combined with the removal of the highest-frequency mode, IMF\(_0\) (as mentioned in Section 5.2 and discussed in detail in Section 7.2), also serves as a manual anti-alias filter for the LI-7500 data.

The USV is based on a conventional ultrasonic anemometer that consists of two main components: 1) a probe located on the nose of the HOP that senses the three-dimensional aircraft-relative airflow vector and ambient \( T \) by measuring ultrasonic pulse transit time between three mounts (see Figure 1); and 2) a control box and a junction box (located in the aft cabin), which control ultrasonic pulse emissions and output the measured data. The main advantage of the USV as compared to a pitot-static system is that it can provide accurate measurements at low speeds and in crosswinds, which is obviously important for helicopters. Unlike conventional ultrasonic anemometers, the USV uses high-frequency (200 kHz) ultrasonic pulses to reduce acoustic noise, and its probe shape minimizes airflow disturbance at high airs speeds. These modifications allow a broad range of airflow measurements, from 0 to 70 m s\(^{-1}\), encompassing the entire flight envelope of the HOP.
On ACTOS, Siebert et al. (2006) use a state-of-the-art ultrasonic anemometer whose technical characteristics appear to be superior to those of our USV. This anemometer is thoroughly described in Siebert and Muschinski (2001). They also use an ultrafast thermometer (UFT) with a 500 Hz resolution, which is considerably more precise than our T sensors. However, the particular sensors chosen for the HOP were selected not only for their reasonably good performance but also for their robustness. The HOP instrument suite would be improved, of course, by upgrading to superior sensors that can withstand the harsh environment of low-level flights, where dust, moisture, and insects can endanger delicate equipment.

The computer, located in the cockpit and controlled by the pilot, is used to run a National Instruments LabVIEW (www.ni.com/labview) program that reads the data input from each instrument, parses and displays data, and determines when to log the data to file. The AIMMS-20 and USV communicate via individual RS232 serial lines to the PC. The Licor outputs two 0-10 V analog signals (proportional to H$_2$O and CO$_2$) that are connected to the PC through a National Instruments USB-6008 data acquisition (DAQ) card. An independent pressure sensor (with its own static port located under the HOP) that is used to calculate potential $T(\theta)$ in real time provides a 0-10 V analog signal that is also wired to the DAQ card. Finally, a 0-5 V signal is fed through a switch in the cockpit and back to the DAQ card so that the pilot can easily “mark” the beginning and
the end of a measurement flight leg by creating a signal in the log file. This is a useful marker when processing the data after the flight.

The real-time visualization that is displayed on the monitor located in the cockpit includes the $\theta$ profile, which is calculated from the $T$ measured with the USV and the pressure sensor. This real-time profiling capability is useful for the assessment of the height of the various atmospheric layers and, accordingly, for the selection (in real time) of relevant flight altitudes. It also displays the DAS information in graphic form and a series of green/red virtual buttons indicating the functioning status of the various sensors and instruments.

4.2 Data Preprocessing

It can be easily understood from differential pressure theory as described in the literature mentioned in Section 4.1 (e.g. Brown et al. 1983, Crawford and Dobosy 1992, Wood et al. 1997) that the position of the AIMMS-20 in flight relative to the local Cartesian coordinate system is crucial for obtaining accurate readings of the three components of the wind. Thus, a series of calibration flights were conducted to correct for the effects of the HOP attitude when flying at different airspeeds and in crosswinds. The calibration procedure (Beswick et al. 2008) includes a flight in unchanging, low wind speed where: 1) the yaw is purposefully set 10° to port, then to 0°, then 10° to starboard while flying at a range of forward airspeeds, and 2) similar alterations in pitch and/or a rapid climb and descent are performed. The manufacturer can then analyze the
calibration flight data (for example, steps 1 and 2 above are used to evaluate the sensor’s response to sideslip and angle of attack, respectively) and provide appropriate calibration coefficients to be used in the first step of data preprocessing. It should be noted that while, theoretically, there should be no need to repeat the calibration flights as long as the position of the AIMMS-20 on the HOP remains unchanged, these calibration flights are performed before major field campaigns to ensure the accuracy of the algorithm and to adjust for any minor alteration in the instrument attitude that may have occurred.

The LI-7500 data is calibrated for $H_2O$ and $CO_2$ according to a procedure described by its manufacturer (LI-7500 manual, available at www.licor.com). For the calibration procedure, the LI-7500 is connected via the serial port to the computer running the Licor calibration software, and a calibration tube is connected to the sensor head, across the sampling area. Zero and span gases for $CO_2$ and $H_2O$ are sent through the calibration tube, and the Licor software provides the calibration coefficients. This procedure is repeated before each field campaign to account for any instrument drift over time. As part of the aforementioned AIMMS-20 calibration flights, the LI-7500 was oriented in different directions relative to its mount, including parallel and perpendicular to the AIMMS-20 (and, therefore, the flight direction). However, no noticeable impact of orientation was identified and there is no specific preprocessing procedure required for that sensor.
Occasionally, during a high wind gust that may cause the HOP to pitch, roll and/or yaw excessively and rapidly, the attitude of the HOP is outside the range in which the calibration algorithm is applicable. Indeed, due to the aerodynamics of the hemispherical differential pressure sensor, the optimal operating range is within a sideslip of ±5°. Therefore, as part of our data preprocessing, an algorithm that automatically flags the data for such occurrences, which are typically not more than a few seconds long, was developed. To maintain the continuity of the data series, this algorithm substitutes the anomalous data with randomly-generated data that shares characteristics of the first and second statistical moments with the immediately previous and subsequent 0.1 to 0.25 s of data. Specifically, the replacement data has a variance equal to the average variance of the surrounding data, and its mean follows a linear interpolation between the means of the surrounding data. While not perfect, it seems that the error incurred by this substitution is much less significant than the error present in the flawed data, especially when such events are only occasional, as shown in the example in the next paragraph. For similar reasons, the data collected during steep turns, rapid climbs or descents is typically ignored.

A very large disturbance is incurred in the T data collected with the AIMMS-20 when the HOP radio is activated for communication. Similarly, when flying near radio and TV towers, data is contaminated. These disturbances are easily identified in the time series, and the dataset is correspondingly adjusted as described in the previous
paragraph. These $T$ anomalies typically show a drop on the order of about 25°. Statistics from a typical $T$ disturbance and the surrounding undisturbed data demonstrate the possible effects of such an anomaly, and justify our correction technique. In the example data (chosen from a HOP flight during CLASIC on 19 June 2007), the $T$ disturbance is 1.7 s long, and is compared to the immediately previous and subsequent 10 s of undisturbed data. Before the disturbance, the data mean is 295.02 K and its variance is 0.021 K$^2$ and after the disturbance, the mean is 295.12 K with a variance of 0.011 K$^2$, while the anomaly itself has a mean of 270.91 K and a variance of 1.52 K$^2$. Taking into account the full example section of data (1.7 s outlier along with 10 s before and after), the raw data has a mean of 293.20 K, which is 2° too low, and an unrealistic variance of 42.64 K$^2$. After applying the correction detailed in the previous paragraph to the anomalous data, the example data section has a mean of 295.11 K and a variance of 0.014 K$^2$, which gives much better consistency with the surrounding, undamaged data. Although some flux information is undoubtedly lost by this method, the length of time affected is very short (in this example, about 0.3% of the total flight leg time), so the correction benefits greatly outweigh the errors introduced.

The AIMMS-20 sensor protrudes about 0.25 m ahead of the LI-7500 (Figure 11). The studies described in Chapter 3 suggest 30 m s$^{-1}$ as an ideal HOP airspeed for research missions aimed at measuring the atmospheric variables needed to calculate fluxes using the eddy-correlation technique. This speed is slow enough for high
resolution ABL sampling, fast enough for reasonable flight leg lengths, and optimal for
the sensors to remain clear of the main-rotor wake while simultaneously avoiding the
distortion of airflow due to its airframe. At 30 m s\(^{-1}\), the distance between the AIMMS-20
and the LI-7500 is flown in ~8 ms. One might suspect that this discrepancy could have an
impact on the covariances and cospectra between the wind components and the \(H_2O\) or
\(CO_2\), so studies were conducted to assess any alteration in correlation between \(H_2O\) data
(as output by the LI-7500 and as derived from AIMMS-20 measurements) by slightly
shifting in time one instrument’s data relative to the other. However, no consistent
results could be detected by these time shifts, and it was determined that any effects of
the position difference cannot be captured by the current system. This is not unexpected,
since the instrument response time for the AIMMS-20 is 25 ms, and the typical
instrument response time for the LI-7500 is 50 ms. The electronic reaction time between
the actual sampling and data registering could be a factor that similarly affects such
covariances and cospectra. Due to the inconclusive results of the aforementioned time-
shift studies, estimating any potential bias is problematic. Because of this, the current
system relies on the manufacturers’ information regarding the instrument delays.
5. Development of DEMD

5.1 Considerations for HOP Data

With any aircraft-based observation platform, aircraft movements can be occasionally erratic, which can produce a spurious signal that contaminates ABL measurements and is difficult to dissociate from the atmospheric turbulence motions that are required for ABL studies, including any investigation of LSH effects. A common example can be seen in the potential spurious contribution to measured $T$ data resulting from altitude variations in the presence of a lapse rate. Additional data contamination sources include aircraft vibrations (typically producing high-frequency noise) and the non-stationarity of the atmosphere along the flight path and during the period of sampling (Lenschow 1986). Therefore, it is essential to use an algorithm to “decontaminate” the observed data series.

Traditionally, Fourier methods are used for the treatment of turbulence datasets, but they require stationarity that is often not seen in airborne data. Wavelets provide more flexibility than Fourier methods, but they require that the basis function be known a priori and that this basis function remains the same throughout the dataset. Empirical orthogonal functions (EOFs) allow for an adaptive basis, but they are not unique, so that their interpretation is not necessarily physically based. Yet for the interpretation of airborne turbulence data, it is necessary to adopt a data analysis technique that allows for non-stationarity and an adaptive basis, which is unique and orthogonal.
Many of these concerns are addressed with the implementation of empirical mode decomposition (EMD), which was introduced by Huang et al. (1996) and further discussed by Huang et al. (1998, 1999, and 2003). The purpose of EMD is to separate a signal into its component frequencies, each of which is unique, adaptive and orthogonal. As explained below, this method appears to be particularly appropriate for processing data collected on-board aircraft. While it does not seem to have been used previously for that purpose, EMD coupled with the Hilbert Spectral Analysis (HSA), together known as the Hilbert-Huang Transform (HHT), has been used to analyze many different types of datasets. Among others, Lundquist (2003) used it to separate stationary waves and intermittent events in T time series, Veltcheva and Soares (2004) and Datig and Schlurmann (2004) applied it in ocean wave analysis, Duffy (2004), Pan et al. (2002), and Salisbury and Wimbush (2002) applied it to climatological datasets and Huang et al. (2003) analyzed financial records with it. More recently, it was used to study the spectral properties of turbulent heat and CO$_2$ fluxes (Zhaoyang et al. 2006). In almost all cases, HHT provided signals that are much sharper than any of the traditional analysis methods in time-frequency-energy representation. Importantly, it also provides true physical meaning to many of the datasets examined.

5.2 The EMD Algorithm

With the application of EMD, any complicated data set can be decomposed into a finite and often small number of components, which is a collection of so-called intrinsic
mode functions (IMFs). An IMF represents a generally simple oscillatory mode as a counterpart to the simple harmonic function. By definition, an IMF is any function with the number of extrema and zero crossings being the same or differing by no more than one, and with its envelopes being symmetric with respect to zero (Huang et al. 1998). This decomposition method operating in the time domain is highly efficient, and due to being based on the local characteristic time scale of the data, it can be applied to non-linear and non-stationary processes. EMD is also adaptive, which is especially important over long flights, when the data is unlikely to be stationary. Unlike the EOF expansion, which also has an adaptive basis, the results of EMD are unique and typically have a physical interpretation (Huang et al. 1998).

From a practical point of view, the EMD method consists of “sifting” the data into IMFs through the application of an iterative algorithm (Huang et al. 1998, Rilling et al. 2003), as follows:

1) Locate all extrema of signal \( x(t) \).

2) Form an envelope around \( x(t) \) by interpolating between all maxima \( [e_{\text{max}}(t)] \) and all minima \( [e_{\text{min}}(t)] \) (typically by a spline fit).

3) Compute the mean of the envelope:

   \[
   m(t) = \frac{[e_{\text{max}}(t) + e_{\text{min}}(t)]}{2} \tag{1}
   \]

4) Subtract the envelope mean from the signal to yield the first component, \( h(t) \), sometimes also called the detail:
\[ h(t) = x(t) - m(t) \]  \hspace{1cm} (2)

5) Repeat steps 1 – 4 iteratively with the detail \( h(t) \) replacing the signal \( x(t) \) until the resulting \( h(t) \) meets the aforementioned criteria that define an IMF:

\[ h_{n+1}(t) = h_n(t) - m_n(t) \]  \hspace{1cm} (3)

6) Sift out the IMF \( h(t) \) and restart the process with the remaining data (which is the mean \( m(t) \) from steps 3 and 4 in the last iteration).

Figure 12 shows an illustration of this sifting algorithm, reprinting Figures 2 and 3 from Huang et al. 1998 (by permission of the Royal Society). The original data \( x(t) \) is presented at the top of the figure (a), and below that (b) is \( x(t) \) with the maxima and minima envelopes \([e_{\text{max}}(t)\text{ and } e_{\text{min}}(t)]\) as dot-dashed lines, as well as the envelope mean \( m(t) \) as a thick solid line, as in Eq. (1) above. The result of one iteration of the algorithm, \( h(t) \) from Eq. (2), is given next (c). Finally, after nine iterations, the algorithm obtains the first IMF, shown at the bottom of the figure (d).
This algorithm generates a finite number of IMFs, with the number of extrema decreasing with each mode (Rilling et al. 2003). It should be noted that using the usual HHT notation, the first result of EMD contains the highest-frequency oscillations, and is
referred to as IMF$_0$ (Lundquist 2003). In the notation used here, the IMF containing the lowest-frequency mode is IMF$_0$, the next lowest-frequency mode is IMF$_{0,1}$, etc. As described in detail in Section 7.2, IMF$_0$ encapsulates high-frequency sensor noise, and its removal (by linear subtraction) from all flight legs is straightforward and justified. Proper identification and elimination of potential spurious influences of aircraft motions in the lower-frequency IMFs of HOP data introduces a greater level of complexity.

**5.3 Initial Method and Adjustment**

The initially proposed method for processing turbulent atmospheric data is presented by Holder et al. (2011, hereafter H11), with the goal of isolating and removing spurious signals from true atmospheric turbulence. The approach involves the use of a correlation analysis to determine which HOP motions undesirably influence lower-frequency IMFs of meteorological data. H11 then suggests the elimination from the raw data of those lower-frequency IMFs that present significant correlations. However, while this correlation analysis does effectively identify contributions to the raw data signal from undesirable influences in a particular IMF, or in additive combinations of IMFs, the complete removal of those correlated IMFs would also remove any valuable information (e.g. larger-scale turbulence) present in the raw data signal along with the spurious information. This can have a detrimental impact on the quality of the variances and fluxes that are calculated from the resulting filtered data.
Therefore, the method proposed by H11 has been reevaluated, and has now been adapted to correct for spurious signals in the raw data while attempting to avoid the undesired removal of atmospheric turbulence contributions in the data. Expanding on the developments presented by H11, Detrending with EMD (DEMD) uses EMD to separate raw data signals into IMFs, and then applies a correlation analysis between the meteorological data IMFs and the HOP motions with the intention of isolating (and hopefully removing) significant spurious contributions.

Several differences separate the method proposed by H11 from the DEMD method. First, instead of subtracting the correlated IMFs from the raw data, DEMD detrends the data by applying the negative inverse of the linear regression slope from the determined correlations. Second, H11 only mentions examining the progressive sums of IMFs (e.g. IMF, IMF, IMF for the three lowest-frequency modes), whereas DEMD incorporates a correlation analysis with all possible combinations of IMFs. So for the three lowest-frequency modes, the IMFs examined include: IMF, IMF, IMF, IMF, IMF, IMF, IMF. Finally, using DEMD, instead of eliminating correlated IMFs, the technique uses the linear regression slope to detrend the data, accounting for the effects of HOP movement without unnecessarily removing atmospheric turbulence contributions. The detrending is also weighted by the magnitude of the correlation, which justifies the proportional contribution of the spurious signal.
5.4 DEMD Theory

The rationale behind the DEMD algorithm (Bolch et al., submitted) may be better understood through a straightforward example common to atmospheric sampling via aircraft such as the HOP. One particular quantity of interest in land-atmosphere interaction research is SH from a solar-heated surface to the atmosphere. Heat is carried upward to higher levels of the atmosphere air by means of turbulent eddies in which vertical velocity $w$ and $T$ are positively correlated. In order to determine upward eddy heat flux at some level above the surface, both $w$ and $T$ are measured at high frequency along a flight path that is typically a few km in length, and the time series of their values are interpreted as spatial variations, taking into account the flight velocity. The range of eddy sizes over which to evaluate the heat flux is chosen based on a working definition of eddy versus resolved scales, and $w$ and $T$ are spatially filtered to the eddy cutoff scale.

Local perturbations $w'$ and $T'$ from their spatial means are then multiplied and averaged over the filter scale to obtain the eddy heat flux $\overline{w'T'}$. Accuracy of the calculated eddy heat flux therefore depends on accurate determination of $T'$. The calculation of $T'$ incorporates deviations from a mean taken along a flight leg or a portion thereof, where it is assumed that readings along the flight leg are a valid representation of the flux at some average altitude, despite the fact that conditions generally prohibit a perfectly level flight path. Vertical fluctuations in HOP flight path contribute additional changes in $T$ readings in the presence of a lapse rate, which is a
decrease in $T$ with increasing height that is typical in a CBL. These $T$ variations are unrelated to eddy transport and thus could inhibit proper determination of the horizontal structure of $T$ and adversely influence calculations of SH.

For the purpose of demonstration, assume that the only variation present in the vertical structure of the atmosphere is a constant lapse rate. A linear regression analysis of $T$ and altitude data reveals their relationship, and a simple manipulation shows the adjustment required to correct for the influence:

$$\Delta T = -\left(\frac{1}{m}\right) \Delta z$$

(4)

where $m$ is the linear regression slope, $\Delta z$ and $\Delta T$ represent changes in altitude and $T$, respectively, and the negative sign has been applied so that the unwanted influence is removed from the data. Now if the initial assumption is removed, and $T$ variations other than the lapse rate are considered as well, $T'$ could be decomposed into two parts:

$$T' = T'_a + T'_b$$

(5)

where $T'$ is the total variation in $T$, $T'_a$ is the $T$ variation due to HOP altitude fluctuations in the stratified CBL and $T'_b$ represents other $T$ variations, which are desired for the flux calculation. A combination of $T'_a$ and $T'_b$ are often present in atmospheric readings, and the optimal goal of detrending is to eliminate the unwanted influence of $T'_a$ while maintaining the contribution of atmospheric turbulence in $T'_b$ for turbulence
flux calculations. Once EMD is used to separate the raw $T$ signal into constituent IMFs and the correlation analysis is conducted, assume an ideal situation in which the spurious signal $T'_a$ is completely isolated into a single IMF. For this ideal case, Eq. (4) can be manipulated to show the correction required to detrend the data for the lapse rate influence:

$$T_{adj} = -\left( \frac{1}{m_a} \right) * (z')$$

(6)

where $T_{adj}$ is the correction array to be applied to $T$ for this ideal situation, $m_a$ is the linear regression slope associated with the spurious signal ($T'_a$) (which is assumed to be isolated into a single IMF) and $z$, and $z'$ is the altitude variation. Eq. (6) is only applicable for theoretical conditions in which the spurious influence is perfectly isolated, meaning that the linear regression yields $r_a^2 = 1$ ($r^2$ is the coefficient of determination, the square of the correlation coefficient $r$). Commonly in atmospheric turbulence measurements, the unwanted influence of $T'_a$ is not completely isolated into a single IMF; instead, some contributions from $T'_b$ are present as well. In this case, the idealized detrending shown in Eq. (6) is inappropriate, and should be adjusted to account for the proportional contribution of $T'_a$. If $r_a^2$ is taken as the proportional contribution of $T'_a$ to the total variance of $T'$, then the right-hand side of Eq. (6) can be weighted to account for that proportional contribution, yielding an estimated correction array:
\[ T_\alpha = -\left( \frac{1}{m_\alpha} \right) \ast (z') \ast (r^2_\alpha) \]  \hspace{1cm} (7)

where \( T_\alpha \) is the weighted detrending adjustment to be applied to \( T \), \( z' \) is the altitude variation, and \( r^2_\alpha \) and \( m_\alpha \) are the maximum \( r^2 \) value from the correlation analysis and the associated slope, respectively. Eq. (7) is the central data correction equation of DEMD (as it pertains to this particular example of \( T \) and \( z \)), and combines the EMD and correlation analysis of H11 with an application of the characteristics of the spurious influence (\( m_\alpha \) and \( r^2_\alpha \)) to the detrending algorithm.
6. DEMD Evaluation

6.1 Synthetic Dataset Evaluation

In order to evaluate the efficacy of DEMD, synthetic datasets were created to imitate the HOP meteorological and movement datasets so that atmospheric conditions could be simulated with a prescribed slope, and the slope recovery capabilities of DEMD could be assessed. The synthetic datasets presented here used $T$ as the meteorological parameter of interest and altitude as the HOP motion parameter, and a lapse rate typical for a stratified CBL was prescribed so that DEMD could be tested in a situation where detrending was known to be required.

6.1.1 Experiment Design

A two-dimensional synthetic $T$ field (200 m high by 5000 m long, 1 m resolution) was generated with a vertical lapse rate of $-10 \text{ K km}^{-1}$ (approximating the dry adiabatic lapse rate) and with a surface $T$ (lowest height) of 303 K. To simulate atmospheric turbulence motions, this field was overlaid with sinusoidal $T$ perturbations along the length of the field, and the amplitude and period of the perturbations were varied for the different test cases. An artificial path for HOP sampling was defined as a sinusoidal variation in altitude along the length of the field with the $x$-axis mid-field (i.e. at 100 m height), and the amplitude and period of the sampling path were also varied for the different test cases.
The first series of test cases (Set A) independently varied the amplitude and period of the $T$ perturbations and the sampling path, with both synthetic datasets starting in the same phase. The range of variation for sampling path and $T$ perturbation amplitude and period parameters was determined by a visual inspection of data from several randomly selected HOP flights, as well as an analysis of running averages of standard deviations in those flight legs. As shown in Table 2, the $T$ perturbation periods for the test cases ranged from 20 m to 10 km, and the perturbation amplitudes ranged from 0.1 K to 4 K overall, with the specific amplitude ranges tailored appropriately for each period.

Table 2: Periods and associated amplitudes for synthetic $T$ data

<table>
<thead>
<tr>
<th>Period (m)</th>
<th>Amplitude (K)</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>0.1 0.3 0.5 0.7</td>
</tr>
<tr>
<td>40</td>
<td>0.1 0.3 0.5 0.7</td>
</tr>
<tr>
<td>100</td>
<td>0.2 0.5 1 2</td>
</tr>
<tr>
<td>500</td>
<td>0.2 0.5 1.5 3</td>
</tr>
<tr>
<td>2000</td>
<td>0.5 1 2 3</td>
</tr>
<tr>
<td>10000</td>
<td>0.5 1 2 4</td>
</tr>
</tbody>
</table>

Table 3 shows the sampling path parameters, where amplitudes of 25 m and 50 m were tested, and the periods were varied over a range from 100 m to 1600 m.

Testing every combination of these parameter variations, with six periods and four amplitudes for $T$ and four periods and two amplitudes for the sampling path, yields a total of 192 test cases for Set A.
Table 3: Amplitudes and periods for synthetic sampling path

<table>
<thead>
<tr>
<th>Amp. (m)</th>
<th>Period (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>25</td>
<td>100 200 800 1600</td>
</tr>
<tr>
<td>50</td>
<td>100 200 800 1600</td>
</tr>
</tbody>
</table>

As an example, the synthetic $T$ field for test case a083 is shown in Figure 13, with the $200$ m field height on the y-axis, the first $1000$ m of the field length on the x-axis, and the $T$ (K) indicated by color. Test case a083 has a $T$ amplitude of $1$ K and a period of $100$ m, and is sampled along a path with an amplitude of $25$ m and a period of $800$ m. Figure 14 shows the $T$ data collected along the first $1000$ m of this sampling path.

Figure 13: First 1000 m of the synthetic T field for test case a083
Another two sets of test cases (Sets B and C) followed the same structure for parameter variations, but shifted the sampling path 90° and 180° out of phase from the $T$ perturbations, generating another 384 test cases. The final set of tests (Set D) varied the amplitude of the sinusoidal $T$ perturbation field from a maximum at a specified height in the ABL, to minima at lower and higher altitudes. $T$ period and sampling path period were varied as in the previously mentioned sets of test cases, with the $T$ amplitude maximum and minima set to the maximum and minimum values for each period in Table 2. All combinations of these parameter variations were tested with the peak $T$
amplitude prescribed at 105 m and 117 m height (arbitrary selections), resulting in another 96 test cases for Set D, and a grand total of 672 test cases.

### 6.1.2 DEMD Results

For each of these test cases, DEMD was implemented in an attempt to recover the prescribed lapse rate. The first step of DEMD is to apply EMD (Huang et al. 1998, Rilling et al. 2003) to the meteorological data, in this case, the $T$, which decomposes the data into a finite number of IMFs, as described in Section 5.2. The IMFs are named following the conventions of described in Section 5.2, so the lowest-frequency mode is IMF$_{\ell}$, the next lowest mode is IMF$_{\ell-1}$, etc. A vector sum of different IMFs, such as IMF$_{\ell}$ and IMF$_{\ell-1}$, will be indicated as IMF$_{\ell|\ell-1}$.

DEMD uses a correlation analysis similar to what is presented in H11, but expands the scope of the investigation. In particular, the correlation analysis presented in H11 only mentions examining the progressive sums of IMFs (e.g. IMF$_{\ell}$, IMF$_{\ell-1}$, IMF$_{\ell-1|\ell-2}$ for the three lowest-frequency modes), whereas DEMD incorporates an analysis of the correlation with all possible combinations of IMFs. So for the three lowest-frequency modes, the IMFs examined include: IMF$_{\ell}$, IMF$_{\ell-1}$, IMF$_{\ell-2}$, IMF$_{\ell-1|\ell-2}$, IMF$_{\ell-1|\ell-2|\ell-3}$. The coefficient of determination $r^2$ (square of the correlation coefficient $r$) and the linear regression slope $m$ is assessed for each possible combination of IMFs of $T$ compared to the sampling path data. The maximum $r^2$ indicates the strongest correlation between $T$ and altitude, and the associated $m$ is taken as the lapse
rate. For atmospheric data, the $r^2$ and $m$ are the key components of DEMD and they detrend the raw data according to Eq. (7); however, for the purposes of evaluating the method with these test cases, recovery of the prescribed lapse rate is assessed.

Tables 4 and 5 give several examples from each of the sets of tests where recovery of the prescribed lapse rate is achieved. The test name is shown in the far left column, and examples from Sets A, B, and C are indicated in Table 4 with a prefix a, b, and c on the test name, respectively, and Set D examples have a prefix d in Table 5. Amplitude (Amp) and period (Per) for the sinusoidal $T$ and sampling paths are shown in the next four columns, with the phase shift given for the sampling path. In Table 5, the peak height is given in the second column, and the particular $T$ amplitudes for these tests can be found using Table 2. For example, in test d004, the $T$ period is 20 m, so referencing Table 2, the peak amplitude was 0.7 K, and the amplitude linearly decreased to 0.1 K at the upper and lower borders of the synthetic $T$ field. The last three columns on the right in Tables 4 and 5 show the results of DEMD, indicating the IMF combination with the highest $r^2$ as well as that $r^2$ value and the associated $m$, for which the goal is the prescribed lapse rate of $-10$ K km$^{-1}$. The column giving the IMF combination uses a shorthand notation where $i_1$ is the lowest-frequency IMF (IMF$_{i_1}$), $i_2$ is the next lowest (IMF$_{i_2}$), and $i_{12}$ is the combination of those two (IMF$_{i_{12}}$), as in the results from test case a031 in Table 4. The recovered lapse rate in Table 4 is an average of $-10.019 \pm 0.214$ K km$^{-1}$, with an $r^2$ of $0.9881 \pm 0.0156$, while the Table 5 results show an
average recovered lapse rate of $-10.665 \pm 0.798$ K km$^{-1}$, with an $r^2$ of $0.9049 \pm 0.0868$.

The less effective recovery in Table 5 indicates that the more complex structure in Set D is more challenging for the DEMD technique.

**Table 4: Selected results from Sets A, B, and C**

<table>
<thead>
<tr>
<th>Test</th>
<th>$T$</th>
<th>Sampling Path</th>
<th>DEMD Results</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Amp</td>
<td>Per</td>
</tr>
<tr>
<td>a002</td>
<td>0.3</td>
<td>20</td>
<td>25</td>
</tr>
<tr>
<td>a031</td>
<td>0.5</td>
<td>20</td>
<td>50</td>
</tr>
<tr>
<td>a083</td>
<td>1</td>
<td>100</td>
<td>25</td>
</tr>
<tr>
<td>a135</td>
<td>2</td>
<td>2000</td>
<td>50</td>
</tr>
<tr>
<td>b042</td>
<td>0.3</td>
<td>40</td>
<td>25</td>
</tr>
<tr>
<td>b098</td>
<td>0.5</td>
<td>500</td>
<td>25</td>
</tr>
<tr>
<td>b178</td>
<td>1</td>
<td>10000</td>
<td>25</td>
</tr>
<tr>
<td>c052</td>
<td>0.7</td>
<td>40</td>
<td>25</td>
</tr>
<tr>
<td>c091</td>
<td>1</td>
<td>100</td>
<td>25</td>
</tr>
<tr>
<td>c140</td>
<td>3</td>
<td>2000</td>
<td>25</td>
</tr>
</tbody>
</table>

**Table 5: Selected results from Set D**

<table>
<thead>
<tr>
<th>Test</th>
<th>$T$</th>
<th>Sampling Path</th>
<th>DEMD Results</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
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<td>Amp</td>
<td>Per</td>
</tr>
<tr>
<td>d004</td>
<td>105</td>
<td>20</td>
<td>50</td>
</tr>
<tr>
<td>d013</td>
<td>105</td>
<td>40</td>
<td>25</td>
</tr>
<tr>
<td>d026</td>
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<tr>
<td>d084</td>
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</tbody>
</table>
To better illustrate the DEMD process and its evaluation through these test cases, we take one example each from Tables 4 and 5, a083 and d026. As mentioned previously, test case a083 uses a $T$ perturbation field with an amplitude of 1 K and a period of 100 m, and samples that field along a path with an amplitude of 25 m and a period of 800 m, beginning with the same origin point as the sinusoidal $T$ perturbations (i.e. no phase shift). Figure 13 shows the first 1000 m of the synthetic $T$ field for case a083, with the 200 m height on the y-axis, the 1000 m length on the x-axis, and the $T$ (K) indicated by color. The figure shows an overall decrease in $T$ with height according to the lapse rate, as well as the sinusoidal variations along the length of the field. Figure 14 shows the $T$ data captured from the synthetic $T$ field along the sampling path for test case a083, which is the raw data input for EMD that will be decomposed into IMFs. A key component of the DEMD method can be seen in Figure 15, which shows an overlay of the first 1000 m of the sampling path in blue and the correlated IMF combination in green, and in Figure 16, which shows a scatterplot of the IMF and sampling path data in blue, with the linear regression slope in black. The IMF combination in this case is IMF$_{1235}$, which is indicated in shorthand notation as i1235 in Table 4, and the resulting $r^2$ for test case a083 was 0.9979 and the associated $m$ was -10.091 K km$^{-1}$. The departure of the scatterplot from the regression line indicates that the influence of the prescribed lapse is not completely isolated into this IMF combination, which is reflected in the slight deviations of $r^2$ and $m$ from the ideal.
Figure 15: Overlay of first 1000 m of sampling path (blue) and $T \text{ IMF}_{t(t-4:t-2:t-4}$ (green) for test case a083
For test case d026, the period of the sinusoidal $T$ perturbations was 500 m, the amplitude peaked at 3 K at a height of 105 m, decreasing linearly to 0.2 K at the upper and lower boundaries of the synthetic $T$ field, and the sampling path had a period of 100 m and an amplitude of 50 m. Figure 17 gives the first 2000 m of the $T$ field for test case d026, and as in Figure 13, it shows a clear lapse rate, as well as the sinusoidal variations, but also illustrates the higher amplitude of $T$ perturbations centered around the 105 m height. Figure 18 shows the first 2000 m of $T$ data for test case d026, sampled along the predetermined path, and a comparison of this figure with Figure 14 demonstrates the increased complexity of the fourth set of test cases.
Figure 17: First 2000 m of the synthetic $T$ field for test case d026
Figure 18: First 2000 m of $T$ data captured along the sampling path for test case d026

Figure 19 shows the first 1000 m of the highest correlated IMF (green) and the sampling path (blue) overlaid, and Figure 20 shows a scatterplot of those data (blue) and linear regression slope (black). For this test case, the highest correlated IMF was IMF$_{-4}$, with an $r^2$ value of 0.9445 and an $m$ of -10.844 K km$^{-1}$. Figures 15, 16, 19, and 20 show that for both test cases a083 and d026, the expected negative correlations between altitude and $T$ are evident in the overlays, and the scatterplots show the appropriate recoveries of the prescribed slopes, as well as the tight dispersal of points near the plotted linear regression slope line indicative of very high $r^2$ values.
Figure 19: Overlay of first 1000 m of sampling path (blue) and $T \text{IMF}_{t-4}$ (green) for test case d026
To specify the corrections dictated by DEMD via Eq. (7), examine the particulars of the detrending array on the right side of the equation as it pertains to the two examples discussed above. Test case a083 recovered a lapse rate of $-10.091 \text{ K km}^{-1}$ with an $r^2$ of 0.9979, while test case d026 recovered a lapse rate of $-10.844 \text{ K km}^{-1}$ with an $r^2$ of 0.9445. Recalling that regression slope $m$ in Eq. (7) corresponds to the inverse of the lapse rate, a083 has $m = -99.81 \text{ m K}^{-1}$ and d026 has $m = -92.22 \text{ m K}^{-1}$, compared to the prescribed $m = -100 \text{ m K}^{-1}$. So the “detrending arrays” for the two example cases would be $T\alpha = (9.998 \times 10^{-3}) \times z'$ for a083 and $T\alpha = (1.024 \times 10^{-2}) \times z'$ for d026. This means that for a point in the time series where $z' = 10$, Eq. (7) would require an increase in $T$ of...
9.998 \times 10^{-2} \text{ K for a083}, or an increase in $T$ of 1.024 \times 10^{-1} \text{ K for d026}, in order to detrend for the influence of the lapse rate and account for the significance of its contribution to the signal.

### 6.1.3 Filtering Criteria

The DEMD algorithm may not always recover the appropriate lapse rate or other possible detrending correction, because for some cases, separating the data into IMFs may not sufficiently isolate the spurious influences from desired atmospheric turbulence data. Three filtering criteria are presented here that aid in identifying cases where DEMD can be appropriately applied: 1) the $r^2$ cutoff filter, 2) the next $r^2$ check, and 3) the S/T ratio filter.

The $r^2$ cutoff filter sets a minimum $r^2$ value below which the application of DEMD is deemed inappropriate. As detailed in H11, for the size of HOP datasets collected during CLASIC, the minimum $r^2$ for significance at the 95% confidence level is 0.04, and at the 99% confidence level, the minimum $r^2$ is 0.09. This leads to a choice of an $r^2$ cutoff value of 0.10, with the stipulation that careful examination of datasets can lead to adjustments of that value. This value seems appropriate for HOP data, especially considering the inherent nonlinear complexity of atmospheric turbulence data, but for the test cases examined here, an $r^2$ cutoff value of 0.5 should give ample leeway, given the simplicity and periodicity of the synthetic data. Therefore, test cases resulting in a maximum $r^2 < 0.5$ are eliminated from consideration.
When working with real-world data, the next \( r^2 \) check provides an assessment of DEMD efficacy via an additional correlation analysis on the IMFs of the detrended data. If the detrended data exhibit stronger correlations than the raw data, then another attempt at detrending is made by applying DEMD to the raw data again, but this time using the second highest correlated IMF combination’s \( r^2 \) and \( m \) in Eq. (7). The resulting data, now a second attempt at detrending, is also subjected to a correlation analysis. If there are again stronger correlations with the newly detrended data than with the raw data, then DEMD is not applied to the data; whereas, if the correlations have been reduced, this second attempt at detrending is accepted. These multiple correlation analyses are necessary for real-world data because it is unknown whether detrending is required, and if so, the particular characteristics of the spurious influence (i.e., \( r^2 \) and \( m \)) are not known \textit{a priori}.

However, for the test cases presented here, the prescribed lapse rate is known and the efficacy of its recovery is apparent, so these additional correlation analyses are not needed. Instead, if the \( m \) first resulting from DEMD falls outside of an acceptable range, then it is determined whether the \( m \) associated with the second highest \( r^2 \) falls within the acceptable range. If the \( m \) from the second highest \( r^2 \) is within the acceptable range, it is taken as the DEMD result; otherwise, the first result, though it is outside the acceptable range, is taken as the DEMD result, to maintain objectivity for the test cases. For the purpose of these tests, the next \( r^2 \) check views the acceptable range for \( m \) values
as within \(-15 \leq m \leq -5\), which is arbitrary, but considered appropriate, again taking into account the simplicity and periodicity of the synthetic data.

Intuitively one might suspect that when the period of the \(T\) perturbations is near the same magnitude as the period of the sampling path, a correlation between these two datasets may interfere with the recovery of the prescribed lapse rate. An examination of the ratio of sampling path period to \(T\) perturbation period (S/T ratio) for each test case compared to \(r^2\) and \(m\) resulting from DEMD reveals the presence of this interference, as shown in Figures 21 and 22. When the S/T ratio approaches unity, the \(r^2\) value drops in Figure 21 and the recovered \(m\) veers away from \(-10\) K km\(^{-1}\) in Figure 22. For brevity, only results from Set A are shown in Figures 21 and 22, while the other sets of test cases yield similar results.
Figure 21: S/T ratio vs. $r^2$ for Set A
For the test cases with an S/T ratio near unity, an increase in the amplitude of the $T$ perturbations could lead to greater interference with lapse rate recovery. Table 6 shows a selection of results from Set A that demonstrate this phenomenon. As the $T$ perturbation amplitude increases, the $m$ resulting from DEMD deviates further from the prescribed $m$ (-10 K km$^{-1}$). Due to this obscuring of the lapse rate in cases where the S/T ratio is near unity, test cases resulting in $m$ values outside an acceptable range of $-15 \leq m \leq -5$ and having an S/T ratio within the range of $0.5 \leq S/T \leq 2$ were eliminated.

It should be noted that the S/T ratio filter, unlike the first two filtering criteria, is only appropriate for these test cases, and is unnecessary when working with collected data. These spurious correlations are a result of the periodicity and relative simplicity of the
synthetic data generated here, and such circumstances are highly unlikely to be encountered in nature.

Table 6: Selected results from Set A

<table>
<thead>
<tr>
<th>Test</th>
<th>$T$</th>
<th>Amp</th>
<th>Per</th>
<th>Amp</th>
<th>Per</th>
<th>IMF</th>
<th>$r^2$</th>
<th>$m$</th>
</tr>
</thead>
<tbody>
<tr>
<td>a065</td>
<td>0.2</td>
<td>100</td>
<td></td>
<td>25</td>
<td>100</td>
<td>i6</td>
<td>0.9998</td>
<td>-2.0415</td>
</tr>
<tr>
<td>a066</td>
<td>0.5</td>
<td>100</td>
<td></td>
<td>25</td>
<td>100</td>
<td>i4</td>
<td>1.0000</td>
<td>9.9504</td>
</tr>
<tr>
<td>a067</td>
<td>1</td>
<td>100</td>
<td></td>
<td>25</td>
<td>100</td>
<td>i12</td>
<td>1.0000</td>
<td>29.990</td>
</tr>
<tr>
<td>a068</td>
<td>2</td>
<td>100</td>
<td></td>
<td>25</td>
<td>100</td>
<td>i2</td>
<td>1.0000</td>
<td>69.990</td>
</tr>
<tr>
<td>a069</td>
<td>0.2</td>
<td>100</td>
<td></td>
<td>50</td>
<td>100</td>
<td>i4</td>
<td>1.0000</td>
<td>-5.9861</td>
</tr>
<tr>
<td>a070</td>
<td>0.5</td>
<td>100</td>
<td></td>
<td>50</td>
<td>100</td>
<td>i5</td>
<td>0.9920</td>
<td>0.0110</td>
</tr>
<tr>
<td>a071</td>
<td>1</td>
<td>100</td>
<td></td>
<td>50</td>
<td>100</td>
<td>i4</td>
<td>1.0000</td>
<td>10.014</td>
</tr>
<tr>
<td>a072</td>
<td>2</td>
<td>100</td>
<td></td>
<td>50</td>
<td>100</td>
<td>i12</td>
<td>1.0000</td>
<td>30.024</td>
</tr>
</tbody>
</table>

These three filtering criteria, the $r^2$ cutoff filter, the next $r^2$ check, and the S/T ratio filter, help to identify the cases for which DEMD can be suitably implemented. As mentioned previously, the S/T ratio filter is only meant to be used for the synthetic data in the test cases, as it addresses a unique problem, so this filter is actually applied to the raw data first, followed by the $r^2$ cutoff filter, and then the next $r^2$ check. Out of the total of 672 test cases, the S/T ratio filter is used to eliminate 67 test cases (10.0%), then the $r^2$ cutoff filter eliminated another 53 test cases (7.9%), and lastly, 12 test cases (1.8%) were corrected by the next $r^2$ check. The next $r^2$ check adjusts the results without elimination, so the S/T ratio filter and $r^2$ cutoff filter eliminated a total of 120 test cases (17.9%), leaving 552 test cases (82.1%) deemed appropriate for the application of DEMD. These remaining test cases yield an average recovery of $m = -9.990 \pm 1.093$ K km$^{-1}$ (within 1%).
with \( r^2 = 0.9676 \pm 0.0708 \). Results from these cases are presented in Figures 23 and 24, which depict histograms of the \( r^2 \) and \( m \), respectively, for each of the four sets of test cases. In Figure 23, the \( r^2 \) values fall very near unity in most cases, especially in the first three sets of test cases, with a slightly wider spread for the more complex fourth set of test cases. Figure 24 shows similar results, with the majority of the \( m \) values gathered tightly around the prescribed lapse rate of \(-10\ \text{K km}^{-1}\).

![Figure 23: Histograms for \( r^2 \)](image-url)
6.2 OLAM LES Evaluation

As a means to further explore the capabilities of DEMD, a large-eddy simulation (LES) of an idealized CBL was conducted using the Ocean-Land-Atmosphere Model (OLAM; Walko and Avissar, 2008a, 2008b, 2011). This allows for an assessment of the effects of DEMD on an end product of interest in ABL studies, here, SH. The LES provides the advantage of greater complexity than the synthetic datasets in Section 6.1, while also supplying a field of atmospheric data where the target value is known, as opposed to the HOP datasets to be discussed in Chapter 7.
6.2.1 Simulation Description

OLAM incorporates a finite-volume discretization of the full compressible nonhydrostatic Navier-Stokes equations on either a triangular or hexagonal mesh. While OLAM is most often applied to the sphere, it was configured for a limited-area Cartesian domain in the present application. The horizontal grid cell size for this simulation is 15 m (giving a horizontal cell area of 225 m²), and the vertical grid cell size is 10 m for the lowest 1 km, which then expands by about 3% for each level up to a model top near 2.5 km, with 155 total vertical levels. The computational domain covers a horizontal area in the shape of a hexagon, with about 98,000 grid cells in each level, and periodic lateral boundary conditions. Thus, the hexagonal model domain behaves as if an identical domain with an identical solution exists across each of the six hexagonal faces. The center of each such implied neighboring domain is about 4.4 km from the center of the actual domain. Figure 25 shows vertical velocity at z = 300 m in a cross section of the full horizontal LES domain. The periodic boundary conditions of the simulation are evident in the eddy structures. Figure 26 also shows vertical velocity at z = 300 m, but with a horizontal cross section zoomed in on a small area near the center of the domain, with the hexagonal grid cells shown. This conveys that while there is a small amount of structure down near the grid scale, the main energy-carrying eddies are much larger and are well-resolved, as expected in an LES.
Figure 25: Horizontal cross section of \( w \) at \( z = 300 \) m (full LES domain)
Figure 26: Horizontal cross section of $w$ at $z = 300$ m (zoom view)

The model atmosphere is dry, and initially motionless and horizontally homogeneous, with a surface pressure of 1000 hPa, a surface $T$ of 300 K, and a $T$ lapse rate that is weakly stable for the first 600 m. More specifically, initial $T$ of 296 K, 295 K, 290 K, and 285 K are specified at heights of 600 m, 1 km, 2 km, and 3 km, respectively. The less stable layer below 600 m helps to expedite the development of the CBL up to that height, and the stable layer from 600 m to 1 km similarly expedites the characteristic development of a stable capping layer, thus reducing the computational time to develop a mature CBL. CBL growth is accomplished by specifying a uniform surface SH of 150 W m$^{-2}$. There are no topographical, land cover, or other surface features, nor any
radiative transfer. Subgrid-scale diffusion is represented by a simple Smagorinsky-Lilly parameterization (Walko and Avissar, 2008b).

The time step for the LES is 0.4 s, and the model is run for 2 h, with results taken from the final time. Vertical cross sections are taken that pass through the hexagonal domain three times, yielding a longer cross section than the domain width. Specifically, the first vertical cross section passes through the center grid cell of the hexagonal model domain, then moves through the model in an azimuthal direction of 80° (clockwise from north), sampling the domain at 10 m horizontal increments by horizontally interpolating data from neighboring grid cell center points at each of the lowest 100 vertical levels. As shown in Figure 25, due to the angle of direction of the vertical cross section and the periodic boundary conditions, it passes through the model domain three times, yielding a dataset that is 1 km high and about 13.3 km long. Two additional vertical cross sections were sampled from the final LES time, both passing through the domain center grid cell, with azimuthal directions of 20° and 320°. Plots of $w$ (m s$^{-1}$), $T$ (K), and $\theta$ (K) from the 80° cross section are shown in Figures 27, 28, and 29, respectively.
Figure 27: Vertical cross section of $w$ (80°)
Figure 28: Vertical cross section of $T$ (80°)
Figure 29: Vertical cross section of $\theta$ (80°)

6.2.2 DEMD Results

Similar to the synthetic dataset evaluation described in Section 6.1, artificial sampling paths were defined as sinusoidal variations of altitude through the vertical cross sections, independently varying the amplitude and period of the sampling path with mean altitudes prescribed at 100 m intervals through the LES CBL. Table 7 shows the sampling path parameters, where amplitudes of 25 m and 50 m were used, and the periods were varied over ranges from 100 m to 800 m. DEMD was implemented for all ten permutations of these sampling path parameters at 100 m intervals from 100 m to 800 m high for each of the three vertical cross sections, resulting in a total of 240 samples of the LES results.
Table 7: Amplitudes (m) and periods (m) for LES sampling paths

<table>
<thead>
<tr>
<th>Sampling Path</th>
<th>Amp</th>
<th>Period</th>
<th></th>
<th>Period</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>25</td>
<td>100</td>
<td>200</td>
<td>300</td>
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<tr>
<td></td>
<td>50</td>
<td>100</td>
<td>200</td>
<td>300</td>
</tr>
</tbody>
</table>

Figures 30, 31, and 32 show SH calculated from the raw data (sampling path data with no detrending) and from data with DEMD applied. The black dots indicate SH calculated from a horizontal array taken from the vertical cross section at each vertical level (10 m resolution), which essentially provides target values for the sampling path calculations. The red squares represent the raw data SH for each of the sampling path parameter permutations, plotted at their mean altitudes; likewise, the blue diamonds represent SH calculated from the data processed by DEMD. Finally, the magenta and green dots represent SH horizontally-averaged across the entire model domain at each vertical level, with the magenta indicating model-resolved fluxes and the green including the subgrid-parameterized contributions. As typical for LES, the model-resolved and total SH profiles are nearly the same except close to the ground where most transport is subgrid-scale.
Figure 30: SH profiles for raw data and DEMD for first vertical cross section
Figure 31: SH profiles for raw data and DEMD for second vertical cross section
Figure 32: SH profiles for raw data and DEMD for third vertical cross section

It is clear from Figures 30, 31, and 32 that for each of the three vertical cross sections, at mean altitudes within the CBL (from 100 m to 700 m), the application of DEMD increases the accuracy of SH recovery. For many cases, the improvement is on the order of tens of W m$^{-2}$. In particular, the three lowest-altitude DEMD results in Figure 30 exhibit a significant improvement of the noticeably wide spread in the raw data fluxes, from an average standard deviation of 26.4 W m$^{-2}$ for the raw data fluxes to 4.26 W m$^{-2}$ for the detrended fluxes. The figures show that the sampling paths at 800 m mean altitude are above the CBL, eliminating the need for DEMD application for most of those cases.
The deviation of the vertical cross section SH profiles (black dots) from each other and from the full LES horizontally-averaged SH profile (magenta dots, in particular) indicates the typical degree of sampling error in the given sample size of one of the vertical cross sections. This also refers to the potential inherent inadequacies of aircraft-based sampling data as representations of the characteristics of an observational sampling area. For an example scenario that could lead to such deviations, recall the previous discussion early in Section 5.4 concerning the calculation of SH. An eddy cutoff scale is chosen over which $w$ and $T$ are spatially filtered, leading to the calculation of the eddy heat flux $\overline{w'T'}$ from the perturbations $w'$ and $T'$ over this length. Given the large eddy structure present in the LES domain (see Figure 25), a sample path may pass mostly through an updraft or downdraft branch, with that branch size possibly approaching the eddy cutoff scale, or at least resulting in a misrepresentation of the large eddy structure of the full domain.
7. Application of DEMD to HOP Data

Atmospheric turbulence data collected with the HOP during CLASIC are used to
demonstrate the application of DEMD, and to offer a comparison to the initial
detrending method of H11 (see Section 5.3). Rather than coupling EMD to HSA, as has
been done by others, spectral analyses presented here use the Fourier Transform (FT).
While there are advantages of using the HHT method (e.g., Huang et al. 1998 and
Zhaoyang et al. 2006), turbulence spectra have been studied very extensively with FT
and there is an abundance of theoretical and empirical knowledge available for
comparison with our data.

7.1 Flight Description

As part of a flight performed during CLASIC on 19 June 2007 in Oklahoma, the
HOP flew a triangular pattern (10 km on each side) at three different altitudes, as shown
in Figure 33. Given that the HOP is flown at a more or less constant airspeed of 30 m s\(^{-1}\)
(turbulence causes some small airspeed fluctuation) through the 30 km triangular
pattern, each triangle should be completed in 1,000 s. However, wind speed variations
can lead to differences in the amount of time required to complete a triangle, as
evidenced by the fact that in this particular case, the three triangles were flown in about
47 min, as opposed to the predicted 50 min.
Figure 33: HOP triangular flight pattern at three altitudes, with altitude in m ASL, and lowest-altitude triangle flown a few m AGL

For field campaigns such as CLASIC, geographic locations for each day and a general flight plan (e.g., several triangles at different altitudes with a few vertical profiles interspersed) are usually determined before takeoff. However, the specific details of the flight pattern, particularly how many triangles are flown and at which altitudes, are often chosen during the flight and depend strongly on the CBL height. Flying vertical profiles at climb rates of about 100 m min⁻¹ provides a real-time display of $\theta$ (in the HOP cockpit, as noted in Section 4.1) that is accurate enough to provide a good estimate of the top of the CBL. Typically, if the CBL is less than 300 m high, as could be the case in early-morning flights, three triangles are performed: one near the ground surface, one near (i.e., 30-50m below) the top of the CBL, and one near the middle of the
CBL. When the CBL is deeper, the near-surface and near-top CBL triangles are still flown, with more triangles flown in between these levels with a separation of 100-150 m.

Figure 34 depicts the time series of the flight altitude and of the preprocessed wind components and scalars collected by the AIMMS-20 and the LI-7500 during an afternoon flight on 19 June 2007 during CLASIC. From top to bottom, the figure shows altitude (z, in m ASL), three wind components (u, v and w, in m s$^{-1}$), T (K), $H_2O$ concentration (q, in g m$^{-3}$), and $CO_2$ concentration (C, in mg m$^{-3}$). The x-axis shows elapsed time (s) from the start of data collection, and the continuous blue lines are the data for each flight leg, with the grey portions indicating regions of “undesirable” movements (including turns, rapid climbs and descents).
Figure 34: HOP data from a 19 June 2007 CLASIC flight, showing $z$ (m ASL), $u$, $v$, and $w$ (m s$^{-1}$), $T$ (K), $q$ (g m$^{-3}$), $C$ (mg m$^{-3}$), and elapsed time (s) on the x-axis; blue lines are flight legs, and grey lines show eliminated sections (turns and rapid climbs/descents)
The altitude provides a clear history of this specific flight. During the first ~800 s, the HOP climbed by ~100 m high “steps,” moving from near the ground surface up to just below the top of the CBL, and maintaining a nearly constant altitude for about 2 min for each of the steps. While longer legs help reduce the magnitude of the error (as shown in Section 2.2), this type of step profile pattern provides 2-min flight legs at 6 different altitudes throughout the CBL for turbulence flux calculations. Of course, how well these shorter legs are able to capture the relevant atmospheric turbulence motions should be determined by comparison to the longer triangle flight leg fluxes, and also to a model simulation of the site at the date and time of data collection (as suggested in Section 8.2).

At the end of this pattern, the HOP climbed through the top of the CBL (as identified by the real-time θ profile display described previously), up to above the entrainment layer to provide information on the location of the inversion layer capping the CBL.

For the next section of the flight, three triangles were flown as explained above and shown in Figure 33, one near the top, one near the middle and one near the bottom of the CBL. Data from the three legs of the lowest-altitude triangle are shown in Figures 35, 36, and 37, using the same conventions as in Figure 34. These were the 14th, 15th, and 16th legs of this flight, and are hereafter referred to as Leg 14, Leg 15, and Leg 16. After these three triangles, a continuous climb and descent was flown to profile the CBL and to assess possible changes in CBL height. Figure 38 shows the top of this profile as a plot of virtual potential temperature θv against altitude, and indicates an inversion capping.
the CBL at approximately 720 m ASL (~400 m AGL). Finally, two additional triangles were flown at intermediate altitudes to complete the full characterization of the CBL.

Figure 35: As in Figure 34, but for Leg 14
Figure 36: As in Figure 34, but for Leg 15.
Figure 37: As in Figure 34, but for Leg 16
Figure 38: Vertical profile of $\theta_v$ (K) vs. $z$ (m ASL) from a 19 June 2007 CLASIC HOP flight, with blue dots for raw data and red dots for a 20 s moving average.

The full flight data shown in Figure 34 clearly illustrate the greater intensity of turbulence near the ground surface, which is generated by wind shear and buoyancy. This is particularly evident in the time series of the scalars. Furthermore, there is a visible correlation between altitude and the scalars, showing a decrease of $T$ with height as expected in a CBL. Moisture and CO$_2$ also generally decrease with height, although the CO$_2$ very close to the surface increases slightly with height. This is consistent with the negative mean $F_{CO2}$ at the lowest flight level, which indicates absorption of CO$_2$ by the land surface. The large moisture source at the surface (i.e., evapotranspiration) is
consistent with the relatively low height of the CBL (~400 m, see Figure 38), which is a consequence of a relatively low contribution of buoyancy (SH) and strong LE. June 2007 was the wettest month of June on record in Oklahoma and, therefore, these observations are not surprising. The entire flight displayed in Figure 34 was performed between 1:45 p.m. and 3 p.m. At this time of the year, when the winter wheat crops are senescent and the summer corn crops are not yet growing, the vegetation photosynthesis activity is low and, correspondingly, the sink of CO$_2$ is small.

Figure 39 presents the spectra of atmospheric variables from Leg 14 (see also the raw data in Figure 35). Note that data are normalized to zero mean and unit variance, so units of the spectra are Hz$^{-1}$. The reason for selecting this lowest-altitude triangle is that the near-surface flights are the most challenging to process, given the variations of altitude due to topographical features as well as various obstacles on the ground that need to be avoided (e.g., power lines, trees, houses, etc.). Furthermore, wind shear near the ground affects the stability of the HOP. Additionally, observations in the near-surface layer are the special niche of the HOP among airborne platforms (as noted in Chapter 2), which makes these observations particularly well suited for investigating LSH interactions with the ABL. Considering that the spectra for Leg 15 and Leg 16 are quite similar, the figures and discussion here focus on Leg 14, for brevity.
Figure 39: Normalized spectra of $u$, $v$, and $w$, $T$, $H_2O$ ($q$), and $CO_2$ ($C$) from Leg 14, with red dotted lines for -5/3 slopes

Some aspects of the HOP can be noted here, with several similarities to the spectra in Figure 6 (see Section 3.3.1). Sensor output limitations dictate that the highest frequency of data available for data is $\sim$10 Hz. The Jet Ranger’s main rotor (two blades) spins at 396 RPM ($\pm$1-2%), generating the disturbance peak at $\sim$13 Hz, which can be found in all spectra. The inertial subrange appears with a slope of -5/3 up to sensor limit at $\sim$10 Hz in all spectra, as expected from Kolmogorov Theory. The exception is the $w$ spectra, which shows a slope less than the expected -5/3. This phenomenon is seen consistently in only the lowest-altitude flight legs, when the HOP is operating just above the ground level or canopy top. In flight legs collected anywhere in the ABL other than the lowest-altitude, the $w$ spectra follow a -5/3 slope quite consistently. This could be the result of a relatively greater contribution to the turbulent $w$ in the higher frequency
range, possibly due to the close proximity to the ground surface and more influence from turbulence intensity from smaller-scale shear than larger-scale buoyancy in this altitude range, which may lead to the appearance of a “flatter” spectral slope for the \( w \) spectra. It is also possible that the spectral slope is influenced by the fact that in the lowest-altitude flight legs, the HOP flies close to the ground, following the terrain when possible, and increasing altitude for power lines, etc., which could explain the differences from spectra collected from low-altitude towers (e.g., Kaimal et al. 1972). This is clearly an issue that warrants further study, and the HOP CLASIC dataset provides a notable opportunity for such discovery (see Section 8.2).

As discussed in Section 3.3.1, higher-frequency sensors may yield spectra with a further continuation of the -5/3 slopes above \( \sim10 \) Hz, as seen in Figure 39. Nevertheless, flights so close to the land surface include the risk of potential damage to delicate instrumentation, particularly due to dust and insect collisions. The choice of a robust instrument suite for the HOP is accompanied by a loss of higher sensitivity. As explained below, given the negligible impact that higher frequencies have on the calculation of the turbulence fluxes, this is an acceptable compromise for these types of research missions.

Some of the cospectra between the wind components and \( T, q, \) and \( C \) are shown in Figure 40. As in Figure 39, these data are normalized to zero mean and unit variance, so units of the cospectra are \( Hz^{-1} \). The subrange slopes of the cospectra are close to -5/3
(red dotted lines), and the cospectra of Leg 15 and Leg 16 are very similar (as with the spectra), so only cospectra from Leg 14 is presented, for brevity. Previously, Lumley (1964), Kaimal et al. (1972) and Kader and Yaglom (1991) obtained cospectral subrange slopes of -7/3, and Wyngaard and Cote (1972) report a -3 slope. However, more akin to the results shown in here, Van Atta and Wyngaard (1975), Wyngaard et al. (1978), and Antonia and Zhu (1994) observed a -5/3 cospectral slope. Similar to the aforementioned issue of the lower-altitude w spectral slope less than -5/3, this is certainly a question deserving further consideration, and the HOP CLASIC dataset provides ample opportunity for relevant study (see Section 8.2).

Figure 40: Normalized cospectra of uw, vw, uv, wT, wq, and wC from Leg 14, with red dotted lines for -5/3 slopes
7.2 EMD and the H11 Method

Figures 41, 42 and 43 show some of the IMFs obtained for the $w$, $T$, and $H_2O$, respectively. Specifically, the figures show the highest-frequency IMF ($IMF_0$) and the four lowest-frequency IMFs ($IMF_{-3}$, $IMF_{-2}$, $IMF_{-1}$, and $IMF_t$) as calculated from Leg 14 (see Figure 34 for the raw data). This analysis was also performed for the other variables and for all flight legs, but their inclusion would add no additional insights, so for brevity, they are not presented here.

Figure 41: (top to bottom) $IMF_0$, $IMF_{-3}$, $IMF_{-2}$, $IMF_{-1}$, and $IMF_t$ for $w$ from Leg 14
Figure 42: Same as Figure 41, but for $T$

Figure 43: Same as Figure 41, but for $H_2O$
IMF₀ represents the high-frequency noise that is associated with the sensor and has no physical meaning. The spectra of IMF₀ show flat (zero) slopes, which indicates that the information contained in this highest-frequency IMF is predominantly noise. Often, this can be seen in the spectra of the raw data as well; for example, note the near-zero slope region on the high-frequency end (about 10 Hz and higher) of the T spectra in Figure 39. Interestingly, the flattened slope of the IMF₀ spectra is not always evident in the raw data spectra. Due to the adaptive nature of EMD, each mode contains a range of frequencies, so the contributions from IMF₁ may have an influence in the IMF₀ range of the raw data spectra.

Another reason to remove IMF₀ (aside from instrument noise contributions) is that this mode also contains the signal of the main rotor of the Jet Ranger at 13 Hz, which can be seen as a spike in the same figure, particularly in the spectra of the winds. The elimination of IMF₀ from the original time series is straightforward, and has no practical impact on the variables, their variances or their covariances (i.e., kinematic fluxes). In fact, as can be seen in Table 9 (described in more detail later), which summarizes the impact of the removal of IMFs on turbulent flux calculations, removing IMF₀ changes the SH and FCO₂ by only ~1%, the LE by only ~0.1%, and the TKE by 3%.

The residual of the EMD algorithm, which is the lowest-frequency mode (IMF₀), contains the general trend of the time series and its elimination has the effect of detrending the collected data. Its impact on the variances and covariances is often quite
significant. In addition, it is often apparent that this IMF should be eliminated, along with IMF_{t-1}, because they complete only about two complete cycles, or less, throughout each flight leg, which is not adequate to resolve covariances from a statistical standpoint. Therefore, the inclusion or elimination of IMF_{t} and/or IMF_{t-1} should be individually determined, taking into account the circumstances of each flight leg.

Further justification is considered necessary for the detrending of any other lower-frequency IMFs, and because the relationship of an IMF to the physics of an observed variable is not always straightforward, a correlation analysis is introduced to assist in identifying spurious contributions to the atmospheric turbulence signal. Possible undesirable contributions could include: 1) non-stationarity of the atmosphere observed during the flight leg, 2) altitude variations, and 3) pitch, roll and yaw (attitude) movements of the HOP. The altitude and attitude changes of the HOP are inspected in this correlation analysis because such movements through areas of the ABL with strong stratification could lead to spurious contributions to flux calculations. Since such fluctuations are expected to occur over time scales of at least a few seconds, the lower-frequency IMFs are expected to carry these fluctuations. As will be discussed following, the characteristics of this correlation analysis and the procedure for detrending the identified spurious correlations present the most significant difference between DEMD and the initial method proposed by H11.
Table 8 presents the correlation analysis between these parameters and the progressive sum of IMFs (i.e., IMF\(_i\), IMF\(_{i-1}\), IMF\(_{i-1|-1}\), etc.) for the time series of some of the atmospheric variables from Leg 14. As discussed in Section 6.1.3, the \(r^2\) cutoff filter is applied for \(r^2 < 0.10\), and correlations surpassing this filter are shown in bold type in Table 8. As explained in Sections 5.3 and 6.1.2, the correlation analysis for the H11 method only examines the progressive sums of IMFs (e.g. IMF\(_i\), IMF\(_{i-1}\), IMF\(_{i-1|-1}\), IMF\(_{i-2}\), IMF\(_{i-1|-1}\), IMF\(_{i-2}\) for the three lowest-frequency modes), whereas DEMD prescribes a correlation analysis on all of the possible combinations of additive IMFs. So with DEMD, the IMFs examined for the three lowest-frequency modes include: IMF\(_i\), IMF\(_{i-1}\), IMF\(_{i-2}\), IMF\(_{i-1|-1}\), IMF\(_{i-2}\), IMF\(_{i-1|-1}\), IMF\(_{i-2}\). For the purposes of comparison, and for a more concise presentation, Table 8 presents the correlation analysis for the H11 method.

As an example, the first line of the table shows the \(r^2\) (square of the Pearson’s correlation coefficient \(r\)) values as calculated from the HOP altitude \((z)\) and the successive IMFs of \(u\). In this case, the H11 method dictates the elimination of IMF\(_{i-1}\) for \(u\), and eliminating IMF\(_{i-1|-1|-2}\) is stipulated for \(v\), \(w\), and \(T\). The last four IMFs of \(T\) exhibit a correlation with yaw, so these IMFs would be eliminated as well. This correlation is likely due to the aerodynamics of the sensor mount, which is designed to protect the fragile thermistor. Note that due to the correlation of IMF\(_{i-3}\) of \(C\) with roll, H11 would dictate the removal of IMF\(_{i-1|-1|-2|-3}\).
Table 8: Correlation analysis for atmospheric data IMFs and HOP altitude and attitude from Leg 14, with $r^2 > 0.10$ shown in bold type

<table>
<thead>
<tr>
<th></th>
<th>IMF₀</th>
<th>IMF₁⁺</th>
<th>IMF₂⁺</th>
<th>IMF₃⁺</th>
<th>IMF₄⁺</th>
<th>IMF₅⁺</th>
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<td>0.06</td>
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<tr>
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<td><strong>0.19</strong></td>
<td>0.08</td>
</tr>
<tr>
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<td>0.00</td>
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<td>...</td>
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<td>0.04</td>
<td>0.08</td>
<td>0.01</td>
</tr>
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<td>0.01</td>
<td>0.03</td>
<td><strong>0.10</strong></td>
</tr>
<tr>
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<td>...</td>
<td>0.07</td>
<td>0.01</td>
<td>0.02</td>
<td>0.01</td>
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<tr>
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<td>0.00</td>
<td><strong>0.13</strong></td>
<td><strong>0.18</strong></td>
</tr>
<tr>
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<td>...</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.01</td>
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<tr>
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<td>...</td>
<td>0.00</td>
<td>0.02</td>
<td>0.01</td>
<td><strong>0.10</strong></td>
</tr>
<tr>
<td>C and pitch</td>
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<td>...</td>
<td>0.02</td>
<td>0.00</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
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<td>0.00</td>
<td>0.01</td>
<td>0.05</td>
<td><strong>0.21</strong></td>
</tr>
<tr>
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<td>0.05</td>
<td><strong>0.40</strong></td>
</tr>
<tr>
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<td>0.00</td>
<td>0.03</td>
<td>0.02</td>
<td><strong>0.20</strong></td>
</tr>
<tr>
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<td><strong>0.13</strong></td>
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<td>0.04</td>
<td><strong>0.11</strong></td>
</tr>
<tr>
<td>C and yaw</td>
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<td>...</td>
<td>0.02</td>
<td>0.02</td>
<td>0.03</td>
<td><strong>0.14</strong></td>
</tr>
</tbody>
</table>

Figure 44 illustrates the impact of removing various IMFs from the data on the variable spectra, as suggested by H11. Black lines represent spectra of the raw data, and colored lines show spectra after the removal of subsequent progressive sums of IMFs on both the high- and low-frequency ends of the spectra. Unlike the spectra shown in Figure 39, the data was not normalized for the spectra in Figure 44, so that the raw and
filtered spectra are aligned. The removal of IMFs has a consistent and unsurprising effect on the spectra, reducing the spectra more with each additional IMF eliminated.

**Figure 44:** As in Figure 38 (in black), with colored lines showing spectra filtered by eliminating successive high- and low-frequency IMFs

To further demonstrate the impact of IMF removal, Table 9 presents the resulting CBL end products, including SH (W m$^{-2}$), LE (W m$^{-2}$), F$_{CO_2}$ (mg m$^{-2}$ s$^{-1}$), and TKE (m$^{2}$ s$^{-2}$). The first row shows the fluxes as calculated from the raw data, and the second row shows the resulting fluxes when IMF$_0$ is removed from both variables. The third row of Table 9 shows fluxes calculated from data with IMF$_1$ removed from each variable, and subsequent rows have additional cumulative sums of low frequency IMFs removed from both variables before the flux calculation. It is interesting to note that the impact of the removal of subsequent IMFs is quite nonlinear and that it is not possible, a priori, to
estimate the impact of eliminating a particular IMF on the fluxes. Indeed, in some cases the removal of a specific IMF decreases the variance of a given variable while the following IMF might increase it. For example, the SH and LE resulting from the removal of IMF_{ℓ} are higher in magnitude and the SH and LE resulting from the removal of only IMF_{ℓ}, and this phenomenon is not seen in the F_{CO2} or TKE results in Table 9.

Table 9: The impact IMF removal on CBL end products for Leg 14, with “Best Estimate” values calculated using the H11 method

<table>
<thead>
<tr>
<th>IMFs removed</th>
<th>SH (W m⁻²)</th>
<th>LE (W m⁻²)</th>
<th>F_{CO2} (mg m² s⁻¹)</th>
<th>TKE (m² s⁻²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>None (raw data)</td>
<td>60.1</td>
<td>118.5</td>
<td>-0.733</td>
<td>1.35</td>
</tr>
<tr>
<td>IMF₀</td>
<td>60.6</td>
<td>118.6</td>
<td>-0.729</td>
<td>1.31</td>
</tr>
<tr>
<td>IMFₖ</td>
<td>59.7</td>
<td>104.0</td>
<td>-0.701</td>
<td>1.25</td>
</tr>
<tr>
<td>IMF_{ℓ}</td>
<td>60.6</td>
<td>117.7</td>
<td>-0.639</td>
<td>1.11</td>
</tr>
<tr>
<td>IMF_{ℓ}</td>
<td>52.9</td>
<td>105.0</td>
<td>-0.577</td>
<td>0.87</td>
</tr>
<tr>
<td>IMF_{ℓ}</td>
<td>30.0</td>
<td>77.7</td>
<td>-0.409</td>
<td>0.65</td>
</tr>
<tr>
<td>Best Estimate</td>
<td>36.6</td>
<td>117.3</td>
<td>-0.548</td>
<td>1.05</td>
</tr>
</tbody>
</table>

The “Best Estimate” flux values in Table 9 are calculated by filtering low-frequency IMFs for each variable according to the H11 method, using the \( r^2 \) values shown in Table 8 and the associated correlation analysis described previously. For example, H11 prescribes the removal of IMF_{ℓ} for \( w \) (due to correlations with altitude and pitch) and the removal of IMF_{ℓ} for \( T \) (due to correlations with yaw).

Therefore, the “Best Estimate” calculation of SH uses \( w \) with IMF_{ℓ} removed and \( T \) with IMF_{ℓ} removed, and predictably, the “Best Estimate” value for SH falls between the SH calculated by removing IMF_{ℓ} from both variables and the SH
calculated by removing IMF_{ℓ-1|ℓ-2|ℓ-3} from both variables. As another example, the “Best Estimate” calculation of LE combines \( q \) with IMF_{ℓ-1} removed and \( w \) with IMF_{ℓ-1|ℓ-2} removed, and results in a value between those calculated by removing IMF_{ℓ-1} and IMF_{ℓ-1|ℓ-2} from both variables. For Leg 14, the H11 method leads to a significant reduction in the absolute magnitude of SH, F_{CO₂}, and TKE, which is a cause for concern, as discussed in detail below.

7.3 DEMD Results

To further demonstrate DEMD results and expand the comparison with H11, Leg 14, Leg 15, and Leg 16 (see the raw data in Figures 34, 35, and 36) were processed using both the H11 and DEMD methods. As described previously (see Chapter 5), DEMD begins with the application of EMD to preprocessed meteorological data, including \( u, v, \) and \( w, T, q, \) and \( C \) (generically symbolized by \( \psi \)), which separates each time series into a finite set of IMFs. For each \( \psi \) time series, the six lowest-frequency individual IMFs and all possible additive combinations of those IMFs are correlated with time series of HOP position (generically symbolized by \( \phi \)), including altitude and attitude (pitch, yaw, and roll). The cutoff at six low-frequency IMFs is considered sufficient, because the frequency range of IMF_{ℓ-5} is consistently higher than that of the relevant HOP motions (i.e. variations in altitude, pitch, roll, and yaw). Correlation matrices are formed for each \( \psi \) and \( \phi \) combination (including the raw \( \psi \)), and maximum coefficients of determination (\( r^2 \)) above a threshold of \( r^2 > 0.10 \) are noted
(referred to as the $r^2$ cutoff filter in Section 6.1.3). The maximum $r^2$ value and associated slope ($m$) for each $\psi$ correlation matrix are used in Eq. (8) below, which is a generalized version of Eq. (7), derived previously (see Section 5.4):

$$\psi_\alpha = \frac{1}{m_\alpha} \phi' \left( r^2_\alpha \right)$$

(8)

$$\psi_d = \psi + \psi_\alpha$$

(9)

where $r^2_\alpha$ is the maximum $r^2$ value for a particular $\psi$ correlation matrix, $m_\alpha$ is the slope associated with $r^2_\alpha$, $\phi'$ is the variation from mean of the HOP position time series associated with $r^2_\alpha$, and $\psi_\alpha$ is the DEMD correction array, which is applied (by linear addition) to $\psi$, yielding the detrended data $\psi_d$, as shown in Eq. (9).

Table 10 shows the impact of applying DEMD and H11 techniques to HOP data on several CBL end products: SH (W m$^{-2}$), LE (W m$^{-2}$), $F_{\text{CO}_2}$ (mg m$^{-2}$ s$^{-1}$), and TKE (m$^2$ s$^{-2}$). Note that the raw data and H11 method values for Leg 14 are the same as those from Table 9. For the three legs, the TKE drops an average of 36.0% using the H11 method, and only 4.11% with DEMD. The flux deviations (averaging the change for the three legs) are 49.6% for SH, 6.31% for LE, and 58.6% for $F_{\text{CO}_2}$ with H11, compared to 17.2% for SH, 4.00% for LE, and 5.19% for $F_{\text{CO}_2}$ with DEMD. Focusing on the SH calculated for Leg 14, H11 dictates removal of the three lowest-frequency IMFs ($\text{IMF}_{\ell \leq 1}$) for $w$ and removal of the four lowest-frequency IMFs ($\text{IMF}_{\ell \leq 1}$) for $T$. This leads to a reduction in the variance from 0.2648 m$^2$ s$^{-2}$ to 0.1986 m$^2$ s$^{-2}$ (25.0% loss) for $w$, and from 0.0885 K$^2$ to
0.0461 K² (47.9% loss) for T, which clearly contributes to the 39.0% reduction of SH.

Contrarily, DEMD prescribes a correction adjustment using the appropriate $m_α$ and $r_α^2$ from IMF_{i-3} of $w$ with $z$, and then from IMF_{i-3:i-4} of $T$ with $z$. This yields a variance drop from 0.2648 m² s⁻¹ to 0.2344 m² s⁻¹ (11.5% loss) for $w$, and from 0.0885 K² to 0.0774 K² (12.5% loss) for $T$, and results in only a 2.20% reduction of SH.

Table 10: Impacts of H11 and DEMD methods on Legs 14, 15, and 16

<table>
<thead>
<tr>
<th></th>
<th>SH (W m⁻²)</th>
<th>LE (W m⁻²)</th>
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<tbody>
<tr>
<td></td>
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<td>H11</td>
</tr>
<tr>
<td>Detrend 14</td>
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<td>36.62</td>
</tr>
<tr>
<td>Leg 15</td>
<td>103.0</td>
<td>67.90</td>
</tr>
<tr>
<td>Leg 16</td>
<td>26.33</td>
<td>46.29</td>
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<tr>
<td>Leg 14</td>
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<td>117.3</td>
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<td>Leg 15</td>
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<tr>
<td>Leg 16</td>
<td>44.62</td>
<td>48.53</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>FC02 (mg m⁻² s⁻¹)</th>
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<tr>
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</tr>
<tr>
<td>Leg 15</td>
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</tr>
<tr>
<td>Leg 16</td>
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</tr>
<tr>
<td>Leg 14</td>
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<td>1.049</td>
</tr>
<tr>
<td>Leg 15</td>
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<td>0.9700</td>
</tr>
<tr>
<td>Leg 16</td>
<td>1.344</td>
<td>0.7510</td>
</tr>
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</table>

Applying DEMD to Leg 14 $u$ data presents a real-world example of the next $r^2$ check (see Section 6.1.3). Table 8 shows correlations beyond the $r^2$ cutoff filter for $u$ with $z$ ($r^2 = 0.18$ for IMF_{ℓ:1}), pitch ($r^2 = 0.10$ for IMF_{ℓ:1}), and yaw ($r^2 = 0.21$ for IMF_{ℓ:1}), so H11 would dictate the removal of IMF_{ℓ:1} from $u$, as discussed in Section 7.2. DEMD uses all possible combinations of IMFs in the correlation analysis to find a new correlation with roll ($r^2 = 0.11$ for IMF_{ℓ:1:2:ℓ:6:17}), and a higher $r^2$ with pitch ($r^2 = 0.14$ for IMF_{ℓ:3:ℓ:6}), while correlations with $z$ and yaw are unchanged. DEMD takes the highest $r^2$ value (from $u$ and yaw) as $r^2_α$ and the slope from that correlation as $m_α$, and detrends the data with
Eq. (8) and (9), using $u$ as $\psi$ and yaw as $\phi$, to obtain the detrended $u_d \ [\psi'_d$ in Eq. (9)].

The next $r^2$ check involves forming a correlation matrix for $u_d$, which results in higher correlations with $z$ ($r^2 = 0.20$ for IMF$_{41(4-5)}$, roll ($r^2 = 0.17$ for IMF$_{41(1-5|4-6)}$, pitch ($r^2 = 0.18$ for IMF$_{41(1-5)}$, and yaw ($r^2 = 0.42$ for IMF$_{41(1-5)}$), and this initial $u_d$ is rejected. Returning to the original correlation matrix for $u$, the next highest $r^2$ (from $u$ and $z$) is taken as $r^2_\alpha$, and the associated $m_\alpha$ and Eq. (8) and (9), now with $u$ as $\psi$ and $z$ as $\phi$, are used to produce a new $u_d$. A correlation analysis of this new $u_d$ results in lower correlations with $z$ ($r^2 = 0.11$ for IMF$_{41(1-5|4-6)}$, roll ($r^2 = 0.10$ for IMF$_{41(1-5|4-6)}$, and yaw (no $r^2 > 0.10$), and only a very slight increase with pitch ($r^2 = 0.11$ for IMF$_{31(1-4}$ compared to $r^2 = 0.11$ for the raw $u$ data), so this $u_d$ is accepted as properly detrended data.
8. Conclusions

8.1 Discussion

The interaction of land-surface heterogeneity (LSH) at different scales with atmospheric boundary layer (ABL) processes, and in particular, the vertical propagation scale of this interaction, has been studied for decades via modeling and observational analyses. An assessment of the validity of current blending height theory as the appropriate metric for this vertical propagation scale suggests further study combining model simulations and observations with a pertinent atmospheric dataset. This thesis provides an extensively tested method for collecting and properly detrending relevant atmospheric turbulence data for the observational portion of this suggested study.

The Duke University helicopter observation platform (HOP) presents unique capabilities as an airborne platform for in situ measurements of atmospheric turbulence data at slow airs speeds and at any vertical level of the ABL, down to just above the land-surface, which is not possible with previous airborne platforms. Slower airs speeds translate to a higher resolution for measurements of ABL fluxes over a given horizontal length scale, and the formerly unavailable range of altitudes in the ABL that the HOP has the capacity to observe provides a significant opportunity to study the vertical propagation of LSH effects on ABL processes.

Analytical, numerical, and observational studies identify the airs speeds at which the main rotor downwash does not interfere with HOP measurements. In particular, the
analytical study finds HOP airs speeds greater than 10 m s$^{-1}$ acceptable to separate the
downwash from the HOP nose, noting that the sensors are even farther forward from
the nose. Numerical simulations also take into account an area of compressed air that
commonly forms in front of any aircraft, increasing in size with higher airs speeds, and
narrow the range of optimal HOP sampling airs speeds to 20-40 m s$^{-1}$. Two observational
studies offer further endorsement of HOP capabilities, first with a range of HOP
airs speeds over a homogeneous marine boundary layer (MBL), where no discernable
impact of different airs speeds was found for a range of ~18 m s$^{-1}$ to ~55 m s$^{-1}$. The second
study compares HOP measurements to those from similar instruments on a tower, the
Duke University Mobile Micrometeorological Station (MMS), and finds that the HOP
fluxes of sensible heat (SH), latent heat (LE), and carbon dioxide (FCO$_2$) generally show
acceptable agreement (within one standard deviation) with MMS observations.

Atmospheric turbulence data is collected from the HOP with the AIMMS-20 and
LI-7500 sensors to provide high-frequency measurements of $u$, $v$, and $w$ winds and CO$_2$
and H$_2$O concentrations at a frequency of 40 Hz throughout the ABL. The HOP also
provides an in-flight capability for ABL height estimation via a real-time display of $\theta$
during vertical profiling flight segments, which, in turn, dictates instantaneous flight
planning. Calibration and alignment procedures for the relevant HOP sensors support
their application for ABL measurements, and significant disturbances to the raw data are
adjusted to maintain the characteristics of the raw data while eliminating obviously anomalous influences.

With any airborne platform, aircraft movements can introduce an undesirable contribution to atmospheric measurements. This effect can be accentuated in HOP flights, since slow airspeeds and near land-surface flight paths introduce the increased complexities of large wind disturbances and movements to avoid artificial structures and topographical variations, thereby creating highly variable flight paths. A common example arises in a vertically stratified ABL, where these HOP altitude variations can introduce spurious contributions to measured $T$ that require detrending before the calculation of any relevant ABL end products (such as SH).

Towards detrending data for these spurious contributions, empirical mode decomposition (EMD) is introduced as a mechanism to separate the raw HOP data into a finite set of intrinsic mode functions (IMFs). EMD is adaptive and based on the local characteristic time scale of the data, which provides applicability to non-linear and non-stationary processes, and particular relevance for HOP measurements. Previous studies have shown physical interpretations of IMFs, which suggests the potential for isolation of aircraft motion influences from atmospheric turbulence dynamics.

Detrending with EMD (DEMD) is demonstrated as an effective method to identify and correct for spurious signals. The technique uses a correlation analysis between lower-frequency IMFs of atmospheric turbulence data and HOP motions to
determine probable spurious interactions. The crux of DEMD is that data is adjusted to account for spurious signals by incorporating the characteristics of that signal, as shown in Eq. (8) and (9). Specifically, the disturbance is quantified as the magnitude of the HOP motion perturbation divided by the linear regression slope ($m$) of the determined correlation. The detrending of this disturbance is weighted by the magnitude of the correlation ($r^2$) to account for its proportional contribution to the total variance.

Synthetic datasets of two-dimensional $T$ fields provide an imitation of HOP datasets with prescribed conditions, allowing for an assessment of DEMD efficacy. An approximation of the dry adiabatic lapse rate (-10 K km$^{-1}$) is superimposed with $T$ perturbations, and sampling paths through the field generate $w$ and $T$ time series, with variations of the $T$ perturbation and sampling path characteristics yielding a total of 672 test cases. Two filtering criteria (the $r^2$ cutoff filter and the $S/T$ ratio filter) help identify conditions suitable for DEMD, and a third (the next $r^2$ check) provides quality control. DEMD was applied to the remaining 552 test cases, with an average lapse rate recovery of $-9.990 \pm 1.093$ K km$^{-1}$ (within 1%) and an $r^2 = 0.9676 \pm 0.0708$.

Vertical cross sections taken from the Ocean-Land-Atmosphere Model (OLAM) large-eddy simulation (LES) results enable an evaluation of the ability of DEMD to recover a relevant ABL end product, and couple the advantages of a complex dataset and a known target value. LES resolution is 15 m horizontal and 10 m vertical (for the lowest 1 km), and is interpolated horizontally to 10 m resolution for the cross sections,
which are 1 km high and about 13.3 km long. Sampling paths with varied characteristics generate a total of 240 samples of three vertical cross sections at 100 m vertical intervals from 100 m to 800 m. Within the convective boundary layer (CBL), DEMD noticeably improves the accuracy of SH recovery, reducing scatter and aligning detrended SH with cross section profiles. Vertical profiles of SH in the cross sections differ significantly from each other and from the full LES horizontally averaged profile. This deviation indicates typical sampling error for these length scales, and suggests similar challenges for aircraft-based observations that target characterization of a sampling area.

Three HOP flight legs from a low altitude (just above the ground surface) triangular pattern flown on 19 June 2007 during the Cloud and Land Surface Interaction Campaign (CLASIC) demonstrate DEMD application to atmospheric turbulence measurements. Near-surface observations add challenge to the detrending, given the wind shear effects on HOP stability and the altitude variations due to topography and obstacles, while they also emphasize the unique altitude range of the HOP. The highest-frequency IMF (IMF₀) embodies instrument noise and the main rotor signal at 13 Hz, and is removed from the raw data, resulting in a minimal effect on ABL fluxes.

Detrending the HOP data also presents an opportunity to compare DEMD to the initially proposed method (Holder et al. 2011, hereafter H11). The primary difference between the DEMD and H11 detrending algorithms is that H11 prescribes the removal of cumulative lower-frequency IMFs of atmospheric data that correlate with HOP
motions, which incorporates the elimination of any atmospheric turbulence dynamics embedded in those IMFs. As suspected, this leads to drastic reductions in variances and turbulence kinetic energy (TKE), as well as significant deviations in fluxes compared to DEMD (see Table 10). In particular, the average flux reduction for DEMD is 7.63%, compared to 37.63% for H11 (averaging the three flight legs, and then the TKE, SH, LE, and Fco2 reductions). Focusing on SH and its constituents for the first flight leg, the H11 method reduces $w$ and $T$ variances by an average of 36.5%, and SH by 39.0%, whereas DEMD reduces $w$ and $T$ variances by an average of 12.0%, and SH by only 2.20%. Succinctly, DEMD provides data adjustment without unnecessary elimination. As a detrending technique, DEMD is recommended for use in future ABL studies involving in-situ measurements from helicopter-based or other similar aircraft-based instrument platforms. A strategy for future research combining DEMD-processed CLASIC HOP measurements with OLAM simulations to investigate LSH interactions with ABL processes and evaluate blending height formulations is presented in the next section.

8.2 Future Research

CLASIC was a coordinated effort of multi-platform measurements including four different satellites, seven different aircraft (including the HOP) and multiple surface measurements at several sites. The primary goal of CLASIC was to improve understanding of cumulus convection processes especially as they relate to land surface conditions, with the aim of translating this understanding to climate modeling
improvements. The original reason for conducting CLASIC in June 2007 was to observe areas in Oklahoma before and after the winter wheat harvest, which would have led to extensive changes in land-surface properties such as albedo, SH, and LE. However, due to unusually high levels of precipitation during June, typical harvesting was not conducted, and only 10 days of HOP flights were possible (22 flights). Therefore, the flight plan was updated to include 13 additional measurement flights in August, resulting in a total of 35 flights, approximately 100 h of data between the two months. The contrast between the abnormally wet conditions of June and more typical summer conditions of August provide an opportunity to investigate LSH effects in different hydrological regimes.

Flights during CLASIC were conducted at several different sites, providing a variety of LSH conditions (see Table 11). The Atmospheric Radiation Measurement (ARM) Central Facility (CF) is located near Lamont, OK and almost half of the flights (15) during CLASIC were conducted there (10 in June and 5 in August). Five flights (1 in June and 4 in August) were at Okmulgee ARM Extended Facility (EF) 21, also called the forest site (FS). Five flights (4 in June and 1 in August) were conducted at the Fort Cobb watershed (FC), including several passes over Fort Cobb Lake. Finally, there were five flights (all in June) near Little Washita (LW) ARM EF-24. Finally, Table 11 also mentions two A-Train Satellites overpasses (Overpass), two CO2 Lagrangian sampling flights (Lagrangian), and a flight profiling radon (Radon).
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An example of a typical CLASIC HOP flight is discussed in Section 7.1, and time series of the full flight is shown in Figure 33. Triangle flight patterns at different altitudes were flown at three sites (CF, FS, and FC), and they present a variety of LSH regimes. A regular patchwork of agricultural fields populate the CF area, and although the roads divide the fields into very regular patterns, groups of the same land cover types are aggregated in some areas. The FS site has a mixture of vegetation and bare land, with Okmulgee Lake nearby. The land cover at FS is more aggregated on a larger scale, with a mostly forested area to the east and northeast, while the west and
northwest is sparser, and the watershed continues to the southwest. Finally, the FC site is dominated by Fort Cobb Lake, which is much larger than Okmulgee Lake, and two of the triangle pattern legs spend significant time passing directly over the water. Such conditions may lead to the formation of an internal boundary layer (Mahrt 2000).

The CLASIC HOP dataset provides a unique opportunity to study LSH effects on ABL processes, with particular attention to the efficacy of blending height formulations. First, DEMD application is essential for HOP data, to ensure accurate scalars and fluxes, as indicated by the results in Figures 29, 30, and 31 and the discussion in Section 7.3, with particular attention to Table 10. The detrended dataset contains multiple flights at CF, FS, and FC, with a distinct LSH scale at each site, and at least one flight for each site in wet June and dry August. Remembering the wide altitude range observed by the HOP, the potential for exploring LSH influences is exceptional. However, Section 1.2 suggests that for a complete analysis, these data should be combined with a modeling study of the observed ABL and LSH conditions.

An appropriate numerical model to compliment the CLASIC HOP observations is the Ocean-Land-Atmosphere Model (OLAM), a numerical model based on the Regional Atmospheric Modeling System (RAMS), as described by Pielke et al. (1992) and Cotton et al. (2003). OLAM retains several features from RAMS, including physical parameterizations and many coding and procedural aspects, but incorporates a new dynamic core, including a spherical triangle- or hexagonal-based geodesic grid with the
A key component of OLAM is its local mesh-refinement capabilities, which allow for a larger-scale global horizontal resolution that can telescope to higher resolutions in particular areas of interest (e.g., CF, FS, and FC). A global grid of ~1° resolution should be sufficient to capture large-scale behavior for areas not being directly investigated. However, for the areas of interest, a much higher resolution is desired to obtain values that can be compared to the HOP data, as well as to capture ABL reactions to LSH at a variety of scales. The specific resolution required will be based on a trade-off between necessary computational time and the LSH length scales for the sites, but the highest horizontal resolution should be on the order of tens of meters.

A sensitivity analysis with adjustments to initial conditions should allow for a simulation that better reproduces observations. In particular, OLAM simulations can be compared to observed mesoscale circulations over Oklahoma and the surrounding area. The grid structure there requires a horizontal resolution that resolves mesoscale circulations. Soil moisture and surface water temperature will be important initial conditions to adjust during the sensitivity analysis, as it has been noted by Avissar.
(1992) and Avissar and Schmidt (1998) that water availability for evapotranspiration has a significant effect on SH and LE distribution. Alignment with mesoscale circulations is key, as they provide boundary conditions for the higher resolution areas that resolve large-eddy scale turbulence (at CF, FS, and FC).

Once the sensitivity analysis has produced OLAM simulations that represent well the observed mesoscale conditions, the OLAM mesh can be refined stepwise, while confirming the maintenance of well-represented mesoscale dynamics. HOP flux profiles can also be compared to horizontally- and temporally-averaged simulated flux profiles. Lower-altitude simulated fluxes can be compared to surface-measured fluxes from the ARM Southern Great Plains (SGP) facilities tower data collected during CLASIC.

Note that CLASIC collaborators produced 56 m horizontal resolution land cover categorization image using Advanced Wide Field Sensor (AWiFS) images. The final image has been compiled from April and August of 2007 to compensate for significant cloud cover during the study period. This data can provide characteristic LSH scales for the three CLASIC sites using a two-dimensional autocorrelation analysis (following Detto et al 2008). The highest-resolution mesh areas in the OLAM simulations could use this dataset to replace the model’s current land cover dataset.

While the CLASIC HOP data provides essential in-situ ABL observations, these data are limited by their location and time of collection. OLAM simulations enable exploration of the temporal and spatial evolution of scalars and fluxes of momentum,
heat and moisture. This evolution is driven by LSH and then undermined by the dissipative properties of the ABL turbulence that they helped create. LSH influence propagates vertically into the ABL to the blending height, and this limit changes with the ABL height and local conditions (Molod et al 2003).

Albertson and Parlange (1999) noted lower blending heights for scalars than for fluxes, and lower values for LE than for SH. Mahrt (2000) gives different formulations for thermal and momentum blending heights, and notes a common shortcoming in their failure to incorporate the amplitude of LSH, thereby hindering prediction of the ABL response amplitude. Therefore, OLAM results should evaluate theoretical predictions with consideration for potential scalar/flux differences and LSH amplitude influences.

Several different methods accommodate blending height characterization. For example, vertical cross sections of OLAM results along the prevailing mean wind direction could reveal turbulent structures scaling with LSH. Blending heights may also be investigated by plotting vertical profiles of coefficients of variation (CV) of key scalars and fluxes (e.g. Albertson and Parlange 1999, Huang and Margulis 2009). HOP data can provide CV by flight leg or shorter length scales, and OLAM results can be horizontally averaged for a wide range of scales for comparison. CV should be largest near the land-surface, and decrease up to the blending height. OLAM simulations will also provide the opportunity to examine the temporal evolution of blending height, and thereby the temporal influence of LSH on the ABL.
Finally, Section 7.1 notes some concerns with the spectra and cospectra observed in CLASIC HOP data (see Figures 38 and 39). This dataset contains a wide variety of LSH scales, meteorological conditions, and flight leg altitudes, providing a distinctive opportunity for relevant study. One potential topic for investigation is the $w$ spectra, which shows a slope shallower than the $-5/3$ expected from Kolmogorov Theory in the lowest-altitude flight legs. This anomaly appears only in HOP observations just above the land-surface or canopy top, with $w$ spectra collected higher in the ABL consistently exhibiting $-5/3$ slopes. Section 7.1 postulates that the dominance of small-scale shear over larger-scale buoyancy may cause the phenomenon, but further study is warranted.

Additionally, many HOP flight legs from CLASIC at a variety of altitudes exhibit $-5/3$ slopes for cospectra between wind components and $T$, $q$, and $C$, as in the cospectra shown in Figure 39. Inconsistency is abundant in the literature on cospectral slopes, with $-7/3$ slopes reported by Lumley (1964), Kaimal et al. (1972), and Kader and Yaglom (1991), a slope of $-3$ given by Wyngaard and Cote (1972), and $-5/3$ slope obtained by Van Atta and Wyngaard (1975), Wyngaard et al. (1978), and Antonia and Zhu (1994). This inconsistency could possibly be explained by constraining the turbulent flux budget equations, thus providing a coherent cospectral theory for the ABL. Dimensional analysis reveals mean wind shear and scalar concentration gradient intensities as potential significant influences on cospectral slopes, and these factors are closely related to LSH scales and atmospheric conditions.
References


